Reform Drift:
How Incumbent Protection Undermines Descriptive Representation in Local Government

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Abstract

Institutional reforms designed to enhance democratic representation often place implementation in the hands of incumbents. We examine how incumbents use this control to protect their interests by leveraging the California Voting Rights Act of 2001, which prompted hundreds of jurisdictions to switch from at-large to district elections to improve minority representation. Using a state-of-the-art redistricting simulation algorithm, we show that adopted council maps overwhelmingly placed incumbents alone in their districts—63% of cities' plans ranked in the 99th percentile or higher for avoidance of incumbent pairings. This pattern was especially pronounced in smaller, whiter cities with lower turnout and more competitive elections. Crucially, incumbent protection deters challenger entry and reduces Latino electoral success. In Latino-opportunity districts, a lone incumbent decreases the probability of a Latino being elected by 19 percentage points. Our findings show how reforms can be blunted by those empowered to implement them, ultimately reinforcing existing power structures.

Keywords: local politics, electoral reform, descriptive representation, incumbency advantage, redistricting, city councils

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Introduction

The reform of local electoral and governance institutions has long been viewed as a pathway to improving representation in municipal government. From the adoption of district elections to combat Black voter suppression in the American South (Sass and Mehay 1995; Trebbi, Aghion, and Alesina 2008), to the sweeping Progressive Era reforms in the Southwest (Bridges 1999), and, more recently, to the implementation of ranked choice voting in New York City's mayoral primaries (Colner 2024), reformers have recognized that the rules of the game shape outcomes. Accordingly, they have sought to restructure those rules to empower marginalized groups and create incentives for more democratically responsive and accountable government.

Yet the literature in American local politics is replete with examples of institutions failing to produce substantive differences in representation or policy outcomes (e.g., Tausanovitch and Warshaw 2014; Sahn 2023; Colner 2024). In this paper, we posit an explanation for these surprising results that has not received adequate scholarly attention. We argue that the implementation of reform is often entrusted to the officials currently in government—those with a vested interest in protecting the status quo. When confronted with external pressures to restructure the rules of the game, incumbent politicians may use their superior knowledge and influence over essential features of institutional design to resist meaningful change and remain in power. Ultimately, such efforts undermine the success of any reform that threatens incumbent politicians—whether by regulating their behavior, redistributing resources, or expanding political access to new groups.

Our analysis leverages the California Voting Rights Act (CVRA) of 2001, which compelled hundreds of cities to switch from at-large to district elections for city councils, school boards, and other municipal governments. Under at-large city council elections—in which every resident may vote for candidates running for each seat in first-past-the-post contests—white majorities consistently secured disproportionate representation. Consequently, because these officeholders tended to emerge from the same white, affluent neighborhoods—and to be most responsive to those neighborhoods' interests—minority-dominated swaths of the city would experience structural disinvestment and unequal access to education, infrastructure, and public services. The CVRA was conceived to break this cycle through the adoption of district elections, in which the city is carved into smaller geographic constituencies, each with the ability to elect a resident of only that district to a council seat. According to the logic of the reform, if some of these districts could be drawn to give racial or ethnic minorities—usually, Hispanic or Latino communities in this context—a local majority, then they could elect their candidates of choice from their own neighborhoods and gain a seat at the table in local government.[1]

Recent work evaluating the effects of the CVRA on minority officeholding and policy outcomes has found that district elections have, on average, empowered previously underrepresented communities, though the effects have been more heterogeneous and less pronounced than reformers may have hoped for (Abott and Magazinnik 2020; Collingwood and Long 2021; Hankinson and Magazinnik 2023). Our work highlights an important but understudied mechanism behind the limitations of district elections as a tool for minority empowerment: district maps were consistently drawn to place each at-large incumbent alone in their own district. By avoiding incumbent pairings, cities maximized the number of at-large councilmembers that could retain their office after the reform. While media accounts have documented this practice of incumbent protection anecdotally, our analysis is the first to collect systematic data and apply a principled methodology to quantify the degree of incumbent protection across a large number of cities that were compelled to adopt district elections.

To do so, we collect the newly adopted city council district plans as well as the residential locations of all at-large incumbent councilmembers for as many California cities as possible. In all, we are able to gather complete records for 87 cities, which are

1. Throughout this paper, we will use the terms "Hispanic" and "Latino" interchangeably. While we are primarily interested in the political representation of Latinos—U.S. residents with Latin-American ancestry—much of our analysis relies on the Census classification of "Hispanic," a linguistic category. In practice, there is a great deal of overlap between these two classifications in the California setting.

representative of the universe of 167 cities that converted to district elections for city council under the CVRA. Using these geospatial data, we compute a citywide measure of incumbent protection based on observed incumbent pairings. Then, we apply a state-of-the-art redistricting algorithm (Fifield et al. 2020; Kenny et al. 2021; McCartan et al. 2022) to simulate the distribution of technically feasible plans within each city, given its unique physical and political geography as well as legal requirements such as contiguity and population parity. This allows us to quantify just how unusual the observed degree of incumbent protection is in each city, compared to the distribution of alternatives that could have been counterfactually adopted based on these criteria. Our analysis yields overwhelming and incontrovertible evidence of incumbent protection: 63% of cities' enacted plans are in the 99th percentile or above of their simulation distributions of our measure of avoidance of incumbent pairings.

This systematic approach allows us to make general inferences about the conditions under which incumbent protection is likely to emerge. We find that incumbents are most likely to secure protection when they have the *motive* and the *opportunity* to do so. They have the *motive* in cities with more competitive elections, where incumbents have to fear more serious challengers for their seats. They have the *opportunity* in cities with smaller, whiter populations and lower voter turnout—where both internal mobilization for reform and external monitoring of compliance are likely weaker.

Most importantly, the CVRA presents a unique opportunity to study the downstream effects of incumbent protection on electoral competition and descriptive representation. District elections are meant to attract high-quality newcomers by lowering the bar for them to win elections: instead of competing with the political establishment for citywide majorities, candidates only have to win the support of their home districts, where they can run relatively low-cost, grassroots campaigns. By distributing incumbents over the newly created districts, however, cities undercut this logic. We find that increasing the number of districts containing at least one incumbent decreases overall challenger entry as well as the entry and success of Latino candidates. These effects are particularly pronounced in Latino-opportunity districts—those with a sizable Latino population that were purposefully created to elevate Latino candidates to office. In these districts, having a lone incumbent is associated with a 19 percentage point decrease in the probability of a Latino being elected, compared to districts with no incumbents.

Our findings have important implications beyond the specific institution of district elections. They speak to the limited effectiveness of institutional reform when the actors who are tasked with its design and implementation are the very same ones whose behavior the new rules are meant to shape and constrain. Thus, even well-intentioned efforts can be blunted or repurposed to reinforce the preexisting distribution of power. In this sense, our results echo Trounstine (2008)'s provocative argument that *both* political machines and reform governments exhibit their own pro-incumbent biases. Institutional change alone is not enough to loosen the grip of entrenched "political monopolies." Broadening the coalitions to which government is accountable requires a deeper and more prolonged political struggle.

Theory and Background

When Institutional Reform Reproduces Power

An active literature in local political economy has made significant contributions to understanding how variation in institutional forms shapes outcomes in local government. Sahn (2023), for instance, examines the Progressive Era shift from strong mayor systems to commission and council-manager forms of government. Contrary to expectations, they find no effects on municipal spending or revenue. Similarly, Colner (2024)'s comprehensive analysis of ranked choice voting (RCV) reforms finds that they fail to induce high-quality candidate entry or increase the number of non-white or female candidates in the long run, casting doubt on some of the purported benefits of RCV. Analyzing a wide range of institutional arrangements—including elected mayors, the popular initiative, partisan elections, term limits, and at-large elections—across all U.S. cities and towns with populations greater than 20,000 people, Tausanovitch and Warshaw (2014) find surprisingly limited effects of institutional structure on the alignment between voter preferences and local policy outcomes.

One explanation for these findings is that reform is often implemented by actors who already occupy positions of power, and thus have both the insider knowledge and the authority to design institutions to serve their own interests. For instance, Anzia and Trounstine (2025) show that the early twentieth-century transition from patronage-based to civil service systems of municipal government was driven not by external pressures, but by city employees who stood to gain from this shift—especially where they were organized, had agency, and wielded political influence. Even when reforms are imposed from the outside, the picture is no different. Recently, public outrage over a leaked tape exposing racial gerrymandering on the Los Angeles City Council generated momentum for an ethics overhaul. Yet amendments to the proposed reforms ultimately weakened the ethics commission, barring it from accepting recommendations directly from voters without city council approval. "'The appetite for reform exists from the public, but the will doesn't exist from the city council nor from those who may potentially be regulated,' said Jamie York, whose own nomination to the ethics commission last year was blocked after a controversial vote" (Mason 2024).

A similar pattern played out when Los Angeles adopted term limits for city councilmembers in 1991. The result was a revolving door of termed-out officeholders between Los Angeles and Sacramento, and the creation of small "neighborhood councils" operating within city council districts. Although these councils are presented as "the closest form of government to the people,"[2] in practice they have served as a training ground for city councilmembers' staffers who later run in elections to succeed their former bosses.

2. https://lacity.gov/government/neighborhood-councils.

As a former Los Angeles city councilmember put it, "Council staffers are currently the only viable competitors to those coming out of Sacramento... The net result is a dramatic increase in in-breeding" (Galanter 2013).

Transitioning from At-Large to District-Based City Council Elections Under the California Voting Rights Act

One of the most consequential recent reforms in U.S. local politics has been the shift from at-large to district-based elections for city councils, school boards, and other municipal governments. Under at-large systems, all residents vote for every available seat in first-past-the-post contests. In contexts of racially polarized voting, this allows a bare racial majority to capture every seat, leaving even sizable minority communities completely without representation. Compounding this institutional bias in favor of the majority group, residential segregation—along with stark racial disparities in local political participation (Hajnal 2009; Hajnal and Trounstine 2005), especially in low-salience, off-cycle elections (Anzia 2014)—means that officeholders in at-large systems tend to come from the same white, affluent neighborhoods and direct resources back to those areas. The result is structural disinvestment from minority neighborhoods and the entrenchment of racial inequalities in access to education, infrastructure, and public services.

District-based elections can break this cycle by cleaving local jurisdictions, like cities, into smaller geographic constituencies, each with its own council seat—including some districts where the racial minority constitutes a local majority. Typically, only the residents of a district are permitted to run for that seat. Minority voters are thereby given the opportunity to elect their "candidates of choice" from their own communities and to participate meaningfully in local governance. The federal Voting Rights Act of 1965 established evidentiary standards for showing that at-large elections are causally responsible for minority vote dilution, and that district-based elections would be an effective remedy. In 2001, the California state legislature passed a law reducing these evidentiary standards for proving minority vote dilution under at-large systems, thus making it significantly easier to compel jurisdictions to switch to district elections. Since the passage of the California Voting Rights Act (CVRA), 167 California cities have undertaken this transition in their city council elections, either voluntarily or as the result of legal action.

If effective, the CVRA can serve as a nationwide template for improving minority descriptive representation in local government. To date, eight other states have enacted, and nine more have proposed, state-level voting rights acts that may include provisions similar to California's.[3] However, recent scholarship has not viewed the CVRA as a panacea. While the average effects of conversion from at-large to district elections on minority representation are generally positive, they are highly heterogeneous and conditional (Abott and Magazinnik 2020; Collingwood and Long 2021; Hankinson and Magazinnik 2023). Part of the variation in success may stem from the fact that several preconditions must be in place for the logic of district elections to function as intended: a sufficiently large minority population, residential segregation, and racially polarized voting.[4] However, in this paper, we propose and test a novel explanation for the uneven effectiveness of districting reforms: the strategic behavior of incumbents in shaping district boundaries to remain in office.

Specifically, we examine how incumbents may influence the design of district maps to protect their seats and deter the emergence of viable challengers. Although the CVRA opened the door for more equitable representation, it did not directly address how sitting incumbents should be treated in the districting process. Federal guidance, as articulated in *Larios v. Cox* (2004), permits some degree of incumbent protection in redistricting—provided that it does not interfere with higher-priority goals like equal population requirements and the avoidance of racial discrimination. Put more simply, the protection of incumbents may be considered a legitimate interest so long as it is applied consistently

3. https://www.ncsl.org/elections-and-campaigns/state-voting-rights-acts.

4. These conditions map onto the criteria that constitute the *Gingles* test, articulated in *Thornburg v. Gingles* (1986), which is applied in federal cases against at-large systems—the very criteria that the CVRA relaxed.

and does not take precedence over statutory or constitutional mandates. In practice, the CVRA set up a stark opposition between incumbents and political newcomers: holding council size constant, creating space for historically underrepresented communities necessarily requires displacing at least some at-large officeholders.[5] As such, the CVRA presents an ideal opportunity to examine the effectiveness of institutional reform when implementation is left to those with a vested interest in maintaining the status quo.

Avoidance of Incumbent Pairings in the Design of District Maps

We now turn to a discussion of the precise mechanisms by which incumbents could shape district maps in their favor. The CVRA led to the spread of district elections across California, but implementation was highly heterogeneous. Some cities mobilized internally to convert to districts, be it by city council ordinance or ballot initiative, while others were spurred by letters from external law firms threatening litigation. While these demand letters were enough to initiate reform in most cities, a few resisted, resulting in costly legal fees, unfavorable settlements, and—in every case to date—ultimately being compelled to move forward with districting.

Further, the drawing of district boundaries varied in process and level of citizen engagement. Some cities established citizen-led districting commissions to propose maps for council consideration, while others kept control fully within the city council. Many cities enlisted the services of demographic consultants promising to lend not only technical assistance, but assurance that adopted plans would be in compliance with state and federal law. Despite these procedural variations, incumbent members of at-large councils almost universally oversaw the districting process, gave input into and debated proposed plans, and, ultimately, voted to approve the adopted maps.

While there are several ways in which the (re)drawing of district lines may advantage

5. In practice, most cities in California held council size fixed in the transition from at-large to district elections. While expanding the council can mitigate some tension between incumbents and newcomers, it still requires incumbents to relinquish some share of power.

incumbents—including reducing partisan competition and preserving constituencies intact (Lyons and Galderisi 1995; Makse 2012; Carson, Crespin, and Williamson 2014; Henderson, Hamel, and Goldzimer 2018)—in this context, the primary focus was on avoiding incumbent pairings within the same district (Glazer, Grofman, and Robbins 1987; Gaddie and Bullock 2007; Forgette, Garner, and Winkle 2009; Cottrell 2024). In general, city council elections in California lack meaningful partisan competition: they are officially nonpartisan, and candidates often minimize or conceal their party identification when running for office. Moreover, given that incumbency advantages are often amplified in the low-turnout, low-salience, and low-information context of local elections, the most significant electoral threat to incumbents typically came from other incumbents.

The avoidance of incumbent pairings was commented on in public hearings and local media. In the town of Big Bear Lake, meeting minutes show the council acknowledging such protection: "Councilmember Caretto mentioned that the Green Map is non-polarizing as it has one council member residing in each district" (City Council Meeting Minutes 12/14/2017). It was also noted by the lone citizen who spoke during the final public comment period: "Elbridge Gerry would be very proud. This looks like gerrymandering" (City Council Meeting 1/18/2018).

A common justification for avoiding incumbent pairings was to maintain continuity in voters' choices. In Visalia, community-drawn maps paired two incumbents in one district. The city council's hired consultant redrew the maps to split them into separate districts so that "no one was voted off the island" (Doe 2015). When the consultant's change was noted by the public, Mayor Steve Nelsen expressed offense at the suggestion that the council would approve a map that was gerrymandered. Two other councilors supported the consultant's maps because the voters had chosen them to serve in office, and therefore should be able to vote for them again (Doe 2015). In Yucca Valley, the hired consultant explained that separating incumbents even when they live close together is a standard practice that "allows the voters to determine if the official should be re-elected, and not the demographer" (Staff 2018). Some councilors were less subtle. When it was alleged that the map in Martinez was designed to protect the four out of five incumbents who lived downtown, Councilor Mike Ross responded: "If any reasonable person thinks that we're gonna sit up here and choose a map that basically takes ourselves out of office... God bless you, you can have that as your choice" (Heidorn 2023).

Other cities established citizens' advisory committees—groups of appointed residents tasked with drawing proposed maps for the council's consideration—which sometimes produced maps that ran counter to incumbent protection. In Woodland, the city council had the option to adopt a map that would preserve all five incumbents' seats. Instead, they chose between two alternatives proposed by the advisory committee. The selected map placed three incumbents in the same district (Kalfsbeek 2018), which ultimately prompted one incumbent to relocate to an apartment in his friend's commercial building in order to run in an open district. "There's a few haters out there who don't like the idea that I've moved across the tracks to help another district," the recently moved incumbent said. But "if [citizens in District 4] want someone who wants to work hard and bring up the standard of living... if they want me to work hard for them, then I'm their guy" (Garrison 2016).

Hypotheses and Contribution

The CVRA presents a novel opportunity to systematically measure the *prevalence*, *predictors*, and *consequences* of pro-incumbent bias in local districting reforms. These constitute the three pillars of our analysis.

First, we wish to characterize the extent to which incumbents were protected in cities' new districting plans by being placed alone in their district. While local media accounts have documented a handful of higher-profile cases—usually, where attempts at incumbent protection generated controversy and resistance—our work represents the first attempt to *systematically* measure the prevalence of this practice, based not on secondhand accounts but on the adopted plans themselves, across as many cities as possible.

This descriptive groundwork is important in its own right, because there are competing expectations about the degree of incumbent protection we ought to observe. Of course, we expect incumbents to use whatever influence they have over the districting process to enhance their future electoral prospects. However, there are good reasons to temper these expectations. The CVRA created an environment of unusually high salience, state-level oversight, and monitoring by interest groups and the media. Larger organizations such as the American Civil Liberties Union (ACLU) and the Southwest Voter Registration Education Project (SVREP) were active in threatening cities with litigation and lending legal and technical assistance to local activists. This statewide network supported, and was supported by, grassroots coalitions pushing for city council reform from within: in Anaheim, for instance, legal action against at-large elections was initiated by the ACLU and José Moreno, an elected member of the city's School Board and the president of the Latino community organization Los Amigos of Orange County.[6] To the extent that the CVRA lent a hand to already powerful bottom-up demands for reform, we would expect at-large incumbents to be more constrained in their ability to enact institutionalized advantages. Ultimately, the heightened visibility of districting under the CVRA is relevant for the generalizability of our findings: if we detect incumbent protection here, we can expect similar dynamics to be pervasive elsewhere.

The issues of top-down monitoring and bottom-up mobilization raise a broader question: when are incumbents most likely to secure protection more generally? To answer this—our second research question—we examine a large slate of incumbent- and city-level predictors of an incumbent being alone in a district in the map adopted by their city council. We expect incumbent protection to be strongest amid low internal mobilization and low monitoring. Following Trounstine (2013), we expect cities with low overall turnout and participation to foster more favorable conditions for incumbents.

6. https://dhkl.law/cases/city-of-anaheim/.

Cities with smaller, less mobilized nonwhite populations should see greater incumbent protection. Finally, we expect competitiveness to play an important role, consistent with previous findings that electoral threat predicts the enactment of laws that protect the party in power—most notably, that Republican-controlled state legislatures are most likely to adopt restrictive voter identification laws in states where Republicans are electorally challenged (Hicks et al. 2015; Grumbach 2022).

Third, and equally importantly, we ask whether incumbent protection undermined the CVRA's goal of empowering historically underrepresented communities. The inherently zero-sum nature of competition between political insiders and newcomers makes this an ideal setting to evaluate whether the presence of incumbents deterred new candidate entry and curtailed the electoral success of Latino candidates—particularly in the districts that were designed to give Latino communities the opportunity to elect their representatives of choice. This speaks to the question at the heart of our research: whether placing the implementation of reform in the hands of those already in power erodes the reform's ability to deliver meaningful change.

Given the novelty of the situation created by the CVRA, in which more than 160 cities drew city council district plans for the first time, prior research offers little guidance for generating predictions. Incumbent pairings are also rare in U.S. House elections, typically occurring when redistricting coincides with reapportionment (Ashton, Crespin, and McKee 2022). Still, state and national politics provide some instructive examples. Redistricting alters the composition of incumbents' constituencies—sometimes marginally, but often substantially—thereby introducing electoral uncertainty (Hood and McKee 2013). Challengers strategically exploit this uncertainty, leading to more high-quality challenger entry at the beginning of redistricting cycles than at the end (Hetherington, Larson, and Globetti 2003). Although similar dynamics in local government remain underexplored, Trounstine (2011) finds that the electoral rewards attributable to having served a term in office in the nonpartisan city council context are comparable to those in the U.S. House. Yet there is good reason to expect that the presence of incumbents in newly drawn districts may exert an even stronger dampening effect on challenger entry and minority electoral success in this context. After all, the CVRA was enacted precisely to empower structurally disadvantaged groups who had been unable to compete with entrenched incumbents in the past.

Data

Districting Plans Our sampling frame is the universe of California cities that have switched from at-large to district elections under the CVRA—to date, 167 cities. We obtained city council district shapefiles for over 100 of these cities through online searches and by contacting local government offices.[7] We overlaid these shapefiles on a Census block-level shapefile from 2017[8] to associate each block with a city council district in the adopted map and economic, political, and demographic indicators from the U.S. Census and the California Statewide Database.[9] The resulting standardized and enhanced shapefiles are used as the basis of our districting simulations.[10]

Incumbents For each of the cities for which we obtained a shapefile, we identified the members of the last city council in office before the city's first district election. To identify these incumbents, we searched through city council minutes. To the best of our ability, we located minutes from the meeting in which a city adopted a resolution declaring the city's intention to switch to district elections or enacted an ordinance to switch to district elections and implement a corresponding map. All council members listed in these

7. Of the remaining cities, many have announced their intention to switch to districts but have not adopted a map yet; a handful of others did not respond to our requests or were unable to provide a digital shapefile.

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

9. https://statewidedatabase.org/.

10. See Appendix A.1 for more information on our shapefile construction process.

minutes are considered to be incumbents.[11] To construct our incumbents dataset, we then drew these candidates' records from the California Elections Data Archive (CEDA),[12] usually from the two at-large elections prior to the first district election.

Our approach requires having accurate information about the residential location of each incumbent at precisely the time the city transitioned from at-large to district elections. Given our interest in how a district plan accommodates the residential locations of *all* incumbents, missing data on even one incumbent's location makes it challenging to draw conclusions about the entire plan of a city. We therefore invested considerable effort in compiling complete and accurate data on all incumbents' residential locations as well as their demographic and political characteristics.

We began by searching for incumbents' addresses within voter file records compiled by the commercial data vendor L2, matching the records as closely as possible to the year each city switched to district elections. We also used demographic records collected by de Benedictis-Kessner et al. (2023). Together, these sources provided much of our data on incumbents' residential addresses, race/ethnicity, gender, and party affiliation. If any of these values could not be found within these data sources, we turned to internet searches to fill in the missing information, consulting local media coverage, financial disclosures, and candidates' personal websites and social media profiles.[13] In all, we were able to assemble complete records for the councils of 87 cities.[14] This sample is highly representative of the universe of 167 California cities that have switched to district elections along demographic and economic dimensions.[15]

We used incumbents' addresses to assign them to a Census block and to a district in the adopted plan. To obtain a richer set of incumbent-level characteristics, we associated

11. See Appendix A.2 for more information on our process for identifying incumbents. We provide an example from South San Francisco of the council minutes we collected in Appendix Figure A-1.

12. https://scholars.csus.edu/esploro/outputs/dataset/California-Elections-Data-Archive-CEDA/99257830890201671.

13. See Appendix A.2 for more information on how we collected demographic data for each incumbent candidate serving in the cities included in this study.

14. Please see Appendix Table B-1 for a summary of the data loss over our dataset construction process.

15. Please see Appendix Table B-2 for a comparison.

their residential locations with the block group-level homeownership rate, proportion white, and median income from the Census. Given the homogeneous composition of most block groups in the cities in our sample, these likely serve as good proxies for incumbents' own characteristics, but in any case are informative about the neighborhoods incumbents come from and represent.[16]

City Characteristics We also collected a set of relevant city-level characteristics, including the total population of each city as well as the citizen voting-age population (CVAP) in total and by racial or ethnic group. We computed the median household income as the population-weighted median over the tracts in our shapefiles.

To measure inequality in the distribution of income across census tracts within each city, we computed a population-weighted Gini index of median household income. To measure the degree of residential segregation within each city, we computed the dissimilarity index based on the distribution of white and non-white CVAP across tracts. This statistic is interpretable as the proportion of white residents that would need to swap tracts with non-white residents in order to achieve a uniform distribution across tracts.[17]

Finally, we computed characteristics related to electoral competition and racial representation at the city level. Using our incumbents dataset, we calculated the proportion of the at-large incumbent council that is white. We also computed the degree of *competitiveness* in each city-election as the effective number of candidates (Laakso and Taagepera 1979) divided by the number of seats up for election; we then took the mean of this quantity over the four elections prior to the first district election in each city. We also computed the average *turnout rate* over the same four elections, defined as the number of voters in an election divided by total CVAP. We defined a binary indicator for *off-cycle elections*, equal to 1 if fewer than three of these four elections took place on the same date as a presidential or midterm election (in November of even-numbered years)—an

16. Please see Appendix Table B-3 for a summary of our incumbent characteristics compared to all California voters.

17. Please see Appendix A.3 for formal definitions of these variables.

important predictor of turnout, voter information, and competitiveness at the local level (Anzia 2014).

District Characteristics Our analysis also includes post-districting electoral outcomes at the level of a city council district election within a city. Based on our incumbent data, we coded how many at-large incumbents live within each district. We also computed the number of new candidates who ran within each district (not including the incumbents) in all district elections up to and including 2020.[18] We used a Bayesian prediction procedure (Khanna et al. 2024) to code the probability that each candidate is Latino based on their name and location, then used these probabilities to compute the expected number of Latino candidates as well as Latino winners in every post-districting election. Finally, we identified whether each at-large incumbent ran again in a district election, and whether they won reelection, using CEDA data. Using our city shapefiles, we also computed relevant district-level controls: the proportion of CVAP that is Hispanic and white, the proportion of voters who are Democrats, and median income.

Methodology

Measuring Incumbent Protection The first task at hand is to characterize the degree to which incumbents are protected under a given districting plan. We measure incumbent protection at two levels: the incumbent and the districting plan. At the incumbent level, we define $\textbf{Alone}_{c,i}$, a binary indicator that takes a value of "1" if incumbent i in city c is assigned to their own district and "0" if they are assigned to a district with any number of other incumbents. At the level of a plan, we define $\textbf{Proportion Alone}_{c}$ as the total number of incumbents in city c assigned to their own district, divided by the total number of incumbents sitting on the council when city c switched to district elections. This variable ranges from 0 (all incumbents sharing their district with at least one other

18. After 2020, there was another redistricting cycle and the plan may have shifted.

incumbent) to 1 (every incumbent alone in their own district).

Using an Automated Districting Simulator to Detect Incumbent Protection A central interest of this project is how incumbents exercise *political* influence over the favorability of districting plans for their own electoral fortunes. However, a number of additional factors may also shape and constrain these outcomes. Districting plans must satisfy federally mandated standards of compactness, population parity, and contiguity. These requirements interact with each city's unique physical shape, geography, and spatial distribution of both voters and incumbent councilmembers to limit the universe of possible plans available to local decisionmakers.

To properly assess how favorable the chosen maps were to incumbents *within* each city's own feasible universe, we conduct a set of redistricting simulations using the automated redistricting simulator developed by Fifield et al. (2020) and deployed in the `redist` package for `R` (Kenny et al. 2021). The simulator implements a Sequential Monte Carlo (SMC) algorithm (McCartan et al. 2022), which we apply to the prepared shapefiles from each of the 87 cities in which we were able to identify all incumbents' residential locations. We fix the number of districts in the simulations to be the number of districts in the adopted map. 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.[19]

When using algorithmic districting approaches, it is important to clarify what the distribution of simulated plans represents (Tam Cho and Cain 2024). The algorithm we use generates a "race-neutral baseline": it adheres to binding constraints imposed by federal law but does not account for optional criteria such as the preservation of "communities of interest"—defined by state law as any "population that shares common social or economic interests that should be included within a single supervisorial district for purposes of its effective and fair representation."[20] While some cities prioritized this

19. See Appendix C for more information on the SMC algorithm and our implementation. See Appendix E for simulation diagnostics.

20. CA SB594, https://legiscan.com/CA/text/SB594/id/2434655.

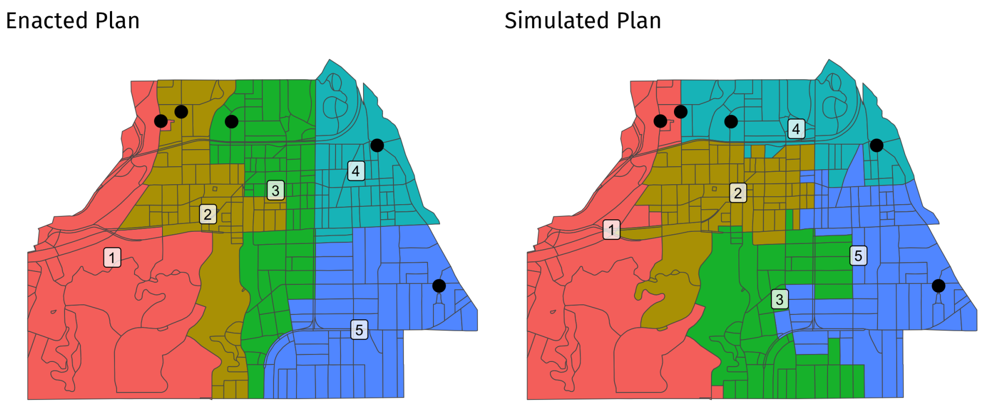

Figure 1: **Avoidance of Incumbent Pairings in South Pasadena, CA**. On the left, district lines adopted by the city council are displayed with shading identifying each district and black dots indicating where each of the 5 incumbents reside. On the right, district lines from a "representative" simulated plan are shown.

goal, we treat this as an endogenous political choice rather than an exogenous constraint on their choice sets. Accordingly, the simulation distribution should be understood as reflecting the broad universe of cities' feasible options, rather than the subset of plans they would most likely adopt given additional, context-specific considerations.

Crucially, the simulator is also blind to incumbents' locations. This allows us to compare the degree of incumbent protection observed in an enacted plan, as measured by $\textbf{Alone}_i$ and $\textbf{Proportion Alone}_{c,i}$, to the overall distribution of the same metrics over the city's feasible alternatives. When the enacted plan lands in a very high percentile of the city's simulation distribution of these quantities, we take this as circumstantial evidence that the map was intentionally constructed with the aim of protecting incumbents.

To illustrate our approach, Figure 1 displays the district lines adopted by South Pasadena, CA on the left; on the right is an example of a simulated plan for the same city. The residential locations of the five incumbents are indicated with black dots. In the enacted plan on the left, all five incumbents are alone in their district (with some apparent care taken to draw one of the incumbents into District 1). Thus, for each incumbent, $\textbf{Alone}_{c,i}$ equals 1 and for the city's enacted plan, $\textbf{Proportion Alone}_c$ equals 1.00.

In the simulated plan shown on the right, only the incumbent in District 5 is assigned to their own district, two incumbents are paired in District 1, two incumbents are paired in District 4, and no incumbents are assigned to Districts 2 or 3. Thus, in this plan, $\textbf{Proportion Alone}_c$ is 0.2 and only for the incumbent in District 5 does $\textbf{Alone}_{c,i}$ take a value of 1. For all other incumbents, $\textbf{Alone}_{c,i}$ equals 0. This plan is a "representative" draw from the distribution of feasible plans for South Pasadena in the sense that across the city's 40,000 simulated plans, the median $\textbf{Proportion Alone}_c$ value is 0.2—meaning only one of the five incumbents is alone in their district.

Explaining Incumbent Protection After estimating the overall prevalence of incumbent protection in our sample of cities, we want to draw some general conclusions about the characteristics that predict which incumbents and which cities are likely to engage in protection. To do so, we estimate the following linear probability model on our incumbent-level dataset:

$$\textbf{Alone}_{c,i} = \beta_0 + \beta_1 \textbf{Simulated Alone Probability}_{c,i} + \mathbf{X}_{c,i}\gamma + \mathbf{Z}_c\zeta + \varepsilon_{c,i} \tag{1}$$

where $\textbf{Alone}_{c,i}$ is our binary indicator of whether city c's enacted plan places incumbent i alone in their district. Within this model, we control for $\textbf{Simulated Alone Probability}_{c,i}$, which is the proportion of city c's simulated plans in which incumbent i is placed alone in a district. Thus, a coefficient from this model may be interpreted as the average effect of a given covariate on the probability that an incumbent ends up alone in their district, controlling for their baseline likelihood of being alone due to all of the structural factors that shape city c's districting process. In other words, it plausibly represents the effect of a covariate on the component of incumbent protection that is driven by *political* discretion, rather than by luck of one's residential location vis-à-vis the city's geography.

Our vector of incumbent-level covariates $\mathbf{X}_{c,i}$ includes binary indicators for whether they are white, Republican, and female, as well as their block group's homeownership rate, proportion white, and logged median income. We include a vector of city-level covariates $\mathbf{Z}_c$, which includes logged population, logged median household income, residential segregation, income inequality, proportion of the incumbent council that is white, competitiveness and turnout in the last four pre-districting elections, and a binary indicator for whether these elections were held off-cycle. We center and scale our measures of competitiveness and turnout to have mean 0, standard deviation 1 for ease of interpretability.

Our model includes two interactions. First, we interact whether the incumbent is white with the proportion of the at-large incumbent council that is white to detect whether white incumbents are better able to secure protection on white-dominated councils. Second, we interact our off-cycle elections indicator with the turnout rate to ensure that we are making apples-to-apples comparisons, since turnout in local elections is systematically much higher when they coincide with elections for national office.

Measuring the Consequences of Incumbent Protection Next, we assess whether incumbents who are alone in their districts are indeed more likely to remain in office than those who are paired with other incumbents. We also estimate the effects of avoiding incumbent pairings on the diversity and openness of councils to new candidates.

Our first model, estimated on the same incumbent-level dataset used previously, is:

$$\mathbf{Y}_{c,i} = \beta_0 + \beta_1 \mathbf{Alone}_{c,i} + \beta_2 \mathbf{Simulated\ Alone\ Probability}_{c,i} + \mathbf{X}_{c,i}\gamma + \mathbf{Z}_c\zeta + \varepsilon_{c,i} \quad (2)$$

Here, $\mathbf{Y}_{c,i}$ represents two binary quantities of interest: whether incumbent i in city c kept their seat on council post-districting, and whether they ran for reelection at the next available opportunity. The key independent variable of interest is whether the incumbent is alone in their district, $\mathbf{Alone}_{c,i}$, and we include as a control the probability the incumbent is alone in their district over the city's simulation distribution. This allows us to interpret the coefficient β_1 as the effect of being placed alone in a district on the incumbent's post-districting outcomes, accounting for their baseline likelihood of being alone in a district due to structural factors; again, this strategy isolates the effect of the *discretionary* or *political* component of incumbent protection. We also include the same vectors of incumbent- and city-level controls from the previous analysis, $\mathbf{X}_{c,i}$ and $\mathbf{Z}_c$.

For our final analysis, we shift the unit of observation to the city–district level in order to observe how the practice of incumbent protection shapes not just the incumbent's own fate, but broader electoral competition and council composition after the districting reform. We have three outcomes of interest: the number of new candidates vying for a district seat (not including the incumbents); the number of Latino candidates vying for a seat; and whether a Latino candidate is elected. We estimate the model:

$$\begin{aligned}\mathbf{Y}_{c,d} &= \beta_0 + \beta_1 \textbf{One Incumbent}_{c,d} + \beta_2 \textbf{Two or More Incumbents}_{c,d} + \\ &\quad \beta_3 \text{Prop. of CVAP, Hispanic}_{c,d} + \beta_4 \text{Prop. of CVAP, White}_{c,d} + \mathbf{Z}_c \zeta + \varepsilon_{c,d}\end{aligned} \tag{3}$$

where $\textbf{One Incumbent}_{c,d}$ and $\textbf{Two or More Incumbents}_{c,d}$ are binary indicators for whether district d in city c has a lone incumbent and two or more incumbents, respectively; the omitted category is districts with zero incumbents. We include two district-level controls—the proportion of CVAP that is white and Hispanic—as well as the vector of city characteristics $\mathbf{Z}_c$ that we have been using throughout.

A Note on Measurement Error Given the manageable number of incumbents in our sample, it was feasible for our research team to manually check every residential location and to validate it across a variety of sources, including media accounts, online records, California voter files, and CEDA data. For all incumbents who ran again post-districting (43% of our sample), we use the district shapefiles to check whether their geolocations indeed fall within the districts in which they subsequently ran according to CEDA. While this exercise uncovered a handful of inconsistencies, which we corrected, it revealed that our process yields accurate addresses in the vast majority of cases, which also gives us a high degree of confidence in our data for the 57% of incumbents who did not run again.

Anecdotally, we know that incumbents may have multiple addresses, including ones they may keep exclusively for the purposes of running in a particular district. Our approach accounts for this strategy: since we ensure that the addresses we record for incumbents who run again line up with the districts in which they actually run, we are likely to record this second address in those cases, and the incumbent is likely to be coded alone in those districts.

If there are inaccuracies in our data, they probably attenuate our estimates. If incumbent protection is based on the true address but we record a false address in a different part of the city, then our $\textbf{Alone}_{c,i}$ and $\textbf{Proportion Alone}_c$ variables are likely to be closer to zero than reality on average, since the false address is likelier than not to fall in a district with another incumbent. Thus, one can interpret our estimates as lower bounds of the extent of incumbent protection in this setting.

Results

Incumbent Protection Is Clearly Detectable and Pervasive

Our first result is that cities overwhelmingly and incontrovertibly protected incumbents by assigning them to their own districts. Comparing the proportion of a city's at-large incumbents who ended up in their own districts in the enacted plan, $\textbf{Proportion Alone}_c$, to the city's simulation distribution of the same metric, we find that *more than half of cities (54%) achieved the maximum degree of incumbent protection that was technically feasible*. In other words, for each of these 47 out of 87 cities, not one of the 40,000 simulated plans could place more incumbents alone in a district than the enacted plan. For an additional 8 cities (9%), the enacted plan fell in the 99th percentile of the simulation distribution, meaning that the observed degree of incumbent protection was only exceeded by a small number of outlying simulated plans. Given that cities were not usually working with the kind of sophisticated software that would help them find these outlying possibilities, it is reasonable to assume that these 8 cities were also maximizing incumbent protection under technical constraints.

Figure 2 shows a histogram of the percentiles in cities' simulation distributions of **Proportion Alone**$_c$ in which the enacted plans fell, with a red dashed line at the median (100th percentile) and a blue dotted line at the mean (89th percentile). As we show in Appendix Figure D-2, there do not seem to be any geographic patterns in incumbent protection. From the Bay Area to southern California, cities avoided incumbent pairings to a far greater extent than would be expected by random chance.

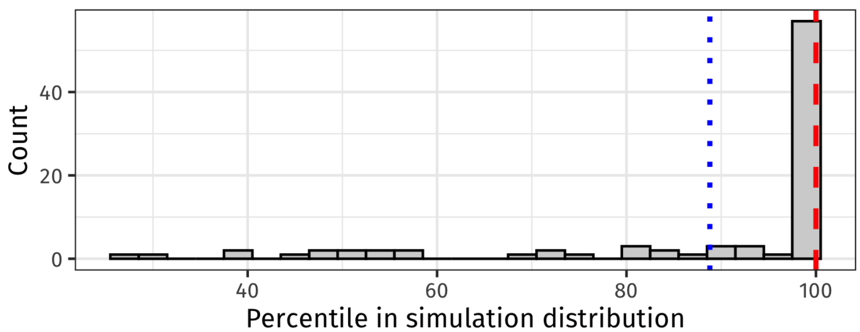

Figure 2: **Location of the Adopted Plan's Proportion Alone**$_c$ **in the City's Simulation Distribution of Proportion Alone**$_c$**.** This histogram shows the distribution of percentiles of **Proportion Alone**$_c$ within cities' own simulation distributions of the same metric, defined as the number of incumbents assigned to their own district divided by the number of incumbents on the council at the time the city switched to district elections. Red dashed line is at the median (100) and blue dotted line is at the mean (89).

Figure 3 displays the simulation distributions of **Proportion Alone**$_c$ in greater detail. Thin black lines indicate the entire range while thick black lines indicate the interquartile range. Black points represent the median in the simulation distribution while red diamonds indicate the percentile of the simulation distribution in which the enacted plan's **Proportion Alone**$_c$ value lands; this percentile is also written at right. It is evident that most cities are not highly constrained by geography when drawing maps to protect incumbents. For 53 of the 87 cities (61%), the simulation distributions span the entire possible range of **Proportion Alone**$_c$ from 0 to 1.

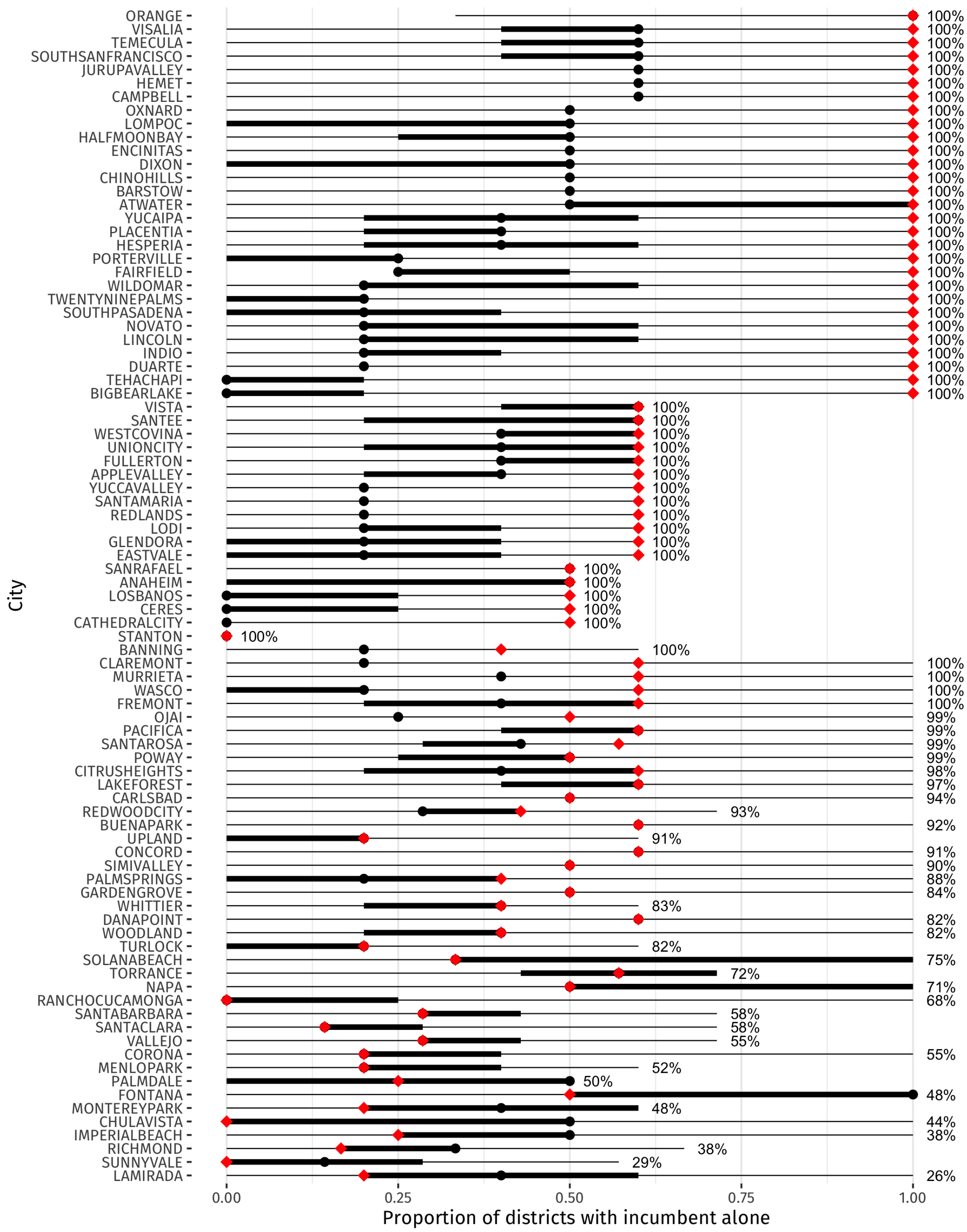

Figure 3: **Simulation Distributions of Proportion Alone**$_c$. Summary statistics of the distributions of **Proportion Alone**$_c$ over simulated plans in every city, defined as the number of incumbents assigned to their own district divided by the number of incumbents on the council at the time the city switched to district elections. Thin black lines span the range of the simulation distribution. Thick black lines span the 25th to 75th percentiles of the simulation distribution—if omitted, this indicates that the range collapses to the median value. Black points represent the median of the simulation distribution. Red diamonds represent the value for the enacted plan. Percentile of the simulation distribution in which the enacted plan falls is shown on the right.

It is no wonder, then, that incumbent protection could be easily achieved while remaining in compliance with not only federally mandated standards such as contiguity and compactness, but the CVRA's target of maximizing the number of districts in which the minority voting bloc is sufficiently large to elect its candidate of choice. In Appendix Figure D-3, we show there is no systematic trade-off between protecting incumbents and creating majority-minority districts: most cities that maximized one metric within their own simulation distributions were simultaneously able to perform very highly on the other. This flexibility is due in large part to the fact that cities were drawing district maps for the first time, with no status quo constraining their choices. It also explains how such a widespread practice could fly under the radar in this relatively high-salience, externally monitored setting: it did not interfere—at least on paper—with the reform's stated goals. However, as our final analysis shows, incumbent protection did, ultimately, act against the aims of the reform in practice: it deterred candidate entry and minority officeholding in precisely the districts that were meant to gain a seat at the table.

When Are Incumbents Protected?

We now turn to the question of which incumbents and which cities are most likely to engage in incumbent protection. Table 1 presents estimates from Equation 1. Unsurprisingly, the main predictor of being alone in a district is the probability of being alone over simulated plans—the structural propensity of the incumbent to end up alone given their residential location and the city's geography. Although this effect is not particularly interesting in its own right, it highlights the importance of controlling for these structural factors to isolate the discretionary component of incumbent protection—especially insofar as they are correlated with other, substantively meaningful characteristics.[21]

Interestingly, incumbent-level covariates have no explanatory value. Rather, certain

21. To underscore the importance of controlling for structural factors that may explain why incumbent candidates avoid pairings, we present estimates from a model that does not include $\textbf{Simulated Alone Probability}_{c,i}$ as a covariate for comparison in Appendix Table D-4.

Table 1: Predictors of Enacted Incumbency Advantage

	(1)
Incumbent: Simulated Alone Probability	0.744***
	(0.066)
Incumbent: White	−0.133
	(0.180)
Incumbent: Republican	0.068
	(0.045)
Incumbent: Female	0.028
	(0.045)
Incumbent's block group: Homeownership Rate	0.092
	(0.117)
Incumbent's block group: Prop. White	0.023
	(0.118)
Incumbent's block group: log(Median Income)	−0.003
	(0.064)
City: log(Population)	−0.216***
	(0.037)
City: log(Median Household Income)	0.099
	(0.108)
City: Residential Segregation	−0.370
	(0.284)
City: Gini coefficient	0.393
	(0.500)
City: Prop. White of Last At-large Council	0.076
	(0.224)
City: Prop. of CVAP, White	0.405+
	(0.209)
City: sd(Pre-Switch Electoral Competition)	0.057*
	(0.025)
City: sd(Pre-Switch Turnout Rate)	−0.181***
	(0.040)
City: Off-cycle city council elections	−0.116
	(0.107)
Incumbent: White x City: Prop. White of Last At-large Council	−0.043
	(0.247)
City: Off-cycle elections x City: sd(Pre-Switch Turnout Rate)	0.108
	(0.075)
(Intercept)	1.479
	(0.910)
N	415
R2	0.363

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

types of *cities* are likelier than others to engage in incumbent protection: smaller, whiter cities with historically lower turnout, though slightly more competitive elections. We interpret these findings as evidence of *motive* and *opportunity*. Less populous municipalities with smaller and less mobilized minority populations were less likely to face homegrown demands for institutional change and more likely to have the reform externally imposed on them by demand letters from lawyers operating statewide campaigns.[22] For them, there was a particularly strong motivation to retain incumbents, who viewed themselves as the internally supported and democratically legitimate candidates. This motivation was strengthened by electoral competition: a one standard-deviation increase in the number of effective candidates per seat is associated with a 0.06-unit increase in the probability of an incumbent being alone in a district ($p < 0.05$). When incumbent candidates expect to face more serious challengers, they have a more pressing interest in securing institutionalized advantages.

While these factors furnish *motive*, low voter turnout presents *opportunity*. A one standard-deviation increase in turnout is associated with a 0.18-unit decrease in the probability of being alone in a district ($p < 0.001$) among cities with on-cycle elections—the vast majority of cities in our sample.[23] When voters are paying attention, incumbent candidates are not as willing or able to use the districting process to their electoral advantage.

22. For instance, the city of Big Bear Lake was spurred to reform by a demand letter from Kevin Shenkman, a lawyer who has become widely known for threatening cities with litigation to get them to switch to district elections. As reported by the San Francisco Chronicle, "The city of Big Bear Lake folded too—angrily. Shenkman sent a demand letter to the tiny ski town of 3,000 voters in 2017. On one page, he switched mid-paragraph to an allegation about 'the Victorville City Council,' a different entity that had received a letter from him two weeks earlier. 'Your letter... appears to be taken from a much overused template,' Big Bear replied. The city enclosed a $30,000 check but noted it was 'making this payment under protest.'"

23. Somewhat unexpectedly, this effect appears to be weaker among cities with off-cycle elections, though the interaction between off-cycle elections and voter turnout is not statistically significant.

Incumbent Protection Deters Candidate Entry and Erodes Diversity on Councils

We have shown that cities consistently designed districting plans to safeguard incumbents, and that doing so was neither technically challenging nor at odds with creating minority-opportunity districts. Nevertheless, creating space to accommodate incumbents had clear downstream electoral consequences: it deterred competition, crowded out political newcomers, and interfered with Latinos' ability to win seats, even in Latino-opportunity districts.

Table 2: Effect of Districting on Incumbents' Reelection Prospects

	Kept Seat	Ran for Reelection
Incumbent: Alone in Adopted Map	0.361***	0.379***
	(0.068)	(0.067)
Incumbent: Simulated Alone Probability	−0.215*	−0.159
	(0.105)	(0.105)
(Intercept)	−0.588	−1.332
	(1.233)	(1.227)
N	325	325
R2	0.162	0.177

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. See Table D-5 for full results.

We first report results from estimating Equation 2 in Table 2: the effect of being drawn into one's own district on an incumbent's subsequent electoral fortunes.[24] In Column 1, we see that being alone is associated with a 36 percentage point increase in the probability of retaining office in the first post-districting election, compared to being paired with at least one other incumbent. The effect on running again is barely higher, at 38 percentage points as shown in Column 2, suggesting that the vast majority of protected incumbents who run again post-districting win their seat. Of course, this relationship is endogenous: incumbents who intend to stay in office are motivated to influence the plan to protect

24. Our sample size is slightly reduced in this analysis compared to Table 1 because we exclude incumbents who get drawn into a district that does not then hold an election by 2020, the last year for which we have council election returns (and the end of the redistricting cycle). For these incumbents, we cannot observe our outcomes of interest within our data.

their seat, while those who intend to retire may willingly pair up with another incumbent; moreover, politically savvy incumbents are better able to both influence the plan and, independently, to win elections. We therefore interpret the strong association between protection and reelection not as a causal effect, but as compelling evidence that our conceptualization and measurement of incumbent protection is working as expected: incumbents who are alone in districts are likely to seek reelection, and to benefit from this institutionalized advantage.

Our final analysis assesses the costs that incumbent protection imposes on the electoral success of newcomers and, ultimately, council diversity. In Table 3, we present results from estimating Equation 3. As shown in Column 1, compared to districts without incumbents, those with one incumbent have, on average, approximately one fewer candidate per seat. They also attract 0.32 fewer Latino candidates (Column 2) and experience a 0.10-point decline in the probability of a Latino winner (Column 3). Districts with two or more incumbents exhibit similar, albeit noisier, effects, likely due to the relatively small number of such districts in the sample.

How counterproductive is this to the CVRA's aim of increasing Latino representation? One might imagine a scenario in which incumbents are elected to represent the whiter and wealthier districts in which they tend to live, while newly drawn Latino-opportunity districts—which are less likely to host incumbents in the first place—provide space for new candidates. This would, in theory, allow the system to balance the preservation of experienced officeholders with the creation of opportunities for greater descriptive representation. Unfortunately, the data do not support this view. In Table 4, we re-estimate Equation 3 on a restricted sample of Latino-opportunity districts, defined as those with at least 30% Latino CVAP. In these districts, the negative effects of incumbent protection are especially pronounced. Districts with one incumbent in them are 19 percentage points less likely than districts with no incumbents to successfully elect a Latino candidate, controlling for the ethnic composition of the district and our full set of city-level covariates

Table 3: Effect of Incumbent Protection on Post-Districting Election Outcomes

	New cands	Lat. cands	Lat. elected
1 Incumbent	−0.969***	−0.318**	−0.097*
	(0.173)	(0.102)	(0.048)
2+ Incumbents	−0.908***	−0.323*	−0.062
	(0.220)	(0.130)	(0.060)
District: Prop. of CVAP, Hispanic	2.340+	2.266**	1.193***
	(1.296)	(0.765)	(0.356)
District: Prop. of CVAP, White	2.842**	0.730	0.246
	(1.088)	(0.643)	(0.299)
District: Prop. of voters, Democrats	−0.100	−0.290	0.147
	(0.769)	(0.454)	(0.211)
District: log(Median household income)	0.064	0.142	0.103
	(0.409)	(0.242)	(0.113)
City: Homeownership Rate	−0.250	−0.218	−0.267
	(0.866)	(0.511)	(0.238)
City: log(Population)	0.364**	0.116	−0.038
	(0.123)	(0.073)	(0.034)
City: log(Median Household Income)	0.007	−0.031	0.083
	(0.493)	(0.291)	(0.136)
City: Residential Segregation	−0.735	−0.259	−0.059
	(0.935)	(0.552)	(0.257)
City: Gini coefficient	−0.619	−0.289	0.425
	(1.680)	(0.992)	(0.462)
City: Prop. White of Last At-large Council	0.419	−0.274	−0.090
	(0.380)	(0.224)	(0.104)
City: Prop. of CVAP, Hispanic	−1.674	0.810	0.150
	(1.531)	(0.904)	(0.421)
City: Prop. of CVAP, White	−3.223*	−0.126	0.246
	(1.281)	(0.757)	(0.352)
City: sd(Pre-Switch Electoral Competition)	0.150*	0.088*	0.026
	(0.072)	(0.043)	(0.020)
City: sd(Pre-Switch Turnout Rate)	0.035	0.057	−0.055
	(0.140)	(0.083)	(0.039)
City: Off-cycle city council elections	0.754*	0.523*	0.046
	(0.382)	(0.226)	(0.105)
City: Off-cycle elections x City: sd(Pre-Switch Turnout Rate)	0.466+	0.140	0.045
	(0.261)	(0.154)	(0.072)
(Intercept)	−2.041	−2.076	−1.775+
	(3.410)	(2.014)	(0.937)
N	359	359	359
R2	0.219	0.315	0.263

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Effect of Incumbent Protection on Post-Districting Election Outcomes, Latino Opportunity Districts

	New cands	Lat. cands	Lat. elected
1 Incumbent	−0.741**	−0.354+	−0.188*
	(0.259)	(0.190)	(0.080)
2+ Incumbents	−0.641+	−0.357	−0.172
	(0.373)	(0.274)	(0.115)
District: Prop. of CVAP, Hispanic	2.176	3.619*	1.351+
	(2.322)	(1.704)	(0.716)
District: Prop. of CVAP, White	2.234	1.271	−0.140
	(2.396)	(1.758)	(0.739)
(Intercept)	−2.766	−2.622	0.128
	(6.761)	(4.961)	(2.084)
N	145	145	145
R2	0.235	0.282	0.280

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(Column 3); they also see a nearly 1-candidate decrease in all candidates and a 0.32-unit decrease in Latino candidates.

Discussion

Leveraging the CVRA, we have shown how those in power can stymie reform and protect the status quo. When switching to district elections, most city councils in our sample chose maps which would avoid incumbent pairings, maximizing the number of councilors with their own district. Incumbent protection was especially prominent in cities with more competitive elections (*motive*), yet lower voter turnout (*opportunity*). This strategy undermined the goal of expanding representation by securing favorable reelection odds for incumbents and deterring challengers. We find that having a lone incumbent in a district discouraged candidate entry and depressed Latino electoral success, even in the opportunity districts specifically drawn to advance Latino representation.

These electoral consequences add nuance to how incumbent protection should be evaluated against competing objectives. In the eyes of the law, drawing maps to separate incumbents may be a legitimate interest so long as it is applied consistently and does not take precedence over other statutory or constitutional mandates. Analyzing a large sample of newly drawn plans, we find that these requirements can easily be met: cities were able to draw maps maximizing both incumbent protection and the creation of majority-minority districts. When taking real-world electoral consequences into account, however, we show that a map that silos a current council member into a Latino opportunity district is a map that protects incumbents at the expense of minority representation.

The ability of incumbents to influence map-making may help explain the conditional success of district-based reforms. Past research emphasizes the structural preconditions for districts to advance representation; our novel analysis of the map-making process highlights the additional importance of internal mobilization. For example, community organizations may be key in elevating the stakes of the moment and driving residents to participate in the districting process. While some cities saw organized groups flood council meetings in the pursuit of representation, others were quiet. Across five public hearings, only four Big Bear Lake residents appeared and commented on the drawing of district maps. In turn, it is not surprising that the council passed a map in the 100th percentile of **Proportion Alone**$_c$. While we find that low turnout elections increase the likelihood of incumbent protection, future research should closely examine the role of community groups and coalitions in the districting process.

Our analysis adds incumbent protection and its electoral consequences to the already substantial list of challenges of using district elections to improve racial representation. Even if the process were managed by a citizen-led, independent districting commission, the reform requires both a large minority population and one that is sufficiently segregated (Abott and Magazinnik 2020)—presenting barriers for collective goods provision and inter-group cooperation. Even when single member districts are successful at changing the composition of the council, they tend to foster local deference, threatening the provision of essential amenities and services with locally concentrated costs such as multifamily housing (Hankinson and Magazinnik 2023). Given these challenges, researchers and reformers should explore proportional representation as a promising alternative that neither relies on the maintenance of residential segregation nor affords incumbents the same degree of control over outcomes.

The nature of reform is to disrupt the status quo. Yet placing control over any reform in the hands of incumbents is likely to limit its effectiveness, ultimately eroding democratic legitimacy. When voters observe the ongoing lack of minority representation on councils or simply see councilors openly prioritize protecting each other's seats, the result is a loss of public trust. Avoiding this fate, and ensuring that electoral reform succeeds in producing broadly representative and accountable government, requires not only new rules, but active public participation, interest group engagement, and alternative models that better insulate outcomes from incumbents' influence.

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Online Appendix for "Reform Drift: How Incumbent Protection Undermines Descriptive Representation in Local Government"

Contents

A Data Construction

A.1 Shapefile 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.[1] 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 87 city council district shapefiles in our possession with this statewide block-level shapefile. This generated 87 block-level shapefiles—one for each city—mapping Census blocks (with covariates) to city council districts. Throughout our analyses, if block group- or district-level measures for any of the following variables are included, they are produced by aggregating block-level values to the corresponding level of geographic abstraction.

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 occupied 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")[2]:

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

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

2. Accessed at: https://statewidedatabase.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.

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 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.

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.

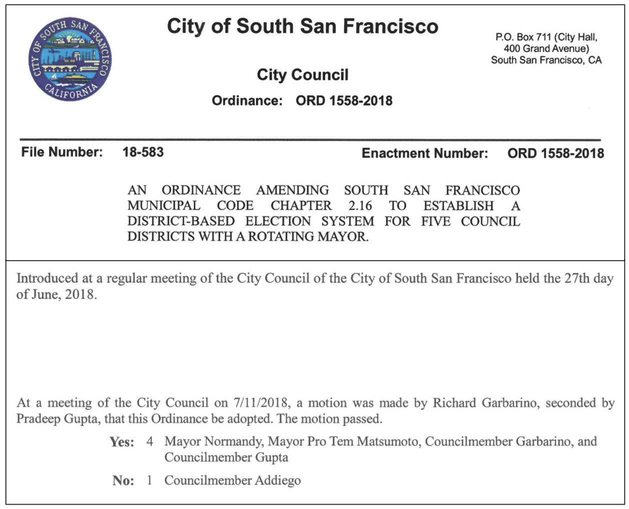
4. *Partisanship.* Here, we wish to compute two block-level variables estimated at the time of a city's first district election: (1) a count of Democratic voters reasonably robust to changes in turnout between elections and (2) the total number of registered voters.

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.[3] To convert SR precinct-level data to block-level estimates, we joined the 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.

3. See documentation here: https://statewidedatabase.org/d10/Creating%20CA%20Official%20Redistricting%20Database.pdf.



City of South San Francisco

P.O. Box 711 (City Hall, 400 Grand Avenue) South San Francisco, CA

City Council

Ordinance: ORD 1558-2018

File Number: 18-583 Enactment Number: ORD 1558-2018

AN ORDINANCE AMENDING SOUTH SAN FRANCISCO MUNICIPAL CODE CHAPTER 2.16 TO ESTABLISH A DISTRICT-BASED ELECTION SYSTEM FOR FIVE COUNCIL DISTRICTS WITH A ROTATING MAYOR.

Introduced at a regular meeting of the City Council of the City of South San Francisco held the 27th day of June, 2018.

At a meeting of the City Council on 7/11/2018, a motion was made by Richard Garbarino, seconded by Pradeep Gupta, that this Ordinance be adopted. The motion passed.

Yes: 4 Mayor Normandy, Mayor Pro Tem Matsumoto, Councilmember Garbarino, and Councilmember Gupta

No: 1 Councilmember Addiego

Figure A-1: **City Council Minutes from South San Francisco, CA**. From the 7/11/2018 meeting of the city council, Mayor Normandy, Mayor Pro Tern Matsumoto, Councilmember Garbarino, and Councilmember Gupta are considered *incumbent* members for the purposes of districting.

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 87 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.

A.2 Incumbent Identification

To identify incumbent city council members, we searched through city council minutes for each of the 87 cities included in this study. Our primary goal was to find minutes from the meeting in which the council either (1) adopted a resolution to declaring the city's intention to switch from at-large to district elections or (2) adopted a city ordinance enacting the switch to district election and implementing the corresponding map. All council members listed in the minutes—as example of which is shown in Appendix Figure A-1 from South San Francisco—are considered to be incumbents for the purposes of this study.

Once incumbent council members are identified, we located their corresponding entries from California voter files that we obtained from L2. From L2, we requested records of all voters residing in each of the cities included in this study as of the year the city switched to district elections. This ensures that any information used from the voter file as much as possible accurately reflects incumbents at the time they were in office and the switch to district elections was implemented.

From L2, we obtain the following values:

- Address: residential address as reported by the voter in the state voter file
- Gender: in this study, coded as "M" (male) or "F" (female)
- Age
- Party: California voters report their political party preference when registering to vote; this information is available from the state voter file
- Race/ethnicity: values are modeled by L2; coded as being "White", "Black", "Hispanic", "Asian", or "Other"

To minimize the amount of missingness in our data, we use the `fastLink` package for `R` (Enamorado, Fifield, and Imai 2017) to perform a fuzzy match to a dataset of local election results compiled by de Benedictis-Kessner et al. (2023). From this data source, we collect additional values of race/ethnicity, partisanship, and gender. As de Benedictis-Kessner et al. (2023) describe, they implement a series of Random Forests to model these values.

If missing values for address, race/ethnicity, partisanship, and gender remained, we relied on a set of internet searches to fill them in. For identifying the race/ethnicity and gender of candidates, we looked for campaign website, social media sites, or news articles that contain pictures of the candidate. To fill in missing addresses, we predominately relied on whitepages.com and truepeoplesearch.com, using a combination of candidate name and city to locate the most appropriate record. Given the manageable number of incumbents in our sample, our research team to manually checked every residential location and validated it across a variety of sources, including media accounts, online records, California voter files, and CEDA data. For all incumbents who ran again post-districting (43% of our sample), we use the district shapefiles to check whether their geolocations indeed fall within the districts in which they subsequently ran according to CEDA. While this exercise uncovered a handful of inconsistencies, which we corrected, it revealed that our process yields accurate addresses in the vast majority of cases, which also gives us a high degree of confidence in our data for the 57% of incumbents who did not run again.

With our incumbent dataset complete, we then used ArcGIS to geocode the address for each incumbent. Using a spatial join, we use the geocoded address of each candidate to determine the Census block in which the incumbent resides.

A.3 City-Level Variables

Gini index. Let $x = (x_1, x_2, \ldots, x_n)$ denote the vector of tract-level median incomes, and let $w = (w_1, w_2, \ldots, w_n)$ denote the corresponding population weights. We first calculated the weighted mean income:

$$\mu = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$$

We then computed all pairwise absolute differences in income $|x_i - x_j|$, weighted by the product of tract populations $w_i w_j$. The Gini index was calculated using the following formula:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j |x_i - x_j|}{2\mu \left(\sum_{i=1}^{n} w_i\right)^2}$$

Dissimilarity index. Let W_i and NW_i denote the white and non-white CVAP in tract i, respectively, and let $W = \sum_i W_i$ and $NW = \sum_i NW_i$ be the total white and non-white CVAP in the city, respectively. The dissimilarity index is given by:

$$D = \frac{1}{2} \sum_{i=1}^{n} \left| \frac{W_i}{W} - \frac{NW_i}{NW} \right|$$

Competitiveness. Our main measure of electoral competitiveness is the *effective number of candidates* divided by the number of seats that are up for election. The effective number of candidates is computed according to the "effective number of parties" formula (Laakso and Taagepera 1979), which is given by:

$$ENC = \frac{1}{\sum_{i=1}^{n} p_i}$$

where i indexes candidates in an election with n total candidates, and p_i is the proportion of all votes cast that went to that candidate.

As an alternative measure, we also compute the difference in vote shares between the winning candidate with the fewest votes and the losing candidate with the most votes, taken over the four elections prior to the first district election. If there are as many candidates as there are seats up for election—that is, if candidates are functionally unopposed—then we take the difference between the vote share of the winning candidate with the fewest votes and zero. All of our results are robust to this definition of competitiveness.

Turnout. The CEDA data includes a unique identifier for each election in a city. However, some at-large elections are for one seat while others are for multiple seats, with voters casting as many votes as there are open seats. We therefore compute the number of voters in an election as the sum of votes cast in that election divided by the number of winning candidates; we divide this value by total CVAP in the city to get the turnout rate. As with competitiveness, we compute the average turnout rate over the last four at-large elections in each city.

B Data Summary

B.1 Cities within Study's Sample

Table B-1: City Data Collection Status

City	Year Switched	Shapefile Collected	Included in Sample
Alhambra	2018	No	No
Anaheim	2015	Yes	Yes
Antioch	2018	No	No
Apple Valley	2019	Yes	Yes
Arcadia	2017	No	No
Arroyo Grande	2019	No	No
Atascadero	2022	No	No
Atwater	2017	Yes	Yes
Bakersfield	2018	No	No
Banning	2016	Yes	Yes
Barstow	2018	Yes	Yes
Bellflower	2016	No	No
Big Bear Lake	2017	Yes	Yes
Brentwood	2019	No	No
Buellton	2018	No	No
Buena Park	2016	Yes	Yes
Camarillo	2019	Yes	No
Campbell	2019	Yes	Yes
Carlsbad	2017	Yes	Yes
Carpinteria	2017	No	No
Carson	2020	No	No
Cathedral City	2017	Yes	Yes
Ceres	2015	Yes	Yes
Chino	2016	No	No
Chino Hills	2016	Yes	Yes
Chula Vista	2012	Yes	Yes
Citrus Heights	2019	Yes	Yes
Claremont	2018	Yes	Yes
Coalinga	2018	No	No
Compton	2012	Yes	No
Concord	2018	Yes	Yes
Corona	2016	Yes	Yes
Costa Mesa	2016	No	No
Dana Point	2018	Yes	Yes
Davis	2019	No	No

Desert Hot Springs	2021	No	No
Diamond Bar	2022	No	No
Dixon	2016	Yes	Yes
Duarte	2017	Yes	Yes
Dublin	2022	No	No
Eastvale	2016	Yes	Yes
El Cajon	2016	No	No
El Monte	2022	No	No
Elk Grove	2019	Yes	No
Encinitas	2017	Yes	Yes
Escondido	2013	Yes	No
Eureka	2016	No	No
Exeter	2017	Yes	No
Fairfield	2019	Yes	Yes
Fontana	2017	Yes	Yes
Fremont	2017	Yes	Yes
Fullerton	2016	Yes	Yes
Garden Grove	2016	Yes	Yes
Glendale	2018	No	No
Glendora	2017	Yes	Yes
Goleta	2017	No	No
Half Moon Bay	2018	Yes	Yes
Hemet	2016	Yes	Yes
Hesperia	2017	Yes	Yes
Highland	2016	No	No
Imperial Beach	2018	Yes	Yes
Indio	2017	Yes	Yes
Jurupa Valley	2017	Yes	Yes
King City	2016	Yes	No
Kingsburg	2018	Yes	No
La Mirada	2016	Yes	Yes
La Palma	2022	No	No
Lake Elsinore	2018	No	No
Lake Forest	2017	Yes	Yes
Lakewood	2021	No	No
Lemoore	2018	Yes	No
Lincoln	2020	Yes	Yes
Livermore	2018	No	No
Lodi	2017	Yes	Yes
Lompoc	2017	Yes	Yes
Los Alamitos	2018	No	No

Los Banos	2014	Yes	Yes
Madera	2010	Yes	No
Malibu	2020	No	No
Manteca	2021	No	No
Marina	2019	Yes	No
Martinez	2017	No	No
Menlo Park	2017	Yes	Yes
Merced	2015	No	No
Millbrae	2022	No	No
Mission Viejo	2022	No	No
Modesto	2008	Yes	No
Monterey Park	2019	Yes	Yes
Moorpark	2018	No	No
Morgan Hill	2017	Yes	No
Murrieta	2017	Yes	Yes
Napa	2020	Yes	Yes
National City	2021	No	No
Novato	2019	Yes	Yes
Oceanside	2017	No	No
Ojai	2018	Yes	Yes
Ontario	2020	No	No
Orange	2018	Yes	Yes
Oroville	2019	No	No
Oxnard	2018	Yes	Yes
Pacifica	2018	Yes	Yes
Palm Desert	2019	No	No
Palm Springs	2018	Yes	Yes
Palmdale	2015	Yes	Yes
Paso Robles	2018	Yes	No
Patterson	2016	Yes	No
Perris	2021	No	No
Petaluma	2021	No	No
Placentia	2016	Yes	Yes
Pleasanton	2021	No	No
Porterville	2018	Yes	Yes
Poway	2017	Yes	Yes
Rancho Cucamonga	2016	Yes	Yes
Redlands	2017	Yes	Yes
Redwood City	2018	Yes	Yes
Richmond	2019	Yes	Yes
Riverbank	2015	No	No

Rohnert Park	2020	Yes	No
Roseville	2019	Yes	No
San Francisco	2000	No	No
San Juan Capistrano	2016	No	No
San Marcos	2016	No	No
San Mateo	2021	No	No
San Rafael	2018	Yes	Yes
San Ramon	2019	No	No
Sanger	2010	Yes	No
Santa Ana	2018	No	No
Santa Barbara	2014	Yes	Yes
Santa Clara	2018	Yes	Yes
Santa Clarita	2016	No	No
Santa Cruz	2020	No	No
Santa Maria	2017	Yes	Yes
Santa Rosa	2017	Yes	Yes
Santee	2018	Yes	Yes
Selma	2019	Yes	No
Simi Valley	2018	Yes	Yes
Solana Beach	2018	Yes	Yes
South Pasadena	2017	Yes	Yes
South San Francisco	2018	Yes	Yes
Stanton	2017	Yes	Yes
Stockton	2016	Yes	No
Sunnyvale	2018	Yes	Yes
Tehachapi	2017	Yes	Yes
Temecula	2017	Yes	Yes
Torrance	2018	Yes	Yes
Tulare	2012	Yes	No
Turlock	2014	Yes	Yes
Tustin	2021	No	No
Twentynine Palms	2018	Yes	Yes
Union City	2019	Yes	Yes
Upland	2016	Yes	Yes
Vacaville	2018	No	No
Vallejo	2018	Yes	Yes
Ventura	2018	Yes	No
Victorville	2021	No	No
Visalia	2014	Yes	Yes
Vista	2017	Yes	Yes
Wasco	2017	Yes	Yes

West Covina	2016	Yes	Yes
Westminster	2019	Yes	No
Whittier	2014	Yes	Yes
Wildomar	2016	Yes	Yes
Windsor	2019	No	No
Woodland	2014	Yes	Yes
Yuba City	2022	No	No
Yucaipa	2016	Yes	Yes
Yucca Valley	2018	Yes	Yes
Total (n=167)	**-**	**109**	**87**

In Table B-1, we list all 167 California cities that have transitioned from at-large to district elections. Column 2 reports the year in which the city council voted—either by ordinance or referendum—to adopt district elections. Column 3 indicates whether a properly formatted shapefile for the city's first district-based election is available and was collected by us. Finally, Column 4 notes whether we were able to identify the full set of incumbent city council members at the time of the transition and map adoption, and thus include the city in our study.

Table B-2: City Summary Statistics

Variable	**All**, N = 482	**Switched**, N = 167	**Included**, N = 87
Population	68,097 (209,042)	87,318 (90,216)	84,596 (61,550)
Prop. Nonwhite	0.367 (0.186)	0.405 (0.164)	0.397 (0.159)
Median Income ($)	85,996 (42,794)	83,922 (28,005)	84,284 (26,992)
Homeownership Rate	0.587 (0.141)	0.590 (0.107)	0.595 (0.097)
Dissimilarity	0.174 (0.087)	0.201 (0.059)	0.201 (0.058)
Gini Coefficient	0.130 (0.056)	0.149 (0.045)	0.152 (0.041)
Unknown	32	0	0

[1] Mean (SD)

In Table B-2, we present mean values for six Census variables across California cities. Column 2 reports means for all 482 cities in the state. Column 3 shows means for cities that have switched from at-large to district election. Column 4 reports means for the subset of cities included in our study. All variables are calculated using the 2020 American Community Survey 5-year estimates.

B.2 Incumbent Candidates

Table B-3: Descriptive Summary of Incumbents in Sample (with Comparision to California Population)

Characteristic	Incumbents, N = 420	CA Population
Race		
White	342 (81%)	41.2%
Black	5 (1.2%)	5.7%
Hispanic	46 (11%)	39.4%
Asian	27 (6.4%)	15.4%
Sex		
Male	294 (70%)	49.7%
Female	126 (30%)	50.3%
Party		
Democrat	176 (42%)	46%
Republican	216 (52%)	24%
Other	23 (5.5%)	30%
Unknown	5	
Homeowner		
Yes	296 (87%)	55.3%
No	45 (13%)	44.7%
Unknown	79	
Mayor	**49 (12%)**	
Terms Served		
1	176 (45%)	
2	114 (29%)	
3	59 (15%)	
4	27 (6.9%)	
5	11 (2.8%)	
6	2 (0.5%)	
Unknown	31	

[1] n (%)

In Table B-3, we present a descriptive summary of incumbent candidates from the cities included in our study. For comparison, we include reference values for the overall population of California. Racial demographics are drawn from the U.S. Census Bureau's 2020 P.L. 94-171 redistricting file, while sex and homeownership data come from the 2020 American Community Survey 5-year estimates. Party registration data are reported by the California Secretary of State.[4]

4. See https://elections.cdn.sos.ca.gov/ror/15day-gen-2020/historical-reg-stats.pdf.

C District Simulations

C.1 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 a Sequential Monte Carlo (SMC) algorithm to obtain a representative sample of plans from the distribution of valid plans as formulated in this way.

C.2 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.[5] Larger values of ρ correspond to a preference for fewer edge cuts and therefore a redistricting plan with more compact districts.

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:

$$\max_{1 \leq l \leq n} \left| \frac{\sum_{i \in V_l} p_i}{\bar{p}} - 1 \right| \tag{4}$$

5. See McCartan et al. (2022), Section 3.3 for further detail on why $\rho = 1$ is recommended.

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). 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. We therefore set the population tolerance parameter as the maximum of 0.01 and the city's own adopted map's largest deviation,[6] 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.

C.3 Plan Measurements

We primarily rely on two quantities of interest to measure the degree of incumbent protection observed in city council districting: $\textbf{Alone}_{c,i}$ and $\textbf{Proportion Alone}_c$. $\textbf{Alone}_{c,i}$ is binary indicator that takes a value of "1" if incumbent i in city c is assigned to their own district; "0" if candidate i is assigned to district with any number of other incumbents. $\textbf{Proportion Alone}_c$ is defined as the total number of incumbents in city c assigned to their own district, divided by the total number of incumbents sitting on the council when city c switched to district elections. We create values for these measures based on the district maps actually adopted by each city as well each simulated plan we create.

To construct values for these measures, we take the geocoded address for each incumbent and determine the Census block they reside in, using `st_within()` from the `sf` package for `R` to perform the necessary spatial join. For analyses using the enacted map only, values of $\textbf{Alone}_{c,i}$ and $\textbf{Proportion Alone}_c$ are determined solely on the district number candidates are determined to live in. In the 40,000 simulated plans we produce for each city, we again calculate values of $\textbf{Alone}_{c,i}$ and $\textbf{Proportion Alone}_c$. In each simulation draw, we determine the city council district to which the Census block of the incumbent is assigned. We are able to determine this through the following procedure using a built-in function from the `redist` package (Kenny et al. 2021):

1. Use the `get_plans_matrix()` function to extract the matrix of district assignments from a redistricting simulation for each Census block. Rows of this matrix represent each Census block within the city's limits. Columns represent district assignments for a single draw.

2. Join the resulting matrix to a data frame of incumbent information by the `GEOID10` value representing the Census block in which the incumbent resides.

3. For each column (representing a single simulation draw), apply the following function to identify whether any two or more candidates are assigned to the same city council district in that draw:

6. 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.

```
check_duplicates <- function(col) {
    as.integer(duplicated(col) |
        duplicated(col, fromLast = TRUE))
}
```

4. For the enacted plan, $\mathbf{Alone}_{c,i} = 1$ if the `check_duplicates()` function returns a "1" based on the first column of the plans matrix. For the simulated plans, $\mathbf{Alone}_{c,i} = 1$ if the `check_duplicates()` function returns a "1" based on the corresponding column for that simulation draw in the plans matrix.

5. For the enacted plan (column 1) and all simulated plans, $\mathbf{Proportion\ Alone}_c$ is calculated as the proportion of incumbents assigned to their own district, divided by the total number of incumbents.

D Additional Tables and Figures

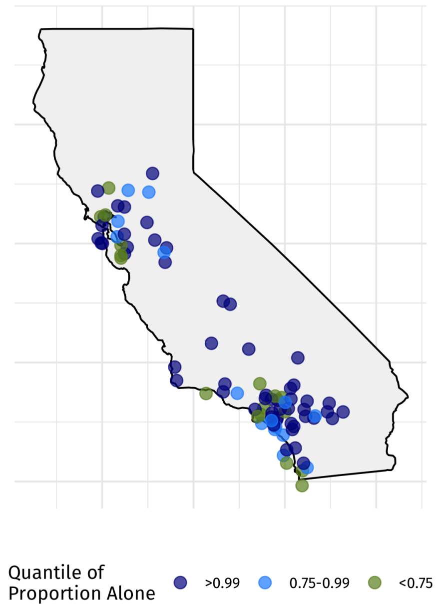


Figure D-2: **Spatial Distribution of Cities in Our Sample**. The locations of our 87 cities, with points slightly jittered for visibility. Points are colored according to the quantile of the city's simulation distribution of **Proportion Alone**$_c$ in which the enacted plan falls.

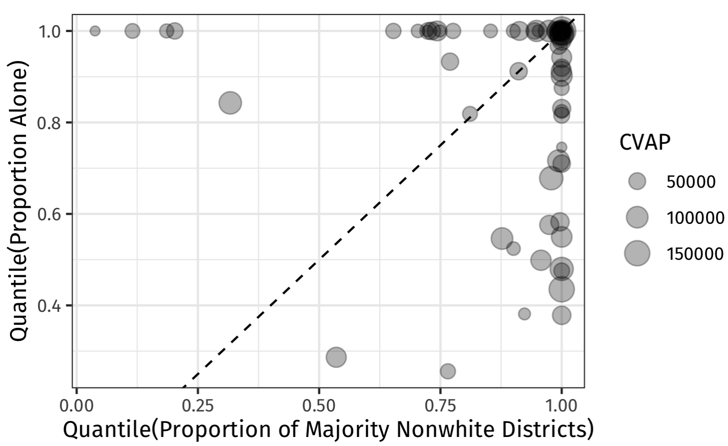


Figure D-3: **Minority Representation versus Incumbent Protection**. Each point represents the quantile of the simulation distribution of **Proportion Alone**$_c$ (y-axis) versus the quantile of the simulation distribution of the proportion of city council districts where a majority of the citizen voting age population is nonwhite (x-axis). The size of points correspond to the city's citizen voting age population (CVAP).

Table D-4: Predictors of Enacted Incumbency Advantage — Robustness with/without Simulate Alone Probability

	With	Without
Incumbent: Simulated Alone Probability	0.744***	
	(0.066)	
Incumbent: White	−0.133	−0.234
	(0.180)	(0.206)
Incumbent: Republican	0.068	0.086+
	(0.045)	(0.052)
Incumbent: Female	0.028	0.034
	(0.045)	(0.052)
Incumbent's block group: Homeownership Rate	0.092	0.110
	(0.117)	(0.135)
Incumbent's block group: Prop. White	0.023	−0.321*
	(0.118)	(0.131)
Incumbent's block group: log(Median Income)	−0.003	−0.060
	(0.064)	(0.073)
City: log(Population)	−0.216***	−0.176***
	(0.037)	(0.042)
City: log(Median Household Income)	0.099	0.249*
	(0.108)	(0.124)
City: Residential Segregation	−0.370	−0.478
	(0.284)	(0.326)
City: Gini coefficient	0.393	0.590
	(0.500)	(0.574)
City: Prop. White of Last At-large Council	0.076	−0.002
	(0.224)	(0.257)
City: Prop. of CVAP, White	0.405+	0.858***
	(0.209)	(0.236)
City: sd(Pre-Switch Electoral Competition)	0.057*	0.071*
	(0.025)	(0.029)
City: sd(Pre-Switch Turnout Rate)	−0.181***	−0.202***
	(0.040)	(0.046)
City: Off-cycle city council elections	−0.116	−0.141
	(0.107)	(0.123)
Incumbent: White x City: Prop. White of Last At-large Council	−0.043	0.135
	(0.247)	(0.283)
City: Off-cycle elections x City: sd(Pre-Switch Turnout Rate)	0.108	0.100
	(0.075)	(0.086)
(Intercept)	1.479	0.240
	(0.910)	(1.038)
N	415	415
R2	0.363	0.157

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table D-5: Effect of Districting on Incumbents' Reelection Prospects

	Kept Seat	Ran for Reelection
Incumbent: Alone in Adopted Map	0.361***	0.379***
	(0.068)	(0.067)
Incumbent: Simulated Alone Probability	−0.215*	−0.159
	(0.105)	(0.105)
Incumbent: White	−0.082	0.174
	(0.264)	(0.263)
Incumbent: Republican	0.122*	0.146*
	(0.061)	(0.061)
Incumbent: Female	0.019	0.004
	(0.061)	(0.061)
Incumbent's block group: Homeownership Rate	−0.084	−0.085
	(0.156)	(0.155)
Incumbent's block group: Prop. White	−0.179	−0.120
	(0.155)	(0.154)
Incumbent's block group: log(Median Income)	0.032	−0.037
	(0.083)	(0.083)
City: log(Population)	0.038	−0.017
	(0.051)	(0.050)
City: log(Median Household Income)	0.025	0.196
	(0.144)	(0.143)
City: Residential Segregation	0.156	0.467
	(0.367)	(0.365)
City: Gini coefficient	−0.799	−0.382
	(0.667)	(0.663)
City: Prop. White of Last At-large Council	−0.394	−0.083
	(0.326)	(0.324)
City: Prop. of CVAP, White	0.653*	0.576*
	(0.274)	(0.273)
City: sd(Pre-Switch Electoral Competition)	0.013	0.027
	(0.032)	(0.031)
City: sd(Pre-Switch Turnout Rate)	0.025	−0.033
	(0.056)	(0.056)
City: Off-cycle city council elections	0.015	0.005
	(0.160)	(0.160)
Incumbent: White x City: Prop. White of Last At-large Council	0.070	−0.301
	(0.360)	(0.358)
City: Off-cycle elections x City: sd(Pre-Switch Turnout Rate)	0.000	0.020
	(0.111)	(0.111)
(Intercept)	−0.588	−1.332
	(1.233)	(1.227)
N	325	325
R2	0.162	0.177

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D-6: Effect of Incumbency Protection on Post-Districting Election Outcomes, Latino Opportunity Districts

	New cands	Lat. cands	Lat. elected
1 Incumbent	−0.741**	−0.354+	−0.188*
	(0.259)	(0.190)	(0.080)
2+ Incumbents	−0.641+	−0.357	−0.172
	(0.373)	(0.274)	(0.115)
District: Prop. of CVAP, Hispanic	2.176	3.619*	1.351+
	(2.322)	(1.704)	(0.716)
District: Prop. of CVAP, White	2.234	1.271	−0.140
	(2.396)	(1.758)	(0.739)
District: Prop. of voters, Democrats	2.016	−0.188	−0.548
	(2.156)	(1.582)	(0.665)
District: log(Median household income)	0.449	0.086	−0.111
	(0.729)	(0.535)	(0.225)
City: Homeownership Rate	0.269	0.665	−0.185
	(1.656)	(1.215)	(0.511)
City: log(Population)	0.386	0.362*	0.032
	(0.238)	(0.175)	(0.073)
City: log(Median Household Income)	−0.510	−0.300	0.055
	(0.818)	(0.601)	(0.252)
City: Residential Segregation	−3.065+	−1.623	−0.131
	(1.578)	(1.158)	(0.486)
City: Gini coefficient	−0.682	−1.182	−0.357
	(3.199)	(2.348)	(0.986)
City: Prop. White of Last At-large Council	0.567	−0.222	−0.095
	(0.653)	(0.479)	(0.201)
City: Prop. of CVAP, Hispanic	−0.924	0.820	0.739
	(2.310)	(1.695)	(0.712)
City: Prop. of CVAP, White	−1.617	0.497	0.891
	(2.419)	(1.775)	(0.746)
City: sd(Pre-Switch Electoral Competition)	0.173+	0.137+	0.049
	(0.101)	(0.074)	(0.031)
City: sd(Pre-Switch Turnout Rate)	0.068	0.109	−0.057
	(0.314)	(0.230)	(0.097)
City: Off-cycle city council elections	0.382	1.017+	0.507*
	(0.820)	(0.602)	(0.253)
City: Off-cycle elections x City: sd(Pre-Switch Turnout Rate)	0.215	0.266	0.243+
	(0.431)	(0.316)	(0.133)
(Intercept)	−2.766	−2.622	0.128
	(6.761)	(4.961)	(2.084)
N	145	145	145
R2	0.235	0.282	0.280

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E Simulation Diagnostics

We run the SMC 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.

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 E-7, and refer the reader to Fifield et al. (2020) as well as the `redist` package documentation[7] for more details.

- *Effective Sample Size* (Column 4)
  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 5)
  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.

- *Standard Deviation of the Log Weights* (Column 6)
  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.

- *Maximum Unique Plans* (Column 7)
  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.

- *Estimated k parameter* (Column 8)
  How many spanning tree edges were considered for cutting at each split.

7. https://alarm-redist.org/redist/reference/summary.redist_plans.html

Table E-7: `redist` Plan Diagnostics

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
ANAHEIM	1	Split 1	9100 (91%)	0.34	0.75	6375	66
	1	Split 2	9008 (90%)	0.33	0.62	6267	36
	1	Split 3	8994 (90%)	0.47	0.58	6123	19
	1	Split 4	8843 (88%)	0.54	0.65	6029	11
	1	Split 5	8681 (87%)	0.26	0.71	5373	7
	1	Resample	4536 (45%)	NA	0.68	7093	NA
	2	Split 1	9084 (91%)	0.42	0.76	6310	53
	2	Split 2	9027 (90%)	0.35	0.61	6299	33
	2	Split 3	8947 (89%)	0.48	0.58	6140	18
	2	Split 4	8901 (89%)	0.56	0.64	6046	10
	2	Split 5	8738 (87%)	0.26	0.69	5359	7
	2	Resample	5255 (53%)	NA	0.68	7151	NA
	3	Split 1	9103 (91%)	0.34	0.75	6307	67
	3	Split 2	9005 (90%)	0.30	0.62	6280	40
	3	Split 3	9029 (90%)	0.43	0.58	6117	21
	3	Split 4	8955 (90%)	0.45	0.63	6000	15
	3	Split 5	8826 (88%)	0.22	0.69	5451	9
	3	Resample	5579 (56%)	NA	0.66	7227	NA
	4	Split 1	9105 (91%)	0.38	0.75	6312	59
	4	Split 2	9030 (90%)	0.37	0.61	6242	31
	4	Split 3	8937 (89%)	0.51	0.59	6142	17
	4	Split 4	8917 (89%)	0.40	0.64	5951	18
	4	Split 5	8651 (87%)	0.21	0.72	5443	10
	4	Resample	4907 (49%)	NA	0.69	7048	NA
APPLEVALLEY	1	Split 1	9850 (98%)	0.19	0.24	6250	44
	1	Split 2	9630 (96%)	0.32	0.40	6300	23
	1	Split 3	9398 (94%)	0.45	0.48	6202	13
	1	Split 4	9135 (91%)	0.18	0.53	5716	11
	1	Resample	6031 (60%)	NA	0.53	7712	NA
	2	Split 1	9848 (98%)	0.14	0.25	6267	60
	2	Split 2	9644 (96%)	0.23	0.40	6297	31
	2	Split 3	9375 (94%)	0.36	0.48	6215	17
	2	Split 4	9081 (91%)	0.19	0.53	5722	10
	2	Resample	5235 (52%)	NA	0.53	7685	NA
	3	Split 1	9854 (99%)	0.21	0.24	6286	39
	3	Split 2	9643 (96%)	0.33	0.40	6248	22
	3	Split 3	9298 (93%)	0.42	0.49	6161	14
	3	Split 4	9037 (90%)	0.23	0.54	5662	8
	3	Resample	4986 (50%)	NA	0.54	7664	NA
	4	Split 1	9853 (99%)	0.22	0.24	6306	38
	4	Split 2	9657 (97%)	0.36	0.40	6294	20
	4	Split 3	9255 (93%)	0.27	0.49	6249	23
	4	Split 4	9037 (90%)	0.15	0.55	5701	13
	4	Resample	5208 (52%)	NA	0.54	7601	NA
ATWATER	1	Split 1	8597 (86%)	0.18	0.64	6389	16
	1	Split 2	8678 (87%)	0.30	0.63	5906	9
	1	Split 3	8321 (83%)	0.10	0.70	5562	10
	1	Resample	3548 (35%)	NA	0.70	6707	NA
	2	Split 1	8565 (86%)	0.15	0.65	6325	20
	2	Split 2	8750 (87%)	0.24	0.62	5828	11
	2	Split 3	8459 (85%)	0.14	0.69	5560	7
	2	Resample	4355 (44%)	NA	0.69	6795	NA
	3	Split 1	8572 (86%)	0.19	0.64	6307	15
	3	Split 2	8769 (88%)	0.29	0.62	5869	9
	3	Split 3	8335 (83%)	0.16	0.71	5549	6
	3	Resample	3919 (39%)	NA	0.70	6668	NA
	4	Split 1	8599 (86%)	0.16	0.64	6354	19
	4	Split 2	8746 (87%)	0.27	0.62	5856	10
	4	Split 3	8426 (84%)	0.16	0.69	5583	6
	4	Resample	4156 (42%)	NA	0.68	6794	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
BANNING	1	Split 1	8886 (89%)	0.14	0.67	6273	17
	1	Split 2	8803 (88%)	0.22	0.70	6038	10
	1	Split 3	8742 (87%)	0.29	0.65	5984	6
	1	Split 4	8297 (83%)	0.14	0.77	5402	4
	1	Resample	3865 (39%)	*NA*	0.74	6662	*NA*
	2	Split 1	8915 (89%)	0.13	0.66	6274	18
	2	Split 2	8755 (88%)	0.22	0.70	6023	10
	2	Split 3	8778 (88%)	0.29	0.65	5947	6
	2	Split 4	8241 (82%)	0.14	0.78	5295	4
	2	Resample	3705 (37%)	*NA*	0.75	6621	*NA*
	3	Split 1	8911 (89%)	0.17	0.67	6358	14
	3	Split 2	8767 (88%)	0.26	0.70	5978	8
	3	Split 3	8653 (87%)	0.29	0.67	5970	6
	3	Split 4	8266 (83%)	0.14	0.79	5389	4
	3	Resample	3989 (40%)	*NA*	0.76	6618	*NA*
	4	Split 1	8900 (89%)	0.17	0.67	6259	14
	4	Split 2	8768 (88%)	0.27	0.69	6009	8
	4	Split 3	8745 (87%)	0.33	0.65	6037	5
	4	Split 4	8299 (83%)	0.14	0.77	5367	4
	4	Resample	3534 (35%)	*NA*	0.74	6658	*NA*
BARSTOW	1	Split 1	9769 (98%)	0.11	0.30	6340	18
	1	Split 2	8751 (88%)	0.14	0.73	6055	18
	1	Split 3	8776 (88%)	0.08	0.65	5550	10
	1	Resample	5180 (52%)	*NA*	0.64	7189	*NA*
	2	Split 1	9764 (98%)	0.07	0.30	6304	27
	2	Split 2	8728 (87%)	0.17	0.74	5983	15
	2	Split 3	8765 (88%)	0.08	0.66	5581	9
	2	Resample	5039 (50%)	*NA*	0.64	7214	*NA*
	3	Split 1	9760 (98%)	0.12	0.31	6278	16
	3	Split 2	8761 (88%)	0.27	0.73	6063	9
	3	Split 3	8823 (88%)	0.11	0.64	5577	7
	3	Resample	5287 (53%)	*NA*	0.63	7278	*NA*
	4	Split 1	9769 (98%)	0.12	0.30	6319	16
	4	Split 2	8651 (87%)	0.27	0.76	5999	9
	4	Split 3	8852 (89%)	0.11	0.63	5543	7
	4	Resample	5311 (53%)	*NA*	0.62	7301	*NA*
BIGBEARLAKE	1	Split 1	9423 (94%)	0.19	0.49	6294	21
	1	Split 2	8405 (84%)	0.30	0.71	6240	12
	1	Split 3	8677 (87%)	0.43	0.63	6027	7
	1	Split 4	8381 (84%)	0.21	0.69	5496	5
	1	Resample	3753 (38%)	*NA*	0.70	6971	*NA*
	2	Split 1	9432 (94%)	0.24	0.49	6314	17
	2	Split 2	8386 (84%)	0.36	0.71	6153	10
	2	Split 3	8648 (86%)	0.39	0.63	6067	8
	2	Split 4	8396 (84%)	0.21	0.69	5476	5
	2	Resample	3769 (38%)	*NA*	0.70	7000	*NA*
	3	Split 1	9430 (94%)	0.22	0.49	6280	18
	3	Split 2	8536 (85%)	0.36	0.69	6131	10
	3	Split 3	8554 (86%)	0.44	0.64	6048	7
	3	Split 4	8439 (84%)	0.18	0.69	5505	6
	3	Resample	3987 (40%)	*NA*	0.70	7033	*NA*
	4	Split 1	9423 (94%)	0.24	0.49	6315	17
	4	Split 2	8337 (83%)	0.36	0.72	6187	10
	4	Split 3	8546 (85%)	0.32	0.65	6027	10
	4	Split 4	8387 (84%)	0.18	0.70	5458	6
	4	Resample	3766 (38%)	*NA*	0.71	6994	*NA*

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
BUENAPARK	1	Split 1	9694 (97%)	0.28	0.37	6367	43
	1	Split 2	9451 (95%)	0.48	0.43	6238	23
	1	Split 3	9273 (93%)	0.62	0.51	6158	14
	1	Split 4	9186 (92%)	0.32	0.59	5613	8
	1	Resample	6727 (67%)	NA	0.55	7801	NA
	2	Split 1	9688 (97%)	0.26	0.37	6323	45
	2	Split 2	9420 (94%)	0.40	0.43	6218	28
	2	Split 3	9216 (92%)	0.51	0.52	6182	19
	2	Split 4	9058 (91%)	0.27	0.62	5567	11
	2	Resample	5897 (59%)	NA	0.58	7632	NA
	3	Split 1	9693 (97%)	0.32	0.37	6315	37
	3	Split 2	9428 (94%)	0.53	0.43	6275	20
	3	Split 3	9230 (92%)	0.48	0.51	6252	21
	3	Split 4	9042 (90%)	0.25	0.63	5663	12
	3	Resample	6065 (61%)	NA	0.58	7532	NA
	4	Split 1	9689 (97%)	0.35	0.37	6350	33
	4	Split 2	9439 (94%)	0.47	0.44	6249	24
	4	Split 3	9293 (93%)	0.65	0.51	6176	13
	4	Split 4	9171 (92%)	0.28	0.59	5624	10
	4	Resample	6528 (65%)	NA	0.55	7704	NA
CAMPBELL	1	Split 1	9705 (97%)	0.43	0.35	6302	50
	1	Split 2	9537 (95%)	0.67	0.41	6259	26
	1	Split 3	9374 (94%)	0.69	0.50	6167	20
	1	Split 4	9075 (91%)	0.35	0.59	5590	13
	1	Resample	5943 (59%)	NA	0.55	7636	NA
	2	Split 1	9699 (97%)	0.40	0.35	6296	54
	2	Split 2	9519 (95%)	0.55	0.41	6218	33
	2	Split 3	9332 (93%)	0.73	0.50	6163	18
	2	Split 4	8999 (90%)	0.40	0.61	5553	10
	2	Resample	5531 (55%)	NA	0.56	7594	NA
	3	Split 1	9698 (97%)	0.39	0.35	6331	55
	3	Split 2	9525 (95%)	0.62	0.41	6243	29
	3	Split 3	9280 (93%)	0.51	0.52	6086	30
	3	Split 4	9001 (90%)	0.30	0.61	5563	16
	3	Resample	5824 (58%)	NA	0.57	7502	NA
	4	Split 1	9697 (97%)	0.38	0.35	6358	56
	4	Split 2	9525 (95%)	0.62	0.41	6258	29
	4	Split 3	9313 (93%)	0.60	0.51	6170	24
	4	Split 4	9048 (90%)	0.33	0.59	5577	14
	4	Resample	5675 (57%)	NA	0.55	7575	NA
CARLSBAD	1	Split 1	9660 (97%)	0.20	0.36	6386	30
	1	Split 2	9386 (94%)	0.31	0.44	6264	17
	1	Split 3	9129 (91%)	0.17	0.58	5733	10
	1	Resample	6034 (60%)	NA	0.54	7672	NA
	2	Split 1	9665 (97%)	0.20	0.36	6331	31
	2	Split 2	9387 (94%)	0.30	0.44	6243	18
	2	Split 3	9089 (91%)	0.12	0.59	5728	14
	2	Resample	5877 (59%)	NA	0.55	7587	NA
	3	Split 1	9661 (97%)	0.26	0.36	6373	24
	3	Split 2	9365 (94%)	0.39	0.45	6225	13
	3	Split 3	9025 (90%)	0.19	0.59	5711	9
	3	Resample	5405 (54%)	NA	0.56	7553	NA
	4	Split 1	9661 (97%)	0.24	0.37	6346	26
	4	Split 2	9315 (93%)	0.36	0.45	6252	14
	4	Split 3	9120 (91%)	0.20	0.58	5742	8
	4	Resample	6189 (62%)	NA	0.54	7669	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
CATHEDRALCITY	1	Split 1	9626 (96%)	0.19	0.39	6321	19
	1	Split 2	9279 (93%)	0.29	0.45	6276	11
	1	Split 3	9107 (91%)	0.28	0.53	6145	10
	1	Split 4	8825 (88%)	0.15	0.60	5633	6
	1	Resample	4514 (45%)	NA	0.59	7372	NA
	2	Split 1	9611 (96%)	0.24	0.39	6321	15
	2	Split 2	9333 (93%)	0.34	0.44	6224	9
	2	Split 3	9223 (92%)	0.33	0.51	6155	8
	2	Split 4	8891 (89%)	0.17	0.59	5690	5
	2	Resample	4420 (44%)	NA	0.56	7509	NA
	3	Split 1	9618 (96%)	0.20	0.39	6316	18
	3	Split 2	9377 (94%)	0.31	0.44	6216	10
	3	Split 3	9236 (92%)	0.42	0.51	6169	6
	3	Split 4	8965 (90%)	0.11	0.57	5729	8
	3	Resample	4807 (48%)	NA	0.55	7575	NA
	4	Split 1	9608 (96%)	0.19	0.40	6305	19
	4	Split 2	9296 (93%)	0.29	0.46	6269	11
	4	Split 3	9084 (91%)	0.37	0.54	6137	7
	4	Split 4	8805 (88%)	0.17	0.61	5681	5
	4	Resample	4178 (42%)	NA	0.58	7396	NA
CERES	1	Split 1	9520 (95%)	0.12	0.46	6366	9
	1	Split 2	9520 (95%)	0.12	0.39	6223	8
	1	Split 3	9351 (94%)	0.06	0.48	5881	5
	1	Resample	6474 (65%)	NA	0.48	8021	NA
	2	Split 1	9520 (95%)	0.11	0.45	6339	10
	2	Split 2	9534 (95%)	0.16	0.40	6187	6
	2	Split 3	9373 (94%)	0.08	0.49	5844	4
	2	Resample	7415 (74%)	NA	0.48	8004	NA
	3	Split 1	9526 (95%)	0.10	0.45	6337	11
	3	Split 2	9539 (95%)	0.14	0.39	6256	7
	3	Split 3	9360 (94%)	0.06	0.48	5794	5
	3	Resample	7076 (71%)	NA	0.48	8016	NA
	4	Split 1	9515 (95%)	0.11	0.46	6263	10
	4	Split 2	9561 (96%)	0.16	0.39	6235	6
	4	Split 3	9385 (94%)	0.04	0.48	5833	8
	4	Resample	7436 (74%)	NA	0.48	8002	NA
CHINOHILLS	1	Split 1	9641 (96%)	0.14	0.38	6311	17
	1	Split 2	9366 (94%)	0.21	0.45	6248	10
	1	Split 3	9122 (91%)	0.29	0.55	6053	6
	1	Split 4	8968 (90%)	0.13	0.61	5388	4
	1	Resample	5709 (57%)	NA	0.59	7453	NA
	2	Split 1	9651 (97%)	0.18	0.38	6302	14
	2	Split 2	9364 (94%)	0.26	0.45	6216	8
	2	Split 3	9147 (91%)	0.25	0.54	6073	7
	2	Split 4	9050 (91%)	0.13	0.59	5441	4
	2	Resample	5925 (59%)	NA	0.57	7598	NA
	3	Split 1	9623 (96%)	0.16	0.39	6355	15
	3	Split 2	9360 (94%)	0.23	0.45	6224	9
	3	Split 3	9109 (91%)	0.32	0.56	6093	5
	3	Split 4	9006 (90%)	0.09	0.60	5448	6
	3	Resample	5835 (58%)	NA	0.58	7519	NA
	4	Split 1	9636 (96%)	0.14	0.38	6311	18
	4	Split 2	9375 (94%)	0.21	0.45	6184	10
	4	Split 3	9110 (91%)	0.28	0.54	6059	6
	4	Split 4	8983 (90%)	0.10	0.60	5470	6
	4	Resample	5683 (57%)	NA	0.59	7510	NA
CHULAVISTA	1	Split 1	9633 (96%)	0.27	0.37	6275	50
	1	Split 2	9154 (92%)	0.44	0.52	6221	26
	1	Split 3	8956 (90%)	0.27	0.57	5815	14
	1	Resample	5043 (50%)	NA	0.56	7546	NA
	2	Split 1	9648 (96%)	0.27	0.36	6372	48
	2	Split 2	9124 (91%)	0.46	0.53	6240	25
	2	Split 3	8968 (90%)	0.26	0.58	5752	14
	2	Resample	4935 (49%)	NA	0.56	7505	NA
	3	Split 1	9642 (96%)	0.31	0.36	6315	42
	3	Split 2	9120 (91%)	0.51	0.52	6187	22
	3	Split 3	8962 (90%)	0.29	0.57	5740	12
	3	Resample	5005 (50%)	NA	0.57	7490	NA
	4	Split 1	9639 (96%)	0.29	0.36	6320	46
	4	Split 2	9134 (91%)	0.48	0.52	6188	24
	4	Split 3	8866 (89%)	0.28	0.58	5778	13
	4	Resample	4249 (42%)	NA	0.57	7428	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
CITRUSHEIGHTS	1	Split 1	9689 (97%)	0.25	0.35	6340	34
	1	Split 2	9468 (95%)	0.41	0.44	6266	18
	1	Split 3	9143 (91%)	0.56	0.55	6160	10
	1	Split 4	8956 (90%)	0.30	0.59	5638	6
	1	Resample	5360 (54%)	NA	0.58	7506	NA
	2	Split 1	9687 (97%)	0.25	0.35	6320	34
	2	Split 2	9516 (95%)	0.41	0.43	6231	18
	2	Split 3	9173 (92%)	0.50	0.55	6180	12
	2	Split 4	8980 (90%)	0.27	0.58	5612	7
	2	Resample	5317 (53%)	NA	0.57	7527	NA
	3	Split 1	9685 (97%)	0.28	0.35	6330	30
	3	Split 2	9489 (95%)	0.46	0.43	6251	16
	3	Split 3	9156 (92%)	0.50	0.54	6156	12
	3	Split 4	9018 (90%)	0.27	0.58	5614	7
	3	Resample	5657 (57%)	NA	0.57	7478	NA
	4	Split 1	9683 (97%)	0.32	0.35	6314	27
	4	Split 2	9500 (95%)	0.48	0.43	6222	15
	4	Split 3	9083 (91%)	0.64	0.56	6193	8
	4	Split 4	8915 (89%)	0.33	0.59	5626	5
	4	Resample	4956 (50%)	NA	0.58	7471	NA
CLAREMONT	1	Split 1	9318 (93%)	0.31	0.50	6289	31
	1	Split 2	9056 (91%)	0.49	0.54	6150	17
	1	Split 3	8917 (89%)	0.58	0.58	6164	11
	1	Split 4	8758 (88%)	0.16	0.65	5505	15
	1	Resample	5046 (50%)	NA	0.64	7194	NA
	2	Split 1	9329 (93%)	0.33	0.50	6367	30
	2	Split 2	9067 (91%)	0.51	0.54	6223	16
	2	Split 3	8918 (89%)	0.58	0.58	6127	11
	2	Split 4	8770 (88%)	0.20	0.64	5554	12
	2	Resample	4993 (50%)	NA	0.63	7217	NA
	3	Split 1	9318 (93%)	0.31	0.50	6327	31
	3	Split 2	9019 (90%)	0.49	0.55	6173	17
	3	Split 3	8894 (89%)	0.58	0.59	6098	11
	3	Split 4	8785 (88%)	0.29	0.64	5534	7
	3	Resample	4906 (49%)	NA	0.63	7215	NA
	4	Split 1	9327 (93%)	0.21	0.50	6341	47
	4	Split 2	9037 (90%)	0.34	0.54	6108	25
	4	Split 3	8841 (88%)	0.50	0.59	6048	14
	4	Split 4	8816 (88%)	0.27	0.64	5576	8
	4	Resample	5053 (51%)	NA	0.63	7293	NA
CONCORD	1	Split 1	9708 (97%)	0.22	0.34	6320	69
	1	Split 2	9433 (94%)	0.38	0.43	6200	36
	1	Split 3	9240 (92%)	0.49	0.51	6144	24
	1	Split 4	9064 (91%)	0.18	0.57	5652	22
	1	Resample	5932 (59%)	NA	0.56	7605	NA
	2	Split 1	9704 (97%)	0.31	0.34	6330	48
	2	Split 2	9482 (95%)	0.51	0.42	6219	25
	2	Split 3	9337 (93%)	0.56	0.49	6199	20
	2	Split 4	9151 (92%)	0.30	0.55	5620	11
	2	Resample	6162 (62%)	NA	0.54	7692	NA
	3	Split 1	9707 (97%)	0.23	0.34	6362	65
	3	Split 2	9436 (94%)	0.40	0.42	6190	34
	3	Split 3	9292 (93%)	0.45	0.50	6139	27
	3	Split 4	9162 (92%)	0.24	0.55	5612	15
	3	Resample	6260 (63%)	NA	0.53	7715	NA
	4	Split 1	9715 (97%)	0.27	0.33	6327	55
	4	Split 2	9433 (94%)	0.46	0.42	6231	29
	4	Split 3	9317 (93%)	0.63	0.49	6210	16
	4	Split 4	9111 (91%)	0.30	0.55	5590	11
	4	Resample	5875 (59%)	NA	0.54	7681	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
CORONA	1	Split 1	9684 (97%)	0.14	0.35	6365	12
	1	Split 2	9518 (95%)	0.21	0.41	6225	7
	1	Split 3	9315 (93%)	0.27	0.50	6154	5
	1	Split 4	9085 (91%)	0.10	0.57	5525	4
	1	Resample	5911 (59%)	*NA*	0.56	7602	*NA*
	2	Split 1	9682 (97%)	0.14	0.35	6360	12
	2	Split 2	9536 (95%)	0.21	0.41	6247	7
	2	Split 3	9306 (93%)	0.18	0.50	6108	8
	2	Split 4	9029 (90%)	0.09	0.57	5445	5
	2	Resample	5024 (50%)	*NA*	0.55	7567	*NA*
	3	Split 1	9676 (97%)	0.12	0.36	6289	14
	3	Split 2	9515 (95%)	0.19	0.41	6202	8
	3	Split 3	9238 (92%)	0.26	0.51	6166	5
	3	Split 4	8924 (89%)	0.13	0.60	5423	3
	3	Resample	5034 (50%)	*NA*	0.58	7461	*NA*
	4	Split 1	9680 (97%)	0.17	0.36	6321	10
	4	Split 2	9523 (95%)	0.24	0.41	6157	6
	4	Split 3	9207 (92%)	0.26	0.52	6120	5
	4	Split 4	9019 (90%)	0.12	0.58	5450	3
	4	Resample	5617 (56%)	*NA*	0.57	7525	*NA*
DANAPOINT	1	Split 1	9143 (91%)	0.32	0.64	6339	36
	1	Split 2	9095 (91%)	0.34	0.53	6279	20
	1	Split 3	9057 (91%)	0.44	0.56	6116	11
	1	Split 4	8740 (87%)	0.20	0.65	5487	8
	1	Resample	4851 (49%)	*NA*	0.64	7180	*NA*
	2	Split 1	9124 (91%)	0.35	0.64	6299	33
	2	Split 2	9105 (91%)	0.36	0.52	6219	18
	2	Split 3	8928 (89%)	0.47	0.59	6086	10
	2	Split 4	8741 (87%)	0.25	0.66	5538	6
	2	Resample	4661 (47%)	*NA*	0.64	7159	*NA*
	3	Split 1	9149 (91%)	0.34	0.63	6292	34
	3	Split 2	9126 (91%)	0.36	0.51	6229	18
	3	Split 3	8932 (89%)	0.34	0.58	6055	15
	3	Split 4	8652 (87%)	0.18	0.67	5447	9
	3	Resample	4580 (46%)	*NA*	0.66	7078	*NA*
	4	Split 1	9135 (91%)	0.31	0.64	6305	37
	4	Split 2	9092 (91%)	0.30	0.52	6214	22
	4	Split 3	8955 (90%)	0.41	0.59	6093	12
	4	Split 4	8662 (87%)	0.22	0.67	5520	7
	4	Resample	4422 (44%)	*NA*	0.65	7099	*NA*
DIXON	1	Split 1	9682 (97%)	0.11	0.35	6310	10
	1	Split 2	9498 (95%)	0.17	0.37	6218	6
	1	Split 3	9096 (91%)	0.08	0.51	5840	4
	1	Resample	5314 (53%)	*NA*	0.50	7791	*NA*
	2	Split 1	9680 (97%)	0.12	0.35	6373	9
	2	Split 2	9493 (95%)	0.17	0.38	6236	6
	2	Split 3	9070 (91%)	0.09	0.52	5782	4
	2	Resample	5237 (52%)	*NA*	0.51	7758	*NA*
	3	Split 1	9679 (97%)	0.10	0.35	6273	11
	3	Split 2	9508 (95%)	0.17	0.39	6248	6
	3	Split 3	9151 (92%)	0.08	0.50	5786	4
	3	Resample	5486 (55%)	*NA*	0.49	7836	*NA*
	4	Split 1	9679 (97%)	0.12	0.35	6274	9
	4	Split 2	9540 (95%)	0.17	0.37	6196	6
	4	Split 3	9157 (92%)	0.08	0.50	5864	4
	4	Resample	5373 (54%)	*NA*	0.49	7848	*NA*

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
DUARTE	1	Split 1	9437 (94%)	0.49	0.49	6320	37
	1	Split 2	9246 (92%)	0.76	0.55	6178	21
	1	Split 3	9058 (91%)	0.90	0.60	6180	13
	1	Split 4	8933 (89%)	0.90	0.66	6129	10
	1	Split 5	8819 (88%)	0.83	0.69	5904	6
	1	Split 6	8519 (85%)	0.25	0.77	5109	11
	1	Resample	4226 (42%)	NA	0.72	7004	NA
	2	Split 1	9434 (94%)	0.40	0.49	6392	45
	2	Split 2	9247 (92%)	0.69	0.55	6151	24
	2	Split 3	8987 (90%)	0.70	0.62	6062	21
	2	Split 4	8926 (89%)	0.65	0.67	6025	19
	2	Split 5	8733 (87%)	0.56	0.70	5760	15
	2	Split 6	8569 (86%)	0.30	0.78	5088	10
	2	Resample	4639 (46%)	NA	0.72	6950	NA
	3	Split 1	9430 (94%)	0.43	0.49	6301	42
	3	Split 2	9219 (92%)	0.74	0.55	6187	22
	3	Split 3	9043 (90%)	0.89	0.61	6153	14
	3	Split 4	8951 (90%)	0.92	0.65	6081	9
	3	Split 5	8790 (88%)	0.58	0.69	5791	14
	3	Split 6	8479 (85%)	0.31	0.80	5156	9
	3	Resample	4262 (43%)	NA	0.74	6920	NA
	4	Split 1	9429 (94%)	0.38	0.49	6302	47
	4	Split 2	9245 (92%)	0.67	0.55	6162	25
	4	Split 3	9058 (91%)	0.63	0.61	6126	24
	4	Split 4	8878 (89%)	0.65	0.67	6085	19
	4	Split 5	8756 (88%)	0.66	0.71	5790	11
	4	Split 6	8571 (86%)	0.33	0.79	5075	8
	4	Resample	4753 (48%)	NA	0.73	6980	NA
EASTVALE	1	Split 1	9701 (97%)	0.19	0.34	6335	12
	1	Split 2	9419 (94%)	0.31	0.44	6125	7
	1	Split 3	9084 (91%)	0.38	0.54	6117	5
	1	Split 4	8798 (88%)	0.19	0.61	5461	3
	1	Resample	4776 (48%)	NA	0.60	7287	NA
	2	Split 1	9700 (97%)	0.19	0.34	6326	12
	2	Split 2	9469 (95%)	0.31	0.43	6195	7
	2	Split 3	9131 (91%)	0.33	0.53	6150	6
	2	Split 4	8813 (88%)	0.16	0.61	5538	4
	2	Resample	4889 (49%)	NA	0.61	7253	NA
	3	Split 1	9702 (97%)	0.18	0.34	6306	13
	3	Split 2	9457 (95%)	0.31	0.44	6266	7
	3	Split 3	9090 (91%)	0.38	0.53	6099	5
	3	Split 4	8166 (82%)	0.09	0.67	5547	7
	3	Resample	2415 (24%)	NA	0.67	6706	NA
	4	Split 1	9696 (97%)	0.16	0.34	6377	14
	4	Split 2	9482 (95%)	0.27	0.43	6099	8
	4	Split 3	9064 (91%)	0.38	0.54	6102	5
	4	Split 4	8721 (87%)	0.19	0.63	5459	3
	4	Resample	4584 (46%)	NA	0.62	7201	NA
ENCINITAS	1	Split 1	9700 (97%)	0.15	0.34	6359	35
	1	Split 2	9444 (94%)	0.24	0.42	6209	19
	1	Split 3	9160 (92%)	0.13	0.53	5841	11
	1	Resample	6230 (62%)	NA	0.53	7760	NA
	2	Split 1	9701 (97%)	0.24	0.34	6305	22
	2	Split 2	9433 (94%)	0.36	0.43	6211	12
	2	Split 3	9102 (91%)	0.18	0.54	5749	8
	2	Resample	5706 (57%)	NA	0.54	7656	NA
	3	Split 1	9700 (97%)	0.19	0.34	6309	27
	3	Split 2	9400 (94%)	0.30	0.44	6243	15
	3	Split 3	9014 (90%)	0.16	0.56	5765	9
	3	Resample	5389 (54%)	NA	0.55	7582	NA
	4	Split 1	9705 (97%)	0.17	0.34	6281	31
	4	Split 2	9415 (94%)	0.26	0.43	6226	17
	4	Split 3	9213 (92%)	0.16	0.52	5681	9
	4	Resample	6517 (65%)	NA	0.51	7774	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
FAIRFIELD	1	Split 1	9245 (92%)	0.20	0.56	6348	18
	1	Split 2	9319 (93%)	0.30	0.46	6231	10
	1	Split 3	9260 (93%)	0.39	0.53	6156	6
	1	Split 4	8932 (89%)	0.43	0.63	6109	4
	1	Split 5	8788 (88%)	0.18	0.66	5415	3
	1	Resample	5046 (50%)	NA	0.65	7215	NA
	2	Split 1	9242 (92%)	0.15	0.56	6303	25
	2	Split 2	9288 (93%)	0.22	0.47	6206	14
	2	Split 3	9199 (92%)	0.32	0.55	6189	8
	2	Split 4	8938 (89%)	0.34	0.64	6057	6
	2	Split 5	8706 (87%)	0.15	0.67	5409	4
	2	Resample	4655 (47%)	NA	0.65	7156	NA
	3	Split 1	9229 (92%)	0.18	0.57	6338	20
	3	Split 2	9290 (93%)	0.25	0.47	6156	12
	3	Split 3	9242 (92%)	0.22	0.53	6177	12
	3	Split 4	8927 (89%)	0.30	0.63	6077	7
	3	Split 5	8728 (87%)	0.11	0.65	5453	6
	3	Resample	4651 (47%)	NA	0.65	7197	NA
	4	Split 1	9237 (92%)	0.19	0.56	6263	19
	4	Split 2	9317 (93%)	0.28	0.47	6149	11
	4	Split 3	9255 (93%)	0.35	0.53	6189	7
	4	Split 4	8891 (89%)	0.38	0.63	6075	5
	4	Split 5	8815 (88%)	0.18	0.65	5400	3
	4	Resample	5233 (52%)	NA	0.64	7263	NA
FONTANA	1	Split 1	9633 (96%)	0.21	0.39	6359	22
	1	Split 2	9450 (94%)	0.34	0.42	6173	12
	1	Split 3	9121 (91%)	0.19	0.50	5914	7
	1	Resample	5125 (51%)	NA	0.53	7782	NA
	2	Split 1	9642 (96%)	0.18	0.38	6317	25
	2	Split 2	9476 (95%)	0.30	0.42	6261	14
	2	Split 3	9084 (91%)	0.17	0.51	5857	8
	2	Resample	5111 (51%)	NA	0.54	7713	NA
	3	Split 1	9638 (96%)	0.18	0.39	6331	25
	3	Split 2	9359 (94%)	0.30	0.43	6240	14
	3	Split 3	9019 (90%)	0.17	0.52	5862	8
	3	Resample	4491 (45%)	NA	0.55	7683	NA
	4	Split 1	9635 (96%)	0.17	0.39	6369	26
	4	Split 2	9393 (94%)	0.30	0.42	6295	14
	4	Split 3	9139 (91%)	0.17	0.52	5897	8
	4	Resample	6162 (62%)	NA	0.55	7706	NA
FREMONT	1	Split 1	9166 (92%)	0.35	0.52	6300	60
	1	Split 2	9080 (91%)	0.55	0.53	6133	31
	1	Split 3	8942 (89%)	0.48	0.58	6093	33
	1	Split 4	8830 (88%)	0.62	0.62	5992	18
	1	Split 5	8707 (87%)	0.33	0.66	5429	10
	1	Resample	4956 (50%)	NA	0.65	7138	NA
	2	Split 1	9187 (92%)	0.28	0.51	6368	75
	2	Split 2	9050 (91%)	0.47	0.54	6179	39
	2	Split 3	8905 (89%)	0.53	0.59	6137	29
	2	Split 4	8843 (88%)	0.66	0.61	6077	16
	2	Split 5	8691 (87%)	0.30	0.65	5466	12
	2	Resample	4537 (45%)	NA	0.64	7162	NA
	3	Split 1	9165 (92%)	0.35	0.51	6319	59
	3	Split 2	9031 (90%)	0.36	0.54	6130	52
	3	Split 3	8927 (89%)	0.56	0.59	6093	27
	3	Split 4	8921 (89%)	0.65	0.61	6056	16
	3	Split 5	8783 (88%)	0.34	0.64	5393	9
	3	Resample	5096 (51%)	NA	0.63	7247	NA
	4	Split 1	9171 (92%)	0.32	0.51	6370	65
	4	Split 2	9006 (90%)	0.52	0.55	6139	34
	4	Split 3	9034 (90%)	0.70	0.57	6149	18
	4	Split 4	8956 (90%)	0.76	0.59	6116	10
	4	Split 5	8738 (87%)	0.37	0.63	5463	7
	4	Resample	4383 (44%)	NA	0.63	7232	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
FULLERTON	1	Split 1	9663 (97%)	0.26	0.37	6343	59
	1	Split 2	9419 (94%)	0.43	0.43	6339	31
	1	Split 3	9181 (92%)	0.61	0.52	6185	17
	1	Split 4	8857 (89%)	0.26	0.60	5612	14
	1	Resample	4390 (44%)	NA	0.58	7433	NA
	2	Split 1	9659 (97%)	0.34	0.37	6322	44
	2	Split 2	9437 (94%)	0.55	0.43	6258	23
	2	Split 3	9206 (92%)	0.69	0.52	6169	13
	2	Split 4	8990 (90%)	0.36	0.59	5564	8
	2	Resample	5072 (51%)	NA	0.57	7521	NA
	3	Split 1	9662 (97%)	0.28	0.37	6345	54
	3	Split 2	9445 (94%)	0.47	0.43	6266	28
	3	Split 3	9168 (92%)	0.65	0.53	6164	15
	3	Split 4	9001 (90%)	0.22	0.59	5719	17
	3	Resample	5597 (56%)	NA	0.57	7541	NA
	4	Split 1	9659 (97%)	0.35	0.37	6297	43
	4	Split 2	9453 (95%)	0.35	0.43	6267	39
	4	Split 3	9181 (92%)	0.56	0.52	6179	20
	4	Split 4	8995 (90%)	0.17	0.58	5650	24
	4	Resample	5457 (55%)	NA	0.56	7578	NA
GARDENGROVE	1	Split 1	9620 (96%)	0.33	0.40	6349	49
	1	Split 2	9437 (94%)	0.50	0.47	6314	27
	1	Split 3	9226 (92%)	0.69	0.53	6157	15
	1	Split 4	8989 (90%)	0.58	0.60	6085	16
	1	Split 5	8720 (87%)	0.32	0.67	5518	9
	1	Resample	4810 (48%)	NA	0.64	7166	NA
	2	Split 1	9622 (96%)	0.31	0.40	6333	50
	2	Split 2	9444 (94%)	0.49	0.47	6210	28
	2	Split 3	9268 (93%)	0.54	0.52	6162	22
	2	Split 4	9023 (90%)	0.68	0.60	6116	12
	2	Split 5	8825 (88%)	0.35	0.66	5415	7
	2	Resample	5343 (53%)	NA	0.63	7244	NA
	3	Split 1	9622 (96%)	0.38	0.40	6379	41
	3	Split 2	9443 (94%)	0.59	0.47	6273	22
	3	Split 3	9197 (92%)	0.75	0.54	6220	12
	3	Split 4	9079 (91%)	0.80	0.59	6090	7
	3	Split 5	8867 (89%)	0.40	0.64	5484	5
	3	Resample	5355 (54%)	NA	0.62	7313	NA
	4	Split 1	9612 (96%)	0.37	0.40	6319	42
	4	Split 2	9428 (94%)	0.59	0.47	6227	22
	4	Split 3	9236 (92%)	0.72	0.53	6222	14
	4	Split 4	9000 (90%)	0.65	0.60	6131	13
	4	Split 5	8730 (87%)	0.26	0.68	5559	12
	4	Resample	4775 (48%)	NA	0.65	7141	NA
GLENDORA	1	Split 1	9670 (97%)	0.17	0.35	6323	24
	1	Split 2	9525 (95%)	0.27	0.40	6160	13
	1	Split 3	9393 (94%)	0.39	0.49	6090	7
	1	Split 4	9103 (91%)	0.21	0.56	5551	4
	1	Resample	5561 (56%)	NA	0.54	7729	NA
	2	Split 1	9671 (97%)	0.22	0.35	6328	18
	2	Split 2	9558 (96%)	0.34	0.40	6165	10
	2	Split 3	9388 (94%)	0.43	0.49	6172	6
	2	Split 4	9004 (90%)	0.20	0.57	5659	4
	2	Resample	4989 (50%)	NA	0.55	7605	NA
	3	Split 1	9683 (97%)	0.15	0.35	6322	27
	3	Split 2	9517 (95%)	0.24	0.41	6212	15
	3	Split 3	9387 (94%)	0.33	0.49	6126	9
	3	Split 4	9134 (91%)	0.12	0.55	5566	8
	3	Resample	5919 (59%)	NA	0.53	7718	NA
	4	Split 1	9666 (97%)	0.22	0.35	6319	18
	4	Split 2	9543 (95%)	0.34	0.39	6236	10
	4	Split 3	9402 (94%)	0.38	0.48	6114	7
	4	Split 4	9178 (92%)	0.18	0.55	5587	5
	4	Resample	6342 (63%)	NA	0.53	7749	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
HALFMOONBAY	1	Split 1	9693 (97%)	0.22	0.35	6335	20
	1	Split 2	9231 (92%)	0.38	0.47	6175	11
	1	Split 3	8893 (89%)	0.19	0.58	5604	7
	1	Resample	4886 (49%)	NA	0.57	7430	NA
	2	Split 1	9693 (97%)	0.25	0.35	6326	18
	2	Split 2	9196 (92%)	0.42	0.47	6099	10
	2	Split 3	8991 (90%)	0.22	0.56	5606	6
	2	Resample	5323 (53%)	NA	0.55	7553	NA
	3	Split 1	9686 (97%)	0.24	0.35	6345	19
	3	Split 2	9276 (93%)	0.39	0.46	6090	11
	3	Split 3	9083 (91%)	0.17	0.54	5533	8
	3	Resample	5789 (58%)	NA	0.54	7649	NA
	4	Split 1	9689 (97%)	0.19	0.35	6260	24
	4	Split 2	9248 (92%)	0.33	0.47	6109	13
	4	Split 3	9062 (91%)	0.19	0.55	5596	7
	4	Resample	5773 (58%)	NA	0.54	7642	NA
HEMET	1	Split 1	9661 (97%)	0.13	0.38	6317	19
	1	Split 2	9451 (95%)	0.19	0.43	6214	11
	1	Split 3	9188 (92%)	0.25	0.54	6124	7
	1	Split 4	8930 (89%)	0.11	0.60	5487	5
	1	Resample	5266 (53%)	NA	0.59	7448	NA
	2	Split 1	9662 (97%)	0.16	0.38	6313	16
	2	Split 2	9460 (95%)	0.19	0.43	6276	11
	2	Split 3	9191 (92%)	0.25	0.54	6051	7
	2	Split 4	8818 (88%)	0.13	0.63	5472	4
	2	Resample	4987 (50%)	NA	0.61	7281	NA
	3	Split 1	9665 (97%)	0.15	0.38	6374	17
	3	Split 2	9454 (95%)	0.21	0.42	6252	10
	3	Split 3	9181 (92%)	0.29	0.54	6089	6
	3	Split 4	8935 (89%)	0.13	0.61	5534	4
	3	Resample	5617 (56%)	NA	0.60	7411	NA
	4	Split 1	9661 (97%)	0.16	0.38	6328	16
	4	Split 2	9440 (94%)	0.23	0.43	6281	9
	4	Split 3	9171 (92%)	0.29	0.54	6138	6
	4	Split 4	8905 (89%)	0.13	0.61	5563	4
	4	Resample	5297 (53%)	NA	0.60	7363	NA
HESPERIA	1	Split 1	9798 (98%)	0.19	0.28	6352	14
	1	Split 2	9545 (95%)	0.28	0.42	6250	8
	1	Split 3	9261 (93%)	0.25	0.51	6175	8
	1	Split 4	9160 (92%)	0.08	0.54	5640	8
	1	Resample	6327 (63%)	NA	0.53	7772	NA
	2	Split 1	9802 (98%)	0.17	0.28	6286	16
	2	Split 2	9538 (95%)	0.26	0.42	6248	9
	2	Split 3	9223 (92%)	0.17	0.50	6196	12
	2	Split 4	8919 (89%)	0.09	0.57	5689	7
	2	Resample	4450 (45%)	NA	0.56	7523	NA
	3	Split 1	9798 (98%)	0.12	0.28	6309	23
	3	Split 2	9546 (95%)	0.18	0.43	6265	13
	3	Split 3	9248 (92%)	0.25	0.50	6178	8
	3	Split 4	8986 (90%)	0.07	0.57	5721	9
	3	Resample	5404 (54%)	NA	0.56	7548	NA
	4	Split 1	9800 (98%)	0.13	0.28	6313	21
	4	Split 2	9591 (96%)	0.21	0.41	6236	11
	4	Split 3	9294 (93%)	0.28	0.50	6195	7
	4	Split 4	8967 (90%)	0.14	0.57	5605	4
	4	Resample	4888 (49%)	NA	0.56	7559	NA
IMPERIALBEACH	1	Split 1	9811 (98%)	0.23	0.27	6265	24
	1	Split 2	9594 (96%)	0.36	0.39	6231	13
	1	Split 3	9281 (93%)	0.19	0.48	5748	8
	1	Resample	6537 (65%)	NA	0.48	7968	NA
	2	Split 1	9807 (98%)	0.22	0.28	6273	25
	2	Split 2	9582 (96%)	0.34	0.39	6219	14
	2	Split 3	9307 (93%)	0.19	0.47	5724	8
	2	Resample	6656 (67%)	NA	0.47	7987	NA
	3	Split 1	9815 (98%)	0.24	0.27	6308	22
	3	Split 2	9595 (96%)	0.39	0.38	6232	12
	3	Split 3	9295 (93%)	0.21	0.47	5769	7
	3	Resample	6369 (64%)	NA	0.47	7998	NA
	4	Split 1	9809 (98%)	0.20	0.28	6350	27
	4	Split 2	9592 (96%)	0.32	0.39	6255	15
	4	Split 3	9259 (93%)	0.17	0.48	5740	9
	4	Resample	6326 (63%)	NA	0.48	7946	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
INDIO	1	Split 1	9651 (97%)	0.17	0.37	6359	21
	1	Split 2	9408 (94%)	0.18	0.45	6186	19
	1	Split 3	9169 (92%)	0.26	0.55	6131	11
	1	Split 4	8870 (89%)	0.09	0.65	5576	11
	1	Resample	5212 (52%)	NA	0.61	7342	NA
	2	Split 1	9641 (96%)	0.13	0.38	6372	27
	2	Split 2	9356 (94%)	0.22	0.45	6199	15
	2	Split 3	9126 (91%)	0.34	0.56	6122	8
	2	Split 4	8976 (90%)	0.16	0.63	5575	5
	2	Resample	5945 (59%)	NA	0.60	7450	NA
	3	Split 1	9639 (96%)	0.15	0.38	6341	25
	3	Split 2	9384 (94%)	0.14	0.45	6218	24
	3	Split 3	9192 (92%)	0.23	0.55	6119	13
	3	Split 4	8901 (89%)	0.13	0.64	5623	7
	3	Resample	5412 (54%)	NA	0.60	7360	NA
	4	Split 1	9637 (96%)	0.14	0.38	6270	26
	4	Split 2	9426 (94%)	0.24	0.44	6141	14
	4	Split 3	9163 (92%)	0.20	0.55	6123	15
	4	Split 4	8835 (88%)	0.11	0.64	5543	8
	4	Resample	4953 (50%)	NA	0.61	7318	NA
JURUPAVALLEY	1	Split 1	9794 (98%)	0.24	0.29	6356	21
	1	Split 2	9525 (95%)	0.36	0.41	6240	12
	1	Split 3	9189 (92%)	0.36	0.51	6194	10
	1	Split 4	9186 (92%)	0.14	0.54	5765	9
	1	Resample	6328 (63%)	NA	0.52	7748	NA
	2	Split 1	9799 (98%)	0.22	0.29	6346	23
	2	Split 2	9497 (95%)	0.34	0.41	6263	13
	2	Split 3	9204 (92%)	0.43	0.51	6237	8
	2	Split 4	9033 (90%)	0.12	0.56	5725	10
	2	Resample	5537 (55%)	NA	0.55	7587	NA
	3	Split 1	9797 (98%)	0.18	0.29	6305	28
	3	Split 2	9515 (95%)	0.30	0.42	6280	15
	3	Split 3	9178 (92%)	0.27	0.51	6153	14
	3	Split 4	8976 (90%)	0.09	0.57	5746	14
	3	Resample	5175 (52%)	NA	0.56	7542	NA
	4	Split 1	9800 (98%)	0.20	0.28	6351	26
	4	Split 2	9532 (95%)	0.32	0.41	6266	14
	4	Split 3	9238 (92%)	0.33	0.50	6188	11
	4	Split 4	9088 (91%)	0.19	0.56	5675	6
	4	Resample	5930 (59%)	NA	0.54	7666	NA
LAKEFOREST	1	Split 1	9660 (97%)	0.18	0.37	6343	30
	1	Split 2	9463 (95%)	0.27	0.42	6261	17
	1	Split 3	9209 (92%)	0.36	0.52	6203	10
	1	Split 4	9024 (90%)	0.18	0.61	5562	6
	1	Resample	5574 (56%)	NA	0.56	7555	NA
	2	Split 1	9660 (97%)	0.19	0.38	6343	28
	2	Split 2	9458 (95%)	0.30	0.43	6215	15
	2	Split 3	9109 (91%)	0.39	0.54	6136	9
	2	Split 4	9023 (90%)	0.18	0.61	5622	6
	2	Resample	5644 (56%)	NA	0.56	7556	NA
	3	Split 1	9662 (97%)	0.22	0.37	6341	24
	3	Split 2	9492 (95%)	0.35	0.42	6233	13
	3	Split 3	9213 (92%)	0.42	0.52	6179	8
	3	Split 4	9093 (91%)	0.16	0.59	5626	7
	3	Resample	6007 (60%)	NA	0.55	7642	NA
	4	Split 1	9663 (97%)	0.22	0.37	6334	24
	4	Split 2	9455 (95%)	0.35	0.43	6269	13
	4	Split 3	9183 (92%)	0.44	0.53	6126	8
	4	Split 4	9119 (91%)	0.21	0.59	5555	5
	4	Resample	6006 (60%)	NA	0.55	7666	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
LAMIRADA	1	Split 1	9718 (97%)	0.20	0.33	6285	21
	1	Split 2	9545 (95%)	0.30	0.41	6184	12
	1	Split 3	9296 (93%)	0.43	0.51	6124	7
	1	Split 4	9072 (91%)	0.19	0.56	5599	5
	1	Resample	5791 (58%)	*NA*	0.55	7636	*NA*
	2	Split 1	9714 (97%)	0.26	0.34	6301	16
	2	Split 2	9543 (95%)	0.39	0.41	6187	9
	2	Split 3	9326 (93%)	0.34	0.51	6138	9
	2	Split 4	9093 (91%)	0.19	0.56	5509	5
	2	Resample	5964 (60%)	*NA*	0.55	7612	*NA*
	3	Split 1	9712 (97%)	0.23	0.34	6362	18
	3	Split 2	9532 (95%)	0.36	0.42	6281	10
	3	Split 3	9356 (94%)	0.35	0.50	6124	9
	3	Split 4	9159 (92%)	0.19	0.54	5564	5
	3	Resample	6483 (65%)	*NA*	0.54	7728	*NA*
	4	Split 1	9717 (97%)	0.18	0.34	6300	23
	4	Split 2	9533 (95%)	0.28	0.41	6282	13
	4	Split 3	9326 (93%)	0.38	0.50	6152	8
	4	Split 4	8951 (90%)	0.19	0.59	5545	5
	4	Resample	5445 (54%)	*NA*	0.57	7479	*NA*
LINCOLN	1	Split 1	9542 (95%)	0.23	0.41	6288	40
	1	Split 2	9157 (92%)	0.38	0.55	6252	21
	1	Split 3	8575 (86%)	0.55	0.71	6061	12
	1	Split 4	8332 (83%)	0.31	0.74	5492	7
	1	Resample	3800 (38%)	*NA*	0.72	6742	*NA*
	2	Split 1	9553 (96%)	0.27	0.40	6378	34
	2	Split 2	9172 (92%)	0.44	0.54	6161	18
	2	Split 3	8620 (86%)	0.47	0.70	6063	15
	2	Split 4	8369 (84%)	0.26	0.72	5492	9
	2	Resample	3911 (39%)	*NA*	0.72	6739	*NA*
	3	Split 1	9560 (96%)	0.18	0.40	6308	51
	3	Split 2	9142 (91%)	0.30	0.55	6196	27
	3	Split 3	8605 (86%)	0.47	0.71	6028	15
	3	Split 4	8334 (83%)	0.26	0.72	5448	9
	3	Resample	3335 (33%)	*NA*	0.71	6776	*NA*
	4	Split 1	9539 (95%)	0.29	0.41	6245	32
	4	Split 2	9193 (92%)	0.46	0.54	6196	17
	4	Split 3	8654 (87%)	0.45	0.69	6123	16
	4	Split 4	8223 (82%)	0.26	0.75	5571	9
	4	Resample	3557 (36%)	*NA*	0.74	6611	*NA*
LODI	1	Split 1	9778 (98%)	0.10	0.30	6335	23
	1	Split 2	9610 (96%)	0.18	0.39	6241	12
	1	Split 3	9308 (93%)	0.26	0.48	6140	7
	1	Split 4	9111 (91%)	0.13	0.54	5620	4
	1	Resample	6192 (62%)	*NA*	0.55	7648	*NA*
	2	Split 1	9770 (98%)	0.08	0.30	6362	29
	2	Split 2	9603 (96%)	0.14	0.40	6252	15
	2	Split 3	9193 (92%)	0.23	0.50	6097	8
	2	Split 4	8929 (89%)	0.11	0.56	5611	5
	2	Resample	4615 (46%)	*NA*	0.56	7526	*NA*
	3	Split 1	9774 (98%)	0.15	0.30	6310	16
	3	Split 2	9610 (96%)	0.23	0.39	6252	9
	3	Split 3	9215 (92%)	0.28	0.48	6190	6
	3	Split 4	9034 (90%)	0.13	0.55	5649	4
	3	Resample	5631 (56%)	*NA*	0.55	7642	*NA*
	4	Split 1	9775 (98%)	0.09	0.30	6347	25
	4	Split 2	9571 (96%)	0.16	0.40	6287	14
	4	Split 3	9288 (93%)	0.23	0.49	6122	8
	4	Split 4	9103 (91%)	0.11	0.54	5648	5
	4	Resample	6057 (61%)	*NA*	0.54	7628	*NA*

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
LOMPOC	1	Split 1	9686 (97%)	0.32	0.34	6357	70
	1	Split 2	9442 (94%)	0.52	0.45	6117	36
	1	Split 3	8932 (89%)	0.26	0.57	5663	23
	1	Resample	4936 (49%)	NA	0.57	7483	NA
	2	Split 1	9675 (97%)	0.34	0.35	6382	67
	2	Split 2	9449 (94%)	0.51	0.45	6230	36
	2	Split 3	8982 (90%)	0.31	0.56	5692	19
	2	Resample	5137 (51%)	NA	0.56	7525	NA
	3	Split 1	9683 (97%)	0.33	0.34	6326	68
	3	Split 2	9474 (95%)	0.53	0.44	6144	35
	3	Split 3	8972 (90%)	0.32	0.57	5680	19
	3	Resample	5021 (50%)	NA	0.56	7558	NA
	4	Split 1	9673 (97%)	0.37	0.35	6302	61
	4	Split 2	9461 (95%)	0.57	0.44	6139	32
	4	Split 3	8914 (89%)	0.34	0.57	5661	17
	4	Resample	4549 (45%)	NA	0.57	7443	NA
LOSBANOS	1	Split 1	9780 (98%)	0.20	0.30	6338	22
	1	Split 2	9519 (95%)	0.29	0.41	6155	12
	1	Split 3	9205 (92%)	0.16	0.51	5642	7
	1	Resample	5835 (58%)	NA	0.49	7884	NA
	2	Split 1	9777 (98%)	0.20	0.30	6316	22
	2	Split 2	9486 (95%)	0.29	0.42	6226	12
	2	Split 3	9164 (92%)	0.14	0.51	5576	8
	2	Resample	5330 (53%)	NA	0.49	7864	NA
	3	Split 1	9774 (98%)	0.22	0.30	6301	20
	3	Split 2	9523 (95%)	0.32	0.41	6236	11
	3	Split 3	9168 (92%)	0.16	0.51	5569	7
	3	Resample	5644 (56%)	NA	0.49	7876	NA
	4	Split 1	9782 (98%)	0.21	0.30	6318	21
	4	Split 2	9510 (95%)	0.29	0.41	6210	12
	4	Split 3	9203 (92%)	0.16	0.51	5627	7
	4	Resample	5819 (58%)	NA	0.49	7868	NA
MENLOPARK	1	Split 1	9513 (95%)	0.34	0.43	6383	32
	1	Split 2	9382 (94%)	0.36	0.47	6239	29
	1	Split 3	9166 (92%)	0.55	0.53	6253	19
	1	Split 4	9068 (91%)	0.29	0.54	5772	11
	1	Resample	6813 (68%)	NA	0.63	7548	NA
	2	Split 1	9509 (95%)	0.25	0.43	6295	43
	2	Split 2	9373 (94%)	0.39	0.48	6208	27
	2	Split 3	9146 (91%)	0.60	0.54	6166	17
	2	Split 4	9074 (91%)	0.29	0.53	5770	11
	2	Resample	6709 (67%)	NA	0.63	7577	NA
	3	Split 1	9510 (95%)	0.31	0.43	6334	35
	3	Split 2	9370 (94%)	0.46	0.48	6304	23
	3	Split 3	9164 (92%)	0.72	0.53	6234	13
	3	Split 4	9082 (91%)	0.19	0.53	5858	18
	3	Resample	6771 (68%)	NA	0.63	7555	NA
	4	Split 1	9522 (95%)	0.24	0.43	6300	45
	4	Split 2	9371 (94%)	0.41	0.48	6190	26
	4	Split 3	9164 (92%)	0.65	0.53	6203	15
	4	Split 4	9076 (91%)	0.33	0.54	5726	9
	4	Resample	6732 (67%)	NA	0.63	7584	NA
MONTEREYPARK	1	Split 1	9650 (96%)	0.09	0.37	6280	16
	1	Split 2	9485 (95%)	0.14	0.43	6232	9
	1	Split 3	9409 (94%)	0.21	0.48	6161	5
	1	Split 4	9231 (92%)	0.06	0.54	5645	6
	1	Resample	6861 (69%)	NA	0.52	7825	NA
	2	Split 1	9641 (96%)	0.11	0.37	6319	13
	2	Split 2	9523 (95%)	0.16	0.42	6215	8
	2	Split 3	9346 (93%)	0.13	0.49	6134	9
	2	Split 4	9086 (91%)	0.07	0.58	5628	5
	2	Resample	6308 (63%)	NA	0.56	7613	NA
	3	Split 1	9644 (96%)	0.13	0.37	6336	11
	3	Split 2	9548 (95%)	0.13	0.41	6189	10
	3	Split 3	9391 (94%)	0.16	0.49	6078	7
	3	Split 4	9025 (90%)	0.07	0.57	5658	5
	3	Resample	5709 (57%)	NA	0.56	7581	NA
	4	Split 1	9629 (96%)	0.10	0.38	6392	15
	4	Split 2	9509 (95%)	0.15	0.42	6215	9
	4	Split 3	9283 (93%)	0.19	0.50	6121	6
	4	Split 4	9104 (91%)	0.09	0.57	5608	4
	4	Resample	6329 (63%)	NA	0.56	7663	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
MURRIETA	1	Split 1	9714 (97%)	0.32	0.33	6324	41
	1	Split 2	9428 (94%)	0.52	0.43	6264	22
	1	Split 3	9196 (92%)	0.64	0.53	6213	14
	1	Split 4	9059 (91%)	0.31	0.57	5662	9
	1	Resample	5538 (55%)	NA	0.55	7612	NA
	2	Split 1	9713 (97%)	0.30	0.33	6306	43
	2	Split 2	9477 (95%)	0.47	0.43	6218	25
	2	Split 3	9190 (92%)	0.63	0.53	6203	14
	2	Split 4	8944 (89%)	0.23	0.59	5664	13
	2	Resample	4968 (50%)	NA	0.57	7493	NA
	3	Split 1	9718 (97%)	0.31	0.33	6330	43
	3	Split 2	9484 (95%)	0.48	0.43	6254	24
	3	Split 3	9225 (92%)	0.66	0.53	6227	13
	3	Split 4	9015 (90%)	0.25	0.58	5667	12
	3	Resample	5100 (51%)	NA	0.56	7550	NA
	4	Split 1	9712 (97%)	0.23	0.33	6273	59
	4	Split 2	9447 (94%)	0.39	0.44	6251	31
	4	Split 3	9187 (92%)	0.55	0.54	6213	17
	4	Split 4	8984 (90%)	0.30	0.59	5648	9
	4	Resample	5239 (52%)	NA	0.57	7488	NA
NAPA	1	Split 1	9745 (97%)	0.27	0.31	6347	42
	1	Split 2	9486 (95%)	0.45	0.43	6234	22
	1	Split 3	9006 (90%)	0.24	0.55	5769	13
	1	Resample	5171 (52%)	NA	0.54	7613	NA
	2	Split 1	9749 (97%)	0.33	0.31	6327	35
	2	Split 2	9489 (95%)	0.51	0.44	6214	19
	2	Split 3	9044 (90%)	0.28	0.54	5800	11
	2	Resample	5103 (51%)	NA	0.53	7661	NA
	3	Split 1	9742 (97%)	0.31	0.31	6296	37
	3	Split 2	9522 (95%)	0.48	0.42	6206	20
	3	Split 3	9006 (90%)	0.28	0.54	5716	11
	3	Resample	4345 (43%)	NA	0.53	7628	NA
	4	Split 1	9749 (97%)	0.24	0.31	6328	47
	4	Split 2	9519 (95%)	0.40	0.42	6213	25
	4	Split 3	9119 (91%)	0.22	0.53	5789	15
	4	Resample	5320 (53%)	NA	0.52	7749	NA
NOVATO	1	Split 1	9691 (97%)	0.30	0.35	6345	22
	1	Split 2	9368 (94%)	0.48	0.46	6282	12
	1	Split 3	9097 (91%)	0.37	0.53	6121	14
	1	Split 4	8964 (90%)	0.20	0.60	5529	8
	1	Resample	5508 (55%)	NA	0.58	7455	NA
	2	Split 1	9692 (97%)	0.28	0.35	6312	24
	2	Split 2	9401 (94%)	0.45	0.46	6252	13
	2	Split 3	9183 (92%)	0.40	0.51	6131	13
	2	Split 4	9024 (90%)	0.17	0.57	5583	10
	2	Resample	5396 (54%)	NA	0.56	7627	NA
	3	Split 1	9703 (97%)	0.25	0.35	6364	27
	3	Split 2	9410 (94%)	0.40	0.46	6194	15
	3	Split 3	9221 (92%)	0.46	0.51	6152	11
	3	Split 4	9078 (91%)	0.22	0.58	5595	7
	3	Resample	5950 (59%)	NA	0.55	7643	NA
	4	Split 1	9701 (97%)	0.21	0.35	6317	32
	4	Split 2	9383 (94%)	0.36	0.46	6221	17
	4	Split 3	9184 (92%)	0.49	0.52	6123	10
	4	Split 4	9019 (90%)	0.25	0.59	5547	6
	4	Resample	5758 (58%)	NA	0.57	7550	NA
OJAI	1	Split 1	9854 (99%)	0.29	0.24	6342	24
	1	Split 2	9697 (97%)	0.44	0.35	6201	14
	1	Split 3	9487 (95%)	0.24	0.43	5716	8
	1	Resample	7614 (76%)	NA	0.42	8245	NA
	2	Split 1	9856 (99%)	0.24	0.24	6297	29
	2	Split 2	9707 (97%)	0.38	0.34	6229	16
	2	Split 3	9490 (95%)	0.22	0.43	5711	9
	2	Resample	7531 (75%)	NA	0.42	8275	NA
	3	Split 1	9854 (99%)	0.28	0.24	6313	25
	3	Split 2	9688 (97%)	0.43	0.35	6230	14
	3	Split 3	9466 (95%)	0.24	0.44	5688	8
	3	Resample	7409 (74%)	NA	0.43	8255	NA
	4	Split 1	9853 (99%)	0.29	0.25	6381	24
	4	Split 2	9704 (97%)	0.46	0.35	6252	13
	4	Split 3	9520 (95%)	0.24	0.42	5744	8
	4	Resample	7828 (78%)	NA	0.42	8283	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
ORANGE	1	Split 1	9356 (94%)	0.33	0.49	6294	40
	1	Split 2	9079 (91%)	0.51	0.58	6147	21
	1	Split 3	9026 (90%)	0.52	0.57	6059	18
	1	Split 4	8930 (89%)	0.63	0.62	6081	10
	1	Split 5	8656 (87%)	0.24	0.69	5485	10
	1	Resample	4718 (47%)	*NA*	0.67	7032	*NA*
	2	Split 1	9376 (94%)	0.31	0.48	6330	41
	2	Split 2	9061 (91%)	0.48	0.58	6131	23
	2	Split 3	9013 (90%)	0.63	0.59	6170	13
	2	Split 4	8800 (88%)	0.69	0.65	6099	8
	2	Split 5	8506 (85%)	0.34	0.73	5397	5
	2	Resample	4519 (45%)	*NA*	0.71	6876	*NA*
	3	Split 1	9382 (94%)	0.28	0.48	6305	47
	3	Split 2	9093 (91%)	0.45	0.57	6098	25
	3	Split 3	8994 (90%)	0.61	0.59	6125	14
	3	Split 4	8897 (89%)	0.63	0.63	6061	10
	3	Split 5	8747 (87%)	0.32	0.69	5427	6
	3	Resample	5353 (54%)	*NA*	0.66	7090	*NA*
	4	Split 1	9354 (94%)	0.27	0.49	6397	48
	4	Split 2	9099 (91%)	0.28	0.58	6136	42
	4	Split 3	8988 (90%)	0.45	0.58	6083	22
	4	Split 4	8821 (88%)	0.57	0.66	6053	12
	4	Split 5	8663 (87%)	0.29	0.71	5422	7
	4	Resample	5285 (53%)	*NA*	0.69	7016	*NA*
OXNARD	1	Split 1	9656 (97%)	0.36	0.37	6366	46
	1	Split 2	9444 (94%)	0.41	0.46	6256	38
	1	Split 3	9230 (92%)	0.53	0.53	6159	25
	1	Split 4	9022 (90%)	0.66	0.58	6104	14
	1	Split 5	8798 (88%)	0.33	0.63	5448	8
	1	Resample	4167 (42%)	*NA*	0.60	7339	*NA*
	2	Split 1	9676 (97%)	0.33	0.36	6352	50
	2	Split 2	9460 (95%)	0.56	0.46	6221	26
	2	Split 3	9161 (92%)	0.58	0.54	6193	22
	2	Split 4	9015 (90%)	0.67	0.58	6118	13
	2	Split 5	8946 (89%)	0.27	0.60	5437	12
	2	Resample	5161 (52%)	*NA*	0.58	7484	*NA*
	3	Split 1	9665 (97%)	0.34	0.36	6299	48
	3	Split 2	9388 (94%)	0.57	0.47	6211	25
	3	Split 3	9261 (93%)	0.72	0.53	6158	14
	3	Split 4	9086 (91%)	0.77	0.57	6098	8
	3	Split 5	8951 (90%)	0.33	0.61	5500	8
	3	Resample	5485 (55%)	*NA*	0.58	7447	*NA*
	4	Split 1	9661 (97%)	0.27	0.36	6300	61
	4	Split 2	9454 (95%)	0.47	0.46	6249	32
	4	Split 3	9237 (92%)	0.55	0.53	6188	24
	4	Split 4	9042 (90%)	0.67	0.58	6100	13
	4	Split 5	9027 (90%)	0.34	0.59	5464	7
	4	Resample	5432 (54%)	*NA*	0.57	7549	*NA*
PACIFICA	1	Split 1	9735 (97%)	0.24	0.33	6362	29
	1	Split 2	9134 (91%)	0.39	0.60	6232	19
	1	Split 3	8943 (89%)	0.57	0.59	6112	11
	1	Split 4	8818 (88%)	0.26	0.64	5512	7
	1	Resample	5393 (54%)	*NA*	0.65	7282	*NA*
	2	Split 1	9739 (97%)	0.21	0.33	6272	33
	2	Split 2	9126 (91%)	0.41	0.60	6215	18
	2	Split 3	8950 (89%)	0.61	0.60	6151	10
	2	Split 4	8793 (88%)	0.29	0.64	5517	6
	2	Resample	5127 (51%)	*NA*	0.65	7285	*NA*
	3	Split 1	9731 (97%)	0.23	0.34	6373	31
	3	Split 2	9187 (92%)	0.43	0.59	6189	17
	3	Split 3	8989 (90%)	0.45	0.59	6087	15
	3	Split 4	8846 (88%)	0.12	0.63	5558	17
	3	Resample	5384 (54%)	*NA*	0.65	7290	*NA*
	4	Split 1	9733 (97%)	0.28	0.33	6301	25
	4	Split 2	9083 (91%)	0.50	0.61	6229	14
	4	Split 3	8965 (90%)	0.43	0.59	6089	16
	4	Split 4	8858 (89%)	0.17	0.64	5612	12
	4	Resample	5721 (57%)	*NA*	0.65	7293	*NA*

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
PALMDALE	1	Split 1	9481 (95%)	0.12	0.48	6319	19
	1	Split 2	9441 (94%)	0.16	0.40	6234	11
	1	Split 3	9192 (92%)	0.08	0.51	5880	7
	1	Resample	5702 (57%)	NA	0.51	7825	NA
	2	Split 1	9474 (95%)	0.16	0.49	6275	14
	2	Split 2	9537 (95%)	0.16	0.38	6231	11
	2	Split 3	9329 (93%)	0.08	0.48	5894	7
	2	Resample	7222 (72%)	NA	0.49	7925	NA
	3	Split 1	9485 (95%)	0.09	0.48	6296	24
	3	Split 2	9526 (95%)	0.12	0.39	6256	15
	3	Split 3	9227 (92%)	0.06	0.49	5861	9
	3	Resample	5593 (56%)	NA	0.50	7810	NA
	4	Split 1	9484 (95%)	0.17	0.48	6329	13
	4	Split 2	9532 (95%)	0.15	0.39	6290	12
	4	Split 3	9293 (93%)	0.08	0.49	5859	7
	4	Resample	6922 (69%)	NA	0.50	7887	NA
PALMSPRINGS	1	Split 1	9583 (96%)	0.20	0.39	6328	32
	1	Split 2	9211 (92%)	0.34	0.49	6222	18
	1	Split 3	8849 (88%)	0.49	0.59	6112	10
	1	Split 4	8698 (87%)	0.25	0.66	5560	6
	1	Resample	4552 (46%)	NA	0.64	7109	NA
	2	Split 1	9581 (96%)	0.22	0.39	6299	30
	2	Split 2	9197 (92%)	0.37	0.50	6209	16
	2	Split 3	8914 (89%)	0.52	0.59	6164	9
	2	Split 4	8805 (88%)	0.24	0.64	5651	6
	2	Resample	4824 (48%)	NA	0.62	7304	NA
	3	Split 1	9581 (96%)	0.26	0.39	6308	25
	3	Split 2	9154 (92%)	0.42	0.50	6246	14
	3	Split 3	8944 (89%)	0.49	0.59	6107	10
	3	Split 4	8832 (88%)	0.20	0.63	5651	8
	3	Resample	5136 (51%)	NA	0.62	7255	NA
	4	Split 1	9598 (96%)	0.20	0.38	6285	33
	4	Split 2	9230 (92%)	0.34	0.48	6265	18
	4	Split 3	8917 (89%)	0.48	0.58	6142	10
	4	Split 4	8870 (89%)	0.24	0.62	5555	6
	4	Resample	5206 (52%)	NA	0.61	7298	NA
PLACENTIA	1	Split 1	9709 (97%)	0.20	0.35	6341	38
	1	Split 2	9531 (95%)	0.25	0.39	6038	22
	1	Split 3	9256 (93%)	0.36	0.49	6095	12
	1	Split 4	9111 (91%)	0.18	0.57	5553	7
	1	Resample	5952 (60%)	NA	0.54	7687	NA
	2	Split 1	9713 (97%)	0.28	0.34	6263	27
	2	Split 2	9562 (96%)	0.36	0.38	6082	15
	2	Split 3	9340 (93%)	0.48	0.47	6088	8
	2	Split 4	8888 (89%)	0.23	0.59	5513	5
	2	Resample	4683 (47%)	NA	0.57	7493	NA
	3	Split 1	9707 (97%)	0.31	0.35	6322	25
	3	Split 2	9523 (95%)	0.38	0.39	6094	14
	3	Split 3	9181 (92%)	0.49	0.50	6191	8
	3	Split 4	8981 (90%)	0.23	0.58	5556	5
	3	Resample	5031 (50%)	NA	0.56	7576	NA
	4	Split 1	9720 (97%)	0.30	0.34	6344	26
	4	Split 2	9529 (95%)	0.38	0.39	6068	14
	4	Split 3	9306 (93%)	0.45	0.48	6152	9
	4	Split 4	9102 (91%)	0.23	0.55	5570	5
	4	Resample	5430 (54%)	NA	0.53	7705	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
PORTERVILLE	1	Split 1	9638 (96%)	0.29	0.37	6266	43
	1	Split 2	9456 (95%)	0.45	0.45	6148	23
	1	Split 3	9286 (93%)	0.59	0.50	6124	13
	1	Split 4	8977 (90%)	0.26	0.59	5607	10
	1	Resample	5496 (55%)	NA	0.58	7516	NA
	2	Split 1	9637 (96%)	0.29	0.37	6354	44
	2	Split 2	9504 (95%)	0.44	0.44	6215	24
	2	Split 3	9267 (93%)	0.52	0.50	6185	16
	2	Split 4	8853 (89%)	0.28	0.62	5549	9
	2	Resample	5083 (51%)	NA	0.60	7359	NA
	3	Split 1	9639 (96%)	0.27	0.37	6358	46
	3	Split 2	9498 (95%)	0.43	0.44	6234	24
	3	Split 3	9275 (93%)	0.58	0.50	6158	13
	3	Split 4	8893 (89%)	0.24	0.59	5633	11
	3	Resample	4433 (44%)	NA	0.58	7452	NA
	4	Split 1	9628 (96%)	0.26	0.38	6334	48
	4	Split 2	9485 (95%)	0.43	0.44	6166	25
	4	Split 3	9308 (93%)	0.52	0.49	6154	16
	4	Split 4	8985 (90%)	0.27	0.59	5617	9
	4	Resample	5655 (57%)	NA	0.58	7499	NA
POWAY	1	Split 1	9812 (98%)	0.23	0.27	6313	14
	1	Split 2	9596 (96%)	0.36	0.39	6165	8
	1	Split 3	9290 (93%)	0.17	0.48	5328	5
	1	Resample	6544 (65%)	NA	0.48	8005	NA
	2	Split 1	9814 (98%)	0.16	0.27	6349	21
	2	Split 2	9602 (96%)	0.25	0.39	6115	12
	2	Split 3	9289 (93%)	0.13	0.48	5355	7
	2	Resample	6471 (65%)	NA	0.48	7941	NA
	3	Split 1	9810 (98%)	0.22	0.27	6307	15
	3	Split 2	9606 (96%)	0.33	0.39	6146	9
	3	Split 3	9295 (93%)	0.13	0.48	5339	7
	3	Resample	6550 (65%)	NA	0.48	7948	NA
	4	Split 1	9810 (98%)	0.20	0.28	6313	17
	4	Split 2	9577 (96%)	0.30	0.40	6186	10
	4	Split 3	9372 (94%)	0.15	0.47	5340	6
	4	Resample	7270 (73%)	NA	0.47	8016	NA
RANCHOCUCAMONGA	1	Split 1	9841 (98%)	0.21	0.25	6292	31
	1	Split 2	9668 (97%)	0.33	0.36	6331	17
	1	Split 3	9371 (94%)	0.19	0.45	5813	9
	1	Resample	7033 (70%)	NA	0.45	8123	NA
	2	Split 1	9847 (98%)	0.24	0.25	6339	27
	2	Split 2	9689 (97%)	0.39	0.35	6315	14
	2	Split 3	9353 (94%)	0.21	0.46	5829	8
	2	Resample	6914 (69%)	NA	0.46	8053	NA
	3	Split 1	9847 (98%)	0.27	0.25	6263	24
	3	Split 2	9679 (97%)	0.41	0.36	6268	13
	3	Split 3	9381 (94%)	0.20	0.45	5873	9
	3	Resample	7015 (70%)	NA	0.45	8110	NA
	4	Split 1	9847 (98%)	0.21	0.25	6346	31
	4	Split 2	9671 (97%)	0.33	0.36	6272	17
	4	Split 3	9342 (93%)	0.20	0.46	5835	9
	4	Resample	6638 (66%)	NA	0.46	8065	NA
REDLANDS	1	Split 1	9824 (98%)	0.15	0.27	6329	13
	1	Split 2	9600 (96%)	0.18	0.41	6252	10
	1	Split 3	9322 (93%)	0.25	0.48	6180	6
	1	Split 4	9098 (91%)	0.11	0.54	5612	4
	1	Resample	5254 (53%)	NA	0.53	7695	NA
	2	Split 1	9828 (98%)	0.07	0.26	6309	29
	2	Split 2	9556 (96%)	0.11	0.43	6165	16
	2	Split 3	9341 (93%)	0.18	0.48	6157	9
	2	Split 4	9159 (92%)	0.08	0.54	5655	6
	2	Resample	6281 (63%)	NA	0.53	7763	NA
	3	Split 1	9830 (98%)	0.09	0.26	6332	21
	3	Split 2	9554 (96%)	0.15	0.43	6208	12
	3	Split 3	9229 (92%)	0.22	0.49	6141	7
	3	Split 4	9189 (92%)	0.11	0.53	5612	4
	3	Resample	6395 (64%)	NA	0.52	7755	NA
	4	Split 1	9822 (98%)	0.08	0.27	6352	25
	4	Split 2	9583 (96%)	0.13	0.42	6265	14
	4	Split 3	9296 (93%)	0.20	0.47	6119	8
	4	Split 4	9043 (90%)	0.10	0.54	5668	5
	4	Resample	5119 (51%)	NA	0.53	7611	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
REDWOODCITY	1	Split 1	9134 (91%)	0.51	0.58	6281	93
	1	Split 2	9291 (93%)	0.76	0.50	6173	49
	1	Split 3	9268 (93%)	0.87	0.50	6200	31
	1	Split 4	9154 (92%)	0.76	0.57	6209	34
	1	Split 5	9030 (90%)	0.78	0.61	5994	18
	1	Split 6	8774 (88%)	0.44	0.66	5182	10
	1	Resample	4278 (43%)	NA	0.61	7334	NA
	2	Split 1	9118 (91%)	0.47	0.58	6361	100
	2	Split 2	9277 (93%)	0.73	0.49	6160	53
	2	Split 3	9275 (93%)	0.90	0.50	6230	28
	2	Split 4	9119 (91%)	0.80	0.57	6215	31
	2	Split 5	9024 (90%)	0.78	0.62	5992	17
	2	Split 6	8816 (88%)	0.34	0.66	5309	17
	2	Resample	4839 (48%)	NA	0.62	7290	NA
	3	Split 1	9113 (91%)	0.48	0.58	6365	98
	3	Split 2	9288 (93%)	0.73	0.50	6199	52
	3	Split 3	9250 (93%)	0.85	0.51	6201	33
	3	Split 4	9181 (92%)	0.94	0.56	6160	19
	3	Split 5	9124 (91%)	0.85	0.60	6032	11
	3	Split 6	8988 (90%)	0.41	0.61	5221	12
	3	Resample	5340 (53%)	NA	0.58	7506	NA
	4	Split 1	9121 (91%)	0.53	0.58	6338	91
	4	Split 2	9247 (92%)	0.74	0.50	6185	52
	4	Split 3	9268 (93%)	0.80	0.51	6153	38
	4	Split 4	9188 (92%)	0.73	0.56	6200	36
	4	Split 5	8949 (89%)	0.65	0.62	5963	27
	4	Split 6	8883 (89%)	0.32	0.64	5266	19
	4	Resample	5066 (51%)	NA	0.60	7354	NA
RICHMOND	1	Split 1	7566 (76%)	0.30	0.79	6362	59
	1	Split 2	7768 (78%)	0.49	0.79	5819	33
	1	Split 3	8037 (80%)	0.71	0.72	5940	17
	1	Split 4	8193 (82%)	0.73	0.70	5953	11
	1	Split 5	7986 (80%)	0.37	0.75	5299	7
	1	Resample	2182 (22%)	NA	0.75	6435	NA
	2	Split 1	7569 (76%)	0.30	0.79	6338	60
	2	Split 2	7740 (77%)	0.37	0.79	5782	45
	2	Split 3	8105 (81%)	0.57	0.72	5877	25
	2	Split 4	8258 (83%)	0.55	0.69	5962	21
	2	Split 5	7977 (80%)	0.29	0.74	5367	12
	2	Resample	2366 (24%)	NA	0.74	6424	NA
	3	Split 1	7577 (76%)	0.33	0.79	6319	55
	3	Split 2	7732 (77%)	0.53	0.79	5806	29
	3	Split 3	7982 (80%)	0.54	0.73	5802	26
	3	Split 4	8097 (81%)	0.67	0.73	5952	14
	3	Split 5	7721 (77%)	0.36	0.79	5202	8
	3	Resample	1966 (20%)	NA	0.78	6190	NA
	4	Split 1	7587 (76%)	0.31	0.79	6382	58
	4	Split 2	7798 (78%)	0.53	0.79	5827	30
	4	Split 3	8026 (80%)	0.57	0.72	5872	25
	4	Split 4	8264 (83%)	0.52	0.69	5927	22
	4	Split 5	7488 (75%)	0.30	0.80	5402	12
	4	Resample	1173 (12%)	NA	0.78	6041	NA
SANRAFAEL	1	Split 1	9662 (97%)	0.13	0.38	6344	18
	1	Split 2	9472 (95%)	0.20	0.43	6184	10
	1	Split 3	8899 (89%)	0.11	0.58	5573	6
	1	Resample	4678 (47%)	NA	0.54	7628	NA
	2	Split 1	9662 (97%)	0.12	0.37	6404	20
	2	Split 2	9503 (95%)	0.19	0.42	6199	11
	2	Split 3	9017 (90%)	0.11	0.56	5605	6
	2	Resample	5000 (50%)	NA	0.52	7770	NA
	3	Split 1	9656 (97%)	0.12	0.38	6355	19
	3	Split 2	9501 (95%)	0.18	0.42	6211	11
	3	Split 3	8995 (90%)	0.11	0.57	5621	6
	3	Resample	4993 (50%)	NA	0.52	7753	NA
	4	Split 1	9664 (97%)	0.14	0.37	6362	17
	4	Split 2	9481 (95%)	0.20	0.43	6229	10
	4	Split 3	8839 (88%)	0.11	0.59	5647	6
	4	Resample	4295 (43%)	NA	0.54	7589	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
SANTABARBARA	1	Split 1	9691 (97%)	0.46	0.34	6340	96
	1	Split 2	9509 (95%)	0.69	0.40	6243	56
	1	Split 3	9342 (93%)	0.91	0.49	6237	29
	1	Split 4	9138 (91%)	0.92	0.55	6168	16
	1	Split 5	9093 (91%)	0.54	0.57	5401	9
	1	Resample	5997 (60%)	*NA*	0.55	7649	*NA*
	2	Split 1	9693 (97%)	0.41	0.34	6316	111
	2	Split 2	9514 (95%)	0.69	0.40	6239	57
	2	Split 3	9335 (93%)	0.68	0.49	6186	52
	2	Split 4	9046 (90%)	0.82	0.56	6079	27
	2	Split 5	8851 (89%)	0.34	0.61	5492	26
	2	Resample	4546 (45%)	*NA*	0.59	7398	*NA*
	3	Split 1	9699 (97%)	0.45	0.34	6347	101
	3	Split 2	9518 (95%)	0.72	0.40	6234	53
	3	Split 3	9361 (94%)	0.84	0.49	6245	37
	3	Split 4	9097 (91%)	0.84	0.56	6111	27
	3	Split 5	8957 (90%)	0.46	0.59	5374	15
	3	Resample	5431 (54%)	*NA*	0.57	7463	*NA*
	4	Split 1	9691 (97%)	0.49	0.34	6349	91
	4	Split 2	9531 (95%)	0.78	0.39	6350	47
	4	Split 3	9397 (94%)	0.74	0.48	6228	46
	4	Split 4	9043 (90%)	0.70	0.57	6083	40
	4	Split 5	8961 (90%)	0.34	0.60	5497	25
	4	Resample	5570 (56%)	*NA*	0.58	7435	*NA*
SANTACLARA	1	Split 1	9709 (97%)	0.30	0.35	6248	44
	1	Split 2	9610 (96%)	0.41	0.38	6296	26
	1	Split 3	9498 (95%)	0.46	0.46	6249	19
	1	Split 4	9208 (92%)	0.57	0.55	6141	10
	1	Split 5	9084 (91%)	0.25	0.56	5475	8
	1	Resample	5725 (57%)	*NA*	0.55	7677	*NA*
	2	Split 1	9709 (97%)	0.24	0.35	6298	54
	2	Split 2	9580 (96%)	0.39	0.38	6203	28
	2	Split 3	9486 (95%)	0.55	0.46	6239	15
	2	Split 4	9244 (92%)	0.50	0.54	6161	13
	2	Split 5	9152 (92%)	0.25	0.54	5518	8
	2	Resample	5971 (60%)	*NA*	0.53	7796	*NA*
	3	Split 1	9708 (97%)	0.25	0.35	6264	53
	3	Split 2	9603 (96%)	0.38	0.37	6266	28
	3	Split 3	9465 (95%)	0.55	0.47	6210	15
	3	Split 4	9184 (92%)	0.53	0.55	6156	12
	3	Split 5	9142 (91%)	0.25	0.56	5561	8
	3	Resample	6474 (65%)	*NA*	0.55	7702	*NA*
	4	Split 1	9712 (97%)	0.16	0.35	6316	84
	4	Split 2	9589 (96%)	0.25	0.37	6215	44
	4	Split 3	9477 (95%)	0.40	0.46	6230	23
	4	Split 4	9260 (93%)	0.50	0.54	6121	13
	4	Split 5	9148 (91%)	0.25	0.54	5526	8
	4	Resample	5834 (58%)	*NA*	0.53	7781	*NA*
SANTAMARIA	1	Split 1	9705 (97%)	0.11	0.34	6344	19
	1	Split 2	9329 (93%)	0.19	0.45	6185	11
	1	Split 3	9193 (92%)	0.10	0.52	5707	7
	1	Resample	6248 (62%)	*NA*	0.52	7796	*NA*
	2	Split 1	9696 (97%)	0.10	0.34	6253	21
	2	Split 2	9415 (94%)	0.16	0.43	6282	13
	2	Split 3	9200 (92%)	0.09	0.51	5758	8
	2	Resample	6090 (61%)	*NA*	0.51	7838	*NA*
	3	Split 1	9706 (97%)	0.12	0.34	6324	18
	3	Split 2	9416 (94%)	0.21	0.43	6226	10
	3	Split 3	9192 (92%)	0.11	0.52	5767	6
	3	Resample	6185 (62%)	*NA*	0.51	7787	*NA*
	4	Split 1	9705 (97%)	0.14	0.34	6269	15
	4	Split 2	9314 (93%)	0.23	0.45	6223	9
	4	Split 3	9141 (91%)	0.11	0.52	5729	6
	4	Resample	5546 (55%)	*NA*	0.52	7771	*NA*

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
SANTAROSA	1	Split 1	9668 (97%)	0.30	0.37	6355	52
	1	Split 2	9503 (95%)	0.52	0.44	6286	27
	1	Split 3	9391 (94%)	0.64	0.50	6231	18
	1	Split 4	9193 (92%)	0.76	0.56	6205	10
	1	Split 5	9063 (91%)	0.59	0.59	6063	14
	1	Split 6	9010 (90%)	0.30	0.60	5363	8
	1	Resample	5332 (53%)	NA	0.58	7561	NA
	2	Split 1	9671 (97%)	0.29	0.37	6310	55
	2	Split 2	9500 (95%)	0.33	0.44	6205	45
	2	Split 3	9404 (94%)	0.53	0.50	6254	24
	2	Split 4	9215 (92%)	0.45	0.56	6127	27
	2	Split 5	9055 (91%)	0.41	0.59	5994	24
	2	Split 6	9006 (90%)	0.23	0.60	5473	13
	2	Resample	5921 (59%)	NA	0.59	7444	NA
	3	Split 1	9677 (97%)	0.31	0.36	6309	51
	3	Split 2	9480 (95%)	0.52	0.44	6272	27
	3	Split 3	9379 (94%)	0.70	0.51	6196	15
	3	Split 4	9106 (91%)	0.78	0.57	6249	9
	3	Split 5	8902 (89%)	0.75	0.60	6068	6
	3	Split 6	8921 (89%)	0.37	0.63	5260	4
	3	Resample	5404 (54%)	NA	0.61	7435	NA
	4	Split 1	9673 (97%)	0.31	0.37	6305	52
	4	Split 2	9489 (95%)	0.41	0.44	6273	36
	4	Split 3	9290 (93%)	0.61	0.51	6190	19
	4	Split 4	9194 (92%)	0.76	0.56	6206	10
	4	Split 5	9005 (90%)	0.57	0.59	6070	15
	4	Split 6	8912 (89%)	0.23	0.62	5422	13
	4	Resample	4787 (48%)	NA	0.60	7451	NA
SANTEE	1	Split 1	9636 (96%)	0.16	0.38	6265	16
	1	Split 2	9368 (94%)	0.26	0.49	6178	9
	1	Split 3	8983 (90%)	0.15	0.59	5670	5
	1	Resample	5674 (57%)	NA	0.58	7509	NA
	2	Split 1	9631 (96%)	0.19	0.39	6337	13
	2	Split 2	9387 (94%)	0.29	0.48	6199	8
	2	Split 3	9081 (91%)	0.15	0.57	5671	5
	2	Resample	5873 (59%)	NA	0.55	7667	NA
	3	Split 1	9637 (96%)	0.19	0.38	6320	13
	3	Split 2	9411 (94%)	0.32	0.48	6165	7
	3	Split 3	9003 (90%)	0.14	0.59	5670	5
	3	Resample	5708 (57%)	NA	0.58	7540	NA
	4	Split 1	9632 (96%)	0.14	0.39	6314	18
	4	Split 2	9379 (94%)	0.23	0.49	6144	10
	4	Split 3	8898 (89%)	0.13	0.59	5693	6
	4	Resample	4917 (49%)	NA	0.58	7476	NA
SIMIVALLEY	1	Split 1	9757 (98%)	0.22	0.31	6330	40
	1	Split 2	9406 (94%)	0.36	0.45	6241	21
	1	Split 3	9028 (90%)	0.22	0.54	5752	11
	1	Resample	4635 (46%)	NA	0.53	7671	NA
	2	Split 1	9754 (98%)	0.25	0.31	6276	34
	2	Split 2	9357 (94%)	0.38	0.46	6252	20
	2	Split 3	9184 (92%)	0.22	0.52	5749	11
	2	Resample	6345 (63%)	NA	0.52	7735	NA
	3	Split 1	9751 (98%)	0.27	0.31	6325	32
	3	Split 2	9406 (94%)	0.43	0.45	6258	17
	3	Split 3	9083 (91%)	0.24	0.53	5864	10
	3	Resample	5076 (51%)	NA	0.52	7709	NA
	4	Split 1	9758 (98%)	0.22	0.31	6340	40
	4	Split 2	9386 (94%)	0.37	0.45	6242	21
	4	Split 3	9109 (91%)	0.20	0.52	5814	12
	4	Resample	5444 (54%)	NA	0.52	7744	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
SOLANABEACH	1	Split 1	9762 (98%)	0.31	0.32	6275	24
	1	Split 2	9575 (96%)	0.45	0.38	6200	13
	1	Split 3	9313 (93%)	0.22	0.47	5642	8
	1	Resample	6448 (64%)	NA	0.46	8056	NA
	2	Split 1	9768 (98%)	0.31	0.31	6322	24
	2	Split 2	9543 (95%)	0.45	0.39	6245	13
	2	Split 3	9214 (92%)	0.24	0.49	5576	7
	2	Resample	4720 (47%)	NA	0.47	7961	NA
	3	Split 1	9765 (98%)	0.30	0.31	6329	25
	3	Split 2	9573 (96%)	0.42	0.39	6245	14
	3	Split 3	9366 (94%)	0.22	0.46	5663	8
	3	Resample	6837 (68%)	NA	0.45	8127	NA
	4	Split 1	9767 (98%)	0.27	0.31	6308	28
	4	Split 2	9593 (96%)	0.39	0.38	6229	15
	4	Split 3	9364 (94%)	0.20	0.47	5542	9
	4	Resample	6937 (69%)	NA	0.46	8104	NA
SOUTHPASADENA	1	Split 1	9810 (98%)	0.18	0.27	6300	19
	1	Split 2	9670 (97%)	0.27	0.36	6246	11
	1	Split 3	9435 (94%)	0.27	0.46	6036	9
	1	Split 4	9218 (92%)	0.13	0.52	5327	6
	1	Resample	6560 (66%)	NA	0.51	7831	NA
	2	Split 1	9812 (98%)	0.19	0.27	6262	18
	2	Split 2	9681 (97%)	0.29	0.35	6288	10
	2	Split 3	9440 (94%)	0.38	0.45	6121	6
	2	Split 4	9131 (91%)	0.17	0.52	5372	4
	2	Resample	5562 (56%)	NA	0.51	7760	NA
	3	Split 1	9809 (98%)	0.14	0.28	6322	24
	3	Split 2	9662 (97%)	0.23	0.36	6287	13
	3	Split 3	9461 (95%)	0.30	0.45	6069	8
	3	Split 4	9275 (93%)	0.14	0.50	5319	5
	3	Resample	6859 (69%)	NA	0.50	7890	NA
	4	Split 1	9814 (98%)	0.17	0.27	6332	19
	4	Split 2	9674 (97%)	0.26	0.36	6223	11
	4	Split 3	9423 (94%)	0.37	0.46	6122	6
	4	Split 4	9245 (92%)	0.11	0.50	5319	7
	4	Resample	6470 (65%)	NA	0.50	7870	NA
SOUTHSANFRANCISCO	1	Split 1	8532 (85%)	0.28	0.90	6297	42
	1	Split 2	8849 (88%)	0.34	0.67	6173	23
	1	Split 3	8612 (86%)	0.35	0.71	5959	17
	1	Split 4	8076 (81%)	0.19	0.85	5404	10
	1	Resample	3119 (31%)	NA	0.79	6477	NA
	2	Split 1	8543 (85%)	0.30	0.90	6348	39
	2	Split 2	8834 (88%)	0.34	0.67	6155	23
	2	Split 3	8647 (86%)	0.43	0.71	5938	13
	2	Split 4	8414 (84%)	0.18	0.81	5350	11
	2	Resample	4399 (44%)	NA	0.76	6768	NA
	3	Split 1	8543 (85%)	0.25	0.90	6284	47
	3	Split 2	8852 (89%)	0.31	0.67	6133	25
	3	Split 3	8698 (87%)	0.42	0.69	5973	14
	3	Split 4	8208 (82%)	0.19	0.83	5370	10
	3	Resample	3512 (35%)	NA	0.78	6600	NA
	4	Split 1	8520 (85%)	0.31	0.91	6354	38
	4	Split 2	8866 (89%)	0.39	0.67	6117	20
	4	Split 3	8729 (87%)	0.49	0.69	5939	11
	4	Split 4	8323 (83%)	0.13	0.81	5371	16
	4	Resample	3731 (37%)	NA	0.75	6712	NA
STANTON	1	Split 1	8750 (87%)	0.19	0.70	6317	15
	1	Split 2	9163 (92%)	0.23	0.50	6075	9
	1	Split 3	9083 (91%)	0.09	0.55	5173	6
	1	Resample	6375 (64%)	NA	0.56	7588	NA
	2	Split 1	8759 (88%)	0.13	0.70	6377	21
	2	Split 2	9146 (91%)	0.17	0.51	6019	12
	2	Split 3	9075 (91%)	0.08	0.56	5209	7
	2	Resample	6403 (64%)	NA	0.57	7549	NA
	3	Split 1	8740 (87%)	0.16	0.70	6383	17
	3	Split 2	9141 (91%)	0.21	0.51	6117	10
	3	Split 3	9002 (90%)	0.09	0.57	5170	6
	3	Resample	6081 (61%)	NA	0.58	7462	NA
	4	Split 1	8722 (87%)	0.20	0.71	6335	14
	4	Split 2	9154 (92%)	0.25	0.51	6043	8
	4	Split 3	9069 (91%)	0.08	0.55	5249	7
	4	Resample	6327 (63%)	NA	0.57	7573	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
SUNNYVALE	1	Split 1	9773 (98%)	0.29	0.30	6316	42
	1	Split 2	9584 (96%)	0.47	0.42	6300	22
	1	Split 3	9365 (94%)	0.49	0.50	6260	18
	1	Split 4	9068 (91%)	0.60	0.57	6220	10
	1	Split 5	9014 (90%)	0.26	0.58	5428	8
	1	Resample	5781 (58%)	NA	0.57	7552	NA
	2	Split 1	9764 (98%)	0.28	0.31	6343	44
	2	Split 2	9541 (95%)	0.45	0.42	6273	23
	2	Split 3	9353 (94%)	0.60	0.52	6212	13
	2	Split 4	9189 (92%)	0.64	0.57	6109	9
	2	Split 5	9039 (90%)	0.21	0.58	5564	11
	2	Resample	5513 (55%)	NA	0.56	7626	NA
	3	Split 1	9773 (98%)	0.28	0.30	6346	43
	3	Split 2	9558 (96%)	0.45	0.43	6258	23
	3	Split 3	9275 (93%)	0.60	0.52	6256	13
	3	Split 4	9132 (91%)	0.61	0.57	6118	10
	3	Split 5	8972 (90%)	0.30	0.57	5490	6
	3	Resample	4335 (43%)	NA	0.56	7568	NA
	4	Split 1	9769 (98%)	0.29	0.31	6328	42
	4	Split 2	9556 (96%)	0.46	0.42	6215	22
	4	Split 3	9340 (93%)	0.63	0.52	6264	12
	4	Split 4	9146 (91%)	0.49	0.56	6124	15
	4	Split 5	9006 (90%)	0.18	0.59	5585	14
	4	Resample	5409 (54%)	NA	0.57	7545	NA
TEHACHAPI	1	Split 1	8481 (85%)	1.00	0.87	6293	193
	1	Split 2	8248 (82%)	0.98	0.90	5933	161
	1	Split 3	8502 (85%)	0.99	0.78	5943	81
	1	Split 4	6838 (68%)	0.02	1.22	2259	41
	1	Resample	3714 (37%)	NA	1.28	4901	NA
	2	Split 1	8420 (84%)	1.00	0.87	6299	202
	2	Split 2	8254 (83%)	0.98	0.89	5933	160
	2	Split 3	8526 (85%)	0.99	0.78	5937	81
	2	Split 4	6924 (69%)	0.02	1.21	2235	41
	2	Resample	3878 (39%)	NA	1.29	4977	NA
	3	Split 1	8441 (84%)	0.99	0.87	6306	202
	3	Split 2	8265 (83%)	0.98	0.87	5889	140
	3	Split 3	8516 (85%)	0.98	0.80	5848	100
	3	Split 4	6602 (66%)	0.01	1.23	2094	87
	3	Resample	3120 (31%)	NA	1.28	4721	NA
	4	Split 1	8416 (84%)	1.00	0.87	6310	199
	4	Split 2	8174 (82%)	0.98	0.90	5896	153
	4	Split 3	8411 (84%)	0.98	0.85	5832	128
	4	Split 4	6866 (69%)	0.01	1.18	1784	69
	4	Resample	3709 (37%)	NA	1.24	4891	NA
TEMECULA	1	Split 1	9729 (97%)	0.27	0.32	6319	28
	1	Split 2	9614 (96%)	0.47	0.39	6277	15
	1	Split 3	9407 (94%)	0.61	0.48	6203	9
	1	Split 4	9270 (93%)	0.28	0.54	5630	6
	1	Resample	6804 (68%)	NA	0.50	7891	NA
	2	Split 1	9727 (97%)	0.21	0.32	6340	36
	2	Split 2	9578 (96%)	0.38	0.40	6193	19
	2	Split 3	9381 (94%)	0.53	0.48	6210	11
	2	Split 4	9226 (92%)	0.20	0.55	5625	10
	2	Resample	6231 (62%)	NA	0.50	7866	NA
	3	Split 1	9730 (97%)	0.19	0.32	6321	40
	3	Split 2	9530 (95%)	0.35	0.40	6254	21
	3	Split 3	9436 (94%)	0.54	0.48	6161	11
	3	Split 4	9292 (93%)	0.26	0.53	5569	7
	3	Resample	6569 (66%)	NA	0.49	7914	NA
	4	Split 1	9731 (97%)	0.26	0.32	6274	29
	4	Split 2	9600 (96%)	0.43	0.39	6224	16
	4	Split 3	9415 (94%)	0.57	0.48	6194	10
	4	Split 4	9338 (93%)	0.28	0.52	5583	6
	4	Resample	6656 (67%)	NA	0.48	8002	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
TORRANCE	1	Split 1	9451 (95%)	0.21	0.46	6377	39
	1	Split 2	9431 (94%)	0.32	0.44	6242	21
	1	Split 3	9361 (94%)	0.49	0.49	6218	11
	1	Split 4	9147 (91%)	0.37	0.58	6080	13
	1	Split 5	9095 (91%)	0.18	0.60	5557	8
	1	Resample	6450 (65%)	NA	0.58	7567	NA
	2	Split 1	9431 (94%)	0.25	0.47	6325	33
	2	Split 2	9419 (94%)	0.37	0.44	6173	18
	2	Split 3	9371 (94%)	0.51	0.50	6181	10
	2	Split 4	9222 (92%)	0.57	0.57	6140	6
	2	Split 5	9091 (91%)	0.14	0.59	5555	11
	2	Resample	6223 (62%)	NA	0.57	7593	NA
	3	Split 1	9440 (94%)	0.19	0.47	6285	44
	3	Split 2	9337 (93%)	0.30	0.45	6211	23
	3	Split 3	9317 (93%)	0.42	0.51	6190	14
	3	Split 4	9195 (92%)	0.50	0.57	6076	8
	3	Split 5	9101 (91%)	0.24	0.59	5532	5
	3	Resample	6193 (62%)	NA	0.57	7631	NA
	4	Split 1	9439 (94%)	0.25	0.47	6284	34
	4	Split 2	9416 (94%)	0.38	0.44	6221	18
	4	Split 3	9362 (94%)	0.51	0.50	6153	10
	4	Split 4	9216 (92%)	0.56	0.56	6136	6
	4	Split 5	9003 (90%)	0.26	0.60	5442	4
	4	Resample	5460 (55%)	NA	0.58	7531	NA
TURLOCK	1	Split 1	9749 (97%)	0.21	0.31	6315	29
	1	Split 2	9545 (95%)	0.32	0.41	6208	16
	1	Split 3	9108 (91%)	0.18	0.51	5881	9
	1	Resample	4846 (48%)	NA	0.50	7815	NA
	2	Split 1	9757 (98%)	0.21	0.30	6333	29
	2	Split 2	9530 (95%)	0.32	0.42	6290	16
	2	Split 3	9233 (92%)	0.18	0.50	5827	9
	2	Resample	6157 (62%)	NA	0.49	7900	NA
	3	Split 1	9761 (98%)	0.18	0.30	6294	33
	3	Split 2	9547 (95%)	0.26	0.41	6288	20
	3	Split 3	9170 (92%)	0.15	0.51	5878	11
	3	Resample	5610 (56%)	NA	0.50	7869	NA
	4	Split 1	9764 (98%)	0.17	0.30	6294	37
	4	Split 2	9583 (96%)	0.26	0.40	6271	20
	4	Split 3	9277 (93%)	0.15	0.49	5855	11
	4	Resample	6660 (67%)	NA	0.48	7962	NA
TWENTYNINEPALMS	1	Split 1	9312 (93%)	0.32	0.52	6248	59
	1	Split 2	7901 (79%)	0.56	0.77	5942	31
	1	Split 3	8355 (84%)	0.79	0.75	5840	21
	1	Split 4	8236 (82%)	0.28	0.80	5805	23
	1	Resample	4307 (43%)	NA	0.81	6535	NA
	2	Split 1	9282 (93%)	0.38	0.53	6366	49
	2	Split 2	7960 (80%)	0.64	0.76	5845	26
	2	Split 3	8407 (84%)	0.83	0.74	5882	18
	2	Split 4	8272 (83%)	0.42	0.79	5748	14
	2	Resample	4316 (43%)	NA	0.80	6572	NA
	3	Split 1	9289 (93%)	0.35	0.53	6283	53
	3	Split 2	7909 (79%)	0.57	0.77	5825	31
	3	Split 3	8401 (84%)	0.76	0.74	5842	22
	3	Split 4	8255 (83%)	0.46	0.80	5760	12
	3	Resample	4061 (41%)	NA	0.80	6588	NA
	4	Split 1	9303 (93%)	0.35	0.53	6374	54
	4	Split 2	7918 (79%)	0.56	0.77	5923	31
	4	Split 3	8335 (83%)	0.61	0.75	5787	31
	4	Split 4	8317 (83%)	0.36	0.79	5737	17
	4	Resample	4465 (45%)	NA	0.79	6596	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
UNIONCITY	1	Split 1	9591 (96%)	0.16	0.39	6319	21
	1	Split 2	9213 (92%)	0.32	0.56	6201	12
	1	Split 3	9306 (93%)	0.17	0.50	5918	7
	1	Resample	6998 (70%)	NA	0.52	7923	NA
	2	Split 1	9596 (96%)	0.21	0.39	6331	16
	2	Split 2	9296 (93%)	0.41	0.55	6218	9
	2	Split 3	9334 (93%)	0.19	0.50	5794	6
	2	Resample	7236 (72%)	NA	0.52	7913	NA
	3	Split 1	9591 (96%)	0.17	0.39	6304	20
	3	Split 2	9259 (93%)	0.34	0.56	6187	11
	3	Split 3	9362 (94%)	0.19	0.49	5864	6
	3	Resample	7486 (75%)	NA	0.51	8001	NA
	4	Split 1	9592 (96%)	0.17	0.39	6311	19
	4	Split 2	9218 (92%)	0.34	0.56	6140	11
	4	Split 3	9299 (93%)	0.17	0.50	5887	7
	4	Resample	6888 (69%)	NA	0.52	7912	NA
UPLAND	1	Split 1	9649 (96%)	0.18	0.37	6406	22
	1	Split 2	9350 (94%)	0.30	0.49	6243	12
	1	Split 3	9028 (90%)	0.15	0.58	5763	8
	1	Resample	6058 (61%)	NA	0.58	7457	NA
	2	Split 1	9653 (97%)	0.15	0.37	6346	27
	2	Split 2	9330 (93%)	0.24	0.50	6266	15
	2	Split 3	8956 (90%)	0.14	0.59	5744	9
	2	Resample	5581 (56%)	NA	0.59	7388	NA
	3	Split 1	9647 (96%)	0.15	0.37	6320	27
	3	Split 2	9351 (94%)	0.24	0.49	6177	15
	3	Split 3	8931 (89%)	0.15	0.59	5782	8
	3	Resample	5373 (54%)	NA	0.59	7384	NA
	4	Split 1	9654 (97%)	0.20	0.37	6291	20
	4	Split 2	9380 (94%)	0.33	0.48	6236	11
	4	Split 3	9004 (90%)	0.19	0.58	5737	6
	4	Resample	5986 (60%)	NA	0.58	7456	NA
VALLEJO	1	Split 1	9731 (97%)	0.14	0.33	6338	20
	1	Split 2	9546 (95%)	0.21	0.41	6194	11
	1	Split 3	9358 (94%)	0.28	0.50	6156	7
	1	Split 4	8971 (90%)	0.29	0.58	6035	5
	1	Split 5	8980 (90%)	0.13	0.60	5360	3
	1	Resample	5735 (57%)	NA	0.59	7497	NA
	2	Split 1	9741 (97%)	0.10	0.33	6257	28
	2	Split 2	9549 (95%)	0.16	0.41	6211	15
	2	Split 3	9273 (93%)	0.23	0.50	6187	9
	2	Split 4	8956 (90%)	0.29	0.59	6026	5
	2	Split 5	8996 (90%)	0.06	0.59	5438	10
	2	Resample	5949 (59%)	NA	0.58	7469	NA
	3	Split 1	9734 (97%)	0.14	0.33	6307	20
	3	Split 2	9506 (95%)	0.21	0.42	6201	11
	3	Split 3	9205 (92%)	0.31	0.52	6151	6
	3	Split 4	9005 (90%)	0.33	0.59	6062	4
	3	Split 5	8877 (89%)	0.06	0.62	5435	9
	3	Resample	5067 (51%)	NA	0.60	7388	NA
	4	Split 1	9742 (97%)	0.16	0.33	6334	17
	4	Split 2	9550 (96%)	0.23	0.41	6251	10
	4	Split 3	9345 (93%)	0.31	0.50	6164	6
	4	Split 4	8979 (90%)	0.26	0.59	6056	6
	4	Split 5	9011 (90%)	0.12	0.60	5363	4
	4	Resample	5954 (60%)	NA	0.59	7462	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
VISALIA	1	Split 1	9826 (98%)	0.28	0.27	6341	63
	1	Split 2	9672 (97%)	0.46	0.37	6251	33
	1	Split 3	9429 (94%)	0.39	0.45	6188	37
	1	Split 4	9180 (92%)	0.22	0.51	5684	20
	1	Resample	6080 (61%)	*NA*	0.51	7784	*NA*
	2	Split 1	9826 (98%)	0.27	0.26	6328	64
	2	Split 2	9684 (97%)	0.41	0.36	6296	37
	2	Split 3	9395 (94%)	0.60	0.46	6186	20
	2	Split 4	9220 (92%)	0.31	0.50	5655	12
	2	Resample	5794 (58%)	*NA*	0.49	7859	*NA*
	3	Split 1	9821 (98%)	0.30	0.27	6318	58
	3	Split 2	9646 (96%)	0.44	0.37	6263	35
	3	Split 3	9416 (94%)	0.62	0.46	6226	19
	3	Split 4	9183 (92%)	0.19	0.50	5754	23
	3	Resample	5439 (54%)	*NA*	0.50	7841	*NA*
	4	Split 1	9820 (98%)	0.25	0.27	6285	71
	4	Split 2	9675 (97%)	0.42	0.37	6270	37
	4	Split 3	9332 (93%)	0.60	0.47	6242	20
	4	Split 4	9221 (92%)	0.28	0.50	5679	14
	4	Resample	6219 (62%)	*NA*	0.50	7859	*NA*
VISTA	1	Split 1	9745 (97%)	0.22	0.33	6394	30
	1	Split 2	9444 (94%)	0.37	0.45	6166	16
	1	Split 3	9097 (91%)	0.18	0.55	5786	11
	1	Resample	5489 (55%)	*NA*	0.52	7722	*NA*
	2	Split 1	9744 (97%)	0.19	0.32	6301	35
	2	Split 2	9431 (94%)	0.32	0.45	6250	19
	2	Split 3	9255 (93%)	0.18	0.52	5733	11
	2	Resample	6665 (67%)	*NA*	0.50	7868	*NA*
	3	Split 1	9744 (97%)	0.23	0.33	6326	29
	3	Split 2	9434 (94%)	0.37	0.45	6298	16
	3	Split 3	9239 (92%)	0.21	0.52	5785	9
	3	Resample	6180 (62%)	*NA*	0.50	7865	*NA*
	4	Split 1	9744 (97%)	0.20	0.32	6333	33
	4	Split 2	9428 (94%)	0.28	0.45	6296	22
	4	Split 3	9246 (92%)	0.17	0.52	5795	12
	4	Resample	6421 (64%)	*NA*	0.50	7860	*NA*
WASCO	1	Split 1	8232 (82%)	0.43	0.75	6312	196
	1	Split 2	7947 (79%)	0.80	0.78	5856	100
	1	Split 3	7759 (78%)	0.79	0.76	5762	51
	1	Split 4	8165 (82%)	0.29	0.74	5145	44
	1	Resample	3373 (34%)	*NA*	0.74	6529	*NA*
	2	Split 1	8222 (82%)	0.44	0.74	6320	196
	2	Split 2	8006 (80%)	0.81	0.77	5955	99
	2	Split 3	8044 (80%)	0.69	0.75	5511	73
	2	Split 4	8300 (83%)	0.17	0.71	5106	68
	2	Resample	3877 (39%)	*NA*	0.72	6687	*NA*
	3	Split 1	8198 (82%)	0.44	0.75	6330	196
	3	Split 2	8006 (80%)	0.81	0.77	5898	99
	3	Split 3	8091 (81%)	0.66	0.75	5425	82
	3	Split 4	8279 (83%)	0.23	0.73	5104	49
	3	Resample	3805 (38%)	*NA*	0.73	6623	*NA*
	4	Split 1	8215 (82%)	0.44	0.75	6349	196
	4	Split 2	7999 (80%)	0.81	0.77	5924	99
	4	Split 3	8005 (80%)	0.73	0.74	5546	67
	4	Split 4	8358 (84%)	0.26	0.72	5044	44
	4	Resample	4080 (41%)	*NA*	0.72	6715	*NA*

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
WESTCOVINA	1	Split 1	8864 (89%)	0.25	0.65	6381	34
	1	Split 2	9243 (92%)	0.43	0.48	5995	18
	1	Split 3	9246 (92%)	0.40	0.54	5998	17
	1	Split 4	8890 (89%)	0.22	0.63	5622	10
	1	Resample	5302 (53%)	NA	0.60	7391	NA
	2	Split 1	8879 (89%)	0.25	0.64	6350	34
	2	Split 2	9232 (92%)	0.37	0.48	5963	21
	2	Split 3	9280 (93%)	0.53	0.54	6076	12
	2	Split 4	8978 (90%)	0.28	0.62	5623	7
	2	Resample	5535 (55%)	NA	0.59	7477	NA
	3	Split 1	8866 (89%)	0.27	0.64	6315	31
	3	Split 2	9228 (92%)	0.42	0.48	5948	18
	3	Split 3	9293 (93%)	0.36	0.53	6052	19
	3	Split 4	9001 (90%)	0.19	0.61	5616	12
	3	Resample	5541 (55%)	NA	0.58	7537	NA
	4	Split 1	8861 (89%)	0.31	0.64	6312	27
	4	Split 2	9228 (92%)	0.42	0.48	5968	18
	4	Split 3	9268 (93%)	0.47	0.54	6055	14
	4	Split 4	9023 (90%)	0.25	0.62	5683	8
	4	Resample	6080 (61%)	NA	0.59	7489	NA
WHITTIER	1	Split 1	9612 (96%)	0.30	0.40	6270	55
	1	Split 2	9353 (94%)	0.49	0.43	6314	29
	1	Split 3	9128 (91%)	0.28	0.55	5772	16
	1	Resample	6065 (61%)	NA	0.53	7699	NA
	2	Split 1	9616 (96%)	0.33	0.40	6313	51
	2	Split 2	9366 (94%)	0.53	0.43	6244	26
	2	Split 3	9070 (91%)	0.25	0.55	5873	19
	2	Resample	5108 (51%)	NA	0.53	7675	NA
	3	Split 1	9627 (96%)	0.38	0.39	6325	44
	3	Split 2	9337 (93%)	0.49	0.43	6219	28
	3	Split 3	9046 (90%)	0.14	0.55	5892	33
	3	Resample	5067 (51%)	NA	0.54	7597	NA
	4	Split 1	9618 (96%)	0.40	0.40	6350	42
	4	Split 2	9316 (93%)	0.59	0.43	6231	22
	4	Split 3	9066 (91%)	0.34	0.56	5831	12
	4	Resample	5654 (57%)	NA	0.54	7649	NA
WILDOMAR	1	Split 1	9813 (98%)	0.25	0.27	6336	18
	1	Split 2	9637 (96%)	0.37	0.41	6308	10
	1	Split 3	9365 (94%)	0.40	0.49	6159	7
	1	Split 4	9114 (91%)	0.17	0.55	5248	5
	1	Resample	6008 (60%)	NA	0.54	7689	NA
	2	Split 1	9811 (98%)	0.23	0.28	6331	20
	2	Split 2	9630 (96%)	0.34	0.42	6242	11
	2	Split 3	9322 (93%)	0.40	0.51	6062	7
	2	Split 4	8973 (90%)	0.18	0.58	5147	5
	2	Resample	5471 (55%)	NA	0.58	7494	NA
	3	Split 1	9814 (98%)	0.18	0.27	6291	25
	3	Split 2	9631 (96%)	0.27	0.42	6297	14
	3	Split 3	9359 (94%)	0.36	0.50	6158	8
	3	Split 4	9055 (91%)	0.18	0.57	5235	5
	3	Resample	5902 (59%)	NA	0.56	7607	NA
	4	Split 1	9811 (98%)	0.27	0.28	6392	17
	4	Split 2	9613 (96%)	0.37	0.42	6222	10
	4	Split 3	9373 (94%)	0.44	0.49	6139	6
	4	Split 4	9082 (91%)	0.18	0.55	5249	5
	4	Resample	5897 (59%)	NA	0.55	7662	NA

Table E-7: `redist` Plan Diagnostics *(continued)*

City	Run	Step	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
WOODLAND	1	Split 1	9553 (96%)	0.30	0.40	6340	60
	1	Split 2	9342 (93%)	0.53	0.46	6158	31
	1	Split 3	9181 (92%)	0.48	0.53	6092	30
	1	Split 4	8880 (89%)	0.27	0.62	5492	16
	1	Resample	5186 (52%)	*NA*	0.60	7396	*NA*
	2	Split 1	9554 (96%)	0.30	0.40	6379	59
	2	Split 2	9324 (93%)	0.53	0.45	6152	31
	2	Split 3	9105 (91%)	0.70	0.52	6075	17
	2	Split 4	8823 (88%)	0.24	0.61	5579	18
	2	Resample	4433 (44%)	*NA*	0.59	7375	*NA*
	3	Split 1	9554 (96%)	0.37	0.40	6350	48
	3	Split 2	9369 (94%)	0.60	0.44	6231	26
	3	Split 3	9206 (92%)	0.76	0.52	6136	14
	3	Split 4	8968 (90%)	0.32	0.59	5587	12
	3	Resample	5362 (54%)	*NA*	0.58	7506	*NA*
	4	Split 1	9560 (96%)	0.37	0.40	6343	48
	4	Split 2	9338 (93%)	0.62	0.45	6134	25
	4	Split 3	9223 (92%)	0.76	0.51	6146	14
	4	Split 4	8895 (89%)	0.37	0.59	5524	10
	4	Resample	4770 (48%)	*NA*	0.58	7396	*NA*
YUCAIPA	1	Split 1	9856 (99%)	0.22	0.24	6363	14
	1	Split 2	9629 (96%)	0.35	0.38	6289	8
	1	Split 3	9348 (93%)	0.28	0.47	6195	9
	1	Split 4	9127 (91%)	0.10	0.53	5709	8
	1	Resample	5957 (60%)	*NA*	0.53	7702	*NA*
	2	Split 1	9853 (99%)	0.15	0.24	6329	21
	2	Split 2	9639 (96%)	0.24	0.38	6311	12
	2	Split 3	9347 (93%)	0.35	0.47	6229	7
	2	Split 4	9133 (91%)	0.18	0.54	5557	4
	2	Resample	6143 (61%)	*NA*	0.53	7664	*NA*
	3	Split 1	9855 (99%)	0.17	0.24	6380	19
	3	Split 2	9643 (96%)	0.26	0.38	6323	11
	3	Split 3	9322 (93%)	0.34	0.48	6171	7
	3	Split 4	9234 (92%)	0.15	0.51	5661	5
	3	Resample	6495 (65%)	*NA*	0.51	7841	*NA*
	4	Split 1	9854 (99%)	0.15	0.24	6330	20
	4	Split 2	9636 (96%)	0.26	0.38	6270	11
	4	Split 3	9327 (93%)	0.34	0.48	6230	7
	4	Split 4	9128 (91%)	0.15	0.53	5612	5
	4	Resample	5969 (60%)	*NA*	0.53	7681	*NA*
YUCCAVALLEY	1	Split 1	9813 (98%)	0.17	0.27	6313	19
	1	Split 2	9665 (97%)	0.26	0.36	6250	11
	1	Split 3	9402 (94%)	0.36	0.46	6252	7
	1	Split 4	9212 (92%)	0.15	0.52	5488	5
	1	Resample	6407 (64%)	*NA*	0.51	7839	*NA*
	2	Split 1	9821 (98%)	0.15	0.26	6253	21
	2	Split 2	9657 (97%)	0.24	0.37	6250	12
	2	Split 3	9413 (94%)	0.35	0.46	6189	7
	2	Split 4	9032 (90%)	0.15	0.54	5412	5
	2	Resample	4942 (49%)	*NA*	0.53	7607	*NA*
	3	Split 1	9817 (98%)	0.20	0.26	6333	16
	3	Split 2	9666 (97%)	0.31	0.37	6244	9
	3	Split 3	9414 (94%)	0.29	0.46	6129	9
	3	Split 4	9029 (90%)	0.07	0.54	5467	11
	3	Resample	4902 (49%)	*NA*	0.53	7651	*NA*
	4	Split 1	9819 (98%)	0.12	0.26	6332	28
	4	Split 2	9665 (97%)	0.20	0.37	6233	15
	4	Split 3	9398 (94%)	0.29	0.46	6193	9
	4	Split 4	9157 (92%)	0.13	0.53	5411	6
	4	Resample	6095 (61%)	*NA*	0.52	7776	*NA*