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Policy Prescriptions and Population Transitions: Essays on Politics, Policy, and Demographic Change

A dissertation submitted in partial satisfaction
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Doctor of Philosophy
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by

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June 2021

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To Mom, Dad, Grandma Barbara, Grandpa Pete, and Dundo Djuro.

Acknowledgements

I am indebted to many people. Too many to name here. First and foremost, however, I thank my mom and dad. Without their unstinting devotion and support, I would not be here today. I had a rather "nontraditional" route to college and graduate school, and no matter how difficult things became, they always stood by my side, offered me words of encouragement, and supported me. I would not have it any other way.

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Curriculum Vitæ
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Education

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Affiliations

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Publications

Mildenberger, M., Howe, P., & Miljanich, C. 2019. "Households with solar installations are ideologically diverse and more politically active than their neighbors." *Nature Energy*, 4, 1033-1039

Hiroyasu, E., Miljanich, C., & Anderson, S. 2019. "Drivers of support: The case of species reintroductions with an ill-informed public." *Human Dimensions of Wildlife*, 24:5, 401-417

In Progress

"Political Geography as Epiphenomenal?: Using Redlining to Understand the Spatial Interplay Between Race, Class, and Politics"

"A Voice for Some but Not All: District Elections and the Character of Representation in Local Government"

"Prevalence and predictors of wind energy protests in the United States" (with *Leah Stokes*)"

"A Catalyst for Change: The Great Migration's Impact on Elite Ideology and Voting Behavior During the 20^{th} Century"

Datasets

	"California Municipal Elections and Electoral Systems"
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Conferences and Presentations

2021	Southern Political Science Association
2020	Western Political Science Association (*Withdrew - COVID 19*); ENVENT Lab group meeting (UCSB)
2019	Urban Affairs Association Annual Conference; Politics of Race, Immigration, and Ethnicity Consortium meeting; American Politics Working Group (UCSB)
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Instructor of Record

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Teaching Assistant

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Fellowships and Grants

2021	Dean's Block Grant Fellowship, $13,784
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2019	UC Center Emerging Scholars Fellowship, *Finalist*

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Professional Service

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Programs and Skills

R, Python, QGIS, SQL, GitHub, ArcGIS, LaTeX, Webscraping

Contents

Chapter 1

Introduction

This dissertation explores the relationship between public policy, demographic change, and politics. It is split between three papers, each exploring a different question on these topics. The first paper examines the impact that electoral systems have on minority representation in local government. To do so, I leverage the California Voting Rights Act (2001) to show that the design of local electoral institutions can have a dramatic impact on minority representation on city council. As I show, district-based electoral systems achieve higher levels of minority representation in local elected office. However, I also show that they do not – *necessarily* – make city councils more demographically representative of the cities they serve. Nonetheless, they do increase representation for traditionally marginalized demographic groups.

The second paper evaluates the impact of the Home Owners' Loan Corporation (HOLC) on the political geography of Los Angeles. HOLC was a New Deal program created to stabilize the housing market during the late 1930s. As part of the program, risk assessment maps were created in cities across the United States. The maps assigned loan default risk scores to neighborhoods within these cities, and they are often credited with institutionalizing the practice of "redlining". I examine the impact that these maps had on the political development of Los Angeles. As I show, HOLC had a lasting impact on the political trajectory of the area, but in surprising ways. Desirable, high-grade, neighborhoods experienced a larger over-time increase in support for Democrats, despite the fact that they were Whiter, wealthier, and home to business and corporate leaders. The findings make clear that public policy can have lasting impacts on the developmental trajectory of geographic areas. They also suggest that an area's political geography is not a simple artifact of its demographic and socioeconomic makeup.

The final paper examines the effect that Black migration during the 20^{th} Century had on elite ideology and voting behavior. The Great Migration was, perhaps, the single largest demographic event in American history. Millions of Black people left the South for the North, Midwest, and West. As a result, the demographic composition of these areas changed dramatically. Traditionally White electorates experienced a sudden influx of Black migrants, and elected officials were faced with the task of incorporating this group into their political schema. As I show, Black migration is associated with a leftward shift in elite ideology. Additionally, it is positively associated with the probability that congressional representative votes in favor of civil rights legislation. The results speak to two themes. First, the adoption of pro-civil rights policies in the early-to-mid 20^{th} Century may have occurred because of electoral incentives to appeal to a new bloc of Black voters. Second, large and fundamental shifts to an electorate's demographic composition can have a drastic impact on its political development decades later.

The unifying theme across all papers is that there is a fundamental, and dynamic, relationship between politics, policy, and demography. As demography changes, the voters entering or exiting an electorate may look different from those who are already in it, or those who remain in it. As was the case in California, this may create a situation where elected officials are not descriptively representative of those they serve. As the Great Migration tells us, it may also force elected officials to adopt policy stances that are in greater alignment with the burgeoning core of their electorate. Conversely, large public policies may fundamentally alter the demographic and socioeconomic composition of an area, setting the stage for large-scale political change later on. All told, the relationship between these forces is dynamic and ever-evolving. And, as this dissertation makes clear, the relationship should be given greater attention.

Chapter 2

A Voice for Some but Not All: District Elections and Minority Representation in Local Government

Abstract

Do district elections increase minority representation in local government? If so, how? I couple non-parametric difference in differences estimators with data on 7,300 city council candidates to answer these questions. The data represents every city council candidate in California over five presidential elections between 2000 and 2016. As I show, district elections increase city council minority representation, minority vote shares, and the number of minority candidates running for office by 17, 38, and 8 percentage points, respectively. They also increase the probability that a minority candidate wins office, even after controlling for electoral competitiveness. However, a novel measure of demographic similarity shows that district elections do not make city councils more representative of the cities they represent. They also do not reduce electoral competitiveness. In all, district elections better represent minorities, but do not – on the whole – make city councils more demographically similar to the cities they serve.

2.1 Introduction

Throughout the United States (US), racial and ethnic minorities are underrepresented in local government (Hajnal, 2009; Warshaw, 2019). Of the US' largest cities, for example, only 20 percent of Southern, and 10 percent of non-Southern cities have Black mayors (Vogl, 2014; Warshaw, 2019). Minority underrepresentation is particularly acute on city council. City council is an important municipal office, and oversees the provision of public goods, sets municipal budgets, and enacts laws. Yet, despite its importance, the office is hardly representative of all voters, and tends to be Whiter than the population it serves (Masket, 2014).

The United States' current racial and political environment underscores this tension. The recent killings of George Floyd, Breonna Taylor, Ahmaud Arbery, and Tatiana Hall have led to mass protests throughout the country. These protests address systemic racism and police brutality by pushing municipal offices such as city council to enact reforms that bring greater socioeconomic and political parity to historically marginalized and underrepresented groups. Some reforms include redistributing funds away from police departments into mental health, education, and social services (Ray, 2020). Many city councils have responded by divesting from police departments (Holder et al., 2020), and by ending the use of carotid chokeholds (Kamp and Calvert, 2020).

The protests make clear that municipal policies often do not reflect the preferences of underrepresented groups. They also show that these groups do not have equitable representation in elected office. The design of electoral institutions may contribute to this very problem. Electoral systems determine the way that citizens vote, whom they vote for, and how their votes are allocated. A consequence of their design, however, is that some groups may be disadvantaged electorally, especially racial and ethnic minorities. Minorities have disproportionately low voting rates (Brace et al., 1995; Hajnal and Lewis, 2003; Hajnal and Trounstine, 2005; Rocha et al., 2010), are less participatory in politics (Banducci et al., 2004; Xu, 2005), less likely to run for office (Shah, 2014), and have lower quality voting precincts available to them (Barreto et al., 2009). These issues may result in fewer minorities holding office, and one wonders whether these problems exist because of the rules governing the way that elections are conducted.

Local elections in the US typically fall under two categories: at-large and district-based systems.[1] At-large systems allow all voters in an electorate to vote for each open seat in an election. In the context of city council elections, this means that each voter, no matter where she lives, can vote for any candidate running for office. However, an implication is that, depending on minority participation rates, their share of the voting population, and their geographic distribution, at-large elections may decrease minority representation because their votes are diluted across the entire electorate.

The suppressive effect that at-large elections have on minority representation occurs, in part, because of political geography (Grofman and Handley, 1989a). Racial and ethnic minorities tend to cluster geographically, and live in high concentrations around each other (Ellis et al., 2004). On one hand, this may result in a collective voter bloc that is well-established on a micro-geographic level. However, in the aggregate, minority voters may only form a small proportion of the entire electorate, decreasing their collective voice, and, in turn, reducing their descriptive representation. So, even while minority voters may form a strong voter bloc in their own communities, at-large systems, because of the way votes are aggregated, may depress their voting power city-wide.

District-based systems address this issue by restructuring the relationship between voters, candidates, and geography. This is achieved by directly accounting for the geographic distribution of racial and ethnic minorities. In a district-based system, a city

[1] "district-based", "by-district", and "district election(s)" are used interchangeably throughout this paper.

is divided into districts that consider the distribution of racial and ethnic groups across physical space. Each district is assigned a single city council seat, and voters may only vote for candidates running in their district. In theory, district-based systems give underrepresented minority populations a better chance at electing their preferred candidate(s) because their votes are not diluted across the entire electorate. Rather, they are concentrated within their own district, giving them a larger electoral voice.

Although the recent protests have not directly advocated for adopting district elections, they make clear that increasing minority representation is important if local governments are to operate effectively. Pursuing electoral systems that, in theory, give traditionally underrepresented groups greater voice may be one way to do so. District-based systems are one possible option. Despite this possibility, however, we do not have a clear consensus about whether district elections work as intended. Moreover, we have not evaluated the causal mechanisms explaining how they work.

This paper uses data on over 7,300 city council candidates across five electoral cycles to provide clarity on this topic by answering unexplored questions about the nature and character of district elections. Econometrically, the paper is fully design based, makes few modelling assumptions, and the data is allowed to speak for itself. As I show, district elections increase minority representation. They also make city councils more demographically representative of the cities they serve, a benefit that extends to all racial groups. However, in some cases, minority groups become overrepresented. I find that district elections do not reduce electoral competitiveness. District elections appear to operate through two causal channels: increased vote shares, and win rates, among minority candidates.

The paper proceeds as follows. First, I describe existing literature, and set forth a series of motivating questions. I then describe California's recent experience with district elections and situate it as the case used in the paper. After, I introduce data and measures, and describe the research design. This is followed by the results, and I end with a discussion.

2.2 Existing Literature

Research on district elections has generally found that they increase minority representation (Davidson and Korbel, 1981; Karnig and Welch, 1982). Jones (1976) uses city-level data to show that Black representation increases in cities that use district elections. Engstrom and McDonald (1981) show that district elections increase Black representation, but that the effect is conditional on population size. Similar work argues that electoral geography determines whether district elections increase Black representation (Grofman and Handley, 1989b). Relatedly, electoral institutions determine whether Blacks are adequately represented, even when they comprise a large percentage of the total population (Engstrom and McDonald, 1982). Later research finds that Black candidates can achieve increased representation in at-large systems when racially polarized voting declines (Sass and Mehay, 1995). Recent work by Shah et al. (2013) uses time series data to show that district elections increase Black representation.

Hispanic and Latinx candidates benefit less from district elections than Black candidates (Taebel, 1978; Zax, 1990). For Hispanic and Latinx candidates, the effects are conditional on patterns of residential segregation (Welch, 1990; Sass, 2000). Recent work examining the interplay between race and gender shows that district elections do not increase representation for Black females, but that they do for Black males (Trounstine and Valdini, 2008a). However, the authors find that district elections are unrelated to Hispanic and Latinx electoral outcomes. Collingwood and Long (2019) show that district elections increase minority representation, especially in cities with large Hispanic and Latinx populations. Similar work shows that district elections increase minority school board representation when there is a high proportion of Latinx voters (Abott and Magazinnik, 2020).

Altogether, the extant research indicates that district elections increase minority representation, but that the effects are conditional on population dynamics and candidate race. These are primarily related to whether there is a sizable minority population in the electorate, and patterns of residential segregation. Naturally, highly segregated cities underrepresent minority candidates, especially if minority groups are highly clustered. Despite this, district elections are shown to improve minority representation in traditionally underrepresented municipal offices.

However, a number of important questions about the character and dynamics of district elections remain unanswered. For one, we know relatively little about the causal mechanisms underlying district elections, and how they impact minority representation. Furthermore, existing research has not examined how district elections affect demographic representation city-wide. One wonders, for instance, whether district elections increase representation for some, but at the expense of others. This has been a point of division among cities debating whether to adopt district elections. Yet, no research has examined this topic.

2.3 Motivating Questions

I probe three sets of questions. The first is whether district elections affect the number of candidates running for office. Electoral districts within a city are smaller than the electorate for an entire city. Because of this, district-based systems may reduce competitiveness because the candidate pool is smaller. To this point, I examine whether district elections affect the number of candidates running for office, per open seat available.

Relatedly, district elections may increase minority representation because the number of candidates running for office changes, not because they, *ceteris paribus*, increase the probability that a minority candidate wins office. Take the case where a single minority candidate runs against four competitors. The probability that the minority candidate wins is 20 percent. If district elections reduce the number of competitors to two, the probability that the minority candidate wins office is now 33 percent. It is commonly assumed that district elections increase minority representation because they encourage more votes for minority candidates. However, it could be that district elections simply reduce the number of candidates running for office which, in turn, increases the probability that a minority candidate wins office. This is a careful, but important, distinction to make, and I examine it.

The second set of questions concern election outcomes and the racial composition of candidates. Specifically, these questions ask whether district elections increase minority representation, whether there are heterogeneous effects for incumbent and non-incumbent candidates, whether district elections increase minority vote shares, and whether win rates differ for minority and White candidates.[2] There are subtle distinctions between each question, and the data structure allows me to answer each in its own way. For example, I examine vote shares for minority candidates in at-large and by-district elections where the number of candidates running for office per seat available is the same. This ensures that the effect of district elections is not biased by the number of candidates running for office, which is deterministically related to the number of votes a candidate receives. I apply the same logic when estimating win rates. In all, I use this set of questions as a pseudo-robustness check against the existing literature, and to identify the causal mechanisms by which district elections affect representation.

The last set of questions asks whether district elections increase the overall demographic similarity between candidates and the cities they represent. It is important to

[2] "non-incumbent" and "challenger" are used interchangeably.

consider that district elections could potentially reduce city-wide demographic overlap even if minority representation increases. While minority candidates may be better represented, the racial composition of city council could become less representative of the city itself. This may be true in cities that have relatively small minority populations, but that adopt district elections. In this case, increased minority representation could reduce demographic overlap if the proportion of minority city councilmembers becomes higher than the proportion of minority residents in the city.

This demographic paradox has been a point of contention for cities debating whether to adopt district elections. Voters and councilmembers are often reticent about adopting district elections because they fear that increased minority representation will come at the expense of others. Such concerns may hinder reform efforts that actually benefit all people. Providing clarity on this topic serves a dual purpose. First, it fills a void in the academic literature about the character of district elections. Second, it can guide voters, elected officials, and practitioners when determining whether to pursue district-based systems.

California's Experience with District Elections: A Useful Case

California's minority population has increased significantly in recent decades (Census, 2012). The state is now majority-minority, with the largest ethnic group being Hispanics. Despite a large minority population, however, city councils throughout the state remain predominantly White. This discrepancy has led some to question whether the design of electoral institutions systematically undermines the ability for minorities to win office.

In 2001, the California Voting Rights Act (CVRA) was adopted to address this very issue. It required that electoral systems be redesigned if minorities and members of protected classes could prove that at-large elections attenuated their ability to win local office. If minorities could show this, action must be taken to reform a city's electoral institutions (Aziz et al., 2018). The CVRA mandated that cities in violation of the act adopt district elections.[3] Though few cities adopted district elections in the early years of the CVRA, numerous cities have since introduced the reforms set forth by this legislation.

Cities typically face two options when choosing whether to adopt district-based systems: select into district elections on their own accord, or face the threat of legal action. The former only occurs scarcely. Unless there is significant pressure from voters to modify an electoral system, elected officials gain no benefit from adopting district elections because doing so may challenge their power. As a result, incumbent councilmembers have little incentive to change existing arrangements, especially if it introduces voters into the electorate who might upset the status quo.

Legal challenges, or at least the threat of them, occur more frequently. Challenges typically start with demand letters sent to cities perceived to be in violation of the CVRA. A Southern California law firm has led this charge, and is responsible for numerous letters that threaten litigation against cities that, in their eyes, are in violation of the CVRA.[4] The firm does not have a clearly devised system for deciding which cities to send letters to, but part of the calculus is based on racial demographics and existing representational patterns (Collingwood and Long, 2019). Cities receiving demand letters face one of two courses of action: preemptively switch to district elections, or be taken to court. Cities opting to go to court often lose, and run up costly legal fees sometimes totaling millions of dollars (Rice, 2018). In 2019, the federal courts upheld the CVRA and deemed it constitutional, making it even more difficult for challenging cities to win court cases (Egelko, 2019).

Most by-district cities in California adopted them over the past 10 years (Plummer,

[3]California Assembly Bill No. 182, September, 2015.
[4]See Abcarian (2017) and Willon (2017) for examples of demand letters.

2019). Large cities in urban areas have longer histories with this electoral system. Mid and small-sized cities have only recently begun to use this electoral system, *en masse*. This likely reflects demographic trends in the state. In recent decades, small and mid-sized cities in more conservative parts of the state (e.g., the Central Valley) have experienced large increases in the minority population. Yet, equitable representation in local government has been slow to follow, and many of the contentious battles over adopting district elections have occurred in these cities.

Qualitative evidence suggests that debates about whether to adopt district elections focus on whether they will exacerbate existing political divides. A Highland, California city councilmember was quoted in 2016 as saying that district elections may result in less effective government because "...people will be only concerned about only their specific district" (Emerson, 2016). For this councilmember, competent city-wide governance would be reduced to political infighting between districts.

A corollary is whether district elections make city councils more demographically representative of cities as a whole. Edward Blum, a member of the Project on Fair Representation, stated in 2019 that the CVRA is an "unconstitutional statute that has the polarizing effect of separating neighbors from one another on the basis of race and ethnicity" (Egelko, 2019). As Blum's quote implies, some fear that district elections may increase representation for some, but also create a racialized political environment that polarizes each other on the basis of race. In this way, reticence about adopting district elections is not simply about political elites losing their power, or increased political division. It is also about the very nature of representation for the city as a whole, and whether all residents see increased demographic representation.

2.4 Data and Measures

Candidate data comes from the California Data Elections Archive (CEDA).[5] This archive contains candidate-level and ballot information for all local elections in California (Archive, 2017). The data provides first and last names for all city council candidates and the city they represent. It also includes covariates such as incumbency status, vote share, the number of seats contested in an election, and the number of candidates seeking office in a particular election. Though the data extends to the mid-1990s, I rely on data from five presidential election cycles: 2000, 2004, 2008, 2012, and 2016.

The data was combined into a single time series, and joined by city and year with an original dataset of municipal electoral systems in California, as well as Census data for each year of study.[6] The electoral systems dataset includes whether a city uses at-large or by-district elections, and, if by-district, when the first district election was held. I gathered this information by reading newspapers, examining city websites, and searching municipal code books and city charters. I restricted my initial search to cities that were coded as by-district in Municipal Democracies Index data (MDI; see Heidorn (2016)). MDI data lists all cities in California, as well as electoral-system type. However, it does not include when a by-district city adopted such elections. Accordingly, I searched for this data on my own (see Appendix for data collection procedures). If I was unable to independently confirm that a city used district elections, or identify the year that district elections were adopted, I refrained from coding the city to reduce the potential for Type I errors.

Candidate first and last names were supplied to NamePrism, a race and ethnicity classifier. NamePrism uses name embeddings to assign probability-based race and eth-

[5]This dataset is assembled jointly by the Center for California Studies, and the Institute of Social Research at the California State University, Sacramento.

[6]Years 2004 and 2008 use linearly imputed data because complete data was not available all cities. See Appendix for imputation formula.

nicity classifications for first and last name strings (see Appendix). I used NamePrism to calculate the probability that a candidate is White, Black, Hispanic or Latinx, Asian, and American Indian.[7] Race information was merged with the original dataset. The final dataset is a repeated cross-section of all candidates running for office in one of the five presidential elections between 2000 to 2016, for all city council elections in California.

The primary dependent variable is the probability that a candidate is non-White. This is calculated by subtracting the probability that a candidate is White from 1. I supplement this measure with dummy variables for minority status that equal 1 if a candidate has a probability of being a minority of 80 percent and above. I chose an 80 percent cutoff because the threshold was high enough to avoid misclassifying White candidates as minority, but it also resulted in a sample size that was large enough for analysis.[8] The choice of dependent variable depends on the question at hand.

My secondary dependent variable is a measure of demographic similarity. I call this measure the Similarity Index. It is measured as 1 minus the absolute value of the difference between the probability that a candidate is non-White and the percentage of the candidate's city that is non-White. The measure exists on the closed interval [0, 1]. Higher values indicate greater demographic overlap between candidates and cities, and lower values indicate less overlap. For context, a one-point increase in the index means that demographic similarity between a candidate and the city they represent increases by one percentage point. In all, I use this measure to explore whether district elections have positive impacts on the overall demographic similarity between candidates and cities, something yet explored, yet consequential.

[7]There is a concern that candidates adopt the last names of spousal, marital, and relationship partners. If so, NamePrism will incorrectly classify a candidate's true race and ethnicity. However, if this pattern is randomly distributed throughout the data, it will differenced out. If anything, the estimates are overly conservative for this reason.

[8]All results are replicated with different cutoffs. See Appendix.

2.5 A Design-Based Approach

The data structure provides a number of empirical advantages. First, I can produce design-based, fully non-parametric, estimates of the impact of district elections over a period of nearly two decades, on a variety of questions. Additionally, I can use the candidate as the unit-of-analysis, which avoids pitfalls associated with aggregating to a higher level. Aggregating to the city level, for example, reduces power, and biases regression coefficients upwards (Clark and Avery, 1976). I overcome these issues by keeping the analysis disaggregated to the candidate level.

I use a set of difference in differences estimators to examine the relationship between district elections and city council representation. To do so, I restrict my pool of treated candidates to include those from cities that experienced their first district election in 2016. While some cities in my sample experienced their first district election in 2018 (and some 2020), the majority experienced their inaugural district election in 2016. To ensure that treated units had similar treatment histories, I restrict the analysis to candidates from cities that switched in 2016.[9] The control group includes candidates representing cities that, as of 2016, did not, or had not planned to, adopt district elections.

I restrict the observations to include presidential election years between 2000 and 2016. I do so because there is likely to be considerable heterogeneity between midterm and presidential elections. Campaign financing, turnout, and political attentiveness vary considerably between midterm and presidential election years (Panagopoulos, 2011; Hayes and Lawless, 2015; Malbin and Glavin, 2018). To avoid any sources of bias resulting from these differences, I omit midterm elections. This has the added benefit of not requiring the assumption that effects are homogeneous across election timing.[10]

[9]A staggered adoption difference in differences design could be used here. However, this assumes that the treatment assignment mechanism is the same across all years of adoption.

[10]It should be noted that subsetting to presidential election years ignores potentially important effects observed during off-year and midterm elections. For instance, it could be that decreased turnout during

While I use separate difference in differences estimators for each outcome, the econometric framework is near identical for all of them. The treatment indicator equals 1 if a candidate is in a by-district city during the 2016 election, and 0 otherwise. I compare 2016 outcomes to 2012 outcomes, the latter of which being the pretreatment period. In addition, I run auxiliary difference in differences for elections between 2000 and 2012, as a means to show pretreatment trends for at-large and by-district cities. I do so because treated cities may have opted into treatment because of 2012 outcomes. For example, cities that experienced decreased minority representation in 2012 may have responded by selecting into treatment for the 2016 election (i.e., Ashenfelter dip). Because of this, it could be the case that a statistically significant treatment effect is simply regression to the mean. Pooling all pretreatment years checks whether an effect is because of the treatment, or because of a sudden shock in 2012.

The data structure and identification strategy allow me to examine parallel trends over an extended timeframe. For all difference in differences estimates, I provide plots showing the evolution of the outcome measure over time. In some cases, parallel trends appears tenable, and others not. In cases where parallel trends appears to hold, causal effects can be identified, and the reader should be primarily interested in the treatment effect for the two-period cases (i.e., 2012 and 2016). In cases where parallel trends is less tenable, the reader is encouraged to evaluate the estimates holistically by comparing the two-period and pooled estimates. The idea behind my approach is be transparent about the data, and to let the reader evaluate the assumptions on their own accord.

Relatedly, I examine whether there are existing differences between treated and control cities. This is not directly related to parallel trends, but may be more important.[11]

midterm elections attenuates the positive impact of district elections. Under the current setup, I am unable to identify this. Additional work should compare the effectiveness of district elections across electoral cycles.

[11]For example, parallel trends can hold even when there are systematic differences between the treatment and control groups.

It could be that cities select into treatment because of long-term representational disparities. I provide time-series visuals that evaluate this possibility. These give insight about the selection process and whether cities opt into treatment because of existing patterns of representation. If treated cities appear different from their control counterparts, we may bring into question the validity of existing research that does not account for these differences.

I refrain as much as possible from employing regression-based techniques, parametric modelling, and other *post-hoc* adjustment strategies. Doing so introduces strong assumptions that may be untenable. For example, one might advocate to use covariate or propensity score matching, but this can only be done on observables. Large differences between the treated and control groups may remain, yet go unnoticed. Model-dependent regression techniques are no panacea either, as they impose strong functional form assumptions. In general, I adjust for bias through design, not modelling. For instance, in cases where the outcome is affected by the number of candidates running for office (e.g., vote share), I subset the analysis by the number of candidates, and run separate difference in differences.[12]

2.6 Sample Description

There are 7,343 candidates in the sample (Table 2.1). 619 (8.4%) are from cities that adopted district elections in 2016. The remaining 6724 (91.6%) are from cities that, as of 2016, did not use district elections, or had not planned to adopt them in the future. The candidates represent 358 California cities in total, 23 (6.4%) of which are by-district cities, and 335 (63.6%) are at-large cities.

[12]The reader should note that because each design is slightly different, I discuss any outstanding design modifications for each outcome separately in the results section.

Year	Control	Treatment
2000	1281	111
2004	1351	105
2008	1402	128
2012	1333	122
2016	1357	153
Total	**6724**	**619**

Table 2.1: Treated and Control Candidates By Year

Table 2.2 provides candidate-level race data from NamePrism. Candidates in at-large cities are three percentage points more White than candidates in by-district cities ($p < .05$). Treated and control cities have roughly equal distributions of Black, American Indian and Alaska Native, and Asian candidates. Candidates in treated cities are slightly more likely to be Hispanic and Latinx. Treated candidates are three percentage points more likely to be classified as a minority ($p < .05$).

Race	Control	Treatment	t	p
White	82.42	78.77	-2.4	$< .05$
Black	3.44	3.60	0.5	$> .10$
Hispanic and Latinx	11.06	13.35	1.7	$< .10$
American Indian and Alaska Native	0.17	0.18	0.8	$> .10$
Asian and Pacific Islander	2.85	4.04	1.5	$> .10$
Minority	17.58	21.23	2.4	$< .05$

Presented are mean percents for each racial category, by treatment status for all pretreatment years.

Table 2.2: Candidate Mean Racial Identification By Treatment Status (2000-2012)

Table 2.3 shows city-level demographic characteristics. Treated cities are larger, on average ($p < .001$). They are also less White ($p < .001$), and have larger Hispanic and Latinx populations ($p < .001$). These differences suggest that treated cities may have faced representational inequities, and it comes as no surprise that they had higher concentrations of Hispanic and Latinx persons. There are only minimal differences with respect to the Black, and Asian populations, and $p > .10$ for each. Altogether, city-level data shows that control and treatment cities are different on a variety of pretreatment dimensions, which likely explains at least part of the selection process.

Race	Control	Treatment	t	p
Total Population	35325.17	76866.24	4.2	$< .001$
White	56.14	40.54	-7.9	$< .001$
Black	3.32	3.79	1.2	$> .10$
Hispanic and Latinx	29.03	45.41	8.6	$< .001$
American Indian and Alaska Native	1.08	0.95	-2.1	$< .05$
Asian	8.11	7.75	-0.3	$> .10$

Presented are mean percents for each racial category, by treatment status for all pretreatment years. The data is subset so that means are calculated using a single, unique, city-year dyads.

Table 2.3: City-Level Demographics By Treatment Status (2000-2012)

2.7 Results

Number of Candidates Running for Office

The top panel of Figure 2.1 shows the number of candidates running for office, standardized by the number of open seats available. I standardize by seats available so that elections with multiple open seats (at-large) can be compared to elections with one open seat (by-district). The long-term trend shows that by-district cities consistently have more candidates running for office. The first posttreatment period (2016) shows a marginal increase in the number of candidates running for office in by-district cities, but the difference in differences estimate is not statistically significant.[13] The effect is unchanged when pooling all pretreatment years.

[13] Refer to Table 2.4 for all remaining difference in differences estimates.

The bottom panel of Figure Figure 2.1 shows the average number of candidates running for election per city. Again, by-district cities yield more candidates running for office throughout the observational period. However, district elections do not significantly increase the number of candidates running for office. The effect remains insignificant when pooling all pretreatment periods. In all, district elections do not affect the number of candidates running for office.

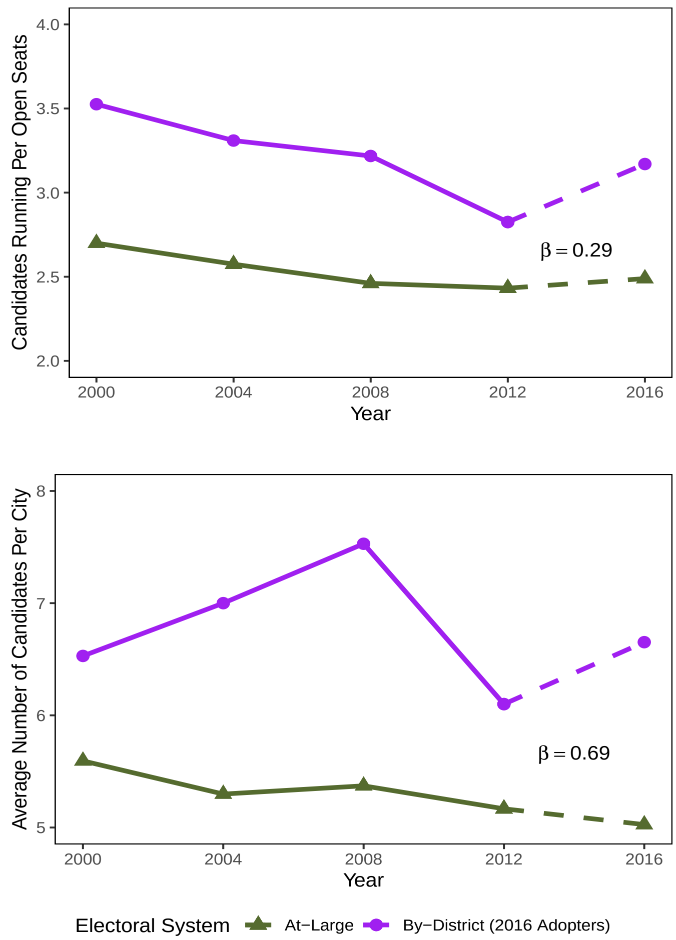


Figure 2.1: District elections do not affect election competitiveness. The first panel shows the number of candidates contesting office per seat available (y-axis), by year (n = 2965). The second panel shows the average number of candidates running for office in each city (y-axis), by year (n = 571). The dashed lines indicate the election years used to estimate the two-period difference in differences. The posttreatment year is 2016. β shows the two-period difference in differences estimate, for each model. The null hypothesis is not rejected. See Table 2.4 for fully reported results, as well as pooled estimates using all pretreatment years. *p <= .1; **p <= .05; ***p <= .01.

Minority Representation on City Council

Figure 2.2 plots the probability that a candidate is non-White for all candidates (top panel), and for winning candidates (lower panel). The top panel shows that candidates in district cities have a higher probability of being non-White across all years, aside from 2008. As the plot shows, by-district cities experienced a 10 percentage point increase in non-White identification in 2016. This effect is significant to $p < .01$. The pooled pretreatment difference in differences reveals similar results, and the effect remains significant to $p < .01$.

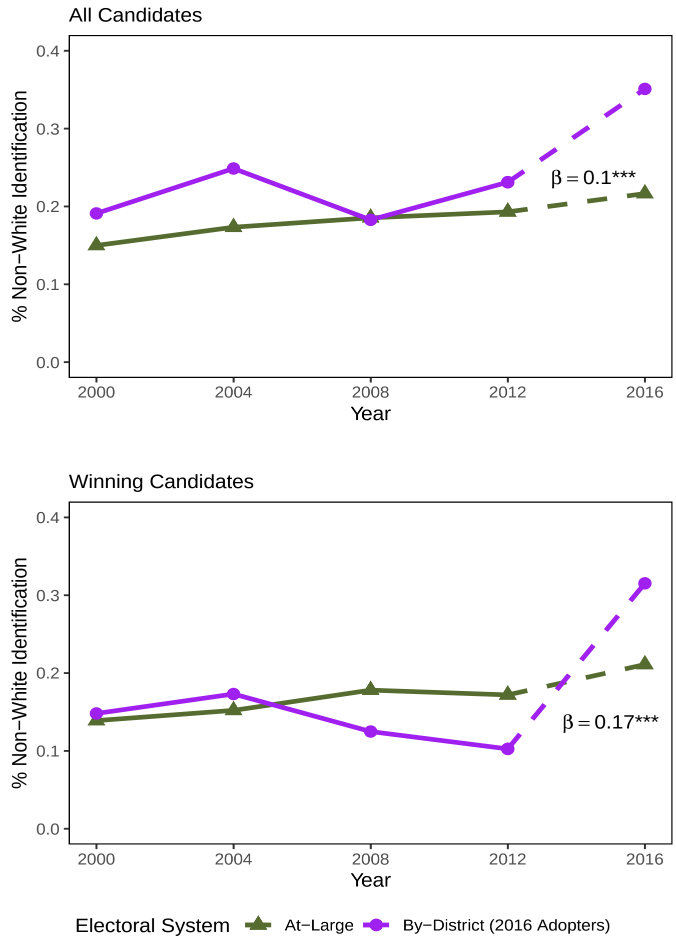


Figure 2.2: District elections increase minority representation on city council. This top row shows the mean percentage non-White identification for all candidates (n = 2965). The second row shows the mean percentage non-White identification for winning candidates (n = 1384). The outcome measure (y-axis) corresponds to the mean probability that a candidate is non-White, by year. The dashed lines indicate the election years used to estimate the two-period difference in differences. The posttreatment year is 2016. β shows the two-period difference in differences estimate, for each model. The null hypothesis is rejected in each model. See Table 2.4 for fully reported results, as well as pooled estimates using all pretreatment years. *p <= .1; **p <= .05; ***p <= .01.

The effect is even more pronounced when restricting the analysis to include winning candidates. The difference in differences estimate shows that minority representation increased by 17 percentage points ($p < .01$). Parallel trends appears to hold in the immediate pretreatment period (2008 and 2012). However, the trend lines intersect and reverse sign between 2004 and 2008. This tells us that a persistent decline in representation between 2004 and 2012 led would-be switchers to adopt district elections in 2016 (i.e., a selection effect). As a robustness check for this possibility, the pooled pretreatment model is useful. The pooled result is similar to the two-period estimate, and shows that district elections increased minority representation by 13 percentage points ($p < .01$).

I subset the analysis by conditioning on incumbency status and election outcome. The top row of Figure 2.3 shows percent non-White identification for all incumbent candidates, and for incumbent winners. The bottom row shows the same, but for non-incumbents. Incumbent non-White identification is unaffected by district elections. This is true for all candidates and those who won election. Interestingly, long-term trends show that incumbents are Whiter in by-district cities. This is true for all incumbent candidates and for those who won election.

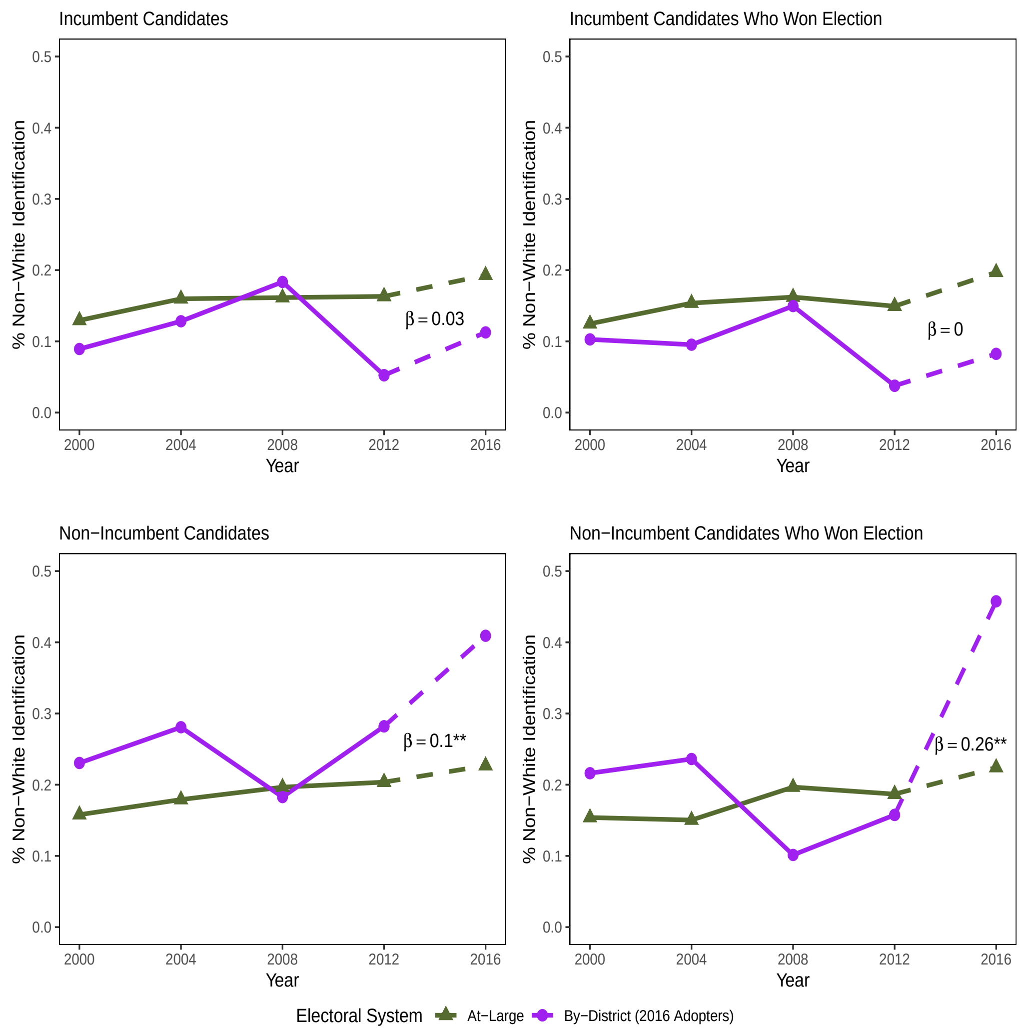


Figure 2.3: District elections increase minority representation among non-incumbent candidates. This plot shows mean non-White identification, by incumbency status, for all candidates and winning candidates. The first row corresponds to incumbent candidates (n = 815, and 607, respectively). The second row corresponds to non-incumbent candidates only (n = 2150, and 777, respectively). The outcome measure (y-axis) is the mean probability that a candidate is non-White. The dashed lines indicate the election years used to estimate the two-period difference in differences. The posttreatment year is 2016. β shows the two-period difference in differences estimate, for each model. The null hypothesis is rejected for non-incumbent candidates only. See Table 2.4 for fully reported results, as well as pooled estimates using all pretreatment years. *p <= .1; **p <= .05; ***p <= .01.

District elections increase non-White identification for all non-incumbents by 10 percentage points ($p < .05$). Non-incumbent winners see a 26 percentage point increase in non-White representation ($p < .05$). For both non-incumbent plots, there are considerable fluctuations in representation during the pretreatment period. As such, it may be useful to rely on the pooled models. The pooled estimates are of the same sign and significance as their two-period counterparts. Interestingly, the plot for non-incumbent winners shows a dip in minority representation between 2004 and 2008. These differences speak to the treatment assignment process, and suggest that at-large and by-district cities had longstanding differences between them.

I leverage a complementary measure of race. The measure is a dummy variable equalling 1 if a candidate has a predicted non-White probability of 80 percent or higher, and 0 otherwise. Figure 2.4 shows the percentage of all candidates (top row), and winning candidates (bottom row), who are non-White. As the top row shows, district elections increase the percentage of all candidates who are non-White by 8 percentage points ($p < .05$). Parallel trends appears plausible in this case, at least moreso than when the percent non-White measure is used. The effect remains of the same sign and significance in the pooled model. Long-term trends reveal no stark differences between at-large and by-district cities.

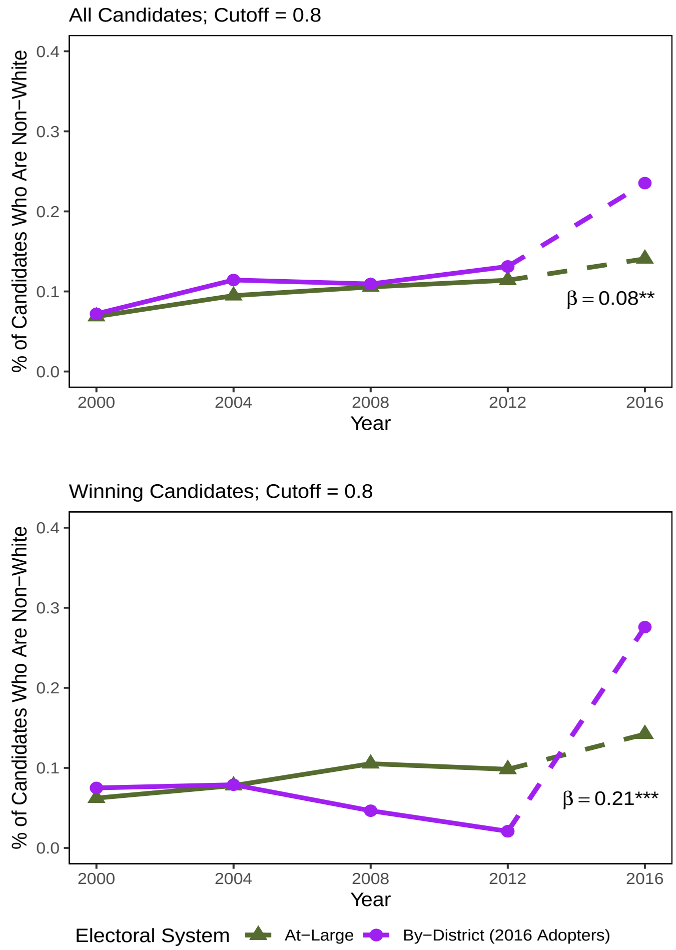


Figure 2.4: District elections increase the percentage of candidates who are non-White. This plot shows percentage of all candidates who are non-White, by year. The first row corresponds to all candidates (n = 2965), and the second row to winning candidates only (n = 1384). The outcome measure is the percentage of all candidates who are non-White (y-axis). Candidates are classified as non-White if the probability that they are non-White is at least 80%. The dashed lines indicate the election years used to estimate the two-period difference in differences. The posttreatment year is 2016. β shows the two-period difference in differences estimate, for each model. The null hypothesis is rejected for both models. See Table 2.4 for fully reported results, as well as pooled estimates using all pretreatment years. See Appendix for replication plots using different cutoffs. *p <= .1; **p <= .05; ***p <= .01.

The effect is more pronounced, but more complex, among winning candidates. District elections increase the percent of candidates who are non-White by 21 points in the two-period differences in differences ($p < .01$), and by 17 points in the pooled model ($p < .01$). Parallel trends appears plausible in the immediate pretreatment period between 2008 and 2012. However, prior to this period there is a clear decrease in minority representation for would-be district cities. Again, it appears that district cities selected into treatment because of a dip in minority representation over the pretreatment period.

Vote Share

Thus far, I have shown that district election increase minority representation. However, we do not know why they do so. For example, it could be that minorities are more likely to run for office in district-based systems. However, this does not mean that minority candidates receive more votes, or benefit individually, in these elections, per se. Rather, it simply means that there are more minority candidates, which increases the likelihood that at least one wins. I examine one possible mechanism of increased representation: vote share. I estimate vote share for minority candidates in elections with two, three, and four candidates per seat, using the 80 percent cutoff variable. I disaggregate in this way because vote share is deterministically related to the number of candidates running for office, and valid estimation is only possible if candidates are binned according to election competitiveness. The dependent variable is the percentage of total votes that a candidate receives. I only include elections where two, three, and four candidates are running per seat. The data is sparse in races with more than four candidates per seat, so I do not examine elections above this threshold

Figure 2.5 shows the main results. When two candidates are competing for one seat (top row), district elections increase minority vote share by 38 percentage points ($p < .01$). Notably, parallel trends appears to hold across all pretreatment periods, and the pooled results are quite similar: district elections increase vote share by 34 percentage points ($p < .01$). At least in the two candidate case, district elections cause minority vote shares to increase. An interesting pattern again emerges with respect to pretreatment trends: minority candidates have systematically lower vote shares in by-district cities.

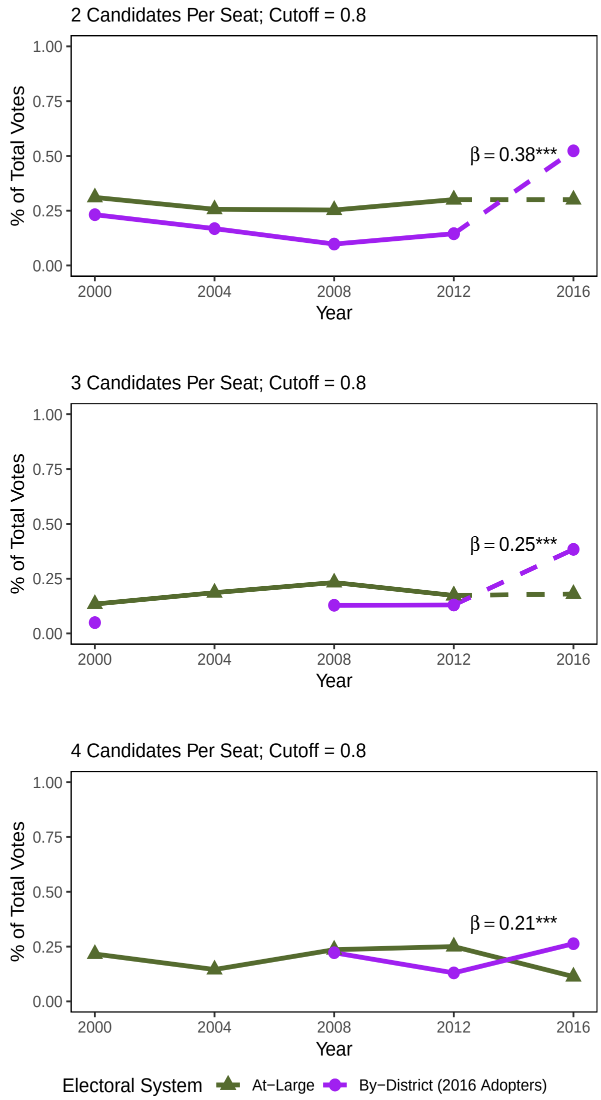


Figure 2.5: District elections increase vote shares for minority candidates. This plot shows vote shares for minority candidates by year, and by the number of candidates running per seat (n = 92, 45, and 42, respectively). The outcome is the mean percentage of votes received by minority candidates (y-axis). Candidates are classified as minority if the probability that they are minority is at least 80%. The dashed lines indicate the election years used to estimate the two-period difference in differences. The posttreatment year is 2016. β shows the two-period difference in differences estimate, for each model. The null hypothesis is rejected for all models. See Table 2.4 for fully reported results, as well as pooled estimates using all pretreatment years. See Appendix for replication plots using different cutoffs. The four candidates per seat model pools across all years because the sample is too small to estimate a two-period model. *p <= .1; **p <= .05; ***p <= .01.

Similar results are present in the three and four candidate per seat plots (middle and bottom rows, respectively). District elections increase minority vote share by 25 points ($p < .01$) in the three candidate case, and by 21 points ($p < .01$) in the four candidate case. The estimates are of the same sign, size, and significance when using the pooled data.[14] There are some years where no candidates run for election in by-district cities. This is likely because the dual requirement that, in this setup, a minority candidate be above the 80 percent cutoff *and* be in an election where three or four candidates are running for office is overly stringent. Despite this, there is evidence that district elections are associated with increased minority vote shares in the three and four candidate elections.[15]

Win Rate

A related causal mechanism is win rate. District elections may increase the number of minority candidates running for office, and their vote shares. However, it does not mean that minority candidates have an overall higher win rate. To estimate win rate, I create a dummy variable that equals 1 if a minority candidate won election, and 0 if not. I omit cases in which there were runoff elections. Again, I subset the analysis by the number of candidates running for office per seat. I also subset by race, such that separate analyses are performed on minority candidates and White candidates. Each race subset uses an 80 percent cutoff (to be classified as White a candidate must have at least an 80 percent probability of being White).

Figure 2.6 shows the percentage of minority candidates who won election. The top

[14] I only estimate a pooled difference in differences for the four candidates per seat model because there are not enough candidates to reliably estimate a two-period model.

[15] I include difference in differences estimators that control for the number of seats, as well as the percentage of candidates who are minority as defined by the 80 percent cutoff. This is because minority vote share is related to the percentage of all candidates who are minority. These results do not change from those reported here. They are reported in Table 2.9 in the Appendix. The difference in differences are replicated for minority and White candidates, across all cutoffs.

row shows that there is a 46 percentage point increase in the minority win rate in elections where there are two candidates running per seat. The effect is significant to ($p < .01$). District cities have categorically lower pretreatment minority win rates, aside from year 2004. They dive to near zero in 2008 and 2012, and rebound in 2016. While parallel trends is plausible in the immediate pretreatment period, these fluctuations make it less tenable over the long-haul. The pooled pretreatment model shows a 35 point increase in the win rate, but significance drops to ($p < .10$). While the effect of district elections on win rates is opaque, there appear to be long-standing substantive differences in win rates between at-large and by-district cities.

The middle row shows win rates for minority candidates in elections with three candidates running per seat. District elections increase minority win rate by 50 points ($p < .05$). Similar to the two candidate case, minorities have lower win rates during the pretreatment period. The pooled model shows that district elections increase the win rate by 37 points, but the effect is only significant to ($p < .10$). Minority win rate is unrelated to district elections in races with four candidates per seat. Altogether, the emergent theme is that district elections increase win rates to levels found in at-large cities. However, the effect is probably driven by abnormally low win rates in 2008 and 2012 among by-district cities. It is less clear whether district elections actually increase the probability that minority candidates win office, all else held equal.[16]

[16] I include difference in differences estimators that control for the number of seats, as well as the percentage of candidates who are minority as defined by the 80 percent cutoff. This is because win rate may be related to the percentage of all candidates that are minority. These results do not change from those reported here. They are reported in Table 2.9 in the Appendix. The difference in differences are replicated for minority and White candidates, across all cutoffs.

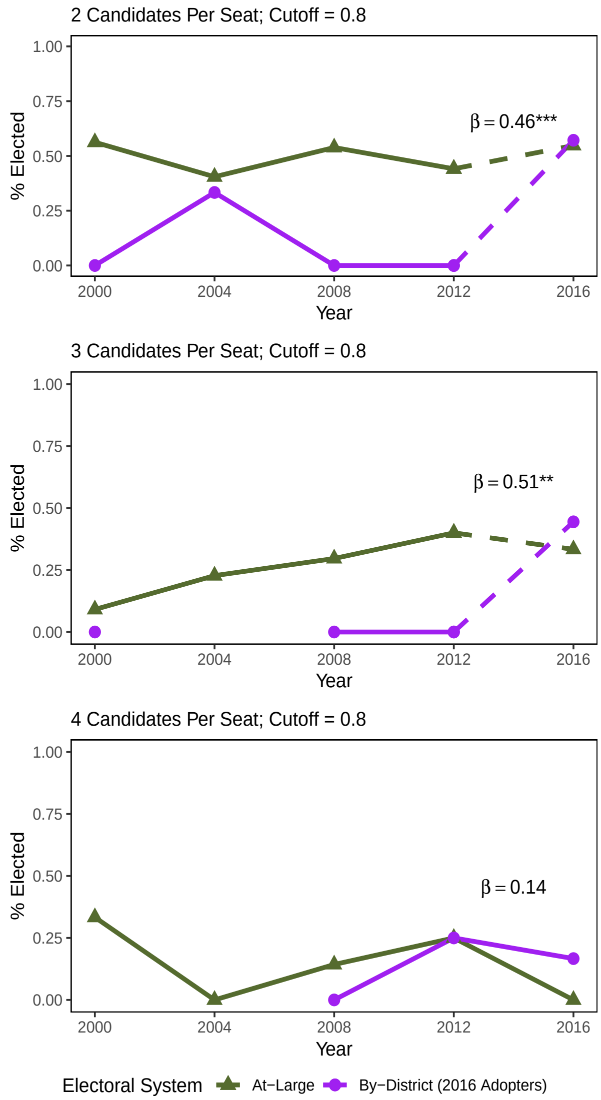


Figure 2.6: District elections increase the percent of minority candidates who win office. This plot shows win rates for minority candidates by year, and by the number of candidates running per seat (n = 92, 45, and 41, respectively). The outcome is the mean percentage of minority candidates who won office in a given year (y-axis). Candidates are classified as minority if the probability that they are minority is at least 80%. The dashed lines indicate the election years used to estimate the two-period difference in differences. The posttreatment year is 2016. β shows the two-period difference in differences estimates. See Table 2.4 for fully reported results, as well as pooled estimates using all pretreatment years. See Appendix for replication plots using different cutoffs. The four candidates per seat model pools across all years because the sample is too small to estimate a two-period model. *p <= .1; **p <= .05; ***p <= .01.

Figure 2.7 shows win rates for White candidates. District elections are unrelated to White win rates. An interesting pattern does emerge, however. In two and three candidate per seat elections, White win rates are remarkably similar in by-district and at-large cities over time. This suggests that the treatment assignment process was likely unexplained by the success of White candidates. Rather, minority electoral outcomes appear the significant determinant of whether cities elected to adopt district elections.

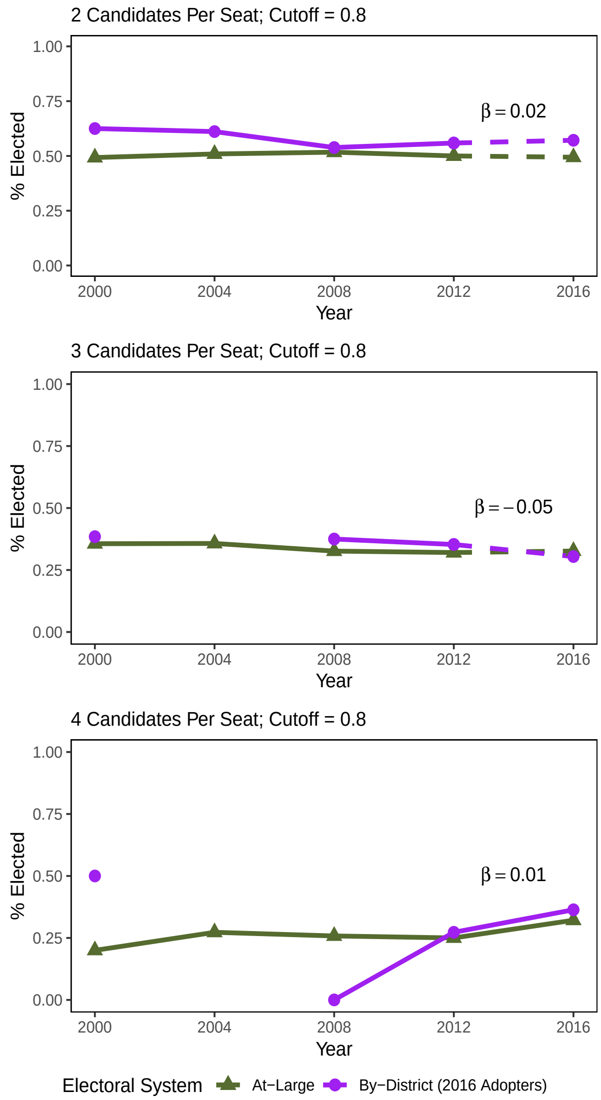


Figure 2.7: District elections do not increase the percent of White candidates who win office. This plot shows win rates for White candidates by year, and by the number of candidates running per seat (n = 509, 216, and 208, respectively). The outcome is the mean percentage of White candidates who won office in a given year (y-axis). Candidates are classified as White if the probability that they are White is at least 80%. The dashed lines indicate the election years used to estimate the two-period difference in differences. The posttreatment year is 2016. β shows the two-period difference in differences estimate, for each model. The null hypothesis is not rejected for all models. See Table 2.4 for fully reported results, as well as pooled estimates using all pretreatment years. See Appendix for replication plots using different cutoffs. The four candidates per seat model pools across all years because the sample is too small to estimate a two-period model. $^{*}p <= .1$; $^{**}p <= .05$; $^{***}p <= .01$.

Demographic Similarity

Here, I expand on the previous analyses to examine the demographic overlap between cities and candidates. I use local regression (LOESS) to plot the relationship between the race and ethnicity of candidates, and the cities they represent. Figure 2.8 presents a LOESS plot for two variables: the percentage of a city that is non-White (x-axis), and the probability that a candidate is non-White (y-axis). I plot the relationship for four groups: at-large candidates in 2016, at-large candidates pre-2016, by-district candidates in 2016, and by-district candidates pre-2016. The 45 degree line represents perfect demographic overlap between cities and their councilmembers. Anything above this line indicates minority overrepresentation, and anything below this line indicates minority underrepresentation.

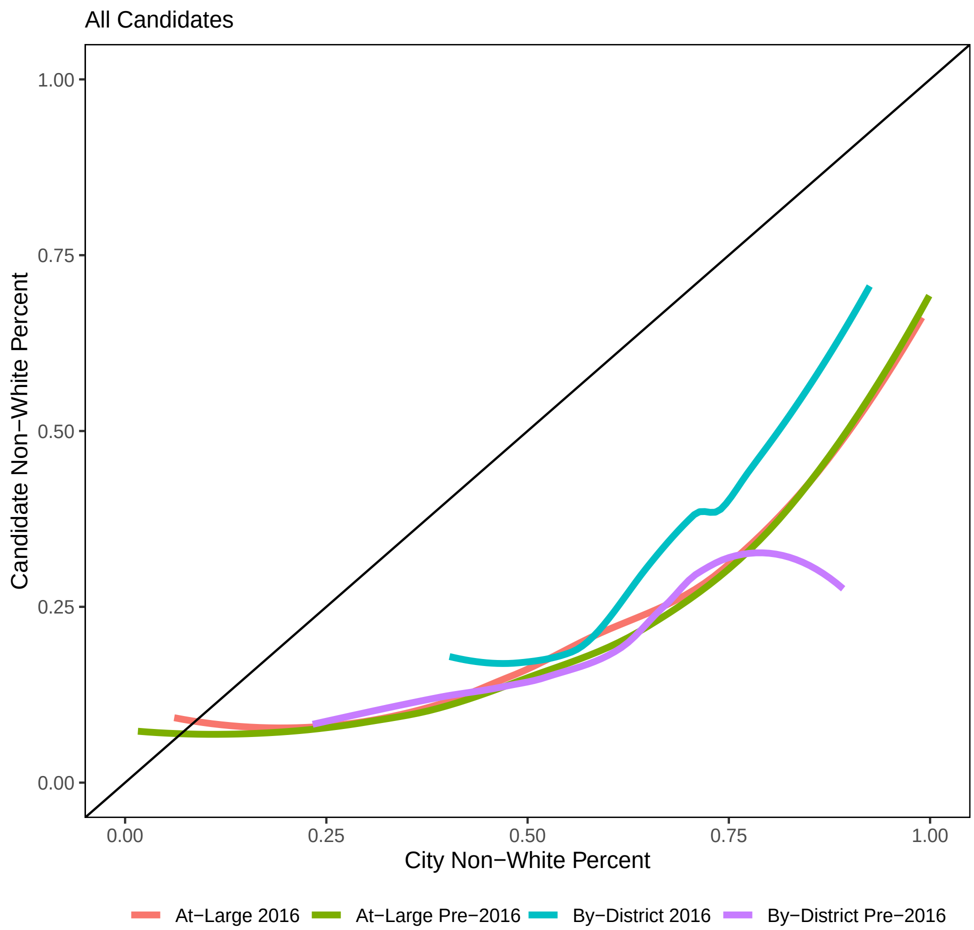


Figure 2.8: District elections increase demographic overlap between city council candidates and the cities they are running in. This figure provides LOESS curves showing the relationship between city and candidate demographics. The x-axis shows the percentage of a candidate's city that is non-White, and the y-axis shows the probability that a candidate is non-White. Four treatment and period conditions are provided: at-large cities in 2016 and pre-2016, and by-district cities in 2016 and pre-2016. The 45 degree line indicates a scenario in which a candidate is perfectly representative of the city she represents. Curves below this line indicate that minorities are under-represented on city council, and curves above this line would indicate that minorities are over-represented on city council.

The blue line in Figure 2.8 shows that by-district candidates in 2016 achieve better demographic overlap than in any other city-period dyad. This becomes more apparent as cities become less White. By-district cities pre-2016 (purple) experience a notable decrease in demographic overlap as cities approach 75 percent non-White. This is in stark contrast to candidates in by-district cities during 2016. The green and red lines are for at-large cities pre-2016 and in 2016, respectively. Their trend does not change during the posttreatment period. While 2016 by-district candidates are more demographically similar to their cities, they still underrepresent minorities.

The top row of Figure 2.9 shows the relationship between city and candidate demographics, for all candidates. The y-axis shows the percentage of candidates that are non-White and the x-axis shows the percentage of a city that is non-White. Means are shown for each year, by electoral system. At-large cities are much Whiter than by-district cities. However, the percentage of candidates who are non-White is remarkably similar. Despite the fact that by-district cities have larger non-White populations, by-district candidates were roughly as White as those in at-large cities. There is an increase in the number of non-White candidates in 2016 for by-district cities.

Among winners (row 2), by-district cities actually had a smaller percentage of minority candidates during the pretreatment period. This is striking and underscores the severity of the representational inequities that by-district cities dealt with. The percentage of minority candidates who won office increased in 2016 for these cities, however. Even so, minorities were still underrepresented. Only 30 percent of winning candidates in by-district cities were non-White in 2016, but they represented cities that were roughly 70 percent non-White. Accordingly, these city councils were only about half as demographically representative of the city as they could be.[17]

[17]For example, .3/.7 is roughly .5. If city councils were perfectly similar to the city non-White population overall similarity would be expressed at .7/.7, or, alternatively, 1.

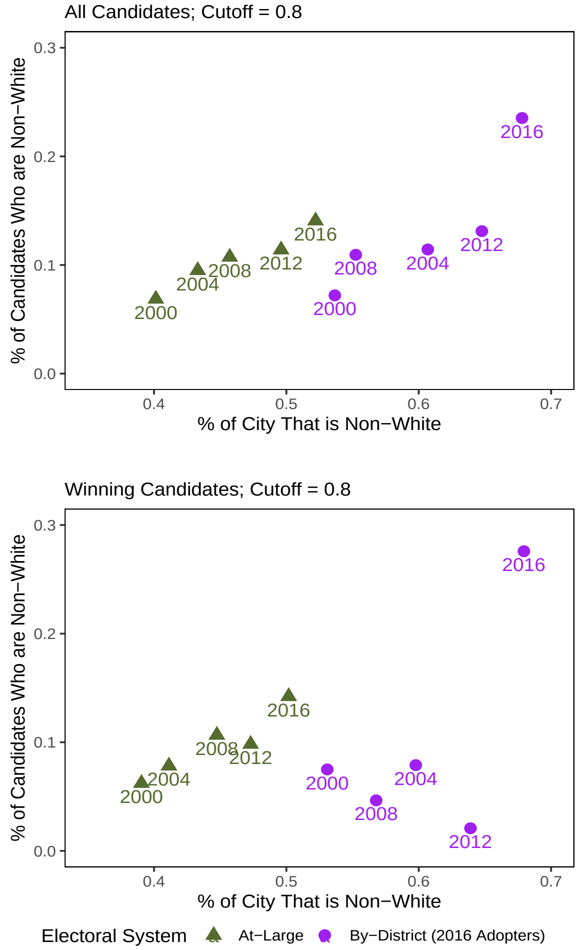


Figure 2.9: District elections increase the average demographic overlap between candidates and the cities they represent, especially for cities with high concentrations of minorities. This plot shows the evolution of the relationship between city demographics and candidate demographics. The x-axis shows the percentage of a city that is not White, and the y-axis shows the percentage of candidates that are non-White, using a cutoff of 0.8. Please see Appendix for replication plots using different cutoffs.

Figure 2.10 shows the demographic similarity index. Candidates in by-district cities (row 1) are less demographically similar to the cities they are drawn from over the pretreatment period. Focusing on 2016 and 2012, district elections increase the similarity index by 6 points ($p < .05$). Parallel trends appears to hold in this case, so it is likely that the effect is identified. The pooled model shows an increase of 5 points, but the effect is significant to ($p < .10$). The standard errors are roughly the same in this model, but the coefficient is smaller because early pretreatment observations had higher values. This reduces the coefficient estimate for 2016. For the two-period case, however, the results show that district elections lead to increased demographic overlap between candidates and the cities they represent.

Among winning candidates, district elections do not lead to increased demographic similarity. District elections increase demographic similarity by 5 points and 1 point in the two-period and pooled models, respectively. But, the coefficients are not significant below $p < .10$. As with all candidates, winners in by-district cities are less representative than those in at-large cities during the pretreatment period.

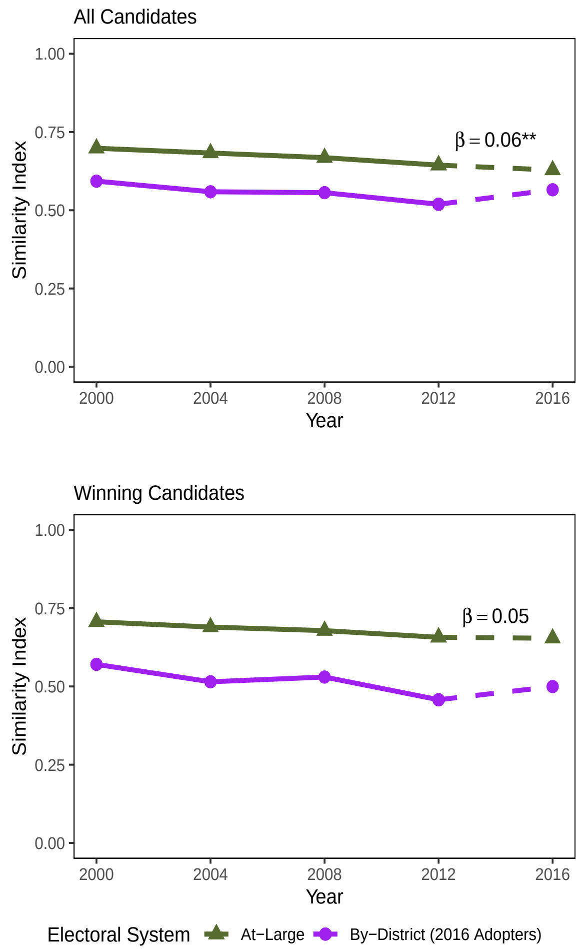


Figure 2.10: District elections increase demographic overlap between all candidates and the cities they are from, but not for winning candidates alone. This plot shows the similarity index by year, for all candidates and for winning candidates (n = 2965, and 1389, respectively). The outcome is the mean similarity index, by year (y-axis). The dashed lines indicate the election years used to estimate the two-period difference in differences. The posttreatment year is 2016. β shows the two-period difference in differences estimate, for each model. The null hypothesis is rejected for all candidates, but not for winning candidates. See Table 2.4 for fully reported results, as well as pooled estimates using all pretreatment years. *p <= .1; **p <= .05; ***p <= .01.

Why Is Demographic Similarity Unchanged?

The null effect on the similarity index suggests that district elections increase minority representation for some, but not all. Why is this? One possibility is that, in some cities, district elections actually increase minority representation above the percentage of the population that is non-White. For example, in cities that are 50 percent non-White, if two of three winning candidates are non-White, then the winning candidates overrepresent minorities relative to their share of the total population. I investigate this scenario by creating a dummy variable that equals 1 if the percentage of non-White candidates who won election in a by-district city is greater than the percentage of that city that is non-White. I then calculate the mean of this variable for every election year.

For each pretreatment year exactly zero cities overrepresent minority candidates who won office (Appendix Table 2.7). In 2016, however, 17% of cities overrepresented this group. That is, the percentage of minority candidates who won election was higher than their share of the total population. Paradoxically, the similarity index accounted for this by not changing its value in 2016. In effect, demographic similarity remained largely the same for some of these cities, but White overrepresentation among winning candidates was replaced by minority overrepresentation. As a result, the index stayed roughly the same.

This result underscores an important feature of district elections. In some cases, it can be the case that district elections do not make city councils more representative for all groups. Rather, once underrepresented groups become overrepresented.

2.8 Discussion

Where do the findings leave us? On the whole, district elections increase minority representation. This increase operates in three ways. First, minorities are better represented across the entire pool of candidates, regardless of incumbency status and electoral outcome. Among these subgroups, representation increases substantially for non-incumbents, and for winners. It is not simply that district elections draw a more racially diverse pool of candidates. More importantly, district elections increase minority representation among candidates who win office.

The effect is exclusive to non-incumbent candidates. This is not surprising. Incumbents already hold office, and year-to-year fluctuations in representation are only explained by candidates who are first-time incumbents. One needs to examine multiple post-2016 election years to identify whether district elections increase representation among incumbent candidates. If the cohort of non-incumbent minority candidates who won election in 2016 remains in office after 2016, we would see an increase in non-White representation among incumbents. This is an important point. If district elections increase minority representation in the short-run, but minority councilmembers do not remain in office, representation may decrease. Examining long-term trends can test this possibility, and future research should take up this endeavor.

What are the mechanisms underlying this increase? I show that it is not because of a larger candidate pool. Null effects are present for both measures of election competitiveness. This discounts one possible mechanism: the number of candidates increases making it more likely that at least one minority candidate wins office. There is no evidence to support this possibility. However, it is true that the number of minority candidates seeking office increases. At the least, this suggests that the design of city council districts may adequately account for patterns of residential segregation.

A related story is told by the null results. District elections are not less competitive than their at-large counterparts. One might fear that district-based systems are less competitive because the candidate pool within a district is smaller than the candidate pool across an entire city. However, this fear ignores the fact that the absolute number of candidates running for office is not what determines competitiveness. Rather, it is the number of candidates running for office per seat available. When standardized by this metric, district elections are actually more competitive than their at-large counterparts.

Minority candidates fare better in district elections because they have higher vote shares. This may seem obvious, but vote share is but one of potentially many mechanisms that explain increased representation. For example, it could be that the number of candidates stays the same in district elections (which is true), but that there are simply more minority candidates among this group (which, again, is true). This does not mean that minority candidates *receive* higher vote shares, or receive an electoral benefit from district-based systems. Rather, it simply means that the number of minority candidates running for office increases, thereby increasing the likelihood that at least one wins office. This paper provides clear, causal, evidence that district elections actually give minority candidates an electoral boon.

The win rate results show that district elections increase the probability that a minority candidate wins office. This is an important finding because increased minority representation among all candidates does not mean that any single minority candidate has a higher probability of winning office. It simply means that there is an average increase in the number of minority candidates who hold office, which could be attributable to a variety of factors (e.g., number of candidates). Win rate is different because it asks how the probability of winning office changes when switching from one electoral system to another, while holding all else constant. The difference in differences estimates support this logic, and indicate that the probability that any single minority candidate wins office increases in by-district elections.

District elections increase the demographic similarity between the pool of city council candidates and the cities they represent. However, the same is not true for those who eventually win office. This is an understudied, yet crucial, component about the character of district elections. As discussed earlier, some worry that district elections create a racialized political environment that may increase representation for some, but at the expense of others. I show that among all candidates, this is a largely unfounded concern.

In some cases, however, minority candidates are overrepresented relative to their share of the total population. This poses questions about the nature and character of substantive representation. While these councilmembers may be elected from districts, they are on councils that are intended to serve the entire city. If elected councilmembers operate with the entire city in mind, fears about racial discord will likely be assuaged. On the contrary, if residents feel that district elections strip power away from some groups (albeit those who benefited from at-large systems), or that district elections come at the expense of improved demographic representation for all, political infighting and factiousness may occur. Future work should explore this topic.

Finally, the plots and descriptive data shed light on existing differences between at-large and by-district cities. To date, most research has simply evaluated balance on city-level demographic features such race, income, and voting patters. I show that the story is much more complex than this. At-large and by-district cities are different on nearly every outcome over the pretreatment period. By-district cities have more candidates running for office, have lower minority vote shares, have lower minority win rates, and are less demographically representative than at-large cities. These trends likely inform much of the treatment assignment process, and point to a clear selection effect.

Future research should pay careful attention to these processes. The benefit of this paper is that it uses disaggregated time series data and non-parametric designs, which allow the data to speak for itself. In doing so, it shows that there are clear differences between the treatment and control groups. However, existing research has not devoted itself to examining these differences, nor has it given them ample attention. This paper highlights the importance of having a robust understanding of pretreatment trends, and shows that future work should evaluate the treatment assignment process more thoroughly. This will allow readers to more adequately assess the validity of the estimates, as well as the plausibility of the underlying assumptions used to generate them.

I close by contextualizing this paper within the larger body of research on electoral systems. First, I examine presidential election years only. Future work should incorporate, or examine exclusively, off-year and midterm elections. It could be that the effects found in this paper do not hold in other election cycles, especially during those with lower turnout and media coverage. Moreoever, future research should examine the impact of district elections in other geographic regions. Assessing the viability of district elections in regions with different political, social, and economic characteristics will allow a more comprehensive understanding of how they work. Nonetheless, this paper can be used to guide municipalities that are seeking to reform their electoral institutions in an effort to increase minority representation.

2.9 Appendix

Main Results Table

Here I provide numerical results for the the difference in differences estimates shown in the main text.

Table 2.4: Difference in Differences Estimates

Model	β	*se*	*t*	*Period*	*N*	*Cutoff*	*# Seats*
			Number of Candidates Running for Office				
Cands. Per Seat	0.29	0.27	1.06	2012-2016	2965	-	-
Cands. Per Seat	0.01	0.30	0.04	2000-2012	7343	-	-
Cands. Per Place	0.69	0.82	0.85	2012-2016	571	-	-
Cands. Per Place	0.22	0.79	0.28	2000-2012	1365	-	-
			Candidate Percent Non-White Identification				
% Non-White	0.1***	0.04	2.65	2012-2016	2965	-	-
% Non-White	0.1***	0.03	3.25	2000-2012	7343	-	-
% Non-White (W.)	0.17***	0.06	3.13	2012-2016	1384	-	-
% Non-White (W.)	0.13***	0.05	2.74	2000-2012	3342	-	-
% Non-White (Inc.)	0.03	0.06	0.52	2012-2016	815	-	-
% Non-White (Inc.)	-0.04	0.06	-0.63	2000-2012	2101	-	-
% Non-White (Inc. W.)	0	0.04	-0.06	2012-2016	607	-	-
% Non-White (Inc. W.)	-0.06	0.05	-1.31	2000-2012	1635	-	-
% Non-White (Chal.)	0.1**	0.04	2.37	2012-2016	2150	-	-
% Non-White (Chal.)	0.12***	0.04	3.26	2000-2012	5242	-	-
% Non-White (Chal. W.)	0.26**	0.10	2.56	2012-2016	777	-	-
% Non-White (Chal. W.)	0.23***	0.09	2.68	2000-2012	1707	-	-
			Percent of Candidates Who are Non-White				
% Non-White	0.08**	0.04	1.97	2012-2016	2965	0.8	-
% Non-White	0.08**	0.04	2.31	2000-2012	7343	0.8	-
% Non-White (W.)	0.21***	0.05	3.95	2012-2016	1384	0.8	-
% Non-White (W.)	0.17***	0.05	3.09	2000-2012	3342	0.8	-
			Percent Vote Share Among Minority Candidates				
% Vote Share	0.38***	0.05	7.96	2012-2016	92	0.8	2
% Vote Share	0.34***	0.04	8.57	2000-2012	194	0.8	2
% Vote Share	0.25***	0.06	4.46	2012-2016	45	0.8	3
% Vote Share	0.28***	0.06	4.99	2000-2012	109	0.8	3
% Vote Share	0.21***	0.04	5.72	2000-2012	42	0.8	4

Difference in Differences Estimates (continued)

Model	β	*se*	*t*	*Period*	*N*	*Cutoff*	*# Seats*
			Percent of Minority Candidates Who Won Office				
Minority Win Rate	0.46***	0.16	2.92	2012-2016	92	0.8	2
Minority Win Rate	0.35*	0.20	1.80	2000-2012	194	0.8	2
Minority Win Rate	0.51**	0.23	2.23	2012-2016	45	0.8	3
Minority Win Rate	0.37*	0.19	1.90	2000-2012	109	0.8	3
Minority Win Rate	0.14	0.15	0.92	2000-2012	41	0.8	4
			Percent of White Candidates Who Won Office				
White Win Rate	0.02	0.06	0.31	2012-2016	509	0.8	2
White Win Rate	0.01	0.05	0.15	2000-2012	1236	0.8	2
White Win Rate	-0.05	0.09	-0.61	2012-2016	216	0.8	3
White Win Rate	-0.05	0.08	-0.62	2000-2012	562	0.8	3
White Win Rate	0.01	0.11	0.13	2000-2012	208	0.8	4
			Similarity Index				
Similarity Index	0.06**	0.03	2.05	2012-2016	2965	-	-
Similarity Index	0.05*	0.03	1.81	2000-2012	7316	-	-
Similarity Index (W.)	0.05	0.04	1.06	2012-2016	1384	-	-
Similarity Index (W.)	0.01	0.04	0.30	2000-2012	3331	-	-

[a] *p <= .1; **p <= .05; ***p <= .01
[b] *Model* indicates dependent variable
[c] β indicates coefficient
[d] *se* indicates standard error of β
[e] *t* indicates t-statistic of β
[f] *Period* indicates period under observation
[g] *N* indicates sample size
[h] *Cutoff* indicates race cutoff, if applicable
[i] *# Seats* indicates number of seats in contest, if applicable
[j] All standard errors are clustered at the city level
[k] The dependent variables for the *Percent of Candidates Who Won Election*, *Percent of Minority Candidates Who Won Office*, and *Percent of White Candidates Who Won Office* models are dummy variables that equal 1 if the candidate won office, is a minority candidate, or is a White candidate, respectively.
[l] The following abbreviations are used: “Cands.” = Candidates; “W.” = Winner; “Inc.” = Incumbent; and, “Chal.” = Challenger.

NamePrism

NamePrism is an application programming interface (API) classification tool that uses name embeddings to assign race and ethnicity to first and last names. Classifiers such as these use F1 scores to measure their overall performance. An F1 score measures overall precision and recall. Precision indicates the percentage of positive predictions across all possible positive predictions, and recall is the percentage of positive predictions across all positive elements. A precision score of one indicates that no false positives were predicted, and a recall score of one means that no false negatives were predicted (see Losada and Fernández-Luna (2005) and Fujino et al. (2008) for more information). Together, both measures are used to calculate an F1 score, which is simply the average of precision and recall. As equation (4) shows, F1 is calculated as

$$F1 = 2\left(\frac{1}{P} + \frac{1}{R}\right)^{-1} \tag{2.1}$$

where P and R represent measures of precision and recall, respectively, and each equals one if perfect precision and recall exists. As is clear, an F1 score of one indicates perfect precision and recall as the sum of $\left(\frac{1}{P} + \frac{1}{R}\right)$ is two.

According to Ye et al. (2017), NamePrism's F1 score is .795, which is superior to F1 scores from competing classifiers.[18] And, through September 2018, it has been used on over 100 social science research projects. Considering its appreciably high F1 score and popularity in similar contexts, using it for this project seemed appropriate. In addition, using a classifier like NamePrism was deemed the most feasible way to classify more than 19,000 names, as doing so by hand would incur considerable time costs.

However, classifying by name embeddings alone leaves the researcher blind to whether the correct racial and ethnic categories are assigned to each name. To check whether NamePrism's classification scheme was viable, I randomly sampled 50 names from the full dataset and searched the internet for pictures of each sampled candidate name. If a picture of the candidate was located, I manually coded what I perceived to be the candidate's primary and secondary racial and ethnic identification. For sampled names *with* pictures on the internet, the coding proceeded in the following steps:

1) Copy candidate's first and last name into Google;

2) Search for image(s) of the candidate;

3) Use picture(s) to identify the primary race and ethnicity of the candidate;

[18] While a score of .795 implies that some units are misclassified, it is assumed that misclassifications are distributed uniformly throughout the sample. As such, measurement error is normally distributed, as well, and, by way of this assumption, no racial and ethnic category, or treatment status, is more (less) likely to be misclassified. If measurement error were to affect anything, it would be the size of the regression coefficients, and it would actually reduce the size of the coefficients. As a result, the population estimands may be larger than the estimates generated in this paper.

4) Code the candidate's primary race and ethnicity;

5) If candidate appears mixed race or racially ambiguous, repeat 3), but for secondary race and ethnicity of candidate;

6) Code the candidate's secondary race and ethnicity

In total, the primary and secondary race and ethnicity of 39 candidates was classified.

Table 2.5 provides comparisons between NamePrism's classifications and the hand coded classifications. Each column shows the percentage of units coded as White, Hispanic/Latinx, and non-White by NamePrism (left column) and using hand coding (right column). As is shown, both coding schemes produced similar results, with NamePrism identifying that the primary race of 87.2 of the sample is White, and the hand coding scheme identifying that the primary race of 84.6 of the sample is White. NamePrism identified that the primary identification of 10.3 percent of the sample is Hispanic/Latinx, and the hand coding scheme identifying that 7.7 percent of the sample is Hispanic/Latinx. Last, NamePrism identified that the primary racial and ethnic identification of 21.8 percent of the sample is non-White, and 15.4 percent of the sample is identified this way when using hand coding.

	Percentage	
Variable	NamePrism	Hand Coded
White	87.2	84.6
Non-White	12.8	15.4
Hispanic/Latinx	10.3	7.7

Notes: Presented are percentages of randomly sampled units that fall into a given racial/ethnic category, for each coding scheme. 50 units were randomly sampled, but due to photo availability constraints, 39 were able to be hand-coded. Reported percentages are only for units that *were* able to be hand-coded.

Table 2.5: NamePrism Reliability Check

While hand coding has its issues,[19] the results suggest that NamePrism keys in on racial and ethnic characteristics in a way similar to what we would expect if it were done visually, by hand. Both classification strategies converge to similar results, suggesting that, in the least, using NamePrism is a more efficient way classifying thousands of candidate names. In addition, it may be likely that NamePrism is a more precise classification

[19]For instance, it requires that pictures of candidates exist, which was true for only 78 percent of candidates in the sample. Furthermore, it requires that the coder can accurately predict the candidate's race and ethnicity based on pictures alone, which may not be tenable in certain situations. For example, mixed race individuals may be more likely to be miscoded, as could be individuals who are racially ambiguous.

tool because it does not rely on subjective judgements of a candidate's physiognomy to identify racial and ethnic characteristics. Rather, it relies on patterned name embeddings that are likely to be more representative of an individuals true racial and ethnic heritage than visual inspection. This lends further support for the decision to use NamePrism.

Data Collection

As discussed in the main text, existing data sources were incomplete. Because of this, I engaged in an original data collection effort that expanded on existing data and source information, and triangulated it with other sources to ensure that it was correct. The starting point for this process involved identifying cities in the Municipal Democracies Index (MDI) data that were purported to use district elections (N = 58). As mentioned in the main text, this dataset includes important city-level electoral information such as electoral system type, election cycle, and campaign contribution limits. However, it does not provide information on year-of-switch, a necessary variable for the identification strategies used in this paper. Despite this, it is quite comprehensive, and I opted to use it as the main sampling frame from which I could gather additional information on cities using district elections.

Although MDI data provided a viable starting point for additional data collection, it did not include cities that switched to district elections after year 2016. To locate these cities, I used internet search engines and news databases to search for recent news articles, publications, and news stories about city council elections in California. This allowed me to identify cities that recently switched to district elections, or cities that were planning to do so. Additionally, it ensured that my sample did not omit cities that, for whatever reason, used district elections (or were planning to), but were not listed in the MDI data. After combining MDI data with results from the internet searches, 96 cities were identified as either using district elections by 2016, or planning to use them in the future.[20]

For cities included in this sample, I conducted additional internet news searches, and read both city charters and municipal codebooks to corroborate the evidence found in the MDI dataset and from other online sources, and to identify year-of-switch. If the data in my sample was supported by other sources, I coded the city accordingly. Additionally, if outside sources provided information on year-of-switch, I coded this information, as well. However, if the search process was inconclusive, or generated conflicting evidence, I contacted city officials directly to get this information. My primary modes of contact were email and phone. In total, 20 cities were contacted because I was unable to find this information on my own, or existing sources presented conflicting information. If city offices did not respond to my requests, or were unable to provide the information I needed, I refrained from coding the city to reduce the potential for Type I error. In total, I was unable to corroborate evidence for 6 of the 96 cities in the sample, and 90 out

[20]Cities that moved to adopt district elections, regardless of year of future implementation, are included in the full sample.

of the 96 cities in the original sample were successfully identified as either using district elections by the 2016 election, or planning to use them in subsequent elections.

Census Imputation

I impute data where missing. This is typically for small cities that do not have American Community Survey data for all years prior to 2010 study. The imputation takes the form: $est00_{vtj} + \left(\frac{est09_{vjt} - est00_{vjt}}{9}\right) \times n$, where $est00_{vjt}$ is the 2000 decennial census estimate for the v^{th} census variable for city j in year t, n is the number of years post-2000 that the data is being imputed for, and $est09_{vjt}$ is the 2009 ACS estimate for the v^{th} independent variable for city j in year t.

Supplementary Tables

This section provides additional sample statistics, and results from supplemental analyses.

Control	Treatment	**Total**
335	23	**358**

Table 2.6: Treated and Control Cities

Year	Control	Treatment
2000	0.698	0.593
2004	0.683	0.559
2008	0.668	0.556
2012	0.644	0.519
2016	0.628	0.565

Similarity Index exists on [0,1]. Higher values indicate greater racial similarity between candidates and the cities they represent.

Table 2.7: Similarity Index By Year and Treatment Status Among All Candidates

Year	90% Cutoff	80% Cutoff	70% Cutoff	60% Cutoff	50% Cutoff
2000	0.00	0.00	0.00	0.00	0.00
2004	0.00	0.00	0.00	0.00	0.00
2008	0.00	0.00	0.00	0.00	0.00
2012	0.00	0.00	0.00	0.00	0.00
2016	0.17	0.17	0.17	0.22	0.22

Table 2.8: Percentage of By-District Cities That Overrepresent Minority Candidate Winners

Table 2.9: Supplementary Difference in Differences Estimates

Model	β	*se*	*t*	*Period*	*N*	*Cutoff*	*# Seats*
			Percent of Candidates Who Are Non-White				
% Non-White	0.11***	0.04	2.63	2012-2016	2965	0.5	-
% Non-White	0.1**	0.04	2.43	2012-2016	2965	0.6	-
% Non-White	0.07**	0.04	1.98	2012-2016	2965	0.7	-
% Non-White	0.05	0.04	1.45	2012-2016	2965	0.9	-
% Non-White	0.11***	0.03	3.39	2000-2012	7343	0.5	-
% Non-White	0.11***	0.03	3.26	2000-2012	7343	0.6	-
% Non-White	0.09***	0.03	3.01	2000-2012	7343	0.7	-
% Non-White	0.07**	0.03	2.03	2000-2012	7343	0.9	-
% Non-White (W.)	0.21***	0.06	3.72	2012-2016	1384	0.5	-
% Non-White (W.)	0.2***	0.06	3.64	2012-2016	1384	0.6	-
% Non-White (W.)	0.16**	0.07	2.28	2012-2016	1384	0.7	-
% Non-White (W.)	0.17***	0.06	3.02	2012-2016	1384	0.9	-
% Non-White (W.)	0.15***	0.05	3.06	2000-2012	3342	0.5	-
% Non-White (W.)	0.15***	0.05	2.99	2000-2012	3342	0.6	-
% Non-White (W.)	0.13**	0.06	2.12	2000-2012	3342	0.7	-
% Non-White (W.)	0.14**	0.05	2.55	2000-2012	3342	0.9	-
			Percent Vote Share Among Minority Candidates				
% Vote Share	0.29**	0.12	2.43	2012-2016	132	0.5	2
% Vote Share	0.3**	0.12	2.48	2012-2016	127	0.6	2
% Vote Share	0.28**	0.12	2.28	2012-2016	114	0.7	2
% Vote Share	0.41***	0.06	7.26	2012-2016	69	0.9	2
% Vote Share	0.18*	0.09	1.92	2000-2012	289	0.5	2
% Vote Share	0.19**	0.09	2.01	2000-2012	276	0.6	2
% Vote Share	0.18	0.12	1.57	2000-2012	240	0.7	2
% Vote Share	0.41***	0.04	9.73	2000-2012	149	0.9	2
% Vote Share	0.18	0.11	1.66	2012-2016	67	0.5	3
% Vote Share	0.18*	0.11	1.69	2012-2016	63	0.6	3
% Vote Share	0.18*	0.11	1.68	2012-2016	55	0.7	3
% Vote Share	0.27***	0.06	4.59	2012-2016	34	0.9	3
% Vote Share	0.22***	0.07	3.29	2000-2012	150	0.5	3
% Vote Share	0.22***	0.07	3.30	2000-2012	144	0.6	3
% Vote Share	0.25***	0.07	3.53	2000-2012	132	0.7	3
% Vote Share	0.34***	0.06	5.85	2000-2012	84	0.9	3

Supplementary Difference in Differences Estimates (continued)

Model	β	*se*	*t*	*Period*	*N*	*Cutoff*	*# Seats*
% Vote Share	0.15***	0.04	3.98	2000-2012	65	0.5	4
% Vote Share	0.16***	0.04	3.88	2000-2012	64	0.6	4
% Vote Share	0.16***	0.05	3.34	2000-2012	55	0.7	4
% Vote Share	0.26***	0.04	6.76	2000-2012	29	0.9	4
% Vote Share (c+p)	0.22***	0.05	4.12	2012-2016	554	0.5	-
% Vote Share (c+p)	0.22***	0.05	4.12	2012-2016	525	0.6	-
% Vote Share (c+p)	0.24***	0.06	4.30	2012-2016	463	0.7	-
% Vote Share (c+p)	0.28***	0.04	7.32	2012-2016	395	0.8	-
% Vote Share (c+p)	0.29***	0.04	7.96	2012-2016	291	0.9	-
% Vote Share (c+p)	0.16**	0.06	2.81	2000-2012	1179	0.5	-
% Vote Share (c+p)	0.16**	0.06	2.75	2000-2012	1114	0.6	-
% Vote Share (c+p)	0.19**	0.06	3.15	2000-2012	979	0.7	-
% Vote Share (c+p)	0.24***	0.04	5.85	2000-2012	793	0.8	-
% Vote Share (c+p)	0.24***	0.04	5.52	2000-2012	583	0.9	-
Percent of Minority Candidates Who Won Office							
Min. Win Rate	0.32***	0.09	3.62	2012-2016	394	0.8	-
Min. Win Rate	0.13	0.25	0.51	2012-2016	132	0.5	2
Min. Win Rate	0.13	0.26	0.50	2012-2016	127	0.6	2
Min. Win Rate	0.08	0.31	0.27	2012-2016	114	0.7	2
Min. Win Rate	0.6***	0.21	2.91	2012-2016	69	0.9	2
Min. Win Rate	0.06	0.16	0.40	2000-2012	289	0.5	2
Min. Win Rate	0.07	0.16	0.48	2000-2012	276	0.6	2
Min. Win Rate	-0.01	0.27	-0.05	2000-2012	240	0.7	2
Min. Win Rate	0.59***	0.20	3.01	2000-2012	149	0.9	2
Min. Win Rate	0.11	0.31	0.37	2012-2016	67	0.5	3
Min. Win Rate	0.13	0.31	0.42	2012-2016	63	0.6	3
Min. Win Rate	0.23	0.33	0.70	2012-2016	55	0.7	3
Min. Win Rate	0.58*	0.29	2.00	2012-2016	34	0.9	3
Min. Win Rate	0.21	0.21	1.01	2000-2012	150	0.5	3
Min. Win Rate	0.23	0.21	1.06	2000-2012	144	0.6	3
Min. Win Rate	0.31	0.23	1.34	2000-2012	132	0.7	3
Min. Win Rate	0.46**	0.23	2.02	2000-2012	84	0.9	3
Min. Win Rate	0.13	0.12	1.10	2000-2012	62	0.5	4
Min. Win Rate	0.13	0.12	1.10	2000-2012	61	0.6	4
Min. Win Rate	0.1	0.13	0.75	2000-2012	53	0.7	4
Min. Win Rate	-0.06	0.13	-0.50	2000-2012	28	0.9	4
Min. Win Rate	0.18*	0.10	1.82	2012-2016	552	0.5	-

Supplementary Difference in Differences Estimates (continued)

Model	β	*se*	*t*	*Period*	*N*	*Cutoff*	*# Seats*
Min. Win Rate	0.18*	0.10	1.82	2012-2016	523	0.6	-
Min. Win Rate	0.16	0.13	1.17	2012-2016	462	0.7	-
Min. Win Rate	0.35***	0.12	2.99	2012-2016	290	0.9	-
Min. Win Rate	0.1	0.07	1.34	2000-2012	1173	0.5	-
Min. Win Rate	0.09	0.07	1.20	2000-2012	1108	0.6	-
Min. Win Rate	0.09	0.11	0.86	2000-2012	975	0.7	-
Min. Win Rate	0.21**	0.09	2.23	2000-2012	792	0.8	-
Min. Win Rate	0.22*	0.13	1.77	2000-2012	582	0.9	-
Min. Win Rate (c+p)	0.15	0.10	1.43	2012-2016	552	0.5	-
Min. Win Rate (c+p)	0.16	0.10	1.54	2012-2016	523	0.6	-
Min. Win Rate (c+p)	0.15	0.14	1.08	2012-2016	462	0.7	-
Min. Win Rate (c+p)	0.29***	0.09	3.19	2012-2016	394	0.8	-
Min. Win Rate (c+p)	0.33**	0.13	2.54	2012-2016	290	0.9	-
Min. Win Rate (c+p)	0.02	0.08	0.25	2000-2012	1173	0.5	-
Min. Win Rate (c+p)	0.02	0.08	0.30	2000-2012	1108	0.6	-
Min. Win Rate (c+p)	0.01	0.11	0.13	2000-2012	975	0.7	-
Min. Win Rate (c+p)	0.12	0.10	1.24	2000-2012	792	0.8	-
Min. Win Rate (c+p)	0.1	0.14	0.75	2000-2012	582	0.9	-
Percent of White Candidates Who Won Office							
White Win Rate	-0.05	0.05	-0.99	2012-2016	2265	0.8	-
White Win Rate	0.02	0.05	0.40	2012-2016	534	0.5	2
White Win Rate	0.05	0.05	1.13	2012-2016	527	0.6	2
White Win Rate	0.02	0.05	0.51	2012-2016	521	0.7	2
White Win Rate	0.07	0.08	0.91	2012-2016	447	0.9	2
White Win Rate	0	0.05	0.10	2000-2012	1301	0.5	2
White Win Rate	0.04	0.05	0.89	2000-2012	1285	0.6	2
White Win Rate	0.01	0.05	0.28	2000-2012	1268	0.7	2
White Win Rate	0.03	0.06	0.47	2000-2012	1088	0.9	2
White Win Rate	-0.04	0.09	-0.41	2012-2016	233	0.5	3
White Win Rate	-0.04	0.09	-0.40	2012-2016	231	0.6	3
White Win Rate	-0.04	0.09	-0.44	2012-2016	230	0.7	3
White Win Rate	0.05	0.10	0.45	2012-2016	185	0.9	3
White Win Rate	-0.05	0.08	-0.61	2000-2012	613	0.5	3
White Win Rate	-0.05	0.08	-0.65	2000-2012	606	0.6	3
White Win Rate	-0.07	0.07	-0.97	2000-2012	595	0.7	3
White Win Rate	0.03	0.09	0.31	2000-2012	474	0.9	3
White Win Rate	-0.02	0.06	-0.40	2000-2012	226	0.5	4

Supplementary Difference in Differences Estimates (continued)

Model	*β*	*se*	*t*	*Period*	*N*	*Cutoff*	*# Seats*
White Win Rate	-0.03	0.06	-0.42	2000-2012	223	0.6	4
White Win Rate	0.03	0.07	0.49	2000-2012	219	0.7	4
White Win Rate	0.13	0.14	0.96	2000-2012	187	0.9	4
White Win Rate	-0.06	0.05	-1.25	2012-2016	2411	0.5	-
White Win Rate	-0.05	0.05	-1.05	2012-2016	2376	0.6	-
White Win Rate	-0.05	0.05	-1.01	2012-2016	2346	0.7	-
White Win Rate	-0.03	0.07	-0.51	2012-2016	1966	0.9	-
White Win Rate	-0.02	0.05	-0.37	2000-2012	6156	0.5	-
White Win Rate	-0.01	0.05	-0.16	2000-2012	6080	0.6	-
White Win Rate	-0.01	0.05	-0.26	2000-2012	5998	0.7	-
White Win Rate	-0.01	0.05	-0.11	2000-2012	5814	0.8	-
White Win Rate	0	0.06	0.02	2000-2012	5056	0.9	-
White Win Rate (c+p)	0.01	0.04	0.23	2012-2016	2411	0.5	-
White Win Rate (c+p)	0.02	0.04	0.57	2012-2016	2376	0.6	-
White Win Rate (c+p)	0.03	0.04	0.61	2012-2016	2346	0.7	-
White Win Rate (c+p)	0.02	0.05	0.50	2012-2016	2265	0.8	-
White Win Rate (c+p)	0.04	0.05	0.73	2012-2016	1966	0.9	-
White Win Rate (c+p)	0.01	0.03	0.42	2000-2012	6156	0.5	-
White Win Rate (c+p)	0.03	0.03	0.87	2000-2012	6080	0.6	-
White Win Rate (c+p)	0.03	0.03	0.81	2000-2012	5998	0.7	-
White Win Rate (c+p)	0.03	0.04	0.82	2000-2012	5814	0.8	-
White Win Rate (c+p)	0.04	0.03	1.23	2000-2012	5056	0.9	-
Percent of Candidates and Cities That Are Non-White							
% Min. Similarity	0.08*	0.04	1.86	2012-2016	571	0.5	-
% Min. Similarity	0.05	0.04	1.38	2012-2016	571	0.6	-
% Min. Similarity	0.05	0.04	1.18	2012-2016	571	0.7	-
% Min. Similarity	0.07	0.04	1.47	2012-2016	571	0.8	-
% Min. Similarity	0.03	0.04	0.77	2012-2016	571	0.9	-
% Min. Similarity	0.08**	0.04	2.10	2000-2012	1362	0.5	-
% Min. Similarity	0.06*	0.04	1.72	2000-2012	1362	0.6	-
% Min. Similarity	0.08*	0.04	1.91	2000-2012	1362	0.7	-
% Min. Similarity	0.08*	0.05	1.73	2000-2012	1362	0.8	-
% Min. Similarity	0.05	0.04	1.36	2000-2012	1362	0.9	-
% Min. Similarity (W.)	0.09*	0.05	1.79	2000-2012	1362	0.5	-
% Min. Similarity (W.)	0.09*	0.05	1.74	2000-2012	1362	0.6	-
% Min. Similarity (W.)	0.08	0.06	1.28	2000-2012	1362	0.7	-
% Min. Similarity (W.)	0.11**	0.05	1.97	2000-2012	1362	0.8	-

Supplementary Difference in Differences Estimates (continued)

Model	β	*se*	*t*	*Period*	*N*	*Cutoff*	*# Seats*
% Min. Similarity (W.)	0.08	0.05	1.52	2000-2012	1362	0.9	-
% Min. Similarity (W.)	0.17***	0.05	3.35	2012-2016	571	0.5	-
% Min. Similarity (W.)	0.17***	0.05	3.29	2012-2016	571	0.6	-
% Min. Similarity (W.)	0.13**	0.06	2.20	2012-2016	571	0.7	-
% Min. Similarity (W.)	0.15***	0.05	2.98	2012-2016	571	0.8	-
% Min. Similarity (W.)	0.11**	0.05	2.23	2012-2016	571	0.9	-

[a] *p <= .1; **p <= .05; ***p <= .01
[b] *Model* indicates dependent variable
[c] β indicates coefficient
[d] *se* indicates standard error of β
[e] *t* indicates t-statistic of β
[f] *Period* indicates period under observation
[g] *N* indicates sample size
[h] *Cutoff* indicates race cutoff, if applicable
[i] *# Seats* indicates number of seats in contest, if applicable
[j] "(c+p)" indicates that candidates-per-seat has been controlled for, as well as the percentage of all candidates who are in that racial cutoff
[k] All standard errors are clustered at the city level
[l] The dependent variables for the *Percent of Candidates Who Won Election*, *Percent of Minority Candidates Who Won Office*, and *Percent of White Candidates Who Won Office* models are dummy variables that equal 1 if the candidate won office, is a minority candidate, or is a White candidate, respectively.
[m] The following abbreviations are used: "Cands." = Candidates; "W." = Winner; "Inc." = Incumbent; and, "Chal." = Challenger, "Min." = Minority.

Supplementary Figures

The figures in the following section replicate the analyses and figures in the main text, but under slightly different model specifications, and with different race cutoffs.

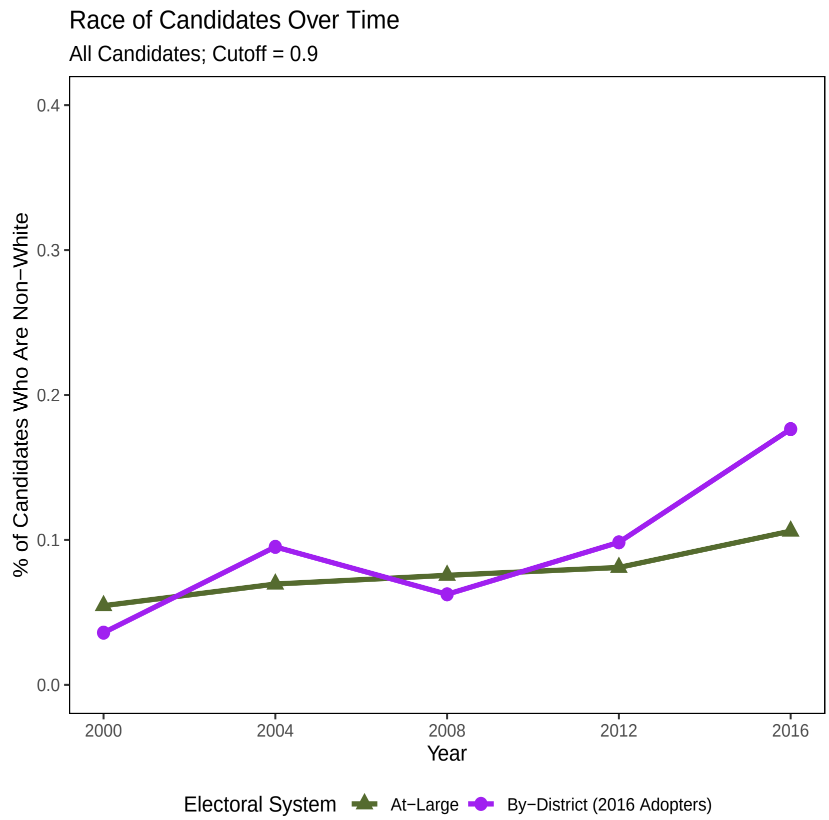


Figure 2.11

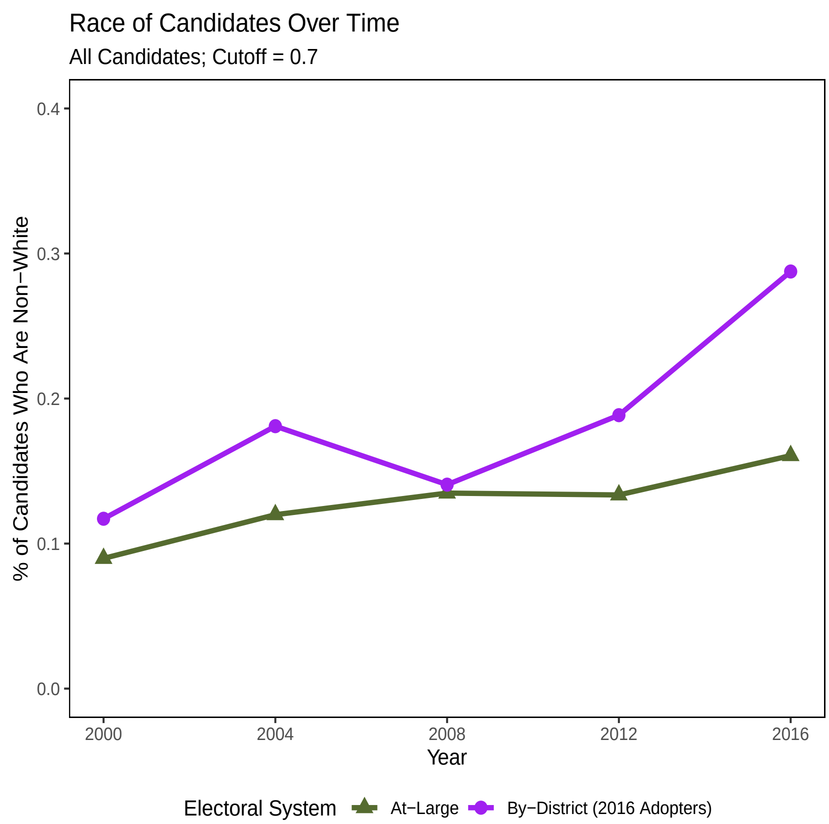
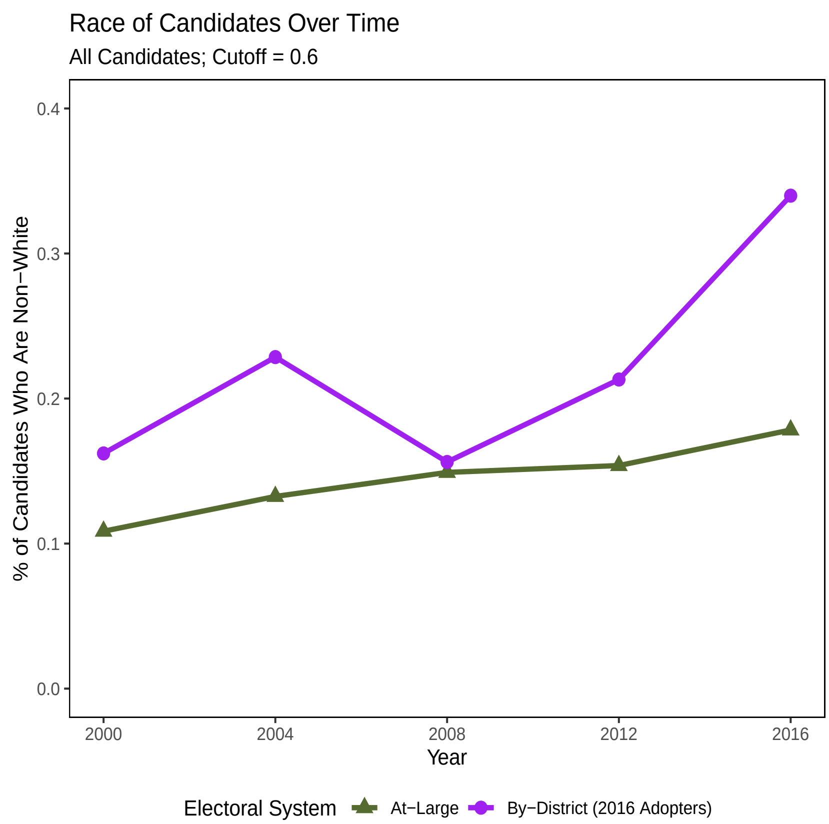

Race of Candidates Over Time
All Candidates; Cutoff = 0.7
% of Candidates Who Are Non−White
0.0
0.1
0.2
0.3
0.4
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.12



Race of Candidates Over Time
All Candidates; Cutoff = 0.6
% of Candidates Who Are Non−White
0.0
0.1
0.2
0.3
0.4
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.13

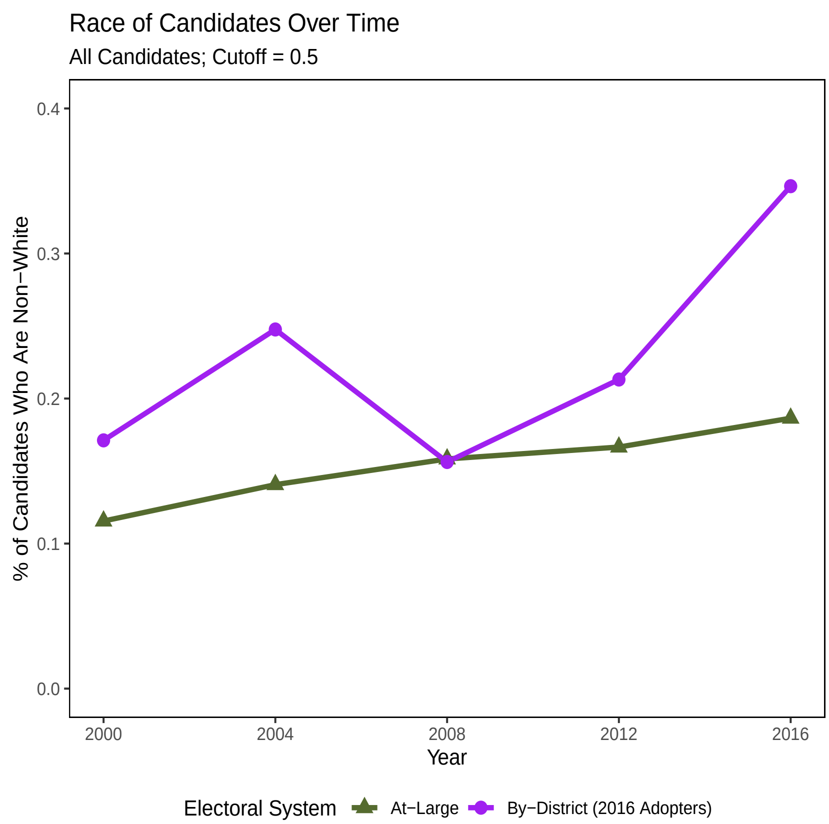

Race of Candidates Over Time
All Candidates; Cutoff = 0.5
% of Candidates Who Are Non−White
0.0
0.1
0.2
0.3
0.4
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.14

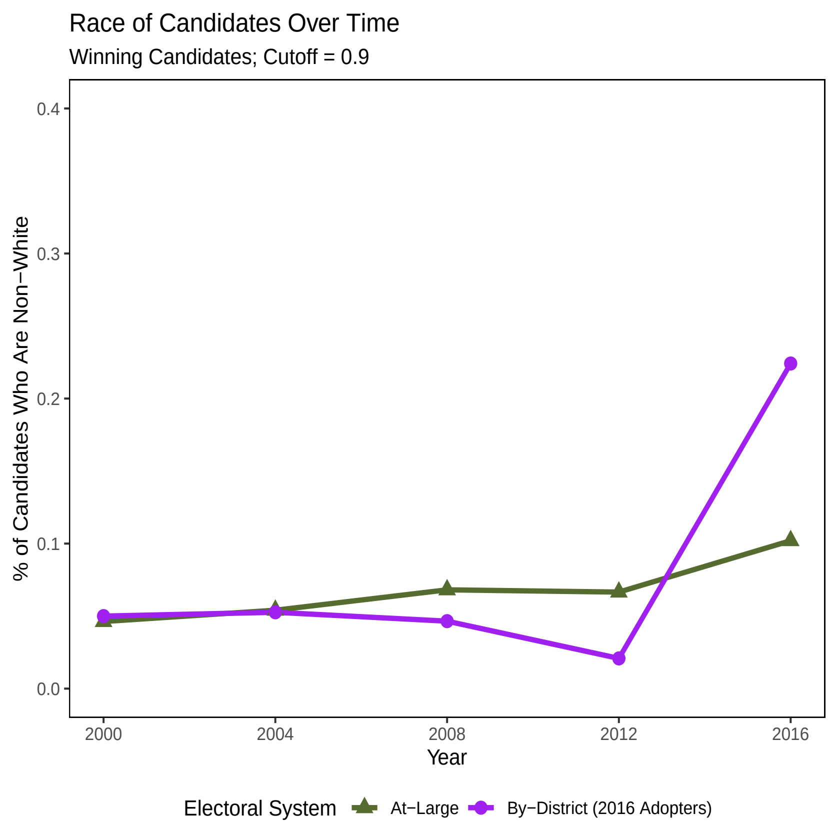

Race of Candidates Over Time
Winning Candidates; Cutoff = 0.9
% of Candidates Who Are Non−White
0.4
0.3
0.2
0.1
0.0
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.15

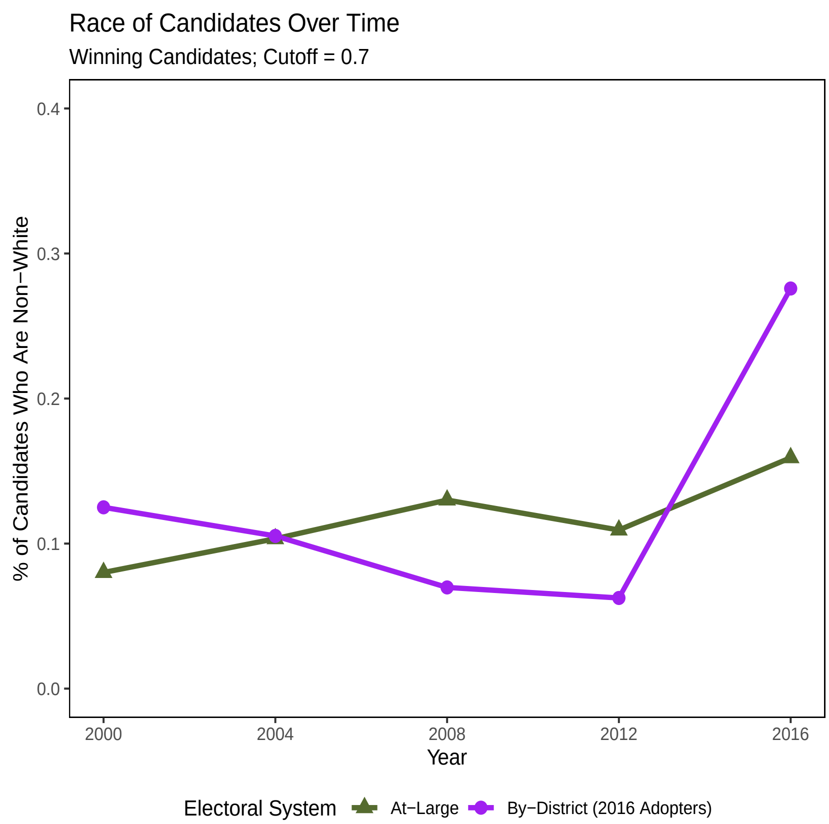

Race of Candidates Over Time
Winning Candidates; Cutoff = 0.7
% of Candidates Who Are Non−White
0.4
0.3
0.2
0.1
0.0
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.16

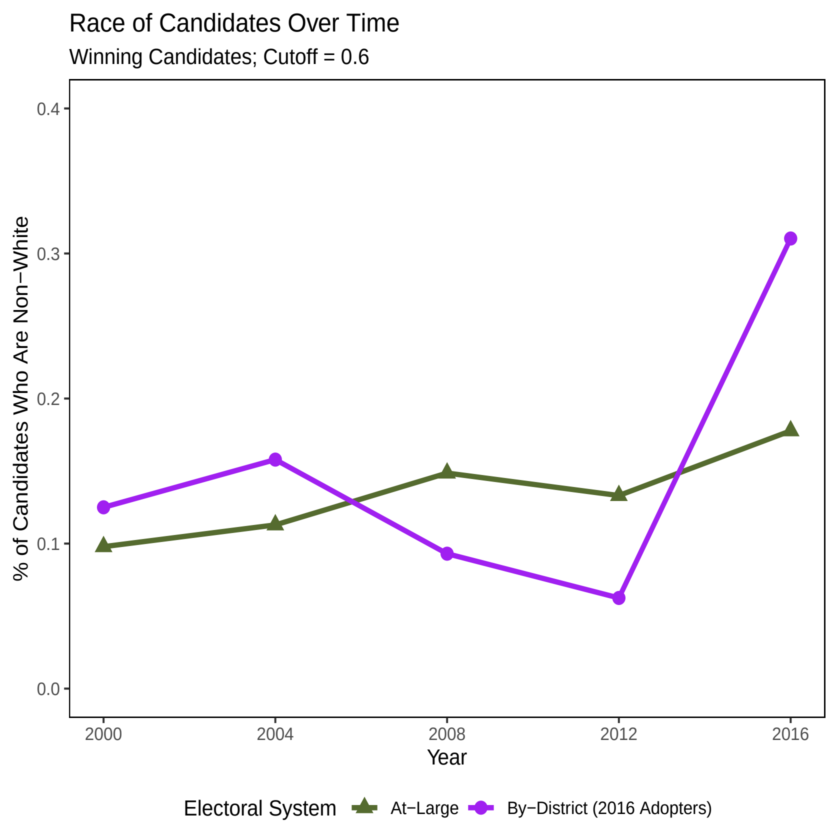

Race of Candidates Over Time
Winning Candidates; Cutoff = 0.6
% of Candidates Who Are Non−White
0.0
0.1
0.2
0.3
0.4
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.17

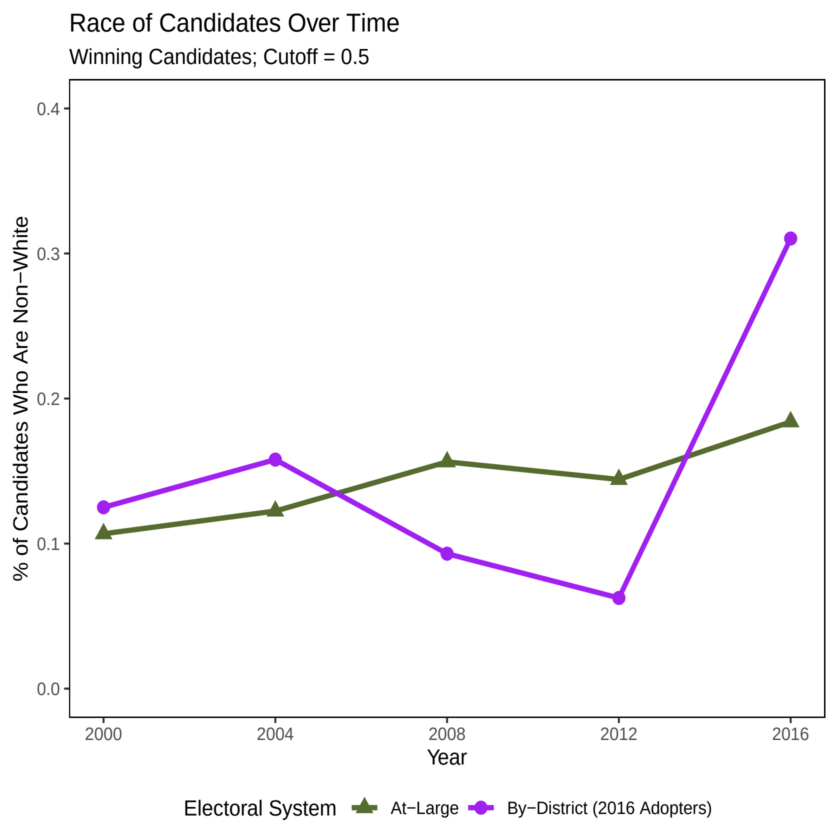

Race of Candidates Over Time
Winning Candidates; Cutoff = 0.5
% of Candidates Who Are Non−White
0.0
0.1
0.2
0.3
0.4
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.18

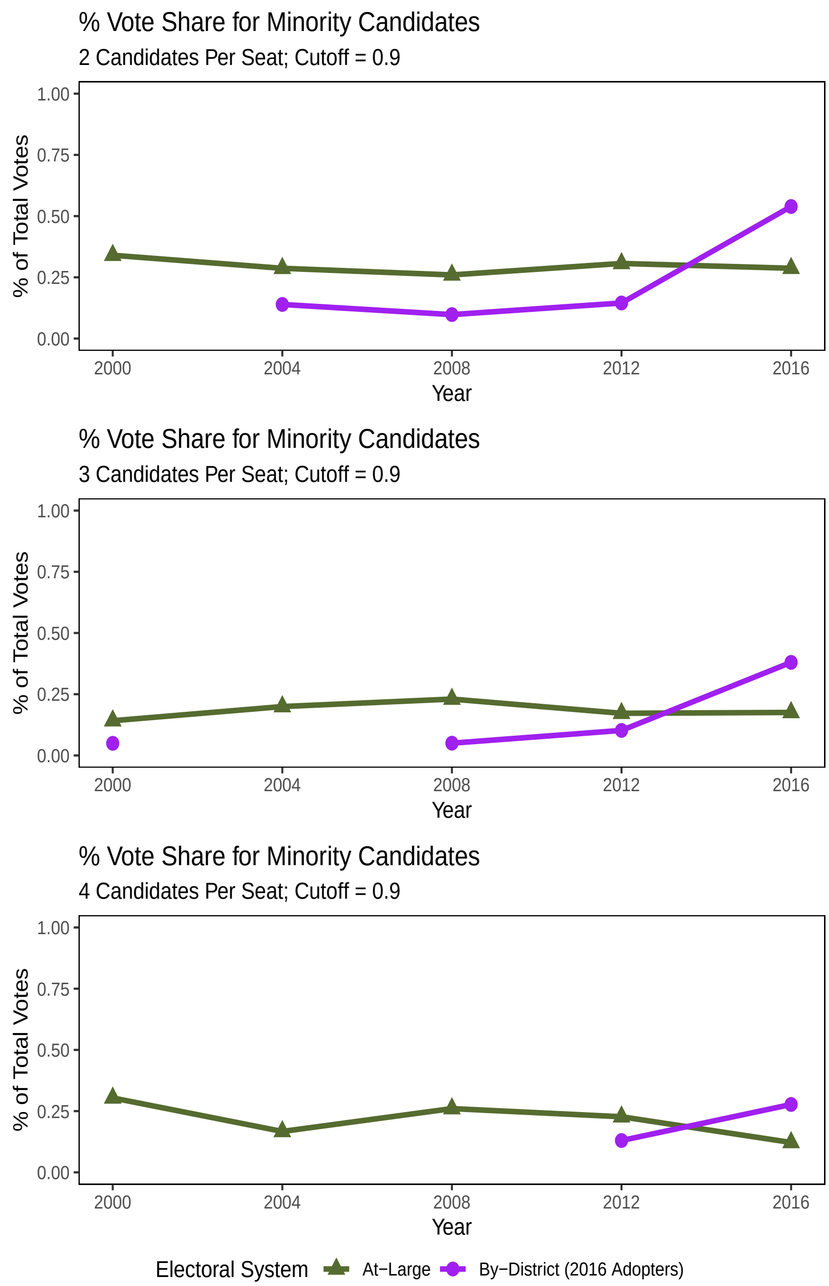

% Vote Share for Minority Candidates
2 Candidates Per Seat; Cutoff = 0.9
% of Total Votes
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
% Vote Share for Minority Candidates
3 Candidates Per Seat; Cutoff = 0.9
% of Total Votes
2000
2004
2008
2012
2016
Year
% Vote Share for Minority Candidates
4 Candidates Per Seat; Cutoff = 0.9
% of Total Votes
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.19

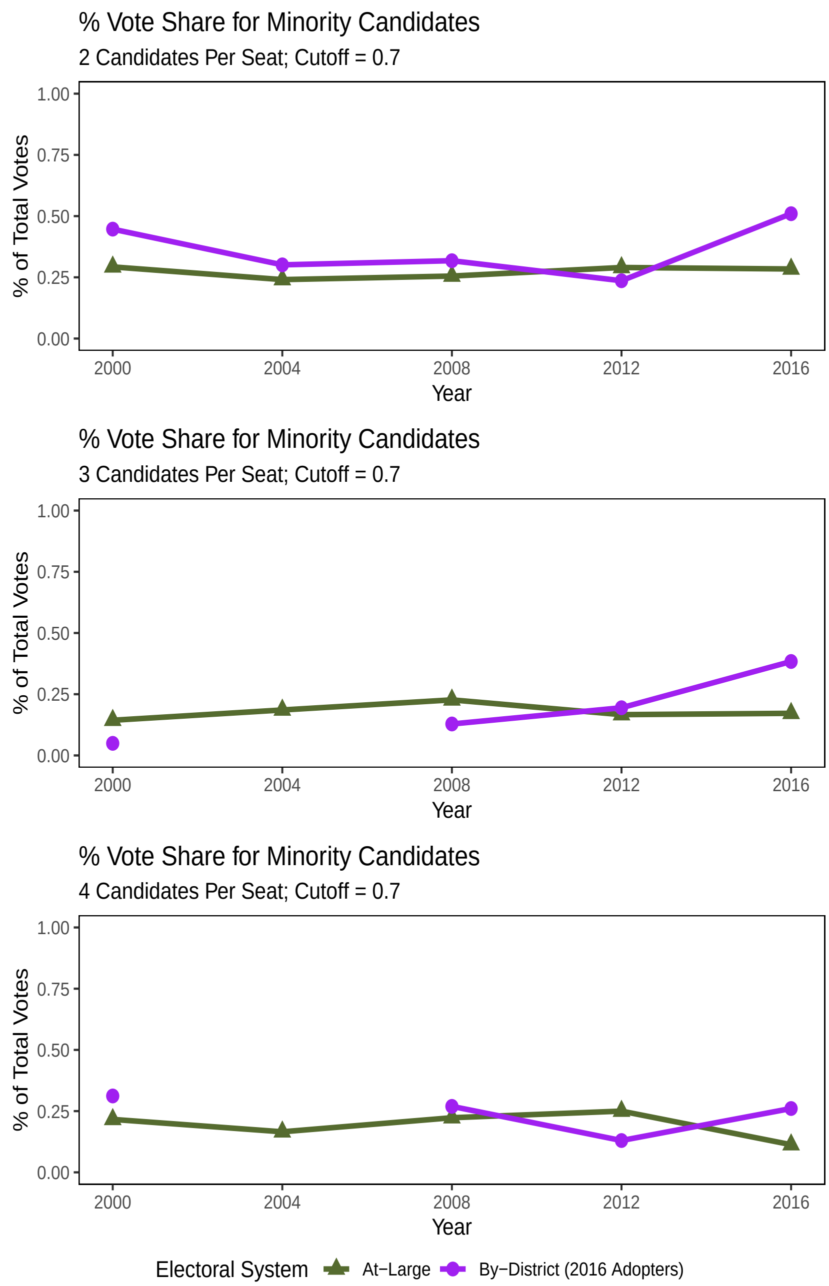

% Vote Share for Minority Candidates
2 Candidates Per Seat; Cutoff = 0.7
% of Total Votes
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
% Vote Share for Minority Candidates
3 Candidates Per Seat; Cutoff = 0.7
% of Total Votes
Year
% Vote Share for Minority Candidates
4 Candidates Per Seat; Cutoff = 0.7
% of Total Votes
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.20

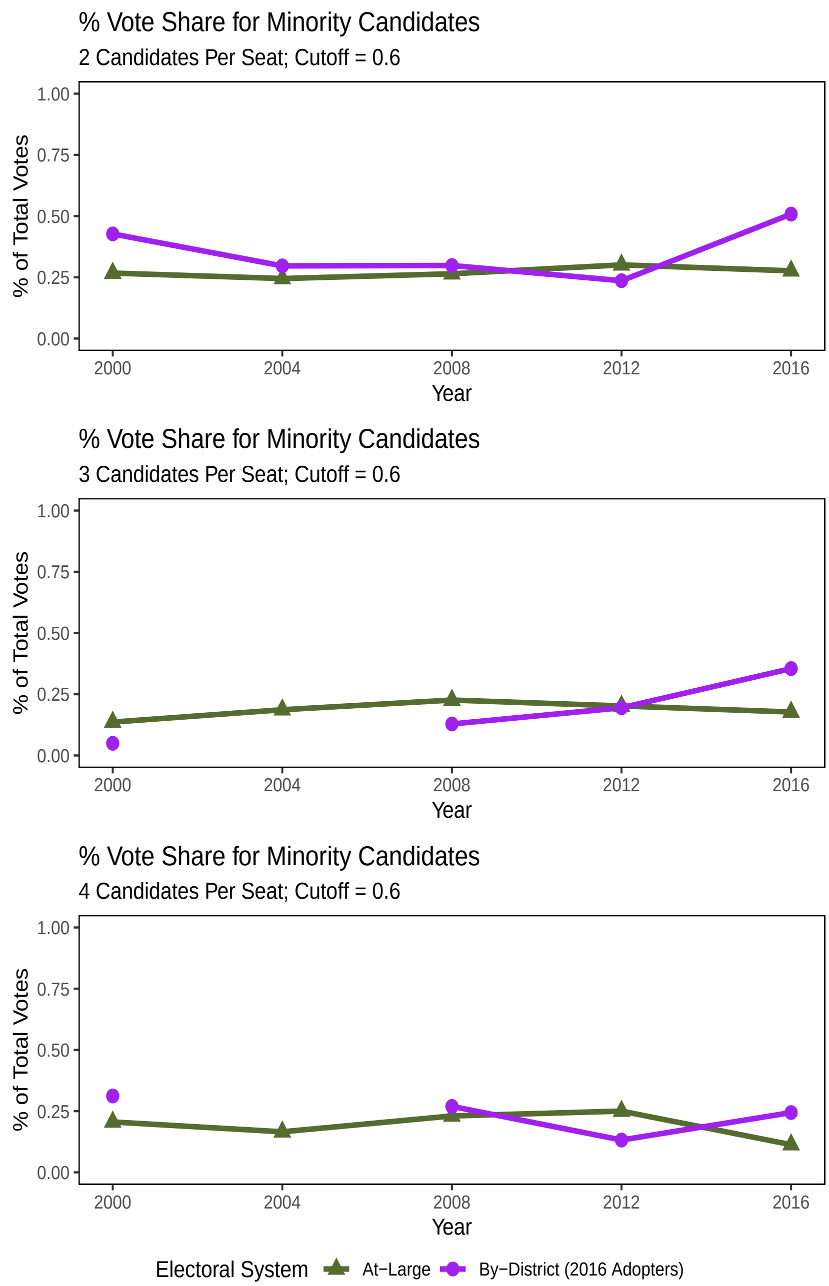

% Vote Share for Minority Candidates
2 Candidates Per Seat; Cutoff = 0.6
% of Total Votes
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
% Vote Share for Minority Candidates
3 Candidates Per Seat; Cutoff = 0.6
% of Total Votes
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
% Vote Share for Minority Candidates
4 Candidates Per Seat; Cutoff = 0.6
% of Total Votes
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.21

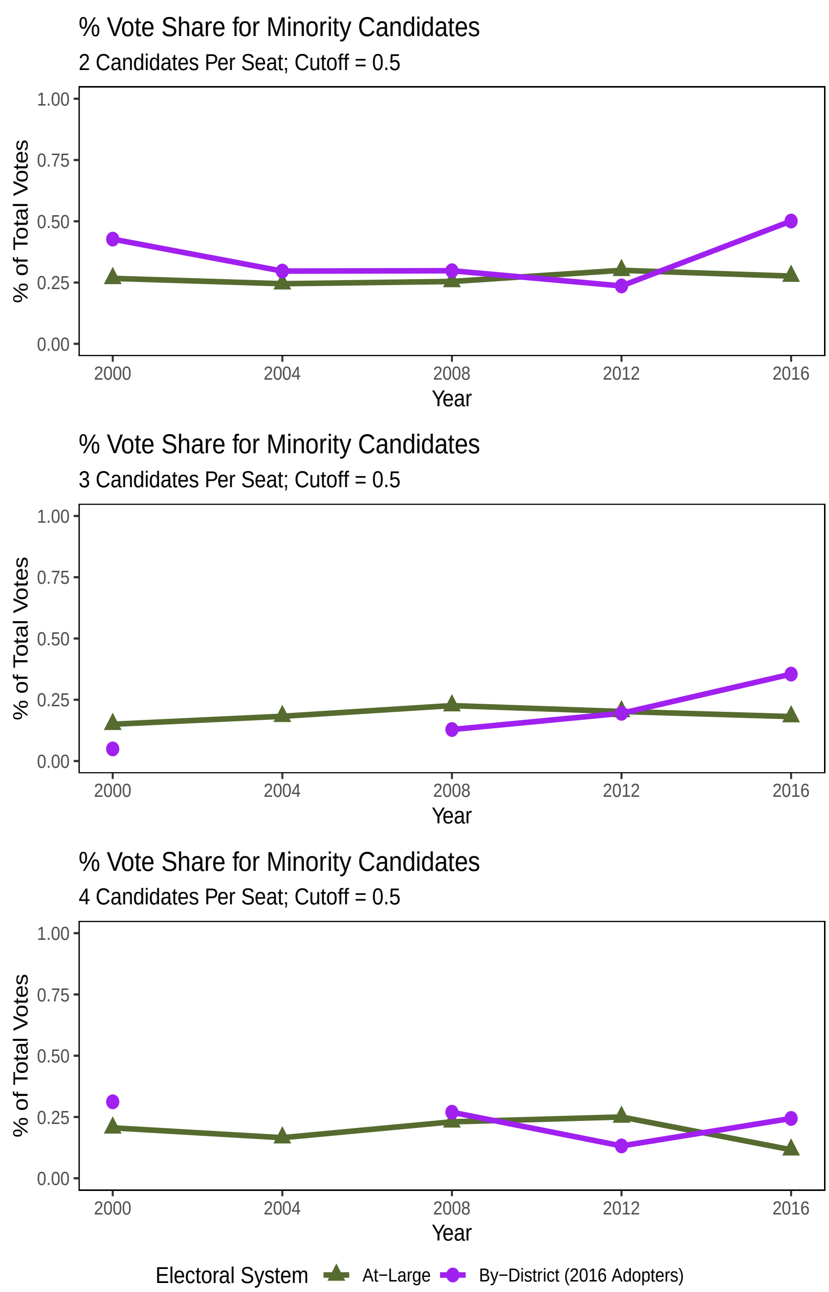

% Vote Share for Minority Candidates
2 Candidates Per Seat; Cutoff = 0.5
% of Total Votes
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
% Vote Share for Minority Candidates
3 Candidates Per Seat; Cutoff = 0.5
% of Total Votes
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
% Vote Share for Minority Candidates
4 Candidates Per Seat; Cutoff = 0.5
% of Total Votes
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.22

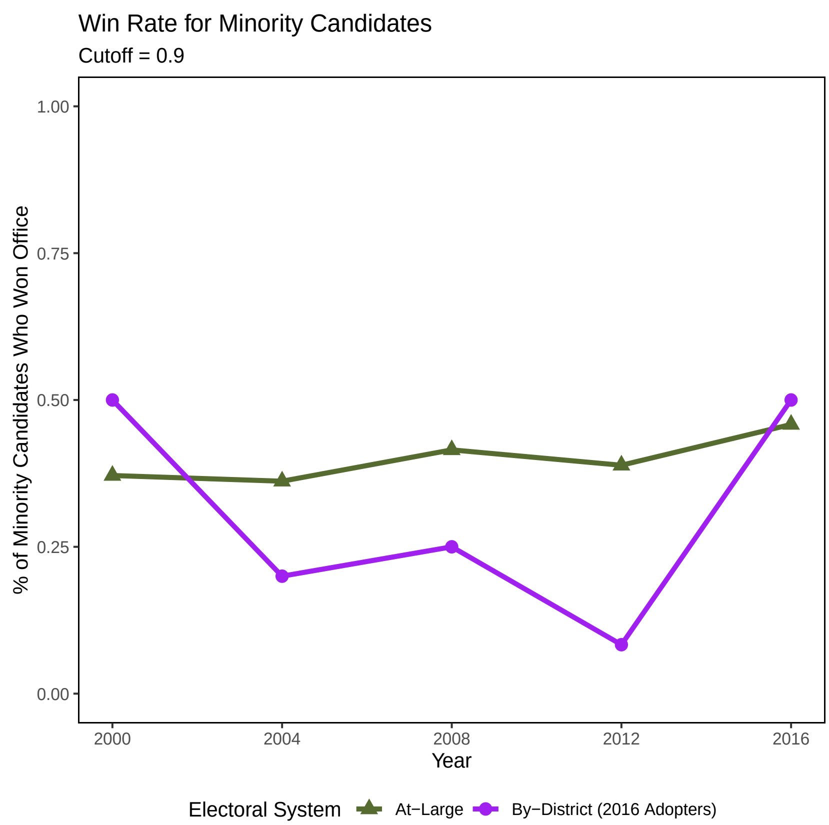

Win Rate for Minority Candidates
Cutoff = 0.9
% of Minority Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.23

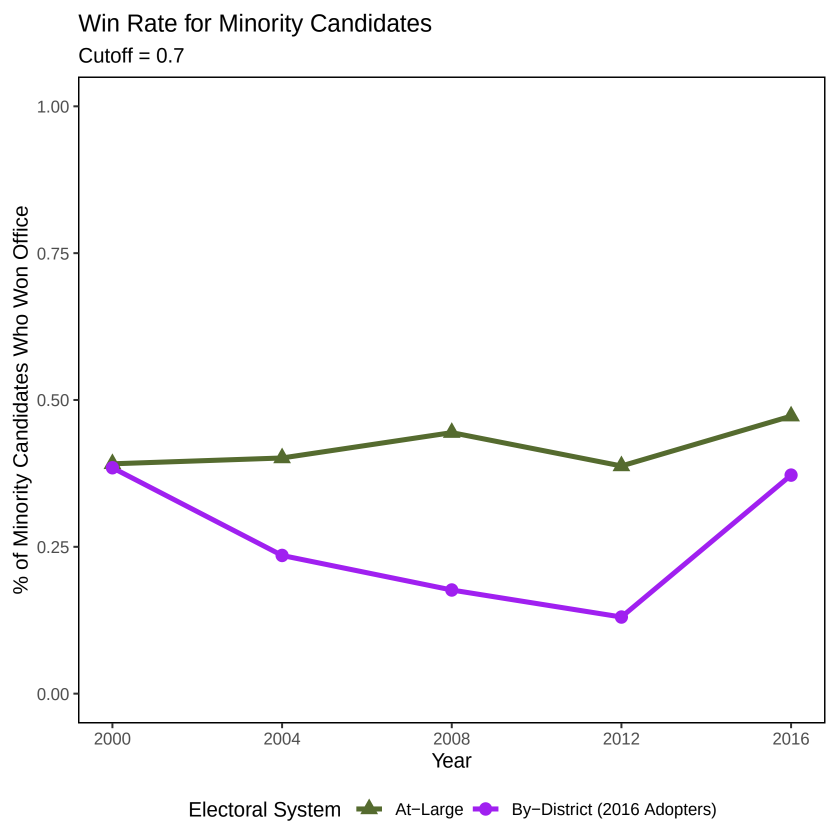

Win Rate for Minority Candidates
Cutoff = 0.7
% of Minority Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.24

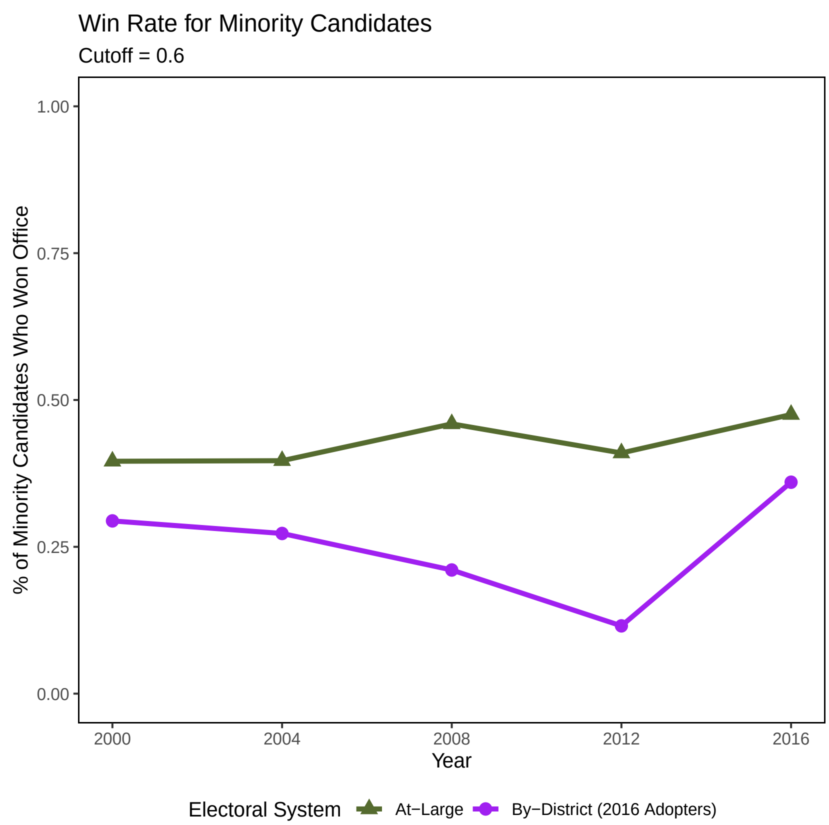

Win Rate for Minority Candidates
Cutoff = 0.6
% of Minority Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.25

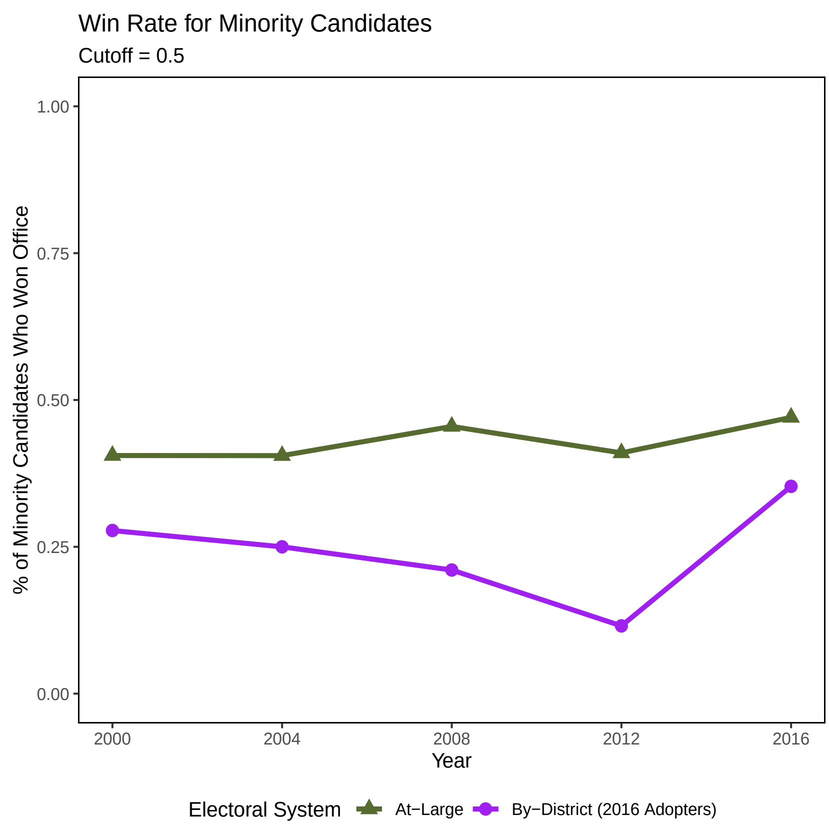

Win Rate for Minority Candidates
Cutoff = 0.5
% of Minority Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.26

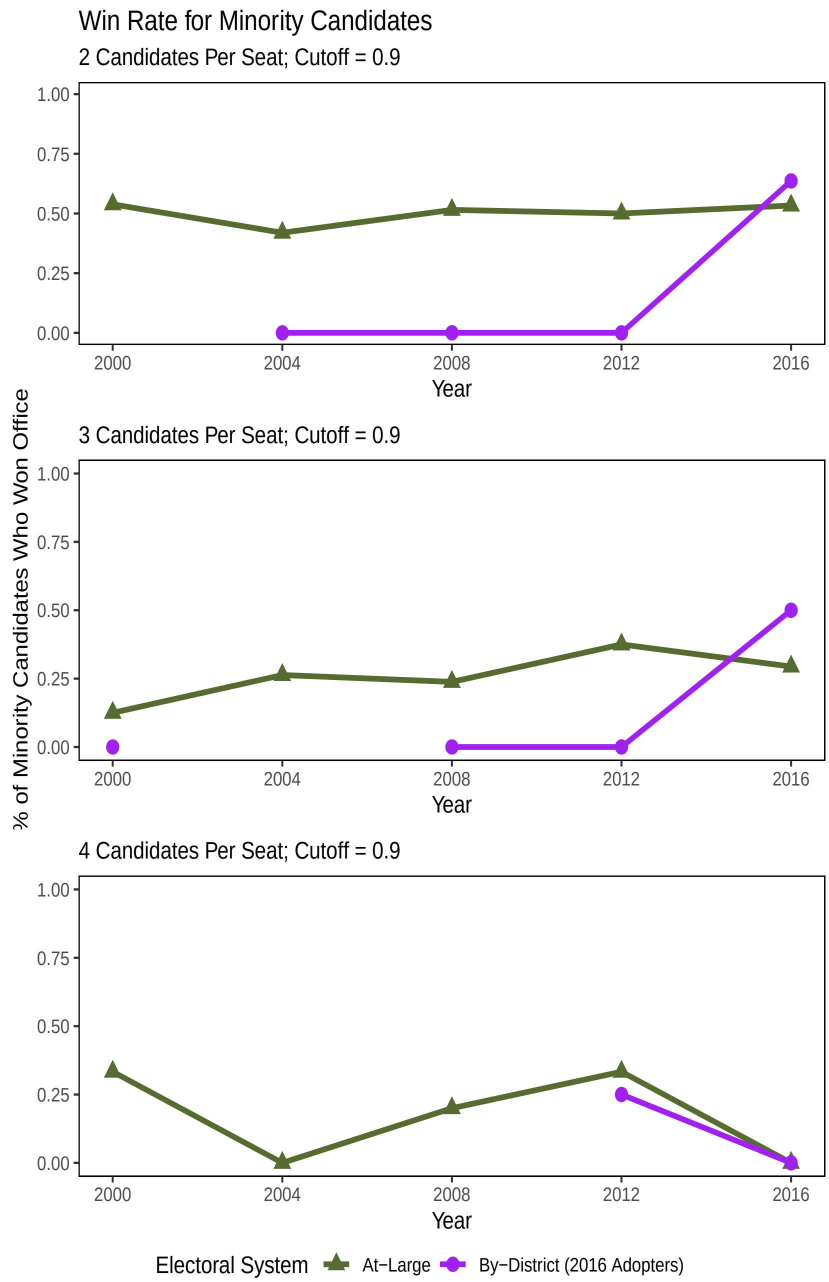

Win Rate for Minority Candidates
2 Candidates Per Seat; Cutoff = 0.9
3 Candidates Per Seat; Cutoff = 0.9
4 Candidates Per Seat; Cutoff = 0.9
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
% of Minority Candidates Who Won Office
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.27

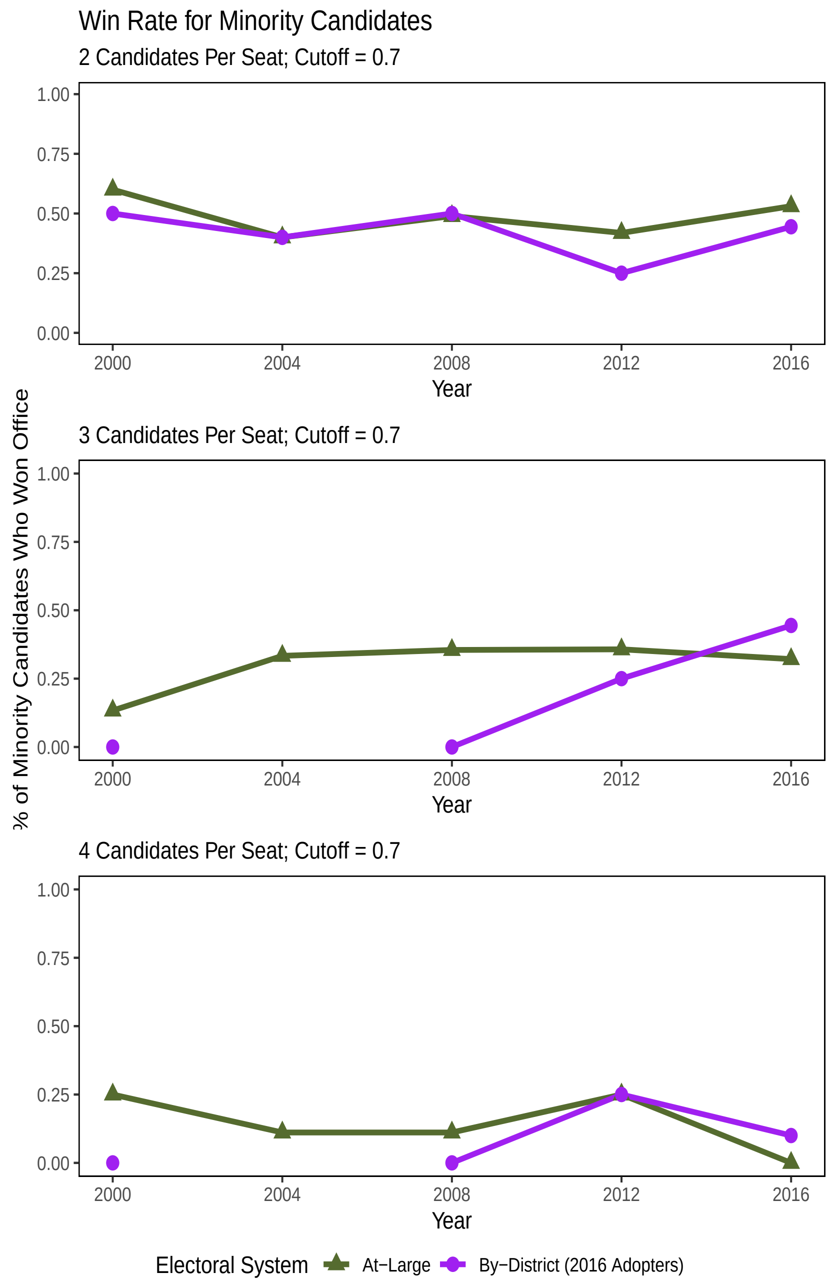

Win Rate for Minority Candidates
2 Candidates Per Seat; Cutoff = 0.7
3 Candidates Per Seat; Cutoff = 0.7
4 Candidates Per Seat; Cutoff = 0.7
% of Minority Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.28

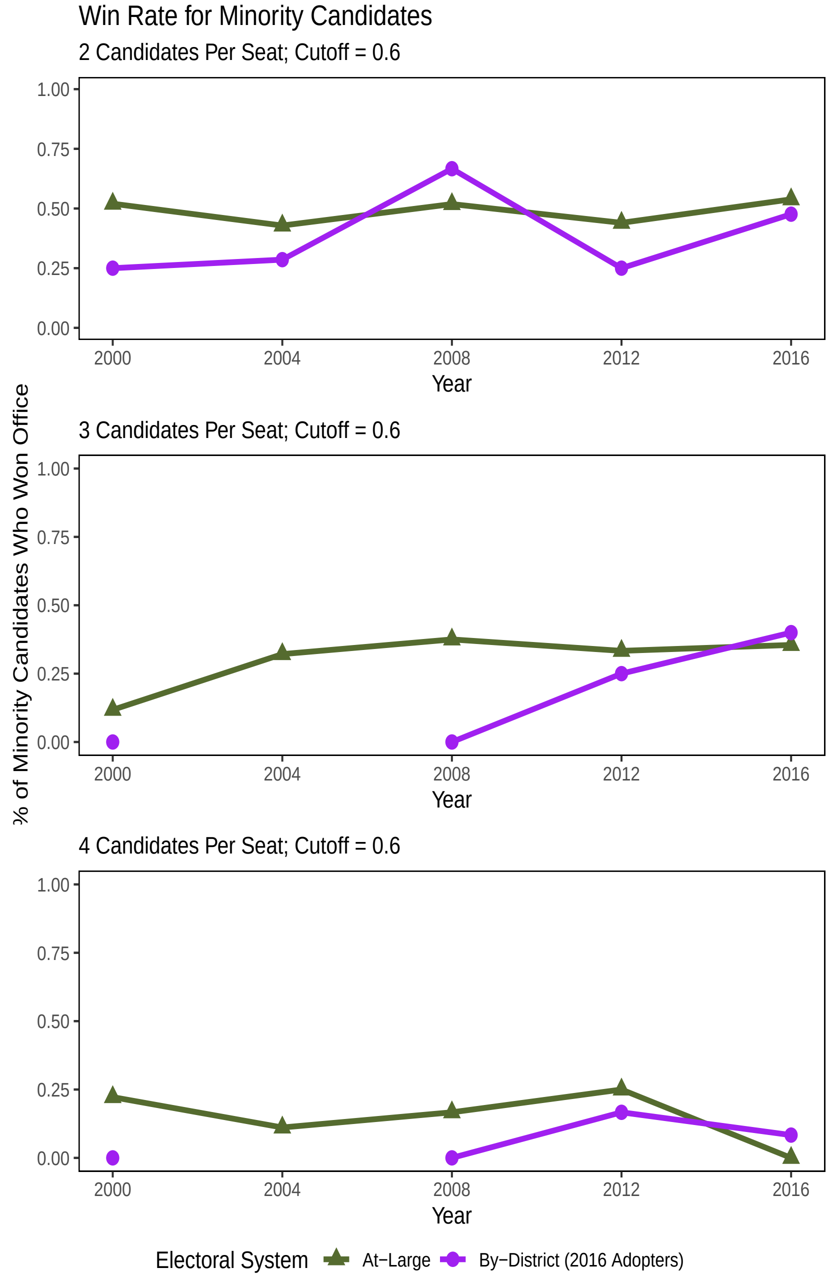

Win Rate for Minority Candidates
2 Candidates Per Seat; Cutoff = 0.6
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
% of Minority Candidates Who Won Office
3 Candidates Per Seat; Cutoff = 0.6
4 Candidates Per Seat; Cutoff = 0.6
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.29

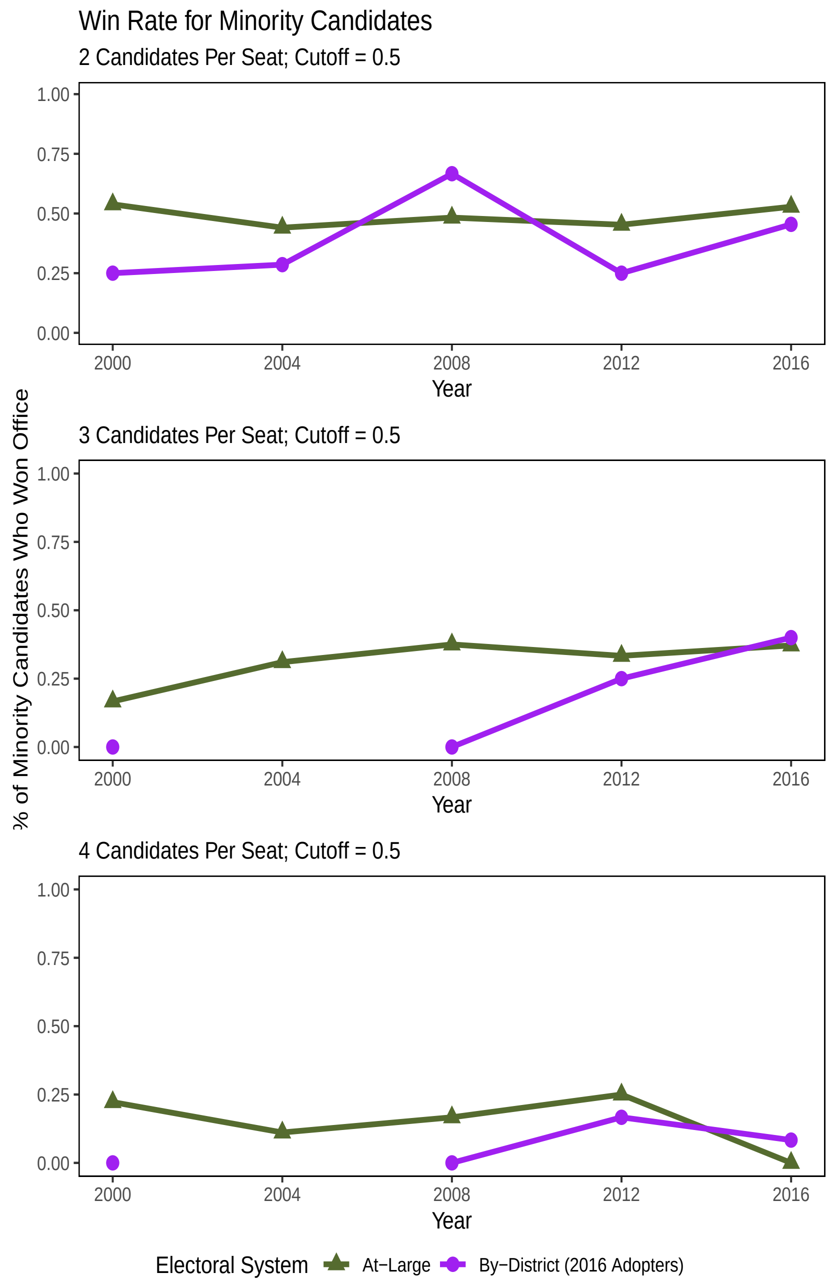

Win Rate for Minority Candidates
2 Candidates Per Seat; Cutoff = 0.5
3 Candidates Per Seat; Cutoff = 0.5
4 Candidates Per Seat; Cutoff = 0.5
% of Minority Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.30

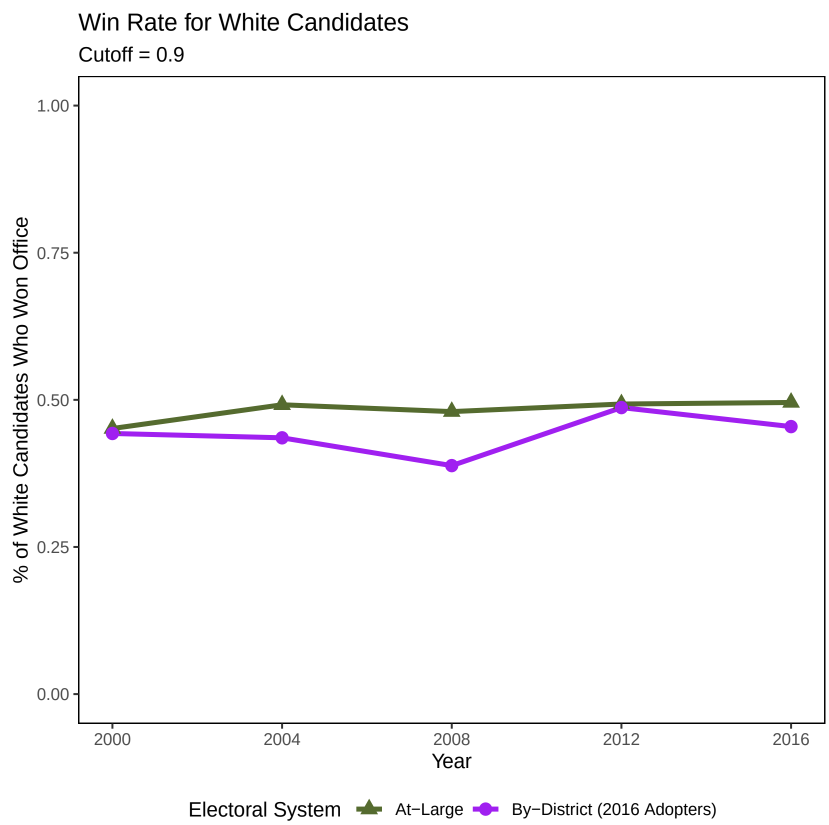

Win Rate for White Candidates
Cutoff = 0.9
% of White Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.31

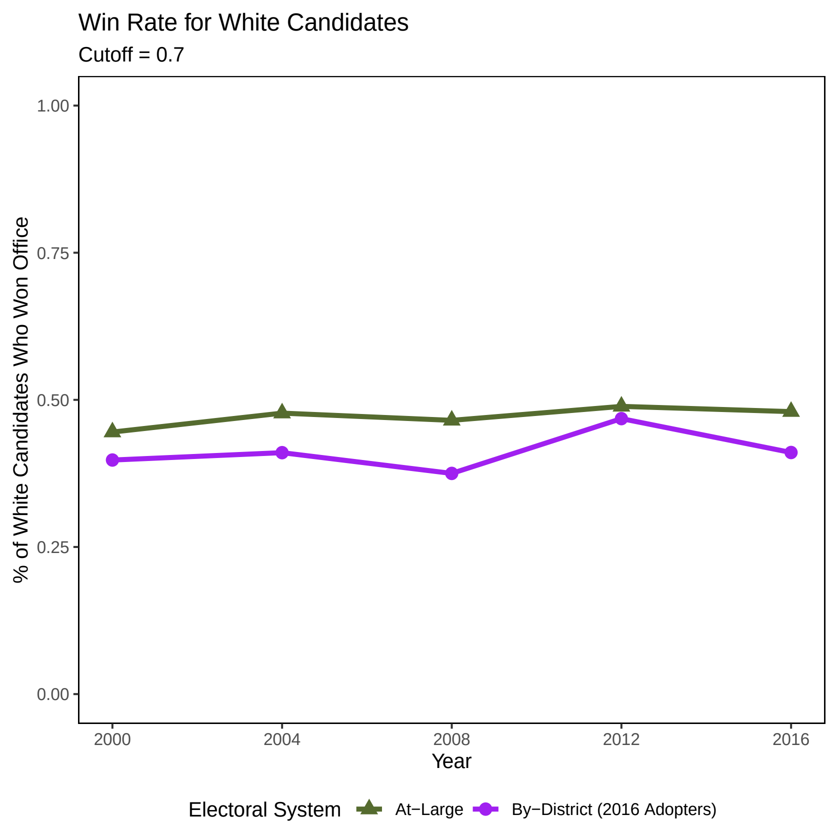

Win Rate for White Candidates
Cutoff = 0.7
% of White Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.32

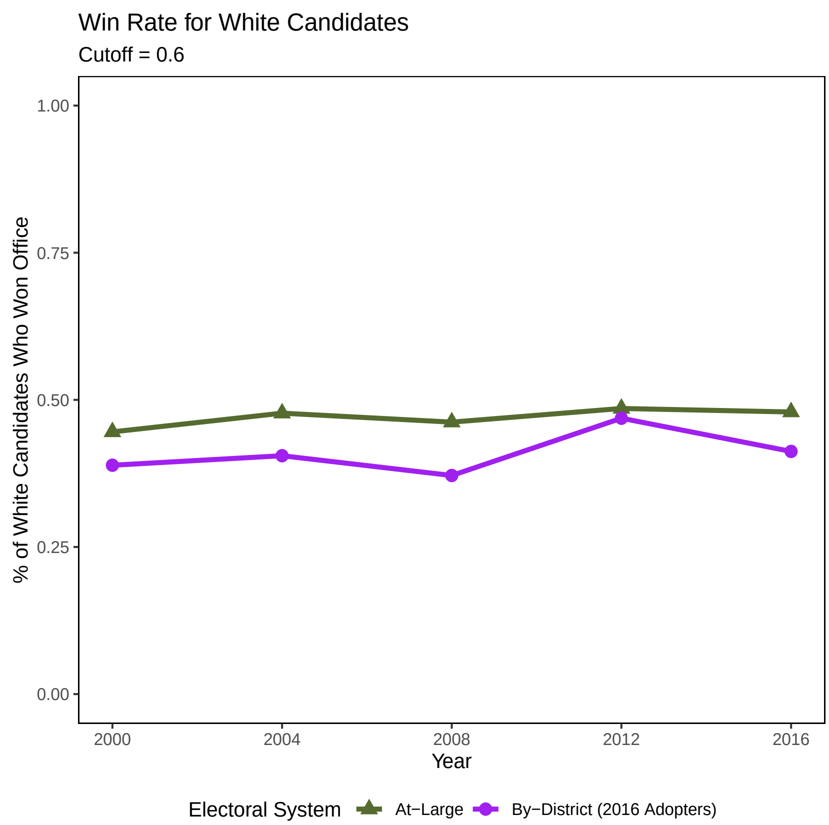
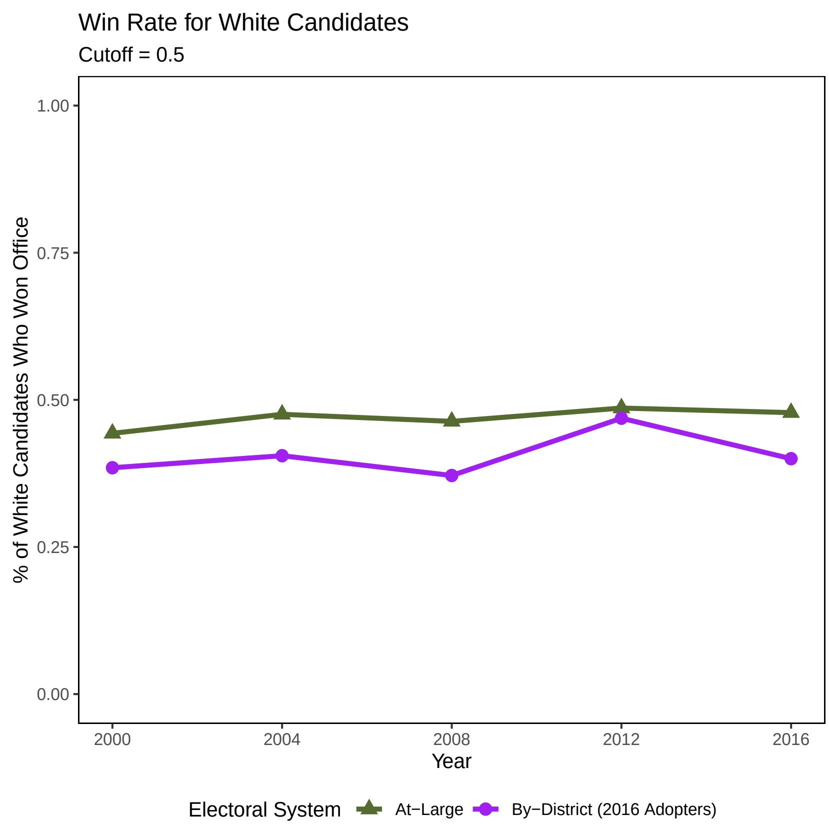
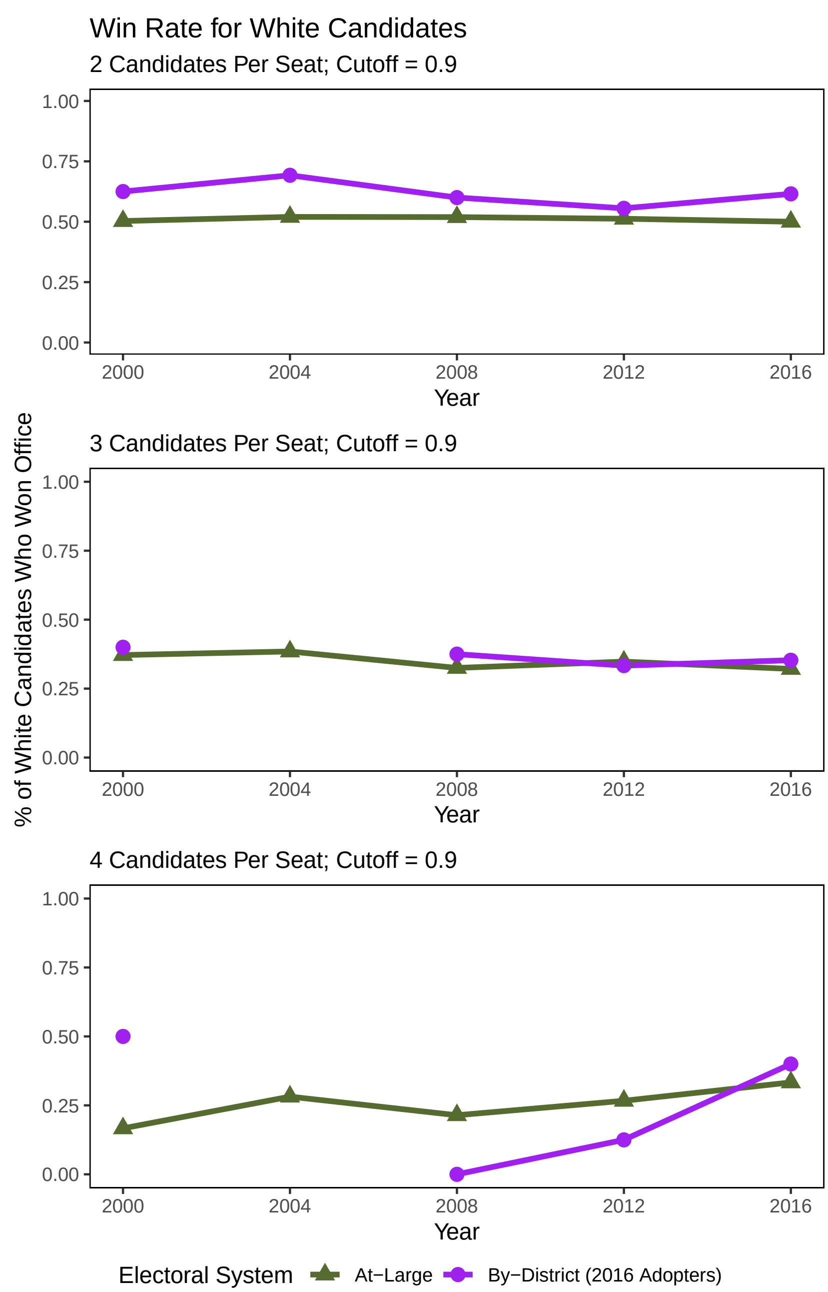

Win Rate for White Candidates
Cutoff = 0.6
% of White Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.33



Win Rate for White Candidates
Cutoff = 0.5
% of White Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.34



Win Rate for White Candidates
2 Candidates Per Seat; Cutoff = 0.9
3 Candidates Per Seat; Cutoff = 0.9
4 Candidates Per Seat; Cutoff = 0.9
% of White Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.35

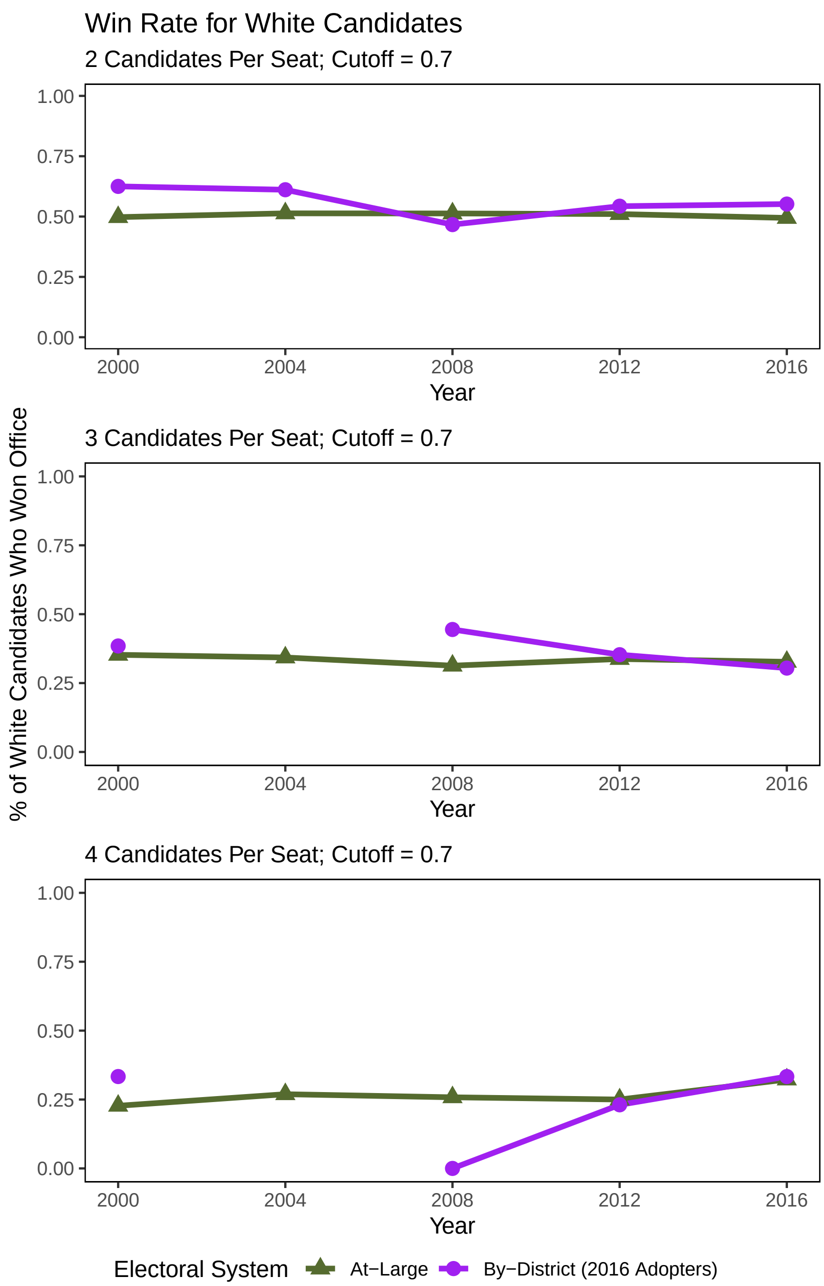

Win Rate for White Candidates
2 Candidates Per Seat; Cutoff = 0.7
3 Candidates Per Seat; Cutoff = 0.7
4 Candidates Per Seat; Cutoff = 0.7
% of White Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.36

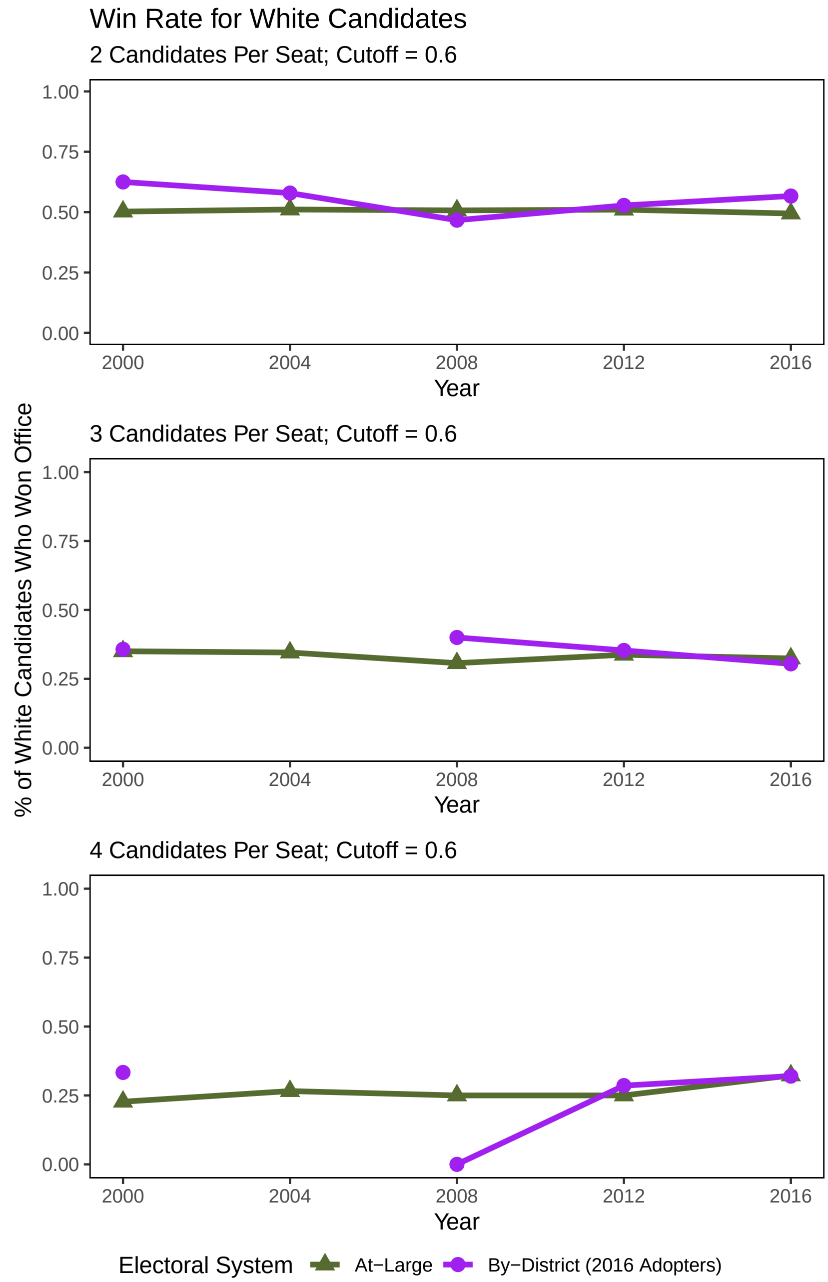

Win Rate for White Candidates
2 Candidates Per Seat; Cutoff = 0.6
3 Candidates Per Seat; Cutoff = 0.6
4 Candidates Per Seat; Cutoff = 0.6
% of White Candidates Who Won Office
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Year
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.37

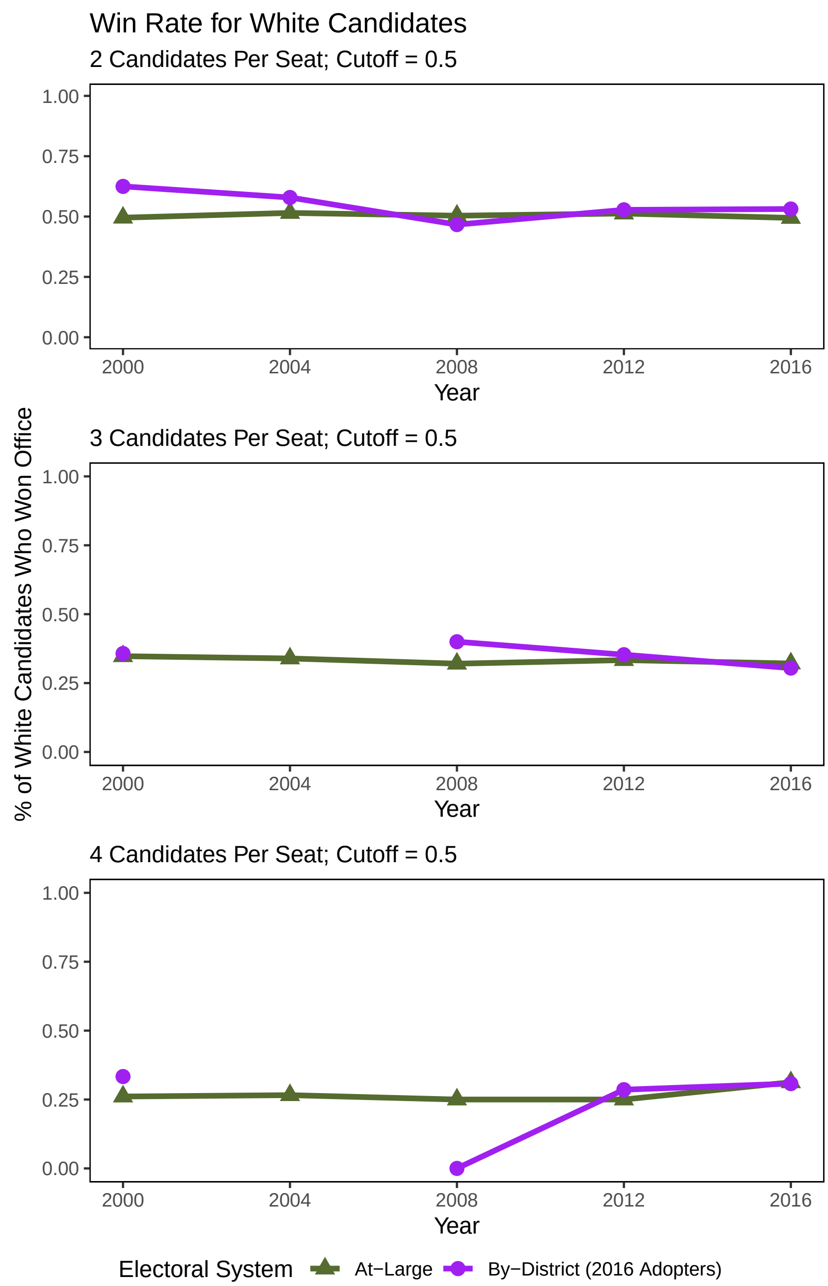

Win Rate for White Candidates
2 Candidates Per Seat; Cutoff = 0.5
3 Candidates Per Seat; Cutoff = 0.5
4 Candidates Per Seat; Cutoff = 0.5
% of White Candidates Who Won Office
Year
1.00
0.75
0.50
0.25
0.00
2000
2004
2008
2012
2016
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.38

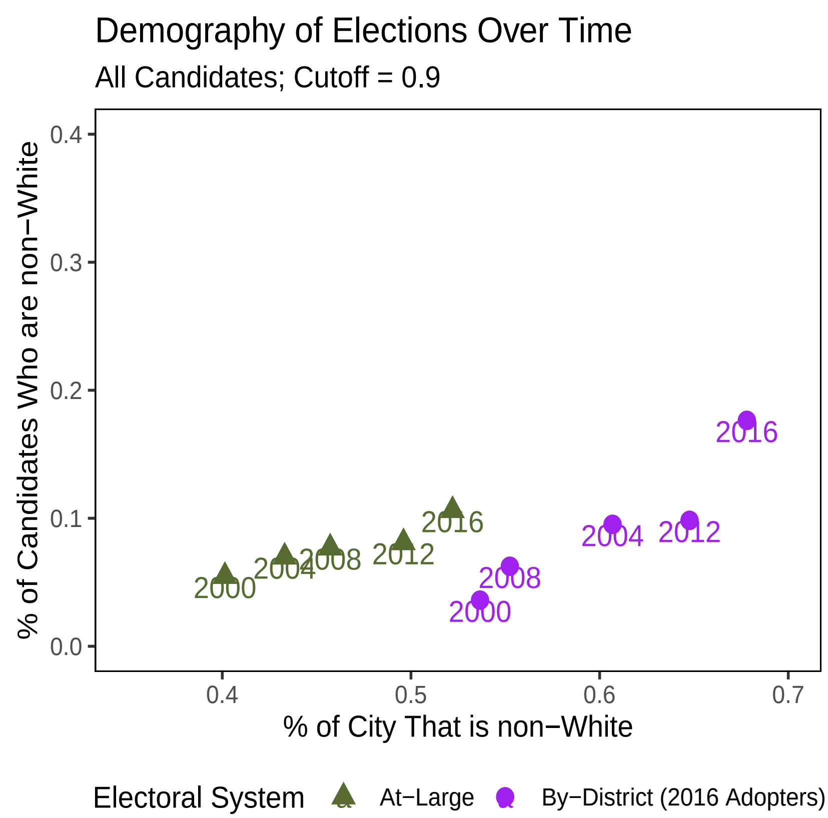

Demography of Elections Over Time
All Candidates; Cutoff = 0.9
% of Candidates Who are non−White
0.4
0.3
0.2
0.1
0.0
2000
2004
2008
2012
2016
2000
2008
2004
2012
2016
0.4
0.5
0.6
0.7
% of City That is non−White
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.39

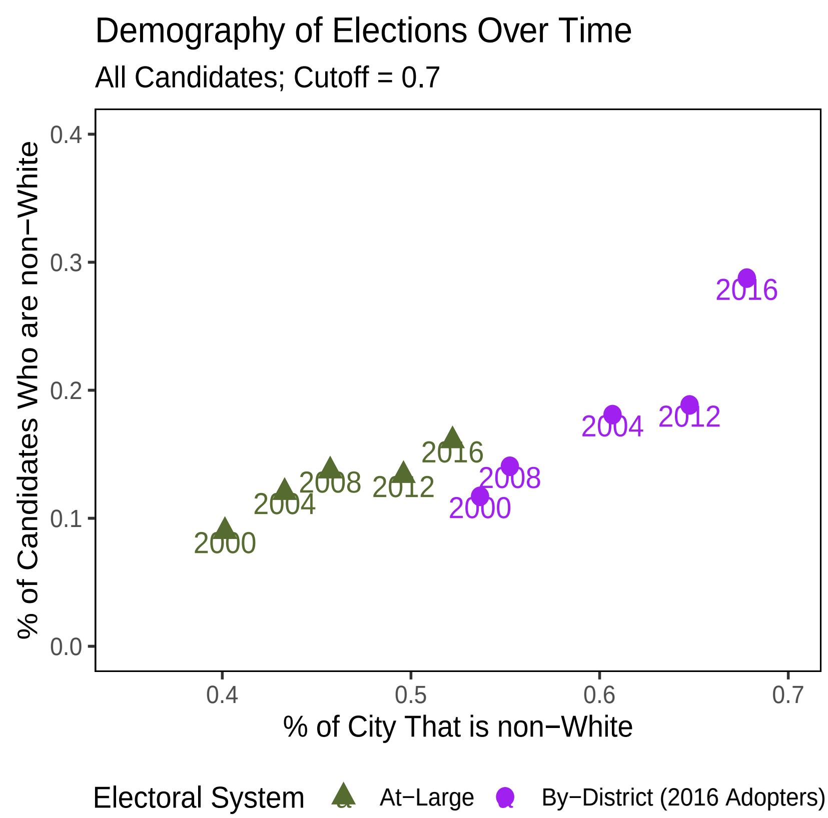

Demography of Elections Over Time
All Candidates; Cutoff = 0.7
% of Candidates Who are non−White
% of City That is non−White
0.0
0.1
0.2
0.3
0.4
0.4
0.5
0.6
0.7
2000
2004
2008
2012
2016
2000
2008
2004
2012
2016
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.40

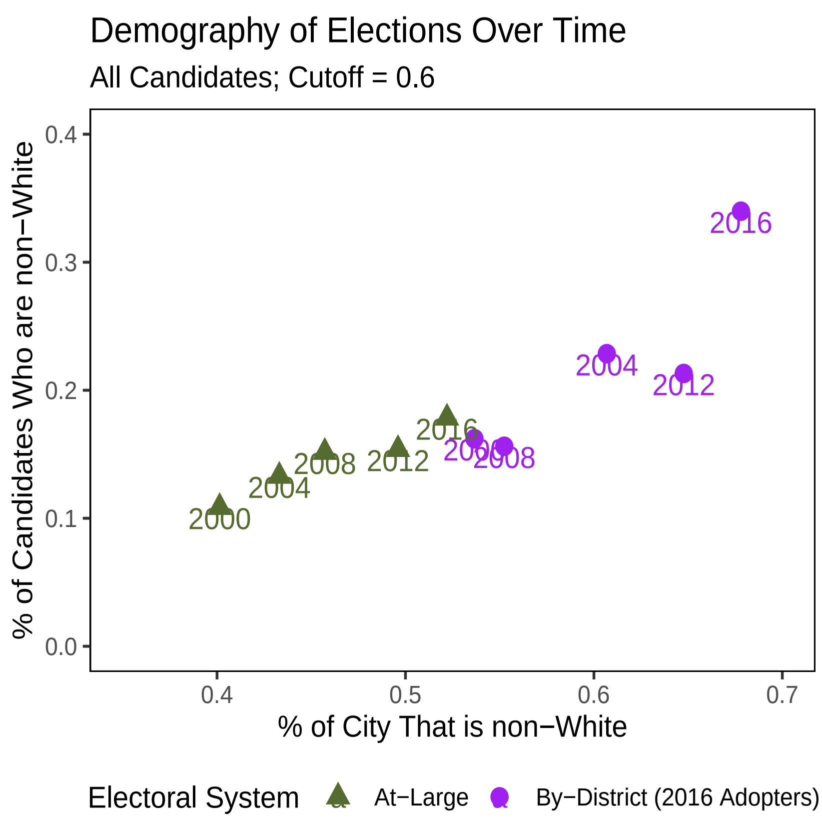

Demography of Elections Over Time
All Candidates; Cutoff = 0.6
% of Candidates Who are non−White
% of City That is non−White
0.0
0.1
0.2
0.3
0.4
0.4
0.5
0.6
0.7
2000
2004
2008
2012
2016
2000
2004
2008
2012
2016
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.41

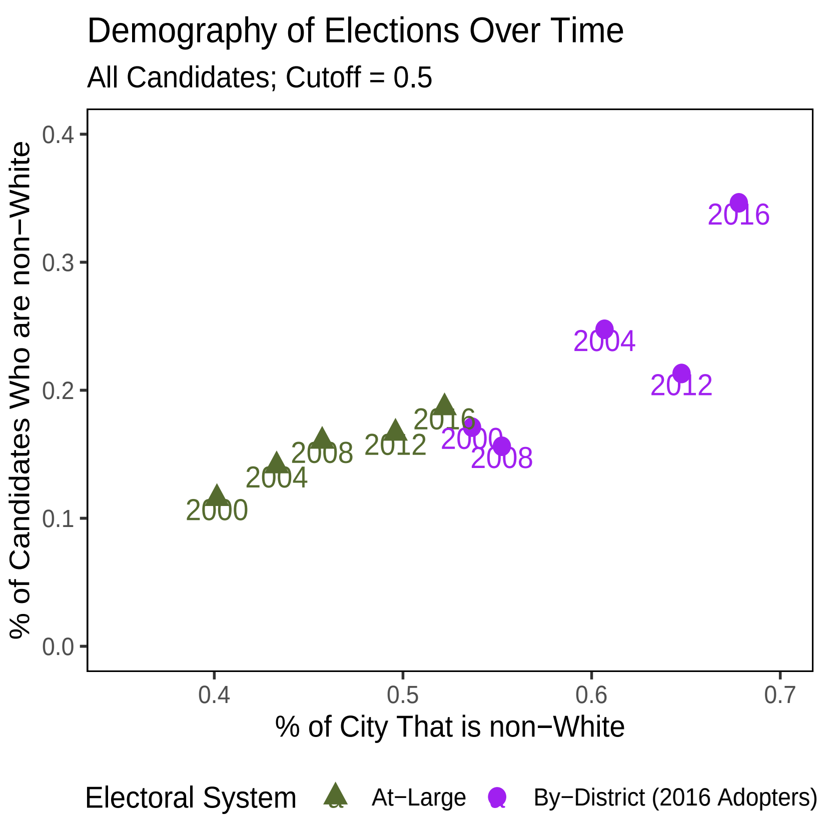

Demography of Elections Over Time
All Candidates; Cutoff = 0.5
% of Candidates Who are non−White
0.0
0.1
0.2
0.3
0.4
% of City That is non−White
0.4
0.5
0.6
0.7
2000
2004
2008
2012
2016
2000
2004
2008
2012
2016
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.42

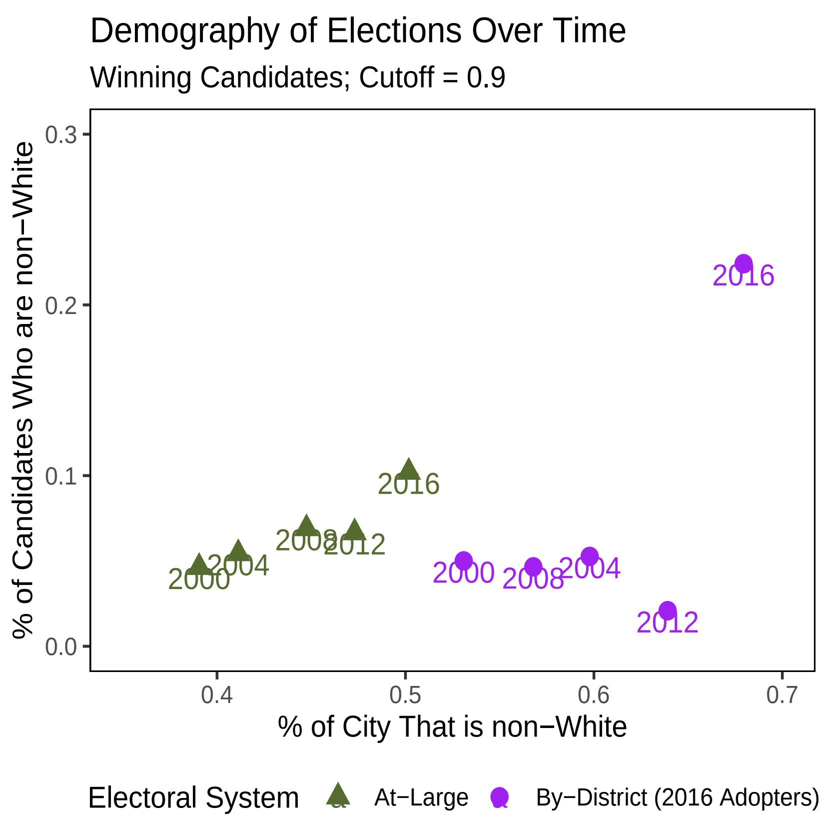

Demography of Elections Over Time
Winning Candidates; Cutoff = 0.9
% of Candidates Who are non−White
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
% of City That is non−White
2000
2004
2008
2012
2016
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.43

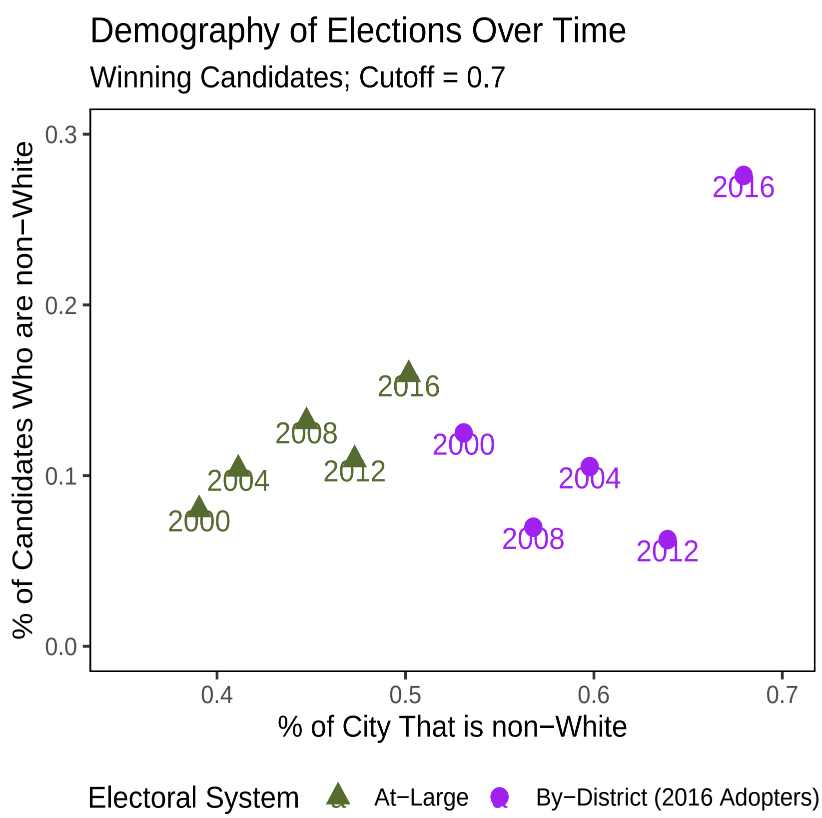

Demography of Elections Over Time
Winning Candidates; Cutoff = 0.7
% of Candidates Who are non−White
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
% of City That is non−White
2000
2004
2008
2012
2016
2000
2004
2008
2012
2016
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.44

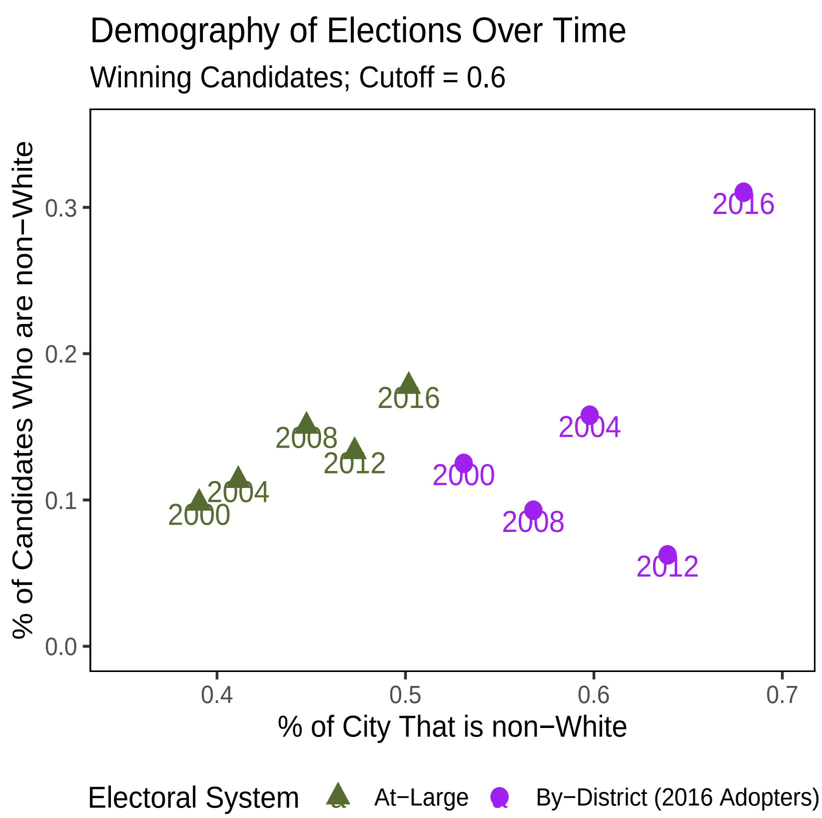

Demography of Elections Over Time
Winning Candidates; Cutoff = 0.6
% of Candidates Who are non−White
% of City That is non−White
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
2000
2004
2008
2012
2016
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.45

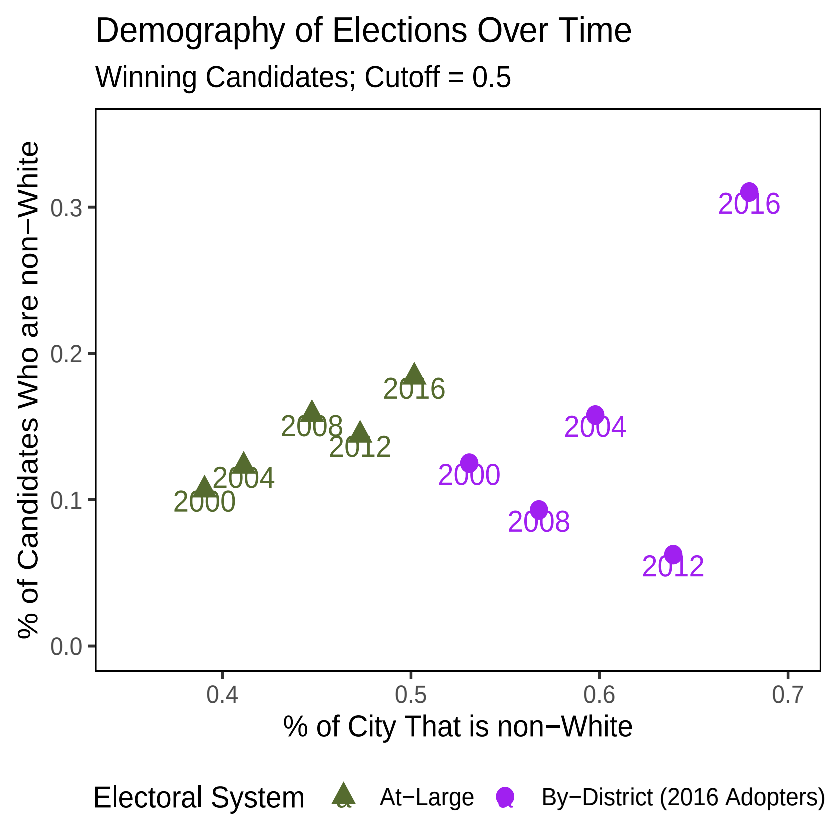

Demography of Elections Over Time
Winning Candidates; Cutoff = 0.5
% of Candidates Who are non−White
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
% of City That is non−White
2000
2004
2008
2012
2016
2000
2004
2008
2012
2016
Electoral System
At−Large
By−District (2016 Adopters)

Figure 2.46

Chapter 3

Political Geography as Epiphenomenal?: Using Redlining to Understand the Spatial Interplay Between Race, Class, and Politics

Abstract

In the 1930s, a New Deal Program called the Home Owners' Loan Corporation (HOLC) created mortgage risk assessment maps in over 200 American cities. These maps stabilized housing markets by identifying the loan default risk of households across the United States. While research has explored how the maps impacted local housing markets, racially-motivated lending practices, and "redlining", little is known about how they affected politics. Using an original panel dataset of geocoded historical voting precinct maps, HOLC risk assessment maps, address-level 1930 Census data, and the California voter file, this project identifies the effect that redlining had on partisan sorting and the political geography of Los Angeles County. Contrary to expectations, redlined neighborhoods experienced larger over-time increases in support for Republicans. Wealthy, predominately White, high-grade areas became more supportive of Democrats. Preliminary evidence suggests that this is driven by the replacement of pro-business conservatives with white collar liberals in high-grade areas. The results point to the lasting impact that public programs can have on political geography, and they inform us that strong partisan coalitions may exist between dissimilar social and economic groups. Last, they force us to reconsider the narrative that political geography is merely epiphenomenal to the spatial structure of society, and that it can be adequately predicted by race, ethnicity, and class.

3.1 Introduction

Spatial inequalities are pervasive in the United States (US). Wealth is concentrated among elites living in urban areas (Nijman and Wei, 2020), high quality schools are located in high income neighborhoods (Barrow et al., 2020), and adequate healthcare services are often inaccessible for rural Americans (Canto et al., 2014). Society is segregated along racial lines, and recent research suggests that we are more segregated now than we ever have been (Stepinski and Dmowska, 2019; Hess, 2020).

Politically, the US fares much in the same way. Large states are underrepresented in the Senate, partisanship is divided along urban–rural lines (Gimpel et al., 2020), and territories and districts such as Puerto Rico and the District of Columbia pay federal taxes, but have no congressional representation. These spatial inequities extend to state and local politics, as well. Local political offices are shown to underrepresent minority voters (Trounstine and Valdini, 2008b; Warshaw, 2019), and states often enact policies that make voting more difficult for those living in rural areas.[1]

These trends are not without consequence. Areas with substandard representation may be overlooked when deciding where to site important infrastructure projects such as hospitals, schools, and transportation centers. Moreover, residents from under-served areas may lack the social capital and resources necessary to get their voices heard. Too often, the areas in greatest need of public investment do not have a seat at the table during public debates, deepening their plight.

While American political geography has always been divided, these spatial divisions took new form in the period after World War II. Following the war, the federal government invested heavily into the US' housing and transportation infrastructure (Chambers et al., 2014). Returning soldiers were eager to use the GI Bill and Federal Housing Admin-

[1] A recent example was the effort made by Texas Governor Greg Abbott to allow only one ballot dropoff location per county in the 2020 location. See Lerner (2020) for more information.

istration (FHA) loans to purchase homes, and the supply of new housing allowed them to do so. Over time, spatial divides emerged as newly developed suburban areas became populated by White Republicans, while minorities and blue-collar Democrats remained in the city core (Lassiter and Kruse, 2009; Boustan, 2016). Since then, dense urban areas have become increasingly Democratic, while rural and low density areas have remained reliably Republican (Chen and Rodden, 2013). Today, voters are clustered among themselves, creating distinct geographic boundaries that are highly correlated with party identification.

Though often overlooked as *source* of spatial inequality and polarization, we should expect that government programs may, in part, be responsible for the political geography we live in today. At every level, government sets policy and regulatory standards, provides social services, and is a source of investment capital for infrastructure projects. For example, zoning regulations determine where housing can be located, section 8 housing vouchers are only accepted at certain dwelling types, and affordable housing is often funded by government grants.

The story told during post-war era elucidates this point. Veterans used the GI Bill to purchase homes in newly-constructed suburbs. However, suburbs only became accessible because of the Interstate Highway Act of 1956, one of the largest transportation infrastructure projects in American history. While the act expanded transportation networks into previously uninhabited regions, it also led to partisan sorting because conservative White voters flocked to suburban areas (Nall, 2015). Though perhaps not its intent, the federal government fostered spatial polarization because it afforded the financial resources and infrastructure necessary for certain groups to cluster among themselves. Had it not been for veterans' benefits and a new federally-funded transportation network, the suburban–urban divide that dominated 20^{th} Century American politics may not have occurred.

At the least, this should make us aware that government programs and investment projects may create problems worse than those they attempt to solve or address. Seemingly virtuous programs may have deleterious consequences that do not appear until later on. Spatial polarization is one of these consequences, yet it impacts the political system in profound ways. Careful attention should be paid to the design of government programs if we are to ensure that they do not yield outcomes that negatively impact society.

This paper provides a novel perspective on the way that government interacts with our daily lives. I exploit a Depression-era program called the Home Owners' Loan Corporation (HOLC) to examine the effect that public policy has on political geography. HOLC was designed to stabilize the housing market during the Great Depression by refinancing mortgages to homeowners in loan default. As part of the program, residential security maps were created for 239 cities across the US. These maps graded neighborhoods according to their real estate market, demographic characteristics, and loan default risk. However, these maps were discriminatory toward areas with high concentrations of non-White residents, and are argued to have institutionalized the practice "redlining" (Rothstein, 2017). I combine Los Angeles's HOLC map with an original dataset comprising full-count 1930 Census data, the 2016 voter file, and archival voting precinct maps to generate causally-identified, street-level, estimates of HOLC's impact on spatial polarization in Los Angeles.

As I show, HOLC impacted Los Angeles's political geography in unexpected ways. Low and medium grade areas experienced a smaller increase in support for Democrats than did high grade areas. These areas also experienced a larger increase in support for Republicans. Such a pattern occurred despite the fact that low and medium grade areas were less wealthy and had higher concentrations of racial and ethnic minorities. I show that these results are consistent across two identification strategies: a pseudo-panel examining over-time change in support, and a geographic regression discontinuity

(GRD) measuring partisan sorting on either side of a HOLC border. The results point toward the powerful and lasting impact that seemingly apolitical public programs can have on spatial polarization and long-term trends in political geography. They also make clear that political geography is neither easily predicted by an area's socioeconomic and demographic distribution, nor is political geography epiphenomenal to sociodemographic processes.

The paper proceeds as follows. First, I discuss existing literature on partisan sorting in the US. I then describe HOLC in greater detail, and situate the program in historical context. After, I discuss the causal process behind HOLC's possible impact on political geography, and provide a set of expectations about its effect. I follow with a discussion of data and identification. Results are presented, and are followed by a descriptive analysis explicating the findings in greater detail. The paper ends with a discussion.

3.2 Sorting Through Sorting: An Examination of Existing Literature

Increased attention was given to partisan sorting following the release of Bill Bishop's *The Big Sort: Why the Clustering of Like-Minded America is Tearing Us Apart.* In his book, Bishop asserts that Americans are clustering into like-minded and distinct communities, and that this pattern is contributing to polarization and political discontent (Bishop, 2008). Bishop claims that urban, suburban, and metropolitan areas have become politically homogeneous, and that this threatens politics because it increases political extremism. Though popular, the hypothesis was somewhat provocative, and scholars began to test his argument and put it under greater scrutiny.

There is mixed evidence for the claims made by Bishop. Although American politics is geographically diverse (McKee and Shaw, 2003; Glaeser and Ward, 2006; Hopkins, 2009; Rodden, 2010; Gelman, 2009), divisions among Democrats and Republicans on core political values are smaller than we think (Strickler, 2016). While increasing polarization in the electorate may exist, it is not because Democrats and Republicans are sorting geographically. Rather, it is because voters are becoming more like-minded among members of their own party (Abrams and Fiorina, 2012). Moreover, changes in the geography of partisanship are because voters have become likely to register as Independent, not because of self-selection into areas that match one's political preferences (McGhee and Krimm, 2009).

Though sorting may not exist in the way Bishop describes, there is evidence that American political geography has, indeed, become bifurcated along partisan lines (McKee and Teigen, 2009; Sussell, 2013). However, this is a recent phenomenon, and one that is driven by changes in voting behavior, not because of migration (Lang and Pearson-Merkowitz, 2015). Long-term divergence on cultural issues between Democrats and Republicans may explain part of this trend (Morrill et al., 2007, 2011).

The political implications of sorting notwithstanding, scholars have attempted to better understand why partisans cluster geographically (McPherson et al., 2001). There is at least a modicum of evidence suggesting that political motivations inform locational preferences (McDonald, 2011; Motyl et al., 2014). *Ceteris paribus*, voters evaluate copartisan neighborhoods more favorably than those not matching their party identification (Gimpel and Hui, 2015), and voters are more likely to relocate to neighborhoods with high concentrations of like-minded party identifiers (Tam Cho et al., 2013).

However, the relationship between ideology, party, and location is more complex than we think. Ideology is correlated with non-political attributes (e.g., income, education, race, and wealth), and these are shown to affect locational decisions just as much, if not more than, explicit political preferences (Hui, 2013; Martin and Webster, 2020).

For example, variations in political geography are, in part, explained by the fact that Democrats prefer to live in dense urban areas with high levels of racial diversity (Chen and Rodden, 2013; Mummolo and Nall, 2017). While Democrats may not explicitly choose to live near copartisans, the locational characteristics they prefer are found in areas with high concentrations of Democrats. In all, spatial polarization may be an artifact of mobility constraints and non-political preferences rather than politically-motivated migration searches.

A small, but insightful, strand of research explores the impact of large-scale demographic processes and public infrastructure programs on sorting. This research is unique because it shows that factors seemingly unrelated to politics can impact the spatial structure of political life in profound ways. For example, support for presidential candidates is shown to be spatially dependent on the degree to which a state has experienced the Second Demographic Transition (Lesthaeghe and Neidert, 2009a). Additional research shows that the development of the Interstate Highway System's transportation network has made American suburbs less supportive of the Democratic party (Nall, 2015). These studies show that sorting need not occur because of individual-level motivations and processes. Rather, long-term trends and seemingly innocuous infrastructure projects can fundamentally alter the spatial organization of American politics.

The following paper adds to the existing literature in three ways. First, it uses fully disaggregated geographic data to examine sorting at fine spatial scales, such as within voting precincts, and at the street level. To this point, the literature has only examined sorting at aggregate spatial scales such as the county (see Morrill et al. (2007); McKee and Teigen (2009); Morrill et al. (2011); Lang and Pearson-Merkowitz (2015); Nall (2015)), or state (see Gelman (2009); Sussell (2013)).[2] Second, it builds on Bishop's initial thesis by

[2]McDonald (2011) makes use of address-level data through the US Postal Service's change of address database.

examining sorting *within* metropolitan, urban, and suburban areas, rather than between them.

Third, it shows that public policy can have a profound impact on the spatial organization of politics. In this way, the paper is novel because it divorces itself from the individual, and interrogates the interplay between large public programs and their latent (or perhaps manifest) consequences on politics. To date, this relationship has been understudied. Yet, as Nall (2015) shows, it can be incredibly powerful.

3.3 The Home Owners' Loan Corporation: A Brief History

The Home Owners' Loan Corporation was created by President Franklin Delano Roosevelt in 1933, as part of the New Deal. The program operated under the Federal Home Loan Bank Board (FHLBB), which supervised the loan and banking industries (Aaronson et al., 2019). HOLC was designed to combat a foreclosure crisis that gripped the nation during the Great Depression (White, 2014; Aaronson et al., 2019). The program refinanced mortgages to homeowners who were in loan default in an attempt to shore up the real estate market, and to prevent the existing foreclosure crisis from worsening. The program's scope was quite large, and it was successful in its initial aim. Over the course of the program, HOLC issued over 1 million loans totaling \$3.5 billion dollars, and 81% of homes affected by the program were saved (Tough, 1951).

As part of the program, the FHLBB sent HOLC surveyors to cities with more than 40,000 residents (N = 239), and the surveyors appraised local neighborhoods (Hillier, 2005). Surveyors assessed real estate conditions and demographic characteristics within neighborhoods of each city, and filled out "area descriptions". Area descriptions were used to document characteristics such as median rent price, median home value, and real estate sales demand within a neighborhood, as well as racial characteristics such as the percent of the area that is "foreign born", percent "negro", and whether non-White groups were infiltrating the neighborhood. Each neighborhood was assigned a loan default risk score based on the surveyor's appraisal. Maps were created with color coded grades corresponding to loan default risk. These grades ranged between "A - Best" (green), "B - Still Desirable" (blue), "C - Definitely Declining" (yellow), and "D - Hazardous" (red). High grade zones (e.g., "A" and "B") were identified as having lower risk of loan default, while low grade areas (e.g., "C" and "D") had higher risk of default.

Presumably, the maps were intended to make the appraisal process more efficient, but their exact use is debated. By grouping geographic areas according to loan default risk, creditors could make loans based on the HOLC score of the area that an applicant's house was in (Hillier, 2005). However, loan appraisals were primarily made on the basis of household-level characteristics, rather than those of the surrounding area. If, however, a house was foreclosed on, HOLC assigned rent and sale values based on the real estate characteristics of the area the house was in (Harriss, 1951). Though their exact use is enigmatic, it is likely that, in the least, the maps were used to formalize and standardize the loan appraisal process (Hillier, 2003).

There is evidence that private industry worked with the government to create the maps, and that the maps, or similar versions developed by banks, were used by the private-sector to inform lending practices (Jackson, 1980; Louis Lee Woods, 2012). Hillier (2005) disputes these claims, however, and suggests that the maps were largely clandestine. She further asserts that only 50-60 copies of each map were made (Hillier, 2005, p. 399). Some argue that the maps were never provided to private interests in the first place, and that surplus maps were destroyed in 1942 (Crossney and Bartelt, 2005, p. 549).

It is plausible that the maps informed practices used by other government agencies. For example, the Federal Housing Authority's (FHA) lending policies used appraisal systems that relied on neighborhood-level real estate and demographic trends (Jackson, 1985). The FHA's policies are often cited as having contributed to the practice of redlining, wherein prospective minority home buyers were steered into less desirable areas, creating racial and income segregation across the US (Jackson, 1980). Despite debates about how, or even whether, HOLC maps were used in practice, it is possible that they were adapted by other agencies, and that these agencies used them to practice redlining. At the least, the practices set forth by HOLC likely institutionalized the racialized lending practices that exist to this day (Greer, 2013).

Los Angeles's HOLC map was created in 1939 (Figure 3.1). The map covers parts of the City of Los Angeles, but also extends into surrounding areas. Visually, higher grade areas ("A" and "B" zones) tend to be located in the hills and mountains surrounding the Los Angeles basin, such as Bel Air and parts of the Hollywood Hills. Lower grade areas ("C" and "D") zones tend to lie in the flatlands, and in the region surrounding the city center. For example, these areas comprise neighborhhods such as Koreatown, Inglewood, and South Los Angeles.

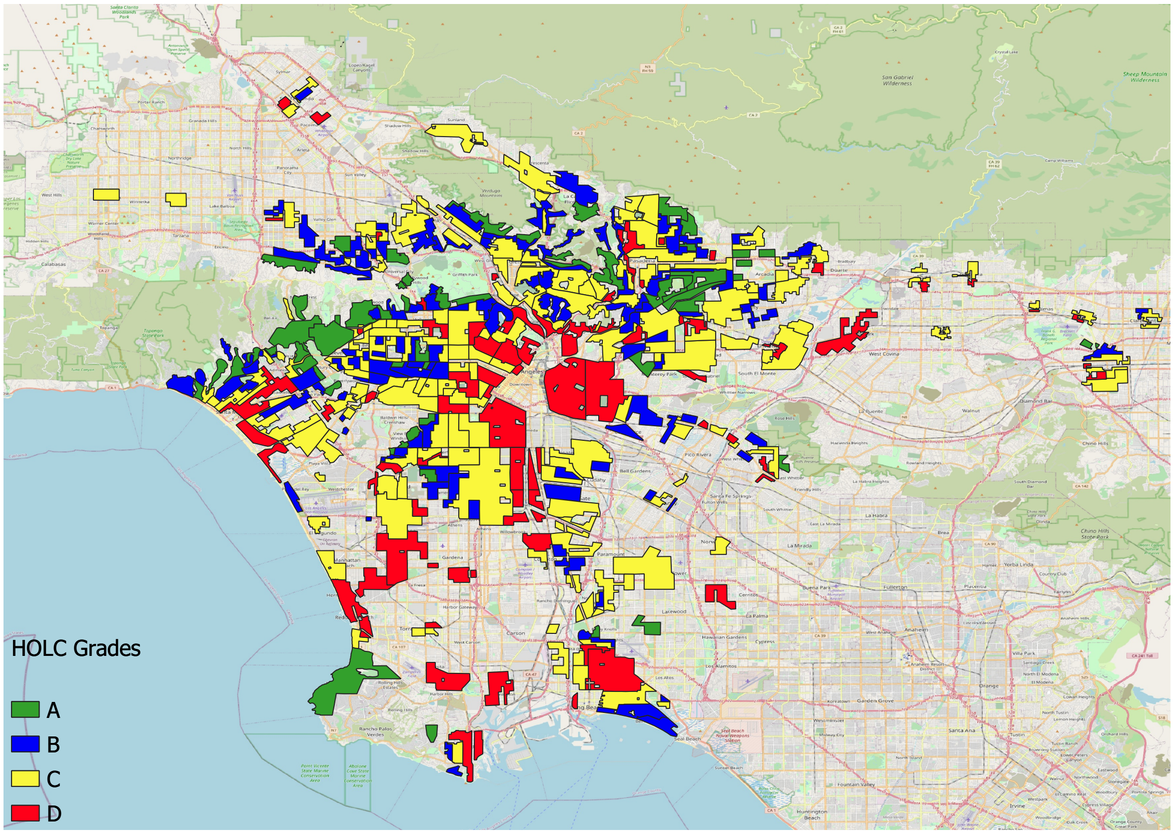


Figure 3.1: HOLC zones across the Los Angeles area. Note that in the pseudo-panel analyses, “A” and “B zones are combined to form the “high grade” group, “C” zones form the “medium grade” group, and “D” zones form the “low grade” group. For transparency, however, I use the original coding scheme in this figure.

I make a core assumption about Los Angeles’s HOLC map, which states that the map affected neighborhood-level lending and appraisal practices in some way, even if not directly by HOLC. Regardless of whether HOLC used the map, or whether a similar map was used by other agencies, I assume that Los Angeles’s initial HOLC zones reflected the racialized geographic lending patterns that came to define redlining in the area. So long as patterns of redlining follow the initial map boundaries, I can be agnostic about whether Los Angeles’s map was used to redline, or whether it served as progenitor of maps that did so later on.

3.4 The Causal Process and Expectations

HOLC impacted neighborhood demographic and economic conditions, as well as local real estate markets (Hillier, 2003). Comparative to high grade zones, Low grade areas experienced increased segregation, lower real estate values, reduced access to credit, and lower rates of home ownership (Aaronson et al., 2019). We might expect that these impacts extended to politics, as well. Socioeconomic features such income, wealth, and race that were affected by HOLC are also correlated with partisanship and political participation (Schlozman et al., 2012; Hersh and Nall, 2016; Peterson, 2016). Because HOLC promoted spatial clustering among members of the same racial and economic groups, it is likely that political sorting occurred as a result.

Given this process, two expectations emerge. First, I expect that high grade areas became *less* Democratic and *more* Republican, over time. This is because high grade areas likely attracted wealthy business and corporate leaders. At the time Los Angeles's map was released (1939), the Republican party was decidedly pro-business (Miller and Schofield, 2008; Gelman, 2014), and, as a result, we might expect that high grade areas became concentrated with pro-business Republican identifiers.

Second, I expect that low grade areas became more supportive of the Democratic party. During the New Deal Era, the Democratic party's coalition was comprised of working-class voters (Rae, 1992; Abramowitz, 2018), and the party was centered on pro-labor policies (Goldfield, 1989). Low grade zones likely attracted working-class residents who supported the party's pro-labor stance, increasing the concentration of Democrats in these areas.

A similar story may be told along racial lines. It is well-documented that racial minorities have lower incomes and wealth in the United States (Keister, 2000; Keister and Moller, 2000; Margo, 2016; Chetty et al., 2019), and that they are more supportive of the Democratic party (Carmines and Stimson, 1989; Kuziemko and Washington, 2018; Westwood and Peterson, 2020). Because racial minorities may have been unable to afford high grade areas, or been steered away from them altogether through redlining, it is likely that they agglomerated in low grade zones, increasing the Democratic party's footing in these areas.

3.5 Data

I created an original dataset that combines data from multiple sources. These include restricted-use 1930 Census data, the 2016 voter file, archival precinct maps and voting data for the 1937 Los Angeles mayor's race, and a shapefile of the Los Angeles HOLC map. Each data source is discussed briefly, below.

HOLC Map. I retrieved Los Angeles's HOLC map through the University of Richmond's Digital Scholarship Lab (Nelson et al., 2021). The Digital Scholarship Lab contains a repository of all HOLC maps, along with their area description files. I downloaded the map for Los Angeles, as well as area descriptions for each HOLC zone. The area descriptions contained quantitative data such as a zone's median rent and home value, as well as a qualitative assessment of a zone's overall quality and characteristics.[3]

1937 Precinct Maps and Election Returns. I accessed precinct-level election data for the 1937 Los Angeles Mayor's race. The data was accessed through the Los Angeles City Archives, and comprised two parts: historical precinct maps, and their corresponding elections returns. There were four precinct maps in total, each corresponding to separate precinct districts. Each hard-copy precinct map was scanned, digitized, and overlaid on a modern street map in QGIS. Precinct polygons were drawn by tracing each precinct's boundary to a modern street grid. After precinct polygons were drawn for each map, the

[3]See Appendix Figure 3.6 for a sample area description.

maps were combined into a single polygon, with subpolygons for each precinct. Election returns for the 1937 mayor's race were merged to the data. In total, 2,343 precinct polygons were drawn.[4]

1930 Census Data. This data includes a full-count of every resident in Los Angeles County in 1930 (N = 2.2 million), and was accessed through the Integrated Public Use Microdata Series. The data includes traditional variables such as age, race, and employment status, but also confidential data such as first and last name and address. I geocoded each unit in the data using the unit's address. The data was used to build demographic profiles for each 1937 voting precinct, as well as to assess covariate balance. Importantly, all Census data was collected *prior* to the release of Los Angeles's HOLC map.

2016 Voter File. This data contains the 2016 Los Angeles County voter file (N = 4.4 million). The voter file contains party identification, first and last name, as well as addresses for each unit. As with the Census data, addresses were used to geocode each unit. These were used to create partisan profiles for each precinct in the 1937 election. I also used the data in conjunction with the HOLC shapefile to calculate each voter's distance to a HOLC border.

I created two datasets. The first was a pseudo-panel that combined all of the above data sources. The dataset was created by overlaying the HOLC map on the 1937 precinct polygons, and assigning a HOLC grade to each precinct. Census units were then geolocated to precincts, and aggregate precinct-level Census characteristics were calculated. The process was repeated with the voter file, and the resulting dataset yielded precinct-level partisan characteristics such as the percentage of the precinct that identified as Democrat or Republican. The data is a pseudo-panel because each precinct contained

[4]A sample map for Los Angeles's Central Precinct District is included in Appendix Figure 3.7.

pre and posttreatment outcome measures using the precinct-level election returns (pretreatment) and voter file (posttreatment), as well as a full set of pretreatment Census variables.

The second dataset was structured for use with a geographic regression discontinuity design, and it used the HOLC map, Census data, and voter file. The data was combined such that each voter was geolocated within a HOLC zone, assigned that zone's HOLC grade, assigned the grade of the nearest HOLC zone that its HOLC zone bordered, and assigned the distance to the nearest bordering HOLC zone. Alas, the data was structured so that each geocoded voter was assigned a treatment status corresponding to the grade of the zone it was in, as well as a distance measure, which was used as the running variable. The Census data was geocoded as well, and used to assess covariate balance between bordering HOLC zones.

Two caveats should be noted. First, the 1937 and 2016 data sources do not use identical measures of party support. The former uses precinct-level support for the Democrat or Republican mayoral candidates in 1937, while the latter uses party registration data, as of 2016. Unfortunately, there is scant data for mayoral elections after the HOLC map was released, in 1939. Most often, precinct-level election results exist, but corresponding shapefiles do not. Additionally, mayoral elections became consistently less partisan after the HOLC maps were released, sacrificing their comparability to the 1937 mayoral election, which was between a Democrat and a Republican. Digitized party registration data is unavailable before 1939, as well, making it impossible for perfectly analogous measures of party identification to be used.[5]

Second, I am unable to assess intervening outcomes between 1937 and 2016 because of the data availability constraints outlined above. That is, I can examine over-time

[5] *ancestry.com* does have digitized party registration data for the period before 1939. However, this data is unavailable to the general public, and requires a special license.

change between 1937 and 2016, but not for any elections in between. Again, this is due to the fact that complete data for intervening elections is incomplete, and because I do not have access to digitized party registration records before 1939. I chose to use the 2016 registration records in lieu of this issue. The idea is that while intervening elections and party registration records are unobserved, it is best to observe outcomes using the most recent data that is available.

3.6 Identification

Pseudo-Panel

The pseudo-panel is shown in (1). The model is estimated separately on two outcome measures (described in greater detail below), each corresponding to precinct i's over-time change in support for Democrats, or Republicans, between 1937 and 2016. Support in 1937 is measured as the percentage of voters in precinct i who supported the Democratic, or Republican, mayoral candidate. Support in 2016 is measured as the percentage of voters in precinct i who were registered as Democrat, or Republican. The over-time change between these measures represents the longitudinal, pseudo-panel, aspect of the design.

The full model is represented as:

$$\Delta Y_i = \alpha + \sum_{k=1}^{K-1} \beta_k D_{ki} + X_i'\theta + \epsilon_i \tag{3.1}$$

where ΔY_i is the percentage point change in support for Democrats, or Republicans, between 1937 and 2016, α is the model intercept, $\beta_k D_{ki}$ is a vector of $K-1$ treatment dummies, and $X_i'\theta$ is a vector of pretreatment covariates from the 1930 Census. β_k represents the effect of a precinct being zoned into one of the following categories: having no grade, or having a high, medium, or low grade. High grade precincts are those that were zoned as "A" or "B". I combine these categories because there are too few "A" zones to reliably estimate their effect. Medium and low grade precincts are those with "C", and "D" grades, respectively.

I estimate four models for each outcome measure. Eight models are estimate in total. First, I compare precincts that received low, medium, and high grades to those that received no grade. This represents that counterfactual of what a graded precinct would have looked like had it received no grade. In this setup, there are four possible conditions (i.e., $K = 4$), and the base category represents ungraded precincts. I include precincts that received either one, or no, HOLC grade.[6]

I estimate three additional models for each outcome measure. These compare graded precincts to each other, and the estimates represent the effect of being in a higher, or lower, graded precinct. In these models, $K = 3$, and each of the K conditions represent having a high, medium, or low HOLC grade. Three models are estimated so that each treatment condition can be used as the base reference category. Precincts are included in these models if they received one HOLC grade.

I include X_i to condition on a variety of pretreatment covariates. These include 1930 median rent price, 1930 median house value, racial demographics, total population, a measure of socioeconomic status, the percentage of a precinct's total area that is graded, and the mean elevation of the precinct. I include these variables because HOLC scores were in part assigned based on neighborhood real estate trends, the demographic composition of the area, and the socioeconomic quality of the area. Conditioning on these potential sources of bias is crucial for unconfounded estimates of β_k to be identified.

[6] In this setup, a precinct can be overlapped by multiple HOLC zones, so long as the overlapping zones have the same grade.

Assessing the Validity of Combining Outcome Measures

Although the outcome measure uses different measures of partisanship, I argue that they can be used together, for two reasons. First, voters typically support copartisan candidates (Campbell et al., 1960; Green et al., 2002; Lewis-Beck et al., 2008; Rock and Baum, 2010; Bonneau and Cann, 2015). While defection may occur, the modal scenario is that registered Democrats vote for Democratic party candidates, while registered Republicans vote for Republican party candidates. Although there is no way to prove that supporters of the Democratic candidate in 1937 were Democrat, and that supporters of the Republican candidate in 1937 were Republican,this is likely true given what we know about the dynamics of partisanship and vote choice. At the least, I am assuming that party registration and vote choice are, on average, predictive of each other.

Second, the 1937 election was, in fact, divided along traditional party lines, and highly partisan. Frank L. Shaw, the Republican candidate, was a noted conservative who was intensely fearful of communism, and who opposed the Congress of Industrial Organizations (CIO) (Viehe, 1980), a prominent pro-labor group. His opponent on the other hand, John Anson Ford, was a liberal Democrat who served as Chairman of the Democratic County Central Committee.

Historical evidence suggests that the 1937 campaign was fierce, and that it reflected traditional party loyalties. According to Ford, strenuous efforts were made by Shaw's supporters to link him to the Communist Party. Immediately prior to the election, Shaw's supporters flew a plane over the City with a streamer reading "Vote for John Anson Ford for Mayor", signed by the *Young Communist League of America*. However, the *Young Communist League of America* did not exist. It was a fake organization used to rile voters against Ford's campaign (Dixon et al., nd). Shaw won the election, but was recalled in 1939. Ford was thought of as a potential candidate against Shaw in the recall election, but his name was pulled from the running because he was thought to be too liberal (Dixon et al., nd). All told, both candidates were intensely loyal to their bases, and the 1937 election bore out across traditional party lines.

Geographic Regression Discontinuity

I expand on the pseudo-panel with a geographic regression discontinuity design (GRD). I use a GRD because it allows for causal effects to be estimated, but with weaker assumptions than a model-based approach. In effect, the GRD is used to corroborate the pseudo-panel, and to identify whether HOLC *caused* partisan sorting to occur. Broadly, I examine this possibility by comparing the percentage of voter file units living on either side of a HOLC border that identify as Democrat or Republican.

To set up the GRD, I created a preprocessing algorithm that returned a subset of HOLC border segments that appeared to be drawn "as-if" randomly. I call this subset of borders the "5-degree" sample, and it contains border segments that do not follow existing transportation and infrastructure networks, but that were likely drawn to simply close an open polygon. I created this sample because the original HOLC boundaries were not drawn randomly, and appeared to have simply reflected existing settlement patterns, transportation networks, and civic infrastructure.[7] Estimating the GRD on the full set of borders would generate biased estimates because treatment status is endogenous with myriad factors affecting the treatment assignment process. We might expect, for example, that borders drawn parallel to transportation arteries simply reflect that fact that, prior to the HOLC map, there may have been existing differences on either side of the artery that the map merely followed. If so, the HOLC map would not have caused any

[7] Appendix section "Geographic Regression Discontinuity Balance Statistics" provides pretreatment balance statistics on the 5-degree sample, as well as that using the full set of borders. These statistics can be used to assess whether HOLC borders were drawn at random, or whether they reflected existing settlement patterns. As is shown, there is evidence indicating that the full set of borders were correlated with a host of economic, social, and demographic factors.

observed differences to emerge. Rather, it would have simply matched existing spatial structures. If treatment status were correlated with factors affecting how the borders were drawn (i.e., an existing transportation network) the estimates would be biased. Instead of attempting to parametrically model the treatment assignment process, I leverage a design that controls for these sources of bias explicitly.

Formally, the 5-degree sample includes a subset of HOLC border segments whose acute angle to all roads within 50 meters of each is at least 5-degrees. To extract these segments, I identified all borders between HOLC zones that received different grades, but that abutted each other. I overlaid these borders on a modern street map of Los Angeles. I dissolved each HOLC border segment by the streets that intersected it. That is, the original border segments were sliced into smaller segments whose length was determined by the distance between the roads that intersected them. I buffered each dissolved HOLC border segment by 50 meters and intersected the buffered area with the street map. This returned a set of road segments that were within 50 meters of each HOLC dissolved border segment. For each dissolved HOLC segment, I calculated the acute angle between it and all road segments within the buffer. HOLC border segments that did not have a single acute angle measurement below 5-degrees were retained in the final sample. Figure 3.2 provides an example of the 5-degree sample.

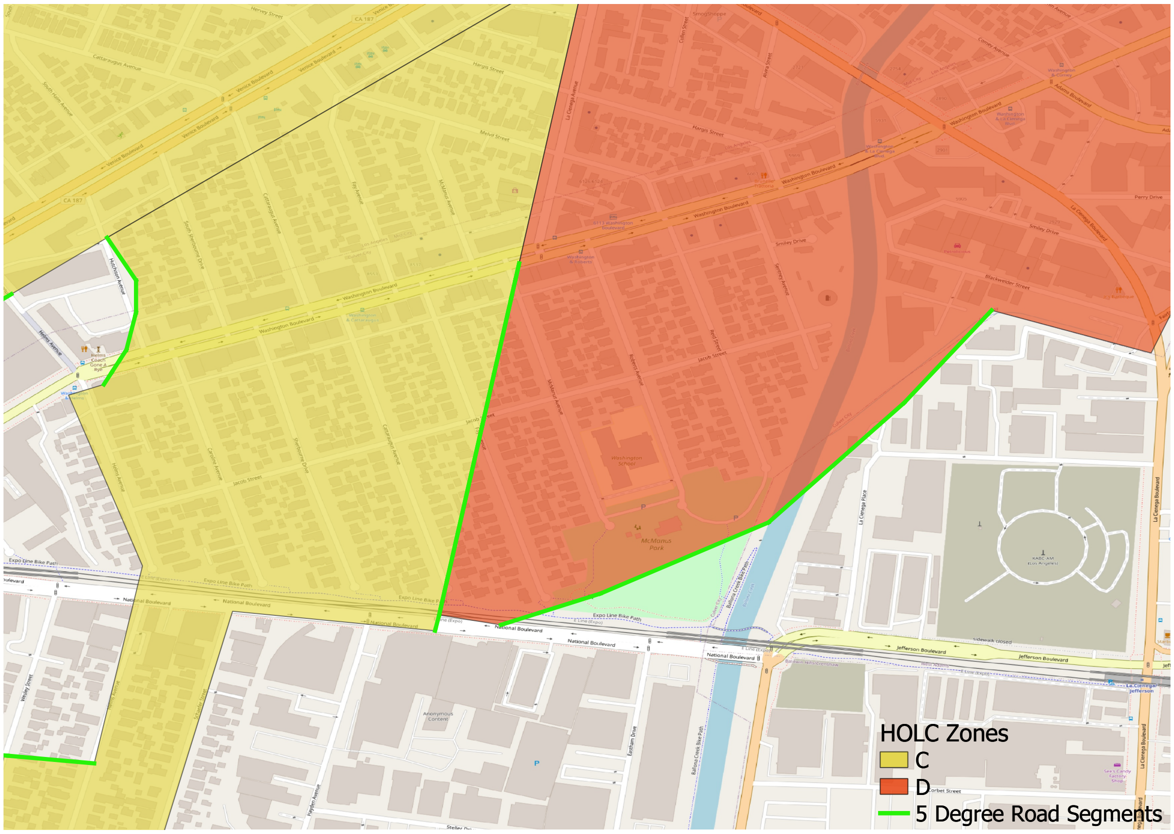


Figure 3.2: This figure provides an example of the HOLC border zones that were selected into the "5-Degree" sample. 5-degree borders are shaded in green, and are selected based on whether the segment's acute angle relative to all roads within 50 meters of it is at least 5-degrees.

After creating the 5-degree sample, I buffered each border by 200 meters. Geocoded Census and voter file units located inside of a buffer zone were retained. Each retained unit was assigned the grade of the HOLC zone it was in, the grade of the HOLC zone that its HOLC zone bordered, as well as the the Euclidean distance to the border shared by its HOLC zone, and the zone that it bordered.

I split the 5-degree sample into subsamples corresponding to five comparison group dyads: AB, AC, BC, BD, CD.[8] Each dyad contained units that were in either HOLC grade for that comparison group. The GRD was estimated on units in each subsample,

[8]There were no shared borders between "A" and "D" zones, hence why there is no AD comparison sample.

and units in the lower graded zone were considered treated. For example, in the AB comparison dyad, units in the "B" zones are in the treated group, and units in the "A" zones are in the control group.

Two outcome measures are used for each comparison dyad. The first uses a dummy variable indicating whether voter i is a Democrat, and the second uses a dummy variable indicating whether voter i is a Republican. The GRD is estimated at the unit level (i.e., voter). In effect, I am measuring whether there are higher percentages of Democrats, or Republicans, on either side of a HOLC border.

The 1930 Census data is not used in the GRD itself. Rather, the data is used to evaluate covariate balance on either side of a HOLC border. Balance tests are conducted using Census units located within 200 meters of the borders in the 5-degree sample. Statistics are calculated for each comparison group dyad, and at distances of 50, 100, 150, and 200 meters from the border.[9]

I use local polynomial regression to estimate the GRD. The equation used to estimate the GRD is shown by

$$Y_i = \alpha + \beta 1(dist_i \geq 0) + f(dist_i) + \epsilon_i \tag{3.2}$$

where Y_i is a dummy indicating voter i's party identification. In the Democrat models, this equals 1 if voter i is a Democrat. In the Republican models, this equals 1 if the voter i is a Republican. α is the intercept, $\beta 1(dist_i \geq 0)$ is the local average treatment effect (LATE), and $f(dist_i)$ is a polynomial function for distance, $dist_i$, which ranges between -200 to 0 for control units, and between 0 to 200 for treated units. I force control unit distances to be negative by multiplying them by -1. I do this because distance is strictly positive, but control units need to be below the cutpoint, which is 0.

[9]Appendix section "Geographic Regression Discontinuity Balance Statistics" provides full balance statistics.

The function for $f(dist_i)$ is shown by

$$f(dist_i) = \lambda_1(dist_i) + \lambda_2 1(dist_i \geq 0) \times (dist_i) \tag{3.3}$$

and

$$\begin{gathered} f(dist_i) = \psi_1(dist_i) + \psi_2 1(dist_i \geq 0) \times (dist_i) + \\ \psi_3(dist_i)^2 + \psi_4 1(dist_i \geq 0) \times (dist_i)^2 \end{gathered} \tag{3.4}$$

where the interaction term, $\lambda_2 1(dist_i \geq 0) \times (dist_i)$, is the slope coefficient for treated units. Estimating the distance function in this way allows for separate slopes to be estimated on either side of the cutpoint. In addition to the linear and quadratic forms shown in (3) and (4), I include cubic terms to reduce higher-order bias (Pei et al., 2020). However, to save space, I do not include the functional forms here.

3.7 Results

Pseudo-Panel Estimates

Figure 3.3 provides treatment effect estimates for the pseudo-panel models. Standard errors are clustered by the HOLC zone(s) that a precinct is overlapped by. 95% confidence intervals are represented by the blue (Democratic outcome) and red (Republican outcome) lines. The y-axis shows over-time change in support for Democrats and Republicans. The x-axis corresponds to the precinct grade being that is being compared to the base group.[10]

The top-left plot ("No Grade Base Group") compares high, medium, and low grade

[10] To save space I do not include the full regression tables here. These are reported in Appendix section "Pseudo-Panel Results".

precincts to those that were ungraded. This represents the counterfactual condition describing what graded precincts would have looked like had they not received a grade. High, medium, and low grade precincts are no different from their ungraded counterparts. None of the coefficients are significant to $p < .05$, which suggests that graded precincts would have been no different had they not been graded.

The remaining three plots compare graded precincts to each other. These show whether precincts graded higher or lower became more or less supportive of Democrats and Republicans. The top right plot ("High Grade Base Group") compares medium and low grade precincts to high grade precincts (the base group). Relative to high grade precincts, those receiving a medium grade become 7.3 percentage points less supportive of Democrats ($p < .01$). Low grade precincts become 7.7 percentage points less supportive of Democrats ($p < .01$).[11]

[11] An important consideration is required when interpreting the pseudo-panel results. The estimates do not mean that certain precincts are more, or less, supportive of either party. Nor do they mean that certain precincts are, or are not, supportive of either party altogether. Rather, they simply show that the over time evolution in support for either party was greater, or less, in certain precincts.

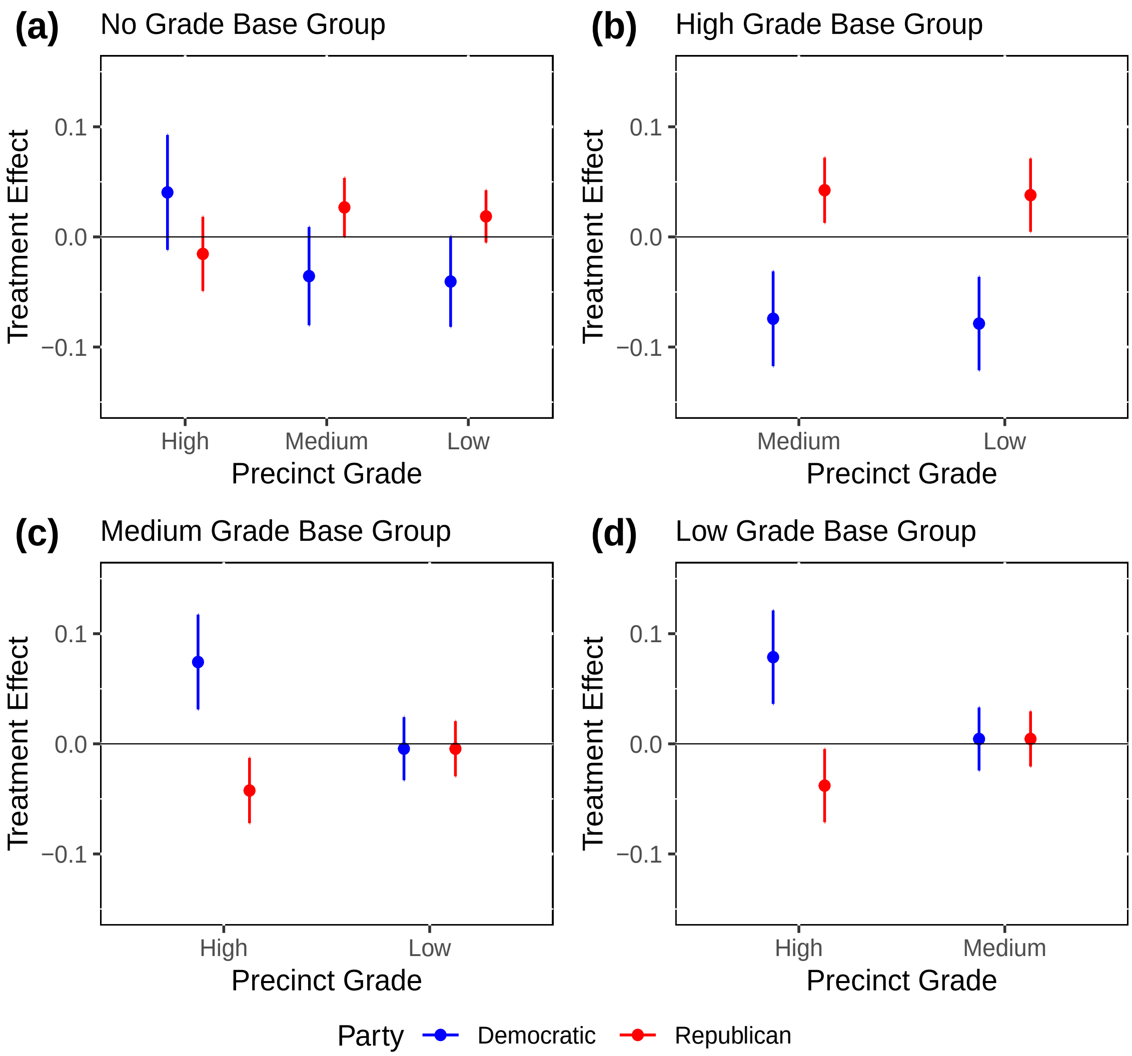


Figure 3.3: Changes in support for Democrats and Republicans are heterogeneous by HOLC grade. "No Grade Base Group" compares precincts graded high, medium, or low to those that did not receive a grade; "High Grade Base Group" compares precincts zoned medium or low to those with a high grade; "Medium Grade Base Group" compares precincts graded high or low to those with a medium grade; and, "Low Grade Base Group" compares precincts graded high or medium to those with a low grade. Comparisons are made for precincts receiving no or one HOLC grade. "High" grade precincts are zoned graded A or B, "Medium grade" precincts are graded C, and "Low" grade precincts are graded D. All treatment effects are estimated using models with full controls and fixed effects. 95% confidence intervals are provided. Standard errors are clustered by a precinct's overlapping HOLC zone(s). Columns 3 and 6 of all tables in Appendix section "Pseudo-Panel Results" provide results.

The Republican outcome reveals a similar pattern, but in the opposite direction, which is expected given the two-party nature of American politics. Medium grade precincts become 4.2 points more supportive of Republicans than high grade precincts ($p < .01$). Low grade precincts become 3.7 points more supportive of Republicans ($p < .05$).

The bottom left plot ("Medium Grade Base Group") compares high and low grade precincts to medium grade precincts (the base category). Relative to medium grade precincts, high grade precincts become 7.3 points more supportive of Democrats ($p < .01$), and 4.2 points less supportive of Republicans ($p < .01$). These effects are the same as those in the high grade base group plot, but the signs are reversed. Low grade precincts are no different from their medium grade counterparts on either outcome measure.

The final plot ("Low Grade Base Group") restates the findings shown in the high and medium base group plots, but the signs are reversed. High grade precincts become 7.7 points more supportive of Democrats ($p < .01$), and 3.7 points less supportive of Republicans ($p < .05$). Low and medium grade precincts are no different on either outcome measure.[12]

Geographic Regression Discontinuity

Prior to estimating the GRD, I evaluate the assumption of continuity, which states that the conditional expectation function of the running variable is continuous. I test this assumption using the sorting test devised in McCrary (2008). The test identifies whether there is sorting around the cutpoint, and provides evidence as to whether units may have manipulated the running variable as a means to self-select into the control or

[12] I supplement all pseudo-panel analyses with additional models that use party identification in 2016 as an outcome, and 1937 mayoral election outcomes as a lagged dependent variable. I do so because 1937 and 2016 measures of party support are not identical, and I want to check that the results are robust to different outcome measures. The reports are largely similar to what is reported here. See Appendix section "Additional Panel Analyses Using Lagged Dependent Variable."

treatment group. If voters chose to live in a particular neighborhood based on its HOLC grade, the assumption would likely be violated. We might see this if there were a known penalty to living in a neighborhood with a low grade, such as having reduced real estate values. If so, we may find high numbers of units living on the high-grade side of a HOLC border, which would violate the assumption of continuity.

Table 3.1 provides estimates for this test. All tests use units from the 5-degree sample. The null hypothesis is that there is no sorting. As is shown, in only one condition is the null hypothesis rejected to $p < .05$ (AC border zones, with a cubic polynomial (row 3)). No other test rejects the null to $p < .05$. Though no assumption can be proven, the results here indicate that the continuity assumption likely holds.[13]

[13] I also calculate pretreatment balance statistics for each comparison sample at distances of 200, 150, 100, and 50 meters from a HOLC comparison group border. These are used to provide additional evidence about whether the treatment and control groups are similar on observables. These results are reported in Appendix section "Geographic Regression Discontinuity Balance Statistics."

	Comparison Groups				
Order	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	0.06	0.77	-0.24	0.65	-1.52
	[1704]	[70]	[3765]	[340]	[2449]
2(3)	-0.17	1.38	-1.25	-0.31	-1.81*
	[2003]	[783]	[5043]	[354]	[3399]
3(4)	1.24	-8.87***	-1.23	0.50	-1.01
	[5681]	[1814]	[10190]	[552]	[8151]

*p < .1; **p < .05; ***p < .01
Robust t-values for each density test are provided, and the corresponding (effective) sample sizes are in brackets. These tests use units in the 5-degree sample only. The null hypothesis is that the discontinuity is continuous at the cutpoint. The tests are performed on voters that are within one of the five sample comparison groups. For each comparison group, treated units are in the zone with the lower grade (i.e., the descending letter). Masspoints are ignored. Column "Order" shows the polynomial order used to estimate the discontinuity, and the bias order is in parenthesis.

Table 3.1: Density Tests on Units in 5-degree Sample

Table 3.2 provides GRD estimates. The columns indicate the outcome measure (Democrat or Republican), and the comparison groups used to estimate the GRD (AB, AC, BC, BD, CD). The rows indicate the polynomial order used to estimate the GRD. As is shown, the results are largely null for both outcomes, and across all but one of the comparison groups.

Statistically significant effects are detected, however, when estimating Democratic identification among voters in B and D zones. The effects are quite large. For context, when estimating a GRD of polynomial order 1 (top row) among voters in B and D border zones, the probability of identifying as a Democrat decreases by 32.8 percentage points when on the D side of the border ($p < .01$). On average, the results suggest that HOLC caused Democratic identification to decrease by 32.8 percentage points in D graded areas, relative to their B grade counterparts. Treatment effect estimates for this comparison group are similar across all polynomial orders, and each is significant to $p < .01$.

	Democrat					**Republican**				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	-0.002	-0.004	-0.006	-0.328***	-0.059**	-0.065	0.060	0.005	0.118	0.028
	(0.047)	(0.074)	(0.024)	(0.119)	(0.029)	(0.043)	(0.073)	(0.019)	(0.082)	(0.018)
	[2837]	[3029]	[10422]	[264]	[6579]	[2051]	[2313]	[6926]	[376]	[7683]
2(3)	0.012	-0.019	-0.019	-0.372***	-0.060	-0.071	0.041	0.005	0.121	0.045*
	(0.054)	(0.110)	(0.034)	(0.127)	(0.040)	(0.048)	(0.090)	(0.023)	(0.089)	(0.026)
	[4526]	[3003]	[9672]	[377]	[7545]	[3545]	[2941]	[10147]	[603]	[6370]
3(4)	0.130*	0.033	-0.048	-0.388***	-0.064	-0.048	-0.015	0.020	0.147	0.044*
	(0.068)	(0.147)	(0.043)	(0.129)	(0.052)	(0.048)	(0.111)	(0.030)	(0.103)	(0.027)
	[4366]	[2919]	[9553]	[625]	[7849]	[6440]	[2962]	[10294]	[336]	[9816]

*p < .1; **p < .05; ***p < .01
Robust standard errors in parenthesis. The sample size used to estimate each discontinuity is shown in brackets. The discontinuities are estimated on the 5-degree sample only. The dependent variable is a dummy indicating whether a voter is Democrat or Republican. For each comparison group, treated units are in the zone with the lower grade (i.e., the descending letter). Masspoints are ignored. Column "Order" shows the polynomial order used to estimate the discontinuity. Each outcome is estimated for five comparison zones: AB, AC, BC, BD, and CD. Bias order is shown in parenthesis.

Table 3.2: Party Identification

Though largely null, the GRD points in the same direction as the pseudo-panel. In the pseudo-panel, lower graded areas became less favorable to Democrats over time. The same is true in the GRD, albeit for voters in B and D border zones. Overall, the results from both analyses point to the same overall pattern: lower grade areas became less favorable to Democrats.

3.8 Why Less Democratic?

Contrary to expectations, lower grade precincts became less supportive of Democrats, and slightly more favorable to Republicans. Why did this occur? For one, it should be noted that low and medium grade precincts did not become unfavorable to Democrats, nor did they become favorable to Republicans. As Figure 3.4 shows, low and medium grade precincts were still more than 60 percent Democrat in 2016. And, while support for Republicans increased more in low and medium grade precincts than in high grade precincts, no precinct type was more than 20 percent supportive of Republicans. Across the study area, there appears to have been a secular decrease in support for Republicans, but a steady increase in support for Democrats. Area-wide, this may not have been driven by redlining, but it is likely that *neighborhood-level* changes in partisanship were driven by HOLC.

Figure 3.4 also shows that high grade precincts were the least supportive of Democrats in 1937 (43% support), but were the most supportive in 2016 (63%). These precincts had a larger Democratic support margin to makeup, which likely explains the seemingly anomalous results we observe. Stated alternatively, because high grade precincts were the least supportive of the Democratic party in 1937, they simply had more room to increase support.

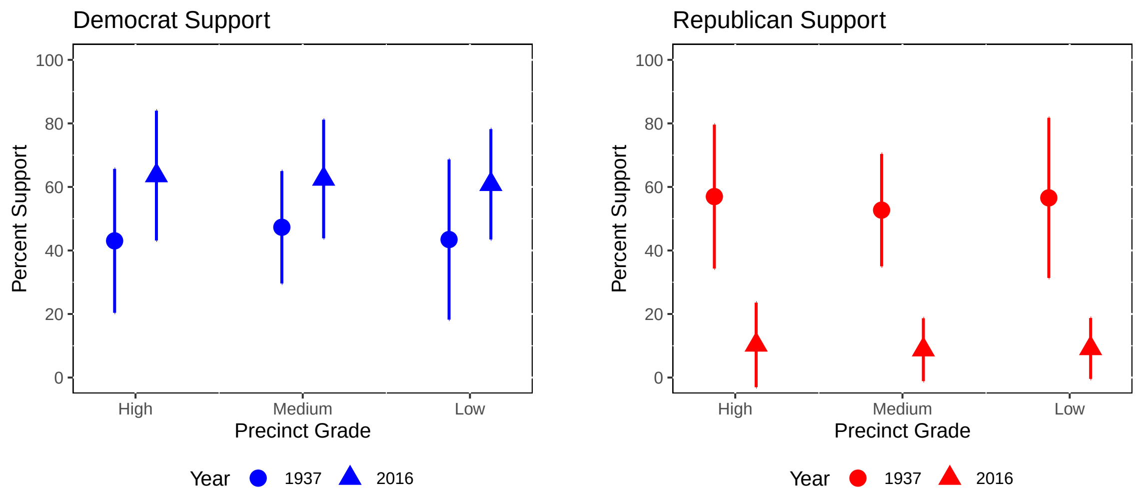


Figure 3.4: Support for the Democratic party increases over time, while support for the Republican party decreases. Statistics are calculated at the precinct level. 1937 data uses vote share for the Democratic and Republican mayoral candidates. 2016 data uses percent of voters registered as Democrat or Republican. 95% confidence intervals are presented.

Dramatic change is observed when examining over-time shifts in Republican support. As Figure 3.4 shows, all precincts were far more supportive of Republicans in 1937 than they were in 2016. Republican support reduces significantly in 2016, and no more than 20 percent of voters were registered Republicans. Moreover, voters were more supportive of the Republican mayoral candidate in 1937 than they were the Democratic candidate. All told, Los Angeles appears to have evolved from a strongly Republican city to one that consistently favors Democrats.

High grade precincts are somewhat of an enigma. In 1937, they were least supportive of Democrats, and most supportive of Republicans. However, in 2016, they were most supportive of Democrats, which is paradoxical. We might expect that high grade areas were, and are, populated by wealthy residents who favor the Republican party's economically conservative policies. However, this appears not to be the case, and the reverse is true.

The paradox may be explained by long-term population change and replacement. The HOLC area descriptions confirm that high grade areas were populated by business and corporate leaders, and it is likely that these individuals identified as Republican because of the party's pro-business policies. Over time, however, they may have been replaced by young Hollywood executives, actors, and musicians who, while wealthy, were liberal on social issues and supportive of Democrats. This describes the stereotype of the "Hollywood liberal", a typically wealthy Hollywood executive, actor, musician, or artist who lives in the hills surrounding Los Angeles, and who supports liberal causes and Democratic candidates (McIntosh et al., 2003; Frost, 2017; Paul, 2018). These "Hollywood liberals" may have replaced the business and corporate leaders who lived in high grade areas during he 1930s, leading these areas to become more supportive of Democrats later on.

I explore this possibility by calculating the correlation between a precinct's HOLC grade and its mean elevation, to establish whether high grade precincts were located at higher elevations. If so, it suggests that the population change described above, wherein Republican business and corporate leaders were replaced by Hollywood liberals, likely occurred. To calculate the correlation coefficient, I coded precincts on a scale between 1 and 4. Lower HOLC grades received higher scores. For example, an "A" grade received a score of 1, while a "D" grade received a 4. The correlation coefficient is -.08, and significant to $p < .01$ (t = -3.22). The result tells us that higher grade precincts were located at higher elevations, which is where Hollywood liberals currently reside, but where conservative business and corporate leaders once did.

3.9 HOLC's Impact on Other Outcomes

I evaluate HOLC's impact on socioeconomic outcomes, as well. The econometric setup is similar to the pseudo-panel, but 2010 Census block groups are the units of observation. In this setup, I assign HOLC grades by overlaying the 1939 HOLC map on the 2010 Census block groups. I then assign a HOLC grade to each block group that is at least partially overlapped by the HOLC map. I also create a set of pretreatment controls by aggregating the geocoded 1930 Census data within each 2010 block group, and calculating area-wide statistics.

I estimate regression models on a series of outcome measures, all of which are measured as percentages. Treatment effect estimates from these models are presented in Figure 3.5, as are 95% confidence intervals, with standard errors clustered at the HOLC zone level. As is shown, HOLC had a substantial impact on socioeconomic life in Los Angeles, and the results largely comport with expectations. Medium and low grade block groups are, on average, less White, have a higher percentage of the population living in poverty, and have a higher percentage of residents who receive public assistance (left panel). They are also less educated, and are younger. For reference, medium and low grade block groups are roughly 14 percentage points less White, but are between 16 and 22 percentage points more Hispanic and Latinx. Interestingly, the coefficient for Black population is not statistically distinguishable from zero. This is unexpected given that popular discourse typically associates redlining with its impact on Black people.

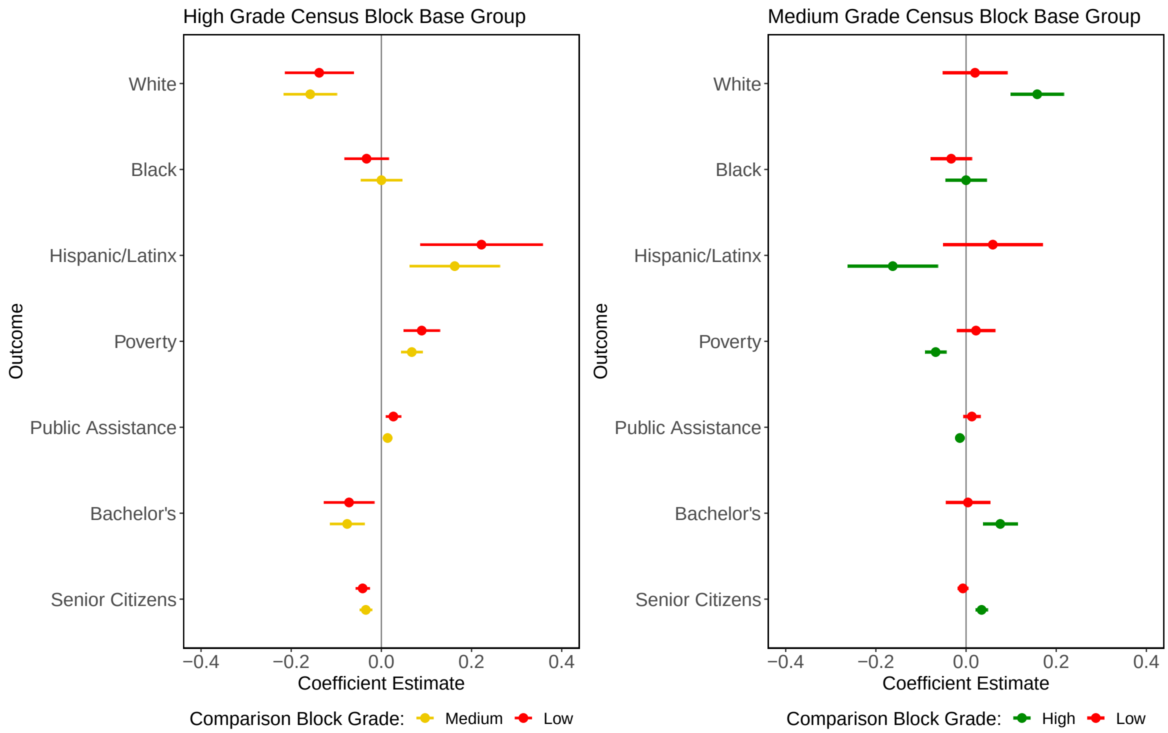


Figure 3.5: HOLC had a substantial impact on socioeconomic life in Los Angeles. Presented are coefficient estimates that compare various outcomes for Census block groups receiving High, Medium, and Low grade HOLC scores. The estimates represent the effect of receiving a particular HOLC score, relative to a base category. The base categories are block groups that received a high grade (left panel), or those that received a medium grade (right panel). All outcome measures are calculated as percentages, and are presented on the y-axis. Coefficient estimates are provided, along with 95% confidence intervals. Standard errors are clustered by the HOLC zone that a block group is overlapped by. All estimates are generated from models that control for 1930 Census covariates. These covariates are aggregated to the 2010 Census block group level, using geocoded address-level data from the 1930 Census. All models include 2010 Census block groups that received one HOLC grade.

As the right panel shows, medium and low grade precincts are no different from one another. The red point estimates compare low and medium grade block groups to each other. Throughout all outcomes, the two groups are not statistically different, and all coefficient estimates fail to reject the null hypothesis. Together, the results tell us that HOLC's long-term impacts stem from the creation of high grade areas that had a distinct developmental trajectory.

3.10 Discussion

The latent consequences of public programs and policy are understudied. Yet, as this paper shows, they can have a profound impact on political life. HOLC's initial purpose was to stabilize the housing market during the late 1930s by refinancing mortgages that were in default. In large part, HOLC achieved this goal. Billions of dollars were invested into households in need of assistance, and over 80 percent of these homes were saved.

By intent or not, however, HOLC impacted society in other, potentially more impactful, ways. Real estate markets in neighborhoods throughout the US diverged to follow unique trends, leaving a lasting impact on home values and wealth. HOLC's policies also increased neighborhood segregation, and led to reduced credit access and investment in minority neighborhoods.

I examine a yet unexplored tendril of HOLC's impact: its effect on political geography and partisan sorting. Although HOLC may not have intended to increase spatial polarization, it did. As shown, the program led neighborhoods to evolve in politically distinct ways. High grade areas experienced increased support for Democrats, while medium and low grade areas experienced larger over-time increases in support for Republicans. These effects are robust to two separate identification strategies: a pseudo-panel using historical election data, and a geographic regression discontinuity design that estimates the program's causal effect on sorting around HOLC zones.

The findings are unique in the context of research on HOLC. Existing research leads us to believe that low grade areas would become more supportive of Democrats because these areas had higher concentrations of minorities and blue collar workers. Furthermore, we might be inclined to think that high grade areas become more supportive of Republicans because they attracted white collar workers who were partial to the party's economic conservatism.

Surprisingly, the exact opposite occurred. This forces us to reconsider how we conceptualize the interplay between socioeconomic, demographic, and political characteristics. It is taken for granted that core political characteristics such as party identification and vote choice can be predicted by a small number of demographic characteristics. As I show, political geography is not epiphenomenal to the socioeconomic and demographic distribution of individual across space. Rather, changes to the political geography of an area can occur in ways that seem counter to the area's overall demography.

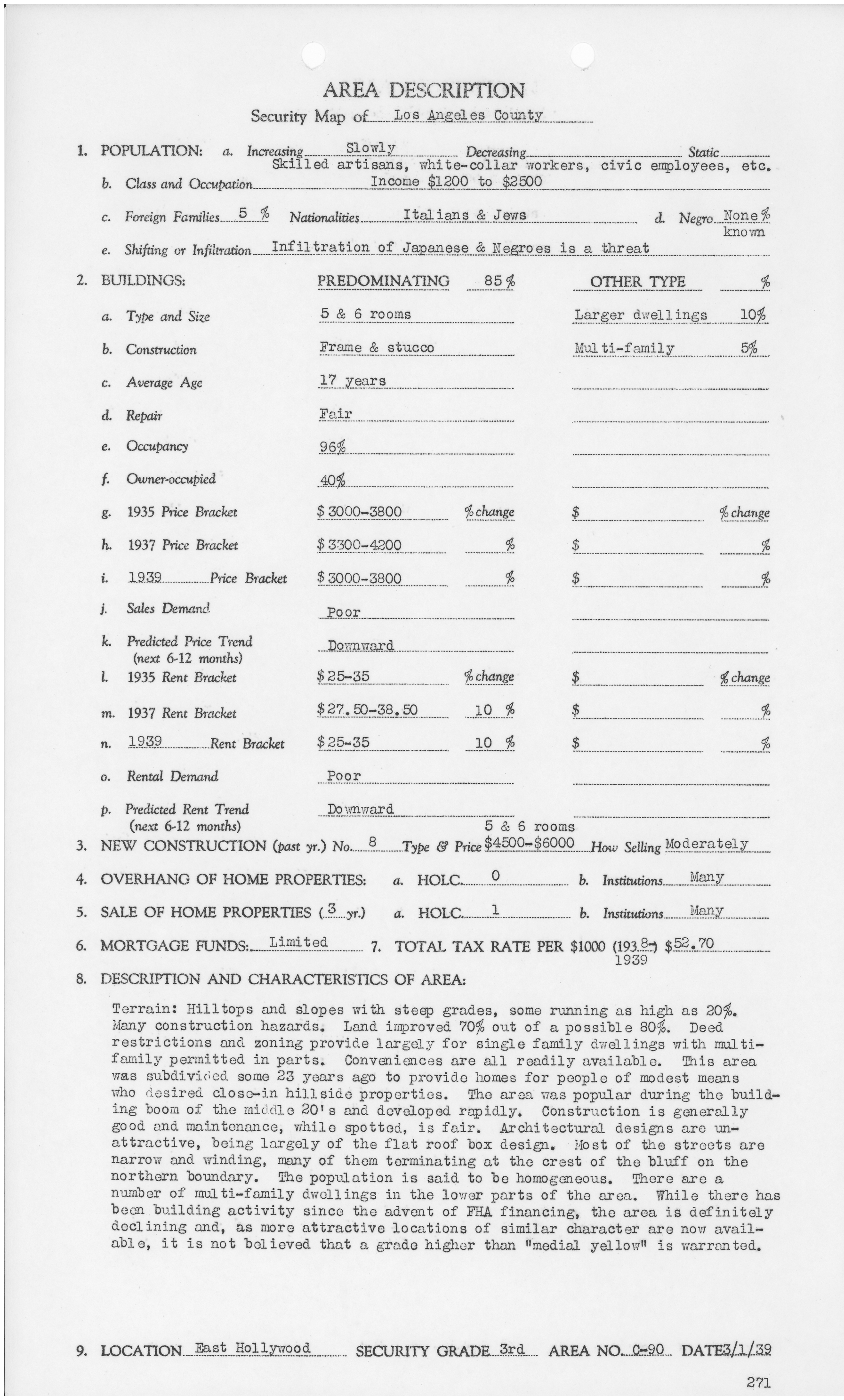
We must keep in mind that this paper uses voter file data. Even in areas with high concentrations of minorities and blue collar workers, it is likely that the registered voting population is Whiter and more affluent, given what is known about the nature of political participation in the US (Schlozman et al., 2012). The voter file may represent a subpopulation that looks different from the neighborhoods that the voters were drawn from. The expectation that blue collar, high minority, areas are more supportive of Democrats is less tenable if the registered voters from these areas are from altogether different socioeconomic groups. If so, the results may be partially explained by the fact that registered voters simply do not look like their neighbors, even though the demographic characteristics of their neighbors are used to make predictions about HOLC's impact on politics.

Future research should extend to other aspects of politics. I identify *whether* HOLC affected political geography and partisan sorting. However, a number of important questions remain. It is imperative, for example, to identify whether HOLC grades are associated with quality of representation. Relatedly, the narrative forwarded in this paper is that government programs have the potential to reshape political geography. With that in mind, one might ask whether infrastructure and investment projects are more likely to be funneled to high grade areas. Future work should engage with questions like these if we are to develop a more nuanced understanding of the latent consequences that government programs have on our daily lives. At present, however, this paper makes clear that these programs, whether by intent or not, have the potential to fundamentally restructure the spatial character of political life.

3.11 Appendix

Maps and Figures

This section provides various maps and figures that complement the main analyses.



AREA DESCRIPTION

Security Map of Los Angeles County

1. POPULATION: a. Increasing Slowly Decreasing Static
   b. Class and Occupation Skilled artisans, white-collar workers, civic employees, etc. Income $1200 to $2500
   c. Foreign Families 5 % Nationalities Italians & Jews d. Negro None % known
   e. Shifting or Infiltration Infiltration of Japanese & Negroes is a threat

2. BUILDINGS:

	PREDOMINATING 85 %		OTHER TYPE %	
a. Type and Size	5 & 6 rooms		Larger dwellings	10%
b. Construction	Frame & stucco		Multi-family	5%
c. Average Age	17 years			
d. Repair	Fair			
e. Occupancy	96%			
f. Owner-occupied	40%			
g. 1935 Price Bracket	$ 3000-3800	% change	$	% change
h. 1937 Price Bracket	$ 3300-4200	%	$	%
i. 1939 Price Bracket	$ 3000-3800	%	$	%
j. Sales Demand	Poor			
k. Predicted Price Trend (next 6-12 months)	Downward			
l. 1935 Rent Bracket	$ 25-35	% change	$	% change
m. 1937 Rent Bracket	$ 27.50-38.50	10 %	$	%
n. 1939 Rent Bracket	$ 25-35	10 %	$	%
o. Rental Demand	Poor			
p. Predicted Rent Trend (next 6-12 months)	Downward			

3. NEW CONSTRUCTION (past yr.) No. 8 Type & Price 5 & 6 rooms $4500-$6000 How Selling Moderately
4. OVERHANG OF HOME PROPERTIES: a. HOLC 0 b. Institutions Many
5. SALE OF HOME PROPERTIES (3 yr.) a. HOLC 1 b. Institutions Many
6. MORTGAGE FUNDS: Limited 7. TOTAL TAX RATE PER $1000 (193 8) 1939 $52.70
8. DESCRIPTION AND CHARACTERISTICS OF AREA:

Terrain: Hilltops and slopes with steep grades, some running as high as 20%. Many construction hazards. Land improved 70% out of a possible 80%. Deed restrictions and zoning provide largely for single family dwellings with multi-family permitted in parts. Conveniences are all readily available. This area was subdivided some 23 years ago to provide homes for people of modest means who desired close-in hillside properties. The area was popular during the building boom of the middle 20's and developed rapidly. Construction is generally good and maintenance, while spotted, is fair. Architectural designs are unattractive, being largely of the flat roof box design. Most of the streets are narrow and winding, many of them terminating at the crest of the bluff on the northern boundary. The population is said to be homogeneous. There are a number of multi-family dwellings in the lower parts of the area. While there has been building activity since the advent of FHA financing, the area is definitely declining and, as more attractive locations of similar character are now available, it is not believed that a grade higher than "medial yellow" is warranted.

9. LOCATION East Hollywood SECURITY GRADE 3rd AREA NO. C-90 DATE 3/1/39

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Figure 3.6: Image of Area Description for Los Angeles HOLC zone C-90.

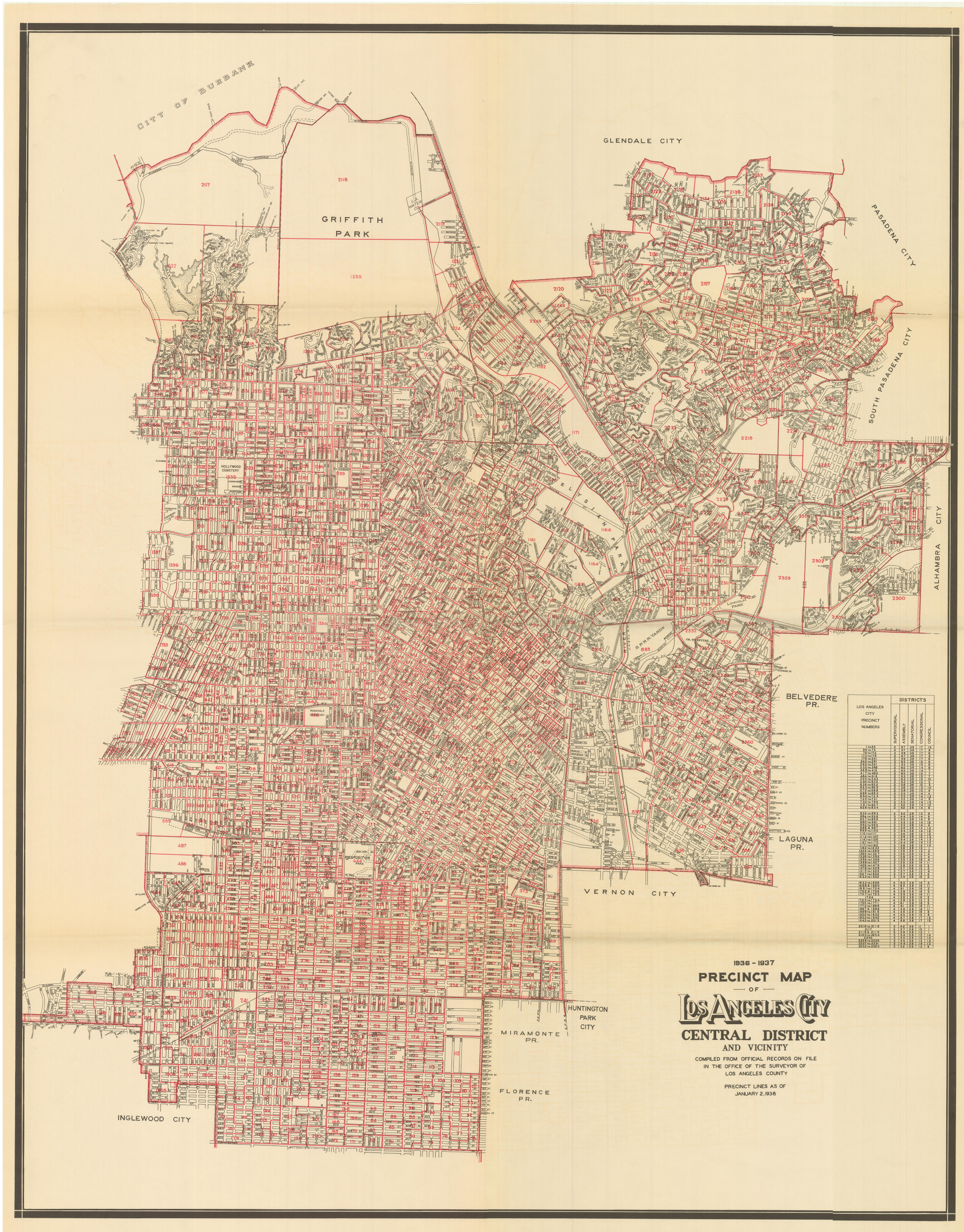
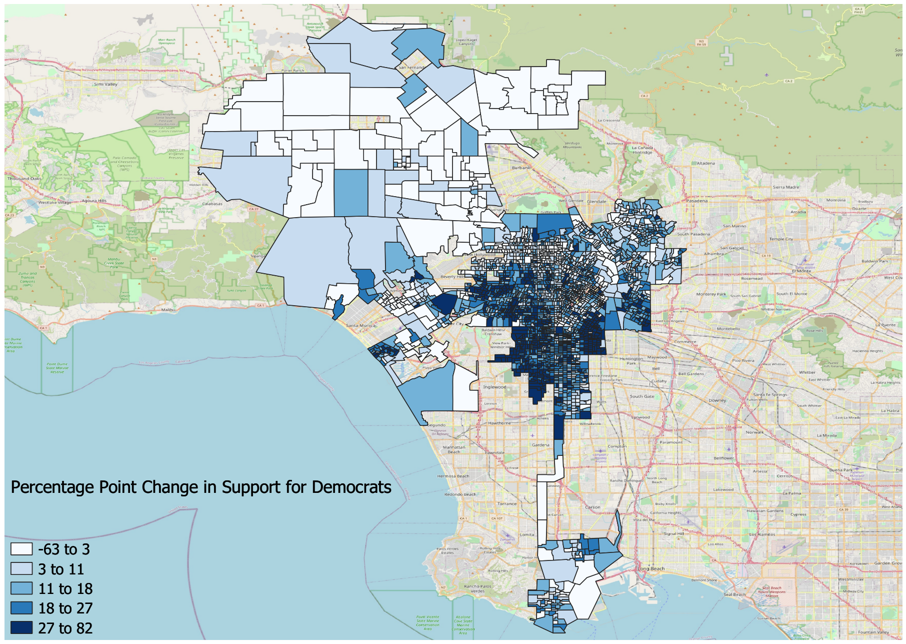
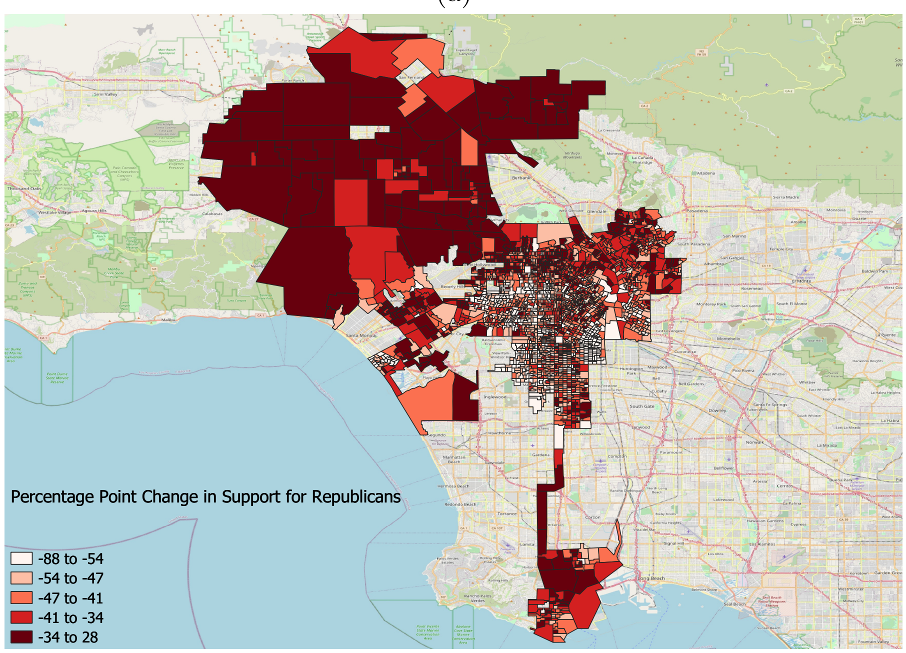


Figure 3.7: This shows election precincts for the 1937 Los Angeles mayoral election in the Central District. This is one of four maps that are used to construct the full set of precincts for the 1937 election across the entire City of Los Angeles.

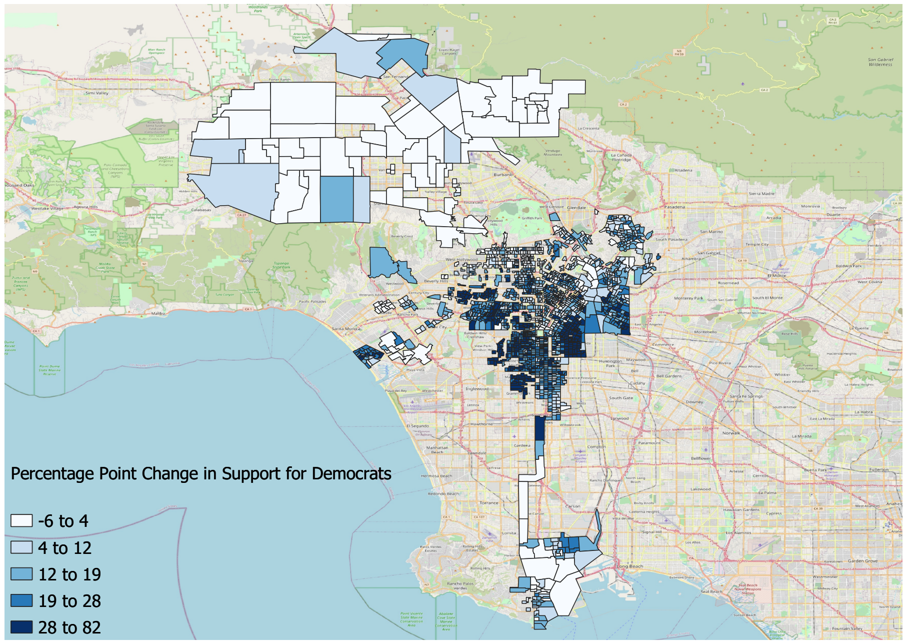


(a)

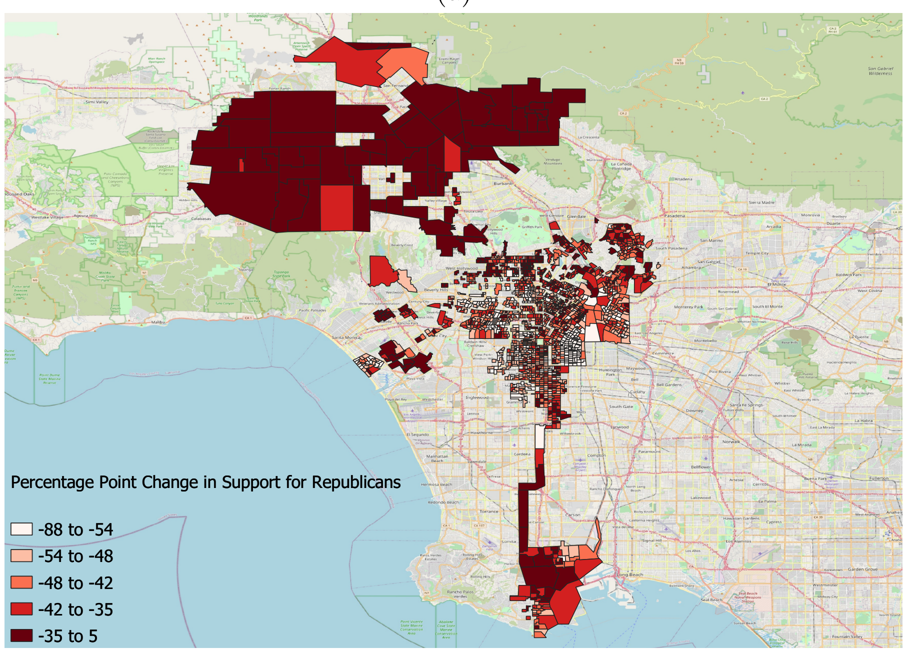


(b)

Figure 3.8: Panel (a) shows percentage point change in support for Democrats. Panel (b) shows percentage point change in support for Republicans. Each is calculated between year 1937 and 2016. Statistics are calculated using all 1937 mayoral precinct boundaries.

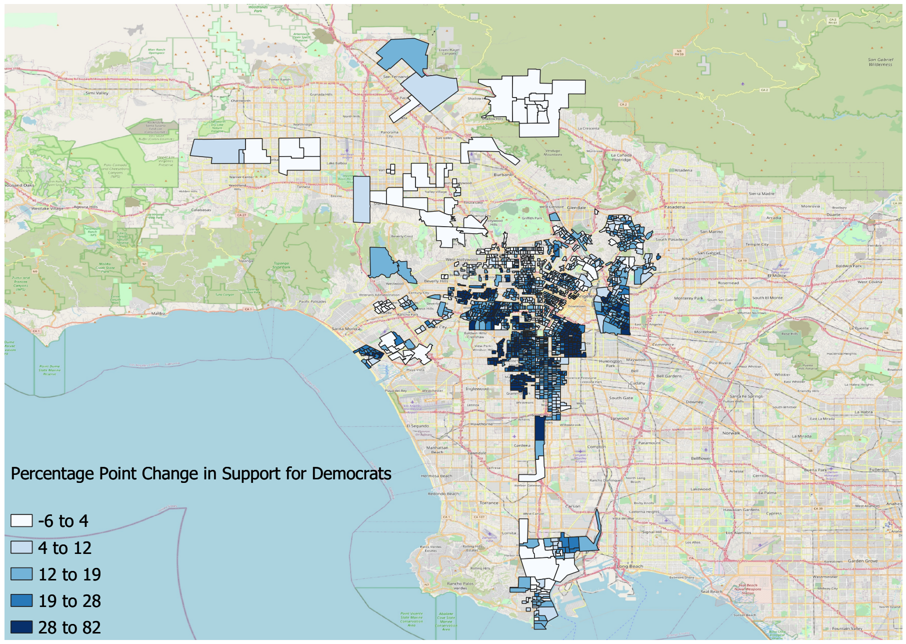


(a)

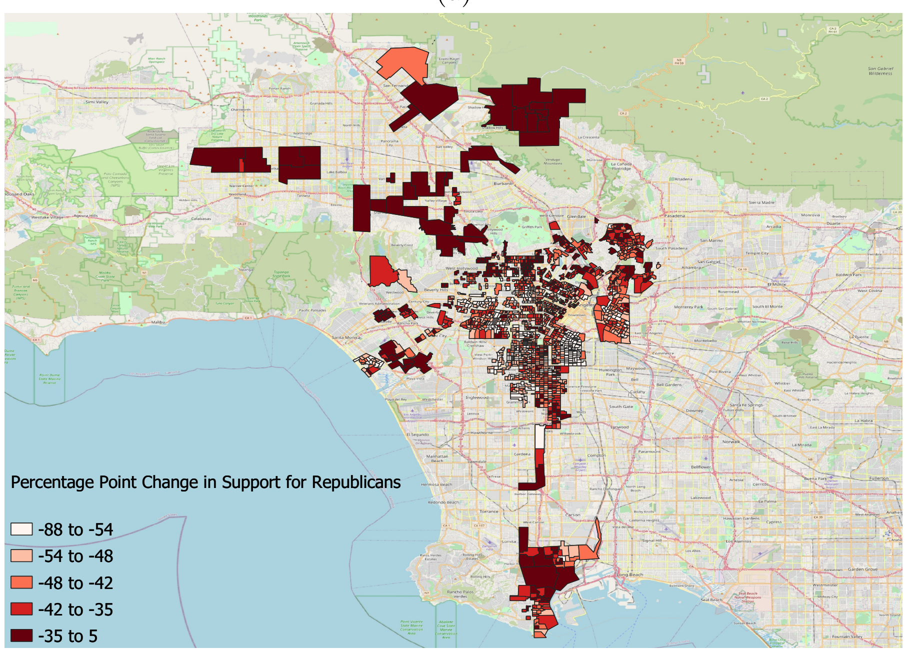


(b)

Figure 3.9: Panel (a) shows percentage point change in support for Democrats. Panel (b) shows percentage point change in support for Republicans. Each is calculated between year 1937 and 2016. Statistics are calculated using all 1937 mayoral precinct boundaries that received one or no grade.

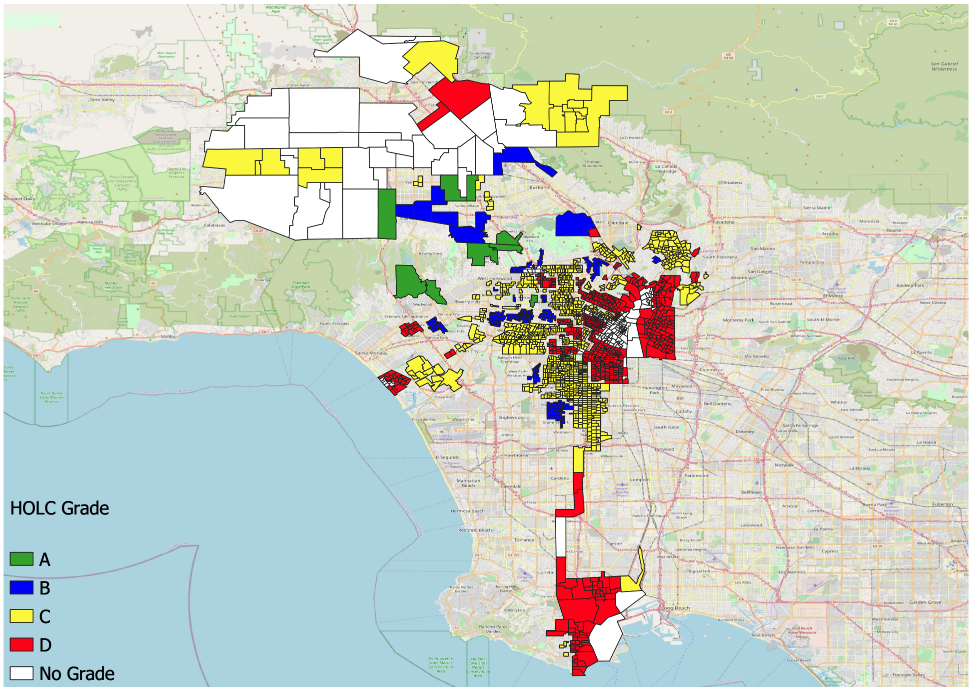


(a)

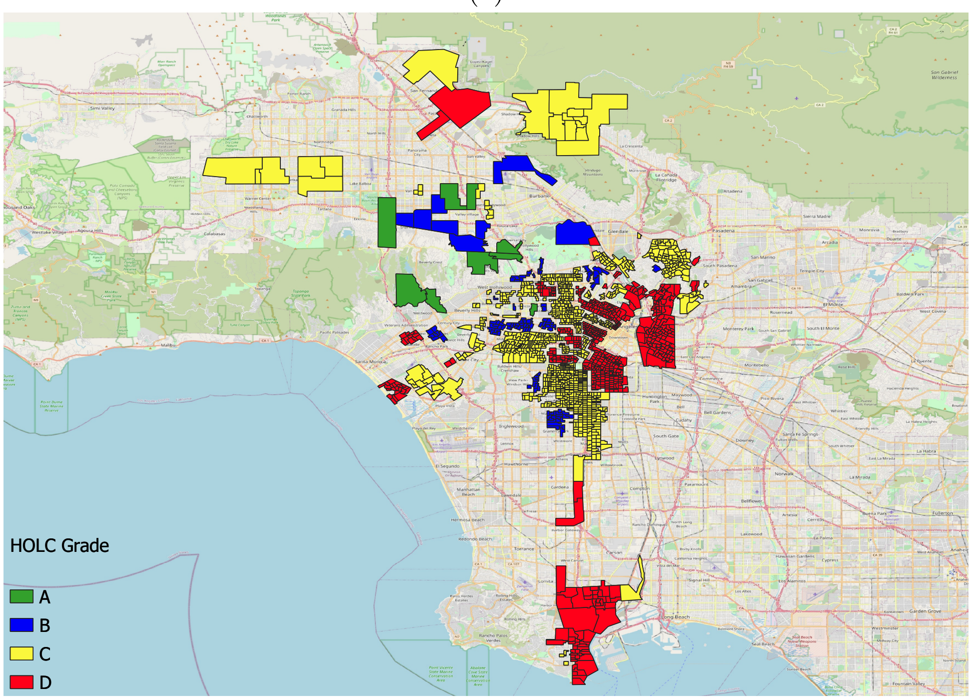


(b)

Figure 3.10: Panel (a) shows percentage point change in support for Democrats. Panel (b) shows percentage point change in support for Republicans. Each is calculated between year 1937 and 2016. Statistics are calculated using all 1937 mayoral precinct boundaries that recevied one HOLC grade.



(a)



(b)

Figure 3.11: Panel (a) shows HOLC grades for precincts that received one or no grade. Panel (b) shows HOLC grades for precincts that received one grade.

Pseudo-Panel Sample Characteristics

This subsection provides descriptive statistics for the precincts used in the pseudo-panel. Statistics are calculated for precincts with no or one HOLC grade.

Grade	# of Precincts
High	122
Medium	860
Low	565
No Grade	169
Total	1716

Shown are the number of 1937 voting precincts in each HOLC zone. The sample is restricted to include precincts that received only one HOLC grade, or no grade at all. "High" grade precincts include those graded A or B; "Medium" grade precincts include those graded C; "Low" grade precincts include those graded D.

Table 3.3: Number of Precincts in Each HOLC Zone

	Precinct Grade			
	High	**Medium**	**Low**	**No Grade**
Total Population	382	429	525	749
White	98%	98%	78%	78%
Black	0%	0%	10%	3%
Mexican	0%	1%	10%	12%
Asian	1%	0%	3%	7%
Age	33	33	31	35
Occupation Score (1950)	450	490	550	541
SEI	48	47	27	19
House Value	9,500	7,000	6,000	6,000
Rent (1930)	50	37	30	27
Unemployment Rate	6%	9%	12%	14%
Elevation	95	87	81	125
Total Graded Area	85%	92%	85%	0%
Dwelling Size	4	4	4	5
Size Place	80	80	80	80
# of Families	1	1	1	1
Family Size	3	3	3	2

Descriptive demographic statistics for precincts in each HOLC zone are provided. All statistics use full-count 1930 Census data. Precinct means are calculated for "Total Population", "White", "Black", "Mexican", "Asian", "Unemployment Rate", "Elevation", and "Total Graded Area". Medians are calculated for "Age", "Occupation Score (1950), "SEI", "House Value", "Rent (1930)", "Dwelling Size", "Size Place", "# of Families", and "Family Size". Statistics are calculated for precincts that received only one grade, or no grade at all. "High" grade precincts include those graded A or B; "Medium" grade precincts include those graded C; "Low" grade precincts include those graded D. Due to rounding, percents may not sum to 100.

Table 3.4: Demographic and Economic Characteristics of Precincts By HOLC Grade

	Democratic Support			Republican Support		
Grade	**1937**	**2016**	**Change**	**1937**	**2016**	**Change**
High	43%	64%	+21	57%	10%	-47
Medium	47%	62%	+15	53%	9%	-44
Low	43%	61%	+18	57%	9%	-48
No Grade	47%	54%	+7	53%	12%	-41

Presented are the percentage of voters who supported the Democratic and Republican mayoral candidates in 1937, as well as the percentage of voters who identified as either Democrat or Republican, as of 2016. All statistics are calculated at the precinct-level, using 1937 precinct boundaries. Column "1937" shows the percentage of voters who supported the Democratic or Republican candidate. Column "2016" shows the percentage of voters who identify as Democrat or Republican in 2016. Column "Change" shows the change in support between 1937 and 2016 for Democrats and Republicans. Statistics are calculated with precincts that received one HOLC grade, or those that were not graded.

Table 3.5: Partisan and Voting Distribution By HOLC Grade

Pseudo-Panel Results

This section provides full estimates for the main pseudo-panel models. These correspond to Figure 3.3 in the main text.

Table 3.6: Change in Party Support - No Grade Base

	Democrat Δ			*Republican* Δ		
High Grade	0.14***	0.02	0.04	−0.06***	0.01	−0.01
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Medium Grade	0.08***	−0.05**	−0.04	−0.03***	0.04***	0.03*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Low Grade	0.11**	−0.06***	−0.04*	−0.07*	0.04**	0.02
	(0.04)	(0.02)	(0.02)	(0.04)	(0.01)	(0.01)
SES Index		0.000	−0.000		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.02***	0.02***		0.001	−0.001
		(0.01)	(0.01)		(0.01)	(0.01)
Dwelling Size		0.001***	0.001**		−0.000	−0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Age		0.002	0.001		−0.002**	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Unemployed		−0.000	−0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Veterans		−0.001**	−0.001*		0.001***	0.001***
		(0.000)	(0.000)		(0.000)	(0.000)
Farming		−0.000	−0.000		0.000***	0.000*
		(0.000)	(0.000)		(0.000)	(0.000)
Total Population		0.001	0.001		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
White		−0.001	−0.001		0.001	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		−0.001	−0.001		0.001	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.000	0.000		−0.000	−0.000
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		−0.001	−0.001		0.001	0.001
		(0.001)	(0.001)		(0.001)	(0.001)

Change in Party Support - No Grade Base (Continued)

Chinese		−0.001	−0.001		0.000	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Rent (1930)		−0.000***	−0.000***		0.000**	0.000**
		(0.000)	(0.000)		(0.000)	(0.000)
House Value (1930)		0.000***	0.000***		−0.000***	−0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
% Graded		0.11***	0.10***		−0.05***	−0.03**
		(0.02)	(0.02)		(0.02)	(0.01)
Elevation (mean)		−0.001***	−0.001***		0.001***	0.001***
		(0.000)	(0.000)		(0.000)	(0.000)
FEs			✓			✓
N	1,686	1,670	1,662	1,686	1,670	1,662
R^2	0.04	0.37	0.38	0.03	0.43	0.44
Adj. R^2	0.04	0.36	0.37	0.03	0.42	0.43
Resid. Std. Err.	0.15	0.13	0.12	0.13	0.10	0.10
F Stat.	24.88***	48.25***	43.83***	16.62***	61.12***	56.51***

[a] *p < .1; **p < .05; ***p < .01
[b] The dependent variable is the percentage point change in support for each party between 1937 and 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct *i* is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that received no HOLC grade. Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.7: Change in Party Support - High Grade Base

	Democrat Δ			*Republican* Δ		
Medium Grade	−0.056**	−0.066***	−0.073***	0.029	0.036**	0.042***
	(0.028)	(0.022)	(0.022)	(0.021)	(0.016)	(0.015)
Low Grade	−0.030	−0.072***	−0.077***	−0.009	0.032*	0.037**
	(0.049)	(0.021)	(0.022)	(0.042)	(0.018)	(0.017)
SES Index		0.0002	0.0001		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.016**	0.019**		0.003	−0.00002
		(0.008)	(0.008)		(0.006)	(0.006)
Dwelling Size		0.001	0.001		−0.001***	−0.001***
		(0.001)	(0.001)		(0.0004)	(0.0004)

Change in Party Support - High Grade Base (Continued)

Age		0.002	0.001		−0.001	−0.001
		(0.002)	(0.002)		(0.001)	(0.001)
Unemployed		−0.001	−0.001		0.0003	0.0003
		(0.0004)	(0.0004)		(0.0004)	(0.0004)
Veterans		−0.002***	−0.001**		0.002***	0.001***
		(0.001)	(0.001)		(0.0004)	(0.0003)
Farming		−0.0001	−0.0002		0.0004	0.0005
		(0.0003)	(0.0004)		(0.0003)	(0.0003)
Total Population		−0.001	−0.0003		−0.0004	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
White		0.001	0.0003		0.0003	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		0.001	0.0003		0.0003	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.002*	0.001		−0.001	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		0.0005	0.0002		0.0003	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.001	0.001		−0.0001	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Rent (1930)		−0.0001***	−0.0001***		0.00005***	0.00004***
		(0.00001)	(0.00001)		(0.00002)	(0.00002)
House Value (1930)		0.00000***	0.00000***		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
% Graded		0.105***	0.090***		−0.049***	−0.032***
		(0.023)	(0.024)		(0.015)	(0.012)
Elevation (mean)		−0.001***	−0.001***		0.001***	0.001***
		(0.0001)	(0.0002)		(0.0001)	(0.0001)
FEs			✓			✓
N	1,521	1,512	1,504	1,521	1,512	1,504
R^2	0.15	0.38	0.39	0.02	0.42	0.44
Adj. R^2	0.12	0.37	0.39	0.02	0.41	0.43
Resid. Std. Err.	0.15	0.12	0.12	0.12	0.10	0.10
F Stat.	9.89***	48.06***	43.77***	16.60***	56.22***	52.44***

[a] *p < .1; **p < .05; ***p < .01

[b] The dependent variable is the percentage point change in support for each party between 1937 and 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that received a high HOLC grade (A and B grades). Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.8: Change in Party Support - Medium Grade Base

	Democrat Δ			*Republican* Δ		
High Grade	0.056**	0.066***	0.073***	−0.029	−0.036**	−0.042***
	(0.028)	(0.022)	(0.022)	(0.021)	(0.016)	(0.015)
Low Grade	0.025	−0.005	−0.004	−0.038	−0.004	−0.005
	(0.045)	(0.015)	(0.015)	(0.039)	(0.014)	(0.013)
SES Index		0.0002	0.0001		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.016**	0.019**		0.003	−0.00002
		(0.008)	(0.008)		(0.006)	(0.006)
Dwelling Size		0.001	0.001		−0.001***	−0.001***
		(0.001)	(0.001)		(0.0004)	(0.0004)
Age		0.002	0.001		−0.001	−0.001
		(0.002)	(0.002)		(0.001)	(0.001)
Unemployed		−0.001	−0.001		0.0003	0.0003
		(0.0004)	(0.0004)		(0.0004)	(0.0004)
Veterans		−0.002***	−0.001**		0.002***	0.001***
		(0.001)	(0.001)		(0.0004)	(0.0003)
Farming		−0.0001	−0.0002		0.0004	0.0005
		(0.0003)	(0.0004)		(0.0003)	(0.0003)
Total Population		−0.001	−0.0003		−0.0004	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
White		0.001	0.0003		0.0003	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		0.001	0.0003		0.0003	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.002*	0.001		−0.001	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		0.0005	0.0002		0.0003	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.001	0.001		−0.0001	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Rent (1930)		−0.0001***	−0.0001***		0.00005***	0.00004***
		(0.00001)	(0.00001)		(0.00002)	(0.00002)
House Value (1930)		0.00000***	0.00000***		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
% Graded		0.105***	0.090***		−0.049***	−0.032***
		(0.023)	(0.024)		(0.015)	(0.012)

Change in Party Support - Medium Grade Base (Continued)

Elevation (mean)		−0.001***	−0.001***		0.001***	0.001***
		(0.0001)	(0.0002)		(0.0001)	(0.0001)
FEs			✓			✓
N	1,521	1,512	1,504	1,521	1,512	1,504
R^2	0.01	0.38	0.39	0.02	0.42	0.44
Adj. R^2	0.01	0.37	0.39	0.02	0.41	0.43
Resid. Std. Err.	0.15	0.12	0.12	0.12	0.10	0.10
F Stat.	9.88***	48.06***	43.70***	16.60***	56.22***	52.44***

[a] *p < .1; **p < .05; ***p < .01
[b] The dependent variable is the percentage point change in support for each party between 1937 and 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that received a medium HOLC grade (C grade). Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.9: Change in Party Support - Low Grade Base

	Democrat Δ			*Republican* Δ		
High Grade	0.030	0.072***	0.077***	0.009	−0.032*	−0.037**
	(0.049)	(0.021)	(0.022)	(0.042)	(0.018)	(0.017)
Medium Grade	−0.025	0.005	0.004	0.038	0.004	0.005
	(0.045)	(0.015)	(0.015)	(0.039)	(0.014)	(0.013)
SES Index		0.0002	0.0001		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.016**	0.019**		0.003	−0.00002
		(0.008)	(0.008)		(0.006)	(0.006)
Dwelling Size		0.001	0.001		−0.001***	−0.001***
		(0.001)	(0.001)		(0.0004)	(0.0004)
Age		0.002	0.001		−0.001	−0.001
		(0.002)	(0.002)		(0.001)	(0.001)
Unemployed		−0.001	−0.001		0.0003	0.0003
		(0.0004)	(0.0004)		(0.0004)	(0.0004)
Veterans		−0.002***	−0.001**		0.002***	0.001***
		(0.001)	(0.001)		(0.0004)	(0.0003)
Farming		−0.0001	−0.0002		0.0004	0.0005
		(0.0003)	(0.0004)		(0.0003)	(0.0003)

Change in Party Support - Low Grade Base (Continued)

Total Population		−0.001	−0.0003		−0.0004	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
White		0.001	0.0003		0.0003	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		0.001	0.0003		0.0003	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.002*	0.001		−0.001	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		0.0005	0.0002		0.0003	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.001	0.001		−0.0001	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Rent (1930)		−0.0001***	−0.0001***		0.00005***	0.00004***
		(0.00001)	(0.00001)		(0.00002)	(0.00002)
House Value (1930)		0.00000***	0.00000***		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
% Graded		0.105***	0.090***		−0.049***	−0.032***
		(0.023)	(0.024)		(0.015)	(0.012)
Elevation (mean)		−0.001***	−0.001***		0.001***	0.001***
		(0.0001)	(0.0002)		(0.0001)	(0.0001)
FEs			✓			✓
N	1,521	1,512	1,504	1,521	1,512	1,504
R^2	0.01	0.38	0.39	0.02	0.42	0.44
Adj. R^2	0.01	0.37	0.39	0.02	0.41	0.43
Resid. Std. Err.	0.15	0.12	0.12	0.12	0.10	0.10
F Stat.	9.88***	48.06***	43.77***	16.60***	56.22***	52.44***

[a] *p < .1; **p < .05; ***p < .01
[b] The dependent variable is the percentage point change in support for each party between 1937 and 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that received a low HOLC grade (D grade). Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Additional Panel Analysis Using Lagged Dependent Variable

This section replicates the main results, but by using 1937 election results as a lagged dependent variable, and using partisanship from the 2016 voter file as the outcome measure. The primary difference is that these models do not measure over-time change, but estimate voter identification, as of 2016. The specification used to estimates these models is shown by

$$Y_i = \alpha + \sum_{k=1}^{K-1} \beta_k D_{ki} + \lambda Supp1937_i + X_i'\theta + \epsilon_i \qquad (3.5)$$

where $\lambda Supp1937_i$ shows the impact that support for the Democratic, or Republican, mayoral candidate in 1937 has on 2016 voter identification, shown by Y_i. The model is indexed by precinct. I estimate this model to check whether the results are robust when using different outcome measures. This is because some may be concerned that the first difference ΔY_i in the main models do not use perfectly analogous measures of party support. The results remain largely the same under both specifications. I use the pseudo-panel in the main models because it allows for a temporal dimension to be estimated, rather than simply examining current trends in partisanship. Merely examining modern partisanship may obscure pretreatment trends that may confound the results. Including the term $\lambda Supp1937_i$ controls for this possibility, but generating unconfounded estimates requires that the functional form is specified correctly. By taking a first difference, I account for this possible source of bias directly.

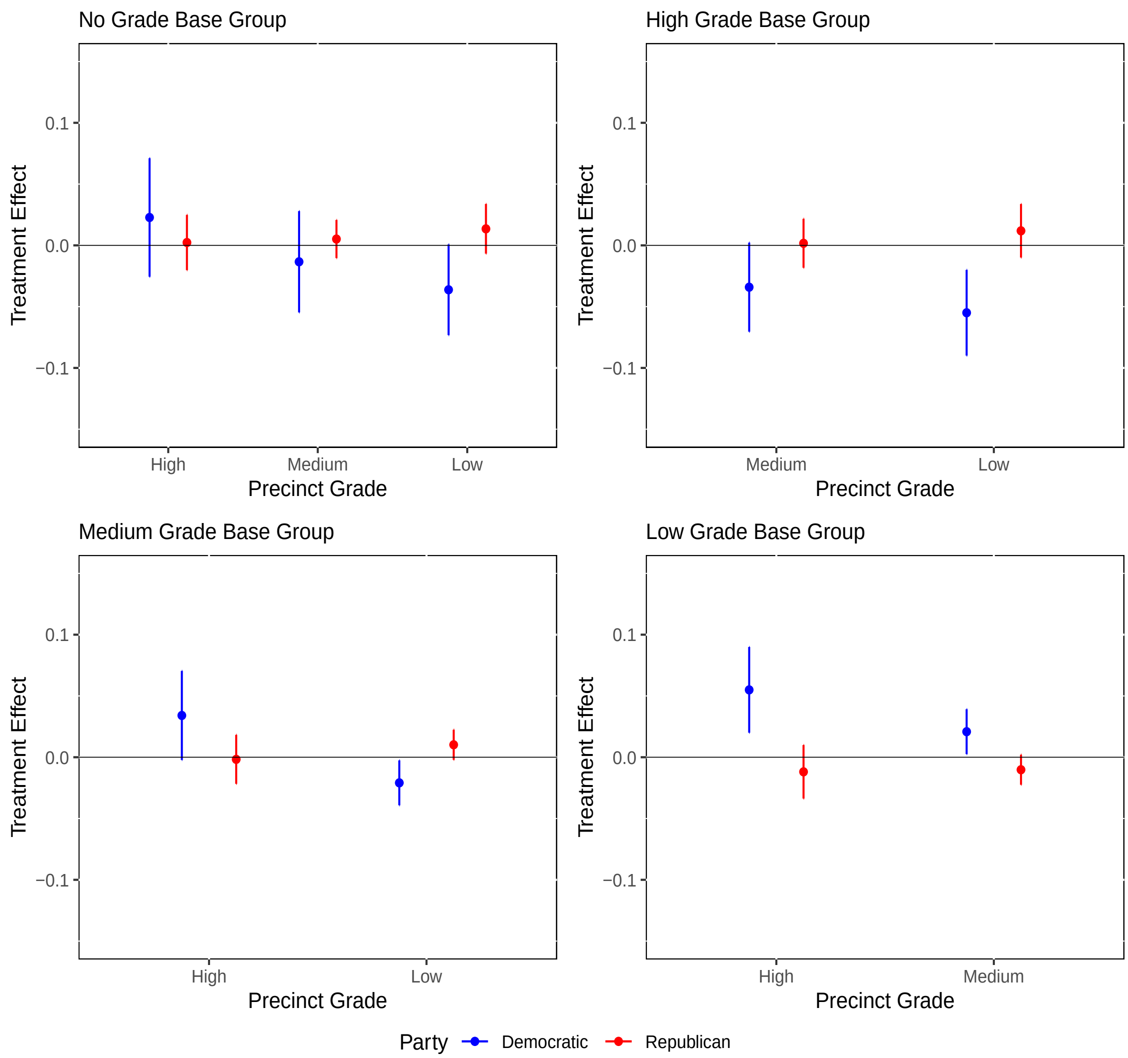


Figure 3.12: Change in support for Democrats and Republicans is heterogeneous by HOLC grade. “No Grade Base Group” compares precincts graded high, medium, or low to those that did not receive a grade; “High Grade Base Group” compares precincts zoned medium or low to those with a high grade; “Medium Grade Base Group” compares precincts graded high or low to those with a medium grade; and, “Low Grade Base Group” compares precincts graded high or medium to those with a low grade. All comparisons are made between precincts that received one HOLC grade, or to ungraded precincts (i.e., “No Grade Base Group”). “High” grade precincts are zoned graded A or B, “Medium grade” precincts are graded C, and “Low” grade precincts are graded D. All treatment effects are estimated using models with full controls and fixed effects. The dependent variable is the percentage of a precinct that is registered as Democrat or Republican in 2016. 95% confidence intervals are provided. Standard errors are clustered by HOLC zone.

Table 3.10: Change in Party Support - No Grade Base and Lagged Dependent Variable

	Democrat Δ			*Republican* Δ		
High Grade	0.10***	0.01	0.02	−0.02**	0.02	0.002
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Medium Grade	0.09***	−0.02	−0.01	−0.04***	0.02	0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Low Grade	0.07***	−0.05**	−0.04*	−0.03***	0.02*	0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
SES Index		−0.001**	−0.001**		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Family Size		0.02***	0.02***		−0.000	−0.002
		(0.01)	(0.01)		(0.002)	(0.002)
Dwelling Size		0.000*	0.000*		−0.000	−0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Age		0.000	−0.000		0.000	0.001
		(0.001)	(0.001)		(0.001)	(0.000)
Unemployed		−0.000	−0.000		−0.000	−0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Veterans		−0.000	0.000		0.001***	0.000*
		(0.000)	(0.000)		(0.000)	(0.000)
Farming		−0.000	−0.000		0.000***	0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
Total Population		−0.001	−0.001		0.001*	0.001
		(0.001)	(0.001)		(0.000)	(0.000)
White		0.001	0.001		−0.001*	−0.001
		(0.001)	(0.001)		(0.000)	(0.000)
Mexican		0.001	0.001		−0.001*	−0.001
		(0.001)	(0.001)		(0.000)	(0.000)
Black		0.001	0.001		−0.001**	−0.001*
		(0.001)	(0.001)		(0.000)	(0.000)
Japanese		0.000	0.000		−0.001	−0.001
		(0.001)	(0.001)		(0.000)	(0.000)
Chinese		0.000	0.000		−0.001	−0.001
		(0.001)	(0.001)		(0.000)	(0.001)
Rent (1930)		−0.000	−0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
House Value (1930)		−0.000	−0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)

Change in Party Support - No Grade Base (Continued) and Lagged Dependent Variable

% Graded		0.10***	0.09***		−0.03***	−0.02**
		(0.02)	(0.02)		(0.01)	(0.01)
Elevation (mean)		−0.000***	−0.000***		0.000***	0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
Dem. Cand.		0.000	0.000			
		(0.000)	(0.000)			
Rep. Cand.					0.000	0.000
					(0.000)	(0.000)
FEs			✓			✓
N	1,691	1,670	1,670	1,691	1,670	1,670
R^2	0.06	0.27	0.28	0.03	0.28	0.31
Adj. R^2	0.06	0.26	0.27	0.03	0.27	0.30
Resid. Std. Err.	0.10	0.09	0.09	0.13	0.05	0.05
F Stat.	38.94***	28.71***	26.51***	20.24***	29.96***	31.25***

[a] *p < .1; **p < .05; ***p < .01

[b] The dependent variable is the percentage of a precinct that identifies as Democrat or Republican, as of 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that received no HOLC grade. Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.11: Change in Party Support - High Grade Base and Lagged Dependent Variable

	Democrat Δ			*Republican* Δ		
Medium Grade	−0.011	−0.028	−0.034*	−0.015	−0.002	0.002
	(0.021)	(0.018)	(0.019)	(0.012)	(0.010)	(0.010)
Low Grade	−0.027	−0.049***	−0.055***	−0.011	0.008	0.012
	(0.022)	(0.017)	(0.018)	(0.013)	(0.012)	(0.011)
SES Index		−0.001	−0.001		0.0002	0.0003
		(0.0004)	(0.0004)		(0.0003)	(0.0002)
Family Size		0.018***	0.020***		−0.001	−0.002
		(0.006)	(0.006)		(0.002)	(0.002)
Dwelling Size		−0.001	−0.001		0.00004	0.00002
		(0.001)	(0.001)		(0.0003)	(0.0003)
Age		−0.0002	−0.001		0.0004	0.001*
		(0.001)	(0.001)		(0.001)	(0.0005)
Unemployed		−0.0002	−0.0002		−0.0002**	−0.0002**
		(0.0002)	(0.0002)		(0.0001)	(0.0001)
Veterans		−0.0003	−0.00005		0.0005***	0.0002
		(0.0003)	(0.0003)		(0.0002)	(0.0002)
Farming		−0.00000	−0.0001		0.0003	0.0003*
		(0.0002)	(0.0003)		(0.0002)	(0.0002)
Total Population		−0.001	−0.001		0.001	0.0003
		(0.001)	(0.001)		(0.0004)	(0.0004)
White		0.001*	0.001		−0.001	−0.0003
		(0.001)	(0.001)		(0.0005)	(0.0004)
Mexican		0.001	0.001		−0.001	−0.0003
		(0.001)	(0.001)		(0.0004)	(0.0004)
Black		0.002*	0.001		−0.001	−0.0004
		(0.001)	(0.001)		(0.0005)	(0.0004)
Japanese		0.001	0.001		−0.001	−0.0003
		(0.001)	(0.001)		(0.0005)	(0.0004)
Chinese		0.001	0.001		−0.0004	−0.0002
		(0.001)	(0.001)		(0.0004)	(0.0004)
Rent (1930)		−0.00002	−0.00002		0.00001	0.00001
		(0.00002)	(0.00002)		(0.00002)	(0.00002)
House Value (1930)		−0.00000	−0.00000		0.00000	0.00000
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
% Graded		0.092***	0.082***		−0.036***	−0.025**
		(0.022)	(0.022)		(0.013)	(0.010)

Change in Party Support - High Grade Base (Continued) and Lagged Dependent Variable

Elevation (mean)		-0.0004^{***}	-0.001^{***}		0.0003^{***}	0.0004^{***}
		(0.0001)	(0.0001)		(0.00005)	(0.00004)
Dem. Cand.		0.0004^{*}	0.0004^{**}			
		(0.0002)	(0.0002)			
Rep. Cand.					0.0001	0.0001
					(0.0001)	(0.0001)
FEs			✓			✓
N	1,525	1,512	1,512	1,525	1,512	1,512
R^2	0.01	0.25	0.27	0.01	0.25	0.30
Adj. R^2	0.01	0.24	0.26	0.01	0.23	0.29
Resid. Std. Err.	0.10	0.10	0.08	0.05	0.04	0.04
F Stat.	7.23^{***}	25.12^{***}	23.53^{***}	4.83^{***}	24.19^{***}	27.24^{***}

[a] $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

[b] The dependent variable is the percentage of a precinct that identifies as Democrat or Republican, as of 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that received a high HOLC grade (A and B grades). Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.12: Change in Party Support - Medium Grade Base and Lagged Dependent Variable

	Democrat Δ			*Republican* Δ		
High Grade	0.011	0.028	0.034*	0.015	0.002	−0.002
	(0.021)	(0.018)	(0.019)	(0.012)	(0.010)	(0.010)
Low Grade	−0.017	−0.021**	−0.021**	0.004	0.010	0.010
	(0.019)	(0.010)	(0.009)	(0.011)	(0.007)	(0.006)
SES Index		−0.001	−0.001		0.0002	0.0003
		(0.0004)	(0.0004)		(0.0003)	(0.0002)
Family Size		0.018***	0.020***		−0.001	−0.002
		(0.006)	(0.006)		(0.002)	(0.002)
Dwelling Size		−0.001	−0.001		0.00004	0.00002
		(0.001)	(0.001)		(0.0003)	(0.0003)
Age		−0.0002	−0.001		0.0004	0.001*
		(0.001)	(0.001)		(0.001)	(0.0005)
Unemployed		−0.0002	−0.0002		−0.0002**	−0.0002**
		(0.0002)	(0.0002)		(0.0001)	(0.0001)
Veterans		−0.0003	−0.00005		0.0005***	0.0002
		(0.0003)	(0.0003)		(0.0002)	(0.0002)
Farming		−0.00000	−0.0001		0.0003	0.0003*
		(0.0002)	(0.0003)		(0.0002)	(0.0002)
Total Population		−0.001	−0.001		0.001	0.0003
		(0.001)	(0.001)		(0.0004)	(0.0004)
White		0.001*	0.001		−0.001	−0.0003
		(0.001)	(0.001)		(0.0005)	(0.0004)
Mexican		0.001	0.001		−0.001	−0.0003
		(0.001)	(0.001)		(0.0004)	(0.0004)
Black		0.002*	0.001		−0.001	−0.0004
		(0.001)	(0.001)		(0.0005)	(0.0004)
Japanese		0.001	0.001		−0.001	−0.0003
		(0.001)	(0.001)		(0.0005)	(0.0004)
Chinese		0.001	0.001		−0.0004	−0.0002
		(0.001)	(0.001)		(0.0004)	(0.0004)
Rent (1930)		−0.00002	−0.00002		0.00001	0.00001
		(0.00002)	(0.00002)		(0.00002)	(0.00002)
House Value (1930)		−0.00000	−0.00000		0.00000	0.00000
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
% Graded		0.092***	0.082***		−0.036***	−0.025**

Change in Party Support - Medium Grade Base (Continued) and Lagged Dependent Variable

		(0.022)	(0.022)		(0.013)	(0.010)
Elevation (mean)		-0.0004^{***}	-0.001^{***}		0.0003^{***}	0.0004^{***}
		(0.0001)	(0.0001)		(0.00005)	(0.00004)
Dem. Cand.		0.0004^{*}	0.0004^{**}			
		(0.0002)	(0.0002)			
Rep. Cand.					0.0001	0.0001
					(0.0001)	(0.0001)
FEs			✓			✓
N	1,525	1,512	1,512	1,525	1,512	1,512
R^2	0.10	026	0.27	0.01	0.25	0.30
Adj. R^2	0.01	0.24	0.26	0.01	0.23	0.29
Resid. Std. Err.	0.10	0.08	0.08	0.05	0.04	0.04
F Stat.	7.23^{***}	25.12^{***}	23.53^{***}	4.84^{***}	24.19^{***}	27.24^{***}

[a] *p < .1; **p < .05; ***p < .01
[b] The dependent variable is the percentage of a precinct that identifies as Democrat or Republican, as of 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct *i* is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that received a medium HOLC grade (C grade). Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.13: Change in Party Support - Low Grade Base and Lagged Dependent Variable

	Democrat Δ			*Republican* Δ		
High Grade	0.027	0.049***	0.055***	0.011	−0.008	−0.012
	(0.022)	(0.017)	(0.018)	(0.013)	(0.012)	(0.011)
Medium Grade	0.017	0.021**	0.021**	−0.004	−0.010	−0.010
	(0.019)	(0.010)	(0.009)	(0.011)	(0.007)	(0.006)
SES Index		−0.001	−0.001		0.0002	0.0003
		(0.0004)	(0.0004)		(0.0003)	(0.0002)
Family Size		0.018***	0.020***		−0.001	−0.002
		(0.006)	(0.006)		(0.002)	(0.002)
Dwelling Size		−0.001	−0.001		0.00004	0.00002
		(0.001)	(0.001)		(0.0003)	(0.0003)
Age		−0.0002	−0.001		0.0004	0.001*
		(0.001)	(0.001)		(0.001)	(0.0005)
Unemployed		−0.0002	−0.0002		−0.0002**	−0.0002**
		(0.0002)	(0.0002)		(0.0001)	(0.0001)
Veterans		−0.0003	−0.00005		0.0005***	0.0002
		(0.0003)	(0.0003)		(0.0002)	(0.0002)
Farming		−0.00000	−0.0001		0.0003	0.0003*
		(0.0002)	(0.0003)		(0.0002)	(0.0002)
Total Population		−0.001	−0.001		0.001	0.0003
		(0.001)	(0.001)		(0.0004)	(0.0004)
White		0.001*	0.001		−0.001	−0.0003
		(0.001)	(0.001)		(0.0005)	(0.0004)
Mexican		0.001	0.001		−0.001	−0.0003
		(0.001)	(0.001)		(0.0004)	(0.0004)
Black		0.002*	0.001		−0.001	−0.0004
		(0.001)	(0.001)		(0.0005)	(0.0004)
Japanese		0.001	0.001		−0.001	−0.0003
		(0.001)	(0.001)		(0.0005)	(0.0004)
Chinese		0.001	0.001		−0.0004	−0.0002
		(0.001)	(0.001)		(0.0004)	(0.0004)
Rent (1930)		−0.00002	−0.00002		0.00001	0.00001
		(0.00002)	(0.00002)		(0.00002)	(0.00002)
House Value (1930)		−0.00000	−0.00000		0.00000	0.00000
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
% Graded		0.092***	0.082***		−0.036***	−0.025**
		(0.022)	(0.022)		(0.013)	(0.010)

Change in Party Support - Low Grade Base (Continued) and Lagged Dependent Variable

Elevation (mean)		−0.0004***	−0.001***		0.0003***	0.0004***
		(0.0001)	(0.0001)		(0.00005)	(0.00004)
Dem. Cand.		0.0004*	0.0004**			
		(0.0002)	(0.0002)			
Rep. Cand.					0.0001	0.0001
					(0.0001)	(0.0001)
FEs			✓			✓
N	1,525	1,512	1,512	1,525	1,512	1,512
R^2	0.01	0.25	0.27	0.01	0.25	0.30
Adj. R^2	0.01	0.24	0.26	0.01	0.23	0.29
Resid. Std. Err.	0.10	0.10	0.10	0.05	0.04	0.04
F Stat.	7.23***	25.12***	23.53***	4.84***	24.19***	27.24***

[a] *p < .1; **p < .05; ***p < .01
[b] The dependent variable is the percentage of a precinct that identifies as Democrat or Republican, as of 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that received a low HOLC grade (D grade). Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Pseudo-Panel Using Continuous Treatment

Here I provide models using a continuous measure of treatment. The measure is calculated by taking the average HOLC grade for precinct i. HOLC grades are scored between 1 and 4, with higher grade areas receiving a lower numeric score (e.g., “A” grades are scored as 1), and lower grade areas receiving a higher numeric score (e.g., “D” grades are scored as 4). Two measures are calculated: the weighted and unweighted average HOLC grade for precinct i. The former is weighted by the total area of a precinct that is covered by a particular HOLC grade. This gives more weight to grades that cover a larger area, and less weight to grades that cover a small area. The unweighted measure is simply the arithmetic average HOLC grade for precinct i. The outcome measure in these models is the same as used in the main pseudo-panel models.

As is shown, precincts graded worse (i.e., having a higher average HOLC score) experience smaller over-time increases in support for Democrats. Support for Republicans is unchanged. The results are consistent when using the weighted and unweighted measures.

	Democrat Δ			Republican Δ		
	(1)	(2)	(3)	(4)	(5)	(6)
HOLC Score	−0.002	−0.004	−0.022***	−0.015	−0.010	0.004
	(0.022)	(0.009)	(0.008)	(0.019)	(0.008)	(0.007)
SES Index		0.001*	0.001		−0.001**	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.022***	0.021***		−0.004	−0.004
		(0.007)	(0.007)		(0.005)	(0.005)
Dwelling Size		0.0003	0.0004		−0.001*	−0.001**
		(0.001)	(0.001)		(0.001)	(0.0005)
Age		0.001	−0.0004		−0.001	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Unemployed		−0.001	−0.001*		0.0004	0.0004
		(0.0004)	(0.0004)		(0.0003)	(0.0004)
Total Population		−0.002	−0.002		0.0005	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
White		0.002	0.002		−0.0005	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		0.002	0.002		−0.001	−0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.003**	0.003**		−0.002	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		0.002	0.002		−0.0004	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.003*	0.002*		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
House Value		0.00000***	0.00000***		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
FEs			✓			✓
N	2,145	2,133	2,133	2,145	2,133	2,133
R^2	0.0001	0.196	0.250	0.007	0.236	0.284
Adj. R^2	−0.0004	0.191	0.244	0.007	0.232	0.278
F Stat.	0.112	39.728***	44.109***	15.194***	50.458***	52.414***

*p < .1; **p < .05; ***p < .01. Coefficients are interpreted as percentage point change in support for Democrats or Republicans between 1937 and 2016. SES Index, Family Size, Dwelling Size, Age, and House Value use medians. FEs correspond precinct-district fixed effects. HOLC Score is the average HOLC grade for precinct *i*, weighted by the percentage of total precinct area that a HOLC grade covers. Regressions include units receiving at least one HOLC grade. Standard errors are clustered by HOLC zone.

Table 3.14: Change in Party Support (Weighted Continuous Treatment)

	Democrat Δ			Republican Δ		
	(1)	(2)	(3)	(4)	(5)	(6)
HOLC Score	0.002	−0.001	−0.021**	−0.019	−0.014	0.002
	(0.024)	(0.010)	(0.009)	(0.021)	(0.009)	(0.008)
SES Index		0.001*	0.001		−0.001**	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.023***	0.022***		−0.005	−0.004
		(0.007)	(0.007)		(0.005)	(0.005)
Dwelling Size		0.0003	0.0004		−0.001*	−0.001**
		(0.001)	(0.001)		(0.001)	(0.0005)
Age		0.001	−0.0003		−0.001	0.0001
		(0.001)	(0.001)		(0.001)	(0.001)
Unemployed		−0.001*	−0.001*		0.0004	0.0005
		(0.0004)	(0.0004)		(0.0003)	(0.0004)
Total Population		−0.002	−0.002		0.001	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
White		0.002	0.002		−0.0005	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		0.002	0.002		−0.001	−0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.003**	0.003**		−0.002	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		0.002	0.002		−0.0005	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.003*	0.002*		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
House Value		0.00000***	0.00000***		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
FEs			✓			✓
N	2,145	2,133	2,133	2,145	2,133	2,133
R^2	0.0001	0.196	0.249	0.010	0.238	0.284
Adjusted R^2	−0.0004	0.191	0.243	0.009	0.233	0.278
F Statistic	0.140	39.676***	43.733***	21.496***	50.845***	52.333***

*p < .1; **p < .05; ***p < .01. Coefficients are interpreted as percentage point change in support for Democrats or Republicans between 1937 and 2016. SES Index, Family Size, Dwelling Size, Age, and House Value use medians. FEs correspond precinct-district fixed effects. HOLC Score is the average HOLC grade for precinct i, weighted by the percentage of total precinct area that a HOLC grade covers. Regressions include units receiving at least one HOLC grade. Standard errors are clustered by HOLC zone.

Table 3.15: Change in Party Support (Unweighted Continuous Treatment)

Pseudo-Panel Using Alphabetic HOLC Grades

This section replicates the main analyses, but with the original HOLC scores. In this setup, I do not combine "A" and "B" zones into the same group.

Table 3.16: Change in Party Support - No Grade Base

	Democrat Δ			*Republican* Δ		
A Precinct	−0.049	−0.056	−0.015	0.100**	0.090**	0.054**
	(0.043)	(0.042)	(0.026)	(0.043)	(0.039)	(0.027)
B Precinct	0.151***	0.135***	0.124***	−0.070***	−0.060***	−0.049**
	(0.023)	(0.029)	(0.027)	(0.018)	(0.023)	(0.022)
C Precinct	0.081***	0.077***	0.047***	−0.028***	−0.034**	−0.008
	(0.015)	(0.018)	(0.016)	(0.011)	(0.015)	(0.014)
D Precinct	0.106**	0.072***	0.032*	−0.066*	−0.046***	−0.011
	(0.043)	(0.021)	(0.019)	(0.037)	(0.017)	(0.015)
SES Index		0.001	−0.0003		−0.001*	−0.0004
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.020**	0.024***		−0.001	−0.005
		(0.008)	(0.008)		(0.006)	(0.006)
Dwelling Size		0.001***	0.0004*		−0.0003	−0.0001
		(0.0002)	(0.0002)		(0.0002)	(0.0003)
Age		0.001	0.001		−0.001	−0.001
		(0.002)	(0.002)		(0.001)	(0.001)
Unemployed		−0.0003	−0.001**		0.0002	0.0004
		(0.0003)	(0.0003)		(0.0002)	(0.0002)
Total Population		0.00001	−0.00002		−0.0001	−0.0001
		(0.001)	(0.001)		(0.001)	(0.001)
White		−0.00002	0.00003		0.0001	0.0001
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		0.00002	0.00004		−0.00002	0.00001
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.001	0.001		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		−0.0001	−0.0001		0.00005	0.0001
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.0002	0.0001		−0.0004	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
House Value		0.00000**	0.00000		−0.00000***	−0.00000***

Change in Party Support - No Grade Base (Continued)

		(0.00000)	(0.00000)		(0.00000)	(0.00000)
FEs			✓			✓
N	1,686	1,670	1,670	1,686	1,670	1,670
R^2	0.051	0.253	0.305	0.037	0.310	0.373
Adj. R^2	0.048	0.246	0.297	0.035	0.303	0.366
F Stat.	22.364***	35.046***	38.033***	16.349***	46.315***	51.714***

[a] *p < .1; **p < .05; ***p < .01
[b] The dependent variable is the percentage of a precinct that identifies as Democrat or Republican, as of 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that did not receive a HOLC grade. Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.17: Change in Party Support - A Grade Base

	Democrat Δ			*Republican* Δ		
B Precinct	0.200***	0.191***	0.126***	−0.170***	−0.159***	−0.108***
	(0.049)	(0.051)	(0.037)	(0.046)	(0.043)	(0.033)
C Precinct	0.130***	0.136***	0.050*	−0.128***	−0.132***	−0.065**
	(0.046)	(0.045)	(0.030)	(0.044)	(0.039)	(0.029)
D Precinct	0.155**	0.133***	0.035	−0.166***	−0.141***	−0.064*
	(0.061)	(0.047)	(0.034)	(0.057)	(0.042)	(0.033)
SES Index		0.001	−0.0002		−0.001	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.024***	0.023**		−0.004	−0.004
		(0.009)	(0.009)		(0.007)	(0.007)
Dwelling Size		0.00003	0.00003		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.0005)
Age		0.002	0.001		−0.001	−0.001
		(0.002)	(0.002)		(0.001)	(0.001)
Unemployed		−0.001	−0.001*		0.0003	0.0004
		(0.0004)	(0.0004)		(0.0004)	(0.0004)
Total Population		−0.001	−0.001		0.0002	−0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
White		0.001	0.001		−0.0001	0.0004
		(0.001)	(0.001)		(0.001)	(0.001)

Change in Party Support - A Grade Base (Continued)

Mexican		0.001	0.001		−0.0003	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.003**	0.002*		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		0.001	0.001		−0.0002	0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.002	0.001		−0.001	−0.00003
		(0.001)	(0.001)		(0.001)	(0.001)
House Value		0.00000**	0.00000		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
FEs			✓			✓
N	1,521	1,512	1,512	1,521	1,512	1,512
R^2	0.023	0.252	0.299	0.032	0.306	0.355
Adj. R^2	0.021	0.245	0.291	0.030	0.300	0.347
F Stat.	11.661***	33.669***	35.386***	16.457***	44.078***	45.615***

[a] *p < .1; **p < .05; ***p < .01
[b] The dependent variable is the percentage of a precinct that identifies as Democrat or Republican, as of 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that did not receive a HOLC grade. Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.18: Change in Party Support - B Grade Base

	Democrat Δ			*Republican* Δ		
A Precinct	−0.200***	−0.191***	−0.126***	0.170***	0.159***	0.108***
	(0.049)	(0.051)	(0.037)	(0.046)	(0.043)	(0.033)
C Precinct	−0.070**	−0.056**	−0.076***	0.042**	0.027	0.043**
	(0.028)	(0.028)	(0.026)	(0.021)	(0.021)	(0.019)
D Precinct	−0.045	−0.058**	−0.091***	0.004	0.018	0.045**
	(0.048)	(0.028)	(0.026)	(0.041)	(0.023)	(0.021)
SES Index		0.001	−0.0002		−0.001	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.024***	0.023**		−0.004	−0.004
		(0.009)	(0.009)		(0.007)	(0.007)
Dwelling Size		0.00003	0.00003		−0.001	−0.001

Change in Party Support - B Grade Base

		(0.001)	(0.001)		(0.001)	(0.0005)
Age		0.002	0.001		−0.001	−0.001
		(0.002)	(0.002)		(0.001)	(0.001)
Unemployed		−0.001	−0.001*		0.0003	0.0004
		(0.0004)	(0.0004)		(0.0004)	(0.0004)
Total Population		−0.001	−0.001		0.0002	−0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
White		0.001	0.001		−0.0001	0.0004
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		0.001	0.001		−0.0003	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.003**	0.002*		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		0.001	0.001		−0.0002	0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.002	0.001		−0.001	−0.00003
		(0.001)	(0.001)		(0.001)	(0.001)
House Value		0.00000**	0.00000		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
FEs			✓			✓
N	1,521	1,512	1,512	1,521	1,512	1,512
R^2	0.023	0.252	0.299	0.032	0.306	0.355
Adj. R^2	0.021	0.245	0.291	0.030	0.300	0.347
F Stat.	11.661***	33.669***	35.386***	16.457***	44.078***	45.615***

[a] *p < .1; **p < .05; ***p < .01
[b] The dependent variable is the percentage of a precinct that identifies as Democrat or Republican, as of 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that did not receive a HOLC grade. Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.19: Change in Party Support - C Grade Base

	Democrat Δ			*Republican* Δ		
A Precinct	−0.130***	−0.136***	−0.050*	0.128***	0.132***	0.065**
	(0.046)	(0.045)	(0.030)	(0.044)	(0.039)	(0.029)

Change in Party Support - C Grade Base

B Precinct	0.070**	0.056**	0.076***	−0.042**	−0.027	−0.043**
	(0.028)	(0.028)	(0.026)	(0.021)	(0.021)	(0.019)
D Precinct	0.025	−0.002	−0.015	−0.038	−0.009	0.002
	(0.045)	(0.020)	(0.018)	(0.039)	(0.018)	(0.016)
SES Index		0.001	−0.0002		−0.001	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.024***	0.023**		−0.004	−0.004
		(0.009)	(0.009)		(0.007)	(0.007)
Dwelling Size		0.00003	0.00003		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.0005)
Age		0.002	0.001		−0.001	−0.001
		(0.002)	(0.002)		(0.001)	(0.001)
Unemployed		−0.001	−0.001*		0.0003	0.0004
		(0.0004)	(0.0004)		(0.0004)	(0.0004)
Total Population		−0.001	−0.001		0.0002	−0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
White		0.001	0.001		−0.0001	0.0004
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		0.001	0.001		−0.0003	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.003**	0.002*		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		0.001	0.001		−0.0002	0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.002	0.001		−0.001	−0.00003
		(0.001)	(0.001)		(0.001)	(0.001)
House Value		0.00000**	0.00000		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
FEs			✓			✓
N	1,521	1,512	1,512	1,521	1,512	1,512
R^2	0.023	0.252	0.299	0.032	0.306	0.355
Adj. R^2	0.021	0.245	0.291	0.030	0.300	0.347
F Stat.	11.661***	33.669***	35.386***	16.457***	44.078***	45.615***

[a] *p < .1; **p < .05; ***p < .01

[b] The dependent variable is the percentage of a precinct that identifies as Democrat or Republican, as of 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct i is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that did not receive a HOLC grade. Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Table 3.20: Change in Party Support - D Grade Base

	Democrat Δ			*Republican* Δ		
A Precinct	−0.155**	−0.133***	−0.035	0.166***	0.141***	0.064*
	(0.061)	(0.047)	(0.034)	(0.057)	(0.042)	(0.033)
B Precinct	0.045	0.058**	0.091***	−0.004	−0.018	−0.045**
	(0.048)	(0.028)	(0.026)	(0.041)	(0.023)	(0.021)
C Precinct	−0.025	0.002	0.015	0.038	0.009	−0.002
	(0.045)	(0.020)	(0.018)	(0.039)	(0.018)	(0.016)
SES Index		0.001	−0.0002		−0.001	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Family Size		0.024***	0.023**		−0.004	−0.004
		(0.009)	(0.009)		(0.007)	(0.007)
Dwelling Size		0.00003	0.00003		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.0005)
Age		0.002	0.001		−0.001	−0.001
		(0.002)	(0.002)		(0.001)	(0.001)
Unemployed		−0.001	−0.001*		0.0003	0.0004
		(0.0004)	(0.0004)		(0.0004)	(0.0004)
Total Population		−0.001	−0.001		0.0002	−0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
White		0.001	0.001		−0.0001	0.0004
		(0.001)	(0.001)		(0.001)	(0.001)
Mexican		0.001	0.001		−0.0003	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Black		0.003**	0.002*		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Japanese		0.001	0.001		−0.0002	0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
Chinese		0.002	0.001		−0.001	−0.00003
		(0.001)	(0.001)		(0.001)	(0.001)
House Value		0.00000**	0.00000		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
FEs			✓			✓
N	1,521	1,512	1,512	1,521	1,512	1,512
R^2	0.023	0.252	0.299	0.032	0.306	0.355
Adj. R^2	0.021	0.245	0.291	0.030	0.300	0.347
F Stat.	11.661***	33.669***	35.386***	16.457***	44.078***	45.615***

Change in Party Support - D Grade Base

[a] *p < .1; **p < .05; ***p < .01

[b] The dependent variable is the percentage of a precinct that identifies as Democrat or Republican, as of 2016. SES Index, Family Size, Dwelling Size, Age, Rent (1930) and House Value (1930) use medians. FEs represent whether precinct *i* is in the Central, Harbor, San Fernando, or Western precinct district. The base group is precincts that did not receive a HOLC grade. Standard errors (in parentheses) are clustered by the HOLC zone that a precinct is intersected by.

Geographic Regression Discontinuity Sample Characteristics

This section shows various sample and descriptive characteristics for the samples used to estimate the GRD models. These statistics are calculated on 1930 Census and 2016 voter file units in the 5-degree border sample, the sample used to estimate the GRD using all HOLC borders, and for each unit in the Census and voter file datasets.

	1	**2**	**3**
Total Population	75,510	365,363	2,209,547
White	69,948	345,917	1,950,134
	92.6%	*94.7%*	*88.3%*
Black	1,658	3,953	46,533
	2.2%	*1.1%*	*2.1%*
Mexican	2,565	10,793	167,268
	3.4%	*3.0%*	*7.6%*
Asian	1,290	4,434	43,930
	1.7%	*1.2%*	*2.0%*
Veterans	4,370	22,101	122,985
	5.8%	*6.0%*	*5.6%*
Age (median)	33	33	32
Occupation Score (1950)	465	467	511
SEI	42	42	37
Dwelling Size (median)	3	3	3
Number of Families	1.3	1.2	1.2
House Value (median)	7,000	6,650	6,000
1930 Rent (median)	35	35	32
Family Size	2.9	2.9	2.9
Number of Children	0.4	0.4	0.4

Presented are 1930 Census sample characteristics. Column 1 corresponds to units who are within 200 meters of a HOLC zone, and who are in the 5-degree sample. Column 2 corresponds to all units within 200 meters of a HOLC zone. Column 3 corresponds to all units in the 1930 Census for Los Angeles County. Where relevant, percentages are listed in italics. Unless otherwise noted, raw counts or means are calculated. Statistics for dwelling size, number of families, house value, 1930 rent, family size, and number of children are calculated for unique households. Due to rounding, percentages may not sum to 100.

Table 3.21: 1930 Census Sample Descriptions

	200 Meter + 5-degree				**200 Meter**			
	A	**B**	**C**	**D**	**A**	**B**	**C**	**D**
Total Population	4,550	20,243	32,953	17,764	14,953	97,809	170,960	81,641
White	4,386	19,844	31,462	14,256	14,337	95,701	164,441	71,438
	96.4%	*98.0%*	*95.5%*	*80.2%*	*95.9%*	*97.8%*	*96.2%*	*87.5%*
Black	83	108	185	1,282	227	603	986	2,137
	1.8%	*0.5%*	*0.6%*	*7.2%*	*1.5%*	*0.6%*	*0.6%*	*2.6%*
Mexican	53	176	910	1,426	272	926	3,772	5,823
	1.2%	*0.9%*	*2.8%*	*8.0%*	*1.8%*	*0.9%*	*2.2%*	*7.1%*
Asian	24	103	375	788	107	522	1,651	2,154
	0.5%	*0.5%*	*1.1%*	*4.4%*	*0.7%*	*0.5%*	*0.9%*	*2.6%*
Veterans	286	1,234	1,888	962	980	6,327	10,237	4,557
	6.3%	*6.1%*	*5.7%*	*5.4%*	*6.6%*	*6.5%*	*6.0%*	*5.6%*
Age (median)	35	34	33	32	34	33	33	31
Occupation Score (1950)	427	430	457	520	448	435	462	514
SEI	46	46	42	36	44	45	42	37
Dwelling Size (median)	3	3	3	3	3	3	3	3
Number of Families	1.4	1.2	1.3	1.3	1.3	1.2	1.2	1.3
House Value (median)	14,000	8,000	6,000	5,500	12,500	8,000	6,000	5,000
1930 Rent (median)	50	40	35	32	45	40	35	32
Family Size	3.1	3	2.8	2.7	3.1	3	2.8	2.8
Number of Children	0.5	0.5	0.4	0.4	0.5	0.5	0.4	0.4

Presented are 1930 Census sample characteristics. Column titled "200 Meters + 5-degree" corresponds to units who are within 200 meters of a HOLC zone, and who are in the 5-degree sample. Column titled "200 Meter" corresponds to all units within 200 meters of a HOLC zone. Where relevant, percentages are listed in italics. Unless otherwise noted, raw counts or means are calculated. Statistics for dwelling size, number of families, house value, 1930 rent, family size, and number of children are calculated for unique households. Due to rounding, percentages may not sum to 100.

Table 3.22: 1930 Census Sample Descriptions By HOLC Grade

Grade	**1**	**2**
A	4,550	14,953
	6.0%	*4.0%*
B	20,243	97,809
	27.0%	*27.0%*
C	32,953	170,960
	44.0%	*47.0%*
D	17,764	81,641
	24.0%	*22.0%*
Total	75,510	365,363

Shown are HOLC grade breakdowns for Census units. Each row shows the number of Census units in each sample that are within that HOLC zone. Column 1 corresponds to units who are within 200 meters of a HOLC zone, and who are in the 5-degree sample. Column 2 corresponds to all units within 200 meters of a HOLC zone. Percentages are provided in italics. Due to rounding, percentages may not sum to 100.

Table 3.23: HOLC Grades By Census Sample

Grade	**1**	**2**
A	7,406	28,325
	12.03%	*8.14%*
B	19,548	105,226
	31.75%	*30.23%*
C	26,337	159,217
	42.78%	*45.74%*
D	82,80	55,341
	13.45%	*15.90%*
Total	61,571	348,109

Shown are HOLC grade breakdowns for voter file units. Each row shows the number of voters in each sample that are within that HOLC zone. Column 1 corresponds to voters who are in the 5-degree sample. Column 2 corresponds to all units within 200 meters of a HOLC zone. Percentages are provided in italics. Due to rounding, percentages may not sum to 100.

Table 3.24: HOLC Grades By Voter File Sample

Measure Type	Race	A	B	C	D
Continuous	White	72.34	66.26	57.28	49.88
	Black	9.32	9.26	9.17	11.61
	Hispanic and Latinx	9.60	16.14	24.16	29.91
	Asian	8.75	8.34	9.40	8.59
Dichotomous	White	78.62	71.12	59.87	50.29
	Black	4.39	4.39	4.79	7.77
	Hispanic and Latinx	8.39	16.41	26.24	33.54
	Asian	8.60	8.08	9.10	8.35

Shown are percentage HOLC grade breakdowns for voter file units. The sample used to estimate these quantities consists of voters in the 5-degree sample. The continuous measures show the mean probability that a voter is of that race, by HOLC grade. The dichotomous measure shows the percentage of all units in that HOLC grade that are a given race. For each dichotomous race measure, a voter is coded 1 if the probability that the voter is from that race is higher than all other races.

Table 3.25: Racial Breakdown of Voters in the 5-degree Sample By HOLC Grade

Measure Type	Race	A	B	C	D
Continuous	White	71.43	63.05	56.55	49.82
	Black	11.14	10.77	10.13	10.83
	Hispanic and Latinx	9.54	18.05	25.19	32.63
	Asian	7.89	8.14	8.13	6.72
Dichotomous	White	77.90	67.41	58.97	50.00
	Black	5.92	5.96	5.82	6.97
	Hispanic and Latinx	8.48	18.84	27.49	36.79
	Asian	7.69	7.78	7.71	6.22

Shown are percentage HOLC grade breakdowns for voter file units. The sample used to estimate these quantities consists of all voters within 200 meters of a HOLC zone. The continuous measures show the mean probability that a voter is of that race, by HOLC grade. The dichotomous measure shows the percentage of all units in that HOLC grade that are a given race. For each dichotomous race measure, a voter is coded 1 if the probability that the voter is from that race is higher than all other races.

Table 3.26: Racial Breakdown of All Voters Within 200 Meters of a HOLC Boundary By HOLC Grade

Measure Type	Race	1	2
Continuous	White	60.95	58.65
	Black	9.54	10.52
	Hispanic and Latinx	20.64	22.94
	Asian	8.88	7.89
Dichotomous	White	64.41	61.64
	Black	5.02	6.05
	Hispanic and Latinx	21.95	24.81
	Asian	8.61	7.49

Shown are percentage HOLC grade breakdowns for voter file units. Column 1 corresponds to voters who are in the 5-degree sample. Column 2 corresponds all voters within 200 meters of a HOLC zone. The continuous measures show the mean probability that a voter is of that race, by HOLC grade. The dichotomous measure shows the percentage of all units in that HOLC grade that are a given race. For each dichotomous race measure, a voter is coded 1 if the probability that the voter is from that race is higher than all other races.

Table 3.27: Racial Breakdown of Voters

Geographic Regression Discontinuity Balance Statistics

This section provides balance statistics for the samples used to estimate the GRD models. I report results from numerous balance tests using pretreatment 1930 Census data. Balance tests are conducted at varying distances from the cutpoint. The reader should pay attention to whether the null hypothesis of no difference between the treatment and control is rejected, and to whether the difference in means between the treatment and control group decreases as the distance threshold decreases. Balance tests for the 5-degree and full sample are provided in the same table for ease of comparison. Each table corresponds to balance tests using different comparison zones.

Table 3.28: Balance Statistics - AB Graded Zones

5-Degree Sample

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	0.92	0.03	1.58	0.00	1.90	0.00	1.58	0.05
Occupational Score	0.67	0.26	0.46	0.47	-0.27	0.72	-1.20	0.28
Duncan SEI Index	2.36	0.02	1.89	0.10	0.66	0.61	-1.66	0.39
Siegel Prestige	13.14	0.03	12.86	0.06	4.87	0.54	-8.52	0.47
Nam-Powers-Boyd	43.17	0.00	33.29	0.01	19.49	0.20	-6.01	0.78
Employed	0.01	0.46	0.01	0.21	0.02	0.21	0.02	0.27
Veterans	-0.00	0.83	-0.00	0.76	-0.00	0.85	0.01	0.53
White	0.02	0.00	0.03	0.00	0.01	0.00	-0.01	0.17
Black	-0.01	0.00	-0.01	0.00	-0.01	0.02	-0.00	0.68
Mexican	-0.01	0.00	-0.01	0.00	-0.00	0.24	0.01	0.02
Asian	-0.00	0.84	-0.00	0.44	-0.00	0.18	0.00	0.16
Family Size	-0.17	0.00	-0.25	0.00	-0.27	0.00	-0.45	0.00
# Children	-0.03	0.32	-0.06	0.11	-0.03	0.43	-0.06	0.31
# Families	-0.17	0.00	-0.14	0.00	-0.08	0.04	-0.04	0.41
Dwelling Size	-0.45	0.00	-0.49	0.00	-0.41	0.00	-0.51	0.00
House Value	-8238.90	0.00	-7722.84	0.00	-6699.95	0.00	-4950.80	0.08
Rent (1930)	22.39	0.41	39.25	0.28	36.89	0.42	27.83	0.66

Full Sample

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	0.93	0.00	0.86	0.00	0.87	0.00	-0.07	0.87
Occupational Score	0.80	0.01	0.61	0.08	0.17	0.69	-0.76	0.20
Duncan SEI Index	2.68	0.00	1.95	0.00	1.04	0.16	-0.78	0.46
Siegel Prestige	15.54	0.00	12.05	0.00	6.39	0.15	-3.13	0.61
Nam-Powers-Boyd	39.21	0.00	30.03	0.00	14.97	0.08	-11.44	0.34
Employed	0.00	0.61	0.01	0.37	0.01	0.07	0.03	0.01
Veterans	-0.00	0.10	-0.00	0.65	-0.00	0.73	0.00	0.75
White	0.02	0.00	0.02	0.00	0.01	0.00	-0.01	0.01
Black	-0.01	0.00	-0.01	0.00	-0.00	0.01	0.00	0.14
Mexican	-0.01	0.00	-0.01	0.00	-0.01	0.00	0.00	0.33
Asian	-0.00	0.08	-0.00	0.07	-0.00	0.35	0.00	0.02
Family Size	-0.08	0.01	-0.10	0.00	-0.15	0.00	-0.17	0.00

Balance Statistics - AB Graded Zones (Continued)

# Children	-0.02	0.36	-0.02	0.37	-0.02	0.41	-0.03	0.34
# Families	-0.12	0.00	-0.11	0.00	-0.08	0.01	0.02	0.65
Dwelling Size	-0.27	0.00	-0.27	0.00	-0.27	0.00	-0.15	0.06
House Value	-6400.45	0.00	-5927.90	0.00	-3548.02	0.00	-125.94	0.91
Rent (1930)	54.22	0.21	0.04	1.00	53.53	0.22	-59.48	0.40

[a] τ indicates difference-in-means; p provides corresponding p-value. Balance statistics for Family Size, # Children, # Families, Dwelling Size, House Value, and Rent (1930) are calculated using household-level unique values. All other statistics use person-level data. Balance statistics are calculated for units within 200, 150, 100, and 50 meters from a border. "Full Sample" includes all units within 200 meters from a border. "5-degree Sample" includes units within 200 meters of a border section whose acute angle is at least 5-degrees relative to the nearest road. Treated units are those in the lower grade HOLC zone (i.e., descending letter).

Table 3.29: Balance Statistics - AC Graded Zones

5-Degree Sample

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	1.08	0.31	3.30	0.02	6.16	0.00	6.76	0.00
Occupational Score	0.58	0.68	2.66	0.16	3.50	0.11	4.14	0.18
Duncan SEI Index	-0.32	0.90	0.07	0.98	1.98	0.60	3.17	0.52
Siegel Prestige	7.53	0.63	8.41	0.68	13.41	0.57	27.75	0.38
Nam-Powers-Boyd	29.61	0.29	41.72	0.26	51.88	0.21	43.52	0.45
Employed	0.01	0.64	-0.03	0.45	-0.01	0.80	-0.00	0.99
Veterans	-0.01	0.56	-0.01	0.58	-0.01	0.65	-0.02	0.48
White	0.00	0.54	-0.00	0.71	-0.00	0.90	-0.01	0.56
Black	-0.01	0.09	-0.00	0.59	-0.00	0.54	0.00	0.95
Mexican	0.00	0.32	0.00	-	0.00	-	0.00	-
Asian	-0.00	0.82	-0.00	1.00	0.00	0.94	0.00	0.95
Family Size	-0.09	0.55	-0.06	0.74	-0.16	0.42	-0.17	0.37
# Children	-0.08	0.29	-0.11	0.18	-0.09	0.28	-0.07	0.46
# Families	0.02	0.79	-0.09	0.20	-0.12	0.16	-0.14	0.16
Dwelling Size	-0.11	0.52	-0.20	0.36	-0.30	0.18	-0.29	0.23
House Value	-3084.19	0.16	-5342.70	0.06	-3638.57	0.33	3127.14	0.62
Rent (1930)	43.52	0.00	76.53	0.00	96.38	0.00	125.62	0.00

Full Sample

Balance Statistics - AC Graded Zones (Continued)

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	-0.03	0.95	0.18	0.73	0.50	0.44	1.86	0.04
Occupational Score	-0.25	0.65	-0.36	0.58	-0.57	0.47	-1.09	0.28
Duncan SEI Index	0.24	0.82	0.08	0.95	-0.29	0.84	-2.30	0.25
Siegel Prestige	3.76	0.55	8.16	0.25	6.29	0.46	1.69	0.88
Nam-Powers-Boyd	17.79	0.14	13.03	0.35	0.62	0.97	-21.05	0.35
Employed	0.04	0.00	0.04	0.00	0.03	0.10	0.01	0.74
Veterans	0.01	0.29	0.00	0.94	-0.01	0.47	-0.02	0.09
White	0.00	0.53	0.01	0.02	0.01	0.32	0.03	0.00
Black	-0.01	0.00	-0.01	0.00	-0.01	0.00	-0.01	0.00
Mexican	0.00	0.11	-0.00	0.15	-0.00	0.05	-0.01	0.05
Asian	0.00	0.92	0.00	0.78	0.01	0.04	-0.01	0.00
Family Size	-0.40	0.00	-0.32	0.00	-0.19	0.05	0.05	0.70
# Children	-0.11	0.01	-0.08	0.11	-0.07	0.18	-0.02	0.77
# Families	-0.01	0.80	-0.00	0.96	-0.00	0.96	0.08	0.15
Dwelling Size	-0.43	0.00	-0.33	0.00	-0.17	0.10	0.24	0.08
House Value	-5790.01	0.00	-5439.12	0.00	-5138.75	0.00	-2471.07	0.10
Rent (1930)	14.46	0.00	7.74	0.20	14.48	0.03	19.20	0.29

[a] τ indicates difference-in-means; p provides corresponding p-value. Balance statistics for Family Size, # Children, # Families, Dwelling Size, House Value, and Rent (1930) are calculated using household-level unique values. All other statistics use person-level data. Balance statistics are calculated for units within 200, 150, 100, and 50 meters from a border. "Full Sample" includes all units within 200 meters from a border. "5-degree Sample" includes units within 200 meters of a border section whose acute angle is at least 5-degrees relative to the nearest road. Treated units are those in the lower grade HOLC zone (i.e., descending letter).

Table 3.30: Balance Statistics - BC Graded Zones

5-Degree Sample

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	-0.66	0.01	-0.90	0.00	-0.95	0.00	-0.08	0.86
Occupational Score	-1.12	0.00	-1.06	0.00	-0.75	0.03	-0.69	0.18
Duncan SEI Index	-3.06	0.00	-3.26	0.00	-3.18	0.00	-2.97	0.00
Siegel Prestige	-12.76	0.00	-13.05	0.00	-13.22	0.00	-11.97	0.04
Nam-Powers-Boyd	-24.70	0.00	-23.63	0.00	-20.84	0.00	-26.40	0.01
Employed	0.00	0.46	0.01	0.27	0.00	0.64	0.01	0.48
Veterans	-0.01	0.06	-0.01	0.08	-0.00	0.33	-0.00	0.99
White	-0.01	0.00	-0.02	0.00	-0.02	0.00	-0.01	0.06
Black	0.00	0.23	0.00	0.00	0.00	0.02	0.00	0.06
Mexican	0.01	0.00	0.01	0.00	0.02	0.00	0.01	0.01
Asian	0.00	0.03	0.00	0.38	0.00	0.10	-0.00	0.03
Family Size	-0.09	0.01	-0.01	0.83	-0.03	0.50	-0.06	0.37
# Children	-0.03	0.12	-0.01	0.67	-0.01	0.63	0.02	0.53
# Families	0.01	0.76	-0.00	1.00	-0.02	0.43	0.03	0.39
Dwelling Size	4.11	0.00	0.00	0.97	-0.02	0.69	-0.01	0.84
House Value	-1052.15	0.00	-1184.48	0.00	-613.59	0.14	-379.60	0.44
Rent (1930)	-8.23	0.57	-13.65	0.37	-10.09	0.48	-11.39	0.22

Full Sample

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	0.05	0.62	0.04	0.75	-0.26	0.06	-0.48	0.01
Occupational Score	-0.42	0.00	-0.46	0.00	-0.17	0.26	0.16	0.46
Duncan SEI Index	-1.21	0.00	-1.35	0.00	-0.92	0.00	0.31	0.45
Siegel Prestige	-5.66	0.00	-6.47	0.00	-3.81	0.02	1.46	0.54
Nam-Powers-Boyd	-5.31	0.02	-7.17	0.01	-2.44	0.43	7.07	0.11
Employed	0.00	0.16	0.00	0.15	-0.00	0.32	-0.01	0.01
Veterans	-0.00	0.00	-0.00	0.00	-0.00	0.16	-0.00	0.29
White	-0.01	0.00	-0.01	0.00	-0.01	0.00	0.00	0.21
Black	0.00	0.04	0.00	0.04	-0.00	0.90	-0.00	0.06
Mexican	0.01	0.00	0.01	0.00	0.00	0.00	-0.00	0.07
Asian	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.06
Family Size	-0.07	0.00	-0.06	0.00	-0.01	0.58	0.10	0.00

Balance Statistics - BC Graded Zones (Continued)

# Children	-0.03	0.00	-0.02	0.01	-0.01	0.33	0.04	0.01
# Families	0.00	0.70	0.01	0.39	-0.01	0.12	-0.01	0.33
Dwelling Size	0.82	0.00	0.16	0.06	-0.34	0.00	-0.51	0.00
House Value	-1628.47	0.00	-1619.36	0.00	-1486.28	0.00	-818.48	0.02
Rent (1930)	-5.64	0.38	-13.50	0.08	-8.36	0.38	-22.34	0.11

[a] τ indicates difference-in-means; p provides corresponding p-value. Balance statistics for Family Size, # Children, # Families, Dwelling Size, House Value, and Rent (1930) are calculated using household-level unique values. All other statistics use person-level data. Balance statistics are calculated for units within 200, 150, 100, and 50 meters from a border. "Full Sample" includes all units within 200 meters from a border. "5-degree Sample" includes units within 200 meters of a border section whose acute angle is at least 5-degrees relative to the nearest road. Treated units are those in the lower grade HOLC zone (i.e., descending letter).

Table 3.31: Balance Statistics - BD Graded Zones

5-Degree Sample

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	-3.16	0.00	-3.10	0.01	-2.48	0.06	-2.21	0.28
Occupational Score	-1.27	0.30	-0.81	0.55	0.06	0.97	0.21	0.92
Duncan SEI Index	-4.78	0.04	-2.64	0.31	-0.74	0.80	2.04	0.64
Siegel Prestige	-32.21	0.02	-24.08	0.12	-12.62	0.46	2.99	0.90
Nam-Powers-Boyd	-17.09	0.55	0.12	1.00	22.07	0.53	32.91	0.53
Employed	-0.00	0.89	0.01	0.64	0.03	0.41	0.08	0.12
Veterans	0.00	0.96	0.01	0.33	0.02	0.16	0.01	0.58
White	-0.09	0.00	-0.02	0.21	0.04	0.00	0.02	0.26
Black	0.05	0.00	0.03	0.00	0.01	0.13	0.02	0.03
Mexican	0.04	0.00	0.01	0.66	-0.05	0.00	-0.05	0.01
Asian	-0.00	0.78	-0.01	0.06	-0.00	0.84	0.00	0.59
Family Size	0.25	0.10	0.05	0.76	-0.18	0.32	-0.50	0.09
# Children	0.10	0.22	0.05	0.53	-0.06	0.48	-0.19	0.13
# Families	-0.08	0.34	-0.04	0.68	0.02	0.90	0.02	0.78
Dwelling Size	0.17	0.30	0.01	0.97	-0.13	0.55	-0.42	0.16
House Value	-7905.91	0.00	-7205.79	0.00	-5113.22	0.08	-977.44	0.85
Rent (1930)	-767.20	0.00	-921.04	0.00	-1162.56	0.00	10.10	0.42

Full Sample

Balance Statistics - BD Graded Zones (Continued)

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	-2.74	0.00	-2.92	0.00	-2.18	0.00	-1.88	0.02
Occupational Score	-2.03	0.00	-1.46	0.00	-0.49	0.36	0.60	0.44
Duncan SEI Index	-6.58	0.00	-4.53	0.00	-1.55	0.16	3.68	0.02
Siegel Prestige	-39.70	0.00	-30.22	0.00	-12.23	0.05	11.32	0.23
Nam-Powers-Boyd	-64.47	0.00	-45.15	0.00	-18.35	0.13	26.36	0.14
Employed	-0.02	0.04	-0.01	0.44	-0.01	0.36	0.03	0.21
Veterans	-0.01	0.22	-0.00	0.58	0.00	0.90	0.01	0.52
White	-0.09	0.00	-0.08	0.00	-0.07	0.00	-0.01	0.27
Black	0.04	0.00	0.03	0.00	0.02	0.00	0.02	0.00
Mexican	0.05	0.00	0.05	0.00	0.05	0.00	-0.00	0.68
Asian	0.00	0.63	0.00	0.07	0.01	0.00	-0.00	0.29
Family Size	0.24	0.00	0.17	0.01	0.17	0.02	-0.20	0.06
# Children	0.04	0.25	0.03	0.28	0.04	0.36	-0.10	0.06
# Families	-0.03	0.30	-0.01	0.66	0.00	0.92	-0.04	0.43
Dwelling Size	0.21	0.00	0.17	0.01	0.20	0.02	-0.21	0.07
House Value	-6838.02	0.00	-6497.41	0.00	-5483.95	0.00	-4701.34	0.02
Rent (1930)	-281.98	0.00	-245.96	0.00	-177.98	0.00	-5.70	0.06

[a] τ indicates difference-in-means; p provides corresponding p-value. Balance statistics for Family Size, # Children, # Families, Dwelling Size, House Value, and Rent (1930) are calculated using household-level unique values. All other statistics use person-level data. Balance statistics are calculated for units within 200, 150, 100, and 50 meters from a border. "Full Sample" includes all units within 200 meters from a border. "5-degree Sample" includes units within 200 meters of a border section whose acute angle is at least 5-degrees relative to the nearest road. Treated units are those in the lower grade HOLC zone (i.e., descending letter).

Table 3.32: Balance Statistics - CD Graded Zones

5-Degree Sample

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	-1.46	0.00	-1.32	0.00	-1.62	0.00	-1.03	0.02
Occupational Score	-1.72	0.00	-0.98	0.00	-0.90	0.00	0.14	0.71
Duncan SEI Index	-5.66	0.00	-3.36	0.00	-2.57	0.00	0.44	0.59
Siegel Prestige	-33.27	0.00	-19.77	0.00	-17.50	0.00	-0.26	0.96
Nam-Powers-Boyd	-61.47	0.00	-35.37	0.00	-31.56	0.00	5.40	0.52
Employed	-0.01	0.13	-0.01	0.38	0.01	0.32	0.03	0.02
Veterans	-0.01	0.03	-0.00	0.24	-0.00	0.65	0.01	0.16
White	-0.14	0.00	-0.09	0.00	-0.08	0.00	-0.01	0.12
Black	0.07	0.00	0.03	0.00	0.03	0.00	0.01	0.01
Mexican	0.04	0.00	0.04	0.00	0.04	0.00	-0.00	0.49
Asian	0.03	0.00	0.02	0.00	0.01	0.00	0.01	0.20
Family Size	0.08	0.02	0.05	0.16	0.07	0.08	-0.03	0.66
# Children	-0.01	0.47	-0.02	0.19	-0.03	0.24	-0.07	0.03
# Families	0.01	0.76	-0.00	0.90	0.01	0.65	0.03	0.47
Dwelling Size	0.99	0.00	1.36	0.00	1.80	0.00	-0.01	0.91
House Value	-1382.85	0.00	-1161.30	0.01	-965.96	0.10	-1111.86	0.09
Rent (1930)	-10.09	0.10	-5.43	0.38	-0.50	0.94	-2.73	0.82

Full Sample

	200 meters		**150 meters**		**100 meters**		**50 meters**	
	τ	p	τ	p	τ	p	τ	p
Age	-1.00	0.00	-1.07	0.00	-0.89	0.00	-1.13	0.00
Occupational Score	-0.96	0.00	-0.61	0.00	-0.19	0.11	0.23	0.16
Duncan SEI Index	-3.50	0.00	-2.39	0.00	-1.43	0.00	-0.29	0.43
Siegel Prestige	-20.44	0.00	-14.47	0.00	-9.29	0.00	-2.80	0.19
Nam-Powers-Boyd	-35.65	0.00	-24.45	0.00	-14.56	0.00	0.18	0.96
Employed	0.00	0.87	-0.00	0.34	0.00	0.48	-0.01	0.22
Veterans	-0.00	0.08	-0.00	0.08	-0.00	0.43	0.00	0.95
White	-0.08	0.00	-0.05	0.00	-0.03	0.00	-0.02	0.00
Black	0.02	0.00	0.01	0.00	0.01	0.00	0.00	0.00
Mexican	0.04	0.00	0.04	0.00	0.02	0.00	0.01	0.00
Asian	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00
Family Size	0.06	0.00	0.08	0.00	0.10	0.00	0.15	0.00

Balance Statistics - CD Graded Zones (Continued)

# Children	0.01	0.08	0.01	0.10	0.02	0.14	0.04	0.02
# Families	0.01	0.53	-0.02	0.06	-0.01	0.36	-0.05	0.03
Dwelling Size	-0.40	0.01	-0.90	0.00	-4.16	0.00	-8.00	0.00
House Value	-535.70	0.00	-373.42	0.04	299.92	0.21	505.88	0.16
Rent (1930)	-4.63	0.22	4.05	0.33	5.99	0.22	2.88	0.67

[a] τ indicates difference-in-means; p provides corresponding p-value. Balance statistics for Family Size, # Children, # Families, Dwelling Size, House Value, and Rent (1930) are calculated using household-level unique values. All other statistics use person-level data. Balance statistics are calculated for units within 200, 150, 100, and 50 meters from a border. "Full Sample" includes all units within 200 meters from a border. "5-degree Sample" includes units within 200 meters of a border section whose acute angle is at least 5-degrees relative to the nearest road. Treated units are those in the lower grade HOLC zone (i.e., descending letter).

Geographic Regression Discontinuity Density Tests: Full Sample

Here I report results from a sorting test using the full sample. This sample corresponds to all voters located within 200 meters of a HOLC boundary. These area analogous to the sorting tests in main text, but the ones here use the full sample, rather than the 5-degree sample

Comparison Groups

Order	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	-2.27**	-2.03**	-0.55	2.56**	0.36
	[3746]	[1120]	[7375]	[282]	[4998]
2(3)	-1.24	-8.54***	-0.02	0.56	-2.70***
	[6057]	[3711]	[13980]	[874]	[10169]
3(4)	-1.32	-11.68***	3.14***	1.51	-0.86
	[10314]	[5815]	[28031]	[1590]	[11037]

*p < .1; **p < .05; ***p < .01
Robust t-values for each density test are provided, and the corresponding (effective) sample sizes are in brackets. This tests use units in the full sample only. The null hypothesis is that the discontinuity is continuous at the cutpoint. For each comparison group, treated units are in the zone with the lower grade (i.e., the descending letter). Mass-points are ignored. Column "Order" shows the polynomial order used to estimate the discontinuity, and the bias order is in parenthesis.

Table 3.33: Density Tests on Units in Full Sample

GRD Exploring Race and Ethnicity of Registered Voters: 5-Degree Sample

Here I use a GRD to explore whether HOLC affected the racial and ethnic characteristics of voters living on either side of a HOLC border. To do so, I use Python's ehtnicolr package to estimate a voter's race. This package uses first and last name strings to assign probability-based estimates that a voter is from a given race. I estimate the GRD using two measures. The first is the probability that a voter is from a given race. This is a continuous measure. The second is a binary variable that equals 1 if a voter's most probable racial category is either White, Black, Hispanic and Latinx, or Asian, and 0 if not. That is, there are four binary variables for each voter, three of which are coded 0 because they do not represent the race that the voter is most likely to be identified as, and one is coded 1 because it corresponds to the race that the voter is most likely to be classified as. GRD models are estimated for four racial categories. GRDs are used on the 5-degree sample, and the full dataset.

	White					Black				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	-0.057**	0.177***	-0.006	0.245***	0.042*	0.000	-0.038	-0.011	-0.014	0.024
	(0.027)	(0.051)	(0.017)	(0.083)	(0.024)	(0.014)	(0.036)	(0.008)	(0.025)	(0.016)
	[2635]	[2085]	[7091]	[262]	[4389]	[2565]	[1163]	[6132]	[331]	[2924]
2(3)	-0.090***	0.155***	-0.063**	0.285***	0.040	0.004	-0.046	-0.007	-0.025	0.029
	(0.035)	(0.059)	(0.027)	(0.088)	(0.026)	(0.015)	(0.041)	(0.008)	(0.028)	(0.019)
	[3192]	[2971]	[5225]	[387]	[7424]	[4459]	[2102]	[11065]	[415]	[4491]
3(4)	-0.103***	0.131	-0.095***	0.306***	0.065*	0.005	-0.028	-0.026**	-0.052	0.031*
	(0.038)	(0.090)	(0.032)	(0.095)	(0.036)	(0.017)	(0.043)	(0.013)	(0.036)	(0.018)
	[4920]	[2714]	[5994]	[585]	[6942]	[5795]	[3038]	[7698]	[435]	[8405]

	Hispanic and Latinx					Asian				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	0.026*	-0.207***	0.013	-0.169**	-0.013	0.025	0.092***	0.021**	-0.044	-0.033**
	(0.015)	(0.053)	(0.017)	(0.080)	(0.021)	(0.021)	(0.024)	(0.009)	(0.055)	(0.016)
	[5017]	[1115]	[6957]	[306]	[4570]	[1961]	[1056]	[9581]	[346]	[4177]
2(3)	0.028	-0.243***	0.057**	-0.187**	-0.048	0.039*	0.092***	-0.002	-0.060	-0.031*
	(0.021)	(0.057)	(0.023)	(0.089)	(0.031)	(0.023)	(0.027)	(0.014)	(0.061)	(0.017)
	[5912]	[2681]	[6319]	[404]	[5263]	[3047]	[2525]	[5313]	[507]	[7678]
3(4)	0.041	-0.257***	0.138***	-0.199**	-0.052	0.050**	0.103**	-0.012	-0.076	-0.049**
	(0.026)	(0.068)	(0.032)	(0.098)	(0.035)	(0.025)	(0.042)	(0.017)	(0.067)	(0.023)
	[5795]	[3031]	[5820]	[601]	[7674]	[4849]	[2741]	[6051]	[601]	[6800]

*p < .1; **p < .05; ***p < .01
Robust standard errors in parenthesis. Sample sized used to estimate each discontinuity in brackets. The discontinuities are estimated on the 5-degree sample only. The dependent variable is the probability that a voter is White, Black, Hispanic and Latinx, or Asian. For each comparison group, treated units are in the zone with the lower grade (i.e., the descending letter). Masspoints are ignored. Column "Order" shows the polynomial order used to estimate the discontinuity. Each outcome is estimated for five comparison zones: AB, AC, BC, BD, and CD. Bias order is in parenthesis.

Table 3.34: Voter Race Using Continuous Measure: 5-Degree Sample

	White					Black				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	-0.106***	0.382***	-0.034	0.336***	0.042	0.014	-0.076	-0.014	-0.015	0.022
	(0.041)	(0.086)	(0.023)	(0.119)	(0.033)	(0.017)	(0.049)	(0.010)	(0.033)	(0.019)
	[2052]	[1113]	[8612]	[271]	[4601]	[2641]	[2237]	[6142]	[343]	[3417]
2(3)	-0.127***	0.408***	-0.070**	0.387***	0.040	0.017	-0.078	-0.014	-0.017	0.030
	(0.045)	(0.092)	(0.035)	(0.127)	(0.037)	(0.020)	(0.054)	(0.012)	(0.035)	(0.023)
	[3619]	[2906]	[6022]	[395]	[7574]	[4606]	[3040]	[9176]	[434]	[5120]
3(4)	-0.121***	0.414***	-0.145***	0.428***	0.085*	0.011	-0.084	-0.019	-0.026	0.033
	(0.046)	(0.123)	(0.044)	(0.136)	(0.051)	(0.022)	(0.062)	(0.015)	(0.039)	(0.023)
	[6066]	[2950]	[6302]	[615]	[7182]	[5797]	[3827]	[8503]	[494]	[8854]

	Hispanic and Latinx					Asian				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	0.038*	-0.372***	0.024	-0.249**	-0.015	0.038	0.077**	0.018	-0.054	-0.037**
	(0.021)	(0.078)	(0.021)	(0.105)	(0.028)	(0.024)	(0.030)	(0.012)	(0.069)	(0.019)
	[4749]	[1056]	[8078]	[306]	[4919]	[1867]	[1091]	[7993]	[343]	[4299]
2(3)	0.038	-0.422***	0.063**	-0.284**	-0.057	0.050*	0.087**	0.004	-0.077	-0.037*
	(0.027)	(0.085)	(0.030)	(0.121)	(0.039)	(0.026)	(0.036)	(0.018)	(0.076)	(0.020)
	[6312]	[2298]	[6705]	[393]	[5364]	[3089]	[2375]	[5293]	[488]	[8009]
3(4)	0.042	-0.455***	0.168***	-0.297**	-0.061	0.063**	0.111**	0.001	-0.103	-0.065**
	(0.032)	(0.098)	(0.042)	(0.134)	(0.044)	(0.028)	(0.054)	(0.020)	(0.085)	(0.028)
	[7358]	[3022]	[6038]	[585]	[7841]	[5064]	[2717]	[6464]	[585]	[6587]

*p < .1; **p < .05; ***p < .01
Robust standard errors in parenthesis. Sample sized used to estimate each discontinuity in brackets. The discontinuities are estimated on the 5-degree sample only. The dependent variable is a dummy indicating whether a voter is White, Black, Hispanic and Latinx, or Asian. For each comparison group, treated units are in the zone with the lower grade (i.e., the descending letter). Masspoints are ignored. Column "Order" shows the polynomial order used to estimate the discontinuity. Each outcome is estimated for five comparison zones: AB, AC, BC, BD, and CD. Bias order is in parenthesis.

Table 3.35: Voter Race Using Binary Measure: 5-Degree Sample

Geographic Regression Discontinuity: Full Sample

Here I replicate the main analyses using the 5-degree sample, but on the full sample. Units are included in the full sample if they are located within 200 meters of a HOLC border zone, and the HOLC zone they are located in borders a HOLC zone with a different grade.

	Democrat					**Republican**				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	-0.028	0.063*	-0.018	0.026	-0.015	0.027*	-0.036	0.011	0.064**	-0.002
	(0.019)	(0.035)	(0.012)	(0.050)	(0.014)	(0.015)	(0.027)	(0.007)	(0.031)	(0.009)
	[11701]	[4227]	[28773]	[2077]	[26240]	[11001]	[3890]	[40887]	[1539]	[24908]
2(3)	-0.027	0.062	-0.020	0.026	-0.013	0.020	-0.026	0.012	0.074**	0.001
	(0.020)	(0.040)	(0.014)	(0.056)	(0.016)	(0.017)	(0.028)	(0.008)	(0.038)	(0.011)
	[20751]	[6769]	[42010]	[3868]	[39202]	[14294]	[8013]	[72912]	[2129]	[34169]
3(4)	-0.008	0.056	-0.021	-0.117	-0.033*	0.015	-0.061*	0.009	0.078*	-0.001
	(0.029)	(0.051)	(0.014)	(0.081)	(0.020)	(0.021)	(0.037)	(0.010)	(0.045)	(0.012)
	[15335]	[7415]	[66743]	[2276]	[37299]	[16203]	[6942]	[68825]	[2899]	[52797]

*p < .1; **p < .05; ***p < .01
Robust standard errors in parenthesis. Sample sized used to estimate each discontinuity in brackets. The discontinuities are estimated on the full sample only. The dependent variable is a dummy indicating whether a voter is Democrat or Republican. For each comparison group, treated units are in the zone with the lower grade (i.e., the descending letter). Masspoints are ignored. Column "Order" shows the polynomial order used to estimate the discontinuity. Each outcome is estimated for five comparison zones: AB, AC, BC, BD, and CD. Bias order is in parenthesis.

Table 3.36: Party Identification

GRD Exploring Race and Ethnicity of Registered Voters: Full Sample

Here I estimate GRD models on the race and ethnicity of registered voters, but on the full sample.

	White					Black				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	0.005	-0.031	0.033***	-0.077**	0.003	-0.024***	-0.005	0.005	0.023	0.005
	(0.010)	(0.023)	(0.008)	(0.032)	(0.008)	(0.008)	(0.010)	(0.004)	(0.019)	(0.006)
	[17195]	[3618]	[28398]	[1963]	[33746]	[10384]	[3888]	[32343]	[1566]	[21672]
2(3)	-0.005	-0.029	0.025***	0.023	0.004	-0.021**	-0.002	0.014***	0.016	0.007
	(0.013)	(0.026)	(0.010)	(0.047)	(0.009)	(0.009)	(0.013)	(0.005)	(0.021)	(0.006)
	[16360]	[6522]	[37376]	[1598]	[52525]	[16429]	[4855]	[39076]	[2206]	[34747]
3(4)	-0.001	-0.030	-0.009	0.063	0.023*	-0.028**	-0.005	0.010**	-0.001	-0.019**
	(0.014)	(0.031)	(0.012)	(0.055)	(0.014)	(0.011)	(0.015)	(0.004)	(0.024)	(0.008)
	[28240]	[8011]	[39129]	[1937]	[34438]	[15947]	[7913]	[72552]	[2250]	[29586]

	Hispanic and Latinx					Asian				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	-0.004	0.029*	-0.029***	0.032	-0.003	0.021***	0.004	-0.008*	-0.009	-0.010**
	(0.008)	(0.015)	(0.009)	(0.031)	(0.009)	(0.008)	(0.016)	(0.005)	(0.022)	(0.005)
	[12728]	[3951]	[24249]	[1774]	[15057]	[10370]	[4227]	[33657]	[1541]	[32731]
2(3)	-0.003	0.030*	-0.040***	0.015	-0.008	0.023***	0.011	-0.000	-0.034	-0.017***
	(0.009)	(0.016)	(0.009)	(0.040)	(0.011)	(0.009)	(0.017)	(0.006)	(0.027)	(0.006)
	[18366]	[7515]	[37509]	[1873]	[31870]	[16079]	[6940]	[37552]	[1896]	[33759]
3(4)	0.018	0.014	-0.042***	0.022	-0.007	0.023**	0.031	0.006	-0.030	0.011
	(0.012)	(0.024)	(0.009)	(0.045)	(0.011)	(0.010)	(0.023)	(0.007)	(0.029)	(0.008)
	[15263]	[7594]	[58464]	[2586]	[51855]	[21306]	[6948]	[38584]	[3520]	[27254]

*p < .1; **p < .05; ***p < .01
Robust standard errors in parenthesis. Sample sized used to estimate each discontinuity in brackets. The discontinuities are estimated on the full sample only. The dependent variable is the probability that a voter is White, Black, Hispanic and Latinx, or Asian. For each comparison group, treated units are in the zone with the lower grade (i.e., the descending letter). Masspoints are ignored. Column "Order" shows the polynomial order used to estimate the discontinuity. Each outcome is estimated for five comparison zones: AB, AC, BC, BD, and CD. Bias order is in parenthesis.

Table 3.37: Voter Race Using Continuous Measure of Racial Identification

	White					Black				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	-0.006	-0.029	0.042***	-0.100**	0.004	-0.019*	-0.006	-0.005	0.038	-0.000
	(0.016)	(0.030)	(0.012)	(0.044)	(0.011)	(0.010)	(0.012)	(0.004)	(0.025)	(0.007)
	[12326]	[3838]	[28372]	[1937]	[34760]	[6613]	[4288]	[61873]	[1816]	[25357]
2(3)	-0.017	-0.026	0.038***	-0.002	0.034**	-0.018*	-0.003	0.019***	0.041	0.001
	(0.019)	(0.032)	(0.013)	(0.063)	(0.016)	(0.011)	(0.014)	(0.006)	(0.026)	(0.007)
	[15521]	[7164]	[40984]	[1716]	[31939]	[21999]	[6530]	[35879]	[3595]	[45091]
3(4)	-0.009	-0.025	-0.018	0.045	0.043**	-0.027*	-0.001	0.026***	0.025	-0.023**
	(0.019)	(0.038)	(0.017)	(0.074)	(0.020)	(0.015)	(0.016)	(0.007)	(0.031)	(0.010)
	[28788]	[9224]	[38023]	[2086]	[33479]	[17458]	[9016]	[46126]	[2845]	[33582]

	Hispanic and Latinx					Asian				
Order	**AB**	**AC**	**BC**	**BD**	**CD**	**AB**	**AC**	**BC**	**BD**	**CD**
1(2)	-0.012	0.026	-0.038***	0.047	-0.000	0.030***	0.002	-0.011**	-0.005	-0.008
	(0.009)	(0.019)	(0.012)	(0.039)	(0.011)	(0.010)	(0.020)	(0.006)	(0.027)	(0.006)
	[15763]	[4206]	[23994]	[1794]	[27017]	[10453]	[4251]	[35741]	[1558]	[33207]
2(3)	-0.009	0.028	-0.051***	0.006	-0.015	0.033***	0.010	-0.001	-0.020	-0.016**
	(0.011)	(0.021)	(0.012)	(0.052)	(0.015)	(0.011)	(0.021)	(0.007)	(0.032)	(0.007)
	[19836]	[7799]	[37058]	[1816]	[30878]	[15873]	[7375]	[39315]	[2088]	[35303]
3(4)	0.024	0.013	-0.053***	0.014	-0.012	0.032***	0.029	0.010	-0.031	-0.001
	(0.016)	(0.032)	(0.011)	(0.060)	(0.015)	(0.012)	(0.028)	(0.009)	(0.034)	(0.009)
	[15589]	[7658]	[67283]	[2386]	[48865]	[21682]	[7348]	[37928]	[3636]	[32818]

*p < .1; **p < .05; ***p < .01
Robust standard errors in parenthesis. Sample sized used to estimate each discontinuity in brackets. The discontinuities are estimated on the full sample only. The dependent variable is a dummy indicating whether a voter is White, Black, Hispanic and Latinx, or Asian. For each comparison group, treated units are in the zone with the lower grade (i.e., the descending letter). Masspoints are ignored. Column "Order" shows the polynomial order used to estimate the discontinuity. Each outcome is estimated for five comparison zones: AB, AC, BC, BD, and CD. Bias order is in parenthesis.

Table 3.38: Voter Race Using Binary Measure of Racial Identification

Chapter 4

A Catalyst for Change: The Great Migration's Impact on Elite Ideology and Voting Behavior During the 20^{th} Century

Abstract

The United States underwent dramatic change during the 20^{th} century. One such change was the pronounced leftward shift in elite ideology on racial issues and civil rights. During this time, the United States also experienced one of the largest demographic events in the nation's history: The Great Migration. This paper seeks to better understand the interplay between demographic change and long-term shifts in the nature of congressional politics. Using a novel panel dataset, identification strategy, and historical passenger railroad routes, I identify the Great Migration's impact on elite ideology and voting behavior. Results show that increased Black migration is associated with a marked leftward shift in elite ideology. Moreover, Black migration is positively associated with voting in favor of the Civil Rights Act. This paper offers a new explanation of the relationship between demography and politics, and shows that the Great Migration may have initiated widespread political change during the 20^{th} century. Additionally, it speaks to the complex – ever evolving – relationship between elites and their constituents.

4.1 Introduction

The 20^{th} century brought fundamental change to the structure of American society and politics. One source of this change was the Great Migration. At the advent of World War I (WWI), the Great Migration led millions of southern-born Blacks to migrate *en masse* to the North and Midwest. The migration continued throughout the mid-20^{th} century, and Black migrants fundamentally changed the social fabric in the North, Midwest, and West. At the same time, political elites moved left on racial issues, and became more conciliatory toward civil rights and racial equality.

While these changes had a profound impact on American political life, little is known about their intersection. Some research posits that Black migration may have initiated the leftward drift in elite ideology and behavior.[1] However, this relationship has not been explored comprehensively. The following paper provides clarity on this topic. Keeping core aspects of demographic theory in mind, as well as existing research on political demography, this paper leverages the Great Migration to identify the effect that demographic change had on elite ideology and voting behavior during the 20^{th} century. Broadly, I show that, as electorates undergo demographic change, elites respond in tow. More specifically, I show that the leftward shift in elite ideology during the 20^{th} century likely occurred because of long-term demographic change brought about by sustained Black migration.

Existing research on the intersection between demography and politics is relatively scant. Despite this, extant research suggests that long-term demographic processes can have a significant effect on politics. An oft-cited example in public discourse is the impact that Hispanic and Latinx immigration may have on future election outcomes in the United States (Bullock and Hood, 2006; Frey, 2015). Additional work shows that Pres-

[1] Throughout, "elite(s)" refers specifically to members of congress.

idential election results are correlated with whether American states have experienced the second demographic transition (Lesthaeghe and Neidert, 2009b). Some research has used traditional demographic and cohort projection modeling to estimate the impact that myriad demographic forces have on elections (Lyons and Durant, 1980; Kodras, 1988; McMahon et al., 1992; Jurjevich and Plane, 2012; Kaufmann et al., 2012).

Demographic change is shown to affect the strength and persistence of political coalitions. Kaufmann (2004) argues that the once large and dominant Anglo-Protestant core of the United States has dissolved because of growing minority and non-White populations. Relatedly, party switching may be motivated by the threat of demographic change, as it is shown that Whites have defected to the Republican party because of its more punitive stance on immigration policy (Abrajano and Hajnal, 2015). Enos (2017) shows that demographic change occurring in one's local area affects voting patterns. It has also been shown that a larger minority group presence in urban metropolitan areas is associated with increased racial intolerance (Oliver, 2010).

Additional research discusses the possible impact that demographic change has on policy (Key, 1949), as well as electoral realignments (Campbell et al., 1960). Some research argues that fundamental changes to the House of Representatives during the 1960s and 1970s occurred because of demographic change decades earlier (Polsby, 2014). Schickler (2016) shows that the leftward shift in racial policy during the 20^{th} century may have been a result of long-term Black migration to the North and Midwest. As Blacks occupied a large share of the electorate in these areas, elites took notice and catered their policies to this newfound constituency group.

Together, previous research suggests that demographic processes can affect politics, especially as it relates to long-term changes in voting patterns, political coalitions, and party restructuring. However, this literature base is comparatively small, and suffers from identification challenges. Moreover, it relies heavily on cross-sectional data that is relegated to examining a single point in time. As a result, it has proven difficult to gain a complete understanding of the impact that demographic change has on politics. With this in mind, the following paper builds on existing research to answer the following question: How does long-term demographic change affect elite ideology and voting behavior? I leverage an original panel dataset and unique estimation techniques provide an answer.

I show that as Black migrants entered traditionally White electorates throughout the Northeast and Midwest, elite behavior and ideology changed in predictable ways. More specifically, I reveal that elites representing congressional districts that experienced Black in-migration became more liberal, and were more likely to vote in favor of liberal civil rights legislation. The findings provide evidence that, as hypothesized by Schickler (2016), Black migration to the Northeast and Midwest may have catalyzed the leftward shift in civil rights policy during the 20^{th} century.

The remainder of the paper proceeds as follows. First, I describe how demographic change affects politics. Second, I describe the Great Migration and situate it as the case used throughout the paper. I then introduce data and measures and describe identification. I follow this by showing results, and end with a discussion.

4.2 Demography's Impact on Politics and Electoral Behavior

Demographic change occurs through processes of mortality, fertility, and migration. Together, these processes describe population growth and decline. Fertility and in-migration determine population growth, and mortality and out-migration describe population decline. One can use these features to calculate total population size by summing the difference between fertility and mortality with the difference between in-migration and out-migration, over a given time period. Traditionally, these demographic processes have been used to describe the core descriptive features of a population. However, they can also describe how demographic change affects electoral politics.

As population change occurs within an electorate, the demographic composition of the electorate changes, altering the underlying distribution of individuals who comprise its constituent body. When individuals enter an electorate, for instance, they bring their political preferences and behaviors with them. If these preferences and behaviors are different from those who already exist in the electorate, the electorate's aggregate status quo preferences can be moved in the direction of the new entrants. An example of this occurs when individuals migrate to a new electorate. In this scenario, the addition of new members to an electorate upsets the status quo equilibrium of the electorate's preferences and behaviors, pushing them in the direction of the migrants.

A similar logic applies when individuals leave an electorate, which can occur through out-migration or death. In the case of out-migration, individuals take their preferences and behaviors to a new electorate. In the case of death, their preferences and behaviors disappear entirely. In both cases, an electorate's status quo preferences and behaviors drift in the direction of the individuals who remain in it because the counterbalancing effect of those who were in the electorate, but exited, is nullified, pushing aggregate preferences and behaviors in the direction of those who stay put.

For demographic change to affect politics in the way described, two assumptions must hold. First, individuals entering or exiting an electorate must hold political preferences and behaviors different from those who are already in it, or those who remain in it. For example, in-migrants must hold political attitudes and preferences different from the electorate they migrate to. Alternatively, out-migrants must hold attitudes and preferences different from those who remain in the electorate they left. If this assumption were not true, then any demographic change would simply replicate the existing status quo, rather than change it.

Second, the preferences and behaviors of individuals entering, or remaining in, an electorate must remain stable. This assumption ensures that, over time, entrants to an electorate do not drift toward the status quo of the electorate's preferences. It also ensures that individuals already in an electorate do not experience sudden changes to their preferences. While short-term changes to the preferences and behaviors of individuals initiating demographic change could occur, long-run trends should reveal relative stability.

Existing research shows that the first assumption likely holds. Demographic processes do not affect population subgroups equally, and political preferences vary across these groups. Mortality rates, for example, vary by age and country (Zheng et al., 2016; Torre et al., 2016), race and ethnicity (Hummer et al., 1999; Bos et al., 2005), and socioeconomic background (Guest et al., 1998; Huie et al., 2003). Migration is more likely to occur among individuals with either high or low education levels (Caponi, 2010), and fertility rates have historically been higher among certain immigrant groups in the United States (Kahn, 1994; Carter, 2000; Parrado and Morgan, 2008).[2]

Additionally, political preferences and attitudes are shown to vary across subgroups, as well. This is true for race and ethnicity (Sanchez, 2006; Tate, 2010; Segura, 2012), income (Ellis, 2017), age (Wong, 2000; Tilley, 2002), and gender (Verba et al., 1997). It is not only the case that population subgroups are responsible for demographic change. They also create political diversity within an electorate. As a result, we can be confident that the individuals responsible for demographic change are different from the status quo demographically and politically, lending support for the first assumption.

There is ample evidence supporting the assumption that attitudes and preferences

[2]Parrado and Morgan (2008) shows that fertility rates for Mexican-American immigrants converge to that of Whites over time, even though they initially hold higher fertility goals. This is also shown by Carter (2000).

are mostly stable over the long-haul. At the individual-level, attitudes are shown to crystallize during early adulthood (Osborne et al., 2011), and they remain relatively stable throughout one's life (Alwin et al., 1992; Sears and Funk, 1999). Additionally, individuals are less open to change as they age (Stoker and Jennings, 2008), especially for partisanship and issues forming the core of one's political identity (Jennings and Markus, 1984; Krosnick and Alwin, 1989). The same is true for aggregate-level preferences, which are characterized by long-term attitudinal stability (Campbell et al., 1960; Page and Shapiro, 1992). Individual-level attitudes and preferences may change, but there is ample evidence indicating that once established, they remain reasonably stable over the life course.

When these assumptions hold, demographic change can affect electoral politics by altering the population composition of an electorate. Demographic change upsets the electorate's status quo preferences and behaviors, pushing them in a new direction. As a result, the electorate may endorse policies and candidates it previously had not, fundamentally changing its political fabric.

4.3 The Great Migration: A Brief History

The Great Migration represents the mass migration of Blacks from the South to the Northeast, Midwest, and West during the 20^{th} century. The migration occurred throughout most of the early to mid-20^{th} century, but was marked by two waves. The first began at the beginning of World War I, when a labor shortage in the North and Midwest emerged because of an exodus of White male laborers who joined the war effort.[3] Southern-born Blacks migrated to urban centers in these regions in search of work and better economic opportunities (Collins, 1997). Many of these areas had only a small Black

[3] See Yokelson (1998) for a detailed description of military service during World War I.

presence prior to WWI. However, due to the migration, Black population centers emerged in major cities such as Chicago, Philadelphia, and New York City. Black migration continued after the war ended, and even increased in the years thereafter (Boustan, 2017).

The second migratory wave occurred during World War II (WWII) (Gregory, 2009). Wartime labor market shortages and economic opportunities in the North, Midwest, and West attracted Blacks to these areas. In this wave, emerging airline and shipbuilding industries in the Pacific states brought droves of Black migrants to areas such as the San Francisco Bay Area, Los Angeles, and Seattle (Nash, 1985; Johnson, 1994). The cumulative impact of the migration was impressive. During the 1950s, roughly 2.5 million southern-born Blacks resided in the North, Midwest, and West (Tolnay, 2003, p. 210), representing roughly 20.4 percent of the total Southern-born Black population (Collins, 1997, p. 607). In the decades following, Black migration from the South continued, but slowed, and reverse migration to the South began to occur during the 1990s (Frey, 2004; Boustan, 2017).

Over approximately six decades, the Great Migration brought millions of Blacks to areas largely devoid of their presence. Yet, while this migration was one of the largest demographic events in American history, relatively little is known about its impact on American politics. Migrants brought their political ideologies, preferences, and voting behaviors with them, and we may expect that their presence upset the political status quo in areas across the US. As I show, this is exactly what occurred. Congressional districts receiving Black migrants became more liberal, and elites from these districts were more likely to support the Civil Rights Act (CRA).

4.4 Data and Measures

I compile an original dataset consisting of congressional district demographic data, congressmember ideology and roll call vote data, and historical railroad routes. Demographic data is from the Congressional District Data File (Adler, nd). The Data File contains economic, social, and geographic variables for each congressional district between the 78^{th} through 105^{th} congresses (1943 - 1998). Social, economic, and demographic data contained in this dataset is from Congressional District Databooks, or the Census of Population. Geographic data is from various sources, such as United States Geological Survey maps, Rand McNally Road Atlases, and Congressional district maps.[4]

Congressmember ideology data is from DW-Nominate. DW-Nominate provides ideal-point estimates of congressmember ideology on a liberal-conservative dimension. I also include roll call vote data on the Civil Rights Act of 1964 (Lewis et al., 2019).[5] These data sources are merged with the Congressional District Data File to create a panel of district-level social, economic, and demographic characteristics, as well as ideological and roll call vote data for each district's respective House member(s). The full panel covers the 78^{th} through 105^{th} congresses. However, I restrict the panel to fall between the 78^{th} and 88^{th} congresses.

I also include historical railroad routes, which I use as an instrumental variable for part of the empirical analysis. The instrument is created from two data sources: congressional district shapefiles (Lewis et al., 2013), and a shapefile of historical railroad routes in the continental US (Atack, 2016). The railroad data covers major railroad routes in the US that were in operation between 1830 and 1972. The two data sources were combined such that, for every congress, the Euclidean distance between the centroid of a congressional

[4]See Adler (nd) for specific details about how the dataset was constructed.

[5]Please see Lewis et al. (2019) for information about how the ideal points are calculated, as well as other technical features of DW-Nominate's scaling methods.

district and the nearest railroad line was calculated. I did so for each congress-district dyad, and the final distances were merged with the demographic and political data.

The primary independent variable is the total Black population of congressional district d, in congress session t.[6] Various district-level demographic control variables are used, as well. These soak up important economic, demographic, and labor market characteristics that may be endogenous with elite ideology *and* total Black population. Select control variables include number total number of individuals employed in manufacturing jobs, number of blue collar workers, total population, and percent unionized in the state.

There are two dependent variables. The first is DW-Nominate's ideal point estimate for the first ideological dimension, which ranges between [-1, 1]. Values closer to -1 are more liberal, and values closer to 1 are more conservative. For each district-congressional term dyad, the mean score on this variable is calculated. I calculate the mean because, in some cases, there can multiple elected congressmembers for a single district (e.g., death, retirement). I use this variable to observe ideological change among elected officials. The second dependent variable is representative i's vote on the Civil Rights Act, during the 88^{th} Congress (July 2, 1964). This variable is coded as 1 if a representative voted in favor of the CRA, and 0 if not.

[6]I use total Black population for three reasons. First, I include district-level fixed effects, which allows within-unit observations to be made, such that the measured effect of Black migration is the within-unit difference of the total Black population, over time. Second, using percent Black correlates the measure with other racial groups by definition, which could lead to biased estimates, or multicollinearity. For instance, if percent Black increases, then percent White decreases, assuming these are the only two racial groups in a district. Third, percent Black may not respond to changes in the total Black population if concurrent population change occurrs among other racial groups.

4.5 Design and Identification

Panel Setup

I estimate the impact of Black migration using a two-way fixed effect panel model. The model covers the time period between the 78^{th} and 88^{th} congresses. I cover this period for two reasons. First, the earliest congress for which demographic data is available is the 78^{th} congress. Second, the Civil Rights Act (1964) was voted on during the 88^{th} congress, and it is natural to explore ideological change up until this point, which represents the zenith of the Civil Rights Movement. Moreover, Black migration to areas outside of the South declined steadily after this period.

Formally, the model is shown in equation 1

$$Y_{dt} = \alpha_d + \lambda_t + \rho log\left(Black_{dt}\right) + X'_{dt}\beta + \epsilon_{dt} \tag{4.1}$$

where Y_{dt} is the DW-Nominate score (i.e., ideology) for the congressmember representing district d at congressional session t, α_d is a district fixed effect, and λ_t is a time effect representing congressional session. The primary independent variable is $\rho log\left(Black_{dt}\right)$ which represents district d's logged total Black population in congressional session t. Finally, $X'_{dt}\beta$ is a vector of control variables for district d, in congress t. This setup allows for within-district variation to be observed over time, wherein time-invariant district-varying (α_d), and district-invariant time-varying (λ_t), confounders are removed.

In this setup, I only include districts that have constant geographies between the 78^{th} and 88^{th} congresses. I subset to these districts because it ensures that any change to district d's Black population is due to migration alone.[7] To create this subsample,

[7] Changes to a district's Black population could be due to redistricting, fertility, mortality. By subsetting to unchanging districts, the former is taken care of by design. I assume that the latter two factors are negligible.

I develop an algorithm that selects districts whose geographic shape does not change over time. Beginning with the 78^{th} congress, I take the symmetric difference between the geographic area that district d covers at congress t, and the geographic area that it covers at time $t + 1$. The difference is calculated iteratively for all periods, up to the 88^{th} congress. Congressional districts are retained in the panel if the difference across these periods is zero. In total, 90 congressional districts are retained.[8]

Instrumental Variables

In addition to the panel model, I use instrumental variables. I do so because there could be confounding that the panel design fails to account for. For example, it is possible that ρ in equation 1 is correlated with unobserved aspects of the treatment assignment process, such as access to migration routes. We might expect, for instance, that districts located closer to major transportation routes, or those that had ready access to the supply of Black migrants, had a larger Black population.

To account for this possibility, I instrument district d's Black population at congress t as a function of its distance to the nearest North-South railroad line. I use railroad lines as an instrument because passenger railroads were a primary source of transportation for Black migrants. Many Southern railroads either had direct service to Midwestern and Northeastern states, or shared a connection with major railroads that passed through

[8] Calderon et al. (2019) account for shifting geographies in a different way. Rather than subset the analysis to include districts that do not change over time, they use district boundaries during the 78^{th} congress as a base group, and calculate weighted area averages using county-level demographic and political variables. That is, they keep the geographies constant to the 78^{th} congress, overlay these geographies on later maps, weight later geographies according to the area of a district that it covers, and calculate a weighted average of Census and political variables. However, doing so assumes that demographic and political characteristics are constant across geographic areas, which may be untenable. For example, it assumes that Black migration rates are constant across a geography, which is unlikely given that migration was primarily to urban areas, and to specific neighborhoods within those areas. Moreoever, it assumes that the distribution of Black residents in a geographic area is constant across the entire area. Because of these challenges, I opt to subset the data rather than using a weighted imputation strategy that makes strong assumptions.

these areas. For example, a noteworthy passenger railroad for Black migrants was the Illinois Central Railroad, which linked Midwestern cities such as Chicago and St. Louis with Southern cities such as Memphis, and New Orleans (Grossman, 1989).

In addition to their importance as a means of transportation, railroads also served as a source of employment. Railroad companies in need of labor offered free transportation for northern-bound Black migrants who pledged to work on the railroad. This was true of the Pennsylvania Railroad (Bodnar et al., 1982), for instance, which recruited over 16,000 Black migrants in 1916 (Museum, 2014). In this way, railroads operated not only as a crucial mode of transportation, but also as a source of employment for Blacks migrants.

It is likely that districts located closer to railroad routes received more Black migrants. For Northern-bound Blacks, it would have been less costly to migrate to districts located near major railroad routes. Over time, these districts likely received more migrants because of their proximity to railroad transit, thereby increasing their total Black population.

The first stage of the instrumental variables setup is modeled by

$$log\,(Black_{dst}) = \psi_s + \lambda_t + \tau log\,(Distance_{dt}) + X'_{dt}\beta + \varepsilon_{dt} \tag{4.2}$$

where ψ_s and λ_t are state and congress effects, respectively, and $X'_{dt}\beta$ is a vector of controls. The endogenous regressor is $log\,(Black_{dst})$, which is the log of the total Black population. The instrument is $\tau Distance_{dt}$, and is measured as the minimum distance between the centroid of district d at time t and the nearest rail line, in meters.[9] The second stage is modeled as:

$$Y_{dst} = \psi_s + \lambda_t + \rho log(\widehat{Black_{dt}}) + X'_{dt}\beta + \epsilon_{dt} \tag{4.3}$$

[9]See Appendix section titled "Creating the Instrument" for details about how the instrument was created.

and is near identical to equation 1. However, it replaces district fixed effects with state effects, and uses predicted values for logged total Black population from the first stage.

Importantly, this setup includes *all* districts observed between the 78^{th} and 88^{th} congresses, regardless of whether they change shape. I am able to include all districts by removing district-level intercepts and replacing them with state effects. As a result, I, technically, do not observe within-district variation, which obviates the need to ensure that districts cover the same geographic area over time.

Despite this, I still estimate migration inflows. District d's Black population at any given t is explained by migration, fertility, and mortality, regardless of whether the district's shape changed between times t - 1 and t. By omitting district intercepts, I need not worry about constant geographies because any district, at any point in time, is defined solely by these demographic processes, no matter how its underlying geography evolved.

For the purposes of this analysis, I assume that both fertility and mortality had a negligible (if any) impact on determining a district's Black population. This is plausible because, during this time period, migration rates were so high that it is likely that any competing impact from fertility and migration was negligible. Under this assumption, district d's Black population at congress t is informed solely by migration.

The panel and instrumental variable models are estimated on two samples. The first includes all congressional districts across the US. The second is a subsample of congressional districts located in the Midwest and Northeast. I subset the analysis for three reasons. First, Black migration was primarily to the Midwest and Northeast, and it makes sense to examine its impact in districts located in these areas. Second, I am able to observe whether the effects are heterogeneous by region. Third, the railroad network used to create the instrument is comparatively sparse west of the Mississippi River. While Black migration to western states increased during the 1940s, the sparsity of railroad lines in the region precludes the instrument from being a useful tool to evaluate Black migration in the West.

Exclusion Restriction

Obtaining unbiased estimates of ρ in the instrumental variables models requires that τ and ϵ are unrelated. If they were not, then the instrument would have a direct effect on the outcome, violating the exclusion restriction. While this assumption is not directly testable, I argue in this section that it is likely to hold.

For the exclusion restriction to be violated, the instrument would need to affect the ideological preferences and voting behavior of congressmembers. I argue that this is unlikely for two reasons. First, the railroad routes used to construct the instrument were built between 77 and 108 years prior to first year of measurement for this study. This dispels issues regarding railroad route siting and reverse causality. Simply, congressmembers in office between the 78^{th} and 88^{th} congresses could not have affected railroad siting that occurred roughly one century prior. This would be of concern if we expected siting to be correlated with congressmember characteristics, or patronage.

Second, $X'_{dt}\beta$ rules out potential sources of confounding that relate to district-level economic and labor market conditions. For example, railroad density and location could have affected district-level labor market conditions. Migrants may have been attracted to districts with a favorable labor market, and congressmembers may have become more conciliatory toward industries that were experiencing growth. Relatedly, congressmembers may have lobbied for the construction of railroad routes if they thought that it would bring about favorable labor market conditions. The former issue is directly controlled for by the vector of labor market controls contained in $X'_{dt}\beta$; the latter, as discussed above, is untenable because routes were sited long before the first year of observation.

Relatedly, the Great Migration was primarily to well-defined urban areas in the North, Midwest, and West (Cahill, 1974; Tolnay and Beck, 1992; Baldwin, 2007; Price-Spratlen, 2008). The instrument, however, is calculated as the distance between the *centroid* of a district and the nearest railroad. Therefore, it is agnostic to the social, economic, and political considerations that defined the areas that migrants were attracted to. As a result, it is orthogonal to the myriad urban-area characteristics that attracted Black migrants (e.g., labor market, social networks, political conditions, etc.). In this way, the instrument is plausibly valid because it is determined by a location that had no bearing on where migrants decided to settle.

Physical geography also lends credence to the exclusion restriction. The exact siting of railroad routes is partly a function of fluctuations in geography, terrain, and topography (Yi, 2017). Because of this, the instrument is, at least in part, determined by randomly-varying geographic features. Atack and Passell (1994), for example, show that subtleties in physical geography determined the exact placement of railroad routes. All told, it is plausible that physical geography determined the exact siting of railroads, rather than socioeconomic forces endogenous with congressmember ideology and voting behavior.

Previous research provides additional clarity. Distance-based instruments are relatively common in economics and medical research. Card (1993) uses proximity to university as an instrument to estimate returns to schooling. McCleary and Barro (2006) use distance from the equator to estimate the effect of economic development on religiosity. Distance to Bujumbura is used as an instrument for violent conflict (Voors et al., 2012). Additional work uses the distance between African ethnic groups and coastal areas to identify the effect of the slave trade on interpersonal mistrust in Africa (Nunn and Wantchekon, 2011). Similar research uses distance to the US-Mexico border to instrument for immigration (Peri, 2012). Travel time between a mother's home and the nearest neonatal intensive care unit (NICU) is used to examine childhood mortality

(Baiocchi et al., 2010, p. 1286). McClellan et al. (1994) leverage differential distances to hospital-type to estimate the effect of health treatments for acute myocardial infarction and elderly.

A handful of studies explicitly use railroad routes as instruments. Black et al. (2015) use the distance between place of birth and nearby railroad routes to identify the impact of the Great Migration on Black mortality. Ananat (2011) uses railroad length as an instrument to identify how Black migrants affected spatial segregation in the US. In general, this literature argues that railroad routes are a valid instrument because their exact placement is determined by their proximity to surrounding locations and ground slope (Ananat, 2011).[10]

All told, there is reason to believe that the exclusion restriction holds. This is because of the significant time gap between initial railroad route siting and the study's timeframe, as well as the vector of controls that net out the impact of endogenous labor market and economic conditions. Moreover, random fluctuations in physical geography, along with using district centroids, likely make the instrument orthogonal to socioeconomic characteristics determining migration patterns. Finally, previous research has used distance as an instrument, lending further credibility to its use.

Stable Unit Treatment Value Assumption

A related concern is whether district d's outcomes are independent of the treatment status of other districts. Formally, this is known as the Stable Unit Value Treatment Assumption (SUTVA), which states that the potential outcomes of unit d are unaffected by the treatment assignment mechanism, and the treatment status of other units (Morgan and Christopher, 2017). SUTVA, for instance, would be violated if demographic change occurring in neighboring districts affects the potential outcomes of unit d.

[10] See also Atack and Passell (1994), and Wellington (1911).

I argue that SUTVA is not violated. It is unlikely that congressmember behavior responds to demographic change occurring outside of their district because congressmembers act with their own constituents in mind (Mayhew, 1974). At the least, electoral incentives alone preclude congressmembers from acting in the interests of constituents other than their own. With this in mind, I am confident that SUTVA is not violated.

4.6 Results

Elite Ideology

Coefficient estimates for the effect of Black migration on elite ideology are presented in Figure 4.1 (corresponding results can be found in Appendix Table 4.1). The outcome measure is DW-Nominate's first ideological dimension. The results are organized according to whether the congressional districts used in the analysis changed shape (y-axis); whether instrumental variables are used (point type); and, whether districts across the entire US, or the Midwest and Northeast are included (line type). 95% confidence intervals are provided for each point estimate, and standard errors are clustered by district.

The panel results are shown in the first two rows. Again, these estimates are generated using the subset of districts that did not change shape between the 78^{th} and 88^{th} congresses. Neither estimate reaches statistical significance. This is true when using the full panel (N = 990), and when restricting the analysis to districts in the Northeast and Midwest (N = 495). For these districts, Black migration appears unrelated to elite ideology.

The third and fourth rows provide estimates for all districts, regardless of whether their geography was constant across time. In this setup, I omit district-level fixed effects, and include state effects in their place. By doing so, I am able to observe how Black population change affected elite ideology, but without the requirement that geography was unchanged. Both models are equivalent to a pooled repeated cross section with state and year effects. However, they do not use the instrument.

The point estimate for each of these two models is statistically different from zero, and they are identical (ρ = -.072; $p < .01$). Substantively, this means that a one-percent increase in the total Black population of district d in state s at congress t moves congressmember ideology in a liberal direction by .00072 points. Interestingly, the estimates are the same when using all congressional districts across the US, and when restricting the analysis to those located in the Northeast and Midwest. It appears that the impact of having Black constituents is homogeneous across region.

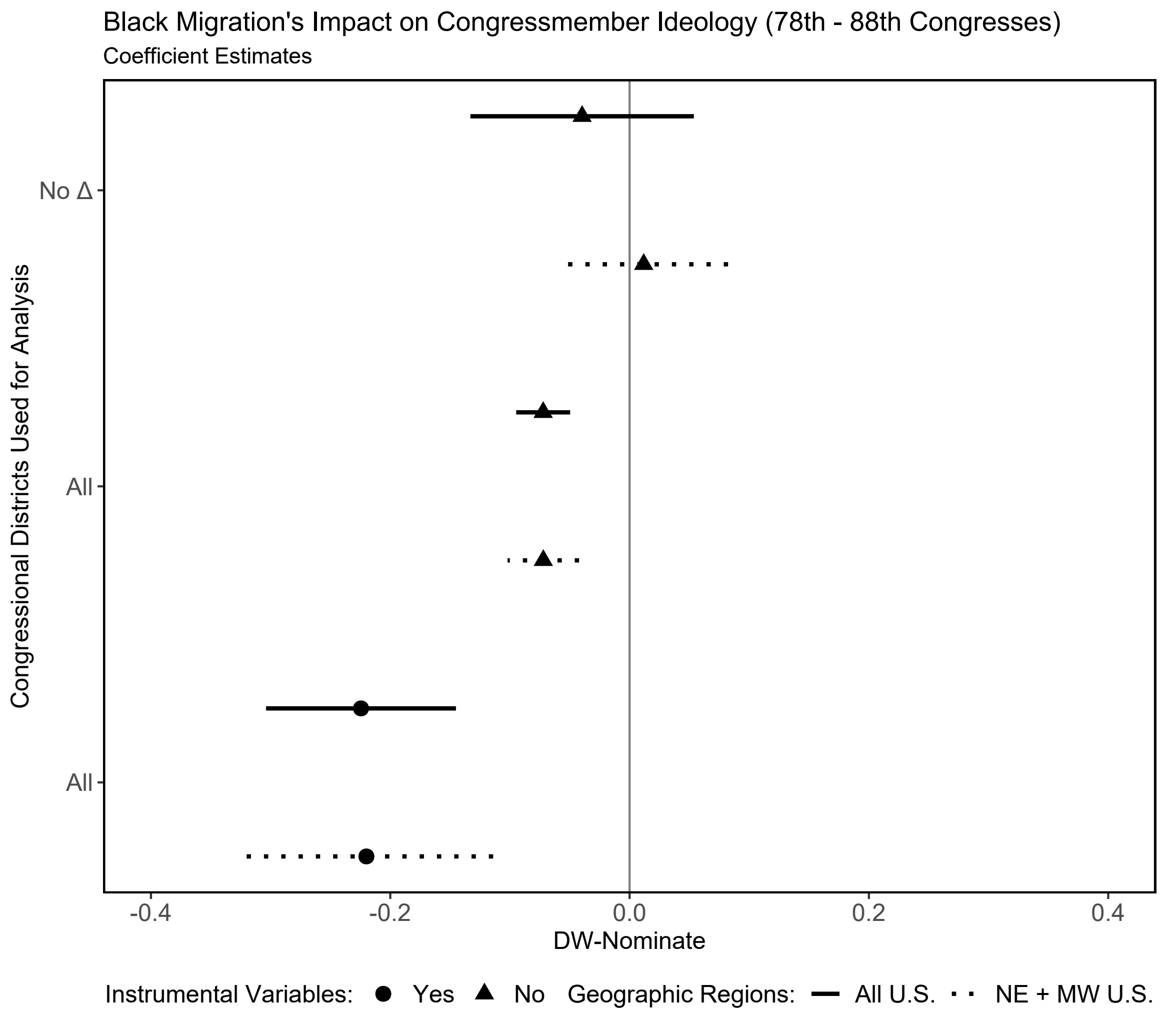


Figure 4.1: Black migration pushed elite ideology in a liberal direction. This figure shows coefficient estimates of the impact of Black migration on elite ideology, using various regression models. Sample sizes for each regression, from the top row to the bottom, are 990, 495, 3,859, 1,943, 3,815, and 1,921. The dependent variable is DW-Nominate's first ideological dimension. The independent variable is total Black population in district d at congress t. The estimates are subset on the y-axis according to whether the analysis contains districts that did not change shape between the 78^{th} and 88^{th} congresses ("No Δ"), or whether it contains all congressional districts ("All"). 95% confidence intervals are provided. Standard errors are clustered by congressional district. All models control for district-level economic, labor market, and demographic features. See Appendix Table 4.1 for full regression results.

The last two rows show estimates from the instrumental variable models. Both coefficients are statistically significant and negative. The coefficient estimate when using the sample of districts across the entire US is -.22 ($p < .01$).[11] The estimate and significance level stays the same when restricting the analysis to Midwestern and Northeastern districts, as well. For both, a one-percent increase in the total Black population is associated with a leftward shift in ideology of .002 points. Again, this comports with the expectations laid out in the paper.

The Civil Rights Act

I also estimate the effect of Black migration on the probability of voting in favor of the Civil Rights Act. In this setup, the analysis is restricted to the 88^{th} congress. I create a dummy variable that equals 1 if congressmember i from district d voted in favor of the CVRA, and 0 if not. To keep the analysis consistent with previous models, I again subset the analysis by whether districts changed shape over time, and present the results the same way. Because the data is a cross-section, I remove unit and time effects, but include state effects along with a vector of control variables. I use the linear probability model (LPM) to estimate all regression functions.

Figure 4.2 provides coefficient estimates (see Appendix Table 4.2 for corresponding results). As the first four rows show, Black migration did not affect the probability of voting in favor of the CRA in districts with unchanged geographies. In none of these four models did the coefficient estimate reach significance. It is important to consider, however, that the samples are small because they are cross-sections of a small subset of districts. Because of this, the models are likely underpowered, making it more difficult to reject the null hypothesis. Nonetheless, the point estimates are positive, as we would expect.

[11] F-tests for the first-stage effect are reported in Appendix Table 4.1. The F-statistics are 554.2 and 263.1 for the model using all districts, and the model restricting the analysis to Midwestern and Northeastern districts, respectively.

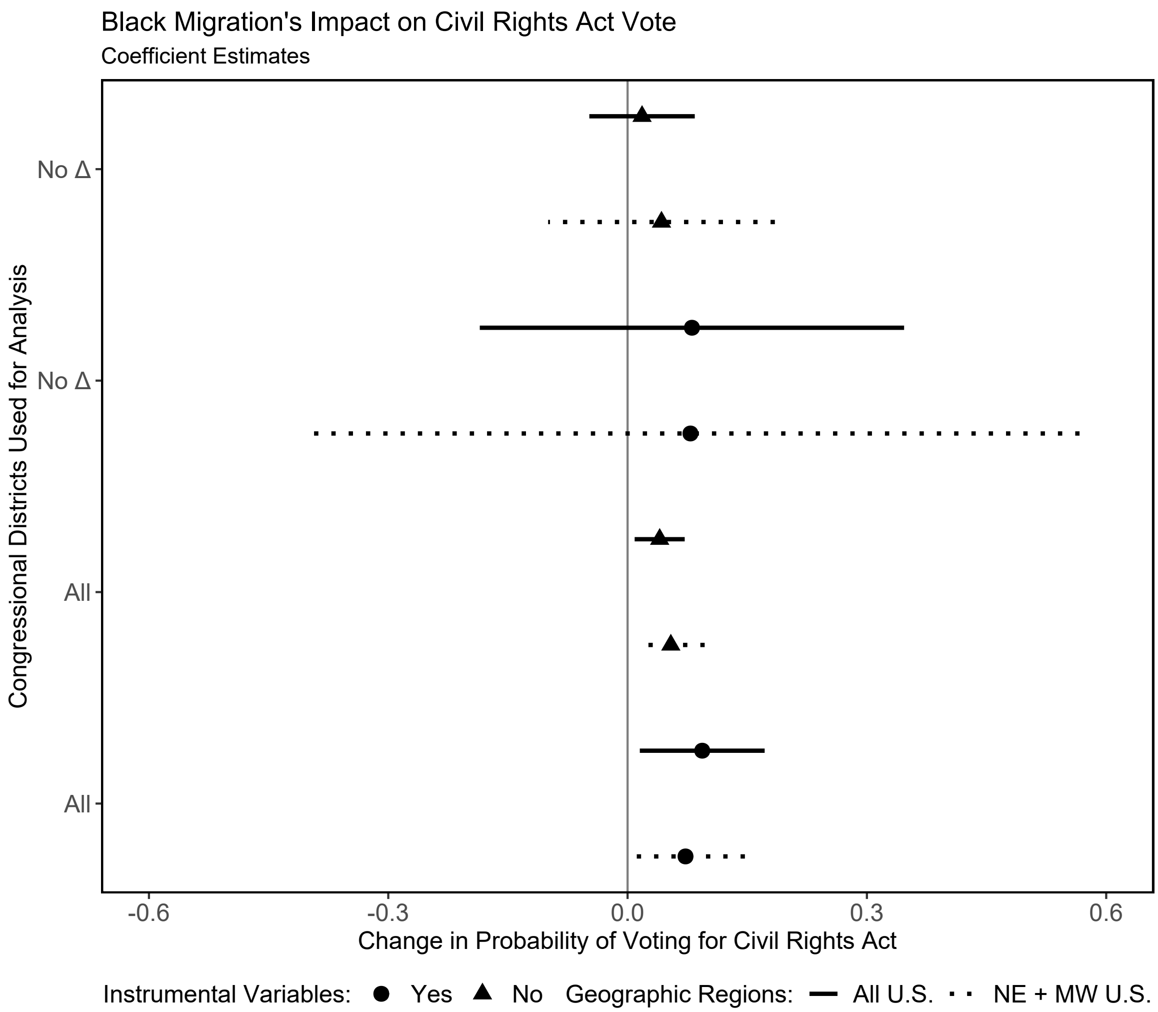


Figure 4.2: Black migration increased the probability of voting in favor of the Civil Rights Act. This figure shows coefficient estimates of the impact of Black migration on the probability of voting for the Civil Rights Act, using various regression models. Sample sizes, from the top row to the bttom, are 89, 45, 89, 45, 341, 173, 337, and 171. The dependent variable is dummy variable for whether district i's congressional representative voted in favor of the Civil Rights Act. The independent variable is total Black population in district d, at the time the CRA was voted on. The estimates are subset on the y-axis according to whether the analysis contains districts that did not change shape between the 78^{th} and 88^{th} congresses ("No Δ"), or whether it contains all congressional districts ("All"). 95% confidence intervals are provided. Standard errors are clustered by congressional district. All models control for district-level economic, labor market, and demographic features. See Appendix Table 4.2 for full regression results.

The remaining estimates support the expectation that Black migration made elites more likely to support civil rights legislation. As rows five through eight show, the coefficient estimates for Black migration are positive, and all are significant to $p < .05$. Row eight uses instrumental variables on the sample of all districts located in the Northeast and Midwest. While it is only significant to $p < .10$, it is positive, and the effect size (7%) is similar to the previous results.

4.7 Were Districts With Constant Geographies Different?

The results above are twofold. On one hand, there is evidence that Black migration pushed elite ideology to the left, and that it increased the probability that congressmembers voted in favor of the Civil Rights Act. This is demonstrated by the instrumental variables analyses, and when examining districts located in the Northeast and Midwest, two of the most popular destination regions for Black migrants. However, when restricting the sample to only include districts that did not change shape over time, the results are consistently null, for both outcomes. What explains this discrepancy?

First, increased internal validity may have sacrificed the generalizability of the results. While subsetting the analysis to include districts with unchanging geographies ensured that I identified the direct effect of migration, doing so may have yielded a sample that was not representative of the overall population. If so, the null coefficient for Black migration is unbiased, but not representative of what occurred in districts that *changed* shape. To explore whether this may be driving the results, I conducted a series of balance tests between districts with changing and unchanging geographies. I calculate difference in means statistics for a series of demographic and economic variables between 78^{th} through

88^{th} congresses.

I report the full results in Appendix section "Balance Tests". The general theme is that unchanging districts had a larger Black population, were further from railroad lines, and had fewer union jobs. Over time, however, these differences decreased. By the 88^{th} congress, the sample of unchanging districts had only marginally fewer union jobs, and were not substantively different in any other way. Overall, the balance tests suggest that the estimates for unchanging districts are simply not generalizable across the full set of congressional districts, despite them being more internally robust. For this reason, one might be inclined to rely on the analyses using the full set of districts, even if it means increasing measurement error.

Relatedly, omitting districts that changed shape reduced the sample size used to estimate each model, sacrificing statistical power. Broadly, this is less of a concern in the elite ideology models because the unchanging sample contained 990 observations across the entire US, and 495 when limiting the sample to those in the Northeast and Midwest. For both models, there was likely enough power to reject the null hypothesis, had the effect sizes been large enough. Statistical power is more of a concern in the Civil Rights Act models. Because these models used cross-sections, the samples are comparatively smaller. At the extreme, for instance, the instrumental variable model using the sample of unchanging districts in the Northeast and Midwest only had 45 observations. The coefficient estimate was similar to the other models, but was not be rejected because the estimator was underpowered. All told, some estimators relied on samples that may have simply been too small to reach the significance levels detected when using the full sample.

4.8 Who Were the Migrants?

Relationship with Government

Thus far, I have shown that Black migration pushed congressmember ideology to the left, and that it increased the probability of voting in favor of the CRA. How did this occur, and what did the migrants' political preferences look like? I shed light on these questions using data from the *Racial Attitudes in Fifteen American Cities Survey*. The survey was conducted in 1968, and explored social attitudes toward various racial and urban issues in the United States. The sample consisted of Northern-born and migrant Blacks who, at the time of the survey, lived in one of 15 major cities in the northern US. There are 2809 observations (Campbell and Schuman, 1968).[12]

First, I use regression to measure migrant trust in government. I do so because Southern and Northern-born Blacks may have differed in the amount to which they trusted government to protect them and enact civil rights legislation. Prominent segregationists such as Strom Thurmond, Lester Maddox, and George Wallace hailed from the South, and Southern-born Blacks may have been especially weary about the role of government in their daily lives, given that numerous political officials in the South supported segregationist policies.

Trust is measured as a composite score of multiple variables, and ranges from 3 to 9. Higher scores indicate less trustworthiness toward government. The primary independent variable is a dummy indicating whether the respondent lived in the South for the first ten years of life. I also include controls for age, total family income, education, sex, and a vector of sampling weights.[13]

[12]There is an additional sample of Whites, but the survey questions are not consistent across the Black and White samples.

[13]With this, and all subsequent regressions using this data, I omit all units that respond as "do not know", or "not applicable".

Results are provided in Appendix Table 4.3. Southern Blacks are .39 points more trusting in government. The coefficient is significant to $p < .01$. Family income is positively associated with trust, but is only significant to $p = .06$. No other variables are significantly associated with the outcome.

Column 2 shows results for a regression that asks whether the respondent feels that laws and persuasion are the only way to increase Black well-being in the US. The outcome is a binary variable that equals 1 if the respondent feels this is true, and 0 if not. Migrant Blacks are only marginally different from their non-migrant counterparts on this measure ($p = .10$). Age and education are positive and statistically significant, the former to $p < .01$, and the latter to $p < .01$.[14]

A final regression measures the degree to which the respondent feels that the federal government is working to solve problems in their city (column 3). Thie variable ranges from 1 to 3, and higher values indicate that the respondent feels that the government is trying less hard to solve problems. As with the previous regression, migrant Blacks are not different from their northern counterparts ($p = .33$). Total family income and education are positively associated with the outcome. Each is significant to $p < .05$.

Leaders and Organizations

The survey also asked respondents to indicate support for various civil rights leaders. I use these measures to examine whether Black migrants supported different civil rights leaders and platforms than Northern-born Blacks. This sheds light on whether migrants held different views about civil rights ideologies, and how best to achieve equality. Respondents indicated support for the Reverend Dr. Martin Luther King Jr., Roy Wilkins, Stokely Carmichael, H. Rap Brown, and the National Association for the Advancement of Colored People (NAACP). Support is measured on a three point scale, and higher

[14]Note that the sample is restricted to individuals who, at the time of the survey, were of voting age.

values indicate less support.

Black migrants are significantly more supportive of the Reverend Dr. Martin Luther King Jr. (column 1; $p < .01$; Appendix Table 4.4). They are also more supportive of Roy Wilkins (column 2; $p < .05$). Southern Blacks are no more (less) likely to approve of Stokely Carmichael, or H. Rap Brown (columns 3 and 4, respectively). Black migrants are more supportive of the NAACP, however (column 5; $p < .01$).

I use the LPM to measure whether migrants were more (less) likely to contribute money to a civil rights organization (Appendix Table 4.5). The outcome is a binary variable equaling 1 if the respondent contributed money, and 0 if not. The null of no difference fails to be rejected ($p = .68$). Each of the control covariates is significant to $p < .001$, however, and the effects are not unexpected. Older, higher income, and better educated respondents are more likely to contribute. The same is true for men, as well.

Taken comprehensively, migrant Blacks differed in their trust in government, and in whom they supported. Rather surprisingly, Black migrants are more trusting in government, despite the fact that they come from states with overtly segregationist political officials. Unsurprisingly, however, they are more supportive of the Reverend Dr. Martin Luther King Jr., Roy Wilkins, and the NAACP. This could be because of the Black religious tradition in the South, and the fact that these leaders were, in the eyes of many, more centrist than other leaders and organizations such as Malcolm X, Angela Davis, and the Black Panthers.

Comparing Migrants

Did migrant attitudes change once in the North? I examine this possibility to shed light on socialization processes, and, more specifically, whether long-term exposure to a new social milieu fundamentally changes one's political preferences and attitudes. To answer this question, I run a similar analysis, but use a continuous variable measuring years that the respondent has lived in the North, and restrict the sample to include migrant Blacks. The model specification and remaining variables remain the same as in the previous regressions.

The number of years spent in the North is unrelated to trust in government (Appendix Table 4.6). However, it is negatively associated with the probability of responding that laws and persuasion are the only way to increase Black well-being ($p < .01$). Years spent in the North is unrelated to the perception that the government is trying hard to fix problems in the respondent's city.

There is no relationship between years spent in the North and support for civil rights leaders, as well as the NAACP (Appendix Table 4.7, columns 1 through 5). Although, years spent in the North is positive and significantly related to contributions (Appendix Table 4.8; $p < .01$). Altogether, the results show that migrant attitudes did not change when they entered a new social milieu.

4.9 Discussion

As this paper shows, demographic change affects congressmember ideology and voting behavior. As the number Blacks living outside of the South increased during the 20^{th} century, elite ideology moved left and became more progressive on civil rights. I argue that this occurred through a multi-step process. Existing electoral demography was uprooted by Black migrants who relocated to areas largely devoid of their presence. These migrants brought their political ideologies with them and changed the status quo preferences of the electorates the settled in. In turn, elites took notice and moved in the direction of these migrants. All told, the Great Migration may have been the catalyst that spurned the leftward shift on civil rights issues during the 20^{th} century.

The findings speak to the dynamic between street-level partisans and political elites. Lenz (2012) suggests a top-down political model in which voters attach themselves to political leaders, and then adopt the leaders' policy preferences. In this way, political elites are responsible for cultivating the public's policy preferences and political behavior. The current paper provides evidence of an alternative model of politics, one where ground-level changes to the distribution of constituent preferences affects elite ideology and behavior. Surely, elites may be capable of molding the public's preferences. However, as I show, elites may be keen to adapt their preferences to meet the demands of shifting electoral tides.

Speaking more directly to this point, a longstanding argument in political science is that elected officials need to stay in ideological alignment with their electorate in an effort to win, or remain in, office (Mayhew, 1974). Moreover, congressmembers must actively engage with their electorates, and show that they are working on their behalf to keep support (Fenno, 1978). I find support for these claims. Surely, congressmembers were aware of the demographic change unfolding in their electorates during the Great Migration, and it is plausible that they faced increased pressure from the emergent Black population to pursue liberal civil rights policy. Either out of fear of electoral backlash, or because of a calculated effort to seize, and incorporate, this group into their constituency base, congressmembers took ideological stances and policy positions that would win migrants' approval. It has been shown that the Democratic party had an incentive to support pro-civil rights legislation because it wanted to win the burgeoning Black vote (Schickler, 2016, ch. 6). I provide indirect evidence that this line of inquiry is true.

Results from the *Racial Attitudes in Fifteen American Cities Survey* speak not only to the political character of Black migrants, but to the assumptions required for demographic change to affect the political system. Black migrants were more trusting in government, but did not differ in the degree to which they felt that laws and persuasion could affect Black well-being. Moreover, they were no different in the perception of the federal government's role in solving everyday problems in the cities they settled in. However, they were significantly more supportive of the Reverend Dr. Martin Luther King Jr., Roy Wilkins, and the NAACP. Both Dr. King and Roy Wilkins were more conservative in their approach to civil rights than Carmichael and Brown, and Black migrants may have been more supportive of Dr. King and Wilkins for this reason.[15] This is further reflected by increased migrant support for the NAACP, an organization that has traditionally been associated with a more temperate view toward civil rights than other organizations (Marger, 1984).

Additionally, Black migrants did not change their attitudes once outside of the South. Years spent in the North does not affect support for key variables explaining interaction with government. It also does not explain support for civil right leaders and organizations. Despite this, the null results speak to the validity of the assumption that attitudes among individuals entering an electorate must remain stable for political change to occur. As the survey data shows, Black migrants possess high levels of attitudinal stability. We can be confident that demographic change affected elite behavior because migrants were different from non-migrants, *and* because migrant attitudes did not change over time.

With this in mind, there is mixed evidence that congressmember ideology shifted left because Black migrants were, on average, more liberal than the electorates the relocated to. For one, the survey data does not have measures of partisanship or ideology, so it is impossible to directly test this possibility. Even if these measures did exist, comparisons would have only been possible between migrant and non-migrant Blacks, because the survey does not include respondents from other racial groups. Despite these shortcomings, however, the data does show that Black migrants were more supportive of two

[15]Carmichael, for instance, promoted the phrase "Black Power", which Dr. King was skeptical of. Additionally, Rap Brown was a member of the Black Panther Party which, in many ways, was more progressive than the NAACP, an organization that Roy Wilkins served as executive director of.

important civil rights leaders, more supportive of a major civil rights organization, and more trusting in government.

It is possible that Black migrants pushed congressmember ideology to the left because they were more vocal on civil rights issues. But, the survey data presented here is opaque on that point. A more likely explanation is that Black migrants affected congressmember ideology through critical mass. An increasingly Black electorate may have, through sheer size, forced congressmembers to pursue civil rights policies and adopt liberal political platforms. In this way, Black migrants need not have held political sentiments that were more liberal. Rather, their presence alone may have increased the size of Black electorate to the point that elected officials could not ignore them. The evidence here suggests that this was likely true, but that there were a combination of forces was at work: Black migrants were more supportive of popular civil rights leaders and organizations that formed the core of the Civil Rights Movement. As a result, elites may have taken notice, and adapted their policy preferences in tow. However, electoral incentives behooved elites to adopt preferences that were in greater lockstep the increasingly large Black vote, regardless of the particular political preferences that this emergent constituency had.

Examining the relationship between demography and politics is crucial if we are to better understand past, and future, political trajectories. While important, this is not without challenge: demographic change is best characterized as a long, gradual, process, one that may not be readily visible, identifiable, or easily studied. However, as this paper shows, it has an enduring effect on politics, one that directly affects elite ideology and behavior. This paper focuses on a single demographic event, and chronicles its impact on a sole political entity: congress. However, demographic processes are constantly (re)shaping the face of electorates, whether through fertility, mortality, or aging. Identifying each's impact on electoral demography, and the political system more broadly, will afford us the ability to comprehend politics with greater nuance, clarity, and depth.

4.10 Appendix

Black Migration's Impact on Congressmember Ideology and Voting Behavior

This section presents full regression results for the elite ideology and Civil Rights Act vote models. These estimates for the row "Black" correspond to those in Figure 4.1 and 4.2 in the main results section.

	DV: *DW-Nominate Score (1st Dimension)*					
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.040	0.012	−0.072***	−0.072***	−0.224***	−0.220***
	(0.048)	(0.036)	(0.012)	(0.015)	(0.040)	(0.054)
Total Pop.	0.094	−0.290	0.259***	0.403**	0.454***	0.277
	(0.250)	(0.223)	(0.085)	(0.160)	(0.124)	(0.203)
Manufacturing	−0.088	−0.055	−0.021	−0.010	0.152*	0.348**
	(0.088)	(0.193)	(0.054)	(0.078)	(0.084)	(0.146)
Blue Collar	0.055	−0.098	−0.176*	−0.423***	−0.395***	−0.867***
	(0.079)	(0.296)	(0.101)	(0.158)	(0.149)	(0.226)
Construction	0.053*	0.020	0.215***	0.311***	0.225**	0.554***
	(0.028)	(0.127)	(0.059)	(0.078)	(0.089)	(0.131)
Unemployed	−0.069	0.004	−0.174***	−0.279***	−0.034	−0.001
	(0.060)	(0.060)	(0.037)	(0.052)	(0.060)	(0.119)
Union Jobs	0.023	0.053	−0.068	−0.056	−0.116*	−0.168
	(0.077)	(0.115)	(0.051)	(0.086)	(0.060)	(0.105)
CD Sample	No Δ	No Δ	All	All	All	All
Region US	All	NE + MW	All	NE + MW	All	NE + MW
State Effects	-	-	✓	✓	✓	✓
Time Effects	✓	✓	✓	✓	✓	✓
Unit Effects	✓	✓	-	-	-	-
2SLS	-	-	-	-	✓	✓
1^{st} Stage F Stat.	-	-	-	-	554.2***	263.1***
Observations	990	495	3,859	1,943	3,815	1,921
R^2	0.009	0.019	0.325	0.421	0.251	0.353
Adjusted R^2	−0.110	−0.119	0.314	0.411	0.239	0.343

*p<0.1; **p<0.05; ***p<0.01. All independent variables are log transformed. "CD Sample" refers to the set of congressional districts used in the model. Standard errors are clustered by district. "No Δ" corresponds to congressional districts whose shape did not change between the 78^{th} and 88^{th} congress. "Region US" corresponds to whether all districts are used in the analysis ("All"), or those located in the Northeast and Midwest ("NE + MW").

Table 4.1: Regression of Black Migration on Elite Ideology (78^{th} -88^{th} congresses)

	DV: *CRA Vote*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	0.018	0.043	0.081	0.079	0.040**	0.054**	0.094**	0.073*
	(0.034)	(0.073)	(0.136)	(0.249)	(0.016)	(0.022)	(0.040)	(0.038)
Total Pop.	0.266	0.486	0.146	0.660	−0.053	−0.237	−0.157	−0.282
	(0.331)	(1.096)	(0.465)	(1.389)	(0.189)	(0.321)	(0.204)	(0.344)
Manufacturing	−0.215	0.117	−0.240	0.129	0.050	0.344*	0.006	0.332*
	(0.210)	(0.626)	(0.221)	(0.649)	(0.068)	(0.180)	(0.077)	(0.176)
Blue Collar	0.510	−0.311	0.443	−0.541	−0.124	−0.367**	−0.060	−0.356**
	(0.471)	(1.288)	(0.524)	(1.907)	(0.141)	(0.179)	(0.155)	(0.172)
Construction	−0.283	−0.185	−0.188	−0.224	0.067	0.066	0.126	0.090
	(0.285)	(0.645)	(0.368)	(0.665)	(0.096)	(0.143)	(0.100)	(0.151)
Unemployed	0.017	0.007	−0.009	−0.057	0.072	0.029	0.020	0.010
	(0.299)	(0.444)	(0.278)	(0.593)	(0.094)	(0.119)	(0.098)	(0.122)
Union Jobs	−0.218	0.087	0.169	0.282	1.303*	0.682	1.191***	0.917
	(0.290)	(0.971)	(0.855)	(1.796)	(0.739)	(0.636)	(0.099)	(0.838)
CD Sample	No Δ	No Δ	No Δ	No Δ	All	All	All	All
Region US	All	NE + MW	All	NE + MW	All	NE + MW	All	NE + MW
2SLS	-	-	✓	✓	-	-	✓	✓
1^{st} Stage F Stat.	-	-	4.9**	1.9	-	-	43.3***	37.0***
Observations	89	45	89	45	341	173	337	171
R^2	0.762	0.261	0.748	0.254	0.701	0.254	0.684	0.250
Adjusted R^2	0.650	−0.084	0.630	−0.093	0.650	0.145	0.634	0.150

*p<0.1; **p<0.05; ***p<0.01. All independent variables are log transformed. The outcome is a dummy variable for voting in favor of the Civil Rights Act. All models are estimated using the linear probability model. All models use state effects. Standard errors are clustered by district. "CD Sample" refers to the congressional districts used in the model. "No Δ" corresponds to districts whose shape did not change between the 78^{th} and 88^{th} congress. "Region US" corresponds to whether all districts are used in the analysis ("All"), or those in the Northeast and Midwest ("NE + MW").

Table 4.2: Regression of Black Migration on CRA Vote (88^{th} Congress)

Racial Attitudes in Fifteen American Cities Survey

This section presents results from the *Racial Attitudes in Fifteen American Cities Survey*.

	Attitudes Toward Government		
	Model Type:		
	OLS	LPM	OLS
	(1)	(2)	(3)
Southern Homestate	-0.397^{***}	-0.038^{*}	-0.037
	(0.099)	(0.022)	(0.038)
Age	-0.0004	0.003^{***}	-0.0002
	(0.004)	(0.001)	(0.001)
Total Family Income	0.029^{*}	-0.004	0.015^{**}
	(0.015)	(0.003)	(0.006)
Years of Schooling	-0.008	0.014^{***}	0.016^{**}
	(0.019)	(0.004)	(0.007)
Male	-0.096	-0.017	-0.049
	(0.094)	(0.021)	(0.036)
Constant	5.883^{***}	0.227^{***}	1.647^{***}
	(0.275)	(0.064)	(0.104)
N	1,911	2,286	2,253
R^2	0.012	0.009	0.010
Adjusted R^2	0.009	0.007	0.008

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.
Notes: Southern Homestate is a binary term coded as 1 if the respondent spent the first 10 years of life in a southern state. Column 1 measures trust in government, and higher values indicate *less* trust. Column 2 uses the LPM to estimate whether respondents feel that laws and persuasion are the only way to increase Black well being, coded as 1 if yes and 0 if no. Last, column 3 measures how hard respondents feel that the government is trying to solve problems in their city, and higher levels indicate that the government is perceived as trying *less* hard.

Table 4.3: Migrant Characteristics (Government and Laws)

	Civil Rights Leaders and Organizations				
	Support For:				
	MLKJ	RW	SC	RB	NAACP
Southern Homestate	−0.097***	−0.064**	−0.002	−0.029	−0.061***
	(0.023)	(0.027)	(0.038)	(0.037)	(0.020)
Age	−0.001	−0.004***	0.011***	0.013***	−0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Family Income	−0.004	0.0002	0.013**	0.012**	−0.004
	(0.003)	(0.004)	(0.006)	(0.006)	(0.003)
Years of Schooling	0.006	−0.001	0.021***	0.047***	0.007*
	(0.004)	(0.005)	(0.008)	(0.007)	(0.004)
Male	0.086***	0.045*	−0.204***	−0.169***	0.038**
	(0.022)	(0.026)	(0.037)	(0.036)	(0.019)
Constant	1.303***	1.427***	1.692***	1.514***	1.169***
	(0.065)	(0.079)	(0.111)	(0.105)	(0.056)
N	2,487	1,710	1,764	1,829	2,374
R^2	0.017	0.017	0.057	0.074	0.009
Adjusted R^2	0.015	0.014	0.054	0.072	0.007

*p < .1; **p < .05; ***p < .01.
Notes: All dependent variables are on a scale ranging from 1 to 3, with higher levels indicating *less* support toward the respective leader/organization. Southern Homestate is a binary term coded as 1 if the respondent spent the first 10 years of life in a southern state. Columns titled "MLKJ", "RW", "SC", "RB", and "NAACP" represent support for Dr. Martin Luther King Jr., Roy Wilkins, Stokely Carmichael, H. Rap Brown, and the National Association for the Advancement of Colored People, respectively.

Table 4.4: Migrant Characteristics (Leaders and Organizations)

	Contributions
	Model Type:
	LPM
	(1)
Southern Homestate	0.008
	(0.019)
Age	0.010***
	(0.001)
Total Family Income	0.027***
	(0.003)
Years of Schooling	0.047***
	(0.004)
Male	0.098***
	(0.018)
Constant	−0.672***
	(0.052)
N	2,597
R^2	0.177
Adjusted R^2	0.175

*p < .1; **p < .05; ***p < .01.
Notes: The dependent variable is a dummy equaling 1 if the respondent has contributed money to a civil rights organization, and 0 if not. Southern Homestate is a binary term coded as 1 if the respondent spent the first 10 years of life in a southern state.

Table 4.5: Migrant Characteristics (Contributions)

	Attitudes Toward Government		
	Model Type:		
	OLS	LPM	OLS
	(1)	(2)	(3)
Years in North	0.012	−0.005***	0.002
	(0.008)	(0.002)	(0.003)
Age	−0.014*	0.004**	−0.003
	(0.008)	(0.002)	(0.003)
Total Family Income	0.009	−0.002	0.019**
	(0.021)	(0.005)	(0.008)
Years of Schooling	−0.001	0.005	0.017*
	(0.024)	(0.005)	(0.009)
Male	0.115	−0.037	−0.018
	(0.134)	(0.029)	(0.051)
Constant	5.847***	0.326***	1.659***
	(0.401)	(0.087)	(0.149)
N	958	1,229	1,128
R^2	0.005	0.009	0.016
Adjusted R^2	−0.001	0.005	0.012

*p < .1; **p < .05; ***p < .01.
Notes: All dependent variables are on a scale ranging from 1 to 3, with higher levels indicating *less* support toward the respective leader/organization. Years in North corresponds to the number of years that a Black migrant has spent in the North. Column 1 measures trust in government, and higher levels indicate *less* trust. Column 2 uses the LPM to estimate whether respondents feel that laws and persuasion are the only way to increase Black well being, coded as 1 if yes and 0 if no. Last, column 3 measures how hard respondents feel that the government is trying to solve problems in their city, and higher levels indicate that the government is perceived as trying *less* hard. All regressions are restricted to include individuals who migrated to the North.

Table 4.6: Migrant Comparison (Government and Laws)

	Civil Rights Leaders and Organizations				
	Support For:				
	MLKJ	RW	SC	RB	NAACP
Years in North	0.001	−0.001	0.001	0.005	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Age	−0.002	−0.002	0.010***	0.009***	−0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Total Family Income	−0.001	−0.001	0.010	0.005	−0.004
	(0.005)	(0.005)	(0.009)	(0.008)	(0.004)
Years of Schooling	0.003	0.006	0.036***	0.058***	0.003
	(0.005)	(0.006)	(0.010)	(0.010)	(0.005)
Male	0.101***	0.066*	−0.216***	−0.190***	0.014
	(0.029)	(0.034)	(0.055)	(0.053)	(0.025)
Constant	1.240***	1.248***	1.539***	1.408***	1.168***
	(0.086)	(0.107)	(0.164)	(0.157)	(0.075)
N	1,285	884	821	858	1,217
R^2	0.012	0.014	0.061	0.089	0.001
Adjusted R^2	0.008	0.008	0.055	0.084	−0.003

*p < .1; **p < .05; ***p < .01.
Notes: All dependent variables are on a scale ranging from 1 to 3, with higher levels indicating *less* support toward the respective leader/organization. Years in North corresponds to the number of years that a Black migrant has spent in the North. Columns titled "MLKJ", "RW", "SC", "RB", and "NAACP" represent support for Dr. Martin Luther King Jr., Roy Wilkins, Stokely Carmichael, H. Rap Brown, and the National Association for the Advancement of Colored People, respectively. All regressions are restricted to include individuals who migrated to the North.

Table 4.7: Migrant Comparison (Leaders and Organizations)

	Contributions
	Model Type:
	LPM
	(1)
Years in North	0.005***
	(0.002)
Age	0.006***
	(0.002)
Total Family Income	0.025***
	(0.004)
Years of Schooling	0.041***
	(0.005)
Male	0.087***
	(0.026)
Constant	−0.527***
	(0.076)
N	1,343
R^2	0.154
Adjusted R^2	0.151

*p < .1; **p < .05; ***p < .01.
Notes: The dependent variable is a dummy equaling 1 if the respondent has contributed money to a Civil Rights organization, and 0 if not. Years in North corresponds to the number of years that a Black migrant has spent in the North. All regressions are restricted to include individuals who migrated to the North.

Table 4.8: Migrant Comparison (Contributions)

Creating the Instrument

I created the instrument by manually identifying all railroad routes that connected the South to the Northeast and Midwest.[16] I then identified whether each route was named to a particular railroad company, or known route. If it was, I checked the name against the historical record to identify whether it was, or could have been, used during the Great Migration. If it was mentioned in the historical record as being a relevant source of transportation, I kept it in the final sample. If it was not, I removed it from the sample. Railroad routes not meeting any of these criteria were excluded from the analysis to reduce the potential for Type I error, and to make sure that only well-documented routes were retained.

After the final set of routes was established, I manually inspected each spatial line segment of each route to ensure that it was, in fact, associated with its given name. I did this because some sections of railroad routes were not named, despite them being a part of, or next to, named lines. If portions were not named, I deleted them from the full line segment to ensure that only route segments that were verified to have a name, *and* be historically-relevant were kept for the final sample. This safeguards against including irrelevant or erroneous routes in the sample, which would increase measurement error.

I used the congressional district shapefiles to calculate the distance metric. This was done iteratively for each congressional term for which there was available congressional district demographic data. In total, distances were calculated for all congressional districts located in the Midwest and Northeast, from the 78^{th} through 88^{th} congresses.

[16] Due to the comparatively sparse railroad network in the western US, I exclude this region from the instrumental variables analyses.

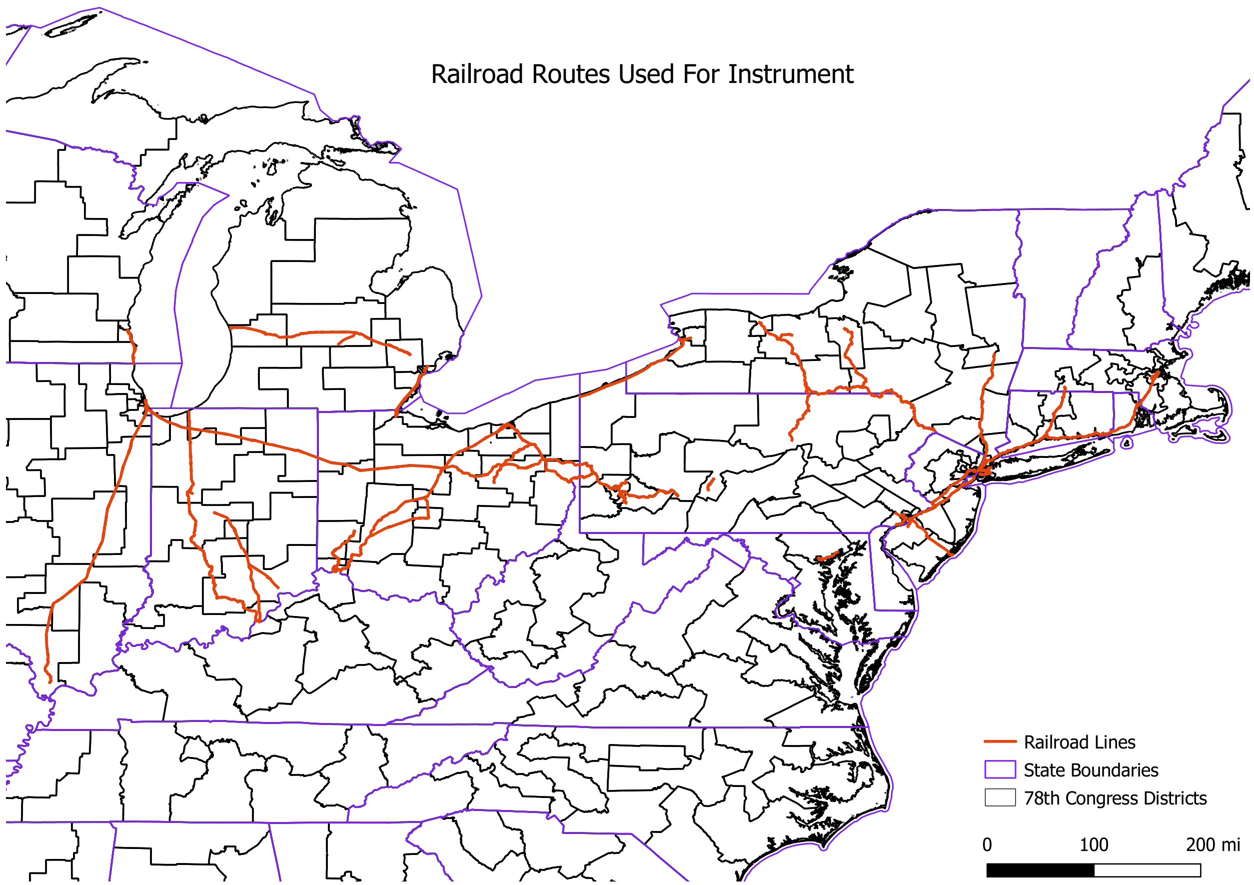


Figure 4.3: Railroad Routes

Note: Shown are railroad routes used to create the instrument. These include railroad routes located in the North and Midwest, only. Railroad routes were cleaned, and the final set included only those that were named. Map created in QGIS.

Balance Tests

This section performs balance checks between congressional districts that did not change shape between the 78^{th} and 88^{th} congresses and those that did. "Treated" districts are those that changed shape, and "control" districts are those that did not. These tests establish whether there are observable differences between districts that changed shape, and those that did not. These tests speak to the generalizability of the results using the restricted sample. I calculate balance statistics iteratively for each of the 78^{th} through 88^{th} congresses, and tables are presented *seriatim*.

	Treatment	Control	T P-Value	KS P-Value
Black	36581.76	26530.98	0.09	0.02
Total Population	302118.18	304125.53	0.78	0.72
Manufacturing	25665.80	24917.19	0.72	0.35
Blue Collar	37790.93	38316.26	0.79	0.22
Construction	4565.41	4977.65	0.05	0.01
Unemployed	15384.83	18122.72	0.00	0.01
Union	17.66	20.78	0.00	0.00
Railroad Distance	589443.72	512317.28	0.41	0.04

Table 4.9: 78^{th} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	35549.10	26133.93	0.11	0.01
Total Population	300386.25	304153.21	0.59	0.79
Manufacturing	25748.34	24838.82	0.67	0.21
Blue Collar	37309.18	38225.86	0.65	0.14
Construction	4592.91	4959.84	0.08	0.01
Unemployed	15251.56	18172.75	0.00	0.00
Union	17.82	20.88	0.01	0.00
Railroad Distance	599214.51	513591.77	0.37	0.05

Table 4.10: 79^{th} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	36581.76	26497.33	0.09	0.02
Total Population	302118.18	303842.34	0.81	0.74
Manufacturing	25665.80	24984.50	0.74	0.39
Blue Collar	37790.93	38387.94	0.77	0.22
Construction	4565.41	4982.83	0.05	0.01
Unemployed	15384.83	18124.13	0.00	0.00
Union	17.66	20.77	0.01	0.00
Railroad Distance	589443.72	513502.43	0.41	0.04

Table 4.11: 80^{th} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	36581.76	26530.98	0.09	0.03
Total Population	302118.18	304125.53	0.78	0.73
Manufacturing	25665.80	24917.19	0.72	0.31
Blue Collar	37790.93	38316.26	0.79	0.25
Construction	4565.41	4977.65	0.05	0.02
Unemployed	15384.83	18122.72	0.00	0.00
Union	17.66	20.78	0.00	0.00
Railroad Distance	589443.72	510943.18	0.40	0.04

Table 4.12: 81^{st} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	36581.76	26530.98	0.09	0.02
Total Population	302118.18	304125.53	0.78	0.70
Manufacturing	25665.80	24917.19	0.72	0.32
Blue Collar	37790.93	38316.26	0.79	0.24
Construction	4565.41	4977.65	0.05	0.01
Unemployed	15384.83	18122.72	0.00	0.00
Union	17.66	20.78	0.00	0.00
Railroad Distance	589443.72	510943.18	0.40	0.05

Table 4.13: 82^{nd} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	39705.61	34396.60	0.38	0.01
Total Population	351642.61	351478.41	0.99	0.18
Manufacturing	36245.78	34803.50	0.57	0.79
Blue Collar	53707.78	52543.46	0.61	0.50
Construction	7977.97	8119.01	0.73	0.03
Unemployed	5828.45	6916.90	0.00	0.00
Union	30.06	31.69	0.26	0.01
Railroad Distance	590242.05	513841.32	0.42	0.04

Table 4.14: 83^{rd} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	40226.96	34396.60	0.34	0.02
Total Population	352113.09	351478.41	0.95	0.25
Manufacturing	36532.33	34803.50	0.49	0.77
Blue Collar	53998.83	52543.46	0.52	0.51
Construction	7990.96	8119.01	0.75	0.03
Unemployed	5828.97	6916.90	0.00	0.00
Union	29.84	31.69	0.20	0.01
Railroad Distance	589443.72	513841.32	0.42	0.03

Table 4.15: 84^{th} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	40226.96	34396.60	0.34	0.03
Total Population	352113.09	351478.41	0.95	0.26
Manufacturing	36532.33	34803.50	0.49	0.76
Blue Collar	53998.83	52543.46	0.52	0.46
Construction	7990.96	8119.01	0.75	0.05
Unemployed	5828.97	6916.90	0.00	0.00
Union	29.84	31.69	0.20	0.00
Railroad Distance	589443.72	513715.50	0.42	0.04

Table 4.16: 85^{th} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	40226.96	34396.60	0.34	0.01
Total Population	352113.09	351478.41	0.95	0.26
Manufacturing	36532.33	34803.50	0.49	0.78
Blue Collar	53998.83	52543.46	0.52	0.46
Construction	7990.96	8119.01	0.75	0.06
Unemployed	5828.97	6916.90	0.00	0.00
Union	29.84	31.69	0.20	0.00
Railroad Distance	589443.72	513715.01	0.42	0.06

Table 4.17: 86^{th} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	40226.96	34396.60	0.34	0.02
Total Population	352113.09	351478.41	0.95	0.26
Manufacturing	36532.33	34803.50	0.49	0.71
Blue Collar	53998.83	52543.46	0.52	0.46
Construction	7990.96	8119.01	0.75	0.02
Unemployed	5828.97	6916.90	0.00	0.00
Union	29.84	31.69	0.20	0.00
Railroad Distance	589443.72	513797.89	0.42	0.04

Table 4.18: 87^{th} Congress

	Treatment	Control	T P-Value	KS P-Value
Black	46681.92	44456.94	0.75	0.05
Total Population	423688.35	413683.29	0.50	0.01
Manufacturing	44250.07	40895.86	0.23	0.19
Blue Collar	60988.79	56816.80	0.06	0.12
Construction	9120.62	8621.83	0.24	0.47
Unemployed	7643.81	8154.49	0.11	0.24
Union	26.40	29.75	0.01	0.00
Railroad Distance	589443.72	522494.11	0.48	0.04

Table 4.19: 88^{th} Congress

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