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**Working Paper**

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Working Paper, No. 2017-12

**Provided in Cooperation with:**

Federal Reserve Bank of Chicago

*Suggested Citation:* Aaronson, Daniel; Hartley, Daniel; Mazumder, Bhashkar (2017) : The effects of the 1930s HOLC "redlining" maps, Working Paper, No. 2017-12, Federal Reserve Bank of Chicago, Chicago, IL

This Version is available at:

<https://hdl.handle.net/10419/200568>

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Federal Reserve Bank of Chicago

## **The Effects of the 1930s HOLC “Redlining” Maps**

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and Bhashkar Mazumder*

August 3, 2017

WP 2017-12

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## **The Effects of the 1930s HOLC “Redlining” Maps\***

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Abstract: In the wake of the Great Depression, the Federal government created new institutions such as the Home Owners’ Loan Corporation (HOLC) to stabilize housing markets. As part of that effort, the HOLC created residential security maps for over 200 cities to grade the riskiness of lending to neighborhoods. We trace out the effects of these maps over the course of the 20<sup>th</sup> and into the early 21<sup>st</sup> century by linking geocoded HOLC maps to both Census and modern credit bureau data. Our analysis looks at the difference in outcomes between residents living on a lower graded side versus a higher graded side of an HOLC boundary within highly close proximity to one another. We compare these differences to “counterfactual” boundaries using propensity score and other weighting procedures. In addition, we exploit borders that are least likely to have been endogenously drawn. We find that areas that were the lower graded side of HOLC boundaries in the 1930s experienced a marked increase in racial segregation in subsequent decades that peaked around 1970 before beginning to decline. We also find evidence of a long-run decline in home ownership, house values, and credit scores along the lower graded side of HOLC borders that persists today. We document similar long-run patterns among both “redlined” and non-redlined neighborhoods and, in some important outcomes, show larger and more lasting effects among the latter. Our results provide strongly suggestive evidence that the HOLC maps had a causal and persistent effect on the development of neighborhoods through credit access.

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\*The authors thank participants at the spring 2016 Federal Reserve System Meeting on Applied Microeconomics, fall 2016 Federal Reserve System Meeting on Regional Economics, DePaul University, UIC, Vanderbilt University, University of Pittsburgh, University of Bergen, University of North Carolina, the Cleveland Fed and the NBER DAE. We also thank Leah Boustan, Bill Collins, Price Fishback, Jeff Lin, Raven Molloy, Allison Shertzer, Tate Twinam, and Randall Walsh for helpful comments. We are especially grateful to Joey Reiff for outstanding research assistance and The Digital Scholarship Lab at the University of Richmond for the digitized HOLC maps. The views expressed here do not necessarily represent the views of the Federal Reserve Bank of Chicago or the Federal Reserve System.

## **I. Introduction**

There is a growing recognition that place matters in determining socioeconomic success in the United States. Where you grow up is highly consequential for academic performance, economic mobility, and longevity (e.g. Reardon et al 2016; Chetty et al 2014, 2016). There are also striking differences in these same outcomes by race. It is therefore not surprising that researchers have long been interested in the possible role of residential segregation in explaining the wide disparities in outcomes by location (e.g. Cutler and Glaeser 1997; Cutler, Glaeser, and Vigdor 1999; Ananat 2007; Boustan 2011; Chetty and Hendren 2017). Our study focuses on one potentially important channel that could drive both place- and race-based differences, namely access to credit.

Our setting is the aftermath of the Great Depression, when the Federal Government undertook dramatic reforms to limit foreclosures and stabilize the housing market. One relatively minor component of these reforms was an effort to fundamentally change property appraisal practices. The Home Owners Loan Corporation (HOLC), a now-defunct but at the time new Federal agency, drew maps for over 200 cities in order to document the relative riskiness of lending to different neighborhoods. Neighborhoods were classified based on detailed information about housing age, occupancy, prices, and other related risk-based characteristics. However, non-housing characteristics such as the racial and ethnic makeup appear to have been influential factors as well. As a result, it has been hypothesized that the HOLC maps contributed to institutionalized racial discrimination in lending practices among financial institutions (Jackson 1980) and may have contributed to modern-day differences in neighborhood development. Since the lowest rated neighborhoods were drawn in red and often had high shares of black residents, these maps have been associated with the so-called practice of “redlining” in which borrowers are denied access to credit due to the racial composition of their neighborhood. Indeed, concerns over redlining in later decades prompted the Federal Government to pass legislation, most notably the 1968 Fair Housing Act (FHA), the 1974 Equal Credit Opportunity Act (ECOA), and the 1977 Community Reinvestment Act (CRA), which were designed to expand access to lending markets for families living in low and

moderate-income neighborhoods.<sup>1</sup> However, credit was also potentially restricted to neighborhoods scoring in the next lowest neighborhood grade marked in yellow, which has received much less public and academic attention.

A voluminous literature studies the channels in which restrictions on access to credit can limit the pathway to economic opportunity for disadvantaged households.<sup>2</sup> In total, that work makes a compelling case that policies that improperly restrict credit are potentially objectionable on the grounds of both equity and efficiency. Moreover, entire neighborhoods that are inappropriately deprived credit could suffer from insufficient investment and become further magnets for an array of social problems related to poverty.

We systematically analyze the impact of the HOLC maps on a range of outcomes using data from nearly the entire urban U.S. over the full period since the maps were drawn (1940 to 2010). This study has become feasible because The Digital Scholarship Lab at the University of Richmond has digitized and generously made available 149 of the city HOLC maps. We merge this geocoded information with (a) address level data from the 100 percent count of the 1910 to 1940 U.S. decennial Censuses (Minnesota Population Center and Ancestry.com, 2013), (b) census tract-level data from the 1950 to 1980 Censuses, and (c) block-level data from the 1990 to 2010 Censuses. This combination provides up to a century of data on household characteristics such as race, homeownership, house values, and population flows. We further merge block-level data on Equifax Risk Scores™ (credit scores) from the 1999 to 2016 Federal Reserve Bank of New York Consumer Credit Panel/Equifax (CCP) to capture even more detail about current credit conditions in urban neighborhoods.

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<sup>1</sup> It is worth noting that the practice of redlining remains an active concern in some cities (see e.g. Washington Post 5/28/15 and New York Times 10/30/15). Some recent lawsuits involve lending practices in New York City, Philadelphia, Buffalo, Chicago, Milwaukee, Miami, and Los Angeles, and there are on-going investigations at the Consumer Financial Protection Bureau and Department of Justice.

<sup>2</sup> See for example, Cameron and Taber (2004), Stinebrickner and Stinebrickner (2008), Lovenheim (2011), and Lochner and Monge-Naranjo (2011) on skill investment; Evans and Jovanovic (1989), Black and Strahan (2002), and Banerjee et al (2017) on entrepreneurship; Zeldes (1989), Deaton (1991), and Carroll (2001) on consumption; and Bernanke et al (1999), Greenstone et al (2014), Bassetto et al (2015), and Breza and Kinnan (2017) on economic activity.

Our analysis begins by documenting the demographic and economic characteristics of neighborhoods prior to the mid-1930s when the maps were drawn. The HOLC graded neighborhoods on a scale of A (least risky) to D (most risky). We find a clear monotonic relationship between economic characteristics associated with credit worthiness measured prior to the drawing of the maps and the eventual HOLC grade. We also find that racial composition is roughly the same in neighborhoods graded A to C but strikingly different in neighborhoods graded D, those shaded in red. While previous research (Hillier 2005 and Fishback 2014) has shown similar patterns for Philadelphia and New York, ours is the first systematic evidence across a full range of U.S. cities of the extent to which the maps were correlated with measures of creditworthiness and race.

Our main goal is to estimate the causal effects of the HOLC grades on the evolution of neighborhoods. Given that our analysis takes place in a non-experimental setting, our methodology must address confounding factors for valid inference. Perhaps the most critical concern is that the maps may have simply reflected and codified pre-existing differences in neighborhoods, but didn't actually *cause* any changes in lending practices. We address this concern through a multi-pronged approach.

The first part of our strategy relies on multiple levels of differencing. We begin by tracking changes over time in the difference in outcomes between neighbors that live on either side of a HOLC boundary within a very tightly defined geographic band, typically a few city blocks. Comparisons of spatially proximate neighbors address some confounding factors like access to labor markets, public transportation, or other amenities of local areas, that might differentially influence neighborhood growth.

However, a border design on its own is insufficient since there were likely pre-existing differences and differential trends, even among nearby neighbors, which were well known to contemporary real estate professionals. A classic example is railroad tracks that mark a visible border between a good and bad neighborhood (i.e. "living on the wrong side of the tracks"). In fact, we document an increase in racial and economic gaps along the HOLC borders between 1910 and 1930. To address this concern, we compare our "treated" boundaries with a set of counterfactual boundaries that are made to look like the treated boundaries pre-period using propensity score weighting or synthetic control

methods. The patterns in racial segregation and other characteristics in our weighted counterfactual boundaries in the pre-period are virtually identical to the treated boundaries but begin to depart in the post-period. As an additional robustness check, we exclude borders that overlap with railroads and rivers.

We also use a second strategy to address pre-existing differences and trends that does not rely directly on counterfactual boundaries. We limit our sample to a subset of HOLC borders that are least likely to have been predicted to be borders based on our propensity score analysis and instead may simply reflect idiosyncratic factors. For example, we suspect that some borders may have been chosen simply to close a polygon rather than to reflect a gap in creditworthiness. This sample of low propensity score borders exhibits no pre-existing difference or trend between lower and higher grade sides of the same boundary.

Our first finding is that the HOLC maps affected the degree of racial segregation as measured by the fraction of black residents on each side of a neighborhood boundary. We show that areas graded “D” become more segregated than nearby C-rated areas over the 20<sup>th</sup> century. The segregation gap rises steadily from 1930 until about 1970 or 1980 before declining thereafter. We find a strikingly similar pattern in “C” neighborhoods that bordered “B” neighborhoods, even though there were *virtually no black residents in either neighborhood type prior to the maps*. That result, and the implication that there were no pre-trends in racial segregation along the C-B boundaries, provides further support for our research design. The finding of effects along C-B boundaries reveals for the first time the importance of “yellow-lining” as an historical phenomenon.

That the pattern begins to revert starting in the 1970s is at least suggestive that FHA, ECOA, CRA, and perhaps other public policies introduced around this time may have played a role in reversing the increase in segregation caused by the HOLC maps. Glaeser and Vigdor (2012), using very different measures, document a similar hump-shaped time pattern in racial segregation and likewise speculate that housing policies may be a key cause of the decline in segregation post-1970. Nevertheless, a small difference in racial segregation along both the C-B and D-C borders remains in 2010.

The maps also had an economically important negative impact on homeownership and house values.<sup>3</sup> Intriguingly, the effects on housing markets dissipate over time along the D-C boundaries but remain highly persistent along the C-B boundaries where pre-existing racial differences were minimal. A possible explanation is that housing policies enacted later in the century, such as CRA, perhaps successfully targeted D- but not C-rated areas.

Our paper contributes to several literatures. The HOLC maps provide an important example of how access to credit influences economic development (e.g. cites listed in footnote 2), with a particular focus on the development of urban neighborhoods (e.g. Rosenthal and Ross 2014; Baum-Snow and Hartley 2016; and Lee and Lin 2017). More broadly, our results are similar in nature to other recent papers (e.g. Hornbeck 2012; Hornbeck and Keniston 2016; Feigenbaum et al 2017; and Shertzer et al 2016) that document how an important intervention can have large and strikingly persistent effects on the long-run development of local communities. Our findings are also the first to quantify one key explanation for the robust rise of segregation and inequality in homeownership in American cities during the decades immediately following WWII (Cutler and Glaeser 1997; Cutler, Glaeser, and Vigdor 1999; Ananat 2007; Boustan 2011). Some research has linked housing with the growing Black-White wealth gap throughout the latter half of the 20<sup>th</sup> century (Blau and Graham 1990; Conley 2001; Charles and Hurst 2002; Krivo and Kaufman 2004).

While our results are quite robust across outcomes, specifications, and identification strategies, our framework is ultimately non-experimental in nature. Therefore, further research that can confirm our findings using alternative research strategies or other data would be useful in bolstering our claim of

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<sup>3</sup> The paper most similar to ours, Appel and Nickerson (2016), also finds that the HOLC maps affected home prices. Their analysis differs from ours in several important respects. First, they use a regression discontinuity strategy that relies on the assumption of no pre-existing differences (or trends) along HOLC borders. Our results suggest that assumption is invalid. Second, they combine all HOLC border types in their analysis and thus assume that the effects are the same across all types. Our results suggest important differences across border types. Third, their focus is solely on home prices and they do not analyze patterns of segregation, home ownership or credit scores. Fourth, they study only a single outcome year (1990), which misses much of the interesting dynamics over the 20<sup>th</sup> century. Fifth, their data only go back to 1940 which they consider to be a pre-treatment period, even though maps were completed before then. This sample period does not allow them to consider pre-existing trends. Sixth, they use a much smaller set of cities. Other studies, such as Hillier's (2005) seminal study of Philadelphia and Fishback's (2014) on New York, focus on individual cities.



causality. The rest of the paper proceeds as follows: section II provides background information and discusses the related literature, section III describes the data and descriptive facts, section IV shows our methodology, section V presents our results, and section VI concludes.

## **II. Background and Related Literature**

### *The HOLC and the City Survey Program*

In the wake of the Great Depression, house prices fell precipitously and a foreclosure crisis ensued (White 2014).<sup>4</sup> Foreclosures were not only devastating to borrowers but were costly to lenders as well (Nicholas and Scherbina 2013). To address adversity in the housing markets, the Roosevelt Administration initiated a series of Federal programs intended to alter the nature of housing finance. These included policies that fostered a shift away from the provision of short duration loans of 3 to 5 years with large balloon payments to fully amortized higher loan-to-value mortgages with longer durations of 15 to 20 years, the introduction of mortgage insurance through the Federal Housing Agency (FHA), and the creation of a secondary market for loans through the Federal National Mortgage Agency (FNMA).<sup>5</sup>

In 1932, the Federal Home Loan Bank Act was enacted which created the Federal Home Loan Bank Board (FHLBB) to “organize, charter, and supervise Federal savings and loan associations” (Woods 2012 p.1032). The FHLBB essentially oversaw the operations of the newly created Federal consumer banking system. One important new agency operating at the direction of the FHLBB was the Home Owners’ Loan Corporation (HOLC). Created in 1933, the HOLC was initially tasked with issuing bonds in order to buy and refinance mortgages at more favorable terms to borrowers. By 1936, the HOLC refinanced over 1 million home loans or roughly 1 in 10 non-farm mortgages (Fishback et al 2011).

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<sup>4</sup> For example, foreclosure rates in New York City rose from essentially zero throughout the 1920s to as high as 7 percent in 1935 and averaged about 2 to 3 percent per year during the early and mid-1930s (Ghent 2011).

<sup>5</sup> Several studies describe details of the residential real estate environment at the time and evaluate the effectiveness of various HOLC and FHA initiatives to deal with the foreclosure crisis (Wheelock 2008, White 2014, Fishback et al 2011, Rose 2011, Ghent 2011, and Fishback et al 2017). Fishback et al (2017) emphasize the many complications in the mortgage market that ultimately slowed the 1930s housing recovery.

The focus of our study is an initiative undertaken by the HOLC at the behest of the FHLBB to introduce a systematic appraisal process that considered neighborhood-level characteristics when evaluating individual residential properties. In particular, between 1935 and 1940 the HOLC drew residential “security” maps for 239 cities as part of its City Survey Program. The FHLBB was concerned both about the long-term value of the real estate investments now owned by the Federal Government and the general health of the lending industry in a new regime of long-term amortized loans (Hillier 2005). The maps and the underlying appraisal process were also seen as a mechanism for solving a coordination problem that would help ensure the continued stability of property values throughout American cities.<sup>6</sup> Ultimately the HOLC completed more than 5 million residential appraisals (Woods 2012).

The maps were drawn based on the input of local brokers and appraisers, as well as surveys of home prices, the quality of the housing stock, and the demographic and economic characteristics of the neighborhood. Neighborhoods were graded on a scale of A (least risky/most stable) to D (most risky/least stable), with households living in lower ranked neighborhoods likely facing more difficulty accessing formal lending markets compared to an otherwise identical household in a higher ranked community. The appraisal manuals were candid in how they differentiated grades. Hillier (2005) quotes the 1937 FHLBB Appraisal Manual as describing neighborhoods as:

- Grade A = “homogeneous,” in demand during “good times or bad.”
- Grade B = “like a 1935 automobile-still good, but not what the people are buying today who can afford a new one”
- Grade C = becoming obsolete, “expiring restrictions or lack of them” and “infiltration of a lower grade population.”

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<sup>6</sup> Hillier (p. 210) cites an FHLBB document: “[HOLC] experts believe that since its interest is duplicated by that of all home-financing and mortgage institutions, a program can be evolved which will reclaim large residential areas which are doomed unless some concerted action is taken. Those experts believe that a joint program of Government agencies and private capital can save millions of dollars in property values now being wasted each year. If such efforts are undertaken in the future, the HOLC will be able to contribute surveys made of more than 300 cities throughout the United States—an accumulation of real estate and mortgage data never before available.”

- Grade D = “those neighborhoods in which the things that are now taking place in the C neighborhoods, have already happened.”

The term “redlining” is thought by many to derive from the red shading that marks the lowest ranked D neighborhoods (Jackson 1980 although see Fishback 2014).

### *FHA Manuals and Maps*

The FHA created parallel maps that likewise rated neighborhoods on a color-coded A to D scale and were based on a systematic appraisal process that took the demographic characteristics (race, ethnicity) of neighborhoods into account. Indeed, the 1930s FHA manuals explicitly emphasize “undesirable racial or nationality groups” as one of the underwriting standards.<sup>7</sup> We consider the possibility that the HOLC maps influenced the FHA maps later in this section.

It is unclear how long the FHA maps were used but FHA manuals continued to include race and nationality as an appraisal factor thru at least the 1940s. The 1968 FHA and 1977 CRA legislation outlawed the use of security maps because it was believed to unfairly target low and moderate-income neighborhoods that tended to be heavily minority. Unfortunately, the FHA maps are only sporadically available (Light 2011). That said, at least for Chicago, there do not appear to be major differences between the FHA and HOLC maps. Our estimates capture the sum of any HOLC and FHA effects where the boundaries align, and only the HOLC effect where the boundaries differ.

### *How Were the HOLC Maps Used?*

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<sup>7</sup> See Jackson (1980) and Light (2010) for discussions of how FHA risk maps were created and the instructions provided to underwriters to evaluate areas. The 1934 FHA manual includes race as one of the underwriting standards to be applied to new loans: “The more important among the adverse influential factors (of a neighborhood’s character) are the ingress of undesirable racial or nationality groups...All mortgages on properties in neighborhoods definitely protected in any way against the occurrence of unfavorable influences obtain a higher rating. The possibility of occurrence of such influences within the life of the mortgage would cause a lower rating or disqualification.” See <http://archives.ubalt.edu/aclu/pdf/Plex48.pdf>. Frederick Babcock, a Chicago realtor who later became the director of the underwriting division of the FHA wrote in a 1932 book, *The Valuation of Real Estate* that “most of the variations and differences between people are slight and value declines are, as a result, gradual. But there is one difference in people, namely race, which can result in a very rapid decline. Usually such declines can be partially avoided by segregation and this device has always been in common usage in the South where white and Negro populations have been separated.” (Rutan 2016 p.36)

There is an active debate among researchers about the degree to which lenders accessed the HOLC maps. For example, citing evidence from an FHLBB survey of New Jersey bankers and the participation of local realtors as consultants in constructing the St. Louis maps, Jackson (1980) argues that “private banking institutions were privy to and influenced by the government security maps” (p. 430). We similarly find that in Cuyahoga County (Cleveland), 6 of the 14 individuals listed as having reviewed the HOLC map were from local lending institutions and 2 others were local appraisers.<sup>8</sup> Greer (2012) suggests that in total, thousands of real estate professionals played some role in the development of the maps and many likely remained actively involved in the industry through the post-war era.

In contrast, Hillier (2003) stresses that access was not widespread despite high demand for the maps among private lenders. She argues that the FHLBB sought to preserve their confidentiality from the private sector as a matter of policy and thereby allowed only a limited number of copies (50 to 60) of each map to be made. She further asserts that there is little historical record of the use of the maps prior to researchers discovering them in the U.S. National Archives.

In more recent research based on archived FHLBB documents, Woods (2012) argues that the FHLBB widely distributed information concerning the HOLC appraisal practices and that this had a profound influence on national lending practices by creating a uniform appraisal process.<sup>9</sup> Woods specifically argues that “there existed a relationship between the HOLC security maps and FHLBB lending policies” (p. 1043). In particular, as a matter of policy, the balance sheets of lending institutions had to include a “security map of the institution’s lending area” and that institutions were instructed that

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<sup>8</sup> See the “Cuyahoga County Explanation and Area Description File available at: [https://library.osu.edu/projects/redlining-maps-ohio/area-descriptions/CuyahogaCounty\\_Explanation\\_and\\_A1-A31\\_Area\\_Description.pdf](https://library.osu.edu/projects/redlining-maps-ohio/area-descriptions/CuyahogaCounty_Explanation_and_A1-A31_Area_Description.pdf). In future work it may be possible to assemble counts of the number of bankers and appraisers who viewed the maps as the introductory material for area description files for more cities become available.

<sup>9</sup> The mechanisms for dissemination of HOLC appraisal practices include: the creation of a Joint Committee on Appraisal and Mortgage Analysis in 1937 that included three private agencies whose purpose was “to share appraisal data throughout all segments of the national lending industry”; the dissemination of a monthly FHLBB journal entitled the *Federal Home Loan Bank Review* that contained articles “that provided painstaking detail regarding the influence of neighborhood demographics on mortgage finance.” 6,000 copies of the review were circulated each month and the list of subscribers “was so extensive that it reached a representative cross section of the national urban housing industry;” the FHLBB as a matter of regulatory policy required that lending practices must take into account neighborhood demographics (Woods 2012).

“the best method of grading residential neighborhoods as lending areas is to make a scientific analysis of the entire community and of each neighborhood within it.” Woods further notes that: “The FHLBB widely distributed the instructions necessary for creating this critical appraisal material throughout the national lending industry. The Mortgage Rehabilitation Division of the FHLBB ‘has prepared simple instructions for making the security maps of residential neighborhoods’ available ‘to any experienced mortgage lender.’ The Rehabilitation Division of the FHLBB ‘recognize[d] four broad categories of lending areas, ranging from most desirable to least desirable. Each category was represented by a different color, so that the map could be read at a glance.’ These four categories were identical to those created by the HOLC.”

The combination of direct instructions from the FHLBB to utilize security maps in their lending decisions coupled more generally with the close communication between the private sector and government institutions fostered by the FHLBB (Woods 2012), certainly makes it at least plausible that the information contained in the HOLC maps could have filtered out and been used in lending decisions. Given the FHLBB’s large investment in the City Survey Program, it would seem to have been in their interest to have shared the information in the maps despite its stated policy.<sup>10</sup>

We may never know with certainty the degree to which the original HOLC maps were used by lending institutions. It is worth pointing out that, at a minimum, there is clear evidence that the FHLBB fostered the general practice of using maps to classify the credit worthiness of entire neighborhoods. If, in fact, the maps developed by lenders differed from the original HOLC maps such that boundaries were drawn along slightly different streets, it suggests that our estimates are, if anything, likely to *understate the overall effects of the general practice of redlining* even if they capture the effects of the HOLC maps.

Perhaps more important than whether lenders had direct access to the maps is whether the maps were shared with the FHA and therefore still influenced the provision of housing credit through the

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<sup>10</sup> Woods (2012) cites a 1935 Federal Home Loan Bank Review article: “[i]t is inevitable, therefore, that the HOLC’s appraisals should exert a major influence in setting values on urban-home properties throughout the country. The magnitude of the operation insures that this influence shall be more than temporary, and that the Corporation’s appraisals will affect all property values for many years.”

FHA's decisions to insure loans in low graded neighborhoods.<sup>11</sup> On this issue there is more agreement among researchers. Light (2010) argues that there is "ample evidence" that the HOLC and FHA shared ideas and highlights evidence to support the influence of the HOLC appraisal methods and maps on the FHA's practices.<sup>12</sup> Woods (2012) similarly cites evidence from a 1938 FHA underwriting manual that used illustrations of examples from HOLC appraisals. Hillier (2003) also states that the HOLC maps were shared with the FHA as well as other government agencies, but argues that the FHA had their own independent sources of information for developing their maps and minimizes the influence of the HOLC maps.

### **III. Data and Descriptive Facts**

#### *HOLC Maps*

The Digital Scholarship Lab at the University of Richmond has provided us with geocoded renderings of the original HOLC maps for 149 cities.<sup>13</sup> Figure 1 shows that the geographic coverage is quite extensive especially relative to the distribution of the population in 1930. The 149 cities comprise 89 percent of the population living in the 100 largest U.S. cities in 1930 and 1940, including 9 of the largest 10, 17 of the largest 20, and 30 of the 42 cities with populations above 200,000.<sup>14</sup> The HOLC maps for three prominent cities -- New York, Chicago, and San Francisco -- are displayed in Figure 2. The large set of boundaries separating neighborhood types, especially evident in the New York City and San Francisco maps, illustrate the variation we utilize for our main identification strategy where we only use households living in a narrow band (i.e. within a few city blocks) on each side of an HOLC border.

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<sup>11</sup> The enormous influence of the FHA is highlighted by the fact that, by 1949, one-third of newly constructed homes were insured by the FHA (Woods 2012).

<sup>12</sup> See footnote 85 of Light (2010). For example, Light writes: "FHA records indicate the agency kept the HOLC security maps on file in connection with the construction of its Economic Data System ... and comments from Federal Home Loan Bank Board general counsel Horace Russell on how the FHA 'was fortunate in being able to avail itself of much of the (t)raining and experience in appraisal and the development of appraisal data by Home Owners Loan Corporation' underscores the two agencies' close ties."

<sup>13</sup> See Appendix Table A2 for the list of cities.

<sup>14</sup> Of the 20 most populous cities, we are only missing Los Angeles (#5), Washington DC (#11), and Cincinnati (#17). About 30 percent of the total U.S. population lived in the largest 100 cities in 1930 and 1940.

To create a sample of HOLC borders, we begin by assigning an ID to each straight line segment of a HOLC boundary that is at least a ¼ mile in length. Next we draw rectangular areas that extend either ¼ or ⅛ of a mile on each side of a boundary. We call these areas boundary buffers. Each boundary has two buffers -- the lower graded side (LGS) and higher graded side (HGS). We provide a visual depiction of the boundary buffer zones for New York City in Appendix Figure A1. Throughout the paper, we refer to these boundary buffer zones interchangeably as buffer zones, boundaries, or borders. We also refer to boundaries between C and D neighborhoods as “D-C” and those separating B and C areas as “C-B”.<sup>15</sup>

### *1910 to 2010 Censuses*

We match the geocoded maps to Census data on various characteristics such as homeownership, house values, housing age, race, and population. The earliest Census years, 1910 to 1940, provide the most detailed geographic data since they come from 100 percent files containing street addresses. Of the universe of household heads with non-missing street addresses, we successfully match between 60 and 80 percent per Census to modern street locations.<sup>16</sup> That allows us to locate 49, 50, 79 and 62 percent of 1910 to 1940 Census respondents and ultimately assign them to HOLC neighborhoods (see Appendix Table A1 for details). Variables are then aggregated to the boundary buffer by taking means of all observations which fall inside of a boundary buffer zone so long as a buffer contains at least 3 households.<sup>17</sup>

Complete 100 percent Censuses with corresponding street addresses have not yet been released beyond 1940. Therefore, we use publicly available aggregated data to map later years into our buffer zones. The smallest geographic units currently available for 1950 to 1980 are census tracts. Since census

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<sup>15</sup> There are not enough A neighborhoods to estimate effects along the B-A boundaries. In the spirit of analyzing similar neighbors separated by a boundary, we do not look at boundaries separated by more than one grade (i.e. D-B).

<sup>16</sup> Given our empirical strategy based on using boundary differences described below, we see no reason why differential rates of address reporting or successful geocoding across Censuses should affect our estimates.

<sup>17</sup> We analyzed how specific characteristics influenced the probability of geocoding in the 1940 Census. For example, we find that being African American was associated with a 6.5 percentage point lower conditional geocoding rate, being a homeowner was associated with a 16.9 percentage point higher conditional geocoding rate, and being foreign born with a 4.6 percentage point lower conditional geocoding rate. In the next draft, we will consider how this selection might influence our results.

tracts change over time, we overlay the tract boundaries from each Census with the boundary buffer shapes and calculate weighted means of any tract for which 15 percent or more of the area of the tract lies within the boundary buffer.<sup>18</sup>

Starting in 1990, the Census provides smaller geographic tabulations called blocks, which contain on average roughly 100 people.<sup>19</sup> Since blocks are much smaller than census tracts, we use a 50 percent threshold for calculating weighted means of the boundary buffer (i.e. we take the block population weighted means of all blocks for which the area of the block is more than 50 percent within the boundary buffer). Our analysis uses the panel of boundary buffer means created for each decade from 1910 to 2010.

#### *1999-2016 Federal Reserve Bank of New York Consumer Credit Panel/Equifax (CCP)*

We supplement our Census-based boundary buffer panel with modern credit bureau data from the Federal Reserve Bank of New York Consumer Credit Panel/Equifax (CCP). The CCP, which covers roughly 5 percent of the population, provides block-level data on credit scores between 1999 and 2016.

#### *Summary Statistics*

Table 1 shows summary statistics for our key variables by neighborhood grade. Columns (1) to (4) report means for all households, not just those living along boundaries. This largest sample encompasses 543 areas with an A grade, 1,351 with a B grade, 2,156 with a C grade, and 1,399 with a D grade. Panel A shows the share of African Americans over time across the grade types. For example, in 1930 before the maps were drawn, African Americans comprised 15.8 percent of the residents living in D-rated neighborhoods but only 2.1 percent of those living in C-rated neighborhoods, a gap of 13.7 percentage points. By 1980, African Americans accounted for 45.5 percent of residents in D-rated neighborhoods and 28 percent of residents living in C-rated neighborhoods. By 2010, these rates began to

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<sup>18</sup> The choice of the 15 percent threshold balances a tradeoff between sample size and measurement precision. Our results are robust to reasonable alternative census tract inclusion thresholds.

<sup>19</sup> Some variables, notably house value, house age, and foreign born population, are only reported at the block group level, which are aggregates of blocks and typically contain between 600 and 3,000 people. For these variables, we assign the block the values of the block group it is in. In 2000 (2010), there were over 8 (11) million blocks, 208,790 (217,740) block groups, and 65,443 (73,057) census tracts.



converge and were 38.1 percent and 29.9 percent, respectively. The time patterns for selected years are shown graphically in Panel A of Figure 3.

Comparable statistics for those living in a buffer zone of a quarter mile along the C-B and D-C boundary are shown in columns (5) to (8). For the D-C boundaries (columns 7 and 8), the gap in the share of African Americans is smaller than in the full neighborhood sample (columns 1 to 4). For example, in 1930, the gap in the D-C boundary buffer is 6.4 percentage points (9.9 percent in D and 3.5 percent in C) compared to a 13.7 percentage point gap among all D-C residents. By 1970, over thirty years after the maps were drawn, the racial gap within the  $\frac{1}{4}$  mile boundary buffers grew to 15.1 percentage points (45.4 percent in D and 30.3 percent in C). Thereafter, the gap declined, hitting 3.5 percentage points (42.7 percent in D and 39.2 percent in C) in 2010.

This secular pattern -- of a rising racial gap through 1970 and a decline thereafter -- arises in B and C neighborhoods as well. However, there is a relatively meager  $\frac{1}{2}$  percentage point gap in 1930 that grows to just under 5 percentage points by 1970, and then subsequently wanes. Columns (9) to (12) show similar patterns for those living within the  $\frac{1}{8}$  mile boundary buffers.

Panel B of Table 1 and Panel B of Figure 3 show corresponding time-series patterns for home ownership. In 1930, the D-C and C-B home ownership gaps in the  $\frac{1}{4}$  mile buffer zone were 3.6 and 5.9 percentage points, respectively. Again, by 1960, these differences had increased to 5.1 and 8.0 percentage points. As of 2010, the D-C gap in home ownership had fallen to just 2.0 percentage points. However, the homeownership gap remained elevated along the C-B boundary at 7.0 percentage points. In Panel C through E of Table 1 (and Panel C of Figure 3 for home values), we show the analogous patterns for house values, fraction foreign born, and modern day credit scores. In brief, like homeownership, we find that house value and credit score gaps along these borders exist even today and they are larger among the C-B borders than the D-C borders. The share of immigrants has equalized along the D-C borders after growing faster in C areas in the middle of the century. In contrast, the immigrant share along the C-B borders has remained higher in the C areas for the entire 1910 to 2010 period.

### *Determinants of HOLC Grades*

Table 2 shows a series of regressions that associate neighborhood grades with pre-HOLC 1930 housing and demographic characteristics, as well as changes between 1920 and 1930 when available. Columns (1) and (2) report marginal effects from an ordered logit where D is coded as 4 and A is coded as 1. Columns (3) to (8) are marginal effects of the probability of moving one grade lower: i.e. from A to B, from B to C, or from C to D, respectively. All specifications include city fixed effects, are weighted by the log of neighborhood population in 1930, and cluster standard errors at the city level.

Like Hillier (2005) and Fishback (2014), who were only able to examine single cities, we find a clear monotonic relationship between grades and nearly all the key economic and housing covariates that are available in the Census whether considered individually or, as in the table, simultaneously.<sup>20</sup> Unsurprisingly, a higher homeownership rate, log home value, log rent, occupational earnings, radio ownership, and literacy are associated with a higher HOLC grade. To take one example, the results in column (2) imply that a 10 percentage point increase in homeownership rates raises the probability of a being assigned one letter grade higher by 7.6 (0.7) percentage points. These results are unsurprising because they jibe with what we know about the appraisal process from the detailed forms, called “area description files,” that were recorded at the time. The area description files consistently document that homeownership, vacancy, housing age, housing quality, and economic and demographic characteristics of neighbors were key factors used to grade neighborhoods.

Table 2 also shows that the marginal effect of most of our observable housing and employment variables is roughly the same for grade determination between B versus C (columns 5 and 6) and C versus D (columns 3 and 4). For example, in the sample of C and D neighborhoods, a 10 percentage point increase in the homeownership rate increases the probability of a C grade by 4.5 (0.5) percentage points.

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<sup>20</sup> We find weaker evidence that recent changes in housing and household characteristics between 1920 and 1930 affected HOLC grades. These coefficients are suppressed in Table 2 for space but are available on request. However, it is plausible that changes between 1920 and 1930 are not the correct time frame for evaluating appraisals that were taking place in the mid-1930s.

Likewise, in the C-B sample, a 10 percentage point increase in the homeownership rate increases the probability of a B grade by 4.8 (0.6) percentage points.

The case of race is somewhat more complicated. Similar to previous studies, we show that a neighborhood is more likely to be graded D than C if the African-American share is higher, even after conditioning on a set of housing and economic characteristics and city fixed effects. To highlight the pivotal role of race in grading D neighborhoods, Appendix Figure A2 shows the area description file for a particular neighborhood in Tacoma, Washington which was graded D. The notes at the bottom of the document clarify: “This might be classed as a ‘low yellow’ area if not for the presence of the number of Negroes and low class Foreign families who reside in the area.” It is worth noting that the fraction of African Americans in this Tacoma neighborhood was 2 percent. However, interestingly, the share African-American has the opposite effect when we examine grade determination among A versus B neighborhoods and B versus C neighborhoods. That is, B grades are more likely than C grades, and A grades are more likely than B grades, in areas with a higher share of African Americans.

#### **IV. Identification and Methodology**

In this section, we describe our primary empirical strategy. Our approach is very much guided by the historical narrative that suggests that the appraisal process underlying the residential security maps explicitly considered existing characteristics of neighborhoods and their trends when drawing the borders. This is confirmed by the area description files mentioned in the previous section. Therefore, we use multiple approaches to try to overcome this obstacle to identification.

##### *Differencing*

We begin by considering a straightforward difference-in-differences (DD) strategy and then discuss the problems with this approach and how we further refine our strategy. The basic idea is to compare changes over time in neighborhood-level outcomes, pre- and post- the construction of the HOLC maps in places that are spatially proximate but on different sides of an HOLC boundary. Along the line

segments that make up these boundaries, we can compare nearby neighbors that live within a tightly defined distance from the boundary – what we refer to as boundary “buffers.” The benefit of focusing on differences within buffers is that we can remove potentially important, but typically hard to measure, factors that influence residents on both sides of a border. In our case, neighbors living within hundreds of feet of each other, but on opposite sides of a border, are likely facing the same access to labor markets, public transportation, retail stores, perhaps schools, and other local area amenities. This strategy is highly related to a border regression discontinuity design (RD) used in previous work (e.g. Holmes 1998; Black 1999; Bayer et al 2007; and Dube et al 2010).

The statistical model underlying the DD estimator is:

$$y_{gbt} = \sum_{t=1910}^{2010} \beta_t 1[lgs] \gamma_t + \beta_{lgs} 1[lgs] + \gamma_t + \alpha_b + \epsilon_{gbt}$$

where  $y_{gbt}$  is an outcome (e.g. share African-American) in geographic unit  $g$  (e.g. boundary buffer) on boundary  $b$ , at census year  $t$ ,  $1[lgs]$  is an indicator that the buffer is on the lower-graded side of the HOLC boundary,  $\gamma_t$  are year dummies, and  $\alpha_b$  are boundary fixed effects. We define boundary buffers as either  $\frac{1}{4}$  or  $\frac{1}{8}$  of a mile (about 1,300 or 650 feet) on each side of the HOLC boundary. Differencing across the boundary is captured by the  $\alpha_b$ 's. Our coefficients of interest, the  $\beta_t$ 's, capture the change in the mean outcome in year  $t$  relative to 1930 (the Census year before the maps were drawn, which we omit). The gap in the mean outcome in year  $t$  is therefore  $\beta_t + \beta_{lgs}$  for years other than 1930 and  $\beta_{lgs}$  for 1930.

#### *Parallel Trends Assumption Violated*

The key problem with relying on the DD strategy is that the approach relies on the assumption of parallel pre-trends which does not appear to hold in our application. First, we know from the area description files that the borders were endogenously drawn based on information on where racial and housing gaps were already diverging. Second, this divergence can be seen empirically in Figure 4, which

plots the mean share of African-Americans on the D side of D-C boundaries relative to the mean share of African-Americans on the C sides of D-C boundaries in  $\frac{1}{4}$  mile boundary buffers for the period 1910 through 1940. As early as 1910 and 1920, there was a 3 percentage point racial gap between the D-C buffers, which grew to 6 percentage points by 1930, a clear violation of the assumption of parallel trends. Similar pre-map patterns appear in other variables, including homeownership rates and home values.

The anecdotal evidence and the patterns in the data along the buffer zone also suggest that an RD design will likely not satisfy the assumptions of continuity along the HOLC borders. We verify this concern visually by showing a set of distance plots in Appendix Figure A3. Each dot represents the mean characteristic (regression adjusted for border fixed effects) in bins of  $\frac{1}{100}$ <sup>th</sup> of a mile of distance in each direction from the border. The dashed vertical lines represent  $\frac{1}{8}$ <sup>th</sup> mile cutoffs. It is clear that in each of the charts that even limiting our sample to observations that are just a city block away from the border would lead to meaningful discontinuities and render an RD design invalid.

### *Control Boundaries*

To address the concern that the parallel trends assumption does not hold, we propose two strategies. The first strategy is to create a set of counterfactual or control boundaries with similar characteristics and trends before the maps were drawn. To implement this approach, we take advantage of what we refer to as “missing” HOLC borders. The idea is that there may have been difficulties in constructing polygons that fully reflected homogeneous neighborhoods --especially if there were small areas within larger neighborhoods that had fundamentally different characteristics. A prototypical example is a small island of, say, C type streets within a larger ocean of D. We provide a stylized example of this in the top panel of Appendix Figure A4. The Chicago HOLC map, shown in Panel A of Figure 2, also illuminates the plausibility of such missing borders. Among the large swath of D (red) in the heart of Chicago, there undoubtedly lies small pockets of streets that might be better labeled C (yellow) or even higher.

We identify these potential yellow areas, which we then use as control boundaries, in two ways. First, we draw  $\frac{1}{4}$  mile by  $\frac{1}{4}$  mile grids over each city. We then locate  $\frac{1}{4}$  and  $\frac{1}{8}$  mile buffers around any quarter mile line segment in the grid that does not overlap with HOLC treatment boundaries. We refer to this set of potential control boundaries as our “grid” controls. See Appendix Figure A5 for an example of a grid placed over New York City. Second, the HOLC often drew boundaries separating two “unique” neighborhoods with the same grade. For example, returning again to the large red area in Chicago, there are many HOLC-defined line segments, each at least  $\frac{1}{4}$  mile long, between D graded neighborhoods. We do not fully understand why the HOLC felt it necessary to draw these divisions. But we see this as evidence that there may have been borders that were considered but ultimately rejected because they did not rise to the same level of dissimilarity as our treated borders. We refer to these same grade (e.g. B-B, C-C, or D-D) line segments as our “same-grade” controls.

Having defined the two types of counterfactual borders, we apply propensity scoring methods to choose weights to minimize the pre-treatment differences in outcomes and covariates. We use the logic that if pre-treatment differences are eliminated using these weights, then it may be valid to interpret any post-treatment difference between treatment and controls as estimates of the causal effects of the HOLC grades. Since each set of treated boundaries has a side which has been deemed riskier by the HOLC (such as the D side of a D-C boundary), we need a similar construct for the control boundaries. We do this by randomly picking one of the sides of each control boundary to be the riskier, or lower graded side.<sup>21</sup> We then construct a measure of the difference across the boundary by subtracting the mean of our outcome variable on the higher-graded side from the mean of our outcome variable on the lower-graded side. We refer to these differences across the boundaries as gaps. For example, the mean share of residents that are African American on the D side minus the mean share of residents that are African American on the C side of a D-C boundary is the D-C gap in the share African American.

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<sup>21</sup> We find similar results if, instead of random assignment, the side with a lower predicted grade in 1930 is assigned the lower-grade.

To construct the propensity score, we pool a set of control and treatment boundaries, where each boundary is an observation. For each grade type difference (e.g. D-C, C-B) we only use controls from the same HOLC graded areas. For example, when we estimate the effects of the D-C borders, the controls only include C-C or D-D boundaries (from the grid or same grade set of controls) and not A-A or B-B boundaries. We then estimate a probit where the dependent variable receives a value of “1” if the observation was actually treated by the HOLC and “0” otherwise. The right hand side variables include pre-existing (lagged) gaps of the outcome of interest and city fixed effects.<sup>22</sup> For example, when the outcome is the share African American across D-C boundaries, we use the 1910, 1920, and 1930 gaps in share African American as regressors. Estimating the propensity score in this manner means that we have a balanced panel of boundaries with no missing values on either side of the boundary from 1910 through 1930. We then use these propensity scores, or predicted probabilities of being treated, to weight the control boundaries. We do not require balance in the estimation dataset.

We also use the Synthetic Control Method (SCM) of Abadie et al (2010). SCM is a matching procedure that creates a synthetic comparison group composed of a weighted average of non-treated cases. In our application, the estimate of the effect of the HOLC borders on outcomes is obtained by taking the difference in means between treated boundaries and a weighted average of non-treated boundaries but only in the post-map period. The approach assumes that pre-intervention differences between treatment and control groups are zero and the comparison group is selected by using weights that minimize the differences in the dependent variable between the treatment and control groups in the pre-period.<sup>23</sup>

One issue with implementing the standard SCM is that it requires a balanced panel. This restriction turns out to be problematic in our application because we have to shift from data at the street

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<sup>22</sup> The probit models are weighted by the log population of the boundary. Because house values are not available prior to 1930, we use lagged values of share African American when we estimate the probit for house values. We have also tried nearest neighbor matching but found our samples are generally too thin once we limit the neighbors to the same city as the treatment.

<sup>23</sup> For any given outcome, we use the same variables for the SCM as we do with propensity score analysis.

address level (1910 to 1940) to census tracts (1950 to 1980) to blocks (1990 to 2010). The tract-based sample of borders in particular is much smaller. To maximize the power of our data, we decided to perform the synthetic control analysis in two separate specifications: (a) using blocks from 1910 to 1940 and 1990 to 2010 and (b) census tracts from 1910 to 1980. As a means of highlighting that the census tract and block synthetic control samples are computed differently, we illustrate the former results using a dashed line (e.g. Figure 6, Panel C). The balanced panel issue is the main reason we consider the SCM to be primarily a robustness check of the propensity score method.

When we turn to our results, the figures will depict separate lines for the treatment and our various “weighted” controls. We also show triple difference estimates that use Inverse Probability Weighting (IPW) where the weight is set to 1 for the treated or  $[P(\text{treated})/(1-P(\text{treated}))]$  for the controls.

#### *Exploiting Borders Drawn to Close a Polygon*

A second, and perhaps simpler, approach to resolving the problem of a lack of parallel trends takes advantage of the possibility that some HOLC treatment boundaries might have been more idiosyncratic and were simply drawn in order to close a polygon. Consider the hypothetical example of a “misaligned” border in the bottom panel of Appendix Figure A4. The northern part of the neighborhood contains largely “red” blocks and the Southern area contains largely “yellow” blocks. It may not have been entirely clear where exactly to draw the Southern border and the HOLC agents may have just chosen a major street to define the neighborhood. These “treated” boundaries may not have reflected a discontinuous change in creditworthiness and likely would exhibit a small pre-trend gap. A possible example of this is found in the Area Description File for a neighborhood (D98) in Chicago where the notes mention that “The eastern portion of the area is not quite so heavily populated with foreign



element.”<sup>24</sup> It may therefore have been somewhat random which particular street was used to demarcate the Eastern boundary of this neighborhood.

We identify these more idiosyncratic boundaries by computing the propensity score – or predicted probability of being treated -- for each HOLC boundary and then using *only those borders whose propensity score is below the median*. As we show later, this subsample of treated borders exhibits virtually no pre-trends in the share of African Americans. While this strategy is simple and straightforward it may reduce power and introduce a form of selection based on the observables used to construct the *p*-score.<sup>25</sup>

## V. Main Results

We start by describing the results for racial segregation along the D-C boundaries. For this particular analysis, we use the full set of empirical approaches. We then turn our attention to the C-B boundaries and thereafter to the other outcomes.

### *Racial Segregation in Redlined Areas*

Our description of the results begins in Table 3, where we consider the D-C gap in the share of African Americans. In column (1), we use entire neighborhoods (not just the buffer boundaries) and do not include city fixed effects. As might be expected based on what we previously showed in Panel A of Figure 3, the D-C gap in the share African American is quite large in 1930, at 13.5 percentage points, rises to 25 percentage points in 1960, and then falls to 8.1 percentage points by 2010. Adding city fixed effects (column 2) has little impact. The advantage of using buffer zones becomes apparent when we move to column (3), which limits the analysis to households living within ¼ mile of the D-C boundaries where the households are presumably much more similar. In this specification, the D-C gap starts at just

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<sup>24</sup> Price Fishback has generously provided us a transcribed file of the HOLC Area Description Files. In the next draft, we hope to provide representative information about the frequency of these types of anecdotes and estimate their impact on our results.

<sup>25</sup> In principle, this is similar to standard heterogeneity analysis which selects subsets of the data based on observables.

6.7 percentage points in 1930, rises to 14.6 percentage points by 1970 and thereafter falls to under 4 percentage points by 2010. These estimates are lowered somewhat but are not appreciably different when we include border fixed effects (column 4). In this last specification, we restrict variation to within borders and compare residents living, at most, a quarter mile from the border. Nevertheless, even within this confined sample, we know that that there are significant pre-trends as we showed in Figure 4.

#### *Estimates with Control Boundaries*

In column (5), we show the estimates obtained from using our weighted grid counterfactuals based on the propensity score analysis. Note that these estimates almost perfectly capture the pre-trends in the treated boundaries. For example, the grid counterfactuals have a D-C gap in African American share of 6.6 percentage points compared to 6.5 percentage points in the treated boundaries. However, after the maps were drawn, the treated and control estimates begin to diverge sharply. This can be seen most clearly in panel A of Figure 5. This figure constitutes the first of our main results on the effects of the maps on segregation. We find that while the D-C gap in the share African American rises to 11.7 percentage points by 1970 in the treated group, the same gap in the control group falls to about zero by 1950. By 2010, the analogous estimates are 3.4 (0.8) and 0.8 (0.3) percentage points.

Column (6) of Table 4 and Panel B of Figure 5 show “triple difference” estimates that take the difference between the treated and control groups (benchmarked to equal 0 in 1930). Here we see the gap opens up in 1940, widens appreciably in 1950, mostly flattens out through 1970 at about 10 to 13 percentage points and then subsequently begins to converge back. Nevertheless, as of 2010, there still remains an economically relevant 2.7 (1.2) percentage point racial gap over 70 years after the maps were drawn.

Figure 6 shows the robustness of our results when using a) a narrower  $\frac{1}{8}$  mile boundary buffer, b) the same grade control group instead of the grid control group, and c) the synthetic control method rather than the propensity score and inverse probability weighted regressions. The results are all similar.<sup>26</sup>

#### *Estimates from Low Propensity Score Borders*

Our second strategy attempts to identify borders that may have been more idiosyncratic in nature, perhaps in order to arbitrarily close a polygon. We attempt to hone in on this sample by dividing the treated D-C borders into 2 groups: those below the median propensity score, and those at or above the median.<sup>27</sup> We demonstrate the credibility of this research design in Appendix Figure A6 where we show a distance plot for the African American share similar to what we showed in Panel A of Figure A3, only now we present those D-C borders below the median propensity score. This racial gap is now a smooth continuous function with no abrupt change near the border.

The results are shown in Figure 7. The black line simply reproduces the baseline treated estimate ( of the D-C gap in the share African American (Figure 5, Panel A). The blue line shows how this gap evolved for *the actual HOLC treated borders that were least likely to have been predicted to have an actual HOLC border*. Perhaps the most important point to make is that there is no longer a pre-trend for these borders –the gap in 1910, 1920 and 1930 is essentially zero. Nevertheless, for the low propensity borders, we still see a large and meaningful rise in a gap in segregation that peaks at about a 7.6 percentage point difference in 1970 before falling to below 1 percentage point by 2010. The estimates for this group of borders might be interpreted as either a lower bound on the true causal estimates, or more conservatively, as the true causal effect.

We can contrast this pattern with the gray line which depicts the borders most likely to have been treated based on observables. The gap in the share African American rose sharply in those borders

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<sup>26</sup> As we noted earlier, SCM require a balanced panel. Because we shift between census tracts for 1950 to 1980 and blocks for 1990 and onward, we create different samples for the 1950-80 period (highlighted by the dashed lines in the figure). Using the propensity score-based weights does not require a balanced panel so each census uses whatever border segments are available for that year.

<sup>27</sup> The below median point estimates are also shown in column (7) of Table 3.

between 1910 and 1930, reached 15 percentage points by 1940 just after the maps were drawn, and surged to over 25 percentage points by 1950, before also falling sharply in more recent decades.

We considered capturing the phenomenon of “closing the polygon” by looking only at neighborhoods that had “multiple” different grade treated boundaries and then using only the boundary that had the lowest propensity score. The logic is that the lowest propensity score border within a polygon is most likely drawn to close the shape. Unfortunately, the sample of such boundaries is too small. We can get part way to this more ideal sample by doing the same exercise as in Figure 7 but conditioning on boundaries that are part of multiple treated boundary neighborhoods. These results, which are virtually the same as the ones in Figure 7, are shown in Appendix Figure A7.

#### *Racial Segregation Patterns Along “Yellow lined” C-B Boundaries*

We apply our main estimation strategy of comparing treated and counterfactual borders to the C-B boundaries and show the results graphically in Figure 8. As noted in Section 2, the African American population was minimal in both B and C neighborhoods in 1930 so we don’t expect pre-trends to be an issue for racial gaps and, indeed, they are not. After the maps were drawn, however, a meaningful gap of about 4 percentage points opens up by 1950 and continues to rise to a peak of over 8 percentage points by 1970 before falling back down to about 2 percentage points in 2010. These results are almost a perfect inverse V-shape and suggest that “yellow-lining” was a meaningful phenomenon. In contrast, we estimate virtually a flat line around 0 for the control group of boundaries. These results are also robust to using  $\frac{1}{8}$ <sup>th</sup> mile buffer zones and the same-grade counterfactuals (Appendix Figure A8).

#### *Population Dynamics: White Outflow or Black Inflow?*

A divergence in African American share along the D-C and C-B borders may be due to a change to the flow of Blacks or Whites along these buffer zones. Appendix Figure A9 shows that these

population dynamics differ by border type.<sup>28</sup> One key finding is that the white population (and the foreign born population) on the D side notably declines relative to the C side from around 1940 to 1980. This suggests that “white flight” may have been more prevalent in the lower graded neighborhoods.<sup>29</sup> No such dynamic is observed along the C-B boundaries. Instead, the rising African-American gap in those areas was driven primarily by increased inflows of African American residents.

### *Home Ownership, House Values, and Credit Scores*

We next document how the HOLC maps influenced housing markets and thereby impacted the degree of investment in neighborhoods. We concentrate on two measures of the housing market: the rate of homeownership (Figure 9) and house values (Figure 10). In both cases, we again find a large pre-existing gap along the HOLC boundaries which we can mimic using propensity score weighting of grid segment boundaries.<sup>30</sup> After the maps were drawn, we find a gap opening up between the treatment and control boundaries starting in 1940 and generally persisting through 2010.

However, the size of the gap and the speed in which it dissipates varies in an intriguing way. We start with homeownership, where a full 1910 to 2010 time series is available. Panel A of Figure 9 shows the pattern of effects on home ownership along the D-C boundary buffer zones. From 1910 through 1930, both the treated boundaries and the control boundaries were characterized by lower home ownership rates on the D side compared to the C side of about 3 to 6 percentage points. The fluctuations over time were also roughly parallel during this period. After the maps were drawn, however, the gap in the control boundaries closed by 1950 and remained at roughly 0 through 2010. In the treated boundaries, however, the gap stayed relatively constant at around 3 to 4 percentage points through 1980 before falling to under 2 percentage points in the 1990-2010 period. When we use the  $\frac{1}{8}$ <sup>th</sup> mile buffer, we find that the

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<sup>28</sup> This figure plots the evolution of population density rather than population counts of Whites and Blacks because of the changing geographic units (e.g. tracts versus blocks) in our sample across Census years.

<sup>29</sup> There is a long literature in demography, economics, and history that discusses the importance of urban “white flight” on racial segregation. Some recent studies include Card, Mas, and Rothstein (2008), Boustan (2010), and Shertzer and Walsh (2016).

<sup>30</sup> Recall housing values are unavailable prior to 1930. Therefore, we use lagged values of share African American when we estimate the propensity score for house values. Moreover, the 1950 and 1960 census tract files do not contain data on mean house values.

treated borders actually fully converge by 2010. These findings suggest that the HOLC maps resulted in reduced home ownership in D areas relative to C areas for much of the 20<sup>th</sup> century.

The home ownership gaps are consistently larger along the C-B boundary as shown in Panel B of Figure 9. In 1930 there was about a 6 percentage point gap in both treated and control boundaries. By 1950, that gap was eliminated in the control boundaries. However, in the treated areas, the gap has remained in the 6 to 8 percentage point range. In fact, the gap was higher in 2010 than it was in 1930. Similarly, the house value gap (Figure 10) remains elevated along the C-B border relative to the D-C border. As of 2010, C-B gap stood at 8.0 percentage points while the D-C gap was just 2.5 percentage points.<sup>31</sup>

Finally, we examine the long run effects of the HOLC designated borders on modern credit scores in Figure 11. For this analysis, we use the Equifax Risk Score<sup>TM</sup> as our measure. We consider both the level of the score as well as the probability that a score is considered “subprime” (below 620). Subprime borrowers are less likely to access credit or may have to pay higher interest rates. These series begin in 1999 and run through 2016.<sup>32</sup> The cross-border gap in the levels of credit score in our control group hovers around zero for the entire 18-year period for both border types. However, for the treated boundaries, we find statistically significant gaps in 2016 of 7.4 points in the D-C boundaries and 9.5 points in the C-B boundaries. When we examine the probability of being subprime, the gaps in 2016 are just over 3 percentage points in both border samples. However, during the 2000s the subprime gap was as high as 8 percentage points along C-B borders and 6 percentage points along D-C borders.

#### *Why Are the Effects Different Between D-C and C-B Boundaries?*

For many of our housing and credit measures, we find an economically larger and more persistent impact of the maps along the C-B relative to the D-C borders. One hypothesis is that policies enacted later in the 20<sup>th</sup> century, such as the Fair Housing Act of 1968 and the Community Reinvestment

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<sup>31</sup> Appel and Nickerson (2016) estimate a roughly 4 percentage point gap in house values in 1990 aggregating all boundaries.

<sup>32</sup> We use the propensity score derived from a model that includes the share African American in 1910, 1920 and 1930.

Act (CRA) of 1977, designed to address discriminatory housing practices may have successfully targeted D but not C rated areas. The CRA, for example, instituted a process whereby bank regulators examine whether banks were providing adequate levels of loans to low and moderate income individuals in the areas they serve. Since low and moderate income individuals are more likely to be in D-graded neighborhoods than C-graded neighborhoods lending by banks to satisfy CRA compliance could have led to a reduction in home ownership and housing value gaps between D and C areas but less so between C and B areas.

A second hypothesis is that the effects of the HOLC grades may have had significantly more “bite” in C graded neighborhoods than D graded neighborhoods. For example, if lending was more restricted in D areas than C areas in the pre-map period, then the marginal effects of the maps might have been more pronounced in C areas leading to larger sized C-B effects that also take longer to dissipate. Relatedly, it may have been the case that the maps revealed more information concerning the long-term prospects of C rated neighborhoods than D rated neighborhoods. This is consistent with the fact that the pre-existing gaps between B and C areas were much less pronounced than gaps between C and D areas.

A third hypothesis is that D areas were quicker to be redeveloped and perhaps “gentrified” than the C areas and so the gaps were more quickly dissipated. This could arise because the D areas are closer to the central business district and such areas are generally more likely to redevelop first (Brueckner and Rosenthal 2009; Baum-Snow and Hartley 2016). Alternatively, the quality of the building stock in D areas may have depreciated more quickly and thus were more suitable and less costly for redevelopment. We see testing these possible explanations as an important area for future research.

### *Regional Heterogeneity*

While the mean effect of the maps is economically significant, their impact may differ regionally. Figure 12 examines regional differences in segregation along the D-C borders between the

Northeast, Midwest and South.<sup>33</sup> We find that in all three regions there was a sharp rise in the share African American gap along the treated borders between 1950 to 1980 that does not occur in the control borders. The triple difference estimates show that the effects on the racial gap peaks at between 12 to 17 percentage points in all 3 regions before falling to around 3 to 5 percentage points by 2010. Although the timing of the peak effects differs somewhat regionally, the estimates are not precise enough to establish a meaningful pattern. One notable point is that both the level and trend in the African American share gap were much more pronounced in the South in the pre-map period compared to other regions. For example, the gap in 1930 in the South was over 18 percentage points compared to just 4 to 5 percentage points in the Northeast and Midwest. The South is also unique in being the only region where the gap is considerably smaller in 2010 than it was in 1930.

Likewise, there are no notable regional differences in segregation along C-B borders that we are able to precisely observe. The magnitudes and the secular patterns in the Northeast and Midwest are very similar to that for the nation overall (Figure 8) and we do not have enough C-B borders in the South to produce estimates with reasonable precision.

In Appendix Figure A10, we examine regional differences in home ownership and house values. Recall, that for the nation overall, the effects were larger and more persistent along the C-B boundaries than the D-C boundaries, where the effects have largely dissipated. The regional findings suggest that the effects on housing markets were most pronounced and persistent in the Northeast. We find that even as late as 2010, house value gaps in the Northeast are 30 percentage points lower on the C side of C-B boundaries than the B side. The C-B gap in the Midwest is still large at around 10 percentage points. For the South, we again only show the D-C gaps given the high imprecision of the C-B estimates. The South is the one region where the D-C gap remains quite large at 10 percentage points in 2010.

#### *City Specific Estimates (Preliminary)*

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<sup>33</sup> Our sample of cities in the West does not have enough borders to produce precise estimates.



To further characterize heterogeneity in the maps' effects, we also produce a set of estimates by city. The variation in effects across cities may allow researchers to better understand the mechanisms behind the maps' effects and their evolution over time. Ideally, we would be able to estimate triple differences for each city. However, in practice it is difficult to create useful counterfactuals on a city-by-city basis. Instead, to approximate the triple differences we simply use the average *level* of the cross-boundary gaps in 1990 to 2010. Since most of the gaps in the counterfactual borders in our aggregate analysis are close to zero during this time period, we expect that these gaps are roughly equivalent to what we would obtain if we were able to produce triple difference estimates. We only show estimates for cities with at least 5 borders of a given type (D-C, C-B) to eliminate extreme outlier values.

Panel A of Figure 13 arranges the cities by smallest to largest D-C gap in the African American share between 1990 to 2010. While the D-C gap for the nation overall was around 4 percentage points, across cities this gap varies from a negative gap of around 10 percentage points to a gap of over 20 percentage points. Among the cities with the highest gaps include a mix of Rust Belt cities (Akron, Toledo, Grand Rapids, Fort Wayne), Southern cities (New Orleans, Jacksonville) and other Midwestern and Northeast cities (Buffalo, Decatur, New Haven, Evansville, Muncie, Erie).<sup>34</sup>

Panel B of Figure 13 show how cities vary by their C-B gaps in home ownership in the same period. The C-B gap for the nation overall is about negative 7 percentage points, while the city level variation extends from negative 20 percentage points to positive 10 percentage points. In this case, those cities with largest (negative) effects are found at the left of the graph. Here we find a different mix of cities with the largest negative effects including: Troy and Boston in the Northeast; Dayton and Cleveland in the Midwest; and several Western cities including Seattle, San Francisco and Spokane. Of course, it is important to note that these are the effects on “yellow-lined” C areas in Panel B as opposed to the “redlined” D areas in Panel A, and that the long-run effects on home ownership could be different from the effects on segregation. The next draft will contain more analysis of these cross-city differences.

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<sup>34</sup> In the next draft, we plan to correlate these city-specific estimates with demographic, financial, and economic characteristics of the cities.

## **VI. Conclusion**

In response to the Great Depression, the Federal government fundamentally reshaped the nature of housing finance to stabilize housing markets and support the lending industry. A slew of new Federal agencies were created including the FHLBB, and, under its auspices, the HOLC. Among their many initiatives, the FHLBB directed the HOLC to create a systematic and uniform scientific property appraisal process and to produce residential security maps for all major cities during the 1935 to 1940 period. Some have argued that these initiatives had a profound and long-lasting influence on the real estate industry by initiating the so-called practice of “redlining.” The residential security maps, which explicitly took into account demographic characteristics (e.g. race, ethnicity) of entire neighborhoods, were drawn for the purpose of influencing the property appraisal process. This in turn may have influenced lending decisions as well as the provision of Federal mortgage insurance.

We attempt to identify the causal effects of the HOLC maps on neighborhood development from 1940 through 2010. A major challenge for our analysis is that the maps were not exogenous and instead likely reflected existing neighborhood differences and trends. Therefore, there is a concern that the evolution of gaps in the post-map period may have reflected practices that would have occurred even in the absence of the maps. To address these challenges, we use a variety of empirical approaches including the use of counterfactual boundaries that experienced the same pre-existing trends but where the HOLC did not ultimately draw borders. We also exploit borders that appear to have been chosen for idiosyncratic reasons and where endogeneity is much less of a concern.

We document a significant and persistent causal effect of the HOLC maps on the racial composition and housing development of urban neighborhoods. These patterns are consistent with the hypothesis that the maps directly contributed to disinvestment in poor urban American neighborhoods with long-run repercussions. We show that being on the lower graded side of D-C boundaries led to rising racial segregation from 1930 until about 1970 or 1980 before starting to decline thereafter. We also find this same pattern along C-B borders, revealing for the first time that “yellow-lining” was also an

important phenomenon. That the pattern begins to revert starting in the 1970s is at least suggestive that Federal interventions like the Fair Housing Act of 1968, the Equal Credit Opportunity Act of 1974, and the Community Reinvestment Act of 1977 may have played a role in reversing the increase in segregation caused by the HOLC maps. Nevertheless, gaps in racial segregation along both the C-B and D-C borders remains in 2010, almost three quarters of a century later. Moreover, we also find that the maps had sizable effects on homeownership rates and house values. Intriguingly, the effects on homeownership, and to a somewhat lesser extent house values, dissipate over time along the D-C boundary but remain highly persistent along the C-B boundaries. We believe our results highlight the key role that access to credit plays on the growth and long-running development of local communities.

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**Figure 1: Geographic Coverage of Digitized HOLC Maps**

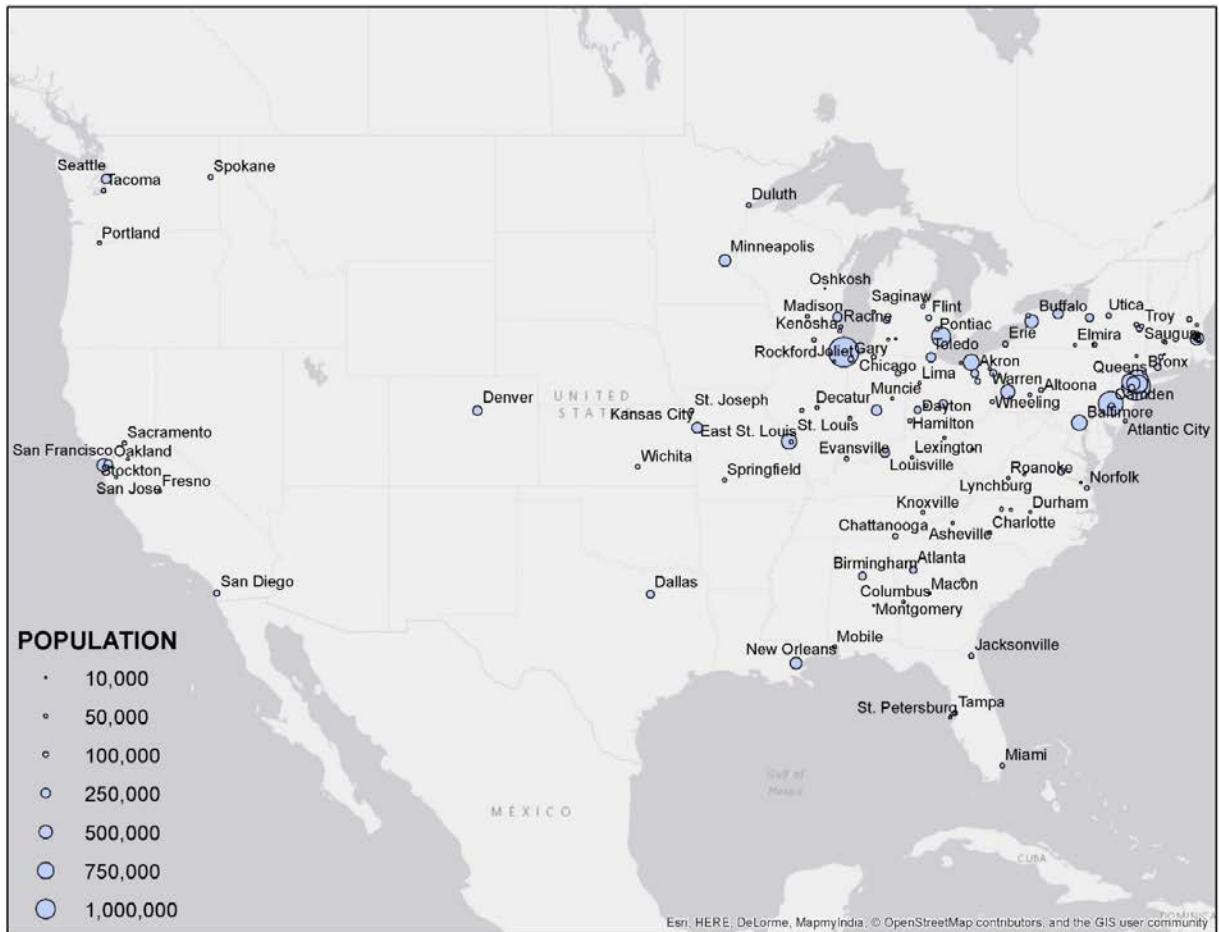
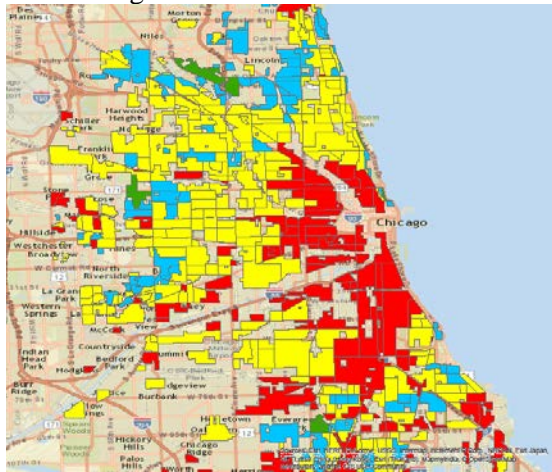




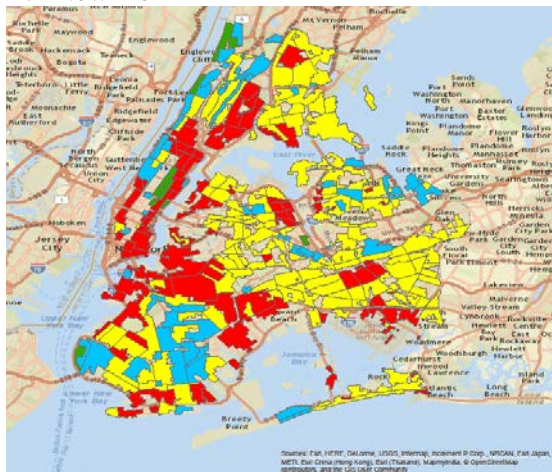
Figure 2: HOLC Maps for Chicago, New York and San Francisco

A. Chicago

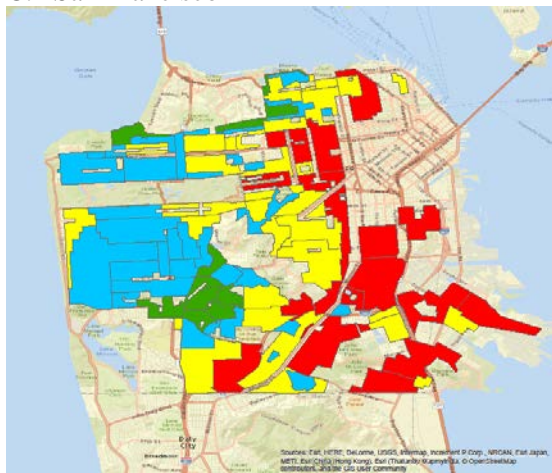


HOLC Grades (in order of riskiness):  
A=green (least)  
B=blue  
C=yellow  
D=red (most)  
U=unclassified

B. New York

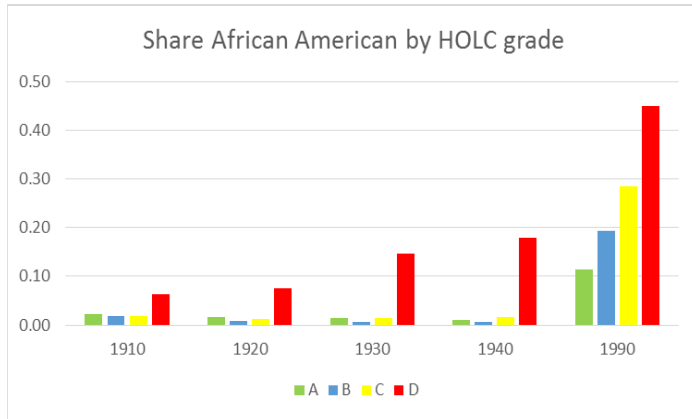


C. San Francisco

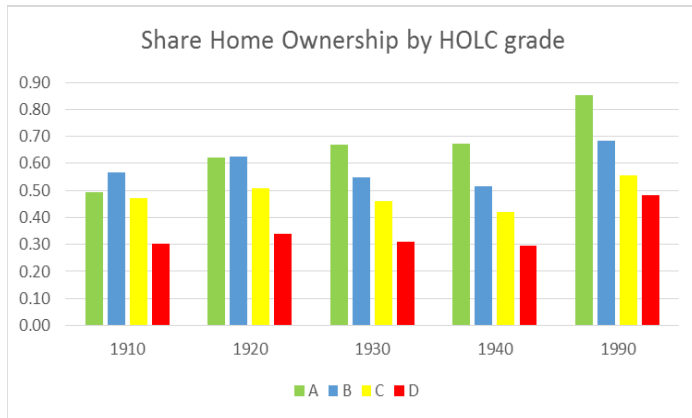


**Figure 3: Changes Over Time in Mean Outcomes by HOLC Neighborhood Grade**

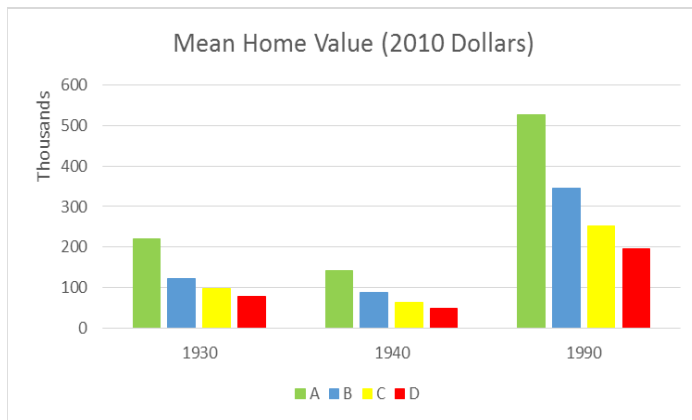
Panel A:



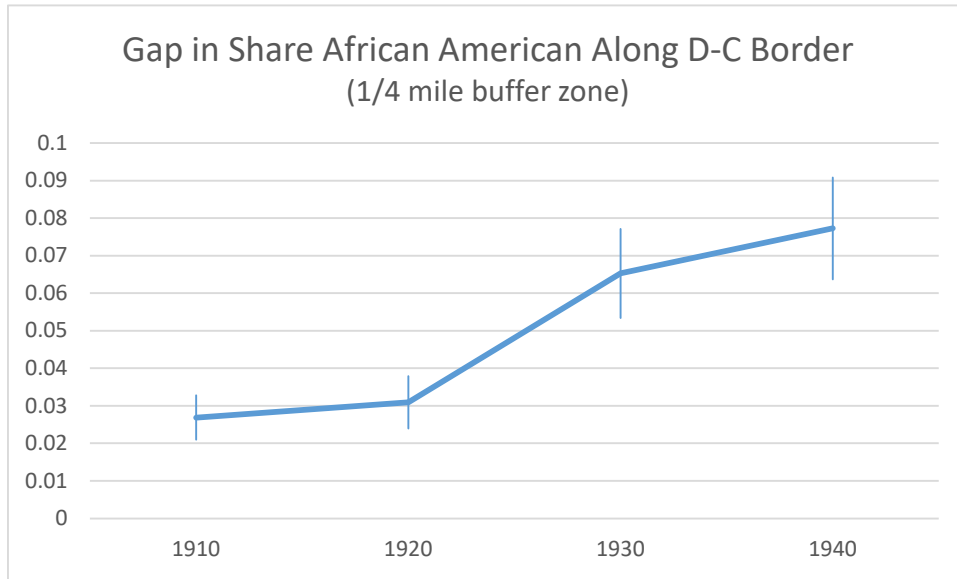
Panel B:



Panel C:

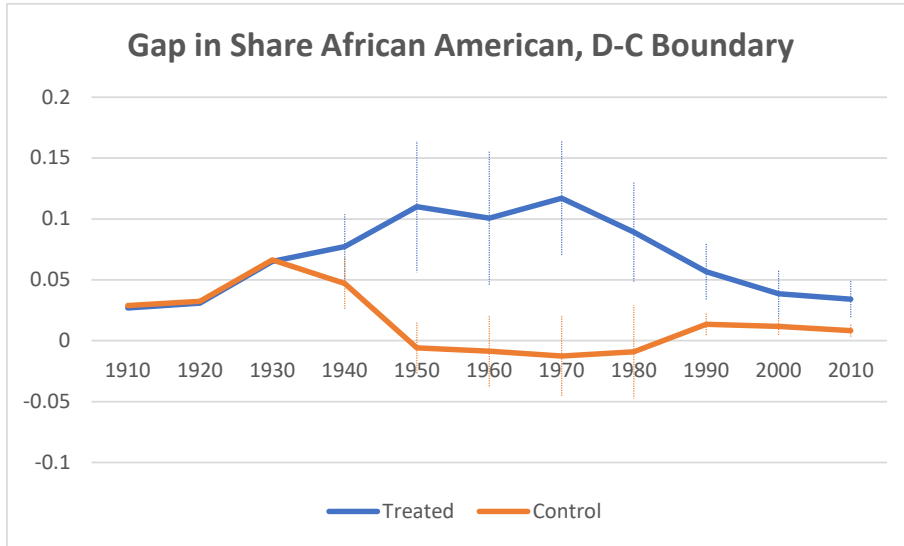


**Figure 4: Parallel Trends Assumption Does Not Hold Along D-C Borders**

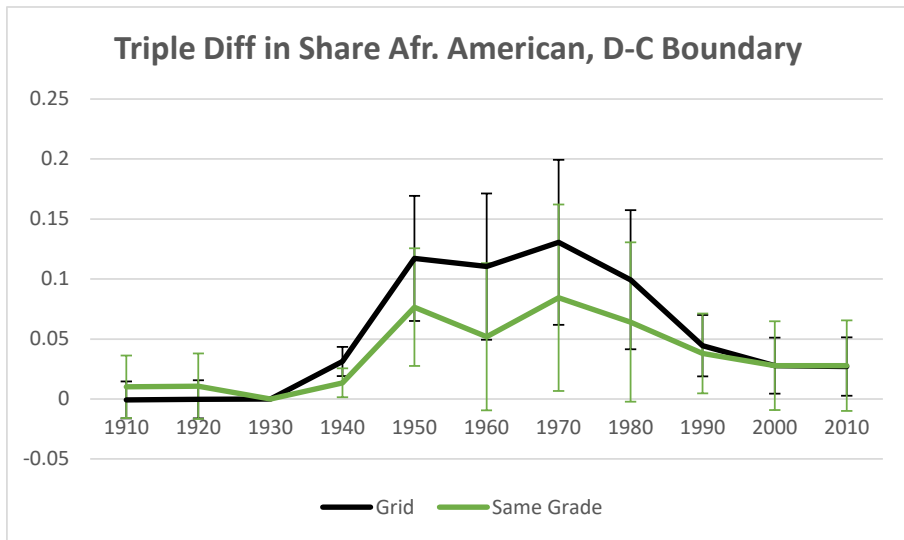


**Figure 5: Effects on D-C Gaps in Share African American, Treated and Grid Counterfactuals**

Panel A: Treated and Grid Counterfactuals

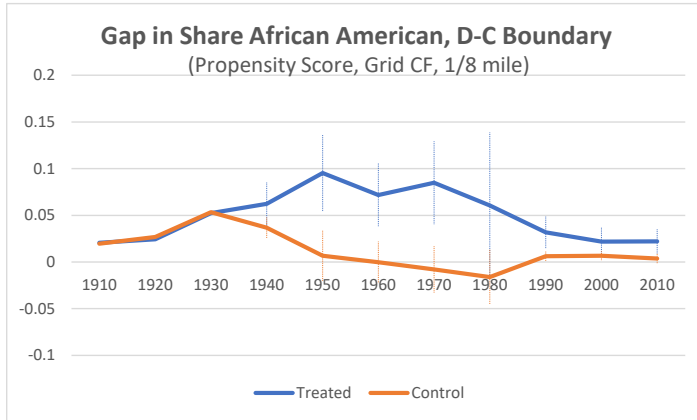


Panel B: Triple Difference Estimates

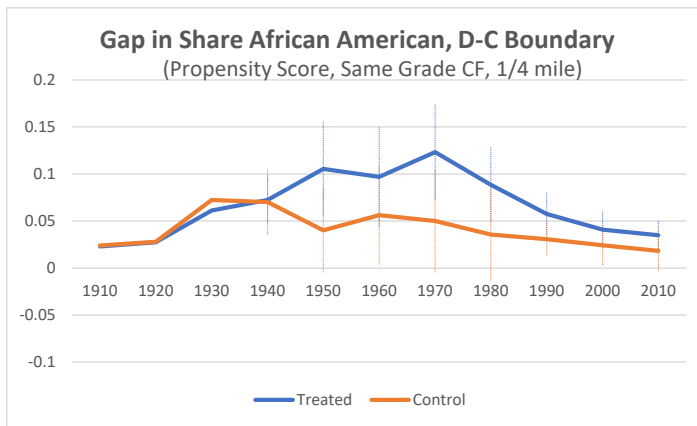


**Figure 6: Robustness of Effects on D-C gaps in Share African American**

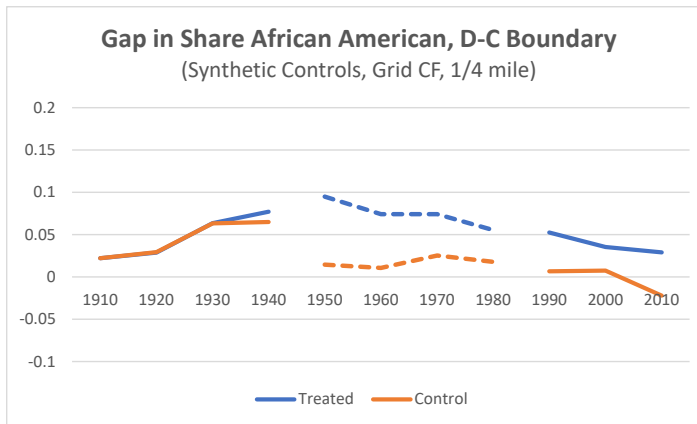
Panel A: Using 1/8<sup>th</sup> mile Boundaries with Propensity Score and Grid Counterfactuals



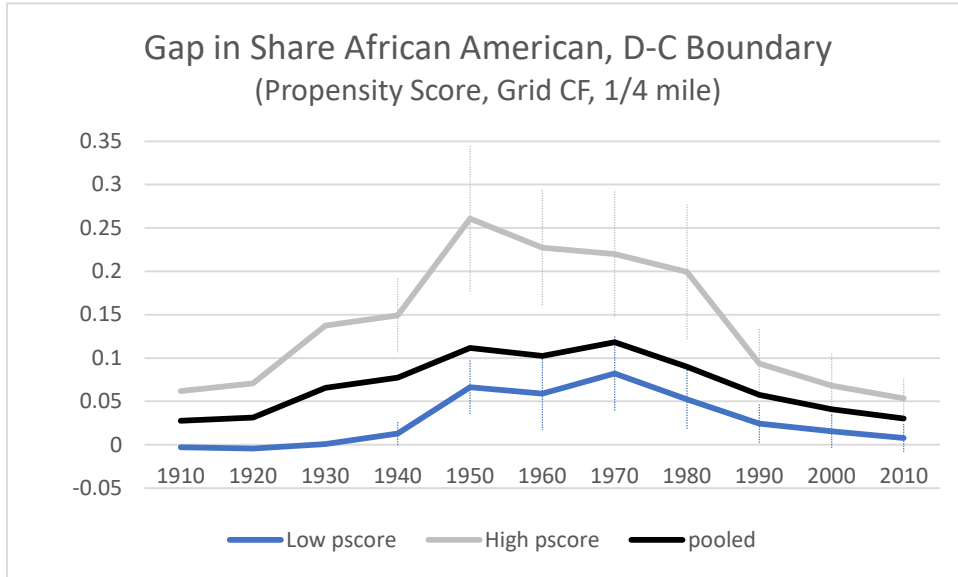
Panel B: Using Propensity Score with Same Grade Control Group



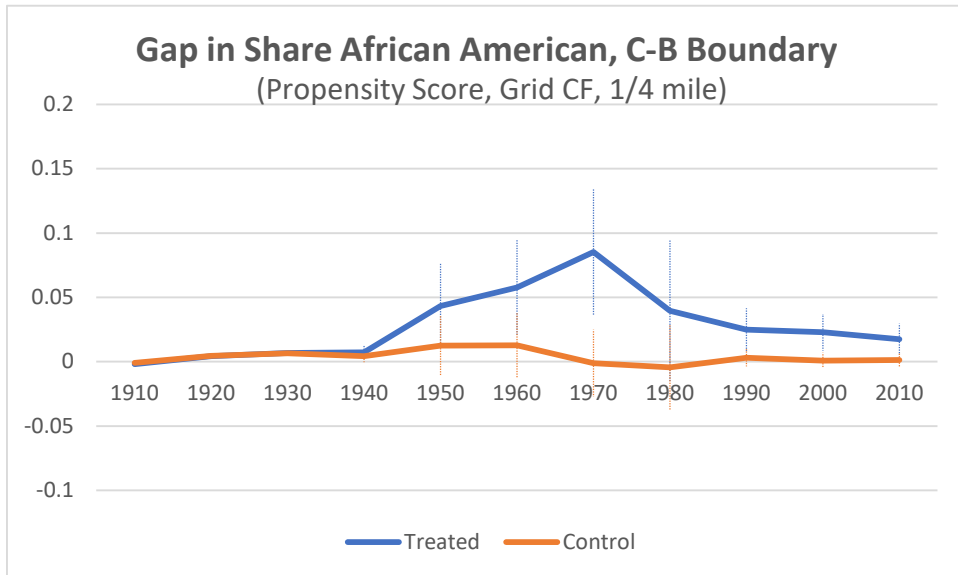
Panel C: Using Synthetic Control Method with Grid Control Group



**Figure 7: Effects on D-C gaps: Comparing Low and High Propensity for Treatment**

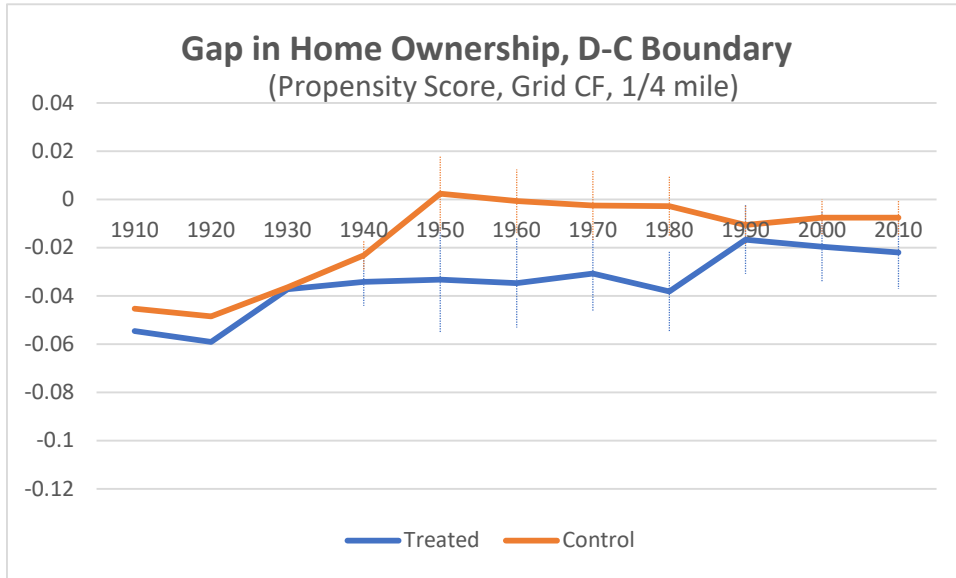


**Figure 8: Effects on C-B Gaps in Share African American, Treated and Grid Counterfactuals**

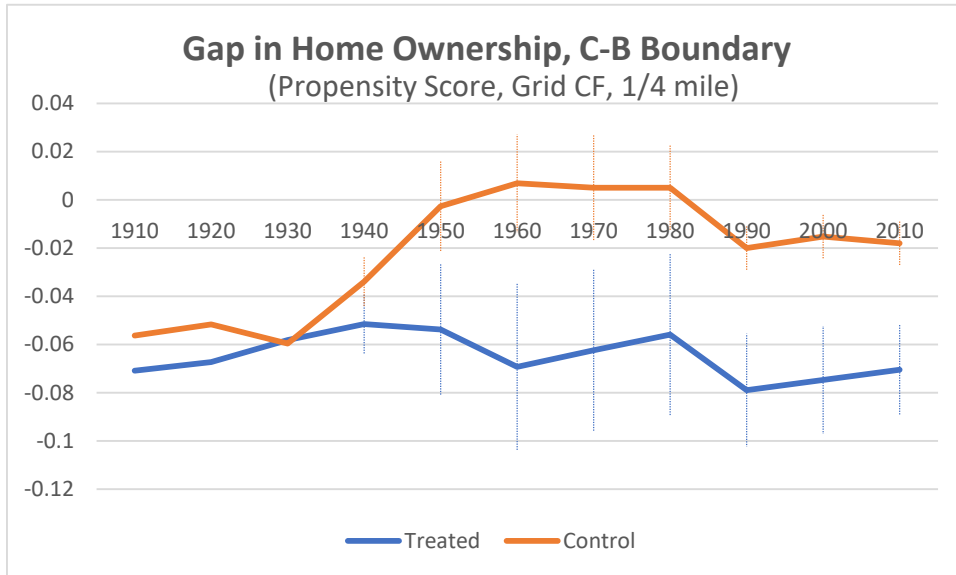


**Figure 9: Effects on D-C and C-B Gaps in Home Ownership**

Panel A: D-C Gaps in Home Ownership

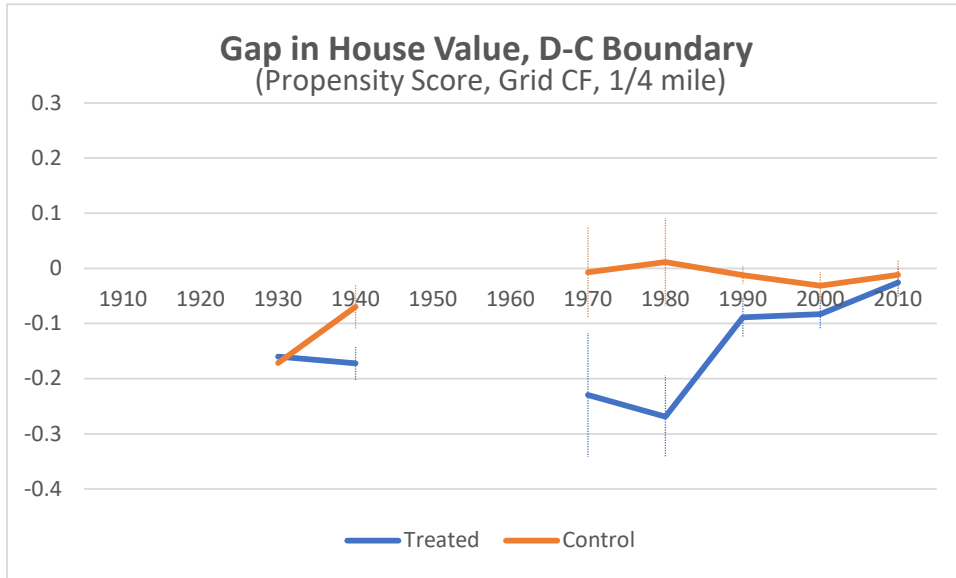


Panel B: C-B Gaps in Home Ownership

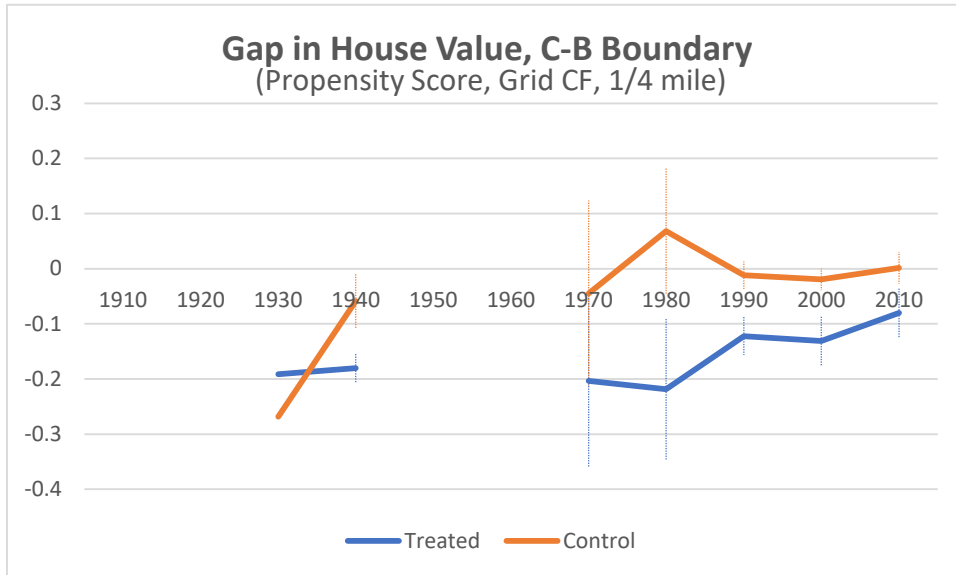


**Figure 10: Effects on D-C and C-B Gaps in House Values**

Panel A: D-C Gaps in House Values



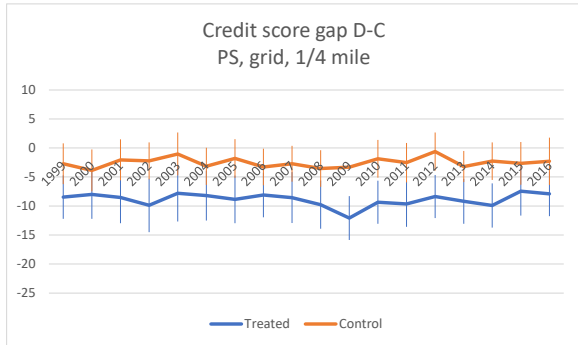
Panel B: C-B Gaps in House Values



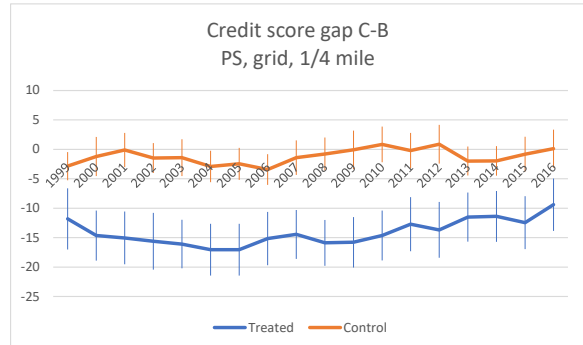


**Figure 11: Effects on D-C and C-B Gaps in Credit Scores**

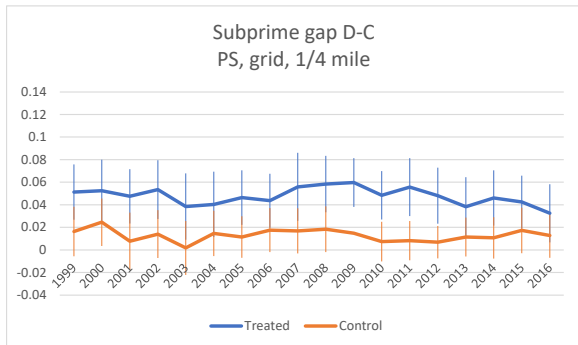
**Panel A: D-C Gaps in Credit Scores**



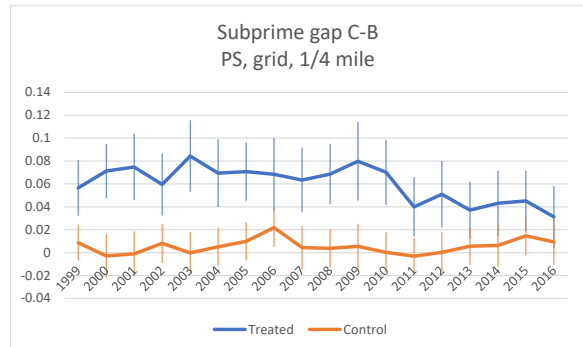
**Panel C: C-B Gaps in Credit Scores**



**Panel B: D-C Gaps in Subprime**



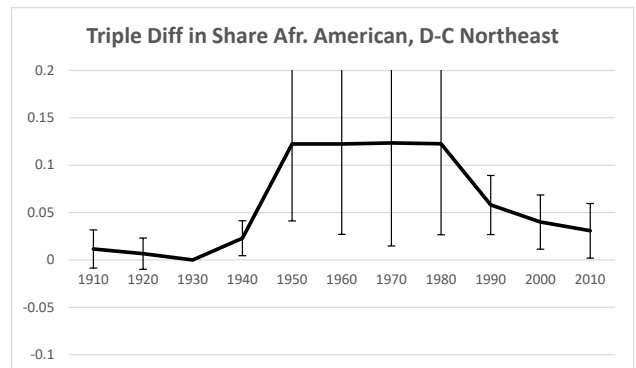
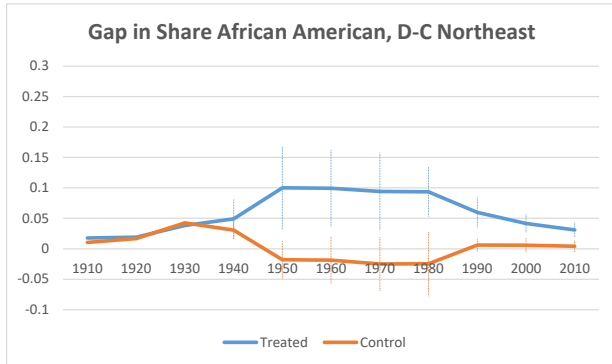
**Panel D: C-B Gaps in Subprime**



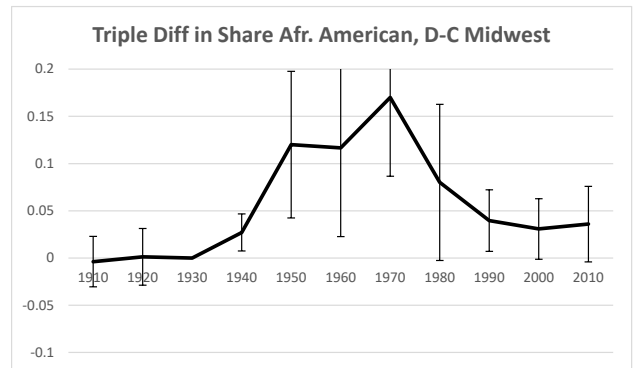
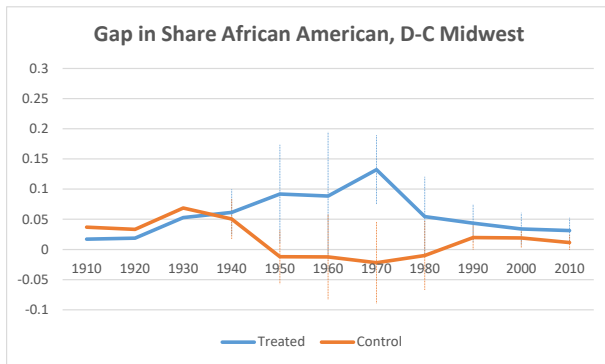
Source: FRBNY Consumer Credit Panel/Equifax

**Figure 12: Effect on D-C gap in Share African American, by Region**

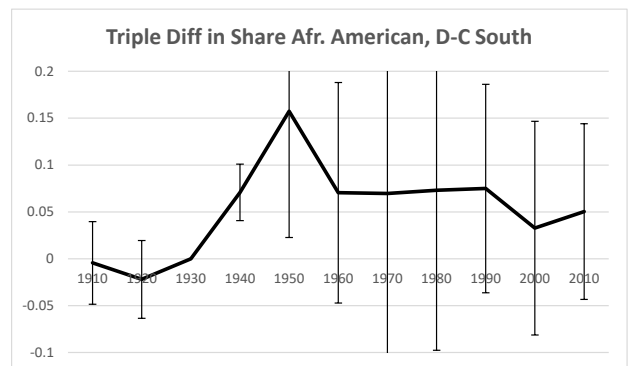
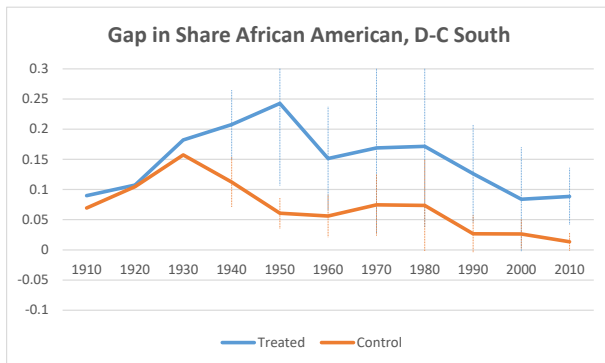
**Panel A: Northeast**



**Panel B: Midwest**

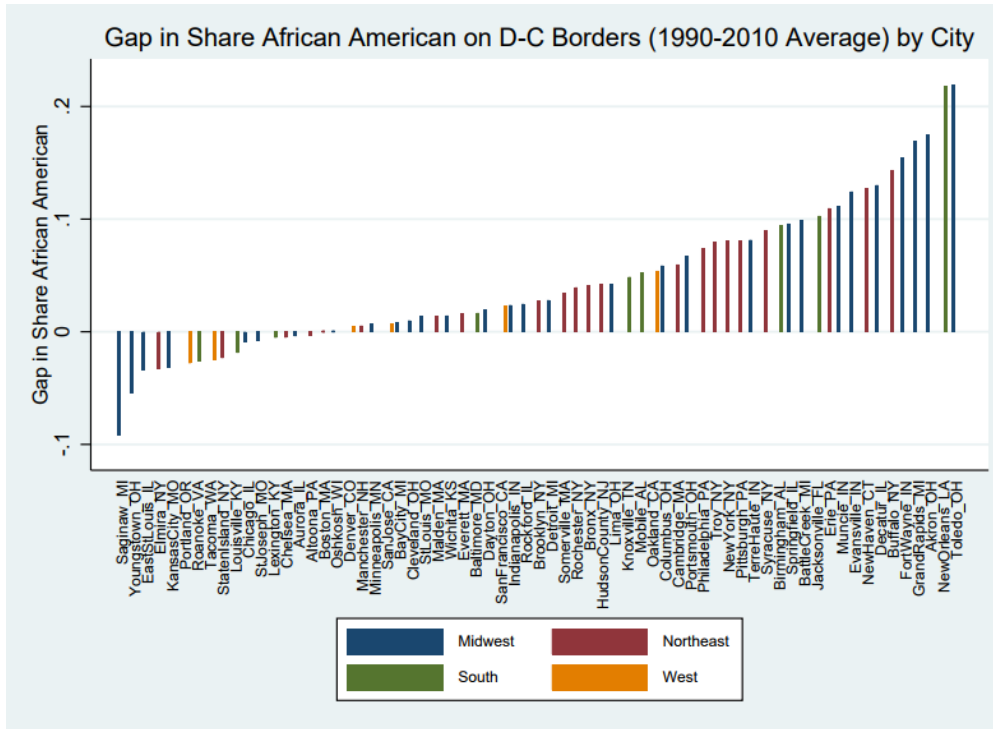


**Panel C: South**

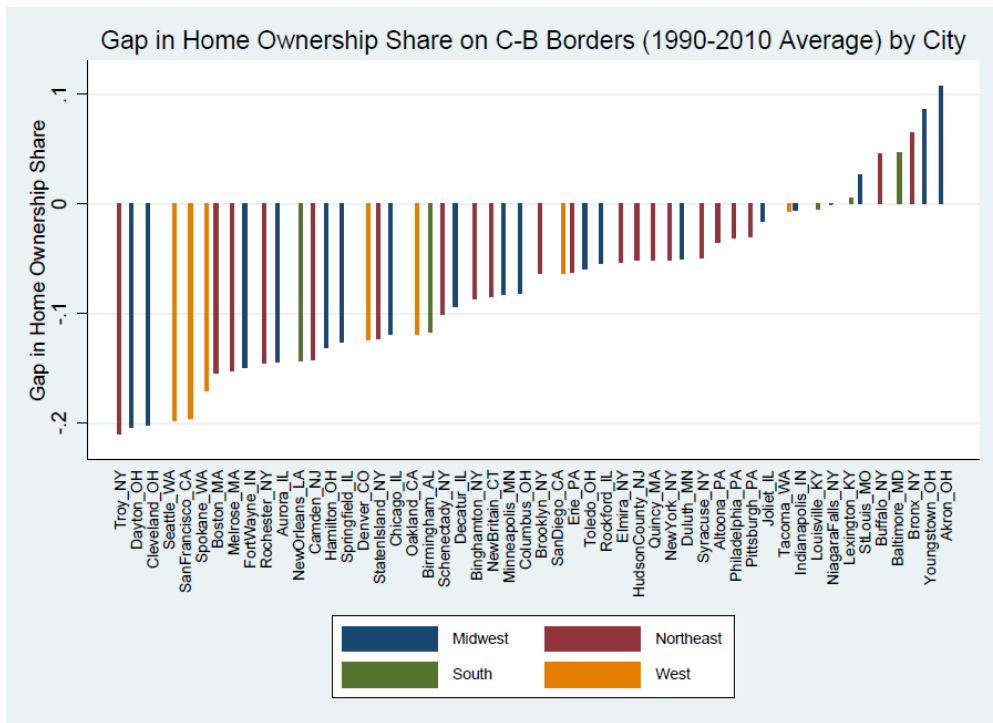


**Figure 13: City-specific Gaps Along D-C and C-B Borders**

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



Panel B: C-B Gaps in Home Ownership by City, Average 1990-2010



**Table 1: Summary Statistics**

Sample Type		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		HOLC Neighborhoods				1/4 Mile Buffer				1/8 Mile Buffer			
		HOLC Neighborhoods				C-B Boundaries		D-C Boundaries		C-B Boundaries		D-C Boundaries	
Grade	N	A	B	C	D	B	C	C	D	B	C	C	D
		543	1351	2156	1399	1965	1965	2111	2111	2000	2000	2047	2047
<u>Panel A.</u>	year												
Share	1910	0.043	0.043	0.041	0.105	0.022	0.024	0.041	0.069	0.021	0.029	0.038	0.061
African	1920	0.026	0.018	0.028	0.095	0.010	0.015	0.030	0.061	0.011	0.015	0.029	0.055
American	1930	0.021	0.015	0.021	0.158	0.009	0.015	0.035	0.099	0.008	0.017	0.034	0.087
	1940	0.012	0.012	0.019	0.166	0.007	0.014	0.036	0.114	0.006	0.017	0.039	0.101
	1950	0.009	0.008	0.021	0.241	0.004	0.021	0.047	0.184	0.005	0.016	0.057	0.160
	1960	0.009	0.029	0.088	0.335	0.050	0.073	0.186	0.326	0.031	0.067	0.242	0.277
	1970	0.044	0.106	0.189	0.405	0.144	0.193	0.303	0.454	0.157	0.190	0.388	0.397
	1980	0.108	0.186	0.280	0.455	0.312	0.303	0.400	0.519	0.284	0.345	0.510	0.483
	1990	0.090	0.157	0.271	0.401	0.253	0.280	0.383	0.442	0.245	0.273	0.400	0.434
	2000	0.114	0.191	0.305	0.412	0.301	0.326	0.420	0.463	0.294	0.322	0.428	0.454
	2010	0.121	0.191	0.299	0.381	0.297	0.312	0.392	0.427	0.287	0.307	0.407	0.424
<u>Panel B.</u>													
Home	1910	0.570	0.598	0.522	0.412	0.614	0.547	0.496	0.444	0.612	0.545	0.487	0.443
Ownership	1920	0.684	0.655	0.559	0.437	0.634	0.575	0.499	0.443	0.627	0.562	0.486	0.441
Rate	1930	0.759	0.654	0.541	0.438	0.585	0.526	0.458	0.422	0.570	0.520	0.447	0.414
	1940	0.734	0.597	0.484	0.383	0.504	0.452	0.398	0.366	0.492	0.446	0.389	0.363
	1950	0.657	0.583	0.497	0.365	0.412	0.337	0.352	0.297	0.332	0.197	0.303	0.281
	1960	0.672	0.592	0.516	0.376	0.413	0.333	0.353	0.302	0.326	0.227	0.294	0.284
	1970	0.659	0.552	0.482	0.360	0.371	0.306	0.324	0.277	0.272	0.216	0.265	0.255
	1980	0.676	0.550	0.469	0.355	0.375	0.305	0.328	0.280	0.271	0.225	0.257	0.259
	1990	0.816	0.660	0.516	0.446	0.546	0.464	0.429	0.416	0.524	0.460	0.421	0.417
	2000	0.816	0.655	0.513	0.444	0.545	0.467	0.435	0.416	0.527	0.464	0.427	0.425
	2010	0.805	0.642	0.494	0.426	0.528	0.458	0.417	0.397	0.512	0.447	0.412	0.398

**Table 1: Summary Statistics (continued)**

Sample Type		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		HOLC Neighborhoods				1/4 Mile Buffer				1/8 Mile Buffer			
		A	B	C	D	C-B Boundaries		D-C Boundaries		C-B Boundaries		D-C Boundaries	
Grade						B	C	C	D	B	C	C	D
N		543	1351	2156	1399	1965	1965	2111	2111	2000	2000	2047	2047
<u>Panel C.</u>	year												
Home	1930	195843	129259	95226	72246	127834	104897	94237	81083	128830	107940	94116	82917
Value	1940	148187	96489	66354	48600	86855	71441	60531	51655	86868	73002	60613	52533
	1970	180854	125966	102906	76396	123666	115735	94073	82982	139920	128305	99131	96742
	1980	229991	148352	112968	85801	139111	129498	100972	83207	160663	156498	98277	93023
	1990	311722	227011	162149	136061	182157	158028	134433	122539	185774	166335	130269	123818
	2000	363810	255757	180783	156701	205430	174695	149684	136939	209620	185257	147221	139799
	2010	208050	161348	125057	111134	128815	120499	107398	103923	131236	122059	106873	104746
<u>Panel D.</u>													
Share	1910	0.184	0.170	0.182	0.205	0.167	0.172	0.179	0.188	0.162	0.175	0.180	0.189
Foreign	1920	0.148	0.146	0.161	0.189	0.141	0.151	0.162	0.178	0.142	0.148	0.164	0.177
Born	1930	0.106	0.120	0.152	0.160	0.138	0.146	0.158	0.163	0.135	0.142	0.159	0.163
	1940	0.078	0.097	0.123	0.126	0.115	0.123	0.129	0.129	0.114	0.118	0.128	0.128
	1950	0.117	0.118	0.133	0.109	0.164	0.171	0.158	0.146	0.207	0.207	0.186	0.166
	1960	0.099	0.108	0.113	0.087	0.159	0.154	0.132	0.112	0.203	0.191	0.155	0.145
	1970	0.081	0.094	0.098	0.077	0.140	0.145	0.109	0.091	0.210	0.188	0.116	0.114
	1980	0.084	0.101	0.113	0.096	0.158	0.182	0.115	0.115	0.211	0.234	0.147	0.143
	1990	0.088	0.128	0.151	0.147	0.117	0.126	0.108	0.108	0.104	0.118	0.108	0.101
	2000	0.081	0.107	0.126	0.116	0.109	0.117	0.112	0.112	0.104	0.111	0.112	0.111
	2010	0.086	0.113	0.137	0.129	0.115	0.125	0.119	0.120	0.114	0.119	0.121	0.121
<u>Panel E.</u>													
Credit	1999	717	687	654	636	663	653	638	631	660	654	636	634
Score	2016	737	704	670	652	680	672	656	648	676	670	653	652

**Table 2: Assessing HOLC Grading Criteria**

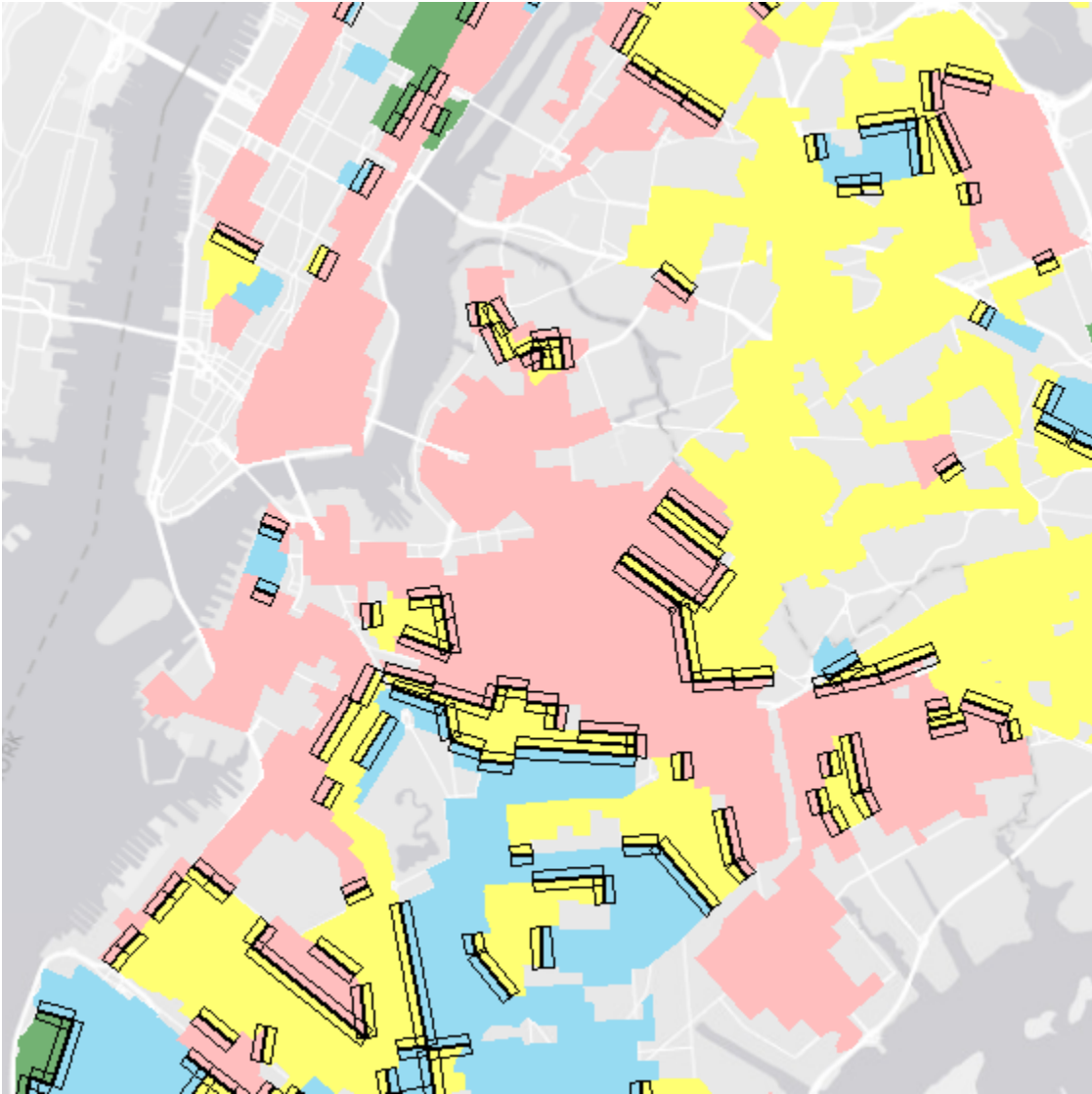
Coefficients	(1) (2)		(3)	(4)	(5)	(6)	(7)	(8)						
	Ordered Logit								Probit					
	ABCD	ABCD							DC	DC	CB	CB	BA	BA
Share AA	2.824 (1.233)	1.510 (1.521)	2.742 (0.870)	2.093 (1.125)	-2.857 (1.146)	-3.531 (1.398)	-5.514 (1.262)	-10.147 (2.283)						
Share Home Ownership	-6.600 (0.594)	-7.590 (0.737)	-3.353 (0.428)	-4.523 (0.529)	-3.966 (0.485)	-4.818 (0.593)	-3.786 (0.565)	-3.857 (0.753)						
Log House Value	-3.057 (0.225)	-3.319 (0.268)	-1.570 (0.239)	-1.936 (0.218)	-1.474 (0.178)	-2.005 (0.189)	-1.598 (0.195)	-1.676 (0.281)						
Log Rent	-0.154 (0.080)	-0.163 (0.091)	-0.095 (0.060)	-0.071 (0.072)	-0.118 (0.061)	-0.145 (0.075)	0.064 (0.073)	0.035 (0.092)						
Occscore	-4.318 (1.166)	-6.012 (1.246)	-0.514 (1.091)	-2.231 (1.177)	-1.593 (0.968)	-3.875 (1.215)	-3.004 (1.055)	-2.971 (1.258)						
Employment	-0.139 (0.031)	-0.148 (0.038)	-0.143 (0.041)	-0.203 (0.049)	-0.132 (0.022)	-0.170 (0.037)	0.030 (0.023)	0.051 (0.030)						
Radio	-6.665 (0.753)	-7.163 (0.910)	-3.812 (0.530)	-2.894 (0.576)	-3.809 (0.622)	-4.260 (0.765)	-1.336 (0.766)	-2.214 (0.930)						
Literacy	-7.825 (2.349)	-10.676 (2.698)	-7.803 (1.802)	-10.726 (2.331)	-0.649 (3.618)	-0.888 (3.596)	-4.699 (3.834)	-4.003 (6.512)						
School Attendance	4.198 (0.811)	6.099 (1.192)	1.059 (0.729)	1.329 (0.947)	2.210 (0.661)	4.537 (1.014)	1.783 (0.721)	2.645 (1.202)						
Share Foreign Born	-0.332 (1.373)	-1.194 (1.757)	-2.548 (0.824)	-3.139 (0.968)	0.466 (1.023)	0.172 (1.139)	0.681 (1.298)	0.609 (1.832)						
Includes changes*	--	X	--	X	--	X	--	X						
Cities	147	146	138	137	144	142	120	102						
N	4717	3928	3146	2704	3045	2506	1479	1088						
Pseudo R <sup>2</sup>	0.482	0.511	0.498	0.538	0.442	0.502	0.348	0.399						

Note: This table reports estimates of the relationship between HOLC map grades and 1930 neighborhood characteristics and 1920 to 1930 trends in characteristics. Each observation represents an HOLC neighborhood. In the ordered logit specification, the dependent variable is coded such that the neighborhood graded as riskiest has the highest value (e.g. the dependent variable is coded as D=4, C=3, B=2, and D=1). All specifications include city fixed effects and are weighted by the log of the population of the HOLC neighborhood in 1930. Standard errors are shown in parentheses and are clustered by city.

**Table 3: Effect of D versus C grade on Share African Americans (using grid controls)**

Sample Type	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	HOLC Neighborhoods		1/4 Mile D-C Boundaries					1/8 Mile D-C Boundaries				
Year			Treated	Treated	Control	Trip Diff	< Med ps Treated	Treated	Treated	Control	Trip Diff	< Med ps Treated
2010	0.081 (0.016)	0.079 (0.012)	0.038 (0.008)	0.034 (0.008)	0.008 (0.003)	0.027 (0.012)	0.009 (0.006)	0.023 (0.007)	0.022 (0.007)	0.004 (0.003)	0.019 (0.008)	0.001 (0.008)
2000	0.106 (0.017)	0.103 (0.013)	0.043 (0.011)	0.038 (0.010)	0.012 (0.004)	0.028 (0.012)	0.015 (0.009)	0.025 (0.008)	0.022 (0.008)	0.007 (0.002)	0.016 (0.009)	0.005 (0.008)
1990	0.130 (0.018)	0.126 (0.014)	0.061 (0.012)	0.057 (0.012)	0.013 (0.005)	0.044 (0.013)	0.027 (0.011)	0.034 (0.009)	0.032 (0.009)	0.006 (0.003)	0.027 (0.009)	0.010 (0.009)
1980	0.172 (0.028)	0.159 (0.023)	0.114 (0.030)	0.089 (0.021)	-0.009 (0.020)	0.099 (0.030)	0.050 (0.017)	0.080 (0.056)	0.061 (0.040)	-0.016 (0.015)	0.078 (0.043)	0.020 (0.050)
1970	0.216 (0.024)	0.203 (0.020)	0.146 (0.029)	0.117 (0.024)	-0.013 (0.017)	0.131 (0.035)	0.076 (0.021)	0.108 (0.034)	0.085 (0.023)	-0.008 (0.013)	0.094 (0.020)	0.074 (0.035)
1960	0.250 (0.021)	0.234 (0.018)	0.132 (0.034)	0.101 (0.028)	-0.009 (0.015)	0.110 (0.031)	0.054 (0.021)	0.094 (0.032)	0.072 (0.017)	0.000 (0.011)	0.073 (0.016)	0.061 (0.025)
1950	0.224 (0.020)	0.214 (0.019)	0.133 (0.030)	0.110 (0.027)	-0.006 (0.011)	0.117 (0.027)	0.064 (0.017)	0.107 (0.029)	0.095 (0.021)	0.007 (0.014)	0.090 (0.022)	0.075 (0.020)
1940	0.150 (0.015)	0.147 (0.013)	0.080 (0.013)	0.077 (0.014)	0.047 (0.011)	0.031 (0.006)	0.012 (0.007)	0.063 (0.012)	0.062 (0.012)	0.037 (0.006)	0.027 (0.005)	0.011 (0.006)
1930	0.135 (0.014)	0.133 (0.013)	0.067 (0.011)	0.065 (0.012)	0.066 (0.013)	-- (0.013)	0.001 (0.005)	0.053 (0.010)	0.052 (0.011)	0.053 (0.008)	-- (0.008)	-0.001 (0.003)
1920	0.069 (0.009)	0.063 (0.008)	0.033 (0.007)	0.031 (0.007)	0.032 (0.008)	0.000 (0.008)	-0.001 (0.004)	0.026 (0.005)	0.024 (0.006)	0.027 (0.005)	-0.001 (0.008)	-0.004 (0.003)
1910	0.061 (0.011)	0.053 (0.009)	0.029 (0.006)	0.027 (0.006)	0.029 (0.011)	-0.001 (0.008)	0.000 (0.004)	0.021 (0.005)	0.021 (0.005)	0.020 (0.005)	0.002 (0.009)	-0.004 (0.003)
Cities	148	148	115	115	115	115	71	114	114	114	114	79
neighs	3535	3555	1139	1139	4280	5419	571	1062	1062	6224	7286	541
N	27814	27814	16781	16781	62334	79115	8796	15018	15018	87986	103004	7840
R squared	0.215	0.383	0.429	0.646	0.672	0.666	0.649	0.429	0.643	0.680	0.675	0.642
Fix Effects	None	City	City	Boundary	Boundary	Boundary	Boundary	City	Boundary	Boundary	Boundary	Boundary

**Appendix Figure A1: Boundary Buffer Zones for New York City**





# Appendix Figure A2: Area Description File for Tacoma, Washington

FORM 8  
10-1-37

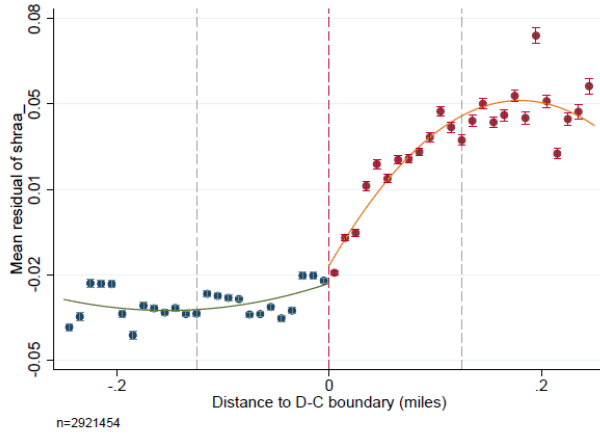
AREA DESCRIPTION - SECURITY MAP OF Tacoma

1. AREA CHARACTERISTICS:
  - a. Description of Terrain. Low lying level.
  - b. Favorable Influences. Schools, churches, stores and transportation conveniently available.
  - c. Detrimental Influences. Unimproved streets - Heterogeneous population.
  - d. Percentage of land improved 50 %; e. Trend of desirability next 10-15 yrs. Static
2. INHABITANTS:
  - a. Occupation Laborers; b. Estimated annual family income \$ 1000 to \$1800
  - c. Foreign-born families few %; American born \_\_\_\_\_ predominating; d. Negro Yes; 2 %
  - e. Infiltration of Lower classes slowly f. Relief families Many
  - g. Population is increasing Slowly; decreasing ----; static ----
3. BUILDINGS:
 

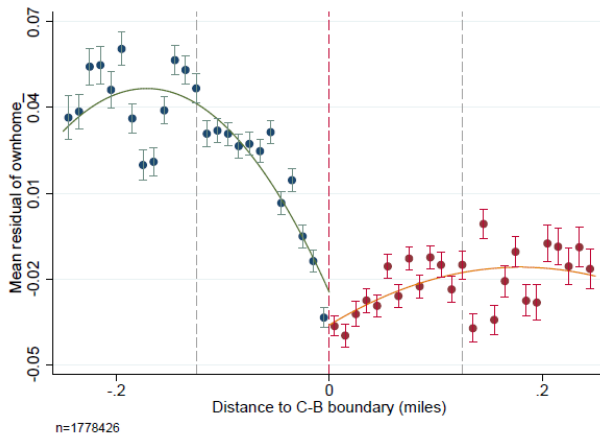
	PREDOMINATING	90 %	OTHER TYPE	10 %	OTHER TYPE	%
a. Type	<u>4 &amp; 5 room</u>		<u>Miscellaneous</u>			
b. Construction	<u>frame</u>					
c. Average Age	<u>15</u> Years		_____	_____	_____	_____
d. Repair	<u>poor to fair</u>					
e. Occupancy	<u>95</u> %		_____ %		_____ %	
f. Home ownership	<u>50</u> %		_____ %		_____ %	
g. Constructed past yr.	<u>None</u>					
h. 1929 Price range	<u>\$ 1000 to \$2500</u>	<u>100</u> %	\$ _____	<u>100</u> %	\$ _____	<u>100</u> %
i. 1933 Price range	<u>\$ 500 to \$1500</u>	<u>60</u> %	\$ _____	_____ %	\$ _____	_____ %
j. 1937 Price range	<u>\$ 800 to \$2000</u>	<u>80</u> %	\$ _____	_____ %	\$ _____	_____ %
k. Sales demand	<u>\$ 1500 - fair</u>		\$ _____		\$ _____	
l. Activity	<u>fair</u>					
m. 1929 Rent range	<u>\$ 10 to \$25</u>	<u>100</u> %	\$ _____	<u>100</u> %	\$ _____	<u>100</u> %
n. 1933 Rent range	<u>\$ 5.00 to \$12</u>	<u>50</u> %	\$ _____	_____ %	\$ _____	_____ %
o. 1937 Rent range	<u>\$ 12 to \$20</u>	<u>95</u> %	\$ _____	_____ %	\$ _____	_____ %
p. Rental demand	<u>\$ 15 good</u>		\$ _____		\$ _____	
q. Activity	<u>good</u>					
4. AVAILABILITY OF MORTGAGE FUNDS: a. Home purchase limited; b. Home building limited
5. CLARIFYING REMARKS: This might be classed as a 'Low Yellow' area were it not for the presence of the number of Negroes and low class Foreign families who reside in the area. Lot values run from \$2.00 to \$5.00 per front foot.
6. NAME AND LOCATION Tacoma SECURITY GRADE D AREA NO. 7

### Appendix Figure A3: Distance Plots Around HOLC Borders

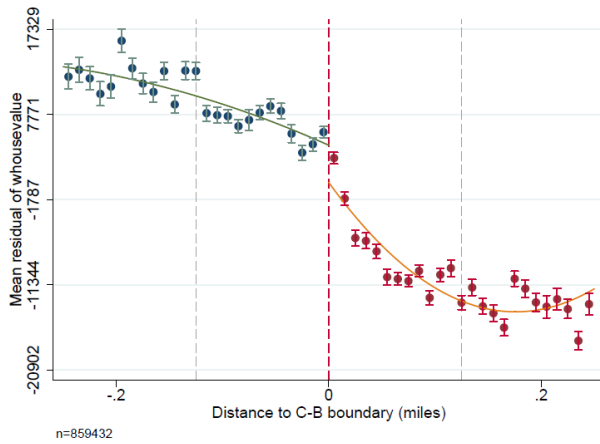
Panel A: African American Share, 1930, D-C boundaries



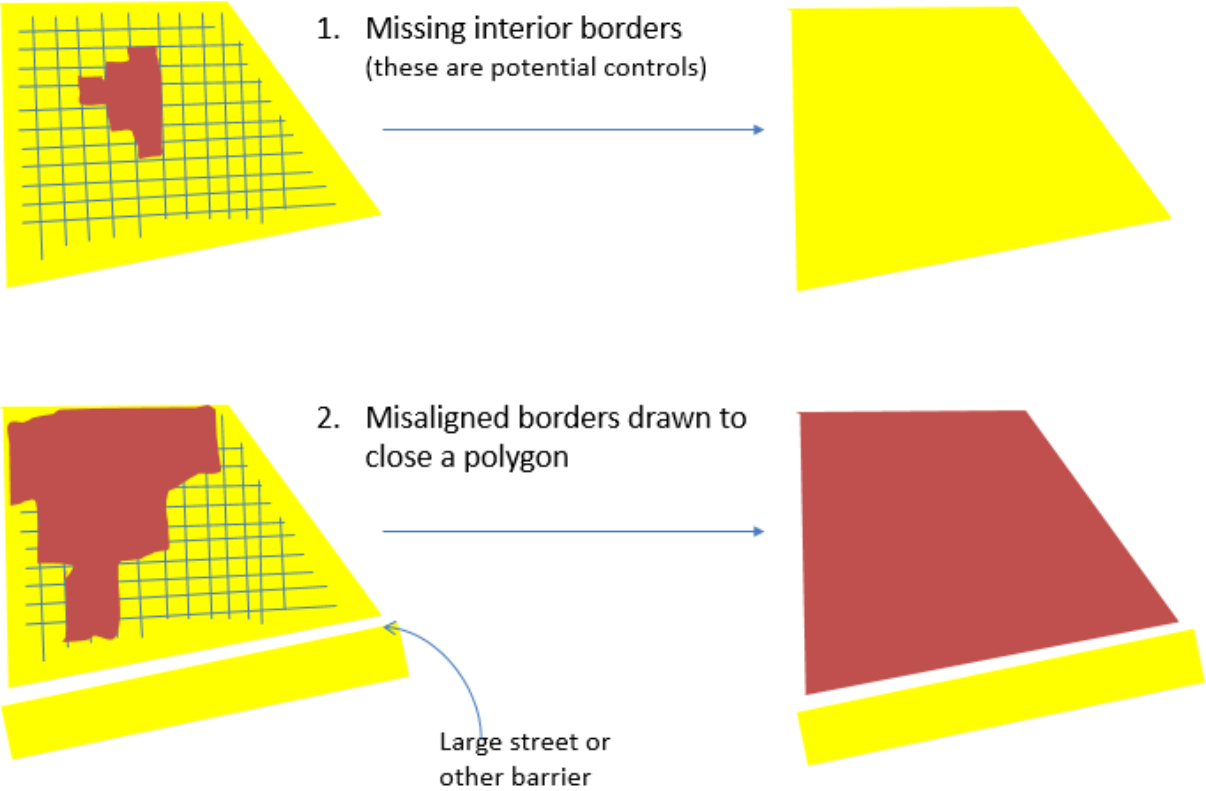
Panel B: Home Ownership, 1930, C-B Boundaries



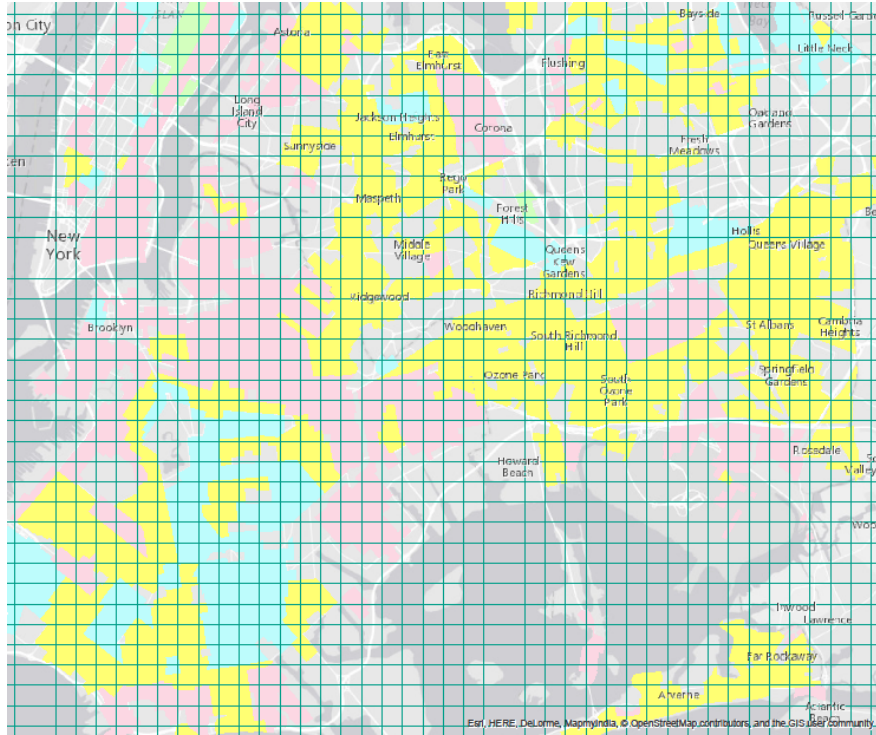
Panel C: House Values, 1930, C-B Boundaries



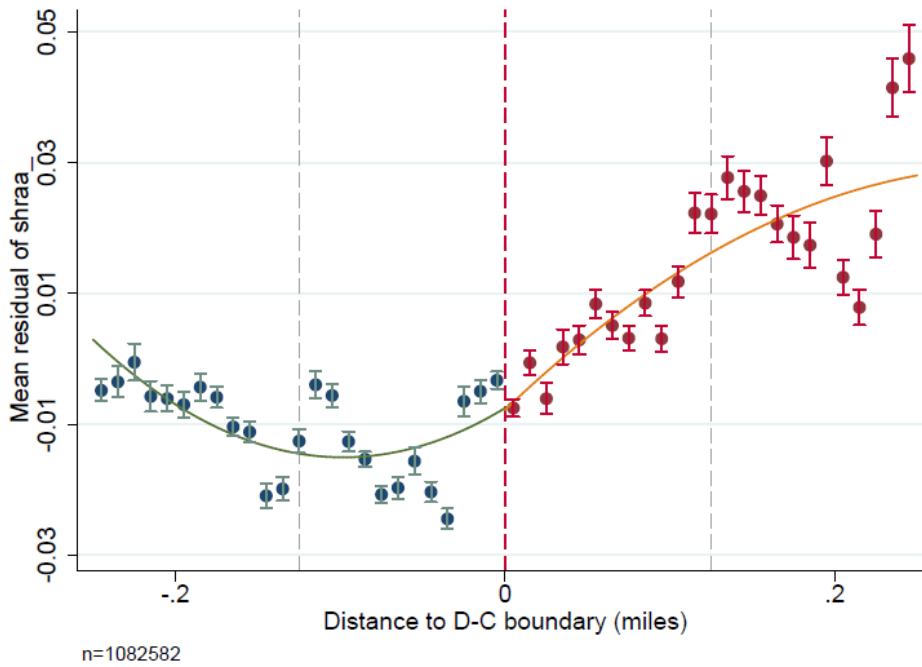
**Appendix Figure A4: Hypothetical Examples of Missing and Misaligned Borders**



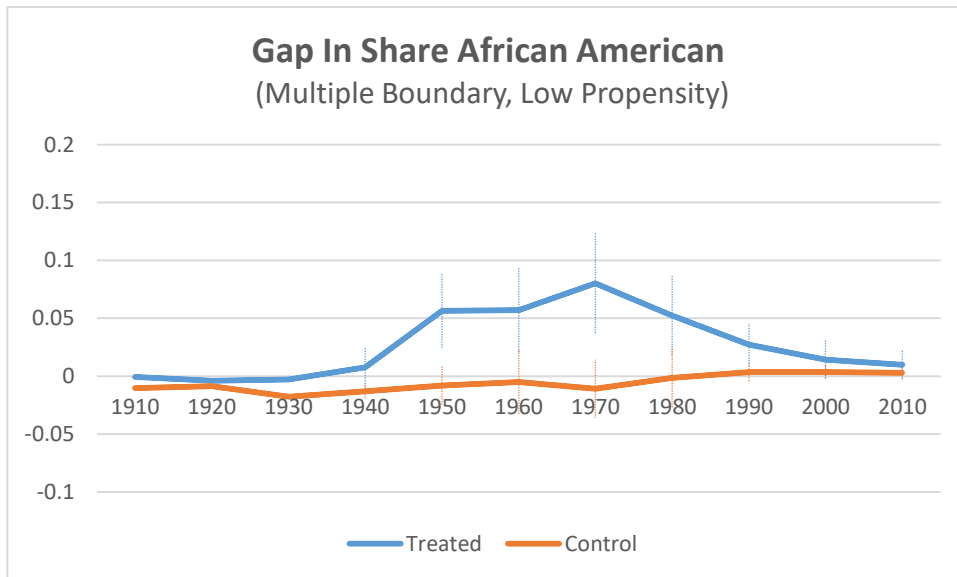
**Appendix Figure A5: Example of Grid Placed over New York City**



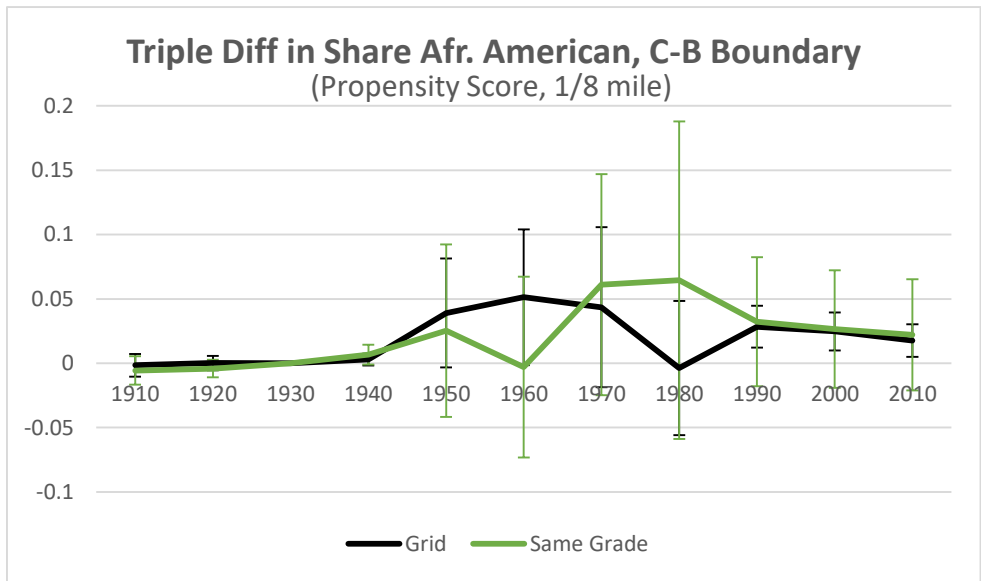
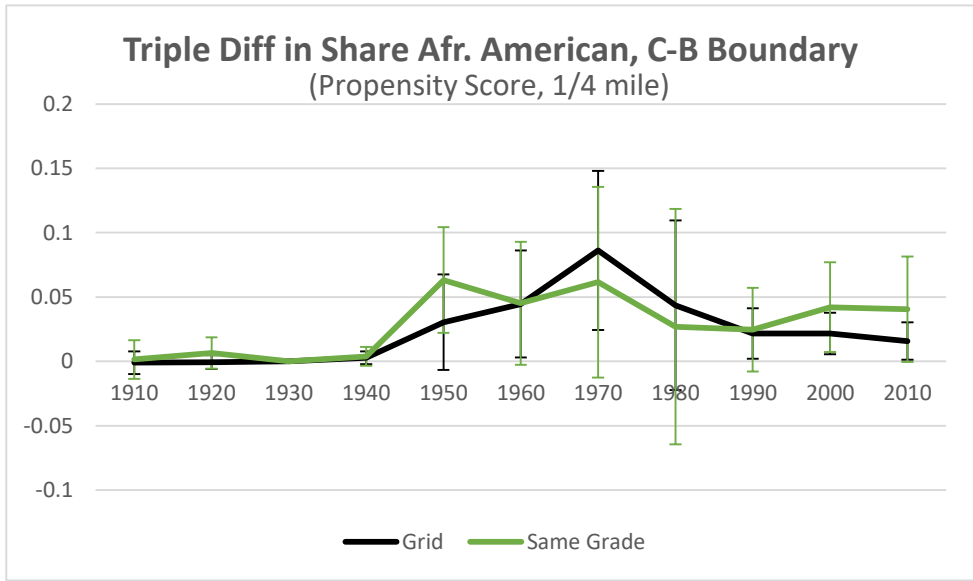
**Appendix Figure A6: Distance Plot of AA Share Using Low Propensity Treated**



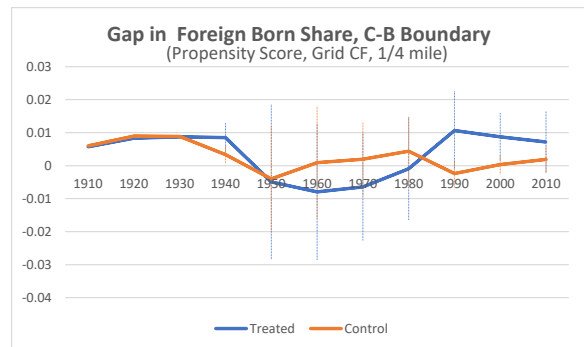
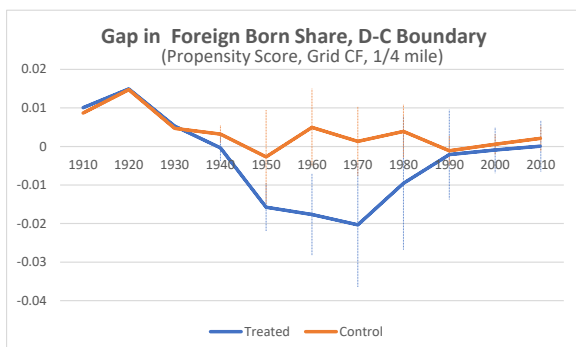
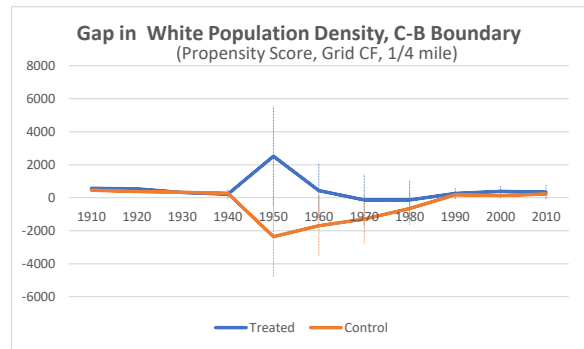
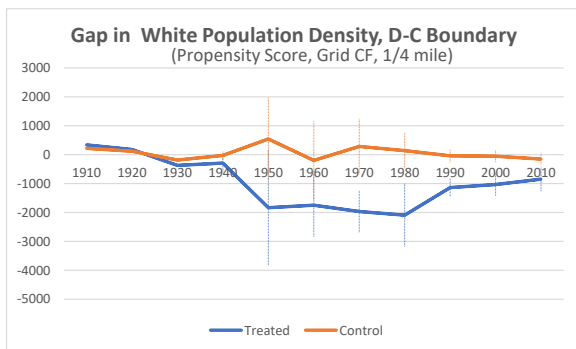
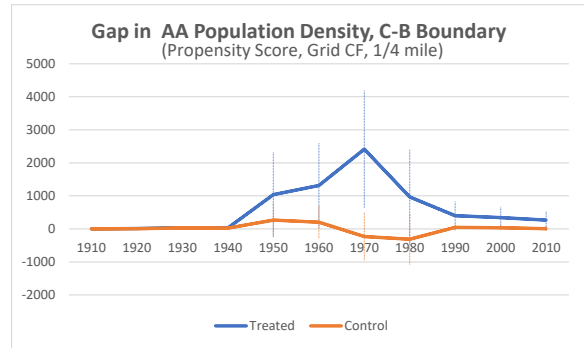
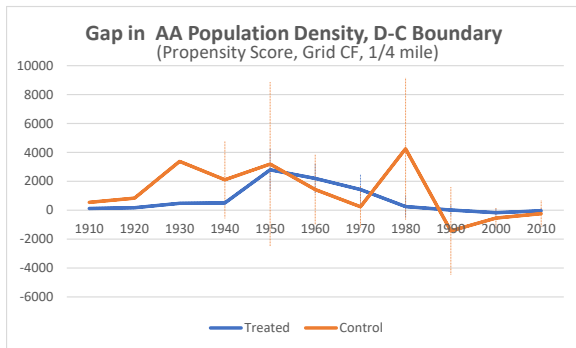
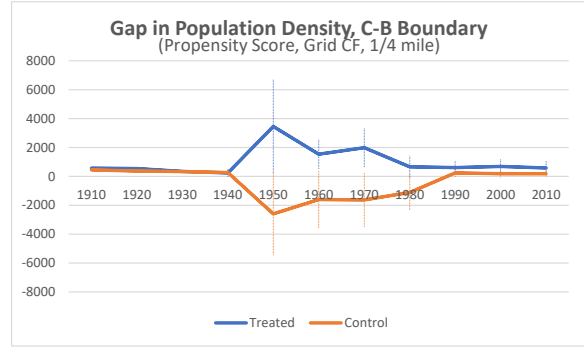
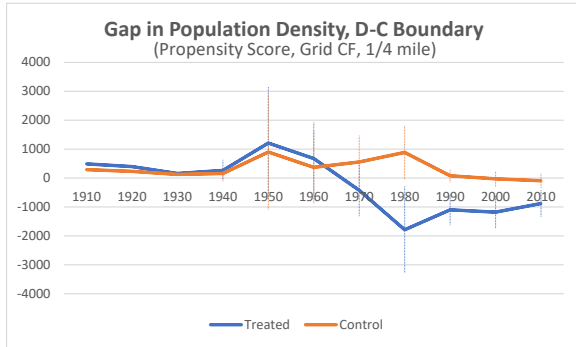
**Appendix Figure A7: Effects on D-C gap in African American Share, Multiple Boundary Neighborhoods and Low Propensity Treated**



**Appendix Figure A8: Effects on Triple Difference in C-B Gaps in Share African American**

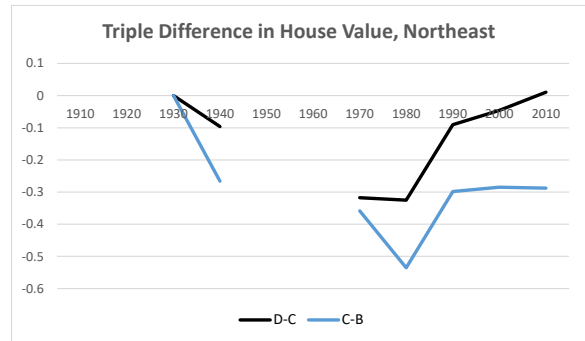
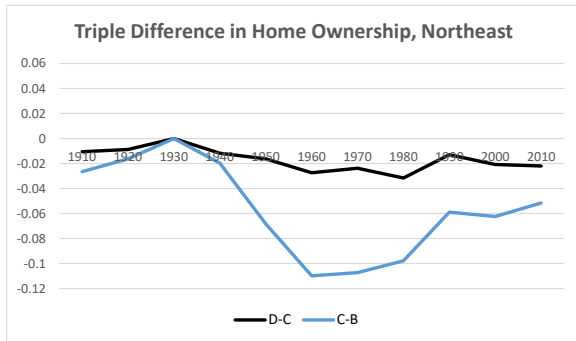


## Appendix Figure A9: Population Dynamics Along the D-C and C-B Boundaries

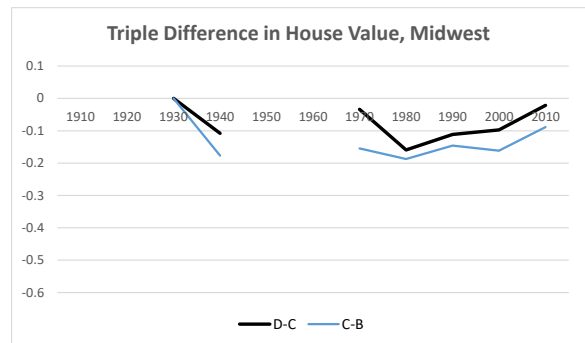
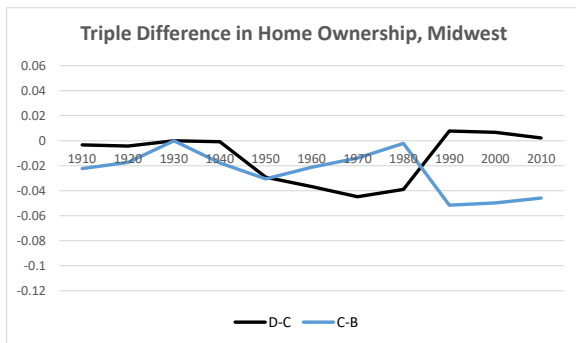


## Appendix Figure A10: Triple Differences Gap in Home Ownership, by Region

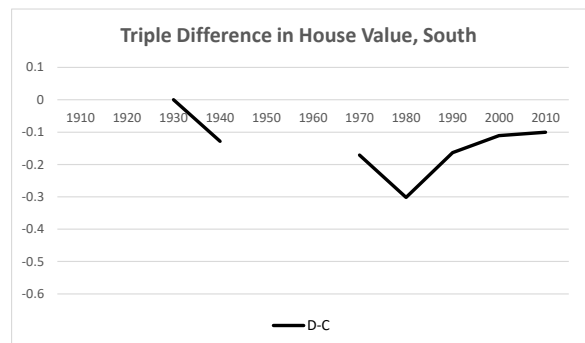
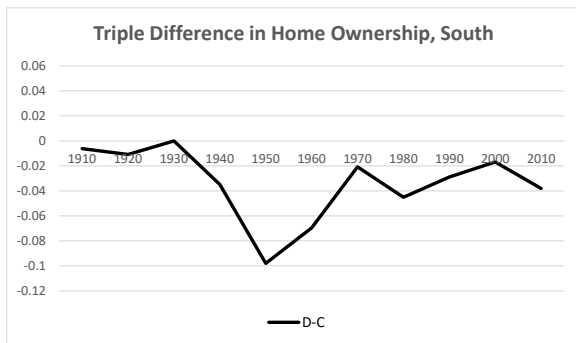
Panel A: Northeast



Panel B: Midwest



Panel C: South





**Table A1: Geocoding Statistics**

	1910	1920	1930	1940
Share of Population with a non-missing address	73%	72%	99%	82%
Share of population successfully geocoded	49%	50%	79%	62%
Share of non-missing addresses successfully geocoded	63%	68%	79%	74%

**Table A2: City Characteristics from 1930 Census**

City	1930 Census Variables													
	Pop'n geo'd	Share AA	Home Own	House Values	Share FB	Radio Own	Att. School	Lab F Part.	Rent	Occ. Score	Earn Score	Educ Score	Emp. Rate	Read or Write
Akron_OH	188,793	0.04	0.54	6174	0.13	0.53	0.63	0.60	53	25	51	14	0.82	0.98
Albany_NY	107,893	0.02	0.40	10432	0.14	0.58	0.63	0.60	74	26	55	17	0.84	0.99
Altoona_PA	70,209	0.01	0.61	5449	0.07	0.45	0.61	0.52	54	27	59	14	0.81	0.98
Arlington_MA	31,589	0.00	0.56	9723	0.22	0.74	0.62	0.55	65	28	57	21	0.84	0.99
Asheville_NC	35,807	0.24	0.40	7839	0.02	0.32	0.59	0.61	56	24	46	17	0.80	0.97
Atlanta_GA	161,227	0.27	0.35	6780	0.02	0.31	0.61	0.63	46	24	47	16	0.84	0.97
AtlanticCity_NJ	46,508	0.23	0.30	19838	0.16	0.57	0.64	0.63	79	23	43	14	0.81	0.98
Augusta_GA	43,210	0.40	0.29	4983	0.01	0.16	0.57	0.65	39	21	41	12	0.83	0.93
Aurora_IL	39,485	0.02	0.66	6641	0.13	0.71	0.62	0.57	81	26	55	15	0.80	0.98
Baltimore_MD	635,110	0.16	0.56	5421	0.09	0.52	0.56	0.62	53	25	50	14	0.85	0.97
BattleCreek_MI	25,244	0.03	0.60	5845	0.08	0.53	0.63	0.60	72	26	55	15	0.82	0.99
BayCity_MI	36,733	0.00	0.71	2974	0.14	0.49	0.64	0.55	61	26	54	14	0.73	0.97
Belmont_MA	19,988	0.00	0.54	11678	0.22	0.78	0.64	0.55	50	28	56	24	0.88	0.98
Binghamton_NY	61,732	0.01	0.48	7888	0.13	0.50	0.65	0.63	38	25	51	14	0.84	0.97
Birmingham_AL	194,055	0.35	0.39	6109	0.02	0.31	0.57	0.60	47	24	49	15	0.86	0.95
Boston_MA	514,816	0.03	0.29	8504	0.31	0.56	0.66	0.61	69	25	49	15	0.79	0.96
Braintree_MA	12,568	0.00	0.70	5985	0.18	0.77	0.63	0.55	61	27	57	18	0.87	0.99
Bronx_NY	1,072,492	0.01	0.13	13455	0.38	0.65	0.61	0.60	71	26	54	17	0.83	0.96
Brookline_MA	38,951	0.01	0.38	21847	0.27	0.80	0.73	0.57	146	25	47	23	0.83	1.00
Brooklyn_NY	2,191,580	0.03	0.30	11738	0.34	0.59	0.61	0.60	73	26	53	16	0.82	0.95
Buffalo_NY	507,445	0.02	0.47	8354	0.21	0.56	0.62	0.58	50	26	55	15	0.80	0.98
Cambridge_MA	101,103	0.05	0.28	9470	0.29	0.56	0.63	0.61	43	25	50	16	0.80	0.97
Camden_NJ	100,093	0.09	0.51	4903	0.16	0.54	0.60	0.61	67	25	53	12	0.80	0.95
Canton_OH	83,883	0.02	0.56	6348	0.12	0.51	0.61	0.57	44	26	56	15	0.83	0.97
Charleston_WV	31,078	0.11	0.40	10311	0.03	0.46	0.63	0.59	44	26	51	20	0.84	0.98
Charlotte_NC	44,003	0.26	0.35	8803	0.01	0.37	0.53	0.64	51	23	45	15	0.84	0.93
Chattanooga_TN	81,609	0.23	0.36	5638	0.01	0.24	0.54	0.61	31	24	49	14	0.85	0.96
Chelsea_MA	39,184	0.01	0.33	6906	0.38	0.51	0.63	0.58	46	26	52	13	0.79	0.93
Chicago_IL	2,416,387	0.07	0.38	9346	0.26	0.64	0.62	0.61	89	25	53	14	0.80	0.97
Chicopee_MA	40,247	0.00	0.46	5822	0.28	0.44	0.62	0.62	27	25	51	10	0.80	0.95

**Table A2: City Characteristics from 1930 Census**

City	1930 Census Variables													
	Pop'n geo'd	Share AA	Home Own	House Values	Share FB	Radio Own	Att. School	Lab F Part.	Rent	Occ. Score	Earn Score	Educ Score	Emp. Rate	Read or Write
Cleveland_OH	736,884	0.07	0.42	7305	0.26	0.48	0.65	0.60	46	25	52	13	0.78	0.96
Columbus_GA	34,395	0.28	0.23	6003	0.01	0.17	0.52	0.66	44	22	43	11	0.85	0.93
Columbus_OH	224,650	0.09	0.46	6597	0.05	0.52	0.62	0.59	43	26	54	16	0.82	0.99
Dallas_TX	182,283	0.11	0.42	6224	0.04	0.45	0.55	0.62	51	25	51	18	0.85	0.98
Dayton_OH	143,851	0.08	0.50	6285	0.06	0.58	0.62	0.60	50	26	53	15	0.83	0.99
Decatur_IL	47,825	0.03	0.56	5238	0.04	0.50	0.59	0.57	38	26	54	16	0.82	0.99
Dedham_MA	12,036	0.00	0.67	6588	0.23	0.63	0.64	0.58	60	25	53	16	0.85	0.98
Denver_CO	248,476	0.03	0.48	5421	0.11	0.53	0.63	0.58	41	26	52	19	0.81	0.99
Detroit_MI	1,058,107	0.05	0.49	8977	0.26	0.60	0.61	0.60	73	26	55	13	0.80	0.98
Duluth_MN	69,910	0.00	0.59	6155	0.23	0.53	0.67	0.57	31	26	53	17	0.77	0.99
Durham_NC	30,791	0.27	0.33	6097	0.01	0.22	0.53	0.67	36	24	47	13	0.85	0.95
EastHartford_CT	14,886	0.01	0.50	8098	0.18	0.62	0.61	0.60	33	26	53	14	0.82	0.97
EastStLouis_IL	58,444	0.17	0.45	4350	0.06	0.43	0.58	0.58	41	26	54	13	0.80	0.98
Elmira_NY	39,621	0.01	0.53	6523	0.09	0.47	0.66	0.58	38	26	54	16	0.79	0.98
Erie_PA	99,410	0.01	0.52	7731	0.15	0.51	0.61	0.56	85	26	53	14	0.83	0.97
EssexCounty_NJ	669,167	0.07	0.42	12616	0.22	0.66	0.63	0.60	51	26	53	17	0.82	0.97
Evansville_IN	75,901	0.06	0.46	4149	0.02	0.34	0.60	0.58	38	25	52	13	0.83	0.99
Everett_MA	43,906	0.02	0.44	6321	0.29	0.65	0.59	0.58	48	26	54	14	0.81	0.97
Flint_MI	102,596	0.02	0.64	5096	0.14	0.55	0.60	0.59	57	26	55	12	0.83	0.99
FortWayne_IN	93,848	0.02	0.60	6398	0.05	0.64	0.60	0.59	35	27	56	15	0.83	0.99
Fresno_CA	28,727	0.01	0.50	5075	0.21	0.38	0.67	0.56	37	26	51	19	0.79	0.96
Gary_IN	86,873	0.19	0.44	7264	0.21	0.46	0.62	0.59	62	25	54	12	0.88	0.95
GrandRapids_MI	117,085	0.02	0.64	5689	0.16	0.50	0.65	0.57	45	26	54	16	0.78	0.98
Greensboro_NC	30,773	0.24	0.47	7648	0.01	0.32	0.56	0.62	36	24	48	17	0.85	0.97
Hamilton_OH	44,014	0.03	0.55	5140	0.04	0.51	0.54	0.57	35	26	55	12	0.84	0.98
Haverhill_MA	42,292	0.01	0.46	5423	0.22	0.51	0.64	0.62	47	25	48	12	0.76	0.97
Holyoke_MA	49,464	0.00	0.27	11802	0.29	0.52	0.68	0.61	34	25	51	13	0.80	0.97
HudsonCounty_NJ	507,548	0.03	0.29	9256	0.26	0.62	0.61	0.62	84	26	54	14	0.84	0.96
Indianapolis_IN	277,757	0.10	0.44	5881	0.04	0.49	0.59	0.60	63	26	53	16	0.83	0.99
Jacksonville_FL	84,535	0.31	0.35	6927	0.04	0.29	0.58	0.61	31	24	47	16	0.84	0.97

**Table A2: City Characteristics from 1930 Census**

City	1930 Census Variables													
	Pop'n geo'd	Share AA	Home Own	House Values	Share FB	Radio Own	Att. School	Lab F Part.	Rent	Occ. Score	Earn Score	Educ Score	Emp. Rate	Read or Write
JohnsonCity_NY	11,678	0.00	0.54	6128	0.07	0.53	0.61	0.66	33	25	49	10	0.83	0.99
Johnstown_PA	52,542	0.02	0.45	6238	0.14	0.40	0.61	0.54	37	25	52	14	0.86	0.96
Joliet_IL	23,480	0.03	0.51	8027	0.16	0.60	0.62	0.57	44	26	55	17	0.82	0.99
Kalamazoo_MI	36,932	0.01	0.66	6181	0.11	0.58	0.66	0.57	45	26	54	18	0.83	1.00
KansasCity_MO	319,031	0.09	0.44	6600	0.07	0.52	0.64	0.61	52	26	52	17	0.85	0.99
Kenosha_WI	45,374	0.00	0.60	7686	0.24	0.63	0.68	0.58	46	25	53	12	0.78	0.96
Knoxville_TN	48,395	0.12	0.42	5279	0.01	0.29	0.56	0.60	42	26	52	16	0.83	0.97
Lexington_KY	35,158	0.27	0.37	6057	0.01	0.31	0.60	0.60	30	23	44	16	0.81	0.96
Lexington_MA	7,490	0.00	0.75	9028	0.20	0.75	0.64	0.55	215	25	50	19	0.87	0.98
Lima_OH	37,340	0.03	0.47	4914	0.04	0.47	0.62	0.58	43	26	55	15	0.84	0.99
Lorain_OH	39,324	0.02	0.62	5137	0.28	0.41	0.62	0.58	46	25	54	11	0.81	0.94
Louisville_KY	241,349	0.13	0.45	5459	0.03	0.37	0.57	0.59	57	25	51	15	0.82	0.98
Lynchburg_VA	31,821	0.23	0.47	5290	0.01	0.24	0.57	0.62	31	24	47	14	0.80	0.95
Macon_GA	18,559	0.34	0.28	4976	0.01	0.18	0.55	0.64	68	23	45	14	0.81	0.95
Madison_WI	51,536	0.00	0.56	8778	0.09	0.65	0.66	0.57	64	27	54	21	0.82	0.99
Malden_MA	53,282	0.01	0.47	6168	0.28	0.66	0.61	0.58	47	26	54	16	0.81	0.98
Manchester_NH	61,731	0.00	0.37	5502	0.29	0.41	0.62	0.64	53	25	49	12	0.79	0.97
Medford_MA	56,087	0.01	0.54	7536	0.23	0.73	0.60	0.57	59	27	56	17	0.84	0.98
Melrose_MA	19,787	0.00	0.67	7033	0.17	0.78	0.65	0.54	65	27	57	22	0.84	1.00
Miami_FL	69,057	0.19	0.35	5993	0.12	0.27	0.58	0.61	60	24	48	17	0.75	0.97
Milton_MA	12,285	0.00	0.69	12359	0.21	0.81	0.68	0.56	50	25	51	21	0.85	1.00
Milwaukee_WI	242,173	0.02	0.46	6719	0.20	0.65	0.66	0.59	52	26	55	14	0.83	0.98
Minneapolis_MN	363,688	0.01	0.51	6070	0.17	0.62	0.67	0.59	53	26	53	18	0.83	0.99
Mobile_AL	47,529	0.33	0.41	4997	0.03	0.22	0.56	0.60	48	23	46	14	0.84	0.94
Montgomery_AL	26,798	0.32	0.33	6288	0.02	0.24	0.57	0.63	29	23	46	16	0.86	0.93
Muncie_IN	34,855	0.06	0.51	4314	0.01	0.47	0.57	0.56	31	26	54	14	0.82	0.99
Muskegon_MI	28,208	0.01	0.61	4640	0.14	0.55	0.66	0.59	43	26	54	15	0.79	0.99
Needham_MA	6,709	0.00	0.73	10936	0.20	0.78	0.66	0.54	63	27	55	22	0.85	0.98
NewBritain_CT	61,671	0.01	0.38	9356	0.31	0.41	0.64	0.61	36	26	54	13	0.83	0.92
NewCastle_PA	41,741	0.02	0.60	5402	0.16	0.42	0.62	0.53	39	26	54	14	0.78	0.94

**Table A2: City Characteristics from 1930 Census**

City	1930 Census Variables													
	Pop'n geo'd	Share AA	Home Own	House Values	Share FB	Radio Own	Att. School	Lab F Part.	Rent	Occ. Score	Earn Score	Educ Score	Emp. Rate	Read or Write
NewHaven_CT	136,643	0.03	0.35	10769	0.25	0.55	0.64	0.60	45	26	53	16	0.81	0.96
NewOrleans_LA	378,493	0.27	0.30	7107	0.04	0.23	0.58	0.60	48	23	47	14	0.81	0.95
NewYork_NY	1,420,354	0.11	0.04	42199	0.38	0.46	0.62	0.66	88	23	45	15	0.83	0.94
NewportNews_VA	25,862	0.34	0.38	4028	0.04	0.33	0.55	0.60	27	26	55	14	0.90	0.96
Newton_MA	16,306	0.01	0.57	12314	0.25	0.69	0.67	0.58	95	25	49	18	0.82	0.98
NiagaraFalls_NY	65,818	0.01	0.50	7505	0.33	0.59	0.65	0.59	43	26	55	14	0.84	0.95
Norfolk_VA	76,526	0.29	0.40	5795	0.04	0.38	0.60	0.60	38	25	50	17	0.84	0.96
Oakland_CA	218,891	0.03	0.53	6026	0.19	0.60	0.66	0.57	46	27	55	18	0.80	0.98
Oshkosh_WI	15,475	0.00	0.64	5568	0.12	0.57	0.67	0.55	45	25	51	16	0.79	0.99
Philadelphia_PA	1,623,342	0.11	0.55	6372	0.20	0.57	0.60	0.62	94	25	51	14	0.82	0.97
Pittsburgh_PA	518,768	0.07	0.46	8994	0.16	0.55	0.61	0.58	65	25	50	15	0.80	0.98
Pontiac_MI	47,428	0.04	0.54	6186	0.14	0.53	0.60	0.62	70	25	53	13	0.73	0.98
Portland_OR	42,912	0.01	0.49	5709	0.16	0.58	0.67	0.61	40	26	51	19	0.79	0.99
Portsmouth_OH	32,464	0.04	0.51	5353	0.02	0.40	0.58	0.57	35	26	55	14	0.83	0.98
Poughkeepsie_NY	34,674	0.03	0.39	9636	0.14	0.59	0.61	0.59	46	26	54	16	0.83	0.97
Queens_NY	837,973	0.02	0.51	9986	0.25	0.76	0.60	0.60	84	27	56	17	0.86	0.98
Quincy_MA	65,037	0.00	0.56	6658	0.25	0.72	0.59	0.58	44	27	58	18	0.86	0.98
Racine_WI	58,532	0.01	0.60	7300	0.21	0.69	0.68	0.58	59	26	56	14	0.83	0.98
Revere_MA	32,016	0.00	0.46	5797	0.27	0.64	0.62	0.56	48	26	55	15	0.79	0.95
Richmond_VA	140,735	0.25	0.37	7659	0.02	0.39	0.60	0.61	48	25	50	16	0.84	0.97
Roanoke_VA	42,518	0.19	0.47	5681	0.01	0.28	0.58	0.58	34	24	50	12	0.84	0.97
Rochester_NY	284,366	0.01	0.58	8052	0.23	0.57	0.67	0.60	68	26	54	16	0.80	0.96
Rockford_IL	77,126	0.01	0.53	7600	0.22	0.62	0.61	0.60	92	26	55	14	0.81	0.98
Sacramento_CA	71,415	0.01	0.50	5698	0.16	0.56	0.66	0.59	40	26	53	18	0.80	0.97
Saginaw_MI	47,237	0.03	0.64	4296	0.15	0.56	0.63	0.57	37	26	54	15	0.78	0.98
SanDiego_CA	117,541	0.02	0.49	6409	0.15	0.55	0.64	0.53	34	25	51	19	0.74	0.99
SanFrancisco_CA	485,501	0.01	0.39	8247	0.27	0.51	0.64	0.61	71	26	52	18	0.82	0.98
SanJose_CA	42,403	0.00	0.60	5193	0.18	0.58	0.69	0.53	47	25	51	18	0.74	0.95
Saugus_MA	12,578	0.01	0.75	4866	0.20	0.74	0.60	0.57	47	27	57	15	0.82	0.98
Schenectady_NY	65,710	0.01	0.51	8295	0.20	0.59	0.68	0.58	43	27	58	18	0.84	0.97

**Table A2: City Characteristics from 1930 Census**

City	1930 Census Variables													
	Pop'n geo'd	Share AA	Home Own	House Values	Share FB	Radio Own	Att. School	Lab F Part.	Rent	Occ. Score	Earn Score	Educ Score	Emp. Rate	Read or Write
Seattle_WA	265,620	0.01	0.53	5422	0.21	0.55	0.67	0.59	47	26	54	18	0.82	0.99
Somerville_MA	93,503	0.00	0.36	7044	0.29	0.64	0.60	0.59	46	26	54	15	0.82	0.97
SouthBend_IN	77,632	0.03	0.62	6006	0.14	0.52	0.60	0.60	71	26	53	14	0.76	0.98
Spokane_WA	70,583	0.01	0.62	3768	0.14	0.52	0.65	0.58	33	26	53	18	0.80	0.99
Springfield_IL	57,261	0.04	0.57	5425	0.09	0.50	0.62	0.60	45	25	52	15	0.78	0.98
Springfield_MO	41,132	0.02	0.52	4162	0.02	0.28	0.61	0.54	24	26	54	17	0.81	0.99
Springfield_OH	55,778	0.11	0.48	5413	0.03	0.56	0.62	0.58	50	26	54	14	0.81	0.99
StJoseph_MO	61,335	0.05	0.43	4172	0.05	0.49	0.62	0.58	30	25	51	15	0.83	0.99
StLouis_MO	665,880	0.08	0.36	7254	0.10	0.53	0.59	0.60	58	25	52	15	0.83	0.98
StPetersburg_FL	30,831	0.17	0.49	6194	0.06	0.25	0.64	0.51	26	24	48	18	0.67	0.98
Stamford_CT	36,991	0.03	0.43	11729	0.27	0.62	0.60	0.60	62	25	52	14	0.84	0.95
StatenIsland_NY	132,112	0.02	0.56	8327	0.25	0.67	0.64	0.59	56	27	57	17	0.84	0.97
Stockton_CA	34,605	0.01	0.46	5334	0.17	0.53	0.67	0.59	35	26	52	18	0.79	0.98
Syracuse_NY	173,151	0.01	0.49	10068	0.17	0.57	0.66	0.59	49	27	55	17	0.80	0.97
Tacoma_WA	70,786	0.01	0.63	3500	0.19	0.52	0.64	0.57	61	26	53	16	0.81	0.99
Tampa_FL	66,802	0.16	0.40	4046	0.16	0.16	0.58	0.62	25	24	47	13	0.79	0.96
TerreHaute_IN	52,646	0.05	0.49	4345	0.05	0.44	0.67	0.56	39	26	53	16	0.75	0.99
Toledo_OH	250,820	0.04	0.53	6688	0.12	0.62	0.63	0.59	49	26	55	14	0.80	0.98
Troy_NY	58,090	0.01	0.40	6558	0.14	0.53	0.65	0.61	83	26	53	15	0.82	0.98
Utica_NY	82,770	0.00	0.48	7994	0.21	0.48	0.66	0.60	43	26	52	14	0.79	0.94
Waltham_MA	31,475	0.00	0.42	7830	0.27	0.65	0.62	0.60	53	26	53	14	0.83	0.98
Warren_OH	29,274	0.05	0.57	6080	0.16	0.48	0.63	0.57	49	26	56	14	0.83	0.97
Watertown_MA	31,759	0.00	0.46	9267	0.28	0.67	0.61	0.59	50	27	55	17	0.83	0.98
Wheeling_WV	45,311	0.03	0.46	7169	0.08	0.50	0.58	0.57	36	25	52	16	0.81	0.98
Wichita_KS	62,996	0.03	0.48	4726	0.02	0.40	0.65	0.57	38	26	53	18	0.83	0.99
Winchester_MA	11,489	0.02	0.69	11351	0.19	0.76	0.67	0.54	80	25	50	20	0.84	0.98
WinstonSalem_NC	44,493	0.31	0.38	8166	0.01	0.22	0.53	0.67	25	24	48	13	0.84	0.94
Winthrop_MA	14,977	0.00	0.55	8466	0.21	0.76	0.67	0.55	78	28	58	23	0.84	0.99
Youngstown_OH	136,985	0.07	0.57	6055	0.20	0.46	0.65	0.56	47	26	55	14	0.78	0.96

**Table A3: Counts of Boundaries by City**

City	4th		8th	
	C-B	D-C	C-B	D-C
	Number of Boundaries			
Akron_OH	62	28	65	29
Albany_NY	6	3	6	3
Altoona_PA	14	7	13	7
Arlington_MA	6	4	6	4
Asheville_NC	11	18	11	21
Atlanta_GA	13	1	12	1
Augusta_GA	1	4	1	5
Aurora_IL	12	13	13	14
Baltimore_MD	19	15	18	16
BattleCreek_MI	6	14	7	12
BayCity_MI	1	19	1	13
Belmont_MA	1		1	
Binghamton_NY	11	2	13	1
Birmingham_AL	19	71	19	69
Boston_MA	6	22	9	24
Braintree_MA	3		3	
Bronx_NY	8	17	8	17
Brookline_MA	4		4	
Brooklyn_NY	44	73	41	75
Buffalo_NY	18	6	15	5
Cambridge_MA	4	8	4	4
Camden_NJ	8	3	3	2
Canton_OH	15	9	15	10
Charleston_WV	5	3	9	3
Charlotte_NC	1	3	1	5
Chattanooga_TN	8	14	6	14
Chelsea_MA		5		5
Chicago_IL	118	117	112	121
Chicopee_MA	2		2	
Cleveland_OH	42	62	45	62
Columbus_GA	1	7	2	8
Columbus_OH	58	41	67	45
Dallas_TX	14	4	12	4
Dayton_OH	17	17	18	20
Decatur_IL	18	16	20	16
Dedham_MA	4	2	3	2
Denver_CO	33	24	34	23
Detroit_MI	41	109	41	109
Duluth_MN	16	3	15	2
Durham_NC	5	6	7	5
EastHartford_CT	2	2	2	2

**Table A3: Counts of Boundaries by City**

City	4th		8th	
	C-B	D-C	C-B	D-C
	Number of Boundaries			
EastStLouis_IL	7	8	7	7
Elmira_NY	10	9	11	8
Erie_PA	11	8	13	8
EssexCounty_NJ	51	46	52	45
Evansville_IN	8	11	8	9
Everett_MA		8		8
Flint_MI	24	7	21	5
FortWayne_IN	16	8	15	10
Fresno_CA	7	11	7	11
Gary_IN	10	11	9	9
GrandRapids_MI	23	23	21	17
Greensboro_NC	3	5	3	5
Hamilton_OH	10	5	11	7
Holyoke_MA	1	1	1	1
HudsonCounty_NJ	8	22	8	21
Indianapolis_IN	25	67	25	65
Jacksonville_FL	12	15	11	14
JohnsonCity_NY	3		4	
Johnstown_PA	2	4	3	4
Joliet_IL	10	8	9	8
Kalamazoo_MI	4	5	3	4
KansasCity_MO	30	50	31	49
Kenosha_WI	8	20	6	21
Knoxville_TN	8	18	5	16
Lexington_KY	5	8	6	8
Lima_OH	5	6	5	6
Lorain_OH	2	3	2	1
Louisville_KY	25	29	23	28
Lynchburg_VA	1	7	1	6
Macon_GA	1	3	2	2
Madison_WI	6	11	9	13
Malden_MA	1	10	1	10
Manchester_NH	5	9	5	8
Medford_MA	3		3	
Melrose_MA	8		8	
Miami_FL	30	25	32	19
Milton_MA	2		2	
Milwaukee_WI	11	18	14	18
Minneapolis_MN	63	40	66	50
Mobile_AL		7	1	7
Montgomery_AL	2	7	3	6



**Table A3: Counts of Boundaries by City**

City	4th		8th	
	C-B	D-C	C-B	D-C
	Number of Boundaries			
Muncie_IN	1	6	1	7
Muskegon_MI	4	8	4	9
Needham_MA	3		3	
NewBritain_CT	6		7	
NewCastle_PA	8	4	10	4
NewHaven_CT	4	11	4	9
NewOrleans_LA	24	53	25	55
NewYork_NY	10	5	10	5
Newton_MA	3	3	3	3
NiagaraFalls_NY	11	5	8	5
Norfolk_VA	6	5	5	3
Oakland_CA	23	23	22	15
Oshkosh_WI		11	1	13
Philadelphia_PA	58	53	61	49
Pittsburgh_PA	25	28	26	31
Pontiac_MI	5	3	5	3
Portland_OR	71	39	63	25
Portsmouth_OH	2	7	2	6
Poughkeepsie_NY	1	3		2
Queens_NY	35	27	32	26
Quincy_MA	5		5	
Racine_WI	9	8	10	9
Revere_MA		3		2
Richmond_VA	5	5	9	5
Roanoke_VA		5		5
Rochester_NY	25	21	23	16
Rockford_IL	10	20	11	20
Sacramento_CA	12		12	
Saginaw_MI	9	11	9	11
SanDiego_CA	30	15	32	15
SanFrancisco_CA	13	25	17	16
SanJose_CA	15	13	15	8
Saugus_MA	3	5	3	5
Schenectady_NY	9	5	9	4
Seattle_WA	68	26	70	28
Somerville_MA	4	6	4	7
SouthBend_IN	11	9	11	10
Spokane_WA	29	37	28	36
Springfield_IL	24	28	29	30
StJoseph_MO	4	6	6	7
StLouis_MO	51	31	50	29

**Table A3: Counts of Boundaries by City**

City	4th		8th	
	C-B	D-C	C-B	D-C
	Number of Boundaries			
StPetersburg_FL	12	20	13	17
Stamford_CT		2		2
StatensIsland_NY	17	20	17	20
Stockton_CA	4	1	5	1
Syracuse_NY	18	8	18	8
Tacoma_WA	22	28	24	28
Tampa_FL	10	6	11	6
TerreHaute_IN	6	25	8	22
Toledo_OH	31	21	33	21
Troy_NY	9	8	10	8
Utica_NY	7	9	8	7
Waltham_MA	3	2	2	2
Warren_OH	9	4	9	2
Watertown_MA	4		4	3
Wheeling_WV	1	2	4	
Wichita_KS	7	22	8	21
Winchester_MA	1		1	
WinstonSalem_NC	3	4	2	4
Winthrop_MA	2		2	
Youngstown_OH	25	31	25	30
Total	1965	2111	2000	2047

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