

# Districting Without Parties: How City Council Maps Increase Minority Representation

Michael Hankinson\*      Asya Magazinnik†

April 19, 2023

## Abstract

District elections have long been considered a tool for promoting minority representation in local government. But surprisingly little is understood about how electoral maps themselves shape political outcomes. We collect over one hundred new districting plans from cities across California that converted from at-large to district elections in the wake of the California Voting Rights Act of 2001. Applying a state-of-the-art automated redistricting simulator, we find that most of these cities could not feasibly produce a plan with even one Latino-majority seat, though those that could generally tried to maximize this quantity. We introduce alternative metrics of descriptive representation that are tailored to a city’s political dynamics and risk tolerance around securing at least one Latino seat. Contrary to intuitions from partisan districting, we see no conflict between the goals of guaranteeing minimal representation and maximizing seats overall; rather, we find that concentrating Latinos within districts often achieves both goals and at no expense for Latinos’ substantive representation.

Word Count: 9,862 words

Keywords: districting, representation, local politics

---

Both authors contributed equally and names are in alphabetical order. We are grateful to Yuxiao Wang and Joseph Loffredo for invaluable research assistance. The manuscript also benefited from generous feedback from Shiro Kuriwaki, Max Palmer, and workshops at Aarhus University, the Hertie School, and the George Washington University. This work has been supported (in part) by Grant # 2105-32770 from the Russell Sage Foundation. Any opinions expressed are those of the principal investigators alone and should not be construed as representing the opinions of the Foundation.

\*Assistant Professor, Department of Political Science, GWU. [hankinson@gwu.edu](mailto:hankinson@gwu.edu)

†Assistant Professor, Department of Political Science, MIT. [asyam@mit.edu](mailto:asyam@mit.edu)

## Introduction

Single-member district elections have long been considered a tool for improving the descriptive representation of minority groups (Davidson and Korbel 1981; Welch 1990), especially where districts can be drawn that make the minority a local majority (Abott and Magazinnik 2020; Dancygier 2014; Trounstein and Valdini 2008). Consequently, legal action and even statewide legislation have prompted hundreds of cities across the United States to switch from multi-member at-large city council elections to district systems in recent decades. An active academic literature has kept apace with these developments, analyzing how the adoption of district elections changes both representation and policy at the local level (Abott and Magazinnik 2020; Boylan 2019; Collingwood and Long 2019; Hankinson and Magazinnik Forthcoming; Mast Forthcoming; Ricca and Trebbi 2022).

Almost universally, these studies have defined districting as a uniform treatment, with no consideration for *how* the districting plans that are actually drawn aggregate votes into council seats. But, as scholars and practitioners of state and federal legislative districting are well aware, the specific shape and location of district boundaries deeply matters for electoral outcomes. In the partisan context, a plan can systematically advantage one party by either diluting its rival party’s voters across multiple districts (“cracking”) or overconcentrating them in a few districts (“packing”) (McGhee 2020). Falling either just below or too far above the threshold of 50% of the two-party vote share “wastes” votes, leading a party to win fewer seats than what would be proportional to its population share (McGhee 2014; Stephanopoulos and McGhee 2015). In the American first-past-the-post system, the massive swings in the compositions of legislatures that can result from even small perturbations of district boundaries have generated enormous scholarly attention, not to mention legal and political dispute.

And yet, the insights from these debates have not yet been systematically applied to the practice of local districting. Our paper fills this gap. We adapt the statistical and computational tools developed for partisan districting to build theory and evidence for a new and important context: minority representation in local government. In so doing, we develop a research design that also advances the study of districting and minority representation more broadly, including at the congressional level. Previous work on this topic has treated individual *districts* as the unit of analysis, studying the population thresholds that racial minorities must clear in order to achieve descriptive

or substantive representation (e.g., Cameron, Epstein and O’Halloran 1996). While this work has yielded important substantive insights, treating districts as the unit of analysis is inadequate: not only does the concentration of minority voters in one district mechanically constrain the compositions of the other districts’ electorates, but how one district’s elected council member represents her constituents is enabled and constrained by other members of the council. To see the full picture of representation, one must zoom out to the entire ecosystem: the district *plan* and the composition of the entire legislative body that it generates. Recent advances in simulation-based methods for studying all possible districting plans within a city enable us to do just that.

A central challenge of this enterprise — and, by the same token, an opportunity to advance the literature — is that the logic of partisan districting does not translate cleanly to the axis of ethnic conflict in local politics. The focus of partisan districting is the 50% two-party vote share threshold. In theory, if a minority voting bloc is greater than 50% of the citizen voting-age population (CVAP) in some district, they have the ability to elect their candidate of choice. But given historically lower levels of turnout among minority voters compared to white voters (Fraga 2018), a threshold greater than 50% may be needed to provide a “realistic opportunity to elect officials of their choice” (*Kirksey v. Board of Supervisors of Hinds County Mississippi*, 554 F.2nd 559 (1977)). By the early 1980s, legal opinions consistently cited 65 percent as the standard for “realistic opportunity,” despite having little empirical basis for this threshold (Brace et al. 1988).

While the “65 percent rule” acknowledges inequalities of resources, turnout, and political organization, it also risks magnifying these disparities. If the threshold for minority representation is set too high, it will lead to the packing of minority voters into fewer districts at the expense of creating realistic opportunities in more districts. For example, research on congressional districting suggests that Black populations well below the 50% threshold have been able to elect Black members of Congress due to coalition voting with non-Black Democrats (Cameron, Epstein and O’Halloran 1996; Lublin 1997). Even in contexts of intense racially polarized voting, such as the American South, concentrating Black voters in excess of 47% CVAP has been found to be inefficient (Cameron, Epstein and O’Halloran 1996).

We tackle this question empirically by developing a novel approach for understanding how different feasible districting plans within a city translate into *citywide* electoral outcomes for the minority group, given the facts on the ground related to the city’s electoral geography and political

behavior. To do so, we leverage the California Voting Rights Act (CVRA), which continues to compel California cities to switch from at-large to district elections in order to increase the electoral success of Latino candidates and therefore the descriptive representation of Latino voters. We combine electoral and administrative data from 107 cities that adopted brand-new districting plans in response to the CVRA. Then, we use the redistricting algorithm developed by Fifield et al. (2020) to characterize the distribution of feasible plans within each city, given its unique physical and residential geography coupled with the federal contiguity, compactness, and equal-population constraints. Finally, we use real-world city council election data to model electoral outcomes under each feasible plan. This gives us novel insight into how district maps can maximize minority electoral success, not just across cities but compared to what is possible *within* each city. Moreover, comparing the adopted maps to these distributions allows us to assess whether cities generally chose plans that were favorable to minority voters — and what they optimized for in their choices.

First, we find that the metric of Latino representation that was the focus of city council meetings, interest groups, and indeed the CVRA itself — the share of districts in which the Latino CVAP is more than 50% of total CVAP — is inadequate for evaluating maps in the majority of our cities. In 60% of our sample (which covers 71% of the universe of cities that converted to districts under the CVRA), it is impossible to draw even one majority Latino CVAP district. Filling this analytical void, we compute alternative measures of minority electoral success: the expected share of council seats held by Latinos; the probability of electing at least one Latino to council; and the probability of Latinos holding the council majority. Which measure a minority voting bloc will seek to maximize depends on the goals it hopes to achieve with descriptive representation, on its level of risk-aversion, and on the political dynamics on councils. However, contrary to intuitions from the partisan districting literature, we do not find systematic trade-offs in optimizing for these different metrics. While some plans are better at maximizing some metrics than others, rarely are any of the various goals in direct tension with one another.

Second, we find that maps which increase the concentration of Latinos within districts tend to increase all four measures of electoral success. In contrast to the partisan context, where segregating copartisans into supermajority districts tends to *decrease* a party's expected seat share, low turnout among Latinos implies that concentrated districts are necessary for the electoral success of Latino minorities. What is more, we find no evidence that concentrating Latinos in districts

has downstream effects on partisan advantage. In particular, because Latinos tend to support the Democratic party (Barreto and Segura 2014), some may worry that concentrating Latino voters in a few districts will disadvantage Democrats across the other districts, sacrificing substantive representation for descriptive representation (Brace, Grofman and Handley 1987; Lublin 1997). We do not find this to be the case. Rather, across risk-neutral, risk-averse, and substantive representation goals, maximizing the concentration of Latino voters is often the simplest strategy.

Third, we show that the positive effect of concentrating Latinos into districts comes from the comparatively poor performance of Latino candidates in comparison to their district's Latino CVAP. When Latinos are a minority in their district, the predicted probability of electing a Latino candidate is below the proportion of Latino voters in the district. This implies that concentrating Latinos is necessary to minimize their risk of underrepresentation on city council. In contrast, we find that non-Hispanic white candidates consistently overperform relative to their share of the electorate, likely due to higher turnout. Thus, electoral maps that concentrate white voters actually decrease the expected share of white representatives on councils.

Compared to the range of feasible maps, the district boundaries selected by city councils in response to the CVRA are generally favorable for the predicted electoral success of Latino candidates. But this underscores our fourth and final contribution: were city councils to select unfavorable maps for Latino candidates, the naive approach of treating the district elections as uniform may find that the reform was ineffective at improving descriptive representation. Thus, our work advances a necessary understanding of *how* to district to effectively advance descriptive representation on city councils. This is not only important for equalizing voice, but vital for democratic legitimacy. When a reform like districting is guided by improper tools and folk wisdom, the promise of representation is unlikely to be fulfilled, undermining trust in the institution.

## Theory and Literature

As of 2012, approximately 64 percent of American municipalities relied on at-large voting for their city council elections, whereas 14 percent used district elections, with the remaining 22 percent utilizing some form of hybrid systems (Clark and Krebs 2012). This city-level variation largely stems from the early 20th century, when municipal reformers sought to counter the influence of

machine-style politics via at-large systems (Trounstine 2009). Reformers believed that at-large elections would produce council members responsive to the city as a whole, not the patronage politics of their own district.

In reality, the constituency of the at-large legislator is rarely the city as a whole. Elected officials are most responsive to those who participate, generally meaning wealthier, more highly educated white voters; low turnout in local elections exacerbates this participation gap (Hajnal and Trounstine 2005). So long as an at-large city maintains a majority white turnout with racially polarized voting, a white coalition can secure an all-white city council. By contrast, cities that can draw districts where the underrepresented minority constitutes a local majority can theoretically create the opportunity for the minority voting bloc to elect its preferred candidate.

How district elections increase minority representation at the local level has been theorized, but not critically assessed. Under the federal Voting Rights Act (VRA), the conditions under which an at-large system may be held legally responsible for minority vote dilution are succinctly stated by the *Gingles* test. To prove that district elections would likely increase minority representation, plaintiffs must show that the relevant racial or language minority group is “sufficiently large and geographically compact to constitute a majority in a single-member district”; that this group is “politically cohesive”; and that the majority usually votes as a bloc to defeat the minority’s preferred candidates (*Thornburg v. Gingles*, 478 U.S. 30, 53 n. 21 (1986)). Absent these conditions, we should not expect the implementation of district elections to improve descriptive representation.

Empirical evidence supporting this theory at the local level has generally come from *across-city* analyses showing that the effects of district elections are greater in cities with large minority populations and high levels of racial segregation (Abott and Magazinnik 2020; Collingwood and Long 2019; Dancygier 2014; Hankinson and Magazinnik Forthcoming; Trounstine and Valdinì 2008). But findings from these studies, particularly the moderating effect of segregation, have been noisy, inconsistent, and undertheorized. For instance, the same segregation that creates the conditions for advantageous maps may just as easily facilitate maps *disadvantaging* minority voters via cracking and packing. Understanding the effect of “districting well” versus districting alone requires evaluating the performance of various plans compared to counterfactual plans that are also available *within the same city*. To our knowledge, no such analysis has been done to date. Consequently, in addition to lacking a complete understanding of the mechanism by which districts improve mi-

nority descriptive representation, the existing literature cannot speak to whether city councils have overperformed or underperformed expectations in their use of district elections to advance this goal.

## **Background: Legislative Districting and the CVRA**

To unpack how district elections shape descriptive representation, we leverage the implementation of the California Voting Rights Act (CVRA). Passed in 2001, the CVRA was designed to increase the representation of Latino voters. As applied to local contests, the law made it easier for plaintiffs to challenge at-large elections for disadvantaging Latino electorates. Specifically, the CVRA lowered the bar set by the federal *Gingles* test, requiring only that plaintiffs show evidence of “racially polarized voting.” As a consequence, the law has brought district elections to over 150 city councils, creating wide variation in the levels of segregation, demographic composition, and political geography among adopters.

The CVRA presents a unique opportunity for opening the black box of how city council maps increase minority representation. First, whereas the *Gingles* test requires that a city be able to draw at least one majority-minority district in order for a court to compel that city to switch to district elections, the CVRA directly relaxes this standard, allowing us to observe the effect of district elections under a wide range of conditions — not just those that are in theory most favorable to minority candidates. Second, the CVRA presents the rare case of districting, not *re*-districting. While redistricting often works around preexisting boundaries and is exceptionally sensitive to protecting incumbents (Henderson, Hamel and Goldzimer 2018), district boundaries in our cities were being drawn from a blank slate. Although incumbent protection certainly may have been taken into consideration, this factor is much more muted when there is no preexisting plan: drawing *new* plans that protect at-large incumbents is a difficult problem, and one with which California’s city councils had little experience.

The process for selecting maps begins with the decision of a city council to switch from at-large to district elections. While many cities appear to switch voluntarily, the threat posed by the CVRA always looms in the background. Every city that has challenged a CVRA claimant in court has lost, with some racking up millions of dollars in legal fees (Schuk 2015). Even receiving a threat letter from a civil rights law firm has serious consequences: not only does it require the city to

reimburse the firm for approximately \$30,000 in research costs, but it starts a countdown requiring fast action to remedy the situation. In contrast, cities that take action prior to any outside legal action can take their time to gather public input and select maps while keeping up with traditional council business. Thus, municipalities that see themselves as targets for litigation may prefer to act early and voluntarily.

Having decided to switch, city councils begin the mapmaking process. In contrast to the highly resourced, sophisticated nature of state and federal mapmaking, districting under the CVRA has been less technical — suggesting that there is much to learn by applying cutting-edge methodologies. First, the city council hires a demographer to both advise the council in the design of their maps and facilitate the ability of community members to submit their own suggestions. The demographer may also work with a “citizens’ committee” designed to collate public input into a single map to recommend to the city council. Eventually, the city council votes directly on a map.

City councils face both internal and external constraints on the range of maps that they can feasibly draw. Internally, a city is limited by both its shape and electoral geography. For example, a city with a small minority population or a minority population that is fully integrated with the majority may be unable to draw a district with a majority-minority CVAP. Externally, the map must comport with federal standards, or risk litigation under the federal VRA: it should be roughly equal in population, relatively compact, and contiguous, with every effort made to keep “communities of interest” together. These external constraints may interact with the internal constraints. For example, a city with an irregular shape may find itself structurally unable to divide certain communities between districts while satisfying the contiguity, compactness, or equal-population requirements, even if so doing would achieve a “fairer” map.

### **Defining Latino Success: Evidence from Anaheim**

The challenge of optimizing representation can be seen in the mapmaking process of Anaheim, a midsize city of approximately 350,000 people located outside of Los Angeles. With 50% of the population and 38% of the citizen voting-age population identifying as Latino, Anaheim was an ideal target for CVRA litigation. Indeed, the city decided to adopt district elections in response to a 2014 lawsuit filed by the ACLU. To aid in the transition, Anaheim’s city council formed a citizens’ committee led by five retired judges. The committee would combine public input with a



legal understanding of the CVRA to propose a community-supported district map. The map would then be voted on by the city council.

But the unexpected debate that erupted around the committee’s map highlights the challenges of defining Latino electoral success and the dearth of tools for evaluating districting plans. Dubbed “The People’s Map,” the committee’s map drew six districts, consisting of one majority Latino CVAP district and two other districts where Latinos were a sizeable minority of around 45% (Elmahrek 2015) — a level that has been found sufficient for Black voters to achieve substantive representation in Congress (Cameron, Epstein and O’Halloran 1996). Yet despite a groundswell of public support, the Anaheim city council voted 3-2 against the People’s Map. Leading the opposition, Councilmember Jordan Brandman expressed concern that the map failed to maximize Latino representation, possibly exposing the city to future CVRA litigation. Brandman favored an alternative map that created two majority Latino CVAP districts.

The meeting ended with the final decision being tabled until the new census data would become available two months later (Elmahrek 2015). Ultimately, advocates of the People’s Map threatened to protest one of Anaheim’s largest annual conventions, spurring the city council to adopt their map (Elmahrek 2016). However, just prior to adoption, there was additional hesitation. The new census data showed that the map’s lone majority Latino CVAP district was no longer majority Latino, dropping to 49% Latino CVAP (Diamond 2016). The city’s demographer assured the council that the 5-year American Community Survey’s margin of error meant that this was not likely to reflect a significant change to the electoral geography, but the public’s focus on this dip highlighted the importance of the 50% CVAP threshold to many stakeholders.

Anaheim’s debate raises meaningful questions about how best to increase descriptive representation. First, which approach would maximize Latino electoral success: concentrating Latinos into two majority-minority districts like Brandman’s map, or the more diffuse approach of the People’s Map? And if Brandman’s map were more effective, would even higher concentrations of Latino voters be more successful in securing seats, or would further packing eventually yield negative returns? Furthermore, was 50% Latino CVAP a meaningful threshold, raising legitimate concerns about the new census data, or folk wisdom that does not reflect on-the-ground voting behavior?

Second, missing from the Anaheim debate was another consideration: what was the risk tolerance of the Latino community? Reliance on the 50% CVAP threshold not only assumes equal

turnout and candidate entry across groups, but also approaches these outcomes without accounting for uncertainty. But variation over time generates swings, such that even a seemingly safe district may occasionally elect the candidate opposed by the typical majority voting bloc. If Latino voters are spread across districts with narrow majorities, there may be cycles where no Latinos are elected to city council. For a risk-averse voting bloc, the loss of all representation may be far worse than failing to fully maximize expected seat share, as the mere presence of a minority member has been found to play a pivotal role in agenda-setting in legislatures (Bratton and Haynie 1999; Canon 1999; Weeks 2022). Thus, Brandman’s “packed” map may have been more attractive to a risk-averse population prioritizing a floor of representation rather than maximizing average representation over election cycles.

## Data and Methodology

To address these questions, we obtained as many city council district shapefiles as we could find for the California cities that have converted to district elections under the CVRA. Through a combination of searching online and contacting city government offices by phone, we ultimately obtained 107 shapefiles, covering 71% of the 153 cities that we have documented as having switched or committed to switching to district elections in the wake of the CVRA. We then overlaid these shapefiles on a Census block-level shapefile from 2017,<sup>1</sup> which allowed us to associate each block with a city council district as well as a set of economic, political, and demographic indicators obtained from the U.S. Census and the California Statewide Database.<sup>2</sup> The resulting standardized and enhanced shapefiles constituted the inputs into our districting simulations.<sup>3</sup>

Additionally, we used several city-level data sources in our analysis. We obtained city council election returns from de Benedictis-Kessner and Bernhard (2022), who built upon data collected by the California Elections Data Archive (CEDA).<sup>4</sup> To measure residential segregation of Latino voters, we computed the dissimilarity index between the Latino and non-Latino citizen voting-age

---

<sup>1</sup>Obtained from: <https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2017&layergroup=Blocks+%282010%29>.

<sup>2</sup><https://statewidedatabase.org/>.

<sup>3</sup>For more details on the data construction process, please see Appendix A.

<sup>4</sup>Available at: [https://csu-csus.esploro.exlibrisgroup.com/esploro/outputs/dataset/California-Elections-Data-Archive-CEDA/99257830890201671?institution=01CALUS\\_USL](https://csu-csus.esploro.exlibrisgroup.com/esploro/outputs/dataset/California-Elections-Data-Archive-CEDA/99257830890201671?institution=01CALUS_USL).

population (CVAP),<sup>5</sup> given by:

$$D = \frac{1}{2} \sum_{t=1}^T \left| \frac{l_t}{L} - \frac{n_t}{N} \right| \quad (1)$$

where  $t$  indexes Census tracts within the city,  $l$  and  $n$  are the sizes of the Latino and non-Latino citizen voting-age populations in tract  $t$ , respectively,  $L$  is the total Latino CVAP in the city, and  $N$  is the total non-Latino CVAP in the city. We obtained all other relevant city-level economic and demographic indicators from the Census.

## Districting Simulations

A central interest of this project is how cities exercise *political* control over the favorability of electoral maps toward minority groups. We have argued that decisionmakers are constrained by two forces: physical and residential geography, and federally mandated standards. In order to understand the universe of choices available to decisionmakers *given* these constraints — and thus to see how favorable their chosen maps were within this feasible universe — we conduct a set of redistricting simulations.

We use the automated redistricting simulator developed by Fifield et al. (2020),<sup>6</sup> which uses Markov chain Monte Carlo to characterize the distribution of feasible districting plans under the contiguity, compactness, and population parity constraints. We apply this algorithm to each of the 107 shapefiles that we prepared, producing for each city a set of counterfactual maps that one just as easily *could have drawn*, and that would also have had roughly contiguous, compact, and equal-population districts. We generate 40,000 draws from the target distribution of districting plans, where a draw is an assignment of Census blocks to city council districts. This allows us to compare *realized* electoral outcomes for the minority and majority groups under the adopted maps to the distribution of *expected* outcomes under the feasible alternatives. For a detailed discussion of the algorithm, the parameter values that we use, and diagnostics, please see Appendix B.

---

<sup>5</sup>Measured three years prior to the year of the first district election. See Appendix A for a justification of this choice.

<sup>6</sup>Implemented by the R package `redist` (Kenny et al. 2021).

## Post-Districting Analysis

Using these sets of maps within each city, we calculate how the maps varied in our electoral outcomes of interest and whether trade-offs exist in the pursuit of one strategy over another. We begin by walking the reader through the example of Anaheim to illustrate the constraints on the ground, and how the algorithm incorporates these considerations. We then formalize our measures of Latino electoral success as well as concentration for a given districting plan. From there, we extend our analysis to the remaining cities in our sample.

### The Constraints of Geography

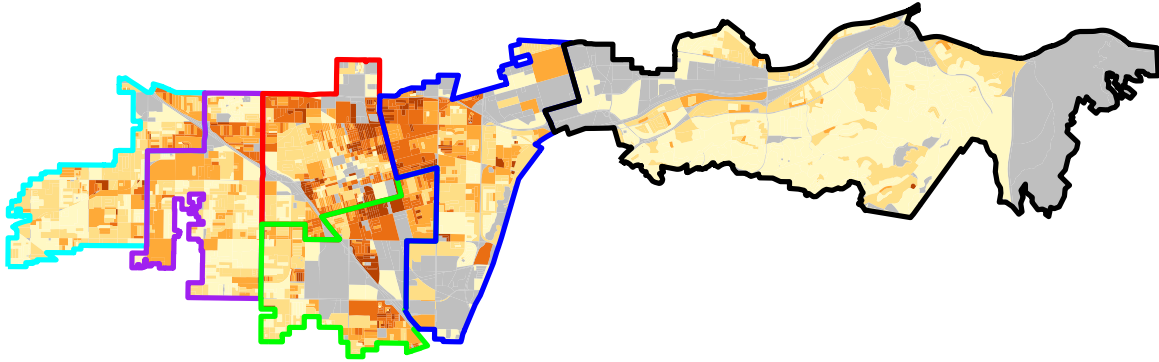
Recall Anaheim’s debate over how to draw district lines. In a sense, that a debate was possible at all was due to Anaheim’s sizeable Latino population. With 38% of the citizen voting-age population identifying as Latino, the city had a meaningful choice between pursuing multiple electoral strategies. By the same token, the city’s geography creates certain limitations. Simple visual examination of a map of Anaheim reveals how both physical and political geography shape and constrain the electoral maps that can be drawn (Figure 1).

Physically, the relatively sparsely populated area on the east side of the city, the Anaheim Hills — home to the city’s parks, nature reserves, a golf course, and expensive homes overlooking the city — forms a natural district (District 6) under the compactness, contiguity, and equal population constraints. Indeed, not only is this a district under the adopted map, but some small variation on District 6 is also a district under the overwhelming majority of simulated maps. The same is true to some extent on the western side of the city, which also has a narrow peninsula that will naturally constitute a district under most maps (District 1). Politically, Figure 1 shows that Anaheim’s Latino population is concentrated in the urban center, whereas white residents tend to live in the less densely populated areas to the west, east, and south. Thus, white voters will constitute the majority in any perturbation of the “naturally occurring” Districts 1 and 6.

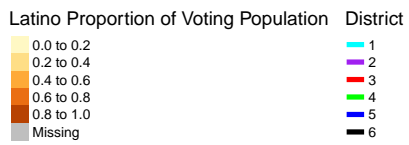
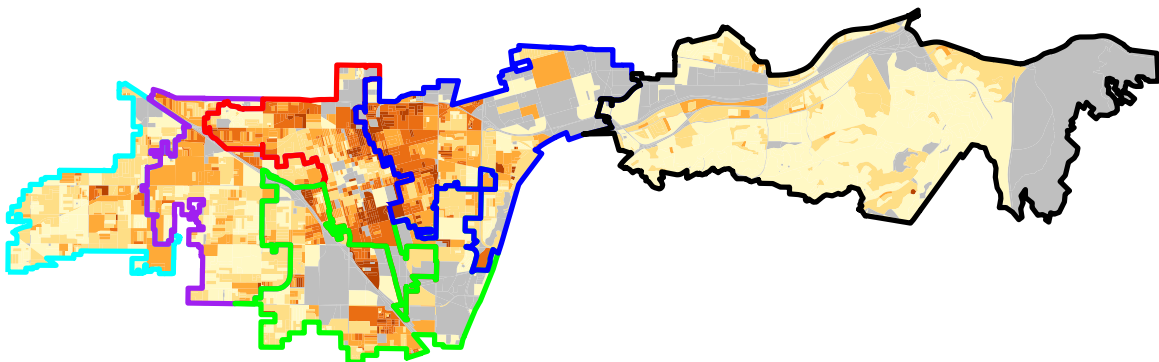
By contrast, the four districts at the center of the city leave a lot of freedom, and account for the lion’s share of the variation in whites’ and Latinos’ relative political advantage. Panel (a) shows the People’s Map, with one (nearly) majority-minority Latino district and two sizeable Latino minority districts. Panel (b) shows a simulated map that maximizes the number of Latino majority districts

Figure 1: Anaheim Example

(a) Map 1: “The People’s Map”



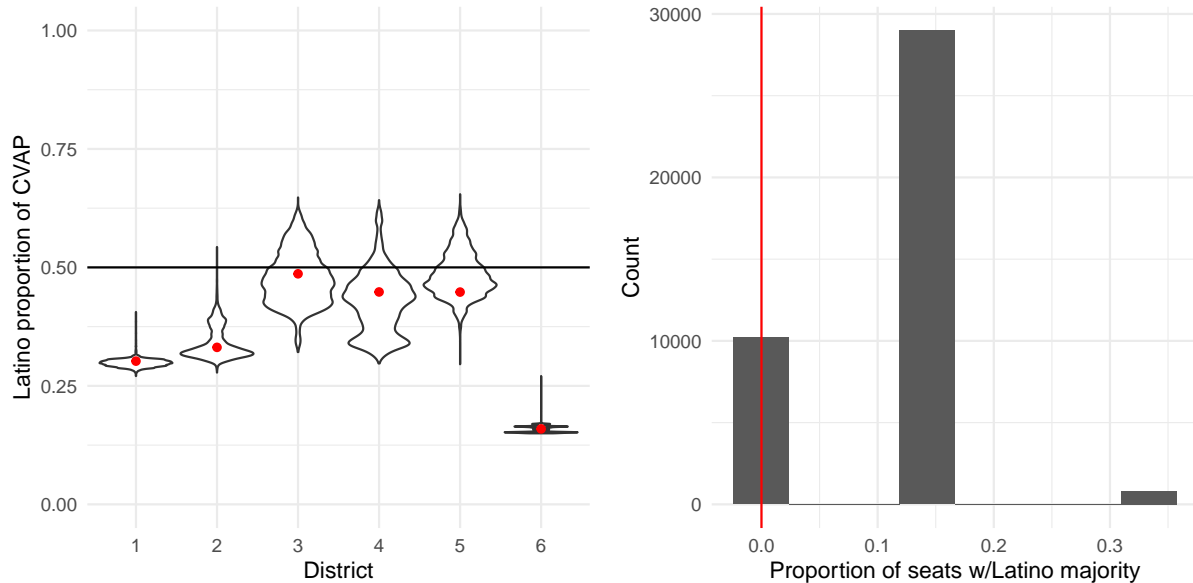
(b) Map 2: Alternative map that maximizes Latino-majority districts



District	<i>Latino % CVAP</i>	
	Map 1	Map 2
1	0.30	0.29
2	0.33	0.33
3	0.49	0.51
4	0.45	0.39
5	0.45	0.51
6	0.16	0.15

— one akin to the map proposed by Councilmember Brandman. By and large, Districts 1 and 6 are unchanged between the maps, with the main difference being that the “concentrated” map below pulls Latino voters from District 4 to elevate the Latino vote shares in Districts 3 and 5.

Figure 2: Simulation Distributions of Council Seats with Latino CVAP Majorities, City of Anaheim



*Notes:* The violin plot in the left panel shows the densities of the proportion of CVAP that is Latino in each district over 40,000 simulations. Red dots correspond to the values for the adopted map. Densities are scaled to a standardized maximum width; thus, we discourage comparisons *across* districts. The histogram in the right panel shows the distribution of the proportion of districts, out of a total of six, with a Latino CVAP above 0.5, also over the 40,000 simulations. Red line corresponds to the value for the adopted map.

Along with visualizing the range of possibilities for each city, our approach allows us to see where the adopted map falls in this range. Figure 2 shows the distribution of Latino proportion of CVAP in each district.<sup>7</sup> Here, we see once more the inescapable fact that Districts 1 and 6 can only be majority white, whereas Districts 2 through 5 are where the crucial choices happen. Furthermore, we see that Anaheim’s adopted map (the People’s Map) lands far from the extremes of these distributions, both within each district (left panel) and for the overall composition of the council (right panel). From this, we can conclude that there was little to no evidence of political manipulation either in favor or against Latinos; rather, the adopted map is in some sense a “typical” map from the range of possibilities available to Anaheim decisionmakers.

<sup>7</sup>Simulated districts are numbered in such a way as to maximize overlap and comparability with the adopted map.

## The Many Definitions of Electoral Success

To judge how well a district map improves Latino representation requires defining a measure of electoral success. Like the federal VRA, conversations surrounding the CVRA have focused on the creation of majority Latino CVAP districts, and for good reason. Not only is the 50% Latino CVAP threshold intuitive to the average citizen attending public meetings and offering input on proposed maps, but it is the simplest measure of empowering a voting bloc. By composing 50% of the citizen voting-age population, Latinos (or any group) can theoretically elect their preferred candidate — regardless of the candidate’s ethnicity.

But the simplicity of the 50% threshold also limits its functionality in evaluating maps. As we show in Figure D-1, 60% of the cities in our sample cannot draw a single district with greater than 50% Latino CVAP, as evidenced by the fact that not one of the city’s 40,000 simulated plans includes a majority-minority district. Furthermore, an additional 3 cities cannot draw a district *without* a majority Latino CVAP. For these cities, there is no variation in the quality of the simulated maps using this simple outcome. However, we can imagine that the choice of maps in these cities is still meaningful for Latino representation.

While the 50% CVAP threshold is the most agnostic to the preferences of the Latino voting bloc, it is important to remember that the CVRA was born partially from the observable lack of descriptive representation in city councils. Thus, we use the actual election of Latinos as a basis for our alternative measures of the reform’s success. Specifically, we use the CEDA dataset of electoral outcomes measured at the district-city-year level for our 107 cities (post-districting). We model the probability that district  $i$  in city  $c$  in election year  $t$  elects a Latino candidate as a function of CVAP, partisanship, and other characteristics of the district, which are computed by aggregating up from the Census block level to the adopted districting plan.<sup>8</sup> Then, for each simulated district, we compute the same covariates and use them to calculate the *predicted* probability of electing a Latino candidate. These district-level probabilities, which we call  $\hat{p}_{c dt} = Pr(\widehat{\text{Latino elected}})_{c dt}$ , are the foundation for the following metrics:<sup>9</sup>

1. **Expected Latino council share:** This is computed as the average of  $\hat{p}_d$  across all districts,

---

<sup>8</sup>See Appendix C for details.

<sup>9</sup>We suppress the  $c$  and  $t$  subscripts when we are focused on a particular plan within a city. The time  $t$  is held fixed at the first year of district elections in that city.

and represents the share of the city council that we would expect to be Latino over many elections.

2. **Probability of at least one Latino on council:** This is computed as the complement of the probability of electing zero Latinos, which is the product of the complements of  $\hat{p}_d$  across districts.
3. **Probability of a Latino council majority:** This is computed as the sum of the probabilities of each configuration of election outcomes that generates a Latino council majority. For example, in a city with three districts, a Latino council majority will occur under the following conditions: Districts A and B elect Latinos, Districts B and C elect Latinos, Districts A and C elect Latinos, or all three districts elect Latinos. To compute the probability that Districts A and B elect Latinos, we multiply  $\hat{p}_A * \hat{p}_B * (1 - \hat{p}_C)$ ; the other configurations are computed analogously. Then, we sum the probabilities of each configuration to calculate the overall probability of a Latino council majority.

Each of these alternatives captures a different strategy for securing some form of descriptive representation. Several considerations inform which measure reformers will prioritize. The first is risk tolerance. Maximizing the first quantity is a risk-neutral strategy, since the same expected council share can be achieved by one certain Latino district and one certain white district, or by two 50% probability Latino districts. And while taking this approach will maximize representation in the long run, in any given election cycle there may be a real danger of ending up with no representation. Given evidence that the presence of just one minority member can affect the agenda, a risk-averse voting bloc may favor plans that maximize the second quantity. Finally, for cities with sufficiently large Latino populations, the city council majority may be within reach. But maximizing this quantity may be risky if having a fighting chance in a majority of districts requires stretching the population too thin to make any safe districts.

A second consideration is what reformers hope to achieve through descriptive representation. Here, it is helpful to separate its deliberative from its aggregative functions (Mansbridge 1999). When it comes to representing voters' interests in council votes, the Latino bloc is well served by having a council share in proportion to, or better yet in excess of, its population share. On the other hand, even one voice may suffice to bring new concerns and perspectives to the table, to



set the agenda, or to have an impact on the behavior and opinions of other councilmembers — especially in a small and collegial legislative body.

Finally, council dynamics also play an important role. At one extreme, city councils may resemble the national legislature, where opposing factions battle to win majorities or otherwise fail to enact their governing agendas. But, at the other extreme, councils may be cooperative and deliberative; they may have a formal or informal norm of unanimity, or grant their members specific veto powers. While in the former case, the minority should seek to maximize its numbers — and pursue council majorities whenever they are within reach — in the latter case guaranteeing one seat is vital, whereas pushing beyond that may be inefficient.

### **Concentrating Latinos as a Strategy**

Aside from their expected electoral outcomes, we can also characterize districting plans with respect to how they distribute Latino voters. A common concern in the partisan districting literature is the concentration of one party in a way that wastes votes, a strategy known as packing. However, this term is typically used to describe maps where concentrating a group diminishes its electoral influence (e.g., Best et al. 2018). In this sense, packing tautologically leads to disadvantage. But we want to know whether the approach of concentrating Latinos in general is electorally effective in increasing their descriptive representation. Thus, we do not use the term packing to describe this strategy, even though that term may be common parlance.

For our purposes, we define the concentration of Latino voters that is associated with each plan using the dissimilarity index of districts under that plan. In other words, we apply the same calculation as in Equation 1, this time with council districts rather than Census tracts as the lower-level geography. Thus defined, the dissimilarity index can be interpreted as the proportion of Latinos that would have to change places with non-Latinos in other districts so that all districts would have the same Latino share as the city overall (Duncan and Duncan 1955). The index ranges from 0 for full integration to 1 for full segregation. By calculating this index for every simulated districting plan, we can see how plans vary in their concentration of Latino voters, holding fixed the city’s underlying residential segregation; we use the term “concentrating” rather than “segregating” to distinguish how maps are drawn from the baseline residential segregation in the city.

## Results

### No Systematic Trade-offs Across Measures of Success

To evaluate trade-offs, we calculate each measure of electoral success for each of the 40,000 maps within all 107 cities. Then, using each city’s set of simulated maps, we calculate the within-city correlations between each possible pair of measures. We begin by looking at how the share of seats with a majority Latino CVAP correlates with our three measures of Latino electoral success. Figure 3 presents three histograms — one for each set of within-city correlations — with a red vertical line showing the average correlation across all cities. Only the 38 cities that had some variation in their simulation distributions of majority Latino CVAP districts are included here. Within this subset, maps that increase the number of majority Latino CVAP districts also tend to improve performance on all three measures of electoral success. Indeed, negative correlations in this column are highly conditional. For instance, we find that a trade-off between maximizing the share of majority Latino CVAP districts and the probability of a Latino council majority only occurs in cities with very large and segregated Latino populations.<sup>10</sup>

In Appendix Figure E-6, we also present correlations between every pair of predicted electoral outcomes: the expected Latino council share with the probability of at least one Latino on council; the expected Latino council share with the probability of a Latino council majority; and the probability of at least one Latino on council with the probability of a Latino council majority. These histograms include all cities, because every city has variation in these probabilities, even those unable to create majority Latino CVAP districts. And here, we see correlations that are overwhelmingly positive and close to 1. The same kinds of maps achieve all three goals.

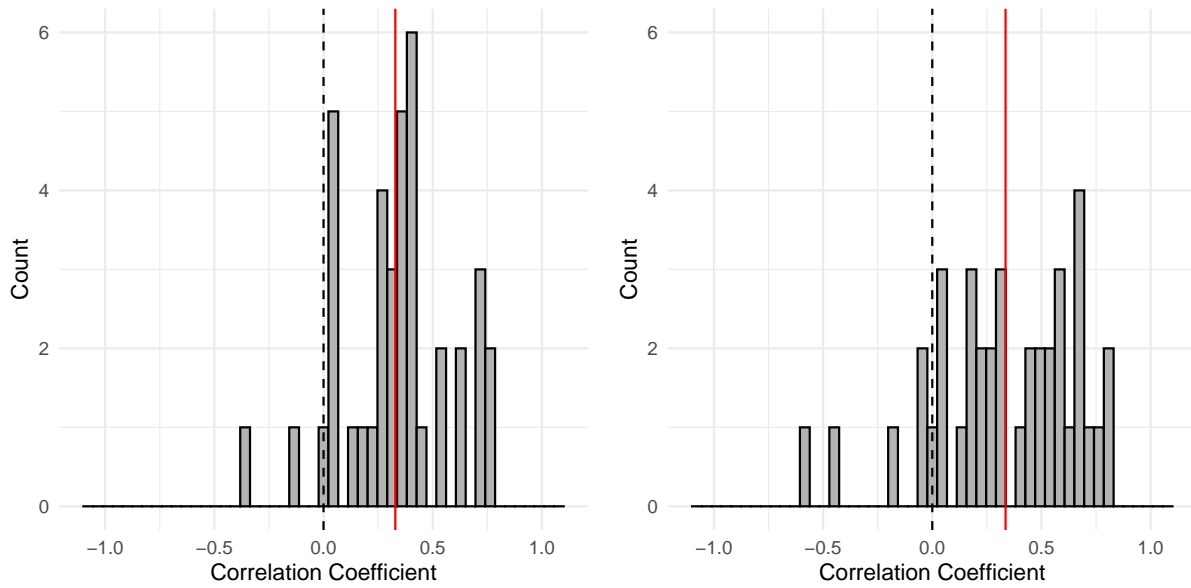
### Concentrating Latinos Improves Descriptive Representation

Given that there are no consistent trade-offs among these electoral measures, are there simple principles for simultaneously maximizing all four outcomes? We measure how these outcomes

---

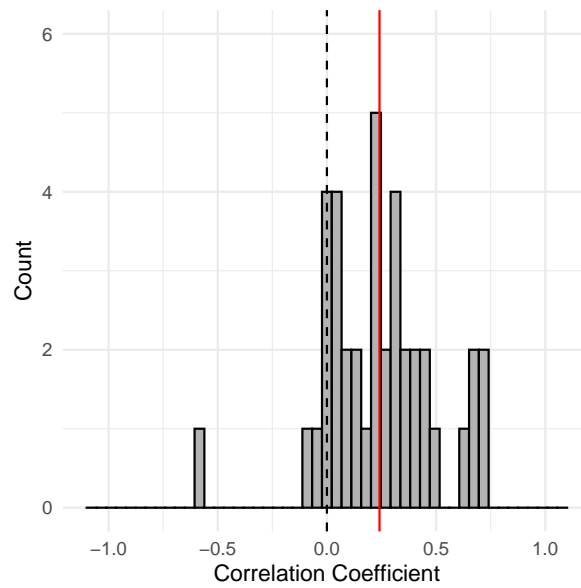
<sup>10</sup>Consider the city of Indio. The plan that maximizes the share of majority Latino CVAP districts has the following Latino CVAP share for Districts 1 through 5: 0.58, 0.50, 0.53, 0.57, and 0.61. The plan that maximizes the probability of a Latino council majority has the following Latino CVAP share for districts 1 through 5: 0.32, 0.41, 0.86, 0.64, and 0.77. When Latinos constitute the majority of the voting population citywide, and when they are sufficiently segregated, then it is possible to concentrate Latino voters in three out of five districts, yielding a higher probability of a Latino council majority than a plan that gives Latinos a bare CVAP majority in every district.

Figure 3: Correlations Between Share of Seats with Majority Latino CVAP and Latino Electoral Advantage



(a) Share of seats w/majority Latino CVAP and Expected Latino Council Share

(b) Share of seats w/majority Latino CVAP and Pr(At Least One Latino on Council)

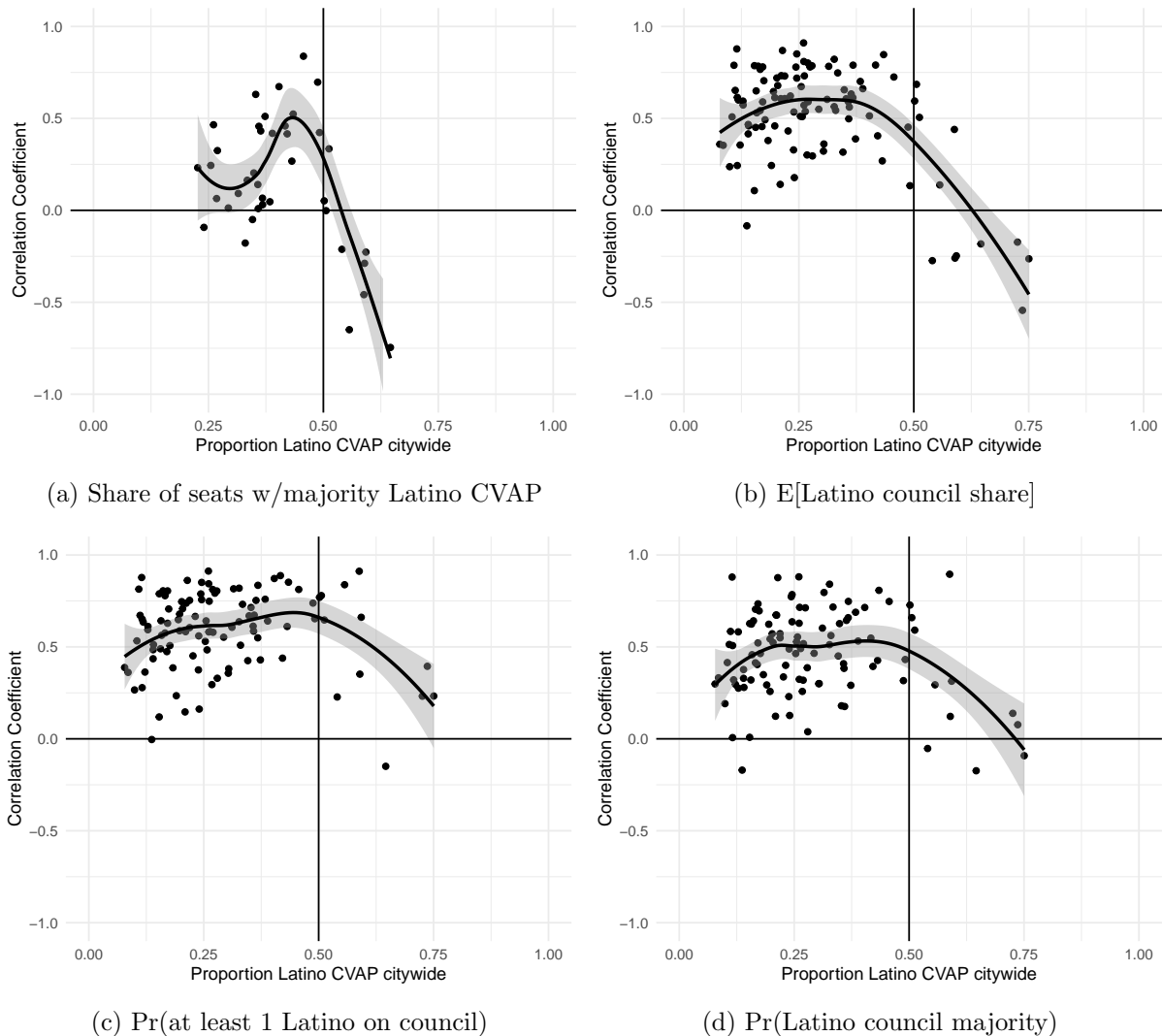


(c) Share of seats w/majority Latino CVAP and Pr(Latino Council Majority)

relate to the strategy of concentrating Latinos, as measured by the dissimilarity index of each map.

Figure 4 plots the correlations between the dissimilarity index and each of our electoral outcomes across simulated plans on the y-axis and the citywide Latino CVAP share on the x-axis. Each point represents an individual city. In Panel (a), we see that concentrating Latinos is effective until the citywide Latino CVAP exceeds 50%. After this point, concentrating Latinos *decreases* the proportion of districts with a majority Latino CVAP, as one would expect.

Figure 4: Correlations, Dissimilarity Index of Plans and Measures of Latino Electoral Advantage — by Citywide Latino Voting-Age Population



What about measures of electoral success that rely on actual electoral outcomes? In Panel (b), the correlation between the dissimilarity index and the expected Latino council share is less sensitive to the 50% CVAP threshold. The strategy of concentrating Latinos helps many cities with

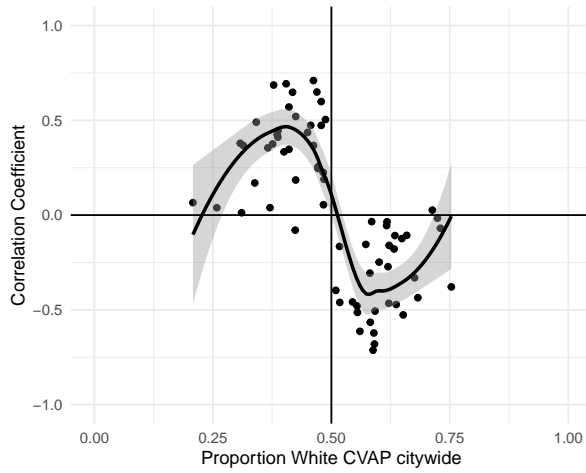
smaller Latino populations, then gradually tails off as the Latino population grows. However, the decline is not nearly as steep as in Panel (a), suggesting that concentrating Latinos is a consistently neutral to beneficial strategy.

As discussed, there are alternative measure of Latino electoral success besides simply maximizing the expected council share. In Panel (c), we see that concentrating Latinos nearly always helps secure at least one Latino seat on city council, regardless of the citywide Latino CVAP. This is not surprising: the relationship holds almost by construction. Finally, Panel (d) shows that concentrating Latinos almost always increases the probability of securing a Latino council majority. Across almost all conditions, concentrating Latinos is an effective strategy.

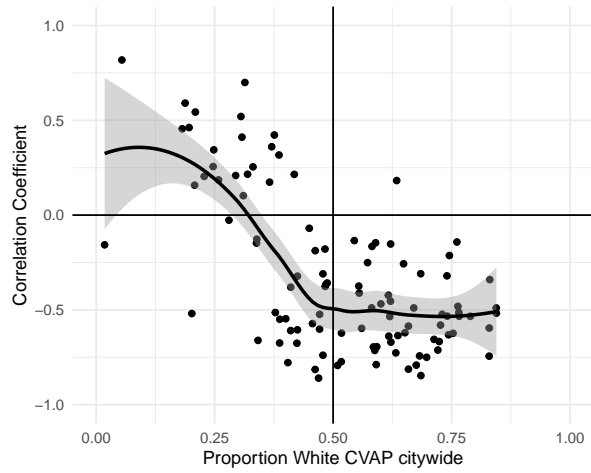
For comparison, we can assess similar relationships between concentrating voters and electoral success but among non-Hispanic white voters and candidates. Figure 5 plots the correlations between the dissimilarity index and each of our electoral outcomes across simulated plans on the y-axis and the citywide white CVAP share on the x-axis. Figure 5 Panel (a) generally matches Figure 4 Panel (a): concentrating white voters does little to create majority white districts except in cities that are more than 30% white. At that point, there is a positive relationship between maps that concentrate white voters and those that create majority-white districts. However, we lack data from many cities with large white majorities, as these cities were less likely to be targeted by the CVRA for district elections. From Panel (a) only, we would assume that the takeaways for white voters are the same as for Latinos. But Panels (b) through (d) suggest otherwise.

Figure 5 Panel (b) shows that in the vast majority of cities concentrating white voters *decreases* the probability of electing white city council members. This is in direct contrast to the same analysis for Latino voters and Latino council members (Figure 4 Panel (b)). Panel (c) shows a generally weak relationship between concentrating whites and the probability of electing at least one white city council member. Finally, Panel (d) again shows a negative relationship between concentrating white voters and the probability of electing a white city council majority. While whites and Latinos exhibit the same patterns in the technical exercise of drawing majority districts (panel a), they differ substantially in how the distributions of voters across districts map onto electoral outcomes.

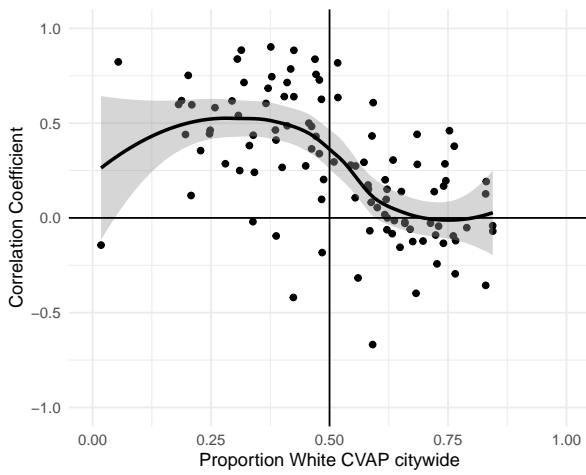
Figure 5: Correlations, Dissimilarity Index of Plans and Measures of White Electoral Advantage – by Citywide White Voting-Age Population



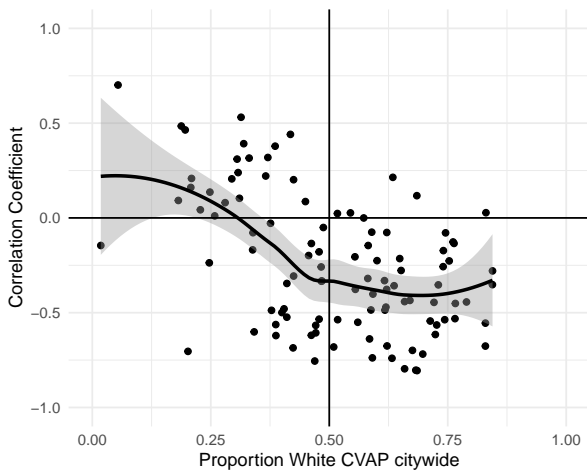
(a) Share of seats w/majority White CVAP



(b)  $E[\text{White council share}]$



(c)  $\text{Pr}(\text{at least 1 White council member})$



(d)  $\text{Pr}(\text{White council majority})$

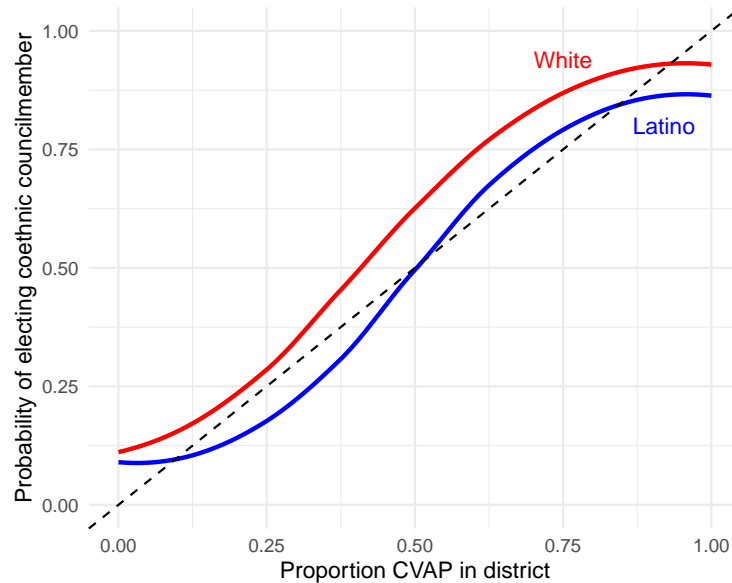
## Why Concentrating Latinos Works

Across all four measures of electoral success, concentrating Latinos generally improves Latino descriptive representation. Even in many majority Latino CVAP cities, concentrating Latinos improves the average Latino council share, the probability of securing at least one seat on city council, and the probability of winning the council majority. However, the same is not true for white voters even when they are in the minority. Why would concentrating their voters work for Latinos, but not work for whites even under similar conditions?

To investigate these contrasting results, Figure 6 shows the relationship between a district's racial composition on the x-axis and its probability of electing a councilmember from that racial group on the y-axis. The relationship for Latinos is shown in blue; the relationship for whites is shown in red. For Latinos, the probability of electing a co-ethnic to city council falls below their proportion of the district's electorate whenever they are the minority. For example, a 25% Latino district only has, on average, a 17% chance of electing a Latino councilmember. In contrast, white candidates almost always overperform their underlying proportion of the district's electorate. As a comparison, a 25% white district has a 28% chance of electing a white councilmember. Given the interquartile range of simulated districts is between 16% to 39% Latino CVAP, this underperformance is a substantively large challenge for the election of Latino candidates and explains why concentrating Latinos improves their electoral success on average. In contrast, the consistent overperformance of white candidates means that similar clustering would waste votes and that white candidates still succeed even when white voters are comparatively dispersed.

There are several potential reasons concentrating voters improves descriptive representation for Latinos, but not for whites. Latino voters have the lowest turnout rates in comparison to white, Black, and Asian electorates. This low turnout is driven by a combination of fewer resources, weaker formal political organization, and lower sense of political efficacy compared to other racial/ethnic groups. Fraga (2018) finds that the pivotality of Latino voters matters, with majority-Latino districts helping to close the turnout gap. Figure 6 Panel (a) supports this argument, as Latino candidate performance matches the Latino share of the electorate only when they compose a majority of the district. Our ongoing work includes a more formal test of whether the majority-minority districts created by the CVRA increase the turnout of Latino voters.

Figure 6: Probability of Electing a Coethnic Councilmember in a District as a Function of CVAP, Latino vs. White



### No Systematic Trade-off with Substantive Representation

A final concern is that concentrating Latinos will hamper the election of Democrats citywide. Given that Latinos tend to share policy views with and support Democratic candidates (Barreto, Segura and Woods 2004), especially in California (Hui and Sears 2018), a decline in Democratic electoral success would entail a meaningful trade-off of descriptive for substantive representation.<sup>11</sup> To test for such a trade-off, we calculate the correlation between each of our measures of electoral success and the share of districts with a Democratic majority of registered voters. As with Latino CVAP, only 44% of our sample exhibits any variation on the latter outcome. Thus, by definition, there is no trade-off in creating majority Democratic districts in more than half of the cities in our sample. Among cities where there is variation in Democratic districting, there is no systematic relationship between pursuing Latino descriptive representation and Democratic districts (Figure E-8).

## Discussion

Across over one hundred cities, we find that not only are multiple measures of minority descriptive representation compatible on average, but they can all be achieved using the same strategy: creat-

<sup>11</sup>Though such a trade-off may be in decline given increasingly durable shifts of the Latino electorate away from the Democratic Party (Fraga, Velez and West 2022).



ing districts with high concentrations of Latino voters. Across a range of electoral outcomes, this strategy promotes descriptive representation without sacrificing substantive representation. Revisiting Anaheim, perhaps Councilmember Brandman was right to support a plan that concentrated Latino voters into two districts rather than spreading them across three districts.

Instead, Anaheim chose the People’s Map. This plan had a somewhat unusually diffuse distribution of Latino voters across districts: it was in the 23rd percentile of Anaheim’s simulation distribution on Latino concentration. Accordingly, the map did not deliver on the full potential of districting to improve Latino descriptive representation in Anaheim: it was in the 26th percentile in majority Latino CVAP seats, the 61st percentile in expected share of council seats held by a Latino, the 17th percentile in probability of electing at least one Latino to council, and the 58th percentile in probability of securing a Latino council majority.<sup>12</sup>

Still, we find that the vast majority of cities that adopted district elections under the CVRA selected maps that were particularly favorable for Latino electoral success, compared to the range of options available to them. Nonetheless, our findings raise some normative concerns, stemming from the basic fact that segregated cities have the widest range of options from which to choose. Appendix Figure D-5 reveals that segregated cities are able to make both very concentrated *and* very diffuse plans, whereas cities where Latinos are residentially integrated generally have lower levels *and* variances of Latino concentration over the simulation distribution. This means that the very tool that we have identified for promoting Latino descriptive representation is subject to the greatest *political* discretion in segregated cities — which may also suffer from the most acute racial inequality and conflict.

While California cities have largely embraced the spirit of the CVRA, their favorable choices may also be due to strong surveillance given the high-profile nature of CVRA implementation. There is no guarantee that such favorable maps would have been selected absent such pressure, nor that they will be selected in the future should monitoring decrease. This adds some important nuance to previous findings: segregation alone is a poorly defined moderator of the effect of district elections. Instead, segregation combined with favorable districting plans is what makes district elections maximally effective. That previous studies find segregation to be a *positive* moderator of the effect of district elections on minority electoral success may better reflect this current incentive

---

<sup>12</sup>See Figures D-1 through D-4.

structure of high compliance rather than any inherent effects of segregation alone.

Moreover, relying on segregation to provide the conditions for district elections to work is concerning. Segregated cities not only struggle to provide collective goods, but also have an incentive to direct goods to coalition members (Trounstine 2018). This tendency is likely to be exacerbated under district elections, given even more clearly spatially-defined constituencies and the history of legislative logrolling. Likewise, segregation heightens inter-group tensions, both threatening cooperation and potentially spurring conflict (Bhavnani et al. 2014; Enos 2017). That low segregation cities would be penalized in their ability to increase minority voice via districting should cause us to question the viability of district elections as panacea for representation. In other words, the *Gingles* test may have been less a conservative barrier to reform and more of a guardrail against false hope in unsuitable cities.

## Conclusion

Using state-of-the-art redistricting software, we have shown how district elections increase minority descriptive representation. District elections are not successful solely by creating majority-minority districts. Were that the case, we would see very little change in electoral outcomes in the majority of cities that are unable to draw majority-minority districts. Rather, using electoral data from cities under district elections, we show how districting maps increase the probability of electing Latinos, of securing at least one Latino seat on council, and even securing a Latino council majority.

Despite theoretical expectations from the partisan districting literature, we find that these four measures of improved descriptive representation are generally compatible. Furthermore, all four measures can be advanced by selecting districting plans which concentrate Latino voters. This concentration not only improves Latino electoral success but does not, on average, come with attendant decreases in the success of Democratic candidates. To the degree that Democrats more closely share policy positions with the Latino electorate, concentrating Latinos does not trade substantive representation for descriptive representation.

The strategy of concentrating Latino voters contradicts existing evidence of optimal districting from the congressional literature, evidence suggesting that spreading minority voters below the 50% CVAP threshold provides the most effective improvement to representation. Instead, in the

context of local elections, we show that the benefits of concentrating Latinos are driven by the general underperformance of Latino candidates in relation to the district-level Latino CVAP. In contrast, white candidates consistently overperform in relation to the district-level white CVAP, meaning concentrating white voters actually decreases the electoral success of white candidates. The exact mechanism behind Latinos underperformance is the focus on ongoing work.

More broadly, our findings are more than a mechanical assessment of how cities should draw district lines. Rather, we have shown how a reform designed to improve minority representation faces constraints, both in the existing physical and electoral geography of a city and in the agency offered to the city councils selecting the maps. Weighing these forces is important both for improving the effectiveness of the reform and tempering expectations of how the reform will shape outcomes. Ineffective maps, be they via geography or intent, will leave politics unchanged, risking apathy and possibly even a sense of illegitimacy in the minds of voters.

## References

- Abott, Carolyn and Asya Magazinnik. 2020. "At-Large Elections and Minority Representation in Local Government." *American Journal of Political Science* 64(3):717–733.
- Barreto, Matt A, Gary M Segura and Nathan D Woods. 2004. "The Mobilizing Effect of Majority–Minority Districts on Latino Turnout." *American Political Science Review* 98(1):65–75.
- Barreto, Matt and Gary Segura. 2014. *Latino America: How America's Most Dynamic Population is Poised to Transform the Politics of the Nation*. Public Affairs.
- Best, Robin E, Shawn J Donahue, Jonathan Krasno, Daniel B Magleby and Michael D McDonald. 2018. "Considering the Prospects for Establishing a Packing Gerrymandering Standard." *Election Law Journal* 17(1):1–20.
- Bhavnani, Ravi, Karsten Donnay, Dan Miodownik, Maayan Mor and Dirk Helbing. 2014. "Group Segregation and Urban Violence." *American Journal of Political Science* 58(1):226–245.
- Boylan, Richard T. 2019. "The Impact of Court-Ordered District Elections on City Finances." *The Journal of Law and Economics* 62(4):633–661.
- Brace, Kimball, Bernard Grofman and Lisa Handley. 1987. "Does Redistricting Aimed to Help Blacks Necessarily Help Republicans?" *The Journal of Politics* 49(1):169–185.
- Brace, Kimball, Bernard N Grofman, Lisa R Handley and Richard G Niemi. 1988. "Minority Voting Equality: The 65 Percent Rule in Theory and Practice." *Law & Policy* 10(1):43–62.
- Bratton, Kathleen A and Kerry L Haynie. 1999. "Agenda Setting and Legislative Success in State Legislatures: The Effects of Gender and Race." *The Journal of Politics* 61(3):658–679.
- Cameron, Charles, David Epstein and Sharyn O'Halloran. 1996. "Do Majority-Minority Districts Maximize Substantive Black Representation in Congress?" *American Political Science Review* 90(4):794–812.
- Canon, David T. 1999. *Race, Redistricting, and Representation: The Unintended Consequences of Black Majority Districts*. University of Chicago Press.

- Clark, Alistair and Timothy B Krebs. 2012. Elections and Policy Responsiveness. In *The Oxford Handbook of Urban Politics*.
- Collingwood, Loren and Sean Long. 2019. “Can States Promote Minority Representation? Assessing the Effects of the California Voting Rights Act.” *Urban Affairs Review* pp. 1–32.
- Dancygier, Rafaela M. 2014. “Electoral Rules or Electoral Leverage? Explaining Muslim Representation in England.” *World Politics* 66(2):229–263.
- Davidson, Chandler and George Korbel. 1981. “At-Large Elections and Minority-Group Representation: A Re-Examination of Historical and Contemporary Evidence.” *The Journal of Politics* 43(4):982–1005.
- de Benedictis-Kessner, Justin and Rachel Bernhard. 2022. “Concatenated Files Fixing Errors in the California Elections Data Archive (CEDA).” GitHub repository, online: <https://github.com/justindbk/ceda/>.
- Diamond, Greg. 2016. “District 3 is Still a Majority Latino CVAP as It Ever Was: A Close Look at Block Groups 93 & 106.” *The Orange Juice* .
- Duncan, Otis Dudley and Beverly Duncan. 1955. “A Methodological Analysis of Segregation Indexes.” *American Sociological Review* 20(2):210–217.
- Elmahrek, Adam. 2015. “Anaheim City Council Stalls Transition to District Elections.” *Voice of OC* .
- Elmahrek, Adam. 2016. “‘People’s Map’ Victory a Lesson in Hardball Activism.” *Voice of OC* .
- Enos, Ryan D. 2017. *The Space Between Us: Social Geography and Politics*. Cambridge University Press.
- Fifield, Benjamin, Michael Higgins, Kosuke Imai and Alexander Tarr. 2020. “Automated Redistricting Simulation Using Markov Chain Monte Carlo.” *Journal of Computational and Graphical Statistics* 29(4):715–728.
- Fraga, Bernard L. 2018. *The Turnout Gap: Race, Ethnicity, and Political Inequality in a Diversifying America*. Cambridge University Press.

- Fraga, Bernard L., Yamil R. Velez and Emily A. West. 2022. Reversion to the Mean, or their Version of the Dream? An Analysis of Latino Voting in 2020. Technical report.
- Hajnal, Zoltan and Jessica Trounstein. 2005. “Where Turnout Matters: The Consequences of Uneven Turnout in City Politics.” *The Journal of Politics* 67(2):515–535.
- Hankinson, Michael and Asya Magazinnik. Forthcoming. “The Supply–Equity Trade-off: The Effect of Spatial Representation on the Local Housing Supply.” *The Journal of Politics* .
- Henderson, John A, Brian T Hamel and Aaron M Goldzimer. 2018. “Gerrymandering Incumbency: Does Nonpartisan Redistricting Increase Electoral Competition?” *The Journal of Politics* 80(3):1011–1016.
- Hui, Iris and David O Sears. 2018. “Reexamining the Effect of Racial Propositions on Latinos’ Partisanship in California.” *Political Behavior* 40(1):149–174.
- Kenny, Christopher T., Cory McCartan, Ben Fifield and Kosuke Imai. 2021. “redist: Simulation Methods for Legislative Redistricting.” Available at The Comprehensive R Archive Network (CRAN).
- URL:** <https://CRAN.R-project.org/package=redist>
- Lublin, David. 1997. *The Paradox of Representation*. Princeton University Press.
- Mansbridge, Jane. 1999. “Should Blacks Represent Blacks and Women Represent Women? A Contingent “Yes”.” *The Journal of Politics* 61(3):628–657.
- Mast, Evan. Forthcoming. “Warding Off Development: Local Control, Housing Supply, and NIM-BYs.” *Review of Economics and Statistics* .
- McGhee, Eric. 2014. “Measuring Partisan Bias in Single-Member District Electoral Systems.” *Legislative Studies Quarterly* 39(1):55–85.
- McGhee, Eric. 2020. “Partisan Gerrymandering and Political Science.” *Annual Review of Political Science* 23:171–185.
- Ricca, Federico and Francesco Trebbi. 2022. Minority Underrepresentation in US Cities. Technical report National Bureau of Economic Research.

- Schuk, Carolyn. 2015. "Fighting CVRA Lawsuit Will Likely Cost Santa Clara \$3.97 Million More Than It Cost Sunnyvale To Avoid One." *The Silicon Valley Voice* .
- Stephanopoulos, Nicholas O and Eric M McGhee. 2015. "Partisan Gerrymandering and the Efficiency Gap." *U. Chi. L. Rev.* 82:831.
- Trounstone, Jessica. 2009. *Political Monopolies in American Cities: The Rise and Fall of Bosses and Reformers*. Chicago: University of Chicago Press.
- Trounstone, Jessica. 2018. *Segregation by Design: Local Politics and Inequality in American Cities*. New York: Cambridge University Press.
- Trounstone, Jessica and Melody E Valdini. 2008. "The Context Matters: The Effects of Single-Member versus At-Large Districts on City Council Diversity." *American Journal of Political Science* 52(3):554–569.
- Weeks, Ana Catalano. 2022. *Making Gender Salient: From Gender Quota Laws to Policy*. Cambridge University Press.
- Welch, Susan. 1990. "The Impact of At-Large Elections on the Representation of Blacks and Hispanics." *The Journal of Politics* 52(4):1050–1076.

# Online Appendix for “Districting Without Parties: How City Council Maps Increase Minority Representation”

## Contents

- A Data Construction . . . . . A-2
- B Districting Simulation . . . . . A-4
- C Estimating Measures of Electoral Success . . . . . A-10
- D Simulation Distributions . . . . . A-11
- E Additional Tables and Figures . . . . . A-17



## A Data Construction

Here, we outline the data construction process by which we prepared city shapefiles for districting simulation. As a baseline, we began with the 2017 TIGER/Line Shapefile for the state of California at the Census block level.<sup>1</sup> We used Census blocks because this seems to be the unit that most cities used for district assignment. Then, we associated each block with a set of demographic, economic, and political variables, described in detail below. Finally, we intersected each of the 107 city council district shapefiles in our possession with this statewide block-level shapefile. This generated 107 block-level shapefiles — one for each city — mapping Census blocks (with covariates) to city council districts.

### Variables

1. *Housing Data.* We collected the following variables from the 2010 Decennial Census:

1. CB Variable ID H003002, the total number of housing units in which a person or group of persons is living at the time of the interview, or if the occupants are only temporarily absent, as for example, on vacation;
2. CB Variable ID H014002, the total number of housing units where the owner or co-owner lives in the unit, even if it is mortgaged or not fully paid for.

We computed the **homeownership rate** as the number of households that are owned (H014002) divided by the total number of occupied housing units (H003002).

2. *Voting-Age Population.* We collected block-level total population from the 2010 Decennial Census (CB Variable ID P001001). In addition, we collected the following variables related to citizen voting-age population (CVAP) from the Redistricting Database for the State of California (“Statewide Database”)<sup>2</sup>:

1. Total citizen voting-age population
2. Black or African American (alone) citizen voting-age population
3. Asian (alone) citizen voting-age population
4. Hispanic or Latino citizen voting-age population
5. Not Hispanic or Latino citizen voting-age population
6. White citizen voting-age population

Because cities districted in different years, we pulled these CVAP estimates from different time periods for each city. In order to approximate as closely as possible the data cities were working with at the time that they districted, we selected 5-year estimates ending 3 years prior to the year of the first election under the newly adopted districting plan. For example, if the year of first

---

<sup>1</sup>Obtained from: <https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2017&layergroup=Blocks+%282010%29>.

<sup>2</sup>Accessed at: <https://statedatabase.org/>. We used CVAP estimates from Statewide Database instead of the Census Bureau because the Census has only block group-level estimates, whereas Statewide Database provides block-level estimates.

election was 2018, we would use 2011–2015 estimates. If the year of first district election was 2012 or earlier, we used 2006–2010 estimates, as this was the closest available option. We arrived at this procedure after examining the supporting documentation of several city redistricting plans, as illustrated by the following examples:

1. Banning: first conducted election in 2016, reports 2010–2014 5-year estimates in supporting documentation;<sup>3</sup>
2. Brea: first conducted election in 2022, reports 2015–2019 5-year estimates in supporting documentation;<sup>4</sup>
3. Menlo Park: first conducted election in 2018, reports 2011–2015 5-year estimates in supporting documentation;<sup>5</sup>
4. Rancho Cucamonga: first conducted election in 2018, reports 2010–2014 5-year estimates in supporting documentation;<sup>6</sup>
5. Richmond: first conducted election in 2020, reports 2012–2016 5-year estimates in supporting documentation.<sup>7</sup>

**3. *Income.*** We collected block group-level median household income from the Census American Community Survey (ACS) (CB Variable ID B19013\_001). We assigned to each block the value from its block group, as that was the lowest level of aggregation for which data was available. We chose the ACS time period for each city according to the same approach outlined for voting-age population, above.

**4. *Partisanship.*** Here, we wish to compute two block-level variables estimated at the time of a city’s first district election: a count of Democratic voters that is reasonably robust to changes in turnout between elections, as well as the total number of registered voters.

To do so, we collected partisanship and registration data from the general election files from Statewide Database. For each city, we used data from the 6 general elections prior to the year of first district election. For presidential election years (2004, 2008, 2012, 2016, 2020), we collected the number of votes cast for the Democratic presidential candidate; for midterm election years (2002, 2006, 2010, 2014, 2018), we collected the number of votes cast for the Democratic gubernatorial candidate.

A challenge of working with these data is translating them across geographies: voter registration and partisanship are reported at the SR precinct level, whereas we require data at the block level. To get around this, we downloaded a crosswalk file between SR precincts and 2010 Census blocks from Statewide Database, which provides the percentage of an SR precinct that falls within a given Census block.<sup>8</sup> To convert SR precinct-level data to block-level estimates, we joined the

<sup>3</sup><http://www.banning.ca.us/DocumentCenter/View/4545/Banning-Draft-Maps-20160607?bidId=>

<sup>4</sup><https://www.ci.brea.ca.us/DocumentCenter/View/12725/January-12-District-Mapping-Workshop-PowerPoint-Presentation>

<sup>5</sup><https://www.menlopark.org/DocumentCenter/View/15883/Presentation---Menlo-Park-Introduction-to-Election-Systems>

<sup>6</sup><http://www.ndcresearch.com/wp-content/uploads/2016/03/20160317-NDC-RC-Kickoff-Presentation-v3.pdf>

<sup>7</sup><https://www.ci.richmond.ca.us/DocumentCenter/View/51558/District-Elections-Community-Workshop-Presentation-11-14-19-and-11-18-19?bidId=>

<sup>8</sup>See documentation here: <https://statewidedatabase.org/d10/Creating%20CA%20official%20Redistricting%20Database.pdf>.

electoral data with the crosswalk file and computed estimates of the number of Democratic votes and registered voters each Census block contributes to the SR total. We then aggregated all block-level contributions by their Census block IDs.

Finally, to compute the block-level estimated count of Democratic voters, we calculated the sum of block-level estimates of Democratic votes cast in the past 6 general elections (both presidential and midterm), divided by the sum of block-level estimates of the number of overall votes in the past 6 general elections, multiplied by the total number of registered voters in the general election year immediately following the year of first district elections.

**5. *Statewide Election Returns.*** We measure the support for Latino candidates in statewide elections using SR precinct returns for four statewide elections: Controller (2014), Secretary of State (2014), US Senate (2016), and Lt. Governor (2018). These returns are also obtained from Statewide Database and mapped to Census blocks according to the procedure described in (4) directly above. We manually coded all candidates in these four elections as Latino or non-Latino.

## Shapefile Preparation

After merging the above variables onto our baseline block-level shapefile for the state of California, we intersected this file with each of our 107 city council district shapefiles. This process produced, for each city, a block-level shapefile with both a vector of city council district assignments and the complete set of variables described above.

As a final step in preparation for districting simulation, we checked that all blocks were contiguous, as the simulation requires contiguous graphs. For disconnected blocks or components, we manually assigned nearest neighbors, determined by visual inspection.

## B Districting Simulation

### Redistricting Algorithm

We use the automated redistricting simulator proposed by Fifield et al. (2020). We select this algorithm for a few reasons. First, it can incorporate contiguity, compactness, and equal population constraints into the estimation process, meaning that it approximates the *particular* distribution of plans that real-world decisionmakers, given the physical and residential geography of their city, can feasibly produce under federal law. To our knowledge this algorithm is the best among currently available methods at approximating this particular distribution that is of substantive interest to us. Second, the algorithm is computationally efficient, scales well, and is easy to implement using the R package `redist` (Kenny et al. 2021).

We refer the interested reader to a detailed discussion of the algorithm in the published articles (Fifield et al. 2020; McCartan et al. 2022), presenting only the intuition here. The approach treats the task of assigning  $m$  geographic units (for us, Census blocks) to  $n$  contiguous council districts as a *graph-cut problem*: partitioning a graph — where nodes represent geographic units and edges between two nodes represent their contiguity — into a set of connected subgraphs, representing districts. It then uses Markov chain Monte Carlo (MCMC) to obtain a representative sample of plans from the distribution of valid plans as formulated in this way.

## Parameter Selection

The algorithm requires a few key user-defined parameters. The first is compactness, which we set at the default level of  $\rho = 1$  for every city.<sup>9</sup> Larger values of  $\rho$  correspond to a preference for fewer edge cuts and therefore a redistricting plan with more compact districts. Based on the literature on *edge-cut compactness* (Dube and Clark 2016; DeFord, Duchin and Solomon 2021), McCartan and Imai (2022) suggest  $\rho = 1$  as a choice that produces reasonably compact districts, and is computationally efficient.

The user is also required to provide a value for the maximal deviation from *population parity* — that is, where the city’s population is divided evenly among districts — that will be tolerated of any district in a feasible plan. Legislative districting at the federal level is held to a very high population equality standard. In the 1983 case *Karcher v. Daggett*, the Supreme Court ruled that there is no deviation that could practically be avoided that is too small to potentially violate the “one person, one vote” standard set by Article I, Section 2 of the Constitution. However, at the local level, larger deviations may be necessary to achieve other districting goals, especially in smaller and more sparsely or unevenly populated municipalities.

Absent concrete legal guidance or precedent at the city level, we approach the determination of the maximum tolerable deviation from population parity as an empirical matter. First we compute, for every adopted district plan, the maximal deviation of any district, given by:

$$\max_{1 \leq l \leq n} \left| \frac{\sum_{i \in V_l} p_i}{\bar{p}} - 1 \right| \quad (2)$$

where  $V_l$  is a district,  $n$  is the number of districts,  $i$  is a Census block,  $p_i$  is the population in block  $i$  from the 2010 Census, and  $\bar{p}$  is defined as  $\sum_{i=1}^m p_i/n$  (where  $m$  is the number of blocks). The second column of Table B-1 reports this maximal value for every city. We find that some cities, in particular smaller ones, have very high values — far beyond what is usually tolerated at the federal level — and the overall mean across cities is 0.10.<sup>10</sup> We therefore set the population tolerance parameter as the maximum of 0.01 and the city’s own adopted map’s largest deviation,<sup>11</sup> with the rationale that if a certain deviation was permitted in practice, then any plan with *smaller* deviations would have been fair game as well — at least on this dimension. While we cannot know how much *larger* a deviation might have been tolerated, our approach yields relatively conservative target distributions — that is, it may exclude some counterfactual possibilities that were in fact on the table. Still, because the deviations are so high in practice, the algorithm still has a large degree of freedom to explore alternative plans.

## Diagnostics

We run the MCMC algorithm with 4 independent chains with 10,000 simulations in each chain to assess convergence. This gives us 40,000 draws from the target distribution. Then we renumber the districts for each plan in a way that minimizes the number of blocks that have changed from the adopted plan.

---

<sup>9</sup>See McCartan and Imai (2022), Section 3.3 for further detail.

<sup>10</sup>By comparison, the maximum deviation of the New Jersey redistricting plan rejected by *Karcher v. Daggett* was 0.004: the decision reports an average district population of 526,059 and smallest district (Sixth District) population of 523,798 (Karcher, Speaker, New Jersey Assembly, et al. v. Daggett et al. 1983).

<sup>11</sup>Although we made this decision as a safeguard against overly conservative restrictions, this constraint never binds in practice: the observed value is never less than 0.01.

The `redist` package helpfully computes several diagnostics to help the user assess whether the algorithm successfully sampled from the target distribution. We briefly describe each of these diagnostics, reported in Table B-1, and refer the reader to Fifield et al. (2020) as well as the `redist` package documentation<sup>12</sup> for more details.

- *Diversity* (Column 3)  
The off-diagonal elements of the variation of information distance matrix for our sample of plans. Column 3 reports the 80% range of this statistic. Generally, diversity is good if most values are greater than 0.5.
- $\hat{R}$  (Columns 4–7)  
 $\hat{R}$  values across the four chains computed for four variables: population overlap (Column 3), which measures how much of the population is in the same district in both a given plan and the reference plan, as well as homeownership rate (Column 4), percent of CVAP that is Latino (Column 5), and percent of voters who are Democrats (Column 6) — all defined in Appendix A above.  $\hat{R}$  is calculated for the first district only; other districts look similar.  $\hat{R}$  values should be close to 1 and generally under 1.05; otherwise, there is too much between-chain variation, indicating not enough samples.
- *Effective Sample Size* (Column 8)  
The ratio of the effective sample size, computed using the SMC weights, to the total samples. Computed for run 1 of chain 1. Reported range is the minimum and maximum value across splits, excluding resample. Larger values (close to 100%) are better.
- *Acceptance Rate* (Column 9)  
Fraction of drawn spanning trees that yield a valid redistricting plan within the population tolerance. Computed for run 1 of chain 1. Reported range is the minimum and maximum value across splits. We seek to avoid very small values (< 1%), which can indicate a bottleneck.
- *Maximum Unique Plans* (Column 10)  
An upper bound on the number of unique redistricting plans that survive each stage. Computed for run 1 of chain 1. Reported range is the minimum and maximum value across splits, excluding resample. Small values indicate a bottleneck.
- *Standard Deviation of the Log Weights* (Column 11)  
Standard deviation of the log weights. Computed for run 1 of chain 1. Reported range is the minimum and maximum value across splits, excluding resample. High standard deviations indicate less efficient sampling; values greater than 3 are likely problematic.

As Table B-1 indicates, **we achieve desirable values on all of the above diagnostics in all cities.**

---

<sup>12</sup>[https://alarm-redist.org/redist/reference/summary.redist\\_plans.html](https://alarm-redist.org/redist/reference/summary.redist_plans.html)

Table B-1: Diagnostics from Redistricting Simulations

(1) City	(2) Pop. Tol.	(3) Diversity	(4) $\hat{R}$ : pop_overlap	(5) $\hat{R}$ : own_rate	(6) $\hat{R}$ : pct_latino	(7) $\hat{R}$ : pct_dem	(8) ESS	(9) Acc. Rate	(10) Max. Un. Plans	(11) SD
Anaheim	0.0562	[0.54,0.76]	1.0029	1.0007	1.0005	1.0023	[88.4%, 91.1%]	[25.3%, 53.7%]	[5392,6319]	[0.58,0.74]
Apple Valley	0.0681	[0.74,0.97]	1.0005	1.0003	1.0005	1.0002	[88.7%, 98.5%]	[10.8%, 30.7%]	[5693,6303]	[0.24,0.55]
Atwater	0.0543	[0.42,0.76]	1.0006	1.0006	1.0004	1.0003	[81.6%, 87.7%]	[9.9%, 26.8%]	[5584,6410]	[0.62,0.72]
Banning	0.0330	[0.37,0.68]	1.0022	1.0012	1.0007	1.0014	[79.6%, 88.6%]	[12.0%, 29.2%]	[5419,6388]	[0.64,0.77]
Barstow	0.0371	[0.45,0.75]	1.0005	1.0007	1.0006	1.0007	[87.6%, 97.6%]	[14.8%, 32.3%]	[5542,6258]	[0.30,0.74]
Big Bear Lake	0.0743	[0.25,0.63]	1.0014	1.0007	1.0007	1.0005	[83.7%, 94.2%]	[17.6%, 29.1%]	[5467,6313]	[0.49,0.71]
Buena Park	0.1243	[0.55,0.85]	1.0001	1.0004	1.0003	1.0003	[90.9%, 96.9%]	[24.2%, 63.2%]	[5622,6295]	[0.37,0.55]
Camarillo	0.1488	[0.65,0.91]	1.0002	1.0005	1.0001	1.0004	[89.6%, 97.4%]	[29.4%, 75.1%]	[5616,6308]	[0.32,0.59]
Campbell	0.2652	[0.49,0.82]	1.0002	1.0002	1.0004	1.0002	[89.9%, 97.0%]	[38.6%, 76.8%]	[5555,6291]	[0.35,0.60]
Carlsbad	0.0624	[0.46,0.84]	1.0004	1.0004	1.0006	1.0004	[91.2%, 96.5%]	[17.1%, 31.4%]	[5759,6372]	[0.37,0.59]
Cathedral City	0.0538	[0.56,0.88]	1.0010	1.0009	1.0007	1.0011	[90.1%, 96.2%]	[14.7%, 36.7%]	[5684,6321]	[0.39,0.56]
Ceres	0.0175	[0.42,0.72]	1.0004	1.0001	1.0001	1.0004	[93.8%, 95.2%]	[6.3%, 13.8%]	[5840,6284]	[0.39,0.48]
Chino Hills	0.0700	[0.60,0.88]	1.0008	1.0018	1.0008	1.0009	[89.3%, 96.2%]	[14.2%, 41.7%]	[5514,6340]	[0.49,0.61]
Chula Vista	0.0995	[0.59,0.86]	1.0004	1.0003	1.0003	1.0005	[89.2%, 96.4%]	[27.9%, 54.7%]	[5792,6294]	[0.36,0.58]
Citrus Heights	0.0980	[0.60,0.87]	1.0005	1.0006	1.0007	1.0008	[88.6%, 96.9%]	[22.4%, 59.6%]	[5679,6315]	[0.35,0.58]
Claremont	0.1195	[0.47,0.82]	1.0009	1.0005	1.0010	1.0002	[85.7%, 93.4%]	[24.8%, 46.5%]	[5501,6282]	[0.50,0.66]
Compton	0.0337	[0.57,0.86]	1.0002	1.0004	1.0002	1.0006	[93.8%, 98.1%]	[14.4%, 26.7%]	[5783,6337]	[0.28,0.45]
Concord	0.1093	[0.75,0.97]	1.0009	1.0014	1.0009	1.0010	[90.8%, 97.2%]	[28.4%, 61.4%]	[5640,6285]	[0.33,0.56]
Corona	0.0169	[0.59,0.86]	1.0008	1.0009	1.0005	1.0007	[91.9%, 96.7%]	[10.3%, 30.3%]	[5482,6359]	[0.36,0.55]
Dana Point	0.0860	[0.48,0.75]	1.0003	1.0021	1.0025	1.0005	[87.7%, 91.6%]	[24.9%, 47.3%]	[5466,6338]	[0.54,0.65]
Dixon	0.0237	[0.62,0.89]	1.0002	1.0007	1.0013	1.0003	[91.0%, 96.8%]	[10.7%, 19.9%]	[5820,6298]	[0.35,0.52]
Duarte	0.4438	[0.46,0.70]	1.0010	1.0034	1.0013	1.0025	[84.3%, 94.3%]	[30.1%, 88.0%]	[5049,6301]	[0.48,0.71]
Eastvale	0.0652	[0.69,0.96]	1.0003	1.0005	1.0002	1.0008	[88.3%, 97.0%]	[15.8%, 33.1%]	[5480,6284]	[0.34,0.61]
Elk Grove	0.0887	[0.57,0.86]	1.0008	1.0003	1.0005	1.0005	[90.6%, 97.5%]	[24.6%, 41.7%]	[5748,6315]	[0.31,0.56]
Encinitas	0.0650	[0.59,0.89]	1.0008	1.0010	1.0005	1.0004	[90.2%, 97.1%]	[11.7%, 19.3%]	[5732,6318]	[0.34,0.57]
Escondido	0.0291	[0.56,0.89]	1.0002	1.0002	1.0002	1.0003	[92.4%, 98.1%]	[9.0%, 16.0%]	[5615,6338]	[0.28,0.50]
Exeter	0.1696	[0.52,0.85]	1.0016	1.0004	1.0012	1.0012	[88.9%, 96.0%]	[32.0%, 62.6%]	[5405,6318]	[0.37,0.61]
Fairfield	0.0354	[0.56,0.82]	1.0005	1.0007	1.0009	1.0006	[96.3%, 93.2%]	[6.1%, 35.4%]	[5503,6364]	[0.47,0.66]
Fontana	0.0368	[0.52,0.81]	1.0000	1.0003	1.0001	1.0001	[90.3%, 96.4%]	[15.0%, 26.0%]	[5865,6366]	[0.39,0.51]
Fullerton	0.0976	[0.63,0.88]	1.0009	1.0002	1.0006	1.0003	[88.9%, 96.7%]	[24.7%, 62.4%]	[5630,6358]	[0.37,0.59]
Garden Grove	0.1182	[0.61,0.87]	1.0011	1.0006	1.0004	1.0003	[87.2%, 96.1%]	[31.5%, 72.1%]	[5485,6302]	[0.40,0.63]
Glendora	0.0475	[0.71,0.94]	1.0009	1.0002	1.0002	1.0006	[92.0%, 96.7%]	[13.4%, 39.4%]	[5604,6346]	[0.35,0.53]
Half Moon Bay	0.1330	[0.61,0.89]	1.0001	1.0003	1.0004	1.0002	[90.2%, 96.9%]	[18.8%, 38.7%]	[5540,6314]	[0.35,0.55]
Hemet	0.0270	[0.63,0.88]	1.0016	1.0012	1.0005	1.0008	[90.3%, 96.7%]	[11.3%, 22.6%]	[5536,6358]	[0.37,0.58]
Hesperia	0.0208	[0.68,0.94]	1.0018	1.0013	1.0006	1.0012	[89.1%, 98.0%]	[17.5%, 35.2%]	[5611,6320]	[0.28,0.56]
Imperial Beach	0.0803	[0.69,0.94]	1.0002	1.0004	1.0003	1.0004	[92.5%, 98.1%]	[20.8%, 39.1%]	[5786,6345]	[0.27,0.49]
Indio	0.0480	[0.60,0.92]	1.0007	1.0001	1.0003	1.0001	[88.5%, 96.4%]	[13.2%, 30.8%]	[5532,6381]	[0.38,0.62]

(1) City	(2) Pop. Tol.	(3) Diversity	(4) $\hat{R}$ : pop_overlap	(5) $\hat{R}$ : own_rate	(6) $\hat{R}$ : pct_latino	(7) $\hat{R}$ : pct_dem	(8) ESS	(9) Acc. Rate	(10) Max. Un. Plans	(11) SD
Jurupa Valley	0.0559	[0.70,0.94]	1.0008	1.0004	1.0003	1.0010	[88.8%, 98.0%]	[18.8%, 42.5%]	[5664,6292]	[0.28,0.57]
King City	0.0466	[0.67,0.93]	1.0016	1.0003	1.0018	1.0003	[89.2%, 97.9%]	[5.2%, 16.0%]	[4660,6399]	[0.28,0.59]
Kingsburg	0.0571	[0.43,0.73]	1.0005	1.0002	1.0007	1.0001	[92.4%, 97.1%]	[10.2%, 34.5%]	[5170,6362]	[0.35,0.55]
Lake Forest	0.0623	[0.55,0.85]	1.0012	1.0016	1.0013	1.0015	[90.0%, 96.7%]	[17.3%, 36.7%]	[5610,6321]	[0.37,0.57]
La Mirada	0.0658	[0.54,0.86]	1.0011	1.0000	1.0005	1.0001	[89.6%, 97.2%]	[19.2%, 37.7%]	[5522,6307]	[0.34,0.57]
Lemoore	0.0350	[0.50,0.85]	1.0020	1.0014	1.0006	1.0024	[96.6%, 94.5%]	[10.8%, 28.4%]	[5467,6337]	[0.42,0.65]
Lincoln	0.1592	[0.47,0.80]	1.0005	1.0002	1.0009	1.0007	[83.5%, 95.5%]	[24.0%, 55.4%]	[5516,6262]	[0.40,0.73]
Lodi	0.0163	[0.72,0.95]	1.0010	1.0007	1.0009	1.0008	[90.2%, 97.8%]	[6.9%, 32.8%]	[5621,6363]	[0.30,0.55]
Lompoc	0.2231	[0.64,0.91]	1.0002	1.0005	1.0001	1.0003	[89.9%, 96.8%]	[31.1%, 53.4%]	[5660,6389]	[0.34,0.57]
Los Banos	0.0670	[0.57,0.85]	1.0002	1.0005	1.0005	1.0002	[92.4%, 97.8%]	[16.1%, 29.1%]	[5533,6319]	[0.30,0.51]
Madera	0.1849	[0.66,0.90]	1.0012	1.0002	1.0005	1.0004	[88.9%, 97.8%]	[29.1%, 73.3%]	[5615,6355]	[0.30,0.58]
Marina	0.1746	[0.61,0.93]	1.0002	1.0003	1.0003	1.0001	[92.7%, 97.6%]	[15.2%, 27.9%]	[5729,6351]	[0.31,0.52]
Menlo Park	0.2046	[0.42,0.74]	1.0008	1.0009	1.0010	1.0008	[90.8%, 95.2%]	[23.6%, 54.6%]	[5779,6332]	[0.43,0.55]
Modesto	0.0991	[0.57,0.83]	1.0007	1.0003	1.0002	1.0002	[86.4%, 94.4%]	[18.4%, 57.5%]	[5525,6350]	[0.47,0.63]
Monterey Park	0.0184	[0.67,0.91]	1.0001	1.0012	1.0011	1.0011	[91.0%, 96.4%]	[5.4%, 21.9%]	[5689,6313]	[0.37,0.55]
Morgan Hill	0.0855	[0.29,0.70]	1.0005	1.0005	1.0001	1.0000	[92.2%, 97.2%]	[18.0%, 30.0%]	[5601,6359]	[0.34,0.56]
Murrieta	0.1599	[0.68,0.94]	1.0002	1.0013	1.0002	1.0014	[88.8%, 97.2%]	[25.1%, 45.4%]	[5632,6313]	[0.33,0.60]
Napa	0.0919	[0.56,0.86]	1.0009	1.0002	1.0005	1.0001	[89.6%, 97.5%]	[28.1%, 50.2%]	[5816,6281]	[0.31,0.54]
Novato	0.1033	[0.63,0.89]	1.0017	1.0016	1.0007	1.0009	[89.6%, 97.0%]	[16.9%, 39.7%]	[5585,6282]	[0.35,0.58]
Ojai	0.1586	[0.59,0.80]	1.0000	1.0002	1.0004	1.0003	[95.2%, 98.5%]	[21.6%, 39.2%]	[5742,6349]	[0.25,0.42]
Orange	0.0869	[0.60,0.86]	1.0007	1.0003	1.0008	1.0010	[87.2%, 93.9%]	[24.9%, 54.2%]	[5408,6296]	[0.48,0.68]
Oxnard	0.1103	[0.69,0.91]	1.0010	1.0005	1.0005	1.0009	[88.3%, 96.7%]	[26.4%, 61.7%]	[5419,6308]	[0.36,0.60]
Pacifica	0.1710	[0.62,0.90]	1.0002	1.0005	1.0001	1.0005	[87.2%, 97.3%]	[25.1%, 64.4%]	[5476,6309]	[0.34,0.65]
Palmdale	0.0166	[0.48,0.72]	1.0002	1.0012	1.0003	1.0005	[92.9%, 95.2%]	[10.8%, 21.8%]	[5903,6335]	[0.39,0.49]
Palm Springs	0.0682	[0.61,0.92]	1.0002	1.0003	1.0004	1.0003	[87.2%, 97.3%]	[25.1%, 64.4%]	[5476,6309]	[0.34,0.65]
Paso Robles	0.1280	[0.45,0.80]	1.0006	1.0000	1.0000	1.0001	[90.0%, 94.6%]	[15.5%, 25.6%]	[5582,6310]	[0.47,0.61]
Patterson	0.0232	[0.59,0.86]	1.0003	1.0002	1.0000	1.0007	[92.1%, 97.5%]	[8.1%, 15.1%]	[5793,6365]	[0.32,0.51]
Placentia	0.0835	[0.55,0.83]	1.0007	1.0028	1.0009	1.0012	[89.1%, 97.1%]	[15.2%, 33.9%]	[5572,6289]	[0.35,0.57]
Porterville	0.0951	[0.65,0.90]	1.0006	1.0021	1.0010	1.0011	[88.4%, 96.3%]	[29.8%, 60.7%]	[5629,6302]	[0.37,0.60]
Poway	0.0779	[0.64,0.91]	1.0008	1.0001	1.0004	1.0005	[93.4%, 98.1%]	[14.7%, 32.4%]	[5304,6333]	[0.27,0.48]
Rancho Cucamonga	0.0489	[0.72,0.97]	1.0002	1.0001	1.0002	1.0003	[93.3%, 98.5%]	[15.5%, 34.6%]	[5858,6349]	[0.25,0.46]
Redlands	0.0184	[0.73,0.96]	1.0005	1.0008	1.0012	1.0013	[91.4%, 98.3%]	[11.5%, 28.5%]	[5669,6334]	[0.26,0.54]
Redwood City	0.2806	[0.71,0.90]	1.0018	1.0001	1.0002	1.0002	[89.4%, 92.9%]	[29.8%, 78.9%]	[5361,6346]	[0.50,0.60]
Richmond	0.1215	[0.55,0.81]	1.0046	1.0054	1.0070	1.0055	[76.0%, 82.3%]	[23.8%, 63.6%]	[5375,6324]	[0.69,0.79]
Rohnert Park	0.1662	[0.52,0.83]	1.0005	1.0005	1.0003	1.0003	[87.6%, 95.7%]	[25.1%, 50.1%]	[5660,6334]	[0.42,0.62]
Roseville	0.0940	[0.57,0.87]	1.0012	1.0003	1.0006	1.0002	[88.8%, 96.9%]	[28.1%, 54.7%]	[5567,6296]	[0.35,0.60]
Sanger	0.0373	[0.59,0.87]	1.0007	1.0005	1.0009	1.0009	[91.2%, 97.9%]	[11.5%, 23.0%]	[5715,6365]	[0.29,0.50]
San Rafael	0.0245	[0.24,0.66]	1.0030	1.0015	1.0026	1.0012	[86.6%, 96.6%]	[7.7%, 13.9%]	[5547,6315]	[0.38,0.61]
Santa Barbara	0.3315	[0.76,0.98]	1.0001	1.0006	1.0001	1.0006	[88.6%, 96.8%]	[47.2%, 93.5%]	[5446,6345]	[0.35,0.60]
Santa Clara	0.0735	[0.66,0.87]	1.0012	1.0010	1.0003	1.0010	[90.6%, 97.1%]	[26.1%, 58.2%]	[5506,6287]	[0.35,0.54]

(1) City	(2) Pop. Tol.	(3) Diversity	(4) $\hat{R}$ : pop_overlap	(5) $\hat{R}$ : own_rate	(6) $\hat{R}$ : pct_latino	(7) $\hat{R}$ : pct_dem	(8) ESS	(9) Acc. Rate	(10) Max. Un. Plans	(11) SD
Santa Maria	0.0161	[0.61,0.91]	1.0008	1.0002	1.0002	1.0001	[91.5%, 97.1%]	[12.3%, 22.9%]	[5757,6288]	[0.34,0.52]
Santa Rosa	0.0919	[0.69,0.93]	1.0027	1.0065	1.0007	1.0073	[82.0%, 96.7%]	[21.1%, 54.3%]	[5372,6348]	[0.37,0.68]
Santee	0.0479	[0.42,0.79]	1.0010	1.0007	1.0002	1.0009	[89.5%, 96.3%]	[12.6%, 25.6%]	[5664,6345]	[0.39,0.60]
Selma	0.0668	[0.49,0.81]	1.0009	1.0004	1.0003	1.0003	[89.9%, 97.3%]	[16.5%, 29.8%]	[5618,6335]	[0.33,0.56]
Simi Valley	0.0716	[0.65,0.92]	1.0008	1.0006	1.0008	1.0007	[91.4%, 97.5%]	[23.6%, 43.1%]	[5764,6302]	[0.31,0.52]
Solana Beach	0.2383	[0.50,0.82]	1.0004	1.0001	1.0002	1.0005	[92.5%, 97.6%]	[19.9%, 37.4%]	[5601,6340]	[0.31,0.49]
South Pasadena	0.0575	[0.66,0.92]	1.0004	1.0005	1.0003	1.0005	[92.6%, 98.1%]	[16.9%, 38.0%]	[5358,6276]	[0.27,0.50]
South San Francisco	0.1096	[0.33,0.63]	1.0008	1.0006	1.0008	1.0004	[82.1%, 88.3%]	[20.7%, 37.5%]	[5354,6289]	[0.68,0.90]
Stanton	0.0545	[0.29,0.63]	1.0003	1.0000	1.0001	1.0002	[87.4%, 91.4%]	[8.0%, 17.6%]	[5200,6361]	[0.51,0.70]
Stockton	0.0605	[0.70,0.94]	1.0016	1.0009	1.0011	1.0007	[87.2%, 96.3%]	[18.5%, 40.4%]	[5325,6333]	[0.38,0.67]
Sunnyvale	0.0829	[0.70,0.91]	1.0014	1.0008	1.0010	1.0003	[90.4%, 97.6%]	[17.8%, 57.9%]	[5495,6297]	[0.31,0.56]
Temecula	0.1160	[0.67,0.92]	1.0004	1.0009	1.0008	1.0010	[91.3%, 97.3%]	[18.5%, 41.2%]	[5673,6319]	[0.32,0.55]
Torrance	0.0531	[0.64,0.87]	1.0005	1.0006	1.0004	1.0004	[90.8%, 94.3%]	[18.4%, 57.5%]	[5450,6394]	[0.45,0.57]
Tulare	0.0303	[0.63,0.92]	1.0018	1.0006	1.0006	1.0012	[85.9%, 96.9%]	[10.2%, 37.8%]	[5523,6311]	[0.36,0.65]
Turlock	0.0640	[0.62,0.88]	1.0006	1.0003	1.0003	1.0003	[92.8%, 97.6%]	[16.8%, 30.6%]	[5832,6322]	[0.30,0.49]
Twentynine Palms	0.2716	[0.53,0.78]	1.0025	1.0010	1.0003	1.0012	[80.1%, 92.9%]	[28.4%, 56.1%]	[5699,6299]	[0.53,0.76]
Union City	0.0504	[0.46,0.79]	1.0004	1.0001	1.0000	1.0001	[92.1%, 96.0%]	[19.3%, 36.8%]	[5861,6333]	[0.39,0.55]
Upland	0.0415	[0.58,0.88]	1.0010	1.0007	1.0002	1.0005	[89.9%, 96.5%]	[16.3%, 31.7%]	[5785,6357]	[0.37,0.58]
Vallejo	0.0163	[0.68,0.96]	1.0008	1.0015	1.0023	1.0004	[89.9%, 97.4%]	[10.0%, 21.5%]	[5365,6325]	[0.33,0.58]
Ventura	0.0373	[0.57,0.82]	1.0031	1.0008	1.0011	1.0010	[83.0%, 94.6%]	[18.8%, 45.1%]	[5179,6282]	[0.49,0.71]
Visalia	0.1042	[0.74,0.97]	1.0005	1.0002	1.0003	1.0006	[92.5%, 98.3%]	[28.3%, 65.2%]	[5704,6308]	[0.26,0.48]
Vista	0.0751	[0.51,0.81]	1.0003	1.0007	1.0003	1.0002	[92.2%, 97.4%]	[20.3%, 35.3%]	[5733,6354]	[0.33,0.52]
Wasco	0.9150	[0.54,0.80]	1.0003	1.0013	1.0009	1.0010	[80.1%, 83.5%]	[15.6%, 81.4%]	[5223,6329]	[0.71,0.77]
West Covina	0.0819	[0.45,0.71]	1.0005	1.0002	1.0005	1.0007	[88.7%, 92.2%]	[25.9%, 58.7%]	[5652,6331]	[0.48,0.64]
Westminster	0.0922	[0.46,0.79]	1.0001	1.0001	1.0002	1.0001	[91.0%, 97.5%]	[19.9%, 43.7%]	[5830,6351]	[0.31,0.54]
Whittier	0.1058	[0.51,0.81]	1.0004	1.0005	1.0005	1.0002	[90.0%, 96.2%]	[29.5%, 50.8%]	[5848,6310]	[0.40,0.56]
Wildomar	0.0948	[0.56,0.81]	1.0004	1.0007	1.0003	1.0003	[90.9%, 98.1%]	[15.2%, 35.6%]	[5209,6354]	[0.27,0.56]
Woodland	0.1780	[0.62,0.89]	1.0002	1.0007	1.0012	1.0002	[88.5%, 95.5%]	[24.4%, 59.1%]	[5532,6300]	[0.40,0.61]
Yucaipa	0.0499	[0.74,0.99]	1.0001	1.0006	1.0002	1.0004	[91.4%, 98.6%]	[17.7%, 34.4%]	[5644,6326]	[0.24,0.52]
Yucca Valley	0.0534	[0.77,1.00]	1.0006	1.0005	1.0008	1.0002	[92.1%, 98.2%]	[11.5%, 38.9%]	[5486,6322]	[0.27,0.51]



## C Estimating Measures of Electoral Success

We take a four-step approach to estimating predicted Latino electoral success for any simulated districting plan.

1. **Estimation Step:** We begin by estimating a logistic regression on real-world city council election data for the 107 cities in our sample, post-districting. Our dataset contains one observation for every election that took place in a city, council district, and election year. Estimated coefficients from this regression are reported in Table C-1.

*Dependent variable:* A binary indicator for whether a Latino won office in a city-district-election year. Names of winning candidates are drawn from the California Elections Data Archive (CEDA) and candidate race is estimated using the R package `wru` (Imai and Khanna 2021).

*Predictors:* We include the following district-level predictors of electing a Latino candidate, which we compute by aggregating our shapefile data (described in detail in Appendix A above) from the Census block to the city council district level under each city’s adopted plan:

- (a) Total citizen voting-age population (CVAP)<sup>13</sup>
  - (b) Proportion of CVAP that is Black/African American, Asian, and Hispanic/Latino<sup>14</sup>
  - (c) Proportion of registered voters who are Democrats<sup>15</sup>
  - (d) Homeownership rate<sup>16</sup>
  - (e) Citywide measure of segregation (dissimilarity index)
  - (f) Vote share to all Latino candidates in the following statewide elections:
    - Controller, 2014
    - Senate, 2016
    - Lieutenant Governor, 2018<sup>17</sup>
2. **Aggregation Step:** For each simulated plan, we compute all of the predictors that went into the estimation model by aggregating up from Census blocks.
  3. **Prediction Step:** Using the model estimated in Step 1 and the predictors computed in Step 2, we generate a predicted  $\hat{p}_d = Pr(\text{Winner is Latino}_d)$  for every simulated district in every city.
  4. **Manipulation Step:** With a set of  $\hat{p}_d$ ’s in hand for every plan, we can manipulate the district-level probabilities of electing Latino candidates into our plan-level electoral outcomes of interest:

---

<sup>13</sup>See section 2 of Appendix A for variable construction.

<sup>14</sup>We leave white and other as the omitted category. See section 2 of Appendix A for variable construction.

<sup>15</sup>See section 4 of Appendix A for variable construction.

<sup>16</sup>See section 1 of Appendix A for variable construction.

<sup>17</sup>See section 5 of Appendix A for variable construction. We omit the 2014 Secretary of State race, on which we have also gathered data, from the model because of its high correlation with the 2014 Controller race.

- $E[\text{Latino council share}] = \frac{1}{D} \sum_{d=1}^D \hat{p}_d$
- $\Pr(\text{At least one Latino on council}) = 1 - \Pr(\text{No Latinos on council}) = 1 - \prod_{d=1}^D (1 - \hat{p}_d)$
- $\Pr(\text{Latino majority on council}) = \sum_{\{L,N\} \in \mathcal{M}} (\prod_{l \in L} \hat{p}_l * \prod_{n \in N} (1 - \hat{p}_n))$  where  $\mathcal{M}$  is the set of all possible ways to make a set  $L$  of Latino-winning districts and  $N$  of non-Latino-winning districts s.t.  $|L| \geq |N|$ .

These computations are valid under the simplifying assumption that district elections are independent of one another. While we recognize that there are almost certainly spillovers across districts — for instance, potential candidates’ calculations about entering a race in one district may also depend on conditions in other districts — such dependencies would be prohibitively computationally intensive to model.

Table C-1: Estimated Coefficients from Logistic Regression Predicting District-Level Probability of Electing Latino Candidates (1) and White Candidates (2)

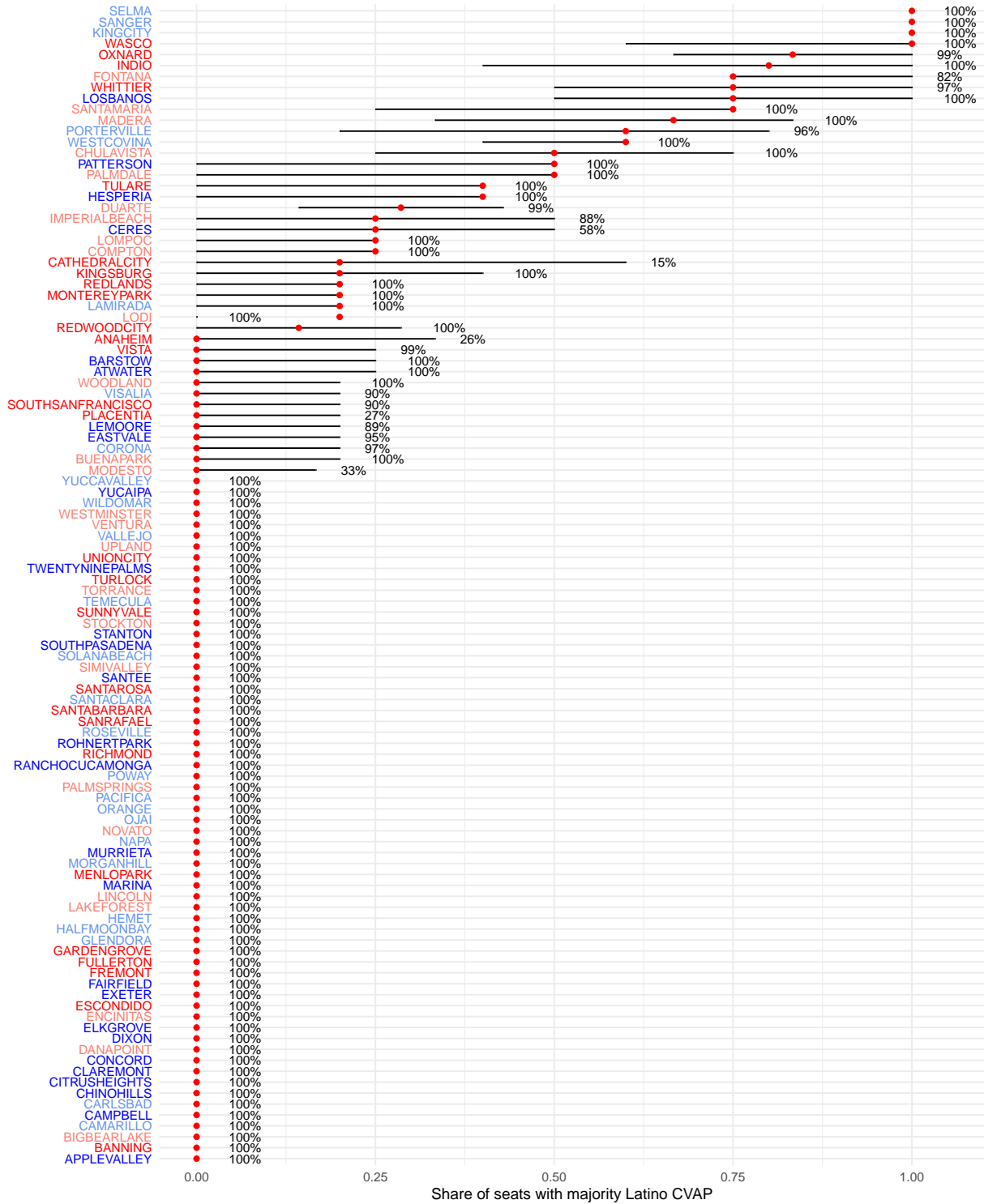
	(1)	(2)
District Proportion of CVAP, African-American	-0.944 (1.408)	-2.150 (1.388)
District Proportion of CVAP, Asian	-2.138 (1.426)	-5.659*** (1.154)
District Proportion of CVAP, Latino	5.130*** (1.260)	-5.545*** (1.207)
District Total CVAP	0.00002 (0.00001)	0.00001 (0.00001)
District Democratic Vote Share	4.092* (2.006)	-0.480 (3.837)
Homeownership Rate in District	-0.046 (0.937)	1.809* (0.805)
Citywide Segregation	1.774 (2.372)	-2.968 (2.126)
District Vote Share to Latino Candidates, 2014 Controller	-5.635 (3.344)	
District Vote Share to Latino Candidates, 2016 Senate	2.912 (1.900)	
District Vote Share to Latino Candidates, 2018 Lieutenant Governor	-0.382 (2.510)	
District Vote Share to White Candidates, 2014 Controller		-0.833 (2.881)
District Vote Share to White Candidates, 2016 Senate		2.193 (3.314)
District Vote Share to White Candidates, 2018 Lieutenant Governor		-0.276 (2.457)
Observations	507	507
Log Likelihood	-245.484	-270.166
Akaike Inf. Crit.	512.968	562.332

Note:

\*p<0.05; \*\*p<0.01; \*\*\*p<0.001

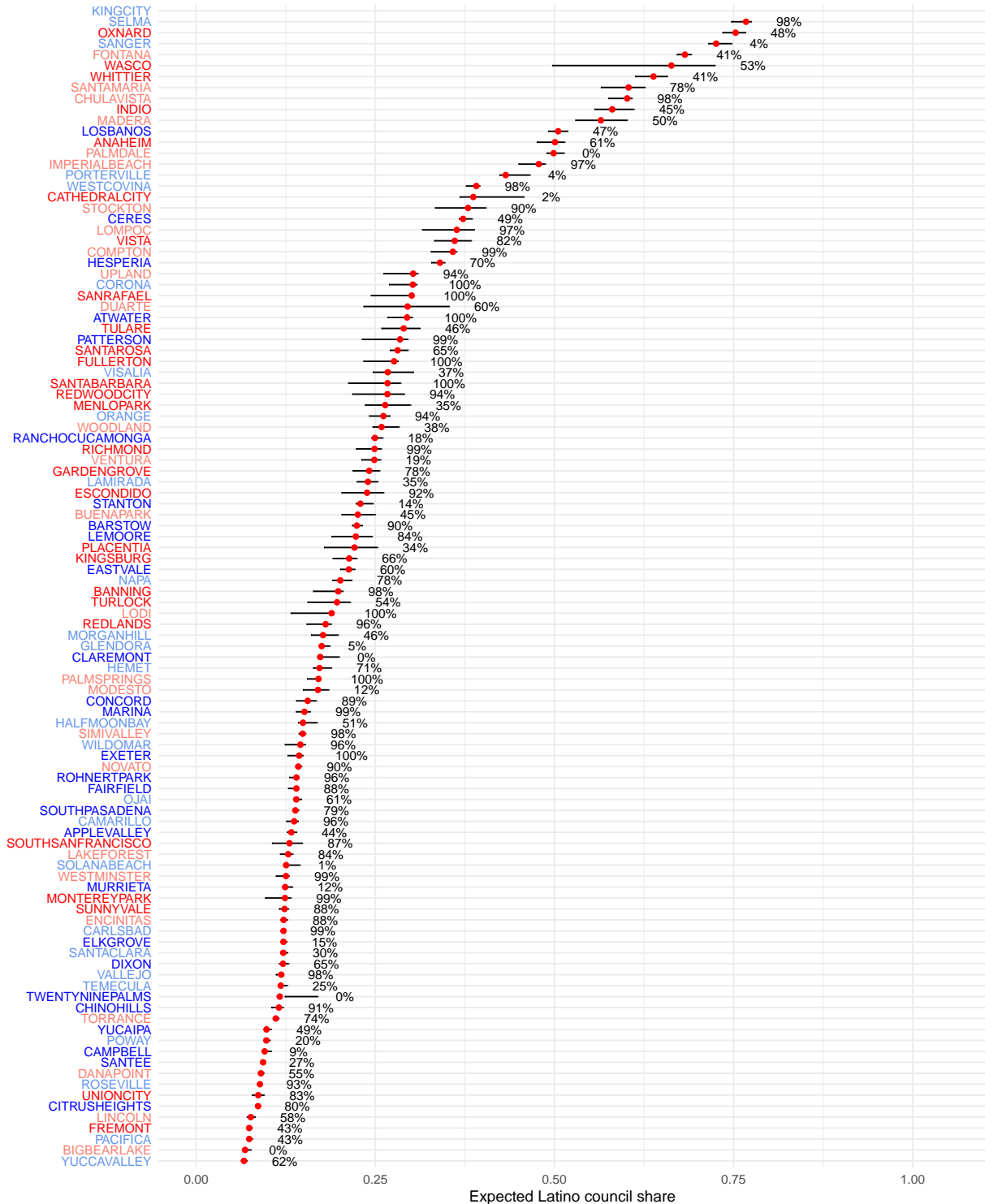
## D Simulation Distributions

Figure D-1: Simulation Distributions: Share of Council Seats Where Latinos Are the Majority of the Citizen Voting-Age Population



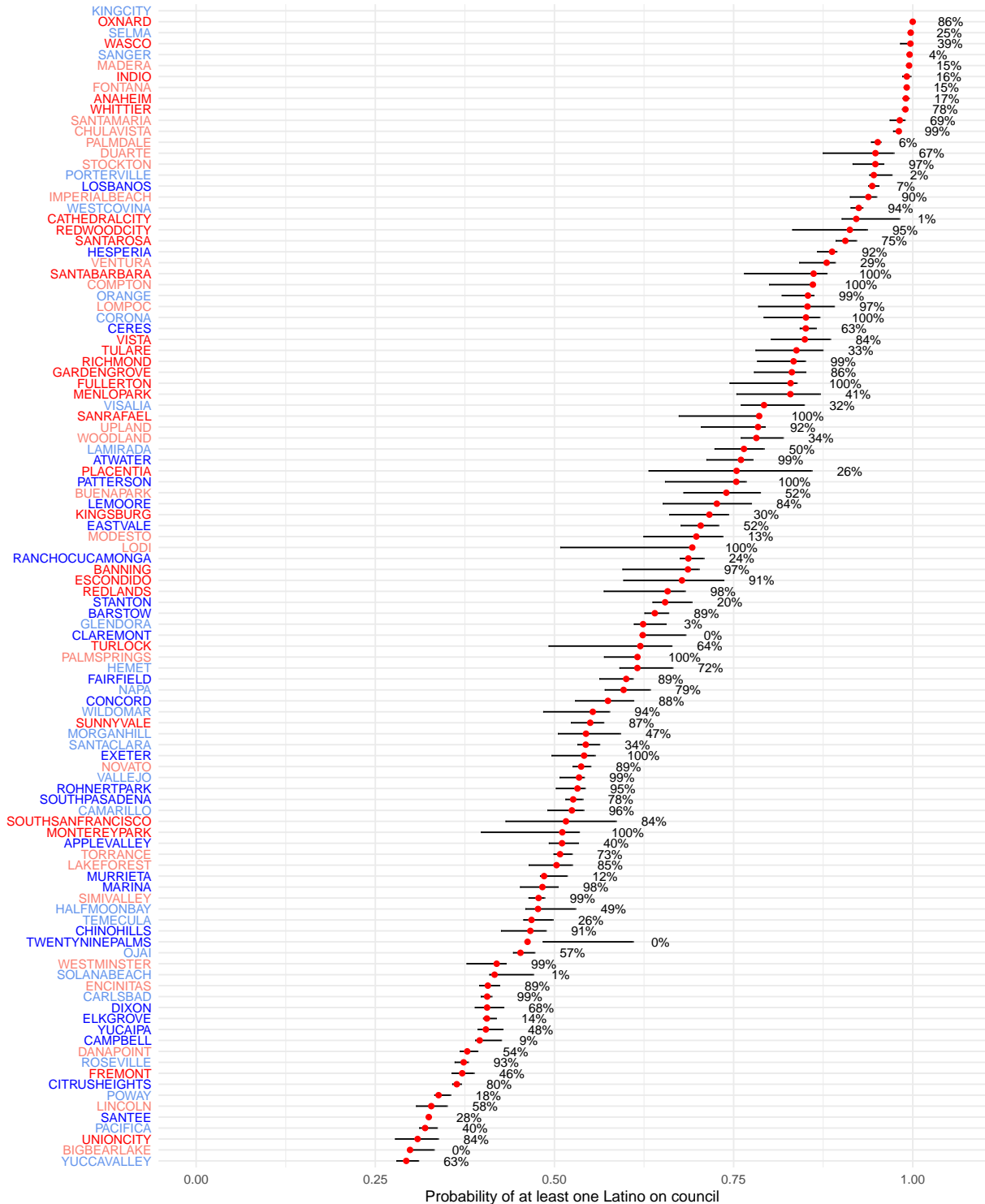
Notes: Red points represent seat shares under the adopted map; black bars represent the ranges of the distributions over 40,000 simulated maps. To the right of each distribution we indicate the percentile within the simulation distribution where the adopted map falls. City labels are colored by quantile of the distribution of segregation (measured by dissimilarity index of Latinos and non-Latinos) across the cities in our sample: highest quantile (> 0.26) in red, next quantile (between 0.21 and 0.26) in light red, next (between 0.17 and 0.21) in light blue, and lowest (< 0.17) in blue.

Figure D-2: Simulation Distributions: Expected Share of Council Seats Held by Latinos



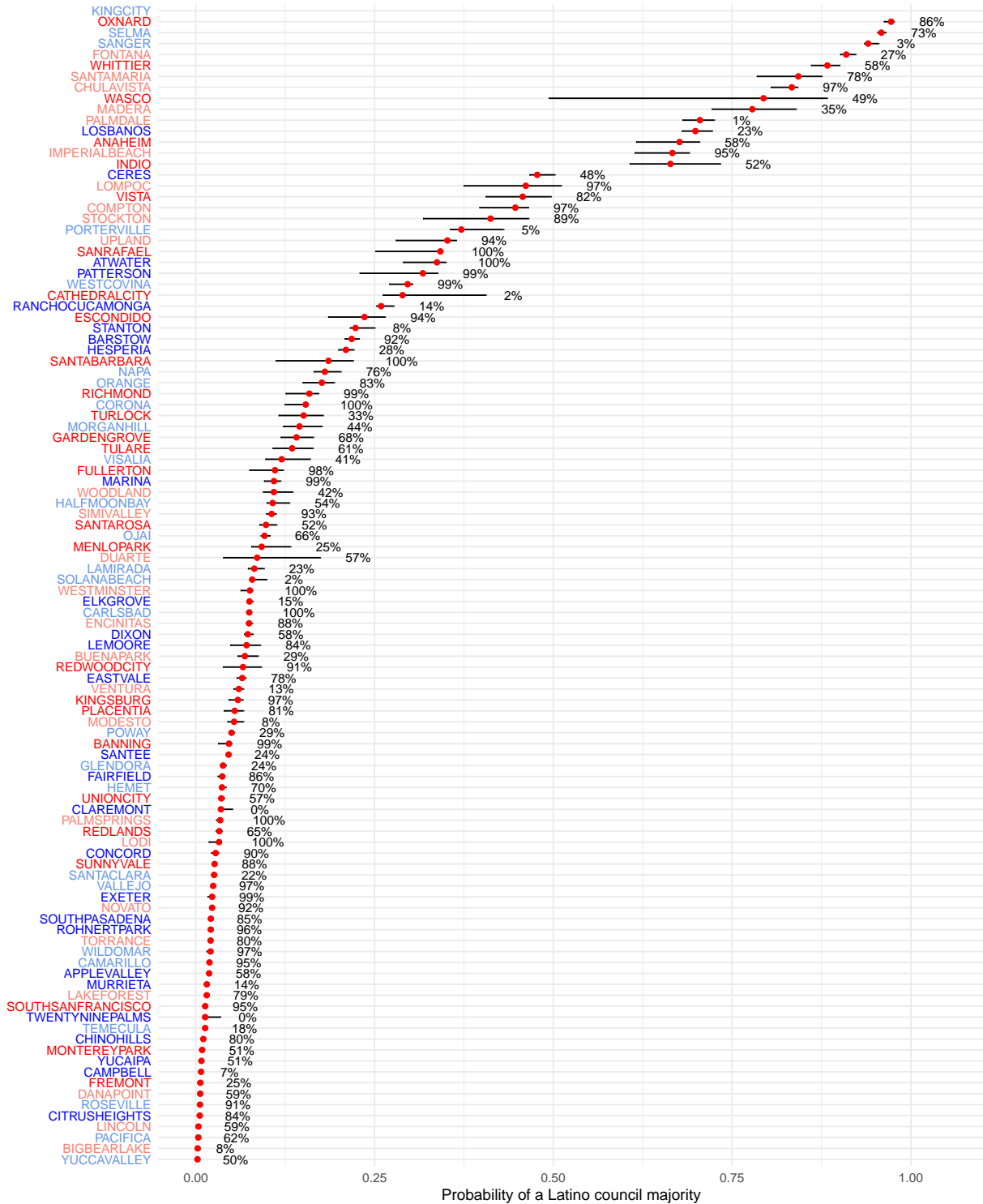
Notes: Red points represent council shares under the adopted map; black bars represent the ranges of the distributions over 40,000 simulated maps. To the right of each distribution we indicate the percentile within the simulation distribution where the adopted map falls. City labels are colored by quantile of the distribution of segregation (measured by dissimilarity index of Latinos and non-Latinos) across the cities in our sample: highest quantile (> 0.26) in red, next quantile (between 0.21 and 0.26) in light red, next (between 0.17 and 0.21) in light blue, and lowest (< 0.17) in blue.

Figure D-3: Simulation Distributions: Probability of at Least One Latino on Council



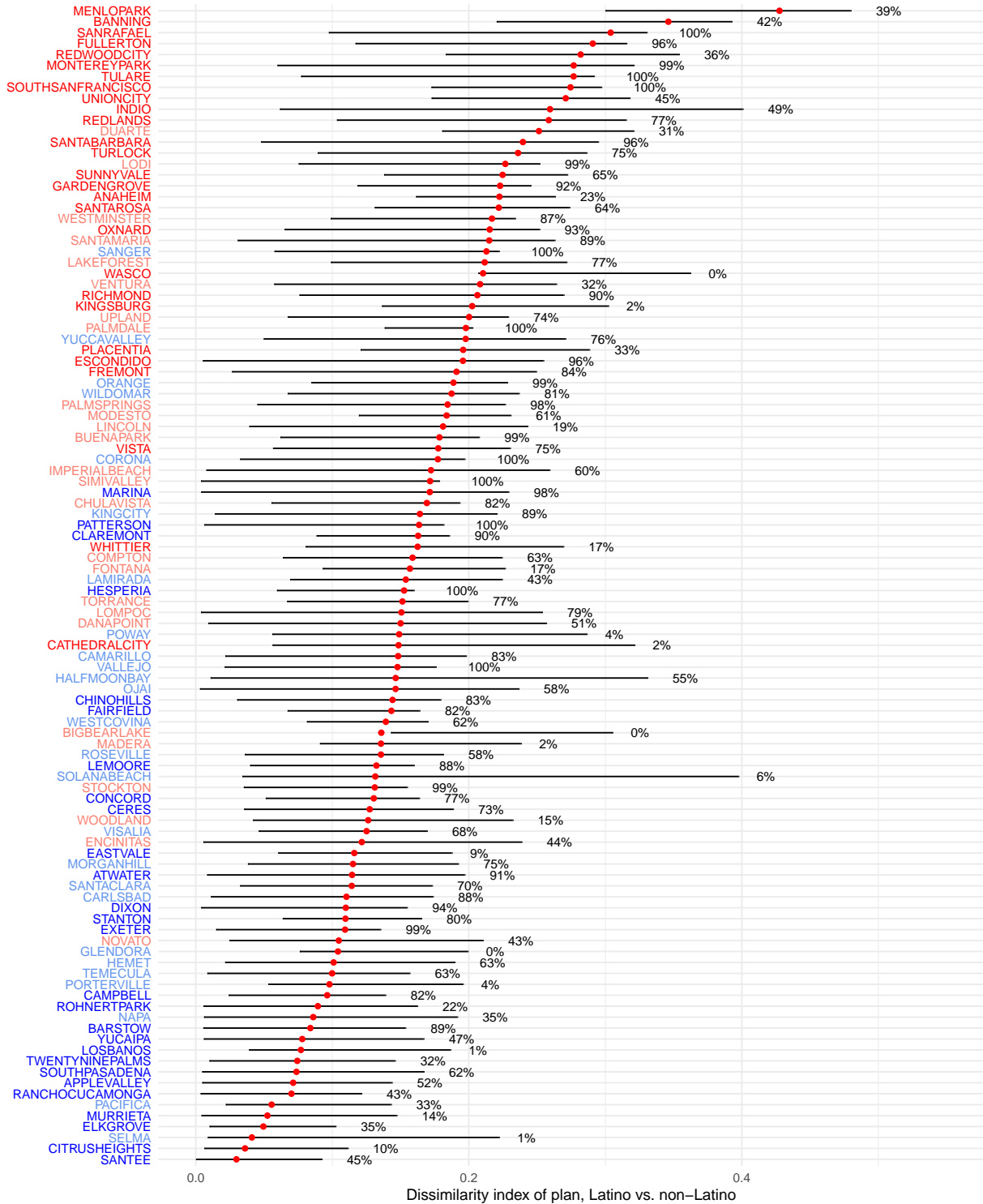
Notes: Red points represent probabilities under the adopted map; black bars represent the ranges of the distributions over 40,000 simulated maps. To the right of each distribution we indicate the percentile within the simulation distribution where the adopted map falls. City labels are colored by quantile of the distribution of segregation (measured by dissimilarity index of Latinos and non-Latinos) across the cities in our sample: highest quantile (> 0.26) in red, next quantile (between 0.21 and 0.26) in light red, next (between 0.17 and 0.21) in light blue, and lowest (< 0.17) in blue.

Figure D-4: Simulation Distributions: Probability of Latino Majority on Council



Notes: Red points represent probabilities under the adopted map; black bars represent the ranges of the distributions over 40,000 simulated maps. To the right of each distribution we indicate the percentile within the simulation distribution where the adopted map falls. City labels are colored by quantile of the distribution of segregation (measured by dissimilarity index of Latinos and non-Latinos) across the cities in our sample: highest quantile (> 0.26) in red, next quantile (between 0.21 and 0.26) in light red, next (between 0.17 and 0.21) in light blue, and lowest (< 0.17) in blue.

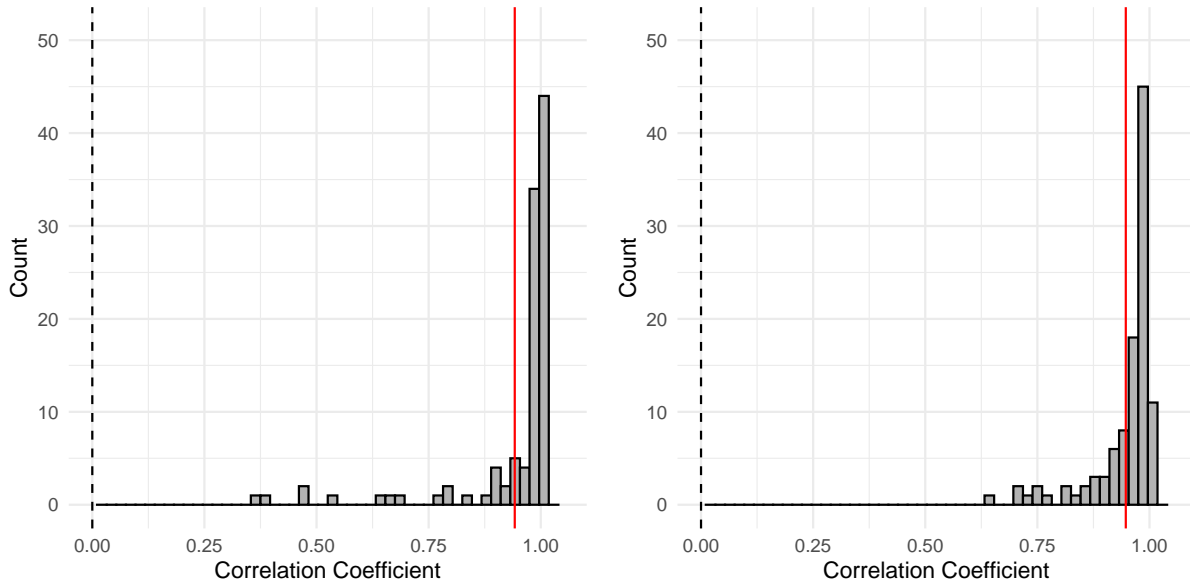
Figure D-5: Simulation Distributions: Dissimilarity Index of Plans, Latino vs. Non-Latino



Notes: Red points represent dissimilarity index under the adopted map; black bars represent the ranges of the distributions over 40,000 simulated maps. To the right of each distribution we indicate the percentile within the simulation distribution where the adopted map falls. City labels are colored by quantile of segregation (measured by dissimilarity index of Latinos and non-Latinos) across the cities in our sample: highest quantile (> 0.26) in red, next quantile (between 0.21 and 0.26) in light red, next (between 0.17 and 0.21) in light blue, and lowest (< 0.17) in blue.

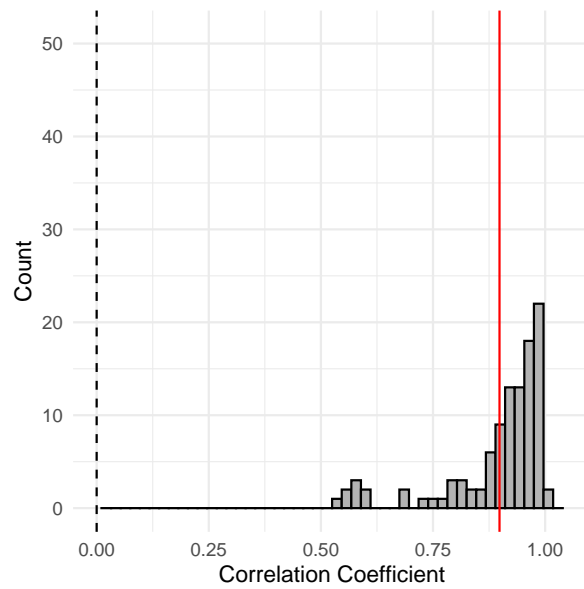
## E Additional Tables and Figures

Figure E-6: Correlations Between Measures of Latino Electoral Advantage



(a) Expected Latino Council Share and Pr(At Least One Latino on Council)

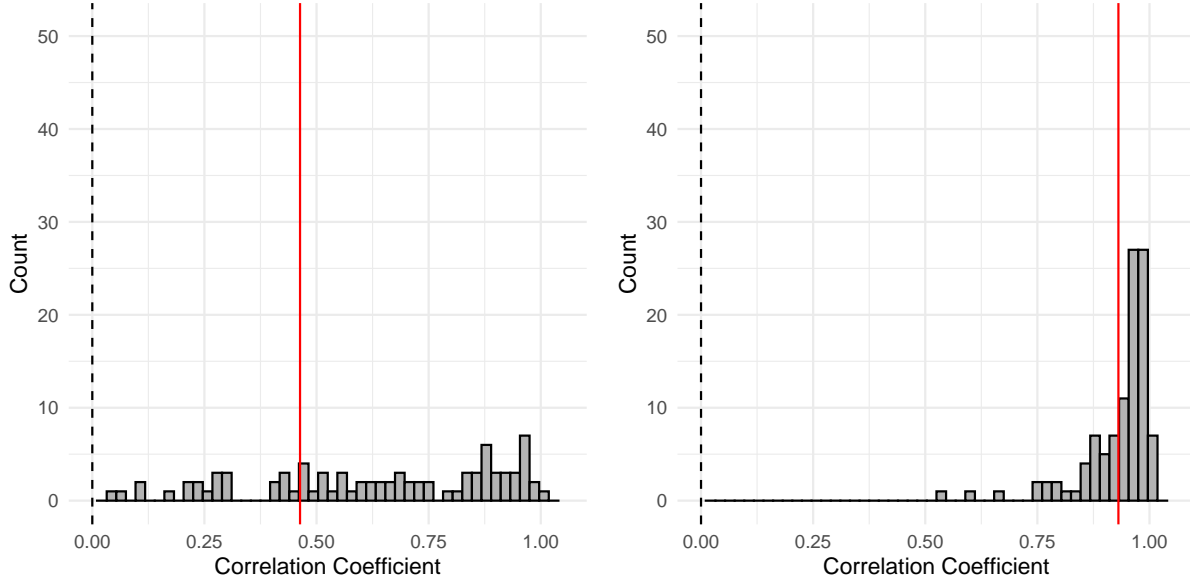
(b) Expected Latino Council Share and Pr(Latino Council Majority)



(c) Pr(At Least One Latino on Council) and Pr(Latino Council Majority)

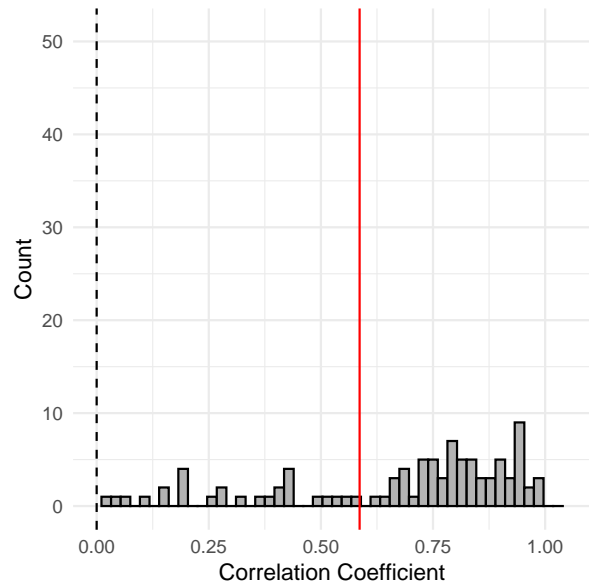


Figure E-7: Correlations Between Measures of White Electoral Advantage



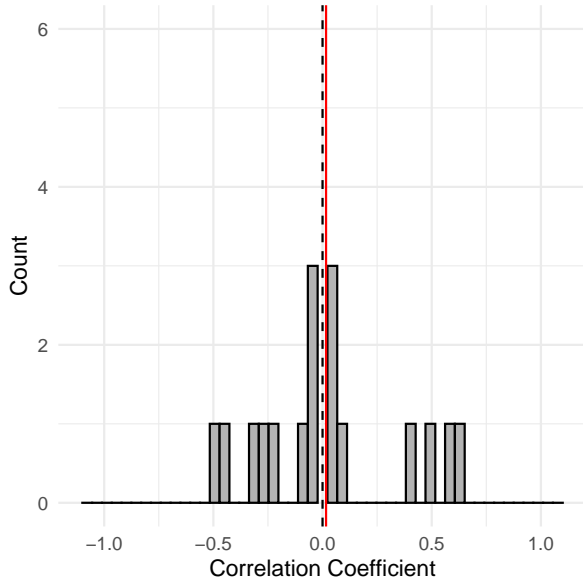
(a) Expected White Council Share and Pr(At Least One White Councilmember)

(b) Expected White Council Share and Pr(White Council Majority)

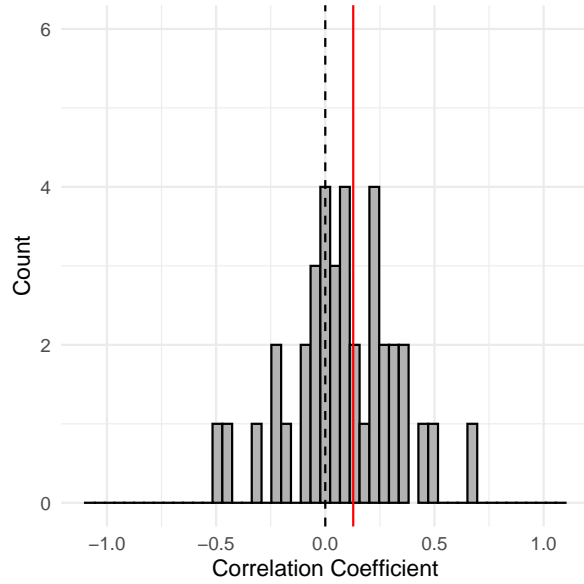


(c) Pr(At Least One White Councilmember) and Pr(White Council Majority)

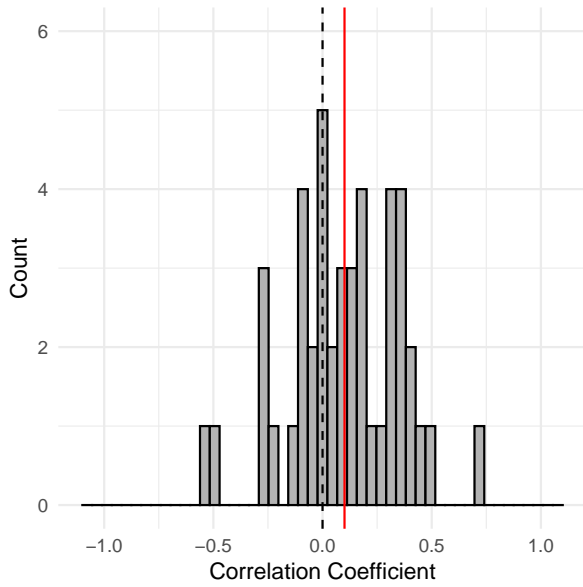
Figure E-8: Correlations Between Share of Seats with Majority Democratic Registered Voters and Latino Electoral Advantage



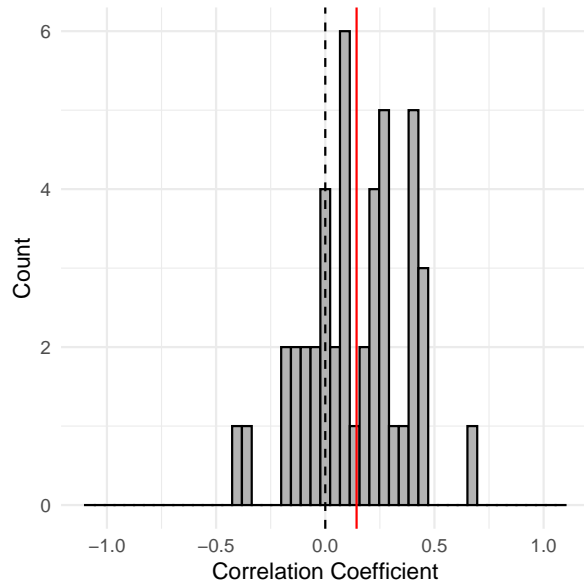
(a) Share of seats w/Democratic registered voter majority and share of seats w/Latino CVAP majority



(b) Share of seats w/Democratic registered voter majority and expected Latino council share



(c) Share of seats w/Democratic registered voter majority and Pr(at least one Latino on council)



(d) Share of seats w/Democratic registered voter majority and Pr(Latino council majority)

## References

- DeFord, Daryl, Moon Duchin and Justin Solomon. 2021. “Recombination: A Family of Markov Chains for Redistricting.” *Harvard Data Science Review*.  
**URL:** <https://hdsr.mitpress.mit.edu/pub/1ds8ptxu>
- Dube, Matthew P. and Jesse Tyler Clark. 2016. “Beyond the Circle: Measuring District Compactness Using Graph Theory.” Northeast Political Science Association Conference — Boston, MA.  
**URL:** [https://www.researchgate.net/publication/311557290\\_Beyond\\_the\\_Circle\\_Measuring\\_District\\_Compactness](https://www.researchgate.net/publication/311557290_Beyond_the_Circle_Measuring_District_Compactness)
- Fifield, Benjamin, Michael Higgins, Kosuke Imai and Alexander Tarr. 2020. “Automated Redistricting Simulation Using Markov Chain Monte Carlo.” *Journal of Computational and Graphical Statistics* 29(4):715–728.
- Imai, Kosuke and Kabir Khanna. 2021. “Who Are You? Bayesian Prediction of Racial Category Using Surname and Geolocation.” <https://github.com/kosukeimai/wru>.
- Karcher, Speaker, New Jersey Assembly, et al. v. Daggett et al. 1983. 462 U.S. 725.  
**URL:** <https://tile.loc.gov/storage-services/service/ll/usrep/usrep462/usrep462725/usrep462725.pdf>
- Kenny, Christopher T., Cory McCartan, Ben Fifield and Kosuke Imai. 2021. “redist: Simulation Methods for Legislative Redistricting.” Available at The Comprehensive R Archive Network (CRAN).  
**URL:** <https://CRAN.R-project.org/package=redist>
- McCartan, Cory, Christopher Kenny, Tyler Simko, Shiro Kuriwaki, George Garcia III, Kevin Wang, Melissa Wu and Kosuke Imai. 2022. “Simulated Redistricting Plans for the Analysis and Evaluation of Redistricting in the United States.” *Nature Scientific Data* 9:689.
- McCartan, Cory and Kosuke Imai. 2022. “Sequential Monte Carlo for Sampling Balanced and Compact Redistricting Plans.” arXiv.  
**URL:** <https://arxiv.org/pdf/2008.06131.pdf>