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Letter
Validating the Applicability of BISG to Congressional Redistricting

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Ensuring descriptive representation of racial minorities without packing them into districts is difficult in states that do not collect race data on their voters. One advance since the 2010 redistricting cycle is the advent of Bayesian Improved Surname Geocoding (BISG), which greatly improves upon previous ecological inference methods in identifying voter race. In this article, we test the viability of employing BISG to create efficient minority majority districts. We validate BISG through 10,000 redistricting simulations of North Carolina and Georgia's congressional districts and compare BISG estimates to actual voter file racial data. We find that summing the BISG probabilities leads to significantly lower error rates at the precinct and district level relative to the plurality method of assigning race, and therefore should be the preferred method when using BISG for redistricting. Our results suggest that BISG can help with the construction of efficient minority majority districts.

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INTRODUCTION

The creation of minority majority districts for underrepresented racial minorities remains a key point of contention within the field of redistricting and representation. There is the constant danger of "packing" racial minorities into too few districts and minimizing their influence within the legislature, or "cracking" racial minorities into districts with no representatives of the same race. Striking the correct balance is one of not only great theoretical concern, but also methodological. It is difficult to identify the optimal racial composition of districts that avoids wasting the votes of racial minorities. Further complicating the problem is calculating individual-level turnout and vote preferences by race given data aggregated to county or precinct levels. While voter file data on registration and turnout can help construct efficient minority majority districts, many states collect no racial information in their voter registration lists. The compounding uncertainty makes it necessary to err on the side of packing districts with minority voters to ensure an acceptable number of minority minority districts.

There have been a number of significant quantitative advancements in the field of redistricting since the 2010 redistricting cycle that can assist in drawing efficient minority majority districts. In addition to the increasing accessibility of redistricting simulation techniques, the advent of Bayesian Improved Surname Geocoding (BISG) estimation of race is a promising development. BISG calculates the joint probability of racial membership given an individual's surname and geographic residence, which could be used to assist in drawing minority majority districts in states where race/ethnicity is missing from voter files. BISG methods have also become increasingly accessible and commonly used in various ways throughout social science research (Clark et al.

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2021; Imai and Khanna 2016). In this letter, we validate the applicability of BISG in the context of redistricting by estimating the error of BISG race estimates relative to self-reported race data from the voter files of North Carolina and Georgia.

Within this letter, we first demonstrate the range of error in implementing BISG against verified voter file race data. Second, we demonstrate the expected error given two methods to implement BISG within redistricting: polygon-aggregated probability summed method estimates (PSM) versus individual level plurality method (PM) assignment. We estimate district-level uncertainty around BISG methods by simulating 10,000 congressional district plans for each state and compare BISG estimates of the racial composition of districts to voter file data. BISG district-level estimates (using PSM) of the share of minority voters in districts typically fall within 5 percentage points of self-reported voter file racial data, though the magnitude of the errors vary across states and racial groups. These findings provide a set of best practices and baseline estimates of uncertainty for researchers, lawyers, and legislators who wish to use BISG in the context of redistricting and simulations.

REDISTRICTING AND RACE

From a representational perspective, ensuring the election of racial minorities through redistricting is of special import. Historical oppression and racism against racial minorities, and African-Americans in particular, often led to districts where election of racial minorities was all but impossible. The Voting Rights Act (VRA) provided the legal inception of minority majority districts through its non-retrogression and pre-clearance provisions (Lublin 1997). The advent of the VRA and states under pre-clearance all but banned the practice of "cracking" racial minorities into several districts in an attempt to thwart their presence in legislative delegations (Cox and Holden 2011).

Despite gains during the VRA era for representation of racial minorities, it is difficult to know the exact percentage of minority voters that are needed for a minority majority district. Two competing and justified concerns exist regarding minority majority districts. First, if racial minorities and their electoral coalition partners number too few, the district plan "cracks" racial minorities into several districts, where racial minorities are unable to elect a member of their preference. Second, if racial minorities and their coalition partners number too many, they will be able to elect a member of their preference, though at the expense of a broader array of allied members within the legislature, victim to "packing" or "bleaching" as it's commonly known (Grose 2011; Lublin 1997). Both cracking and packing lead to racial vote dilution and are forms of illegal racial gerrymandering, though it is easier for redistricting plans to legally justify the practice of "packing" (Cox and Holden 2011).

Cameron et al. (1996) finds that the "optimal" plans for maximizing black representation in the South uses minority majority districts that are 47% black voting age population districts, but that many minority candidates have a good chance of winning in districts that are lower than 50% minority in racial composition. Grose (2011) identifies a threshold at or below 25 percent African-American as nigh impossible to elect a black member. Hicks et al. (2018) find the probability of electing a black member to the legislature in a district where just under 50 percent of the district population is black plummets to near zero in the Deep South. Lublin (1997) notes that minority-influence districts might be a more efficient way to ensure substantive representation of racial minorities through the election of both more racial minority members and Democrats, yet recent research suggests these can easily backfire.

Legislatively and legally, there are often disputes over how many minority voters are needed in a district in order to create minority majority districts or minority-influence districts. Republicans often like to over pack minorities into districts while Democrats like to create a higher number of minority-influence districts, due the partisan effects of each outcome (Bullock III 2018). Until the *Shelby*[1] decision in 2013, the non-retrogression

[1]*Shelby County v. Holder*, 570 US 529 (2013)

provisions of Section 5 of the VRA also pushed mapmakers to err on the side of keeping minority voters packed into districts, as to not degrade or dilute existing minority majority districts (Bullock III 2018; Cox and Holden 2011). In practice, this means that redistricting generally tends pack together too many racial minorities rather than too few (Cox and Holden 2011).[2]

Confounding the substantive question of redistricting and race is a methodological one: how does one actually measure racial preferences and turnout given the Census demographics at the start of the decade so as to ensure a not over- or under-packed minority majority district? Such questioning is the basis of Ecological Inference (EI) methodology, where the goal is to estimate both the electoral turnout by race and electoral preference of those who turn out given the demographics of an area (Goodman 1953; King 1997). Using Citizen Voting Age Population (CVAP) alone does not account for differential levels of registration or turnout rates across racial groups, both of which can significantly affect racial minorities' political influence. Recent evidence suggests that mapmakers target differential voter eligibility and turnout when gerrymandering (Fraga 2015; Henderson et al. 2016). Even the best EI methods coupled with on the ground qualitative research are far from perfect, and often necessarily lead to district plans "erring" on the side of caution so as to prevent cracking (Grose 2011; Grose et al. 2007; Hicks et al. 2018).

Using race data on voters contained in states' voter registration files to measure district-level demographics can aid in the creation of minority majority districts. Voter registration files contain the set of eligible and registered voters, and often individual-level voter history. Therefore, it is possible to estimate an individual-level likely turnout model with a voter registration file, completely negating one stage of EI. However, many states do not collect individual race data in their voter files – including states like Texas, Pennsylvania, and Wisconsin, which are often subjects of contentious gerrymandering litigation.

A promising innovation in the field of EI since the previous redistricting cycle is the development of Bayesian Improved Surname and Geocoding (BISG) estimation of race. Implemented first in the field of public health by Elliott et al. (2008), BISG calculates the joint probability of racial membership given surname and geographic residence. Individually, surname and residence are each susceptible to heterogeneous priors/marginals but jointly they vastly reduce the errors of even advanced EI methods (Imai and Khanna 2016; King 1997). Theoretically, BISG could be used to assist in drawing minority majority districts in states where voter race data is missing or where differential voter registration and turnout rates across racial groups are not reflected in Census estimates of district demographics. To date, however, there has been no research validating the extent to which BISG methods can be used to construct accurate estimates of the racial composition of proposed districts. Given the obvious application of BISG to redistricting yet its untested veracity, we aim to estimate the range of errors associated with BISG in redistricting and provide best practices for those using BISG in redistricting work.

USING BISG IN REDISTRICTING

BISG uses an individual's surname and location to estimate their race via Baye's rule (Elliott et al. 2008; Imai and Khanna 2016). Using individuals' surnames matched to a surname dictionary, joined to Census geography demographics, typically produces accurate racial estimates relative to other methods (Imai and Khanna 2016). While the errors tend to be greatest where the surnames are uninformative and geographic units heterogeneous by race (Imai and Khanna 2016; King

[2]So far we have largely discussed racial minorities as primarily Democratic voters. There will be greater variance among Hispanic and Asian/Pacific-Islander voters, who tend to vote more Republican than African Americans (Masuoka 2006; Masuoka et al. 2019; Hajnal and Lee 2011). As Hicks et al. (2018) show in their analysis of state legislators from the 1990s to the 2010s, over 96 percent of African-American legislators are Democratic, with their bases increasingly relying upon coalitions of African-American and Hispanic voters.

1997), BISG greatly reduces the number of individuals afflicted by such uncertainty. So long as sub-county units are employed, BISG racial estimates outperform alternative methods when verified against states with racial information on their voterfiles, as shown by Imai and Khanna (2016) and Clark et al. (2021). The benefits and ease of use of BISG therefore earned its widespread use within political science, such as estimating the race of political donors (Alvarez et al. 2020; Grumbach and Sahn 2020), voters (Fraga 2015), and candidates (Shah and Davis 2017). These developments in BISG, which were not available at the time of the 2010 redistricting cycle, offer an opportunity for researchers and mapmakers to more easily incorporate racial information in the upcoming redistricting process, and can facilitate the drawing of minority majority districts that are neither overly packed with minority voters nor lacking significant minority populations.

In terms of using BISG in redistricting research, the main question is ascertaining the degree of error given *how* the researcher assigns racial categories given BISG output. Clark et al. (2021) follow the practice of summing the estimated probabilities that an individual is of a given race up to the unit of interest, such as precinct. However, scholarship by Enos (2016) and Enos et al. (2019) assigns a single race to a voter given the racial category with the highest estimated probability. Plurality assignment goes against best practices within population level social sciences (King 1997) given the potential for extreme and clustered errors. Normally, plurality assignment of race would not be considered. However, it is foreseeable that one might apply plurality assignment to redistricting. Following the redistricting revolution of “one person, one vote,” it is necessary to often split precincts in order to ensure literal population equality across districts (Cox and Katz 2002; Grofman 1985). Partisan motivated mapmakers might also prefer to cherry-pick individuals into other districts as a means to break up personal constituencies and force opposing incumbents into retirement (Cox and Katz 2002). Therefore, the ability to assign individuals to a single category, if done accurately, offers benefits tempting to redistricting practitioners and scholars.

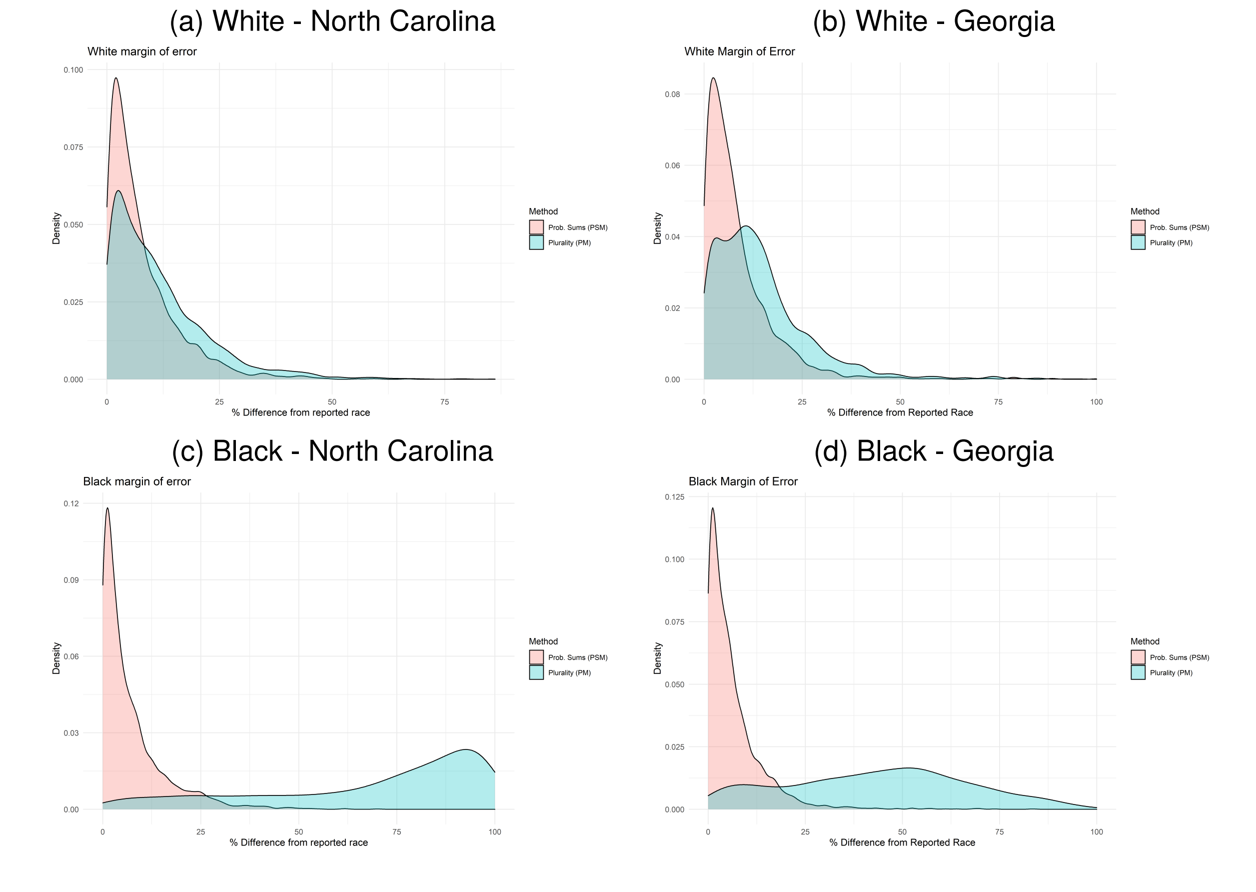
BISG VALIDATION

We validate the application of BISG to two states with racial information on their voter files, North Carolina and Georgia. These states also require minority majority districts at the congressional level. We therefore first calculate the distribution of errors applying BISG to these states. Second, we evaluate both methods of BISG race assignment – the BISG probability sums method (PSM) and the plurality method (PM). Finally, we estimate the degree to which redistricting simulations distribute these errors relative to the voter registration file in creating districts via the ensemble method of swapping districts from a seed map with the required number of minority majority districts within each state.

For the purpose of implementing BISG, we use the R package **zipWRUext** (Clark et al. 2021), which uses surname and ZIP code demographics to calculate the joint probability of racial identification for individuals. This allows us to quickly produce accurate estimates of the predicted race of each voter, without having to undergo a costly and time-consuming geocoding process.[3] We perform diagnostics on the individual-level race BISG predictions in Appendix B, where we calculate the effective number of races, which is the inverse of the Herfindahl index (Clark et al. 2021; Wolak 2009). Appendix B demonstrates that in most cases the BISG estimates range between

[3]Geocoding millions of voter addresses can take weeks and cost thousands of dollars, which often presents an obstacle to utilizing BISG for those without large research budgets. In contrast, when using ZIP codes (which are available in all voter files which contain voter addresses that would be necessary for geocoding) as the BISG geography it takes about 10 minutes to produce race estimates for 7 million voters in the Georgia voter file, on a 3.1GHz MacBook Pro with 8GB of RAM. See Clark et al. (2021) for details and discussion of the relative advantages of using ZIP codes rather than geocoded Census block or tract information.

FIGURE 1. BISG Precinct-Level Error Density Plots



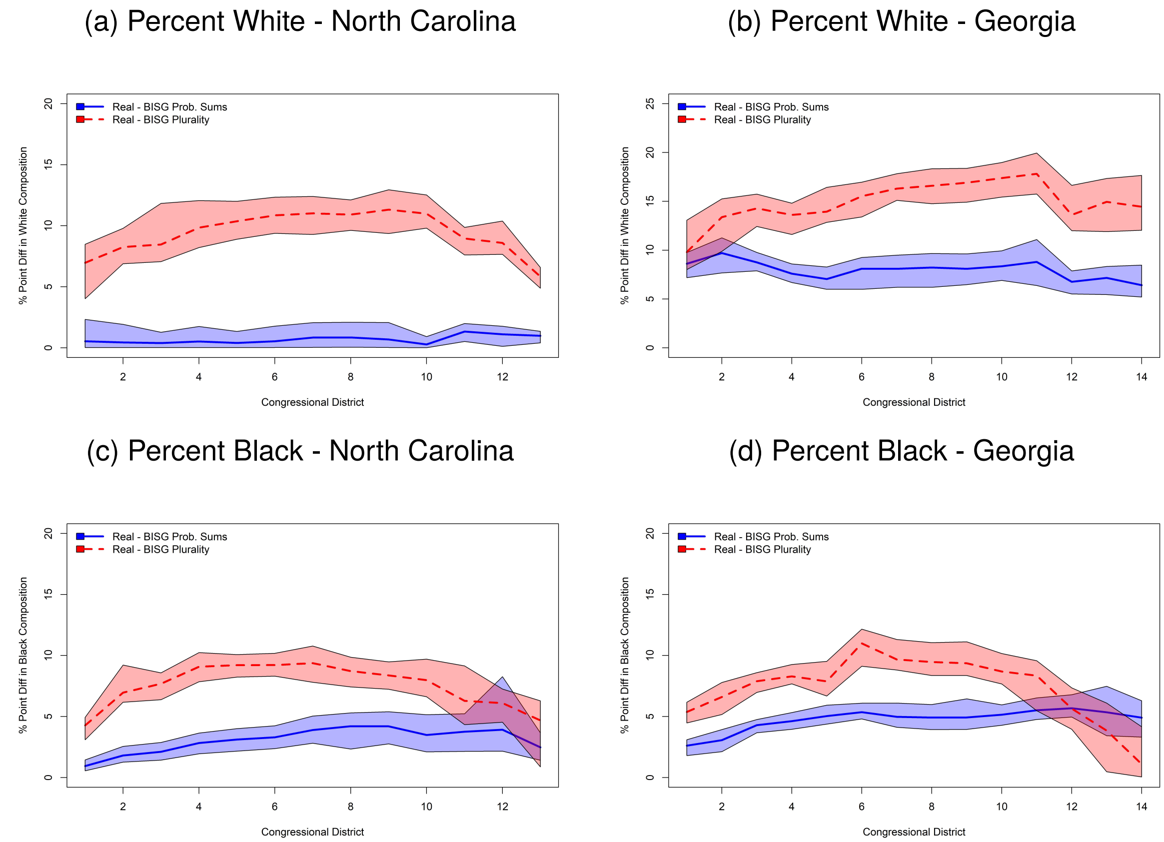
one and two effective races. Next we estimate the proportion of black and white voters using both the PM and PSM assignment procedures. These estimates are benchmarked to the actual self-reported racial data within the voter files.

Figure 1 shows a density plot of the precinct-level errors in racial estimates, calculated as the absolute percentage difference from the reported number of voters for both North Carolina and Georgia, by race. For white voters, the modal error approaches zero for both assignment methods, though PM has a longer right tail, which indicates worse performance relative to PSM. For black voters, PSM also outperforms PM in reducing precinct-level errors, vastly so in this case. A recommendation we make confidently from just these precinct-level results is that PSM should be the preferred method when estimating the racial composition of precincts using BISG on voter files.

REDISTRICTING SIMULATIONS

To evaluate the accuracy and uncertainty of BISG estimates of race at the district level, we perform 10,000 redistricting simulations each of North Carolina and Georgia's congressional district maps using the Redist package in R (Fifield et al. 2020), version 2. The Redist package makes use of ensemble methods, useful in estimating ranges of expected outcomes (Katz et al. 2020). We craft a basemap from the precinct simplified map employed by Curiel and Steelman (2018) for North Carolina, and a modified map of the plan implemented in Georgia following the 2010 redistricting cycle. We then proceed to simulate districts via rook contiguity. For each simulated plan we calculate the absolute percentage point difference between the estimated proportion of each race in each district and the actual proportion using the voter file data. This allows us to calculate the error rates for the BISG PM and PSM at the con-

FIGURE 2. BISG District-Level Error Sensitivity - North Carolina and Georgia



gressional district level. We use our simulations to create a 95 percent confidence interval around these estimates.

The error rates and confidence intervals for North Carolina and Georgia are plotted in Figure 2 for both white and black voters. The x-axis sorts congressional districts in order of increasing white percentage when plotting the absolute error for white voters (plots a and b), and in order of increasing black percentage when plotting the absolute error for black voters (plots c and d). In nearly all district-level estimates, PSM results in significantly lower absolute error rates relative to PM, consistent with the precinct-level diagnostics.

While the error rates are relatively low in general, they vary both across states and across racial groups. In North Carolina, the absolute error for BISG probabilities are close to zero for the percentage of white voters in each district, and never go above five percentage points for the percentage of black voters in each district. In Georgia, the error rates are slightly higher – for white voters, they max out around 10 percentage points, but for black voters the error rates are lower and, like North Carolina, peak around 5 percentage points. Overall, plurality assignment (PM) substantively increases errors relative to summing the estimate probabilities (PSM).

DISCUSSION

As simulations become more common in redistricting (Fifield et al. 2020), and as the next redistricting cycle approaches without the previous protections of VRA preclearance, BISG has the potential to easily provide researchers with a way to construct minority majority districts efficiently. This can be especially useful in states where voter race data is missing from the voter files. Our letter performs the first empirical validation of BISG use in redistricting, and provides a set of simple recommendations and guidelines for researchers that use BISG in redistricting analyses.

First, researchers using BISG should aggregate up to some polygonal unit of interest by summing the estimated probabilities of racial membership. Although it might be tempting to assign race to single voters in order to aid in point-based redistricting attempts, the errors will be drastically higher, reducing the usefulness of BISG. While there might be occasions to follow the practice of plurality assignment of race, redistricting is not one of them.

Second, researchers should be prepared to deal with around a five to ten percentage point error rate in estimating race at the district level. In states where voter race is not collected, BISG offers a fairly accurate workaround. However, context matters. Insofar as electoral preferences can be divided between white and non-white categories, such as the drawing of coalition districts, BISG reaches high levels of accuracy. However, when researchers need to estimate the district composition of a specific racial minority group, such as Blacks or Hispanics, the potential for greater error should be considered.

Finally, it is possible to achieve these BISG estimates at relatively low cost via modern BISG packages in programs such as R. Imai and Khanna (2016) greatly expanded the ease of integrating Census data and surname dictionaries for BISG, and Clark et al. (2021) demonstrate the ability to attain accurate estimates while avoiding the need to geocode altogether with ZIP codes. Therefore, it is possible to provide accurate race estimates for millions of voters in just a couple of minutes. While there is heterogeneity in the errors associated with BISG, keeping such limitations in mind can allow the user to adjust accordingly.

Future work should look at the accuracy of BISG and redistricting in terms of non-black racial minorities. In Texas, for example, the creation of majority-Hispanic districts is a common redistricting controversy. Other work can and should try to incorporate BISG estimates with differential turnout across racial groups from voter history (which is often contained in voter files) to create minority majority district. Further research is also needed to better understand what tempers the effectiveness of BISG in different contexts. Clark et al. (2021) noted that ZIP code BISG works better for black and white voters than for Hispanic or Asian voters, but more could be done to understand the contextual factors that affect how accurate BISG estimates of legislative districts will be when aiming to create and evaluate minority majority districts. The uncertainty in our estimates for North Carolina and Georgia show that while BISG is fairly accurate in general, better understanding the sources of error in the data can further improve BISG's usefulness in redistricting and its general applicability to simulation methods. Additional Bayesian priors might additionally be implemented into existing BISG packages to allow for greater uncertainty, especially for contexts where it is not possible to validate the final results.

Legislators, researchers, and everyday citizens will have access to a whole new set of quantitative tools in the 2020 redistricting cycle. Many of these tools and new methods are aimed at reducing partisan and racial biases in maps in order to promote more fair and equal representation. But these tools and methods can still produce biased or inefficient districts if, for example, voter race data itself is unrepresentative of the actual electorate. Our letter helps to reduce the errors in estimating aggregate racial data, and can assist mapmakers using these new quantitative tools create efficient minority majority districts.

REFERENCES

Alvarez, R. Michael , Jonathan N. Katz, and Seo young Silvia Kim (2020). Hidden donors: The censoring problem in u.s. federal campaign finance data. *Election Law Journal 19*(1), 1–18.

Bullock III, Charles S. (2018). The history of redistricting in georgia. *Georgia Law Review 52*(4), 1057–1104.

Cameron, Charles , David Epstein, and Sharyn O'Halloran (1996). Do majority-minority districts maximize substantive black representation in congress? *American Political Science Review 90*(4), 794–812.

Clark, Jesse T. , John Curiel, and Tyler Steelman (2021). Maximizing of bisg level ups in predicting race. *Political Analysis forthcoming*.

Cox, Adam B. and Richard T. Holden (2011). Reconsidering racial and partisan gerrymandering. *The University of Chicago Law Review 78*(2), 553–604.

Cox, Gary and Jonathan Katz (2002). *Elbridge Gerry's Salamander*. Cambridge University Press.

Curiel, John A. and Tyler Steelman (2020). A response to “tests for unconstitutional partisan gerrymandering in a post-gill world" in a post-rucho world. *Election Law Journal 20*(1).

Curiel, John A. and Tyler S. Steelman (2018). Redistricting out representation: Democratic harms in splitting zip codes. *Election Law Journal 17*(2), 328–53.

Elliott, Marc N. , Allen Fremont, Peter A. Morrison, Philip Pantoja, and Nicole Lurie (2008). A New Method for Estimating Race/Ethnicity and Associated Disparities Where Administrative Records Lack Self-Reported Race/Ethnicity. *Health Services Research 43*(5p1).

Enos, Ryan D. (2016). What the demolition of public housing teaches us about the impact of racial threat on political behavior. *American Journal of Political Science 60*(1), 123–142.

Enos, Ryan D. , Aaron R. Kaufman, and Melissa L. Sands (2019). Can violent protest change local policy support? evidence from the aftermath of the 1992 los angeles riot. *American Political Science Review 113*(4), 1012–1028.

Fifield, Benjamin , Kosuke Imai, Jun Kawahara, and Christopher T. Kenny (2020). The essential role of empirical validation in legislative redistricting simulation. *Statistics and Public Policy 7*(1), 52–68.

Fifield, Ben , Christopher T. Kenny, Cory McCartan, Alexander Tarr, and Kosuke Imai (2020). redist: Simulation methods for legislative redistricting. Available at The Comprehensive R Archive Network (CRAN).

Fraga, Bernard L. (2015). Redistricting and the causal impact of race on voter turnout. *Journal of Politics 78*(1), 19–34.

Gimpel, James G. , Frances E. Lee, and Joshua Kaminski (2006). The political geography of campaign contributions in american politics. *Journal of Politics 68*, 626–39.

Goodman, Leo (1953). Ecological Regressions and the Behavior of Individuals. *American Sociological Review 18*, 663–6.

Grofman, Bernard (1985). Criteria for districting: A social science perspective. *UCLA Law Review 33*, 77–184.

Grose, Christian R. (2011). *Congress in Black and White: Race and Representation in Washington and at Home*. Cambridge University Press.

Grose, Christian R. , Maurice Mangum, and Christopher D. Martin (2007). Race, political empowerment, and constituency service: Descriptive representation and the hiring of african american congressional staff. *Polity 39*(4), 449–78.

Grumbach, Jacob M. and Alexander Sahn (2020). Race and representation in campaign finance. *American Political Science Review 114*(1), 206–221.

Hajnal, Zoltan and Taeku Lee (2011). *Why Americans Don't Join the Party: Race, Immigration, and the Failure of Political Parties to Engage the Electorate*. Princeton, NJ: Princeton University Press.

Henderson, John A. , Jasjeet S. Sekhon, and Rocio Titiunik (2016). Cause or effect? turnout in hispanic majority-minority districts. *Political Analysis 24*(3), 404–412.

Hicks, William D. , Carl E. Klarner, Seth C. McKee, and Daniel A. Smith (2018). Revisiting majority-minority districts and black representation. *Political Research Quarterly 71*(2), 408–23.

Imai, Kosuke and Kabir Khanna (2016). Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Record. *Political Analysis 24*(2), 263–72.

Katz, Jonathan N. , Gary King, and Elizabeth Rosenblatt (2020). Theoretical foundations and empirical evaluations of partisan fairness in district-based democracies. *American Political Science Review 114*(1), 164–78.

King, Gary (1997). *A Solution to the Ecological Inference Problem: Reconstructing Individual Behavior from Aggregate Data*. Princeton, NJ: Princeton University Press.

Lublin, David (1997). *The Paradox of Representation: Racial Gerrymandering and Minority Interests in Congress*. Princeton, NJ: Princeton University Press.

Masuoka, Natalie (2006). Together they become one: Examining the predictors of panethnic group consciousness among asian americans and latinos. *Social Science Quarterly 87*(5), 993–1011.

Masuoka, Natalie , Kumar Ramanathan, and Jane Junn (2019). New asian american voters: Political incorporation and participation in 2016. *Political Research Quarterly 72*(4), 991–1003.

Shah, Paru R. and Nicholas R. Davis (2017). Comparing three methods of measuring race/ethnicity. *Journal of Race, Ethnicity, and Politics 2*(1), 124–139.

Wolak, Jennifer (2009). The consequences of concurrent campaigns for citizen knowledge of congressional candidates. *Political Behavior 31*(2), 211–29.

APPENDIX

DATA

Shapefiles for precincts come from the Census Bureau's Tigerlines data set of tabular blocks.[4] We employed the Census block data to estimate the total population for the purpose of weighting precincts with population data for redistricting simulations, and census estimates of race. We assigned blocks to precincts conditional upon where its geographic centroid was located (Gimpel et al. 2006). We acquired the precinct data for North Carolina from the North Carolina State Board of Elections (NCSBE) precinct map archive[5] and the voter file from the archive snapshots from the NCSBE.[6] We attained a precinct map from the Open Precincts project site for Georgia[7]. We purchased the entire Georgia voter file in December of 2020 for $250 on the Georgia Secretary of State website.[8]. Georgia's voter file exhibited mismatch between the precinct IDs within the voter file, so we therefore geocoded every address using the ESRI 2013 classic geocoder suite, and overlaid ensuing point shapefile onto the precinct shapefile.

DIAGNOSING BISG

In order to diagnose the precision of the BISG estimates at the individual level, we display density plots of the uncertainty in BISG estimates, separately for both North Carolina (a) and Georgia (b) in Figure B1. On the x-axis, we plot the effective number of races, the inverse of the Herfindahl index (Wolak 2009; Curiel and Steelman 2020). Overall, there is a global mode at approximately one estimated racial grouping. However, there are local modes at around two effective races, suggesting a substantive level of uncertainty in the estimation of racial categorization. Figure B2 and Figure B3 plot the average error rates separately for white and black voters based on the effective number of races, in North Carolina and Georgia, respectively, and confirm that as BISG uncertainty increases so does the average error.

[4] U.S. Census Bureau. 2010 Census Tallies of Census, Tracts, Block Groups, and Blocks. (last updated March 26, 2012), `https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2010.html` (accessed October 10, 2020).

[5] "Precinct Maps, 2012." North Carolina State Board of Elections. (last updated February 8, 2016), `https://dl.ncsbe.gov/?prefix=PrecinctMaps/` (accessed February 17, 2021).

[6] "Voter registration snapshots." North Carolina State Board of Elections, November 6, 2012. (last updated March 2, 2017). `https://dl.ncsbe.gov/index.html?prefix=data/Snapshots/` (accessed February 17, 2021).

[7] Georgia. Open Precincts. <https://openprecincts.org/ga/> (accessed February 22, 2021).

[8] Voter list. Georgia Secretary of State. `https://georgiasecretaryofstate.net/collections/voter-list-1` (accessed December 1, 2020).

FIGURE B1. Precision of Individual-Level BISG Estimates

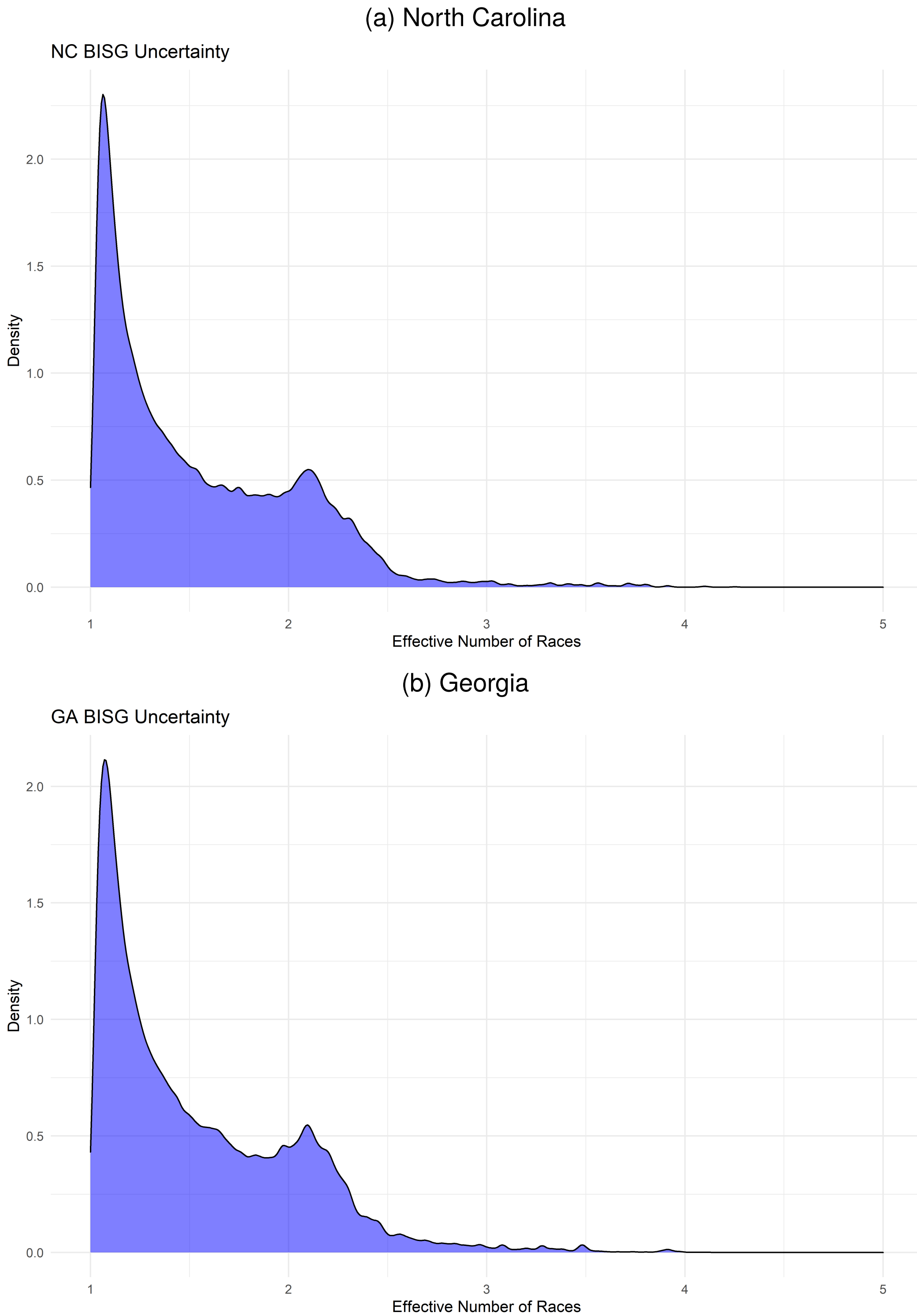


FIGURE B2. Errors by Heterogeneity - North Carolina

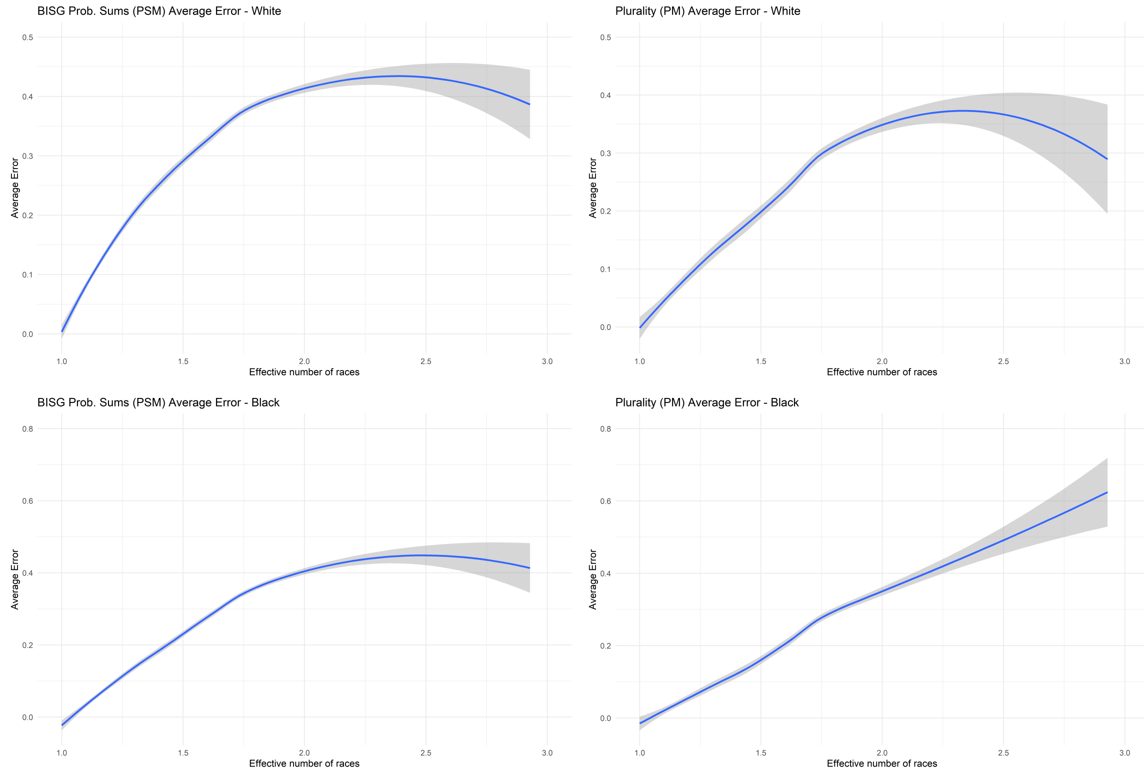


FIGURE B3. Errors by Heterogeneity - Georgia