IN THE SUPREME COURT OF OHIO

Meryl Neiman, *et al.*, **League of Women Voters of Ohio, *et al.*,** **Petitioners,** **v.** **Secretary of State Frank LaRose, *et al.*,** **Respondents.**	**Case No. 2022-298** **Case No. 2022-303** ***Consolidated*** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

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EX.	**DESCRIPTION**	**BATES RANGE**
24	Dr. Rodden's Expert Affidavit, *Adams v. DeWine*, Case No. 2021-1428 (submitted Dec. 10, 2021)	NEIMAN_EVID_00071-NEIMAN_EVID_00148
25	Dr. Chen's Expert Affidavit, *Adams v. DeWine*, Case No. 2021-1428 (submitted Dec. 10, 2021)	NEIMAN_EVID_00149-NEIMAN_EVID_00217
26	Dr. Imai's Expert Affidavit, *League of Women Voters of Ohio v. Ohio Redistricting Commission*, Case No. 2021-1449 (submitted Dec. 10, 2021)	NEIMAN_EVID_00218-NEIMAN_EVID_00276
27	Dr. Handley's Expert Affidavit, *League of Women Voters of Ohio v. Ohio Redistricting Commission*, Case No. 2021-1449 (submitted Dec. 10, 2021)	NEIMAN_EVID_00277-NEIMAN_EVID_00303
28	Dr. Warshaw's Expert Affidavit, *League of Women Voters of Ohio v. Ohio Redistricting Commission*, Case No. 2021-1449 (submitted Dec. 10, 2021)	NEIMAN_EVID_00304-NEIMAN_EVID_00340

CERTIFICATE OF SERVICE

I hereby certify that Neiman Petitioners' Evidence – Volume 2 of Exhibits was sent via email this 25th day of April 2022 to the following:

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/s/ Derek S. Clinger_______________
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Neiman Petitioners' Exhibit 24

IN THE SUPREME COURT OF OHIO

Regina Adams, *et al.* **Relators,** **v.** **Governor Mike DeWine, *et al.*** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

EXPERT AFFIDAVIT OF DR. JONATHAN RODDEN

I, Jonathan Rodden, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge and having personally examined all records referenced in this affidavit, and further state as follows:

I. INTRODUCTION AND SUMMARY

1. For the purpose of this report, I have been asked to examine whether and how the redistricting plan for the Ohio delegation to the United States House of Representatives, adopted by the Ohio General Assembly on November 18, 2021 and signed into law by Governor Mike DeWine two days later, and attached as Exhibit A ("2021 Congressional Plan" or the "Enacted Plan"), conforms to the requirement set forth in Article XIX, Section 1(C)(3)(a), namely, that the plan does not "unduly favor[] or disfavor[] a political party or its incumbents." I have also been asked to examine the extent to which the General Assembly's redistricting plan splits governmental units, and to assess the plan's adherence to other traditional redistricting criteria, including compactness. Finally, I have been asked to examine characterizations of the Enacted Plan made by Senate Majority Whip and primary sponsor of the Enacted Plan Senator Rob McColley.

2. I demonstrate that given the statewide support for the two parties, the 2021 Congressional Plan provides an extreme advantage to the Republican Party. With around 53.2 percent of the statewide vote in the last three general elections, the Republican Party can expect to win around 80 percent of the seats under the new plan. This is an increase over the map that was in effect from 2012 to 2020, under which Republican candidates were able to consistently win 75 percent of the seats. I also demonstrate that this level of partisan advantage is extremely unusual when compared with other states.

3. Comparing past statewide results with congressional results and considering the role of incumbency, I conclude that only two or three of the 15 districts in the Enacted Plan are likely to be competitive.

4. I also examined the extent to which the General Assembly's plan disproportionately favors or disfavors the *incumbents* for one of the two parties. Under the previous plan, there were 12 Republican incumbents, one of whom has already announced his retirement. All the remaining districts with Republican incumbents continue to have Republican majorities—most of them quite comfortable. Of the four Democratic incumbents, only two continue to reside in districts where Democratic candidates receive majorities in statewide elections. The other two districts with Democratic incumbents have been dramatically reconfigured to the significant advantage of Republicans: in one district, Republican candidates win by large majorities in statewide races (although the Democratic incumbent in that district has announced he is running for U.S. Senate); in the other, they typically hold a narrow edge.

5. These outcomes were not forced upon the General Assembly by Ohio's political geography, or by the requirements of the Ohio Constitution. On the contrary, I demonstrate that it is possible to abide by the Constitution and achieve partisan fairness, while drawing districts that are more compact, introduce fewer splits in metropolitan counties and a similar number of county splits overall, introduce similar or even fewer splits to municipal subdivisions, and do a better job keeping communities together. I demonstrate that in contrast to plans that achieve greater partisan balance, the Enacted Plan achieves its extreme partisan advantage in large part by splitting geographically proximate communities of co-partisans (i.e., people who vote the same way)—extracting them from their geographic context and placing them in districts dominated by voters from very different types of communities.

II. QUALIFICATIONS

6. I am currently a tenured Professor of Political Science at Stanford University and the founder and director of the Stanford Spatial Social Science Lab—a center for research and teaching with a focus on the analysis of geo-spatial data in the social sciences. I am engaged in a variety of research projects involving large, fine-grained geo-spatial data sets including ballots and election results at the level of polling places, individual records of registered voters, census data, and survey responses. I am also a senior fellow at the Stanford Institute for Economic Policy Research and the Hoover Institution. Prior to my employment at Stanford, I was the Ford Professor of Political Science at the Massachusetts Institute of Technology. I received my Ph.D. from Yale University and my B.A. from the University of Michigan, Ann Arbor, both in political science. A copy of my current C.V. is included as Exhibit F.

7. In my current academic work, I conduct research on the relationship between the patterns of political representation, geographic location of demographic and partisan groups, and the drawing of electoral districts. I have published papers using statistical methods to assess political geography, balloting, and representation in a variety of academic journals including *Statistics and Public Policy, Proceedings of the National Academy of Science*, *American Economic Review Papers and Proceedings*, the *Journal of Economic Perspectives*, the *Virginia Law Review*, the *American Journal of Political Science*, the *British Journal of Political Science*, the *Annual Review of Political Science*, and the *Journal of Politics.* One of these papers was selected by the American Political Science Association as the winner of the Michael Wallerstein Award for the best paper on political economy published in the last year, and another received an award from the American Political Science Association section on

social networks. In 2021, I received a John Simon Guggenheim Memorial Foundation Fellowship, and received the Martha Derthick Award of the American Political Science Association for "the best book published at least ten years ago that has made a lasting contribution to the study of federalism and intergovernmental relations."

8. I have recently written a series of papers, along with my co-authors, using automated redistricting algorithms to assess partisan gerrymandering. This work has been published in the *Quarterly Journal of Political Science*, *Election Law Journal*, and *Political Analysis*, and it has been featured in more popular publications like the *Wall Street Journal*, the *New York Times*, and *Boston Review*. I have recently completed a book, published by *Basic Books* in June of 2019, on the relationship between political districts, the residential geography of social groups, and their political representation in the United States and other countries that use winner-take-all electoral districts. The book was reviewed in *The New York Times*, *The New York Review of Books*, *Wall Street Journal*, *The Economist*, and *The Atlantic*, among others.

9. I have expertise in the use of large data sets and geographic information systems (GIS), and I conduct research and teaching in the area of applied statistics related to elections. My PhD students frequently take academic and private sector jobs as statisticians and data scientists. I frequently work with geo-coded voter files and other large administrative data sets, including in recent papers published in the *Annals of Internal Medicine* and *The New England Journal of Medicine.* I have developed a national data set of geo-coded precinct-level election results that has been used extensively in policy-oriented research related to redistricting and representation.

10. I have been accepted and testified as an expert witness in several election law and redistricting cases: *Romo v. Detzner,* No. 2012-CA-000412 (Fla. Cir. Ct. 2012); *Mo. State Conference of the NAACP* v. *Ferguson-Florissant Sch. Dist.,* No. 4:2014-CV-02077 (E.D. Mo. 2014); *Lee v. Va. State Bd. of Elections,* No. 3:15-CV-00357 (E.D. Va. 2015); *Democratic Nat'l Committee et al. v. Hobbs et al.*, No. 16-1065-PHX-DLR (D. Ariz. 2016); *Bethune-Hill v. Virginia State Board of Elections*, No. 3:14-cv-00852-REP-AWA-BMK (E.D. Va. 2014); and *Jacobson et al. v. Lee*, No. 4:18-cv-00262 (N.D. Fla. 2018). I also worked with a coalition of academics to file Amicus Briefs in the Supreme Court in *Gill v. Whitford*, No. 16-1161, and *Rucho v. Common Cause*, No. 18-422. Much of the testimony in these cases had to do with geography, electoral districts, voting, ballots, and election administration. I recently worked as a consultant for the Maryland Redistricting Commission. I am being compensated at the rate of $550/hour for my work in this case. My compensation is not dependent upon my conclusions in any way.

III. DATA SOURCES

11. I have collected statewide election data for 2012 to 2020 from the Ohio Secretary of State. I also accessed precinct-level election results from the Ohio Secretary of State for statewide elections from 2016 to 2020 that were matched to 2020 Ohio vote tabulation districts by a team at Harvard University called the Algorithm-Assisted Redistricting Methodology

Project.[1] Additionally, I accessed several proposed Ohio congressional plans uploaded to the web page of the Ohio Redistricting Commission as well as the websites for the Ohio House and Senate, true copies of which are attached as Exhibits B, C, and D.[2] I also consulted geographic boundary files of the Enacted Plan that were provided to me by Counsel. I also consulted the same U.S. Census redistricting data used by the General Assembly, as archived in the "Ohio University Common and Unified Redistricting Database."[3] For comparative analysis, I collected data on U.S. Senate, U.S. House, and presidential elections from state election authorities of a number of states, as detailed below. I also consulted precinct-level presidential results, again from state election authorities, aggregated to the level of U.S. congressional districts.[4] I also used geographic boundary files of communities of Columbus, Ohio from the City of Columbus GIS department.[5] For the analysis conducted in this report, I use three software packages: Stata, Maptitude for Redistricting, and ArcGIS Pro.

12. Through counsel, I also had access to several Maptitude files produced in this case by Ray DiRossi, Finance and Budget Director for the Ohio Senate Majority and, to my understanding, the primary mapmaker for the Enacted Plan. These included .shp files for both the Enacted Plan as well as the plan introduced by Senator McColley on November 3, 2021, produced at Bates DiRossi_000003 and 000005, respectively. Using these files, I was able to reproduce the plans along with any data DiRossi had access to in Maptitude through a very simple process. First, I would open Maptitude and select Ohio from a drop-down menu in the "Plan Manager" section of Maptitude, which allowed me to view a map of Ohio in the program. Next, I would click on "Layers" under the "Map" dropdown, then click "add layer" and choose "County." This allowed me to view Ohio's county borders on the map display in Maptitude. Next, I would open the .shp file produced by DiRossi in Maptitude (I did this once for each .shp file produced by DiRossi to produce a separate map for each file). Next, I would navigate back to the "Layers" dropdown and select a box with the name of the plan produced and click "add layer." This enabled me to see the district lines of the plan produced. So, for example, by uploading the plan entitled "Enacted Plan SB 258 Final SHP," I was able to view the district lines for the Enacted Plan in Maptitude. Uploading this file also allowed me to view the data DiRossi had access to while drawing each of the two plans in Maptitude. To do this, I would navigate to the display manager and right click on the row with the name of the plan produced (in the case of the Enacted Plan, once again "Enacted Plan SB 258 Final SHP"). I would then click "New Dataview" from the right-click drop down menu. As soon as I did that, many columns populated at the top of my Maptitude screen in the "dataview," a table in the Maptitude window that displays information about a draft map including (in this case) target population, district number, total population within a district, a district's performance under certain partisan indices, as well as other pieces of data. This dataview presents the data DiRossi had uploaded into Maptitude while drawing maps. The screenshots of the results of this process were submitted to the court via USB and identified as Exhibit 5 to the affidavit submitted to this Court by Derek Clinger on December 10, 2021. I was also

[1] https://alarm-redist.github.io/posts/2021-08-10-census-2020/.
[2] https://redistricting.ohio.gov/maps.
[3] https://www.redistricting.ohio.gov/resources.
[4]https://docs.google.com/spreadsheets/d/17yr9mcAtuUdNjI9NEPYKxXsEldzzQ2ZaDwEAbnPRyS4/edit?pref=2&pli=1#gid=1641247082.
[5] https://opendata.columbus.gov/datasets/c4b483507f374e62bd705450e116e017/explore.

able to export the data from this window into Microsoft Excel by going to File, export, and then table. This automatically generated an excel spreadsheet with all of the information contained in the dataview just described. I have attached excel spreadsheets extracted from two .shp files (including the file for the Enacted Plan) produced by DiRossi as Exhibits 7 and 8 to the Clinger Affidavit, also submitted via USB. I also performed the same process for the Maptitude files produced by Blake Springhetti, DiRossi's counterpart in the Ohio House, in that case in .BIN and .cdf format at Bates Springhetti_001042 and 001043. I have attached the results of that process as Exhibits 6 and 9 to the Clinger affidavit, both submitted via USB to the Court. Also, as specified in the Clinger affidavit, several of these files were used as exhibits at the depositions of DiRossi and Springhetti.

IV. THE PARTISANSHIP OF THE 2021 CONGRESSIONAL PLAN

13. I have been asked to determine whether the 2021 Congressional Plan favors one of the two major political parties in Ohio and, if so, to what extent. I proceed by first characterizing statewide partisanship in Ohio, and then examining the most likely partisan outcomes associated with the Enacted Plan.

14. Figure 1 provides a visualization of Ohio statewide general election results from 2012 to 2020. Ohio is a hotly contested state with a tradition of split-ticket voting and significant swings from one year to another. The Democratic candidate won the presidential contest in 2012, but the Republican candidate won in 2016 and 2020. Ohio's U.S. Senate delegation is typically split between the parties, and other statewide elections are often very competitive, although 2014 was an exception, as was the 2016 U.S. Senate race.

15. Figure 1 reveals that while Ohio statewide elections have been mostly quite close over the last decade, Republican candidates have held a narrow advantage. To quantify this, Table 1 provides the raw data. Including all the statewide general elections from 2012 to 2020, the Democratic share of the two-party vote (setting aside small parties and write-in candidates) was around 46 percent. If we focus on more recent elections, from 2016 to the present, the Democratic vote share is closer to 47 percent.

16. Next, in order to make inferences about what is likely to happen under the newly enacted districts, the best strategy is to begin by aggregating data from these recent elections, beginning with precinct-level results and calculating the number of votes received by the various candidates within the boundaries of the new districts. I have been able to obtain geo-coded precinct-level results for elections from 2016 to 2020. I calculate the Democratic and Republican shares of the two-party vote in each of the following races: 2016 President, 2016 U.S. Senate, 2018 U.S. Senate, 2018 Governor, 2018 Auditor, 2018 Secretary of State, 2018 Treasurer, 2018 Attorney General, and 2020 President. I then simply add up the votes cast for Democrats and Republicans in these races across all the precincts contained in each of the individual districts under the Enacted Plan, and divide by the total votes cast for the two parties in the respective district. The results of this exercise are displayed on the left side of Table 2.

Figure 1: Statewide General Election Outcomes, Ohio, 2012-2020

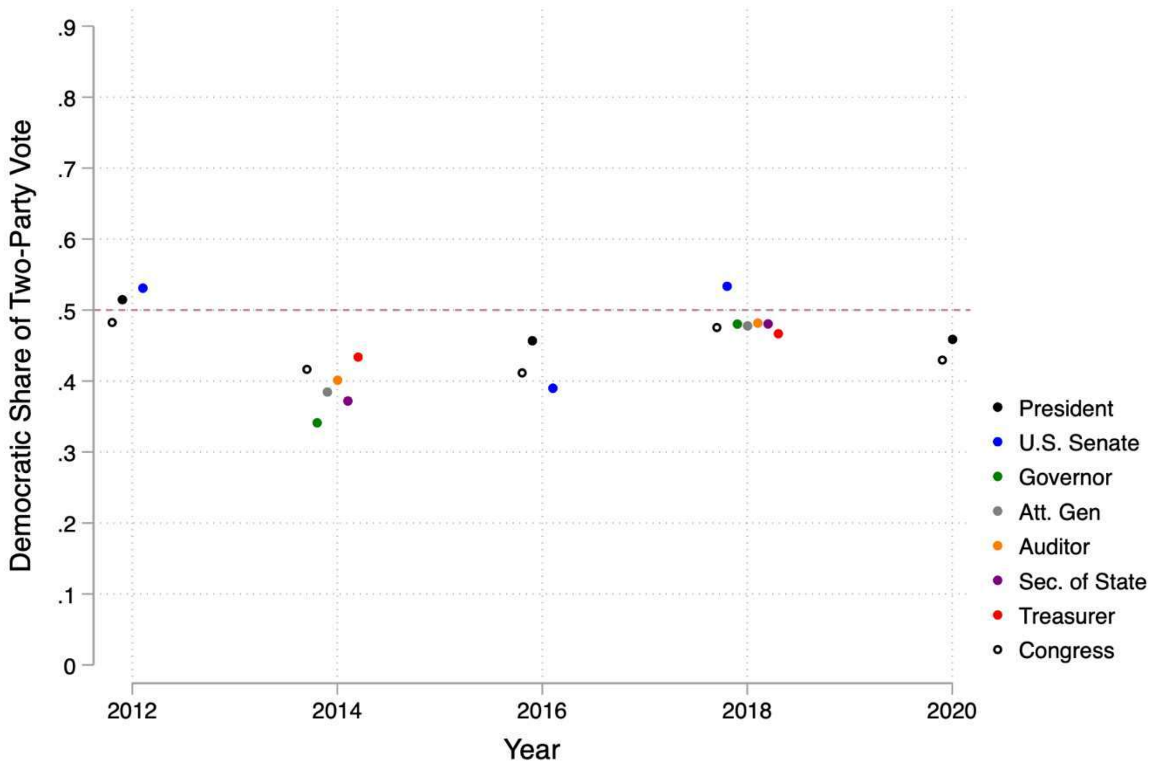

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Table 1: Statewide General Election Outcomes, Ohio, 2012-2020

	Democratic Votes	Republican Votes	Other	Two-party Democratic Vote Share
2012 President	2,827,709	2,661,439	91,791	51.5%
2012 U.S. Senate	2,762,766	2,435,744	250,618	53.1%
2014 Governor	1,009,359	1,944,848	101,706	34.2%
2014 Att. Gen.	1,178,426	1,882,048		38.5%
2014 Auditor	1,149,305	1,711,927	143,363	40.2%
2014 Sec. of State	1,074,475	1,811,020	141,292	37.2%
2014 Treasurer	1,323,325	1,724,060		43.4%
2016 President	2,394,164	2,841,005	261,318	45.7%
2016 Senate	1,996,908	3,118,567	258,689	39.0%
2018 Senate	2,358,508	2,057,559	1,017	53.4%
2018 Governor	2,070,046	2,235,825	129,949	48.1%
2018 Att. Gen.	2,086,715	2,276,414		47.8%
2018 Auditor	2,008,295	2,156,663	175,962	48.2%
2018 Sec. of State	2,052,098	2,214,273	103,585	48.1%
2018 Treasurer	2,024,194	2,308,425		46.7%
2020 President	2,679,165	3,154,834	88,203	45.9%
Sum, all elections	30,995,458	36,534,651	1,747,493	**45.9%**
Sum, 2016-2020	19,670,093	22,363,565	1,018,723	**46.8%**

Table 2: Shares of the Vote Obtained by the Two Major Parties from 2016 to 2020 in the Districts of the 2021 Congressional Plan and in the Districts of the Previous Plan

Newly Enacted Map			Map in Place from 2012 to 2020		
District	Democratic vote share	Republican vote share	District	Democratic vote share	Republican vote share
1	0.484	0.516	1	0.460	0.540
2	0.333	0.667	2	0.426	0.574
3	0.703	0.297	3	0.703	0.297
4	0.327	0.673	4	0.340	0.660
5	0.392	0.608	5	0.383	0.617
6	0.437	0.563	6	0.328	0.672
7	0.421	0.579	7	0.371	0.629
8	0.375	0.625	8	0.327	0.673
9	0.497	0.503	9	0.620	0.380
10	0.467	0.533	10	0.461	0.539
11	0.802	0.198	11	0.811	0.189
12	0.369	0.631	12	0.449	0.551
13	0.508	0.492	13	0.556	0.444
14	0.459	0.541	14	0.456	0.544
15	0.461	0.539	15	0.437	0.563
			16	0.431	0.569

17. As indicated in gray, when considering the specific data referenced above, there are only three districts with Democratic majorities in the Enacted Plan. Two of those districts have very comfortable Democratic majorities, and one has a very slight Democratic lean (District 13). There is one additional district (District 9) that leans just ever so slightly Republican.

18. This represents a considerable change in favor of Republicans from the status quo under the previous map, attached as Exhibit E. Table 2 also provides the results of the same exercise for the map that was in place from 2012 to 2020. That plan included four districts with relatively comfortable Democratic majorities. It is rather remarkable that the General Assembly was able to devise a plan that made the Democratic Party *worse* off, given that, as demonstrated below, the previous plan was one of the most favorable to the Republican Party in the United States in recent history.

19. There were five general elections for each of Ohio's 16 congressional districts from 2012 to 2020, for a total of 80 congressional races. In *every single* race, the candidate of the party with the higher vote share on the right-hand side of Table 2 was victorious.

20. If the same pattern continues, and the statewide aggregates continue to predict congressional outcomes, the Democrats can anticipate winning only 3 of 15 seats for the next four years (after which point a new map must be enacted under Ohio law). Recall from Table 1 that Democrats' statewide vote share was around 47 percent from 2016 to 2020, but their

anticipated seat share under the Enacted Plan is only 20 percent. Correspondingly, with around 53 percent of the statewide vote, the Republican Party can expect 80 percent of the seats.[6]

21. Districts 9 and 13 have statewide vote shares that are very close to 50 percent (within one percentage point). District 9 is a highly reconfigured district in which a Democratic incumbent will now be competing in very different territory with a slight Republican majority. Most of the new voters added to this district typically vote for Republicans. District 13 is an open seat with a slim Democratic majority. Even if one considers both Districts 9 and 13 in the Enacted Plan to be tossups and assigns a 50 percent probability of victory to Democratic candidates in each, the same conclusion holds: Republican candidates can expect to win around 12 of 15 seats.

22. In written remarks in support of the Enacted Plan, Ohio Senate Majority Whip Rob McColley stated that the Enacted Plan created 7 competitive districts.[7] To reach this figure, Senator McColley uses a rather peculiar alternative partisan index, and along with it, an alternative analysis of district competitiveness. Senator McColley presented an index based only on presidential and U.S. Senate elections. In order to understand how his index was constructed, it is useful to return to Figure 1 above. Senator McColley's index is composed of only six elections, represented by the 3 black (presidential) and 3 blue (U.S. Senate) dots in Figure 1. This means one third of the index is composed of elections in which U.S. Senator Sherrod Brown was the Democratic nominee. And one third of the index comes from 2012 alone—an election that took place a full decade before the new districts will come into effect.

23. According to Senator McColley's index, the statewide Democratic vote share in Ohio is 48 percent. Recall from Table 1 that when *all* statewide elections are used during the same period examined by Senator McColley (2012-2020), Ohio's statewide Democratic vote share is just under 46 percent. Using all statewide elections from 2016 to 2020—the years for which I was able to obtain geo-coded precinct-level data—the statewide Democratic vote share is a little under 47 percent.

24. Figure 1 also includes aggregate Democratic vote shares for Ohio's 16 congressional races in each of these elections, indicated with hollow dots with black boundaries.[8] It is important to note that these hollow dots fall well below the black and blue solid dots in every case but one (2016 U.S. Senate). We can see, then, that Senator McColley has chosen not only the most Democratic-skewed possible set of statewide elections, but also a set of elections that is systematically more Democratic-leaning than the *congressional* races that he is ostensibly trying to predict. It is also clear from Figure 1 that if one is trying to come up with a set of

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[6] Note that I refer to statewide results from 2016 to 2020 since those are the years for which I have precinct-level breakdowns that allow me to calculate district-level tallies.

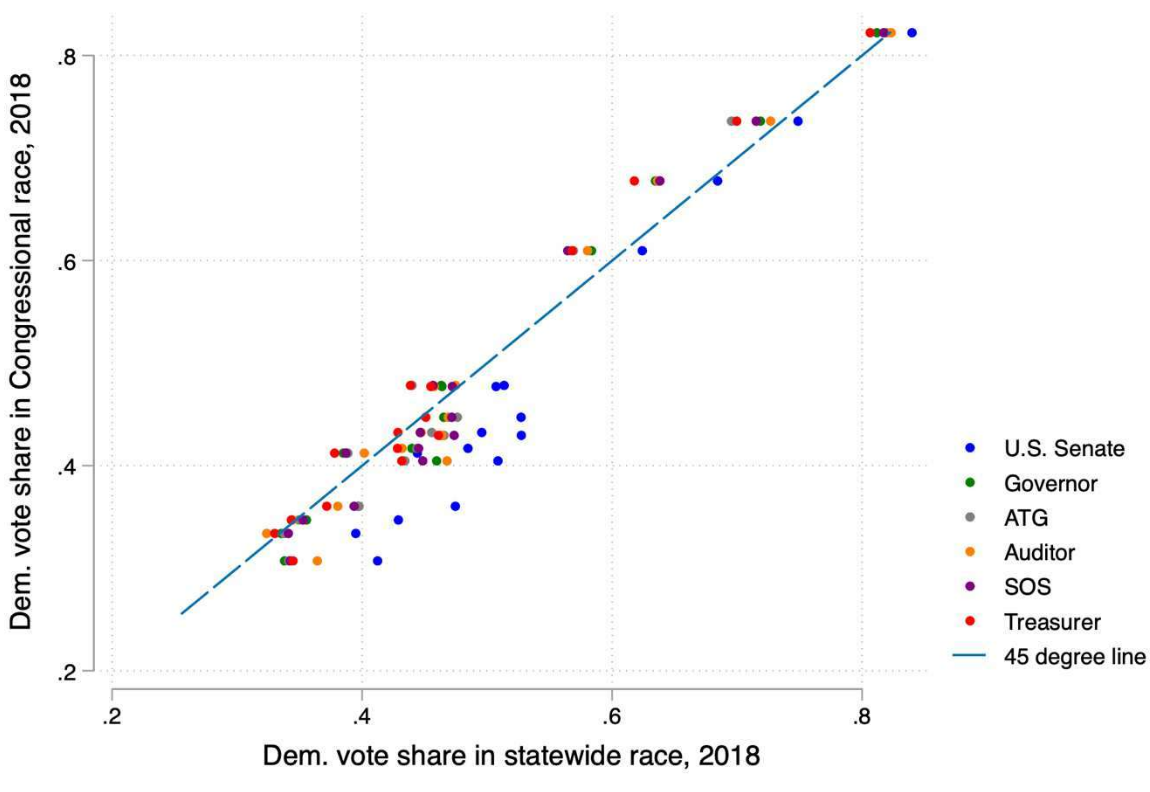
[7] See The Ohio Senate, Local Government and Elections Committee, https://www.ohiosenate.gov/committees/local-government-and-elections/document-archive (testimony of Senator Rob McColley on November 16, 2021).

[8] Note that there were three uncontested races during this period: districts 8 and 11 in 2012, and district 7 in 2014. I imputed the results of these races by taking the average vote shares experienced in these districts during all of the other years when they *were* contested.

races that predict congressional outcomes (the hollow dots), the most predictive races are those that McColley throws out: the statewide races for Governor (green), Attorney General (gray), Auditor (orange), Secretary of State (purple), and Treasurer (red). Note that the hollow dots—the congressional races—move up and down over time with the partisan waves that drive these statewide races. Thus, it is quite misleading to exclude so much of the valuable data—especially from recent years.

25. Moving beyond aggregate data, if we make comparisons across districts within specific elections, it is also notable that Senator McColley has excluded the races that hew most closely with each district's congressional results. He relies instead on an index of partisanship that draws disproportionately on high-turnout presidential races and Senate elections won by Senator Sherrod Brown. To demonstrate the latter problem, Figure 2 presents a scatter plot of district-level results of the 2018 election. On the horizontal axis is the Democratic vote share in statewide races, aggregated to the boundaries of the districts in place in 2018. On the vertical axis is the corresponding vote share of the Democratic candidate in the congressional race in each district in 2018. The dashed line is the 45-degree line.

Figure 2: Statewide Results Aggregated Within Boundaries of 2018 Districts and 2018 District-Level Congressional Results



26. Data markers directly on the 45-degree line are those where the results of the state-wide race are exactly the same as those in the congressional race. In other words, observations on the 45-degree line are districts where there is minimal split-ticket voting, so that the statewide

race perfectly predicts the congressional race. Note that in the four Democratic districts on the right side of the graph, the blue dots—where the horizontal axis represents Senator Sherrod Brown's vote share—are arranged almost exactly on the 45-degree line. However, in all 12 of the Republican-leaning districts, the blue dots are far below the 45-degree line, and far below all the other colored dots, which correspond to the vote shares of Democratic candidates in the other statewide races. In other words, Senator Sherrod Brown has drawn a substantial amount of support from voters who otherwise supported Republican candidates for all other offices. This means that by using Senator Sherrod Brown's vote share and ignoring the other data at his disposal in 2018, Senator McColley has chosen the one race in 2018 that is most out of sync with almost all congressional races in the state, and as a result, badly over-estimates the Democratic congressional vote share. He thereby inaccurately characterizes a number of rather reliable Republican voters as Democrats, and as a result, inaccurately characterizes comfortably Republican districts as "competitive."

Table 3: McColley Partisan Index in Comparative Perspective

District	Republican vote share, all statewide races, 2016-2020	Republican vote share, federal elections only, 2012-2020 (McColley's index)	Difference
1	0.516	0.515	0.001
2	0.667	0.651	0.016
3	0.297	0.304	-0.007
4	0.673	0.66	0.013
5	0.608	0.588	0.020
6	0.563	0.529	0.034
7	0.579	0.567	0.012
8	0.625	0.62	0.005
9	0.503	0.477	0.026
10	0.533	0.522	0.011
11	0.198	0.194	0.004
12	0.631	0.613	0.018
13	0.492	0.486	0.006
14	0.541	0.532	0.009
15	0.539	0.537	0.002

27. It is already clear from Figures 1 and 2 that Senator McColley's index is systematically more Democratic than an index that relies on a more representative set of races, but Table 3

quantifies the difference for each district. In the left-hand column, I reproduce the partisan index (from Table 2) that is based on all statewide races held from 2016 to 2020. In the next column, I reproduce Senator McColley's more limited index, and in the third column, I report the difference. In all districts but one, the McColley index makes districts appear to be more Democratic than the more expansive index. On average across districts, the difference is around 1.1 percentage points, but Senator McColley's index is especially misleading in District 6, where it over-estimates the Democratic vote share by 3.4 percentage points, and in District 9, where the over-estimate is 2.6 percentage points, and where McColley's index classifies the district as Democratic-leaning. Of particular note, McColley's chosen benchmark for competitiveness (46-54 percent) would treat District 6 as competitive under his index, but not under an index that takes account of all statewide races.

28. More generally, it is not clear why districts where average statewide vote shares fall in the rather wide range between 46 and 54 percent should be viewed as "competitive," since as described further below, Ohio congressional races in such districts have not been especially competitive in the past, and over the last decade, the party with the higher partisan index has always been victorious—almost always by a comfortable margin.

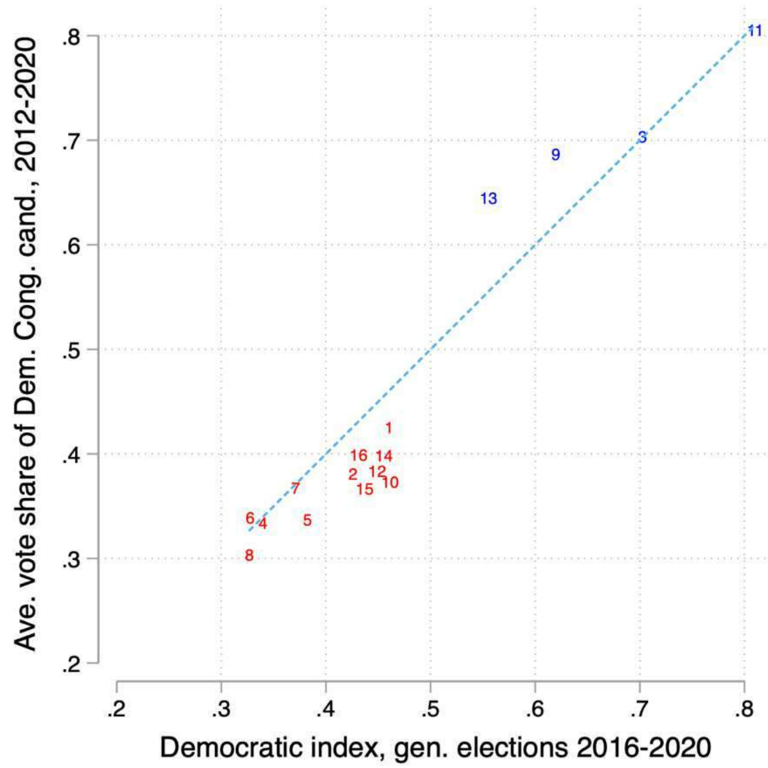
29. Even if we avoid Senator McColley's reliance on a biased sample of statewide races and use a more meaningful partisan index, we should not be so naïve as to assume that statewide races are straightforward predictors of congressional races. Even a better index that uses all the relevant statewide data from recent years will still substantially over-estimate the likely Democratic vote share in almost all the Republican-leaning districts. This is because of the role of incumbency advantage in congressional races. A large empirical literature in American politics establishes that, for a variety of reasons, incumbents typically enjoy a substantial advantage over challengers, especially in legislative elections.[9]

30. To demonstrate this problem, Figure 3 plots, on the horizontal axis, the data from the right-hand side of Table 2 above—the average Democratic vote share in all statewide races from 2016 to 2020—within each of the 16 Ohio congressional districts in use over the last decade. On the vertical axis, it plots the average vote share of the Democratic candidate in congressional races in the same district.[10] Again, the 45-degree line indicates a perfect correspondence between statewide races and congressional races. Blue data markers are districts with Democratic incumbents, and red data markers are districts with Republican incumbents.

[9] See, for instance, Stephen Ansolabehere and James M. Snyder, 2004, "The Incumbency Advantage in U.S. Elections: An Analysis of State and Federal Elections, 1942-2000," *Election Law Journal* 1,3: 315-338.

[10] As above, I impute the results of the uncontested races (districts 8 and 11 in 2012, and district 7 in 2014) by taking the average vote shares experienced in these districts during all of the other years when they *were* contested.

Figure 3: Democratic Partisan Index Based on Statewide Races and Average Vote Share of Democratic Candidates in Congressional Races, 2012-2020

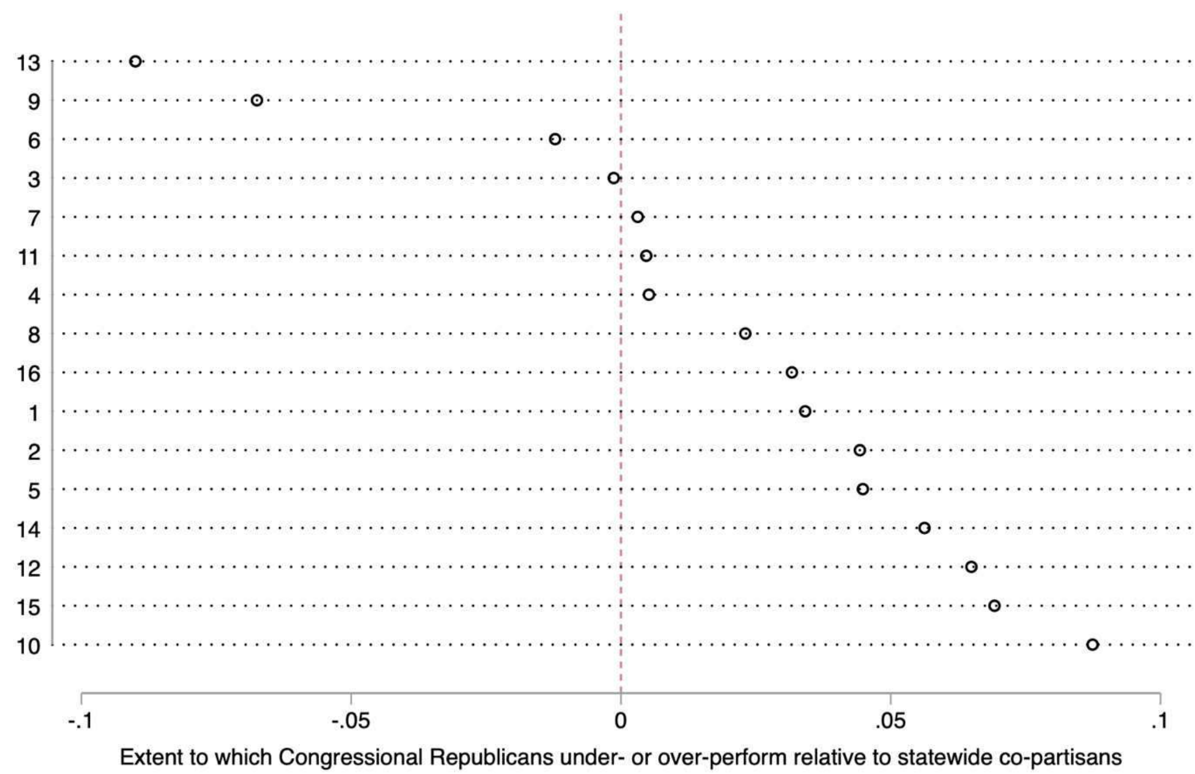


31. We can see that in races in the most overwhelmingly Democratic-leaning and Republican-leaning districts, on the far right and far left of the graph, the correspondence between statewide races and congressional races is quite strong. In the two overwhelmingly Democratic urban districts (3 and 11), for instance, congressional candidates do not significantly outperform their co-partisans in statewide races. The same is true in some of the most Republican districts (e.g., 4, 6, and 7). However, in the districts that are less imbalanced in terms of partisanship, the correspondence between statewide races and congressional races is far weaker, and in a very specific way: incumbents in congressional races outperform their statewide co-partisans. Visually, in Figure 3, we can see that the blue markers for Districts 9 and 13 are well above the 45-degree line, and the red markers for Republican incumbents in districts 1, 2, 5, 10, 12, 14, 15, and 16 are well below the line. The political science literature explores a variety of reasons for this advantage, including name recognition, an advantage in fundraising that translates into disproportionately large campaign war chests that facilitate effective campaigns and scare off challengers, the ability to use the perks of office to provide favors for local groups, and the ability to claim credit for public expenditures that take place in the district. It may also be the case that given the collective nature of legislatures vis-à-vis executive positions, it is easier for legislators to escape blame when things go wrong, either for the nation, the state, or their party. This is

related to a paradox attributed to Richard Fenno: Americans claim to hate Congress, but often express support for the member of Congress from their own district.[11]

32. To convey a better sense of what this means, Figure 4 simply plots the vertical distance between the data markers in Figure 3 and the 45-degree line—that is to say, the extent to which incumbent legislators outperformed their statewide co-partisans from 2012 to 2020. Positive numbers indicate that Republicans running in congressional races do better than their statewide co-partisans. Negative numbers indicate that they do worse.

Figure 4: Extent to which Congressional Republicans Under- or Over-Performed Relative to their Statewide Co-Partisans



33. Three of the first four observations at the top (except District 6) are districts with *Democratic* incumbents, where these incumbents perform better, on average throughout the decade, than their statewide co-partisans. The remaining observations (except District 11) are the districts where Republican incumbents were running throughout the decade, and in every case, they out-perform their statewide co-partisans—often by a considerable margin.

34. Figures 3 and 4 indicate the folly of imagining that a district with a 52 percent statewide Republican vote share throughout the last decade, like District 1 in the new Enacted Plan, is

[11] Richard Fenno, *Home Style: House Members in their Disricts,* 1978, Longman.

a highly competitive district where a moderate statewide swing toward the Democrats might yield a toss-up election in which a Democratic candidate can hope for victory. As we can see in Figure 4, Representative Chabot typically receives an incumbency advantage of around four percentage points. Over the past decade, he received around 58 percent of the votes cast for the two major parties in District 1, even though his statewide co-partisans had received, on average, around 54 percent of the votes in his district.

35. In the Enacted Plan, much of Mr. Chabot's district remains unchanged, including parts of Cincinnati, its western suburbs, and Warren County. I have identified the census blocks that were common to both the old and new districts, summed up their current population, and divided by the population size of the new districts (786,630). This exercise reveals that around 81 percent of Mr. Chabot's current district is composed of people who were in the previous manifestation of District 1. As a result, there is no reason to anticipate that his incumbency advantage will suddenly disappear. If we consider incumbency, a more realistic projection of Mr. Chabot's likely vote share in the future, then, might approach 56 percent.

36. It would be even more misleading to characterize District 10 as competitive. For instance, the Republican vote share in statewide races (from 2016 to 2020) in District 10 is around 53 percent, down slightly from 54 percent in the previous redistricting cycle. However, the Republican incumbent, Mike Turner, won each general election from 2012 to 2020 with an average two-party vote share above 62 percent (see Figure 3). Once again, as with District 1, the incumbent enjoyed a massive incumbency advantage—around 8.7 percentage points. And District 10 is the only district in which the incumbent retained *more* of their old district than District 1: 89.7 percent of the population of District 10 in the new Enacted Plan was in Representative Turner's previous District 10. So again, there is no reason to anticipate that this advantage will suddenly disappear. Putting these facts together, one simply cannot characterize District 10 in the Enacted Plan as competitive.

37. Likewise, Districts 14 and 15 cannot be classified as competitive. As shown in Table 2, both are districts with Republican incumbents where the statewide 2016-2020 Republican vote share hovered around 54 percent. However, as we can see in Figure 4, both incumbents substantially outperformed their party's statewide vote share, by 5.6 percentage points in District 14, and 6.9 percentage points in District 15. District 14 retained 69 percent of the voters from its earlier manifestation, and District 15 retained 42 percent. Again, once we consider incumbency, as with District 10, even if we accept Senator McColley's rather unusual characterization of districts with an anticipated Republican vote share of 54 percent as "competitive," we cannot characterize Districts 14 and 15 as competitive.

38. In sum, it is quite difficult to oust a congressional incumbent in Ohio. Recall from Table 1 that the average Democratic vote share in statewide races from 2012 to 2020 was 45.9 percent. However, recall from Figure 1 that there were substantial year-to-year deviations in statewide results. If we take yearly averages, we see that the biggest pro-Democratic deviations were in 2012, where the average Democratic vote share in statewide offices was 52.3 percent, and in the "blue wave" of 2018, when it was 48.7 percent. There were also large pro-Republican deviations in 2014 (average Democratic vote share of 38.7 percent) and 2016 (42.4 percent). In spite of the presence of several districts that Senator McColley would designate as competitive—with a statewide Republican vote share between 46 and 54

percent—even shifts of 6 and 7 percentage points in statewide vote shares from the decade average did not dislodge a single incumbent.

39. With this fuller understanding of incumbency in hand, we can see that the only districts that appear to be competitive in the Enacted Plan are Districts 9 and 13—both district numbers that corresponded to what were comfortable Democratic districts in the old plan. In District 9, the district leans Republican in statewide races, but in the past, Representative Kaptur has outperformed her statewide co-partisans by over 6 percentage points (Figure 4). However, in contrast to Districts 1 and 10, where Republican incumbents in more competitive districts retained more than 80 percent of their old district population, only around 40 percent of the population of the new version of Representative Kaptur's district was part of her previous configuration of District 9, and the new population in her district is quite Republican. As a result, she may not be able to rely on a similar level of incumbency advantage as Representatives Chabot and Turner.

40. Finally, it is noteworthy in this regard that the Enacted Plan would be in place for only four years; meaning that it can be redrawn in short order if any incumbents retire. The short duration of the Enacted Plan thus allows the mapdrawers to more aggressively rely on incumbency advantages than may be prudent for a map that will remain in effect for a 10-year period.

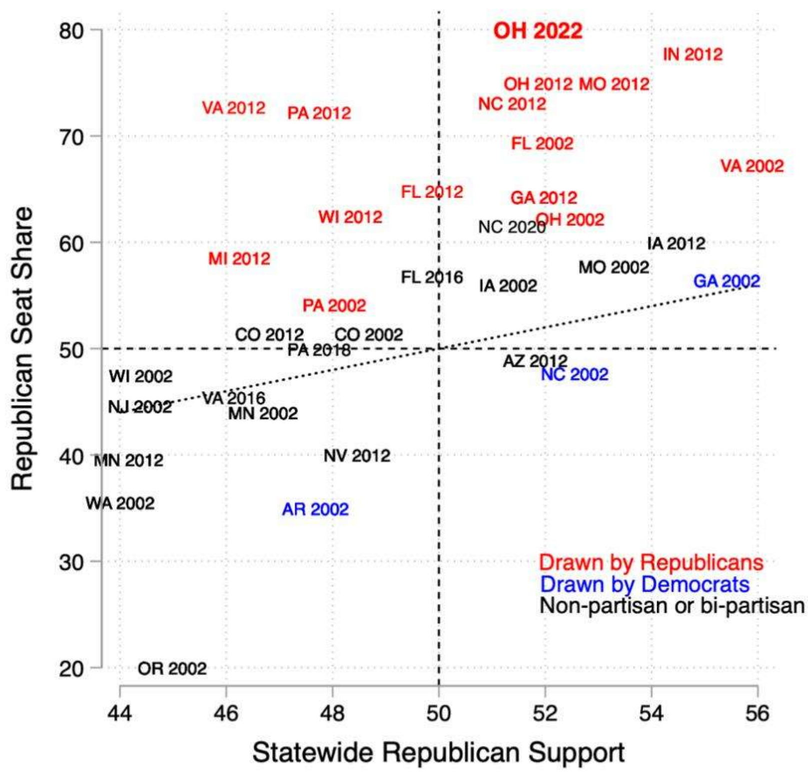
41. In sum, a reliable assessment of the likely partisan results associated with the Enacted Plan—considering all available statewide election results and accounting for the role of incumbency—indicates that the Enacted Plan creates 11 safe Republican districts, 2 safe Democratic districts, and 2 districts that are likely to be quite competitive. If we give each party a 50 percent probability of victory in each of the two competitive districts, we are left with the conclusion that the Democrats can expect to win only 3 of 15 seats under this plan, which corresponds to a 20 percent seat share.

V. PUTTING THE 2021 CONGRESSIONAL PLAN IN PERSPECTIVE

42. In any two-party democracy, it is not normal for a party with an average of 53.2 percent of the vote to receive 80 percent of the seats. In fact, even in the United States, which has maintained the idiosyncratic practice of allowing incumbent partisan majorities to draw their own districts without constraint, this is a highly unusual result. To see this, let us focus on a set of states that are comparable to Ohio in that they have seen relatively competitive statewide races in recent decades and are large enough to have four or more congressional districts. To measure statewide partisanship in a way that facilitates cross-state comparison, I have assembled data on presidential and U.S. Senate elections. For each redistricting cycle, I calculate the average Republican share of the two-party vote in Senate and presidential elections.[12] Next, for each redistricting cycle, I calculate the share of all congressional seats won by Republican candidates.

[12] In a few states, I also have access to data on statewide executive offices, e.g., Governor, Attorney General, Railroad Commissioner, Treasurer, and the like. However, the mix of elected offices

Figure 5: Vote Shares in Statewide Elections and Seat Shares in Congressional Elections, Evenly Divided States with Four or More Districts, 2000 through 2020 Redistricting Cycles



43. In Figure 5, the data markers indicate the state and the year that the relevant redistricting plan went into effect. States with districts drawn by legislatures under unified Republican control are indicated in red. States with districts drawn by independent commissions, courts, or divided legislatures are indicated in black. And states where districts were drawn under unified Democratic control are indicated in blue.[13] The dotted line indicates proportionality—where, for instance, 50 percent of the vote translates into 50 percent of the seats, 52 percent of the vote translates into 52 percent of the seats, and so on. In Figure 5, in order to focus on states most similar to Ohio and facilitate legibility, I zoom in on a group of

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varies from one state to another, and comparable data are unavailable in some states. I elect to use statewide races for *national* elections only (president and U.S. Senate) in order to facilitate cross-state comparison.

[13] Information about control of the redistricting process was obtained from https://redistricting.lls.edu/.

the most evenly divided states. I also include in the appendix a graph that presents the exact same information, but zooms out to include all the states with four or more districts—including those, like Massachusetts and Oklahoma—that are dominated by one party or the other, and where the dominant party ends up winning all, or nearly all, of the seats.

44. For the most part, districts drawn by courts, divided legislatures, and independent commissions come closer to proportionality than those drawn by legislatures with unified party control of state government. This can be seen most clearly *within* states where the districts were redrawn during a redistricting cycle due to litigation—including Virginia, Pennsylvania, North Carolina, and Florida. In these states, Republican-drawn maps led to Republican seat shares far beyond the party's statewide support, and plans drawn by courts came much closer to proportionality. While Democrats have controlled the redistricting process in very Democratic states like Maryland, Illinois, and Massachusetts (see the appendix), they have rarely done so in the relatively competitive states featured in Figure 5. But the Republican Party has been able to draw the districts over the last two redistricting cycles in a large number of relatively competitive states, including Florida, Michigan, Virginia, Pennsylvania, Wisconsin, North Carolina, Georgia, Missouri, Indiana, and Ohio. As can be seen in Figure 5, throughout the range of statewide vote shares—from Democratic-leaning states like Pennsylvania to Republican-leaning states like Indiana—Republican candidates have been able to win surprisingly large seat shares in the states where districts were drawn by unified Republican legislatures. This group includes notoriously gerrymandered states, including North Carolina, Pennsylvania, and Florida, where state courts eventually invalidated maps that favored Republicans in ways that violated state constitutions.

45. Even among this group of highly partisan maps, Ohio stands out. The data marker titled "Ohio 2012" corresponds to the observed seat share of Republican candidates throughout the 2010 redistricting cycle (12 of 16 seats in each election, or 75 percent). And the bold data marker titled "Ohio 2022" is the anticipated seat share, calculated as described above at 80 percent, for the 2021 Congressional Plan. It should be stressed that this data point is different in kind from the others. All of the other data markers in Figure 5 are *observed* congressional seat shares from the past. The "Ohio 2022" data marker is a *predicted* seat share based, as described above, on past statewide elections.

46. As can be visualized in Figure 5, with one exception, the absolute vertical distance from the dotted line of proportionality to the "Ohio 2022" data marker is larger than for all other relatively competitive states with four or more districts over the last two redistricting cycles.[14]

47. When attempting to assess the impact of a redistricting plan on the relative advantage or disadvantage it provides to the parties, it is important to go beyond simply calculating the difference between a party's statewide support and its seat share. For many realistic scenarios in which partisans are distributed across districts without political manipulation of the district

[14] The exception is Oregon between 2002 and 2010, where the Democratic candidates won the four coastal districts and the Republican candidate won the single interior district in spite of a statewide Republican vote share of around 45 percent.

boundaries, we can anticipate that the party with more votes will usually win more than a proportional share of seats. To see why this is true, imagine a simple example of a state with 15 districts, where there are 10 voters in each district, and party registration is distributed as displayed in the columns labeled "Example 1" in Table 4 below.

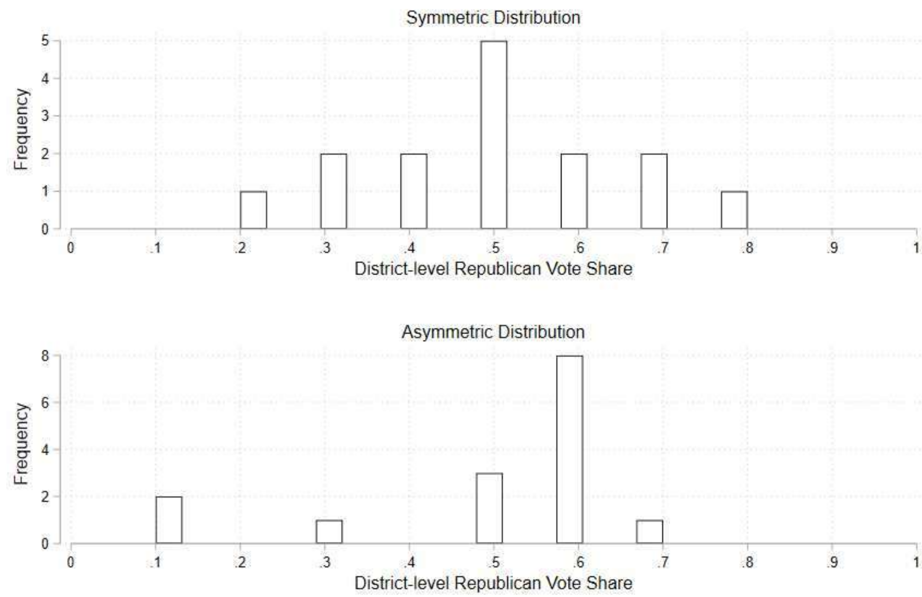
Table 4: Examples of Symmetric and Asymmetric Distributions of Votes Across Districts in a Hypothetical State

	Example 1: Symmetric Distribution		Example 2: Asymmetric Distribution	
District	Democrats	Republicans	Democrats	Republicans
1	2	8	3	7
2	3	7	4	6
3	3	7	4	6
4	4	6	4	6
5	4	6	4	6
6	5	5	4	6
7	5	5	4	6
8	5	5	4	6
9	5	5	4	6
10	5	5	5	5
11	6	4	5	5
12	6	4	5	5
13	7	3	7	3
14	7	3	9	1
15	8	2	9	1

48. In this example, there are 75 Democrats and 75 Republicans. Under normal circumstances, each party can expect to win 5 districts, but 5 districts are toss-ups containing even numbers of Democrats and Republicans.

49. The top panel of Figure 6 below uses a histogram—a simple visual display of the data from Table 4—to display the distribution of expected vote shares of the parties across districts in this hypothetical state, with its symmetric distribution of partisanship.

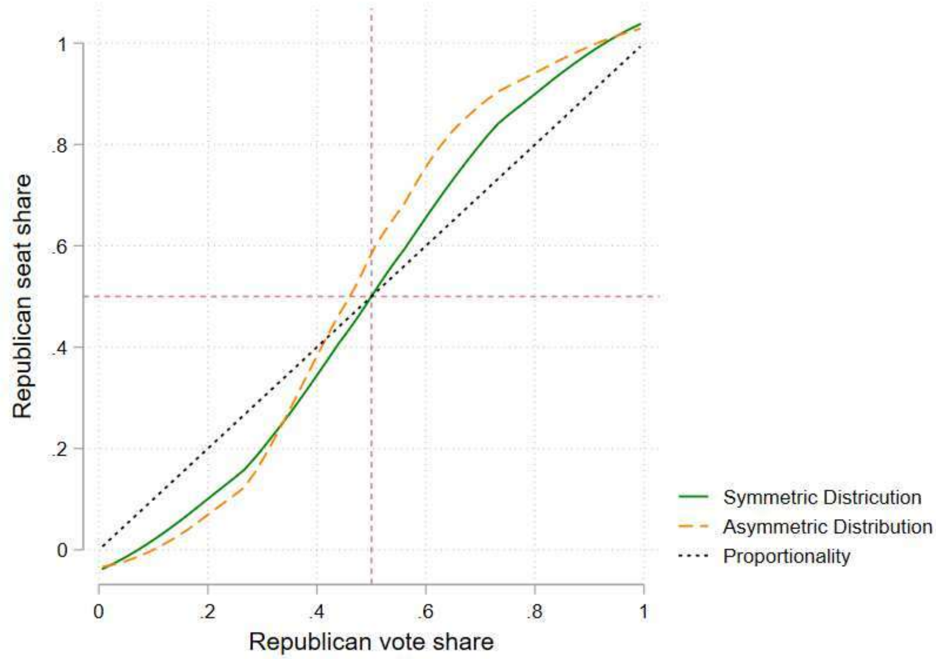
Figure 6: Distribution of Vote Shares Across Districts in Two Redistricting Plans in Hypothetical State



50. Let us assume that the partisanship of some of the individuals in this state is malleable, such that a successful campaign, a good debate performance by a candidate, or a strong economy leads some of the registered Democrats to vote for Republicans. Let us randomly choose one Democrat in the state and turn her into a Republican. Let us perform this random vote-flipping exercise 10,000 times, take the average, and see how this very small change in voting behavior—just one party-switcher out of 150—can be expected to affect the parties' seat shares. Let us do that with two of the Democrats, three, and so on, all the way until the overall Republican vote share approaches 100 percent. We can perform the same operation in the other direction, systematically turning random Republicans into Democrats.

51. How do these alternative scenarios affect the seat share? The result of these simulated scenarios is displayed with the green line in Figure 7. The horizontal axis is the Republican vote share, and the vertical axis is the corresponding seat share. The green line provides a plot of what happens to the seat share as the Republican vote share increases and decreases from 50 percent.

Figure 7: Hypothetical symmetric vote-seat curve



52. The green line in Figure 7 is a standard vote-seat curve associated with a symmetric distribution of partisanship across districts. It is a foundational observation in the literature on majoritarian elections that when the distribution of partisanship across districts approximates the normal distribution, with its bell-shaped appearance, the transformation of votes to seats will look something like the green line in Figure 7. With 50 percent of the vote, a party can expect 50 percent of the seats. However, note what happens when the Republican Party is able to obtain 55 percent of the votes—it receives around 60 percent of the seats. This phenomenon is known as the "winner's bonus." This happens because there are several districts where the underlying partisanship of the electorate is evenly divided, such that with 55 percent of the overall statewide vote, the Republican Party can win several of these pivotal districts, thus providing it with a disproportionate share of the seats.

53. When we observe a situation in which a party wins 55 percent of the vote but something like 59 or 60 percent of the seats, we cannot necessarily conclude, without further analysis, that the district boundaries have been drawn to help or harm a political party. The "winner's bonus" is a basic feature of majoritarian electoral systems. An important feature of the green line in Figure 7, however, is that it treats each party exactly the same. That is, the Democrats can expect the exact same "winner's bonus" as the Republicans when they are able to win over more votes. This partisan symmetry is a lower standard to meet than one that requires proportional outcomes, because it merely ensures that any "winner's bonus" could be applied to either party relatively evenly, and that thus, both parties have similar incentives to be responsive to voters.

54. Next, let us consider the same state, with the same even split in party registration, but with a different set of district boundaries, drawn strategically to favor the Republican Party. In this example, provided numerically on the right-hand side of Table 4 (labeled as "Example 2"), and visually with a histogram in the lower panel of Figure 6, Democrats are "packed" into three extremely Democratic districts, and districts have been drawn so as to avoid Democratic majorities to the extent possible elsewhere. There are fewer truly competitive districts, and there is a much larger number of districts that are comfortably, but not overwhelmingly, Republican. With this type of arrangement, with 50 percent of the vote, the Republicans can expect to win well over half the seats.

55. I apply the same simulation procedure as described above and display the resulting relationship between seats and votes with the orange dashed line in Figure 7. We can see that in this example, the Republican Party enjoys a substantial advantage in the transformation of votes to seats over Democrats. It can lose a majority of votes statewide but still win legislative majorities, and it receives a very large seat premium when it achieves even a slight victory in statewide votes. In this second example, the treatment of the two parties is far from symmetric.

56. Political scientists and geographers have attempted to measure this type of asymmetric distribution of partisans across districts—and the resulting asymmetry in the transformation of votes to seats. What has now become the most common approach is rooted in the work of British political geographers. In his 2000 Annual Political Geography Lecture, Ron Johnston described "wasted votes" as votes obtained in constituencies that a party loses, while "surplus votes" are additional votes obtained by a party in constituencies it wins beyond the number needed for victory.[15] In the example above, for instance, 6 is the number of votes required for victory in each district. Thus, if a party received 9 votes, 3 of them would be considered "surplus." In that same district of 10 voters, the losing party received 1 "wasted" vote. Johnston calculated wasted and surplus votes for the Labour and the Conservative parties in post-war British elections, as well as the share of "effective" votes received by each party: that is, votes that were neither "wasted" nor "surplus." The latter is a measure of the relative efficiency of support for the parties, and the gap between them is an indicator of the extent to which support for the Conservatives has been more efficient than support for Labour (or vice-versa).

57. More recently, Nicholas Stephanopoulos and Eric McGhee have adapted this concept to the context of redistricting and gerrymandering in the United States.[16] The terminology is slightly different. For Stephanopoulos and McGhee, the term "wasted votes" captures not just the votes obtained in a constituency the party lost, but also the surplus votes obtained in districts the party won: what Johnston called "ineffective votes." For Stephanopoulos and McGhee, "wasted votes" are all the votes received by a party in districts that it loses, combined with all the surplus votes beyond the winning threshold in districts it wins. They calculate the total wasted votes for each party in each district, tally them over all districts,

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[15] Ron Johnston. 2002. "Manipulating Maps and Winning Elections: Measuring the Impact of Malapportionment and Gerrymandering." *Political Geography* 21: pages 1-31.

[16] See Nicholas Stephanopoulos and Eric McGhee, 2015, "Partisan Gerrymandering and the Efficiency Gap." *University of Chicago Law Review* 82,831.

and divide by the total number of votes cast. They refer to this construct as the "efficiency gap." To see how this works, let us return to our examples.

58. Table 5 includes columns to capture wasted votes for the Republicans and Democrats in both hypothetical examples. In the first example, the Republicans win the first district in a landslide, 8-2. They waste two votes (since they only needed 6 to win), and the Democrats waste two votes in their losing effort. At the bottom of the table, I sum the wasted votes for each party. The Democrats and Republicans each waste the same number of votes, 20. Thus, the efficiency gap is zero.

59. Next, consider the second example. The Republicans have a very efficient distribution of support such that they received six votes in several districts, while the Democrats wasted votes in a handful of districts that they won by large majorities. In this example, the Republicans waste only three votes while the Democrats waste 42. Thus, there is an efficiency gap of 39, which amounts to 26 percent of all votes cast.

Table 5: Efficiency Gap Calculations in Hypothetical Examples

	Example 1: Symmetric Distribution				Example 2: Asymmetric Distribution			
District	Dem	Rep	Dem Wasted Votes	Rep Wasted Votes	Dem	Rep	Dem Wasted Votes	Rep Wasted Votes
1	2	8	2	2	3	7	3	1
2	3	7	3	1	4	6	4	0
3	3	7	3	1	4	6	4	0
4	4	6	4	0	4	6	4	0
5	4	6	4	0	4	6	4	0
6	5	5	0	0	4	6	4	0
7	5	5	0	0	4	6	4	0
8	5	5	0	0	4	6	4	0
9	5	5	0	0	4	6	4	0
10	5	5	0	0	5	5	0	0
11	6	4	0	4	5	5	0	0
12	6	4	0	4	5	5	0	0
13	7	3	1	3	7	3	1	0
14	7	3	1	3	9	1	3	1
15	8	2	2	2	9	1	3	1
Total	75	75	20	20	75	75	42	3

60. Let us now apply this approach to the 2021 Congressional Plan in Ohio. First, I have summed up all the votes received by Democratic and Republican candidates in each of the statewide races from 2016 to 2020 listed above, and use these sums to calculate the efficiency gap. Aggregating precinct-level data from these races to the level of districts in the Enacted Plan, we see the efficiency gap associated with the Enacted Plan is quite large—24 percent—indicating that Republicans' votes are distributed across districts with far greater efficiency than those of Democrats. In fact, the distribution of partisanship created by the General Assembly's plan is quite similar to that in the second hypothetical example of Table 4.

61. In order to put this in perspective, it is useful to engage in some simple cross-state comparisons. As a metric, the efficiency gap is known to be less reliable in non-competitive states, as well as states with few congressional districts. Thus, I calculate the efficiency gap for the districts used in the last redistricting cycle, focusing on states with more than four congressional districts among the relatively competitive states featured in Figure 5 above. One drawback of the efficiency gap is that the measure is not always stable for a set of districts when one switches from using data from one election to another, depending on the individual quirks of incumbents and challengers, and patterns of split-ticket voting. In order to compare apples with apples and mitigate candidate-specific effects, I use data from the 2016 and 2020 presidential elections, aggregated to the level of congressional districts.

62. Using data from the 2016 presidential election, the efficiency gap associated with the Enacted Plan is almost identical to what I calculated using all of the Ohio statewide elections from 2016 to 2020: 24 percent. I also calculated the efficiency gap using the 2016 presidential election for the other large, competitive states discussed above. The efficiency gap associated with the Enacted Plan is larger than those observed in Colorado, Florida, Missouri, Arizona, Virginia, Indiana, Minnesota, Michigan, Georgia, and Wisconsin, surpassed only by Pennsylvania's notorious (and ultimately invalidated) map, where the efficiency gap calculated using 2016 presidential data was 38 percent.

63. Using data from the 2020 presidential election, the efficiency gap associated with the Enacted Plan is around 16 percent. This is slightly lower than the 24 percent figure associated with all statewide races, largely because relative to a typical statewide race in Ohio, the Republican candidate, Donald Trump, won by larger margins in rural areas, hence producing more wasted votes for Republicans, and Democratic candidate Joseph Biden won by slightly smaller margins in urban core areas, leading to slightly fewer wasted votes for Democrats. A similar phenomenon occurred in other states, however, and 16 percent is larger than the efficiency gap calculated using 2020 data for any of the other states mentioned above, this time with the exception of Wisconsin, where the efficiency gap was 27 percent.[17]

64. In addition to the efficiency gap, another approach to measuring partisan asymmetry is to calculate so-called electoral bias.[18] This approach flows directly from the vote-seat curves in

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[17] Note that I do not have 2020 presidential data aggregated to the level of the court-invalidated Pennsylvania districts that were no longer in use in 2020.

[18] See Edward Tufte. 1973. "The Relationship Between Seats and Votes in Two-Party Systems," *American Political Science Review* 67: pages 540-554; Bernard Grofman. 1983. "Measures of Bias

Figure 7 above. Recall that because of the "winner's bonus" and the typical shape of vote-seat curves, if we observe that a party gets a seat share that is higher than its vote share, it could very well be the case that the other party would receive a similar bonus if it had received a similar vote share. We would like to know if, with a similar share of the vote, the parties can expect similar seat shares. If not, it indicates the presence of electoral bias favoring one party over the other.

65. From the observed distribution of district-level election results, one can simulate the relationship between votes and seats under other hypothetical vote shares than the one observed. Above all, it is useful to examine the hypothetical of a tied election: With 50 percent of the vote, can each party expect 50 percent of the seats? Or can one party expect a larger seat share due to its superior efficiency of support across districts? In the examples above, there is no electoral bias in the symmetric case, but in the asymmetric example, the (pro-Republican) electoral bias is 10 percent. This can be seen in Figure 7 above: a 50 percent vote share on the horizontal axis corresponds to a 60 percent seat share on the vertical axis.

66. I calculate the electoral bias based on all Ohio statewide elections from 2016 to 2020. This approach indicates that in a tied election, the Republican Party could nevertheless expect to win 10 of 15 seats, or around 66.7 percent, under the Enacted Plan. The measure of electoral bias, then, is 16.7 percent.

67. In recent years there has been a lively debate about whether courts should adopt a specific measure as a "talismanic" indicator of impermissible gerrymandering. The approach of this report is neither to contribute to this debate nor endorse a specific measure. For the most part, critics of the various measures often dwell on the prospect that they will produce false negatives. That is, they might fail to recognize a gerrymander when one is in fact present.[19]

68. As can be appreciated from the discussion above, these metrics are not always stable when we switch from the analysis of one type of election to another. Statewide results and the spatial distribution of support can vary across elections in ways that push pivotal districts above the 50 percent threshold in some races but not others—especially when we are simulating hypothetical tied elections in order to calculate electoral bias. Perhaps the most vexing problem with these indicators is that, when we are attempting to assess the likely seat share associated with future elections in the next redistricting cycle from a single statewide election—for instance a presidential election—we ignore the power of incumbency. As described above, Ohio's Republican congressional incumbents typically outperform

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and Proportionality in Seats-Votes Relationships," *Political Methodology* 9: pages 295-327; Gary King and R. Browning, 1987. "Democratic Representation and Partisan Bias in Congressional Elections," *American Political Science Review* 81: pages 1251-1273; Andrew Gelman and Gary King. 1994. "A Unified Method of Evaluation Electoral Systems and Redistricting Plans," *American Journal of Political Science* 38, pages 514-544; and Simon Jackman. 1994. "Measuring Electoral Bias: Australia 1949-1993," *British Journal of Political Science* 24: pages 319-357.

[19] See, for instance, Jonathan Krasno, Daniel Magleby, Michael, D. McDonald, Shawn Donahue, and Robin Best. 2018. "Can Gerrymanders be Measured? An Examination of Wisconsin's State Assembly," *American Politics Research* 47,5: 1162-1201, arguing that the efficiency gap often produces false negatives.

statewide candidates by several percentage points. Thus, there is reason for deep skepticism about the notion that a statewide swing of 3 percentage points, for instance, would yield a Democratic victory in District 1 as drawn by the General Assembly, or that a statewide swing of four percentage points would yield a Democratic victory in District 15.

69. In any case, whether we analyze the map using 1) a simple comparison of the anticipated seat share with the statewide vote share, 2) a measure of the efficiency of support across districts, or 3) electoral bias, it is clear that the Enacted Plan's districts provide a very substantial benefit to the Republican Party. That is, under any of these measures, and with regard to any of the individual elections or aggregated election results considered above, the 2021 Congressional Plan significantly advantages the Republican Party.

VI. HOW DOES THE 2021 CONGRESSIONAL PLAN TREAT INCUMBENTS?

70. In addition to analyzing the extent to which the Enacted Plan favors or disfavors a party in the aggregate, I have also been asked to examine the extent to which it disproportionately favors or disfavors the *incumbents* for one of the two parties. Under the previous plan, there were 12 Republican incumbents. One of these, Anthony Gonzalez, has announced his retirement. All of the remaining districts with Republican incumbents continue to have Republican majorities—most of them quite comfortable.

71. The only district with a Republican incumbent worthy of further discussion is District 1. The district had previously been drawn to bisect Cincinnati, which had the effect of preventing the emergence of a majority-Democratic district in a heavily Democratic urban area by creating two districts in which parts of Cincinnati were subsumed into Republican exurban and rural areas. The Ohio Constitution now requires that Cincinnati be wholly contained within a single district, which, to my understanding, given their residential addresses, required that two Republican incumbents end up in the same district (although there is no in-district residency requirement for candidates for the U.S. House in Ohio). However, one of the ostensibly paired incumbents, Representative Brad Wenstrup, has announced that he intends to seek re-election in District 2, thereby eliminating the possibility of a double-bunking of incumbents in District 1.[20]

72. In the Enacted Plan, District 1 includes many of the suburban and rural areas that existed in the previous District 1, where Steve Chabot is a long-serving incumbent. By carving out the Democratic suburban areas north of Cincinnati and combining the city with extremely Republican rural areas, the legislature has managed to unify Cincinnati while only slightly increasing the district's Democratic vote share, thus likely keeping it safe for the Republican incumbent, who, as mentioned above, has benefited from a large incumbency advantage, and will compete in a new district where over 80 percent of the population was in his old district.

[20] https://highlandcountypress.com/Content/In-The-News/In-The-News/Article/Rep-Wenstrup-announces-intent-to-seek-re-election-in-2nd-District/2/20/74059.

73. In all the other districts with Republican incumbents, as documented above, safe margins have been maintained so that incumbents are likely to survive even a significant statewide swing toward the Democratic Party.

74. In contrast, of the four Democratic incumbents, only two continue to reside in majority-Democratic districts. The other two reside in dramatically reconfigured districts. Marcy Kaptur represented a relatively urban and comfortably Democratic District 9 (drawn in 2011 to pair Kaptur with another Democratic incumbent). This district has been redrawn to separate Ohio's northern industrial cities, thus subsuming Toledo in a much more rural district that now has a Republican majority. As described above, less than 40 percent of the new version of District 9 was in her previous district. Tim Ryan, who has announced that he is running for the U.S. Senate, was the incumbent in the Youngstown-based District 13, which has been completely reconfigured, with Ryan now placed in the predominantly rural, safe Republican 6th District in the Enacted Plan.

VII. HOW DOES THE 2021 CONGRESSIONAL PLAN ACHIEVE THESE RESULTS?

75. Without a doubt, the Enacted Plan favors the Republican Party and its many incumbents, while disfavoring the Democratic Party and its handful of incumbents. One might suspect, however, that this outcome was driven not by the choices of the map-drawers, but by the Ohio Constitution—with its requirements about keeping counties, cities, and townships whole—combined with Ohio's political geography. I have written extensively about the difficulties for parties of the left in majoritarian democracies like the United States in an era when population density is becoming highly correlated with votes for more progressive candidates.[21] Democrats are highly concentrated in cities and, increasingly, their suburbs. When cities are very large relative to the size of districts, this tends to create some districts in which Democrats win very large majorities. This can make their geographic distribution of support relatively less efficient if Republican majorities in rural areas are not correspondingly large. Thinking visually in terms of cross-district histograms, like those in Figure 6 above, the presence of overwhelmingly Democratic cities can pull out the left tail of the distribution, thus wasting some Democratic votes. Anyone drawing congressional districts—including a non-partisan computer algorithm or even a Democratic activist—is likely to draw a very Democratic district in Cleveland or Columbus. It is also the case that such a map-drawer cannot avoid creating some extremely Republican districts in rural areas.

76. However, the larger implication of this type of political geography for the transformation of votes to seats depends crucially on what is happening in the middle of the distribution of districts. This is precisely where those drawing the districts have maximum discretion. With a very Democratic city like Cincinnati that is *not* especially large relative to the size of congressional districts, it is possible to avoid the emergence of a Democratic district altogether by cutting off its most Democratic suburbs—splitting communities of interest along the way—and combining it with far-flung rural areas. If smaller Democratic cities are close to one another, as in northwestern Ohio, or as in the Canton/Akron/Youngstown area,

[21] Jonathan Rodden, 2019, *Why Cities Lose: The Deep Roots of the Urban-Rural Political Divide*. New York: Basic Books.

boundaries can be drawn to make sure they do not combine to form any district with an urban, and hence Democratic, majority. And when cities are sufficiently large that they must be subdivided, and can thus provide *two* Democratic majorities, as in Columbus, it is possible to conduct this subdivision in a way that prevents the emergence of a second Democratic district by packing as many Democratic votes into a single district as possible and subsuming the remaining Democrats in very Republican rural areas. The legislature has pursued each of these strategies to prevent the emergence of majority-Democratic districts in Ohio.

77. In my academic research, I have shown that residential geography can make life easier for those drawing districts with the intent of favoring Republicans. With maneuvers like those described in the preceding paragraph, a Republican map-drawer can produce a substantial advantage for Republican candidates without drawing highly non-compact or odd-shaped districts. My research has also pointed out that a mere concentration of Democrats in cities is insufficient to produce advantages for Republican candidates. It is clearly the case that in states where Republicans have controlled the redistricting process, districts have favored Republican candidates far more than what might be explained by residential geography alone. Recall the striking difference between the black and red data markers in Figure 5 above, indicating that with similar levels of partisanship, districts drawn by Republican legislatures have had far larger Republican seat shares than those drawn by courts, commissions, and divided legislatures. In fact, in my academic writings, I have used Ohio in the 2010 redistricting cycle as a leading example of this phenomenon.[22]

78. In order to verify that the extreme pro-Republican bias described above was not forced upon the legislature by the Ohio Constitution or the residential geography of Ohio, it is useful to conduct a simple exercise: we can examine the congressional maps submitted by Democrats and other groups to the state legislature. The purpose of this exercise is not to recommend these maps for adoption. Rather, these maps are useful because they were available to the legislature prior to adopting the Enacted Plan and, if they comply with the Constitution,[23] demonstrate similar or superior compactness, pursue fewer unnecessary county splits, and are less prone to splitting obvious communities of interest, we can conclude that the extreme pro-Republican slant of the Enacted Plan was not driven by residential geography or constitutional requirements, but by discretionary choices.

79. Figure 8 provides discrete histograms of the composite vote share of statewide Republican candidates from 2016 to 2020—the same measure used extensively above—aggregated to boundaries of proposed congressional districts. The top left panel represents the Enacted Plan. The panels on the right represent districts proposed by the House (top) and Senate (bottom) Democrats, attached as Exhibits C and B, respectively. In the lower left-hand

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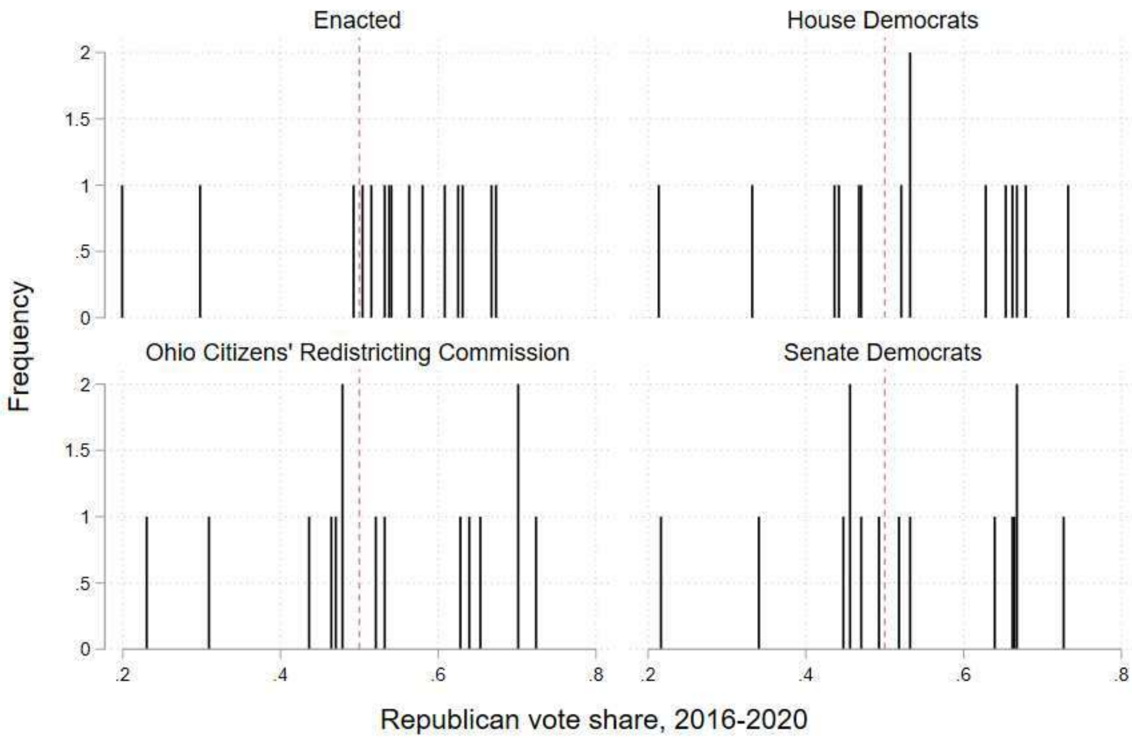
[22] See, for example, *Why Cities Lose*, op cit., Figure 6.2 on page 171 and the surrounding discussion, as well as Figure 6.8 on page 184 and the accompanying discussion in the text.

[23] I have carefully examined these plans, and according to my review, the only clear constitional compliance issue arises with the Senate Democrats' plan, where a single house on the border of Massillon City was mistakenly placed in District 8 rather than District 7, creating a very minor non-contiguity. See the appendix for an image of the misplaced fragment. Needless to say, this mistake does not undermine the usefulness of the map for comparative analysis.

corner, I include a districting plan submitted by a group called the Ohio Citizens Redistricting Committee (OCRC), attached as Exhibit D.

Figure 8: Histograms of Enacted and Alternative Maps



80. Note that all the histograms share something in common: each includes two extremely Democratic districts on the left-hand side of the graph. In each case, one is in Cleveland and one in Columbus. However, as described above, the Enacted Plan only includes a single additional district that is (barely) on the Democratic side of 50 percent, for a total of three. In the other comparison maps, there are seven districts with Democratic majorities in statewide races, six in the case of the House Democrats' plan. Thus, the Senate Democrats' plan and the OCRC plan, where 46.7 percent of the districts have Democratic majorities in statewide races, correspond almost exactly with the statewide aggregate vote share (see Table 1 above), while the House Democrats' plan falls short by one seat. In other words, if these maps were included in Figure 5 above, they would be on, or slightly below, the dotted line of proportionality, much like the court-drawn maps in Figure 5.

81. The Enacted Plan is also unique in that it avoids creating extremely Republican rural districts on the right side of the histogram. The vast majority of districts have comfortable but not staggering Republican majorities. As discussed above, Senator McColley has portrayed the presence of several solidly but not overwhelmingly Republican districts, all with longstanding Republican incumbents, as a virtue of the map, in that it introduces "competition." However, in a state where only 53 to 54 percent of the votes go to

Republicans, it is simply not possible to create 12 of 15 districts in which Republican candidates win with over 54 percent of the vote. In all, the cross-district distribution of support in the Enacted Plan is a textbook example not of a plan with highly competitive districts that may swing from one election to the next, but, rather, of a distribution that is extremely efficient for one party and inefficient for the other. As mentioned above, the efficiency gap (using composite statewide election results between 2016-2020) is 24 percent. The other maps are far more even-handed. For the House Democrats' plan, it is 3.5 percent (still favoring Republicans). For the Senate Democrats' plan and the OCRC plan, the distribution of support is slightly more efficient for the Democrats, with gaps that are swung in the other direction of 3.7 percent and 3.6 percent, respectively.

Table 6: Comparison of Enacted Plan with Alternative Plans	Seats in which statewide Democratic vote share exceeds 50 percent	Efficiency gap
Enacted	3	24%
Senate Democrats	7	-3.7%
House Democrats	6	3.5%
OCRC	7	-3.6%

Note: Efficiency gap is calculated so that a positive number indicates pro-Republican efficiency gap.

82. What accounts for these large differences in the efficiency of support for the two parties in the different maps? Above all, the remainder of this report demonstrates that the answer lies in the treatment of urban areas.

Cincinnati

83. First, consider the Enacted Plan's treatment of Hamilton County. Any treatment of Hamilton County that attempts to minimize splits and keep Cincinnati-area communities together would produce a majority-Democratic district. Any such district would keep northern suburbs with large Black populations together with similar neighborhoods across the Cincinnati boundary. Each of the alternative maps keeps Hamilton County mostly whole and keeps the Black community together in a relatively compact district contained entirely within the county.

84. However, the Enacted Plan traverses the Hamilton County boundary in *three* different places in order to overwhelm Cincinnati's Democratic population with a sufficient number of exurban and rural Republicans. The entire urban, Black population of Northern Hamilton County is carved out from its surroundings and combined with a rural Republican district, number 8, whose northern boundary is 85 miles away. Second, instead of being combined with its immediate inner-ring suburbs, for instance, linking neighborhoods like College Hill and North College Hill (see Figure 11), Cincinnati proper is combined with rural Warren

County via a very narrow corridor in District 1. Finally, Cincinnati's relatively Democratic eastern suburbs are also extracted from the city and combined with District 2, which is extremely rural and Republican.

Figure 9: Partisanship and the Enacted Plan's Districts, Hamilton County and Surroundings

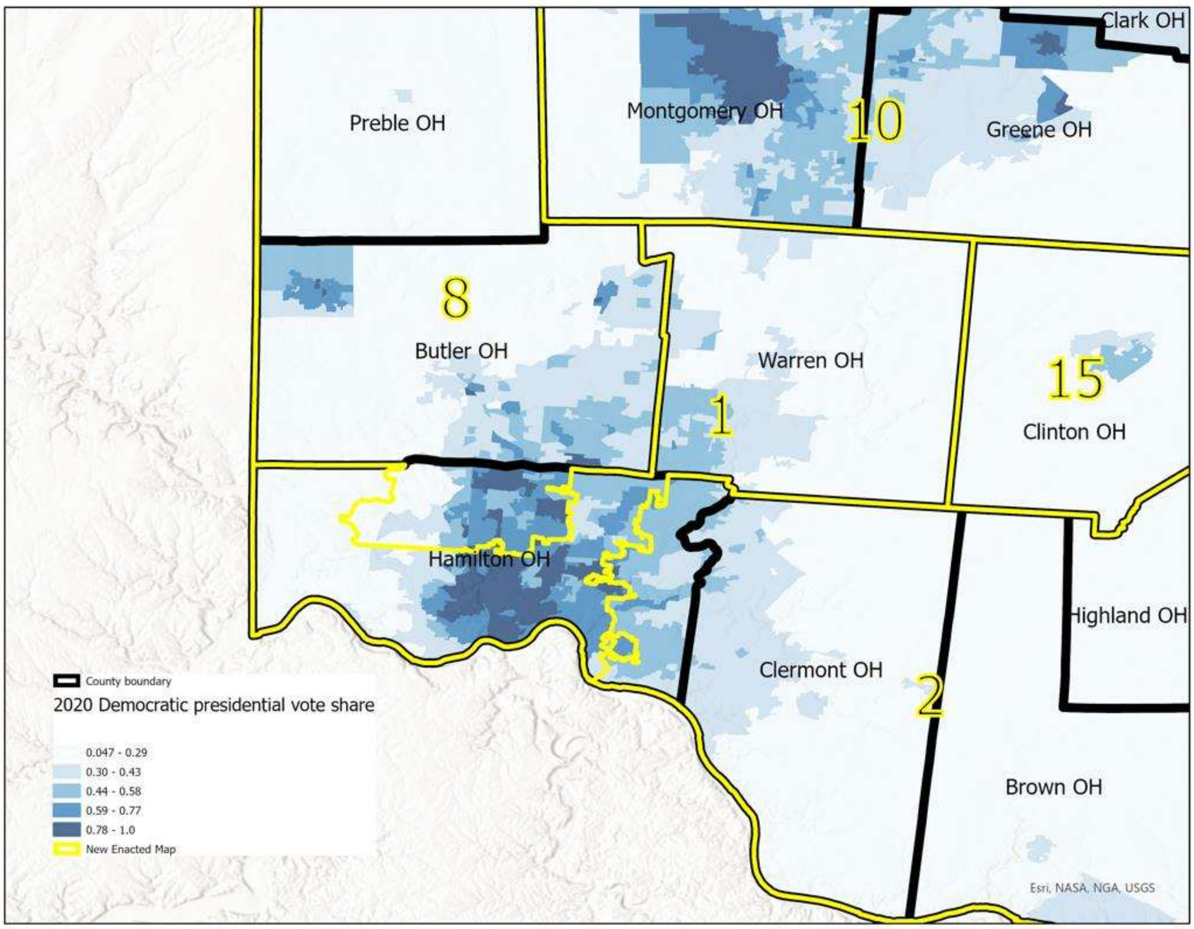


Figure 10: Race and the Enacted Plan's Districts, Hamilton County and Surroundings

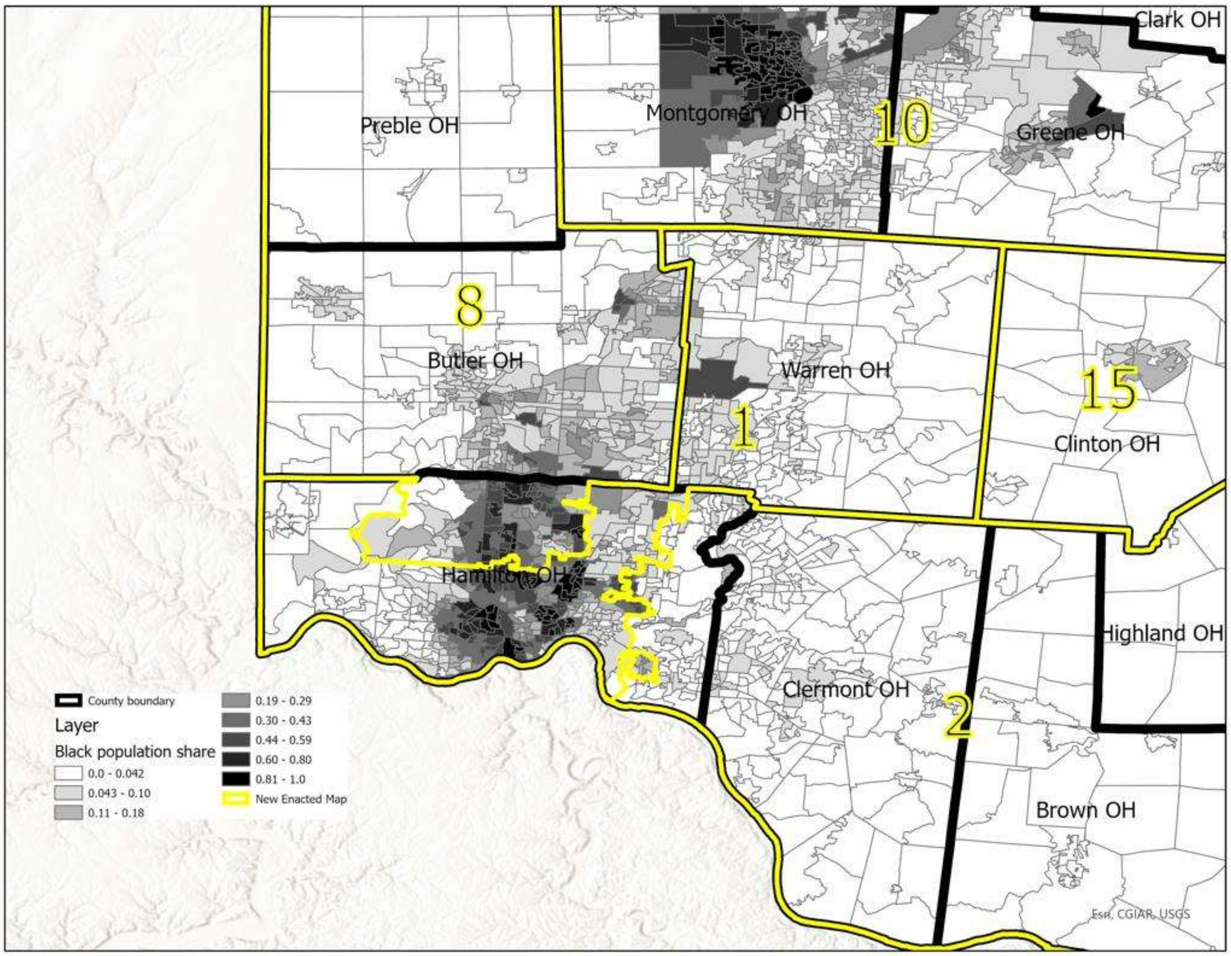


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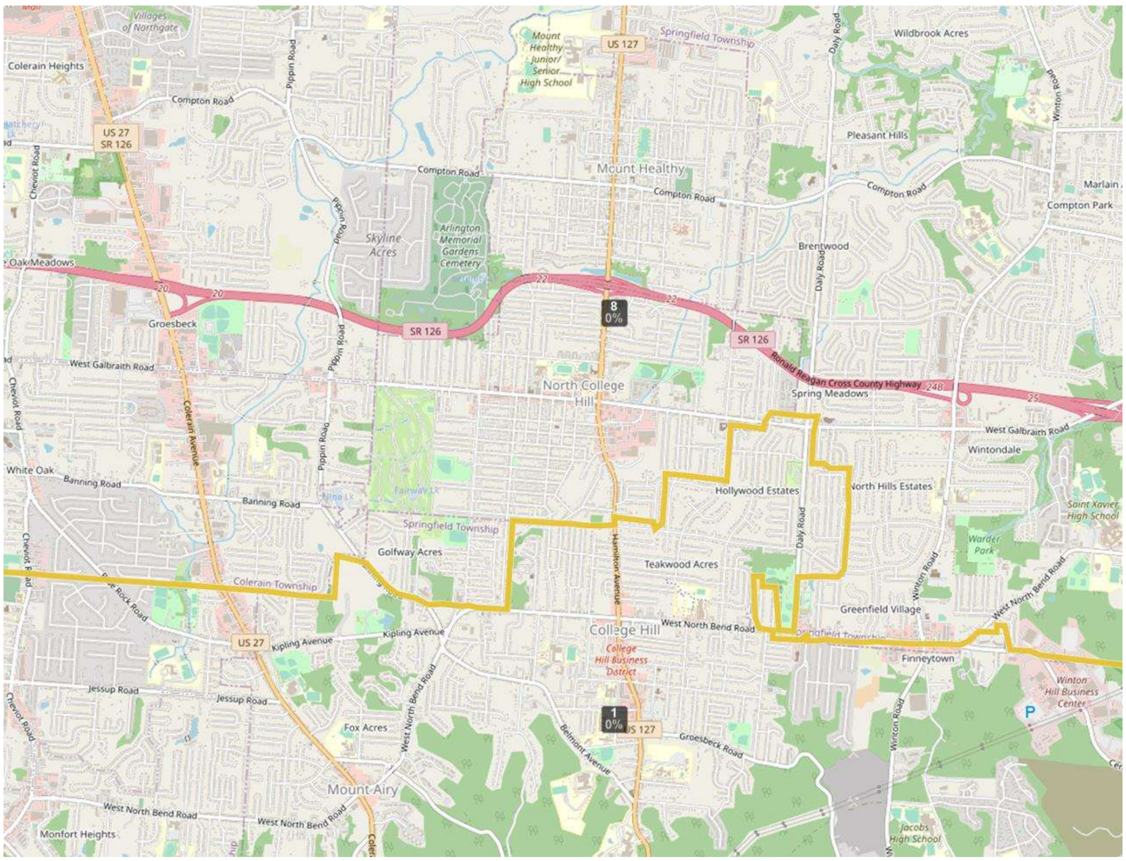
Figure 11: Cincinnati, College Hill Area



85. This can be visualized in Figure 9, which overlays the Enacted Plan on a map of partisanship, from precinct-level results of the 2020 presidential election. Figure 10 then overlays the district boundaries on a map that shows the area's racial composition. It highlights the extent to which the Enacted Plan splits Hamilton County's Black population—cutting the Black community essentially in half and cutting through neighborhoods.

86. Under any method of counting splits, the Enacted Plan's approach involves at least two splits of Hamilton County—a line running north-south on the east side of the county and another one that carves out the northern suburbs. These maneuvers are clearly not necessary for any reason other than partisan advantage. Each of the alternative plans keeps metro Cincinnati together in a compact district remaining within the county, avoids splitting the Black community, and splits the county only once.

87. The arrangement of these alternative plans can be seen in Figure 12. Clearly, it is quite straightforward to draw a district that is compact, minimizes splits, and keeps the Black community together. Notably, these arrangements all produce a majority-Democratic district (56.5 percent for the House Democrats' plan, 55.4 percent for the Senate Democrats' plan, and 56.4 percent for the OCRC plan).

88. These alternative plans are also more compact than the Enacted Plan, both in the areas in and around Hamilton County and (as discussed below) plan-wide. Higher Reock score values indicate greater compactness. The Reock score for the General Assembly's District 1 was .27. The Reock score for District 1 in the OCRC plan is .54, and the score for the comparable district (5) in the Senate Democrats' plan is .44. Summary information about Reock scores for all the districts in each of these plans is provided in Figure 13 below.

Figure 12: Partisanship and Districts of Alternative Plans, Hamilton County and Surroundings

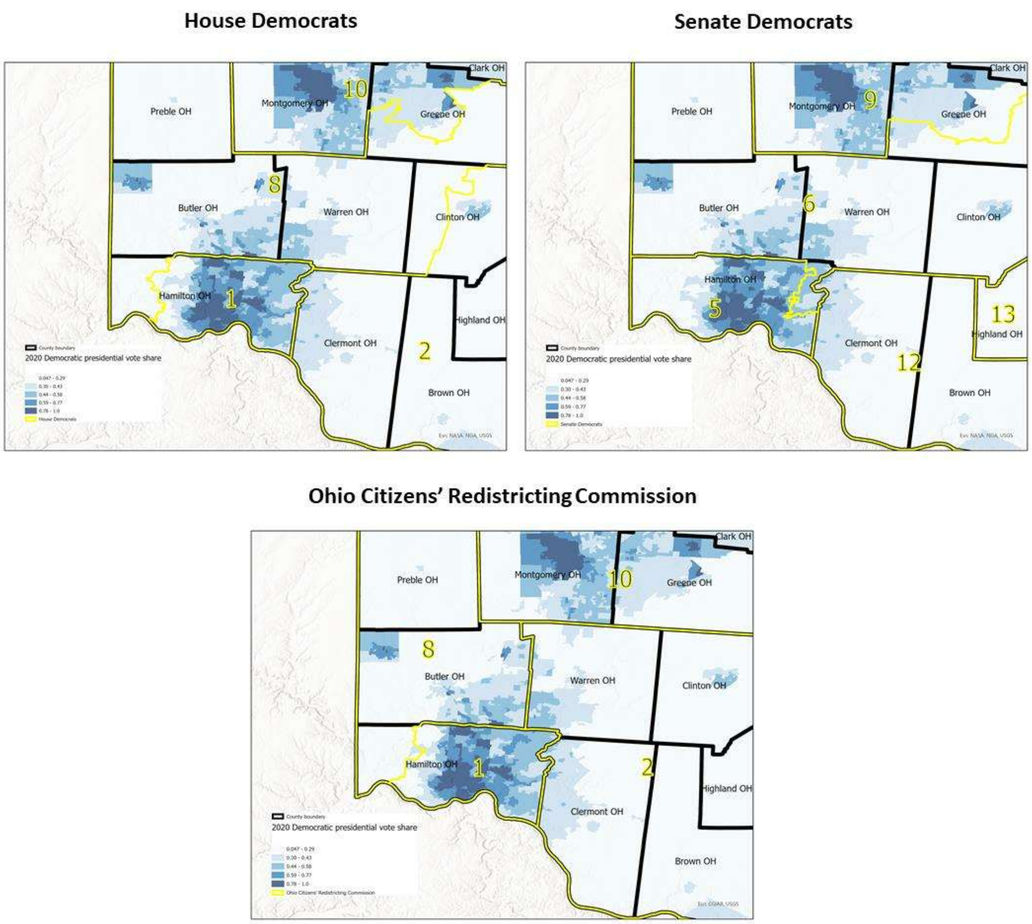


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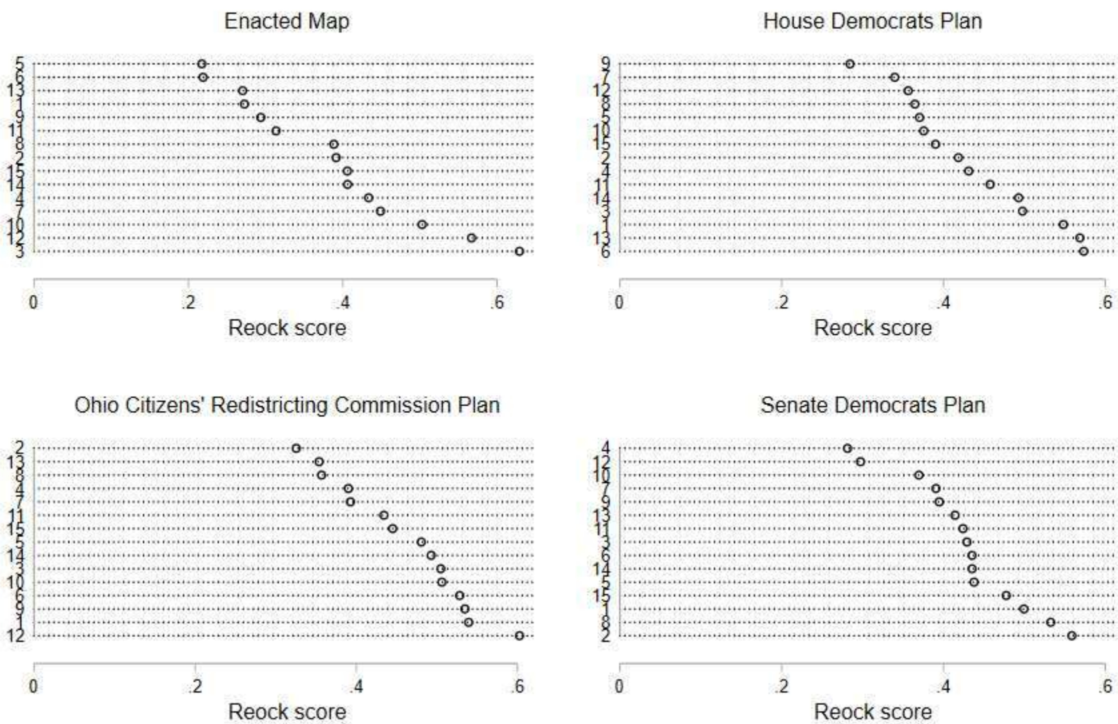
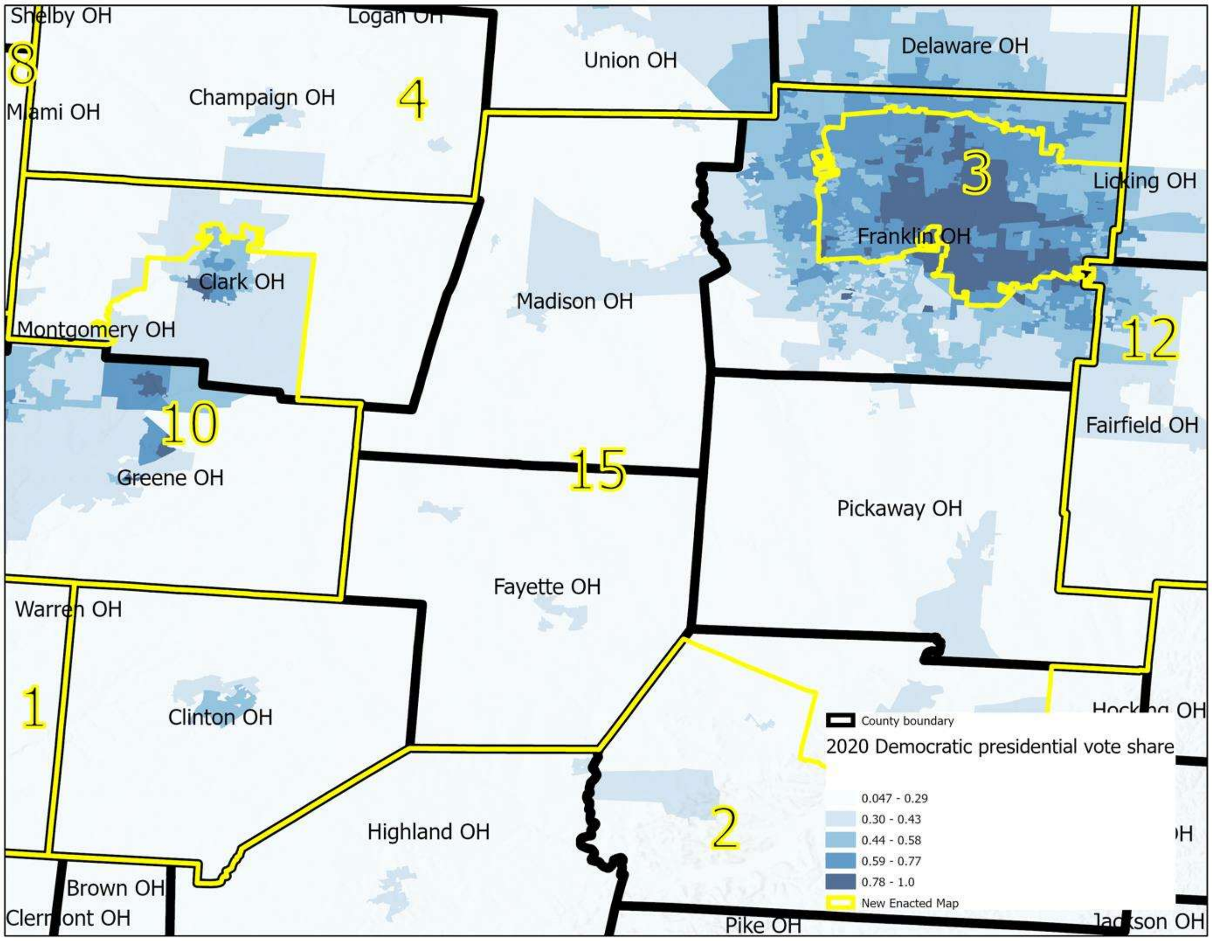
Figure 13: Reock Scores for Districts in Enacted and Alternative Plans



Columbus

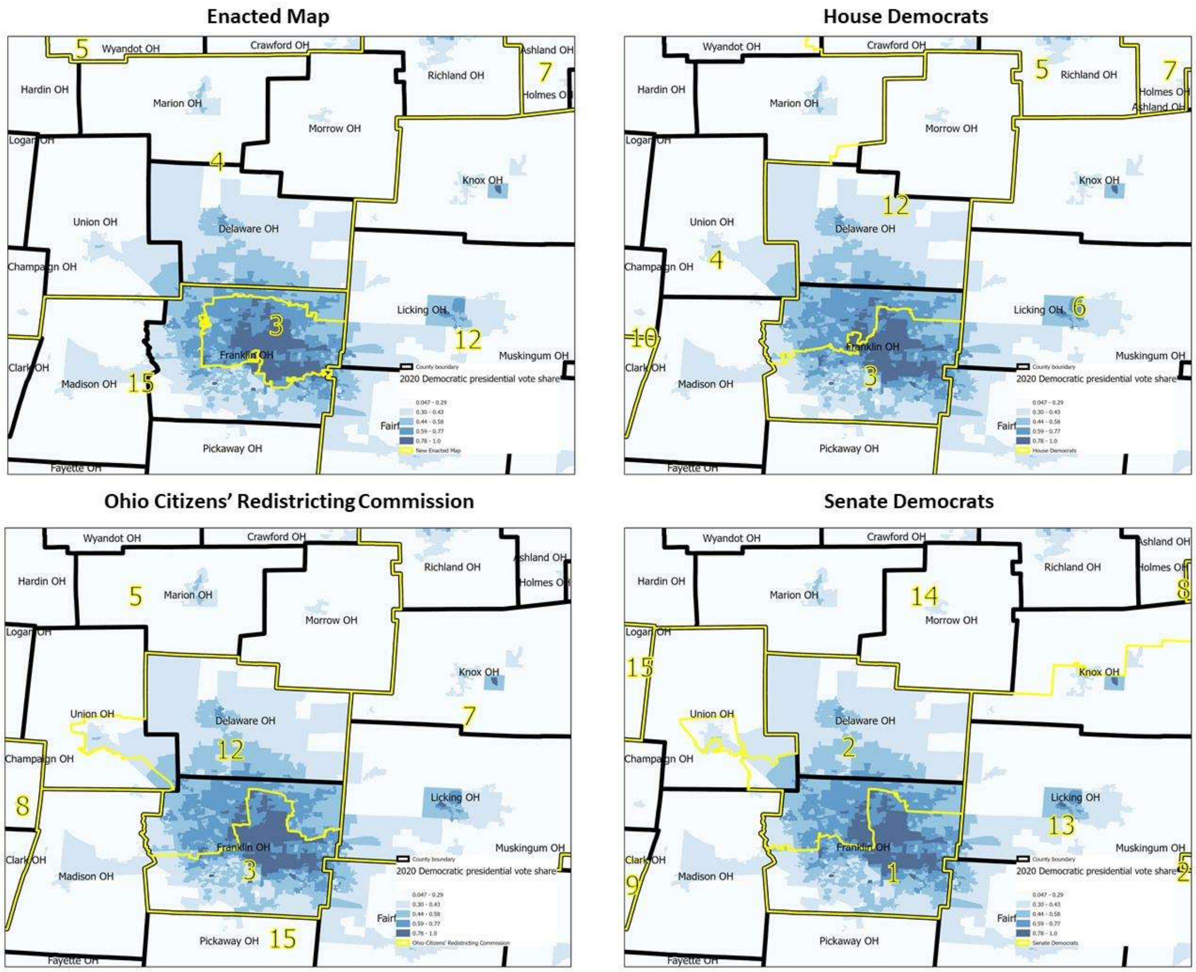
89. Next, consider the Columbus area in Franklin County. The city of Columbus is larger than a unit of congressional representation, so it must be split. In Cincinnati, it was possible to maneuver to avoid the creation of a Democratic district that would have otherwise emerged. But in Columbus, the number of Democratic voters was simply too large to pursue that strategy. Instead, the Enacted Plan in Franklin County packs Democrats into one very Democratic Columbus district (District 3). It then reaches around the city to extract its outer reaches and suburbs, connecting them with far-flung rural communities to the southwest—an arrangement that prevents the emergence of a second Democratic district by removing Democratic Columbus-area neighborhoods from their context and submerging them in rural Republican areas (see Figure 14).

Figure 14: Partisanship and Enacted Districts, Columbus and Surroundings



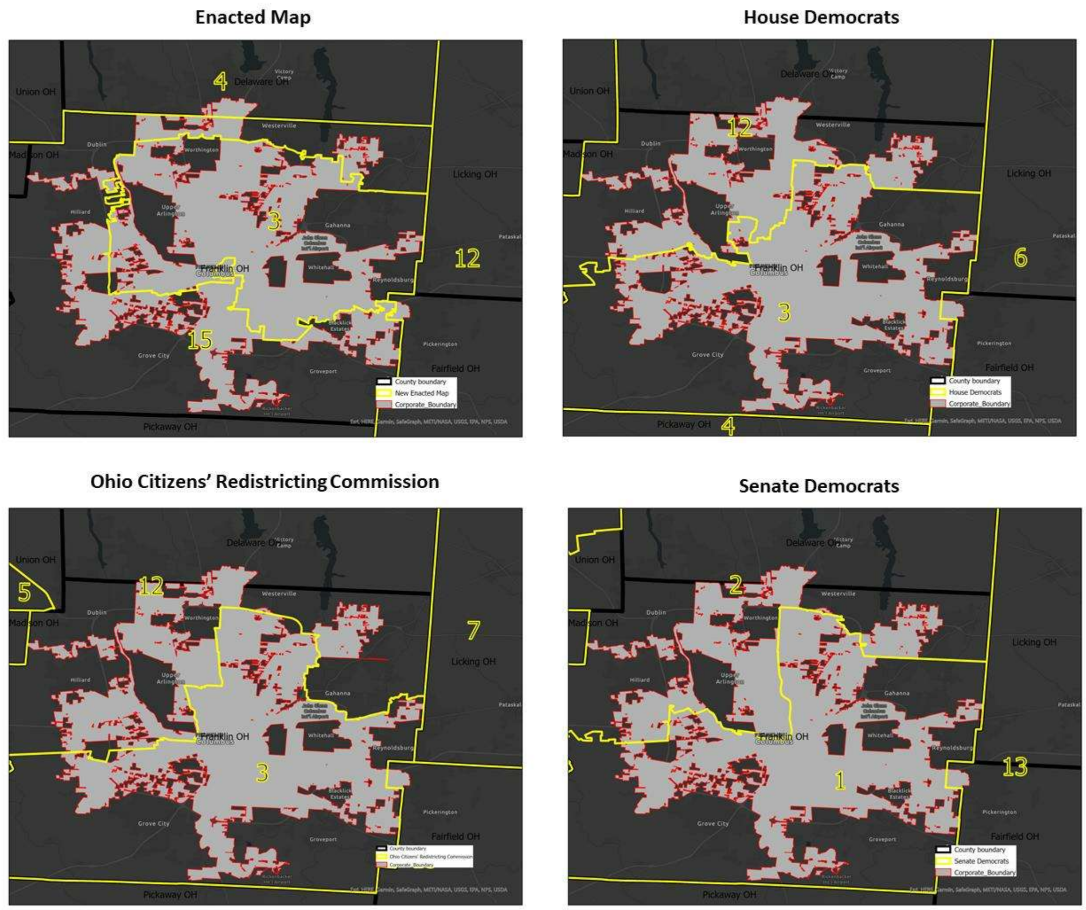
90. In contrast, the alternative plans split Columbus with a line that runs from west to east (see Figure 15). This arrangement creates a compact southern Columbus district that includes much of the city and its southern suburbs, and a relatively compact northern Columbus district that includes all the northern reaches of the city and its suburbs. In northern Franklin County, the cities of Westerville, Columbus, and Dublin all cross over into Delaware County, and these alternative plans keep them together. In fact, Dublin also extends into Union County, and the Senate Democrats' plan and the OCRC Plan extend into Union County and keep Dublin whole. Given the fact that Columbus and its suburbs spill into counties to the north, if one is attempting to keep communities together, the northern border—not the western border—is the obvious place to extend the second Franklin County/Columbus district.

Figure 15: Partisanship and Enacted and Alternative Districts, Columbus and Surroundings



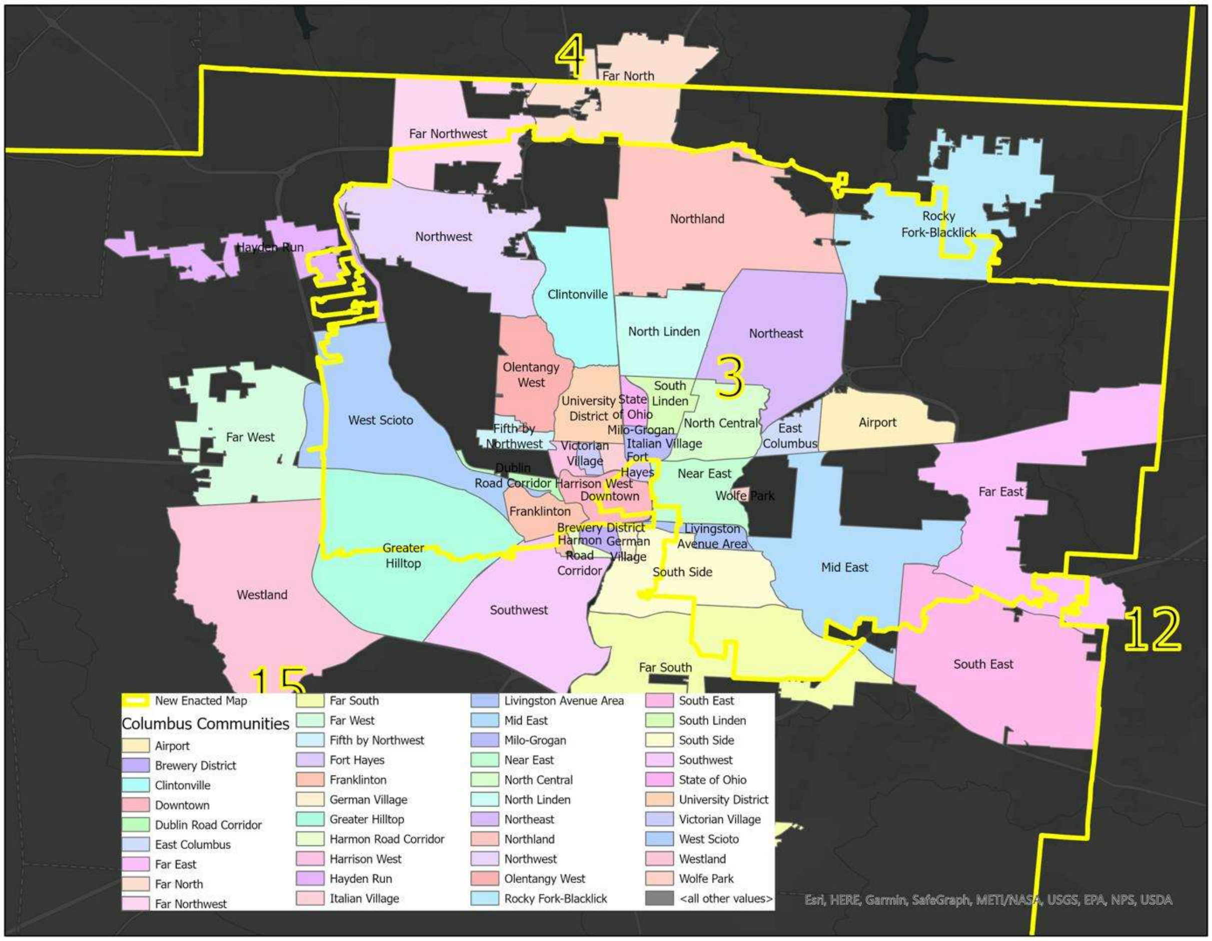
91. The Enacted Plan produces several non-contiguous chunks of Columbus that are removed from the city and placed in largely rural District 15. Figure 16 features the Columbus Corporate Boundary and its interaction with the Enacted Plan as well as the alternative plans. In the Enacted Plan, there are five chunks of non-contiguous territory that are carved away from Columbus and placed in District 15 (two in the north, one in the west, one in the southwest, and one in the southeast). In contrast, each of the alternative plans places two non-contiguous chunks of Columbus in its northern Columbus-oriented district, and the House Democrats' plan also includes a third tiny non-contiguous sliver of Columbus that abuts Upper Arlington and Grandview Heights.

Figure 16: The Boundary of the City of Columbus and Boundaries of the Enacted Plan and Alternative Plans



92. Perhaps a better way to contrast the way these redistricting plans treat Columbus is to examine its communities. The city of Columbus produces maps of areas recognized by the city as distinct communities. Figure 17 provides a map of Columbus communities and the boundaries of the Enacted Plan. Due to its circumnavigation of the city, the Enacted Plan splits 15 of Columbus' communities (16 if we include the Far North, which extends into Delaware County). For instance, the northern part of the Rocky Fork-Blacklick area is extracted and placed in a rural district that curls around the city and extends 100 miles to the southwest. On the south side of Columbus, the Hilltop neighborhood is cleaved down the middle. Residents on the north side of Sullivant Avenue are in an urban district with a large Democratic majority, while residents on the south side of the street are in a rural district that extends to the southwest part of the state. Along the eastern boundary of Franklin County in the southeast part of Columbus, several neighborhoods with large minority populations are split between the Columbus-based District 3 and the rural District 15.

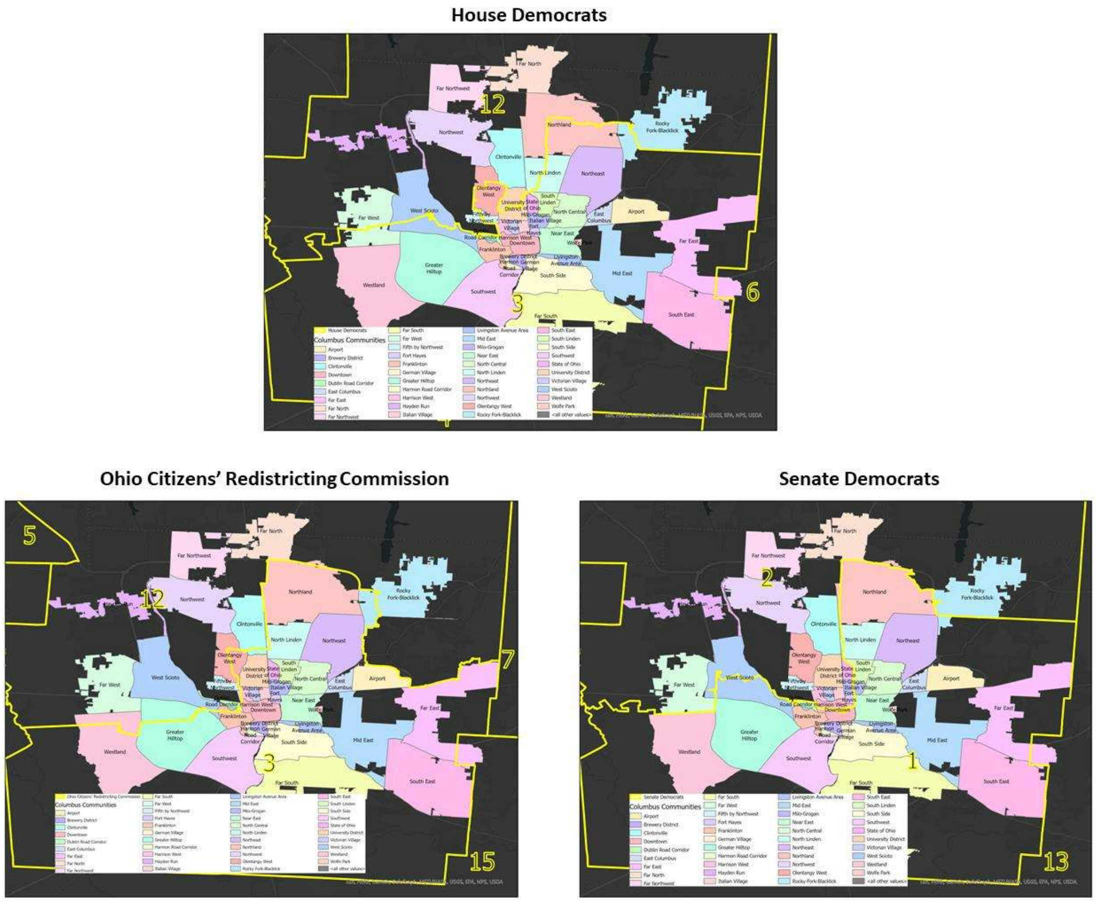
Figure 17: The Boundary of the Communities of the City of Columbus and Boundaries of the Enacted Plan



93. The approaches taken to dividing Columbus in the alternative plans produce fewer subdivisions of Columbus communities. The House Democrats' plan splits eight communities, while the Senate Democrats' plan splits five, and the OCRC plan splits 10 (see Figure 18).[24]

[24] In the Senate Democrats' and OCRC plans, one of these splits, to the community of Northland, involves a single small precinct that is separated from the rest of the community by Highway 270.

Figure 18: The Boundary of the Communities of the City of Columbus and Boundaries of the Alternative Plans



Northeast Ohio

94. Next, consider Summit County and the Akron area. As with Cincinnati, the Enacted Plan cuts off Akron's eastern suburbs from the city. In this case, the maneuver introduces a long, narrow north-south corridor that is, in one spot, less than one mile wide, connecting a number of relatively urban, Democratic-leaning precincts, removing them from their geographic context, and combining them with rural areas well to the southwest. For example, Twinsburg, a small city nestled between Cleveland and Akron near the northern border of Summit County, is in a district with neither of them. Rather, it is part of a rural district well to the south, whose southwest border is over 70 miles away, where Ashland, Knox, and Richland counties come together. And rather than combining Akron with its own suburbs, the Enacted Plan combines it with rural Medina County and the most Republican outer exurbs of Cleveland (see Figures 19 and 20).

Figure 19: Partisanship and the Boundaries of the Enacted Plan, Northeast Ohio

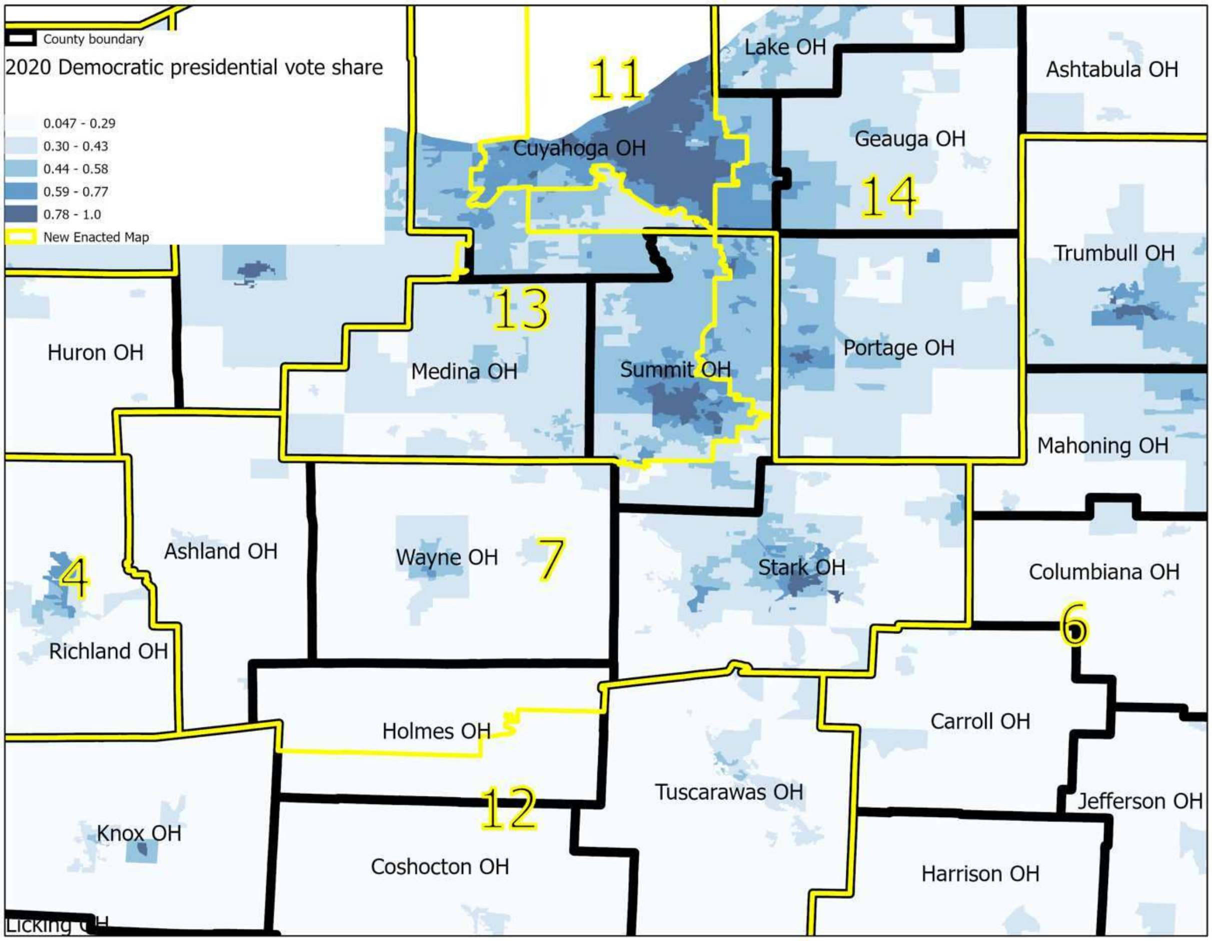


Figure 20: Partisanship and the Boundaries of the Enacted and Alternative Plans, Northeast Ohio

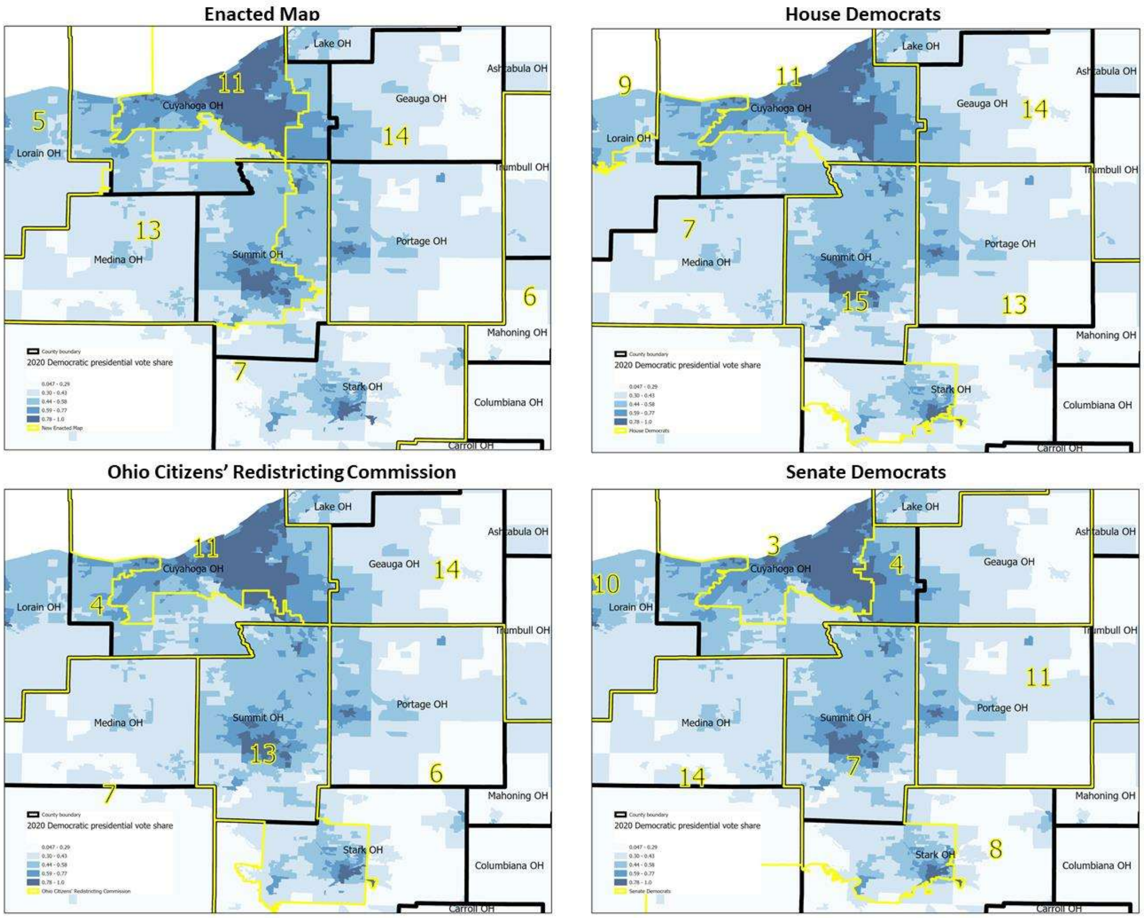


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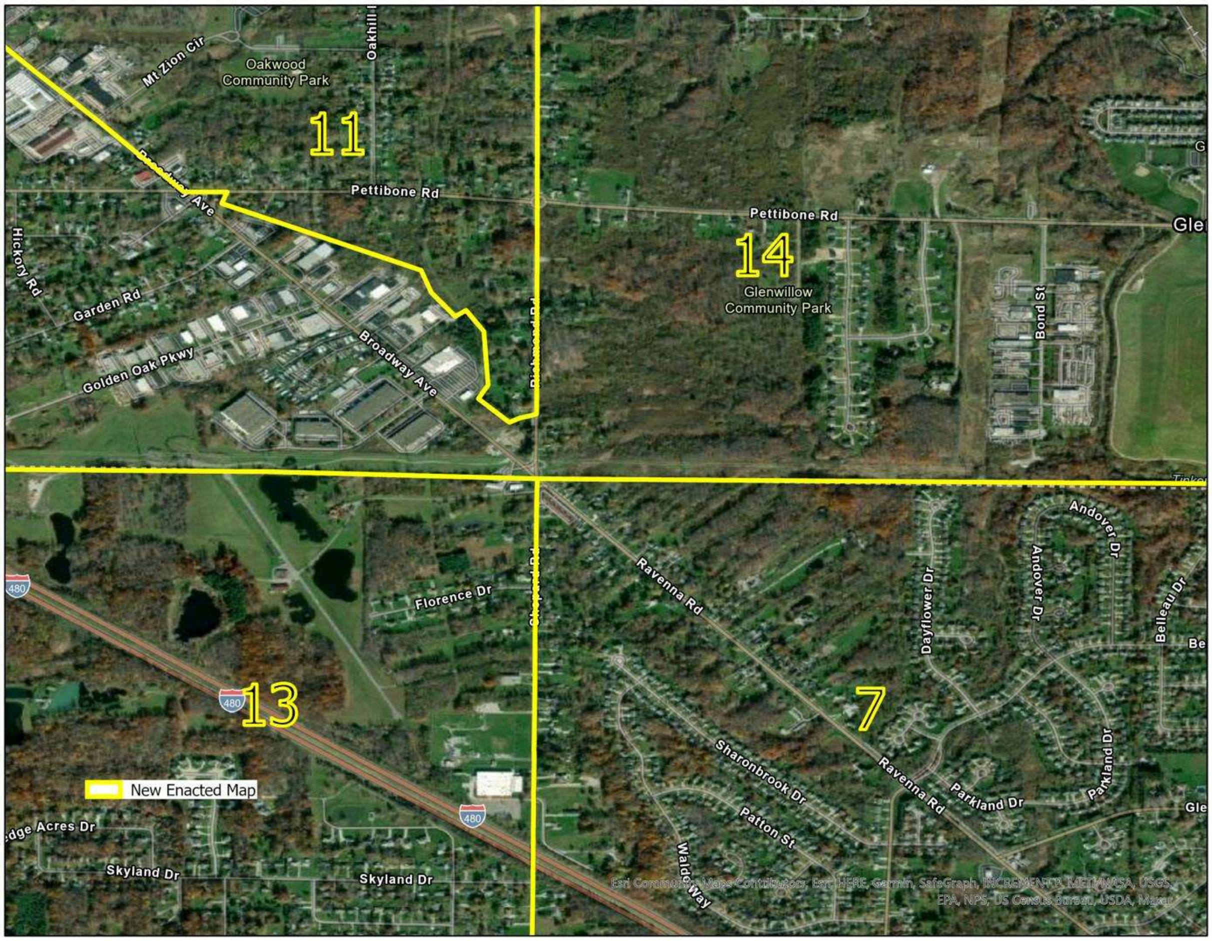
Figure 21: The Cuyahoga Corridor



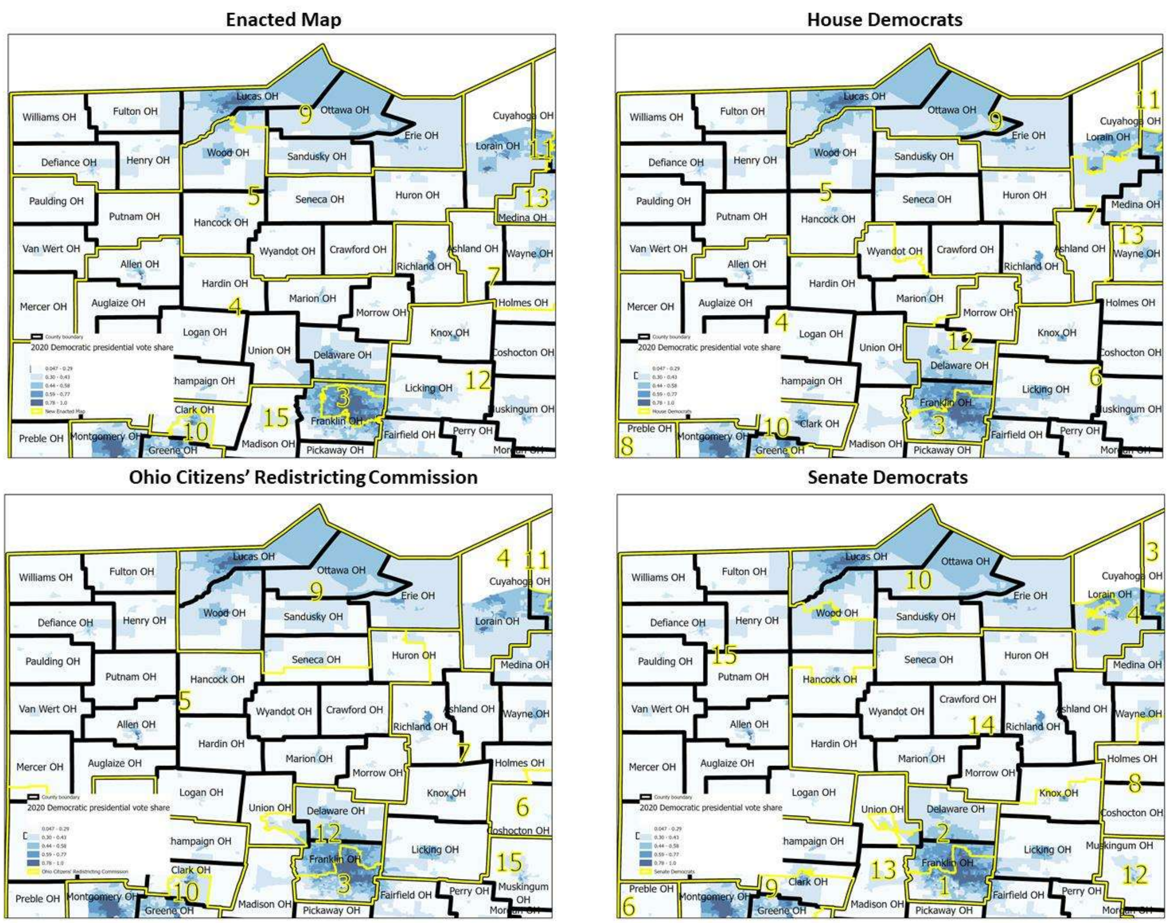
95. Next, consider Cuyahoga County and Cleveland. Here, the Enacted Plan produces multiple splits of Cuyahoga County—placing fragments in three different districts, and an arrangement featuring a narrow corridor (seen in Figure 21) that is, in one spot, the width of one census block, with no road connecting the fragments. In this area, four districts—7, 11, 13, and 14—converge upon an area spanning less than a square mile. The Cleveland-based District 11 nearly splits District 14 in half (i.e., making it noncontiguous), but for the grace of the one census block mentioned above.

96. District 13 in the Enacted Plan appears to have been crafted as part of an effort to make sure there is only one very Democratic district in Northeast Ohio, such that what would otherwise be a comfortable Democratic Akron-based district is instead a toss-up. In addition to separating Akron from its Democratic suburbs, the map avoids a connection to Canton. Moreover, Democratic neighborhoods nestled between Cleveland and Lorain are prevented from joining with either of their surrounding Democratic strongholds and are instead combined with Medina County to the South.

Northwest Ohio

97. Finally, consider Northwest Ohio. The Enacted plan and the three alternative plans are depicted in Figure 22. Each of the plans includes Toledo and draws a relatively narrow district that runs from West to East along the Michigan border and Lake Erie. However, the General Assembly's plan stops short of Lorain County and its Democratic cities, extending instead all the way west to the Indiana border with an arrangement that, reminiscent of the Cincinnati strategy described above, combines Toledo with very rural areas. In this arrangement, the Democratic cities of Lorain County are removed from their geographic context and subsumed within a narrow rural District 5 that reaches all the way to Mercer County, along the Indiana border, which is 180 miles away, more than a 3-hour drive from downtown Lorain.

Figure 22: Partisanship and the Boundaries of the Enacted and Alternative Plans, Northwest Ohio



98. In contrast, the plans created by the House Democrats and Senate Democrats simply extend the district slightly to the East—leaving out the Western rural counties—keeping the string of proximate industrial towns along Lake Erie together. The Senate Democrats' plan and the OCRC plan also extend into Wood County to keep Toledo's Southern suburbs together with the city. In contrast with the General Assembly's plan, each of these plans creates a Democratic-leaning district. According to the Reock score, the Senate Democrats and OCRC version of District 9 is more compact than the General Assembly's version.

County and Municipal Splits

99. In sum, the 2021 Congressional Plan includes consequential extra county splits vis-à-vis the alternative plans in Hamilton, Summit, and Cuyahoga Counties. It includes two counties—Hamilton and Cuyahoga—that are split between three districts, whereas the alternative plans never do this. If we simply add up county splits, there are 12 split counties in the Enacted Plan, but since two of them are split multiple times, the total number of splits is 14. The Senate and House Democrats' plans split 14 individual counties, while the OCRC plan splits 13 individual counties.

100. While prioritizing counties first, the Ohio Constitution also instructs those drawing the districts as a secondary priority to attempt to avoid splits of townships and as a third priority, to avoid splits of municipal corporations. The Enacted Plan, along with those submitted by the Senate and House Democrats, achieved absolute population equality across districts. In order to do so, it was necessary to split a number of townships and/or cities. The General Assembly, along with the Senate and House Democrats, clearly placed considerable effort into minimizing these splits. OCRC did not attempt to achieve absolute population equality, and while its plan achieved fewer county splits than the other plans, it was less successful in avoiding township splits.

101. Of the four plans considered here, the plan submitted by the Senate Democrats performs the best when it comes to avoiding township splits. By my accounting, which is explained in Appendix B, this plan did not split one township, while producing 15 city splits.[25] The Enacted Plan created a total of 17 splits, 8 of which involved townships. The House Democrats' plan creates 19 splits, 13 of which involved townships. The OCRC plan produced 27 splits, all of which were townships except for the city of Columbus.

Compactness

102. In addition to providing guidance about county splits, the Ohio Constitution also calls for compact districts. As already indicated in the discussion above, the Enacted Plan produces a set of districts that are less compact than those of the alternative plans. Average compactness scores across all districts, including the Reock, Polsby-Popper, and Convex Hull scores, are set forth in Table 7. With each of these scores, a higher number indicates a higher level of compactness. On each indicator, the Enacted Plan is less compact than the alternative plans.

[25] Note that in an earlier affidavit I submitted in this case, I missed one instance of a split township—Prairie Township—in Franklin County.

Table 7: Average Compactness Scores

	Reock	Polsby-Popper	Convex Hull
Enacted Plan	0.38	0.28	0.73
House Democrats	0.43	0.33	0.78
Senate Democrats	0.43	0.29	0.76
OCRC	0.46	0.37	0.79

103. As described above, and as explained further elsewhere,[26] highly non-compact districts are sometimes an obvious manifestation of efforts by partisan map-drawers to favor a political party. Among the clearest examples are the notorious maps of Pennsylvania and North Carolina from the last redistricting cycle. In these cases, given the underlying political geography, such maps were necessary in order to generate the maximum possible number of Republican seats. However, it is a myth that such odd-shaped districts are the *sine qua non* of gerrymandering. Depending on the underlying political geography, it is sometimes possible to draw maps that are extremely favorable to a political party— maps that pack and crack one's opponents, divide communities, and maximize a party's seat share—without drawing long tendrils and comical shapes in every region. Likewise, sometimes relatively non-compact districts are forced upon district-drawers by natural geography and the specific rules governing the redistricting process in a state.

104. For this reason, one should approach average, plan-wide compactness scores like those in Table 7 with caution—especially for cross-state comparisons. However, the discussion above demonstrates that the extreme favorability of the Enacted Plan to the Republican Party and its incumbents required specific choices in certain urban areas, many of which clearly required non-compact districts, and a comparison with alternative maps clarifies that these choices were not forced by political geography or constitutional rules. The same is true about the General Assembly's decisions to unnecessarily split several urban counties and the communities within them.

Splits of Partisan Communities

105. It is clear from the maps and analysis above that in the vicinity of Ohio's major cities, the Enacted Plan achieves an unusually large advantage in the efficiency of its support across districts by inserting district boundaries that split geographically proximate groups of Democrats in order to prevent them from forming districts with Democratic majorities, while trying to place as many Republicans as possible in majority-Republican districts. In order to

[26] Rodden, *Why Cities Lose*, op cit.

visualize this type of intentional "cracking" of co-partisans, along with co-authors, I have developed a simple measure that we call "partisan dislocation."[27]

106. We begin with geo-spatial precinct-level geographic boundaries of each precinct, associated with outcomes of past elections—in this case, all the statewide races from 2016 to 2020. We create a series of points within each precinct, where each point is represents a voter, and each representative voter is classified as either a Democrat or Republican, with these classifications made in proportion to the precinct-level vote shares of the parties. For each point, based on the size of an Ohio congressional district, we also find the representative voter's 786,630 nearest neighbors, and then calculate the partisanship of that voter's bespoke "neighborhood." This is akin to asking, for each representative voter: if a congressional district was built with this voter at the absolute center, what would be the vote share of Democrats and Republicans in that district? For a resident of the urban core of Cleveland, Cincinnati, or Columbus, it would be very Democratic. For a resident of a rural county who is far away from a city, it would be quite Republican. For many suburban residents, this bespoke district would be more heterogeneous, but would lean more Democratic as we move closer to the city, and more Republican in the outer exurbs.

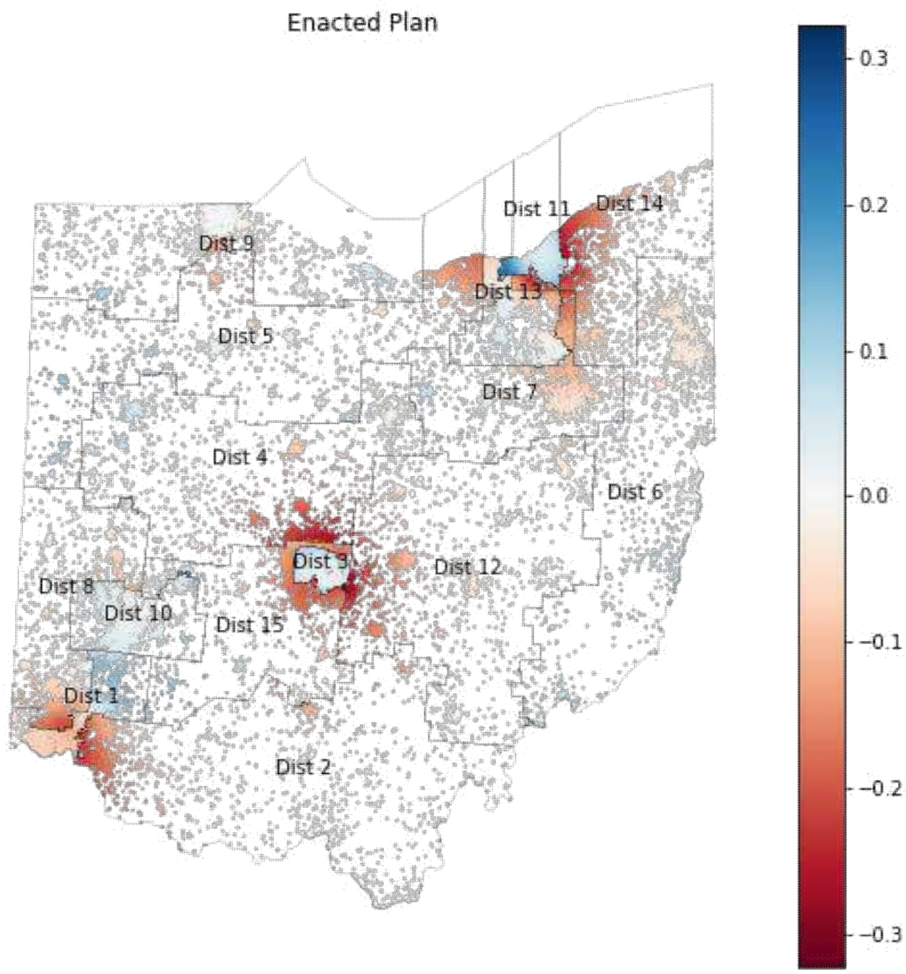
107. An interesting question, then, is whether in an enacted redistricting plan, people end up in districts where the partisanship is roughly similar to that of their geographic neighborhood, or if they end up in districts where the partisanship is quite different. To examine this, for each representative voter, we simply calculate the difference between the partisanship of the district in which they have been placed, and the partisanship of their geographic neighborhood. We refer to this difference as "partisan dislocation." We have discovered that in maps where districts have been drawn to provide an advantage for a political party, we can see telltale patterns of "dislocated" voters clustered near district boundaries. Specifically, when map-drawers are attempting to create an advantage for their in-party, they will produce large numbers of "dislocated" members of the out-party, often near district boundaries—that is to say, large clusters of voters whose nearest neighbors, at the relevant geographic scale for drawing districts, strongly support the opposite party, but have nevertheless been placed in districts where the in-party is a majority.

108. This type of analysis is illuminating in Ohio. In Figure 23, I present a map of the districts in the Enacted Plan, with dots for representative voters, where the dots are colored according to the level of partisan dislocation. A dark red color indicates that the partisanship of the enacted district is much more *Republican* than the representative voter's 786,630 nearest neighbors. A dark blue color indicates that the district is much more *Democratic* than the

[27] Daryl DeFord, Nicholas Eubank, and Jonathan Rodden, 2021, "Partisan Dislocation: A Precinct-Level Measure of Representation and Gerrymandering." ***Political Analysis***. Online early view available here: https://doi.org/10.1017/pan.2021.13. Nicolas Eubank provided assistance with the generation of the Ohio partisan dislocation map presented below.

representative voter's neighborhood. Figure 23 brings to life the extent to which the districts of the Enacted Plan cut up geographic communities of co-partisans.

Figure 23: Partisan Dislocation Associated with the Enacted Congressional Redistricting Plan in Ohio



Note: Dots are representative voters. Darker shades of red indicate the extent to which the voter's district in the Enacted Plan is more Republican than their nearest 786,630 neighbors. Darker shares of blue indicate the extent to which the voter's district is more Democratic than their nearest neighbors.

109. The area around Cincinnati is especially interesting. As discussed above, the Enacted Plan carves out an extremely Democratic section of Northern Hamilton County with a large Black population and places it in the rural-dominated 8th District. And the Democratic-leaning

Eastern suburbs of Cincinnati have been cleaved from the city and placed in the rural-dominated 2nd district. In Figure 23, we can see that levels of partisan dislocation are relatively high for these voters; they have been extracted from their geographic setting and placed in a district where the partisanship is completely different from that of their surrounding neighborhood. Democratic, relatively densely populated neighborhoods have been placed in extremely non-competitive rural districts where they have virtually no chance to elect their preferred candidates.

110. The story in Columbus is similar. As described above, the Democratic suburbs that fall within Franklin County have been pulled from their geographic context and placed in relatively rural District 15, which means that residents of Columbus suburbs are in a district whose partisanship is quite different from that of their neighborhood. The same is true of the suburban communities to the North of Columbus in Delaware County, which have been placed in an even more rural and Republican District 4.

111. Likewise, Figure 23 illuminates the impact of the Enacted districts in Northeast Ohio, where there is a large concentration of Democratic neighborhoods that have been placed in majority-Republican districts. District 14 extracts large numbers of Democrats in suburban areas from Cuyahoga County that are in a largely Democratic geographic context, and places them in the 14th District, where voting behavior is far more Republican. Also, Figure 23 clarifies how the long, narrow appendage of District 7, which extracts Akron's suburbs, removes them from their Democrat-leaning partisan context and places them in a highly Republican district. Likewise, we can see that the partisanship of the enacted 5th district is far more Republican than the partisan neighborhood in the Democratic cities of Lorain County.

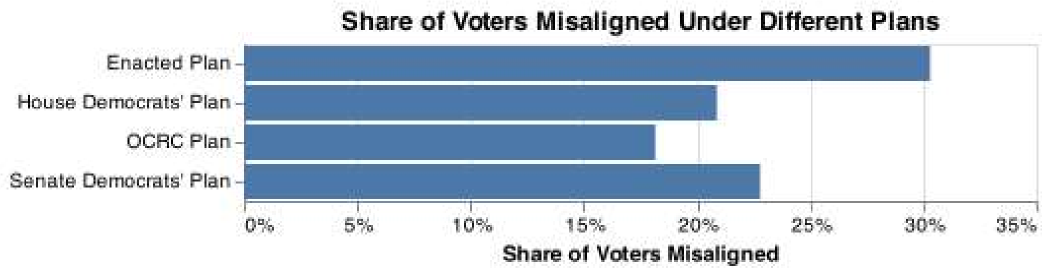
112. Each of these areas shows up as relatively dark red dots in Figure 23. Note, however, that there are very few places on the map where the dots are dark blue; that is, where the partisanship of the Enacted Plan is much more Democratic than the geographic neighborhood. The only exception is part of the Western suburbs of Cleveland within Cuyahoga County, where relatively evenly divided (but still Democratic leaning) neighborhoods are contained in a district that is mostly composed of extremely Democratic parts of Cleveland.

113. There are light blue dots throughout the map. Some of these are in the two very Democratic urban districts, where the partisanship of the district is slightly more Democratic than that of the geographic neighborhood. And Warren County, which was connected via a narrow corridor to Cincinnati, is in a district that is somewhat more Democratic than its neighborhood. The other areas with light-blue dots correspond to places where very Republican rural areas are placed in districts that include college towns, suburbs, or small cities that make the district as a whole more Democratic than the region in question. However, in every case like this, the district remains comfortably Republican.

114. In sum, we can see that the Enacted Plan tended to extract Democratic neighborhoods in and around cities from their partisan geographic context and place them in districts that were far more Republican, while keeping Republican exurban and rural neighborhoods in safely Republican districts.

115. This pattern of partisan dislocation was not forced upon the General Assembly by Ohio's political geography, or by the requirements of the Ohio Constitution. Again, this is made clear through analysis of the alternative plans described above. I have conducted the same dislocation analysis for these alternative maps. Let us consider a simpler, binary rather than continuous notion of dislocation, such that a representative voter is said to be living in a "misaligned" neighborhood if the partisan majority among their 786,630 nearest neighbors is not the same as that in the district to which they were assigned. In the Enacted Plan, over 30 percent of all Ohio residents are living in such misaligned neighborhoods (see Figure 24).

Figure 24:



116. As shown in Figure 24, far fewer voters reside in such misaligned neighborhoods in the alternative plans: around 22.5 percent in the Senate Democrats' Plan, 21 percent in the House Democrats' Plan, and only 18 percent in the OCRC Plan. Of course, not everyone can be in an electoral district where the partisan majority matches their bespoke neighborhood. This is especially true when those drawing the districts must minimize county splits, and thus cannot easily keep groups of co-partisans together, as is the case where a city's Democratic suburbs spill into surrounding counties. It is therefore not surprising that some voters would also live in "misaligned" neighborhoods in the alternative plans. However, the large difference in the percentage of misaligned voters between the Enacted Plan and the alternative plans makes it abundantly clear that the far more efficient Republican support distribution in the Enacted plan relative to the alternative plans was achieved by carving up clusters of geographically proximate Democratic communities and removing them from their neighborhood context. The choices outlined above in the alternative plans—such as splitting Hamilton and Cuyahoga Counties only once, drawing two Columbus-oriented districts rather than one, and keeping Summit County together—achieved greater Democratic representation by keeping such communities of co-partisans in the same district.

VIII. CONCLUSION

117. The 2021 Congressional Plan is highly favorable to the Republican Party and its incumbents, and it disfavors the Democratic Party and its incumbents. This is true not because of the requirements of the Ohio Constitution or the political geography of Ohio, but because of discretionary choices made by those drawing the districts, which had the effect of "packing" Democrats into districts where they win by large majorities and "cracking" Democratic communities that would otherwise have produced majority-Democratic districts. In drawing districts to achieve partisan gain, the legislature sacrificed compactness, introduced

unnecessary splits to urban counties, and divided a number of urban and suburban communities, including minority communities, throughout the state.

Jonathan Rodden

____

Jonathan Rodden

Sworn to before me this __10th__ day of December 2021.

Lester Sauri

____

Notary Public

LESTER SAURI
Notary Public - State of Florida
Commission # HH 6340
Expires on June 3, 2024

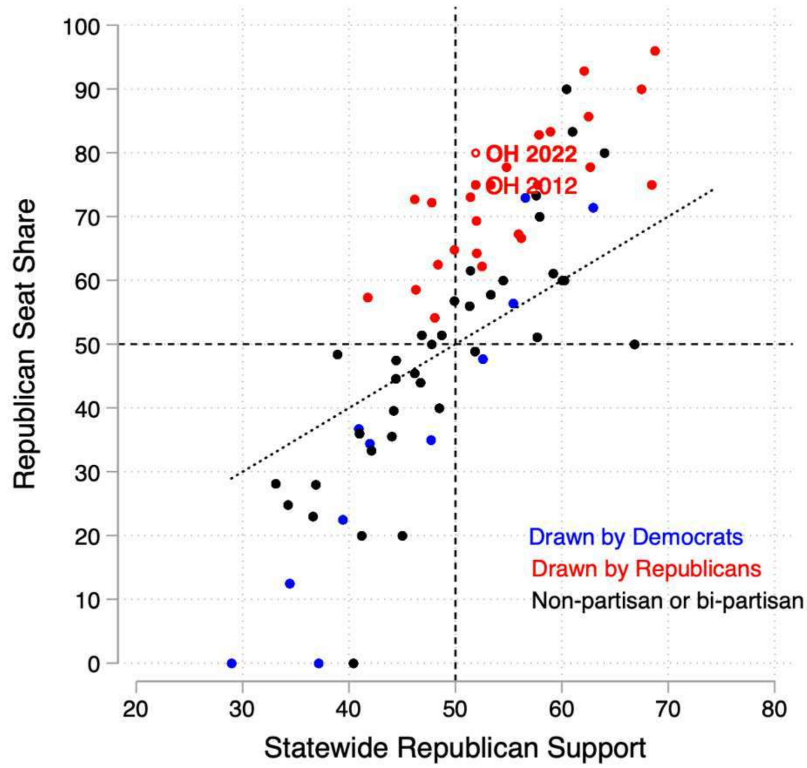
NOTARY PUBLIC • STATE OF FLORIDA •

My commission expires ___________06/03/2024___________

Notarized online using audio-video communication

Appendix A

Figure A1: Vote Shares in Statewide Elections and Seat Shares in Congressional Elections, 2000 and 2020 Redistricting Cycles, All States with 4 or More Seats



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Appendix B: Splits of Municipal Subdivisions

I have attempted to assemble information on all the splits of townships and municipal corporations in the Enacted Plan and the three alternative plans. A complication is that cities and villages sometimes spill slightly over the boundary of a township, such that a district-drawer must choose between splitting the municipal corporation or the township. In such instances, I do not count a township that was clearly split in order to keep a municipal corporation whole, and likewise, I do not count splits of small fragments of cities that were clearly made in order to keep a township whole. I document these decisions in italics below. Furthermore, I attempt to avoid double-counting. If a single split of a municipal corporation also appears to split a township in which it is embedded, I only count a single split. As I discuss in the text, each of the plans introduces multiple splits of the City of Columbus, and I count each of these as a distinct split.

Enacted Plan

Sycamore Township and Kenwood CDP, Hamilton County
(This also splits Rossmoyne CDP, which is also in Sycamore Township, so count once).
Glendale Village, Hamilton County
Union Township, Ross County
City of Columbus, Franklin County (5 splits total, see main text)
Norwich Township is split, but this can potentially be explained by an effort to follow the Hilliard City line. Do not count
Green Township, Shelby County
Perrysburg Township, Wood County
Columbia Township, Lorain County
Belpre Township, Washington County
Berlin Township, Holmes County
Cuyahoga Falls City, Summit County
Stony Ridge CDP, but presumably this was done to keep Lake Township whole, so do not count.
Mad River Township and Green Meadows CDP (only count once), Clark County
Rocky River City, Cuyahoga County
Oakwood Village, Cuyahoga County

Total splits: 17, 8 of which are townships.

Senate Democratic Plan

Columbus City (two splits, see main text)
Prairie Township, Franklin County
Marysville City, Union County
Millcreek Township does not count as a split, as it was split in order to prevent the introduction of an additional split to Marysville City.
Berea City, Cuyahoga County
Madeira City, Hamilton County

Beavercreek City, Greene County
Massillon City, Stark County
Cambridge City, Guernsey County
Campbell City, Mahoning County
Wooster City, Wayne County
Springfield City, Clark County
Pike Township split to keep New Carlisle City together, so do not count
Amherst City, Lorain County
Amherst Township split to keep South Adams Village together, so do not count
Bowling Green City, Wood County
Mount Vernon City, Knox County
Findlay City, Hancock County

Total splits: 16, 1 township and 15 cities.

House Democratic Plan

Mack CDP, Hamilton County
This is a single split that also simultaneously can be viewed as a bisecting the boundary between Green and Miami Townships, Hamilton County; only count once.
Union Township, Clinton County
Liberty Township, Clinton County
Buckskin Township, Ross County
Concord Township, Ross County
According to the Ohio Constitution, the small fragment of Greenfield Village on the Ross County side of the county boundary should not be considered a split.
Dunham Township, Washington
Columbus City (3 splits, see text, see main text), Franklin County
Prairie Township is nominally split, but to keep Lake Darby CDP whole, so do not count
Waldo Township, Marion County
Antrim Township, Wyandot County
Pitt and Salem Townships nominally split in Wyandot County, but to keep the City of Upper Sandusky together, so do not count.
Walnut Creek Township, Holmes County
Dunham Township, Washington County
Fairfield Township, Washington County
Lake Township, Ashland County
Seven Hills City, Cuyahoga County
North Ridgeville City, Lorain County
Beavercreek City, Greene County
Do not double-count Beavercreek Township.
Canton Township, Stark County
Poland Township, Mahoning County

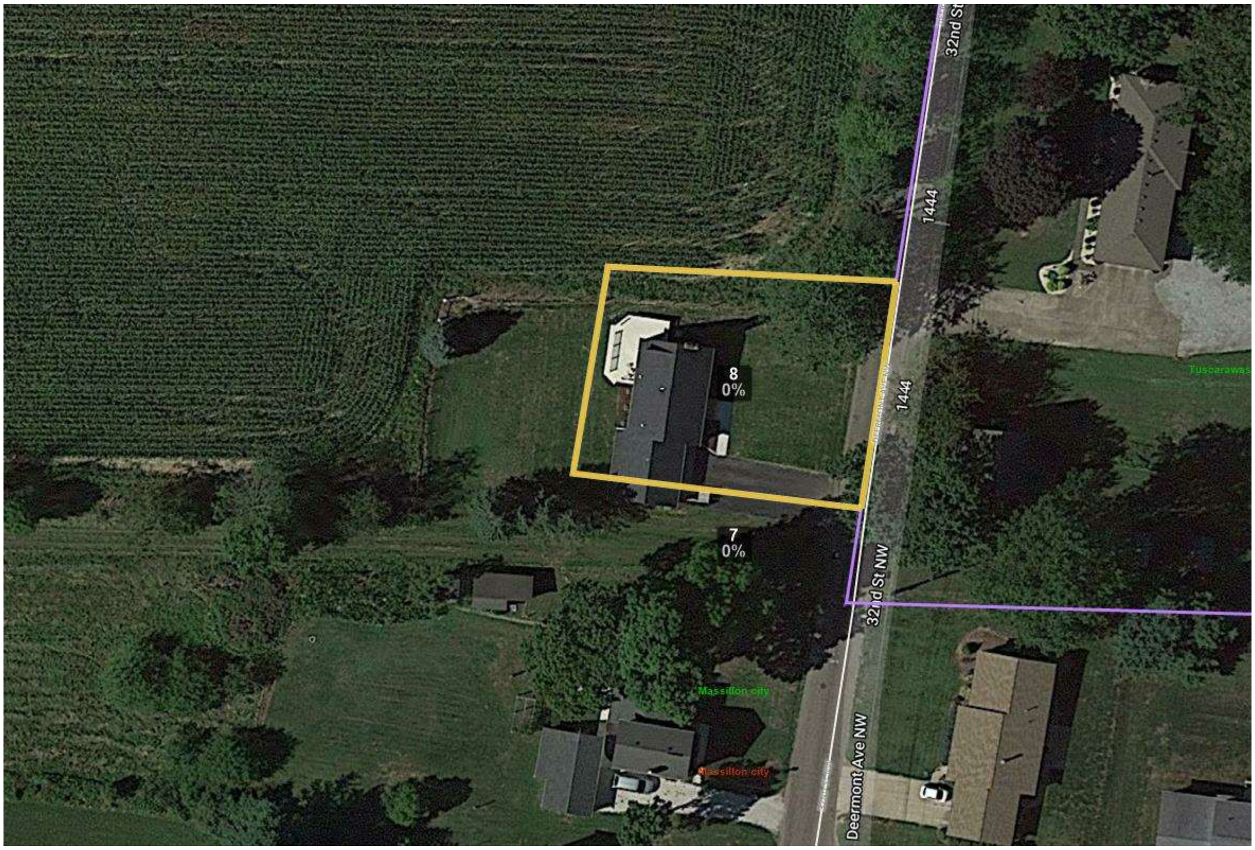
Total splits: 20 total splits, 14 are townships

Ohio Citizens Redistricting Commission

Colerain Township, Hamilton County
Racoon Township, Gallia County
Prairie Township, Franklin County
Columbus City, Franklin County (2 splits)
Blendon Township, Franklin County
Jefferson Township, Franklin County
Hartland Township, Huron
Fitchville Township, Huron
Greenwich Township, Huron
Dover Township, Union County
Paris Township, Union County
Jerome Township, Union County
Granville Township, Mercer County
Recovery Township, Mercer County
Big Spring Township, Seneca County
Richland Township, Guernsey County
Killbuck Township, Holmes County
Tuscarawas Township, Stark County
Lake Township, Stark County
Boardman Township, Mahoning County
Poland Township, Mahoning County
Coitsville Township, Mahoning County
Moorefield Township, Clark County
German Township, Clark County
Bethel Township, Clark County
Mad River Township, Clark County

Total splits: 27, all townships except Columbus

Appendix C: Image of Mistake in Senate Democrats' Redistricting Plan



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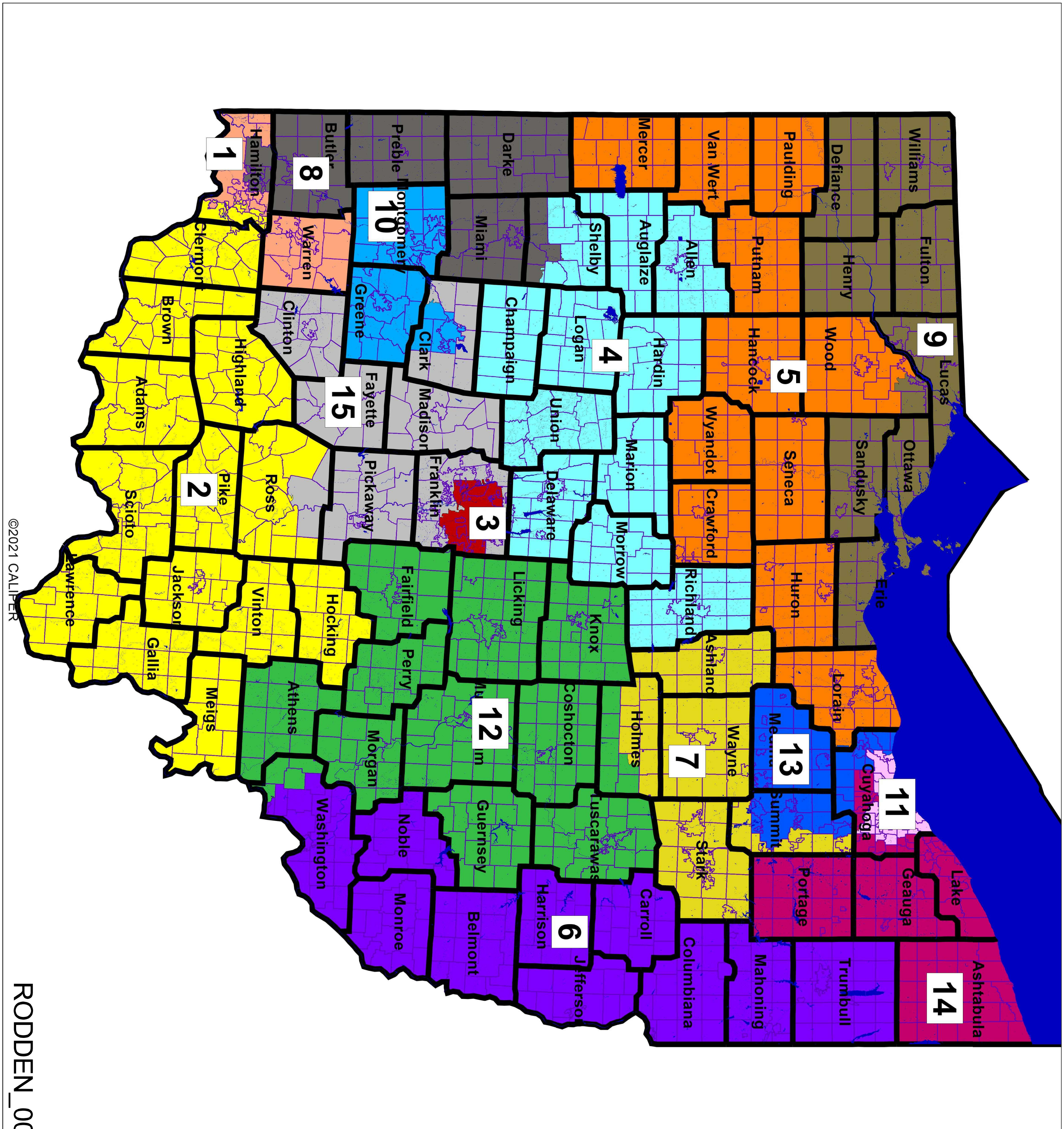
AFFIDAVIT OF DR. JONATHAN RODDEN – APPENDIX OF EXHIBITS

Index of Documents

ITEM	DESCRIPTION	BATES RANGE
A	2021 Congressional Plan	RODDEN_0001-02
B	Proposed Senate Democratic Caucus Plan	RODDEN_0003-04
C	Proposed House Democratic Caucus Plan	RODDEN_0005-06
D	Proposed Ohio Citizens Redistricting Committee Plan	RODDEN_0007-08
E	2011 Congressional Plan	RODDEN_0009-10
F	Curriculum Vitae of Dr. Jonathan Rodden	RODDEN_0011-19

Exhibit A



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Huron
Lorain
Mercer
Allen
Auglaize
Hardin
Shelby
Logan
Union
Marion
Morrow
Delaware
Richland
Ashland
Darke
Miami
Champaign
Preble
Montgomery
Clark
Madison
Franklin
Licking
Knox
Butler
Warren
Greene
Clinton
Fayette
Pickaway
Fairfield
Perry
Hamilton
Clermont
Brown
Highland
Adams
Ross
Pike
Scioto
Lawrence
Jackson
Vinton
Hocking
Gallia
Meigs
Athens
Morgan
Muskingum
Coshocton
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Summit
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Exhibit B

Proposed Sub SB 237 Map

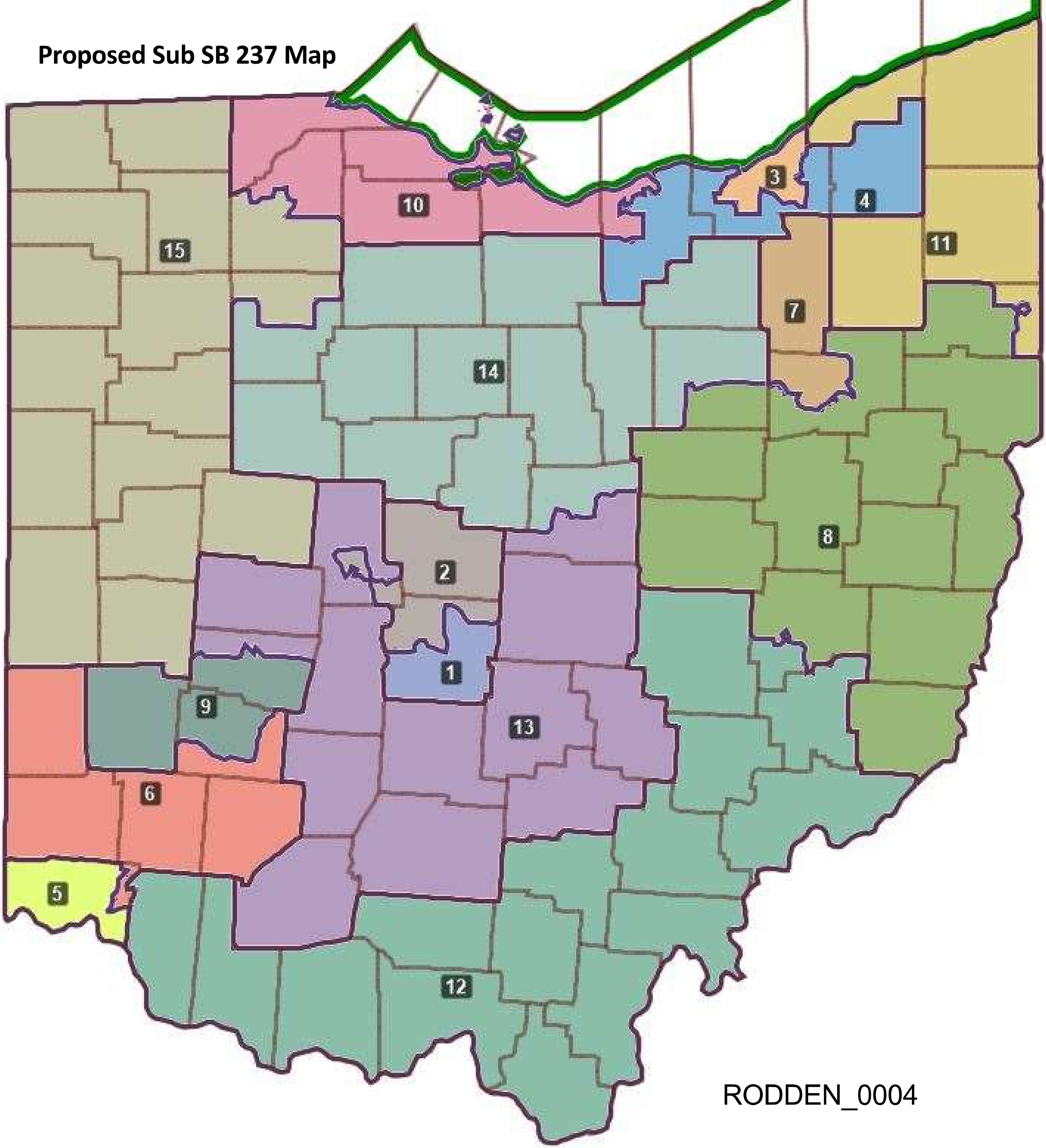

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Exhibit C

Brown/Galonski Congressional District Proposal

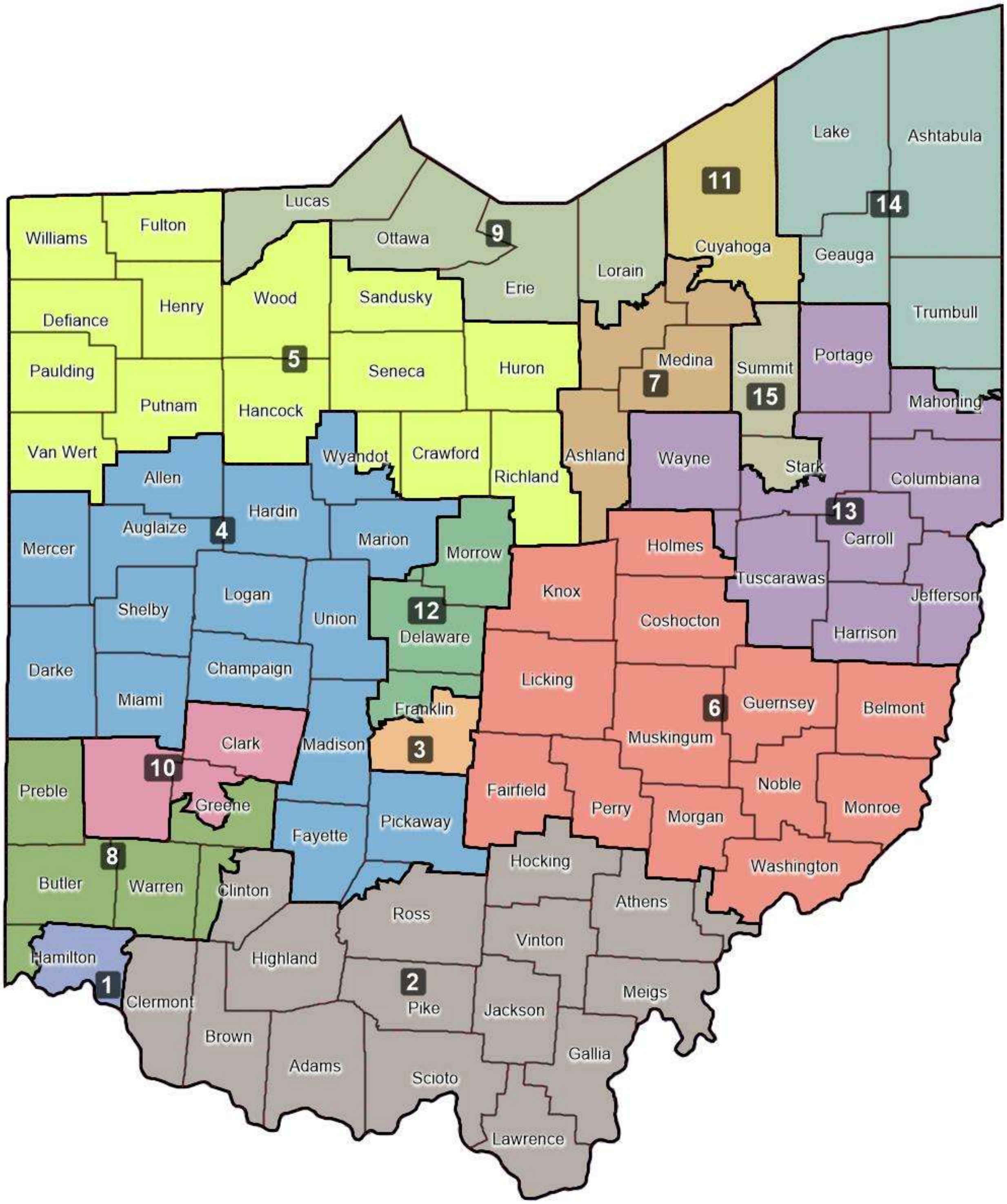
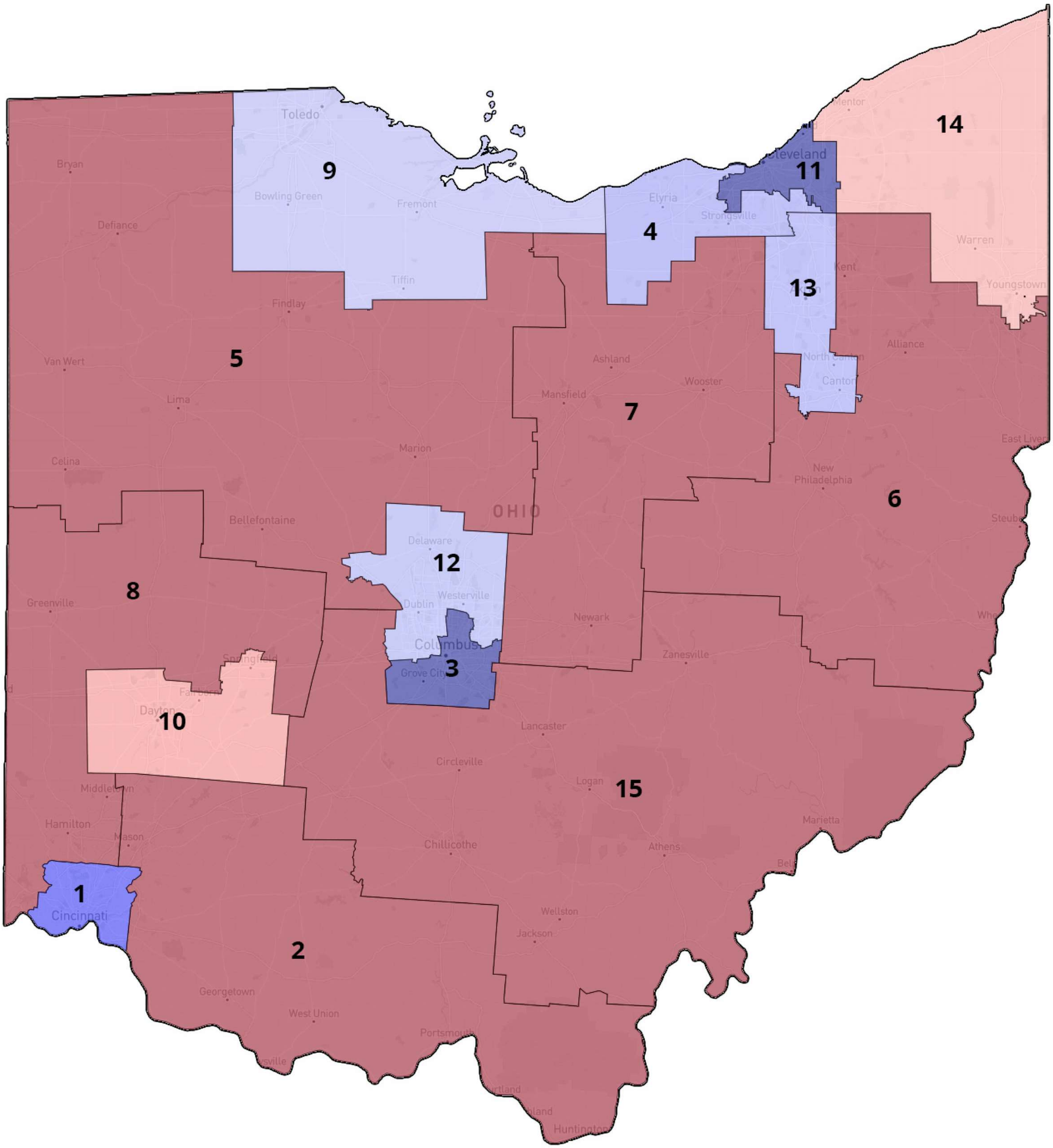


Exhibit D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Tiffin
Findlay
Van Wert
Lima
Celina
Marion
Bellefontaine
Delaware
Westerville
Dublin
Columbus
Grove City
Greenville
Springfield
Dayton
Middletown
Hamilton
Mason
Cincinnati
Georgetown
West Union
Elyria
Cleveland
Strongsville
Mentor
Warren
Youngstown
Kent
Alliance
North Canton
Canton
Ashland
Wooster
Mansfield
New Philadelphia
Newark
Zanesville
Lancaster
Circleville
Logan
Chillicothe
Athens
Marietta
Wellston
Jackson

Exhibit E

Frank LaRose

Ohio Secretary of State

U.S. Congressional Districts 2012-2022 in Ohio

(As Adopted 2012)

For the most up-to-date and detailed information on each district, please contact the local county board of elections.

Last Revised 02/2018

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Exhibit F

Jonathan Rodden

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Personal

Born on August 18. 1971, St. Louis, MO.

United States Citizen.

Education

Ph.D. Political Science, Yale University, 2000.

Fulbright Scholar, University of Leipzig, Germany, 1993–1994.

B.A., Political Science, University of Michigan, 1993.

Academic Positions

Professor, Department of Political Science, Stanford University, 2012–present.

Senior Fellow, Stanford Institute for Economic Policy Research, 2020–present.

Senior Fellow, Hoover Institution, Stanford University, 2012–present.

Director, Spatial Social Science Lab, Stanford University, 2012–present.

W. Glenn Campbell and Rita Ricardo-Campbell National Fellow, Hoover Institution, Stanford University, 2010–2012.

Associate Professor, Department of Political Science, Stanford University, 2007–2012.

Fellow, Center for Advanced Study in the Behavioral Sciences, Palo Alto, CA, 2006–2007.

Ford Career Development Associate Professor of Political Science, MIT, 2003–2006.

Visiting Scholar, Center for Basic Research in the Social Sciences, Harvard University, 2004.

Assistant Professor of Political Science, MIT, 1999–2003.

Instructor, Department of Political Science and School of Management, Yale University, 1997–1999.

Publications

Books

Why Cities Lose: The Deep Roots of the Urban-Rural Divide. Basic Books, 2019.

Decentralized Governance and Accountability: Academic Research and the Future of Donor Programming. Co-edited with Erik Wibbels, Cambridge University Press, 2019.

Hamilton's Paradox: The Promise and Peril of Fiscal Federalism, Cambridge University Press, 2006. Winner, Gregory Luebbert Award for Best Book in Comparative Politics, 2007; Martha Derthick Award for lasting contribution to the study of federalism, 2021.

Fiscal Decentralization and the Challenge of Hard Budget Constraints, MIT Press, 2003. Co-edited with Gunnar Eskeland and Jennie Litvack.

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Purple America, 2006, *Journal of Economic Perspectives* 20,2 (Spring): 97–118 (with Stephen Ansolabehere and James Snyder).

Economic Geography and Economic Voting: Evidence from the U.S. States, 2006, *British Journal of Political Science* 36, 3: 527–47 (with Michael Ebeid).

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Comparative Federalism and Decentralization: On Meaning and Measurement, 2004, *Comparative Politics* 36, 4: 481-500. (Portuguese version, 2005, in *Revista de Sociologia e Politica* 25).

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Working Papers

Elections, Political Polarization, and Economic Uncertainty, NBER Working Paper 27961 (with Scott Baker, Aniket Baksy, Nicholas Bloom, and Steven Davis).

Federalism and Inter-regional Redistribution, Working Paper 2009/3, Institut d'Economia de Barcelona.

Representation and Regional Redistribution in Federations, Working Paper 2010/16, Institut d'Economia de Barcelona (with Tiberiu Dragu).

Chapters in Books

Political Geography and Representation: A Case Study of Districting in Pennsylvania (with Thomas Weighill), in *Political Geometry*, edited by Moon Duchin and Olivia Walch, forthcoming 2021, Springer.

Keeping Your Enemies Close: Electoral Rules and Partisan Polarization, in *The New Politics of Insecurity*, edited by Frances Rosenbluth and Margaret Weir, forthcoming 2021, Cambridge University Press.

Decentralized Rule and Revenue, 2019, in Jonathan Rodden and Erik Wibbels, eds., *Decentralized Governance and Accountability*, Cambridge University Press.

Geography and Gridlock in the United States, 2014, in Nathaniel Persily, ed. *Solutions to Political Polarization in America*, Cambridge University Press.

Can Market Discipline Survive in the U.S. Federation?, 2013, in Daniel Nadler and Paul Peterson, eds, *The Global Debt Crisis: Haunting U.S. and European Federalism*, Brookings Press.

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Federalism and Inter-Regional Redistribution, 2010, in Nuria Bosch, Marta Espasa, and Albert Sole Olle, eds., *The Political Economy of Inter-Regional Fiscal Flows*, Edward Elgar.

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The Political Economy of Federalism, 2006, in Barry Weingast and Donald Wittman, eds., *Oxford Handbook of Political Economy*, Oxford University Press.

Fiscal Discipline in Federations: Germany and the EMU, 2006, in Peter Wierts, Servaas Deroose, Elena Flores and Alessandro Turrini, eds., *Fiscal Policy Surveillance in Europe*, Palgrave MacMillan.

The Political Economy of Pro-cyclical Decentralised Finance (with Erik Wibbels), 2006, in Peter Wierts, Servaas Deroose, Elena Flores and Alessandro Turrini, eds., *Fiscal Policy Surveillance in Europe*, Palgrave MacMillan.

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Soft Budget Constraints and German Federalism (Chapter 5), 2003, in Rodden, et al, *Fiscal Decentralization and the Challenge of Hard Budget Constraints* (see above).

Federalism and Bailouts in Brazil (Chapter 7), 2003, in Rodden, et al., *Fiscal Decentralization and the Challenge of Hard Budget Constraints* (see above).

Lessons and Conclusions (Chapter 13), 2003, in Rodden, et al., *Fiscal Decentralization and the Challenge of Hard Budget Constraints* (see above).

Online Interactive Visualization

Stanford Election Atlas, 2012 (collaboration with Stephen Ansolabehere at Harvard and Jim Herries at ESRI)

Other Publications

Supporting Advanced Manufacturing in Alabama, Report to the Alabama Innovation Commission, Hoover Institution, 2021.

How America's Urban-Rural Divide has Shaped the Pandemic, 2020, *Foreign Affairs*, April 20, 2020.

An Evolutionary Path for the European Monetary Fund? A Comparative Perspective, 2017, Briefing paper for the Economic and Financial Affairs Committee of the European Parliament.

Representation and Regional Redistribution in Federations: A Research Report, 2009, in *World Report on Fiscal Federalism*, Institut d'Economia de Barcelona.

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Decentralization and the Challenge of Hard Budget Constraints, *PREM Note* 41, Poverty Reduction and Economic Management Unit, World Bank, Washington, D.C. (July).

Decentralization and Hard Budget Constraints, *APSA-CP* (Newsletter of the Organized Section in Comparative Politics, American Political Science Association) 11:1 (with Jennie Litvack).

Book Review of *The Government of Money* by Peter Johnson, *Comparative Political Studies 32,7: 897-900.*

Fellowships, Honors, and Grants

John Simon Guggenheim Memorial Foundation Fellowship, 2021.

Martha Derthick Award of the American Political Science Association for "the best book published at least ten years ago that has made a lasting contribution to the study of federalism and intergovernmental relations," 2021.

National Institutes of Health, funding for "Relationship between lawful handgun ownership and risk of homicide victimization in the home," 2021.

National Collaborative on Gun Violence Research, funding for "Cohort Study Of Firearm-Related Mortality Among Cohabitants Of Handgun Owners." 2020.

Fund for a Safer Future, Longitudinal Study of Handgun Ownership and Transfer (LongSHOT), GA004696, 2017-2018.

Stanford Institute for Innovation in Developing Economies, Innovation and Entrepreneurship research grant, 2015.

Michael Wallerstein Award for best paper in political economy, American Political Science Association, 2016.

Common Cause Gerrymandering Standard Writing Competition, 2015.

General support grant from the Hewlett Foundation for Spatial Social Science Lab, 2014.

Fellow, Institute for Research in the Social Sciences, Stanford University, 2012.

Sloan Foundation, grant for assembly of geo-referenced precinct-level electoral data set (with Stephen Ansolabehere and James Snyder), 2009-2011.

Hoagland Award Fund for Innovations in Undergraduate Teaching, Stanford University, 2009.

W. Glenn Campbell and Rita Ricardo-Campbell National Fellow, Hoover Institution, Stanford University, beginning Fall 2010.

Research Grant on Fiscal Federalism, Institut d'Economia de Barcelona, 2009.

Fellow, Institute for Research in the Social Sciences, Stanford University, 2008.

United Postal Service Foundation grant for study of the spatial distribution of income in cities, 2008.

Gregory Luebbert Award for Best Book in Comparative Politics, 2007.

Fellow, Center for Advanced Study in the Behavioral Sciences, 2006-2007.

National Science Foundation grant for assembly of cross-national provincial-level dataset on elections, public finance, and government composition, 2003-2004 (with Erik Wibbels).

MIT Dean's Fund and School of Humanities, Arts, and Social Sciences Research Funds.

Funding from DAAD (German Academic Exchange Service), MIT, and Harvard EU Center to organize the conference, "European Fiscal Federalism in Comparative Perspective," held at Harvard University, November 4, 2000.

Canadian Studies Fellowship (Canadian Federal Government), 1996-1997.

Prize Teaching Fellowship, Yale University, 1998-1999.

Fulbright Grant, University of Leipzig, Germany, 1993-1994.

Michigan Association of Governing Boards Award, one of two top graduating students at the University of Michigan, 1993.

W. J. Bryan Prize, top graduating senior in political science department at the University of Michigan, 1993.

Other Professional Activities

Selection committee, best paper award, American Journal of Political Science.

International Advisory Committee, Center for Metropolitan Studies, Sao Paulo, Brazil, 2006–2010.

Selection committee, Mancur Olson Prize awarded by the American Political Science Association Political Economy Section for the best dissertation in the field of political economy.

Selection committee, Gregory Luebbert Best Book Award.

Selection committee, William Anderson Prize, awarded by the American Political Science Association for the best dissertation in the field of federalism and intergovernmental relations.

Courses

Undergraduate

Politics, Economics, and Democracy

Introduction to Comparative Politics

Introduction to Political Science

Political Science Scope and Methods

Institutional Economics

Spatial Approaches to Social Science

Graduate

Political Economy

Political Economy of Institutions

Federalism and Fiscal Decentralization

Politics and Geography

Consulting

2017. Economic and Financial Affairs Committee of the European Parliament.

2016. Briefing paper for the World Bank on fiscal federalism in Brazil.

2013-2018: Principal Investigator, SMS for Better Governance (a collaborative project involving USAID, Social Impact, and UNICEF in Arua, Uganda).

2019: Written expert testimony in *McLemore, Holmes, Robinson, and Woullard v. Hosemann*, United States District Court, Mississippi.

2019: Expert witness in *Nancy Corola Jacobson v. Detzner*, United States District Court, Florida.

2018: Written expert testimony in *League of Women Voters of Florida v. Detzner* No. 4:18-cv-002510, United States District Court, Florida.

2018: Written expert testimony in *College Democrats of the University of Michigan, et al. v. Johnson, et al.*, United States District Court for the Eastern District of Michigan.

2017: Expert witness in *Bethune-Hill v. Virginia Board of Elections*, No. 3:14-CV-00852, United States District Court for the Eastern District of Virginia.

2017: Expert witness in *Arizona Democratic Party, et al. v. Reagan, et al.*, No. 2:16-CV-01065, United States District Court for Arizona.

2016: Expert witness in *Lee v. Virginia Board of Elections*, 3:15-cv-357, United States District Court for the Eastern District of Virginia, Richmond Division.

2016: Expert witness in *Missouri NAACP v. Ferguson-Florissant School District*, United States District Court for the Eastern District of Missouri, Eastern Division.

2014-2015: Written expert testimony in *League of Women Voters of Florida et al. v. Detzner, et al.*, 2012-CA-002842 in Florida Circuit Court, Leon County (Florida Senate redistricting case).

2013-2014: Expert witness in *Romo v Detzner*, 2012-CA-000412 in Florida Curcuit Court, Leon County (Florida Congressional redistricting case).

2011-2014: Consultation with investment groups and hedge funds on European debt crisis.

2011-2014: Lead Outcome Expert, Democracy and Governance, USAID and Social Impact.

2010: USAID, Review of USAID analysis of decentralization in Africa.

2006–2009: World Bank, Independent Evaluations Group. Undertook evaluations of World Bank decentralization and safety net programs.

2008–2011: International Monetary Fund Institute. Designed and taught course on fiscal federalism.

1998–2003: World Bank, Poverty Reduction and Economic Management Unit. Consultant for *World Development Report*, lecturer for training courses, participant in working group for assembly of decentralization data, director of multi-country study of fiscal discipline in decentralized countries, collaborator on review of subnational adjustment lending.

Last updated: September 23, 2021

Neiman Petitioners' Exhibit 25

IN THE SUPREME COURT OF OHIO

Regina C. Adams, *et al.*, **Relators,** **v.** **Governor Mike DeWine, *et al.*,** **Respondents.**	**Case No. 2021-1428** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

EXPERT AFFIDAVIT OF DR. JOWEI CHEN

I, Jowei Chen, having been duly sworn and cautioned according to law, hereby state that I am over the age of eighteen years and am competent to testify to the facts set forth below based on my personal knowledge and having personally examined all records referenced in this affidavit, and further state as follows:

I. INTRODUCTION AND SUMMARY OF FINDINGS

1. Relators' counsel asked me to analyze Ohio's 2021 Congressional Plan (the "Enacted Plan"), as created by the General Assembly's Substitute Senate Bill 258. Specifically, I was asked to analyze:

   a. Does the 2021 Enacted Plan favor either the Democratic or Republican party in a manner that cannot be explained by the redistricting criteria required by the Ohio Constitution?

   b. Can the 2021 Enacted Plan's treatment of Ohio's most populous counties be explained by the redistricting criteria required by the Ohio Constitution?

   c. Is the 2021 Enacted Plan a product of an attempt to draw districts that are compact?

   d. How do the 2021 Enacted Plan's competitive districts affect the partisan characteristics of the map, if at all?

   e. Can the partisan characteristics of the 2021 Enacted Plan be explained by Ohio's political geography?

2. Article XIX, Section (1)(C)(3) of the Ohio Constitution mandates three requirements for a congressional plan passed by a simple majority of each house of the General Assembly. First, the plan may not "unduly favor[] or disfavor[] a political party." Second, the plan

may not unduly split counties, townships, and municipal corporations. Third, the General Assembly "shall attempt to draw districts that are compact."

3. In summary, I found that the Enacted Plan (a) does clearly and decidedly favor the Republican Party; (b) contains certain splits of political subdivisions that are unnecessary to achieve compliance with any districting requirements; and (c) contains districts that are less compact than those in other plans drawn in compliance with the Ohio Constitution. When compared to 1,000 computer-simulated districting plans drawn according to the nonpartisan criteria specified by the Ohio Constitution,[1] the Enacted Plan is an extreme partisan outlier, both at a statewide level and with respect to the partisan characteristics of its individual districts. The Enacted Plan exhibits partisan characteristics that are more favorable to the Republican Party than the partisan characteristics of nearly all of the computer-simulated plans. These partisan characteristics of the Enacted Plan were enabled by the drawing of districts that are far less geographically compact than was reasonably possible across the state, particularly in Hamilton, Franklin, and Cuyahoga Counties. Most notably, the Enacted Plan creates an extreme partisan outcome in its Cincinnati-based district (CD-1) by splitting Hamilton County excessively and sacrificing geographic compactness in this district. Similarly, the Enacted Plan creates an extreme partisan outcome in Cuyahoga County by unnaturally packing Democratic voters, and in Franklin County by sacrificing geographic compactness to create anomalously partisan districts.

II. QUALIFICATIONS

4. I am an Associate Professor in the Department of Political Science at the University of Michigan, Ann Arbor. I am also a Research Associate Professor at the Center for Political Studies of the Institute for Social Research at the University of Michigan. In 2004, I received a B.A. in Ethics, Politics, and Economics from Yale University. In 2007, I received a M.S. in Statistics from Stanford University, and in 2009, I received a Ph.D. in Political Science from Stanford University. A copy of my current C.V. is included in the Appendix.

5. I have published academic papers on legislative districting and political geography in several political science journals, including *The American Journal of Political Science*, *The American Political Science Review*, and *Election Law Journal*. My academic areas of expertise include legislative elections, spatial statistics, geographic information systems (GIS) data, redistricting, racial politics, legislatures, and political geography. I have expertise in the use of computer simulations of legislative districting and in analyzing political geography, elections, and redistricting.

6. I have authored expert reports in the following redistricting court cases: *The League of Women Voters of Florida v. Detzner* (Fla. 2d Judicial Cir. Leon Cnty. 2012); *Romo v. Detzner* (Fla. 2d Judicial Cir. Leon Cnty. 2013); *Missouri National Association for the Advancement of Colored People v. Ferguson-Florissant School District & St. Louis County*

[1] Block assignments files for each of the 1,000 plans have been submitted to the Court under separate cover. *See* Affidavit of Derek S. Clinger (December 10, 2021).

Board of Election Commissioners (E.D. Mo. 2014); *Raleigh Wake Citizens Association v. Wake County Board of Elections* (E.D.N.C. 2015); Brown v. Detzner (N.D. Fla. 2015); *City of Greensboro v. Guilford County Board of Elections* (M.D.N.C. 2015); *Common Cause v. Rucho* (M.D.N.C 2016); *The League of Women Voters of Pennsylvania v. Commonwealth of Pennsylvania* (No. 261 M.D. 2017); *Georgia State Conference of the NAACP v. The State of Georgia* (N.D. Ga. 2017); *The League of Women Voters of Michigan v. Johnson* (E.D. Mich. 2017); *Whitford v. Gill* (W.D. Wis. 2018); *Common Cause v. Lewis* (N.C. Super. 2018); *Harper v. Lewis* (N.C. Super. 2019); *Baroody v. City of Quincy, Florida* (N.D. Fla. 2020); *McConchie v. Illinois State Board of Elections* (N.D. Ill. 2021). I have testified either at deposition or at trial in the following cases: *Romo v. Detzner* (Fla. 2d Judicial Cir. Leon Cnty. 2013*); Missouri National Association for the Advancement of Colored People v. Ferguson-Florissant School District & St. Louis County Board of Election Commissioners* (E.D. Mo. 2014); *Raleigh Wake Citizens Association v. Wake County Board of Elections* (E.D.N.C. 2015); *City of Greensboro v. Guilford County Board of Elections* (M.D.N.C. 2015); *Common Cause v. Rucho* (M.D.N.C. 2016); *The League of Women Voters of Pennsylvania v. Commonwealth of Pennsylvania* (No. 261 M.D. 2017); *Georgia State Conference of the NAACP* v. *The State of Georgia* (N.D. Ga. 2017); *The League of Women Voters of Michigan v. Johnson* (E.D. Mich. 2017); *Whitford v. Gill* (W.D. Wis. 2018); *Common Cause v. Lewis* (N.C. Super. 2018); *Baroody v. City of Quincy, Florida* (N.D. Fla. 2020); *McConchie v. Illinois State Board of Elections* (N.D. Ill. 2021).

7. I have been retained by Relators in the above-captioned matter. I am being compensated $550 per hour for my work in this case.

III. DATA SOURCES

8. I relied upon the following data files. First, I downloaded the 2020 decennial Census PL 94-171 redistricting data files[2] reporting population at the Census block level in Ohio, as released in the Census Bureau's "legacy format data" on August 12, 2021. Second, I downloaded Census Bureau shapefiles[3] depicting the 2020 boundaries of Ohio's Census geographies, including Ohio's Census blocks, cities, villages, townships, and counties. Third, I downloaded shapefiles reporting the precinct-level election results of Ohio's 2016, 2018, and 2020 statewide election contests from Redistricting Data Hub.[4] Finally, Relators' counsel provided me with a block assignment file depicting the geographic boundaries of the 2021 Enacted Plan.

IV. THE USE OF COMPUTER-SIMULATED DISTRICTING PLANS

9. In conducting my academic research on legislative districting, partisan and racial gerrymandering, and electoral bias, I have developed various computer simulation programming techniques that allow me to produce a large number of non-partisan districting plans that adhere to traditional districting criteria using U.S. Census geographies

[2] Available at: https://www2.census.gov/programs-surveys/decennial/2020/data/01-Redistricting_File--PL_94-171/Ohio/
[3] Available at: https://www2.census.gov/geo/tiger/TIGER2020PL/STATE/39_OHIO/39/
[4] Available at: https://redistrictingdatahub.org/state/ohio/

as building blocks. This simulation process ignores all partisan and racial considerations when drawing districts. Instead, the computer simulations are programmed to draw districting plans following various traditional districting goals, such as equalizing population, avoiding county, municipal, and township splits, and attempting to draw geographically compact districts.

10. By randomly generating a large number of districting plans that adhere to these nonpartisan districting criteria, I am able to assess an enacted plan drawn by a state legislature and determine whether the partisan characteristics of the enacted plan are within the normal range of districting plans produced by a districting process following these criteria. If the enacted plan is a statistical outlier compared to the partisan characteristics of the computer-simulated plans, then I can conclude that the enacted plan's partisanship is not the product of following the non-partisan districting criteria. By holding constant the application of the nonpartisan districting criteria through the simulations, I am able to determine whether the enacted plan could have been the product of something other than partisan considerations. With respect to Ohio's 2021 Congressional Enacted Plan, I determined that it could not.

11. I produced a set of 1,000 valid computer-simulated plans for Ohio's congressional districts using a computer algorithm programmed to follow the required districting criteria enumerated in Article XIX of the Ohio Constitution. In following these constitutional criteria, the computer algorithm uses the same general approach that I employed in creating the simulated congressional and legislative districting plans that I analyzed as an expert witness in several prior partisan gerrymandering redistricting cases, including *Common Cause v. Lewis* (2019), *Harper v. Lewis* (2019), *Whitford v. Gill* (2018), *The League of Women Voters of Pennsylvania v. Commonwealth of Pennsylvania* (2017), *The League of Women Voters of Michigan v. Johnson* (2017), *Common Cause v. Rucho* (2016), *City of Greensboro v. Guilford County Board of Elections* (2016), and *Raleigh Wake Citizens Association v. Wake County Board of Elections* (2015).

12. By randomly drawing districting plans with a process designed to strictly follow non-partisan districting criteria, the computer simulation process gives us an indication of the range of districting plans that plausibly and likely emerge when map-drawers are not motivated primarily by partisan goals. By comparing the Enacted Plan against the distribution of simulated plans with respect to partisan measurements, I am also able to determine the extent to which the map-drawer deviated from non-partisan districting criteria, such as geographic compactness, thereby enabling the map-drawer to produce an enacted plan with extreme partisan characteristics.

13. These computer simulation methods are widely used by academic scholars to analyze districting maps. For over two decades, political scientists have used such computer-simulated districting techniques to analyze the racial and partisan intent of legislative map-

drawers.[5] In recent years, several courts have also relied upon computer simulations to assess partisan bias in enacted districting plans.[6]

V. DISTRICTING CRITERIA REQUIRED BY THE OHIO CONSTITUTION

14. I programmed the computer algorithm to create 1,000 independent simulated plans adhering to the following districting criteria, which are required by Article XIX of the Ohio Constitution:

    a) Population Equality: Because Ohio's 2020 Census population was 11,799,448, districts in every 15-member congressional plan have an ideal population of 786,629.9. Accordingly, the computer simulation algorithm populated each districting plan such that precisely two districts have a population of 786,629, while the remaining thirteen districts have a population of 786,630 (Article XIX, Section 2(B)(3)).

    b) Contiguity: The simulation algorithm required districts to be composed of geographically contiguous territory (Article XIX, Section 2(B)(3)).

    c) Minimizing County Splits: The simulation algorithm avoided splitting any of Ohio's 88 counties, except when doing so was necessary to avoid violating one of the aforementioned criteria. When a county is divided into two districts, the county is considered to have one split. A county divided into three districts is considered to have two splits. For the purpose of creating equally populated districts, each newly drawn congressional district requires only one county split. But the fifteenth and final district drawn in Ohio need not create an additional county split, since this final district should simply be the remaining area unassigned to the first fourteen districts. Therefore, an entire plan of 15 congressional districts requires only 14 county splits. Accordingly, the algorithm required that every simulated plan contain only 14 county splits, which is exactly the same number of county splits the 2021 Enacted Plan contains. Article XIX, Section 2(B)(5) of the Ohio Constitution allows a county to be split up to twice, so I allow some of these 14 county splits to occur within the same county. As a result, the total number of counties containing one or more splits may be fewer than 14.

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[5] *See, e.g.*, Carmen Cirincione, Thomas A. Darling, Timothy G. O'Rourke. "Assessing South Carolina's 1990s Congressional Districting," Political Geography 19 (2000) 189–211; Jowei Chen, "The Impact of Political Geography on Wisconsin Redistricting: An Analysis of Wisconsin's Act 43 Assembly Districting Plan." Election Law Journal _____.

[6] *See, e.g.*, *League of Women Voters of Pa. v. Commonwealth*, 178 A. 3d 737, 818-21 (Pa. 2018); *Raleigh Wake Citizens Association v. Wake County Board of Elections*, 827 F.3d 333, 344-45 (4th Cir. 2016); *City of Greensboro v. Guilford County Board of Elections*, No. 1:15-CV-599, 2017 WL 1229736 (M.D.N.C. Apr 3, 2017); *Common Cause v. Rucho*, No. 1:16-CV-1164 (M.D.N.C. Jan 11, 2018*); The League of Women Voters of Michigan v. Johnson* (E.D. Mich. 2017); *Common Cause v. David Lewis* (N.C. Super. 2018).

d) Township and Municipal Corporation Boundaries: The simulation algorithm avoided splitting any of Ohio's townships, cities, and villages, except when doing so was necessary to avoid violating one of the aforementioned criteria. In doing so, the algorithm followed several principles described in the Ohio Constitution. First, Cleveland and Cincinnati are never split into multiple districts (Article XIX, Section 2(B)(4)(b)). Second, a non-contiguous fragment of a township or municipal corporation that is assigned to a different district than the main portion of that township or municipal corporation does not count as a township or municipal split (Article XIX, Section 2(C)(1)). Third, a township or municipal corporation that crosses a county border can be split at that county border without counting as a split township or municipal corporation (Article XIX, Section 2(C)(2)). Finally, following the Census Bureau's depiction of Ohio's township boundaries, any area that has been annexed into a municipal corporation is considered part of that municipal corporation, rather than part of the township.[7]

e) Geographic Compactness: Following the Ohio Constitution's requirements for a congressional map passed by a simple majority of each house of the General Assembly, the simulation algorithm favors geographic compactness in the drawing of districts whenever doing so does not violate any of the aforementioned criteria (Article XIX, Section 1(C)(3)(c)).

f) Prohibiting Double Traversals: At the conclusion of the districting simulation algorithm, the computer is instructed to reject any plan containing a double traversal. In other words, a district containing non-contiguous area within any single county is prohibited, as specified in Article XIX, Section 2(B)(6).

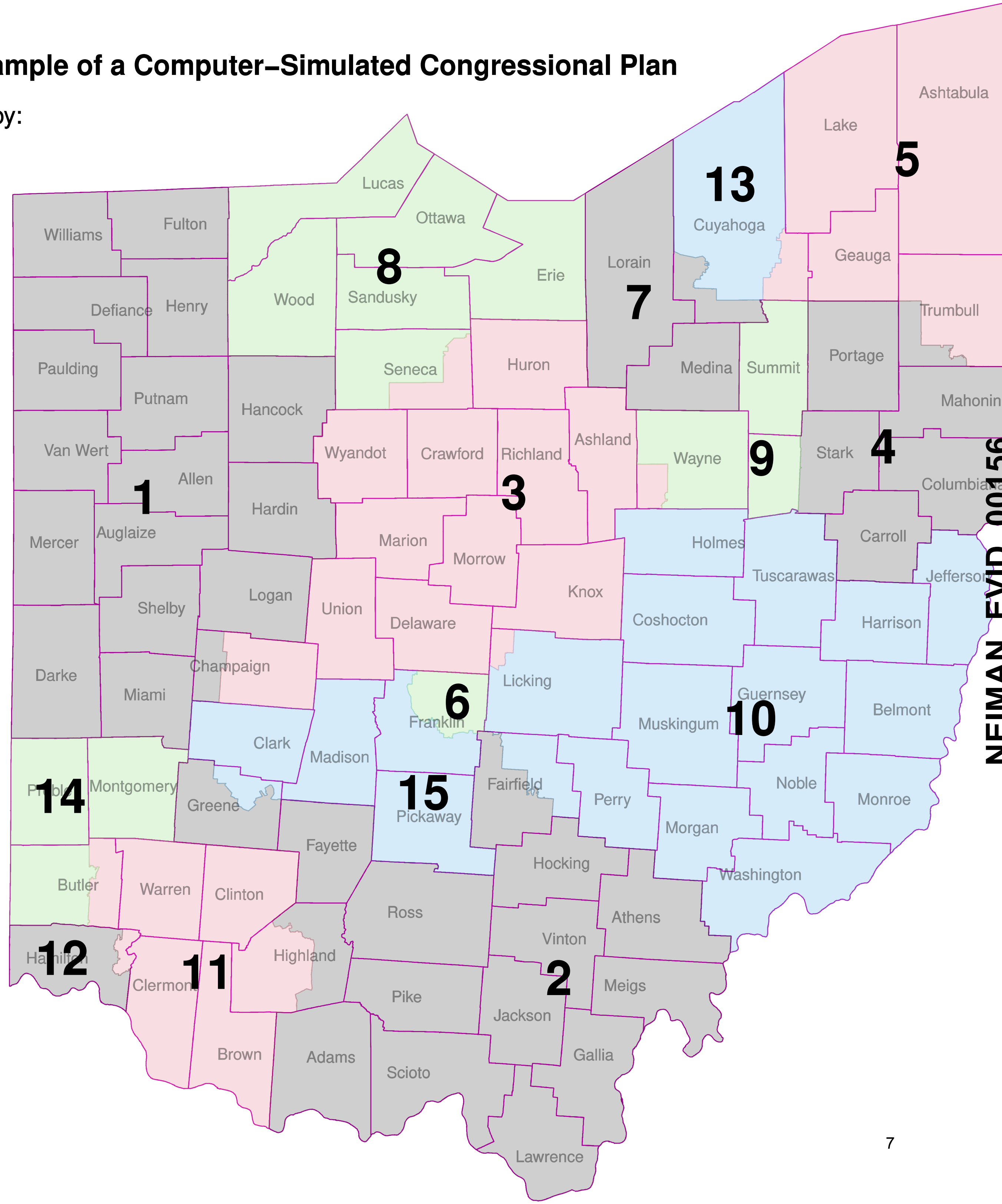
15. On the following page of this report, Figure 1 displays an example of one of the computer-simulated plans produced by the computer algorithm. The left half of this Figure also reports the population of each district, the compactness scores for each district, and the counties split by the plan.

[7] The number of township and municipal corporation splits in the simulated plans range from 13-19, with the vast majority of plans including 14-16 splits. The map-drawers of the Enacted Plan purport that it has 14 such splits. A histogram showing the number of split townships and municipal corporations in the 1,000 computer-simulated plans is included in the Appendix. Also included in the Appendix are figures showing that, even considering only those simulated plans with 13 or 14 township and municipal corporation splits, the Enacted Plan is a partisan outlier.

Figure 1: Example of a Computer–Simulated Congressional Plan

District:	Population:	Reock:	Popper–Polsby:
1	786,630	0.62	0.562
2	786,630	0.37	0.216
3	786,630	0.412	0.377
4	786,630	0.642	0.559
5	786,630	0.558	0.58
6	786,630	0.55	0.527
7	786,629	0.554	0.452
8	786,629	0.435	0.507
9	786,630	0.461	0.409
10	786,630	0.502	0.403
11	786,630	0.513	0.415
12	786,630	0.391	0.348
13	786,630	0.536	0.525
14	786,630	0.459	0.483
15	786,630	0.308	0.307
Average:	786,629.9	0.487	0.445

13 Split Counties:
Butler (Districts 11, 14)
Champaign (Districts 1, 3)
Cuyahoga (Districts 13, 5, 7)
Fairfield (Districts 10, 2)
Franklin (Districts 15, 6)
Greene (Districts 15, 2)
Hamilton (Districts 11, 12)
Highland (Districts 11, 2)
Licking (Districts 10, 3)
Seneca (Districts 3, 8)
Stark (Districts 4, 9)
Trumbull (Districts 4, 5)
Wayne (Districts 3, 9)



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VI. DISTRICTING REQUIREMENTS UNDER ARTICLE XIX, SECTION (1)(C)(3)

16. Article XIX, Section (1)(C)(3) of the Ohio Constitution mandates three requirements for a congressional plan passed by a simple majority of each house of the General Assembly. First, the plan may not "unduly favor[] or disfavor[] a political party." Second, the plan may not unduly split counties, townships, and municipal corporations. Third, the General Assembly "shall attempt to draw districts that are compact."

17. Throughout the remainder of this report, I evaluate the General Assembly's compliance with these three mandates by comparing the 2021 Enacted Plan to the 1,000 computer-simulated plans, which were produced by a computer algorithm following the constitutional districting criteria outlined above. By comparing the Enacted Plan to the computer-simulated plans, I am able to assess whether the Enacted Plan's partisan characteristics, governmental division splits, and compactness can be explained by other redistricting criteria. I determined that they cannot.

VII. MEASURING THE PARTISAN CHARACTERISTICS OF OHIO CONGRESSIONAL DISTRICTS

18. I use actual election results from recent, statewide election races in Ohio to assess the partisan performance of the Enacted Plan and the computer-simulated plans analyzed in this report. Overlaying these past election results onto a districting plan enables me to calculate the Republican (or Democratic) share of the votes cast from within each district in the Enacted Plan and in each simulated plan. I am also able to count the total number of Republican and Democratic-favoring districts within each simulated plan and within the Enacted Plan. All of these calculations thus allow me to directly compare the partisanship of the Enacted Plan and the simulated plans. These partisan comparisons allow me to determine whether or not the partisanship of individual districts and the partisan distribution of seats in the Enacted Plan could reasonably have arisen from a districting process adhering to the Ohio Constitution and its explicit prohibition on unduly favoring either political party. Voting history in federal and statewide elections is a strong predictor of future voting patterns. Mapmakers thus can and do use past voting history to identify the class of voters, at a precinct-by-precinct level, who are likely to vote for Republican or Democratic congressional candidates.

19. In general, a reliable method of comparing the partisanship of different congressional districts within a state is to calculate the percentage of votes from these districts favoring Republican (or Democratic) candidates in recent, competitive *statewide* elections, such as the Presidential, Gubernatorial, Attorney General, and U.S. Senate elections. Recent statewide elections provide reliable bases for comparisons of different precincts' partisan tendencies because in any statewide election, the anomalous candidate-specific effects that shape the election outcome are equally present in all precincts across the state. Statewide elections are thus a better basis for comparison than the results of congressional (or "endogenous") elections because the particular outcome of any congressional election may deviate from the long-term partisan voting trends of that district, due to factors idiosyncratic to the district as currently constructed. Such factors can include the presence or absence of a quality challenger, anomalous difference between the candidates in

campaign efforts or campaign finances, incumbency advantage, candidate scandals, and coattail effects.[8] Because these idiosyncratic factors would change if the district were drawn differently, it is particularly unsuitable to use election results from an existing district when comparing the partisanship of districts in a newly-enacted plan or a computer-simulated plan that would have different boundaries than those used in past congressional elections.

20. Moreover, statewide elections are also a more reliable indicator of a district's partisanship than partisan voter registration counts. Voter registration by party is a uniquely unreliable method of comparing districts' partisan tendencies because many voters who consistently support candidates from one party nevertheless do not officially register with either major party, while others vote for candidates of one party while registering with a different party.[9] As a result, based on my expertise and my experience studying redistricting practices across many states, legislative map-drawers generally do not rely heavily on voter registration data in assessing the partisan performance of districts.

21. ***The 2016-2020 Statewide Election Composite:*** To measure the partisanship of all districts in the computer-simulated plans and the 2021 Enacted Plan, I used the results of all statewide election contests held in Ohio for political (non-judicial) offices during 2016-2020. There were nine such elections: The 2016 U.S. President, 2016 U.S. Senator, 2018 Attorney General, 2018 Auditor, 2018 Governor, 2018 Secretary of State, 2018 Treasurer, 2018 U.S. Senator, and 2020 U.S. President elections.

22. I obtained precinct-level results for these nine elections, and I disaggregated these election results down to the Census block level. I then aggregated these block-level election results to the district level within each computer-simulated plan and the Enacted Plan, and I calculated the number of districts within each plan that cast more votes for Republican than Democratic candidates. I use these calculations to measure the partisan performance of each simulated plan analyzed in this report and of the Enacted Plan. In other words, I look at the Census blocks that would comprise a particular district in a given simulation and, using the actual election results from those Census blocks, I calculate whether voters in that simulated district collectively cast more votes for Republican or Democratic candidates in the 2016-2020 statewide election contests. I performed such calculations for each district under each simulated plan to measure the number of districts Democrats or Republicans would win under that particular simulated districting map.

23. I refer to the aggregated election results from these nine statewide elections as the "2016-2020 Statewide Election Composite." For the Enacted Plan districts and for all districts in each of the 1,000 computer-simulated plans, I calculate the percentage of total two-party votes across these nine elections that were cast in favor of Republican candidates in order to measure the average Republican vote share of the district. In the following section, I present district-level comparisons of the Enacted Plan and simulated plan districts in order

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[8] *E.g.*, Alan Abramowitz, Brad Alexander, and Matthew Gunning. "Incumbency, Redistricting, and the Decline of Competition in U.S. House Elections." *The Journal of Politics*. Vol. 68, No. 1 (February 2006): 75-88.

[9] Kenneth J. Meier, "Party Identification and Vote Choice: The Causal Relationship" Vol. 28, No. 3 (Sep., 1975):496-505.

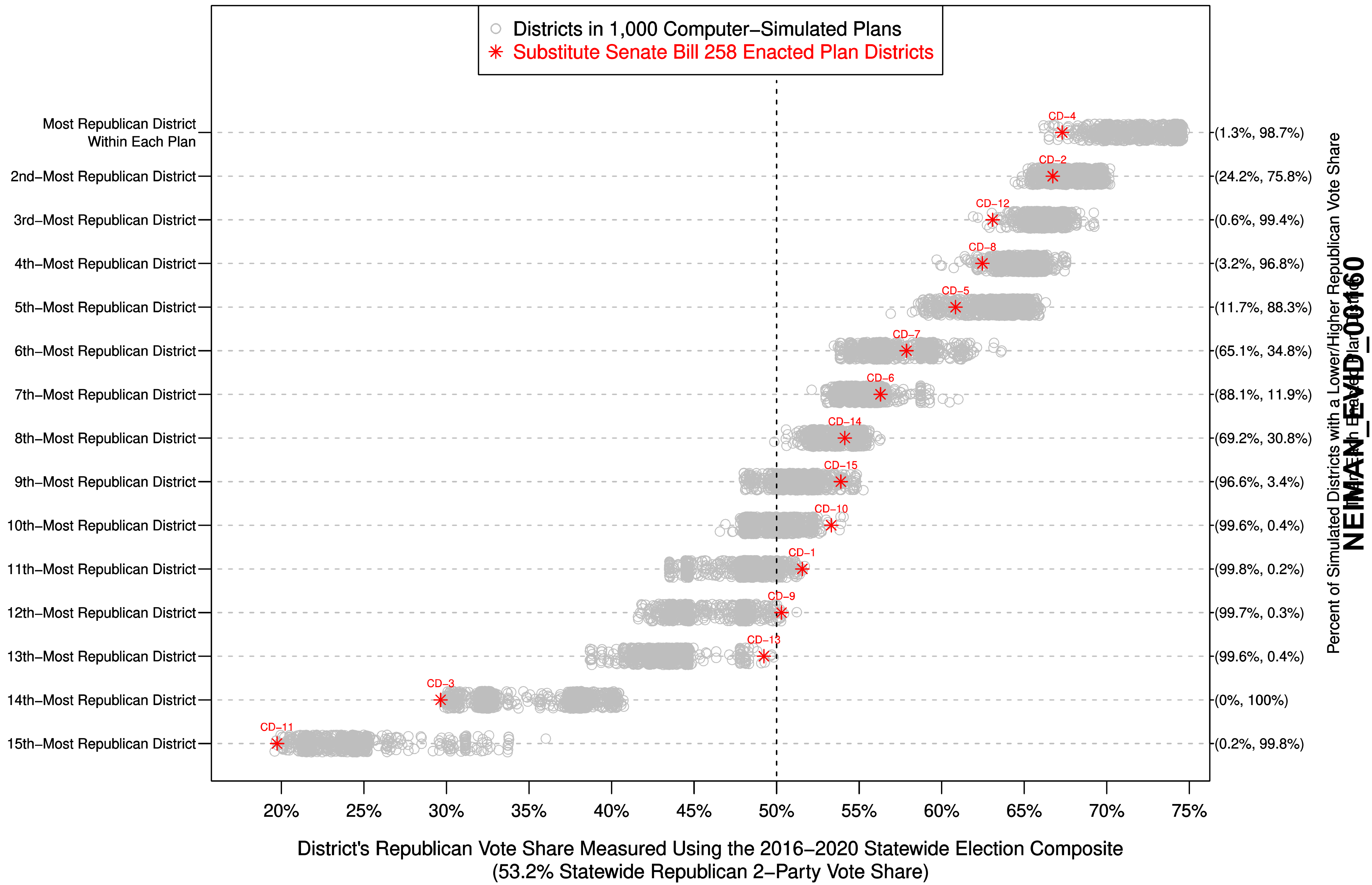
to identify whether any individual districts in the Enacted Plan are partisan outliers. I also present plan-wide comparisons of the Enacted Plan and the simulated plans in order to identify the extent to which the Enacted Plan is a statistical outlier in terms of common measures of districting plan partisanship.

VIII. PARTISAN CHARACTERISTICS OF THE ENACTED PLAN

24. In this section, I present partisan comparisons of the Enacted Plan to the computer-simulated plans at both a district-by-district level as well as a plan-wide level using several common measures of districting plan partisanship. First, I compare the district-level Republican vote share of the Enacted Plan's districts and the districts in the computer-simulated plans. Next, I compare the number of Republican-favoring districts (that is, the number of districts with a two-party Republican vote share of greater than 50%) in the Enacted Plan and in the computer-simulated plans. Finally, I use several common measures of partisan bias to compare the Enacted Plan to the computer-simulated plans. Overall, I find that several individual districts in the Enacted Plan are statistical outliers, exhibiting extreme partisan characteristics that are rarely or never observed in the computer-simulated plan districts drawn according to the Ohio Constitution's districting requirements. The partisan characteristics of the Enacted Plan are consistent with an effort to favor the Republican party by packing Democratic voters into a small number of districts that very heavily favor the Democratic party. Moreover, I find that at the plan-wide level, the Enacted Plan creates a degree of partisan bias favoring Republicans that is more extreme than the vast majority of the computer-simulated plans. I describe these findings in detail below:

25. ***Partisan Outlier Districts in the Enacted Plan***: In Figure 2, I directly compare the partisan distribution of districts in the Enacted Plan to the partisan distribution of districts in the 1,000 computer-simulated plans. I first order the Enacted Plan's districts from the most- to the least-Republican district, as measured by Republican vote share using the 2016-2020 Statewide Election Composite. The most-Republican district appears on the top row, and the least-Republican district appears on the bottom row of Figure 2. Next, I analyze each of the 1,000 computer-simulated plans and similarly order each simulated plan's districts from the most- to the least-Republican district. I then directly compare the most-Republican Enacted Plan district (CD-4) to the most-Republican simulated district from each of the 1,000 computer-simulated plans. In other words, I compare one district from the Enacted Plan to 1,000 computer-simulated districts, and I compare these districts based on their Republican vote share. I then directly compare the second-most-Republican district in the Enacted Plan to the second-most-Republican district from each of the 1,000 simulated plans. I conduct the same comparison for each district in the Enacted Plan, comparing the Enacted Plan district to its computer-simulated counterparts from each of the 1,000 simulated plans.

Figure 2: Comparisons of Enacted Plan Districts to 1,000 Computer–Simulated Plans' Districts



26. Thus, the top row of Figure 2 directly compares the partisanship of the most-Republican Enacted Plan district (CD-4) to the partisanship of the most-Republican district from each of the 1,000 simulated plans. The two percentages (in parentheses) in the right margin of this Figure report the percentage of these 1,000 simulated districts that are less Republican than, and more Republican than, the Enacted Plan district. Similarly, the second row of this Figure compares the second-most-Republican district from each plan, the third row compares the third-most-Republican district from each plan, and so on. In each row of this Figure, the Enacted Plan's district is depicted with a red star and labeled in red with its district number; meanwhile, the 1,000 computer-simulated districts are depicted with 1,000 gray circles on each row.

27. In the Enacted Plan as well as in most computer-simulated plans, the most Democratic district in Ohio is the district containing Cleveland and surrounding areas. As the bottom row of Figure 2 illustrates, the most-Democratic district in the Enacted Plan (CD-11) is *more* heavily Democratic than 100% of the most-Democratic districts in each of the 1,000 computer-simulated plans. This calculation is numerically reported in the right margin of the Figure. Every single one of the computer-simulated counterpart districts would have been more politically moderate than CD-11 in terms of partisanship: CD-11 exhibits a Republican vote share of 19.7%, while all 1,000 of the most Democratic districts in the computer-simulated plans would have exhibited a higher Republican vote share. In other words, CD-11 packs together Democratic voters in the Cleveland area to a more extreme extent than the most-Democratic district in 100% of the computer-simulated plans. I therefore identify CD-11 as an extreme partisan outlier when compared to its 1,000 computer-simulated counterparts, using a standard threshold test of 95% for statistical significance.

28. The next-to-bottom row of Figure 2 reveals a similar finding regarding the Enacted Plan's CD-3, which is located in and around Columbus. This row illustrates that the second-most Democratic district in the Enacted Plan (CD-3) is *more* heavily Democratic than 100% of the second-most Democratic districts in each of the 1,000 computer-simulated plans. Every single one of its computer-simulated counterpart districts would have been more politically moderate than CD-3 in terms of partisanship: CD-3 exhibits a Republican vote share of 29.6%, while 100% of the second-most-Democratic districts in the computer-simulated plans would have exhibited a higher Republican vote share. In other words, CD-3 packs together Democratic voters to a more extreme extent than the second-most-Democratic district in 100% of the computer-simulated plans. I therefore identify CD-3 as an extreme partisan outlier when compared to its 1,000 computer-simulated counterparts, using a standard threshold test of 95% for statistical significance.

29. Meanwhile, the top row of Figure 2 reveals a similar finding: As the top row illustrates, the most Republican district in the Enacted Plan (CD-4) is *less* heavily Republican than 98.7% of the most Republican districts in each of the 1,000 computer-simulated plans. It is thus clear that CD-4 "cracks" Democratic voters who would otherwise reside in surrounding districts by placing them into CD-4.

30. It is especially notable that these three aforementioned Enacted Plan districts – the most-Republican district (CD-4) and the two most-Democratic districts (CD-3 and CD-11) in the

Enacted Plan – were drawn to include more Democratic voters than virtually all of their counterpart districts in the 1,000 computer-simulated plans. These "extra" Democratic voters in the three most partisan-extreme districts in the Enacted Plan had to come from the remaining twelve more moderate districts in the Enacted Plan. Having fewer Democratic voters in these more moderate districts enhances Republican candidate performance in these districts.

31. Indeed, the ninth through thirteenth rows in Figure 2 confirm this precise effect. These five rows in Figure 2 compare the partisanship of districts in the ninth, tenth, eleventh, twelfth, and thirteenth-most Republican districts within the Enacted Plan and the 1,000 computer-simulated plans. In all five of these rows, the Enacted Plan district is a partisan outlier. In each of these five rows, the Enacted Plan's district is more heavily Republican than over 95% of its counterpart districts in the 1,000 computer-simulated plans. The five Enacted Plan districts in these five rows (CD-1, 9, 10, 13, and 15) are more heavily Republican than nearly all of their counterpart computer-simulated plan districts because the three most partisan-extreme districts in the Enacted Plan (CD-3, 4, and 11) are more heavily Democratic than nearly all of their counterpart districts in the computer-simulated plans.

32. I therefore identify the five Enacted Plan districts in the ninth through thirteenth rows (CD-1, 9, 10, 13, and 15) of Figure 2 as partisan statistical outliers. Each of these five districts has a Republican vote share that is higher than over 95% of the computer-simulated districts in its respective row in Figure 2. I also identify the three Enacted Plan districts in the top row and in the bottom two rows (CD-3, 4, and 11) of Figure 2 as partisan statistical outliers. Each of these three districts has a Republican vote share that is lower than over 95% of the computer-simulated districts in its respective row in Figure 2.

33. In summary, Figure 2 illustrates that eight of the 15 districts in the Enacted Plan are partisan outliers: Five districts (CD-1, 9, 10, 13, and 15) in the Enacted Plan are more heavily Republican than over 95% of their counterpart computer-simulated plan districts, while three districts (CD-3, 4, and 11) are more heavily Democratic than over 98% of their counterpart districts in the computer-simulated plans.

34. The Appendix of this report contains nine additional Figures (Figures A1 through A9) that each contain a similar analysis of the Enacted Plan districts and the computer-simulated plan districts. Each of these nine Figures in the Appendix measures the partisanship of districts using one of the individual nine elections included in the 2016-2020 Statewide Election Composite. These nine Figures generally demonstrate that the same extreme partisan outlier patterns observed in Figure 2 are also present when district partisanship is measured using any one of the nine statewide elections held in Ohio during 2016-2020.

35. ***Number of Democratic and Republican Districts:*** I compared the partisan breakdown of the computer-simulated plans to the partisanship of the Enacted Plan, using the 2016-2020 Statewide Election Composite to measure the number of Republican-favoring districts created in each of the 1,000 simulated plans. Across the entire state, Republican candidates collectively won a 53.2% share of the votes in the nine elections in the 2016-2020 Statewide Election Composite. But among the 15 districts in the Enacted Plan, Republicans have over a 50% vote share in 12 out of 15 districts. In other words, the Enacted Plan

created 12 Republican-favoring districts, as measured using the 2016-2020 Statewide Election Composite. By contrast, only 1.3% of the computer-simulated plans create 12 Republican-favoring districts, and no computer-simulated plan ever creates more than 12 Republican districts.

36. Hence, in terms of the total number of Republican-favoring districts created by the plan, the 2021 Enacted Plan is a statistical outlier when compared to the 1,000 computer-simulated plans. The Enacted Plan creates the maximum number of Republican districts that ever occurs in any computer-simulated plan, and the Enacted Plan creates more Republican districts than 98.7% of the computer-simulated plans, which were drawn using a nonpartisan process adhering to the districting requirements in the Ohio Constitution. I characterize the Enacted Plan's creation of 12 Republican districts as a statistical outlier among the computer-simulated plans because the Enacted Plan exhibits an outcome that is more favorable to Republicans than over 98.7% of the simulated plans.

37. ***The Efficiency Gap:*** Another commonly used measure of a districting plan's partisan bias is the efficiency gap.[10] To calculate the efficiency gap of the Enacted Plan and every computer-simulated plan, I first measure the number of Republican and Democratic votes within each Enacted Plan district and each computer-simulated district, as measured using the 2016-2020 Statewide Election Composite. Using this measure of district-level partisanship, I then calculate each districting plan's efficiency gap using the method outlined in *Partisan Gerrymandering and the Efficiency Gap.*[11] Districts are classified as Democratic victories if, using the 2016-2020 Statewide Election Composite, the sum total of Democratic votes in the district during these elections exceeds the sum total of Republican votes; otherwise, the district is classified as Republican. For each party, I then calculate the total sum of surplus votes in districts the party won and lost votes in districts where the party lost. Specifically, in a district lost by a given party, all of the party's votes are considered lost votes; in a district won by a party, only the party's votes exceeding the 50% threshold necessary for victory are considered surplus votes. A party's total wasted votes for an entire districting plan is the sum of its surplus votes in districts won by the party and its lost votes in districts lost by the party. The efficiency gap is then calculated as total wasted Democratic votes minus total wasted Republican votes, divided by the total number of two-party votes cast statewide across all nine elections.

38. Thus, the importance of the efficiency gap is that it tells us the degree to which more Democratic or Republican votes are wasted across an entire districting plan. A significantly positive efficiency gap indicates far more Democratic wasted votes, while a significantly negative efficiency gap indicates far more Republican wasted votes.

39. I analyze whether the Enacted Plan's efficiency gap arises naturally from a map-drawing process adhering to the required districting criteria in the Ohio Constitution, or rather,

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[10] Eric McGhee, "Measuring Partisan Bias in Single-Member District Electoral Systems." Legislative Studies Quarterly Vol. 39, No. 1: 55–85 (2014).

[11] Nicholas O. Stephanopoulos & Eric M. McGhee, *Partisan Gerrymandering and the Efficiency Gap,* 82 University of Chicago Law Review 831 (2015).

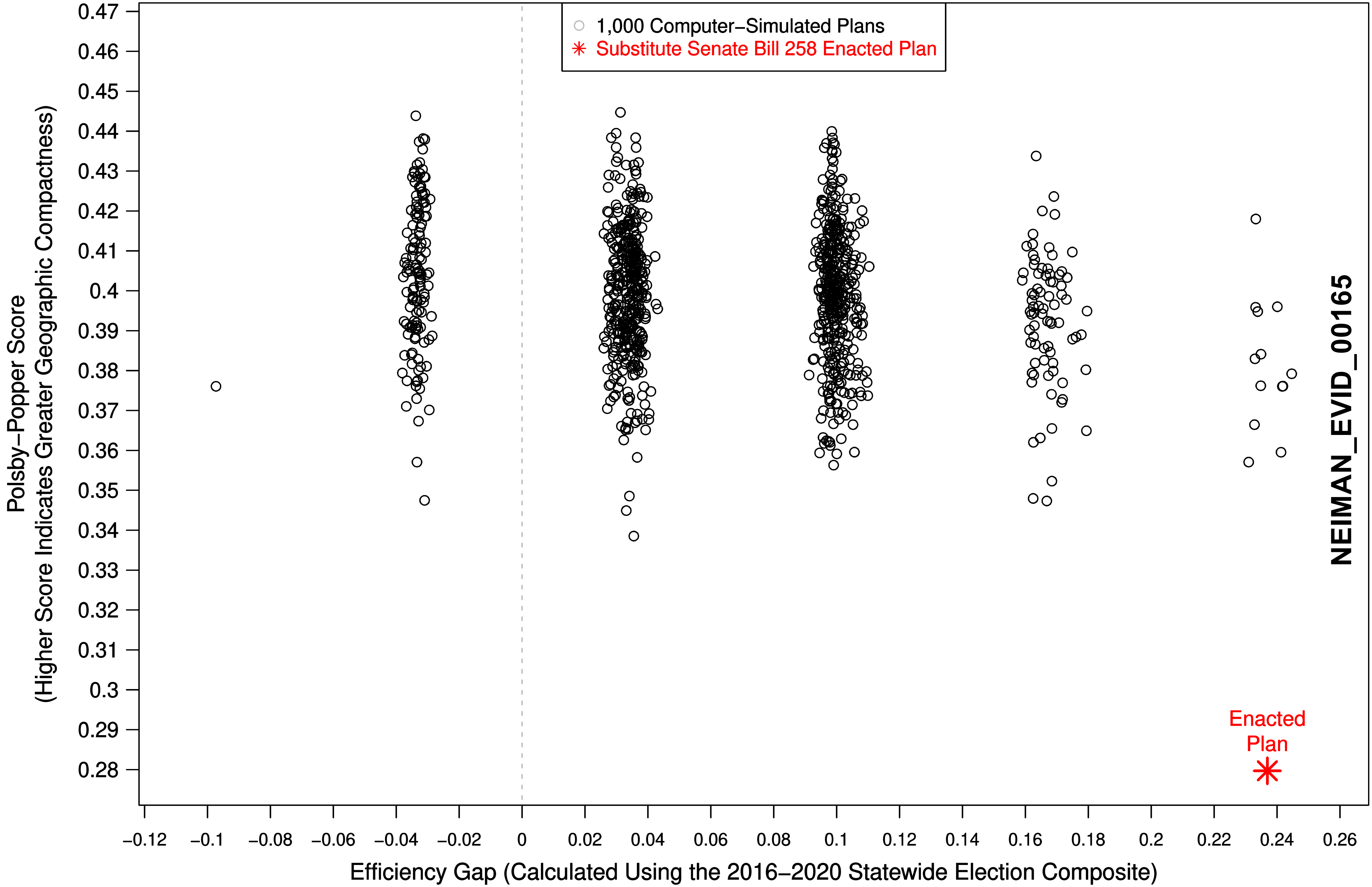
whether the skew in the Enacted Plan's efficiency gap is explainable only as the product of a map-drawing process that intentionally favored one party over the other. By comparing the efficiency gap of the Enacted Plan to that of the computer-simulated plans, I am able to evaluate whether or not such the Enacted Plan's efficiency gap could have realistically resulted from adherence to the Ohio Constitution.

40. Figure 3 compares the efficiency gaps of the Enacted Plan and of the 1,000 computer-simulated plans. As before, the 1,000 circles in this Figure represent the 1,000 computer-simulated plans, while the red star in the lower right corner represents the Enacted Plan. Each plan is plotted along the horizontal axis according to its efficiency gap, while each plan is plotted along the vertical axis according to its Polsby-Popper score.[12]

41. The results in Figure 3 illustrate that the Enacted Plan exhibits an efficiency gap of +23.7%, indicating that the plan results in far more wasted Democratic votes than wasted Republican votes. Specifically, the difference between the total number of wasted Democratic votes and wasted Republican votes amounts to 23.7% of the total number of votes statewide. The Enacted Plan's efficiency gap is larger than the efficiency gaps exhibited by 99.5% of the computer-simulated plans. This comparison reveals that the significant level of Republican bias exhibited by the Enacted Plan cannot be explained alone by Ohio's political geography or the redistricting criteria in the Ohio Constitution.

[12] See paragraph 57, *infra*, for a definition of the Polsby-Popper score.

Figure 3:
Comparisons of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans on Efficiency Gap and Compactness



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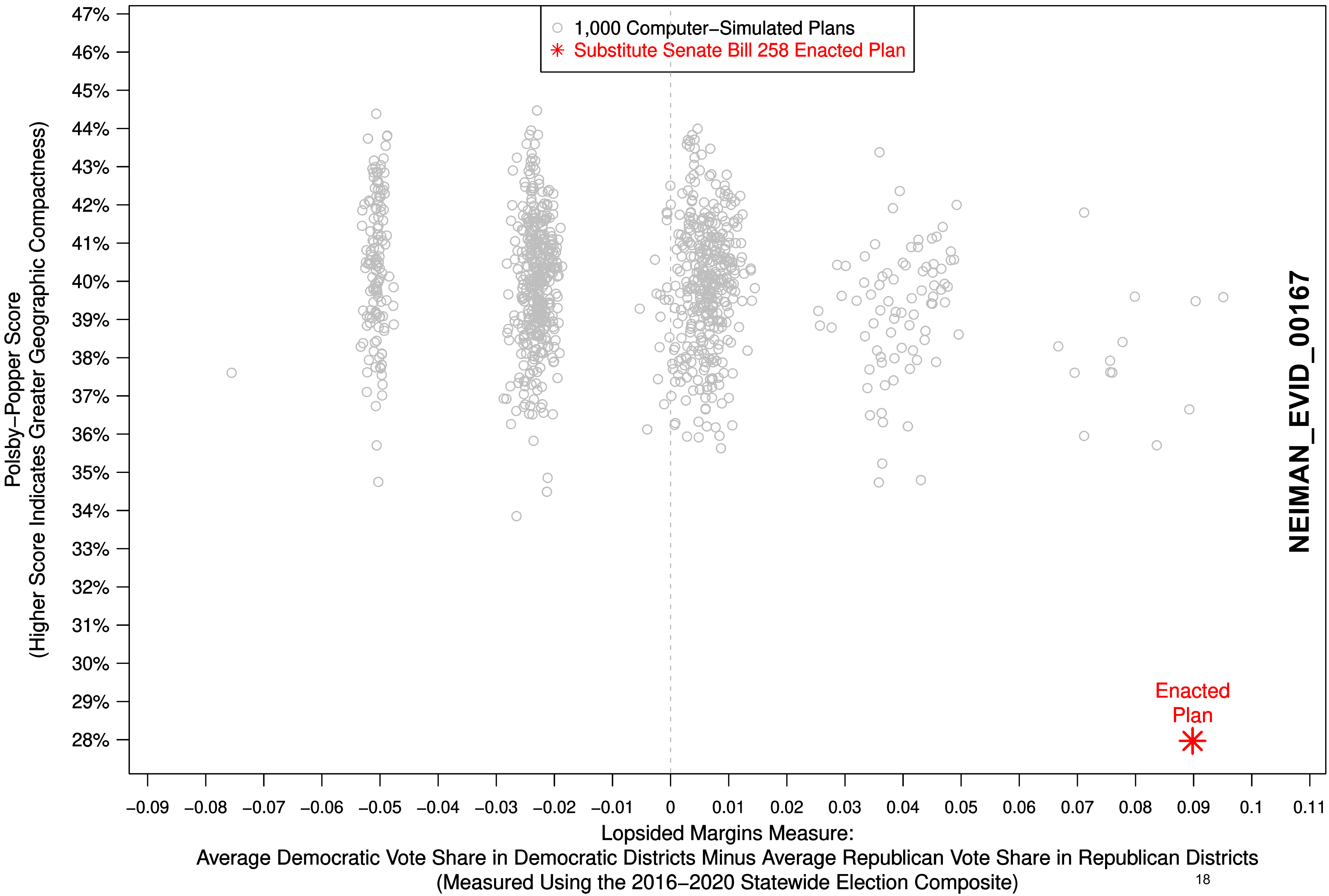
42. ***The Lopsided Margins Measure:*** Another measure of partisan bias in districting plans is the "lopsided margins" test. The basic premise captured by this measure is that a partisan-motivated map-drawer may attempt to pack the opposing party's voters into a small number of extreme districts that are won by a lopsided margin. Thus, for example, a map-drawer attempting to favor Party A may pack Party B's voters into a small number of districts that very heavily favor Party B. This packing would then allow Party A to win all the remaining districts with relatively smaller margins. This sort of partisan manipulation in districting would result in Party B winning its districts by extremely large margins, while Party A would win its districts by relatively small margins. In other words, by packing most of Party B's voters into a handful of districts, and drawing remaining districts as nominally "competitive" but favoring Party A, Party A can maximize its expected performance in an election.

43. Hence, the lopsided margins test is performed by calculating the difference between the average margin of victory in Republican-favoring districts and the average margin of victory in Democratic-favoring districts. The 2021 Enacted Plan contains three Democratic-favoring districts (CD-3, 11, and 13), and these three districts have an average Democratic vote share of 67.1%, as measured using the 2016-2020 Statewide Election Composite. By contrast, the Enacted Plan contains twelve Republican-favoring districts (CD-1, 2, 4, 5, 6, 7, 8, 9, 10, 12, 14, and 15), and these twelve districts have an average Republican vote share of 58.1%. Hence, the difference between the average Democratic margin of victory in Democratic-favoring districts and the average Republican margin of victory in Republican-favoring districts is +9.0%, which is calculated as 67.1% - 58.1%. I refer to this calculation of +9.0% as the Enacted Plan's lopsided margins measure.

44. How does this +9.0% lopsided margins measure of the Enacted Plan compare to the same calculation for the 1,000 computer-simulated plans? Figure 4 reports the lopsided margins calculations for the Enacted Plan and for the simulated plans. In Figure 4, each plan is plotted along the horizontal axis according to its lopsided margins measure and along the vertical axis according to its Polsby-Popper score.[13]

[13] *Id.*

Figure 4:
Comparisons of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans on Lopsided Margins Measure and Compactness



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45. Figure 4 reveals that the Enacted Plan's +9.0% lopsided margins measure is an extreme outlier compared to the lopsided margins measures of the 1,000 computer-simulated plans. Over 99.8% of the simulated plans have a smaller lopsided margins measure than the Enacted Plan. In fact, a significant minority (40.6%) of the 1,000 simulated plans have a lopsided margins measure of between -2% to +2%, indicating a plan in which Democrats and Republicans win their respective districts by similar average margins.

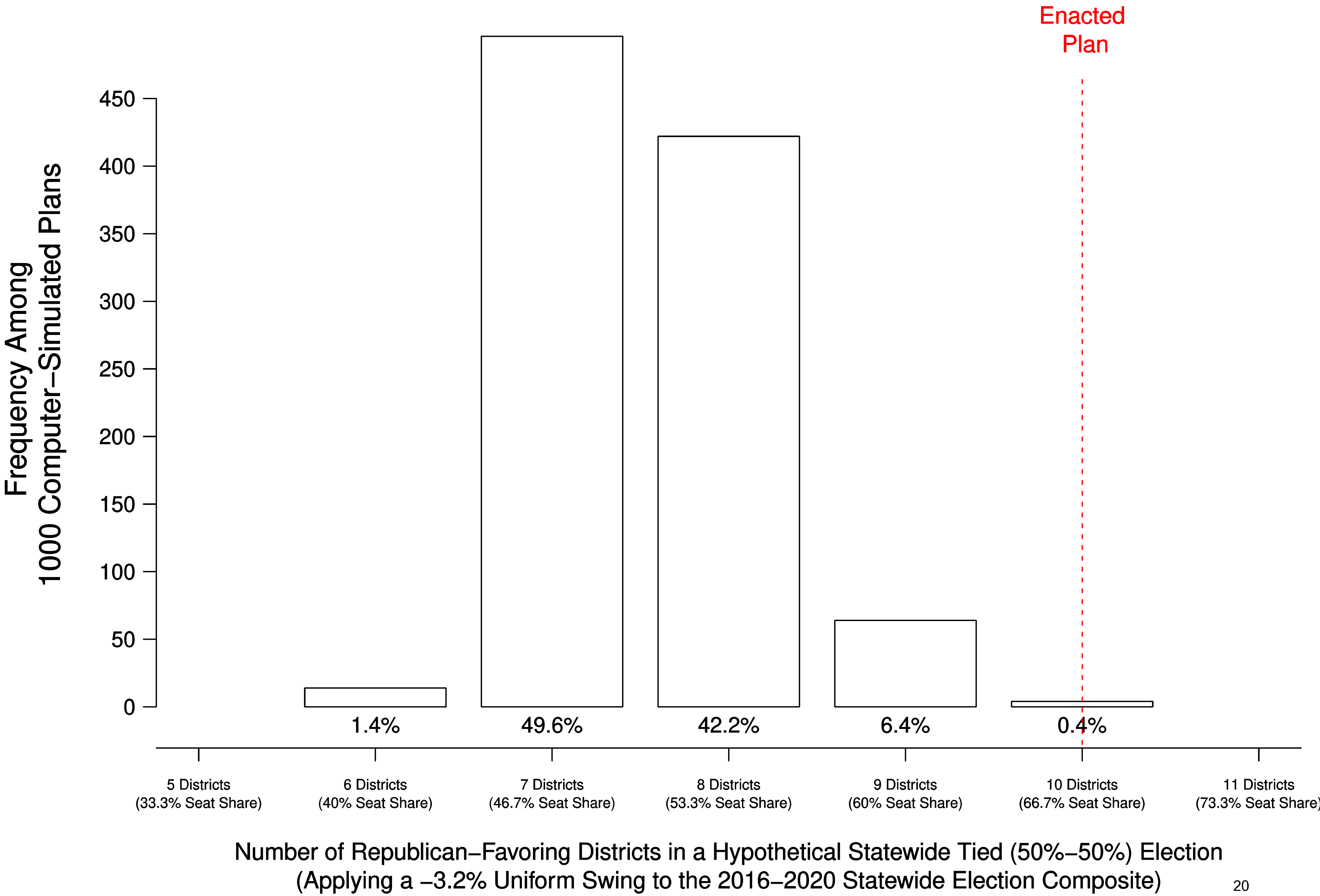
46. By contrast, the Enacted Plan's lopsided margins measure of +9.0% indicates that the Enacted Plan creates districts in which Democrats are extremely packed into their districts, while the margin of victory in Republican districts is significantly smaller. The "lopsidedness" of the two parties' average margin of victory is extreme when compared to the computer-simulated plans. The finding that all 1,000 simulated plans have a smaller lopsided margins measure indicates that the Enacted Plan's extreme packing of Democrats into Democratic-favoring districts was not simply the result of Ohio's political geography, combined with adherence to the districting criteria in the Ohio Constitution.

47. ***Partisan Symmetry Based on Uniform Swing:*** Another common measure of partisan bias is based on the concept of partisan symmetry and asks the following question: Under a given districting plan and given a particular election-based measure of district partisanship, what share of seats would each party win in a hypothetical tied election (i.e., 50% vote share for each of two parties). To approximate the district-level outcomes in a hypothetical tied election, one normally uses a uniform swing in order to simulate a tied statewide election. We then calculate whether each party would receive more than or less than 50% of the seats under this hypothetical tied election in a given districting plan. This particular measure is often referred to in the academic literature as "partisan bias." In order to avoid confusion with other measures of partisan bias described in this report, I will refer to this measure as "Partisan Symmetry Based on Uniform Swing."

48. Specifically, I use the 2016-2020 Statewide Election Composite to calculate the Partisan Symmetry measure for both the Enacted Plan and for the computer-simulated plans. The 2016-2020 Statewide Election Composite produces a statewide Republican vote share of 53.2%. Therefore, I use a uniform swing of -3.2% in order to estimate the partisanship of districts under a hypothetical tied election in which each party wins exactly 50% of the statewide vote. In other words, this uniform swing subtracts 3.2% from the Republican vote share in every district, both in the Enacted Plan and in all simulated plans.

49. After applying this -3.2% uniform swing, I compare the number of Republican-favoring districts in the Enacted Plan and the simulated plans. In the Enacted Plan, 67.7% of the districts (10 out of 15) are Republican-favoring after applying the uniform swing. I then report the Republicans' seat share (67.7%) under this hypothetical tied election in Figure 5 as the "Partisan Symmetry Based on Uniform Swing" measure for the Enacted Plan. Figure 5 also reports the calculations for all 1,000 simulated plans using this identical method.

Figure 5:
Comparisons of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans On Partisan Symmetry Based on Uniform Swing



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50. Figure 5 reveals that in over 90% of the 1,000 simulated plans, the "Partisan Symmetry Based on Uniform Swing" measure would be quite close to 50%, either at 46.7% or 53.3%. This measure is close to 50% in over 90% of the simulated plans because the Republicans would win either 7 or 8 districts in a hypothetical tied election, and the Democrats would win the remaining 7 or 8 districts. In other words, each party would win approximately 50% of the districts in a hypothetical election in which each party's statewide vote share is exactly 50%.

51. By contrast, the Enacted Plan's measure of 66.7% in Figure 5 would be a statistical outlier and is more favorable to Republicans than in over 99% of the simulated plans. Substantively, this 66.7% measure reflects the Enacted Plan's creation of a durable Republican majority for Ohio's congressional delegation, such that even when Democrats win 50% of the statewide vote, Republicans will still be favored in two-thirds (10 out of 15) of the congressional districts, while Democrats will only be favored in one-third (5 out of 15) of the districts.

IX. PARTISAN OUTLIER DISTRICTS IN FRANKLIN, CUYAHOGA, AND HAMILTON COUNTIES

52. I have thus far compared the Enacted Plan to the simulated plans at a statewide level using several common measures of partisan bias and by identifying individual districts that are partisan outliers. However, I also analyzed the extent to which partisan favoritism affected the map-drawing process within Ohio's three largest counties: Franklin, Cuyahoga, and Hamilton Counties. I analyzed the extent to which individual districts in these counties favor a certain political party, split political subdivisions, or lack compactness. I found that the Enacted Plan districts in these three counties are outliers on each of these three metrics, in ways that systematically favor the Republican Party.

53. Specifically, I found that the Enacted Plan's districts in each of Franklin, Cuyahoga, and Hamilton Counties exhibit more favorable partisan characteristics for the Republican Party than the vast majority of districts covering the same local areas in the 1,000 computer-simulated plans.

54. In particular, the Enacted Plan splits Hamilton County excessively, thereby placing Cincinnati into a district that is more Republican than in virtually all of the 1,000 computer-simulated districts containing Cincinnati. The Enacted Plan's splitting of Hamilton County into three districts is an outcome that occurs in under 2% of the computer-simulated plans. Over 98% of the simulated plans split Hamilton County into just two districts. By excessively splitting up voters in Hamilton County, the Enacted Plan managed to combine Cincinnati with more Republican voters in Warren County, thereby splitting Hamilton County into three Republican-favoring districts.

55. Moreover, by comparing the compactness of these computer-simulated districts within these three counties to the Enacted Plan's districts, I found that the Enacted Plan achieved extreme partisan characteristics in these three counties by sacrificing geographic compactness. The compactness scores of the Enacted Plan's districts in these three counties are significantly lower than the compactness scores of virtually all the simulated districts

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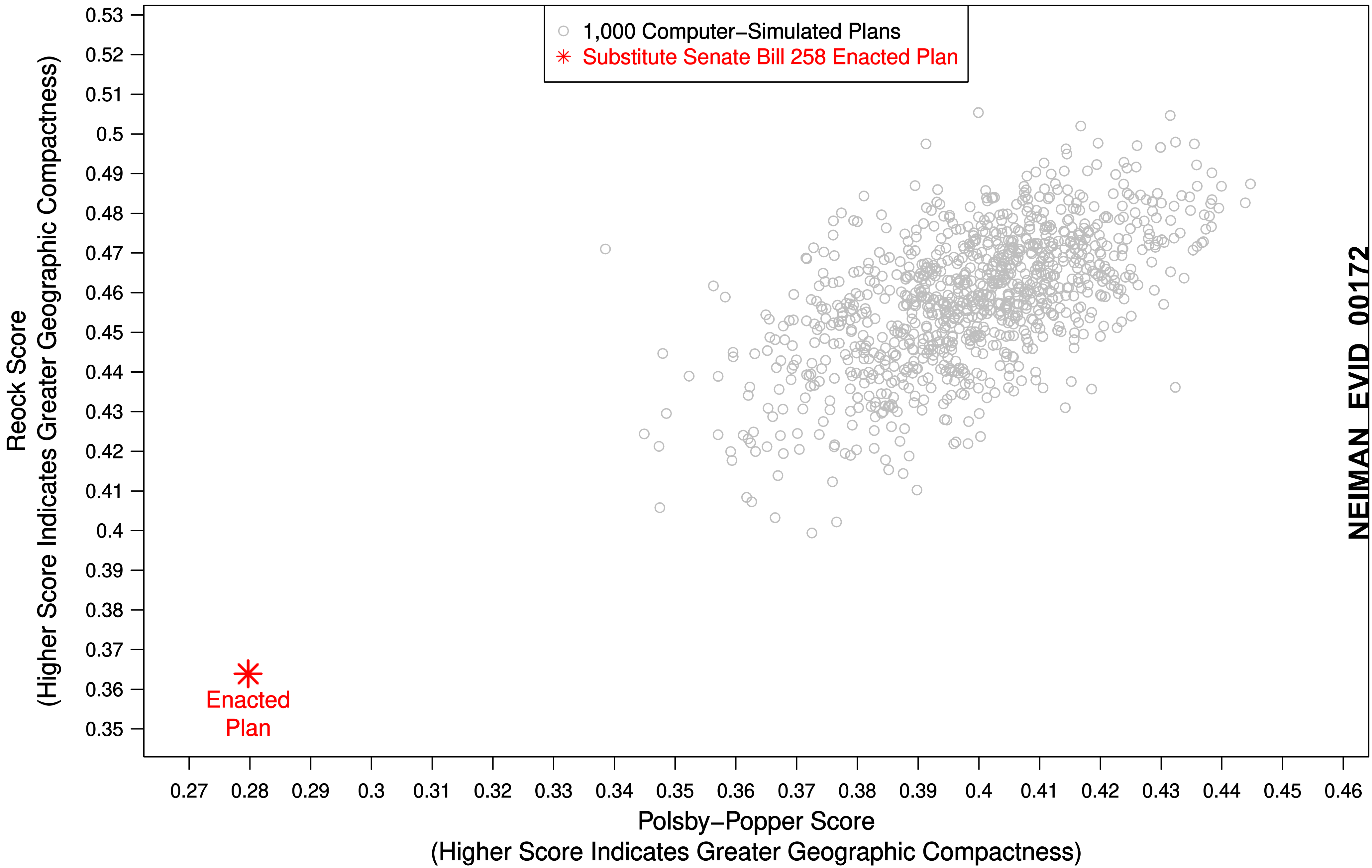
within these same three counties. Thus, it is clear the Enacted Plan's districts in these counties were not drawn in an attempt to favor compactness. Instead, the districts in these counties were clearly drawn to create the most favorable outcome possible for the Republican Party.

56. Article XIX, Section (1)(C)(3) of the Ohio Constitution requires that the General Assembly "shall attempt to draw districts that are compact." In evaluating whether the Enacted Plan follows the compactness requirement of Section (1)(C)(3), it is useful to compare the compactness of the Enacted Plan and the 1,000 computer-simulated plans, both at a plan-wide level and for individual districts in particular counties. The computer-simulated plans were produced by a computer algorithm adhering to the Ohio Constitution's required districting criteria in Article XIX, including ignoring partisan considerations. Thus, the compactness scores of these computer-simulated plans illustrate the statistical range of compactness scores that could be reasonably expected to emerge from a districting process that solely seeks to follow the required constitutional criteria while ignoring partisan considerations.

57. First, I calculate the average Polsby-Popper score of each plan's districts. The Polsby-Popper score for each individual district is calculated as the ratio of the district's area to the area of a hypothetical circle whose circumference is identical to the length of the district's perimeter; thus, higher Polsby-Popper scores indicate greater district compactness. The 2021 Enacted Plan has an average Polsby-Popper score of 0.28 across its 15 congressional districts. As illustrated in Figure 6, every single one of the 1,000 computer-simulated plans in this report exhibits a higher Polsby-Popper score than the Enacted Plan. In fact, the middle 50% of these 1,000 computer-simulated plans have an average Polsby-Popper score ranging from 0.39 to 0.41, and the most compact computer-simulated plan has a Polsby-Popper score of 0.44. Hence, it is clear that the Enacted Plan is significantly less compact, as measured by its Polsby-Popper score, than what could reasonably have been expected from a districting process adhering to the Ohio Constitution's requirements.

58. Second, I calculate the average Reock score of the districts within each plan. The Reock score for each individual district is calculated as the ratio of the district's area to the area of the smallest bounding circle that can be drawn to completely contain the district; thus, higher Reock score indicate more geographically compact districts. The 2021 Enacted Plan has an average Reock score of 0.36 across its 14 congressional districts. As illustrated in Figure 6, every single one of the 1,000 computer-simulated House plans in this report exhibits a higher Reock score than the Enacted Plan. In fact, the middle 50% of these 1,000 computer-simulated plans have an average Reock score ranging from 0.46 to 0.47, and the most compact computer-simulated plan has an average Reock score of 0.50. Hence, it is clear that the Enacted Plan is significantly less compact, as measured by its Reock score, than what could reasonably have been expected from a districting process adhering to the Ohio Constitution's requirements.

Figure 6:
Comparisons of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans on Polsby–Popper and Reock Compactness Scores



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59. Beyond these statewide comparisons, it is also clear that in Franklin, Hamilton, and Cuyahoga Counties, the Enacted Plan contains individual districts that are significantly less compact than the simulated plans' districts in these same counties. Furthermore, I found that the lower compactness of these individual districts enabled the General Assembly to draw these districts with extreme partisan characteristics. Below, I describe and illustrate my findings for these three counties in detail:

X. THE ENACTED PLAN'S DISTRICTS IN FRANKLIN COUNTY

60. Franklin County's population exceeds the required population for a single congressional district. A congressional plan must contain one district that lies fully within Franklin County, and one district must contain a significant portion of Columbus. For the Enacted Plan and each of the 1,000 computer-simulated plans, I analyze two relevant districts:

    a. The district that contains the largest amount of Columbus' population, which is generally also the required district lying fully within Franklin County; and

    b. The district that contains the second-most amount of Columbus' population.

61. Figure 7a and Figure 7b contain two maps. The map in Figure 7a depicts the boundaries of the Enacted Plan's two Columbus-area districts. The map in Figure 7b depicts the boundaries of the Columbus-area districts that had the highest average Polsby-Popper compactness scores among all 1,000 computer-simulated plans. Figures 7a and 7b also report the Polsby-Popper scores and Republican vote shares of these two districts in the Enacted Plan and in the computer-simulated plan.

Figure 7a: Franklin County Districts (CD−3 and CD−15) in the 2021 Enacted Plan:

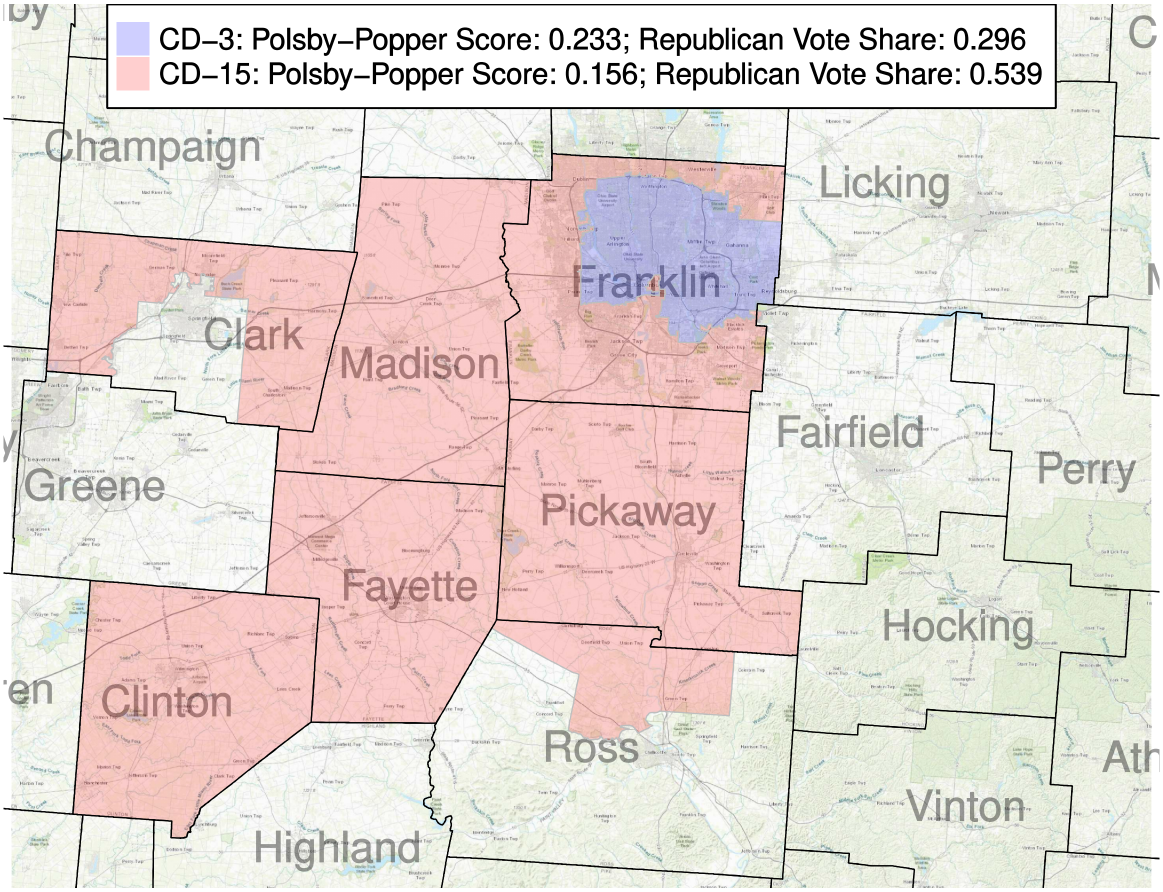
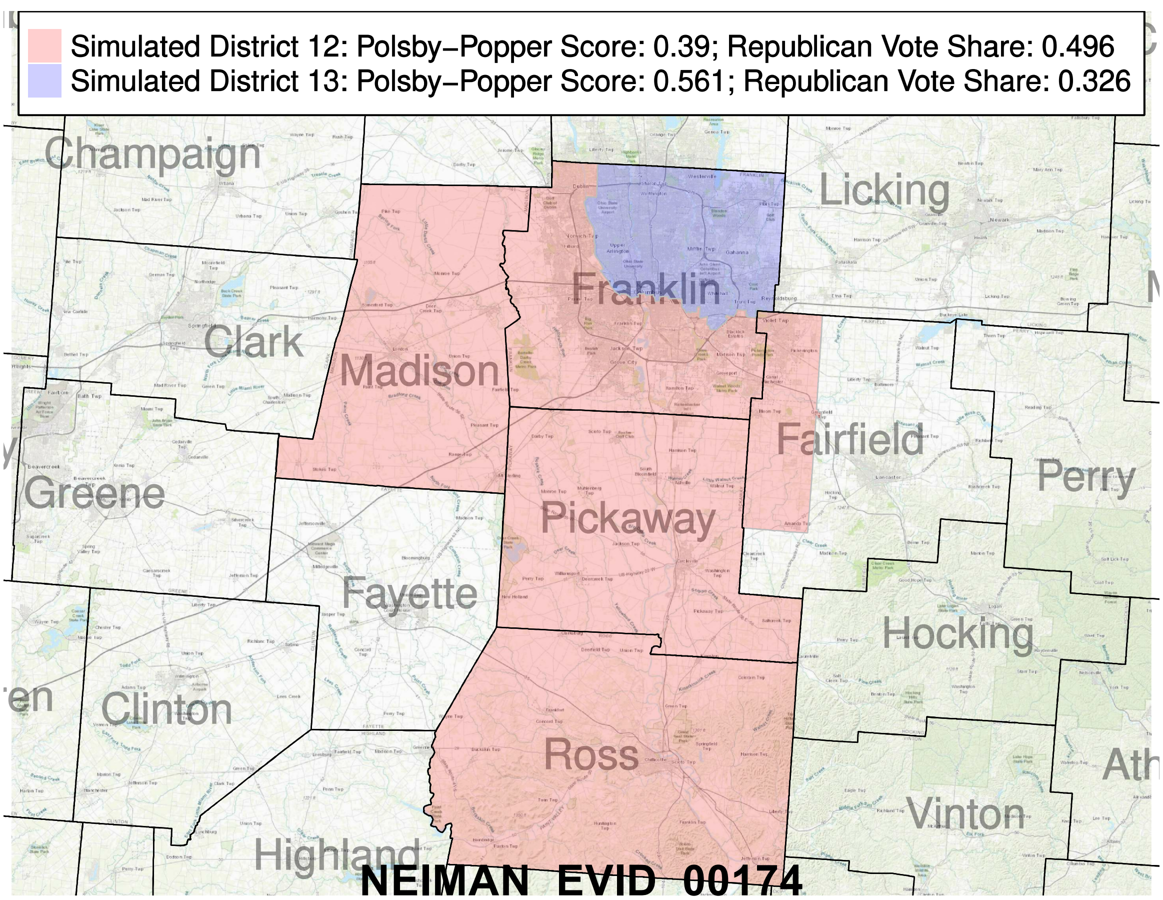


Figure 7b: Computer−Simulated Plan with the Most Compact Franklin County Districts (Computer−Simulated Plan #138 of 1000)

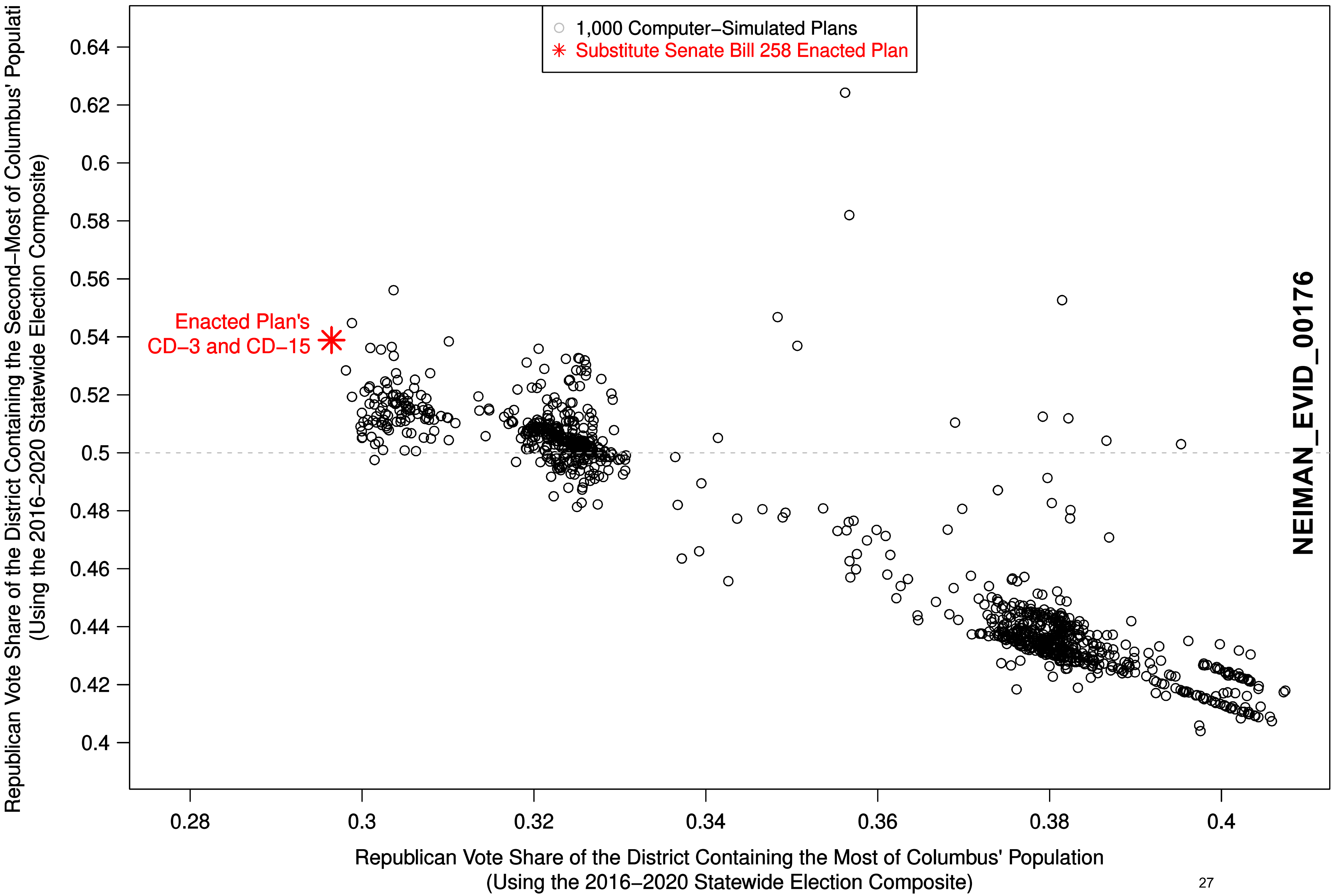


62. For the Enacted Plan and the 1,000 simulated plans, Figure 8 compares the Republican vote share, as measured using the 2016-2020 Statewide Election Composite, of the two districts containing the most and second-most amount of Columbus' population. Figure 8 contains 1,000 black circles, indicating the 1,000 simulated plans, and a red star representing the Enacted Plan. Each plan is plotted in this Figure along the horizontal axis according to the Republican vote share of the plan's district containing the most amount of Columbus' population. The vertical axis then reports the Republican vote share of the plan's district containing the second-most amount of Columbus' population.

63. Columbus' voters are heavily Democratic, while the surrounding suburbs in Franklin County are more Republican. As Figure 8 makes clear, there is a direct tradeoff between the Republican vote shares of the two Columbus districts in any congressional plan. Increasing the number of Republican voters in one Columbus district necessarily means decreasing Republican voters in the other Columbus district. Figure 8 also illustrates that among the 1,000 simulated plans, the district containing the most sizeable portion of Columbus' population is more heavily Democratic, with around a 30-40% Republican vote share, while the district containing the second-most sizeable portion of Columbus' population contains a Republican vote share of generally between 41-51%.

64. Figure 8 reveals that the Enacted Plan's two Columbus-area districts are clear partisan outliers: CD-3, which contains most of Columbus' population, is more heavily Democratic than all 1,000 of the simulated plans' districts with the most Columbus population. Consequently, the Enacted Plan's CD-15, which contains the second-most of Columbus' population, is more heavily Republican than 98% of the simulated plans' districts with the second-most Columbus population. Specifically, CD-15 has a 53.9% Republican vote share, while by contrast, the vast majority of the simulated districts with the second-most Columbus population are either Democratic-favoring districts or have Republican vote shares very close to 50%.

Figure 8:
Comparisons of Columbus–Area Districts in the Enacted Plan and 1,000 Computer–Simulated Plans



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65. Figures 9 and 10 illustrate in detail how statistically extreme the partisanship of the Enacted Plan's two Columbus-area districts are: Figure 9 shows that the Enacted Plan's CD-3 packs together Democratic voters to a more extreme extent than every simulated plan's district containing the most Columbus population. In most simulated plans, this district would generally range from 32% to 40% Republican vote share. The Enacted Plan's CD-3 has a Republican vote share of 29.7%, which is lower than in all 1,000 of the simulated plans.

66. Figure 10 similarly illustrates how statistically extreme the partisanship of the Enacted Plan's CD-15 is. CD-15 contains a Republican vote share of 53.9%, while the most common outcome in the simulated plans' districts containing the second-most of Columbus' population is 43%-44%. Over 98% of these simulated districts are less Republican-favorable than the Enacted Plan's CD-15. It is therefore clear that CD-15 and CD-3 were drawn in order to create a more Republican-favorable outcome than would normally emerge from a districting process following the Ohio Constitution's Article XIX requirements.

Figure 9: District Containing the Most of Columbus' Population in the Enacted Plan and 1,000 Computer–Simulated Plans

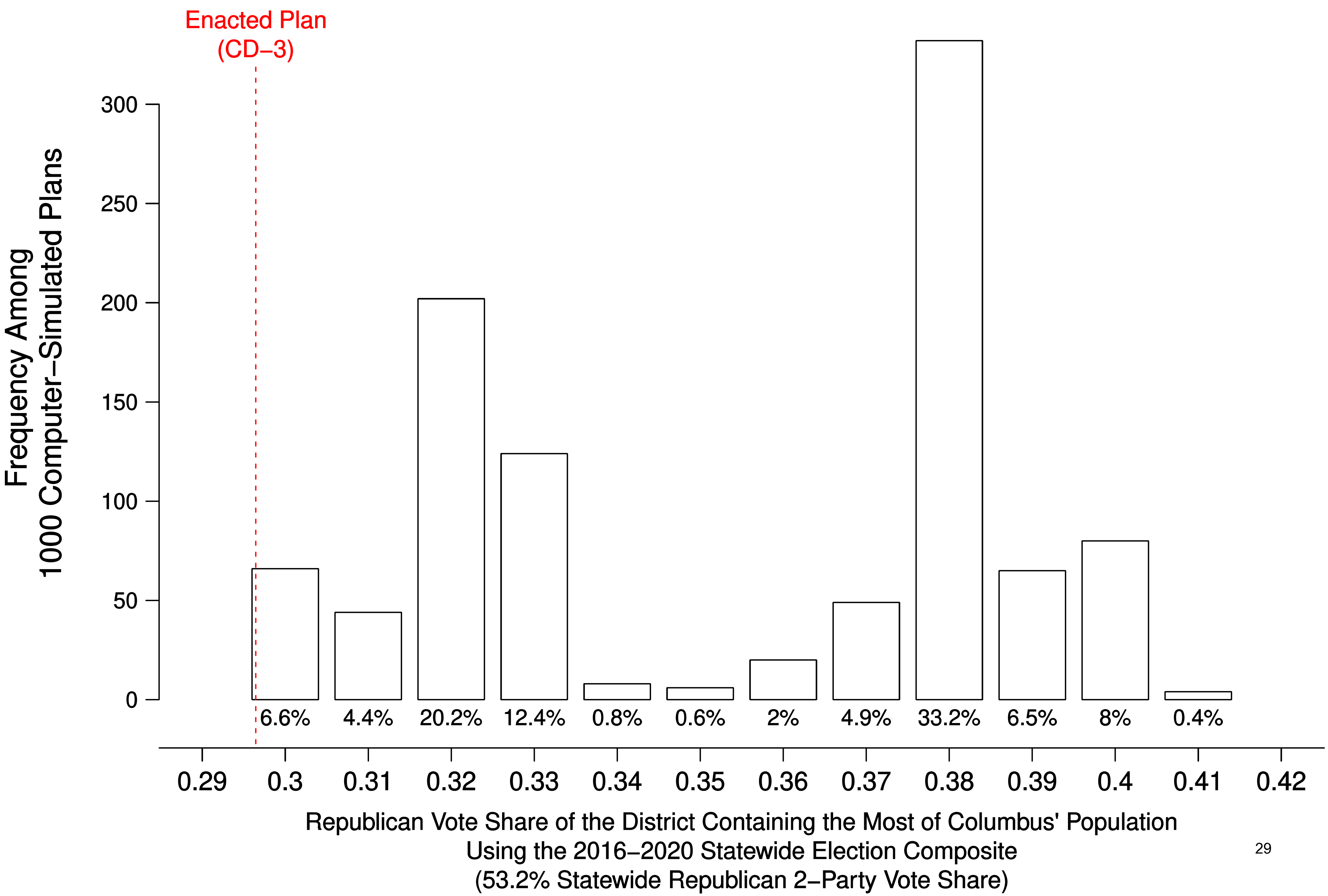

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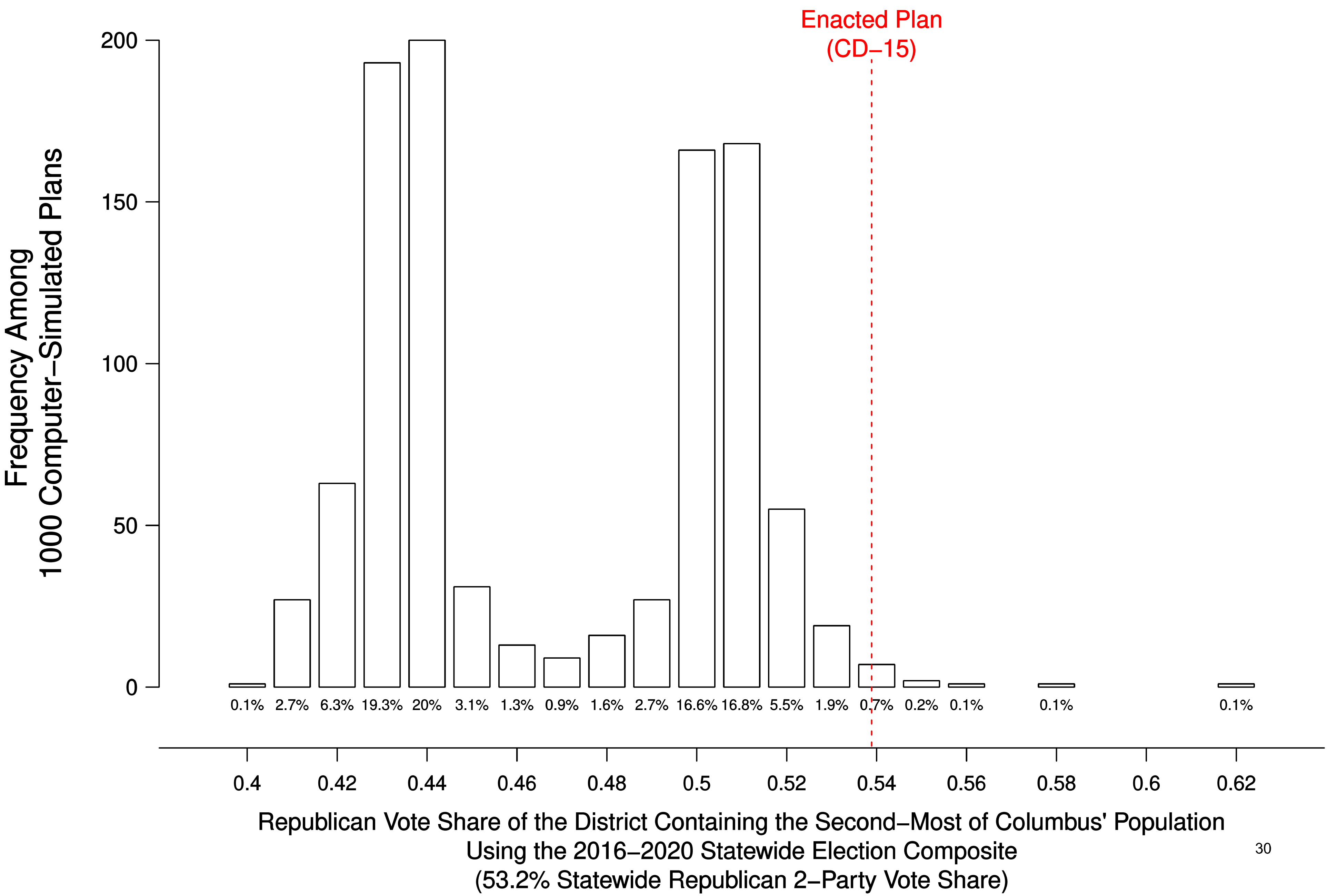
Figure 10: District Containing the Second–Most of Columbus' Population in the Enacted Plan and 1,000 Computer–Simulated Plans



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67. Finally, Figures 11 and 12 illustrate *how* the General Assembly was able to create such statistically anomalous outcomes with respect to the partisan characteristics of CD-3 and CD-15. In Figure 11, the vertical axis compares the Polsby-Popper compactness scores of the district containing the most of Columbus' population in the Enacted Plan and in the computer-simulated plans. As explained earlier, higher Polsby-Popper scores indicate greater district compactness. The horizontal axis reports the Republican vote shares of these Columbus districts. Figure 11 reveals that CD-3 is less geographically compact than nearly every computer-simulated district containing the most of Columbus' population. Hence, it is clear that the Enacted Plan was able to create an anomalously extreme Democratic district in CD-3 by sacrificing the geographic compactness of the district. It is also clear that CD-3 is much less compact than Columbus-area districts that would reasonably emerge from a map-drawing process following the Ohio Constitution's Article XIX requirements.

68. Figure 12 illustrates a similar comparison of the compactness scores of the district containing the second-most of Columbus' population in the Enacted Plan and in the simulated plans. Once again, the horizontal axis reports the Republican vote shares of these districts. Figure 12 reveals that CD-15 is less geographically compact than nearly every computer-simulated district containing the most of Columbus' population. Hence, it is clear that the Enacted Plan was able to create an anomalous 53.9% Republican district in CD-15 by sacrificing the geographic compactness of the district. It is also clear that CD-15 is much less compact than Columbus-area districts that would reasonably emerge from a map-drawing process following the Ohio Constitution's Article XIX requirements.

69. I therefore conclude that the Enacted Plan's Columbus-area districts, CD-3 and CD-15, were collectively drawn in a manner that clearly favors the Republican Party, and these two districts are clearly much less geographically compact than one could reasonably expect from a districting process that follows the districting requirements of the Ohio Constitution.

Figure 11: Comparisons of the District Containing the Most of Columbus' Population in the Enacted Plan and 1,000 Computer−Simulated Plans

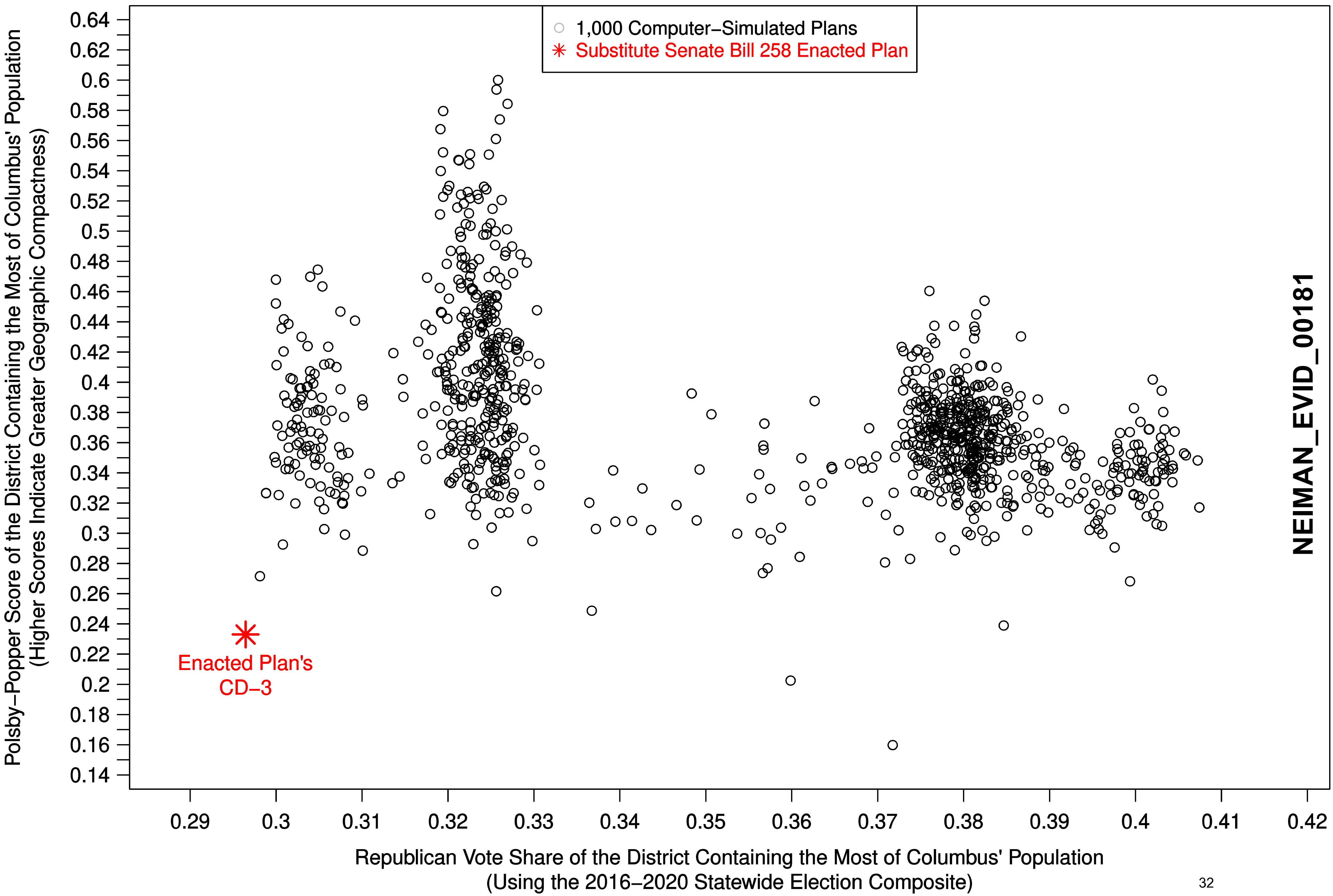

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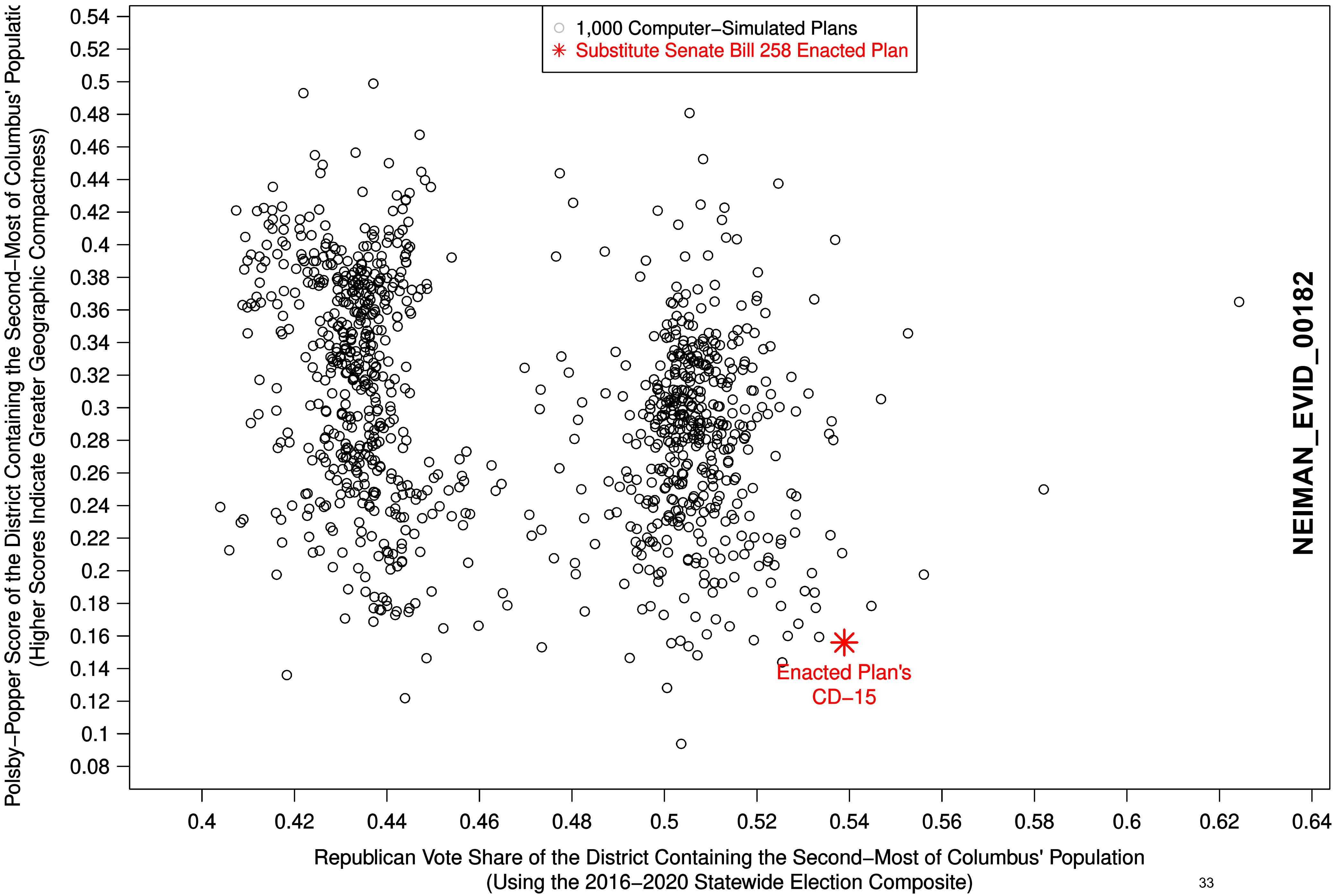
Figure 12:
Comparisons of the District Containing the Second–Most of Columbus' Population in the Enacted Plan and 1,000 Computer–Simulated Plans



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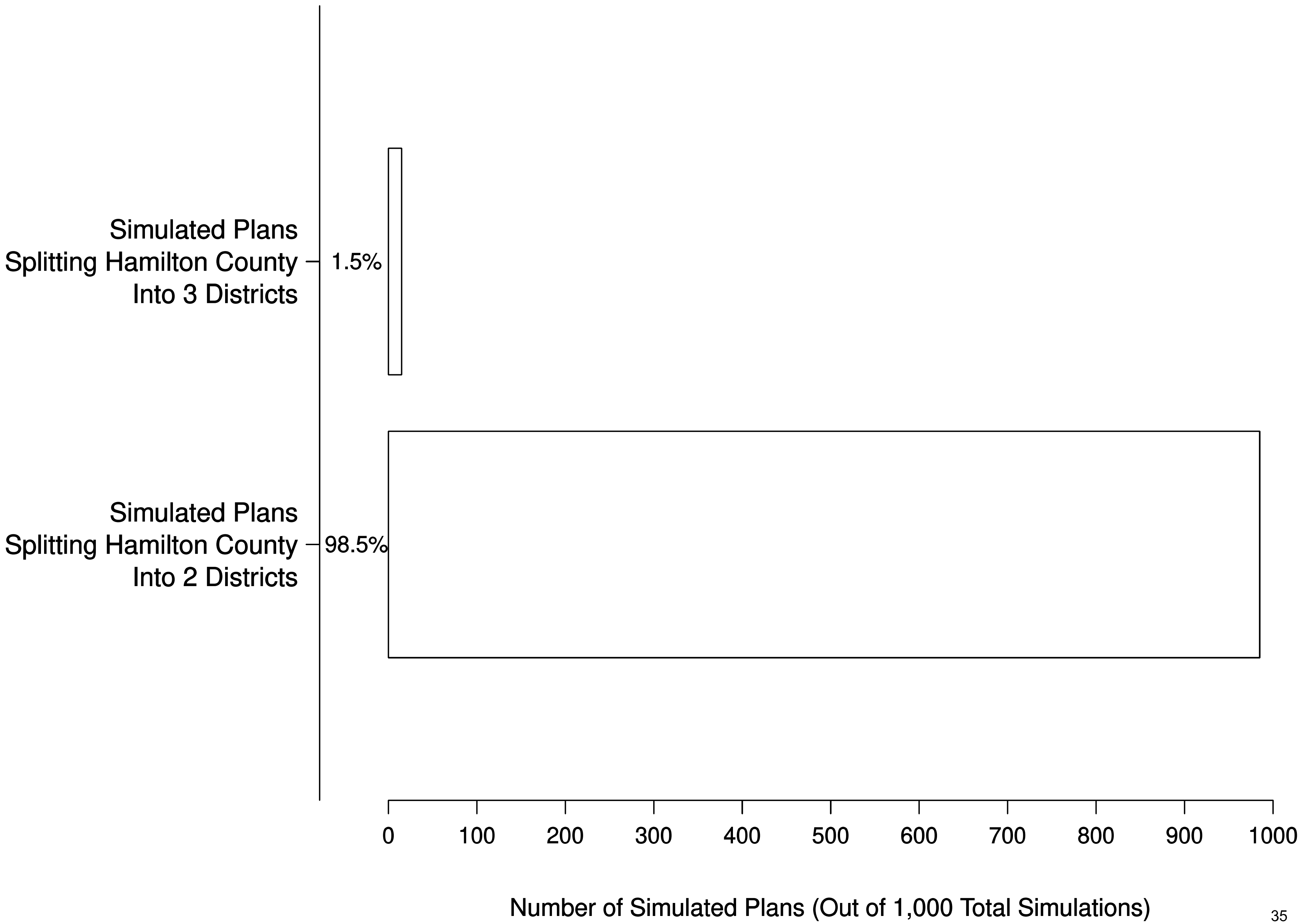
XI. THE ENACTED PLAN'S DISTRICTS IN HAMILTON COUNTY

70. Hamilton County's population exceeds the required population for a single congressional district, so splitting Hamilton County is clearly permissible under the Ohio Constitution. However, Section (1)(C)(3) requires that the congressional plan not "unduly split counties."

71. To follow this constitutional requirement, my computer simulation algorithm split counties only for the purpose of equalizing district populations. As explained earlier in this report, the computer-simulated plans, as well as the Enacted Plan, always contain exactly 14 total county splits, with any county divided into three districts being counted as two total county splits. Hence, the Enacted Plan certainly does not create an excessively large number of total county splits *statewide*.

72. However, the Enacted Plan's splitting of Hamilton County into three districts is statistically anomalous when compared to the 1,000 simulated plans' districts in Hamilton County. As Figure 13 illustrates, only 1.3% of the simulated plans similarly split Hamilton County into three districts. The remaining 98.7% of the simulated plans only split Hamilton County into two districts. This finding, when combined with my findings below regarding the extreme partisanship and the low compactness score of the Enacted Plan's Cincinnati-based district, collectively indicate a districting process in the Hamilton County area that was inconsistent with the Article XIX, Section (1)(C)(3) requirements. Below, I detail my findings regarding the extreme partisanship and the low compactness score of the Enacted Plan's Cincinnati-based district.

Figure 13: Splits of Hamilton County in Computer–Simulated Plans



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73. In the Enacted Plan, as in all 1,000 computer-simulated plans, Cincinnati is always kept together in a single district, following Article XIX, Section 2(B)(4)(b) of the Ohio Constitution. I analyzed and compared these Cincinnati-based districts in the simulated plans and in the Enacted Plan with respect to their partisan characteristics and their compactness scores.

74. Figure 14a and Figure 14b contain two maps. The map in Figure 14a depicts the boundaries of the Enacted Plan's CD-1. The map in Figure 14b depicts the boundaries of the Cincinnati-based district that had the highest average Polsby-Popper compactness scores among all 1,000 computer-simulated plans. Figures 14a and 14b also report the Polsby-Popper scores and Republican vote shares of these two districts in the Enacted Plan and in the computer-simulated plan.

Figure 14a:
CD–1 of the 2021 Enacted Plan:

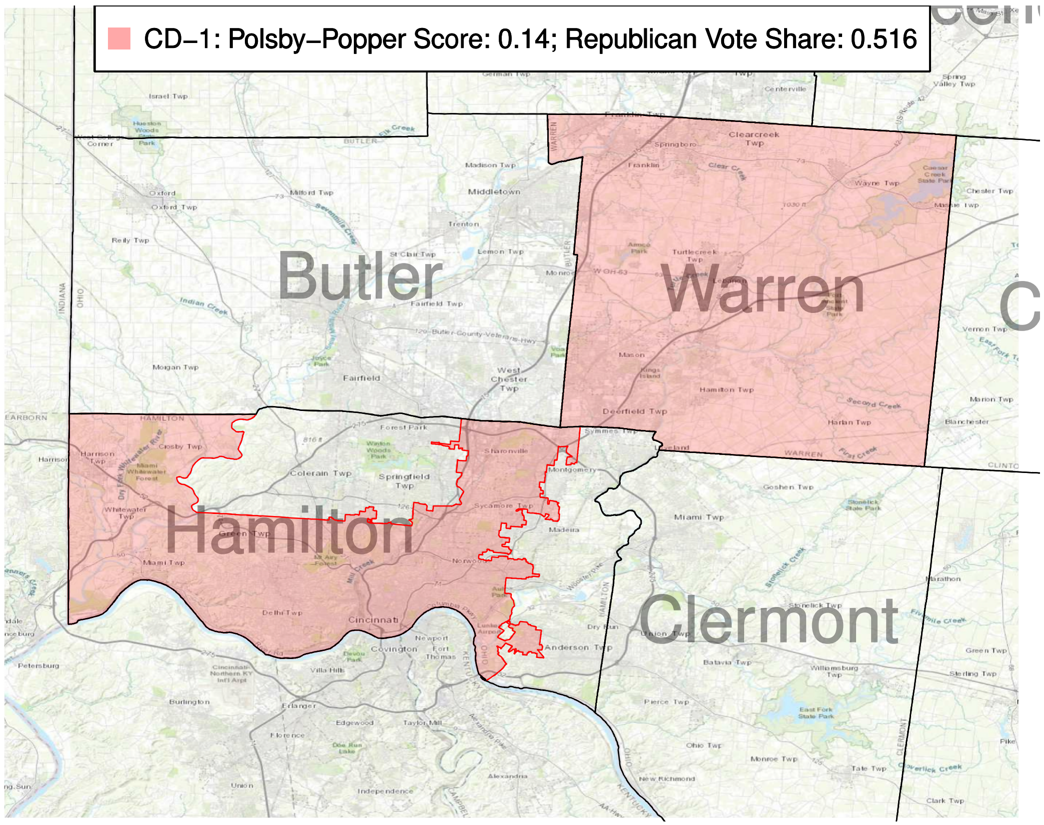
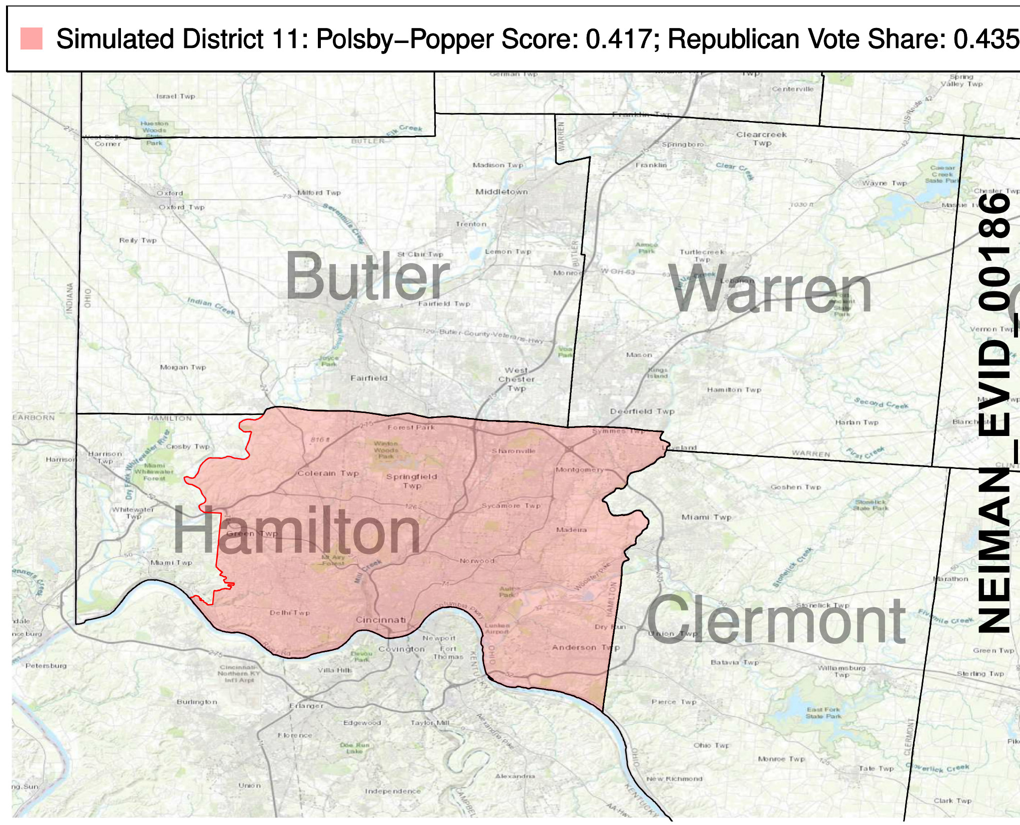


Figure 14b: Computer–Simulated Plan with the Most Compact Cincinnati District (Simulated Plan #639 of 1000):



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75. Figure 15 reports the Republican vote share of every computer-simulated district containing Cincinnati, as well as the Enacted Plan's Cincinnati-based district (CD-1). Cincinnati is a heavily Democratic city surrounded by Republican suburbs in Hamilton County. Thus, it should not be surprising that the vast majority of the simulated districts containing all of Cincinnati are also Democratic-favoring districts. In fact, over 80% of the Cincinnati-based simulated districts have a Republican vote share of 45% or lower, indicating that they clearly favor Democratic candidates by a safe margin. The vast majority of these computer-simulated districts containing Cincinnati are also fully within Hamilton County, following the Section (1)(C)(3) prohibition against unduly splitting counties.

76. But the Enacted Plan's CD-1 is a statistical outlier in terms of its partisanship when compared to these computer-simulated Cincinnati districts. The Enacted Plan's CD-1 has a Republican vote share of 51.6%, which is higher than over 98% of the simulated districts containing Cincinnati. The Enacted Plan's CD-1 achieves this unnaturally high Republican vote share by splitting Hamilton County into three districts and combining the Cincinnati portion of Hamilton County with Warren County, whose voters are far more Republican than Cincinnati's, thereby increasing the Republican vote share of CD-1 to 51.6%.

77. By connecting Warren County with the fragmented portion of Hamilton County containing Cincinnati, CD-1 of the Enacted Plan also exhibits a very non-compact shape, as evidenced by a compactness score much lower than the Cincinnati-based district in virtually all of the computer-simulated districts. Figure 16 compares the Polsby-Popper compactness score of the Enacted Plan's CD-1 to the Polsby-Popper score of all 1,000 of the Cincinnati-based simulated districts. This Figure illustrates that the vast majority of the simulated plans create a Cincinnati district a Polsby-Popper score of 0.34 to 0.42. Over 99% of the simulated districts containing Cincinnati have a higher Polsby-Popper score than CD-1. Hence, it is clear that the geographic shape of the Enacted Plan's CD-1 does not reflect a reasonable attempt to draw geographically compact districts in the Cincinnati area. Instead, I concluded that CD-1 was drawn to create a Republican-favorable district in Cincinnati, and this effort resulted in a district that was more favorable to the Republican Party than the Cincinnati district in over 97% of the computer-simulated plans.

Figure 15:
Comparisons of Cincinnati's District in the Enacted Plan and 1,000 Computer–Simulated Plans

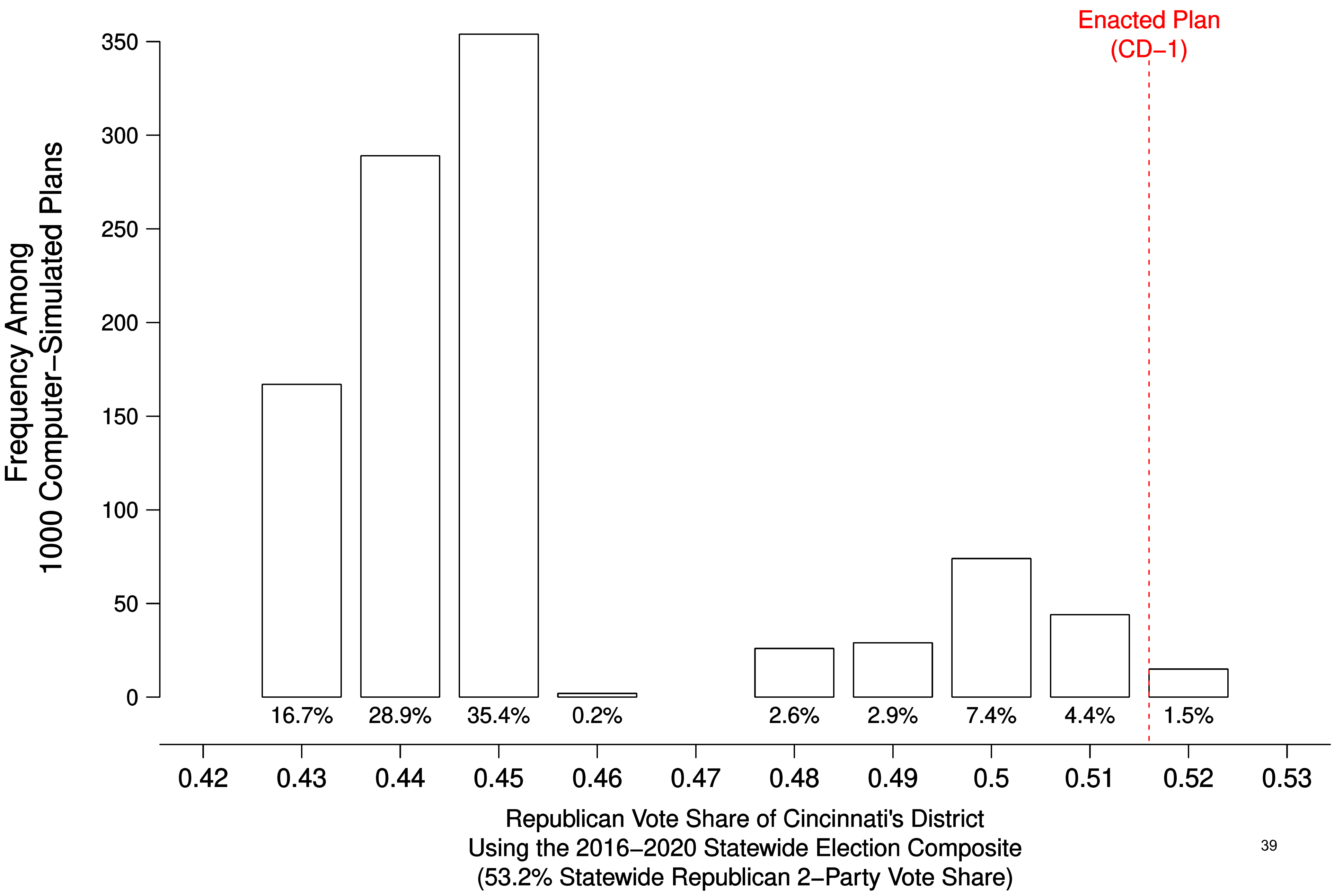

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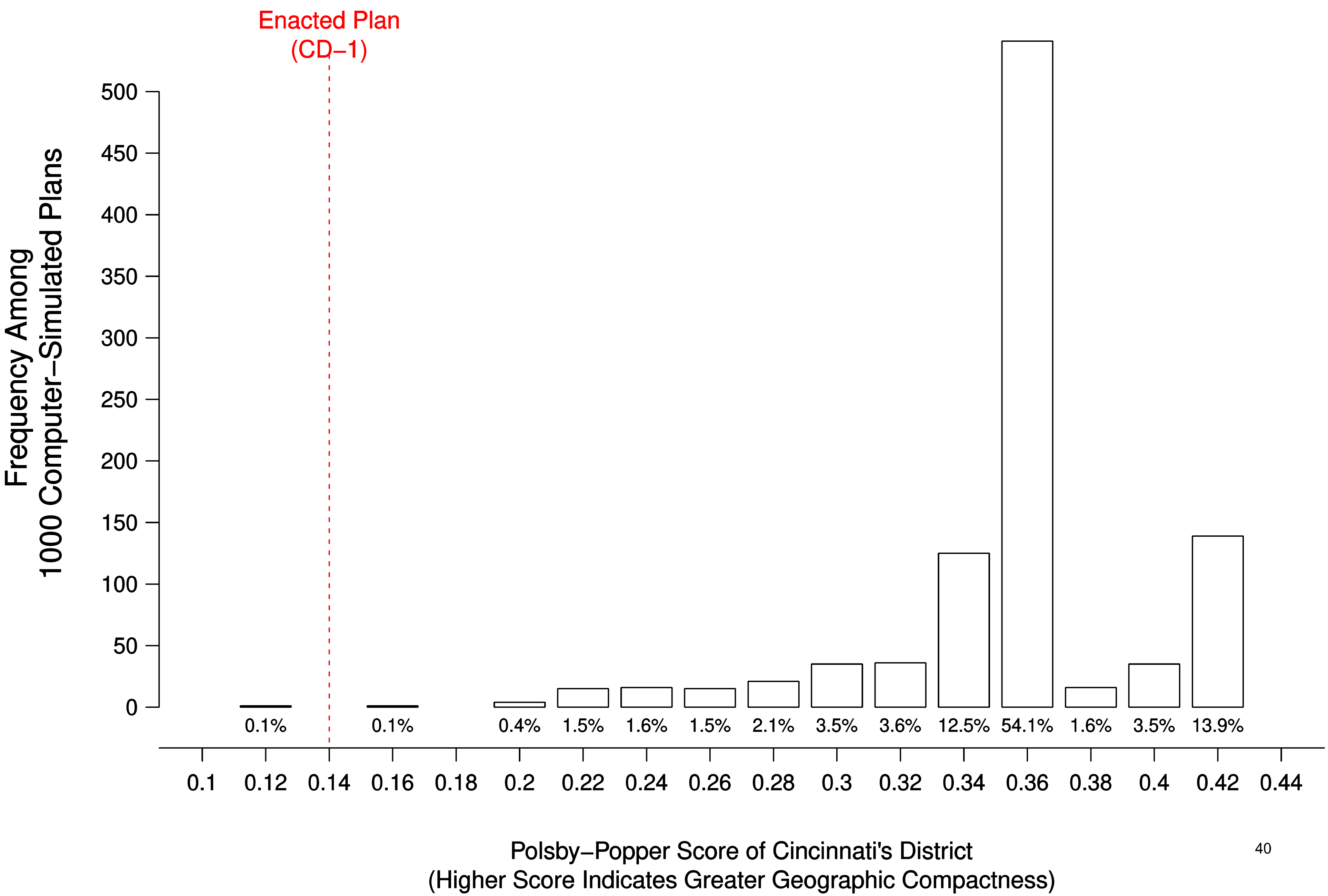
Figure 16:
Comparisons of Cincinnati's District in the Enacted Plan and 1,000 Computer–Simulated Plans



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XII. THE ENACTED PLAN'S DISTRICTS IN CUYAHOGA COUNTY

78. Cuyahoga County's population exceeds the required population for a single congressional district, so the county will generally be split into either two or three districts, with one of these districts containing all of Cleveland (Article XIX, Section 2(B)(4)(b)). Across the Enacted Plan and each of the 1,000 computer-simulated plans, I compare the one district in each plan containing all of Cleveland.

79. Figure 17a and Figure 17b contain two maps. The map in Figure 17a depicts the boundaries of the Enacted Plan's Cleveland-based district, CD-11. The map in Figure 17b depicts the boundaries of the Cleveland-based district that had the highest Polsby-Popper compactness score among all 1,000 computer-simulated plans. Figures 17a and 17b also report the Polsby-Popper scores and Republican vote shares of these districts from the Enacted Plan and the computer-simulated plan.

Figure 17a: CD–11 of the 2021 Enacted Plan:

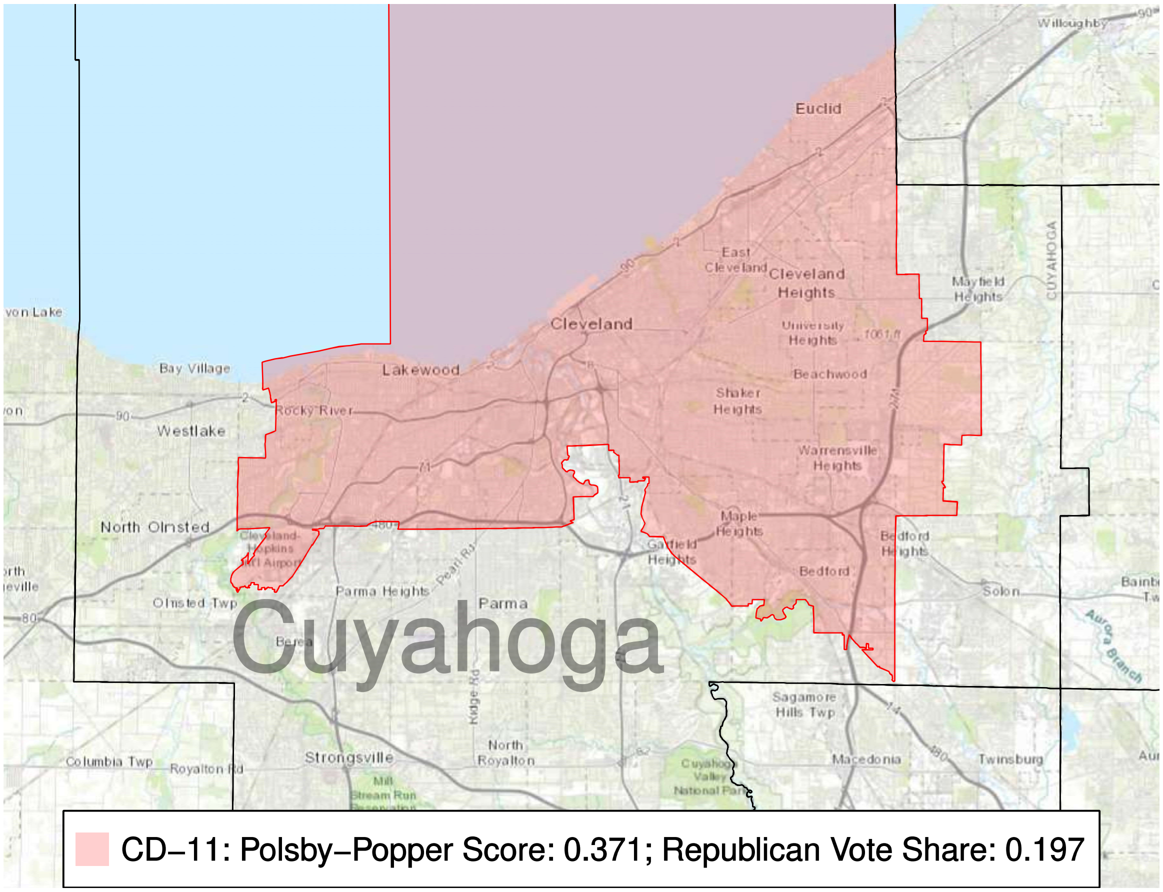
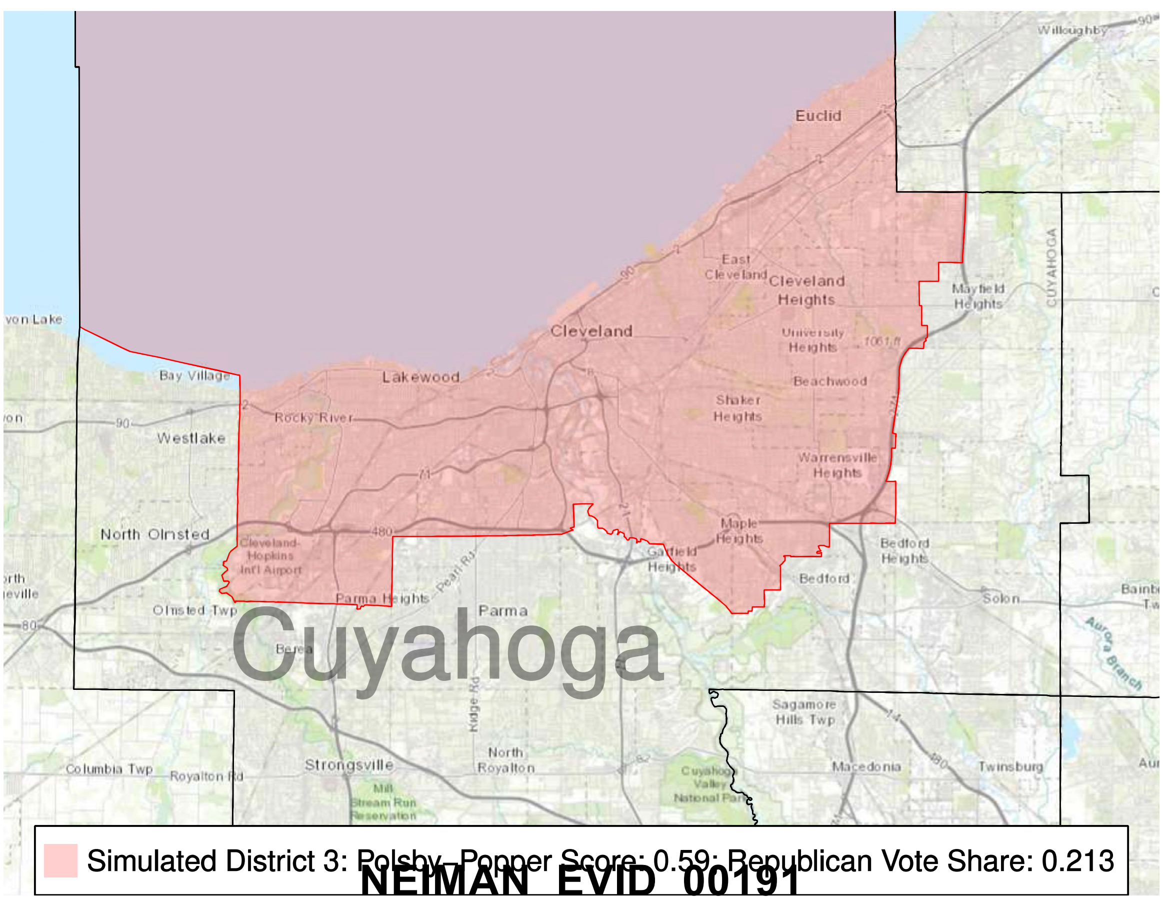


Figure 17b: Computer–Simulated Plan with the Most Compact Cleveland District (Simulated Plan #440 of 1000):



80. For the Enacted Plan and the 1,000 simulated plans, Figure 18 compares the Enacted Plan's CD-11 to the 1,000 simulated plans' Cleveland-based districts with respect to their partisanship and their Polsby-Popper compactness scores. Figure 18 contains 1,000 black circles, indicating the 1,000 simulated plans, and a red star representing the Enacted Plan. Each plan is plotted in this Figure along the horizontal axis according to the district's Republican vote share. The vertical axis then reports the district's Polsby-Popper compactness score, with higher scores indicating greater district compactness.

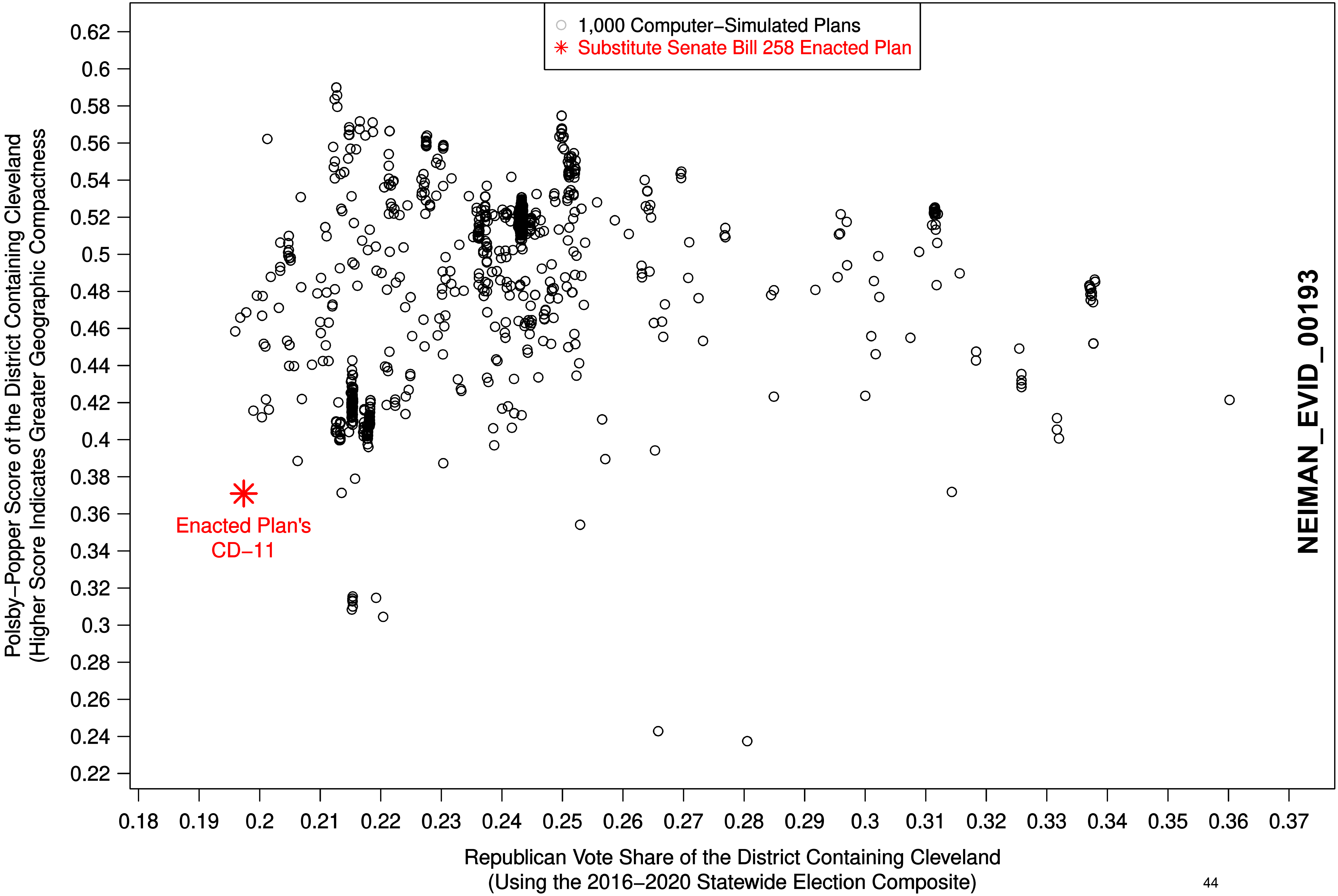
81. Cleveland voters are heavily Democratic, so any Cleveland-based district will always have a significant Democratic majority. As the 1,000 simulated districts in Figure 18 illustrate, there is no reasonable possibility that the Cleveland-based district could be drawn to have a Republican majority.

82. Instead, the Enacted Plan's CD-11 creates an extreme partisan outlier in the opposite direction. CD-11 has a Republican vote share of only 19.7%, which is lower than the Cleveland-based district in 99.8% of the computer-simulated plans. Figure 18 makes clear that Democratic voters are packed together in CD-11 to a more extreme extent than naturally occurs in virtually all of the simulated plans, which were produced by following the districting criteria mandated in Ohio's Constitution.

83. The vertical axis of Figure 18 reveals that CD-11's Polsby-Popper compactness score of 0.371 is lower than the Polsby-Popper score of 98.8% of the simulated Cleveland-based districts. The vast majority of the Cleveland-based simulated districts have Polsby-Popper scores generally ranging from 0.4 to 0.55. I therefore concluded that the Enacted Plan's CD-11 was not drawn by a districting process following Section (1)(C)(3)'s requirement regarding district compactness. CD-11 is clearly less geographically compact than is reasonable for a Cleveland-based district, and the district appears instead to have been drawn in order to create an extreme packing of Democratic voters that would not have naturally emerged from drawing a more compact Cleveland-based district.

84. I therefore conclude that the Enacted Plan's Cleveland-based districts, CD-11, was not drawn in a manner that is consistent with the Ohio Constitution's Article XIX, Section (1)(C)(3) requirements. This district was drawn in a manner that clearly favors the Republican Party by unnaturally packing together Democratic voters to an extent that is not explained by Cuyahoga County's political geography. This unnatural packing of Democrats was accomplished by drawing districting lines in CD-11 that exhibit a lower Polsby-Popper compactness score than is reasonably possible for the Cleveland-based district in the 1,000 computer-simulated plans.

Figure 18:
Comparisons of Cleveland's District in the Enacted Plan and 1,000 Computer−Simulated Plans



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XIII. THE RELATIONSHIP BETWEEN COMPETITIVENESS AND PARTISANSHIP IN THE ENACTED PLAN

85. Relators' counsel also asked me to analyze how the Enacted Plan's competitive districts affect the partisan characteristics of the plan. For the purpose of this inquiry, I used the 2016-2020 Statewide Election Composite and defined a "competitive district" the same way that the map-drawers of the Enacted Plan did: that is, a "competitive district" is one with a two-party Republican vote share between 46% and 54%.[14]

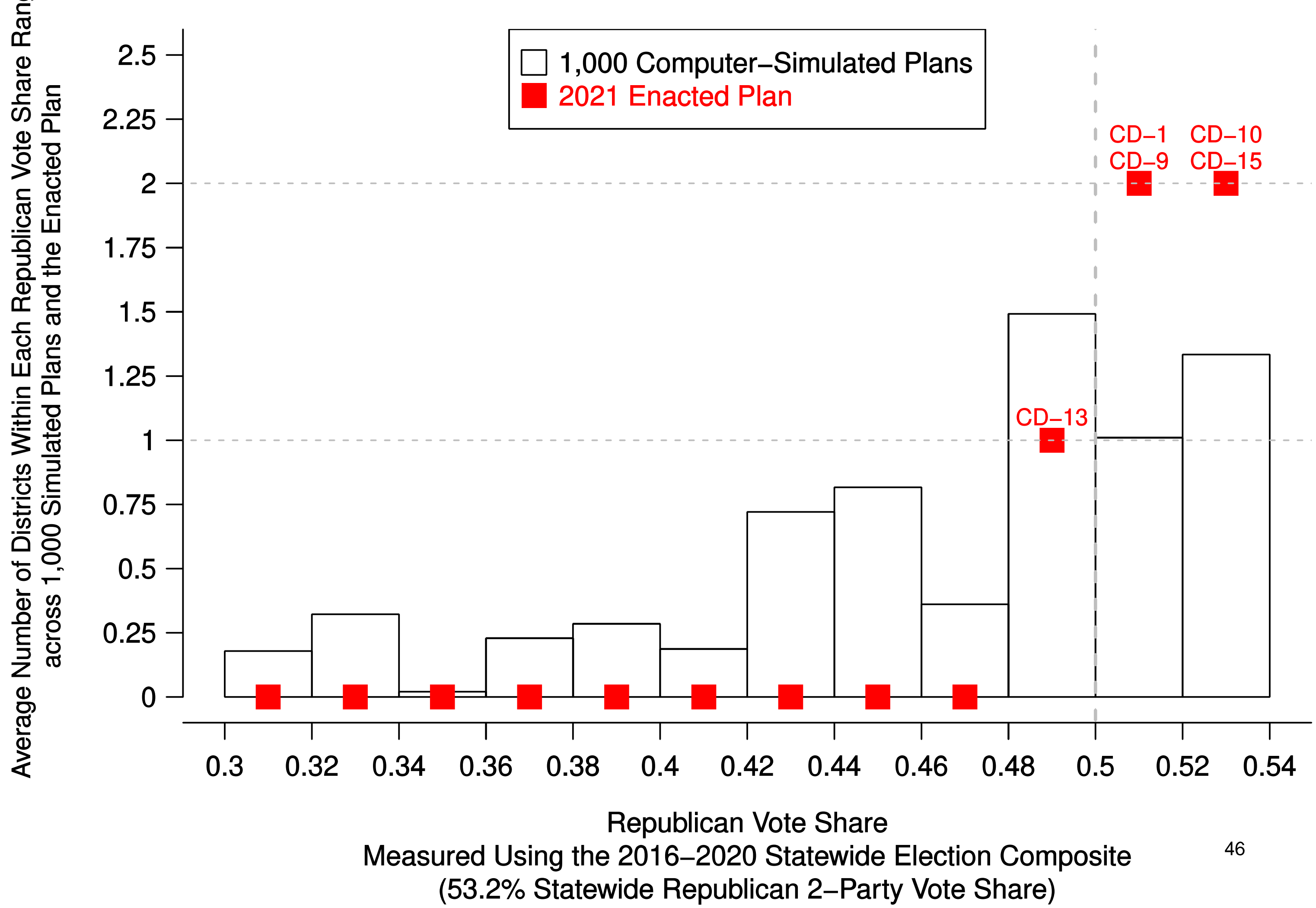
86. The Enacted Plan contains five competitive districts using this definition: CD-1 (51.6% Republican vote share), CD-9 (50.3%), CD-10 (53.3%), CD-13 (49.2%), and CD-15 (53.9%). Among these five competitive districts, four are Republican-favoring, while one is Democratic-favoring.

87. How does the number of Republican-favoring and Democratic-favoring competitive districts in the Enacted Plan compare to the number of such districts in the 1,000 computer-simulated plans? To analyze this question, I counted the average number of districts in each computer-simulated plan containing a Republican vote share within the range of 52-54%, then 50-52%, then 48-50%, and so on. I also counted the number of Enacted Plan districts within each of these two-percent ranges of partisanship.

88. Figure 19 summarizes this analysis. As an example, the last column in Figure 19 reports the number of districts in the Enacted and the simulated plans with a Republican vote share in the range of 52-54%. The red square reports the number of Enacted Plan districts in this partisanship range, while the black bar reports the average number of districts in the 1,000 simulated plans within this partisanship range. Similarly, the next-to-last column in this Figure compares the number of Enacted Plan districts and average number of simulated plan districts in the range of 50-52% Republican vote share.

[14] *See* The Ohio Senate, Local Government and Elections Committee, https://www.ohiosenate.gov/committees/local-government-and-elections/document-archive (testimony of Senator Rob McColley on November 16, 2021).

Figure 19:
Comparisons of 2021 Enacted Plan to 1,000 Computer−Simulated Plans
On Number of Districts Within Each Partisanship Range



89. These final two columns reveal that the Enacted Plan contains more Republican-favoring competitive districts than in the average computer-simulated plan. The Enacted Plan contains two districts within the 50-52% Republican vote share range, while the average simulated plan contains only 1.0. Similarly, the Enacted Plan contains two districts within the 52-54% Republican vote share range, while the simulated plan contains only 1.3.

90. But Figure 19 reveals the opposite finding with respect to Democratic-favoring competitive districts. For every single two-percent interval analyzed in this Figure, the Enacted Plan contains fewer Democratic-favoring competitive districts than the average simulated plan. For example, the average simulated plan contains 1.5 districts within the 48-50% Republican vote share range, but the Enacted Plan contains only 1. Similarly, the average simulated plan contains 0.4 districts within the 46-50% Republican vote share range, but the Enacted Plan contains none.

91. In fact, the same finding holds for every two-percent partisanship range from 30 to 46% Republican vote share. The Enacted Plan contains zero Democratic-favoring districts within this range of partisanship, while the average simulated plan contains some districts within this range.

92. Overall, Figure 19 reveals a clear partisan asymmetry in the Enacted Plan's competitive districts when compared to the competitive districts in the computer-simulated plans. The Enacted Plan certainly contains more Republican-favoring competitive districts than the average simulated plan does. But the Enacted Plan created these Republican-favoring competitive districts at the expense of Democratic-favoring competitive districts, as well as safe Democratic-favoring districts (with a Republican vote share under 46%). In other words, the Enacted Plan created far more Republican-favoring competitive districts with Republican vote shares of 50-54%, compared to the average simulated plan. And this relative abundance of Republican-favoring competitive districts came at the expense of having relatively fewer Democratic-favoring districts than appear in the average computer-simulated plan.

XIV. OHIO'S POLITICAL GEOGRAPHY DID NOT CAUSE THE ENACTED PLAN'S EXTREME PARTISAN BIAS

93. How does Ohio's political geography affect the partisan characteristics of the 2021 Enacted Plan? Democratic voters tend to be geographically concentrated in the urban cores of several of the state's largest cities, including Columbus, Cleveland, Cincinnati, Toledo, Akron, and Dayton. As I have explained in my prior academic research,[15] these large urban clusters of Democratic voters, combined with the common districting principle of drawing geographically compact districts, can sometimes result in urban districts that "naturally" pack together Democratic voters, thus boosting the Republican vote share of other surrounding suburban and rural districts.

[15] Jowei Chen and Jonathan Rodden, 2013. "Unintentional Gerrymandering: Political Geography and Electoral Bias in Legislatures" Quarterly Journal of Political Science, 8(3): 239-269; Jowei Chen and David Cottrell, 2016. "Evaluating Partisan Gains from Congressional Gerrymandering: Using Computer Simulations to Estimate the Effect of Gerrymandering in the U.S. House." Electoral Studies, Vol. 44, No. 4: 329-430.

94. More importantly, my prior academic research explained how I can estimate the precise level of electoral bias in districting caused by a state's unique political geography: I programmed a computer algorithm that draws districting plans using Ohio's unique political geography, including the state's census population data and political subdivision boundaries. In this report, I have also programmed the algorithm to follow the Ohio Constitution's Article XIX districting criteria. I then analyzed the partisan characteristics of the simulated districting plans using Ohio's precinct-level voting data from past elections. Hence, the entire premise of conducting districting simulations is to fully account for Ohio's unique political geography, its political subdivision boundaries, and its unique constitutional districting requirements.

95. This districting simulation analysis allowed me to identify how much of the electoral bias in Ohio's 2021 Enacted Congressional Plan is caused by Ohio's political geography and how much is caused by the map-drawer's intentional efforts to favor one political party over the other. Ohio's natural political geography, combined with the Ohio's Constitution's Article XIX districting requirements, almost never resulted in simulated congressional plans containing 12 Republican-favoring districts out of 15 total districts.

96. The 2021 Enacted Plan's creation of 12 Republican-favoring districts goes well beyond any "natural" level of electoral bias caused by Ohio's political geography or the political composition of the state's voters. The Enacted Plan is a statistical outlier in terms of its partisan characteristics when compared to the 1,000 computer-simulated plans. The Enacted Plan creates more Republican-favoring districts than 98.7% of the simulated plans. This extreme, additional level of partisan bias in the 2021 Enacted Plan can be directly attributed to the map-drawer's clear efforts to favor the Republican Party. This additional level of partisan bias was not caused by Ohio's political geography.

Jowei Chen
____
Dr. Jowei Chen

JURAT

STATE OF FLORIDA
COUNTY OF SAINT LUCIE

Sworn to before me this 10th day of December 2021.

By Jowei Chen

Form of ID Produced: Driver's License

____
Notary Public Darrell Dwayne Evans

My commission expires ___01/19/2025_______________________

NOTARY PUBLIC • STATE OF FLORIDA •

DARRELL DWAYNE EVANS
Notary Public - State of Florida
Commission # HH 81836
Expires on January 19, 2025

Notarized online using audio-video communication

Appendix

Figure A1: Comparison of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans: Districts' Republican Vote Share Measured Using the 2016 US President Election Results

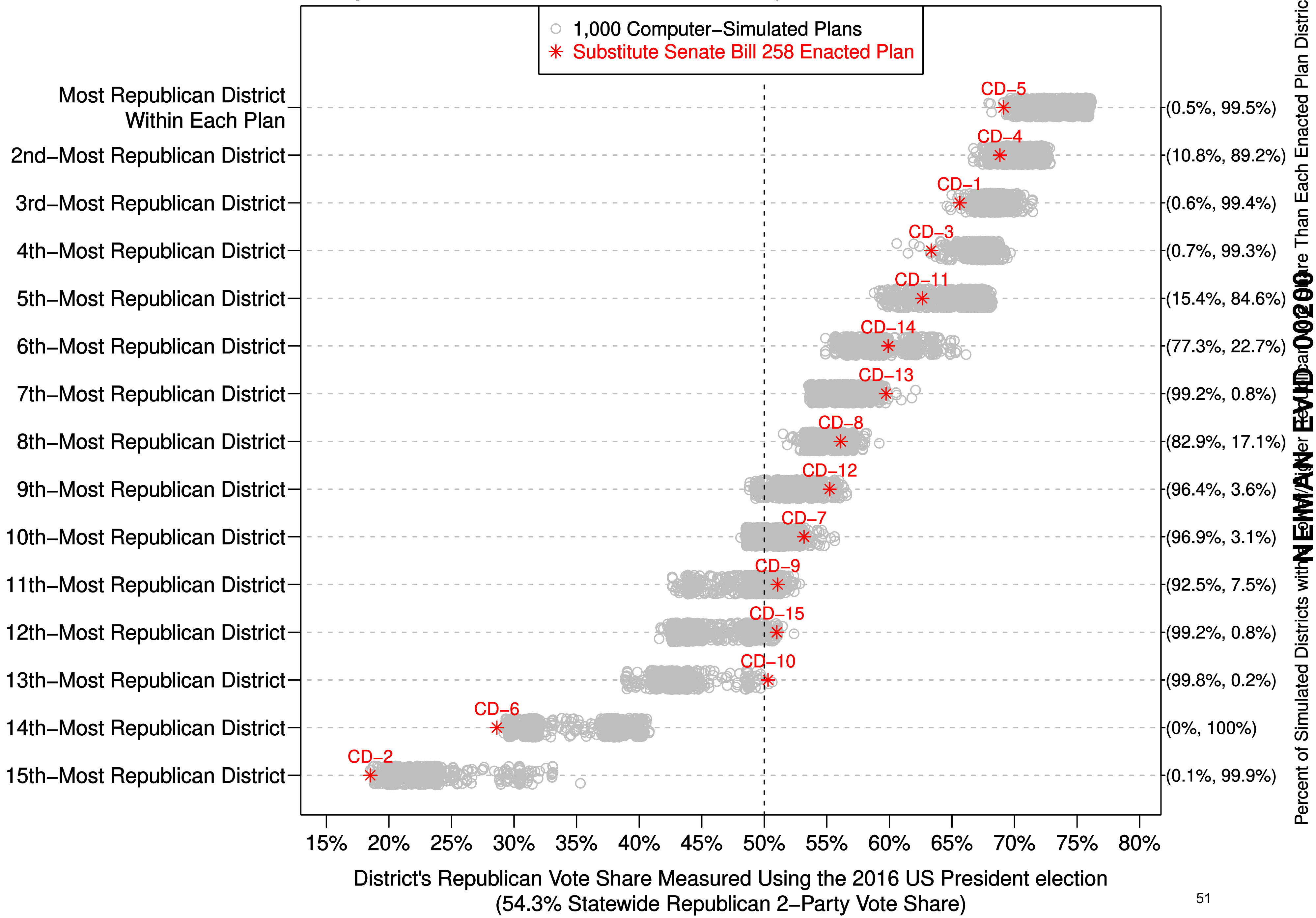


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Figure A2: Comparison of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans: Districts' Republican Vote Share Measured Using the 2016 US Senator Election Results

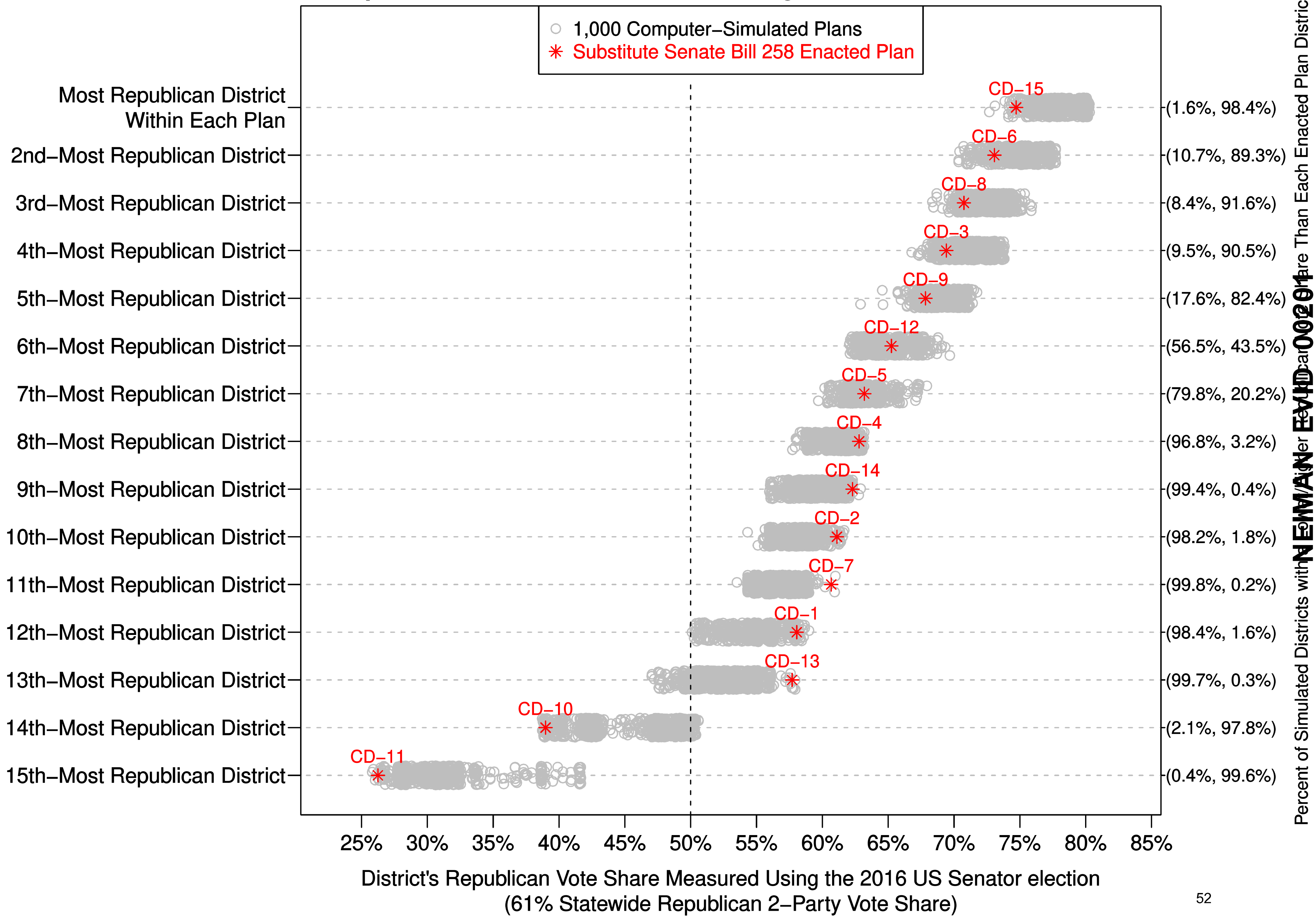

Figure A3: Comparison of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans: Districts' Republican Vote Share Measured Using the 2018 Attorney General Election Results

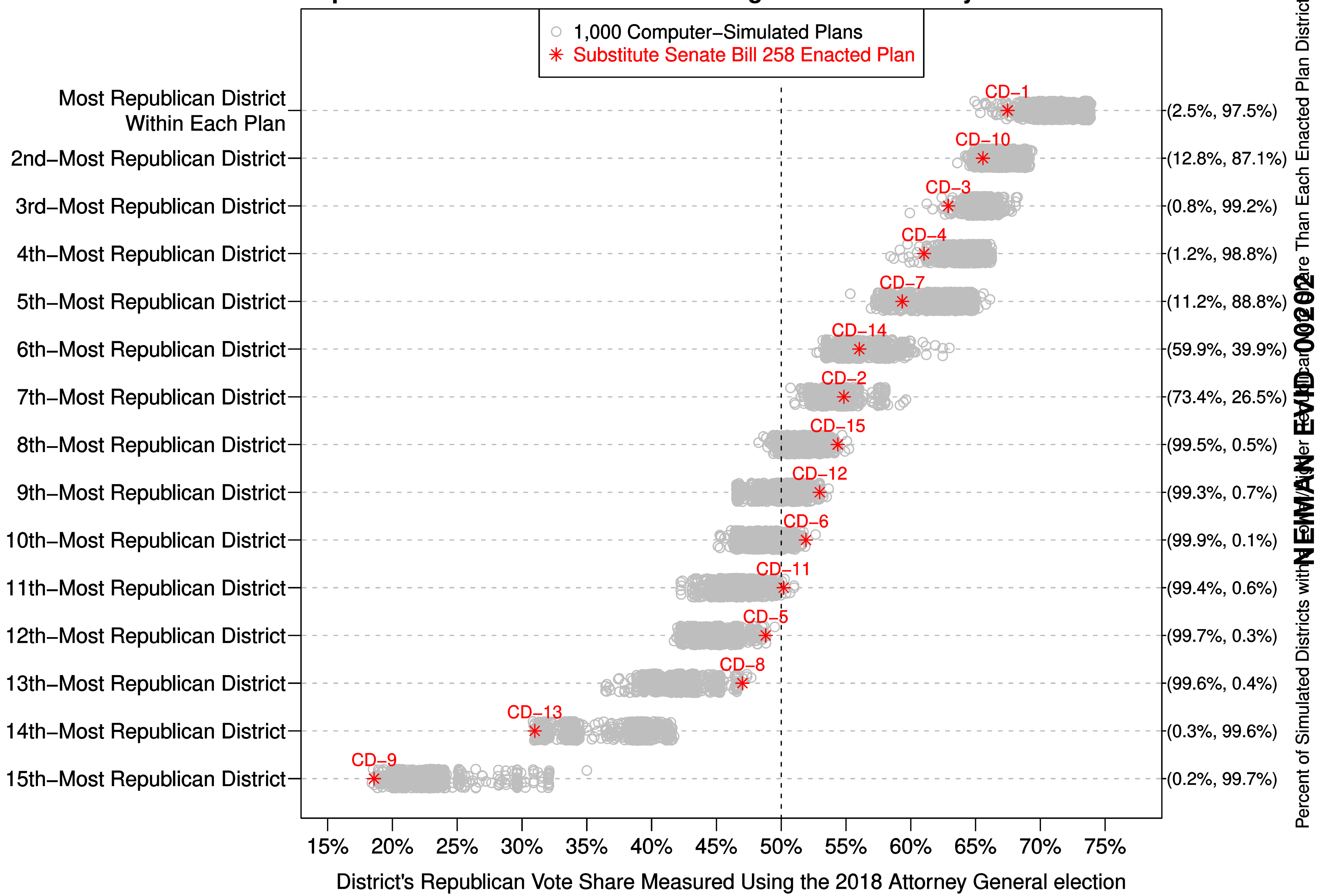

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Figure A4: Comparison of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans: Districts' Republican Vote Share Measured Using the 2018 Auditor Election Results

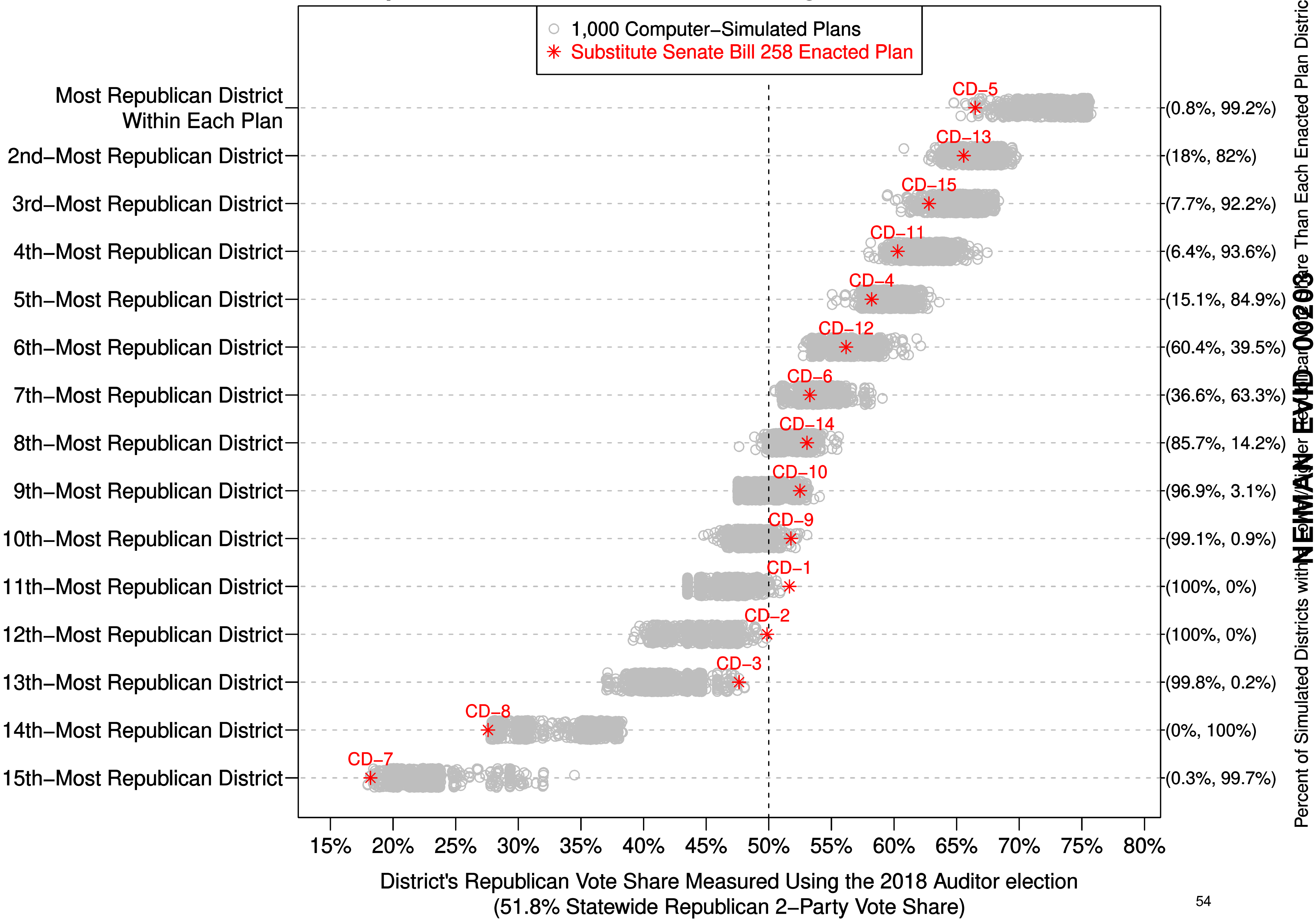

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Figure A5: Comparison of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer−Simulated Plans: Districts' Republican Vote Share Measured Using the 2018 Governor Election Results

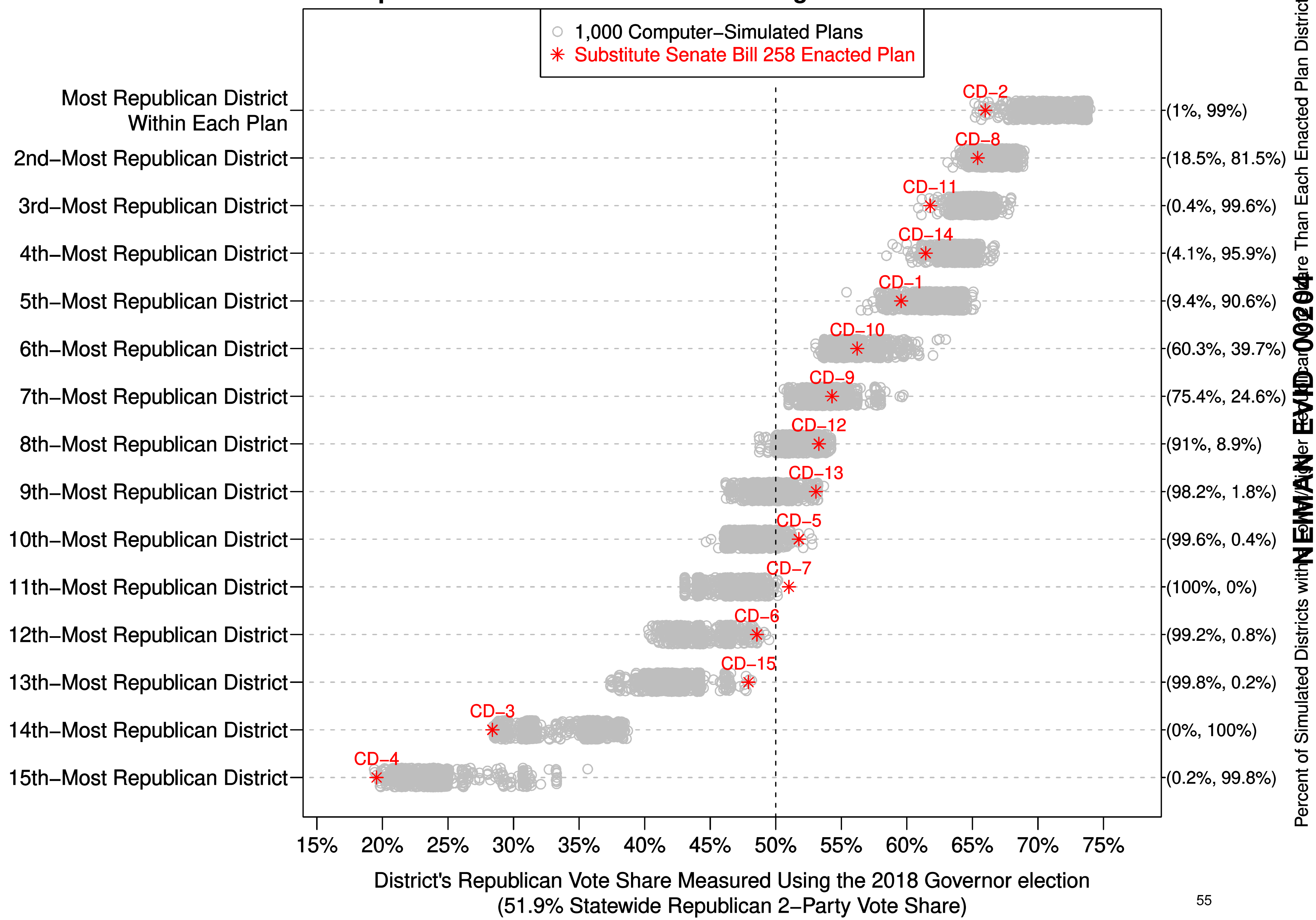
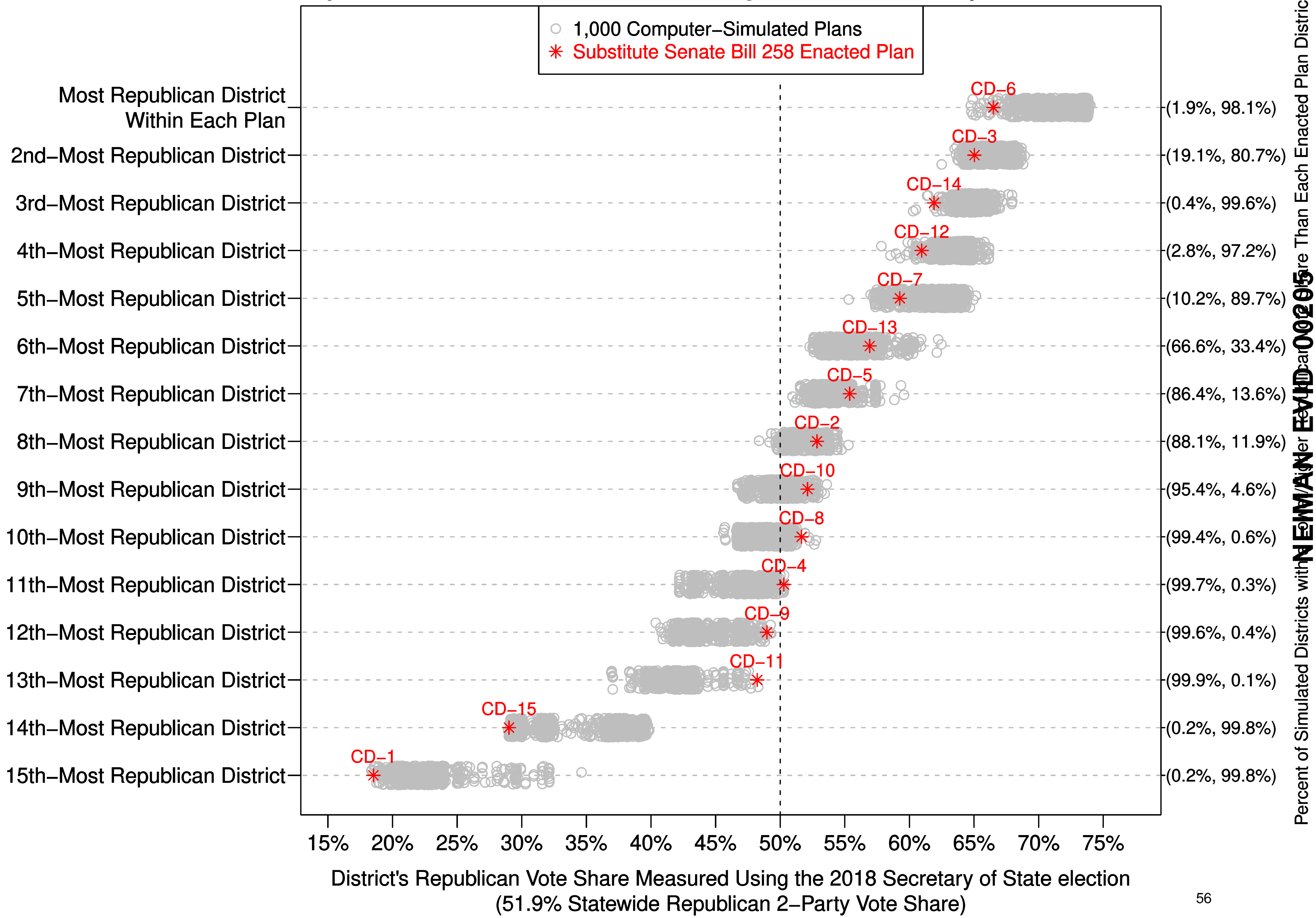
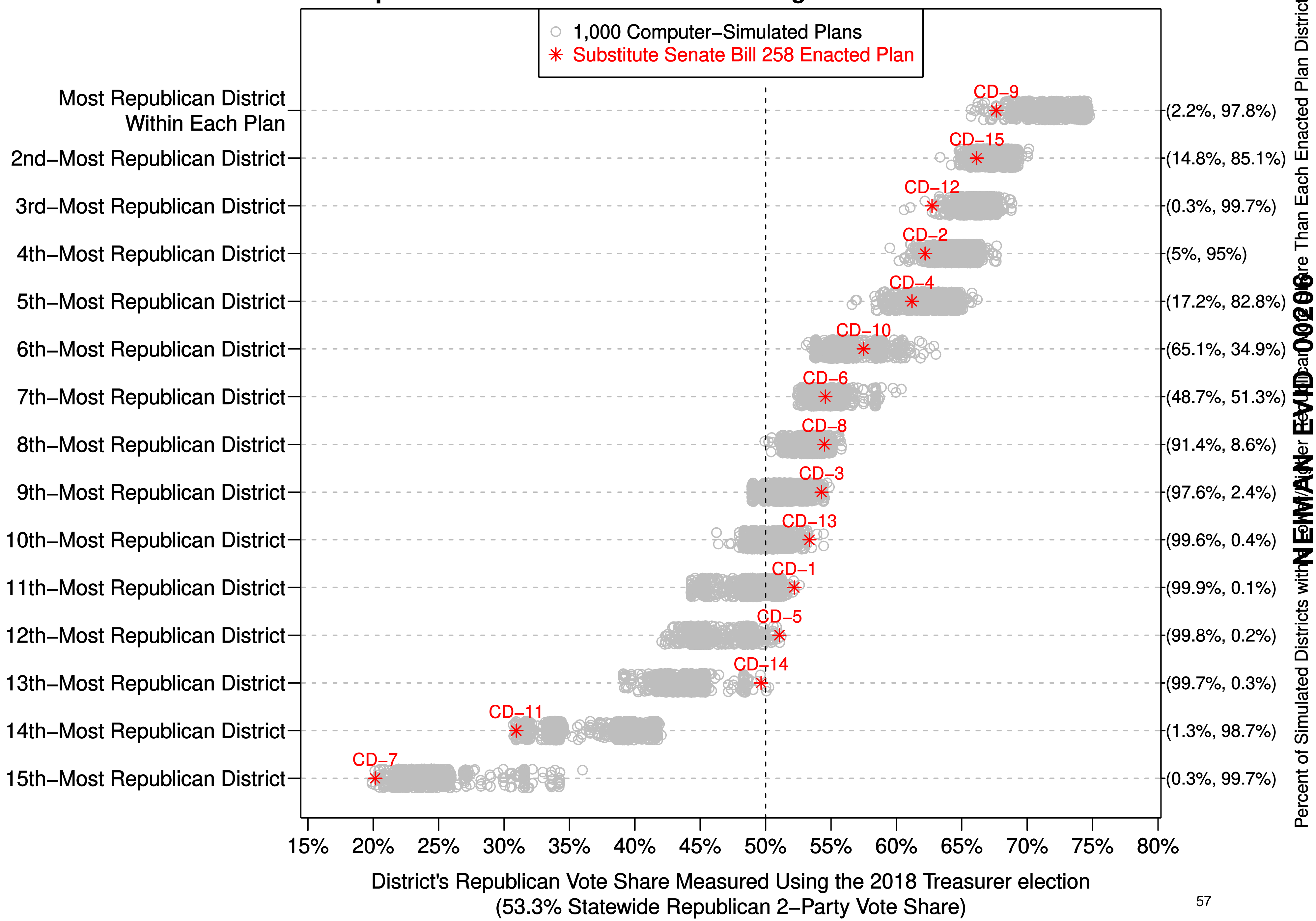


Figure A6: Comparison of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans: Districts' Republican Vote Share Measured Using the 2018 Secretary of State Election Results



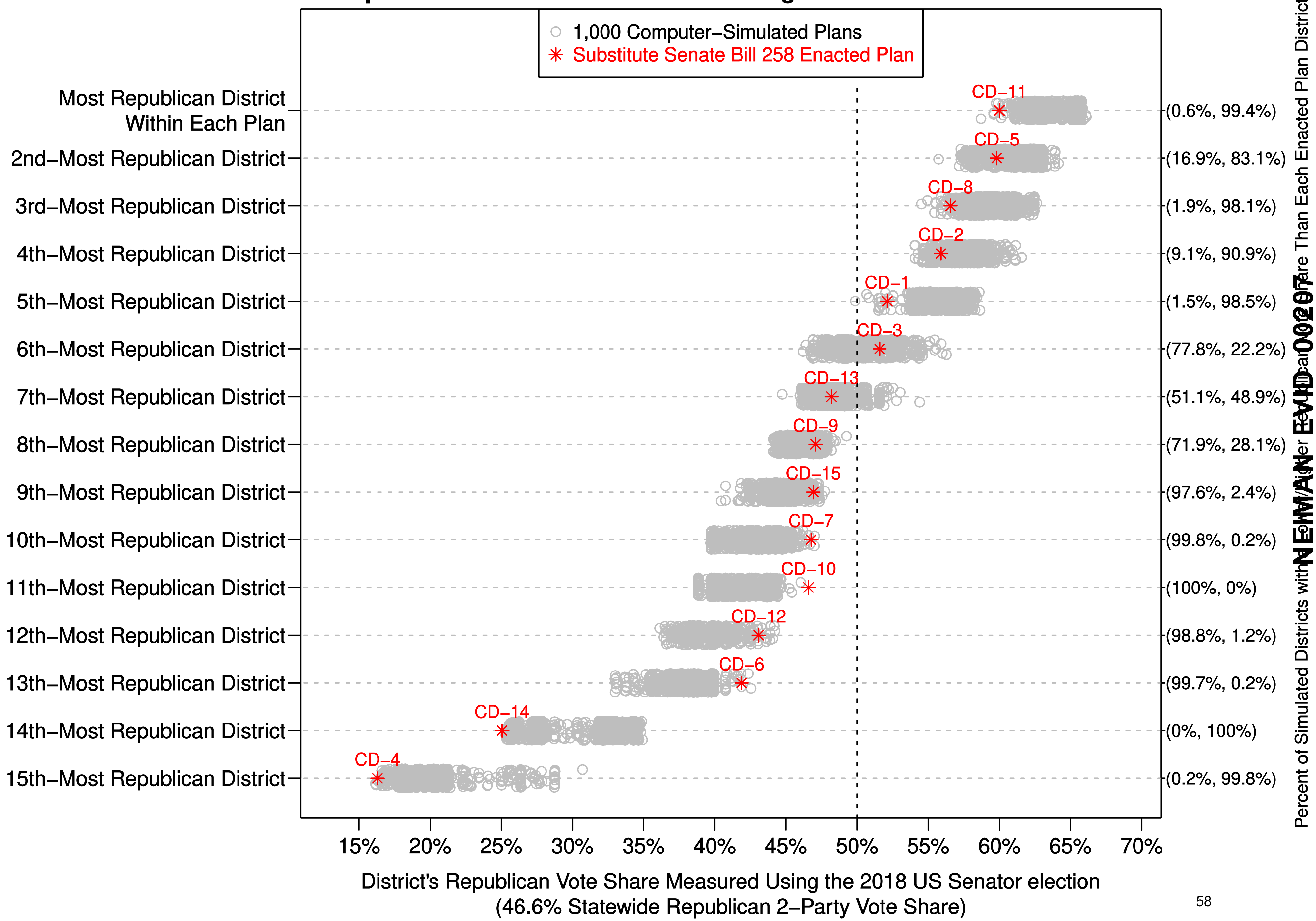
NEIMAN_EVID_00205

Figure A7: Comparison of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer−Simulated Plans: Districts' Republican Vote Share Measured Using the 2018 Treasurer Election Results



NEIMAN_EVID_00206

Figure A8: Comparison of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans: Districts' Republican Vote Share Measured Using the 2018 US Senator Election Results



NEIMAN_EVID_00207

Figure A9: Comparison of Substitute Senate Bill 258 Enacted Plan to 1,000 Computer–Simulated Plans: Districts' Republican Vote Share Measured Using the 2020 US President Election Results

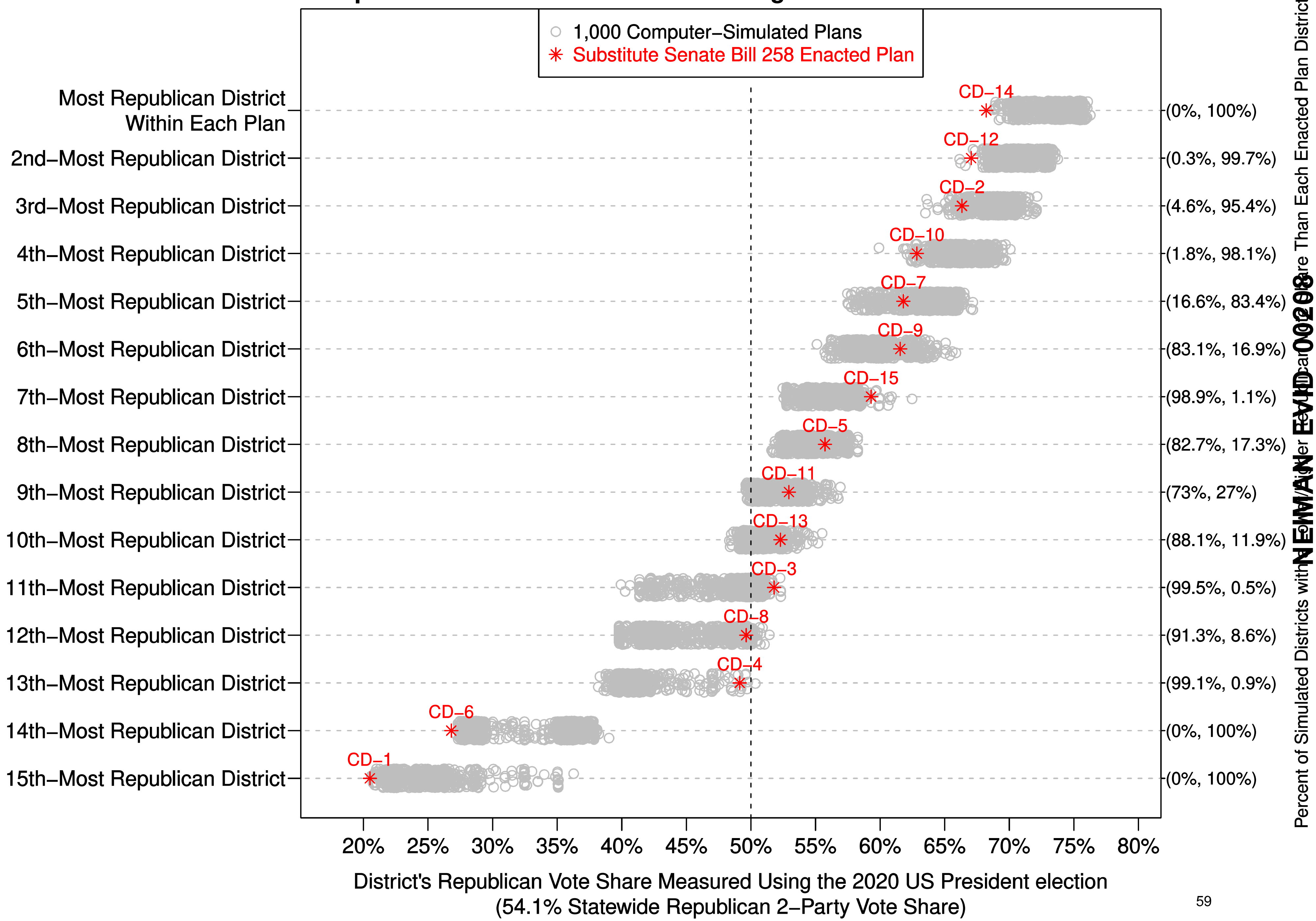


Figure B1:
Split Municipal Corporations and Townships in the 1,000 Computer−Simulated Plans

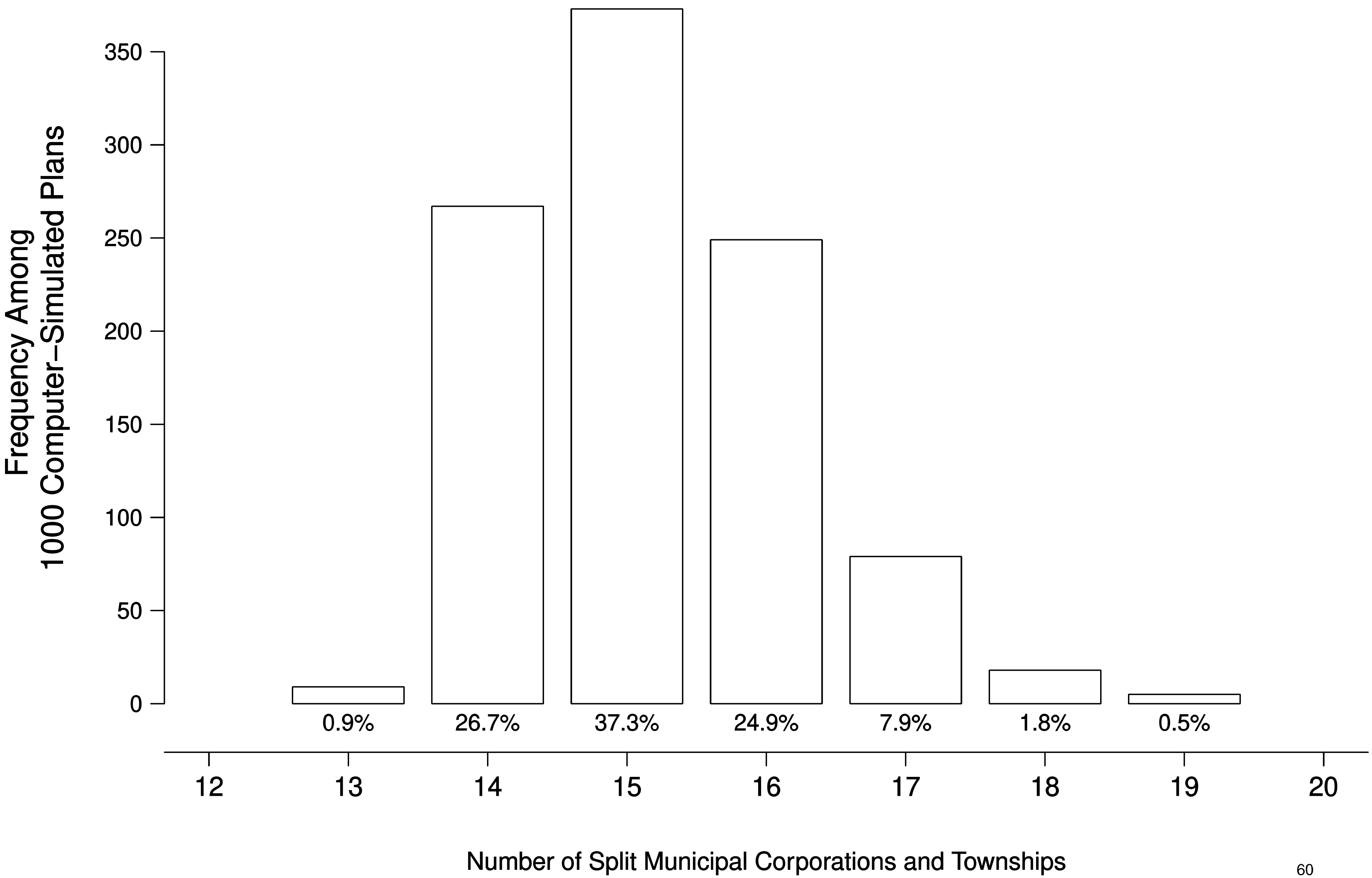


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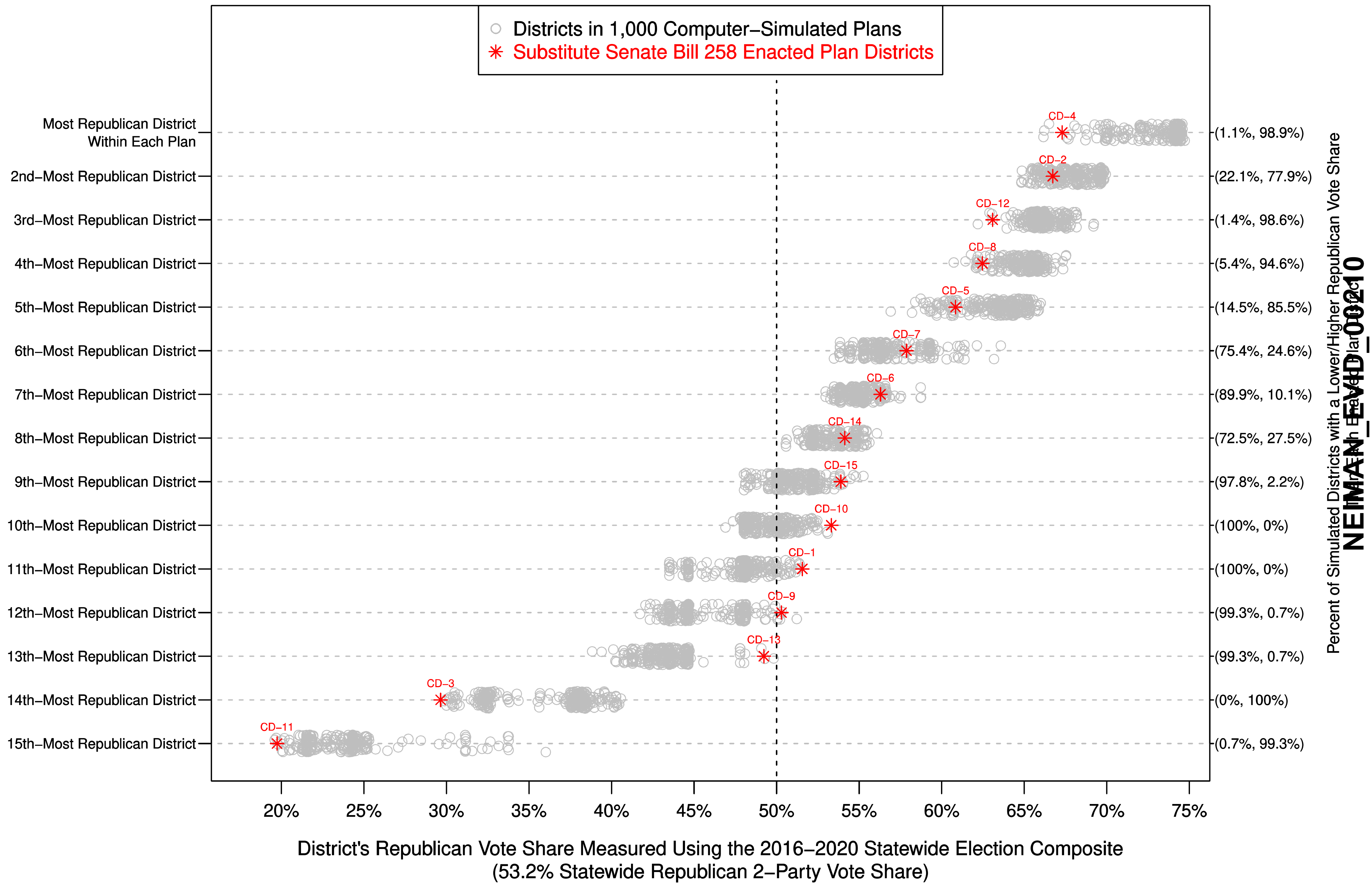
Figure B2: Comparisons of Enacted Plan Districts to Districts in the 276 Computer–Simulated Plans Containing 14 or Fewer Split Townships and Municipal Corporations



NEIMAN_EVID_00210

Jowei Chen
Curriculum Vitae

Department of Political Science
University of Michigan
5700 Haven Hall
505 South State Street
Ann Arbor, MI 48109-1045
Phone: 917-861-7712, Email: jowei@umich.edu
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Academic Positions:
Associate Professor (2015-present), Assistant Professor (2009-2015), Department of Political Science, University of Michigan.
Research Associate Professor (2016-present), Faculty Associate (2009-2015), Center for Political Studies, University of Michigan.
W. Glenn Campbell and Rita Ricardo-Campbell National Fellow, Hoover Institution, Stanford University, 2013.
Principal Investigator and Senior Research Fellow, Center for Governance and Public Policy Research, Willamette University, 2013 – Present.

Education:
Ph.D., Political Science, Stanford University (June 2009)
M.S., Statistics, Stanford University (January 2007)
B.A., Ethics, Politics, and Economics, Yale University (May 2004)

Publications:

Chen, Jowei and Neil Malhotra. 2007. "The Law of k/n: The Effect of Chamber Size on Government Spending in Bicameral Legislatures."
    ***American Political Science Review*. 101(4): 657-676.**

Chen, Jowei, 2010. "The Effect of Electoral Geography on Pork Barreling in Bicameral Legislatures."
    ***American Journal of Political Science*. 54(2): 301-322.**

Chen, Jowei, 2013. "Voter Partisanship and the Effect of Distributive Spending on Political Participation."
    ***American Journal of Political Science*. 57(1): 200-217.**

Chen, Jowei and Jonathan Rodden, 2013. "Unintentional Gerrymandering: Political Geography and Electoral Bias in Legislatures"
    ***Quarterly Journal of Political Science*, 8(3): 239-269.**

Bradley, Katharine and Jowei Chen, 2014. “Participation Without Representation? Senior Opinion, Legislative Behavior, and Federal Health Reform.”
 ***Journal of Health Politics, Policy and Law*. 39(2), 263-293.**

Chen, Jowei and Tim Johnson, 2015. “Federal Employee Unionization and Presidential Control of the Bureaucracy: Estimating and Explaining Ideological Change in Executive Agencies.”
 ***Journal of Theoretical Politics*, Volume 27, No. 1: 151-174.**

Bonica, Adam, Jowei Chen, and Tim Johnson, 2015. “Senate Gate-Keeping, Presidential Staffing of ‘Inferior Offices’ and the Ideological Composition of Appointments to the Public Bureaucracy.”
 ***Quarterly Journal of Political Science*. Volume 10, No. 1: 5-40.**

Chen, Jowei and Jonathan Rodden, 2015. “Cutting Through the Thicket: Redistricting Simulations and the Detection of Partisan Gerrymanders.”
 ***Election Law Journal.* Volume 14, Number 4: 331-345.**

Chen, Jowei and David Cottrell, 2016. “Evaluating Partisan Gains from Congressional Gerrymandering: Using Computer Simulations to Estimate the Effect of Gerrymandering in the U.S. House.”
 ***Electoral Studies.* Volume 44 (December 2016): 329-340.**

Chen, Jowei, 2017. “Analysis of Computer-Simulated Districting Maps for the Wisconsin State Assembly.”
 ***Election Law Journal.* Volume 16, Number 4 (December 2017): 417-442.**

Chen, Jowei and Nicholas Stephanopoulos, 2020. “The Race-Blind Future of Voting Rights.”
 Yale Law Journal, Forthcoming. Volume 130, Number 4: 778-1049.

Kim, Yunsieg and Jowei Chen, 2021. "Gerrymandered by Definition: The Distortion of 'Traditional' Districting Principles and a Proposal for an Empirical Redefinition."
 Wisconsin Law Review, Forthcoming, Volume 2021, Number 1.

Chen, Jowei and Nicholas Stephanopoulos, 2021. "Democracy's Denominator."
 California Law Review, Accepted for Publication, Volume 109.

Non-Peer-Reviewed Publication:

Chen, Jowei and Tim Johnson. 2017. “Political Ideology in the Bureaucracy.”
 ***Global Encyclopedia of Public Administration, Public Policy, and Governance*.**

Research Grants:

"How Citizenship-Based Redistricting Systemically Disadvantages Voters of Color". 2020 ($18,225). Combating and Confronting Racism Grant. University of Michigan Center for Social Solutions and Poverty Solutions.

Principal Investigator. National Science Foundation Grant SES-1459459, September 2015 – August 2018 ($165,008). "The Political Control of U.S. Federal Agencies and Bureaucratic Political Behavior."

"Economic Disparity and Federal Investments in Detroit," (with Brian Min) 2011. Graham Institute, University of Michigan ($30,000).

"The Partisan Effect of OSHA Enforcement on Workplace Injuries," (with Connor Raso) 2009. John M. Olin Law and Economics Research Grant ($4,410).

Invited Talks:

September, 2011. University of Virginia, American Politics Workshop.
October 2011. Massachusetts Institute of Technology, American Politics Conference.
January 2012. University of Chicago, Political Economy/American Politics Seminar.
February 2012. Harvard University, Positive Political Economy Seminar.
September 2012. Emory University, Political Institutions and Methodology Colloquium.
November 2012. University of Wisconsin, Madison, American Politics Workshop.
September 2013. Stanford University, Graduate School of Business, Political Economy Workshop.
February 2014. Princeton University, Center for the Study of Democratic Politics Workshop.
November 2014. Yale University, American Politics and Public Policy Workshop.
December 2014. American Constitution Society for Law & Policy Conference: Building the Evidence to Win Voting Rights Cases.
February 2015. University of Rochester, American Politics Working Group.
March 2015. Harvard University, Voting Rights Act Workshop.
May 2015. Harvard University, Conference on Political Geography.
Octoer 2015. George Washington University School of Law, Conference on Redistricting Reform.
September 2016. Harvard University Center for Governmental and International Studies, Voting Rights Institute Conference.
March 2017. Duke University, Sanford School of Public Policy, Redistricting Reform Conference.
October 2017. Willamette University, Center for Governance and Public Policy Research
October 2017, University of Wisconsin, Madison. Geometry of Redistricting Conference.
February 2018: University of Georgia Law School
September 2018. Willamette University.
November 2018. Yale University, Redistricting Workshop.
November 2018. University of Washington, Severyns Ravenholt Seminar in Comparative Politics.
January 2019. Duke University, Reason, Reform & Redistricting Conference.

February 2019. Ohio State University, Department of Political Science. Departmental speaker series.
March 2019. Wayne State University Law School, Gerrymandering Symposium.
November 2019. Big Data Ignite Conference.
November 2019. Calvin College, Department of Mathematics and Statistics.
September 2020 (Virtual). Yale University, Yale Law Journal Scholarship Workshop

Conference Service:

Section Chair, 2017 APSA (San Francisco, CA), Political Methodology Section
Discussant, 2014 Political Methodology Conference (University of Georgia)
Section Chair, 2012 MPSA (Chicago, IL), Political Geography Section.
Discussant, 2011 MPSA (Chicago, IL) "Presidential-Congressional Interaction."
Discussant, 2008 APSA (Boston, MA) "Congressional Appropriations."
Chair and Discussant, 2008 MPSA (Chicago, IL) "Distributive Politics: Parties and Pork."

Conference Presentations and Working Papers:

"Ideological Representation of Geographic Constituencies in the U.S. Bureaucracy," (with Tim Johnson). 2017 APSA.

"Incentives for Political versus Technical Expertise in the Public Bureaucracy," (with Tim Johnson). 2016 APSA.

"Black Electoral Geography and Congressional Districting: The Effect of Racial Redistricting on Partisan Gerrymandering". 2016 Annual Meeting of the Society for Political Methodology (Rice University)

"Racial Gerrymandering and Electoral Geography." Working Paper, 2016.

"Does Deserved Spending Win More Votes? Evidence from Individual-Level Disaster Assistance," (with Andrew Healy). 2014 APSA.

"The Geographic Link Between Votes and Seats: How the Geographic Distribution of Partisans Determines the Electoral Responsiveness and Bias of Legislative Elections," (with David Cottrell). 2014 APSA.

"Gerrymandering for Money: Drawing districts with respect to donors rather than voters." 2014 MPSA.

"Constituent Age and Legislator Responsiveness: The Effect of Constituent Opinion on the Vote for Federal Health Reform." (with Katharine Bradley) 2012 MPSA.

"Voter Partisanship and the Mobilizing Effect of Presidential Advertising." (with Kyle Dropp) 2012 MPSA.

“Recency Bias in Retrospective Voting: The Effect of Distributive Benefits on Voting Behavior.” (with Andrew Feher) 2012 MPSA.

“Estimating the Political Ideologies of Appointed Public Bureaucrats,” (with Adam Bonica and Tim Johnson) 2012 Annual Meeting of the Society for Political Methodology (University of North Carolina)

“Tobler’s Law, Urbanization, and Electoral Bias in Florida.” (with Jonathan Rodden) 2010 Annual Meeting of the Society for Political Methodology (University of Iowa)

“Unionization and Presidential Control of the Bureaucracy” (with Tim Johnson) 2011 MPSA.

“Estimating Bureaucratic Ideal Points with Federal Campaign Contributions” 2010 APSA. (Washington, DC).

“The Effect of Electoral Geography on Pork Spending in Bicameral Legislatures,” Vanderbilt University Conference on Bicameralism, 2009.

“When Do Government Benefits Influence Voters’ Behavior? The Effect of FEMA Disaster Awards on US Presidential Votes,” 2009 APSA (Toronto, Canada).

“Are Poor Voters Easier to Buy Off?” 2009 APSA (Toronto, Canada).

“Credit Sharing Among Legislators: Electoral Geography’s Effect on Pork Barreling in Legislatures,” 2008 APSA (Boston, MA).

“Buying Votes with Public Funds in the US Presidential Election,” Poster Presentation at the 2008 Annual Meeting of the Society for Political Methodology (University of Michigan).

“The Effect of Electoral Geography on Pork Spending in Bicameral Legislatures,” 2008 MPSA.

“Legislative Free-Riding and Spending on Pure Public Goods,” 2007 MPSA (Chicago, IL).

“Free Riding in Multi-Member Legislatures,” (with Neil Malhotra) 2007 MPSA (Chicago, IL).

“The Effect of Legislature Size, Bicameralism, and Geography on Government Spending: Evidence from the American States,” (with Neil Malhotra) 2006 APSA (Philadelphia, PA).

Reviewer Service:

American Journal of Political Science
American Political Science Review
Journal of Politics
Quarterly Journal of Political Science
American Politics Research
Legislative Studies Quarterly
State Politics and Policy Quarterly
Journal of Public Policy
Journal of Empirical Legal Studies
Political Behavior
Political Research Quarterly
Political Analysis
Public Choice
Applied Geography

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<u>Neiman Petitioners' Exhibit 26</u>

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, *et al.*, **Relators,** **v.** **OHIO REDISTRICTING COMMISSION, *et al.*,** **Respondents.**	**Case No. 2021-1449** **Original Action Filed Pursuant to Ohio Const., Art. XIX, Sec. 1(C)(3)**

<u>AFFIDAVIT OF KOSUKE IMAI</u>

Franklin County
/ss
State of Ohio

Now comes affiant Kosuke Imai, having been first duly cautioned and sworn, deposes and states as follows:

1. I am over the age of 18 and fully competent to make this declaration. I have personal knowledge of the statements and facts contained herein.
2. For the purposes of this litigation, I have been asked by counsel for Relators to analyze relevant data and provide my expert opinions.
3. To that end, I have personally prepared the report attached to this affidavit as Exhibit A, and swear to its authenticity and to the faithfulness of the opinions expressed, and, to the best of my knowledge, the accuracy of the factual statements made therein.

FURTHER AFFIANT SAYETH NAUGHT

Executed on 12/09/2021, 2021.

Kosuke Imai
Signed on 2021/12/09 08:01:53 -8:00

Kosuke Imai

Sworn and subscribed before me this 12/09/2021 day of ________, 2021

NOTARY PUBLIC STATE OF OHIO
Theresa M Sabo
Commission # 2016-RE-619622
Electronic Notary Public
State of Ohio
My Comm Exp. Nov 28, 2026
Notary Stamp 2021/12/09 09:01:53 PST C9A5EA4809AA

Signed on 2021/12/09 08:01:53 -8:00

Notary Public

Notarial act performed by audio-visual communication

Imai Affidavit.pdf

DocVerify ID:	D8970D65-ECBB-4BFE-B639-1BE659039744
Created:	December 09, 2021 07:57:36 -8:00
Pages:	1
Remote Notary:	Yes / State: OH

E-Signature Summary

E-Signature 1: Kosuke Imai (KI)
December 09, 2021 08:01:53 -8:00 [9DB37A030428] [108.26.227.252]
imai@harvard.edu (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
December 09, 2021 08:01:53 -8:00 [C9A5EA4809AA] [74.142.214.254]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

EXHIBIT A

IN THE SUPREME COURT OF OHIO

League of Women Voters of Ohio, *et al.* *Relators*, v. Ohio Redistricting Commission, *et al.* *Respondents*.	Original Action Filed Pursuant to Ohio Const., Art. XIX, Sec. 3(A)

EXPERT REPORT

Kosuke Imai, Ph.D.

December 9, 2021

Table of Contents

I. INTRODUCTION AND SCOPE OF WORK

1. My name is Kosuke Imai, Ph.D., and I am a Professor in the Department of Government and the Department of Statistics at Harvard University. I specialize in the development of statistical methods for and their applications to social science research. I am also affiliated with Harvard's Institute for Quantitative Social Science.

2. I have been asked by counsel representing the relators in this case to analyze relevant data and provide my expert opinions related to whether Ohio's enacted congressional districting plan (SB 258, which I will refer to as the "enacted plan" in this report) meets the criteria in Article XIX, Section 1(C)(3)(a) of Ohio's Constitution. More specifically, I have been asked to statistically analyze the enacted plan's compliance with Article XIX, Section 1(C)(3)(a)'s requirement that "[t]he general assembly shall not pass a plan that unduly favors or disfavors a political party or its incumbents" by comparing it against other alternative plans that are as or more compliant with other relevant requirements of Article XIX.

II. SUMMARY OF OPINIONS

3. I simulated 5,000 hypothetical plans that are at least as compliant with Article XIX as the enacted plan. The comparison of these simulated plans with the enacted plan yields the following findings:

- The enacted plan unduly favors the Republican Party by giving the Republicans a much greater expected number of seats than in any of my 5,000 simulated plans. Even using the General Assembly's assumptions regarding the appropriate election set and calculation of expected number of seats, the Republican candidates are expected to win 2.8 more seats under the enacted plan than under the average simulated plan.

- The expected number of Republican seats under the enacted plan is a clear statistical outlier. Indeed, any plan that provides for more than 9 expected Republican seats is an outlier. Moreover, the probability of generating the enacted plan's extreme partisan outcome under the non-partisan simulation procedure I used is essentially zero.

- The enacted plan exhibits a significant partisan bias in favor of the Republican Party. Even using the General Assembly's assumptions regarding the appropriate election set and calculation of expected number of seats, the magnitude of bias is much greater under the enacted plan than in any of my 5,000 simulated plans and is a clear statistical outlier, according to several standard metrics used in the academic literature.
- In Hamilton County, the enacted plan cracks Democratic voters to create safe Republican seats, while in Franklin and Cuyahoga counties the enacted plan packs Democratic voters to create additional Republican-leaning districts.

III. QUALIFICATIONS, EXPERIENCE, AND COMPENSATION

4. I am trained as a political scientist (Ph.D. in 2003, Harvard) and a statistician (MA in 2002, Harvard). I have published more than 60 articles in peer reviewed journals, including premier political science journals (e.g., *American Journal of Political Science*, *American Political Science Review*, *Political Science*), statistics journals (e.g., *Biometrika*, *Journal of the American Statistical Association*, *Journal of the Royal Statistical Society*), and general science journals (e.g., *Lancet*, *Nature Human Behavior*, *Science Advances*). My work has been widely cited across a diverse set of disciplines. For each of the past four years, Clarivate Analytics, which tracks citation counts in academic journals, has named me as a highly cited researcher in the cross-field category for producing "multiple highly cited papers that rank in the top 1% by citations for field and year in Web of Science."

5. I started my academic career at Princeton University, where I played a leading role in building interdisciplinary data science communities and programs on campus. I was the founding director of Princeton's Program in Statistics and Machine Learning from 2013 to 2017. In 2018, I moved to Harvard, where I am Professor jointly appointed in the Department of Government and the Department of Statistics, the first such appointment in the history of the university. Outside of universities, between 2017 and 2019, I served as the president of the Society for Political Methodology, a primary academic organization of more than one thousand researchers worldwide who conduct methodological research in political science. My introductory statistics textbook for

social scientists, *Quantitative Social Science: An Introduction* (Princeton University Press, 2017), has been widely adopted at major research universities in the United States and beyond.

6. Computational social science is one of my major research areas. As part of this research agenda, I have developed simulation algorithms for evaluating legislative redistricting since the beginning of this emerging literature. At Harvard, I lead the Algorithm-Assisted Redistricting Methodology (ALARM; https://alarm-redist.github.io/) Project, which studies how algorithms can be used to improve legislative redistricting practice and evaluation.

7. Back in 2014, along with Jonathan Mattingly's team at Duke, my collaborators and I were the first to use Monte Carlo algorithms to generate an ensemble of redistricting plans. Since then, my team has written several methodological articles on redistricting simulation algorithms (Fifield, Higgins, et al. 2020; Fifield, Imai, et al. 2020; McCartan and Imai 2020; Kenny et al. 2021).

8. I have also developed an open-source software package titled `redist` that allows researchers and policy makers to implement the cutting-edge simulation methods developed by us and others (Kenny et al. 2020). This software package can be installed for free on any personal computer with Windows, Mac, or Linux operating system. According to a website that tracks the download statistics of R packages, our software package has been downloaded about 30,000 times since 2016 with an increasing download rate.[1]

9. In addition to redistricting simulation methods, I have also developed the methodology for ecological inference referenced in voting rights cases (Imai, Lu, and Strauss 2008; Imai and Khanna 2016). For example, my methodology for predicting individual's race using voter files and census data was extensively used in a recent decision by the Second Circuit Court of Appeals regarding a redistricting case (Docket No. 20-1668; Clerveaux *et al* v. East Ramapo Central School District).

10. A copy of my curriculum vitae is attached as Exhibit A.

11. I am being compensated at a rate of $450 per hour. My compensation does not

1. https://ipub.com/dev-corner/apps/r-package-downloads/ (accessed on December 6, 2021)

depend in any way on the outcome of the case or on the opinions and testimony that I provide.

IV. METHODOLOGY

12. I conducted simulation analyses to evaluate the enacted plan's compliance with Section 1(C)(3)(a) of Article XIX. Redistricting simulation algorithms generate a representative sample of all possible plans under a specified set of criteria. This allows one to evaluate the properties of a proposed plan by comparing them against those of the simulated plans. If the proposed plan unusually favors one party over another *when compared to* the ensemble of simulated plans, this serves as empirical evidence that the proposed plan is a partisan gerrymander. Furthermore, statistical theory allows us to quantify the degree to which the proposed plan is extreme relative to the ensemble of simulated plans in terms of partisan outcomes.

13. A primary advantage of the simulation-based approach, over the traditional methods, is its ability to account for the political and geographic features that are specific to each state, including spatial distribution of voters and configuration of administrative boundaries. Simulation methods can also incorporate each state's redistricting rules. These state-specific features limit the types of redistricting plans that can be drawn, making comparison across states difficult. The simulation-based approach therefore allows us to compare the enacted plan to a representative set of alternate districting plans subject to Ohio's administrative boundaries, political realities, and constitutional requirements. Appendix A provides a brief introduction to redistricting simulation.

A. Simulation Analysis

14. I have ensured that all my simulated plans are equally or more compliant with Section 2(B) of Article XIX than the enacted plan. My simulation procedure achieves this, in part, by being compliant with the U.S. Constitution and federal law protecting racial minority voting rights, generating contiguous and compact districts, limiting the number of county splits, and respecting the other splitting criteria specified in Section 2(B). I also avoid splitting the counties the enacted plan does not split. Appendix B provides detailed information about this process. For all simulations, I ensure districts fall within a 0.5% deviation from population parity. Although this deviation is greater than the population deviation used in the enacted plan, it only accounts for less

than 4,000 people and hence has no impact on the conclusions of my analysis.

15. Here, I provide a brief overview of the procedure while leaving the details to Appendix B. My simulation proceeds in two steps. First, at the instruction of counsel for the relators, I ensured that every simulated plan has one district in Cuyahoga County with the proportion of black voting age population (BVAP) falling above 42% in order to be compliant with the U.S. Constitution and federal law protecting racial minority voting rights. To do this, I sampled a contiguous and compact district that has an appropriate population size and BVAP proportion within Cuyahoga County. This district always contains the entire city of Cleveland because Section 2(B)(4)(b) prohibits splitting it. Once such a district is generated, I then separately run the simulation algorithm on the rest of the state and generate the remaining 14 districts while making sure that the resulting districts satisfy the requirements specified in Section 2(B). I repeat this procedure 5,000 times to obtain the desired number of simulated plans.

B. Metrics Used to Measure Bias

16. Using the redistricting simulation methodology, I evaluate compliance with Section 1(C)(3)(a) of Article XIX in the set of simulated plans generated by the algorithm as well as the enacted plan. To determine whether the enacted plan unduly favors a particular political party, I compare the expected number of Republican and Democratic seats under the enacted plan against the corresponding number under the simulated plans.

17. I understand that the General Assembly assessed the partisan leanings of the enacted plan using the set of six statewide federal elections from 2012 to 2020 (see Appendix E.1 for the list of these elections). I do not endorse the assumption that using this limited data set can accurately predict the expected number of Republican and Democratic seats under the enacted plan.[2] I nonetheless use this same set of election results data in my analysis so that the differences in conclusions between my analysis and the General Assembly's assessment cannot be attributed to the way in which the partisan leanings of districts are evaluated. Given that these elections

2. I have reviewed the Affidavit of Dr. Christopher Warshaw dated November 30, 2021, which concludes that this set of elections artificially enhances the perception of Democratic Party strength under the enacted plan. I agree with his conclusion in this regard.

enhance the perception of Democratic relative strength, using this assumption effectively gives the enacted plan the benefit of the doubt.

18. I also adopt the General Assembly's approach to computing the expected number of Republican seats under a given redistricting plan. Specifically, I first compute the total number of Republican votes for each district and then sum it across the six statewide federal elections. Dividing this by the total number of two-party votes that are similarly aggregated across these elections yields the Republican two-party vote share for each district. This aggregation method may not be ideal because it gives greater weights to general elections, which tend to have higher turnout than midterm elections. In spite of this potential problem, I follow the General Assembly's approach so that the findings of my analysis can be directly compared to the General Assembly's assessment. I have confirmed that the resulting vote share for each district under the enacted plan is essentially identical to the corresponding district-level vote share presented in the November 16, 2021 statement from Senator Rob McColley. Finally, based on these vote shares, I determine likely winners of all districts based on the vote totals for each statewide election. This gives the total number of expected Republican and Democratic seats for a given plan under the General Assembly's approach.

19. In addition to the expected number of seats, I apply a variety of metrics that are commonly used in the academic literature. These metrics are extensively discussed in Dr. Christopher Warshaw's affidavit, dated November 30, 2021, and the references therein. I have reviewed Dr. Warshaw's articulation of these metrics and they are consistent with my understanding, and appear to be applicable to the facts of this case. Specifically, to measure compliance with Section 1(C)(3)(a), I use the following partisan bias metrics whose definitions are discussed in Dr. Warshaw's affidavit and the references therein.

- Efficiency gap
- Mean-median gap
- Symmetry in the vote-seat curve across parties
- Declination

C. The Determination of Whether the Enacted Plan is a Statistical Outlier Can Provide a Useful Measure of its Partisan Bias

20. Another important benefit of using the redistricting simulation methodology is that it can determine whether or not the enacted plan is a statistical outlier relative to the simulated plans generated under a specified set of criteria. If the enacted plan is a statistical outlier, then the observed difference in partisan outcome between the enacted plan and the simulated plans represents a systematic partisan bias.

21. To determine whether the enacted plan is a statistical outlier, I first estimate the probability of generating a simulated plan that favors a political party at least as much as the enacted plan does. This can be done by simply computing the proportion of the simulated plans that favors a political party equally or more than the enacted plan. If this estimated probability is very small (e.g., less than 0.001), then the enacted plan is a statistical outlier because it is highly unlikely to come from the non-partisan distribution that is used to generate the simulated plans. If the data based on the simulated plans follow the normal distribution, which is a bell-shaped symmetric distribution without skew, then this probability of 0.001, for example, implies that the enacted plan is more than three standard deviations away from the average simulated plans.[3]

22. I also compute the difference in partisan outcome between the enacted plan and the average simulated plan. This allows me to measure the magnitude of partisan bias while accounting for its random variability across the simulated plans. I apply the most commonly used definition of an outlier (Tukey 1977). According to this definition, an outlier represents a data point that is beyond a distance of 1.5 interquartile range (IQR) below the first quartile or above the third quartile. If the data based on the simulated plans were normally distributed, the enacted plan is regarded as an outlier if it is at least 2.70 standard deviations away from the average simulated plan.

D. Description of Redistricting Simulation Software

3. Note that a standard deviation represents the average distance between a data point and the mean.

23. In my analysis, I use the open-source software package for redistricting analysis `redist` (Kenny et al. 2020), which implements a variety of redistricting simulation algorithms as well as other evaluation methods. My collaborators and I have written the code for this software package, so that other researchers and the general public can implement these state-of-the-art methods on their own. I supplement this package with code written primarily to account for the redistricting rules and criteria that are specific to Ohio. All of my analyses are conducted on a laptop. Indeed, all of my analysis code can be run on any personal computer once the required software packages, which are also freely available and open-source, are installed.

V. EVALUATION OF THE ENACTED PLAN USING THE GENERAL ASSEMBLY'S APPROACH

24. Using the redistricting simulation methodology, I evaluate the enacted plan's compliance with Section 1(C)(3)(a). Appendix E.1 provides the detailed information about data sources. I simulated 5,000 alternative Congressional redistricting plans, using the simulation procedure described in Section IV. As explained in Appendix B, every simulated plan is at least as compliant with Sections 2(B) as the enacted plan. For example, Appendices C and D show that the simulated plans are more compact and have fewer county splits than the enacted plan.

25. I can easily generate additional compliant plans by running the algorithm longer, but for the purpose of my analysis, 5,000 simulated plans will yield statistically precise conclusions. In other words, generating more than 5,000 plans, while possible, will not materially affect the conclusions of my analysis.

26. To evaluate the enacted plan's compliance with Section 1(C)(3)(a), I first compare the expected number of Republican seats under the enacted plan with that under each of my 5,000 simulated plans. Figure 1 shows that under the enacted plan, the Republican Party is expected to win 11 seats.[4] In contrast, under about 80% of the simulated plans, the expected number of Republican seats is only 8, while the Republican Party is expected to win 9 seats under the remaining

4. This prediction of 11 expected seats is based on using the set of six statewide federal elections from 2012 to 2020 that the General Assembly used. Again, I do not endorse the assumption that using this limited data set can accurately predict the expected number of Republican seats.

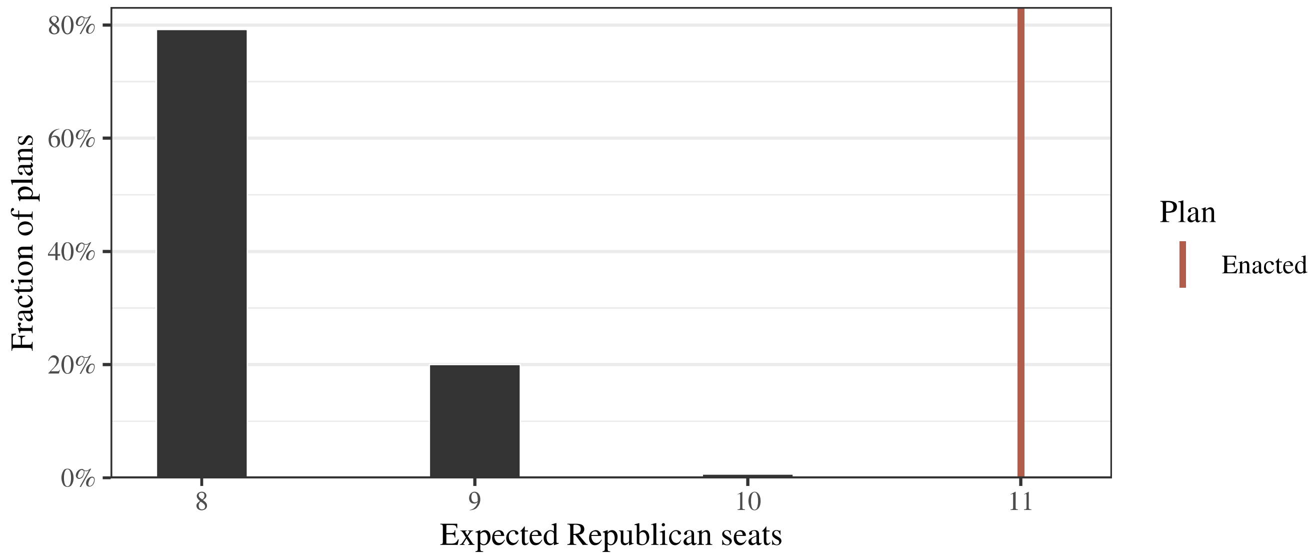

Figure 1: Expected number of Republican seats calculated for the 5,000 simulated plans computed by averaging across the six statewide federal elections from 2012 to 2020. Overlaid is the value for the enacted plan (red).

20% of the simulated plans. In other words, the enacted plan is expected to yield an additional 2.8 Republican seats when compared to the average simulated plan. Indeed, none of my 5,000 simulated plans gives as many Republican seats as the enacted plan. This result implies that the probability of generating the enacted plan's extreme partisan outcome under the non-partisan simulation procedure I used is essentially zero. Thus, any redistricting plan that gives more than 9 seats to the Republican Party, including the enacted plan, is a clear statistical outlier.

27. Under most of the simulated plans, the Republican Party is expected to win 8 seats, which is equivalent to 53% of the Ohio's 15 Congressional seats. This seat proportion is almost identical to the statewide vote share of the Republican Party, which is approximately 52% calculated using the General Assembly's approach and 54% based on the statement made by the Ohio Redistricting Commission in compliance with Section 8(C)(2) of Article XI of the Ohio Constitution. In contrast, under the enacted plan, the expected seat share of the Republican Party is 73%, which is roughly 20 percentage points greater than its expected vote share. As discussed above, this seat share result is a clear statistical outlier. Accordingly, this shows that the enacted plan unduly favors the Republican Party.

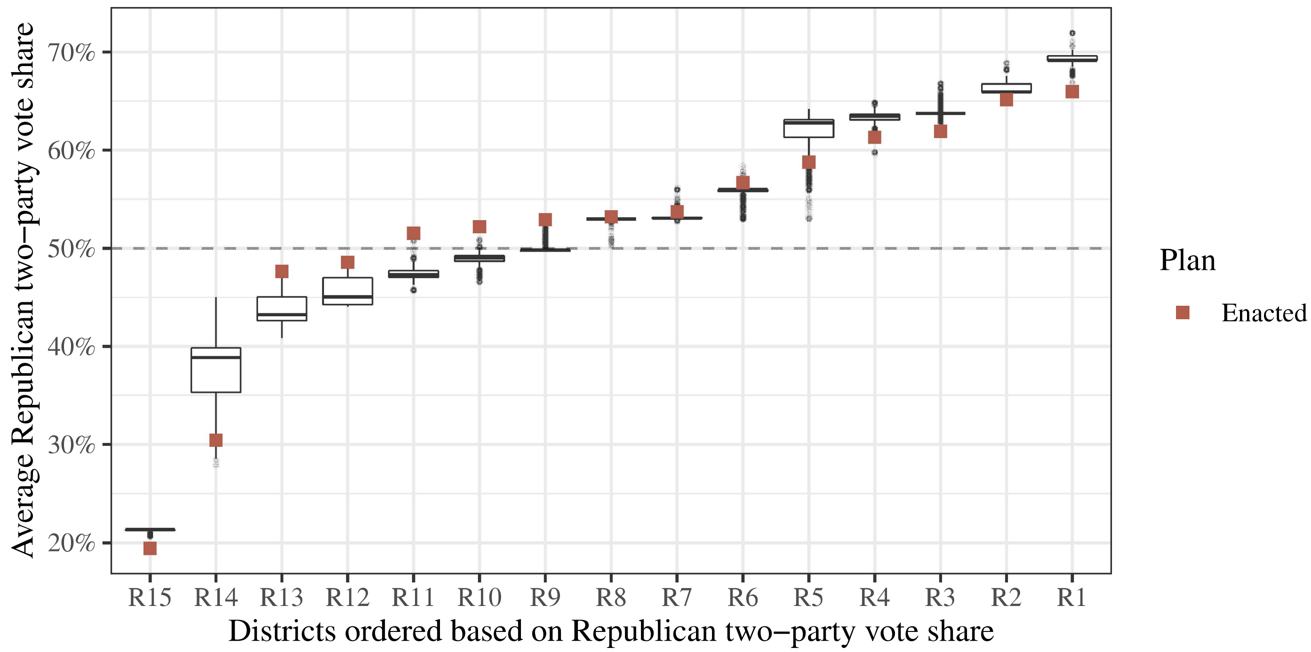

Figure 2: Expected Republican vote share for districts using the six statewide federal elections from 2012 to 2020. For any given plan, the districts are ordered based on their expected Republican vote share. Boxplots represent the distribution of the expected Republican vote share across the simulated plans, whereas the red square correponds to the expected Republican vote share under the enacted plan.

28. Figure 2 further demonstrates the partisan bias of the enacted plan. In this plot, for any given plan (both enacted and simulated), I ordered the districts based on the magnitude of their expected Republican vote share. This means that under any given plan, district R1 yields the highest expected vote share while district R15 is expected to give the least support to the Republican candidate (to be clear, the R1 through R15 district identifiers do not correspond to the Congressional district numbers in the enacted plan). If the expected Republican vote share of each ordered district under the enacted plan (red square) diverges from the corresponding distribution of the simulated plans (boxplot), it constitutes evidence of possible partisan bias. Note that in a boxplot, the "box" contains 50% of the data points (those from 25 percentile to 75 percentile to be exact) with the horizontal line indicating the median value whereas the vertical lines coming out of the box, called "whiskers", indicate the range, which contains most data. Any data points that are beyond these whiskers are considered as outliers according to the second part of the definition

discussed in Section IV.C (paragraph 23).

29. The figure shows clear evidence of the enacted plan's partisan bias. This partisan bias, for the reasons discussed below, further shows that the enacted plan unduly favors the Republican Party. For all of my 5,000 simulated plans, districts R10 and R11 (the 10th and 11th most Republican-leaning districts, respectively) lean toward the Democratic party with the expected median Republican vote share equal to 49.0% and 47.3%, respectively. Indeed, for district R11, none of 5,000 simulated plans are expected to yield as many Republican votes as the enacted plan. Yet under the enacted plan, both of these districts have the expected Republican vote shares above 50%. According to the definition discussed in Section IV.C, these two points associated with the enacted plan are clear statistical outliers, with district R10 and R11 5.2 and 5.8 standard deviations away from the median, respectively.

30. I also find that under the enacted plan, districts R12 and R13 lean much less strongly towards the Democratic party than under all of the simulated plans. Lastly, the enacted plan packs Democratic voters in districts R14 and R15, which are two most Democratic-leaning districts. This is indicated by the fact that these districts have much lower levels of expected Republican vote shares under the enacted plan than under the simulated plans. In contrast, the enacted plan avoids packing Republican voters in the five most Republican districts (districts R1 to R5). Indeed, these districts have much lower levels of expected Republican vote shares under the enacted plan than under the simulated plans. Aside from districts R2 and R5, these points are also statistical outliers. Districts R1 to R5 are 6.8, 1.4, 2.4, 3.7 and 2.0 standard deviations away from the median, respectively.

31. I next use the four partisan bias metrics discussed in Section IV.B to examine the enacted plan's compliance with Section 1(C)(3)(a). I adjusted the sign of each metric so that positive values indicate Republican bias, and values nearer to zero indicate less partisan bias. To summarize the results, as shown in Figure 3, when compared to these simulated plans (black histogram), the enacted plan (red vertical line) is a clear outlier favoring the Republican Party. Indeed, the enacted map is more biased than any of 5,000 simulated plans for all four partisan bias

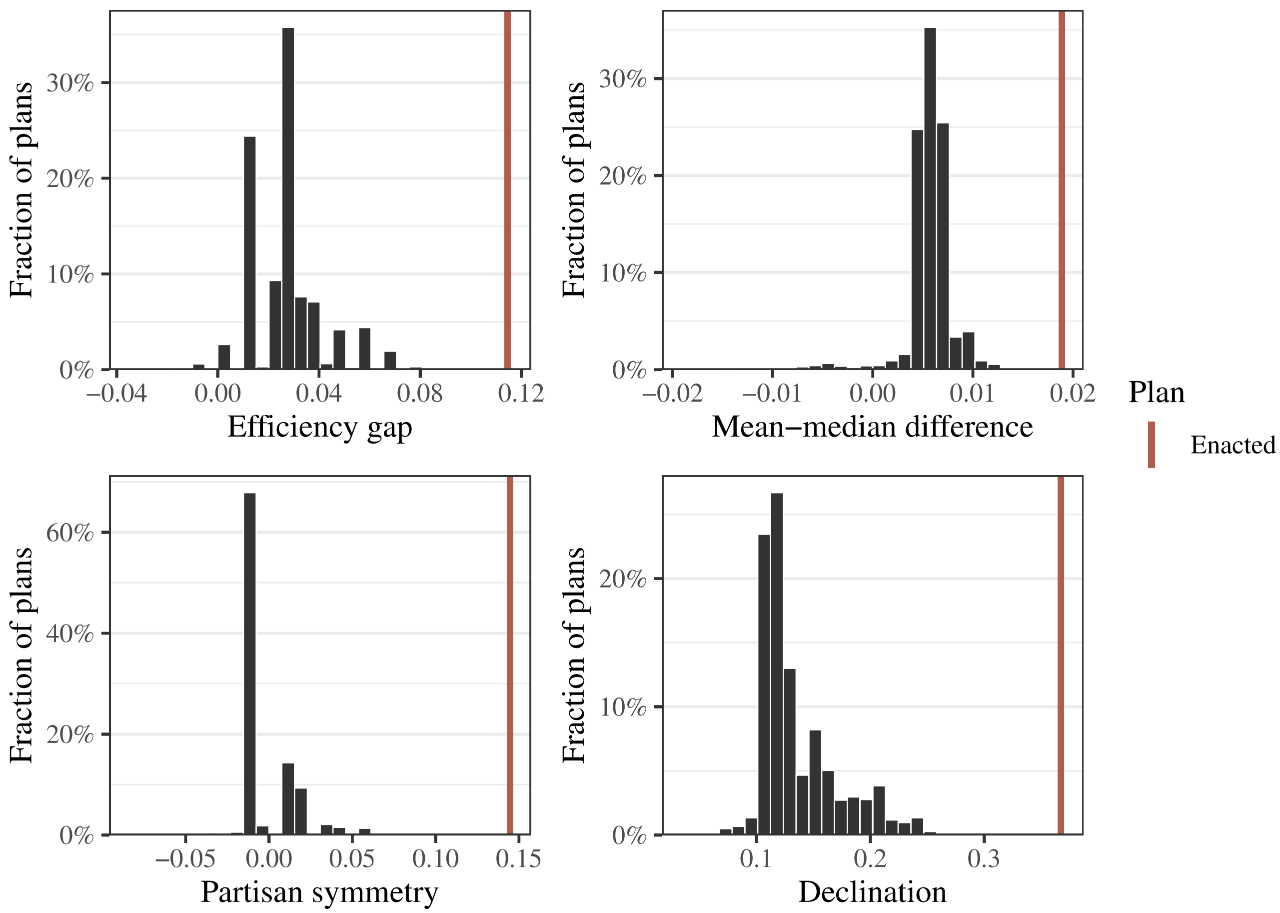

Figure 3: Four partisan bias measures calculated for the 5,000 simulated Congressional redistricting plans computed by averaging across the six federal elections from 2012 to 2020. Overlaid is the value for the enacted plan (red). For each measure, larger values (towards the right) correspond to more Republican-favoring plans.

metrics I considered.

32. The efficiency gap, which captures both cracking and packing, is 15.0% for the enacted map, whereas the average efficiency gap for the simulated plans is only 5.7%. This implies that the enacted plan wastes around 219,000 more Democratic votes on average than the simulated plans, and around 219,000 fewer Republican votes. As shown in the top-left plot of Figure 3, the enacted map is 7.5 standard deviations away from the average simulated plan, and is thus a clear statistical outlier in terms of the efficiency gap metric.

33. The mean-median gap is a measure of asymmetry in the distribution of votes across districts. The existence of packed districts may lead to a large mean-median gap. The top-right plot of the figure shows that the mean-median gap is 0.018 under the enacted plan while the simulated plans score 0.007 on average. Indeed, the enacted plan is 5.7 standard deviations away from the average simulated plan, and is thus a clear statistical outlier in terms of the mean-median gap metric.

34. Partisan symmetry is based on the idea that each party should receive half of the seats if they each receive 50% of votes. The bottom-left plot of Figure 3 shows that the enacted plan scores 14.1% on this metric while the simulated plans score 1.8%, on average. This suggests that under the enacted plan, the Republican Party would gain roughly 2.1 more seats than the Democrats, for a hypothetical tied election. In contrast, the simulated plans would give only 0.3 more seats to the Republican Party than the Democrats in the same situation. The enacted plan is 7.4 standard deviations away from the average simulated plan, and is thus a clear statistical outlier in terms of the partisan symmetry metric.

35. Lastly, the declination metric represents another measure of asymmetry in the vote distribution. As shown in the bottom-right plot of the figure, the enacted plan also scores worse on this metric than any of the 5,000 simulated plans. Specifically, the enacted plan scores 0.42 whereas the simulated plans earn 0.21 on average. The enacted plan is 9.3 standard deviations away from the average simulated plan, and is thus a clear statistical outlier in terms of the declination metric.

36. Thus, all of the partisan bias metrics show that the enacted plan is a clear statistical

outlier, favoring the Republican Party, when compared to the simulated plans. Indeed, the enacted plan has a worse partisan bias than any of my 5,000 simulated plans.

VI. LOCAL ANALYSIS OF SELECTED COUNTIES

37. Partisan bias in the enacted plan is apparent not just in statewide summary statistics, as shown above, but also at the local level. To illustrate this, I performed a detailed analysis of the Congressional districts in Hamilton, Franklin, and Cuyahoga counties. My analysis of these cities shows that the enacted plan packs a disproportionately large number of Democratic voters into some districts while cracking Democratic voters in other districts to create Republican-leaning seats.

38. My analysis of each county proceeds as follows. For each precinct, I first compute the expected two-party vote share of the district to which the precinct is assigned under the enacted plan. I then perform the same calculation under each simulated plan and average these expected vote shares across all of the simulated plans. Comparison of these two numbers reveals whether the enacted plan assigns a precinct to a district whose political leaning is different from what would be expected under the simulated plans. As in Section V, the results shown below are based on the General Assembly's approach that uses the statewide federal elections from 2012-2020.

A. Hamilton County

39. I begin by illustrating the above calculation through an example. Precinct 061031BEZ of Cincinnati lies within District 1 of the enacted map, which has an expected Republican two-party vote share of 51.53%. However, the same precinct belongs to different districts in most of the simulated maps, each with their own Republican vote share. The average Republican vote share for the districts to which this precinct is assigned across all of the simulated plans is 44.85%, which is 6.68 percentage points lower than under the enacted plan. So, based on the representative set of simulated plans that have less partisan bias, precinct 061031BEZ is assigned to a more Republican-leaning district under the enacted plan than under the average simulation plan.

40. The left map of Figure 4 presents the expected vote shares of districts under the

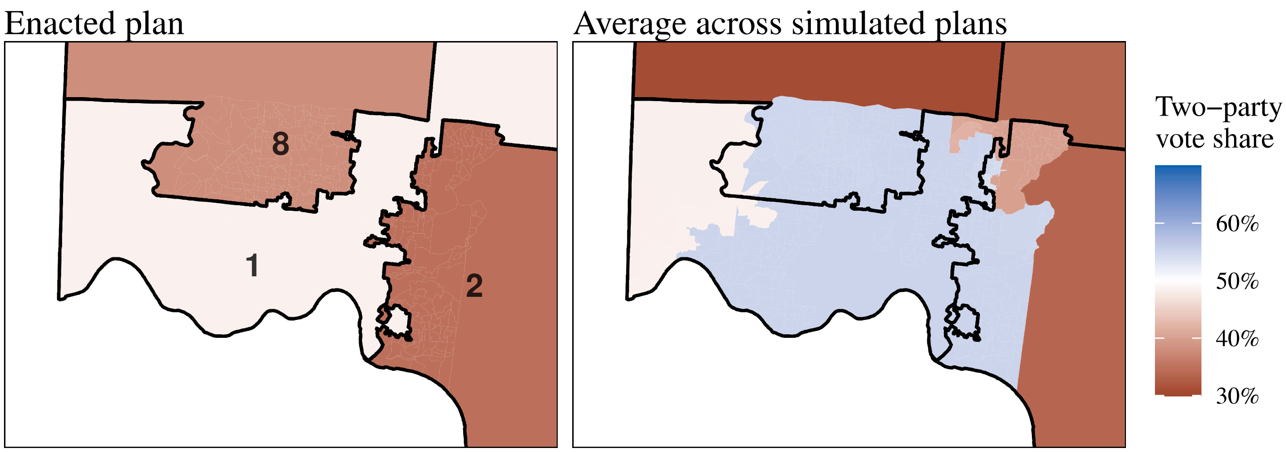

Figure 4: Congressional districts in Hamilton County. The left map presents the expected two-party vote shares of districts under the enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. The enacted district boundaries are shown with thick black lines. While under the simulated plans, Cincinnati and its environs are expected to belong to a Democratic-leaning district, the enacted plan cracks Democratic voters, leading to solely Republican districts.

enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. Under the enacted plan, Democratic areas are cracked to yield three Republican-leaning districts, despite a significant concentration of Democratic voters in and around Cincinnati. This is especially apparent with the two unusual protrusions of Districts 2 and 8 into Hamilton County, which split the county twice. The simulated plans, in comparison, are expected to only split Hamilton County once. As the right figure indicates, the area covered by these protrusions would normally be expected to belong to a Democratic district, but as a result of being lumped with adjacent districts in the enacted plan, instead belongs to safely Republican districts.

41. As a result of these manipulations and additional splits of Hamilton County, the enacted plan has no Democratic seats under the average statewide federal contest, whereas the simulated plans are expected to yield a Democratic seat. So in Hamilton County alone, cracking of Democratic voters nets Republicans an entire seat.

B. Franklin County

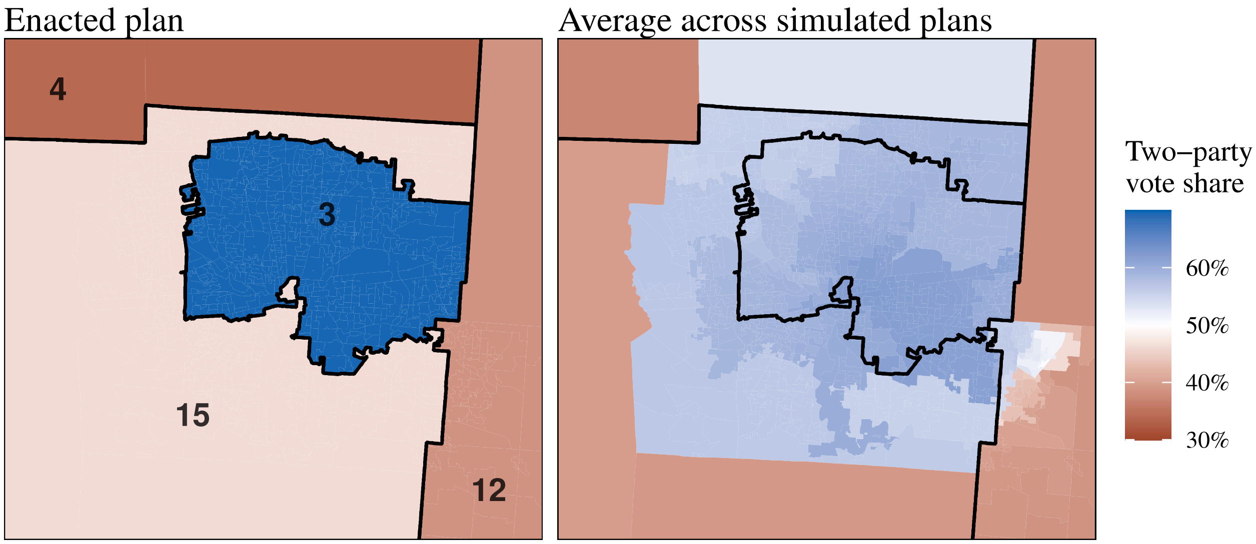

Figure 5: Congressional districts in Franklin County. The left map presents the expected two-party vote shares of districts under the enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. The enacted district boundaries are shown with thick black lines. While under the simulated plans, all of Franklin County are expected to belong to a Democratic district, the enacted plan packs Democratic voters, leaving much of the city of Columbus in a Republican district stretching most of the way to Cincinnati.

42. Analogous to Figure 4, Figure 5 compares the enacted plan with the simulated plans in Franklin County. Unlike in Hamilton County, the enacted plan packs Democratic voters into a single, heavily Democratic, District 3, leaving Districts 4, 12, and 15 to be safely Republican. Much of the area inside Franklin County belongs to a safe Republican district under the enacted plan. In contrast, under the simulated plans, the entire area of Franklin County is expected to belong to a Democratic-leaning district, as is Delaware County and part of Fairfield County.

43. By confining Democratic voters to a single district containing part of Columbus, the enacted plan deprives Democratic voters in the rest of the county of a reasonable opportunity to elect a Democratic candidate. In doing so, the enacted plan yields around one additional seat for Republicans, on average, when compared to the simulated plans.

C. Cuyahoga County

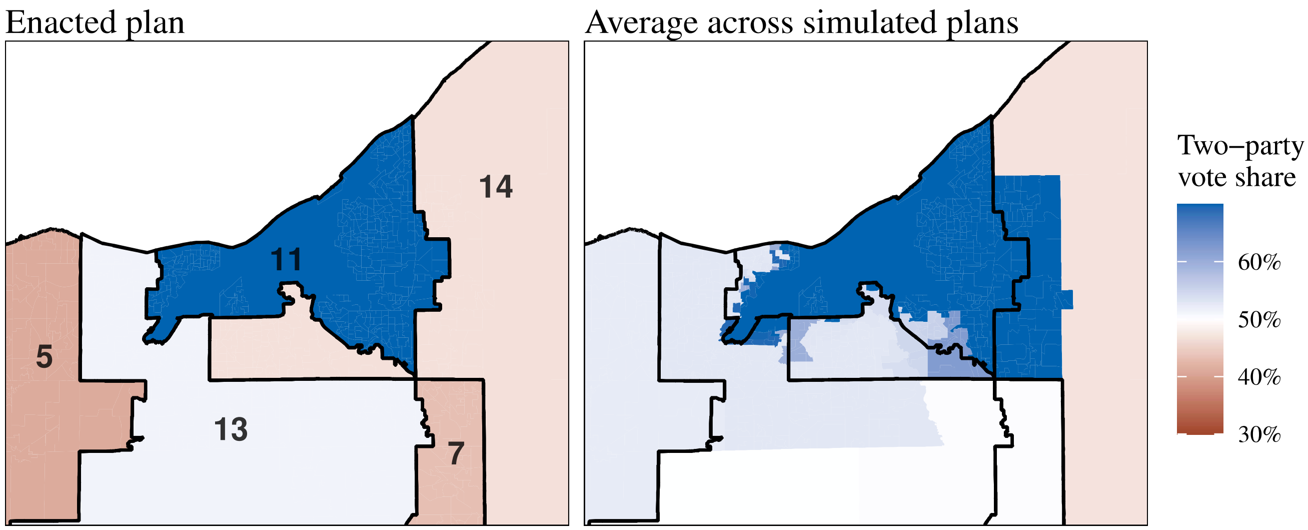

Figure 6: Congressional districts in Cuyahoga County. The left map presents the expected two-party vote shares of districts under the enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. The enacted district boundaries are shown with thick black lines. While under the simulated plans, the suburbs of Cleveland are expected to belong to either Democratic districts or highly competitive districts, the enacted plan packs urban Democratic voters, leaving the remainder of Cuyahoga County and nearby areas in Republican districts.

44. Figure 6 is constructed just like Figures 4 and 5. Districts in Cuyahoga County are more constrained than in Franklin County, based on the need to avoid splitting the city of Cleveland, as well as Voting Rights Act considerations. Even so, the enacted plan differs in key ways from the average simulated plan. First, it overly packs Democratic voters in District 11, as indicated by Figure 2 where District 11 corresponds to the least Republican-leaning district (R15). More importantly, Districts 5, 7, 13, and 14 in the enacted plan are drawn to crack the remaining Democratic voters outside of Cleveland and in the cities of Lorain and Akron. The result of this is to create three Republican-leaning districts and only one competitive district. In contrast, under the simulated plans, all of the areas south and west of Cleveland are generally expected to belong to competitive or Democratic-leaning districts.

VII. APPENDIX

A. Introduction to Redistricting Simulation

1. In recent years, redistricting simulation algorithms have played an increasingly important role in court cases involving redistricting plans. Simulation evidence has been presented to courts in many states, including Michigan, North Carolina, Ohio, and Pennsylvania.[5]

2. Over the past several years, researchers have made major scientific advances to improve the theoretical properties and empirical performance of redistricting simulation algorithms. All of the state-of-the-art redistricting simulation algorithms belong to the family of Monte Carlo methods. They are based on random generation of spanning trees, which are mathematical objects in graph theory (DeFord, Duchin, and Solomon 2021). The use of these random spanning trees allows these state-of-the-art algorithms to efficiently sample a representative set of plans (Autry et al. 2020; Carter et al. 2019; McCartan and Imai 2020; Kenny et al. 2021). Algorithms developed earlier, which do not use random spanning trees and instead rely on incremental changes to district boundaries, are often not able to do so.

3. These algorithms are designed to sample plans from a specific probability distribution, which means that every legal redistricting plan has certain odds of being generated. The algorithms put as few restrictions as possible on these odds, except to ensure that, on average, the generated plans meet certain criteria. For example, the probabilities are set so that the generated plans reach a certain level of geographic compactness, on average. Other criteria, based on the state in question, may be fed into the algorithm by the researcher. In other words, this target distribution is based on the weakest assumption about the data under the specified constraints.

4. In addition, the algorithms ensure that all of the sampled plans (a) are geographically contiguous, and (b) have a population which deviates by no more than a specified amount

5. Declaration of Dr. Jonathan C. Mattingly, Common Cause v. Lewis (2019); Testimony of Dr. Jowei Chen, Common Cause v. Lewis (2019); Testimony of Dr. Pegden, Common Cause v. Lewis (2019); Expert Report of Jonathan Mattingly on the North Carolina State Legislature, Rucho v. Common Cause (2019); Expert Report of Jowei Chen, Rucho v. Common Cause (2019); Amicus Brief of Mathematicians, Law Professors, and Students in Support of Appellees and Affirmance, Rucho v. Common Cause (2019); Brief of Amici Curaiae Professors Wesley Pegden, Jonathan Rodden, and Samuel S.-H. Wang in Support of Appellees, Rucho v. Common Cause (2019); Intervenor's Memo, Ohio A. Philip Randolph Inst. et al. v. Larry Householder (2019); Expert Report of Jowei Chen, League of Women Voters of Michigan v. Benson (2019).

from a target population.

5. There are two types of general Monte Carlo algorithms which generate redistricting plans with these guarantees and other properties: sequential Monte Carlo (SMC; Doucet, Freitas, and Gordon 2001) and Markov chain Monte Carlo (MCMC; Gilks, Richardson, and Spiegelhalter 1996) algorithms.

6. The SMC algorithm (McCartan and Imai 2020; Kenny et al. 2021) samples many redistricting plans in parallel, starting from a blank map. First, the algorithm draws a random spanning tree and removes an edge from it, creating a "split" in the map, which forms a new district. This process is repeated until the algorithm generates enough plans with just one district drawn. The algorithm calculates a weight for each plan in a specific way so that the algorithm yields a representative sample from the target probability distribution. Next, the algorithm selects one of the drawn plans at random. Plans with greater weights are more likely to be selected. The algorithm then draws another district using the same splitting procedure and calculates a new weight for each updated plan that comports with the target probability distribution. The whole process of random selection and drawing is repeated again and again, each time drawing one additional district on each plan. Once all districts are drawn, the algorithm yields a sample of maps representative of the target probability distribution.

7. The MCMC algorithms (Autry et al. 2020; Carter et al. 2019) also form districts by drawing a random spanning tree and splitting it. Unlike the SMC algorithm, however, these algorithms do not draw redistricting plans from scratch. Instead, the MCMC algorithms start with an existing plan and modify it, merging a random pair of districts and then splitting them a new way.

8. Diagnostic measures exist for both these algorithms which allow users to make sure the algorithms are functioning correctly and accurately. The original papers for these algorithms referenced above provide more detail on the algorithm specifics, empirical validation of their performance, and the appropriateness of the chosen target distribution.

B. Implementation Details

9. In my analysis, I use the SMC algorithm for several reasons. First, unlike the MCMC algorithms, the SMC algorithm generates nearly independent samples, leading to a diverse set of redistricting plans that satisfy the specified constraints. Second, the SMC algorithm avoids splitting political subdivision boundaries where possible, an important consideration in the case of Ohio. Third, Sections 2(B)(2) and 2(B)(3) require districts to be compact and contiguous, respectively. The SMC algorithm automatically satisfy both of these requirements. Appendix C shows that most of simulated plans generate more compact districts than the enacted plan according to the Polsby-Popper measure, which is a common metric of compactness used in the academic literature.

10. My simulation proceeds in two steps. First, I sample a district in Cuyahoga County using a Voting Rights Act (VRA) constraint to be compliant with Section 2(B)(1). At the instruction of counsel for the relators, I sample one district within Cuyahoga County such that its BVAP proportion falls above 42%. This is done by using the constraint of the form $\sqrt{\max(x_b - B(x_b), 0)}$, where x_b is the share of a district's VAP that is Black, and $B(x_b)$ returns the target BVAP percentages closest to x_b from the set $\{0.02, 0.08, 0.42\}$. This is a common way to formulate the VRA constraint (Herschlag et al. 2020). Note that I also instructed the algorithm to never split the City of Cleveland, in accordance with Section 2(B)(4)(b), and not to split Cuyahoga County three times or more, in accordance with Sections 2(B)(4)(a) and 2(B)(5).

11. Once a district is sampled within Cuyahoga, I generate the remaining 14 districts within the rest of the state without the VRA constraint. In this second step, I incorporate several split constraints. According to Section 2(B)(4)(b), municipalities with population between 100,000 people and the Congressional ratio of represetation, that reside in a county with population greater than the Congressional ratio of representation, should not be split. In addition to the City of Cleveland, this provision also applies to the City of Cincinnati. I instruct the SMC algorithm to never split either of these municipalities.

12. Section 2(B)(5) requires that of Ohio's 88 counties, at least 65 counties should not

be split; no more than 18 counties can be split no more than once; no more than 5 counties can be split no more than twice. I made sure that all of my simulated plans satisfy this requirement by not splitting the counties the enacted plan does not split and imposing a constraint that discourages the algorithm from splitting a county. This is accomplished in two pieces. First, the SMC algorithm, by design, can be instructed to attempt to follow county boundaries where possible by drawing spanning trees within counties and then between them; I use this feature. Additionally, I penalize a district which splits a county twice with a score of 3, and I penalize a district which splits a county three or more times with a score of 100. A penalty of 100 is so severe that any such district is effectively discarded. These parameter values are chosen such that the diversity of the simulated plans is reasonable while minimizing the number of county splits.

13. As shown in Appendix D, all of my simulation plans have fewer county splits than the enacted plan. In addition, while the enacted plan splits Hamilton and Cuyahoga counties twice, only 8 of my 5,000 simulated plans split two counties twice. 35.9% of the simulated plans split only Franklin County twice whereas the remaining simulated plans split no counties twice.

14. Section 2(B)(4)(a) applies to single municipality or township that exceeds the Congressional ratio of representation. The only municipality or township that satisfies this criteria is the City of Columbus. The provision states that the map drawers "shall attempt to include a significant portion of that municipal corporation or township in a single district and may include in that district other municipal corporations or townships that are located in that county and whose residents have similar interests as the residents of the municipal corporation or township that contains a population that exceeds the congressional ratio of representation." To satisfy this requirement, I impose a penalty of 0.5 for each additional district that encompasses any part of the city. This has the effect of ensuring that the city is not split into many different districts. Again, this parameter value is chosen such that the diversity of the simulated plans is reasonable while appropriately discouraging Columbus splits. Like the enacted plan, all of my simulated plans split Columbus into two districts but in different ways.

15. According to Section 2(B)(6), for counties that are split by a congressional district,

the part of the district that falls within county lines must be geographically contiguous within the county. This requirement is mathematically guaranteed by the properties of the SMC algorithm; by drawing spanning trees hierarchically, within and then across counties, it is impossible to split off a district which has two discontiguous pieces inside one county.

16. Section 2(B)(7) requires that two congressional districts can share at most the territory of a single county, excepting counties with population greater than 400,000, where another county can be shared. Like Section 2(B)(6), this requirement is guaranteed by the SMC algorithm: each new district will split at most one county, whereas a 2(B)(7) violation would require two districts to each split the same two counties.

17. Section 2(B)(8) states, "The authority drawing the districts shall attempt to include at least one whole county in each congressional district." This provision does not apply when a district is contained entirely within a county or when in conflict with federal law. This requirement is guaranteed by the enacted plans' choice of counties to split: with the exception of Cuyahoga and Franklin counties, which are each large enough to have a district contained entirely within them, every other split county is surrounded by counties which are not split. Since I do not permit the algorithm to split these surrounding counties, every other district is either contained within a single county or includes the entirety of one of these surrounding counties.

C. Compactness of the Simulated Plans

18. I now show that the simulated plans are more compliant with Section 2(B)(2), which requires districts to be compact, than the enacted plan. I use the Polsby–Popper (Polsby and Popper 1991) and edge-removal (DeFord, Duchin, and Solomon 2021; McCartan and Imai 2020) scores, two commonly-used quantitative measures of district compactness. For the edge-removal compactness, I present the fraction of edge kept so that like the Polsby–Popper score, a greater value implies a higher level of compactness. Figure 7 shows that a vast majority of the simulated plans are more compact than the enacted plan according to the Polsby–Popper score. If I instead use the edge-removal compactness score, all of the simulated plans have superior compactness when compared to the enacted plan. The result clearly implies that it is possible to be compliant

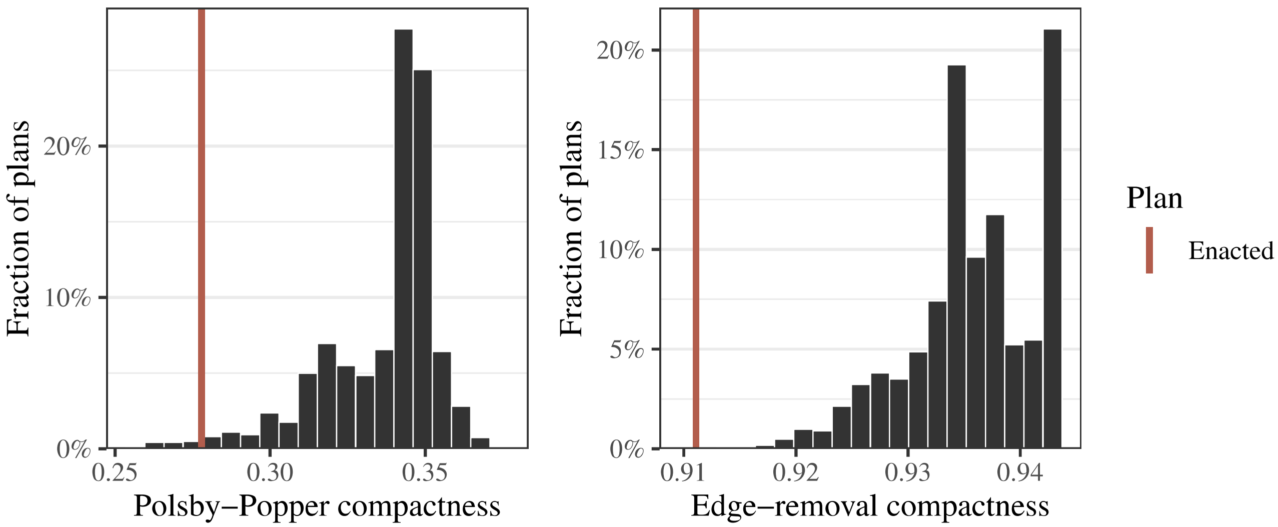

Figure 7: Polsby–Popper and edge–removal compactness scores for the simulated redistricting plans. Overlaid are scores for the enacted plan (red). For both measures, larger values indicate more compact districts.

with Section 1(C)(3)(a) without sacrificing the compliance with Section 2(B)(2).

D. County Splits of the Simulated Plans

19. Similar to compactness, it is possible to be compliant with Section 1(C)(3)(a) without splitting counties more than the enacted plan. The left plot of Figure 8 shows that the number of counties split once is much less under any of the simulated plans than under the enacted plan. The same finding applies to the number of counties that are split twice. As a result, the total number of counties split under the enacted plan is much greater than that under any of the simulated plans.

E. References and Materials Considered

E.1. Data Sources

Data Aquisition

- I analyze a total of 13 statewide elections: US President (2012, 2016, 2020), US Senate (2012, 2016, 2018), Secretary of State (2014, 2018), Governor (2014, 2018), Attorney General (2018), Treasurer (2018), Auditor (2018)

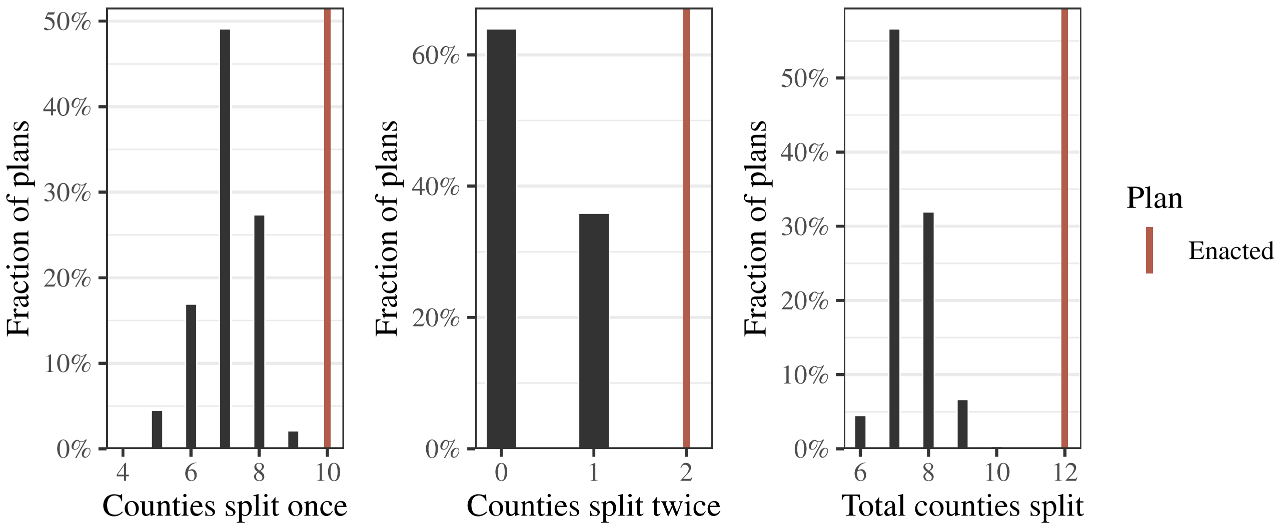

Figure 8: The number of county splits for the simulated redistricting plans. Overlaid are the scores for the enacted plan (red). The left plot shows the number of counties that are split once under each plan, whereas the middle plot presents the number of counties that are split twice under each plan. The right plot shows the number of counties that are split either once or twice. No county is split more than twice under both the enacted plan and any of the simulated plans.

- The six statewide federal elections I use to implement the General Assembly's approach: US President (2012, 2016, 2020), US Senate (2012, 2016, 2018)

- The 2016, 2018, and 2020 precinct-level shapefiles were acquired from the Voting and Election Science Team at the University of Florida and Wichita State University. This data is publicly available on the Harvard Dataverse, an online repository of social science data. Those shapefiles were joined to precinct-level election returns from the Ohio Secretary of State's office, which had been processed and cleaned by OpenElections.

- The 2012 and 2014 election returns pro-rated to the 2010 VTD level were acquired from Bill Cooper. Counsel has informed that Bill Cooper provided the following description of the data: The 2012 results are disaggregated to the block level (based on block centroids) from the statewide 2012 precinct file. The 2014 results are based on a geocoding of about 3.15 million voters who cast ballots in Nov. 2014. These addresses were matched to census blocks and the blocks were aggregated to the precinct level. These virtual precincts were next matched to the 2014 election results and then disaggregated back to the block level, with block-level matches. When aggregated to the congressional level, the differences are measured in the tenths of a percent for House contests. As a final step, these datasets were aggregated from the block-level to the 2010 VTD level. Finally, it is important to note that there is a 2% to 3% undercount statewide for all votes cast in the 2014 election.

- Given the missing votes for the 2014 contests in Lorain County, the VTD-level totals in that county were approximated using the official precinct 2014 returns. First, after identifying the township, city, or village of each 2014 precinct, the official precinct-level returns were aggregated up to that level. Those municipality-level returns were then disaggregated for each candidate down to the VTDs in each municipality, proportionally to the vote counts for the candidate running for the same office and party in the 2018 midterm cycle.

- The 2020 Census Block shapefiles, total population by race and ethnicity, and voting age population by race and ethnicity were obtained directly from the Census FTP portal.

- The 2020 Census place block assignment files (for city and village boundaries and VTD block assignment files) were obtained from the Census website.

- The 2020 Census county subdivision shapefiles (for Ohio township boundaries) were obtained from the Census website.

- The enacted plan data were gathered from the text of SB258, and cleaned into a block equivalency file.

- Geolocated congressional incumbent names and addresses, which were gathered by Carl Klarner, were acquired through Redistricting Data Hub. For new incumbents who came into office following the 2021 general election (Shontel Brown, Mike Carey), their addresses and geolocated locations were given to me by counsel for the plaintiffs.

Data Processing

- The datasets that were on the 2020 census block level (total population, voting age population, Census place assignment, VTD assignment, enacted plan) were joined to the 2020 Census block shapefile.

- The datasets that were not on the level of the census block (2016, 2018, and 2020 election returns – precinct; 2012 and 2014 election returns – 2010 VTD) were disaggregated down to the 2020 census block level. Then, the resulting data were joined to the 2020 Census block shapefile.

- For the 2020 Census county subdivision shapefile, each 2020 Census block was assigned to its corresponding county subdivision assignment by overlaying the county subdivision shapefile onto the 2020 Census blocks.

- Given that some of Ohio's voting districts are geographically discontiguous, the separate discontiguous pieces of each voting district were identified.

Data Aggregation

- The full block-level dataset was aggregated up to the level of the 2020 voting districts, taking into account (a) discontiguous voting districts and (b) splits of voting districts by the enacted plan.

- The final municipality ID was constructed on the aggregated dataset. Where a VTD belonged to a village or a city, the municipality ID took the value of that village or city. Otherwise, it took the value of the county subdivision of the VTD. Then, discontiguous municipalities or townships were identified, and assigned to unique identifiers. The final municipality ID concatenates the original municipality ID, the identifier for each discontiguous piece, and a county identifier, so that it identifies a unique contiguous piece of a municipality within a given county.

E.2. References

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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.

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Herschlag, Gregory, Han Sung Kang, Justin Luo, Christy Vaughn Graves, Sachet Bangia, Robert Ravier, and Jonathan C Mattingly. 2020. "Quantifying gerrymandering in North Carolina: Supplemental Appendix." *Statistics and Public Policy* 7 (1): 30–38.

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Kenny, Christopher T., Shiro Kuriwaki, Cory McCartan, Evan Rosenman, Tyler Simko, and Kosuke Imai. 2021. "The Use of Differential Privacy for Census Data and its Impact on Redistricting: The Case of the 2020 U.S. Census." *Science Advances* 7, no. 41 (October): 1–17.

Kenny, Christopher T., Cory McCartan, Benjamin Fifield, and Kosuke Imai. 2020. *redist: Computational Algorithms for Redistricting Simulation.* https://CRAN.R-project.org/package=redist.

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Tukey, John W. 1977. *Exploratory Data Analysis.* Pearson.

EXHIBIT A

Curriculum Vitae

Kosuke Imai

Curriculum Vitae

November 2021

Contact Information

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Education

Ph.D. in Political Science, Harvard University (1999–2003)

A.M. in Statistics, Harvard University (2000–2002)

B.A. in Liberal Arts, The University of Tokyo (1994–1998)

Positions

Professor, Department of Government and Department of Statistics, Harvard University (2018 – present)

Professor, Department of Politics and Center for Statistics and Machine Learning, Princeton University (2013 – 2018)

> Founding Director, Program in Statistics and Machine Learning (2013 – 2017)

Professor of Visiting Status, Graduate Schools of Law and Politics, The University of Tokyo (2016 – present)

Associate Professor, Department of Politics, Princeton University (2012 – 2013)

Assistant Professor, Department of Politics, Princeton University (2004 – 2012)

Visiting Researcher, Faculty of Economics, The University of Tokyo (August, 2006)

Instructor, Department of Politics, Princeton University (2003 – 2004)

Honors and Awards

1. Invited to read "Experimental Evaluation of Computer-Assisted Human Decision-Making: Application to Pretrial Risk Assessment Instrument." before the Royal Statistical Society Research Section, London (2021).
2. *Excellence in Mentoring Award*, awarded by the Society for Political Methodology (2021).
3. *Statistical Software Award* for developing statistical software that makes a significant research contribution, for "fastLink: Fast Probabilistic Record Linkage," awarded by the Society for Political Methodology (2021).
4. *Highly Cited Researcher* (cross-field category) for "production of multiple highly cited papers that rank in the top 1% by citations for field and year in Web of Science," awarded by Clarivate Analytics (2018, 2019, 2020).
5. *President*, The Society for Political Methodology (2017–2019). *Vice President and President-elect* (2015–2017).
6. *Elected Fellow*, The Society for Political Methodology (2017).
7. *The Nils Petter Gleditsch Article of the Year Award* (2017), awarded by *Journal of Peace Research*.
8. *Statistical Software Award* for developing statistical software that makes a significant research contribution, for "mediation: R Package for Causal Mediation Analysis," awarded by the Society for Political Methodology (2015).
9. *Outstanding Reviewer Award* for Journal of Educational and Behavioral Statistics, given by the American Educational Research Association (2014).
10. *The Stanley Kelley, Jr. Teaching Award*, given by the Department of Politics, Princeton University (2013).
11. *Pi Sigma Alpha Award* for the best paper presented at the 2012 Midwest Political Science Association annual meeting, for "Explaining Support for Combatants during Wartime: A Survey Experiment in Afghanistan," awarded by the Midwest Political Science Association (2013).
12. Invited to read "Experimental Designs for Identifying Causal Mechanisms" before the Royal Statistical Society Research Section, London (2012).
13. Inaugural recipient of the *Emerging Scholar Award* for a young scholar making exceptional contributions to political methodology who is within ten years of their terminal degree, awarded by the Society for Political Methodology (2011).
14. *Political Analysis Editors' Choice Award* for an article providing an especially significant contribution to political methodology, for "Estimation of Heterogeneous Treatment Effects from Randomized Experiments, with Application to the Optimal Planning of the Get-out-the-vote Campaign," awarded by the Society for Political Methodology and Oxford University Press (2011).

15. *Tom Ten Have Memorial Award* for the best poster presented at the 2011 Atlantic Causal Inference Conference, for "Identifying Treatment Effect Heterogeneity through Optimal Classification and Variable Selection," awarded by the Departments of Biostatistics and Statistics, University of Michigan (2011).

16. Nominated for the *Graduate Mentoring Award*, The McGraw Center for Teaching and Learning, Princeton University (2010, 2011).

17. *New Hot Paper*, for the most-cited paper in the field of Economics & Business in the last two months among papers published in the last year, for "Misunderstandings among Experimentalists and Observationalists about Causal Inference," named by Thomson Reuters' ScienceWatch (2009).

18. *Warren Miller Prize* for the best article published in *Political Analysis*, for "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," awarded by the Society for Political Methodology and Oxford University Press (2008).

19. *Fast Breaking Paper* for the article with the largest percentage increase in citations among those in the top 1% of total citations across the social sciences in the last two years, for "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," named by Thomson Reuters' ScienceWatch (2008).

20. *Pharmacoepidemiology and Drug Safety Outstanding Reviewer Recognition* (2008).

21. *Miyake Award* for the best political science article published in 2005, for "Do Get-Out-The-Vote Calls Reduce Turnout? The Importance of Statistical Methods for Field Experiments," awarded by the Japanese Political Science Association (2006).

22. *Toppan Prize* for the best dissertation in political science, for *Essays on Political Methodology*, awarded by Harvard University (2004). Also, nominated for American Political Science Association E.E. Schattschneider Award for the best doctoral dissertation in the field of American government and politics.

Publications in English

Book

Imai, Kosuke. (2017). *Quantitative Social Science: An Introduction.* Princeton University Press. Translated into Japanese (2018), Chinese (2020), and Korean (2021).

Stata version (2021) with Lori D. Bougher.

Tidyverse version (forthcoming) with Nora Webb Williams

Refereed Journal Articles

1. Fan, Jianqing, Kosuke Imai, Inbeom Lee, Han Liu, Yang Ning, and Xiaolin Yang. "Optimal Covariate Balancing Conditions in Propensity Score Estimation." *Journal of Business & Economic Statistics*, Forthcoming.

2. Imai, Kosuke, Zhichao Jiang, D. James Greiner, Ryan Halen, and Sooahn Shin. "Experimental Evaluation of Computer-Assisted Human Decision-Making: Application to Pretrial Risk Assessment Instrument." (with discussion) *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Forthcoming. To be read before the Royal Statistical Society.

3. Imai, Kosuke, In Song Kim, and Erik Wang. "Matching Methods for Causal Inference with Time-Series Cross-Sectional Data." *American Journal of Political Science*, Forthcoming.

4. Imai, Kosuke and Michael Lingzhi Li. "Experimental Evaluation of Individualized Treatment Rules." *Journal of the American Statistical Association*, Forthcoming.

5. de la Cuesta, Brandon, Naoki Egami, and Kosuke Imai."Experimental Design and Statistical Inference for Conjoint Analysis: The Essential Role of Population Distribution." *Political Analysis*, Forthcoming.

6. Kenny, Christopher T., Shiro Kuriwaki, Cory McCartan, Evan Rosenman, Tyler Simko, and Kosuke Imai. (2021). "The Use of Differential Privacy for Census Data and its Impact on Redistricting: The Case of the 2020 U.S. Census." *Science Advances*, Vol. 7, No. 7 (October), pp. 1-17.

7. Imai, Kosuke and James Lo. (2021). " Robustness of Empirical Evidence for the Democratic Peace: A Nonparametric Sensitivity Analysis." *International Organization*, Vol. 75, No. 3 (Summer), pp. 901–919.

8. Imai, Kosuke, Zhichao Jiang, and Anup Malani. (2021). "Causal Inference with Interference and Noncompliance in the Two-Stage Randomized Experiments." *Journal of the American Statistical Association*, Vol. 116, No. 534, pp. 632-644.

9. Imai, Kosuke, and In Song Kim. (2021). "On the Use of Two-way Fixed Effects Regression Models for Causal Inference with Panel Data." *Political Analysis*, Vol. 29, No. 3 (July), pp. 405–415.

10. Imai, Kosuke and Zhichao Jiang. (2020). "Identification and Sensitivity Analysis of Contagion Effects with Randomized Placebo-Controlled Trials." *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 183, No. 4 (October), pp. 1637–1657.

11. Fifield, Benjamin, Michael Higgins, Kosuke Imai, and Alexander Tarr. (2020). "Automated Redistricting Simulation Using Markov Chain Monte Carlo." *Journal of Computational and Graphical Statistics*, Vol. 29, No. 4, pp. 715–728.

12. 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*, Vol. 7, No 1, pp. 52–68.

13. Ning, Yang, Sida Peng, and Kosuke Imai. (2020). "Robust Estimation of Causal Effects via High-Dimensional Covariate Balancing Propensity Score." *Biometrika*, Vol. 107, No. 3 (September), pp. 533—554.

14. Chou, Winston, Kosuke Imai, and Bryn Rosenfeld. (2020). "Sensitive Survey Questions with Auxiliary Information." *Sociological Methods & Research*, Vol. 49, No. 2 (May), pp. 418–454.

15. Imai, Kosuke, Gary King, and Carlos Velasco Rivera. (2020). "Do Nonpartisan Programmatic Policies Have Partisan Electoral Effects? Evidence from Two Large Scale Randomized Experiments." *Journal of Politics*, Vol. 82, No. 2 (April), pp. 714–730.

16. Zhao, Shandong, David A. van Dyk, and Kosuke Imai. (2020). "Propensity-Score Based Methods for Causal Inference in Observational Studies with Non-Binary Treatments." *Statistical Methods in Medical Research*, Vol. 29, No. 3 (March), pp. 709–727.

17. Lyall, Jason, Yang-Yang Zhou, and Kosuke Imai. (2020). "Can Economic Assistance Shape Combatant Support in Wartime? Experimental Evidence from Afghanistan." *American Political Science Review*, Vol. 114, No. 1 (February), pp. 126–143.

18. Kim, In Song, Steven Liao, and Kosuke Imai. (2020). "Measuring Trade Profile with Granular Product-level Trade Data." *American Journal of Political Science*, Vol. 64, No. 1 (January), pp. 102-117.

19. Enamorado, Ted and Kosuke Imai. (2019). "Validating Self-reported Turnout by Linking Public Opinion Surveys with Administrative Records." *Public Opinion Quarterly*, Vol. 83, No. 4 (Winter), pp. 723—748.

20. Blair, Graeme, Winston Chou, and Kosuke Imai. (2019). "List Experiments with Measurement Error." *Political Analysis*, Vol. 27, No. 4 (October), pp. 455–480.

21. Egami, Naoki, and Kosuke Imai. "Causal Interaction in Factorial Experiments: Application to Conjoint Analysis." *Journal of the American Statistical Association*, Vol. 114, No. 526 (June), pp. 529-540.

22. Enamorado, Ted, Benjamin Fifield, and Kosuke Imai. (2019). "Using a Probabilistic Model to Assist Merging of Large-scale Administrative Records." *American Political Science Review*, Vol. 113, No. 2 (May), pp. 353–371.

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24. Imai, Kosuke, and Zhichao Jiang. (2018). "A Sensitivity Analysis for Missing Outcomes Due to Truncation-by-Death under the Matched-Pairs Design." *Statistics in Medicine*, Vol. 37, No. 20 (September), pp. 2907–2922.

25. Fong, Christian, Chad Hazlett, and Kosuke Imai. (2018). "Covariate Balancing Propensity Score for a Continuous Treatment: Application to the Efficacy of Political Advertisements." *Annals of Applied Statistics*, Vol. 12, No. 1, pp. 156–177.

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27. Imai, Kosuke, James Lo, and Jonathan Olmsted. (2016). "Fast Estimation of Ideal Points with Massive Data." *American Political Science Review*, Vol. 110, No. 4 (December), pp. 631–656.

28. Rosenfeld, Bryn, Kosuke Imai, and Jacob Shapiro. (2016). "An Empirical Validation Study of Popular Survey Methodologies for Sensitive Questions." *American Journal of Political Science*, Vol. 60, No. 3 (July), pp. 783–802.

29. Imai, Kosuke and Kabir Khanna. (2016). "Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Record." *Political Analysis*, Vol. 24, No. 2 (Spring), pp. 263–272.

30. Blair, Graeme, Kosuke Imai, and Yang-Yang Zhou. (2015). "Design and Analysis of the Randomized Response Technique." *Journal of the American Statistical Association*, Vol. 110, No. 511 (September), pp. 1304–1319.

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32. Lyall, Jason, Yuki Shiraito, and Kosuke Imai. (2015). "Coethnic Bias and Wartime Informing." *Journal of Politics*, Vol. 77, No. 3 (July), pp. 833–848.

33. Imai, Kosuke, Bethany Park, and Kenneth Greene. (2015). "Using the Predicted Responses from List Experiments as Explanatory Variables in Regression Models." *Political Analysis*, Vol. 23, No. 2 (Spring), pp. 180–196. Translated in Portuguese and Reprinted in *Revista Debates* Vol. 9, No 1.

34. Blair, Graeme, Kosuke Imai, and Jason Lyall. (2014). "Comparing and Combining List and Endorsement Experiments: Evidence from Afghanistan." *American Journal of Political Science*, Vol. 58, No. 4 (October), pp. 1043–1063.

35. Tingley, Dustin, Teppei Yamamoto, Kentaro Hirose, Luke Keele, and Kosuke Imai. (2014). "mediation: R Package for Causal Mediation Analysis." *Journal of Statistical Software*, Vol. 59, No. 5 (August), pp. 1–38.

36. Imai, Kosuke and Marc Ratkovic. (2014). "Covariate Balancing Propensity Score." *Journal of the Royal Statistical Society, Series B (Statistical Methodology)*, Vol. 76, No. 1 (January), pp. 243–263.

37. Lyall, Jason, Graeme Blair, and Kosuke Imai. (2013). "Explaining Support for Combatants during Wartime: A Survey Experiment in Afghanistan." *American Political Science Review*, Vol. 107, No. 4 (November), pp. 679-705. Winner of the Pi Sigma Alpha Award.

38. Imai, Kosuke and Teppei Yamamoto. (2013). "Identification and Sensitivity Analysis for Multiple Causal Mechanisms: Revisiting Evidence from Framing Experiments." *Political Analysis*, Vol. 21, No. 2 (Spring), pp. 141–171. (lead article).

39. Imai, Kosuke and Marc Ratkovic. (2013). "Estimating Treatment Effect Heterogeneity in Randomized Program Evaluation." *Annals of Applied Statistics*, Vol. 7, No. 1 (March), pp. 443–470. Winner of the Tom Ten Have Memorial Award. Reprinted in *Advances in Political Methodology*, R. Franzese, Jr. ed., Edward Elger, 2017.

40. Imai, Kosuke, Dustin Tingley, and Teppei Yamamoto. (2013). "Experimental Designs for Identifying Causal Mechanisms."(with discussions) *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 176, No. 1 (January), pp. 5–51. (lead article) Read before the Royal Statistical Society, March 2012.

41. Imai, Kosuke, and Dustin Tingley. (2012). "A Statistical Method for Empirical Testing of Competing Theories." *American Journal of Political Science*, Vol. 56, No. 1 (January), pp. 218–236.

42. Blair, Graeme, and Kosuke Imai. (2012). "Statistical Analysis of List Experiments." *Political Analysis*, Vol. 20, No. 1 (Winter), pp. 47–77.

43. Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. (2011). "Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies." *American Political Science Review*, Vol. 105, No. 4 (November), pp. 765–789. Reprinted in *Advances in Political Methodology*, R. Franzese, Jr. ed., Edward Elger, 2017.

44. Bullock, Will, Kosuke Imai, and Jacob N. Shapiro. (2011). "Statistical Analysis of Endorsement Experiments: Measuring Support for Militant Groups in Pakistan." *Political Analysis*, Vol. 19, No. 4 (Autumn), pp. 363–384. (lead article)

45. Imai, Kosuke. (2011). "Multivariate Regression Analysis for the Item Count Technique." *Journal of the American Statistical Association*, Vol. 106, No. 494 (June), pp. 407–416. (featured article)

46. Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth Stuart. (2011). "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference." *Journal of Statistical Software*, Vol. 42 (Special Volume on Political Methodology), No. 8 (June), pp. 1–28.

47. Imai, Kosuke, Ying Lu, and Aaron Strauss. (2011). "eco: R Package for Ecological Inference in 2×2 Tables." *Journal of Statistical Software*, Vol. 42 (Special Volume on Political Methodology), No. 5 (June), pp. 1–23.

48. Imai, Kosuke and Aaron Strauss. (2011). "Estimation of Heterogeneous Treatment Effects from Randomized Experiments, with Application to the Optimal Planning of the Get-out-the-vote Campaign." *Political Analysis*, Vol. 19, No. 1 (Winter), pp. 1–19. (lead article) Winner of the Political Analysis Editors' Choice Award.

49. Imai, Kosuke, Luke Keele, and Dustin Tingley. (2010). "A General Approach to Causal Mediation Analysis." *Psychological Methods*, Vol. 15, No. 4 (December), pp. 309–334. (lead article)

50. Imai, Kosuke and Teppei Yamamoto. (2010). "Causal Inference with Differential Measurement Error: Nonparametric Identification and Sensitivity Analysis." *American Journal of Political Science*, Vol. 54, No. 2 (April), pp. 543–560.

51. Imai, Kosuke, Luke Keele, and Teppei Yamamoto. (2010). "Identification, Inference, and Sensitivity Analysis for Causal Mediation Effects." *Statistical Science*, Vol. 25, No. 1 (February), pp. 51–71.

52. King, Gary, Emmanuela Gakidou, Kosuke Imai, Jason Lakin, Ryan T. Moore, Clayton Nall, Nirmala Ravishankar, Manett Vargas, Martha María Téllez-Rojo, Juan Eugenio Hernández Ávila, Mauricio Hernández Ávila, and Héctor Hernández Llamas. (2009). "Public Policy for the Poor? A Randomized Ten-Month Evaluation of the Mexican Universal Health Insurance Program." (with a comment) *The Lancet*, Vol. 373, No. 9673 (April), pp. 1447–1454.

53. Imai, Kosuke, Gary King, and Clayton Nall. (2009). "The Essential Role of Pair Matching in Cluster-Randomized Experiments, with Application to the Mexican Universal Health Insurance Evaluation." (with discussions) *Statistical Science*, Vol. 24, No. 1 (February), pp. 29–53.

54. Imai, Kosuke. (2009). "Statistical Analysis of Randomized Experiments with Nonignorable Missing Binary Outcomes: An Application to a Voting Experiment." *Journal of the Royal Statistical Society, Series C (Applied Statistics)*, Vol. 58, No. 1 (February), pp. 83–104.

55. Imai, Kosuke, Gary King, and Olivia Lau. (2008). "Toward A Common Framework of Statistical Analysis and Development." *Journal of Computational and Graphical Statistics*, Vol. 17, No. 4 (December), pp. 892–913.

56. Imai, Kosuke. (2008). "Variance Identification and Efficiency Analysis in Experiments under the Matched-Pair Design." *Statistics in Medicine*, Vol. 27, No. 4 (October), pp. 4857–4873.

57. Ho, Daniel E., and Kosuke Imai. (2008). "Estimating Causal Effects of Ballot Order from a Randomized Natural Experiment: California Alphabet Lottery, 1978–2002." *Public Opinion Quarterly*, Vol. 72, No. 2 (Summer), pp. 216–240.

58. Imai, Kosuke, Gary King, and Elizabeth A. Stuart. (2008). "Misunderstandings among Experimentalists and Observationalists: Balance Test Fallacies in Causal Inference." *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 171, No. 2 (April), pp. 481–502. Reprinted in *Field Experiments and their Critics*, D. Teele ed., New Haven: Yale University Press, 2013.

59. Imai, Kosuke, Ying Lu, and Aaron Strauss. (2008). "Bayesian and Likelihood Ecological Inference for 2×2 Tables: An Incomplete Data Approach." *Political Analysis*, Vol. 16, No. 1 (Winter), pp. 41–69.

60. Imai, Kosuke. (2008). "Sharp Bounds on the Causal Effects in Randomized Experiments with "Truncation-by-Death"." *Statistics & Probability Letters*, Vol. 78, No. 2 (February), pp. 144–149.

61. Imai, Kosuke and Samir Soneji. (2007). "On the Estimation of Disability-Free Life Expectancy: Sullivan's Method and Its Extension." *Journal of the American Statistical Association*, Vol. 102, No. 480 (December), pp. 1199–1211.

62. Horiuchi, Yusaku, Kosuke Imai, and Naoko Taniguchi. (2007). "Designing and Analyzing Randomized Experiments: Application to a Japanese Election Survey Experiment." *American Journal of Political Science*, Vol. 51, No. 3 (July), pp. 669–687.

63. Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart. (2007). "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference." *Political Analysis*, Vol. 15, No. 3 (Summer), pp. 199–236. (lead article) Winner of the Warren Miller Prize.

64. Ho, Daniel E., and Kosuke Imai. (2006). "Randomization Inference with Natural Experiments: An Analysis of Ballot Effects in the 2003 California Recall Election." *Journal of the American Statistical Association*, Vol. 101, No. 475 (September), pp. 888–900.

65. Imai, Kosuke, and David A. van Dyk. (2005). "MNP: R Package for Fitting the Multinomial Probit Model." *Journal of Statistical Software*, Vol. 14, No. 3 (May), pp. 1–32. abstract reprinted in *Journal of Computational and Graphical Statistics* (2005) Vol. 14, No. 3 (September), p. 747.

66. Imai, Kosuke. (2005). "Do Get-Out-The-Vote Calls Reduce Turnout? The Importance of Statistical Methods for Field Experiments." *American Political Science Review*, Vol. 99, No. 2 (May), pp. 283–300.

67. Imai, Kosuke, and David A. van Dyk. (2005). "A Bayesian Analysis of the Multinomial Probit Model Using Marginal Data Augmentation." *Journal of Econometrics*, Vol. 124, No. 2 (February), pp. 311–334.

68. Imai, Kosuke, and David A. van Dyk. (2004). "Causal Inference With General Treatment Regimes: Generalizing the Propensity Score." *Journal of the American Statistical Association*, Vol. 99, No. 467 (September), pp. 854–866.

69. Imai, Kosuke, and Gary King. (2004). "Did Illegal Overseas Absentee Ballots Decide the 2000 U.S. Presidential Election?" *Perspectives on Politics*, Vol. 2, No. 3 (September), pp. 537–549. Our analysis is a part of *The New York Times* article, "How Bush Took Florida: Mining the Overseas Absentee Vote" By David Barstow and Don van Natta Jr. July 15, 2001, Page 1, Column 1.

Invited Contributions

1. Imai, Kosuke, and Zhichao Jiang. (2019). "Comment: The Challenges of Multiple Causes." *Journal of the American Statistical Association*, Vol. 114, No. 528, pp. 1605—1610.

2. Benjamin, Daniel J., *et al.* (2018). "Redefine Statistical Significance." *Nature Human Behaviour*, Vol. 2, No. 1, pp. 6–10.

3. de la Cuesta, Brandon and Kosuke Imai. (2016). "Misunderstandings about the Regression Discontinuity Design in the Study of Close Elections." *Annual Review of Political Science*, Vol. 19, pp. 375–396.

4. Imai, Kosuke (2016). "Book Review of *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction.* by Guido W. Imbens and Donald B. Rubin." *Journal of the American Statistical Association*, Vol. 111, No. 515, pp. 1365–1366.

5. Imai, Kosuke, Bethany Park, and Kenneth F. Greene. (2015). "Usando as respostas previsíveis da abordagem list-experiments como variaveis explicativás em modelos de regressão." *Revista Debates*, Vol. 9, No. 1, pp. 121–151. First printed in *Political Analysis*, Vol. 23, No. 2 (Spring).

6. Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. (2014). "Comment on Pearl: Practical Implications of Theoretical Results for Causal Mediation Analysis." *Psychological Methods*, Vol. 19, No. 4 (December), pp. 482–487.

7. Imai, Kosuke, Gary King, and Elizabeth A. Stuart. (2014). "Misunderstandings among Experimentalists and Observationalists: Balance Test Fallacies in Causal Inference." in *Field Experiments and their Critics: Essays on the Uses and Abuses of Experimentation in the Social Sciences*, D. L. Teele ed., New Haven: Yale University Press, pp. 196–227. First printed in *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 171, No. 2 (April).

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10. Imai, Kosuke. (2011). "Introduction to the Virtual Issue: Past and Future Research Agenda on Causal Inference." *Political Analysis*, Virtual Issue: Causal Inference and Political Methodology.

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12. Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. (2010). "Causal Mediation Analysis Using R," in *Advances in Social Science Research Using R*, H. D. Vinod (ed.), New York: Springer (Lecture Notes in Statistics), pp. 129–154.

13. Imai, Kosuke, Gary King, and Clayton Nall. (2009). "Rejoinder: Matched Pairs and the Future of Cluster-Randomized Experiments." *Statistical Science*, Vol. 24, No. 1 (February), pp. 65–72.

14. Imai, Kosuke. (2003). "Review of Jeff Gill's *Bayesian Methods: A Social and Behavioral Sciences Approach*," *The Political Methodologist*, Vol. 11 No. 1, 9–10.

Refereed Conference Proceedings

1. Svyatkovskiy, Alexey, Kosuke Imai, Mary Kroeger, and Yuki Shiraito. (2016). "Large-scale text processing pipeline with Apache Spark," *IEEE International Conference on Big Data*, Washington, DC, pp. 3928-3935.

Other Publications and Manuscripts

1. Goldstein, Daniel, Kosuke Imai, Anja S. Göritz, and Peter M. Gollwitzer. (2008). "Nudging Turnout: Mere Measurement and Implementation Planning of Intentions to Vote."

2. Ho, Daniel E. and Kosuke Imai. (2004). " The Impact of Partisan Electoral Regulation: Ballot Effects from the California Alphabet Lottery, 1978–2002." Princeton Law & Public Affairs Paper No. 04-001; Harvard Public Law Working Paper No. 89.

3. Imai, Kosuke. (2003). "Essays on Political Methodology," *Ph.D. Thesis.* Department of Government, Harvard University.

4. Imai, Kosuke, and Jeremy M. Weinstein. (2000). "Measuring the Economic Impact of Civil War," Working Paper Series No. 51, Center for International Development, Harvard University.

Selected Manuscripts

1. McCartan, Cory, Jacob Brown, and Kosuke Imai. "Measuring and Modeling Neighborhoods."

2. Ben-Michael, Eli, D. James Greiner, Kosuke Imai, and Zhichao Jiang. "Safe Policy Learning through Extrapolation: Application to Pre-trial Risk Assessment."

3. Tarr, Alexander and Kosuke Imai. "Estimating Average Treatment Effects with Support Vector Machines."

4. McCartan, Cory and Kosuke Imai. "Sequential Monte Carlo for Sampling Balanced and Compact Redistricting Plans."

5. Imai, Kosuke and Zhichao Jiang. "Principal Fairness for Human and Algorithmic Decision-Making."

6. Papadogeorgou, Georgia, Kosuke Imai, Jason Lyall, and Fan Li. "Causal Inference with Spatio-temporal Data: Estimating the Effects of Airstrikes on Insurgent Violence in Iraq."

7. Eshima, Shusei, Kosuke Imai, and Tomoya Sasaki. "Keyword Assisted Topic Models."

8. Tarr, Alexander, June Hwang, and Kosuke Imai. "Automated Coding of Political Campaign Advertisement Videos: An Empirical Validation Study."

9. Olivella, Santiago, Tyler Pratt, and Kosuke Imai. "Dynamic Stochastic Blockmodel Regression for Social Networks: Application to International Conflicts."

10. Chan, K.C.G, K. Imai, S.C.P. Yam, Z. Zhang. "Efficient Nonparametric Estimation of Causal Mediation Effects."

11. Barber, Michael and Kosuke Imai. "Estimating Neighborhood Effects on Turnout from Geocoded Voter Registration Records."

12. Hirano, Shigeo, Kosuke Imai, Yuki Shiraito, and Masaki Taniguchi. "Policy Positions in Mixed Member Electoral Systems: Evidence from Japan."

Publications in Japanese

1. Imai, Kosuke. (2007). "Keiryō Seijigaku niokeru Ingateki Suiron (Causal Inference in Quantitative Political Science)." *Leviathan*, Vol. 40, Spring, pp. 224–233.

2. Horiuchi, Yusaku, Kosuke Imai, and Naoko Taniguchi. (2005). "Seisaku Jyōhō to Tōhyō Sanka: Field Jikken ni yoru Kensyō (Policy Information and Voter Participation: A Field Experiment)." *Nenpō Seijigaku (The Annals of the Japanese Political Science Association)*, 2005–I, pp. 161–180.

3. Taniguchi, Naoko, Yusaku Horiuchi, and Kosuke Imai. (2004). "Seitō Saito no Etsuran ha Tohyō Kōdō ni Eikyō Suruka? (Does Visiting Political Party Websites Influence Voting Behavior?)" *Nikkei Research Report*, Vol. IV, pp. 16–19.

Statistical Software

1. Eshima, Shusei, Kosuke Imai, and Tomoya Sasaki. "Keyword Assisted Topic Models." The Comprehensive R Archive Network and GitHub. 2020.

2. Li, Michael Lingzhi and Kosuke Imai. "evalITR: Evaluating Individualized Treatment Rules." available through The Comprehensive R Archive Network and GitHub. 2020.

3. Egami, Naoki, Brandon de la Cuesta, and Kosuke Imai. "factorEx: Design and Analysis for Factorial Experiments." available through The Comprehensive R Archive Network and GitHub. 2019.

4. Kim, In Song, Erik Wang, Adam Rauh, and Kosuke Imai. "PanelMatch: Matching Methods for Causal Inference with Time-Series Cross-Section Data." available through GitHub. 2018.

5. Olivella, Santiago, Adeline Lo, Tyler Pratt, and Kosuke Imai. "NetMix: Mixed-membership Regression Stochastic Blockmodel for Networks." available through CRAN and Github. 2019.

6. Enamorado, Ted, Benjamin Fifield, and Kosuke Imai. "fastLink: Fast Probabilistic Record Linkage." available through The Comprehensive R Archive Network and GitHub. Winner of the Statistical Software Award. 2017.

7. Khanna, Kabir, and Kosuke Imai. "wru: Who Are You? Bayesian Predictions of Racial Category Using Surname and Geolocation." available through The Comprehensive R Archive Network and GitHub. 2015.

8. Fifield, Benjamin, Christopher T. Kenny, Cory McCartan, and Kosuke Imai. "redist: Markov Chain Monte Carlo Methods for Redistricting Simulation." available through The Comprehensive R Archive Network and GitHub. 2015.

9. Imai, Kosuke, James Lo, and Jonathan Olmsted. "emIRT: EM Algorithms for Estimating Item Response Theory Models." available through The Comprehensive R Archive Network. 2015.

10. Blair, Graeme, Yang-Yang Zhou, and Kosuke Imai. "rr: Statistical Methods for the Randomized Response Technique." available through The Comprehensive R Archive Network and GitHub. 2015.

11. Fong, Christian, Marc Ratkovic, and Kosuke Imai. "CBPS: R Package for Covariate Balancing Propensity Score." available through The Comprehensive R Archive Network and GitHub. 2012.

12. Egami, Naoki, Marc Ratkovic, and Kosuke Imai. "FindIt: R Package for Finding Heterogeneous Treatment Effects." available through The Comprehensive R Archive Network and GitHub. 2012.

13. Kim, In Song, and Kosuke Imai. "wfe: Weighted Linear Fixed Effects Regression Models for Causal Inference." available through The Comprehensive R Archive Network. 2011.

14. Shiraito, Yuki, and Kosuke Imai. "endorse: R Package for Analyzing Endorsement Experiments." available through The Comprehensive R Archive Network and GitHub. 2012.

15. Blair, Graeme, and Kosuke Imai. "list: Statistical Methods for the Item Count Technique and List Experiments." available through The Comprehensive R Archive Network and GitHub. 2011.

16. Tingley, Dustin, Teppei Yamamoto, Kentaro Hirose, Luke Keele, and Kosuke Imai. "mediation: R Package for Causal Mediation Analysis." available through The Comprehensive R Archive Network and GitHub. 2009. Winner of the Statistical Software Award. Reviewed in *Journal of Educational and Behavioral Statistics*.

17. Imai, Kosuke. "experiment: R Package for Designing and Analyzing Randomized Experiments." available through The Comprehensive R Archive Network. 2007.

18. Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth Stuart. "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference." available through The Comprehensive R Archive Network and GitHub. 2005.

19. Imai, Kosuke, Ying Lu, and Aaron Strauss. "eco: Ecological Inference in 2×2 Tables." available through The Comprehensive R Archive Network and GitHub. 2004.

20. Imai, Kosuke, and David A. van Dyk. "MNP: R Package for Fitting the Multinomial Probit Model." available through The Comprehensive R Archive Network and GitHub. 2004.

21. Imai, Kosuke, Gary King, and Olivia Lau. "Zelig: Everyone's Statistical Software." available through The Comprehensive R Archive Network. 2004.

External Research Grants

Principal Investigator

1. National Science Foundation (2021–2024). "Collaborative Research: Causal Inference with Spatio-Temporal Data on Human Dynamics in Conflict Settings." (Algorithm for Threat Detection Program; DMS-2124463). Principal Investigator (with Georgia Papadogeorgou and Jason Lyall) $485,340.

2. National Science Foundation (2021–2023). "Evaluating the Impacts of Machine Learning Algorithms on Human Decisions." (Methodology, Measurement, and Statistics Program; SES-2051196). Principal Investigator (with D. James Greiner and Zhichao Jiang) $330,000.

3. Cisco Systems, Inc. (2020–2022). "Evaluating the Impacts of Algorithmic Recommendations on the Fairness of Human Decisions." (Ethics in AI; CG# 2370386) Principal Investigator (with D. James Greiner and Zhichao Jiang) $110,085.

4. The Alfred P. Sloan Foundation (2020–2022). "Causal Inference with Complex Treatment Regimes: Design, Identification, Estimation, and Heterogeneity." (Economics Program;

2020–13946) Co-Principal Investigator (with Francesca Dominici and Jose Zubizarreta) $996,299

5. Facebook Research Grant (2018). $25,000.

6. National Science Foundation (2016–2021). "Collaborative Conference Proposal: Support for Conferences and Mentoring of Women and Underrepresented Groups in Political Methodology." (Methodology, Measurement and Statistics and Political Science Programs; SES–1628102) Principal Investigator (with Jeffrey Lewis) $312,322. Supplement (SES–1831370) $60,000.

7. The United States Agency for International Development (2015–2017). "Unemployment and Insurgent Violence in Afghanistan: Evidence from the Community Development Program." (AID–OAA–A–12–00096) Principal Investigator (with Jason Lyall) $188,037

8. The United States Institute of Peace (2015–2016). "Assessing the Links between Economic Interventions and Stability: An impact evaluation of vocational and skills training in Kandahar, Afghanistan," Principal Investigator (with David Haines, Jon Kurtz, and Jason Lyall) $144,494.

9. Amazon Web Services in Education Research Grant (2014). Principal Investigator (with Graeme Blair and Carlos Velasco Rivera) $3,000.

10. Development Bank of Latin America (CAF) (2013). "The Origins of Citizen Support for Narcos: An Empirical Investigation," Principal Investigator (with Graeme Blair, Fabiana Machado, and Carlos Velasco Rivera). $15,000.

11. The International Growth Centre (2011–2013). "Poverty, Militancy, and Citizen Demands in Natural Resource-Rich Regions: Randomized Evaluation of the Oil Profits Dividend Plan for the Niger Delta" (RA–2010–12–013). Principal Investigator (with Graeme Blair). $117,116.

12. National Science Foundation, (2009–2012). "Statistical Analysis of Causal Mechanisms: Identification, Inference, and Sensitivity Analysis," (Methodology, Measurement, and Statistics Program and Political Science Program; SES–0918968). Principal Investigator. $97,574.

13. National Science Foundation, (2009–2011). "Collaborative Research: The Measurement and Identification of Media Priming Effects in Political Science," (Methodology, Measurement, and Statistics Program and Political Science Program; SES–0849715). Principal Investigator (with Nicholas Valentino). $317,126.

14. National Science Foundation, (2008–2009). "New Statistical Methods for Randomized Experiments in Political Science and Public Policy," (Political Science Program; SES–0752050). Principal Investigator. $52,565.

15. National Science Foundation, (2006–2009). "Collaborative Research: Generalized Propensity Score Methods," (Methodology, Measurement and Statistics Program; SES–0550873). Principal Investigator (with Donald B. Rubin and David A. van Dyk). $460,000.

16. The Telecommunications Advancement Foundation, (2004). "Analyzing the Effects of Party Webpages on Political Opinions and Voting Behavior," Principal Investigator (with Naoko Taniguchi and Yusaku Horiuchi). $12,000.

Adviser and Statistical Consultant

1. National Science Foundation (2016–2017). "Doctoral Dissertation Research: Crossing Africa's Arbitrary Borders: How Refugees Shape National Boundaries by Challenging Them." (Political Science Program, SES–1560636). Principal Investigator and Adviser for Co-PI Yang-Yang Zhou's Dissertation Research. $18,900.

2. Institute of Education Sciences (2012–2014). "Academic and Behavioral Consequences of Visible Security Measures in Schools" (R305A120181). Statistical Consultant (Emily Tanner-Smith, Principal Investigator). $351,228.

3. National Science Foundation (2013–2014). "Doctoral Dissertation Research: Open Trade for Sale: Lobbying by Productive Exporting Firm" (Political Science Program, SES–1264090). Principal Investigator and Adviser for Co-PI In Song Kim's Dissertation Research. $22,540.

4. National Science Foundation (2012–2013). "Doctoral Dissertation Research: The Politics of Location in Resource Rent Distribution and the Projection of Power in Africa" (Political Science Program, SES–1260754). Principal Investigator and Adviser for Co-PI Graeme Blair's Dissertation Research. $17,640.

Invited Short Courses and Outreach Lectures

1. Short Course on Causal Inference and Statistics – Department of Political Science, Rice University, 2009; Institute of Political Science, Academia Sinica, 2014.

2. Short Course on Causal Inference and Identification, The Empirical Implications of Theoretical Models (EITM) Summer Institute – Harris School of Public Policy, University of Chicago, 2011; Department of Politics, Princeton University, 2012.

3. Short Course on Causal Mediation Analysis – Summer Graduate Seminar, Institute of Statistical Mathematics, Tokyo Japan, 2010; Society for Research on Educational Effectiveness Conference, Washington DC, Fall 2011, Spring 2012, Spring 2015; Inter-American Development Bank, 2012; Center for Education Research, University of Wisconsin, Madison, 2012; Bobst Center for Peace and Justice, Princeton University, 2014; Graduate School of Education, University of Pennsylvania, 2014; EITM Summer Institute, Duke University, 2014; Center for Lifespan Psychology, Max Planck Institute for Human Development, 2015; School of Communication Research, University of Amsterdam, 2015; Uppsala University, 2016

4. Short Course on Covariate Balancing Propensity Score – Society for Research on Educational Effectiveness Conference, Washington DC, Spring 2013; Uppsala University, 2016

5. Short Course on Matching Methods for Causal Inference – Institute of Behavioral Science, University of Colorado, Boulder, 2009; Department of Political Science, Duke University, 2013.

6. Lecture on Statistics and Social Sciences – New Jersey Japanese School, 2011, 2016; Kaisei Academy, 2012, 2014; Princeton University Wilson College, 2012; University of Tokyo, 2014

Selected Presentations

1. Distinguished speaker, Harvard College Summer Program for Undergraduates in Data Science, 2021.
2. Keynote speaker, Kansas-Western Missouri Chapter of the American Statistical Association, 2021.
3. Invited plenary panelist, Association for Computing Machinery Conference on Fairness, Accountability, and Transparency (ACM FAccT) 2021.
4. Keynote speaker, Taiwan Political Science Association, 2020.
5. Keynote speaker, Boston Japanese Researchers Forum, Massachusetts Institute of Technology, 2020.
6. Keynote speaker, Causal Mediation Analysis Training Workshop, Mailman School of Public Health, Columbia University, 2020.
7. Keynote speaker, Special Workshop on Evidence-based Policy Making. World Economic Forum, Centre for the Fourth Industrial Revolution, Japan, 2020.
8. Distinguished speaker, Institute for Data, Systems, and Society. Massachusetts Institute of Technology, 2019.
9. Keynote speaker, The Harvard Experimental Political Science Graduate Student Conference, Harvard University, 2019.
10. Invited speaker, Beyond Curve Fitting: Causation, Counterfactuals, and Imagination-based AI. Association for the Advancement of Artificial Intelligence, Spring Symposium, Stanford University, 2019.
11. Inaugural speaker, Causal Inference Seminar, Departments of Biostatistics and Statistics, Boston University, 2019.
12. Keynote speaker, The Second Latin American Political Methodology Meeting, Universidad de los Andes (Department of Political Science), 2018.
13. Keynote speaker, The First Latin American Political Methodology Meeting, Pontifical Catholic University of Chile (Department of Political Science), 2017.
14. Keynote speaker, Workshop on Uncovering Causal Mechanisms, University of Munich (Department of Economics), 2016.
15. Keynote speaker, The National Quality Registry Research Conference, Stockholm, 2016.
16. Keynote speaker, The UK-Causal Inference Meeting, University of Bristol (School of Mathematics), 2015.
17. Keynote speaker, The UP-STAT Conference, the Upstate Chapters of the American Statistical Association, 2015.
18. Keynote speaker, The Winter Conference in Statistics, Swedish Statistical Society and Umeå University (Department of Mathematics and Mathematical Statistics), 2015.

19. Inaugural invited speaker, The International Methods Colloquium, Rice University, 2015.
20. Invited speaker, The International Meeting on Experimental and Behavioral Social Sciences, University of Oxford (Nuffield College), 2014.
21. Keynote speaker, The Annual Conference of Australian Society for Quantitative Political Science, University of Sydney, 2013.
22. Keynote speaker, The Graduate Student Conference on Experiments in Interactive Decision Making, Princeton University. 2008.

Conferences Organized

1. The Asian Political Methodology Meetings (January 2014, 2015, 2016, 2017, 2018; co-organizer)
2. The Experimental Research Workshop (September 2012; co-organizer)
3. The 12th World Meeting of the International Society for Bayesian Analysis (June 2012; a member of the organizing committee)
4. Conference on Causal Inference and the Study of Conflict and State Building (May 2012; organizer)
5. The 28th Annual Society for Political Methodology Summer Meeting (July 2011; host)
6. Conference on New Methodologies and their Applications in Comparative Politics and International Relations (February 2011; co-organizer)

Teaching

Courses Taught at Harvard

1. Stat 286/Gov 2003 Causal Inference (formally Stat 186/Gov 2002): introduction to causal inference
2. Gov 2003 Topics in Quantitative Methodology: causal inference, applied Bayesian statistics, machine learning

Courses Taught at Princeton

1. POL 245 Visualizing Data: exploratory data analysis, graphical statistics, data visualization
2. POL 345 Quantitative Analysis and Politics: a first course in quantitative social science
3. POL 451 Statistical Methods in Political Science: basic probability and statistical theory, their applications in the social sciences
4. POL 502 Mathematics for Political Science: real analysis, linear algebra, calculus
5. POL 571 Quantitative Analysis I: probability theory, statistical theory, linear models
6. POL 572 Quantitative Analysis II: intermediate applied statistics

7. POL 573 Quantitative Analysis III: advanced applied statistics
8. POL 574 Quantitative Analysis IV: advanced applied statistics with various topics including Bayesian statistics and causal inference
9. Reading Courses: basic mathematical probability and statistics, applied bayesian statistics, spatial statistics

Advising

Current Students

1. Soubhik Barari (Government)
2. Adam Breuer (Computer Science and Government). To be Assistant Professor, Department of Government and Department of Computer Science, Dartmouth College
3. Jacob Brown (Government)
4. Ambarish Chattopadhyay (Statistics)
5. Shusei Eshima (Government)
6. Georgina Evans (Government)
7. Dae Woong Ham (Statistics)
8. Christopher T. Kenny (Government)
9. Michael Lingzhe Li (MIT, Operations Research Center)
10. Jialu Li (Government)
11. Cory McCartan (Statistics)
12. Sayumi Miyano (Princeton, Politics)
13. Sun Young Park (Government)
14. Casey Petroff (Political Economy and Government)
15. Averell Schmidt (Kennedy School)
16. Sooahn Shin (Government)
17. Tyler Simko (Government)
18. Soichiro Yamauchi (Government)
19. Yi Zhang (Statistics)

Current Postdocs

1. Eli Ben-Michael
2. Evan Rosenman

Former Students

1. Alexander Tarr (Ph.D. in 2021, Department of Electrical and Computer Engineering, Princeton University; Dissertation Committee Chair)

2. Connor Jerzak (Ph.D. in 2021, Department of Government, Harvard University). Post-doctoral Fellow, Linkoping University. To be Assistant Professor, Department of Government, University of Texas, Austin

3. Shiro Kuriwaki (Ph.D. in 2021, Department of Government, Harvard University). Post-doctoral Fellow, Stanford University. To be Assistant Professor, Department of Political Science, Yale University

4. Erik Wang (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political and Social Change, Australian National University

5. Diana Stanescu (Ph.D. in 2020, Department of Politics, Princeton University). Postdoctoral Fellow, Stanford University

6. Nicole Pashley (Ph.D. in 2020, Department of Statistics, Harvard University). Assistant Professor, Department of Statistics, Rutgers University

7. Asya Magazinnik (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Massachusetts Institute of Technology

8. Max Goplerud (Ph.D. in 2020, Department of Government, Harvard University). Assistant Professor, Department of Political Science, University of Pittsburgh

9. Naoki Egami (Ph.D. in 2020, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, Columbia University

10. Brandon de la Cuesta (Ph.D. in 2019, Department of Politics, Princeton University). Postdoctoral Fellow, Center on Global Poverty and Development, Stanford University

11. Yang-Yang Zhou (Ph.D. in 2019, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, University of British Columbia

12. Winston Chou (Ph.D. in 2019, Department of Politics, Princeton University). Senior Data Scientist at Apple

13. Ted Enamorado (Ph.D. in 2019, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, Washington University in St. Louis

14. Benjamin Fifield (Ph.D. in 2018, Department of Politics, Princeton University; Dissertation Committee Chair). Data Scientist, American Civil Liberties Union

15. Tyler Pratt. (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Yale University

16. Romain Ferrali (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Aix-Marseille School of Economics

17. Julia Morse (Ph.D. in 2017, Woodrow Wilson School, Princeton University). Assistant Professor, Department of Political Science, University of California, Santa Barbara
18. Yuki Shiraito (Ph.D. in 2017, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, University of Michigan
19. Carlos Velasco Rivera (Ph.D. in 2016, Department of Politics, Princeton University). Research Scientist, Facebook
20. Gabriel Lopez Moctezuma (Ph.D. in 2016, Department of Politics, Princeton University). Assistant Professor, Division of the Humanities and Social Sciences, California Institute of Technology
21. Graeme Blair (Ph.D. in 2016, Department of Politics, Princeton University). Assistant Professor, University of California, Los Angeles
22. Jaquilyn R. Waddell Boie (Ph.D. in 2015, Department of Politics, Princeton University). Private consultant
23. Scott Abramson (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, University of Rochester
24. Michael Barber (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Brigham Young University
25. In Song Kim (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Massachusetts Institute of Technology
26. Alex Ruder (Ph.D. in 2014, Department of Politics, Princeton University). Senior Community Economic Development Advisor, Federal Reserve Bank of Atlanta
27. Meredith Wilf (Ph.D. in 2014, Department of Politics, Princeton University). Senior Director, Capital Rx
28. Will Bullock. (Ph.D. candidate, Department of Politics, Princeton University). Senior Researcher, Facebook
29. Teppei Yamamoto (Ph.D. in 2011, Department of Politics, Princeton University; Dissertation Committee Chair). Associate Professor, Department of Political Science, Massachusetts Institute of Technology
30. Dustin Tingley (Ph.D. in 2010, Department of Politics, Princeton University). Professor, Department of Government, Harvard University
31. Aaron Strauss (Ph.D. in 2009, Department of Politics, Princeton University). Former Executive Director, Analyst Institute
32. Samir Soneji (Ph.D. in 2008, Office of Population Research, Princeton University; Dissertation Committee Chair). Associate Professor, Department of Health Behavior at the Gillings School of Global Public Health, University of North Carolina, Chapel Hill
33. Ying Lu (Ph.D. in 2005, Woodrow Wilson School, Princeton University; Dissertation Committee Chair). Associate Professor, Steinhardt School of Culture, Education, and Human Development, New York University

Former Predocs and Postdocs

1. Zhichao Jiang (Postdoctoral Fellow, 2016–2019). Assistant Professor, Department of Biostatistics and Epidemiology, School of Public Health and Health Sciences, University of Massachusetts, Amherst

2. Adeline Lo (Postdoctoral Fellow, 2016–2019). Assistant Professor, Department of Political Science, University of Wisconsin, Madison

3. Yunkyu Sohn (Postdoctoral Fellow, 2016–2018). Assistant Professor, School of Political Science and Economics, Waseda University

4. Xiaolin Yang (Postdoctoral Fellow, 2015–2017). Research Scientist, Amazon

5. Santiago Olivella (Postdoctoral Fellow, 2015–2016). Associate Professor, Department of Political Science, University of North Carolina

6. Drew Dimmery (Predoctoral Fellow, 2015–2016). Research Scientist, Facebook

7. James Lo (Postdoctoral Fellow, 2014–2016). Assistant Professor, Department of Political Science, University of Southern California

8. Steven Liao (Predoctoral Fellow, 2014–2015). Assistant Professor, Department of Political Science, University of California, Riverside

9. Michael Higgins (Postdoctoral Fellow, 2013–2015). Associate Professor, Department of Statistics, Kansas State University

10. Kentaro Hirose (Postdoctoral Fellow, 2012–2015). Assistant Professor, Waseda Institute for Advanced Studies

11. Chad Hazlett (Predoctoral Fellow, 2013–2014). Associate Professor, Departments of Political Science and Statistics, University of California, Los Angeles

12. Florian Hollenbach (Predoctoral Fellow, 2013–2014). Associate Professor, Department of International Economics, Government and Business at the Copenhagen Business School

13. Marc Ratkovic (Predoctoral and Postdoctoral Fellow, 2010–2012). Assistant Professor, Department of Politics, Princeton University

Editorial and Referee Service

Co-editor for *Journal of Causal Inference* (2014 – present)

Associate editor for *American Journal of Political Science* (2014 – 2019), *Journal of Business & Economic Statistics* (2015 – 2024), *Journal of Causal Inference* (2011 – 2014), *Journal of Experimental Political Science* (2013 – 2017), *Observational Studies* (2014 – present), *Political Analysis* (2014 – 2017).

Editorial board member for *Asian Journal of Comparative Politics* (2014 – present), *Journal of Educational and Behavioral Statistics* (2011 – present), *Journal of Politics* (2007 – 2008, 2019–2020), *Journal of Research on Educational Effectiveness* (2014 – 2016), *Political Analysis* (2010 – 2013), *Political Science Research and Methods* (2019 – present).

Guest editor for *Political Analysis* virtual issue on causal inference (2011).

Referee for *ACM Computing Surveys*, *American Economic Journal: Applied Economics*, *American Economic Review: Insights*, *American Journal of Epidemiology*, *American Journal of Evaluation*, *American Journal of Political Science*, *American Political Science Review*, *American Politics Research*, *American Sociological Review*, *Annals of Applied Statistics*, *Annals of Statistics*, *Annals of the Institute of Statistical Mathematics*, *Biometrics*, *Biometrika*, *Biostatistics*, *BMC Medical Research Methodology*, *British Journal of Mathematical and Statistical Psychology*, *British Journal of Political Science*, *Canadian Journal of Statistics*, *Chapman & Hall/CRC Press*, *Child Development*, *Communications for Statistical Applications and Methods*, *Computational Statistics and Data Analysis*, *Electoral Studies*, *Econometrica*, *Econometrics*, *Empirical Economics*, *Environmental Management*, *Epidemiology*, *European Union Politics*, *IEEE Transactions on Information Theory*, *International Journal of Biostatistics*, *International Journal of Epidemiology*, *International Journal of Public Opinion Research*, *International Migration Review*, John Wiley & Sons, *Journal of Applied Econometrics*, *Journal of Applied Statistics*, *Journal of Biopharmaceutical Statistics*, *Journal of Business and Economic Statistics*, *Journal of Causal Inference*, *Journal of Computational and Graphical Statistics*, *Journal of Conflict Resolution*, *Journal of Consulting and Clinical Psychology*, *Journal of Econometrics*, *Journal of Educational and Behavioral Statistics*, *Journal of Empirical Legal Studies*, *Journal of Multivariate Analysis*, *Journal of Official Statistics*, *Journal of Peace Research*, *Journal of Politics*, *Journal of Research on Educational Effectiveness*,*Journal of Statistical Planning and Inference*, *Journal of Statistical Software*, *Journal of Survey Statistics and Methodology*, *Journal of the American Statistical Association (Case Studies and Applications; Theory and Methods)*, *Journal of the Japanese and International Economies*, *Journal of the Japan Statistical Society*, *Journal of the Royal Statistical Society (Series A; Series B; Series C)*, *Law & Social Inquiry*, *Legislative Studies Quarterly*, *Management Science*, Multivariate Behavioral Research, National Science Foundation (Economics; Methodology, Measurement, and Statistics; Political Science), Natural Sciences and Engineering Research Council of Canada, *Nature Machine Intelligence*, *NeuroImage*, *Osteoporosis International*, *Oxford Bulletin of Economics and Statistics*, *Pharmaceutical Statistics*, *Pharmacoepidemiology and Drug Safety*, *PLOS One*, *Policy and Internet*, *Political Analysis*, *Political Behavior*, *Political Communication*, *Political Research Quarterly*, *Political Science Research and Methods*, *Population Health Metrics*, *Population Studies*, *Prevention Science*, *Proceedings of the National Academy of Sciences*, Princeton University Press, *Psychological Methods*, *Psychometrika*, *Public Opinion Quarterly*, *Quarterly Journal of Economics*, *Quarterly Journal of Political Science*, *Review of Economics and Statistics*, Routledge, Sage Publications, *Scandinavian Journal of Statistics*, *Science*, Sloan Foundation, Springer, *Sociological Methodology*, *Sociological Methods & Research*, *Statistical Methodology*, *Statistical Methods and Applications*, *Statistical Methods in Medical Research*, *Statistical Science*, *Statistica Sinica*, *Statistics & Probability Letters*, *Statistics in Medicine*, *Systems Biology*, U.S.-Israel Binational Science Foundation, *Value in Health*, *World Politics*.

University and Departmental Committees

Harvard University

Department of Government

Member, Curriculum and Educational Policy Committee (2020–2021)

Member, Second-year Progress Committee (2019–2020)

Member, Graduate Placement Committee (2019–2020)

Member, Graduate Admissions Committee (2018–2019)

Member, Graduate Poster Session Committee (2018–2019)

Department of Statistics

Chair, Senior Faculty Search Committee (2021–2022)

Member, Junior Faculty Search Committee (2018–2019)

Member, Second-year Progress Committee (2018–2019, 2020–2021)

Princeton University

University

Executive Committee Member, Program in Statistics and Machine Learning (2013–2018)

Executive Committee Member, Committee for Statistical Studies (2011-2018)

Member, Organizing Committee, Retreat on Data and Information Science at Princeton (2016)

Member, Council of the Princeton University Community (2015)

Member, Search Committee for the Dean of College (2015)

Member, Committee on the Library and Computing (2013–2016)

Member, Committee on the Fund for Experimental Social Science (2013–2018)

Member, Personally Identifiable Research Data Group (2012–2018)

Member, Research Computing Advisory Group (2013–2018)

Member, Task Force on Statistics and Machine Learning (2014–2015)

Department of Politics

Chair, Department Committee on Research and Computing (2012–2018)

Chair, Formal and Quantitative Methods Junior Search Committee (2012–2013, 2014–2015, 2016–2017)

Chair, Reappointment Committee (2015–2016)

Member, Diversity Initiative Committee (2014–2015)

Member, American Politics Junior Search Committee (2012–2014)

Member, Department Chair's Advisory Committee (2010–2013, 2015–2016)

Member, Department Priority Committee (2012–2013, 2014–2015, 2016–2017)

Member, Formal and Quantitative Methods Curriculum Committee (2005–2006)

Member, Formal and Quantitative Methods Junior Search Committee (2009–2010, 2015–2016)

Member, Formal and Quantitative Methods Postdoc Search Committee (2009–2018)

Member, Graduate Admissions Committee (2012–2013)
Member, Reappointment Committee (2014–2016)
Member, Space Committee (2014–2016)
Member, Undergraduate Curriculum Committee (2014–2015)
Member, Undergraduate Exam Committee (2007–2008)
Member, Undergraduate Thesis Prize Committee (2005–2006, 2008–2011)

Center for Statistics and Machine Learning

Executive Committee Member (2016–2018)
Member, Search Committee (2015–2017)

Services to the Profession

National Academies of Sciences, Engineering, and Medicine

Committee on National Statistics, Division of Behavioral and Social Sciences and Education, Panel on the Review and Evaluation of the 2014 Survey of Income and Program Participation Content and Design (2014–2017)

National Science Foundation

Proposal Review Panel (2020)

The Society for Political Methodology

President (2017–2019)
Vice President and President Elect (2015–2017)
Annual Meeting Committee, Chair (2011)
Career Award Committee (2015–2017)
Program Committee for Annual Meeting (2012), Chair (2011)
Graduate Student Selection Committee for the Annual Meeting (2005), Chair (2011)
Miller Prize Selection Committee (2010–2011)
Statistical Software Award Committee (2009–2010)
Emerging Scholar Award Committee (2013)

American Statistical Association

Journal of Educational and Behavioral Statistics Management Committee (2016 – present)

Others

External Expert, Department of Methodology, London School of Economics and Political Science (2017)

Memberships

American Political Science Association; American Statistical Association; Midwest Political Science Association; The Society for Political Methodology.

Neiman Petitioners' Exhibit 27

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, et al.,	
Relators	**Case No. 2021-1449**
v.	**Original Action Pursuant to Ohio Const., Art. XIX, Sec. 1(C)(3)**
OHIO REDISTRICTING COMMISSION, et al.,	
Respondents.	

AFFIDAVIT OF LISA HANDLEY

Franklin County
/ss
State of Ohio

Now comes affiant Lisa Handley, having been first duly cautioned and sworn, deposes and states as follows:

1. I am over the age of 18 and fully competent to make this declaration. I have personal knowledge of the statements and facts contained herein.
2. For the purposes of this litigation, I have been asked by counsel for LWV Relators to analyze relevant data and provide my expert opinions.
3. To that end, I have personally prepared the report attached to this affidavit as Exhibit A, and swear to its authenticity and to the faithfulness of the opinions expressed and, to the best of my knowledge, the accuracy of the factual statements made therein.

FURTHER AFFIANT SAYETH NAUGHT.

Executed on 12/09/2021, 2021.

Lisa Handley
Signed on 2021/12/09 10:48:23 -8:00

Lisa Handley

Sworn and subscribed before me this 12/09/2021, 2021.

Signed on 2021/12/09 10:48:23 -8:00

Notary Public

NOTARY PUBLIC STATE OF OHIO
Theresa M Sabo
Commission # 2016-RE-619622
Electronic Notary Public
State of Ohio
My Comm Exp. Nov 28, 2026
Notary Stamp 2021/12/09 11:48:23 PST A49D9778307A

Notarial act performed by audio-visual communication

Handley Affidavit.pdf

DocVerify ID:	C76B5C72-ECA6-4B6C-BD16-160A4B8F2C08
Created:	December 09, 2021 10:31:35 -8:00
Pages:	1
Remote Notary:	Yes / State: OH

E-Signature Summary

E-Signature 1: Lisa Handley (LH)
December 09, 2021 10:48:23 -8:00 [1191C7F1544F] [71.191.84.32]
lrhandley@aol.com (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
December 09, 2021 10:48:23 -8:00 [A49D9778307A] [74.142.214.254]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

Exhibit A

Affidavit of Dr. Lisa Handley

PROVIDING BLACK VOTERS WITH AN OPPORTUNITY TO ELECT:
A DISTRICT-SPECIFIC, FUNCTIONAL ANALYSIS OF OHIO VOTING BY RACE

Summary.

1. I was retained by counsel for Relators in this matter to conduct a district-specific, functional analysis of voting patterns by race in Cuyahoga County, where there is a significant Black population and it is possible to draw a majority Black congressional district. My task was to ascertain the Black voting age population ("BVAP") necessary to provide Black voters with an opportunity to elect their candidates of choice based on the participation rates and voting patterns by race in recent elections.[1] This affidavit reports the results of my analysis of voting patterns in Cuyahoga County, including recent congressional elections in the 11th Congressional District.
2. A district-specific, functional analysis is required to determine whether a district is likely to provide minority voters with an opportunity to elect their candidates of choice. There is no single universal or statewide demographic target that can be applied for Black voters to elect their candidates of choice – the population needed to create an "effective minority district" varies by location and depends upon the participation rates and voting patterns of Black and white voters in that specific area.
3. An analysis of voting patterns is required to estimate voter participation rates by race, as well as the level of support from Black and white voters for each of the candidates competing in the examined elections. This information can then be used to calculate the Black population concentration required for the Black voters' preferred candidates to win election to office in a specific district. Drawing districts informed by this percentage avoids creating districts that either fail to provide Black voters with the opportunity to elect their candidates of choice or unnecessarily pack minority voters into districts to reduce the number of minority opportunity districts.
4. In *Ohio APRI v. Householder*, I submitted a report concluding that the previous 11th Congressional District of Ohio would be an effective minority district with 45% Black BVAP. 373 F.Supp.3d 978 (S.D. Ohio, May 3, 2019). As summarized by the court, I

[1] I am being compensated at a rate of $300 per hour.

concluded: "[W]ith a 45% BVAP in District 11, African-American voters would have a realistic opportunity to elect their candidate of choice with a 'comfortable margin.' In fact, even with a BVAP as low as 40%, African-American voters would have elected the Black-preferred candidate in the elections studied. [I] concluded that there is no need to draw a majority African-American District 11 in order to allow African-American voters to elect their candidate of choice there." *Id*. at 1044-46.

5. In this report, I shift the focus of my analysis from residents of the 11th Congressional District to residents of Cuyahoga County more broadly and I update the elections analyzed to include those held since I submitted my 2018 report. My reason for studying voting patterns in Cuyahoga County in its entirety is the recognition that the congressional district boundaries will change – no longer including all of the same voters as the current Congressional District 11 – and Congressional District 11 is likely to be redrawn to fall entirely within Cuyahoga County as a consequence of recent amendments to the Ohio Constitution.[2]
6. The results of this updated analysis of voting patterns in Cuyahoga County are consistent with my previous findings: a majority Black district is not required to provide Black voters with a realistic opportunity to elect candidates of their choice to Congress in this area of Ohio. My estimates of participation rates and voting patterns by race in Cuyahoga County has led me to conclude, on the basis of the most challenging election for a Black-preferred candidate to win in Cuyahoga County that I examined (the 2014 gubernatorial election), a 42% BVAP district would offer Black voters an effective opportunity to elect their preferred candidates to Congress.

Professional Experience.

7. I have over thirty-five years of experience as a voting rights and redistricting expert. I have advised scores of jurisdictions and other clients on minority voting rights and redistricting-related issues. I have served as an expert in dozens of voting rights cases. My clients have included state and local jurisdictions, independent redistricting

[2] The Ohio State Constitution was amended in 2018 to specify that if the general assembly draws the congressional plan, the assembly "shall not unduly split governmental units, giving preference to keeping whole, in the order named, counties, then townships and municipal corporations." Article XIX Section 1. (C)(3)(b) of the Ohio Constitution.

commissions (Arizona, Colorado, Michigan), the U.S. Department of Justice, national civil rights organizations, and such international organizations as the United Nations.

8. I have been actively involved in researching, writing, and teaching on subjects relating to voting rights, including minority representation, electoral system design, and redistricting. I co-authored a book, *Minority Representation and the Quest for Voting Equality* (Cambridge University Press, 1992) and co-edited a volume, *Redistricting in Comparative Perspective* (Oxford University Press, 2008), on these subjects. In addition, my research on these topics has appeared in peer-reviewed journals such as *Journal of Politics*, *Legislative Studies Quarterly*, *American Politics Quarterly*, *Journal of Law and Politics*, and *Law and Policy,* as well as law reviews (e.g., *North Carolina Law Review*) and a number of edited books. I hold a Ph.D. in political science from The George Washington University.
9. I have been a principal of Frontier International Electoral Consulting since co-founding the company in 1998. Frontier IEC specializes in providing electoral assistance in transitional democracies and post-conflict countries. In addition, I am a Visiting Research Academic at Oxford Brookes University in Oxford, United Kingdom. Attached to the end of this report as Appendix B is a copy of my *curriculum vitae*.

Calculating the Black Voting Age Population Needed to Elect Black-Preferred Candidates.

10. The Black voting age population (BVAP) percentage needed to elect Black-preferred candidates is calculated by taking into account the relative participation rates of Black and white Ohioans, as well as the expected level of Black support for the Black-preferred candidates (their "cohesiveness") in an area, and the expected level of white voters' "crossover" voting for the Black-preferred candidates. This requires constructing a database that combines demographic information and election results, then analyzing the data for patterns. These patterns are then used to produce estimates of participation rates and voting patterns by race.
11. **Database.** To analyze voting patterns in Ohio requires a database that combines election returns and population data by race (or registration or turnout by race if this information is available). To build this dataset in this instance, 2016, 2018, and 2020 precinct-level shapefiles were acquired from the Voting and Election Science Team. These shapefiles

were joined to precinct-level election returns from the Ohio Secretary of State's office, which were processed and cleaned by OpenElections. In addition, 2012 and 2014 election returns pro-rated to the 2010 voting district ("VTD") level, were acquired from Bill Cooper, who submitted an expert affidavit in *LWVO v. Ohio Redistricting Commission*, 2021-1193. The 2020 Census Block shapefiles, and total and voting age population by race and ethnicity, were obtained from the Census FTP portal. The election returns data was disaggregated down to the level of the 2020 Census block and, for the 2016, 2018, and 2020 election cycles separately, re-aggregated up to the level of the voting precincts used in those years, accounting for precincts split by congressional districts. For the 2012 and 2014 election cycles, the block-level election results were re-aggregated up to the level of the 2010 VTDs, taking into account splits of VTDs by congressional districts.

12. **Elections Analyzed.** I analyzed all recent statewide Ohio general elections held in 2016, 2018, and 2020 to estimate voting patterns by race in Cuyahoga County. This included contests for U.S. President, U.S. Senate, Governor, Attorney General, Secretary of State, Treasurer, and Auditor. I also examined the 2014 general election contests for Governor and Secretary of State,[3] as well as the 2012 election contests for U.S. President and U.S. Senate. In addition, I analyzed the 2016, 2018, and 2020 general elections for U.S. Congress in District 11.

13. **Primary Elections.** As is usually the case in the United States, there is a two-stage election process in Ohio – a primary election and a general election. Black-preferred candidates must win both elections to gain office. The overwhelming majority of Black voters in Ohio vote in the Democratic primary rather than the Republican primary. As a consequence, it is not possible to estimate Black voting behavior in Republican primaries and, in any case, Black voters' candidates of choice are found in Democratic primaries. In the past ten years, there were two statewide Democratic primaries that included African American candidates: the 2018 Democratic primary for Governor and the 2016 Democratic primary for U.S. Senate. I analyzed both of these elections. (Although both contests included African American candidates, these candidates were not, in fact, the candidates preferred by Black voters.) In addition, I analyzed recent Democratic primaries for Congressional District 11.

[3] Data on the other statewide elections held in 2014 (Attorney General, Treasurer, and Auditor) was not readily available. No minority candidates competed in these three statewide election contests.

There were no contested primaries for the congressional seats in 2016 or 2018, but the district had a primary in 2020. There was also a special Democratic primary held in Congressional District 11 in August 2021 when President Biden appointed the incumbent, Rep. Marcia Fudge, as Secretary of the U.S. Department of Housing and Urban Development.[4]

14. The results of the 2016 elections reported here vary slightly from those in my *Ohio APRI v. Householder* report. There are two reasons for this. First, this analysis incorporates all Cuyahoga County precincts, not simply those precincts that fall within the prior boundaries of Congressional District 11. (Congressional District 11 previously included Summit County precincts – these were included in the analysis for my *Ohio APRI v. Householder* report but are excluded here from the countywide analysis; they are, however, included in the congressional elections analyzed.) Second, my *Ohio APRI v. Householder* report relies on 2010 census data, whereas my analysis in this report uses 2020 census data to determine the demographic composition of the precincts for 2016.
15. **Racial Bloc Voting Analysis.** Direct information on how Black and white voters cast their votes is not available; voters' race is not included in their voter registration in Ohio and the race of the voter is not, of course, obtainable from a ballot. To estimate vote choices by race, I used three standard statistical techniques: homogeneous precinct analysis, ecological regression, and ecological inference.
16. Two of these analytic procedures – homogeneous precinct analysis and ecological regression – were employed by the plaintiffs' expert in *Thornburg v. Gingles*, 478 U.S. 30 (1986), and have the benefit of the Supreme Court's approval in that case, and other courts' approval in most subsequent voting rights cases. The third technique, ecological inference, was developed after the *Gingles* decision, and was designed, in part, to address the issue of out-of-bounds estimates (estimates that exceed 100 percent or are less than zero percent), which can arise in ecological regression analysis. Ecological inference analysis has been introduced and accepted in numerous federal and state court proceedings.

[4] The precinct election results for the November 2021 general election have yet to be released by the Secretary of State so I have been unable to analyze the 2021 general election for Congressional District 11.

17. *Homogeneous precinct* ("HP") analysis is the simplest technique: it involves comparing the percentage of votes received by each of the candidates in precincts that are racially homogeneous. The general practice is to label a precinct as homogeneous if at least 90 percent of the voting age population is composed of a single race. In fact, the homogeneous results reported are not estimates – they are the actual precinct results. However, most voters in Ohio do not reside in homogeneous precincts, and voters who reside in homogeneous precincts may not be representative of voters who live in more integrated precincts. For this reason, I refer to these percentages as estimates.

18. The second statistical technique I employed, *ecological regression* ("ER"), uses information from all precincts, not simply the homogeneous ones, to derive estimates of the voting behavior of Black and white Ohioans. If there is a strong linear relationship across precincts between the percentage of Blacks (or whites) and the percentage of votes cast for a given candidate, this relationship can be used to estimate the percentage of Blacks and whites voting for each of the candidates in the election contest being examined.

19. The third technique, *ecological inference* ("EI"), was developed by Professor Gary King. This approach also uses information from all precincts but, unlike ecological regression, it does not rely on an assumption of linearity. Instead, it incorporates maximum likelihood statistics to produce estimates of voting patterns by race. In addition, it utilizes the method of bounds, which uses more of the available information from the precinct returns and provides more information about the voting behavior being estimated.[5] The method of bounds also precludes the estimates from exceeding the possible limits. However, unlike ecological regression, EI does not guarantee that the candidate estimates add to 100 percent of each racial group in the elections examined.

20. In addition, I utilized a more recently developed version of ecological inference which I have labeled "EI RxC" in the summary tables found in Appendix A. EI RxC expands the

[5] The following is an example of how the method of bounds works: if a given precinct has 100 voters, of which 75 are Black and 25 are white, and the Black candidate received 80 votes, then at least 55 of the Black voters voted for the Black candidate and at most all 75 did. (The method of bounds is less useful for calculating estimates for white voters, as anywhere between none of the whites and all of the whites could have voted for the candidate.) These bounds are used when calculating EI estimates but not when using ecological regression.

analysis so that differences in the relative rates of minority and white turnout can be taken into account in deriving the estimates of minority and white support for the candidates.

21. Estimates using all four methodological approaches (homogeneous precinct analysis, ecological regression, and the two approaches to ecological inference) are reported in the summary racial bloc voting tables for Cuyahoga County found in Appendix A.

22. **Equalizing Black and white turnout.** Because Black Ohioans who are eligible to vote often turn out to vote at lower rates than white Ohioans (this is consistently the case in Cuyahoga County in recent elections, as indicated by the summary table of voting patterns found in Appendix A), the BVAP needed to ensure that Black voters comprise at least half of the voters in an election is often higher than 50 percent. Once I estimated the respective turnout rates of Black and white voters using the statistical techniques described above, I could mathematically calculate the percentage needed to equalize minority and white voters.[6] But equalizing turnout is only the first step in the process – it does not take into account the voting patterns of Black and white voters. If voting is

---

[6] The equalizing percentage is calculated mathematically by solving the following equation:

Let

M	=	the proportion of the district's voting age population that is Black
W = 1-M	=	the proportion of the district's voting age population that is white
A	=	the proportion of the Black voting age population that turned out to vote
B	=	the proportion of the white voting age population that turned out to vote

Therefore,

M(A)	=	the proportion of the population that is Black and turned out to vote (1)
(1-M)B	=	the proportion of total population that is white and turned out to vote (2)

To find the value of M that is needed for (1) and (2) to be equal, (1) and (2) are set as equal and we solve for M algebraically:

$$M(A) = (1 - M)\,B$$
$$M(A) = B - M(B)$$
$$M(A) + M(B) = B$$
$$M\,(A + B) = B$$
$$M = B/\,(A+B)$$

Thus, for example, if 39.3% of the black population turned out and 48.3% of the white population turned out, B= .483 and A = .393, and M = .483/ (.393+.483) = .483/.876 = .5513, therefore a black VAP of 55.1% would produce an equal number of black and white voters. (For a more in-depth discussion of equalizing turnout see Kimball Brace, Bernard Grofman, Lisa Handley and Richard Niemi, "Minority Voting Equality: The 65 Percent Rule in Theory and Practice," *Law and Policy*, 10 (1), January 1988.)

racially polarized but a significant number of white voters typically "crossover" to vote for Black voters' preferred candidate, it may be that white crossover voting can compensate for depressed Black turnout relative to white turnout. If this is the case, Black voters need not make up at least 50 percent of the voters in an election for the Black-preferred candidate to win.

23. **Incorporating Minority Cohesion and White Crossover Voting.** Even if Black voters are turning out at lower rates than whites, and voting is racially polarized, if a relatively consistent percentage of white voters support Black-preferred candidates, these candidates can be elected despite the lower Black turnout. This is especially true if Black voters are very cohesive in supporting their preferred candidates. A district-specific, functional analysis should take into account not only differences in the turnout rates of Black and white voters, but also voting patterns by race.[7]

24. To illustrate this mathematically, consider a district that has 1000 persons of voting age, 50% of who are Black and 50% of who are white. Let us begin by assuming that Black turnout is lower than white turnout in a two-candidate general election. In our hypothetical election example, 42% of the Black voting age population (VAP) turn out to vote and 60% of the white VAP vote. This means that, for our illustrative election, there are 210 Black voters and 300 white voters. Further suppose that 96% of the Black voters supported their candidate of choice and 25% of the white voters cast their votes for this candidate (with the other 75% supporting her opponent in the election contest). Thus, in our example, Black voters cast 200 of their 210 votes for the Black-preferred candidate and their other 8 votes for her opponent; white voters cast 75 of their 300 votes for the Black-preferred candidate and 225 votes for their preferred candidate:

[7] For an in-depth discussion of this approach to creating effective minority districts, see Bernard Grofman, Lisa Handley and David Lublin, "Drawing Effective Minority Districts: A Conceptual Framework and Some Empirical Evidence," *North Carolina Law Review*, volume 79 (5), June 2001.

	VAP	turnout	voters	support for Black-preferred candidate	votes for Black-preferred candidate	support for white-preferred candidate	votes for white-preferred candidate
Black	500	0.42	210	0.96	202	0.04	8
White	500	0.60	300	0.25	75	0.75	225
			510		277		233

The candidate of choice of Black voters would receive a total of 277 votes (202 from Black voters and 75 from white voters), while the candidate preferred by white voters would receive only 233 votes (8 from Black voters and 225 from white voters). The Black-preferred candidate would win the election with 55.4% (277/500) of the vote in this hypothetical 50% Black VAP district. And the Black-preferred candidate would be successful despite the fact that the election was racially polarized and that Blacks turned out to vote at a lower rate than whites.

25. The candidate of choice of Black voters would still win the election by a very small margin (50.9%) in a district that is 45% Black with these same voting patterns:

	VAP	turnout	voters	support for Black-preferred candidate	votes for Black-preferred candidate	support for white-preferred candidate	votes for white-preferred candidate
Black	450	0.42	189	0.96	181	0.04	8
White	550	0.60	330	0.25	83	0.75	248
			519		264		255

In a district with a 40% BVAP, however, the Black-preferred candidate would garner only 47.5% of the vote.

Cuyahoga County and Congressional District 11

26. Table 1, below, incorporates the estimates of turnout and votes by race reported in the summary table for Cuyahoga County found in Appendix A,[8] and calculates the percentage of the vote the candidate preferred by Black voters would receive in a district with a given BVAP. The BVAP percentages considered are 35, 40, 45, 50, and 55%. Looking down the last few columns of Table 1, it is apparent that the Black-preferred candidate would win all but one of the 13 statewide general election contests considered in a district with a BVAP of 40%. Moreover, the Black-preferred candidate would win the three congressional general election contests in landslides.
27. Only the 2014 Governor's race would require a district with more than a 40% BVAP for the candidate of choice of Black voters to win. More precisely, the percent BVAP needed for the Black-preferred candidate to win the 2014 Governor's race is 41.4%. This is because the white incumbent (John Kasich) received more support from white voters in Cuyahoga County than any other Republican in the elections I examined.
28. In every general election since 2018, the Black-preferred candidate would receive at least 67% of the vote – and as much as 73% (75% in a congressional contest)– in a 40% BVAP district.
29. Primary elections are more challenging for Black-preferred candidates, but only when there are more than two or three candidates competing. For example, in the 2018 Democratic primary for Governor, six candidates ran for the nomination. The 2021 Special Primary for Congressional District 11 drew 13 candidates, although only two received more than 2% of the vote.
30. On the basis of my analysis of voting patterns in statewide elections over the past decade, and an examination of recent congressional contests, I conclude that a district with a 42% BVAP is likely to provide Black voters with a realistic opportunity to elect their candidates of choice in a newly drawn congressional district located within Cuyahoga County. This is because the election contest that proved the most challenging for the candidate of choice of Black voters to win was the 2014 Governor contest and the percent BVAP needed for the Black-preferred candidate to win this election is 41.4%.

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[8] The EI estimate that controls for differential turnout – labeled "EI RxC" in the summary racial bloc voting results tables in the Appendix – was used to calculate the percent Black VAP needed to win.

31. A congressional district that is less than majority Black provides Black voters with an opportunity to elect their candidates of choice in Cuyahoga County because, although Black voters in the county usually turn out to vote at lower rates than white voters, Black voters are very cohesive in supporting their preferred candidates, and white voters vote for these Black-preferred candidates in sufficient percentages for the candidate of choice of the Black voters to prevail.

Table 1: Percent Black VAP Needed to Win Election in Cuyahoga County and Congressional District 11

Cuyahoga County Percent Black VAP needed to win	race of B-P candidate	turnout rate for office and percent vote for black-preferred candidates						percent of vote B-P cand would have received if district was 55% black VAP	percent of vote B-P cand would have received if district was 50% black VAP	percent of vote B-P cand would have received if district was 45% black VAP	percent of vote B-P cand would have received if district was 40% black VAP	percent of vote B-P cand would have received if district was 35% black VAP
		Black votes			White votes							
		votes cast for office	B-P	all others	votes cast for office	B-P	all others					
GENERAL ELECTIONS												
2020 President	W	54.1	97.1	2.9	75.3	53.2	46.8	73.7	71.6	69.5	67.4	65.4
2018 Governor	W	46.2	96.1	3.9	58.2	52.9	47.1	74.2	72.0	69.9	67.9	65.8
2018 Treasurer	AA	45.8	98.1	1.9	56.0	51.9	48.1	75.0	72.7	70.4	68.2	66.0
2018 Attorney General	W	45.5	97.7	2.3	57.2	56.4	43.6	76.8	74.7	72.7	70.7	68.8
2018 Auditor	W	45.2	95.9	4.1	55.9	52.7	47.3	74.2	72.0	69.9	67.8	65.8
2018 Secretary State	W	45.7	96.8	3.2	56.7	54.2	45.8	75.3	73.2	71.1	69.1	67.1
2018 U.S. Senate	W	45.9	98.3	1.7	57.9	60.4	39.6	79.1	77.2	75.3	73.5	71.7
2016 President	W	63.8	97.8	2.2	65.9	47.9	52.1	74.9	72.4	70.0	67.5	65.0
2016 U.S. Senate	W	59.9	93.9	6.1	64.4	36.2	63.8	66.9	64.0	61.1	58.3	55.5
2014 Governor	W	30.4	88.0	12.0	41.2	30.2	69.8	57.6	54.7	52.0	49.3	46.6
2014 Secretary State	AA	32.1	97.8	2.2	40.3	40.7	59.3	68.9	66.0	63.2	60.5	57.8
2012 President	AA	71.6	99.0	1.0	65.7	53.9	46.1	79.7	77.4	75.2	72.9	70.6
2012 U.S. Senate	W	66.3	98.7	1.3	62.6	57.4	42.6	80.7	78.6	76.6	74.5	72.4
DEMOCRATIC PRIMARIES												
2018 Governor	W	17.8	51.0	49.0	15.4	31.4	68.6	42.9	41.9	40.9	39.9	38.9
2016 U.S. Senate	W	30.3	69.2	30.8	16.2	55.8	44.2	65.1	64.5	63.9	63.2	62.5
CONGRESSIONAL DISTRICT 11												
2020 General	AA	53.6	97.4	2.6	71.6	61.2	38.8	78.5	76.7	75.0	73.3	71.6
2018 General	AA	47.2	98.0	2.0	58.7	62.7	37.3	80.2	78.4	76.7	75.0	73.4
2016 General	AA	62.0	98.0	2.0	60.0	53.4	46.6	78.3	76.1	73.8	71.6	69.3
2020 Dem Primary	AA	16.2	93.0	7.0	22.8	88.6	11.4	90.6	90.4	90.2	90.0	89.8
2021 Special Primary	AA	18.0	48.6	51.4	21.8	53.2	46.8	50.9	51.1	51.3	51.6	51.8

Cuyahoga County, Ohio			Estimates for Black Voters				Estimates for White Voters			
	Party	Race	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
General Elections										
2020 General										
U.S. President										
Joseph Biden	D	W/AA*	95.8	100.6	98.4	97.1	50.3	48.9	50.1	53.2
Donald Trump	R	W/W	3.3	-1.6	1.2	1.7	48.8	49.9	48.7	46.0
others			0.9	1.0	1.0	1.2	1.0	1.1	1.2	0.8
votes for office			*57.1*	*50.5*	*54.1*	*54.1*	*79.9*	*73.2*	*75.3*	*75.3*
2018 General										
Governor										
Richard Cordray	D	W/W	94.8	99.7	97.5	96.1	48.9	48.9	49.8	52.9
Mike Dewine	R	W/W	3.6	-1.6	1.2	1.8	48.9	48.3	47.3	45.0
others			1.7	1.9	1.7	2.1	2.2	2.7	2.5	2.1
votes for office			*48.6*	*42.7*	*46.2*	*46.2*	*63.2*	*55.7*	*58.2*	*58.2*
Treasurer										
Rob Richardson	D	AA	97.2	103.0	99.2	98.1	47.6	48.0	49.4	51.9
Robert Sprague	R	W	2.8	-3.0	0.8	1.9	52.4	52.0	50.6	48.1
votes for office			*48.0*	*42.4*	*45.8*	*45.8*	*60.7*	*53.6*	*56.0*	*56.0*
Attorney General										
Steve Dettelbach	D	W	96.2	101.4	98.7	97.7	51.9	52.5	53.8	56.4
Dave Yost	R	W	3.8	-1.4	1.4	2.3	48.1	47.4	46.2	43.6
votes for office			*47.8*	*42.0*	*45.5*	*45.5*	*62.1*	*54.8*	*57.2*	*57.2*
Auditor										
Zack Space	D	W	95.0	100.3	97.7	95.9	48.5	48.5	49.6	52.7
Keith Faber	R	W	2.3	-3.1	0.7	1.4	47.4	46.7	45.2	43.0
Robert Coogan	Lib	W	2.7	2.8	2.5	2.7	4.1	4.8	4.6	4.3
votes for office			*47.3*	*41.8*	*45.2*	*45.2*	*60.6*	*53.5*	*55.9*	*55.9*
Secretary of State										
Kathleen Clyde	D	W	95.8	101.0	98.4	96.8	49.9	50.2	51.2	54.2
Frank LaRose	R	W	3.0	-2.3	0.9	1.6	48.0	47.3	46.0	43.8
Dustin Nanna	Lib	W	1.2	1.3	1.3	1.5	2.1	2.5	2.4	2.0
votes for office			*47.9*	*42.3*	*45.7*	*45.7*	*61.5*	*54.3*	*56.7*	*56.7*

Cuyahoga County, Ohio			Estimates for Black Voters				Estimates for White Voters			
	Party	**Race**	**HP**	**ER**	**EI 2x2**	**EI RxC**	**HP**	**ER**	**EI 2x2**	**EI RxC**
2018 General (cont)										
U.S. Senate										
Sherrod Brown	D	W	97.8	102.6	99.3	98.3	55.9	56.5	57.8	60.4
Jim Renacci	R	W	2.2	-2.7	0.6	1.7	44.1	43.5	42.3	39.6
votes for office			*48.3*	*42.5*	*45.9*	*45.9*	*62.8*	*55.4*	*57.9*	*57.9*
2016 General										
U.S. President										
Hillary Clinton	D	W	97.3	103.0	99.3	97.8	45.9	45.1	46.2	47.9
Donald Trump	R	W	1.7	-9.8	0.6	1.1	50.1	50.2	48.8	47.7
others			1.0	0.8	0.9	1.1	4.1	4.8	4.7	4.4
votes for office			*67.1*	*61.3*	*63.8*	*63.8*	*72.5*	*63.4*	*65.9*	*65.9*
U.S. Senate										
Ted Strickland	D	W	91.6	97.5	95.0	93.9	35.1	33.9	34.2	36.2
Rob Portman	R	W	4.6	-1.8	1.5	1.7	60.4	60.7	60.0	59.1
others			3.8	4.3	4.0	4.3	4.5	5.4	5.2	4.7
votes for office			*62.9*	*57.2*	*59.9*	*59.9*	*71.1*	*62.1*	*64.4*	*64.4*
2014 General										
Governor										
Edward FitzGerald	D	W	85.1	89.8	88.2	88.0	29.2	29.2	28.4	30.2
Joh Kasich	R	W	14.9	10.2	11.9	12.0	70.8	70.8	71.7	69.8
votes for office			*31.3*	*27.4*	*30.4*	*30.4*	*42.8*	*37.9*	*41.2*	*41.2*
Secretary of State										
Nina Turner	D	AA	97.2	103.2	98.8	97.8	38.1	38.9	39.2	40.7
Jon Husted	R	W	2.8	-3.2	1.3	2.2	61.9	61.0	60.8	59.3
votes for office			*32.5*	*29.0*	*32.1*	*32.1*	*41.6*	*36.9*	*40.3*	*40.3*
2012 General										
U.S. President										
Barack Obama	D	AA	99.1	104.5	99.4	99.0	51.6	53.3	54.6	53.9
Mitt Romney	R	W	0.9	-4.5	0.4	1.0	48.4	46.7	45.4	46.1
votes for office			*73.2*	*69.7*	*71.6*	*71.6*	*70.2*	*64.3*	*65.7*	*65.7*

Cuyahoga County, Ohio			Estimates for Black Voters				Estimates for White Voters			
	Party	Race	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
2012 General (cont)										
U.S. Senate										
Sherrod Brown	D	W	98.2	103.1	99.4	98.7	55.2	56.6	57.4	57.4
Josh Mandel	R	W	1.8	-3.2	0.6	1.3	44.8	43.4	42.6	42.6
votes for office			*67.5*	*64.4*	*66.3*	*66.3*	*66.5*	*60.8*	*62.6*	*62.6*
Democratic Primaries										
2018 Primary										
Governor										
Richard Cordray	D	W/W	43.0	39.5	42.0	41.2	58.3	59.5	61.8	60.7
Dennis Kucinich	D	W/AA*	50.5	53.3	51.2	51.0	34.1	33.0	31.5	31.4
Bill O'Neill	D	W/AA*	29.0	3.3	3.1	3.3	1.5	1.3	1.3	1.5
Paul Ray	D	W/W	0.7	0.7	0.7	1.0	0.5	0.5	0.6	0.6
Joe Schiavoni	D	W/W	1.8	1.8	1.8	2.2	5.3	5.5	4.9	5.2
Larry Ealy	D	AA/W	1.2	1.4	1.0	1.3	0.3	0.2	0.4	0.6
votes for office			*17.5*	*14.9*	*17.8*	*17.8*	*14.4*	*12.9*	*15.4*	*15.4*
2016 Primary										
U.S. Senator										
Kelli Prather	D	AA	12.4	13.4	13.0	13.4	10.4	11.5	11.3	10.3
P.G. Sittenfeld	D	W	17.5	15.9	16.4	17.4	31.8	32.1	32.4	33.9
Ted Strickland	D	W	70.1	70.7	70.7	69.2	57.8	56.4	56.3	55.8
votes for office			*29.4*	*27.9*	*30.3*	*30.3*	*16.6*	*14.1*	*16.2*	*16.2*

Congressional District 11				Estimates for Black Voters				Estimates for White Voters			
	Party	**Race**	**Vote**	**HP**	**ER**	**EI 2x2**	**EI RxC**	**HP**	**ER**	**EI 2x2**	**EI RxC**
2016 General											
Marcia Fudge	D	AA	80.3	96.4	100.4	98.6	98.0	42.0	51.5	53.7	53.4
Beverly Goldstein	R	W	19.8	3.6	-0.4	1.4	2.0	58.0	48.5	46.3	46.6
votes for office				*62.8*	*58.9*	*62.0*		*69.6*	*57.6*	*60.0*	
2018 General											
Marcia Fudge	D	AA	82.2	97.5	100.6	99.2	98.0	46.7	57.5	59.4	62.7
Beverly Goldstein	R	W	17.8	2.5	-0.6	0.7	2.0	53.4	42.5	40.6	37.3
votes for office				*48.4*	*43.7*	*47.2*		*64.8*	*55.5*	*58.7*	
2020 General											
Marcia Fudge	D	AA	80.1	95.5	98.9	97.6	97.4	44.7	55.5	57.4	61.2
Laverne Gore	R	AA	20	4.5	1.1	2.4	2.6	55.3	44.6	3.6	38.8
votes for office				*54.9*	*49.8*	*53.6*		*78.5*	*70.0*	*71.6*	
2020 Democratic Primary											
Marcia Fudge	D	AA	90.5	93.1	92.6	93.9	93.0	87.2	85.3	86.7	88.6
Others	D		9.5	6.9	7.3	6.1	7.0	12.8	14.7	13.2	11.4
votes for office				*16.7*	*13.4*	*16.2*		*15.9*	*17.4*	*22.8*	
2021 Special Primary											
Shontel Brown	D	AA	50.1	49.3	48.0	49.6	48.6	52.9	49.7	52.1	53.2
Nina Turner	D	AA	44.6	44.7	45.8	44.5	45.3	37.1	44.4	43.3	41.9
Others	D		5.3	6.0	6.1	5.7	6.1	10.0	5.8	4.6	4.9
Turnout/VAP				*18.4*	*15.1*	*18.0*		*11.8*	*14.6*	*21.8*	
2021 Special General											
Shontel Brown	D	AA	78.8								
Laverne Gore	R	AA	21.2								
votes for office											

Lisa R. Handley
CURRICULUM VITAE

Professional Experience

Dr. Handley has over thirty years of experience in the areas of redistricting and voting rights, both as a practitioner and an academician, and is recognized nationally and internationally as an expert on these subjects. She has advised numerous clients on redistricting and has served as an expert in dozens of redistricting and voting rights court cases. Her clients have included the U.S. Department of Justice, civil rights organizations, independent redistricting commissions and scores of state and local jurisdictions. Internationally, Dr. Handley has provided electoral assistance in more than a dozen countries, serving as a consultant on electoral system design and redistricting for the United Nations, UNDP, IFES, and International IDEA. In addition, Dr. Handley served as Chairman of the Electoral Boundaries Commission in the Cayman Islands.

Dr. Handley has been actively involved in research, writing and teaching on the subjects of redistricting and voting rights. She has co-written a book, Minority Representation and the Quest for Voting Equality (Cambridge University Press, 1992) and co-edited a volume (Redistricting in Comparative Perspective, Oxford University Press, 2008) on these subjects. Her research has also appeared in peer-reviewed journals such as *Journal of Politics*, *Legislative Studies Quarterly*, *American Politics Quarterly*, *Journal of Law and Politics*, and *Law and Policy,* as well as law reviews and edited books. She has taught political science undergraduate and graduate courses related to these subjects at several universities including the University of Virginia and George Washington University. Dr. Handley is a Visiting Research Academic at Oxford Brookes University in the United Kingdom.

Dr. Handley is the President of Frontier International Consulting, a consulting firm that specializes in providing electoral assistance in transitional and post-conflict democracies. She also works as an independent election consultant both in the United States and internationally.

Education

Ph.D. The George Washington University, Political Science, 1991

Present Employment

President, Frontier International Electoral Consulting LLC (since co-founding company in 1998).

Senior International Electoral Consultant Technical assistance for clients such as the UN, UNDP and IFES on electoral system design and boundary delimitation

Visiting Research Academic, Centre for Development and Emergency Practice (CENDEP), Oxford Brookes University

U.S. Clients since 2000

American Civil Liberties Union (expert testimony in Ohio partisan gerrymander challenge and challenge to Commerce Department inclusion of citizenship question on 2020 census form)

Lawyers Committee for Civil Rights Under Law (expert testimony in challenges to statewide judicial elections in Texas and Alabama)

US Department of Justice (expert witness testimony in several Section 2 and Section 5 cases)

Alaska: Alaska Redistricting Board (redistricting consultation, expert witness testimony)

Arizona: Arizona Independent Redistricting Board (redistricting consultation, expert witness)

Arkansas: expert witness for Plaintiffs in Jeffers v. Beebe

Colorado: Colorado Redistricting Board (redistricting consultation)

Connecticut: State Senate and State House of Representatives (redistricting consultation)

Florida: State Senate (redistricting consultation)

Kansas: State Senate and House Legislative Services (redistricting consultation)

Louisiana: Louisiana Legislative Black Caucus (expert witness testimony)

Massachusetts: State Senate (redistricting consultation)

Maryland: Attorney General (redistricting consultation, expert witness testimony)

Miami-Dade County, Florida: County Attorney (redistricting consultation)

Nassau County, New York: Redistricting Commission (redistricting consulting)

New Mexico: State House (redistricting consultation, expert witness testimony)

New York: State Assembly (redistricting consultation)

New York City: Redistricting Commission and Charter Commission (redistricting consultation and Section 5 submission assistance)

New York State Court: Expert to the Special Master (drew congressional lines for state court)

Ohio: State Democratic Party (redistricting litigation support, expert witness testimony)

Pennsylvania: Senate Democratic Caucus (redistricting consultation)

Rhode Island: State Senate and State House (litigation support, expert witness testimony)

Vermont: Secretary of State (redistricting consultation)

International Clients since 2000

United Nations
- Afghanistan – electoral system design and district delimitation expert
- Bangladesh (UNDP) – redistricting expert
- Sierra Leone (UNDP) – redistricting expert
- Liberia (UNMIL, UN peacekeeping mission) – redistricting expert
- Democratic Republic of the Congo (MONUC, UN peacekeeping mission) – election feasibility mission, electoral system design and redistricting expert
- Kenya (UN) – electoral system design and redistricting expert
- Haiti (UN) – election feasibility mission, electoral system design and redistricting expert
- Zimbabwe (UNDP) – redistricting expert
- Lead Writer on the topic of boundary delimitation (redistricting) for ACE (Joint UN, IFES and IDEA project on the Administration and Cost of Elections Project)

International Foundation for Election Systems (IFES)
- Afghanistan – district delimitation expert
- Sudan – redistricting expert
- Kosovo – electoral system design and redistricting expert
- Nigeria – redistricting expert
- Nepal – redistricting expert
- Georgia – electoral system design and district delimitation expert
- Yemen – redistricting expert
- Lebanon – electoral system design and redistricting expert
- Malaysia – electoral system design and redistricting expert
- Myanmar – electoral system design and redistricting expert
- Ukraine – electoral system design and redistricting expert
- Pakistan – consultant for developing redistricting software
- Principal consultant for the Delimitation Equity Project – conducted research, wrote reference manual and developed training curriculum
- Writer on electoral boundary delimitation (redistricting), Elections Standards Project
- Training – developed training curriculum and conducted training workshops on electoral boundary delimitation (redistricting) in Azerbaijan and Jamaica

International Institute for Democracy and Electoral Assistance (International IDEA):
- Consultant on electoral dispute resolution systems
- Technology consultant on use of GIS for electoral district delimitation
- Training – developed training material and conducted training workshop on electoral boundary delimitation (redistricting) for African election officials (Mauritius)
- Curriculum development – boundary delimitation curriculum for the BRIDGE Project

Other international clients have included The Cayman Islands; the Australian Election Commission; the Boundary Commission of British Columbia, Canada; and the Global Justice Project for Iraq.

Publications

Books:

Does Torture Prevention Work? Liverpool University Press, 2016 (served as editor and author, with Richard Carver)

Comparative Redistricting in Perspective, Oxford University Press, 2008 (first editor, with Bernard Grofman).

Delimitation Equity Project: Resource Guide, Center for Transitional and Post-Conflict Governance at IFES and USAID publication, 2006 (lead author).

Minority Representation and the Quest for Voting Equality, Cambridge University Press, 1992 (with Bernard Grofman and Richard Niemi).

Academic Journal Articles:

“Drawing Electoral Districts to Promote Minority Representation” Representation, forthcoming, published online DOI:10.1080/00344893.2020.1815076.

"Evaluating national preventive mechanisms: a conceptual model,” Journal of Human Rights Practice, Volume 12 (2), July 2020 (with Richard Carver).

“Minority Success in Non-Majority Minority Districts: Finding the ‘Sweet Spot’,” Journal of Race, Ethnicity and Politics, forthcoming (with David Lublin, Thomas Brunell and Bernard Grofman).

”Has the Voting Rights Act Outlived its Usefulness: In a Word, “No,” Legislative Studies Quarterly, volume 34 (4), November 2009 (with David Lublin, Thomas Brunell and Bernard Grofman).

“Delimitation Consulting in the US and Elsewhere,” Zeitschrift für Politikberatung, volume 1 (3/4), 2008 (with Peter Schrott).

“Drawing Effective Minority Districts: A Conceptual Framework and Some Empirical Evidence,” North Carolina Law Review, volume 79 (5), June 2001 (with Bernard Grofman and David Lublin).

“A Guide to 2000 Redistricting Tools and Technology” in The Real Y2K Problem: Census 2000 Data and Redistricting Technology, edited by Nathaniel Persily, New York: Brennan Center, 2000.

"1990s Issues in Voting Rights," Mississippi Law Journal, 65 (2), Winter 1995 (with Bernard Grofman).

"Minority Turnout and the Creation of Majority-Minority Districts," American Politics Quarterly, 23 (2), April 1995 (with Kimball Brace, Richard Niemi and Harold Stanley).

"Identifying and Remedying Racial Gerrymandering," Journal of Law and Politics, 8 (2), Winter 1992 (with Bernard Grofman).

"The Impact of the Voting Rights Act on Minority Representation in Southern State Legislatures," Legislative Studies Quarterly, 16 (1), February 1991 (with Bernard Grofman).

"Minority Population Proportion and Black and Hispanic Congressional Success in the 1970s and 1980s," American Politics Quarterly, 17 (4), October 1989 (with Bernard Grofman).

"Black Representation: Making Sense of Electoral Geography at Different Levels of Government," Legislative Studies Quarterly, 14 (2), May 1989 (with Bernard Grofman).

"Minority Voting Equality: The 65 Percent Rule in Theory and Practice," Law and Policy, 10 (1), January 1988 (with Kimball Brace, Bernard Grofman and Richard Niemi).

"Does Redistricting Aimed to Help Blacks Necessarily Help Republicans?" Journal of Politics, 49 (1), February 1987 (with Kimball Brace and Bernard Grofman).

Chapters in Edited Volumes:

"Effective torture prevention," Research Handbook on Torture, Sir Malcolm Evans and Jens Modvig (eds), Cheltenham: Edward Elgar, 2020 (with Richard Carver).

"Redistricting" in Oxford Handbook of Electoral Systems, Erik Herron Robert Pekkanen and Matthew Shugart (eds), Oxford: Oxford University Press, 2018.

"Role of the Courts in the Electoral Boundary Delimitation Process," in International Election Remedies, John Hardin Young (ed.), Chicago: American Bar Association Press, 2017.

"One Person, One Vote, Different Values: Comparing Delimitation Practices in India, Canada, the United Kingdom, and the United States," in Fixing Electoral Boundaries in India, edited by Mohd. Sanjeer Alam and K.C. Sivaramakrishman, New Delhi: Oxford University Press, 2015.

"Delimiting Electoral Boundaries in Post-Conflict Settings," in Comparative Redistricting in Perspective, edited by Lisa Handley and Bernard Grofman, Oxford: Oxford University Press, 2008.

"A Comparative Survey of Structures and Criteria for Boundary Delimitation," in Comparative Redistricting in Perspective, edited by Lisa Handley and Bernard Grofman, Oxford: Oxford University Press, 2008.

"Drawing Effective Minority Districts: A Conceptual Model," in Voting Rights and Minority Representation, edited by David Bositis, published by the Joint Center for Political and Economic Studies, Washington DC, and University Press of America, New York, 2006.

"Electing Minority-Preferred Candidates to Legislative Office: The Relationship Between Minority Percentages in Districts and the Election of Minority-Preferred Candidates," in Race and Redistricting in the 1990s, edited by Bernard Grofman; New York: Agathon Press, 1998 (with Bernard Grofman and Wayne Arden).

"Estimating the Impact of Voting-Rights-Related Districting on Democratic Strength in the U.S. House of Representatives," in Race and Redistricting in the 1990s, edited by Bernard Grofman; New York: Agathon Press, 1998 (with Bernard Grofman).

"Voting Rights in the 1990s: An Overview," in Race and Redistricting in the 1990s, edited by Bernard Grofman; New York: Agathon Press, 1998 (with Bernard Grofman and Wayne Arden).

"Racial Context, the 1968 Wallace Vote and Southern Presidential Dealignment: Evidence from North Carolina and Elsewhere," in Spatial and Contextual Models in Political Research, edited by Munroe Eagles; Taylor and Francis Publishing Co., 1995 (with Bernard Grofman).

"The Impact of the Voting Rights Act on Minority Representation: Black Officeholding in Southern State Legislatures and Congressional Delegations," in The Quiet Revolution: The Impact of the Voting Rights Act in the South, 1965-1990, eds. Chandler Davidson and Bernard Grofman, Princeton University Press, 1994 (with Bernard Grofman).

"Preconditions for Black and Hispanic Congressional Success," in United States Electoral Systems: Their Impact on Women and Minorities, eds. Wilma Rule and Joseph Zimmerman, Greenwood Press, 1992 (with Bernard Grofman).

***Electronic Publication**:*

"Boundary Delimitation" Topic Area for the Administration and Cost of Elections (ACE) Project, 1998. Published by the ACE Project on the ACE website (www.aceproject.org).

***Additional Writings of Note**:*

Amicus brief presented to the US Supreme Court in Gill v. Whitford, Brief of Political Science Professors as Amici Curiae, 2017 (one of many social scientists to sign brief)

Amicus brief presented to the US Supreme Court in Shelby County v. Holder, Brief of Historians and Social Scientists as Amici Curiae, 2013 (one of several dozen historians and social scientists to sign brief)

Amicus brief presented to the US Supreme Court in Bartlett v. Strickland, 2008 (with Nathaniel Persily, Bernard Grofman, Bruce Cain, and Theodore Arrington).

Recent Court Cases

In the past ten years, Dr. Handley has served as an testifying expert or expert consultant in the following cases:

Ohio Philip Randolph Institute v. Larry Householder (2019) – partisan gerrymander challenge to Ohio congressional districts; testifying expert for ACLU on minority voting patterns

State of New York v. U.S. Department of Commerce/ New York Immigration Coalition v. U.S. Department of Commerce (2018-2019) – challenge to inclusion of citizenship question on 2020 census form; testifying expert on behalf of ACLU

U.S. v. City of Eastpointe (settled 2019) – minority vote dilution challenge to City of Eastpointe, Michigan, at-large city council election system; testifying expert on behalf of U.S. Department of Justice

Alabama NAACP v. State of Alabama (decided 2020) – minority vote dilution challenge to Alabama statewide judicial election system; testifying expert on behalf of Lawyers Committee for Civil Rights Under Law

Lopez v. Abbott (2017-2018) – minority vote dilution challenge to Texas statewide judicial election system; testifying expert on behalf of Lawyers Committee for Civil Rights Under Law

Personhuballuah v. Alcorn (2015-2017) – racial gerrymandering challenge to Virginia congressional districts; expert for the Attorney General and Governor of the State of Virginia; written testimony on behalf of Governor

Perry v. Perez (2014) – Texas congressional and state house districts (Section 2 case before federal court in San Antonio, Texas; testifying expert for the U.S. Department of Justice)

Jeffers v. Beebe (2012) – Arkansas state house districts (testifying expert for the Plaintiffs)

State of Texas v. U.S. (2011-2012) – Texas congressional and state house districts (Section 5 case before the Circuit Court of the District of Columbia; testifying expert for the U.S. Department of Justice)

In RE 2011 Redistricting Cases (2011-2012) – State legislative districts for State of Alaska (testifying expert for the Alaska Redistricting Board)

Contact Information

Email: lrhandley@aol.com; lrhandley.Frontier@gmail.com
Telephone: ++1.301.765.5024

CERTIFICATE OF SERVICE

I, Freda J. Levenson, hereby certify that on this 10th day of December, 2021, I caused a true and correct copy of the foregoing document to be served by email upon the counsel listed below:

Bridget C. Coontz, bridget.coontz@ohioago.gov
Julie M. Pfeiffer, julie.pfeiffer@ohioago.gov
Michael Walton, michael.walton@ohioago.gov

Counsel for Respondent Ohio Secretary of State LaRose

Phillip J. Strach, phil.strach@nelsonmullins.com
Thomas A. Farr, tom.farr@nelsonmullins.com
John E. Branch, III, john.branch@nelsonmullins.com
Alyssa M. Riggins, alyssa.riggins@nelsonmullins.com

Counsel for Respondents House Speaker Robert R. Cupp and Senate President Matt Huffman

/s/ Freda J. Levenson
Freda J. Levenson (0045916)
Counsel for Relators

<u>Neiman Petitioners' Exhibit 28</u>

Warshaw Affidavit.pdf

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E-Signature 1: Christopher Warshaw (CW)
November 30, 2021 08:13:08 -8:00 [9105E3126672] [68.33.74.68]
warshaw@email.gwu.edu (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
November 30, 2021 08:13:08 -8:00 [0C271766C922] [74.142.214.254]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, et al.,	
Relators	**Case No.**
v.	**Original Action Pursuant to Ohio Const., Art. XIX**
GOVERNOR MIKE DEWINE, et al.,	
Respondents.	

AFFIDAVIT OF CHRISTOPHER WARSHAW

Franklin County
/ss
State of Ohio

Now comes affiant Christopher Warshaw, having been first duly cautioned and sworn, deposes and states as follows:

1. I am over the age of 18 and fully competent to make this declaration. I have personal knowledge of the statements and facts contained herein.
2. For the purposes of this litigation, I have been asked by counsel for Relators to analyze relevant data and provide my expert opinions.
3. To that end, I have personally prepared the report attached to this affidavit as Exhibit A, and swear to its authenticity and to the faithfulness of the opinions expressed and, to the best of my knowledge, the accuracy of the factual statements made therein.

FURTHER AFFIANT SAYETH NAUGHT.

Executed on 11/30/2021, 2021.

Christopher Warshaw
Signed on 2021/11/30 08:13:08 -8:00

Christopher Warshaw

Sworn and subscribed before me this ____ day of 11/30/2021, 2021.

NOTARY PUBLIC
STATE OF OHIO

Theresa M Sabo
Commission # 2016-RE-619622
Electronic Notary Public
State of Ohio
My Comm Exp. Nov 28, 2026

Notary Stamp 2021/11/30 09:13:08 PST 0C271766C922

Signed on 2021/11/30 08:13:08 -8:00

Notary Public

Notarial act performed by audio-visual communication

EXHIBIT A

An Evaluation of the Partisan Bias in Ohio's Enacted Congressional Districting Plan

Christopher Warshaw*

November 30, 2021

*Associate Professor, Department of Political Science, George Washington University. warshaw@gwu.edu. Note that the analyses and views in this report are my own, and do not represent the views of George Washington University.

Contents

1 Introduction

My name is Christopher Warshaw. I am an Associate Professor of Political Science at George Washington University. Previously, I was an Associate Professor at the Massachusetts Institute of Technology from July 2016 - July 2017, and an Assistant Professor at MIT from July 2012 - July 2016.

I have been asked by counsel representing the relators in this case to analyze relevant data and provide my expert opinions about whether Ohio's enacted congressional districting plan meets the requirement in Article XIX.01, Section 3(A) of Ohio's Constitution that "If the general assembly passes a congressional district plan under division (C)(1) of this section by a simple majority of the members of each house of the general assembly, and not by the vote described in division (C)(2) of this section", then "The general assembly shall not pass a plan that unduly favors or disfavors a political party or its incumbents."

2 Qualifications, Publications and Compensation

My Ph.D. is in Political Science, from Stanford University, where my graduate training included courses in political science and statistics. I also have a J.D. from Stanford Law School. My academic research focuses on public opinion, representation, elections, and polarization in American Politics. I have written over 20 peer reviewed papers on these topics. Moreover, I have written multiple papers that focus on elections and two articles that focus specifically on partisan gerrymandering. I also have a forthcoming book that includes an extensive analysis on the causes and consequences of partisan gerrymandering in state governments.

My curriculum vitae is attached to this report. All publications that I have authored and published appear in my curriculum vitae. My work is published or forthcoming in peer-reviewed journals such as: the *American Political Science Review*, the *American Journal of Political Science*, the *Journal of Politics*, *Political Analysis*, *Political Science Research and Methods*, the *British Journal of Political Science*, the *Annual Review of Political Science*, *Political Behavior*, *Legislative Studies Quarterly*, *Science Advances*, the *Election Law Journal*, *Nature Energy*, *Public Choice*, and edited volumes from Cambridge University Press and Oxford University Press. My book entitled *Dynamic Democracy in the American States* is forthcoming from the University of Chicago Press. My non-academic writing has been published in the *New York Times* and the *Washington Post*. My work has also been discussed in the *Economist* and many other prominent media outlets.

My opinions in this case are based on the knowledge I have amassed over my education, training and experience, including a detailed review of the relevant academic literature. They also follow from statistical analysis of the following data:

- In order to calculate partisan bias in congressional elections on the enacted plan in Ohio, I examined:
  - GIS Files with the 2012-2020 Ohio Congressional plan and the enacted 2022-24 plan): I obtained the 2012-2020 plan from the state website and the enacted plan from Counsel in this case.
  - Precinct-level data on recent statewide Ohio elections: I use precinct-level data on Ohio's statewide elections between 2016-20 from the Voting and Election Science Team (University of Florida, Wichita State University). I obtained these data from the Harvard Dataverse.[1] As far as I know, there are no publicly available datasets with precinct-level returns from 2012-14 that are linked to precinct boundaries (e.g., shapefiles). For these elections, I obtained data via the ACLU that Bill Cooper, the relators' expert in League of Women Voters v. Ohio Redistricting Commission, No. 2021-1193, put together.[2]
  - Precinct-level data on recent statewide Ohio elections: I use a GIS file with precinct-level data on the results of the 2020 congressional elections in Ohio that I obtained from Counsel in this case.
  - The Plan Score website: PlanScore is a project of the nonpartisan Campaign Legal Center (CLC) that enables people to score proposed maps for their partisan, demographic, racial, and geometric features. I am on the social science advisory team for PlanScore.

1. See https://dataverse.harvard.edu/dataverse/electionscience.

2. Cooper provided the following description of the data via Counsel: The 2012 results are disaggregated to the block level (based on block centroids) from the statewide 2012 precinct file. The 2014 results are based on a geocoding of about 3.15 million voters who cast ballots in Nov. 2014. These addresses were matched to census blocks and the blocks were aggregated to the precinct level. These "virtual" precincts were next matched to the 2014 election results and then disaggregated back to the block level, with block-level matches. When aggregated to the congressional level, the differences are measured in the tenths of a percent for House contests. As a final step, these datasets were aggregated from the block-level to the 2010 VTD level. Finally, it is important to note that there is a 2% to 3% undercount statewide for all votes cast in the 2014 election. Given the missing votes for the 2014 contests in Lorain County, the VTD-level totals in that county were approximated using the official precinct 2014 returns. First, after identifying the township, city, or village of each 2014 precinct, the official precinct-level returns were aggregated up to that level. Those municipality-level returns were then disaggregated for each candidate down to the VTDs in each municipality, proportionally to the vote counts for the candidate running for the same office and party in the 2018 midterm cycle.

- In order to compare the maps in Ohio to other congressional elections across the nation over the past five decades, I examined:
  - A large data set on candidacies and results in Congressional elections: I obtained results from 1972-2018 collected by the Constituency-Level Elections Archive (CLEA) (Kollman et al. 2017). The results from 1972-1990 are based on data collected and maintained by the Inter-university Consortium for Political and Social Research (ICPSR) and adjusted by CLEA. The data from 1992-2018 are based on data collected by CLEA from the Office of the Clerk at the House of the Representatives. I supplemented this dataset with recent election results collected by the MIT Election and Data Science Lab (MIT Election and Data Science Lab 2017) and Dave Leip's Atlas of U.S. Presidential Elections.
  - Data on presidential election returns and incumbency status in Congressional elections. I used data on elections in congressional districts from 1972-2020 collected by Professor Gary Jacobson (University of California, San Diego). This dataset has been used in many Political Science studies and has canonical status in the political science profession (Jacobson 2015).
  - Information on who controlled each redistricting plan in Congressional elections (e.g., Democrats, Republicans, or a Commission) from 1972-2012 assembled by the Brennan Center (Brennan Center 2017).
  - I imputed vote shares and turnout in uncontested districts and then calculated the partisan bias metrics described on pp. 6-14 of this report using the methodology described in Stephanopoulos and Warshaw (2020).

I have previously provided expert reports in five redistricting-related cases:

- Between 2017 and 2019, I provided reports for *League of Women Voters of Pennsylvania v. Commonwealth of Pennsylvania*, No. 159 MM 2017, *League of Women Voters of Michigan* v. *Johnson*, 17-14148 (E.D. Mich), and *APRI et al.* v. *Smith et al.*, No. 18-cv-357 (S.D. Ohio). My testimony was found to be credible in each of these cases and was extensively cited by the judges in their decisions.

- In the current redistricting cycle, I have provided reports in *League of Women Voters* v. *Ohio Redistricting Commission*, No. 2021-1193 and *League of Women Voters* vs. *Kent County Apportionment Commission.*

In addition, I have provided expert testimony and reports in several cases related to the U.S. Census: *State of New York et al.* v. *United States Department of Commerce*, 18-cv-2921 (S.D.N.Y.), *New York* v. *Trump*; *Common Cause* v. *Trump*, 20-cv-2023 (D.D.C.), and *La Union Del Pueblo Entero (LUPE)* v. *Trump*, 19-2710 (D. Md.).

I am being compensated at a rate of $325 per hour. The opinions in this report are my own, and do not represent the views of George Washington University.

3 Summary

Ohio's Congressional redistricting plan was proposed by Republican leaders and passed on party lines, with nearly all Republicans voting in favor and all Democrats opposed.[3] This report examines whether this plan meets the criteria in the Ohio Constitution. Article XIX.01, Section 3(A) of Ohio's Constitution requires that "If the general assembly passes a congressional district plan under division (C)(1) of this section by a simple majority of the members of each house of the general assembly, and not by the vote described in division (C)(2) of this section", then "The general assembly shall not pass a plan that unduly favors or disfavors a political party or its incumbents."

Ohio's Constitutional criteria, which require that congressional districting plans not unduly favor or disfavor a political party, are related to a long-line of Political Science literature on partisan gerrymandering and democratic representation. The relationship between the distribution of partisan support in the electorate and the partisan composition of the government—what Powell (2004) calls "vote–seat representation"—is a critical link in the longer representational chain between citizens' preferences and governments' policies. If the relationship between votes and seats systematically advantages one party over another, then some citizens will enjoy more influence—more "voice"—over elections and political outcomes than others (Caughey, Tausanovitch, and Warshaw 2017).

I use three complementary methodologies to project future election results in order to evaluate whether Ohio's newly enacted Congressional map meets the requirements of Article XIX.01, Section 3(A) in its Constitution. First, I analyze the results of the 2020 Congressional election on the newly enacted map. Second, I use a composite of previous statewide election results between 2012-2020 to analyze the new map.[4] Third, I

3. See Jeremy Pelzer, Cleveland Plain Dealer, November 18, 2021, https://www.cleveland.com/news/2021/11/ohio-legislature-passes-congressional-redistricting-plan-giving-republicans-a-likely-13-2-advantage.html.

4. These include the following elections: 2012 Presidential, 2012 Senate, 2014 gubernatorial, 2014 Secretary of State, 2016 Presidential, 2016 Senate, 2018 Senate, 2018 gubernatorial, 2018 attorney's general, 2018 Secretary of State, 2018 Auditor, 2018 Treasurer, and 2020 Presidential. Geographic data on the other three statewide elections in 2014 is not available. But this probably doesn't affect my results

complement this approach using the open source PlanScore.org website, which is a project of the Campaign Legal Center.[5] PlanScore uses a statistical model to estimate district-level vote shares for a new map based on the relationship between presidential election results and legislative results between 2012-2020.[6] Based on these three approaches, I characterize the bias in Ohio's plans based on a large set of established metrics of partisan fairness. I also place the bias in Ohio's plans into historical perspective. I also analyze whether the map unduly favors incumbents from one party.

All of these analyses indicate an extreme level of pro-Republican bias in Ohio's enacted Congressional plan. There are 10 strongly Republican districts, 2 strongly Democratic districts, and 3 potentially competitive districts, each of which leans toward Republicans. In the average election, Republicans are likely to get about 55% of the statewide vote and about 80% of the seats in Ohio's congressional delegation. Thus, the plan clearly unduly favors the Republican party.

In the actual 2020 congressional election, Democrats received 43% of the two-party vote (and Republicans 57%), but Democrats only won 25% (4) of the seats (and Republicans won 75%). This was already one of the most extreme partisan gerrymanders of a congressional map in modern history (See *APRI et al.* v. *Smith et al.*, No. 18-cv-357 (S.D. Ohio)). Based on the congressional election results, the new plan is even more extreme than the last one. On the new map, Democrats would only win 13% (2) of the seats using the precinct-level results of the 2020 congressional election.

The new plan also displays an extreme level of partisan bias when I evaluate it based on the results of recent statewide elections. In the 2020 presidential election, Democrat Joe Biden received about 46% of the two-party vote.[7] However, he would have only won 27% (4) of the Congressional districts. In the 2018 gubernatorial election, Democrat Richard Cordray did a little bit better. He received about 48% of the two-party vote. Yet again, however, he would have only won 27% of the districts under the enacted plan. In the 2016 presidential election, Democrat Hillary Clinton received about 46% of the two-party vote. But she would have only won 13% of the seats. In the 2012 presidential election, Democratic President Barack Obama received about 52% of the two-party vote. But he would have still won only 40% of the seats.

Based on all the available statewide elections in Ohio between 2012-2020, I find that

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much since these elections were similar to the average of the 2014 gubernatorial and Secretary of State elections.

5. I am on the social science advisory board of Plan Score, but do not have any role in PlanScore's evaluation of individual maps.

6. See `https://planscore.campaignlegal.org/models/data/2021C/` for more details.

7. Following standard convention, throughout my analysis I focus on two-party vote shares.

the enacted Congressional plan leads to a much higher Republican share of the seats than their share of the statewide vote. Indeed, across all statewide elections during this period, the Democrats' statewide two-party vote share averaged about 45% of the vote, but they are only likely to win about 26% of the seats.[8]

I reach the same conclusion using the predictive model on the PlanScore website. It indicates that the enacted plan favors Republican candidates in 97% of scenarios. Even though Republicans only get about 56% of the statewide vote in recent elections (and Democrats get 44%), PlanScore analysis indicates that Republicans are expected to win 79% of the seats in Ohio's Congressional delegation (and Democrats would win 21% of the seats).[9] Based on generally accepted Political Science metrics (the Efficiency Gap and the Declination), PlanScore indicates that Ohio's enacted plan would have historically extreme levels of pro-Republican bias. In fact, the pro-Republican bias in Ohio's Congressional plan is larger than 98% of previous plans in the United States from 1972-2020.

Overall, this analysis indicates that the enacted plan unduly favors the Republican party. This conclusion is based on a wide variety of approaches to project future election results and to estimate the partisan bias of the plan. Regardless of the approach I use, it is clear that the enacted map has an extreme level of bias in favor of the Republican party.

The enacted plan also favors incumbents from the Republican Party. It puts two of the four Democratic incumbents from the previous plan into largely new districts that will now have a majority of Republican voters. It does not put any Republican incumbent into a district with a majority of Democratic voters. This bias against Democratic incumbents is especially clear in the case of Representative Marcy Kaptur. In 2020, she comfortably won reelection with 63% of the two-party vote. The new plan slices her old district into five districts. On the new map, she would have only won about 46% in the 2020 House election, and thus would likely lose in 2022.

4 Background on Partisan Gerrymandering

The goal of partisan gerrymandering is to create legislative districts that are as "efficient" as possible in translating a party's vote share into seat share (McGhee 2014, 2017; Caughey, Tausanovitch, and Warshaw 2017). In practice, this entails drawing districts in which the supporters of the advantaged party constitute either a slim majority (e.g., 55%

8. I weight the composite scores to give each election cycle equal weight in the index. The seat-level projections are based on the 13 statewide elections where I have precinct-level data.

9. This is a probabilistic estimate based on 1000 simulations of possible elections using a model of the elections between 2012-2020.

of the two-party vote) or a small minority (e.g., 20%). The former is achieved by "cracking" local opposing-party majorities across multiple districts and the latter by "packing" them into a few overwhelming strongholds. In a "cracked" district, the disadvantaged party narrowly loses, while in a "packed" district, the disadvantaged party wins overwhelmingly (Buzas and Warrington 2021). The resulting *asymmetry* or *advantage* in the efficiency of the vote–seat relationships of the two parties lies at the core of normative critiques of partisan gerrymandering. Asymmetries in the translation of votes to seats "offer a party a means of increasing its margin of control over policy without winning more votes from the public" (McGhee 2014).

In addition to creating a plan that skews the vote-seat curve toward their party, the advantaged party also often seeks to build a map that is *insulated* against changes in the public's preferences. This type of unresponsive map enables the advantaged party to continue to win the majority of seats even in the face of large gains in the disadvantaged party's statewide vote share. It ensures that the gerrymander is durable over multiple election cycles.

There are a number of approaches that have been proposed to measure partisan advantage in a districting plan. These approaches focus on asymmetries in the efficiency of the vote–seat relationships of the two parties. In recent years, at least 10 different approaches have been proposed (McGhee 2017). While no measure is perfect, much of the recent literature has focused on a handful of related approaches that I describe below.

4.1 Efficiency Gap

Both cracked and packed districts "waste" more votes of the disadvantaged party than of the advantaged one (McGhee 2014; Stephanopoulos and McGhee 2015).[10] This suggests that gerrymandering can be measured based on asymmetries in the number of wasted votes for each party. The *efficiency gap* (EG) focuses squarely on the number of each party's wasted votes in each election. It is defined as "the difference between the parties' respective wasted votes, divided by the total number of votes cast in the election" (Stephanopoulos and McGhee 2015, 831; see also McGhee 2014, 2017).[11] All of the losing

10. The authors of the efficiency gap use the term "waste" or "wasted" to describe votes for the losing party and votes for the winning party in excess of what is needed to win an election. Since the term is used by the efficiency gap authors, I use it here when discussing the efficiency gap.

11. The efficiency gap calculations here focus on wasted votes in *congressional elections* since these results directly capture voters' preferences in these elections. However, we might also calculate the efficiency gap using district-level results from presidential elections or other statewide races. These have the "advantage of being (mostly) unaffected by district-level candidate characteristics" (Stephanopoulos and McGhee 2015, 868). This feature is particularly useful for simulating efficiency gaps from randomly generated districting plans since candidate characteristics are clearly influenced by the final districting

party's votes are wasted if they lose the election. When a party wins an election, the wasted votes are those above the 50%+1 needed to win.

If we adopt the convention that positive values of the efficiency gap imply a Democratic advantage in the districting process and negative ones imply a Republican advantage, the efficiency gap can be written mathematically as:

$$EG = \frac{W_R}{n} - \frac{W_D}{n} \tag{1}$$

where W_R are wasted votes for Republicans, W_D are wasted votes for Democrats, and n is the total number of votes in each state.

Table 1 provides a simple example about how to calculate the efficiency gap with three districts where the same number of people vote in each district. In this example, Democrats win a majority of the statewide vote, but they only win 1/3 seats. In the first district, they win the district with 75/100 votes. This means that they only wasted the 24 votes that were unnecessary to win a majority of the vote in this district. But they lose the other two districts and thus waste all 40 of their votes in those districts. In all, they waste 104 votes. Republicans, on the other hand, waste all 25 of their votes in the first district. But they only waste the 9 votes unnecessary to win a majority in the two districts they win. In all, they only waste 43 votes. This implies a pro-Republican efficiency gap of $\frac{43}{300}$ - $\frac{104}{300}$= -20%.

Table 1: Illustrative Example of Efficiency Gap

District	Democratic Votes	Republican Votes
1	75	25
2	40	60
3	40	60
Total	155 (52%)	145 (48%)
Wasted	104	43

In order to account for unequal population or turnout across districts, the efficiency gap formula in equation 1 can be rewritten as:

$$EG = S_D^{margin} - 2 * V_D^{margin} \tag{2}$$

plan. Presidential elections or other statewide races are less closely tied, however, to voters' preferences in legislative races given the district lines that actually exist. In practice, though, both legislative races and other statewide races produce similar efficiency gap results for modern elections where voters are well sorted by party and ideology. Indeed, the data indicate that the correlation between efficiency gap estimates based on congressional elections and presidential elections is approximately 0.8 for elections held after 2000 and about 0.9 for elections held after the 2011 redistricting cycle.

where S_D^{margin} is the Democratic Party's seat margin (the seat share minus 0.5) and V_D^{margin} is is the Democratic Party's vote margin. V_D^{margin} is calculated by aggregating the raw votes for Democratic candidates across all districts, dividing by the total raw vote cast across all districts, and subtracting 0.5 (McGhee 2017, 11-12). In the example above, this equation also provides an efficiency gap of -20% in favor of Republicans. But it could lead to a slightly different estimate of the efficiency gap if districts are malapportioned or there is unequal turnout across districts.[12]

In the case of Ohio's enacted Congressional map, equation 2 implies there would have been a pro-Republican efficiency gap of approximately 23% using the votes from the 2020 election re-aggregated onto the enacted plan. This is a larger pro-Republican Efficiency Gap than 99% of previous congressional plans with more than 6 seats over the past 50 years.

The efficiency gap mathematically captures the packing and cracking that are at the heart of partisan gerrymanders (Buzas and Warrington 2021). It measures the extra seats one party wins over and above what would be expected if neither party were advantaged in the translation of votes to seats (i.e., if they had the same number of wasted votes). A key advantage of the efficiency gap over other measures of partisan bias is that it can be calculated directly from observed election returns even when the parties' statewide vote shares are not equal.

4.2 Declination

Another measure of asymmetries in redistricting plans is called *declination* (Warrington 2018b, 2018a). The declination metric treats asymmetry in the vote distribution as indicative of partisan bias in a districting plan (Warrington 2018a). If all the districts in a plan are lined up from the least Democratic to the most Democratic, the mid-point of the line formed by one party's seats should be about as far from the 50 percent threshold for victory on average as the other party's (McGhee 2018).

Declination suggests that when there is no gerrymandering, the angles of the lines (θ_D and θ_R) between the mean across all districts and the point on the 50% line between the mass of points representing each party will be roughly equal. When they deviate from each other, the smaller angle (θ_R in the case of Ohio) will generally identify the favored party. To capture this idea, declination takes the difference between those two angles (θ_D

12. In general, the two formulations of the efficiency gap formula yield very similar results. Because Democrats tend to win lower-turnout districts, however, the turnout adjusted version of the efficiency gap in equation 2 tends to produce results that suggest about a 2% smaller disadvantage for Democrats than the version in Equation 1 (see McGhee 2018).

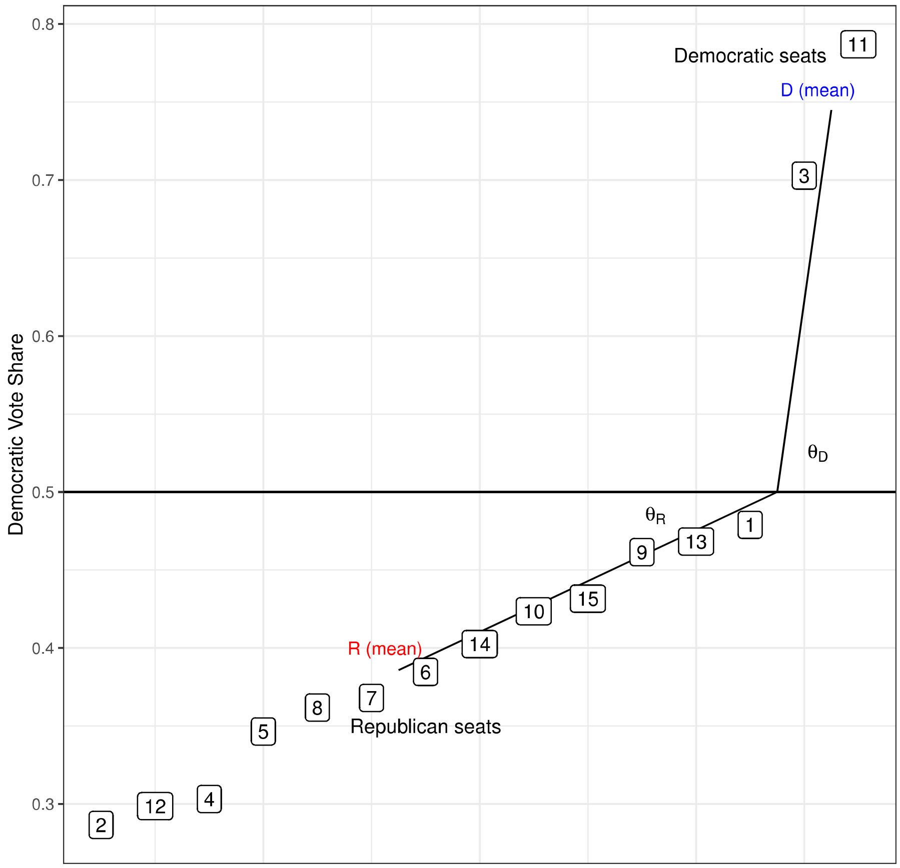

Figure 1: Plot illustrating declination based on votes in 2020 Congressional election re-aggregated to new plan

and θ_R) and divides by $\pi/2$ to convert the result from radians to fractions of 90 degrees.[13] This produces a number between -1 and 1. As calculated here, positive values favor Democrats and negative values favor Republicans. Warrington (2018b) suggests a further adjustment to account for differences in the number of seats across legislative chambers. I use this adjusted declination estimate in the analysis that follows.[14]

In the case of Ohio's 2020 congressional elections, the declination metric indicates that the plan has a pro-Republican bias of .90. This is a larger absolute level of bias than 97% of previous congressional elections in states with more than 6 seats, and more pro-Republican than 97% of previous plans.

13. This equation is: $\delta = 2^*\ (\theta_R - \theta_D)\ /\ \pi$.
14. This adjustment uses this equation: $\hat{\delta} = \delta\ *\ \ln(\text{seats})\ /\ 2$

4.3 Mean-median Gap

Another metric that some scholars have proposed to measure partisan bias in a districting plan is the *mean-median gap*: the difference between a party's vote share in the median district and their average vote share across all districts. If the party wins more votes in the median district than in the average district, they have an advantage in the translation of votes to seats (Krasno et al. 2018; Best et al. 2017; Wang 2016). In statistics, comparing a dataset's mean and median is a common statistical analysis used to assess skews in the data and detect asymmetries (Brennan Center 2017).

The mean-median difference is very easy to apply (Wang 2016). It is possible, however, for packing and cracking to occur without any change in the mean-median difference (Buzas and Warrington 2021). That is, a party could gain seats in the legislature without the mean-median gap changing (McGhee 2017).[15] It is also sensitive to the outcome in the median district (Warrington 2018b). In addition, the mean-median difference lacks a straightforward interpretation in terms of the number of seats that a party gains through gerrymandering. Finally, the assumptions of the mean-median gap are less tenable in less electorally competitive states.

District	Democratic Vote Share
2	0.29
12	0.30
4	0.30
5	0.35
8	0.36
7	0.37
6	0.38
14	0.40
10	0.42
15	0.43
9	0.46
13	0.47
1	0.48
3	0.70
11	0.79
Mean	43.4%
Median	40.3%

Table 2: Results in 2020 Ohio Congressional Elections Re-Aggregated onto Enacted Map

15. As McGhee (2017), notes, "If the median equals the win/loss threshold–i.e., a vote share of 0.5–then when a seat changes hands, the median will also change and the median- mean difference will reflect that change. But if the median is anything other than 0.5, seats can change hands without any change in the median and so without any change in the median-mean difference." See also Buzas and Warrington (2021) who make a similar point using simulated packing and cracking.

Table 2 illustrates the mean-median approach using the results in the 2020 Ohio congressional elections re-aggregated to the districts in the enacted map. In the actual 2020 congressional elections, Democrats won 4 seats. But on the enacted plan, Democrats would only have won 2 seats. Moreover, Table 2 shows that many Democratic voters were packed into just 2 districts where the Democratic candidates won by overwhelming margins. The remaining Democratic voters were cracked across the other districts. This table shows the disproportionate percentage of the statewide vote that Democrats would have needed to win a majority of Ohio's congressional seats in 2020. Across all districts, Democrats won an average of 43.4% of the vote. But they only won 40.3% in the median district. This translated into a pro-Republican mean-median difference of 3.1%.

4.4 Symmetry in the Vote-Seat Curve Across Parties

Basic fairness suggests that in a two-party system each party should receive the same share of seats for identical shares of votes. The *symmetry* idea is easiest to understand at an aggregate vote share of 0.5—a party that receives half the vote ought to receive half the seats—but a similar logic can apply across the "seats- votes curve" that traces out how seat shares change as vote shares rise and fall. For example, if a party receives a vote share of 0.57 and a seat share of 0.64, the opposing party should also expect to receive a seat share of 0.64 if it were to receive a vote share of 0.57. An unbiased system means that for V share of the votes a party should receive S share of the seats, and this should be true for all parties and vote percentages (Niemi and Deegan 1978; Gelman and King 1994a; McGhee 2014; Katz, King, and Rosenblatt 2020).

Gelman and King (1994a, 536) propose two ways to measure partisan bias in the symmetry of the vote-seat curve. First, it can be measured using counter-factual election results in a range of statewide vote shares between .45 and .55. Across this range of vote shares, each party should receive the same number of seats. Symmetry captures any departures from the standard that each party should receive the same seat share across this range of plausible vote shares. For example, if partisan bias is -0.05, this means that the Democrats receive 5% fewer seats in the legislature than they should under the symmetry standard (and the Republicans receive 5% more seats than they should).

To illustrate the symmetry metric, Table 3 calculates what each party's share of the seats would have been in Ohio's 2020 Congressional elections (re-aggregated onto the enacted map) across a range of statewide vote shares from 45%-55%. It shows that Democrats only received a third or less of the seats in most of the scenarios where they received less than 50% of the votes. This might not have been problematic under the symmetry standard if Republicans also only received a third of the seats when they received less than 50% of the votes. However, Table 3 shows that Republicans still would have received half of the seats even when they won a minority of the votes. Across this range of statewide vote shares from 45%-55%, Democrats receive an average of 39% of the seats (and Republicans win 61%). This implies a partisan bias of 11% using the symmetry metric. That is, Republicans won 11 percentage points more of the seats than they would have won if the seat-vote curve was symmetric between the two parties.

Dem. Vote Share	Dem. Seat Share	Rep. Vote Share	Rep. Seat Share
45%	13%	55%	87%
46%	20%	54%	80%
47%	33%	53%	67%
48%	33%	52%	67%
49%	33%	51%	67%
50%	40%	50%	60%
51%	47%	49%	53%
52%	47%	48%	53%
53%	53%	47%	47%
54%	53%	46%	47%
55%	60%	45%	40%
Mean Seat Share	39%		61%
Bias	-11%		11%

Table 3: Symmetry Calculations for 2020's Congressional Elections Re-Aggregated onto Enacted Map

The symmetry metric is closely related to the efficiency gap. In the special case where each party receives half of the statewide vote, the symmetry and the efficiency gap metrics are mathematically identical (Stephanopoulos and McGhee 2015, 856). More generally, the symmetry and efficiency gap yield very similar substantive results when each party's statewide vote share is close to 50% (as is the case in Ohio). When elections are uncompetitive, however, and one party wins a large percentage of the statewide vote, the efficiency gap and these symmetry metrics are less correlated with one another (857).

A weakness of the symmetry approach is that it requires the analyst to calculate counterfactual elections. This approach has both conceptual and empirical limitations. At a conceptual level, it is not clear that it aligns perfectly with the usual definition of a gerrymander. Indeed, "when observers assert that a district plan is a gerrymander, they usually mean that it systematically benefits a party (and harms its opponent) in actual elections. They do not mean that a plan would advantage a party in the hypothetical event of a tied election, or if the parties' vote shares flipped" (Stephanopoulos and McGhee 2015, 857). At an empirical level, in order to generate symmetry metrics, we need to simulate counter-factual elections by shifting the actual vote share in each district a uniform amount (McGhee 2014).[16] In general, this uniform swing assumption seems reasonable based on past election results (though is probably less reasonable in less competitive states). Moreover, it has been widely used in past studies of redistricting. But there is no way to conclusively validate the uniform swing assumption for any particular election.

An important strength, however, of the symmetry approach is that it is based on the shape of the seats-votes curve and not any particular point on it. As a result, it is relatively immune to shifts in party performance (McGhee 2014). For instance, the bias toward Republicans in Ohio's symmetry metric was very similar in 2012-2020. Moreover, the symmetry approach has been very widely used in previous studies of gerrymandering and redistricting (Gelman and King 1994a; McGhee 2014). Overall, the symmetry approach is useful for assessing partisan advantage in the districting process.

4.5 Comparison of Partisan Bias Measures

All of the measures of partisan advantage discussed in the previous sections are closely related both theoretically and empirically (McGhee 2017; Stephanopoulos and McGhee 2018). Broadly speaking, all of the metrics consider how votes between the two parties are distributed across districts (Warrington 2018a). For example, the efficiency gap is mathematically equivalent to partisan bias in tied statewide elections (Stephanopoulos and McGhee 2018). Also, the median-mean difference is similar to the symmetry metric, since any perfectly symmetric seats-votes curve will also have the same mean and median (McGhee 2017).

Second, each of the concepts are closely related empirically, particularly in states with competitive elections. Figure 2 shows the correlation between each measure. The various measures have high correlations with one another.[17] Moreover, most of the variation in the metrics can be summarized on a single latent dimension (Stephanopoulos and McGhee 2018; Stephanopoulos and Warshaw 2020). So, overall, while there may be occasional

16. In principle, the uniform swing election could be relaxed, and swings could be estimated on a district-by-district basis. But this is rarely done in practice since it would require a much more complicated statistical model, and probably would not improve estimates of symmetry very much.

17. While each measure is highly correlated with one another, the efficiency gap and declination measures are particularly closed related and the symmetry and mean-median measures are very closely related. This could be because the efficiency gap and the declination consider the seats actually won by each party, while the symmetry metric and the mean-median difference do not (Stephanopoulos and McGhee 2018, 1557). In addition, the efficiency gap and the declination appear to best capture the packing and cracking that characterize partisan gerrymandering (Buzas and Warrington 2021).

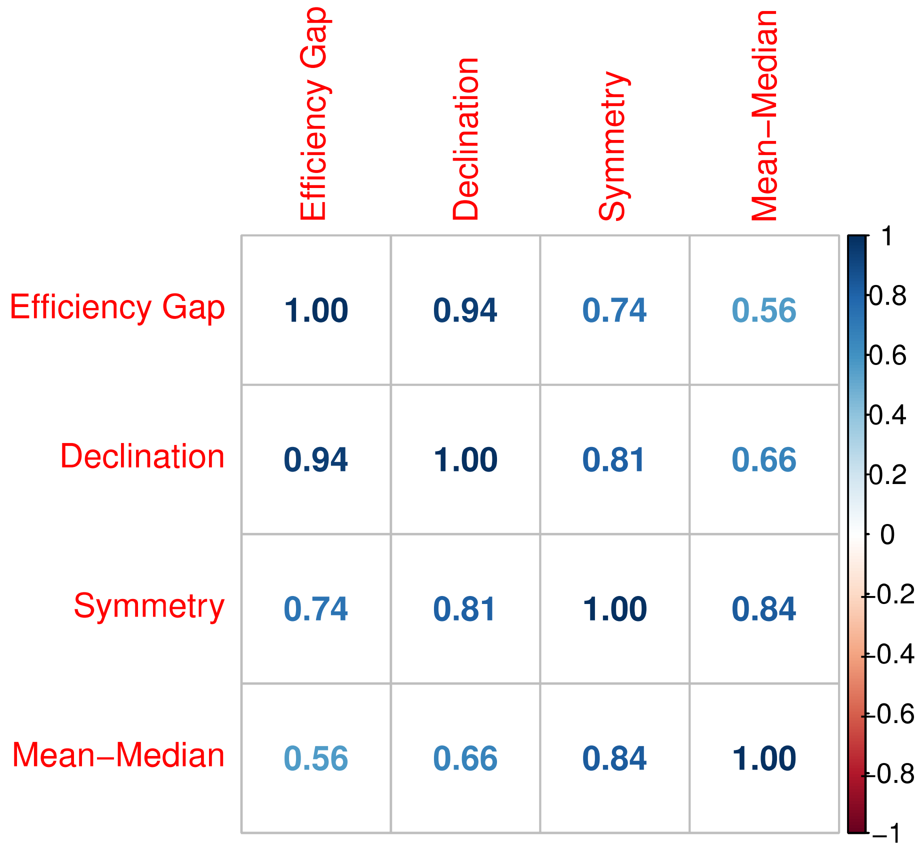

Figure 2: Correlation between measures of partisan bias in states.

cases where the metrics disagree about the amount of bias in a particular plan, the various metrics usually yield similar results for the degree of partisan bias in a districting plan (Nagle 2015). Where none of the metrics is an outlier and they all point in the same direction, we can draw a particularly robust conclusion.

While all the metrics are useful for summarizing partisan bias in a districting plan, Buzas and Warrington (2021) shows that the efficiency gap and the declination capture the packing and cracking that characterize partisan gerrymandering extremely well. In contrast, "partisan bias and mean-median difference are unable to consistently record simulated packing and cracking... As a result, we recommend that neither partisan bias nor the mean-median difference be used for the "outlier" or "ensemble" method, where it is crucial that more extreme values of the measure indicate more extreme levels of partisan gerrymandering." Moreover, McGhee (2017, 9) shows that the assumptions of the symmetry and mean-median measures become progressively less plausible as the statewide vote shares in a plan move away from 50% (McGhee 2017, 9). In my analysis below, I generally show all four metrics. But I particularly focus on the efficiency gap and declination since these best capture packing and cracking, and these metrics are best suited for a state such as Ohio where there is typically about a 45-55 split of the two-party vote in statewide elections.

4.6 Responsiveness and Competitive Elections

Another benchmark for a districting plan is the percentage of districts likely to have competitive elections under that plan and the responsiveness of the plan to changes in voters' preferences (Cox and Katz 1999). There are a number of normative reasons to care about the number of competitive districts in a plan. First, this affects the responsiveness of a map as the two parties' statewide vote shares rise and fall. A plan with more competitive elections is likely to be more responsive to changes in voters' preferences than a plan with fewer competitive elections (McGhee 2014). An unresponsive map ensures that the bias in a districting plan toward the advantaged party is insulated against changes in voters' preferences, and thus is durable across multiple election cycles. Second, uncompetitive districts tend to protect incumbents from electoral sanctions (Tufte 1973; Gelman and King 1994a). This could harm political representation by making legislators less responsive and accountable to their constituents' preferences.

To illustrate the concept of responsiveness, Figure 3 shows the vote-seat curve in Ohio generated by applying uniform swings to the 2020 election results.[18] Specifically, I apply a uniform swing in the actual election results until I achieve an average Democratic vote share of 40%. Then I steadily increase the average Democratic vote share until it reaches 60%. Figure 3 indicates that Republicans win two thirds or more of the seats across all of the range of actual election swings over the past decade.

There are a couple of approaches we might use to evaluate whether individual districts on a plan are likely to have competitive elections. We could measure whether a district was competitive in an election based on whether the winning party received less than 55% of the two-party vote (Fraga and Hersh 2018; Jacobson and Carson 2015, 91).[19] While this definition is sometimes used in the literature, though, it is not clear that a sharp threshold at 55% is the best measure of competitiveness.

Another possible definition of competitiveness might be whether a district is likely

18. The layout of this chart is adapted from charts in Royden, Li, and Rudensky (2018).

19. Fraga and Hersh (2018) justify this definition based on the fact that the Cook Political Report's "median 'leaning' race ended up with a vote margin of 10 percentage points (a 55%–45% race)."

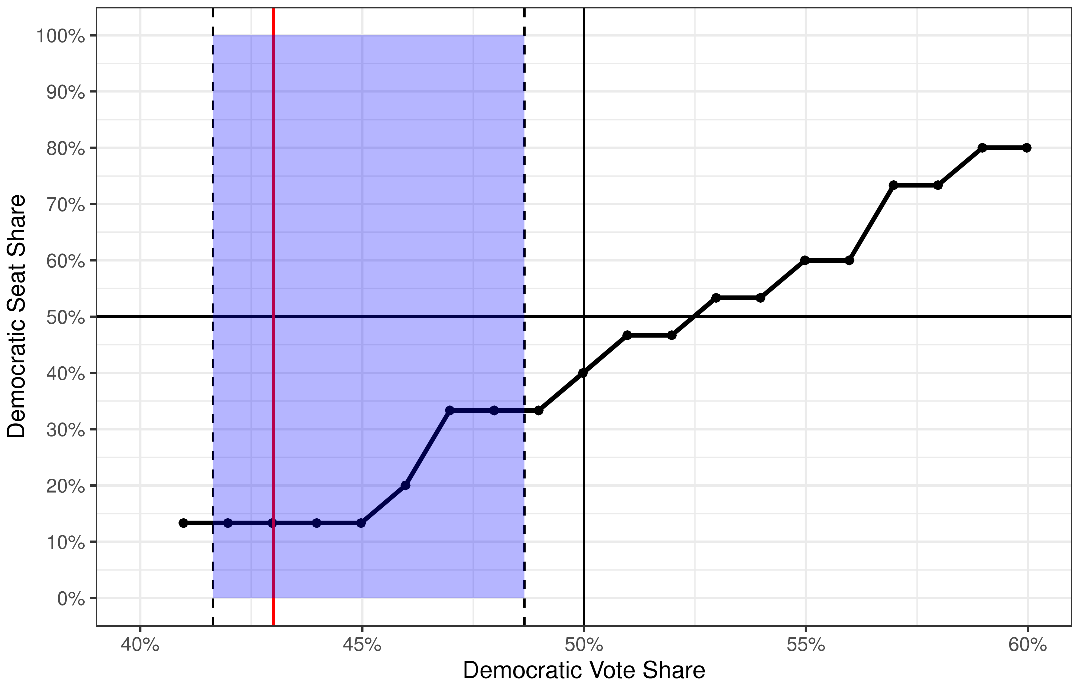

Figure 3: Vote-seat curve in Ohio using uniform swings in 2020 election results re-aggregated using enacted plan. The shaded area shows the range between the minimum and maximum Democratic statewide vote share in congressional elections from 2012-2020. The red line shows the actual Democratic statewide vote share in the 2020 House elections.

to switch parties at least once per decade (Henderson, Hamel, and Goldzimer 2018). This definition is more empirically robust because it is not dependent on any particular electoral threshold for competitiveness. Indeed, in a state with swing voters where the two parties' statewide shares vary substantially over the course of the decade, a district where the winning party normally wins 56% of the vote could be competitive. In another state with few swing voters and very inelastic election results, a district where the winning party normally wins 53% of the vote might not even be competitive.

4.7 Partisan Control of the Redistricting Process and Gerrymandering

While many factors could influence the degree of partisan advantage in the districting process,[20] there is a wide body of evidence from previous studies that control of the redistricting process has a large effect on partisan advantage in subsequent elections carried

20. Partisan advantage in the districting process can differ across states for reasons unrelated to the drawing of district lines, such as variation in how groups are distributed across geography (Chen and Rodden 2013). It can also be affected by goals other than maximizing partisan seat share, such as representation of racial minorities (e.g., Brace, Grofman, and Handley 1987).

out under a given plan. Cox and Katz (2002) show that Democratic control of the redistricting process in many states during the 1960s led to a lasting partisan advantage for Democrats in House elections. More generally, Gelman and King (1994b) find that the party in control of redistricting shifts outcomes in its favor, and that "the effect is substantial and fades only very gradually over the following 10 years" (543). This result has been confirmed in numerous recent articles. McGhee (2014) finds that "parties seek to use redistricting to shift bias in their favor and that they are successful in these efforts" (74).[21] Finally, Stephanopoulos (2018) shows that partisan control of the districting process has a substantial effect on the efficiency gap.[22] This past literature indicates that districting plans passed by one political party with unified control of government, as in Ohio, often unduly favor that party.

5 Partisan Bias in Ohio's Enacted Congressional Map

In this section, I will provide a comprehensive evaluation of the partisan fairness of Ohio's enacted congressional districting plan (see Figure 4 for a map of the enacted plan). In order to evaluate the enacted plan, we need to predict future election results on this map. Unfortunately, there is no way to know, with certainty, the results of future elections. Thus, I use three complementary methodologies to predict future congressional elections in Ohio and generate the various metrics I discussed earlier.

Figure 4: Map of Enacted Congressional Districts from PlanScore.org

21. McGhee (2014) finds that partisan control affects the districting process using both the Gelman and King (1994b) measure of partisan symmetry and the efficiency gap as outcome variables.

22. He shows that states with unified Republican control have about 5 percentage points more pro-Republican efficiency gaps than states with split control, and states with unified Democratic control have about 3 percentage points more pro-Democratic efficiency gaps than states with split control.

5.1 2020 Congressional election results

First, I use the 2020 precinct-level congressional results on both the 2012-20 map and re-aggregated to the enacted map to estimate the various metrics. This approach implicitly assumes that future elections will look like the 2020 election. These endogenous election are likely to be an excellent predictor of future voting patterns in congressional elections. Based on these results, Republicans would win 57% of the votes, but 87% of the seats on the enacted plan. In other words, Republicans would win thirty percentage points more seats than votes.

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Republican Seat Share	75%		
Efficiency Gap	-11%	78%	91%
Declination	-.51	85%	91%
Mean-Median Diff	-4%	57%	78%
Symmetry Bias	-12%	78%	87%
Average		75%	87%
Enacted Plan			
Republican Seat Share	87%		
Efficiency Gap	-23%	98%	99%
Declination	-.90	97%	97%
Mean-Median Diff	-3%	42%	72%
Symmetry Bias	-10%	69%	83%
Average		77%	88%

Table 4: Partisan bias metrics for Congressional plan based on 2020 Congressional election results re-aggregated onto enacted map

The average efficiency gap of the enacted plan based on the precinct-level 2020 House results is -23% (see Table 4). This is more extreme than 98% of previous plans and more pro-Republican than over 99% of previous plans. The enacted plan is more pro-Republican than 97% of prior plans in the country using the declination metric. The other metrics also show that Ohio's enacted plan has a large pro-Republican bias. When we average across all four metrics, the plan is more extreme than 77% of previous plans and more pro-Republican than 88% of previous plans.

5.2 Composite of previous statewide elections

Next, I use a composite of previous statewide election results between 2012-2020 re-aggregated to the enacted map.[23] For each year, I estimate each party's vote share, seat share, and the average of the partisan bias metrics across races. I then average them together to produce a composite result. This approach implicitly assumes that future voting patterns will look like the average of these recent statewide elections.

		2012-2020 Composite	
Metric	Value	> Biased than this % Plans	> Pro-Rep. than this % Plans
2012-2020 Plan			
Republican Seat Share	75%		
Efficiency Gap	-15%	90%	96%
Declination	-.54	88%	93%
Mean-Median	-4%	47%	74%
Symmetry Bias	-19%	94%	95%
Average		80%	89%
Enacted Plan			
Republican Seat Share	74%		
Efficiency Gap	-14%	87%	95%
Declination	-.54	88%	92%
Mean-Median	-2%	28%	65%
Symmetry Bias	-13%	81%	88%
Average		70%	85%

Table 5: Composite bias metrics for enacted Congressional plan based on statewide elections

When I average across these statewide elections from 2012-2020, Democrats win 45% of the votes and 26% of the seats (see Table 5). The average efficiency gap of the enacted plan based on these previous election results is -14%. This is more extreme than 87% of previous plans and more pro-Republican than 95% of previous plans. The enacted plan is also more pro-Republican than 92% of previous plans using the declination metric. The mean-median and symmetry also show that Ohio's enacted plan has a substantial pro-Republican bias. When I average across all four metrics, the plan is more extreme than 70% of previous plans and more pro-Republican than 85% of previous plans.[24]

23. These include the following elections: 2012 Presidential, 2012 Senate, 2014 gubernatorial, 2014 Secretary of State, 2016 Presidential, 2016 Senate, 2018 Senate, 2018 gubernatorial, 2018 attorney's general, 2018 Secretary of State, 2018 Auditor, 2018 Treasurer, and 2020 Presidential. Geographic data on the other three statewide elections in 2014 is not available. But this probably doesn't affect my results much since these elections were similar to the average of the 2014 gubernatorial and Secretary of State elections. I weight the elections so that each year is given equal weight in the composite.

24. In the Appendix, I show that I reach very similar results using a variety of other combinations of past elections to construct the composite index.

5.3 PlanScore

Third, I evaluate the enacted plan using a predictive model from the PlanScore.org website. PlanScore uses a statistical model of the relationship between districts' latent partisanship and election outcomes. This enables it to estimate district-level vote shares for a new map and the corresponding partisan gerrymandering metrics.[25] It then calculates various partisan bias metrics. In this case, PlanScore provides estimates of the efficiency gap and declination.[26]

PlanScore also indicates that the enacted Congressional plan has a substantial pro-Republican bias (Table 6). According to PlanScore, the enacted plan has a pro-Republican efficiency gap of 16%. The enacted plan favors Republicans in 99% of the scenarios estimated by PlanScore.[27] Moreover, it is more extreme than 96% of previous plans and more pro-Republican than 98% of previous plans.

Metric	Value	Favors Rep's in this % of Scenarios	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan				
Republican Seat Share	74%			
Efficiency Gap	-12%	96%	90%	97%
Declination	-.42	95%	87%	93%
Average		96%	89%	95%
Enacted Plan				
Republican Seat Share	79%			
Efficiency Gap	-16%	99%	97%	97%
Declination	-.58	99%	95%	98%
Average		99%	96%	98%

Table 6: PlanScore partisan bias metrics for enacted Congressional plan

5.4 Competitiveness of Districts

In their summary of the enacted plan, the Ohio state legislature asserted that "the plan contains six Republican-leaning districts, two Democratic-leaning districts, and seven competitive districts. The number of competitive districts in the plan significantly exceeds the number of competitive districts contained in Ohio's current plan."[28] In this section, I

25. See https://planscore.campaignlegal.org/models/data/2021C/ for more details.

26. The partisan symmetry and mean-median difference scores are only shown when the parties' statewide vote shares fall between 45% and 55% because outside this range the metrics' assumptions are less plausible (McGhee 2017, 9). In the PlanScore model, the Democrats' two-party vote share is just below 45%.

27. See https://planscore.campaignlegal.org/plan.html?20211127T135358.249351808Z

28. See https://www.legislature.ohio.gov/download?key=17868&format=pdf. It is important to note the analysis underlying this assertion only includes federal statewide elections, which is an odd set

analyze the accuracy of this statement.

I use a variety of approaches to estimate the number of competitive districts in both the 2012-20 congressional plan and the enacted plan (see Table 7). None of these approaches, however, indicate there are seven competitive districts in the enacted plan. Instead, they indicate there are approximately three competitive districts. Moreover, none of these approaches indicate that the number of competitive districts significantly exceeds the number of competitive districts contained in Ohio's 2012-20 plan. On average, my analysis indicates that the enacted plan has just one more competitive district than the 2012-2020 plan. As a result, I find that the state legislature's claims regarding the competitive districts on the enacted plan are inaccurate.

Data:	2020 House Results		Composite (2012-20)	PlanScore			**Mean**
Metric:	45-55	Historical Swing	45-55	45-55	20%+ Prob. of Each Party Win.	50%+ Prob. Flip in Dec.	
Plan	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2012-20 Plan	2	1	1	3	2	5	2
Enacted Plan	3	3	3	4	2	4	3

Table 7: Number of competitive districts using various data sources and metrics.

First, I use the actual 2020 House results to examine the number of competitive districts. In column 1 of Table 7, I begin by tallying the number of districts where each party's two-party vote share was between 45 and 55%. This approach indicates there are 2 competitive districts on the 2012-20 plan and 3 competitive districts on the enacted plan. As I discussed earlier, however, it is not clear that a sharp threshold at 55% is the best measure of competitiveness.

Based on the approach in Henderson, Hamel, and Goldzimer (2018, Appendix, p. 2), we can also define competitiveness based on whether a district is likely to switch parties at least once per decade based on the maximal swing in the two-party vote. In column 2 of Table 7, I use this approach to tally the number of districts that each party would win at least once over the course of the decade based on the historical range of statewide election results between 2012-2020. Specifically, I conduct a uniform swing to simulate what would happen if the 2020 congressional election were held in the best year for Democrats (2012).[29] I then examine the number of districts that would have been

of elections to focus on. First, this composite does not include the Republican wave year in 2014, but it does include the Democratic wave year in 2018. It also includes two elections from 2012, which implicitly heavily weights this election in the index.

29. It is worth noting, however, that 2012 appears to have been a high-water mark for Democrats in Ohio, and their electoral performance has not come close to this level in subsequent elections.

won at least once by each party. This approach indicates there was 1 competitive district on the 2012-20 plan and 3 competitive districts on the enacted plan.

Next, I use a composite of the 2012-2020 statewide election results to estimate the number of competitive districts. Once again, in column 3 of Table 7, I tally the number of districts where each party's two-party vote share was between 45 and 55%. This approach indicates there was 1 competitive district on the 2012-20 plan and 3 competitive districts on the enacted plan.

Lastly, I use PlanScore to estimate the potential competitiveness of individual districts on the enacted plan. In column 4 of Table 7, I show the number of districts where PlanScore estimates that each party's two-party vote share is expected to be between 45 and 55%. This approach indicates there were 3 competitive districts on the 2012-20 plan and 4 competitive districts on the enacted plan.

It is also possible to use PlanScore to evaluate whether a district is likely to switch parties at least once per decade (Henderson, Hamel, and Goldzimer 2018). PlanScore conducts 1,000 simulations of possible electoral scenarios based on the results of the 2012-2020 congressional and state legislative elections in every state. Using these simulations, PlanScore provides an estimate of the probability that each party will win each seat as well as whether they are likely to have at least a 50% chance of winning each seat once over the course of the decade. In column 5 of Table 7, I estimate the number of districts where each party has at least a 20% chance of winning according to PlanScore. This approach indicates there were 2 competitive districts on the 2012-20 plan and 2 competitive districts on the enacted plan. In column 6 of Table 7, I conduct a similar analysis where I tally the number of districts that each party would have at least a 50% chance of winning at least once over the course of the decade. This approach indicates there are 5 competitive districts on the 2012-20 plan and 4 competitive districts on the enacted plan.

Finally, column 7 of Table 7 averages across all of these approaches. It indicates there are about 2 competitive districts on the 2012-2020 plan and 3 competitive seats on the enacted plan. Thus, there is neither support for the notion that there are seven competitive districts nor that the the enacted plan yields significantly more competitive districts than the 2012-20 plan.

Moreover, it is important to note that the fact that there are about three potentially competitive districts on the enacted plan does not mean that each party has a 50-50 chance at winning these districts. In fact, Republicans are favored in each of these districts and heavily favored in several of them. We can see this using each of the predictive approaches I've used in this report that are summarized in Table 8. The table shows that none of the competitive districts (shown in grey) lean toward Democrats. Indeed, the Republican

	Projected Democratic Vote Share				Probability
District	House 2020	Composite (2012-2020)	PlanScore	Average Dem. Share	Dem. Wins (PlanScore)
1	0.48	0.46	0.48	0.47	36%
2	0.29	0.33	0.30	0.30	1%
3	0.70	0.66	0.70	0.69	99%
4	0.30	0.31	0.31	0.31	1%
5	0.35	0.38	0.35	0.36	1%
6	0.38	0.44	0.36	0.40	1%
7	0.37	0.40	0.38	0.39	1%
8	0.36	0.36	0.36	0.36	1%
9	0.46	0.49	0.45	0.47	16%
10	0.42	0.45	0.46	0.44	18%
11	0.79	0.77	0.76	0.77	99%
12	0.30	0.36	0.32	0.33	1%
13	0.47	0.48	0.48	0.47	31%
14	0.40	0.44	0.42	0.42	4%
15	0.43	0.43	0.44	0.44	13%

Table 8: Democratic Vote Share Projections for Each District on Enacted Plan using a Variety of Methods. Competitive districts in grey.

candidate is likely to win District 1 by 5%, District 9 by 7%, and District 13 by 5%.[30] So Republicans are likely to win all, or nearly all, of these districts in the average election (see right-most column in Table 8). This is especially true if Republicans also have an incumbency advantage in most of these districts (see Jacobson 2021, for more on the incumbency advantage in 2020). Overall, 13 of the 15 districts on the enacted plan lean toward Republicans.

6 Incumbency

Article XIX.01, Section 3(A) of Ohio's Constitution requires that "The general assembly shall not pass a plan that unduly favors or disfavors a political party or its incumbents" (emphasis added). In previous sections of this report, I have shown that the enacted plan unduly favors the Republican Party. In this section, I will examine whether it favors incumbents from the Republican Party. I find that it does.

In order to examine whether the new plan favors incumbents from the Republican Party, I first examine the percentage of the Democratic and Republican voters in each

30. Note that the margins here are based on the unrounded vote shares in each district. Also, according to PlanScore, Republicans have at least a 64% chance of winning each of these districts.

2020 Districts	2022 District	% Overlap	Dem. Vote Share Old District	Dem. Vote Share New District
1	1	0.81	0.46	0.48
2	2	0.68	0.39	0.29
3	3	0.71	0.71	0.70
4	4	0.53	0.30	0.30
5	9	0.56	0.32	0.46
6	6	0.61	0.26	0.38
7	7	0.41	0.30	0.37
8	8	0.80	0.31	0.36
9	9	0.44	0.63	0.46
10	10	0.97	0.42	0.42
11	11	0.79	0.80	0.79
12	4	0.41	0.43	0.30
13	6	0.54	0.54	0.38
14	14	0.73	0.40	0.40
15	15	0.43	0.37	0.43
16	13	0.48	0.37	0.47

Table 9: Evaluation of how incumbent in each of the old districts would perform on the enacted plan based on re-aggregating the 2020 House results to new districts. Districts won by Democrats in 2020 in blue.

of the 16 districts used in the 2020 congressional election that will be in each of the 15 districts on the enacted plan. This enables me to determine the new district that most overlaps with each of the old districts. I then compare the incumbent's vote share in each district of the old plan to their expected vote share in the new plan by re-aggregating the 2020 House elections to the new district that most overlaps with the old districts.

Table 9 shows the results. It shows that the enacted plan favors incumbents from the Republican Party. It puts the Democratic incumbents in districts 9 and 13 into largely new districts that will now have a majority of Republican voters. Democratic incumbent Tim Ryan in district 13 is retiring and running for Senate, so maybe we should put less weight on this district. But it is very clear that the plan is drawn to harm Representative Marcy Kaptur.

Representative Kaptur's old district 9 went along the Lake Erie coastline from Toledo to the Cleveland suburbs. In 2020, she comfortably won reelection with 63% of the two-party vote on the 2020 map. Her new district, however, goes from the Indiana border to a bit west of Lorain. It no longer includes any of the Democratic-leaning Cleveland suburbs. Overall, the new district 9 only includes 44% of the voters from Kaptur's old district 9. On the new map, she would have only won about 46% in the 2020 House election, and thus would likely lose in 2022.

7 Conclusion

Overall, there is a substantial Republican bias in the translation of votes to seats in the enacted congressional plan in Ohio. Based on a variety of metrics, the pro-Republican bias in Ohio's congressional districting plan is very large relative to other states over the past 50 years. Moreover, the new map does not contain significantly more competitive districts than the 2012-2020 plan. The plan unduly favors congressional candidates from the Republican Party.

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Supplementary Appendix

A Alternative Composite Indices

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Efficiency Gap	-13%	86%	94%
Declination	-.47	83%	89%
Mean-Median Diff	-3%	45%	73%
Symmetry	-19%	93%	94%
Average		77%	88%
Enacted Plan			
Efficiency Gap	-10%	75%	89%
Declination	-.38	78%	85%
Mean-Median Diff	-2%	24%	63%
Symmetry	-14%	84%	90%
Average		65%	82%

Table A1: Composite partisan bias metrics for Congressional plan based on federal statewide elections from 2012-2020

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Efficiency Gap	-10%	74%	89%
Declination	-.41	79%	86%
Mean-Median Diff	-3%	39%	71%
Symmetry	-17%	91%	93%
Average		77%	88%
Enacted Plan			
Efficiency Gap	-11%	79%	91%
Declination	-.44	81%	88%
Mean-Median Diff	-1%	19%	61%
Symmetry	-13%	82%	88%
Average		70%	85%

Table A2: Composite partisan bias metrics for Congressional plan based on all federal elections from 2016-2020

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Efficiency Gap	-16%	90%	96%
Declination	-.56	89%	93%
Mean-Median Diff	-3%	39%	71%
Symmetry Bias	-17%	91%	93%
Average		77%	88%
Enacted Plan			
Efficiency Gap	-18%	93%	97%
Declination	-.59	92%	95%
Mean-Median Diff	-2%	24%	63%
Symmetry Bias	-10%	69%	83%
Average		70%	85%

Table A3: Composite partisan bias metrics for Congressional plan based on all 2016-2020 statewide elections