

An Evaluation of North Carolina's Congressional, State Senate, and State House District Maps

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1 Introduction

I am an Associate Professor in the Department of Political Science at Binghamton University, SUNY where I also hold a courtesy appointment in the Department of Economics. At Binghamton, I am also the director of the Center for the Analysis of Voting and Elections at Binghamton University. In 2007, I received an M.S. in Mathematical Methods in the Social Sciences from Northwestern University. I hold an M.A. in political science from the University of Michigan, Ann Arbor where I also received a Ph.D in political science in 2011. I have published academic papers on legislative districting and political geography in several political science journals, including *Political Analysis*, the *Election Law Journal*, *American Politics Research*, and *Social Science Quarterly*. My academic areas of expertise include legislative elections, geographic information systems (GIS) data, redistricting, voting rights, legislatures, and political geography. I have expertise in analyzing political geography, elections, and redistricting using computer simulations and other techniques. I have been retained by plaintiff Common Cause to perform the analysis described below at a rate of \$250 an hour. My compensation is not predicated on arriving at any particular opinion.

1.1 Data

My opinions follow from analysis of the following data:

- VTD boundaries provided as ESRI Shapefiles by the US Census Bureau available on at the following URL
- Census block boundaries and population data provided by the US Census Bureau. These are collected as part of the constitutionally mandated decennial census that most recently concluded in 2020.
- County boundaries as reported by the US Census Bureau.
- County clusterings provided Christopher Cooper, Blake Esselstyn, Gregory Herschlag,

Jonathan Mattingly, and Rebecca Tippett in a report that may be accessed at the following URL. <https://sites.duke.edu/quantifyinggerrymandering/files/2021/08/countyClusters2020.pdf>

- Election returns as reported by the Voting and Election Science Team¹ group and aggregated to Census-provided VTD boundaries and provided on the Redistricting Data Hub² website. I aggregate statewide elections returns from 2016 and 2020 to set of legislature drawn districts and to the districts in each of the hypothetical alternative maps. In my analysis, I set aside election returns from 2018 because the only statewide races held that year were judicial elections which follow very different patterns compared to elections for other offices.
- 1,000 alternative, hypothetical maps of North Carolina’s congressional, Senate, and House districts generated by a neutral, partisan-blind computer algorithm. The redistricting algorithm I use in my analysis was developed by me and a collaborator, Daniel Mosesson (consultant in private practice), in a paper that is forthcoming in *Political Analysis*. In our published work, we show that the algorithm produces a large number of unique maps of legislative districts without any indication of bias.
- Legislature-drawn boundaries of districts intended to elect representatives to Congress, the North Carolina Senate, and the North Carolina House of Representatives. These data are available on the North Carolina General Assembly website and may be accessed at the following URLs. <https://www.ncleg.gov/Redistricting>

2 Methods and Data

In this section I inform my analysis of North Carolina’s map using computer-simulated redistricting methods. I discuss the data I use to analyze the maps, and describe the methods

¹<https://dataverse.harvard.edu/dataverse/electionscience>

²<https://redistrictingdatahub.org>

for measuring partisan bias in electoral maps. The purpose of these methods is to assess and describe potential biases that arise from the legislature-drawn electoral maps. In particular, I will describe how computer simulations may be used to evaluate alternative, hypothetical scenarios that are free of bias that human mapmakers may incorporate into a system of electoral districts. For the purposes of this report, I will define bias to mean a party receiving more representation than it should given underlying patterns of partisan support. Critically, I will not measure bias as an absolute deviation from proportionality, but rather as deviation from patterns of representation we would expect if an electoral map were drawn in a neutral manner.

2.1 Computer-Drawn Maps

The purpose of my analysis is to determine if the legislature intended to discriminate against a particular group in North Carolina, or if the dilution of one group's influence arises for other more benign reasons. For example, political scientists have observed that even in systems that award representation in an unbiased manner, political parties receive a representational "bonus" for votes they receive over the majoritarian threshold of 50%. That is, a 1% increase in votes produces an increase of more than 1% in representation. As a result, parties that receive a little more than a majority of the votes may receive much more than a majority of seats in a legislature (see Edgeworth 1898; Butler 1952, 1951; Niemi and Deegan 1978). Likewise, electoral advantages may arise out of the geographic distribution of voters. For example, one group of voters may be evenly distributed across a jurisdiction that must be divided into multiple districts. If the distribution is even enough, it may be that it is impossible for a neutral process to draw a single-member district in which that group constitutes a majority. Alternatively, it may be that voters of one particular type are concentrated in an area or region. If that is the case, even a neutral process may collect those voters into a district in which they form a large majority leaving likeminded voters in neighboring districts in which they form a modest minority. My academic work focuses on developing

tools to account for natural sources of bias through dilution and over-concentration of voters as a result of residential geography (Magleby and Mosesson 2018).

One way to evaluate a districting plan’s bias is to compare a set of districts to an alternative set that we know to be unbiased. If the enacted plan is similar to the unbiased alternative, we may conclude that the enacted plan is also unbiased. Alternatively, if the enacted plan differs significantly from the alternative we know to be unbiased, we may conclude that the enacted plan is biased.

For this report, I used a computer algorithm I developed as part of my academic research to generate a large set of fair, hypothetical alternatives against which we may compare the North Carolina’s legislature drawn maps. The algorithm has been subject to peer review (see Magleby and Mosesson 2018) and has formed an important part of the analysis for several other peer reviewed articles (see e.g. Best et al. 2017; Krasno et al. 2018). The algorithm simulates a redistricting process constrained to draw districts that are contiguous and contain roughly equal population.³ For the purposes of this report, I have constrained the algorithm to prioritize maintaining VTDs, roughly voting precincts, in North Carolina whole. The algorithm builds districts using data provided by the US Census Bureau. Census data include information about the number of people who reside within a geographic units and the geographies to which blocks are adjacent. Critically, the algorithm is blind to partisanship and race, so it does not consider the political preferences or race of residents as it constructs various hypothetical districts.

I use the algorithm to generate large sets (between 20,000 and 100,000) of maps from which I take a random sample of 1,000 maps that meet the set of redistricting criteria announced by the North Carolina legislature in advance of the last round of redistricting there. Each iteration of the computer algorithm combines geographies in different ways, so the result is 1,000 maps that contain unique combinations of contiguous districts that meet the legislature’s announced criteria. This large set of maps constitutes a sample of the larger

³For a more technical discussion of the algorithm please see Appendix ??

set of possible maps that mapmakers could have drawn. Each map represents a distinct, hypothetical example of a map of North Carolina’s congressional, Senate, or House districts that was produced by a neutral process.

The maps generated by the computer are examples of outcomes we would expect if mapmakers were not motivated by partisan goals. Since each map is slightly different, the set of maps represents a range of possible outcomes from a neutral redistricting process. If the partisan characteristics of the enacted plan of congressional, Senate, and House districts in North Carolina falls outside the normal range of neutral outcomes generated by the algorithm, we can conclude that the map represents a significant deviation from a fair outcome.

This approach to evaluating districting plans is common in academic settings. Advances in computers made it possible for scholars to implement methods for developing a neutral, unbiased counterfactual of a jurisdiction’s legislative districts (see Chen and Cottrell 2014; Chen and Rodden 2013; Tam Cho and Liu 2016; Cirincione, Darling and O’Rourke 2000; Engstrom and Wildgen 1977; Fifield et al. 2015; McCarty, Poole and Rosenthal 2009; O’Loughlin and Taylor 1982). Recently, courts have also relied upon maps generated by computer algorithms to determine the presence of dilution in enacted plans of legislative districts.

2.2 Measuring Gerrymanders

Measuring Partisanship in the Simulated Districts

To assess the partisanship of the maps produced by the computer algorithm, I use election returns from the 2016 and 2020 general election in North Carolina aggregated to the VTD-level. For each hypothetical map, I determine which simulated district a precinct would fall, and assign the votes cast in that precinct to that district. If a precinct falls in more than one simulated district, I assign the the votes in that precinct to a simulated district according to the proportion of the precinct’s population that falls inside that district.

I use statewide races (as opposed to congressional races) because scholars have shown

those data to be reliable predictors of future behavior (Meier 1975). Moreover, a focus on statewide races serves to avoid problems of endogeneity that could be a problem with data from congressional elections. That is, differences in partisan performance in congressional elections can arise for many reasons besides the location of district boundaries. For example, incumbency, quality of challengers, campaign contributions, and campaign organization have all been shown to influence election outcomes, and those can vary widely across districts. By contrast, all those factors are held constant in statewide elections.

Statewide races have an additional advantage: the candidates on the ballot in statewide races appear in every precinct across the state. For this reason, returns from statewide contests are imperative when analyzing the computer generated, hypothetical maps. The computer frequently assigns precincts that fall in different districts in North Carolina's legislature-drawn map to the same district in a hypothetical map. In such a scenario, voters considered different candidates for Congress, and comparing a vote for Democratic candidate for Congress in one district to a Democrat running for Congress in another district requires that we assume away possible differences between contests and candidates. On the other hand, these factors are held constant when if we consider statewide contests.

For robustness, I use returns from multiple statewide contests. For each district in the legislature-drawn map and algorithm drawn maps I calculate a composite partisan score based the election results from the 2016 and 2020 election cycles. In those elections North Carolina held statewide contests for President, US Senate, Governor, Lieutenant Governor, Attorney General, Treasurer, Secretary of State, Auditor, Agriculture Commissioner, Insurance Commissioner, Labor Commissioner, and Superintendent of Public Instruction. To calculate the composite score, I take the sum the votes cast for Republican candidates for statewide office in 2016. I likewise sum the votes cast for Democratic candidates for statewide office. Then I determine the proportion of votes cast for the Democratic candidates by dividing the total votes cast for the Democratic candidates by the sum of the total votes cast for Republicans and total votes cast for Democrats. The result, the Democratic

proportion of total votes cast in that district, is a composite measure of underlying support of for Democrats for voters living that district.

Using precinct-level returns for statewide races, I can determine the partisanship of the hypothetical districts drawn by the computer algorithm. The vast majority of VTDs are wholly contained within one district; however, I allow the computer algorithm to “break” VTDs into census blocks. It is therefore possible for the districts drawn by the algorithm to split existing VTDs. When that happens, I presume that the votes are distributed across blocks according to the proportion of a VTD’s voting age population (VAP) that resides within a block. For example, suppose a precinct has a VAP of 100, and that voters cast 20 votes for a Republican candidate and 30 votes for a Democratic candidate. If a block within that precinct has a VAP of 10 people, I calculate that 2 votes for the Republican and 3 votes for the Democrat came from that block.

Districts Carried

I use the composite partisanship to calculate the number of districts carried in each map. I presume that districts in which the Democratic proportion of the composite votes exceeds 0.5 is a district that is more likely than to elect a Democrat than a Republican. Conversely, if the Democratic proportion of the composite vote falls below 0.5, I presume that that Republicans carried the district. For example, suppose Democrats received proportions of the composite vote equaling 0.47, 0.58, and 0.52 in a three-district jurisdiction. In such a scenario, I say that Democrats “carried” the second and third district and failed to carry the first. In this analysis I consider three jurisdictions, a 14-district congressional map, a 50-district Senate map, and a 120-district House map.

Median-Mean Difference

I also use the proportion of the composite partisan vote to calculate the median-mean difference metric. Consider the same example districts in which Democrats received proportions of the voted equaling 0.47, 0.58, and 0.52. To find the mean, we divide the sum of the Democratic proportions by the number of districts. In this case, $(0.47+0.58+0.52)/3$

$= 1.57/3 = 0.52$. To find the median we sort the Democratic proportions so that they are ordered from smallest to largest. The median is the proportion for which number of proportions that are larger is equal to the number of proportions that are smaller. In this example, we would order 0.47, 0.52, 0.58. Here, the median is 0.52 because there is one proportion that is larger and one that is smaller. Of course, in my analysis in this report, I take the number of districts in the map as the denominator in each map I analyze.

3 Findings: Partisan Bias

In this section, I describe the results of 1000 simulations of the redistricting process for North Carolina's congressional districts, Senate districts, and House districts. I show that the legislature drawn map of electoral districts for Congress, the Senate, and the House show significant bias against Democratic voters and that bias goes beyond anything we would expect based on the patterns of electoral geography in North Carolina. I begin by discussing the results of my simulations of the House map and comparing those results to the characteristics of the map drawn by the legislature. Next, I present the results of computer simulated redistricting for the North Carolina Senate electoral map and show that the legislature-drawn map exhibits more bias than we would expect based on chance alone. Finally, I repeat the analysis focused on the electoral map used to elected North Carolina's congressional delegation. I show that, as with the other maps, the legislature-drawn map shows bias above and beyond what we would expect had the legislature used a neutral process, free from an intent to produce a partisan bias, to determine district boundaries.

3.1 State House Districts

To draw a set neutral and partisan-blind maps of North Carolina's House districts, I take the following steps.

1. Build a map consisting of VTDs that are appropriate to the electoral map.

2. Divide that map into House-specific clusters as described by Cooper et. al.
3. Determine which VTDs are adjacent to each other in the cluster by cluster maps.
4. Run simulations for up to 40,000 maps per cluster.
5. For each cluster, I aggregate the characteristics of each VTD to the district to which it is assigned in each hypothetical map.
6. Aggregate the characteristics of each hypothetical map to ascertain its demographic and partisan characteristics. At this point, I subset the resulting maps to remove any maps in which the population of each district does not fall within 1.5% of constitutional requirements that districts contain equal population.⁴ For the purposes of exposition, I randomly sample remaining maps and focus my analysis on 1000 of those randomly sampled.
7. Finally, I combine the data from each of the clusters and describe the partisan characteristics of the full set of maps.

The result of this process is a set of maps that approximate the legislatures announced districting criteria. Each systemwide map is a unique combination of North Carolina's geography. At no point in developing the sample of 1000 maps upon which I base my analysis do I consider any factors besides population and the geographic characteristics of units of geography upon which the maps are base. Thus, taken together, the maps represent the distribution of outcomes we might expect from a neutral redistricting process.

⁴Because of the compressed time available, a few counties posed coding problems because the average population deviation within clusters abutted the constitutional limit. Thus I allowed the algorithm slightly more flexibility. The algorithm draws maps randomly, there is no reason to believe this slight deviation from exact population parity should create an advantage for either Democrats or Republicans.

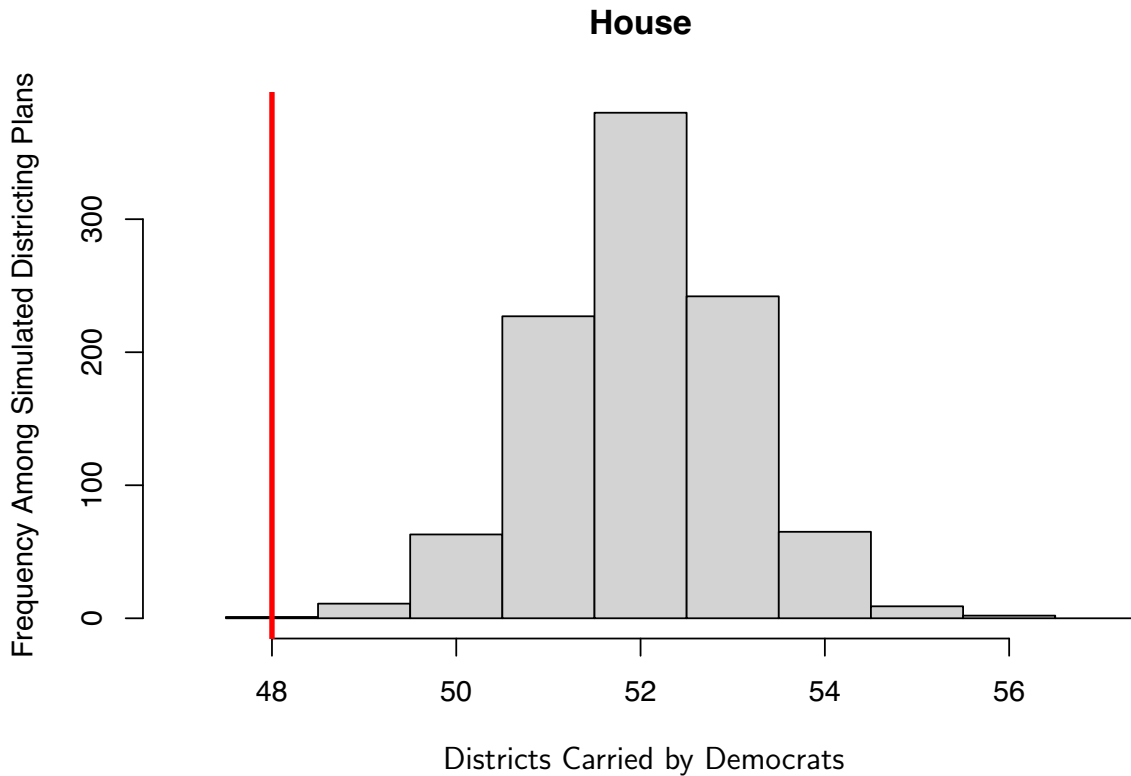


Figure 1: Distribution of outcomes from 1000 simulations of the redistricting process used to draw North Carolina’s House districts. The x-axis represents the number of districts carried (out of 120) by Democrats using the partisan composite score. The vertical red line corresponds to the number of districts carried by Democrats in the legislature-drawn map. Democrats carried in 48/120 districts in the legislature-drawn map. Democrats carried just one of the 1000 sampled algorithm-drawn maps ($p = 0.001$).

Figure 1 summarizes the partisan characteristics of set of algorithm-drawn maps and compares the distribution of those characteristics to the characteristics of the Legislature-drawn map of House districts. Here, I summarize the number of districts carried by Democrats. Recall that I say a Democrats carry a district if Democrats received more votes in that district in statewide contests during the 2016 and 2020 elections. Along the x -axis, numbers correspond to the number of districts favoring Democrats in a particular map. The y -axis describes the frequency with which I observe maps that exhibit a particular set of partisan characteristics. Thus, the relative height of the bars corresponds to the relative frequency with which I observe maps with particular characteristics in the set of Algorithm-drawn maps I analyzed.

In the sample of maps represented here, Democrats carried as few as 48 (out of 120) and as many as 56. In the sample, the most common outcome was one in which Democrats carried in 52/120 districts. By contrast, Democrats carried just 48 of the legislature-drawn districts. The algorithm drew just one map in which Democrats carried so few districts. Thus, based on this sample of maps, I may say that there is about a 1 in 1000 chance of drawing a map in which Democrats carried as few or fewer districts. In short, it is highly unlikely that the legislature-drawn map was developed through a process that treated partisanship of voters neutrally.

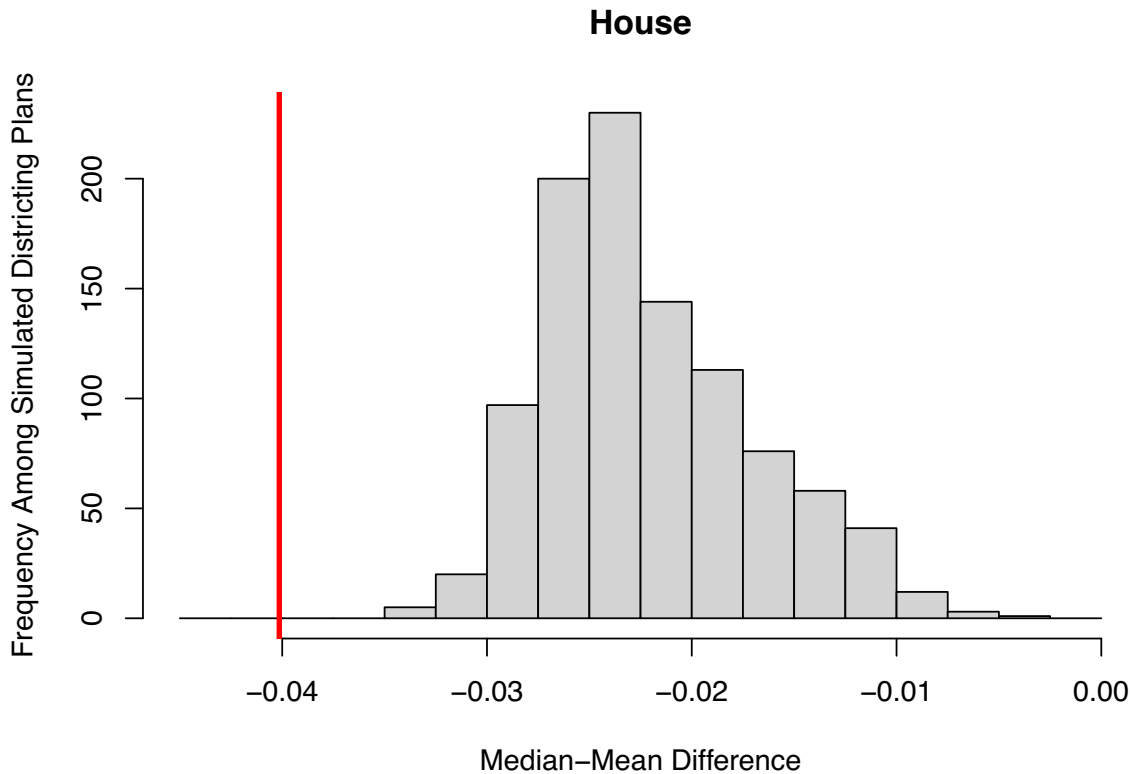


Figure 2: Distribution of outcomes from 1000 simulations of the redistricting process used to draw North Carolina’s House districts. The x-axis represents the difference in the median Democratic vote share and the mean Democratic vote share calculated using the partisan composite score. The vertical red line corresponds to the difference in the median Democratic vote share and mean of Democratic vote share in the legislature-drawn map. The legislature drawn map has a median-mean difference of -0.04 . None of the algorithm-drawn maps had a median-mean difference that extreme ($p = 0.0$).

The degree to which Democrats are disadvantaged by the legislature drawn map is even more stark when I consider the median-mean difference. Figure 4 summarizes the partisan characteristics of set of algorithm-drawn maps and compares the distribution of those characteristics to the characteristics of the Legislature-drawn map. Here, I summarize the median-mean difference in the algorithm-drawn map and the legislature-drawn map. Recall that the median-mean difference is found by taking the map-level median and the map-level mean of Democratic share of the two-party vote. If the difference takes a negative number, the map is biased against Democrats. If the difference takes a positive value, the map is biased in favor of Democrats. If the difference equals 0, then the map is neither biased in

favor nor biased against Democrats. Along the x -axis, numbers correspond to the number of districts carried by Democrats in a particular map. Maps are sorted into bins depending on whether the median-mean difference exhibited in the map falls into the interval the bar covers on the x -axis. The y -axis describes the frequency with which I observe maps that exhibit a particular set of partisan characteristics. Thus, the relative size of the bars corresponds to the relative frequency with which I observe maps with particular characteristics in the set of algorithm-drawn maps I analyzed.

In the sample of maps represented in my analysis, the most common median-mean difference in Democratic vote share fell between -0.0225 and -0.025 . The lowest median-mean difference in the sample of maps I analyze here was -0.034 , and the highest median-mean difference was -0.005 . By contrast, the legislature-drawn map has a median-mean difference of -0.04 . No map in the sample of algorithm drawn maps showed a degree of bias as extreme as the bias I observe in the legislature-drawn map. The data indicate that there is less than a 1 in 1000 chance that we would observe a map as extreme as the map drawn by the legislature if the legislature was following a neutral, party-blind process.

3.2 State Senate Districts

To draw a set neutral and partisan-blind maps of North Carolina's House districts, I take follow the same steps I took to develop maps for the House.

1. Build a map consisting of VTDs that are appropriate to the electoral map.
2. Divide that map into Senate-specific clusters as described by Cooper et. al.
3. Determine which VTDs are adjacent to each other in the cluster by cluster maps
4. Run simulations for up to 40,000 maps per cluster
5. For each cluster, I aggregate the characteristics of each VTD to the district to which it is assigned in each hypothetical map.

6. Aggregate the characteristics of each hypothetical map to ascertain its demographic and partisan characteristics. At this point, I subset the resulting maps to remove any maps in which the population of each district does not fall within 1.5% of constitutional requirements that districts contain equal population.⁵ For the purposes of exposition, I randomly sample remaining maps and focus my analysis on the 1000 randomly sampled maps.
7. Finally, I combine the data from each of the clusters and describe the partisan characteristics of the full set of maps.

The result of this process is a set of maps that approximate the legislatures announced districting criteria. Each systemwide map is a unique combination of North Carolinas geography. At no point in developing the sample of 1000 maps upon which I base my analysis do I consider any factors besides population and the geographic characteristics of units of geography upon which the maps are base. Thus, taken together, the maps represent the distribution of outcomes we might expect from a neutral redistricting process.

⁵As described in an earlier footnote, we allow the algorithm more leeway to account for highly constrained average population deviations in some clusters.

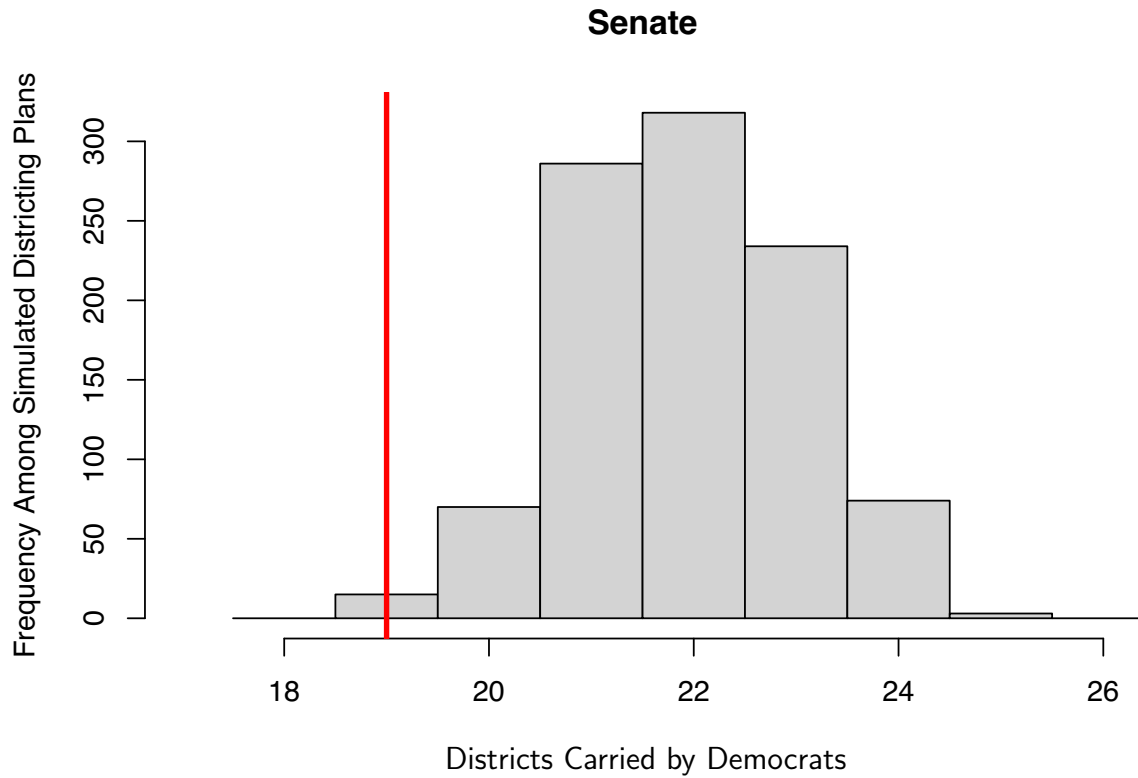


Figure 3: Distribution of outcomes from 1000 simulations of the redistricting process used to draw North Carolina’s Senate districts. The x-axis represents the number of districts carried (out of 50) by Democrats using the partisan composite score. The vertical red line corresponds to the number of districts carried by Democrats in the legislature-drawn map. Democrats carried 19/50 districts in the legislature-drawn map. Just 15 out of 1000 of the algorithm-drawn maps had so few districts carried by Democrats ($p = 0.015$).

Figure 3 summarizes the partisan characteristics of set of algorithm-drawn maps and compares the distribution of those characteristics to the characteristics of the Legislature-drawn map of Senate districts. Here, I summarize the number of districts carried by Democrats. Recall that I say Democrats carry a district if Democrats received more votes in that district in statewide contests during the 2016 and 2020 elections. Along the x -axis, numbers correspond to the number of districts carried by Democrats in a particular map. The y -axis describes the frequency with which I observe maps that exhibit a particular set of partisan characteristics. Thus, the relative size of the bars corresponds to the relative frequency with which I observe maps with particular characteristics in the set of Algorithm-drawn maps I analyzed.

In the sample of maps represented here, Democrats carried as few as 19 (out of 50) and as many as 25. In the sample, the most common outcome was one in which Democrats carried 22/50 districts. By contrast, Democrats carried just 18 of the legislature-drawn districts. The algorithm drew 15 maps in which Democrats carried so few districts. Thus, based on this sample of maps, I may say that there is about a 1.5 in 100 chance of drawing a map in which Democrats carried as few or fewer districts. In short, it is highly improbable that the legislature-drawn map was developed through a process that treated partisanship of voters neutrally.

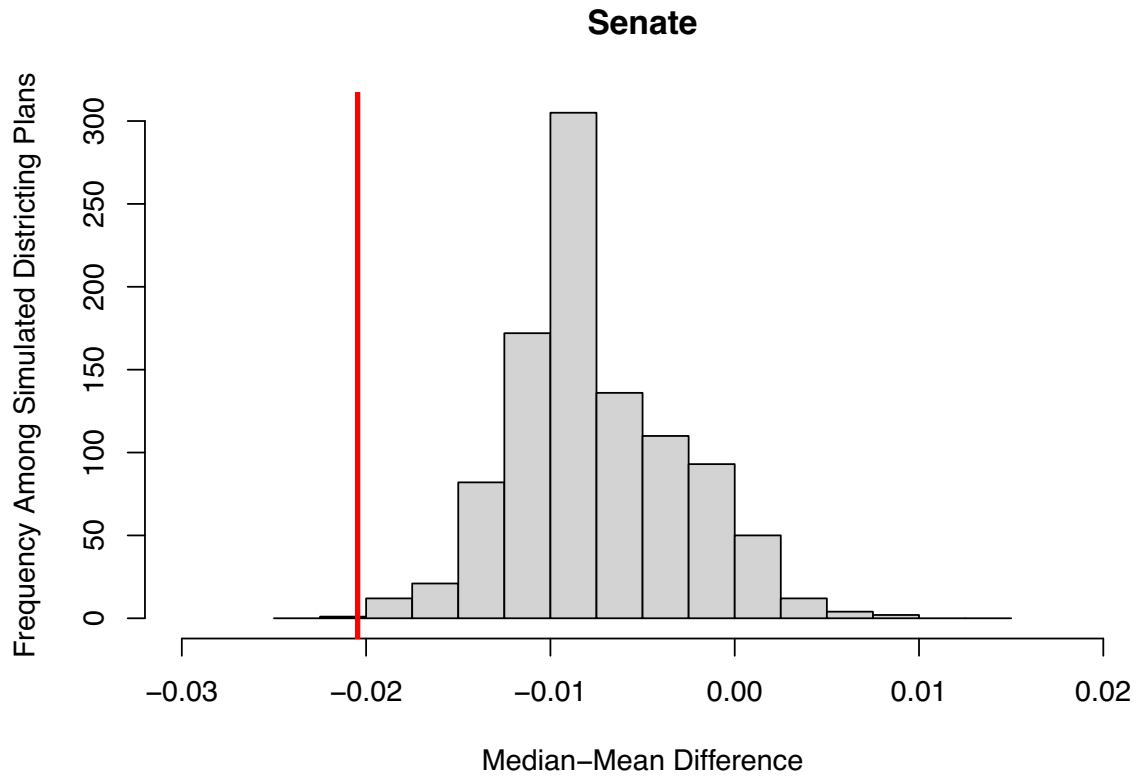


Figure 4: Distribution of outcomes from 1000 simulations of the redistricting process used to draw North Carolina’s Senate districts. The x-axis represents the difference in the median Democratic vote share and the mean Democratic vote share calculated using the partisan composite score. The vertical red line corresponds to the difference in the median Democratic vote share and mean of Democratic vote share in the legislature-drawn map. The legislature drawn map has a median-mean difference of -0.0204 . None of the algorithm-drawn maps had a median-mean difference that extreme ($p = 0.0$).

The degree to which Democrats are disadvantaged by the legislature drawn map is even more stark when I consider the median-mean difference. Figure 4 summarizes the partisan characteristics of set of algorithm-drawn maps of Senate districts and compares the distribution of those characteristics to the characteristics of the Legislature-drawn map in terms of median-mean difference. Recall that the median-mean difference is found by taking the map-level median and the map-level mean of Democratic share of the two-party vote. If the difference takes a negative number, the map is biased against Democrats. If the difference takes a positive value, the map is biased in favor of Democrats. If the difference equals 0, then the map is neither biased in favor nor biased against Democrats. Along the x -axis, numbers correspond to the number of districts carried by Democrats in a particular map. Maps are sorted into bins depending on whether the median-mean difference exhibited in the map falls into the interval the bar covers on the x -axis. The y -axis describes the frequency with which I observe maps that exhibit a particular set of partisan characteristics. Thus, the relative size of the bars corresponds to the relative frequency with which I observe maps with particular characteristics in the set of algorithm-drawn maps I analyzed.

In the sample of maps represented in my analysis, the most common median-mean difference in Democratic vote share fell between -0.0075 and -0.01 . The lowest median-mean difference in the sample of maps I analyze here was -0.0201 , and the highest median-mean difference was -0.005 . By contrast, the legislature-drawn map has a median-mean difference of -0.009 . No map in the sample of algorithm drawn maps showed a degree of bias as extreme as the bias I observe in the legislature-drawn map. The data indicate that there is less than a 1 in 1000 chance that the legislature would arrive a map as biased as their map of Senate districts if they followed a neutral, party-blind process.

3.3 Congressional Districts

To draw a set neutral and partisan-blind maps of North Carolina's House districts, I take follow the same steps I took to develop maps for the House.

1. Build a map consisting of VTDs that are appropriate to the electoral map. In the case of the congressional map, I maintained whole all counties that the legislature did not break in their map.
2. Divide that map into Senate-specific clusters as described by Cooper et. al.
3. Determine which VTDs are adjacent to each other in the cluster by cluster maps.
4. Run simulations for 100,000 maps.
5. For each cluster, I aggregate the characteristics of each VTD to the district to which it is assigned in each hypothetical map.
6. Aggregate the characteristics of each hypothetical map to ascertain its demographic and partisan characteristics. At this point, I subset the resulting maps to remove any maps in which the population of each district does not fall within 0.01 of constitutional requirements that districts contain equal population. For the purposes of exposition, I randomly sample remaining maps and focus my analysis on 1000.
7. Finally, I combine the data from each of the clusters and describe the partisan characteristics of the full set of maps.

The result of this process is a set of maps that approximate the legislature's announced districting criteria. Each systemwide map is a unique combination of North Carolinas geography. At no point in developing the sample of 1000 maps upon which I base my analysis do I consider any factors besides population and the geographic characteristics of units of geography upon which the maps are based. Thus, taken together, the maps represent the distribution of outcomes we might expect from a neutral redistricting process.

Figure 5 presents histogram summarizing findings from 1000 simulations of the redistricting process in North Carolina. The x-axis corresponds the possible number of districts that Democrats could carry by the composite partisan vote. The y-axis corresponds to the

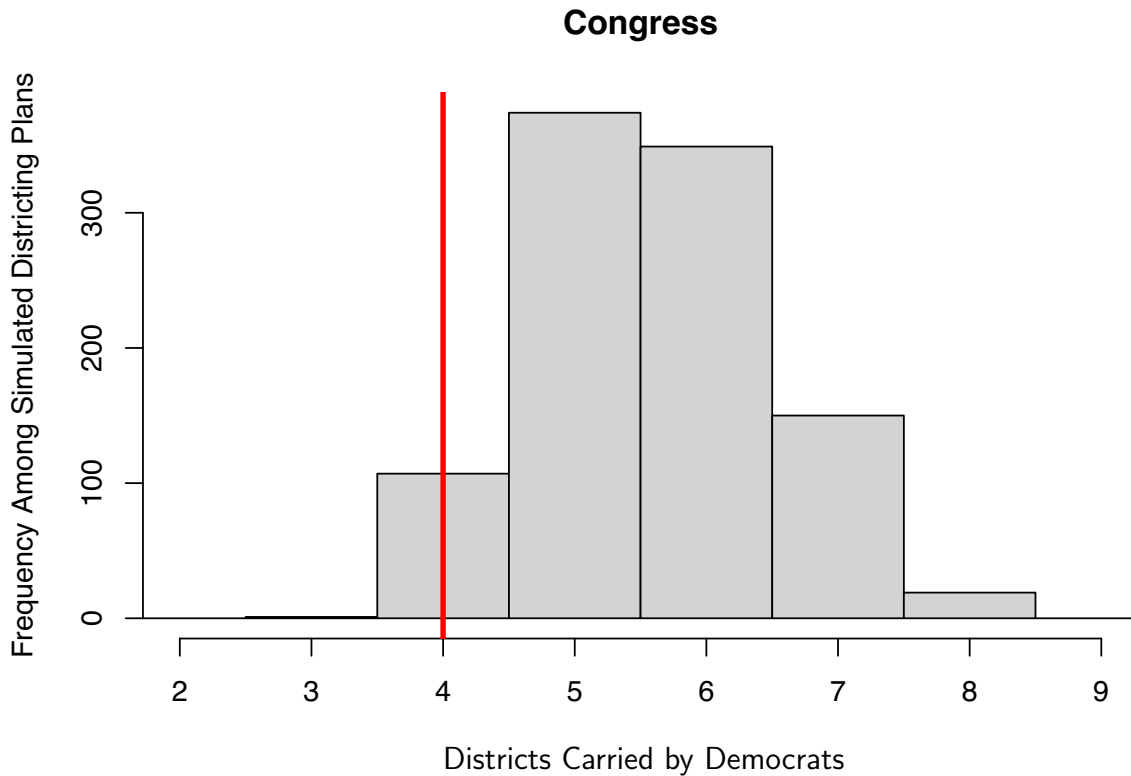


Figure 5: Distribution of outcomes from 1000 simulations of the redistricting process used to draw North Carolina’s congressional districts. The x-axis represents the number of districts carried (out of 14) by Democrats using the partisan composite score. The vertical red line corresponds to the number of districts carried by Democrats in the legislature-drawn map.

frequency with which maps with a particular count of districts carried appear in the set of simulated maps. Higher bars correspond do outcomes that occurred more often in the set of simulated maps. The simulations produced maps with as few as 3 and as many as 8 districts that would favor a Democratic candidate. The most common outcome, occurring in 374/1000 simulations, in the simulation was Democrats carrying 5/14 districts based on the composite partisan score. Democrats carried 6/14 districts in nearly as many districts (349/1000 simulations). Democrats carried 7/10 and 8/10 districts in 150/1000 and 19/1000 maps respectively. In the enacted map, we would expect Democrats to carry 4 districts by the composite partisan index. In 108/1000, Democrats carried 4 or fewer districts. Thus the legislature drawn map shares characteristics with roughly 1/10 of the maps drawn by the algorithm.

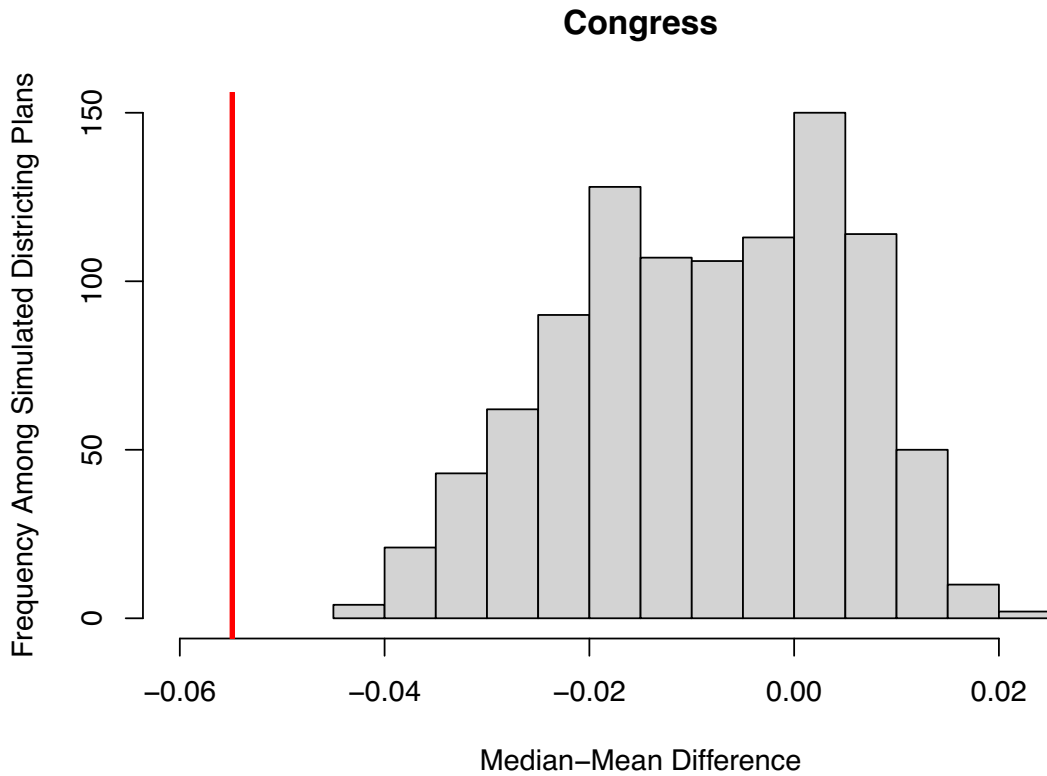


Figure 6: Distribution of outcomes from 1000 simulations of the redistricting process used to draw North Carolina’s congressional districts. The x-axis represents the difference in the median Democratic vote share and the mean Democratic vote share calculated using the partisan composite score. The vertical red line corresponds to the difference in the median Democratic vote share and mean of Democratic vote share in the legislature-drawn map.

Figure 6 presents a histogram that summarizes the difference in median composite partisan vote share and mean composite partisan vote share for 1000 simulated maps of North Carolina’s Congressional districts. Here the x-axis corresponds to possible values that the median-mean difference may take. The y-axis corresponds to frequency with which particular values appear in the algorithm-drawn map. As before, the vertical red line corresponds to the median-mean difference in the legislature-drawn map.

In the simulated maps, the median-mean difference ranged from -0.042 to 0.025 . the distribution is bimodal with two peaks at just greater than -0.02 and another peak at a little above 0.0 . The fact that simulations regularly median-mean difference of greater than 0.0 which corresponds to no votes being weight roughly equally in the system of districts.

In fact, 326/1000, just shy of a third of the simulations, corresponds to maps that were not skewed against Democrats. The legislature drawn map showed a median-mean score of -0.055 . Not a single algorithm-drawn map was more extreme than the map drawn by the legislature. By contrast, the minimum median-mean difference observed in the simulated maps was just -0.041 .

4 Conclusion

Each legislature-drawn map represents a significant deviation from unbiased alternatives produced by the computer algorithm I describe here. Based on the simulations, there is less than a 1 in 1000 chance that a neutral process produced the House map. There is less than a 2 in 100 chance that a neutral process led to the Senate map. The odds of arriving at the a congressional map as biased as the legislature-drawn map are similarly long.

As independent events, the emergence of these three maps would be cause for concern that partisan biased actions were taken in the construction. Taken together, concern compounds. The computer simulations that I described in this report suggest that the legislature drew three maps that represent gerrymanders in favor of Republicans.

A A Description of the Magleby-Mosesson Algorithm

The process we use to develop a large set of neutral counterfactuals draws maps in a four-step process. For a more technical representation along with evaluations of the authors' claims of neutrality (see Magleby and Mosesson 2018).

Step 1: Convert map into a graph

We reduce the map to a connected graph where each geographic unit, a VTD in this setting, is a vertex of the graph. Two vertices are connected by edges if the units of geography share more than a single point of their boundary (thus, the resulting districts will be “rook” contiguous).

Step 2: Divide the graph randomly

The algorithm randomly collects connected vertices into groups and joins them into a new vertex that aggregates the demography of each of its constituent vertices and preserves the connectedness with any vertex with which a constituent vertex was adjacent. It continues to randomly join groups of vertices until the number of groups is equal to the number of districts in the state.

Step 3: Refine the divided graph

In order to achieve balance (population parity between districts), Magleby and Mosesson use an algorithm proposed by Kernigan and Lin to switch constituent vertices between groups of vertices. If it is not possible to achieve balance with a moderate number of switches, then we discard the map and start over. If balance is possible after a fixed number of switches, then we record the map for future analysis.

Step 4: Repeat

Repeat steps 1, 2, and 3 until we find a large sample maps that contain roughly equal district populations.

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I declare under penalty of perjury under the laws of NC that the foregoing is true and correct

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