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The Geography of Racially Polarized Voting: Calibrating Surveys at the District Level

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Debates over racial voting, and over policies to combat vote dilution, turn on the extent to which groups' voting preferences differ and vary across geography. We present the first study of racial voting patterns in every congressional district (CD) in the United States. Using large-sample surveys combined with aggregate demographic and election data, we find that national-level differences across racial groups explain 60% of the variation in district-level voting patterns, whereas geography explains 30%. Black voters consistently choose Democratic candidates across districts, whereas Hispanic and white voters' preferences vary considerably across geography. Districts with the highest racial polarization are concentrated in the parts of the South and Midwest. Importantly, multiracial coalitions have become the norm: in most CDs, the winning majority requires support from non-white voters. In arriving at these conclusions, we make methodological innovations that improve the precision and accuracy when modeling sparse survey data.

INTRODUCTION

The United States is a nation divided by color. Generations of social science have documented that the areas of the country with high Black and Hispanic populations, such as the Black Belt counties of the South or the Hispanic neighborhoods in southwestern cities, usually vote for candidates different than those who win in predominantly white areas (Davidson and Grofman 1994; Key 1948; Kousser 1974). Most scholarship attributes such differences to strong group identities and even animus between white and non-white groups (Dawson 1995; Grofman 1991; Kinder and Sanders 1996; King 1996). Yet other scholars identify instances where context and geography generate variation in group behavior (Enos 2017; Gay 2001; Gimpel et al. 2020; Hopkins 2010). It is difficult to gauge the relative importance of racial groups and of geography from aggregate data (Gelman 2009). The patterns that scholars think they see in aggregate election outcomes could, as Freedman et al. (1991) argued, be due to differences across neighborhoods instead of differences between groups.

This study uses survey data to offer the first nationwide assessment of racial voting patterns at the congressional district (CD) level. We find that racial groups, on average, vote differently from each other, but the differences across Black, Hispanic, white, and Other voters also vary across states and across CDs within states. Specifically, 60% of the variation in 2016 presidential vote shares at the district-racial group level is explained by national differences across racial groups. Variation across regions, states, and CDs explains another 30% of the variation, with CDs explaining twice as much variation as states do. Nearly everywhere, Black voters vote at high rates for Democratic candidates. The voting behavior of Hispanic voters and of white voters is far more variable across geography. At least as far as racial group voting is concerned, then, our results reveal that national divisions (Hopkins 2018; Kinder and Sanders 1996) are more prominent than local divisions (Cramer 2016; Gimpel et al. 2020).

One of the most striking features of contemporary politics that emerge is the degree to which both the Democratic and Republican parties rely on the support of white and minority voters. In most CDs, the winning candidate relied on some support from at least one non-white racial group in order to win a majority of votes. In two-thirds of Democratic-leaning districts, the Democratic majority consisted of combinations of Black, Hispanic, and white voters, with no single group determining the majority. In one out of five Republican-leaning districts, the white vote alone was not sufficient to reach a majority in 2016. Republican majorities in

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those districts depended on the Republican votes of Hispanic or other racial minorities.

Our study makes contributions in three fields: race and voting behavior, survey methodology, and election law. First, we contribute to the study of racial voting in the United States by providing the first comprehensive picture of racial group voting patterns across all CDs. This allows us to test competing claims about whether racial group differences in vote choice are explained by national groups or to the local context of where people live. Survey research has long documented national group differences: the 2016 Exit Polls estimate that about 60% of white voters nationwide voted for the Republican presidential candidate, whereas 92% of Black voters, 70% of Hispanic voters, and 70% of Asian voters voted for the Democrat. A lengthy literature argues that people have clear, distinct vote preferences that are rooted in racial group identities (e.g., Kinder and Sanders 1996). Increasingly, though, scholarship on race and American elections has emphasized the importance of geographic variation in voting behavior of racial groups (Cho 1995; Enos 2017; Erikson 2010; Gelman 2009), especially differences between urban and rural areas (McKee 2008; Rodden 2019), differences across counties (Acharya, Blackwell, and Sen 2018), and variation across districts (Donovan 2010). We show that racial groups are not monolithic in their voting behaviors (Cho 1995; Erikson 2010). We find that Black voters vote overwhelmingly Democratic regardless of where they live, but the voting preferences of white and Hispanic voters vary across regions, states, and, even, districts within states. That said, we show that the variation in district-level presidential voting behavior is explained primarily by differences across racial groups at the national level. In short, who people are is more important than where they live.

Second, we improve upon existing survey modeling methods by developing two new calibration techniques. Even large surveys such as exit polls suffer from insufficient sample sizes to estimate group behavior in each CD with much precision. Political scientists have recently deployed multilevel regression and poststratification (MRP) for small area estimation. MRP uses hierarchical modeling and calibration weights derived from population statistics to make subgroup estimates more precise (Gelman and Little 1997). However, the characteristics of the target population required for weighting are often not available (Leemann and Wasserfallen 2017). This is partly why MRP estimates for political polls can still be unrepresentative of small areas (Lauderdale et al. 2020). We create demographic weighting targets of the electorate at the district level using a technical innovation we call survey-assisted synthetic target estimation. This improves weighting estimates to the distribution of race, age, sex, and education within the actual electorate of each district. Furthermore, we develop a two-way survey calibration, which simultaneously calibrates estimates to both election results by geography and an external survey, instead of only to geography (e.g., Ghitza and Gelman 2013; Rosenman, McCartan, and Olivella 2023). This adjustment reduces the bias in the estimates of group voting behavior at the CD level that is due to unobservable selection bias in the survey.

Third, our analysis informs ongoing debates over election laws and voting rights. Measuring the extent of racially polarized voting has been social science's key contribution to the development of election laws designed to protect minority voters (Pildes 2002). Significant questions remain as to where and how the law ought to apply. If voting patterns largely reflect national group differences, then a broad national policy is the best approach to fight vote dilution, as some have argued (Cain and Zhang 2016; Charles and Fuentes-Rohwer 2014). If a racial group's preferences vary substantially across geography, then a narrowly tailored approach to the law may be more effective and appropriate, as in the case of *Alabama Legislative Black Caucus* v. *Alabama* (2015). Almost all of the prior scholarship stops at state-level estimates (Ansolabehere, Persily, and Stewart 2010; 2013; Shaw 1997; Smith, Kreitzer, and Suo 2020; Stephanopoulos 2016). Only Elmendorf and Spencer (2015) and Ghitza and Gelman (2020) provide estimates at the county level, but those analyses do not apply to the most common application—redistricting. Our findings regarding the substantial national division in racial voting patterns and the variations across areas point to the need for both a broad national approach and some degree of narrow tailoring to particular districts and areas.

MEASURING VOTE CHOICE BY RACE USING SURVEYS

Social scientists frequently seek to measure how individual behavior varies across geographic areas and demographic subgroups. Aggregate data alone cannot distinguish how much of the variation is attributable to differences across demographic groups or variation across levels of geography. Ecological inference techniques attempt to infer the characteristics of groups by studying how aggregate outcomes vary by the composition of the group in each aggregate unit. In doing so, standard ecological inference assumes that variations in the behavior of a racial group in different geographies are independent of the composition of the group (Ansolabehere and Rivers 1995; Cho 1998; Freedman et al. 1991, see also Appendix A.4 of the Supplementary Material for a formal exposition). Moreover, ecological inference struggles to identify any estimate at all in districts where racial groups are highly integrated within all precincts. Our study estimates the contributions of racial groups and geography directly using individual-level survey data, rather than making assumptions about the structure of aggregate data.

Quantities of Interest

Our central quantity of interest is the share of a candidate's support among a particular racial group in a particular district. Let $i \in \{1, \ldots, N\}$ index all individual voters who voted for a Republican or Democratic presidential candidate. We index the voter's racial group as $g \in \{1, \ldots, G\}$, and CDs as $j \in \{1, \ldots, J\}$ with $J = 435$. We let $\mathcal{I}_{gj}$ denote the set of voters with race g in district j, and N_{gj} denote the total number of such voters. A voter has $Y_i = 1$ if they voted for the Republican candidate, and $Y_i = 0$ if they voted for the Democratic candidate. We are interested in the Republican vote share in each racial group in each CD,

$$\tau_{gj} = \frac{1}{N_{gj}} \sum_{i \in \mathcal{I}_{gj}} Y_i.$$

To report racial group differences, we then define the racial gap in district j between whites and a non-white racial group g as

$$\text{Racial Gap}_{gj} = \tau_{\text{white},j} - \tau_{gj}. \tag{1}$$

Voting is racially polarized if the vote shares of white and non-white groups are on the opposite sides of 50%.

Survey Data

We use the 2016 Cooperative Congressional Election Study (CCES) and 2020 Cooperative Election Study (CES). These surveys interview over 60,000 respondents nationwide and validate records by matching them to vote histories available from voter registration data. It is one of the largest political surveys of American Politics and contains the information necessary for our model: vote choice, CD, turnout matched from the voter file, racial group identification, and other demographics.

Throughout this study, we group race into four categories: $g \in \{\text{White, Black, Hispanic, All Others}\}$. Black is used interchangeably with African American and Hispanic is used interchangeably with Latino in our analysis. As with the U.S. Census, the CCES asks Hispanic ethnicity as a separate question from race. Respondents who are "any-part" Hispanic are coded as Hispanic (see Appendix A.2 of the Supplementary Material for more details of the survey and question wording). In the 2016 CCES, about 2% of white respondents and about 2% of Black respondents also identified as Hispanic. Coding these respondents as Hispanics rather than whites or Blacks typically increases the estimated Republican vote among the Hispanic group by 2 percentage points and decreases the estimated Republican vote of whites and Blacks by a few tenths of a percentage point. Separating voters in the "Other" categories into Asian, Native American, and multiracial respondents requires even more data than are available with the CCES and Census surveys. We replicate our analysis for Asian American voters limited to four states where they comprise over 10% of the population (Appendix B of the Supplementary Material).

Our outcome of interest is the respondent's self-reported vote in the election for President in each year. We focus on the office of President in this study because it is the only ticket elected nationwide, and our goal is a 50-state, 435-district comparison of voter preferences between the same set of contesting candidates. Party choice across votes for U.S. Senate, U.S. House, and Governor within a single respondent may differ, though less so in the modern era (Jacobson 2015; Kuriwaki 2021). We limit our analysis to validated voters, who are respondents whose personally identifiable information records have been matched to public voter rolls. We also limit our analysis to those who reported voting for a major party presidential candidate. The choice to drop third-party voters is in part for the convenience of modeling the outcome as a binary variable, but also for comparability across states and districts. Working with vote shares as a proportion of the two-party vote is also desirable because the two-party vote decides who wins the district or state. Thus, we focus on a subset of $n = 28,462$ of the entire CCES in 2016 and $n = 34,539$ for 2020.

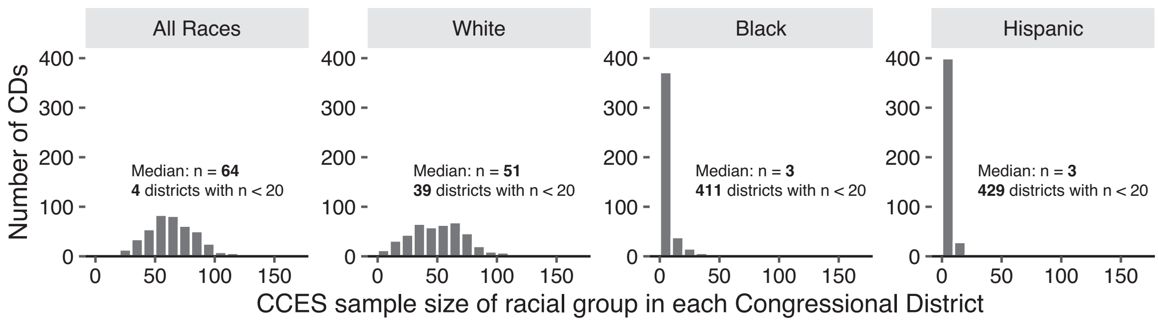
Challenges in Survey Inference

Even with large surveys, including exit polls and the CCES, the number of observations for substate-level geographies is still too small to estimate with precision individual-level variables within districts. In the subsample of the 2016 CCES studied here, the median sample size validated to be voters per CD is $n = 64$ and the median district only includes $n = 13$ voting respondents who are non-white (Figure 1). Recently, researchers have studied similarly sized samples in counties to draw inferences about racial groups' preferences in substate-level geographies (Acharya, Blackwell, and Sen 2018; Kuziemko and Washington 2018). Inferences from small subgroups can be dangerously misleading (Ansolabehere, Luks, and Schaffner 2015). Even with a sample of $n = 50$ in each group, the margin of error in the difference in proportions of those two groups is roughly 20 percentage points with a simple random sample, making any comparison uninformative. Hierarchical modeling proposed here offers a potential solution.

Another challenge for survey data is that the sample of each race and district subgroup may be unrepresentative of the population counterpart (Grimmer et al. 2018). The CCES release includes poststratification weights that render its state subsamples representative of each state. However, these weights have no guarantees of making *district* subsamples representative of each district and may only increase variance while failing to eliminate selection bias (Kuriwaki 2021, chap. 4).

Some summary statistics of the population are known. A CD's composition of race and other demographics of adult citizens are reported by high-quality Census surveys. The total presidential vote in each district, across all races, is also known from election results. We model the noisy and potentially unrepresentative survey data to improve the estimate of the quantity of interest τ_{gj} by calibrating to Census statistics and electoral results.

FIGURE 1. Sample Sizes in Each Congressional District in the 2016 Cooperative Congressional Election Study



Note: Samples are limited to validated voters who report voting for Donald Trump or Hillary Clinton, which we use in the survey model.

CALIBRATING SURVEYS AT THE DISTRICT LEVEL

Estimation proceeds in three steps: (1) conduct a hierarchical regression to predict the probability of a Republican vote in each geographic and demographic subgroup, (2) weight these probabilities to the estimated population size of these subgroups, and (3) calibrate these estimates to external targets at higher levels of aggregation. Steps (1) and (2) together constitute MRP (Gelman and Little 1997). Dozens of studies, including many that use the CCES, have implemented MRP to estimate subgroup political behavior at the national or state level (e.g., Broockman and Skovron 2018; Elmendorf and Spencer 2015; Hertel-Fernandez, Mildenberger, and Stokes 2019; Lax and Phillips 2009; Warshaw and Rodden 2012).

We make two innovations to existing MRP methods. First, we develop in step (2) a method of *survey-assisted synthetic target estimation* that combines partially available Census statistics into a single joint distribution. Poststratification in prior MRP work has been limited by the lack of population variables jointly available in off-the-shelf datasets. Using our method, we can guarantee through weighting that the estimates are representative of the age group, sex, race, and education level of the population (according to the American Community Survey [ACS]) and the turnout rate in every CD. But this weighting may still be incomplete because of unmeasured selection bias. Second, we develop in step (3) a method of *two-way calibration* that matches targets both by geography and racial group, further reducing the potential bias in our estimates.

We generate estimates for both the 2016 CCES and the 2020 CES. Because there are no substantive differences in the methodology, we use the 2016 data as the running example and present 2020 results in Appendix C of the Supplementary Material. In addition, we offer a validation analysis of voter registration by party and race in the state of Florida to show the accuracy and coverage of our approach compared to only using precinct-level aggregate data (ecological inference).

Hierarchical Regression

Traditional survey weights assign weights to each subgroup of respondents based on the demographic composition of the population within specific strata (such as states, regions, or districts). The estimated average vote Y among subgroups of respondents may be highly imprecise because subgroup samples within strata become very small. MRP compensates for the sparsity of data within strata samples by borrowing information across strata about particular groups. We estimate a hierarchical regression that returns the probability that voters in district j of race g and of a certain age, sex, and education vote for the Republican in a given year. The model applies a shrinkage estimator to impute these probabilities even for demographic combinations for which few respondents exist, respecting the geographic grouping of districts. This first step of our process is similar to the approach in Ghitza and Gelman (2013; 2020).

Our model takes the form

$$\Pr(Y_i = 1) = \operatorname{logit}^{-1}\Big(\alpha_{j[i]} + \beta_{1j[i]}\text{Black}_i + \beta_{2j[i]}\text{Hispanic}_i + \beta_{3j[i]}\text{Other}_i + \boldsymbol{\zeta}_{j[i]}^{\top}\mathbf{W}_i\Big), \tag{2}$$

where the notation $j[i]$ denotes the district that respondent i resides in; the indicator variables Black_i, Hispanic_i, and Other_i equal 1 if respondent i is of that race (with white as the omitted baseline); and $\mathbf{W}_i$ are individual-level predictors of education, age group, sex, and the interaction of education and race. The function $\operatorname{logit}^{-1}(\cdot)$ is the inverse logit function and transforms an unbounded value to a probability scale between 0 and 1.

Importantly, this model specifies a hierarchical structure to the coefficients. We allow the coefficients to vary across CDs and as a function of the demographic composition of the districts. The intercept $\boldsymbol{\alpha}$ is a batch of 435 coefficients with each value representing a district, rather than a single national intercept for all voters.

We further encoded geographic hierarchy into these coefficients. Districts are nested within states and states are nested within divisions, as follows:

$$\alpha_j \sim \mathcal{N}\left(\alpha_{\text{state}[j]} + \boldsymbol{\rho}^\top \mathbf{V}_j, \sigma^2_{\texttt{cd}}\right),$$
$$\alpha_{\text{state}} \sim \mathcal{N}\left(\alpha_{\text{division[state]}}, \sigma^2_{\texttt{state}}\right),$$
$$\alpha_{\text{division}} \sim \mathcal{N}\left(\alpha, \sigma^2_{\texttt{division}}\right),$$

where district-level variables $\mathbf{V}_j$ contain a spline expansion of the Republican presidential vote share in district j (Daily Kos 2021) and the proportion of white voters in district j. The coefficients $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, $\boldsymbol{\beta}_3$ are each batches of coefficients that represent the difference in Republican vote among racial minorities relative to white voters. These also vary by CD. Here, we specified the coefficient structure so that the values are centered to a national-level coefficient for each race shifted by the contextual effect of the group's population size in the district.[1] Including the racial composition of the CD incorporates what the ecological inference literature calls linear contextual effects (Appendix A.4 of the Supplementary Material). The coefficients $\boldsymbol{\zeta}$ on other covariates have a similar structure, but with the division-level parameter being centered at 0.

We estimate the model with a Bayesian framework using the `brms` interface (Bürkner 2017; Stan Development Team 2021). We index posterior Monte Carlo samples from the model as $m = 1, \ldots, M$ and we retained $M = 2,000$ thinned samples across four chains. The full specification of the implementation is described in Appendix A of the Supplementary Material.

The modeling literature refers to this structure of modeling coefficients as random effects, with $\boldsymbol{\alpha}$ called random intercepts, and $\boldsymbol{\beta}$ and $\boldsymbol{\zeta}$ called random slopes (Gelman and Hill 2006). Random effects use sparse data effectively by shrinking estimates toward a state, regional, or national estimate. If there is no geographic variation, our model reduces to the standard logistic regression with district-level vote share and national racial group differences (Ghitza and Gelman 2013, 765).

The specification of the model, clearly, can affect estimates. We examined a range of specifications through iterative model building (Gelman et al. 2020). We found that models with race coefficients varying by district lead to more variability in the final estimates than models that let race coefficients vary by region. For example, the choice of specification affected the estimates for Hispanics by 6–10 percentage points.

[1] For instance, the batch of coefficients for Black voters are drawn from a similar geographic hierarchy as the $\boldsymbol{\alpha}$ terms: $\beta_{1j} \sim \mathcal{N}\left(\beta_{1,\text{state}[j]} + \gamma \mathbf{X}_j, \nu^2_{\texttt{cd}}\right)$, $\beta_{1,\text{state}} \sim \mathcal{N}\left(\beta_{1,\text{division[state]}}, \nu^2_{\texttt{state}}\right)$, $\beta_{1,\text{division}} \sim \mathcal{N}\left(\beta_1, \nu^2_{\texttt{division}}\right)$, such that the coefficients are ultimately centered on a value β_1, a national-level average difference between Black and white voters. Here, $\mathbf{X}_j$ is the proportion of Black voters in district j. The coefficients $\boldsymbol{\beta}_2$ and $\boldsymbol{\beta}_3$ follow a similar structure. N denotes the Normal distribution.

Survey-Assisted Synthetic Target Estimation

We develop a new algorithm for computing the target population. Standard MRP takes the weighted average of the predicted outcome from the hierarchical model, with weights designed to make the sample representative of demographics in the district. Doing so requires knowing the target distribution, or population size, of each [age × sex × education] group for each [race × CD] combination. Unfortunately, no such table of data is available from the U.S. Census. The Current Population Survey from the Census does not produce statistics at the CD level. The ACS, the largest survey conducted by the Census, provides a table of the population for each [age × sex × education× CD] combination and a table of [race × CD], but not the joint table of the five variables (Appendix A.5 of the Supplementary Material). In fact, no such weighting target has been provided by public MRP studies.

We therefore develop an algorithm—survey-assisted synthetic target estimation—for fusing together two ACS tables and construct a table of [age × sex × education × race × CD]. The current recommendation in the MRP literature is either to avoid modeling by assuming independence between the covariates or to take survey estimates of the joint distribution at face value (Kastellec et al. 2015; Leemann and Wasserfallen 2017). Both the survey data and known marginal constraints inform the joint distribution. Specifically, we estimate a multinomial regression predicting the four categories of education from race, age, and sex on survey data, with a constraint that the implied marginal distribution of education from that regression matches the education composition in each CD as reported in the ACS.[2] The constraint is imposed simultaneously with estimation, instead of applied after fitting the regression (Ghitza and Steitz 2020). This algorithm, available in the `synthjoint` R package, will improve future implementations of MRP and of survey weighting generally as it offers a solution to the limited release of Census tables.

The ACS statistics we use are for the general adult population (i.e., the voting age population), not for voters. We, therefore, repeat the survey-assisted synthetic target estimation and model the turnout rate within each demographic cell. The turnout model involves predicting validated vote among CCES voters and nonvoters with education, race, age, and sex, with a constraint that the implied turnout rate matches the actual turnout rate in each CD.

Our synthetic target estimation produces a turnout-adjusted [age × sex × education] table of population

[2] Formally, let Z be a categorical variable for education and let $\mathbf{X}$ be the demographic predictors. The marginal distribution of Z and the joint distribution of $\mathbf{X}$ are given by the ACS, but the joint distribution of Z and $\mathbf{X}$ is unknown. A regression of Z on $\mathbf{X}$ in the survey produces fitted probabilities $\widehat{\Pr}(Z|\mathbf{X})$ and allows us to compute the joint. We estimate this regression but with the constraint that $\sum_{\boldsymbol{x}} \widehat{\Pr}(Z|\mathbf{X} = \boldsymbol{x}) \Pr(\mathbf{X} = \boldsymbol{x})$ matches $\Pr(Z)$ for every district up to a small tolerance. Appendixes A.6 and A.7 of the Supplementary Material describe the estimation strategy and the specification in this example.

sizes for each [race × CD]. Formally, we index a cell in the table for a given race × CD combination by $s \in \mathcal{S}_{gj} =$ [age × sex × education], so that N_{gjs} denotes the population size of each cell s for racial group g at CD j. Each posterior sample m of the estimated coefficients in the hierarchical model provides predicted probabilities of the Republican vote share in each cell, denoted $\hat{\pi}^{(m)}_{gjs}$. Then, we poststratify cell estimates by weighting them proportional to its associated size in the population:

$$\hat{\tau}^{(m)}_{gj} = \sum_{s \in \mathcal{S}_{gj}} \frac{N_{gjs}}{N_{gj}} \hat{\pi}^{(m)}_{gjs}. \tag{3}$$

This approach does not rely on acquiring a voter file or using estimates of race or education, such as Ghitza and Gelman (2020). Self-reported race is only available in the voter files of six states, all of them in the Deep South, and education is never available. Furthermore, the survey-assisted synthetic target algorithm is open-source; it does not rely on proprietary data or algorithms.[3] Appendix A.3 of the Supplementary Material describes the specifics of this modeling.

Two-Way Calibration to Election Results and External Surveys

MRP also assumes ignorable selection into the survey conditional on available covariates (Si 2023). Violation of those assumptions would yield biased estimates (Buttice and Highton 2013). Standard MRP cannot control for a variable that is not measured in the weighting target.

To adjust for selection bias that may remain even after poststratification, we calibrate the MRP estimates from Equation 3 so that the implied district vote matches the actual Republican presidential vote share in each CD, and the implied vote choice by race matches an external national estimate. For example, we can sum our estimates across racial groups as $\hat{\tau}_j = \sum_{g=1}^{G} (N_{gj}/N_j)\hat{\tau}_{gj}$ and denote the actual Republican vote share in district j as τ_j. Here, τ_j is a target and both $\hat{\tau}_j$ and τ_j are observable. We do not observe a target for our main quantity of interest τ_{gj}, but any observed difference between $\hat{\tau}_j$ and τ_j can be due to bias in our estimates $\hat{\tau}_{gj}$ that does not cancel out when aggregated.

Existing work proposes to shift each estimate by a constant so that the implied sum matches an election result (Ghitza and Gelman 2013; Rosenman, McCartan, and Olivella 2023). Unfortunately, such a one-way calibration may make the estimates of the racial gap $\tau_{\text{white},j} - \tau_{\text{black},j}$ even more biased if the estimates of each race-specific vote share are biased in opposite directions. We find that this is precisely the case in the Florida subset of the CCES we use for validation in the subsequent section.

A two-way calibration adjusts the estimates to a racial group target at the national level (i.e., targets τ_g), in addition to targeting the district-level election results. It imposes two sets of additive corrections to the MRP estimates $\hat{\tau}_{gj}$,

$$\tilde{\tau}^{(m)}_{gj} = \text{logit}^{-1}\left(\text{logit}(\hat{\tau}^{(m)}_{gj}) + \hat{\delta}^{(m)}_{g} + \hat{\delta}^{(m)}_{j}\right),$$

where δ_g denotes the racial group correction and δ_j denotes the geographic correction. The optimal values of the correction minimize the sum of squared deviances at the national and district levels:

$$\hat{\boldsymbol{\delta}}^{(m)} = \underset{\boldsymbol{\delta}}{\arg\min} \left\{ \sum_{g=1}^{G} \frac{N_g}{N} \underbrace{\left(\tau_g - \sum_{j=1}^{J} \frac{N_{gj}}{N_g} \text{logit}^{-1}\left(\text{logit}\left(\hat{\tau}^{(m)}_{gj}\right) + \delta_g + \delta_j\right)\right)^2}_{\text{Deviation from racial group target for race } g} + \sum_{j=1}^{J} \frac{N_j}{N} \underbrace{\left(\tau_j - \sum_{g=1}^{G} \frac{N_{gj}}{N_j} \text{logit}^{-1}\left(\text{logit}\left(\hat{\tau}^{(m)}_{gj}\right) + \delta_g + \delta_j\right)\right)^2}_{\text{Deviation from geographic target for district } j} \right\}.$$

In other words, for each posterior sample m, we identify the correction factors that make all the weighted sums of adjusted quantities $\tilde{\tau}^{(m)}_{gj}$ match the known election result τ_j and external estimate by racial group τ_g as close as possible. We estimate these corrections through numerical optimization.

We use the presidential vote share at the CD level as district-level targets τ_j and use the national estimates of vote choice reported by Catalist as the race-level national targets τ_g. The Catalist targets are similar to the National Exit polls. Appendix B of the Supplementary Material presents and compares these targets. The Catalist estimates of the Hispanic vote is about 2–3 percentage points more Democratic than the CCES before this calibration.

The mean of each posterior sample's calibrated estimate, $\tilde{\tau}_{gj} = \sum_m \tilde{\tau}^{(m)}_{gj}/M$, represents our best estimate of the vote choice for a specific racial group in a specific district. Our method guarantees that this estimate is (a) computed from a sample that is representative of each CD electorate's joint composition of sex, age, education, and race up to estimation error in the weighting target and (b) further calibrated so that the estimates for each racial group approximately sum to known election results in the district or at higher levels of geography.

In the 2016 example, the one-way calibration to election results shifts the estimates of white voters' Trump vote up by 4 percentage points on average and shifts the estimates among Hispanics up by 1 percentage point, although some districts are shifted in the opposite direction (Appendix A.10 of the Supplementary Material). The two-way calibration shifts the one-way calibrated white vote up even further toward Trump by 1 percentage point and pulls the Hispanic vote down by 5 percentage points. These differences suggest that the underlying survey data underrepresented Trump voters in most places even after weighting, but that pattern further varied across racial groups.

[3] Poststratification tables for years other than 2016 and 2020 are also available in the Dataverse (Kuriwaki et al. 2023a).

Evaluation and Validation

It is impossible to validate these methods for vote choice directly because individual votes are not observed. Voter registration statistics in the state of Florida offer an excellent opportunity for evaluating the accuracy of our approach (de Benedictis-Kessner 2015). Florida and North Carolina are the only states that record voter registration by party and by race, and their data are publicly available. Party registration in Florida is highly correlated with Trump vote at the precinct level. In the CCES, 83% of registered Republicans in Florida report voting for the Republican President, whereas only 50% of registered voters with no party affiliation voted for Trump. We choose to study Florida as the state has substantial Black, Hispanic, and white populations and a large number of districts.

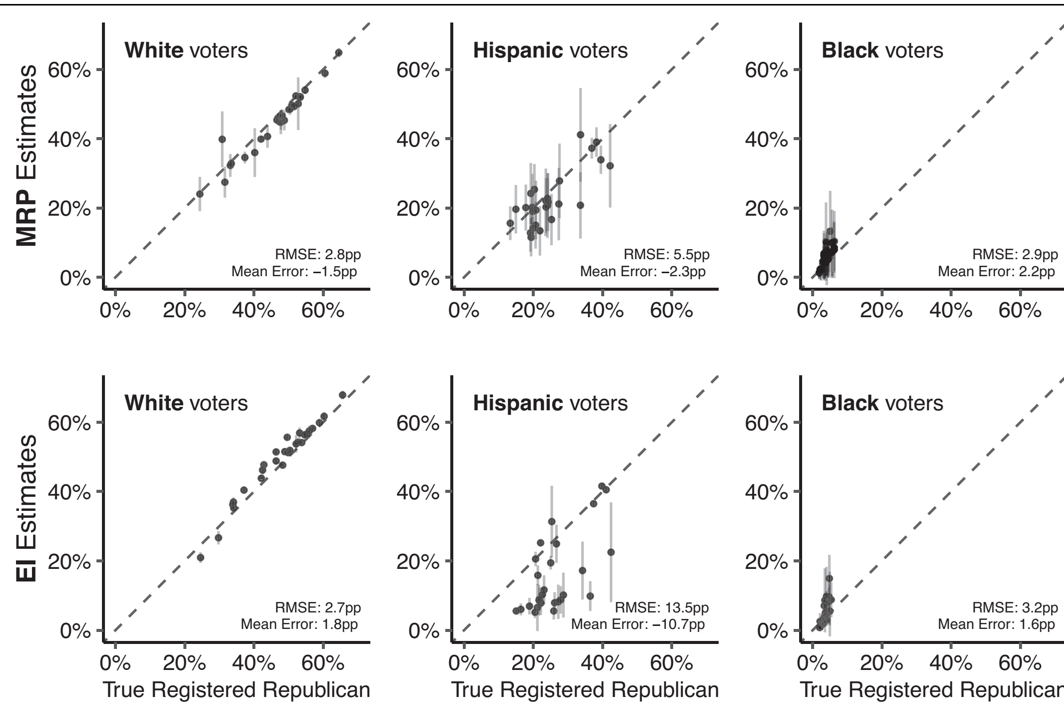
We follow the same methods and the poststratification target as our main analysis and refer to our estimates as the MRP estimates. Instead of modeling the Trump vote in the hierarchical regression stage, we model whether or not the respondent's validated voter registration records them as a Republican registrant. We use the subset of our survey respondents who are in Florida because unlike the Trump vote, only some states record party registration on their voter files. This means that we partially pool across districts within Florida, which vary in their racial and partisan characteristics.

We also perform a validation with ecological inference (EI) using precinct aggregate data, which is the dominant method used to study vote choice by race. We acquired an aggregate dataset recording the racial composition and the party registration composition in each Florida precinct. The average CD in these data is represented by two hundred precincts and the median precinct includes 1,300 voters (details of the dataset are in Appendix B.3 of the Supplementary Material). We ran a standard multinomial ecological inference model (Collingwood et al. 2016) with the same four racial categories as MRP and three party categories (Republican, Democrat, and all other parties with Non-Party Affiliated). We run a separate model from each district, using that district's precincts only.

We find that our method produces reasonably accurate estimates and reasonable measures of uncertainty. Moreover, these estimates have better coverage properties than a standard ecological inference method (EI) that has access to data on the entire population aggregated into precincts. Figure 2 compares Republican registration share for a racial group in a CD on the x-axis with the corresponding estimates from our MRP method and traditional EI in the y-axis. Each graph shows the root-mean-square error (RMSE), which captures the total error across all districts, and the mean error, which distinguishes whether these errors systematically tend to overestimate or underestimate.

Our survey-based estimates and EI have similarly sized error in estimating the Republican registration of white voters, with an RMSE of around 3 percentage

FIGURE 2. Validation of MRP and Ecological Inference Models in Florida



Note: Each model predicts the proportion of each racial group electorate in each congressional district that is registered Republicans. Statistics in each facet show Root-Mean-Square Error across districts and the Mean Error (estimate minus truth) across 27 districts. Uncertainty intervals are 80% credible intervals. See Appendix B.3 of the Supplementary Material for detailed methodology.

points. However, the errors go in opposite directions: our survey-based approach tends to underestimate the Republicanness, whereas EI tends to overestimate. For Hispanic voters, our estimates outperform EI estimates more than twofold (an RMSE of 5.5 percentage points vs. 13.5 for EI estimates). Using the survey methods developed here, thus, indicates promise in estimating more accurately the voting preferences for groups. Using ecological inference can lead to substantively different conclusions about racial cohesion and polarization and tends to show higher levels of polarization than do the survey data.

Survey estimates using hierarchical regression quantify uncertainty reasonably well, while the confidence intervals for EI are too tight. For all four racial groups, the 80% confidence intervals of each of our survey-based estimates cover the true value in 78.7% of 108 district × race combinations. The 80% confidence intervals of the EI estimates cover the true value in only 38% of the 108 estimates. The lack of coverage for EI owes partly to the inaccuracy of EI for Hispanic registrants and partly to the fact that the standard errors are overly tight for Black and white registrants. Appropriately calibrating survey data using our three-step approach, then, can lead to more accurate estimates and inferences than traditional survey data with weights or aggregate data methods such as EI. We leave to further research the questions of diagnosing issues with EI and how applications of that method might be improved. Although our method, and MRP, in general, does have its own estimation errors, we rely on individual-level data and can provide reasonably accurate estimates of the relationship between race and vote choice.

Our validation using data from Florida is the best setting for a comparison of the accuracy of EI and our survey-based approach. However, in Appendix B.4 of the Supplementary Material, we obtain EI estimates for all 435 districts based on election data produced by the Voting and Election Science Team (2020) and precinct-level race statistics from the 2020 Census prepared by McCartan et al. (2022), and show where our estimates differ. In the average district, EI differs from our survey estimates by over 10 percentage points for white voters and Black voters, and over 20 percentage points for Hispanic voters.

THE POLITICAL GEOGRAPHY OF VOTE CHOICE BY RACE

The estimates offer a nuanced picture of the geography of racial voting preferences. Consistent with the group voting literature, Black voters overwhelmingly prefer Democrats and that preference does not appear to vary by geography. Consistent with the perspective that geography and context matter, the preferences of white and Hispanic voters vary considerably with place.

The Racial Gap at the District Level

The gap between white and non-white voting preferences varies considerably across the United States. Figure 3 maps the racial gap between white and all non-white voters (defined in Equation 1) from our final estimates. Because CDs are roughly equal in population but vary in land area, we use the cartogram by Daily Kos that sizes districts equally while approximating each district's location within a state.[4]

The dark red area of the map, centered in Louisiana, Mississippi, and Alabama, are the CDs that exhibit the highest racial gaps, in excess of 60 percentage points. The seven highest racial gap estimates all appear in Mississippi and Alabama. In these districts, the gap between white and non-white voters is close to 70 percentage points.

The districts with the lowest racial gap tend to be urban areas. In 2016, the five least polarized districts include NY-12 (East side of Manhattan and parts of Queens[5]), CA-12 (San Francisco, represented by Speaker Pelosi), CA-13 (Oakland, Rep. Barbara Lee [D]), and WA-07 (city of Seattle, Rep. Pramila Jayapal). In these districts, the racial gap ranges from 6 to 8 percentage points. The distribution of the racial gap is skewed, with large racial gaps in the Deep South pulling the average district's racial gap to be about 2 percentage points higher than the median district (Appendix C of the Supplementary Material).

Although the deep red parts of the map are visually striking, the interpretation of the gap and its magnitude depends on the context. A racial gap of 35 percentage points would arise from an electorate in which 70% of white voters vote for the Republican and 35% of non-white voters vote for the Republican candidate. Such a situation exhibits racially polarized voting and may require creation of a majority minority district under Section 2 of the VRA. However, a CD in which 95% of non-whites vote for Democratic and 60% of whites vote for Democratic has a similarly large racial gap (35 points) but is not racially polarized, because a majority of both groups prefer the same candidate.

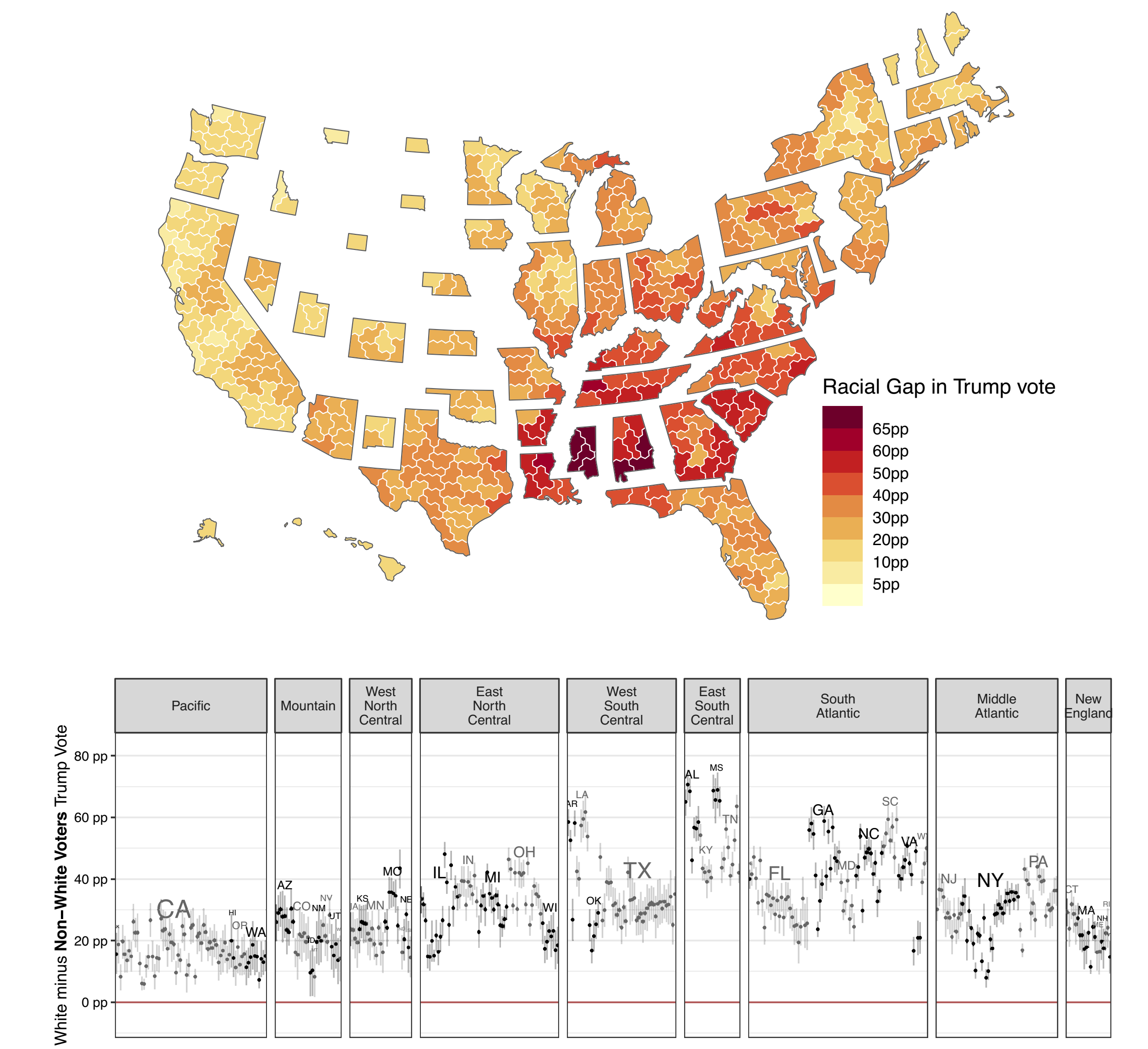
Disaggregation by district highlights the variation within a state. For example, Chicago and the northern parts of Illinois have the lowest racial gap estimates in the Midwest, but districts in Southern Illinois adjacent to St. Louis have racial gaps as high as those in Tennessee and TX-01 (northeastern Texas, represented by Rep. Louie Gohmert). A similar pattern occurs in Virginia, where the DC suburbs of VA-08, VA-10, and VA-11 have low racial gap values similar to the Boston suburbs, but other Virginia districts have racial gap values that are in the top quarter of all districts.

From coast to coast, the racial gap rises in the Midwest and the South and falls again in New England. The bottom panel of Figure 3 shows the same estimates of

[4] As a result, locations are not exact. For example, districts in New York City are placed closer to upstate New York because there are too many NYC districts to fit in the southeast corner. The correspondence between polygons in this map and each district is given in Appendix C of the Supplementary Material. Substantively interpretable names of those districts (e.g. East Bronx) are given in the estimates in Dataverse, https://doi.org/10.7910/DVN/MAZNJ6.

[5] Throughout the article, we refer to the geographies and representatives as of 2021.

FIGURE 3. Racial Gap between White and Non-White Voters



Note: Colors in each congressional district show the point estimate of the estimated racial gap in the 2016 Republican vote between whites and non-whites in that district (Equation 1). The map is displayed in the Daily Kos cartogram (http://dkel.ec/map): Districts are placed in their approximate place within the state and states are sized by their population. In the bottom panel, each district point estimate is represented by a point on the vertical axis. Districts are sorted first by Division in facets (from West to East), then by state (alphabetical within Division), and then by district number. States are annotated and alternatively colored black and gray for visual clarity.

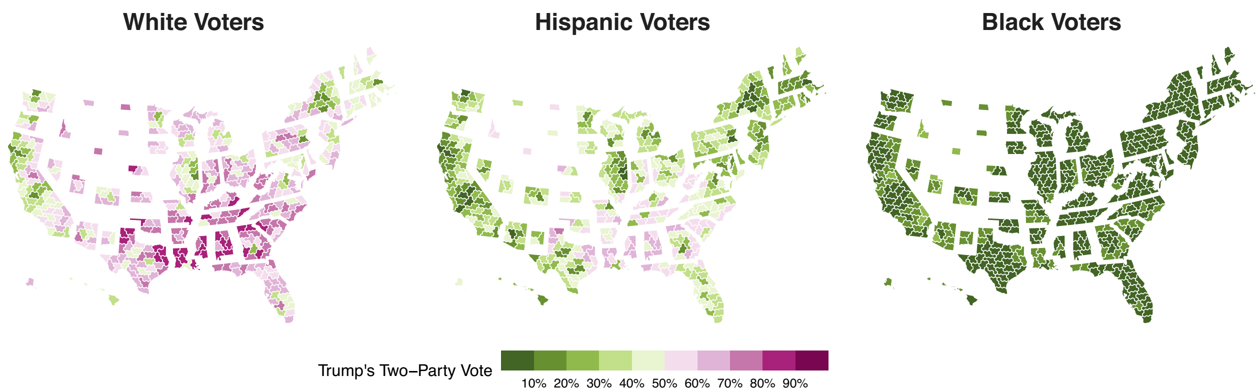
differences on a common vertical axis and shows the 80% credible interval for the uncertainty in the estimates. None of the districts have intervals that include zero.[6] In 2020, the racial gap was 7 points smaller and 5 out of 435 districts had intervals including zero (Appendix C of Supplementary Material).

Group Cohesion

The variation in the racial gap between white and non-white voters is largely driven by white voters and Hispanic voters. Black voters cohesively vote for the Democratic party in all CDs. Here, we examine the cohesiveness of each group nationally and across districts, states, and regions. Figure 4 decomposes the cohesion estimates of vote choice into the two-party vote share by the three major racial groups.

[6] We compute the 80% credible interval of the difference in $\tilde{\tau}_{\text{white},j}$ and non-white vote $\tilde{\tau}_{g,j}$ by taking the 10th and 90th quantiles of the 2,000 posterior sample estimates of differences. The posterior distribution also allows us to account for the dependency between the white vote and the minority vote conditional on a district, which could be positively or negatively correlated and violate the standard assumption in two-sample t-tests.

FIGURE 4. 2016 Republican Vote by Racial Group in Congressional Districts



Note: Each district is colored by the estimated two-party vote share for the Republican presidential candidate.

The voting tendencies of white voters in the urban areas of California, New York, and Illinois are a stark contrast to white voters in the Deep South, where over 80% of white voters voted for Trump. Hispanic voters also exhibit high levels of variation. Hispanic voters in Southern Florida are more Republican than the Hispanics in San Francisco or Chicago. Among districts where over 40% of the electorate is Hispanic, the district in which the Hispanic voters are the most Republican is FL-25, which has the largest Cuban American population in the United States and is represented by Rep. Díaz-Balart (R).

We use the term *cohesion* to refer to the voting behavior of a group (Atsusaka 2021; Pildes 2002). Cohesion equals the absolute deviation of the point estimate of the percentage of a group that votes for the Republican from 50%. For example, white voters voting 85% for Donald Trump will have the same cohesion value as Hispanic voters voting 15% for Trump: 35 percentage points. Figure 5 shows the range of these district cohesion scores for white, Hispanic, and Black voters. Black voters are highly cohesive in their preferred candidate, whereas Hispanic and white voters show considerable variation in the degree of cohesion across CDs. In 400 districts, Black voters' cohesion is over 0.35 (i.e., 85% vote for one party); white voters have the same level of cohesion in only 13 districts and Hispanic voters in only 35. Using ecological inference on precinct-level election data produced higher cohesion estimates for white voters (by 6 percentage points on average) and Hispanic voters (12 percentage points), with lower cross-district variance.

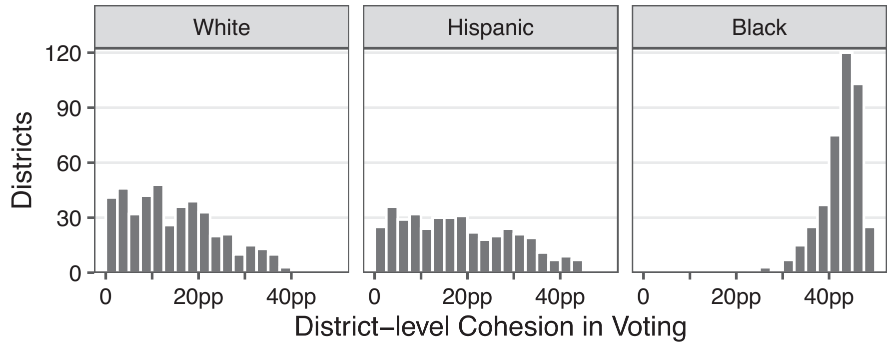
Our goal is to measure the magnitude and patterns of racial group preferences, not to explain their source.[7] Nonetheless, it is worth noting that there is a clear urban–rural gradient evident in Figure 4. Our estimates reveal a substantial difference between the most urban and most rural CDs among white voters and among Hispanic voters. White voters in urban districts are more Democratic than white voters in suburban districts, and even more so than white voters in rural districts. That pattern is consistent with research on group preferences as a function of ZIP code density and distance to large cities (Gimpel et al. 2020) and it is consistent with the notion that voting rights law needs to be narrowly tailored to the voting patterns in particular areas. Even still, within urban, suburban, and rural CDs, a 20-percentage point difference between white and Hispanic voters remain. Substantial racial group differences, then, are not just a matter of where people live.

Districts are, in turn, nested within states and regions. Table 1 shows our point estimates of vote by race at the national level, then separates this estimate to the four U.S. Census regions, then by the nine Census divisions, and then by each of the 50 states. Our statewide and national estimates differ from other surveys such as the National Exit Polls by only a few percentage points (Appendix B of the Supplementary Material).[8] Our procedure increases the precision, that is, decreases the standard error, in subgroup estimates, relative to the raw or poststratification-weighted survey data at the CD or state level. The standard error of our state-level estimates ranges from about 0.005 to 0.10, inversely proportional to the size of the group (Appendix C.4 of the Supplementary Material). For example, there are roughly $n = 300$ Alabama voters in our survey data, a quarter of whom are Black. That implies a standard error of about 0.033 for white voters in Alabama and 0.06 for Black voters when the sample is taken as-is with no modeling. The comparable standard error of our modeled estimates is about 0.01 for white voters and 0.023 for Black voters.

[7] Work that seeks to explain geographic or racial variations in preferences highlight place-based identities (Cramer 2016; Munis 2020), racialized social constraint (White and Laird 2020), and political incorporation (Alvarez and Bedolla 2003; Masuoka et al. 2018).

[8] An exception is a 10–15 point difference with Latino Decisions and the Collaborative Multiracial Post-Election Survey (CMPS) on the Republican vote of Hispanics, which we discuss in Appendix B.2 of the Supplementary Material.

FIGURE 5. District-Level Cohesion



Note: The range of district-level cohesion of each of the three racial groups, quantified as the absolute distance of the point estimate of the group's two-party support in the district from 50%. States where the Black or Hispanic population is less than 2% of the electorate are not analyzed.

In 2016, the white–non-white gap was 37 percentage points: 59% of white voters voted for Trump, whereas only 29% of Hispanic voters and 7% of Black voters voted for Trump. But whites in the Northeast were 8 points less likely to support Trump than whites in the Midwest (North Central), and 18 points less likely than whites in the South (Table 1a). Within the Northeast, moreover, voting among whites differed by 10 points between New England (45%) and the Middle Atlantic states (54%) of New York, New Jersey, and Pennsylvania (Table 1b). At the state level, we see further variation. The Republican voting patterns among white voters in the Deep South states are different from those in the peripheral South states (McKee and Springer 2015), as well as different within other regions.

Overall, Table 1 shows how measuring the racial gap only at the state or national level masks important variation in large states. With state-level estimates, white voters appear solidly Republican: in all states but five in New England and four in the Pacific West, the majority of white voters vote for Donald Trump in 2016. But state groupings mask other differences in CD constituencies like the urban–rural divide.

An analysis of variance (ANOVA) is an ideal framework for summarizing the relative importance of racial group differences and nested geographic group differences (Gelman and Hill 2006, chap. 22). An ANOVA can partition the overall variation in our estimates by the variation explained by a race-level average, a geography-level average, or the interaction of race and geography. Recall that we have $G \times J \times M$ estimates of vote choice $\tilde{\tau}_{gj}$ for each racial group g and CD j. We first consider the following three-part decomposition:

$$\tilde{\tau}_{gj} = \mu + \phi_g + \eta_j + \gamma_{gj} + \varepsilon_{gj}, \tag{4}$$

where we partition the estimates of vote choice into the racial group component (ϕ), the geography component (η), and their interaction (γ). The error term ε represents sampling variation. By decomposing district–race vote shares in this way, we are defining the geography component as a single Republican vote share for a given district j that does not vary by racial group. It can be thought of as the normal partisan lean of the entire district. The definition is agnostic as to whether this partisan lean is due to factors such as rurality, or place-based identities.

We are interested in how much variation in the patterns we found is explained by each component. In ANOVA, these relative importance measures are given by

$$\hat{\kappa}_{\texttt{race}} = \frac{J\sum_{g=1}^{G}\hat{\phi}_g^{\,2}}{\mathrm{TSS}(\tilde{\tau})} \quad \text{and} \quad \hat{\kappa}_{\texttt{cd}} = \frac{G\sum_{j=1}^{J}\hat{\eta}_j^{\,2}}{\mathrm{TSS}(\tilde{\tau})},$$

where TSS is the total sums of squares $\mathrm{TSS}(\tilde{\tau}) = \sum_g\sum_j(\tilde{\tau}_{gj} - \hat{\mu})^2$. The components are estimated via OLS with the sum-to-zero constraint on each group of coefficients, $\sum_g \phi_g = \sum_j \eta_j = \sum_j\sum_g \gamma_{gj} = 0$.[9] We interpret the κ term for each component as a proportion because they sum to 1.[10] A large value of $\hat{\kappa}_{\texttt{race}}$ would indicate that the variation in the final estimate is largely explained by a single national racial group difference in Republican vote share that does not vary with geography, whereas a large value of $\hat{\kappa}_{\texttt{region}} + \hat{\kappa}_{\texttt{state}} + \hat{\kappa}_{\texttt{cd}}$ would imply that a region, state, or district-level vote share explains more of the total variation in the estimates. A large value of $\hat{\kappa}_{\texttt{residual}}$ would imply that much of variability is posterior estimation uncertainty rather than anything systematic.

The simple model in Equation 4 can be made more elaborate to partition the geographic component η

[9] For computational speed, we use every 10th sample from M total.

[10] We define the quantity for the interaction term $\hat{\kappa}_{\texttt{race}\times\texttt{cd}}$ and for the residual similarly,

$$\hat{\kappa}_{\texttt{race}\times\texttt{cd}} = \frac{\sum_{g=1}^{G}\sum_{j=1}^{J}\hat{\gamma}_{gj}^{\,2}}{\mathrm{TSS}(\tilde{\tau})} \quad \text{and} \quad \hat{\kappa}_{\texttt{residual}} = \frac{\sum_{g=1}^{G}\sum_{j=1}^{J}\hat{\varepsilon}_{gj}^{\,2}}{\mathrm{TSS}(\tilde{\tau})},$$

where $\hat{\varepsilon}_{gj} = \tilde{\tau}_{gj} - \hat{\mu} - \hat{\phi}_g - \hat{\eta}_j - \hat{\gamma}_{gj}$. Then the four quantities sum to one, $\hat{\kappa}_{\texttt{race}} + \hat{\kappa}_{\texttt{cd}} + \hat{\kappa}_{\texttt{race}\times\texttt{cd}} + \hat{\kappa}_{\texttt{residual}} = 1$.

TABLE 1. 2016 Republican Vote by Racial Group in Regions, Divisions, and States

(a) By Region

	White	Non-whites All	Non-whites Black	Non-whites Hisp.	All
Northeast	51	17	4	20	43
South	69	23	8	37	55
North Central	59	19	5	29	53
West	50	26	9	25	42
National	59	22	7	29	49

(b) By Division, nested within Region

	White	Non-whites All	Non-whites Black	Non-whites Hisp.	All
Northeast					
New England	45	19	3	19	41
Middle Atlantic	54	16	4	21	44
South					
South Atlantic	64	21	7	37	51
East South Central	77	16	7	50	64
West South Central	72	30	9	37	58
North Central					
East North Central	57	17	5	25	51
West North Central	61	28	6	39	57
West					
Mountain	59	33	13	29	53
Pacific	44	24	9	23	36
National	59	22	7	29	49

(c) By State, nested within Division

	White	Non-whites All	Non-whites Black	Non-whites Hisp.	All
New England					
Connecticut	50	20	4	24	43
Maine	49	33	(4)	(26)	49
Massachusetts	40	16	2	15	36
New Hampshire	51	32	(4)	(25)	50
Rhode Island	45	21	3	21	42
Vermont	36	21	(2)	(15)	35
Middle Atlantic					
New Jersey	55	20	4	22	43
New York	50	15	4	18	39
Pennsylvania	58	15	3	28	51
South Atlantic					
Delaware	54	14	5	26	44
Florida	63	27	6	37	51
Georgia	73	19	8	44	53
Maryland	51	13	6	25	36
North Carolina	66	19	8	39	52
South Carolina	73	17	10	50	58
Virginia	60	19	7	32	47
West Virginia	74	29	9	(54)	72
East South Central					
Alabama	83	17	7	60	65
Kentucky	71	21	3	40	66
Mississippi	84	15	10	(60)	60
Tennessee	74	15	3	44	64
West South Central					
Arkansas	74	23	8	45	65
Louisiana	81	22	13	54	61
Oklahoma	73	48	6	48	70
Texas	70	31	6	36	55
East North Central					
Illinois	51	15	5	19	41
Indiana	65	23	7	38	60
Michigan	57	17	5	31	51
Ohio	61	16	6	(34)	55
Wisconsin	54	23	3	31	51
West North Central					
Iowa	57	35	7	43	55
Kansas	65	37	8	43	61
Minnesota	53	24	4	27	50
Missouri	66	20	6	(43)	60
Nebraska	66	39	8	46	64
North Dakota	71	55	(12)	(52)	70
South Dakota	67	53	(10)	(47)	66
Mountain					
Arizona	60	28	13	23	52
Colorado	52	31	12	30	48
Idaho	69	59	(24)	53	69
Montana	62	54	(16)	(38)	62
Nevada	57	32	12	28	49
New Mexico	55	34	(14)	32	46
Utah	65	48	(18)	39	63
Wyoming	77	63	(27)	59	76
Pacific					
Alaska	62	47	16	45	59
California	43	23	9	22	34
Hawaii	42	26	9	23	33
Oregon	46	29	(6)	27	44
Washington	45	28	7	30	42
National	59	22	7	29	49

Note: Numbers show estimated two-party vote share for the Republican presidential candidate for each geography and racial group rounded to the nearest full percentage point. Columns represent, from left to right, the Republican vote among white voters, all non-white voters, Black voters, any-part Hispanic voters (denoted Hisp.), and all racial groups in the geography. Numbers in parentheses are those where we estimate the racial group comprises only 2% or less of the geography's electorate. See Appendix C.4 of the Supplementary Material for standard errors of the state-level point estimates.

TABLE 2. Proportion of Variance Explained by Race and Geography

	Fraction of variation explained				
	Across races		Within race		
			White	Black	Hispanic
	(1)	(2)	(3)	(4)	(5)
Race / Ethnicity					
Racial group	0.60	0.60			
Geography					
Congressional district	0.28	0.15	0.54	0.30	0.39
State		0.06	0.19	0.14	0.16
Region		0.07	0.26	0.18	0.23
Race × Geography					
Race × Congressional district	0.07	0.03			
Race × State		0.02			
Race × Region		0.03			
Sampling variation					
Residuals	0.05	0.05	0.01	0.38	0.22
Total variance	0.056	0.056	0.027	0.0034	0.029
Samples	348,000	348,000	87,000	87,000	87,000

Note: Each column represents an ANOVA model estimated from a 10% of the posterior sample estimates of the 2016 district- and race-level vote. Proportions show the fraction of variance in the outcome explained by each type of variable ($\hat{\kappa}$), and sum to 1. The last two rows present the variance across samples (or the total sums of squares divided by the sample size) and the number of posterior samples used.

to states and regions, in addition to districts. This amounts to estimating separate terms for state and region components—for example, $\eta_{\text{state}[j]}$ and $\eta_{\text{region}[j]}$. If a single value for an entire state or entire region is sufficient to entirely explain district-level geographic variation, all of the variation previously attributed to η_{cd} will shift to the variation explained by η_{state}.

The ANOVA results are summarized in Table 2. Model 1, corresponding to Equation 4, shows that about 60% of the total variation in the district- and race-level votes is explained by a national race pattern, 28% is explained by geography, and the interaction of the two (i.e., differences between races that vary depending on the geography) explains the remaining 5%. Model 2 decomposes the geographic component into districts (nested within states), states (nested within regions), and regions. CDs explain 15% of the variation above and beyond larger geographies, whereas states explain only 6% and regions explain 7% Estimation uncertainty accounts for about 5 percent of the variation in our data.

The weight of geography (i.e., CD, state, and region) also varies within each racial group. Models 3–5 use the estimates of one racial group at a time so that there is no race-level variation. The penultimate row shows that the total variation in the Trump vote among white and Hispanic voters is more than five times larger than the total variation observed for Black voters. In all racial groups, the district level accounts for more than twice as much variability in the total estimates than state- or region-level averages. White and Hispanic voters vary more than Black voters and the bulk of the variation occurs at the district level.

At a high level, then, differences in the average vote choice of racial groups nationwide explain twice as much of the systematic variation in voting as does the CD, state, or region. Sixty percent of the variation in the vote of racial groups within a particular CD can be accounted for by the average national vote of the groups. The normal vote of a CD, state, or region explains 30% of the remaining variation. A final 10% of the variation is due to the fact that voting patterns of a given racial group change by geography. In other words, while we do find substantial substate variation, geography (i.e., CD, state, and region) explains at most a third of the total variation across all district–race combinations.

Ecological inference estimates yield different conclusions on the explanatory power of geography. We applied the same ANOVA modeling to the posterior sample of ecological inference estimates, which were generated from applying EI one district at a time, described in Appendix B of the Supplementary Material. The national race component explains roughly the same amount of variation across both methods (both 0.52 in 2020). However, state, region, and district explain twice as much of the variation using MRP than using EI (0.34 vs. 0.15). Because MRP models district-level variation as a random effect, it allows for more efficient estimation of the district component $\kappa_{\texttt{cd}}$. EI implemented at the district level forces that variation onto the interaction component $\kappa_{\texttt{race}\times\texttt{cd}}$. One may improve EI by allowing partial pooling across districts, but that is not conventionally done.

Our analysis examines a group's voting behaviors, rather than beliefs, ideologies, or issue preferences.

Our findings reaffirm the lack of variation in party vote among Black voters, but there are certainly diverse dynamics within that group beyond party choice (Jefferson Forthcoming; White and Laird 2020). Even still, we examine correlates of ideology or belief and the methods developed here open up opportunities to model any survey item to explore how ideology or public opinion may vary within groups.

Groups and Coalitions

Finally, we turn to the potential of groups to form coalitions. The emerging voting power of Black and Hispanic groups over the past three decades and the cohesiveness of these groups raises the possibility that the two groups may vote sufficiently strongly together in general elections to be able jointly to elect their preferred candidates (Atsusaka 2021; Axelrod 1972; Barreto, Collingwood, and Manzano 2010; Grofman, Handley, and Lublin 2001). The demographic realities of contemporary America are putting pressure on voting rights law to accommodate the possibility of multiracial coalitions (Pildes 2002).

Coalition voting can be operationalized two ways. First, how often do the majority of each group of minority voters prefer the same candidates? The point estimates underlying Figure 4 indicate that in 356 out of 435 CDs (82%), a majority of Black voters and a majority of Hispanic voters voted for the same candidate. Majorities of white and Hispanic voters voted for the same candidate in 216 CDs (49%) and majorities of white and Black voters voted for the same candidate in 136 (31%).

Second, which group or groups are pivotal (Ingham 2019; Snyder 1989)? We identify the pivotal racial group or groups in each CD using the 2016 presidential vote. We divide each CD into whether it reports more votes won by the Republican, Donald Trump, or the Democrat, Hilary Clinton. We then use the point estimates of the vote shares of the Democratic and Republican candidates for each racial group in each CD and then calculate the total vote for each group that went to the Democrat and to the Republican.[11] Using those totals, we determine which groups were pivotal in giving the winning candidate her or his majority. We distinguish these districts in Figure 6 and tabulate the frequency of each type in Table 3.

The striking finding in Table 3 is that minority voters are pivotal in more than half of the districts. In 236 of the 435 CDs, minority voters, either one group singly or together with white voters, were pivotal in determining which candidate won the majority of the vote. For example, in UT-04, which includes Salt Lake County, white voters comprise close to 80% of the electorate but voted sufficiently for Clinton that white Trump voters alone fall short of a majority. Given their large population, white voters are often part of a pivotal set of racial groups as well (Cohn 2016): their vote is needed in 390 districts for the winning candidate.

Among the 236 districts where minority voters are part of a pivotal coalition, 45 are those in which minority voters are pivotal without white voters. Black voters are large and cohesive enough to deliver a majority of the district vote alone (i.e., without relying on other racial groups) in 10 districts and Hispanics voters are pivotal alone in 2 (Table 3). In a separate 33 districts, minority groups (including Asian Americans, Native Americans, and multiracial voters) voted with sufficient cohesion to account for a majority of the votes. The center-left panel of Figure 6 identifies these districts. All 45 of districts were won by Hillary Clinton, the Democrat. In no district did Trump's majority rest solely on non-white voters.

In 199 of the 435 districts, white voters alone are large enough to deliver the majority of the votes cast for the winning candidate. The overwhelming majority (179 out of 199) of these heavily white districts voted for Trump.

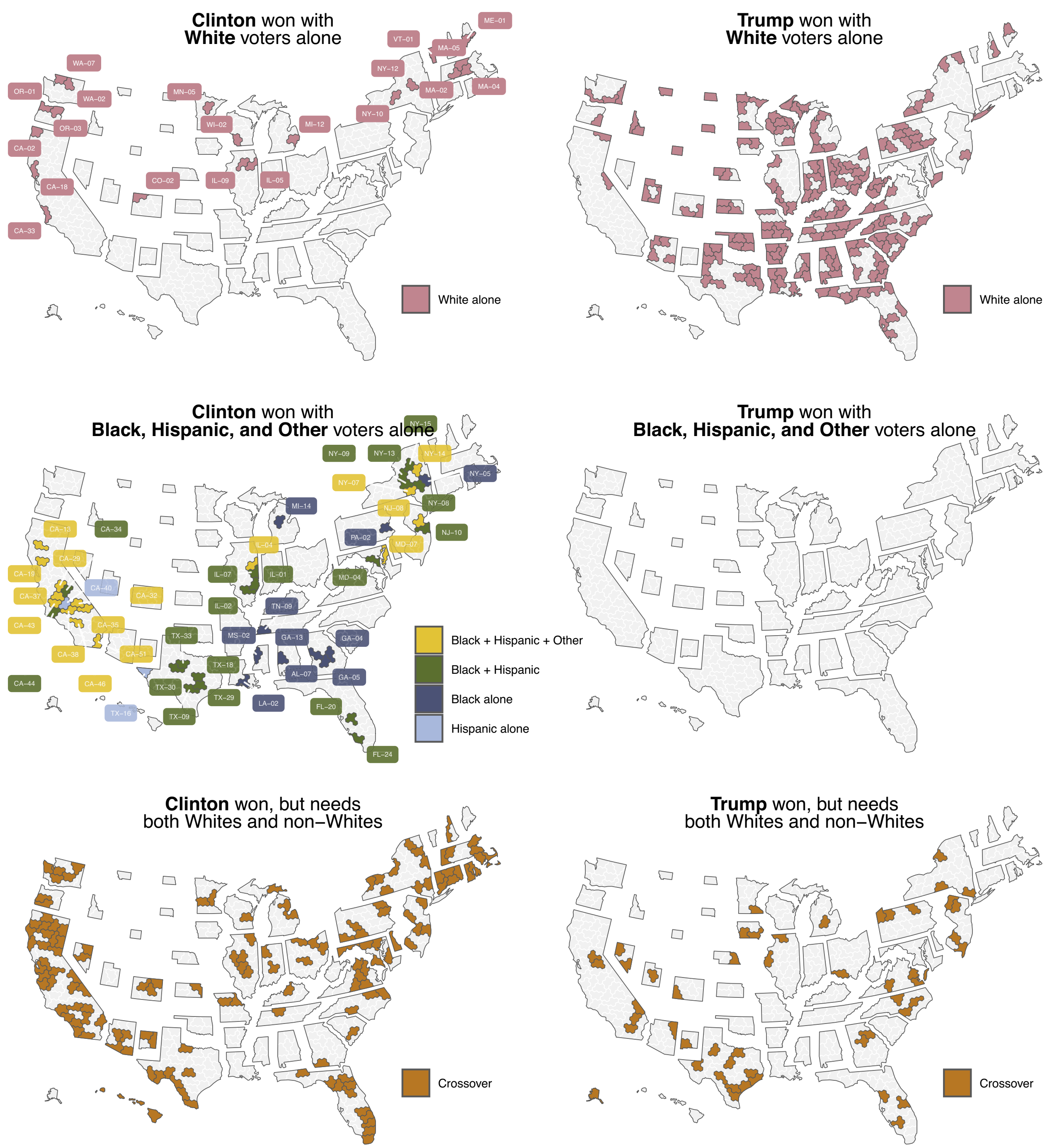
These statistics suggest that both parties rely on coalitions of white and minority voters. In a fifth of districts Trump won in 2016, Trump needed support of both white and non-white voters to win (Table 3). The Democratic party relies much more on the votes from multiple racial groups. Among the 205 districts won by Clinton in 2016, her majorities relied on a coalition of white and minority voters in 140 districts. Clinton won only 20 districts in which the white vote alone was sufficient to win a majority. This is the multiracial electoral context that Pildes (2002) foresaw and it presents new complexities for the crafting and application of voting rights laws. However, the degree of reliance is asymmetric. White voters alone were sufficient to win a majority of votes in the majority of districts Trump won, whereas in the majority of districts Clinton won, Democrats needed votes from both white voters and minority voters (Table 3).

CONCLUSION

This study offers the first set of estimates of racially polarized voting at the CD level for all 435 CDs and 50 states. Our findings immediately inform debates over persistence of importance of race and regionalism in U.S. elections, specifically the extent to which the racial divide in the United States is a national phenomenon or is regionally concentrated. We find national division in the average vote across racial groups that explains 60% of the variation in our estimates. Nationally, 22% of non-white voters voted Republican, whereas 59% of whites voted for the Republican in 2016—a 37-point difference. There are, however, significant cross-state and within-state variations in group voting behavior as well. Black voting behavior is far more consistent across districts and states than Hispanics or whites. Hispanic and white voting behavior varies considerably. For instance, only 40% of white voters voted for the Republican in Massachusetts, compared with 84% in Mississippi. The structure of the

[11] Our hierarchical regression model estimates a vote share. We multiply this with the total number of voters for the race–district combination, estimated in our target distribution.

FIGURE 6. Coalitional and Crossover Districts



Note: Four hundred thirty-five congressional districts in the 2016 presidential election are classified into one of six types listed in Table 3. Maps on the left show districts won by the Democrat and maps on the right show districts won by the Republican. Districts are placed in the same map as Figure 3.

variation we find within groups across the CD, state, and regional levels is analogous to that of Erikson, Wright, and McIver (1989), which finds ideological variation within the Republican and Democratic party across states.

Our findings show the complex dynamics of racial group politics in the United States. Differences in election outcomes are explained by both differences across groups and the aggregate differences by geography. And, through analyzing patterns of vote share, within-district polarization, and group size, we find that most CDs were won either with a multiracial coalition or a significant cross-over vote of either whites of minorities in 2016. These group dynamics are present

TABLE 3. Typology of Racial Coalitions

Racial group composition for sufficient for a majority	Democratic CDs	Republican CDs
White voters alone	20	179
Black voters alone	10	0
Hispanic voters alone	2	0
Black and Hispanic voters	18	0
Black, Hispanic, and other non-white voters	15	0
White and non-white	140	51
Total	205	230

Note: Ability of party supporters in each racial group to win a majority of votes either on its own or as a coalition. Republican versus Democratic CDs refers to the party that won the two-party presidential vote in each congressional district in 2016.

even though white and non-white voters are polarized nationally. This fact points to an increasingly important reality for both major political parties in the United States: support from minority voters is a necessity for both parties to win a congressional majority. Demographic trends will only increase the importance of Asian, Black, and Hispanic votes within both parties.

As the voting behavior of the U.S. electorate shifts, so too must the laws and policies that prevent racial vote dilution. Our analysis supports both the need for federal voting rights law and the need for the narrow tailoring of federal and state rules to specific areas in line with the principles of federalism. Many of the divisions across racial groups that existed in the past remain. Those divisions do, however, vary across regions and states and, even, within states. Majority minority districts may be required, then, in some areas within a state but not others. Our study offers a new assessment, informed by individual-level data, of where such districts may be required to protect minority voters.

Our article also offers innovations in the analysis of survey data that open the possibility of using individual data where only aggregates were available before. The modifications to the existing MRP procedure in our framework can integrate more survey data and aggregate statistics together, generating more reliable estimates of group voting behavior at different levels of geographic aggregation. Use cases for these methods abound in the social sciences. We have focused on racial voting patterns at the levels of districts and states, but this approach could easily be applied to other geographies, such as metropolitan areas, counties, and cities, or to other demographic groups. For example, the tools developed here allow researchers to distinguish specific cultures or nations of origin of more precisely defined groups, such as Mexican Americans, Puerto Ricans, and Cuban Americans, who are often combined under the label Hispanic or Latino.

There is much potential to extend these methods to more difficult settings with even sparser data, but we also think that such applications must be interpreted with care, must be attuned to the particular problem at hand, and must be validated whenever possible. Important extensions to the method include accounting for geographic adjacency of districts (Morris et al. 2019) and the integration of multiple surveys to increase the sample sizes of particular groups (Barreto et al. 2018; Frasure-Yokley et al. 2020). Integrating other surveys will require extending the methods presented here to reflect the surveys' timing, mode, question-wording, and sampling that could confound the interpretations of differences. There is also a practical implication for ecological inference methods. Pooling across all districts as in a nationwide EI may violate constancy assumptions, but running separate EI methods by district can underestimate the shared explanatory power of cross-district geography. Implementing partial pooling in EI methods may improve estimation.

Finally, our analysis speaks to one of the most important emerging problems in voting rights law. The Voting Rights Act (VRA) of 1965 was developed in an era when politics was often Black versus white. Today, Hispanics are the second largest racial group and Asians are growing quickly. Should the VRA require minority coalition districts, and if so, where (Pildes 2002)? Our results show that in most districts, the majorities of Black and Hispanic voters both support the same party. That does not mean that minority coalition districts can always be drawn, but there is considerable potential for such districts throughout the United States. This approach to representation would more accurately reflect the realities of racial voting patterns in American politics today.

SUPPLEMENTARY MATERIAL

The supplementary material for this article can be found at https://doi.org/10.1017/S0003055423000436.

DATA AVAILABILITY STATEMENT

Documentation, data, and code that reproduce the findings of this study are openly available in the American Political Science Review Dataverse at https://doi.org/10.7910/DVN/VX5N1V. Similar estimates for years outside the scope of this study are available at https://doi.org/10.7910/DVN/MAZNJ6. Data and software to implement our methods are available through the R packages `ccesMRPprep` (https://github.com/kuriwaki/ccesMRPprep), `ccesMRPrun` (https://github.com/kuriwaki/ccesMRPrun), and `synthjoint` (https://github.com/kuriwaki/synthjoint). The packages are also archived in the Dataverse replication repository.

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CONFLICT OF INTERESTS

The authors declare no ethical issues or conflict of interests in this research.

ETHICAL STANDARDS

The authors affirm this research did not involve human subjects.

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