IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, ET AL., **MERYL NEIMAN, ET AL.,** ***v.*** **SECRETARY OF STATE FRANK LAROSE, ET AL.**	**Case No. 2022-0303** **Case No. 2022-0298** ***Consolidated*** **Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)**

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E-Signature Summary

E-Signature 1: Freda Levenson (FJL)
April 25, 2022 17:52:49 -8:00 [D9E8F5FF23FF] [98.97.176.160]
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E-Signature Notary: Theresa M Sabo (TMS)
April 25, 2022 17:52:49 -8:00 [3D869F05F54E] [65.60.141.105]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

Affidavit of Freda J. Levenson

I, Freda J. Levenson, 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 as 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:

1. The Ohio Supreme Court entered an order in the above-captioned consolidated cases, *League of Women Voters of Ohio, et al. v. Secretary of State Frank LaRose, et al.*, No. 2022-0303, and *Meryl Neiman, et al., v. Secretary of State Frank LaRose, et al.*, No. 2022-0298, providing that the parties shall file any evidence they intend to present no later than Monday, April 25, 2022.
2. I am one of the counsel for Petitioners in the above-captioned case, No. 2022-0303.
3. Alongside this affidavit, Petitioners submit an Appendix of Exhibits. The Index included below provides a description of each document and states where it appears in the Appendix.
4. **The Exhibits Appendix** includes a true and correct copy of the Report of Dr. Kosuke Imai, as filed in *League of Women Voters of Ohio, et al., v. Ohio Redistricting Commission*, No. 2021-1449 on December 10, 2021.
5. **The Exhibits Appendix** includes a true and correct copy of the Report of Dr. Kosuke Imai, as filed in *League of Women Voters of Ohio, et al., v. Ohio Redistricting Commission*, No. 2021-1449 on March 7, 2022.
6. **The Exhibits Appendix** includes a true and correct copy of the Report of Dr. Jonathan Rodden, as filed in *Regina C. Adams, et al., v. Governor Mike DeWine*, *et al.*, No. 2021-1428 on March 4, 2022.

7. **The Exhibits Appendix** includes a true and correct copy of the Report of Dr. Jonathan Rodden, as filed in *Regina C. Adams, et al., v. Governor Mike DeWine*, *et al.*, No. 2021-1428 on November 22, 2021.

8. **The Exhibits Appendix** includes a true and correct copy of the Report of Dr. Christopher Warshaw, as filed in *League of Women Voters of Ohio, et al., v. Ohio Redistricting Commission*, *et al.*, No. 2021-1449 on March 7, 2022.

9. **The Exhibits Appendix** includes a true and correct copy of the Report of Dr. Christopher Warshaw, as filed in *League of Women Voters of Ohio, et al., v. Ohio Redistricting Commission*, *et al.*, No. 2021-1449 on November 30, 2021.

Freda Levenson
D9E8F5FF23FF
Signed on 2022/04/25 17:52:49 -8:00

Freda J. Levenson

Signed at Columbus, Franklin, Ohio.
City County State

Sworn to and subscribed before me this 04/25/2022 day of April, 2022

3D869F05F54E
Signed on 2022/04/25 17:52:49 -8:00

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 2022/04/25 17:52:49 PST 3D869F05F54E

Notarial act performed by audio-visual communication

EXHIBITS APPENDIX - EXPERT REPORTS
Volume 1 of 1

Index of Documents

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

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Imai Affidavit.pdf

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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

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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.

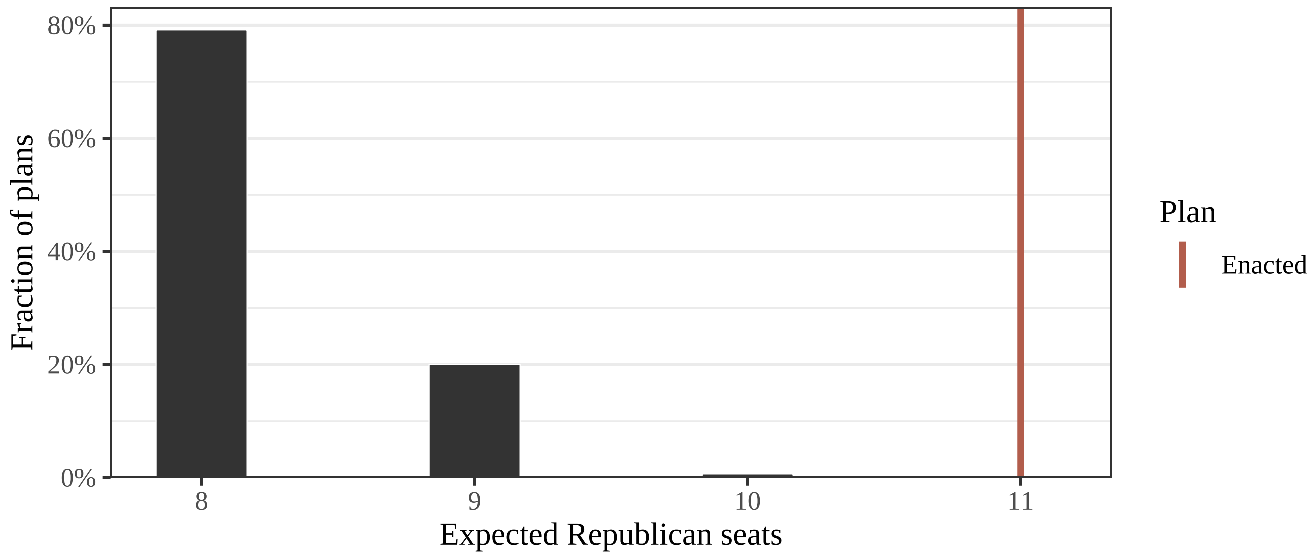

Figure 1: Expected number of Republican seats calculated for the 5,000 simulated plans computed by averaging across the six statewide federal elections from 2012 to 2020. Overlaid is the value for the enacted plan (red).

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.

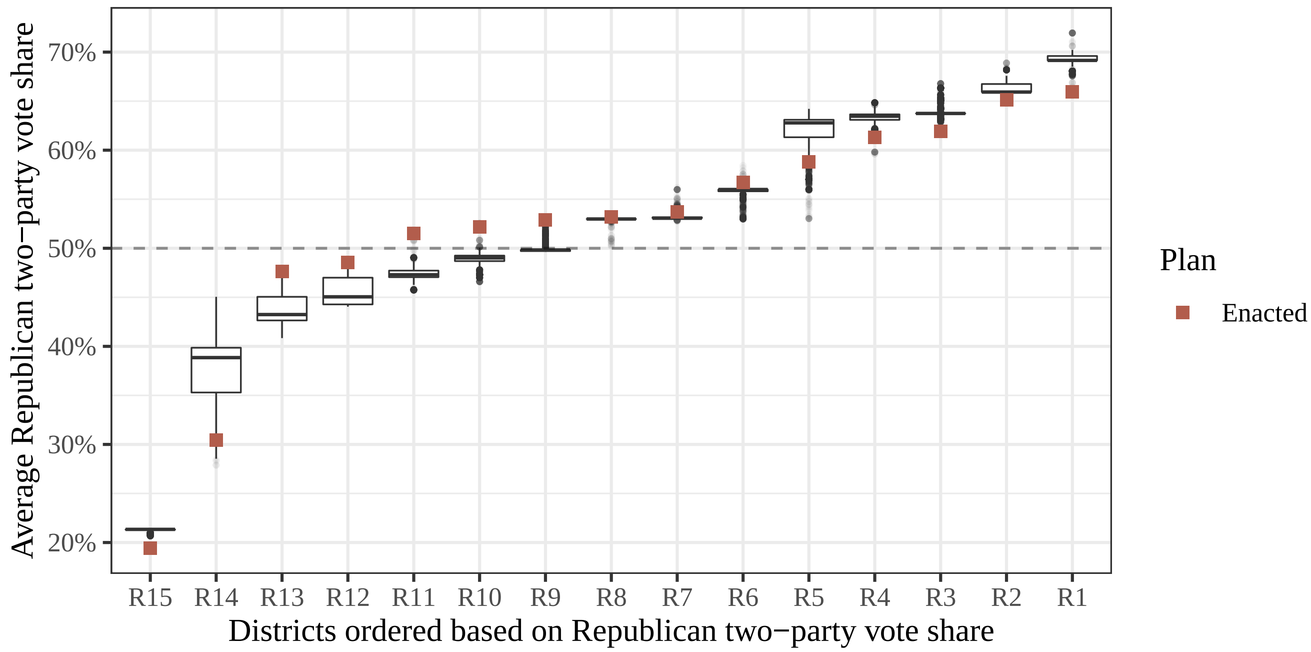

Figure 2: Expected Republican vote share for districts using the six statewide federal elections from 2012 to 2020. For any given plan, the districts are ordered based on their expected Republican vote share. Boxplots represent the distribution of the expected Republican vote share across the simulated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

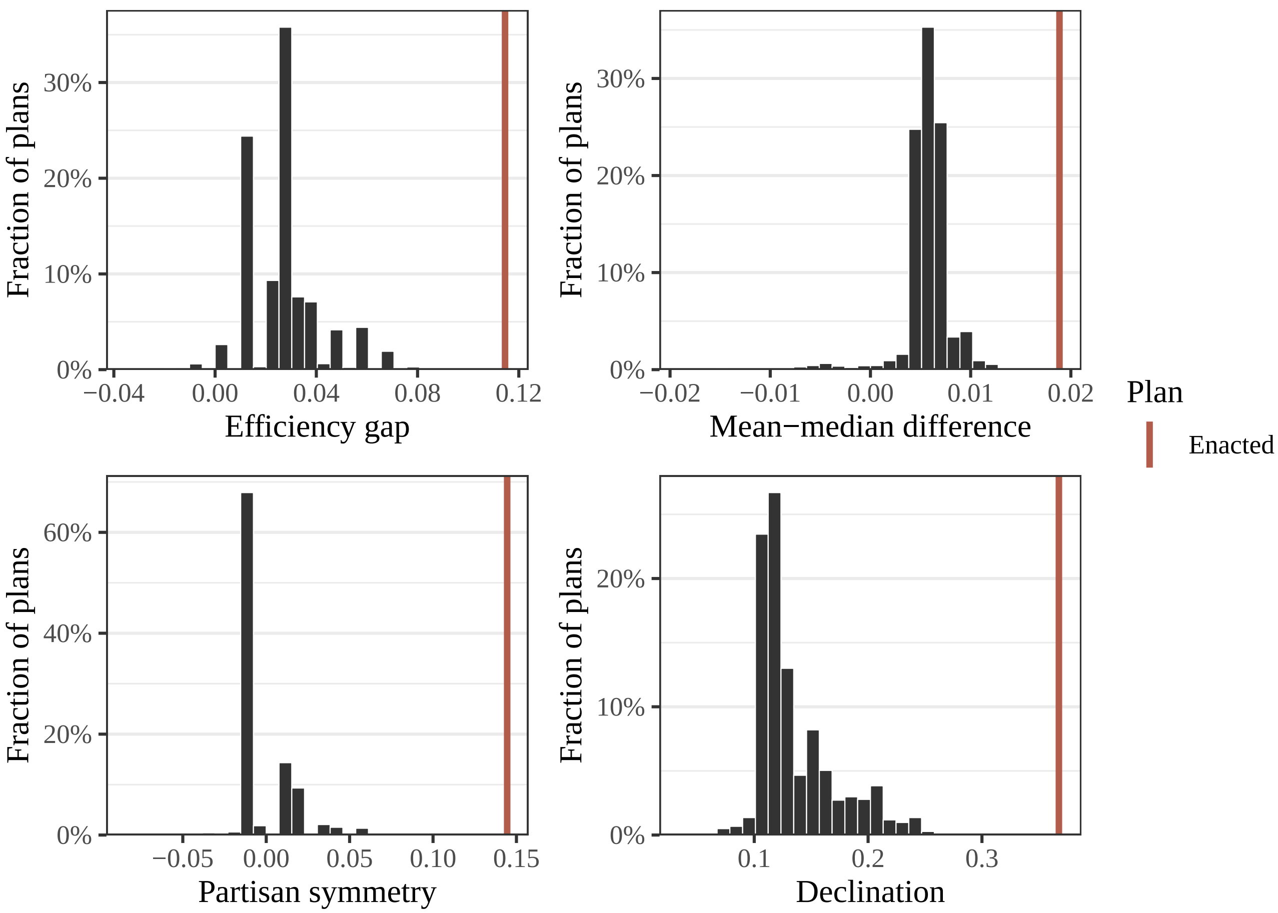

Figure 3: Four partisan bias measures calculated for the 5,000 simulated Congressional redistricting plans computed by averaging across the six federal elections from 2012 to 2020. Overlaid is the value for the enacted plan (red). For each measure, larger values (towards the right) correspond to more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

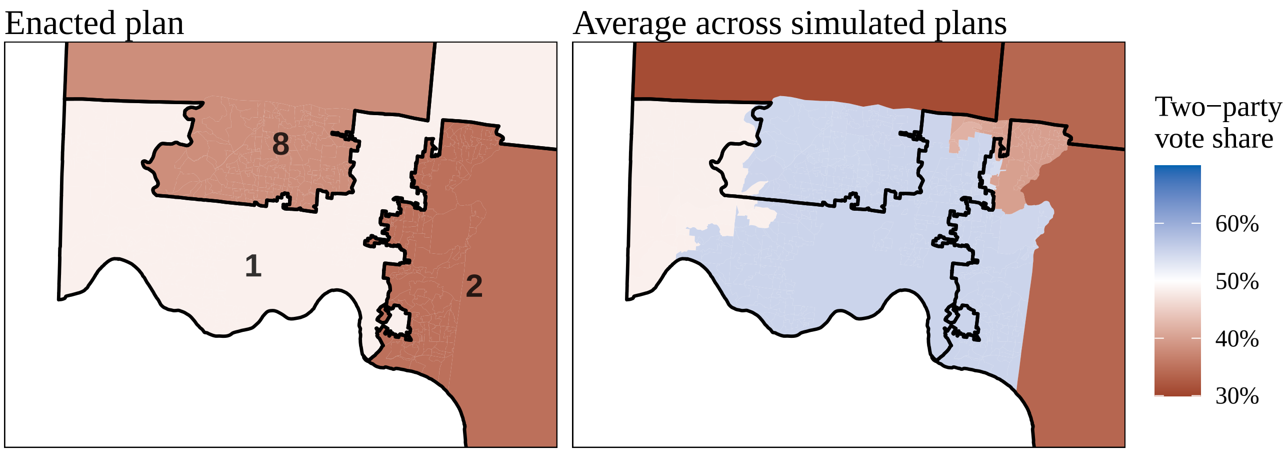

Figure 4: Congressional districts in Hamilton County. The left map presents the expected two-party vote shares of districts under the enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated 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

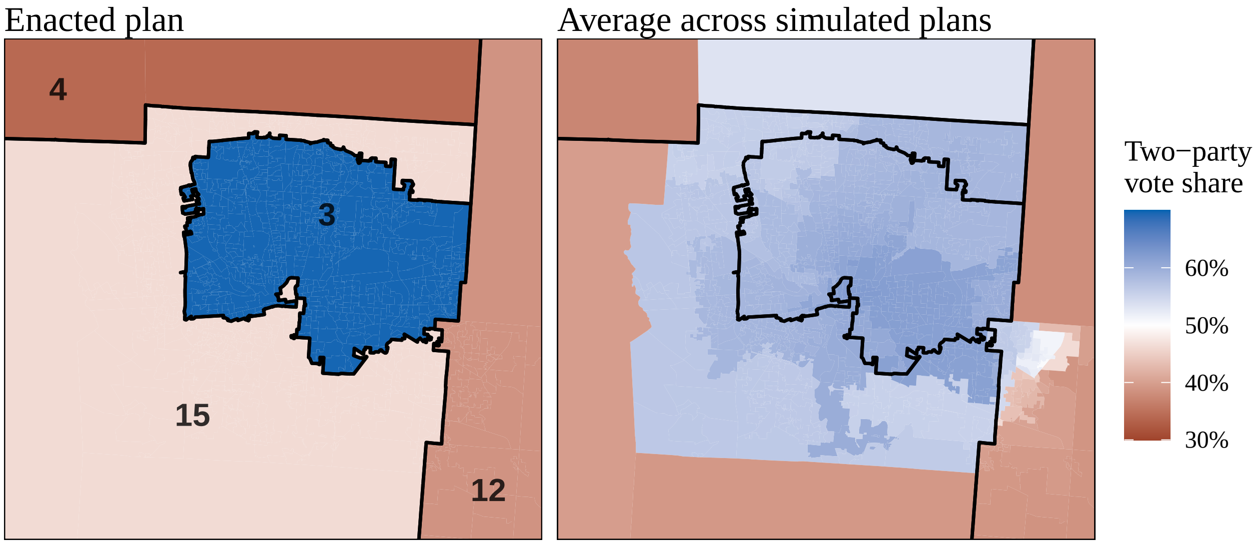

Figure 5: Congressional districts in Franklin County. The left map presents the expected two-party vote shares of districts under the enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated 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

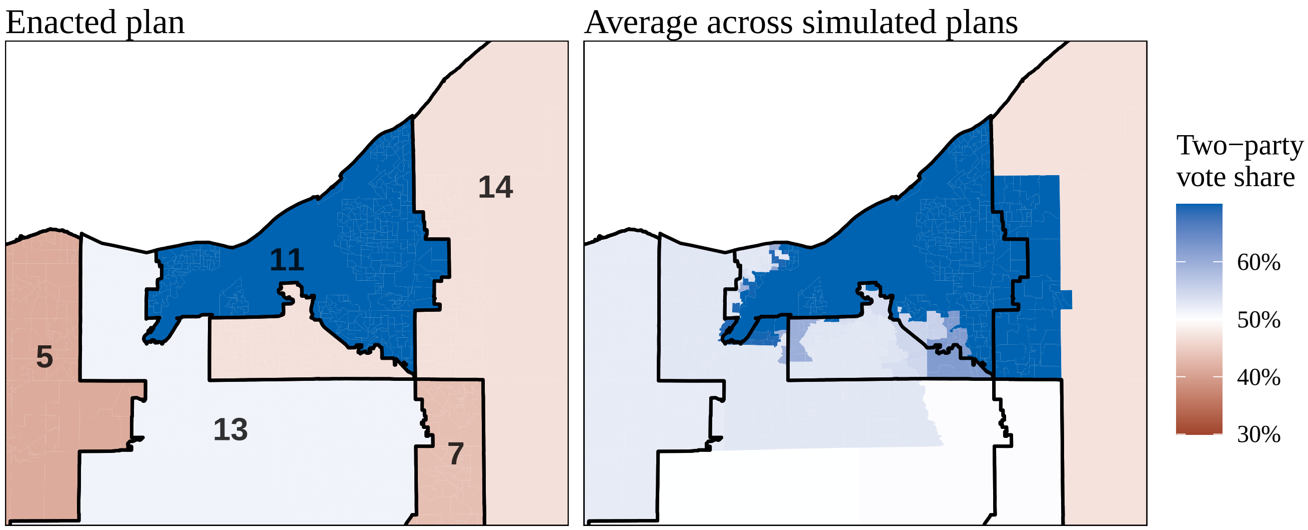

Figure 6: Congressional districts in Cuyahoga County. The left map presents the expected two-party vote shares of districts under the enacted plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated 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

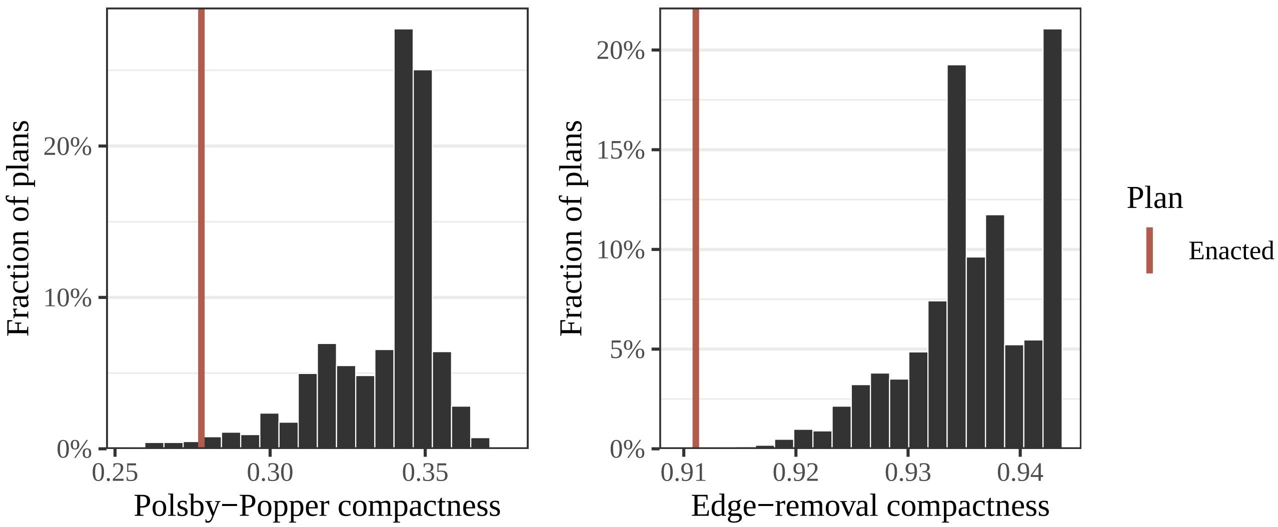

Figure 7: Polsby–Popper and edge–removal compactness scores for the simulated redistricting plans. Overlaid are scores for the enacted plan (red). For both measures, larger values indicate more compact districts.

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)

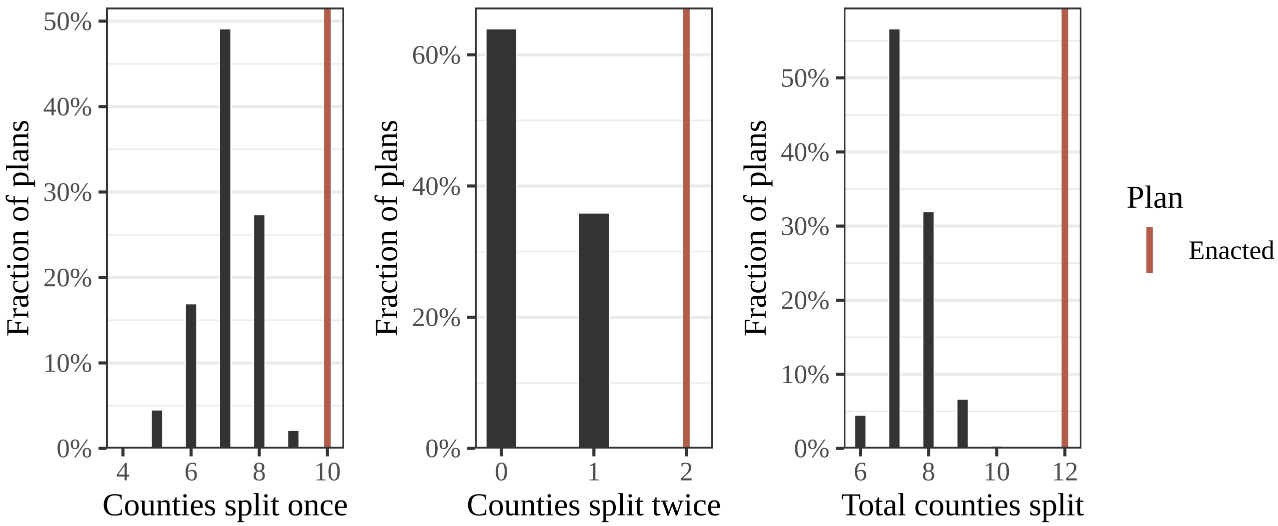

Figure 8: The number of county splits for the simulated redistricting plans. Overlaid are the scores for the enacted plan (red). The left plot shows the number of counties that are split once under each plan, whereas the middle plot presents the number of counties that are split twice under each plan. 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.

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EXHIBIT A

Curriculum Vitae

Kosuke Imai

Curriculum Vitae

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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.

23. Imai, Kosuke and In Song Kim. (2019) "When Should We Use Linear Fixed Effects Regression Models for Causal Inference with Longitudinal Data?." *American Journal of Political Science*, Vol. 63, No. 2 (April), pp. 467–490.

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.

26. Hirose, Kentaro, Kosuke Imai, and Jason Lyall. (2017). "Can Civilian Attitudes Predict Insurgent Violence?: Ideology and Insurgent Tactical Choice in Civil War" *Journal of Peace Research*, Vol. 51, No. 1 (January), pp. 47–63.

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.

31. Imai, Kosuke and Marc Ratkovic. (2015). "Robust Estimation of Inverse Probability Weights for Marginal Structural Models." *Journal of the American Statistical Association*, Vol. 110, No. 511 (September), pp. 1013–1023. (lead article)

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).

8. Imai, Kosuke, Dustin Tingley, and Teppei Yamamoto. (2013). "Reply to Discussions of "Experimental Designs for Identifying Causal Mechanisms"." *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 173, No. 1 (January), pp. 46–49.

9. Imai, Kosuke. (2012). "Comments: Improving Weighting Methods for Causal Mediation Analysis." *Journal of Research on Educational Effectiveness*, Vol. 5, No. 3, pp. 293–295.

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.

11. Imai, Kosuke, Booil Jo, and Elizabeth A. Stuart. (2011). "Commentary: Using Potential Outcomes to Understand Causal Mediation Analysis." *Multivariate Behavioral Research*, Vol. 46, No. 5, pp. 842–854.

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). Postdoctoral 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). Postdoctoral 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.

IN THE SUPREME COURT OF OHIO

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

PETITIONERS' EVIDENCE TO MOTION TO ENFORCE COURT'S ORDER
(Affidavit of Dr. Kosuke Imai)

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Imai Affadavit.pdf

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E-Signature Summary

E-Signature 1: Kosuke Imai (KI)
March 06, 2022 17:05:54 -8:00 [7EDA8D976B76] [108.26.227.252]
imai@harvard.edu (Principal) (Personally Known)

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March 06, 2022 17:05:54 -8:00 [193A8906B96C] [96.27.183.41]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

EXPERT_0061

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, *et al.*, **Petitioners,** **v.** **OHIO REDISTRICTING COMMISSION, *et al.*,** **Respondents.**	**Case No. 2021-1449** **Original Action Filed Pursuant to Ohio Const., Art. XI**

AFFIDAVIT OF KOSUKE IMAI

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 Petitioners 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 B, 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 03/06/2022, 2022.

Kosuke Imai
Signed on 2022/03/06 17:05:54 -8:00

Kosuke Imai

Sworn and subscribed before me this ____ day of 03/06/2022, 2022

Signed on 2022/03/06 17:05:54 -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 2022/03/06 18:05:54 PST 193A8906B96C

Notarial act performed by audio-visual communication

EXPERT_0062

EXHIBIT B

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.
March 6, 2022

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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 and computational algorithms for and their applications to social science research. I am also affiliated with Harvard's Institute for Quantitative Social Science. My qualifications and compensation are described in my initial report that was submitted to this court.

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 recently revised congressional districting plan (which I will refer to as the "revised 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 revised 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 the 5,000 alternative plans that were generated as the basis of simulation analysis in my initial report for this case.

II. SUMMARY OF OPINIONS

3. My analysis yields the following findings:

- The revised plan exhibits a significant partisan bias in favor of the Republican Party. Under the revised plan, the vote share margins for three nominally Democratic-leaning districts are unusually narrow when compared to my 5,000 simulated plans. In contrast, Republican-leaning districts are much safer under the revised plan than the corresponding districts in the simulated plans. These differences are substantial in magnitude and statistically significant.

- This partisan bias of the revised plan originates from the Congressional districts in Hamilton and Franklin Counties. In Hamilton County, the revised plan cracks Democratic voters into Districts 1 and 8, reducing the Democratic advantage of District 1. In Franklin County, the revised plan packs a disproportionately large number of Democratic voters into District 3, increasing the Republican advantage of the surrounding districts.

- The revised plan's decision to favor the Republican party in Hamilton and Franklin Counties led to highly non-compact districts. District 1, which combines a part of Cincinnati and its environs with Warren County, is much less compact than the corresponding county under the simulated plans. Similarly, District 15, which combines a part of Franklin County with five other counties in the western part of the state, splits a total of five counties and is much less compact than the corresponding districts under the simulated plans.
- I submitted an example plan to the Ohio Redistricting Commission on February 22, 2022 that is compliant with Article XIX of the Ohio Constitution. This example plan is less biased, has fewer county splits, and is more compact than the revised plan.

III. METHODOLOGY

4. In my initial expert report for this case, I conducted simulation analyses to evaluate the enacted plan (SB 258; hereafter "enacted plan"). As explained in that report, the redistricting simulation analysis has the ability to directly account for political geography and redistricting rules specific to the state. By comparing a proposed plan with simulated plans that are generated using a set of redistricting criteria, it is possible to assess the partisan bias of the plan relative to the set of alternative plans one could have drawn by following those specified criteria.

5. I evaluate the revised plan's compliance with Article XIX, Section 1(C)(3)(a) by comparing it with the same set of 5,000 simulated plans as those used in my initial report to evaluate the enacted plan. Recall that these simulated plans are equally or more compliant with other relevant requirements of Article XIX than the enacted plan (see the initial report for details). In Appendices A and B, I show that my simulated plans are also more compact and have fewer county splits than the revised plan. I present the evaluation of the revised plan based on a total of nine statewide elections from 2016 to 2020, which were used by the Commission.

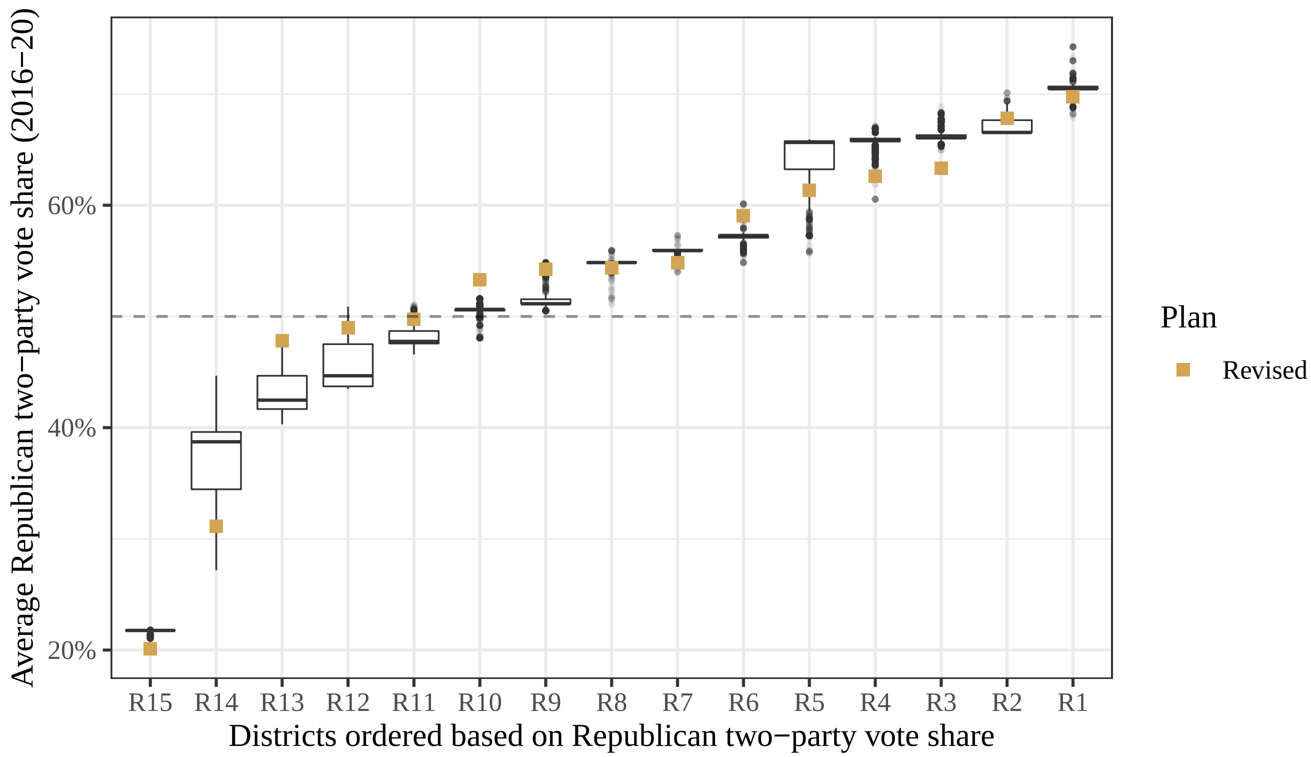

Figure 1: Expected Republican vote share for districts using the statewide elections from 2016 to 2020. For any given plan, the districts are ordered based on their expected Republican vote share. Boxplots represent the distribution of the expected Republican vote share across the simulated plans, whereas the orange square correponds to the expected Republican vote share under the revised plan.

IV. OUTLIER ANALYSIS

6. I evaluate the partisan bias of the revised plan by comparing its district-level vote shares against those under my 5,000 simulated plans. In Figure 1, for any given plan (revised or 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 revised or enacted plan). If the expected Republican vote share of each ordered district under the revised 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 most common definition, which was also used in my initial report.[1]

7. The figure shows clear evidence that the revised plan favors the Republican party. For all of my 5,000 simulated plans, districts R9 and R10 (the 9th and 10th most Republican-leaning districts, respectively) slightly lean toward the Republican party with narrow margins. The expected median Republican vote shares for these districts are equal to 51.1% and 50.6%, respectively. In other words, they are toss-up districts under the simulated plans. Yet under the revised plan, both of these districts are safely Republican with the expected Republican vote shares equal to 54.2% and 53.3%. According to the aforementioned definition, these two points associated with the revised plan are clear statistical outliers, with the vote shares of district R9 and R10 under the revised plan being 3.4 and 5.5 standard deviations away from the simulation median, respectively.

8. Furthermore, under the revised plan, districts R11, R12, and R13 lean much less strongly towards the Democratic party than under a vast majority of the simulated plans. For example, the expected median Republican vote share for R11 under the simulated plans is 47.8%. In other words, this district strongly leans towards the Democratic party under the simulated plans. Under the revised plan, however, it becomes a toss-up district. Its expected Republican vote share is 49.7%, which is 1.9 percentage points (or 1.9 standard deviations) higher than the simulation median. Indeed, 86.6% of my 5,000 simulated plans have a lower expected Republican vote share for R11 than the revised plan.

9. Similarly, the expected median Republican vote shares for R12 and R13 are 44.7% and 42.5%, respectively, under my simulated plans, implying that these are safe Democratic dis-

1. According to this definition (Tukey, John W. 1977. *Exploratory Data Analysis*. Pearson), 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 revised plan is regarded as an outlier if it is at least 2.70 standard deviations away from the average simulated plan.

tricts. Under the revised plan, however, the expected vote shares for R12 and R13 are 49.0% and 47.8%, respectively, which are 4.3 and 5.3 percentage points (or 2.8 and 3.5 standard deviations) higher than the corresponding simulation median. That is, the Democratic advantages of these districts are substantially reduced under the revised plan. Indeed, for these two districts, less than 0.25% of my 5,000 simulated plans yield as high levels of expected Republican vote share as the revised plan.

10. Lastly, the revised plan packs Democratic voters in districts R14 and R15, which are the 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 revised plan than under the simulated plans. In contrast, the revised plan avoids packing Republican voters in the five safest Republican districts (districts R1 to R5). Indeed, R3, R4, and R5 have much lower levels of expected Republican vote shares under the revised plan than under the simulated plans. The expected Republican vote shares for districts R3 and R4 are also statistical outliers, which are 5.0 and 5.1 standard deviations away from the simulation median, respectively.

11. In sum, my outlier analysis shows that the revised plan clearly favors the Republican party in comparison with my 5,000 simulated plans. The revised plan does so by turning Democratic-leaning districts into toss-up districts while making slightly Republican-leaning districts into safe Republican districts.

V. LOCAL ANALYSIS

12. Next, as done in my initial report, I conduct a detailed analysis of the Congressional districts in Hamilton and Franklin Counties. I show that the partisan bias of the revised plan identified in my outlier analysis above originates in these districts. In Hamilton County, the revised plan cracks Democratic voters into Districts 1 and 8, substantially reducing the Democratic advantage of District 1. In Franklin County, the revised plan packs Democratic voters into District 3, increasing the Republican advantage of the surrounding districts.

13. 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 revised

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 revised plan assigns a precinct to a district whose political leaning is different from what would be expected under the simulated plans.

A. Hamilton County

14. I begin by illustrating the above calculation through an example. Precinct 061031BEZ of Cincinnati lies within District 1 of the revised map, which has an expected Republican two-party vote share of 49.00%. The same precinct, however, 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 44.42%, which is 5.48 percentage points lower than under the revised 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 revised plan than under the average simulation plan.

15. The left map of Figure 2 presents the expected vote shares of districts under the revised 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 revised plan, Democratic areas are cracked to yield two Republican-leaning districts and one highly competitive district, despite a significant concentration of Democratic voters in and around Cincinnati. As the right figure indicates, a large part of the area north of the city of Cincinnati, which is part of District 8 under the revised plan, would normally be expected to belong to a safe Democratic district. Because the revised plan lumps it with District 8, this area instead belongs to safely Republican districts.

16. Similarly, voters in Cincinnati would normally be expected to belong to a strongly Democratic-leaning district under the simulated plans, as indicated by its darker blue color in the right map. The unusual pairing of Hamilton and Warren counties in the revised plan's District 1, however, makes these voters part of a much less Democratic-leaning district.

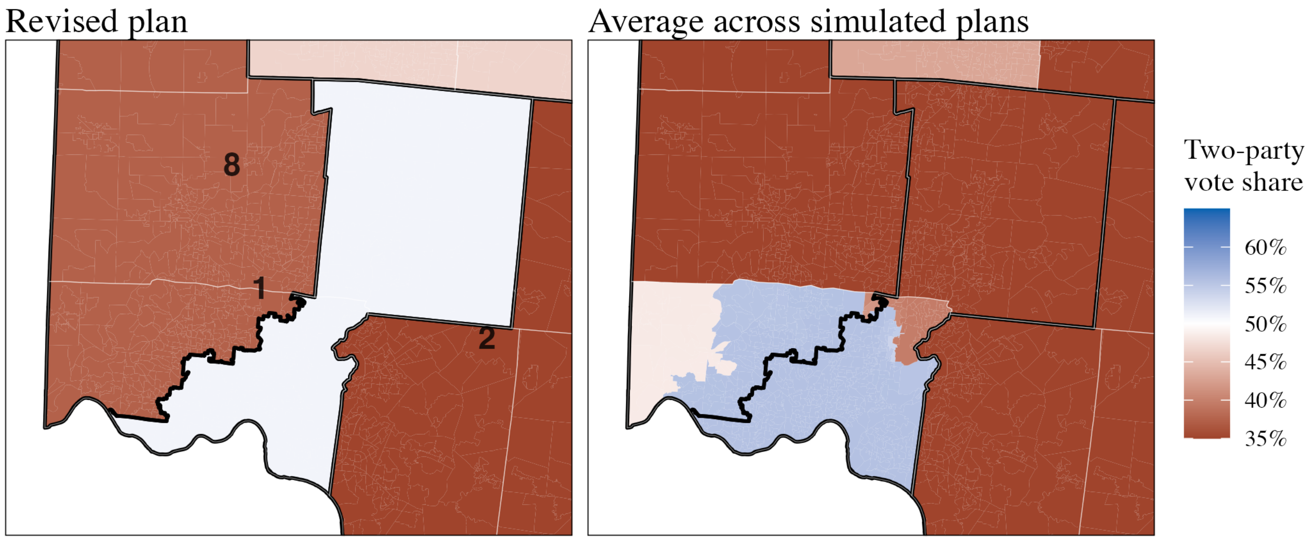

Figure 2: Congressional districts in Hamilton County. The left map presents the expected two-party vote shares of districts under the revised plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. The revised plan's district boundaries are shown with thick black lines. While under the simulated plans, Cincinnati and its environs are expected to belong to a safe Democratic-leaning district, the revised plan cracks Democratic voters, resulting in a toss-up district.

17. As a result of these manipulations and additional splits of Hamilton County, the revised plan has no safe Democratic seats under the average statewide contest, whereas the simulated plans are expected to yield a relatively safe Democratic seat. In sum, in Hamilton County, the revised plan turns one safe Democratic district into a toss-up district by cracking Democratic voters.

B. Franklin County

18. Analogous to the above analysis of Hamilton county, Figure 3 compares the revised plan with the average across the simulated plans in Franklin County. In this county, the revised 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 District 15, which is a safe Republican district, under the revised plan. In contrast, under the simulated plans, the entire area of Franklin County is expected to belong to a Democratic-leaning district, as is

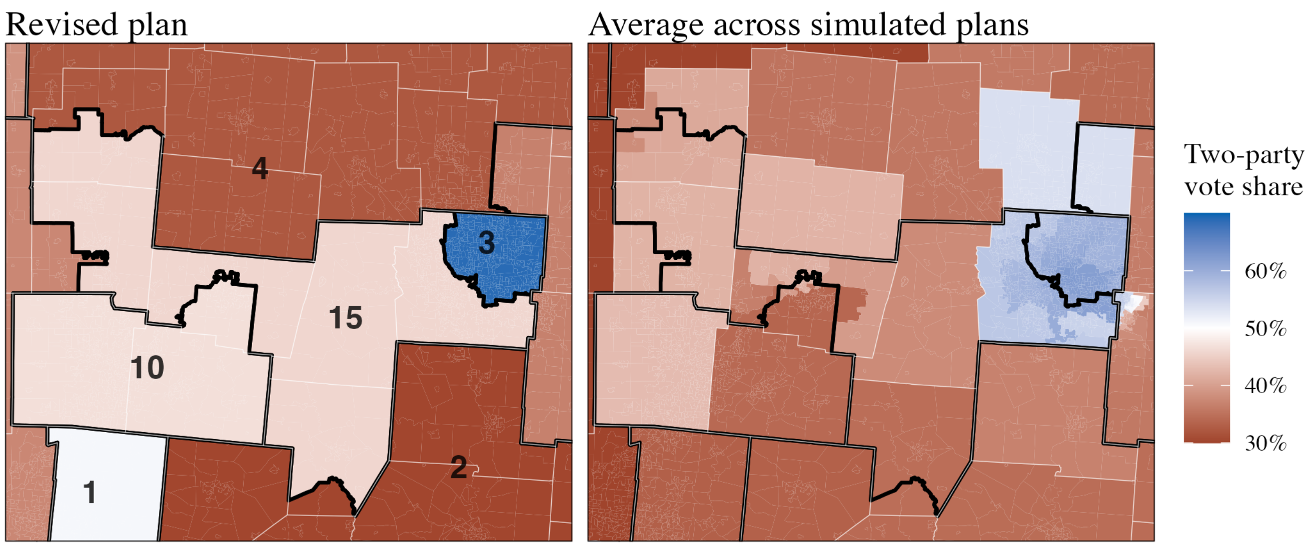

Figure 3: Congressional districts in Franklin County. The left map presents the expected two-party vote shares of districts under the revised plan, while the right map shows, for each precinct, the average expected two-party vote share of districts to which the precinct is assigned across the simulated plans. The revised plan's 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 revised plan packs Democratic voters, leaving much of the city of Columbus in a Republican district stretching most of the way to Cincinnati.

Delaware County and part of Fairfield County.

19. In other words, the revised plan packs Democratic voters into District 3 and submerges the Democratic voters in the rest of Franklin County into District 15 that stretches out to the west. By doing so, the revised plan creates a safe Republican district and deprives Democratic voters in the rest of the county of a reasonable opportunity to elect a Democratic candidate.

VI. COMPACTNESS ANALYSIS

20. The signs of partisan biases in Hamilton and Franklin Counties under the revised plan manifest as highly non-compact districts in these counties. I analyze the compactness of two relevant districts, Districts 1 and 15 of the revised plan, by comparing them with the average compactness under my simulated plans. My analysis shows that these two districts are highly non-compact in comparison to the corresponding districts in my simulated plans.

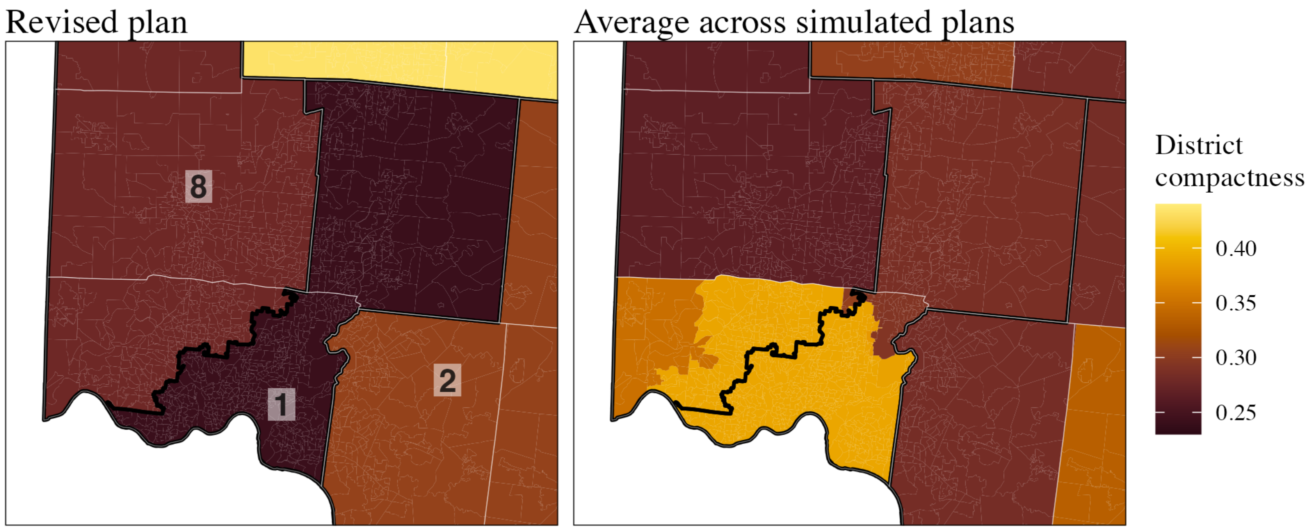

Figure 4: Compactness of District 1 under the Revised Plan. The left map presents the Polsby-Popper compactness score of each district under the revised plan, while the right map shows, for each precinct, the average compactness of districts to which the precinct is assigned across the simulated plans. The revised plan's district boundaries are shown with thick black lines. District 1 is highly non-compact as indicated by a dark color while under the simulated plans the precincts of District 1 are expected to belong to much more compact districts as indicated by a much lighter color.

A. District 1 of the Revised Plan

21. The left map of Figure 4 shows the compactness of District 1 under the revised plan. This district combines part of Cincinnati and its environs with Warren County, resulting in a highly non-compact shape with the Polsby-Popper compactness score of 0.241. In contrast, as shown in the right map of the figure, the simulated plans on average assign the precincts of District 1 to much more compact districts. In particular, because a majority of my simulated plans keep Cincinnati and its environs in the same district, these areas are expected to belong to a more compact district (indicated by a lighter color). In fact, the average district compactness score for these precincts under the simulated plans is 0.341, which is 42% higher than the compactness score of District 1 under the revised plan.

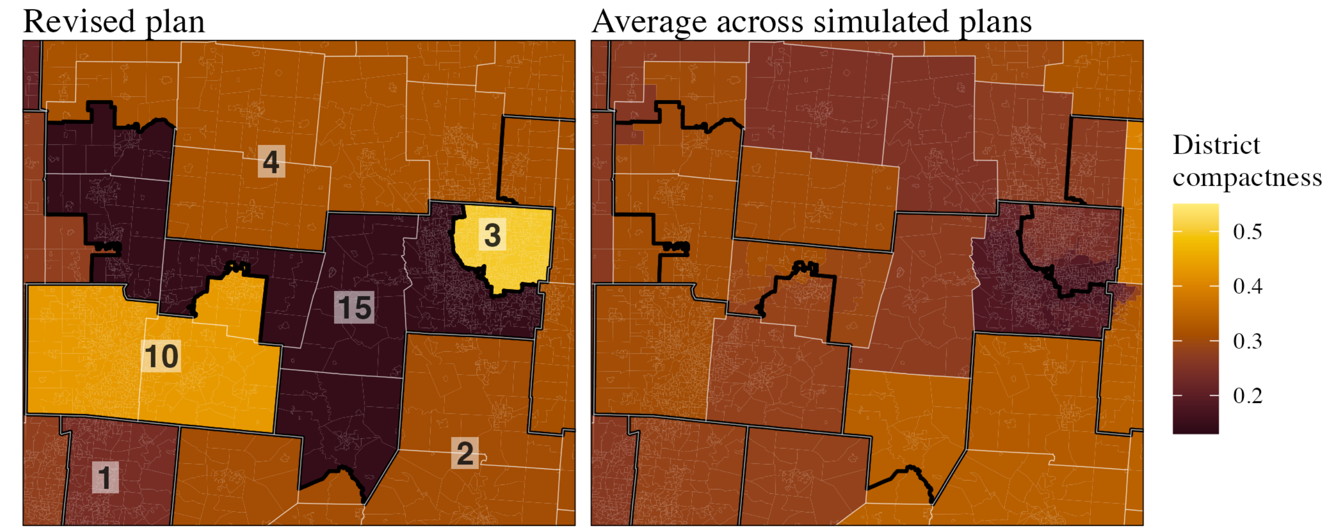

Figure 5: Compactness of District 15 under the Revised Plan. The left map presents the Polsby-Popper compactness score of each district under the revised plan, while the right map shows, for each precinct, the average compactness of districts to which the precinct is assigned across the simulated plans. The revised plan's district boundaries are shown with thick black lines. District 15 is highly non-compact as indicated by a dark color while under the simulated plans the precincts of District 15 are expected to belong to much more compact districts as indicated by a much lighter color.

B. District 15 of the Revised Plan

22. The left map of Figure 5 shows the compactness of District 15 under the revised plan. This district combines part of Columbus and its environs with Madison County and extends into five other counties in the west. As a result, the district splits a total of five counties and has a highly non-compact shape with the Polsby-Popper compactness score of 0.144, the lowest of all fifteen districts under the revised plan (though District 3 that packs Democratic voters of Columbus is highly compact). In contrast, as shown in the right map of the figure, the simulated plans on average assign the precincts of District 15 to much more compact districts (indicated by a lighter color). In fact, the average district compactness score for these precincts under the simulated plans is 0.224, which is 56% higher than the compactness score of District 15 under the revised plan.

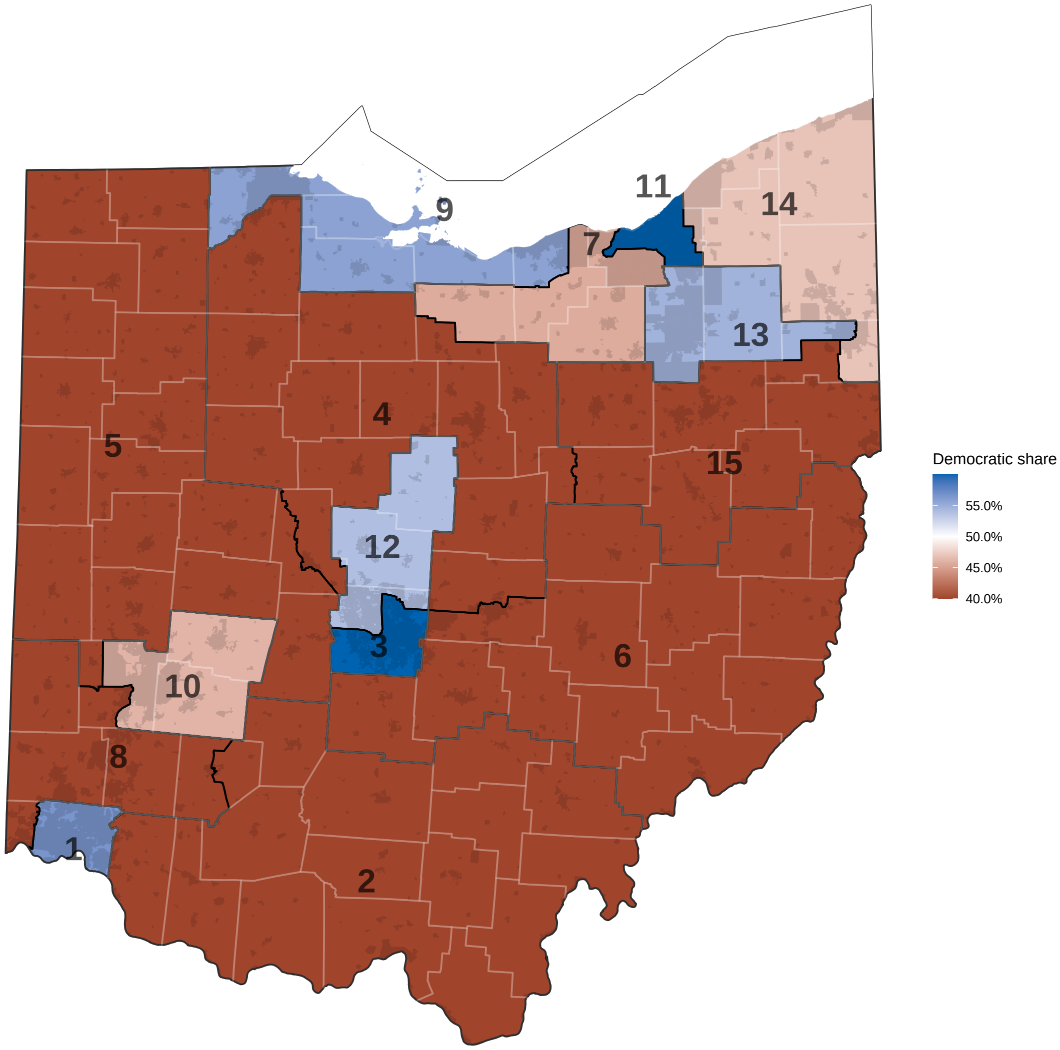

Figure 6: Example Congressional Plan Submitted to the Ohio Redistricting Commission on February 22, 2022.

VII. EXAMPLE PLAN

23. On February 22, 2022, I submitted an example plan (hereafter "example plan") that is more compliant with Article XIX of the Ohio constitution than the enacted plan. This example plan, shown in Figure 6, demonstrates that it is possible to generate a redistricting plan, which is free of the partisan bias and compactness problems while complying with the other redistricting requirements of the Ohio Constitution.

24. One important difference between the example plan and the revised plan is how Hamilton County is treated. Under the example plan, District 1 is wholly contained in Hamilton County without spilling into Warren County as done in the revised plan. As a result, District 1 does not cross a county line and is much more compact under the example plan (Polsby-Popper compactness score of 0.474) than under the revised plan (compactness score of 0.241). Unlike the revised plan, which cracks Democratic voters in Cincinnati and its northern environs into two districts (Districts 1 and 8), the example plan keeps these areas together in a single compact district (District 1). This makes District 1 a safer Democratic district under the example plan (Democratic vote share of 56.3%) than under the revised plan (Democratic vote share of 51.0%).

25. Another key difference lies in Franklin County. Under the example plan, this county is split into two districts. District 3 contains the southern part of Franklin County while the northern part of the county is included in District 12. This way of splitting Franklin County is consistent with a majority of my simulated plans and avoids creating a highly non-compact district. The revised plan's decision to spill into Madison County rather than Delaware County led to the creation of District 15, which splits five counties and has an extremely low compactness score of 0.144. In contrast, District 12 of the example plan is much more compact with a compactness score of 0.250. The partisan implication of this difference is clear. Under the example plan, both Districts 3 and 12 are Democratic-leaning with Democratic vote shares of 65.7% and 53.7%, respectively, whereas the revised plan ends up with one packed Democratic district (District 3 with the Democratic vote share of 68.9%) and one safe Republican district (District 15 with the Democratic vote share of 45.8%).

26. Beyond these two key differences, the example plan is much more compact than the revised plan. Indeed, the example plan is even more compact than the simulated plans (see Appendix A). The example plan also has fewer county splits than the revised plan (see Appendix B).

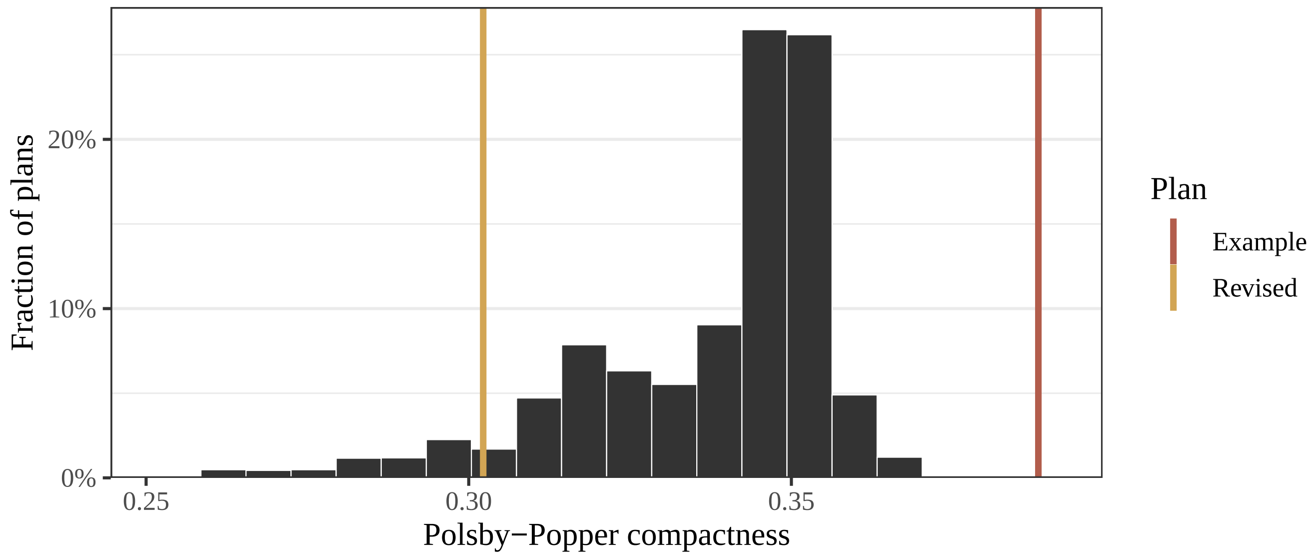

Figure 7: Polsby–Popper compactness scores for the simulated redistricting plans. Overlaid are scores for the revised plan (orange) and example plan (red). Larger values indicate more compact districts.

VIII. APPENDIX

A. Compactness of the Revised, Simulated and Example Plans

1. In this appendix, I show that the simulated plans are more compliant with Section 2(B)(2), which requires districts to be compact, than the revised plan. I also show that the example plan is more compact than either the revised plan or simulated plans. I use the Polsby–Popper score, a commonly-used quantitative measures of district compactness. Figure 7 shows that a vast majority (roughly 93%) of the simulated plans are more compact than the revised plan according to the Polsby–Popper score. Moreover, the example plan is more compact than any of the simulated plans. The result clearly implies that it is possible to be compliant with Section 1(C)(3)(a) without sacrificing compliance with Section 2(B)(2).

B. County Splits of the Revised, Simulated and Example Plans

2. Similar to compactness, it is possible to be compliant with Section 1(C)(3)(a) without splitting counties more than the revised 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 revised plan. The bulk of the simulated plans, as well as the revised plan, do not split any counties twice. As a

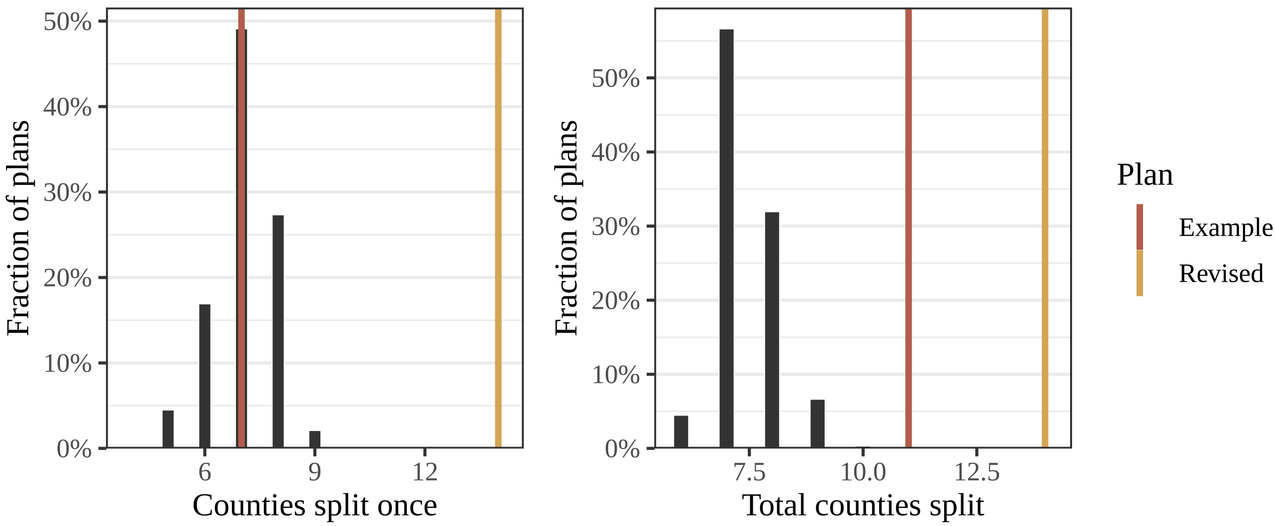

Figure 8: The number of county splits for the simulated redistricting plans. Overlaid are the scores for the revised plan (orange) and example plan (red). The left plot shows the number of counties that are split once under each plan, whereas the right plot shows the number of counties that are split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

result, the total number of counties split under the revised plan is much greater than that under any of the simulated plans, and is also greater than the total number of counties split under my example plan (see the right plot of the figure).

IN THE SUPREME COURT OF OHIO

Regina C. Adams, *et al.*, ***Petitioners,*** ***v.*** **Governor Mike DeWine, *et al.*,** ***Respondents.***	**Case No. 2021-1428** **Original Action Filed Pursuant to Ohio Const., Art. XIX, Sec. 3(A)**

EVIDENCE TO MOTION TO ENFORCE COURT'S ORDER – VOLUME 3
(Expert Affidavit of Dr. Jonathan Rodden & Exhibits)

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IN THE SUPREME COURT OF OHIO

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

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. In a previous affidavit filed in this case, I examined whether 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, conformed 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 presented evidence that the plan (the "Overturned Plan," attached as Exhibit A) unduly favored the Republican Party and its incumbents, elevating partisan advantage over traditional redistricting criteria like compactness and the preservation of communities.

2. I have now been asked to conduct a similar exercise with a new plan, passed by the Ohio Redistricting Commission on March 2, 2022 (the "New Plan," attached as Exhibit B). After doing so, I discovered that the key conclusions of my initial report still apply. The New Plan favors the Republican Party and its incumbents in rather obvious and consequential ways and disfavors the Democratic Party and its incumbents.

3. A comparison of the New Plan with the Overturned Plan reveals only small changes in the treatment of the two parties. Both the Overturned Plan and the New Plan produce two extremely Democratic districts: one in Columbus and one in Cleveland. And both produce three districts where the statewide Democratic vote share in recent years was rather close to 50 percent. This means that with around 47 percent of the statewide vote shares, Democratic Party can likely expect 20 or 27 percent of the seats. As with the Overturned Plan, even if Democratic candidates are very fortunate and win all three "swing" districts in a given year, the Democrats can expect no more than 33 percent of the seats. In fact, even if Democrats experience a large swing in their favor of 3 percentage points, so that the Democratic Party

wins 50 percent of the statewide vote, it still cannot anticipate winning more than 33 percent of the seats. By contrast, a similar 3 percentage point swing would result in the Republican Party winning roughly 56 percent of the statewide vote, and 87 percent of the seats.

4. As in my previous report, I seek to explain how the New Plan achieves this rather striking counter-majoritarian outcome. The answer is largely the same: subverting traditional redistricting principles by splitting communities in metro areas and strategically subsuming urban fragments in their surrounding rural areas, often relying on relatively non-compact districts. Specifically, the New Plan 1) splits the Cincinnati metro area in a way that prevents the emergence of a Democratic district; 2) splits the Columbus and Cleveland areas in ways that pack Democrats into a single district in each metro area, combining urban and suburban Democratic communities with far-flung rural areas so as to avoid the emergence of a second Democratic district; 3) separates Toledo from proximate metro areas and combines it with very rural counties; and 4) carves out Lorain County from its geographic environment and places it in a highly non-compact rural district that reaches to the Indiana border. All of these features were present in the Overturned Plan as well.

5. By examining alternative plans that were before the General Assembly and the Commission, it is clear to see that it is possible to achieve higher levels of compactness, greater respect for communities, and a better reflection of the partisan preferences of Ohio voters by drawing districts that are not crafted to advantage one political party and its incumbents. That is to say, drawing districts that adhere to Ohio's political and economic geography does not require the degree of advantage for the Republican Party exhibited in the New Plan.

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 H.

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, and I drew a Pennsylvania Congressional redistricting plan, known as the "Carter Plan," that was chosen by the Pennsylvania Supreme Court for implementation. *Carter v. Chapman*, No. 7 MM 2022, 2022 WL 549106 (Pa. Feb. 23, 2022). 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 C, D, E, F, and G.[2] I also consulted geographic boundary files of the New Plan that were provided to me by Counsel (and available on the Ohio Redistricting Commission's website). 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 the analysis conducted in this report, I use three software packages: Stata, Maptitude for Redistricting, and ArcGIS Pro.

IV. THE PARTISANSHIP OF THE NEW CONGRESSIONAL PLAN

12. In my earlier report, I assembled data for the two major parties from statewide elections in Ohio from 2012 to 2020 and demonstrated that statewide support for Democratic candidates was around 46 percent in the period since 2012, but in more recent years, from 2016 to 2020, it was around 47 percent.

13. I then examined the plan that had been passed by the Ohio Legislature, but that has been subsequently overturned (the "Overturned Plan"). I summed up precinct-level results of elections from 2016 to 2020 within the boundaries of each of the districts of the overturned plan, and then demonstrated that Democratic candidates in statewide elections had comfortable majorities in only two districts—one in Cleveland and one in Columbus. Beyond those, the Overturned Plan included two districts in which the statewide vote share for the two parties was very evenly split, such that with 47 percent of the statewide vote, Democrats could anticipate only 20 percent of the seats (i.e., to win three of fifteen districts).

14. First, let us examine the new Congressional plan promulgated on March 2, 2022 ("the New Plan") using a similar approach. Again, there are two extremely Democratic districts, one in Cleveland and one in Columbus. In this plan, there are also three very evenly divided districts. In each of these districts, the Democratic statewide vote share from 2016 to 2020 is slightly above 50 percent. Specifically, in District 1, which combines urban parts of Cincinnati with rural Warren County, the Democratic vote share in statewide races aggregates to 51 percent. In District 9, in Northwest Ohio, the Democratic vote share was 50.2 percent. In District 13, which combines Summit County and the Northern part of Stark County, it was 52.2 percent. The remainder of the seats have relatively comfortable Republican majorities—all equal to or greater than 53.3 percent.

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[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.

15. If one wishes to assess the anticipated division of seats for the two parties under this plan, one must come up with a way to allocate these three evenly divided seats. As described in my previous report, District 1 has a longstanding Republican incumbent, Steve Chabot, who over the last decade, 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. If we consider his 4-point incumbency advantage, and the fact that around 70 percent of the population in the new version of District 1 was in the old version of District 1, this district should be viewed as having a Republican lean.

16. District 9 has been very evenly divided between the parties when we sum over all statewide races from 2016 to 2020. However, in the most recent election, Donald Trump won 51.5 percent of the vote. The Democratic incumbent, Marcy Kaptur, has outperformed her statewide co-partisans in the past, but her district has been redrawn so that only around half of the population of the new, more rural version of District 9 was in the old version of District 9. As a result, this district is probably best seen as a true tossup.

17. To my knowledge, District 13 does not include any incumbents. With a Democratic vote share of just over 52 percent in statewide races, and a Democratic vote share of 51.4 percent in the most recent presidential election, it is best understood as a district with a slight Democratic lean.

18. If one accepts this analysis, and considers that one of these districts leans Democratic, another leans Republican, and a third is a toss-up where the expected probability of a Democratic victory is .5, we would end up with the conclusion that Democratic candidates can anticipate 3.5 seats, or 23 percent.

19. Alternatively, we might simply classify all three seats as tossups in which Democratic candidates would win with probability .5. Summing over these probabilities, we would end up with the same expectation: 3.5 seats, or 23 percent.

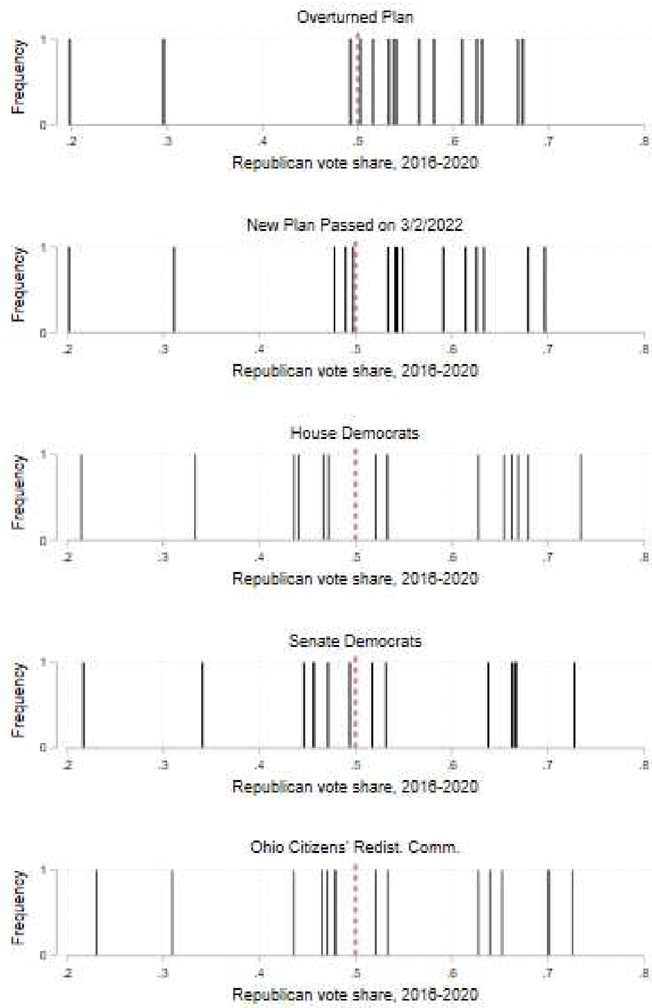
20. If one considered the seat with a 52.2 percent Democratic majority as a safer Democratic seat and focused only on the bare majority Districts 1 and 9 as toss-ups, Democrats would still win only 4 districts, giving them 27 percent of the seats.

21. Another approach might be to ignore these 3 evenly divided seats, and simply ask how many of the remaining 12 seats lean Democratic, and how many Republican. With this approach, we would view the Democratic seat share as 2 out of 12, or 17 percent. Even if we ignored only 2 of the seats (District 1 and 9), we would view the Democratic seat share as 3 out of 13, or 23 percent.

22. In the event of a pro-Democratic wave, if Democrats would win all three seats, giving them a total of 5, they would have a seat share of 33 percent.

23. In short, with around 47 percent of the statewide vote share, the Democrats could anticipate anywhere from 13 percent of the seats if they lose all three of the competitive districts, to 33 percent if they win all three. Perhaps the most reasonable (but still optimistic) expectation, ex ante, is 27 percent. In other words, the Democrats' expected seat share falls far short of their vote share.

Figure 1: Discrete Histograms for Several Ohio Congressional Redistricting Plans



24. Moreover, it is important to note that 33 percent is very likely the ceiling on the number of seats the Democratic Party could possibly win under the New Plan. This is because the other 10 seats have been drawn to be very comfortable for Republican candidates. To comprehend this, see the top two panels in Figure 1, which provides discrete histograms for the Overturned Plan, and then for the New Plan. A discrete histogram simply displays a bar for each district, arranged on the horizontal axis according to the Republican vote share, with a red dotted line indicating 50 percent.

25. Figure 1 demonstrates that the main difference between the Overturned Plan and the New Plan is that a couple of the bars have moved ever so slightly to the left, to the other (Democratic) side of the 50 percent line. Note that this leaves a large gap on the *right* side of 50 percent in the New Plan. That is to say, there are no highly competitive Republican-leaning districts that Democratic candidates might hope to capture in a pro-Democratic wave election.

26. The most competitive Republican-leaning district is District 10, where the statewide Democratic vote share aggregates to 46.7 percent. However, as explained in my previous report, the Republican incumbent, Mike Turner, won each general election from 2012 to 2020 with an average two-party vote share above 62 percent, outperforming his statewide co-partisans by around 8.7 percentage points. In the New Plan, Representative Turner keeps 90 percent of the population of his old district, so there is no reason to anticipate that District 10 would be competitive in a typical election scenario.

27. Due to the lack of competitive but Republican-leaning districts, it is difficult to envision a scenario in which the Democratic Party would be able to win more than 5 seats under this plan. Relative to their 47 percent vote share in the period from 2016 to 2020, imagine a very large uniform shift of 3 percentage points toward the Democratic Party in all districts, giving them 50 percent of the statewide vote. Democratic candidates could *still* only anticipate only 33 percent of the seats. If we take a naïve approach and ignore incumbency advantage, focusing only on statewide vote shares, we might imagine that a truly extraordinary 4-point uniform swing would be enough to tip District 10 to the Democrats, but it would be too little for the Democrats to gain majorities in any other districts. This would generate a highly counter-majoritarian result in which the Democrats received 51 percent of the votes but 40 percent of the seats.

28. In stark contrast, if the Republican Party experienced the same large uniform shift of 3 percentage points, it would win 56 percent of the statewide vote and all three of the competitive seats—just about *87 percent* of the congressional seats.

29. There is nothing about the geography of Ohio or the requirements of the Ohio Constitution that requires this type of counter-majoritarian redistricting plan. In my previous report, I discussed three alternative redistricting plans: one that was introduced by the House Democrats on November 5, 2021 (Exhibit C); one that was introduced by the Senate Democrats on November 10, 2021 (Exhibit D); and one that was introduced by the Ohio Citizens' Redistricting Commission on September 30, 2021 (Exhibit E).

30. Discrete histograms for these three plans have also been included in Figure 1. Note that the distribution of partisanship is quite different in these plans than in the Overturned Plan and the New Plan. Not only do they include a larger number of plans where the Democratic vote share is above 50 percent—7 districts in the Senate Democrats' and OCRC plans, 6 in the House Democrats' Plan—but the Democratic-leaning districts are not tightly clustered around the 50 percent line.

V. HOW DOES THE NEW PLAN TREAT INCUMBENTS?

31. In addition to analyzing the extent to which the New 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. Representative Brad Wenstrup has announced that he intends to seek re-election in District

2, which is a comfortably Republican district.[4] All the remaining districts with Republican incumbents continue to have Republican majorities—most of them quite comfortable. The only exception is District 1, where it was necessary to make changes due to the Ohio Constitution's requirement that Cincinnati be kept whole and the Ohio Supreme Court's opinion striking down the Overturned Plan. Nevertheless, as described above, though statewide races have been evenly divided in the redrawn version of the district, the incumbent has enjoyed a large incumbency advantage in recent years and has been able to retain most of the population of his old district. 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.

32. In contrast, of the four Democratic incumbents, only two continue to reside in districts that are clearly Democratic. 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 is now evenly divided. Only around half of the new version of District 9 was in her previous dIstrict. While the 2011 version of District 9 was rather non-compact, the version of District 9 in the alternative maps discussed in my previous report are markedly more compact than the 2011 version, while retaining more of the northern industrial cities that comprised the 2011 version. 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 District 6 in the New Plan.

VI. HOW DOES THE NEW PLAN ACHIEVE THESE RESULTS?

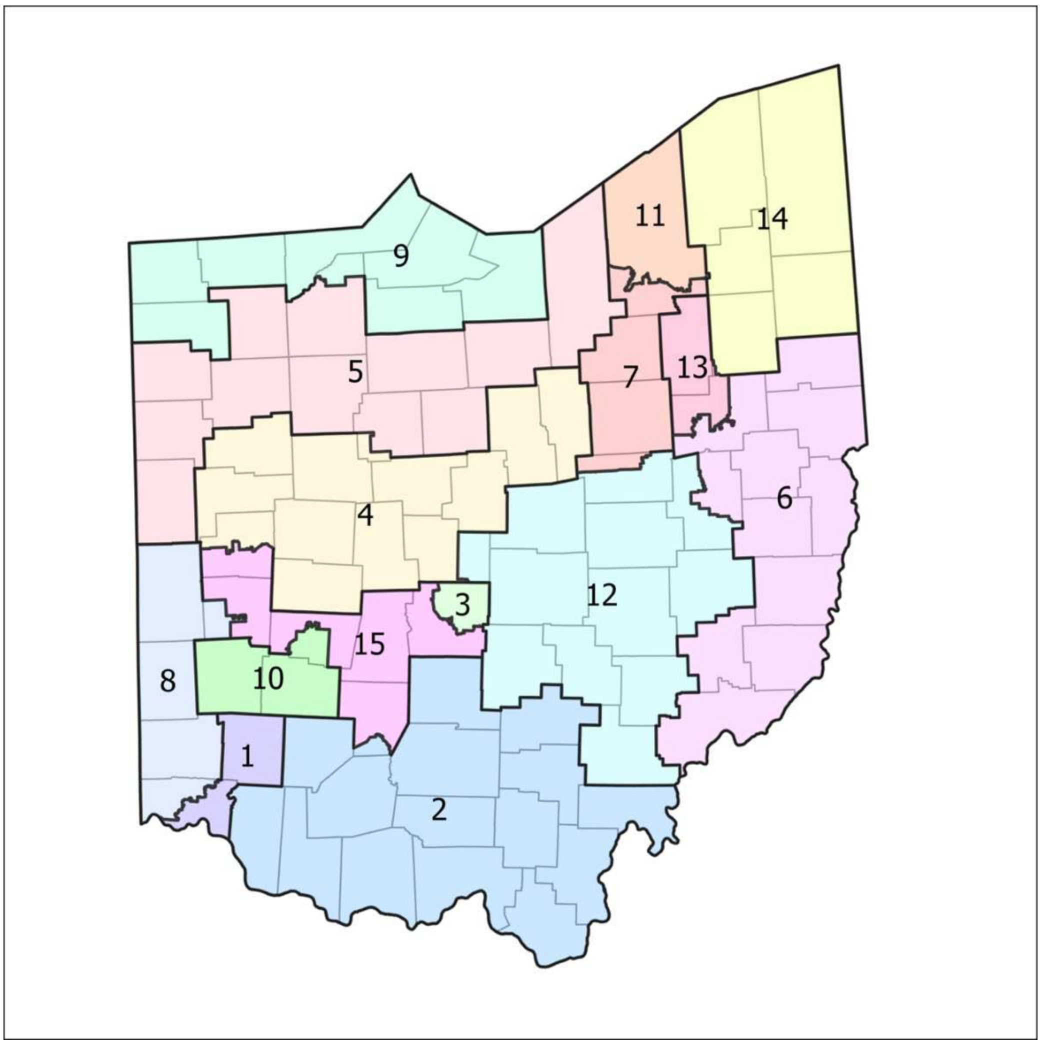
33. Like the Overturned Plan, the New Plan favors the Republican Party and its incumbents, while disfavoring the Democratic Party and its incumbents. My previous report demonstrated that in order to achieve this partisan advantage, the Overturned Plan subordinated traditional redistricting principles in several ways. Above all, the Overturned Plan contained needlessly non-compact districts and split metropolitan area communities in order to prevent the emergence of districts with Democratic majorities. The following decisions stood out most clearly: 1) the Cincinnati metro area was split in a way that prevented the emergence of an obvious, compact district with a clear Democratic majority, 2) Columbus and Cleveland-area districts were drawn to prevent the creation of a second metro-area Democratic district, 3) District 9 in Northwest Ohio was drawn so as to overwhelm Toledo and other Democratic communities on Lake Erie with more rural communities, and 4) rather than being combined with suburban Cleveland to its East or other proximate Democratic-leaning communities to its West on Lake Erie, Lorain County is extracted from Northeast Ohio and connected via a corridor of rural counties to the Western border of the state.

34. Each of these features remains in the New Plan. Before taking a closer look at specific regions, it is useful to view the overall architecture of the New Plan, along with several

[4] 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.

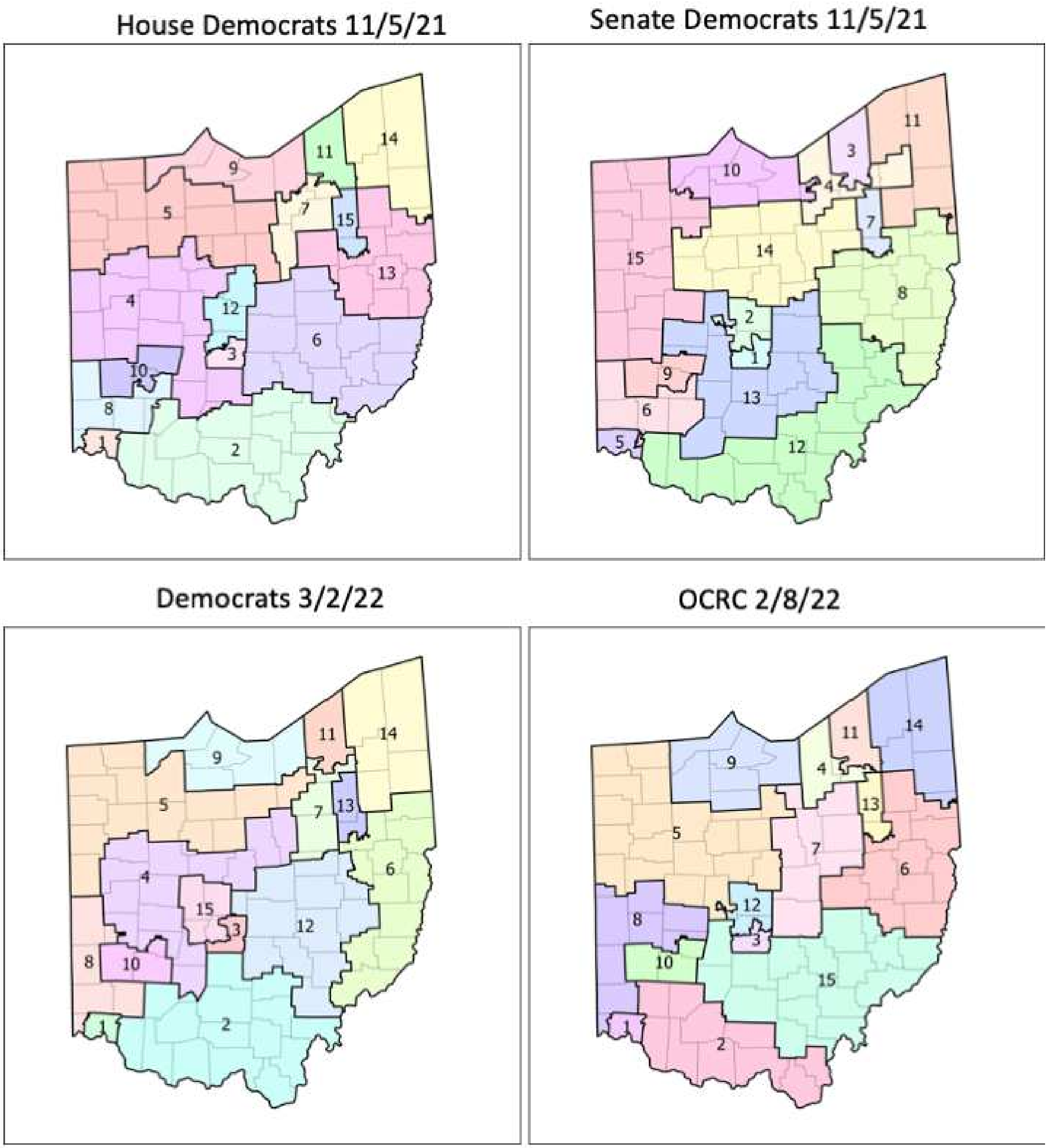
alternative plans. Figure 2 displays a map of the New Plan. For comparison, Figures 3 displays four alternative maps. First, it includes the maps produced by the Ohio House and Senate Democrats that were discussed in my previous report. Additionally, I have examined two additional redistricting plans that were submitted to the General Assembly and Commission: The first was proposed by the Senate Democrats on March 2 (Exhibit F), and the second was proposed by the Ohio Citizens' Redistricting Committee (OCRC) on February 8 (Exhibit G).[5] I note that the February 8 OCRC Plan is very similar to the earlier OCRC Plan that was discussed in my initial report, so in Figure 3 and subsequent figures, I only include the more recent OCRC map. It is not my intention to endorse any of these maps. Rather, they provide valuable comparisons that help illuminate certain features of the New Plan.

Figure 2: The New Plan



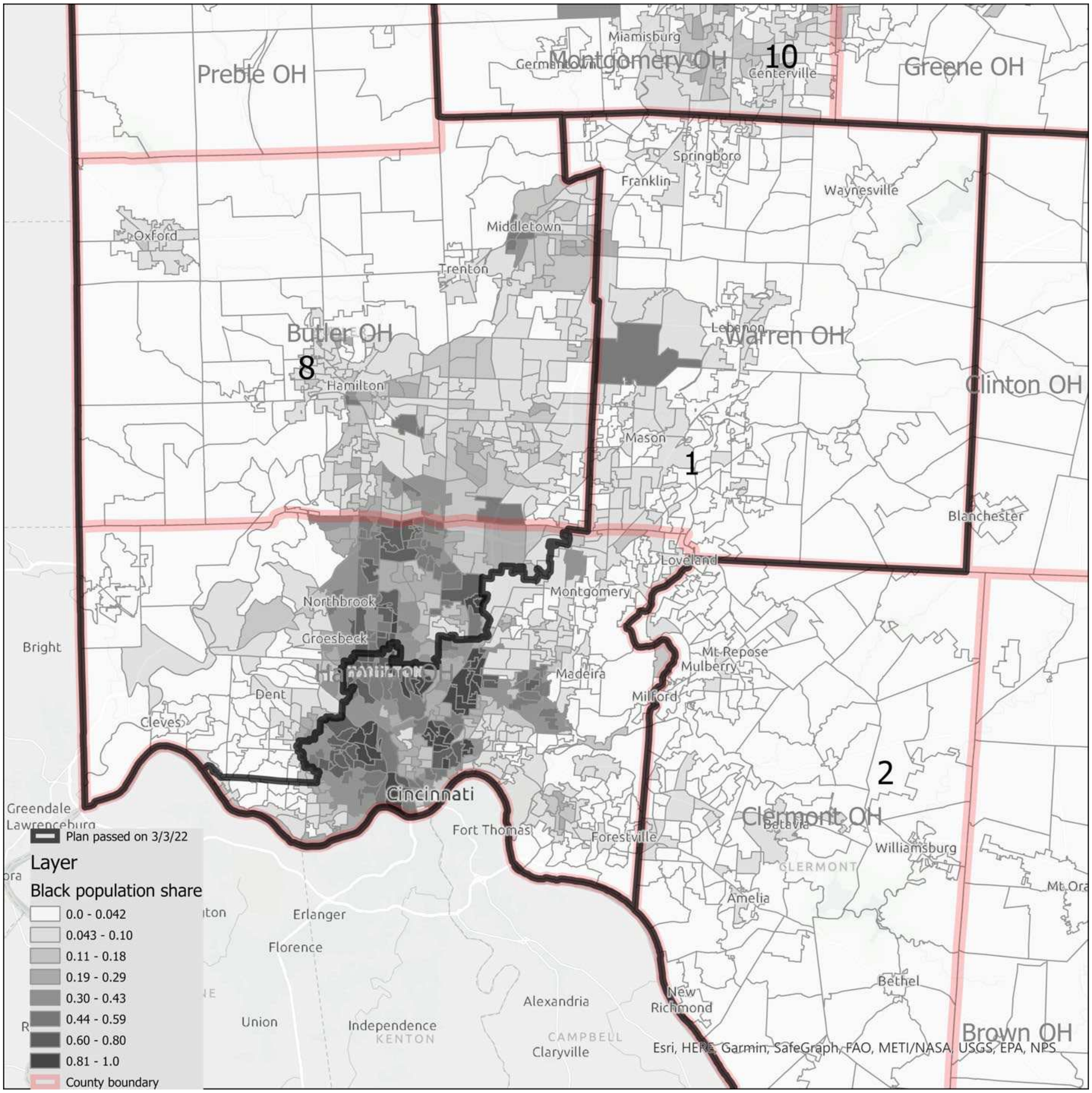
[5] I note that the OCRC Plan includes population deviations that may be greater than those allowed under equal population requirements. I nevertheless consider the OCRC Plan's partisanship and district configuration for demonstrative purposes.

Figure 3: Four Alternative Plans



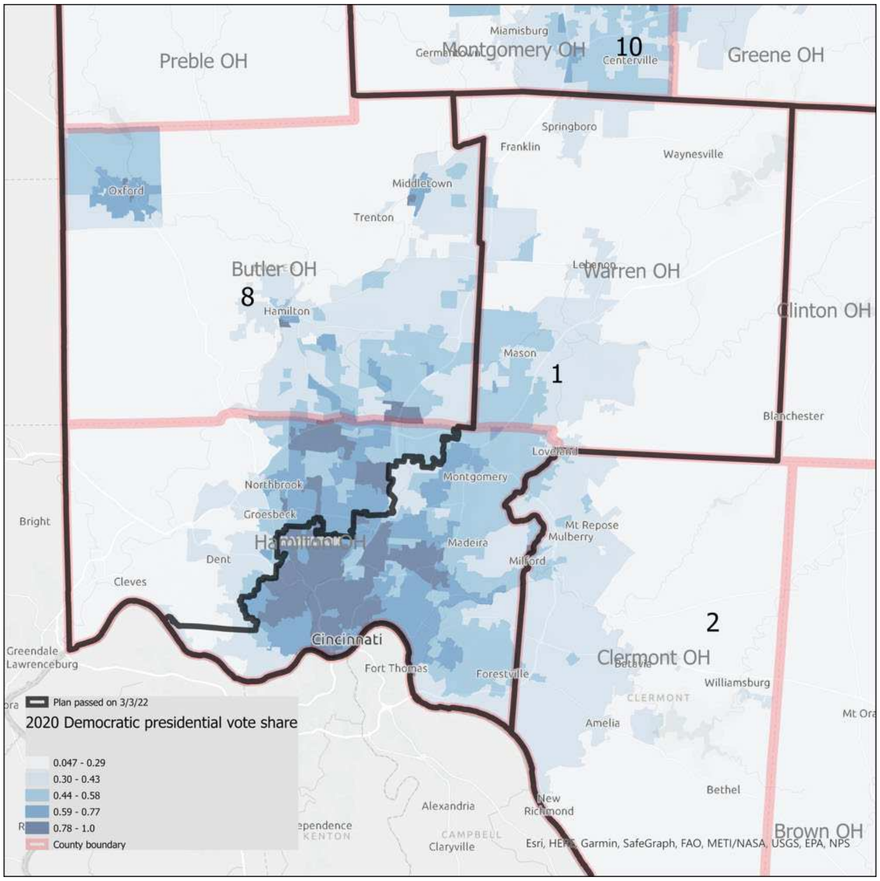
35. Already from this bird's eye view, it is possible to appreciate the non-compact arrangement of District 1 in the New Plan relative to the alternatives, the extraction of part of Columbus and its placement into a highly non-compact District 15, the non-compact arrangement of District 9 designed to add Republicans to the Toledo district, and the extraction of Lorain County from its geographic environment and placement in District 5. Let us now take a close look at each of these maneuvers.

Figure 4: Black Population and New Districts, Cincinnati Area



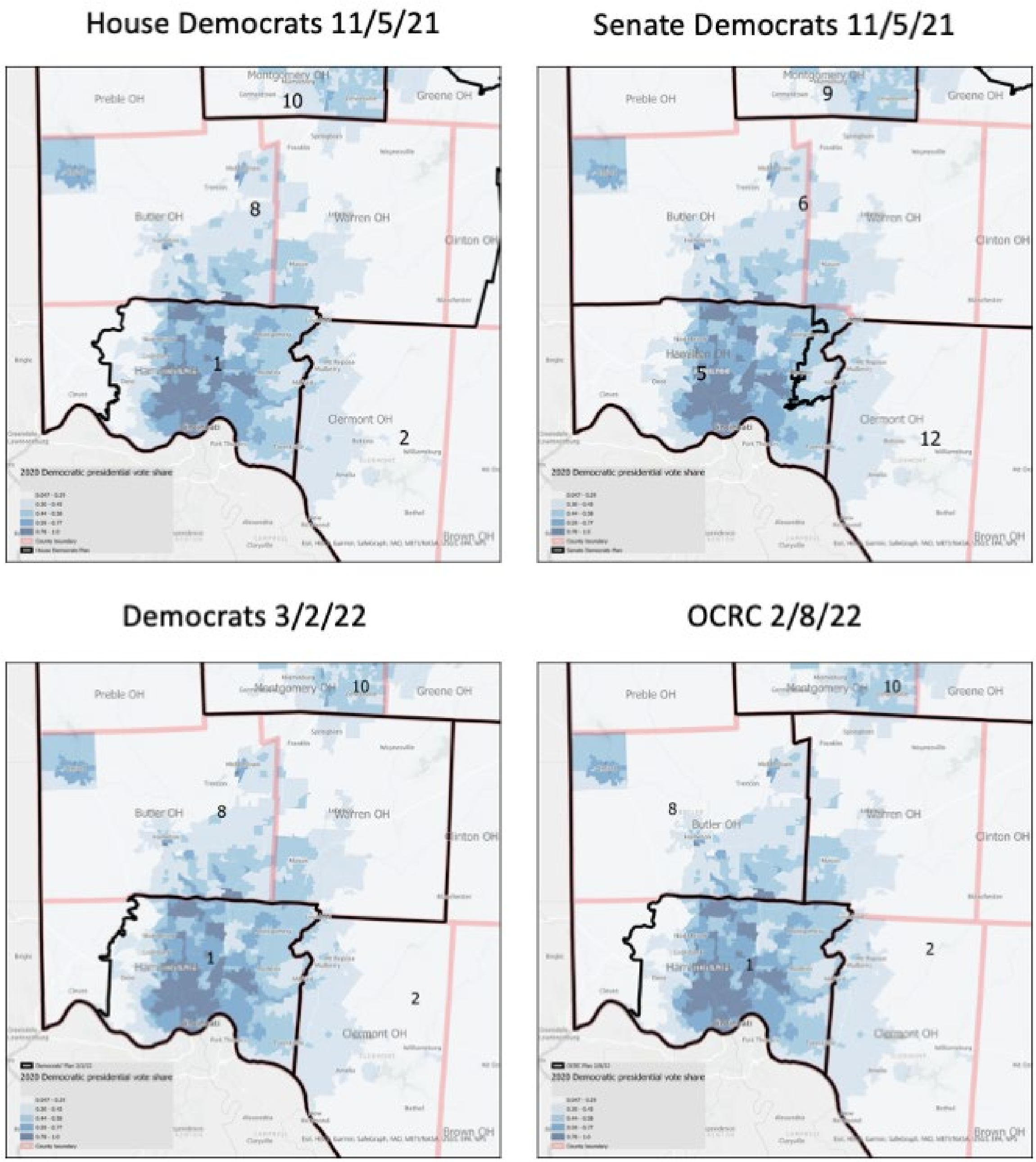
36. Figure 4 displays the boundaries of the New Plan, along with data from the most recent census on race. It shows that the boundary between Districts 1 and 8 bisect the Black community of Cincinnati, ensuring that it cannot contribute to the creation of a clear Democratic district. District 1 maintains its old architecture, splitting the Black community of Cincinnati from that of the Northern suburbs, combining the city of Cincinnati with exurban and rural white areas to the Northeast, traveling via a narrow corridor to Warren County.

Figure 5: Democratic Vote Share and Boundaries of the New Plan, Cincinnati Area



37. Figure 5 replaces the data on race with data on partisanship, using darker colors of blue to capture more Democratic precincts. A comparison of Figures 4 and 5 reveals that partisanship and race are highly correlated in the Cincinnati area, and demonstrates how the line between Districts 1 and 8 in the New Plan not only needlessly splits the Black community in two, but prevents the emergence of a clear Democratic district by generating a highly non-compact arrangement.

Figure 6: Democratic Vote Share and Boundaries of Alternative Plans, Cincinnati Area



38. Figure 6 present the boundaries of four alternative maps, demonstrating that it is quite straightforward to draw a compact Cincinnati district that keeps metro area communities together. For instance, the Reock compactness score for District 1 in the New Plan is .31, while it is .56 in the Democrats' most recent (3/2/2022) plan, and .55 in the most recent OCRC Plan. A higher Reock score indicates a greater level of compactness. The same is true for the Polsby-Popper score, which is .24 in the New Plan, .43 in the Democrats' 3/2/2022 Plan, and .46 in the OCRC 2/8/2022 Plan.

39. Next, Figure 7 displays the districts of the New Plan in the Columbus Area, again overlaying them on precinct-level partisanship. It demonstrates that District 3 is drawn to pack the most Democratic part of Columbus in one district, extracting Democratic-leaning parts of Columbus (including downtown Columbus) and its suburbs, and combining them with some of the most rural, Republican communities of West-Central Ohio, circumnavigating Springfield along the way, and splitting 4 counties to create a single, highly non-compact District 15. These maneuvers made it possible to avoid the emergence of a second Columbus-area Democratic district, creating a relatively comfortable Republican district with a Republican incumbent.

Figure 7: Columbus Area: New Plan

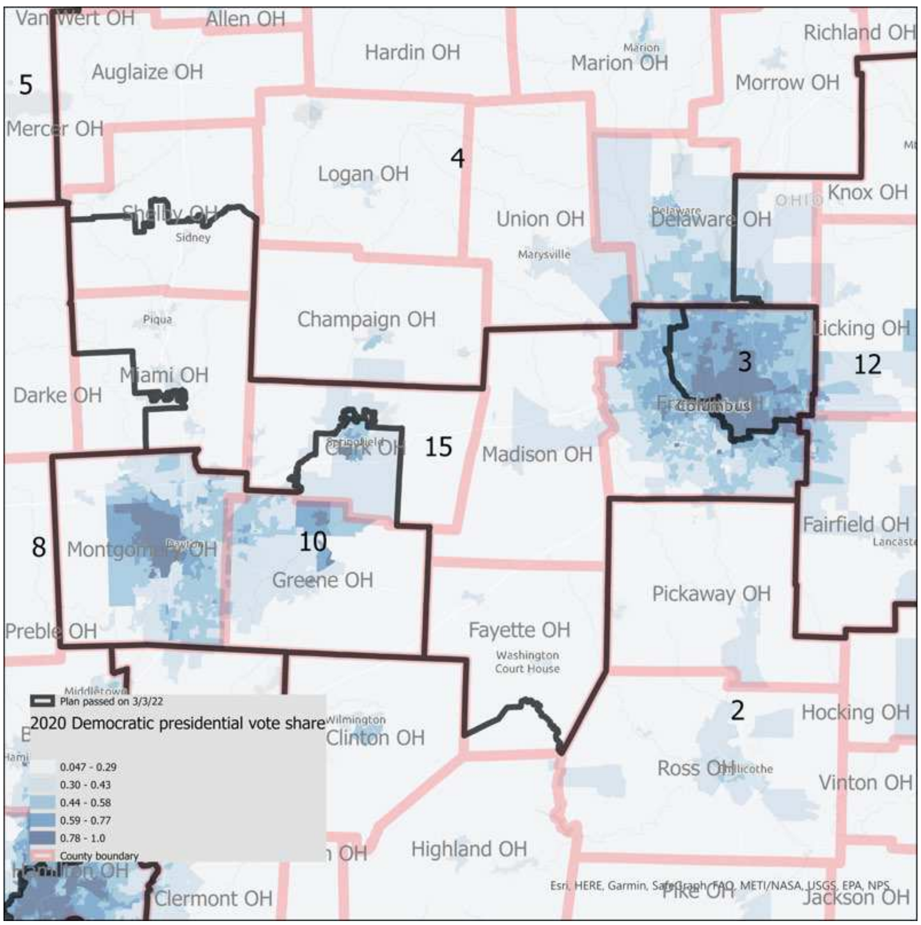
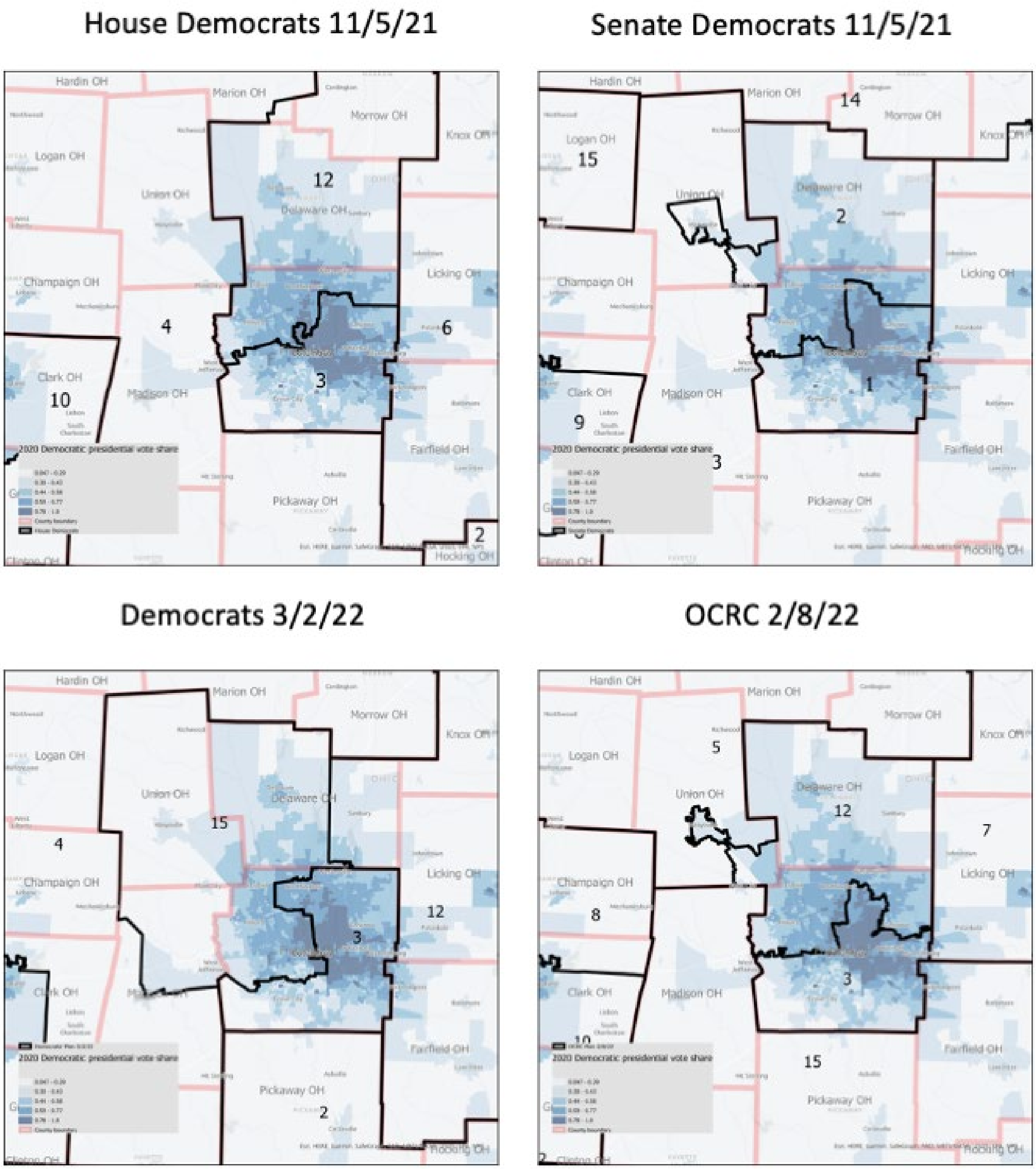


Figure 8: Columbus Area: Alternative Plans



40. Figure 8 displays the Columbus-area districts for four alternative plans. Each demonstrates ways to split fewer counties and draw more compact districts while keeping metro area communities together. District 15 in the New Plan has a Reock score of .28, whereas District 15 in the Democrats' most recent plan is .56, and District 12 in the most recent OCRC Plan is .59. As for the Polsby-Popper Score, it is .14 for the New Plan, .42 for the Democrats' Plan, and .3 for the OCRC Plan.

41. Next, let us examine the Cleveland Area. Figure 9 provides a map of the districts of the New Plan, and Figure 10 examines the alternative plans. A familiar strategy emerges again in the New Plan. The most Democratic parts of metro Cleveland are packed into one district, District 11, with the district lines carefully following the precinct-level vote shares. Instead of keeping the Western suburbs together and extending District 7 into Lorain County, the district reaches to the South and combines Democratic-leaning suburban areas with very rural areas to produce a comfortable Republican district 7 with a Republican incumbent.

Figure 9: Cleveland Area, New Plan

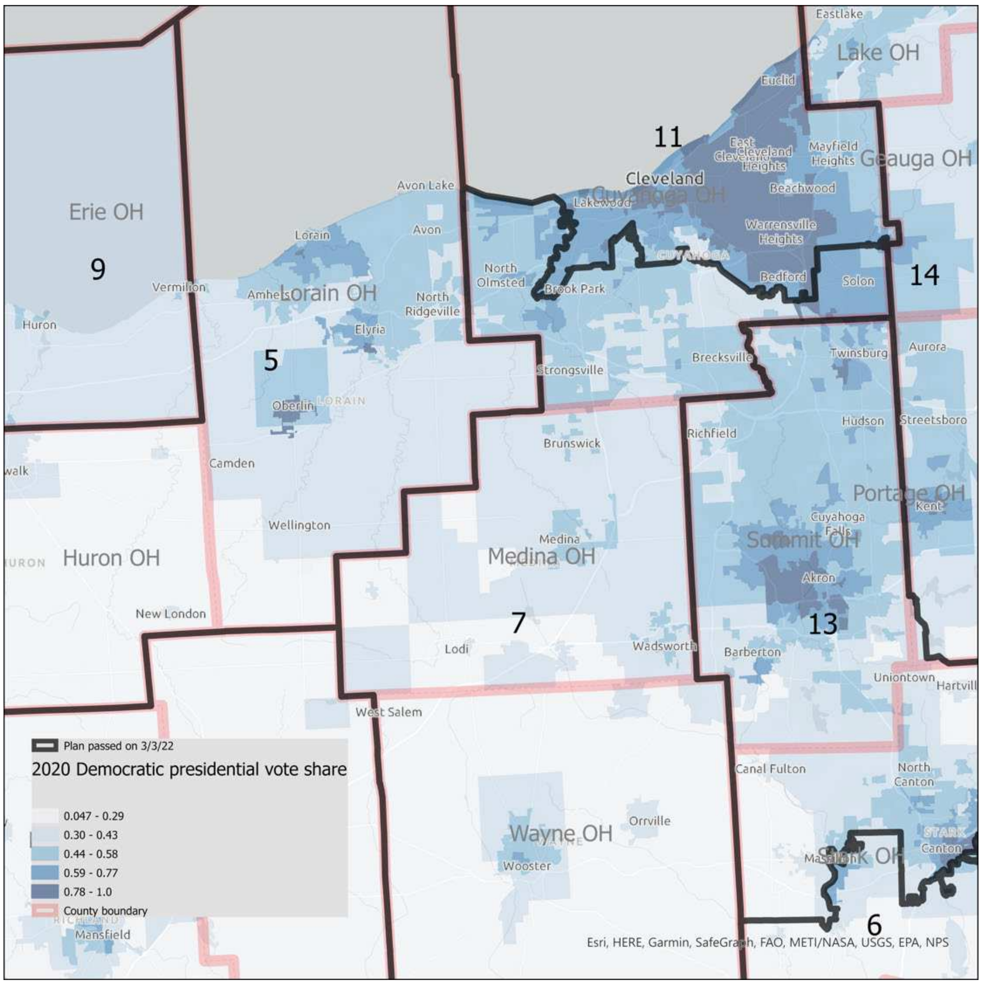
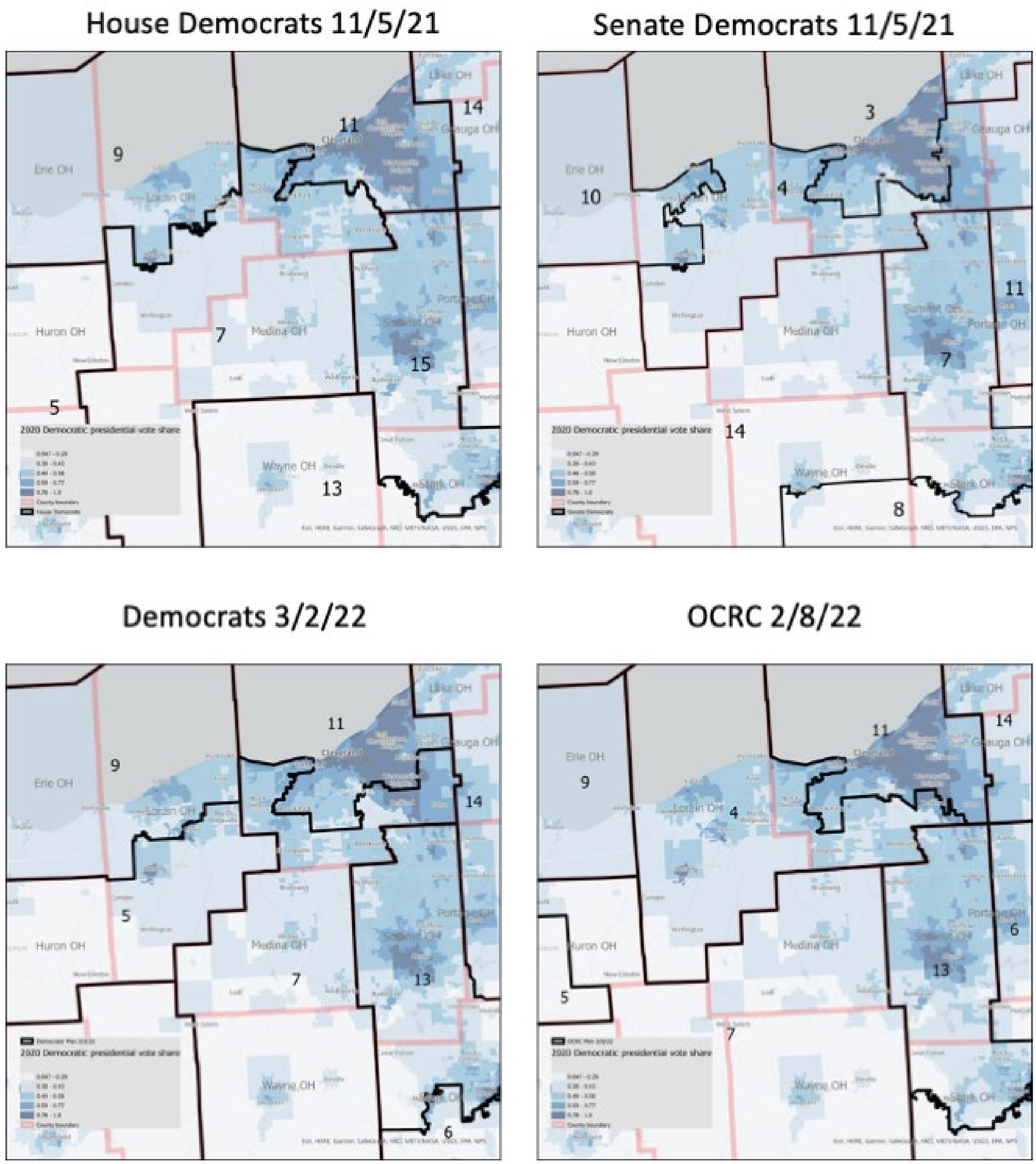


Figure 10: Cleveland Area: Alternative Plans



42. The alternative maps display a number of alternative approaches to the Cleveland area, several of which keep Democratic-leaning communities of Cuyahoga County together. For instance, using the most compact arrangement of the three, the OCRC Plan keeps the Western suburbs together, combining all of Lorain County with the suburban parts of Cuyahoga, creating a rather natural Western Cleveland district with a Democratic majority of the statewide vote.

43. Finally, let us consider Northwest Ohio. Figure 11 presents the districts of the New Plan, and Figure 12 displays the districts of alternative plans. The New Plan studiously avoids the creation of a clear Democratic district by combining metro Toledo with rural counties and avoiding a link to Lorain County. This results in a highly non-compact District 5, which extracts Lorain County and connects it via a narrow corridor of rural counties all the way to the Western border of the state.

44. In contrast, the alternative plans display more natural metro-oriented versions of District 9 that are also more compact. The Reock Score for District 9 in the New Plan is .26, compared with .33 for the Democrats' most recent plan, and .53 for the newest OCRC Plan. The Polsby-Popper Score for the New Plan is .27, compared with .34 for the Democrats' Plan and .58 for the OCRC Plan.

Figure 11: Northwest Ohio: New Plan

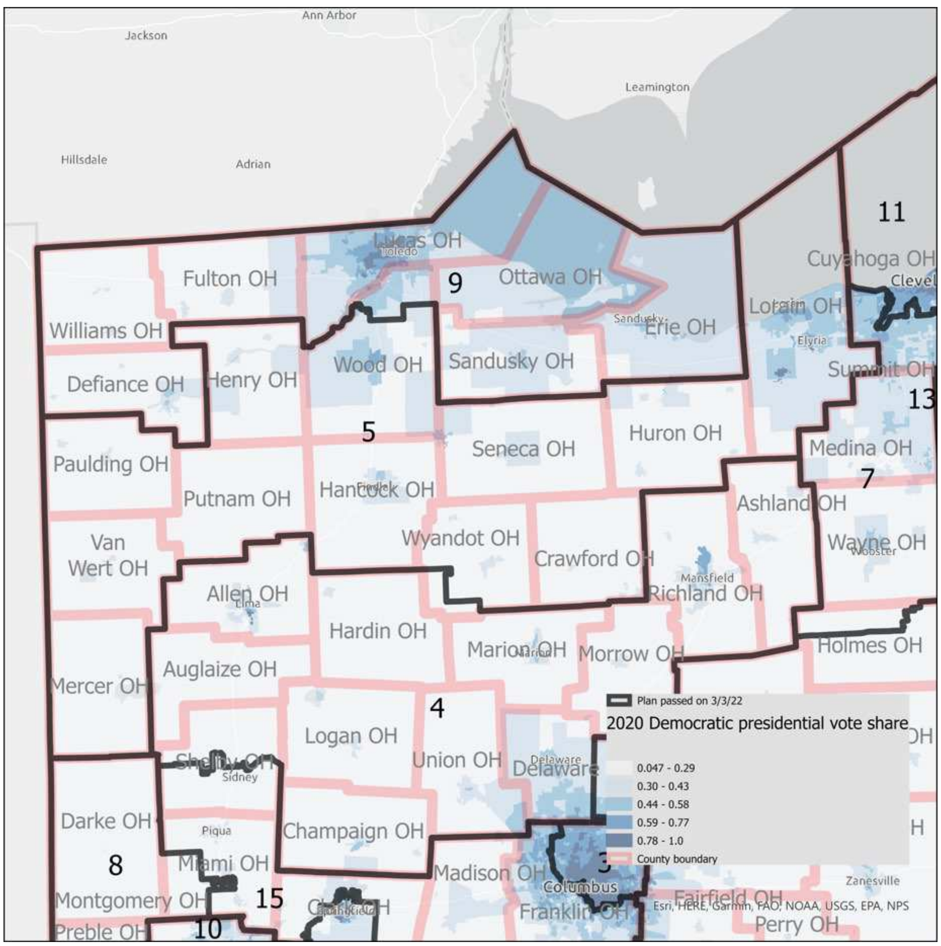


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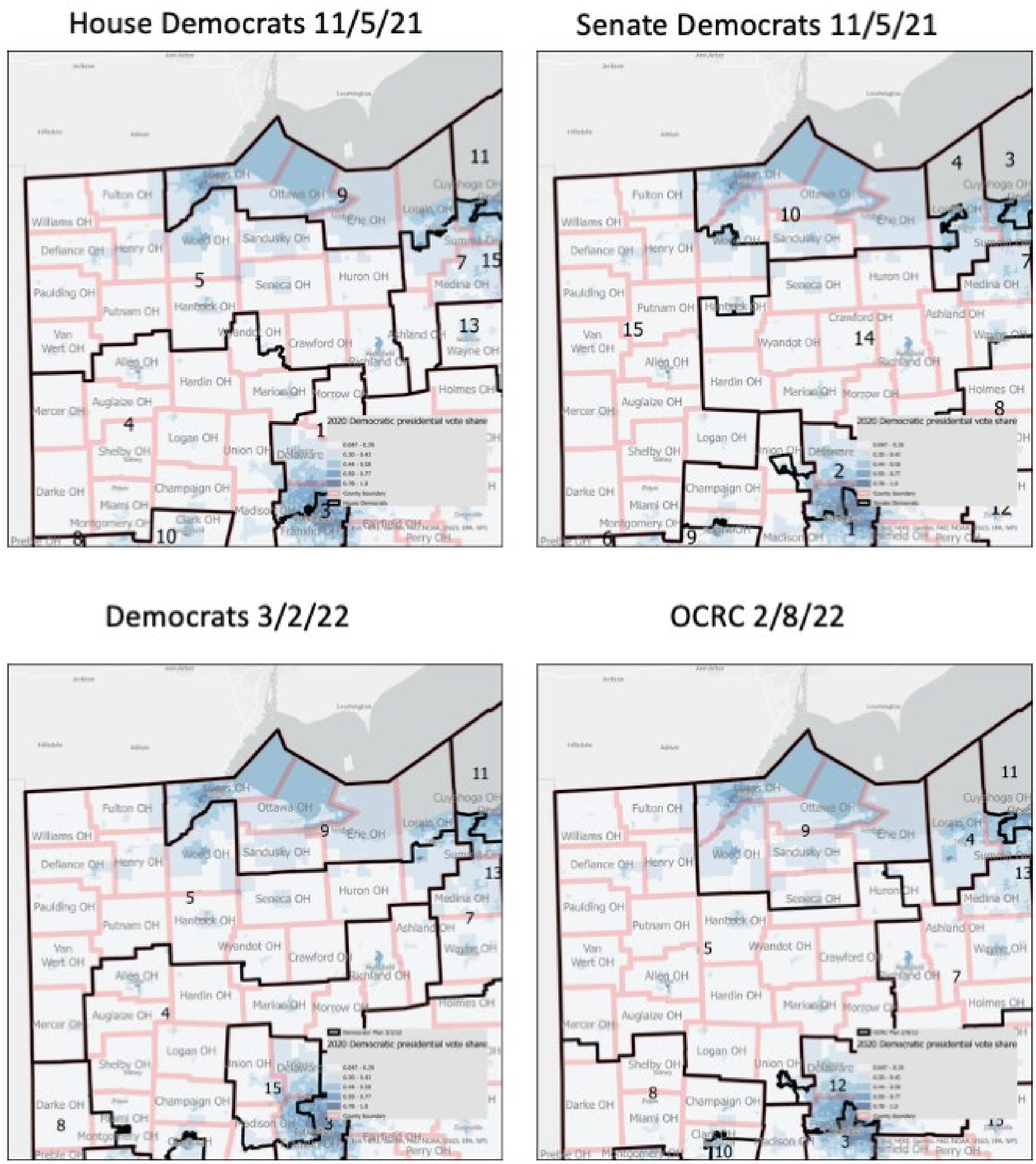
Figure 12: Northwest Ohio, Alternative Plans



45. The House Democrats' approach to Northwest Ohio, also reflected in the Democrats' March 2 map, includes the cities of Lorain County in District 9, while the OCRC version, as described above, combines Lorain with Western Cleveland in District 4. Needless to say, not only do they produce more compact districts, but both are more respectful of communities of interest than the New Plan, which extracts Lorain County from its environment altogether.

Table 1: Average Compactness Scores

	Reock	Polsby-Popper	Area/Convex Hull
New Plan	0.4	0.32	0.75
House Democrats 11/5/21 Plan	0.43	0.33	0.78
Senate Democrats 11/5/21 plan	0.43	0.29	0.76
Democrats 3/2/22 Plan	0.42	0.33	0.77
OCRC 2/8/22 Plan	0.46	0.34	0.79

46. In the paragraphs above, I have shown that efforts to split Democratic-leaning metro-area neighborhoods from their communities and combine them with rural areas while keeping Republican incumbents in their old districts sometimes required rather obvious violations of traditional redistricting criteria and non-compact districts. This also leads to districts that are, on average, less compact than those of the alternative plans, as set forth in Table 1. On each of three common measures of compactness, the House Democrats' Plan, the most recent Democratic Plan of March 2, 2022, and especially the OCRC Plan are more compact than the New Plan. The only exception is the Senate Democrats' Plan on the Polsby-Popper metric.

47. In my earlier report, I also reported simple statistics on the efficiency gap and electoral bias. Recall that electoral bias involves imagining a hypothetical tied election, and asking whether, and by how much, a party would exceed 50 percent of the seat share. As discussed above, the Democratic Party could expect 5 seats in this scenario, which corresponds to 33 percent of the seats for Democrats, and 67 percent for Republicans, for a bias measure of around 17 percent. As discussed in my initial report, this is identical to the Overturned Plan.

48. Table 2 provides information on the efficiency gap, using the statewide aggregate district-level votes shares that have been described throughout this report. By making the three swing districts slightly more Democratic, the New Plan reduces the efficiency gap from 24% to 10%, but this is still relatively high in comparison to other states, and to alternative Ohio Congressional plans.

Table 2: Efficiency Gap

	Efficiency Gap
Overturned Plan	24%
New Plan	10%
House Democrats 11/5/21 Plan	3.5%
Senate Democrats 11/5/21 plan	-3.7%
Democrats 3/2/22 Plan	-3.6%
OCRC 2/8/22 Plan	-3.6%

VII. CONCLUSION

49. Like the Overturned Plan, the New 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

NOTARY PUBLIC • STATE OF FLORIDA

KERRIAN C ROBERTSON
Notary Public - State of Florida
Commission # HH76461
Expires on February 20, 2025

Sworn to before me this 4th day of March 2022.

Kerrian C Robertson

Notary Public

Broward County, FL

Jurat
Jonathan Andrew Rodden
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Exhibit A

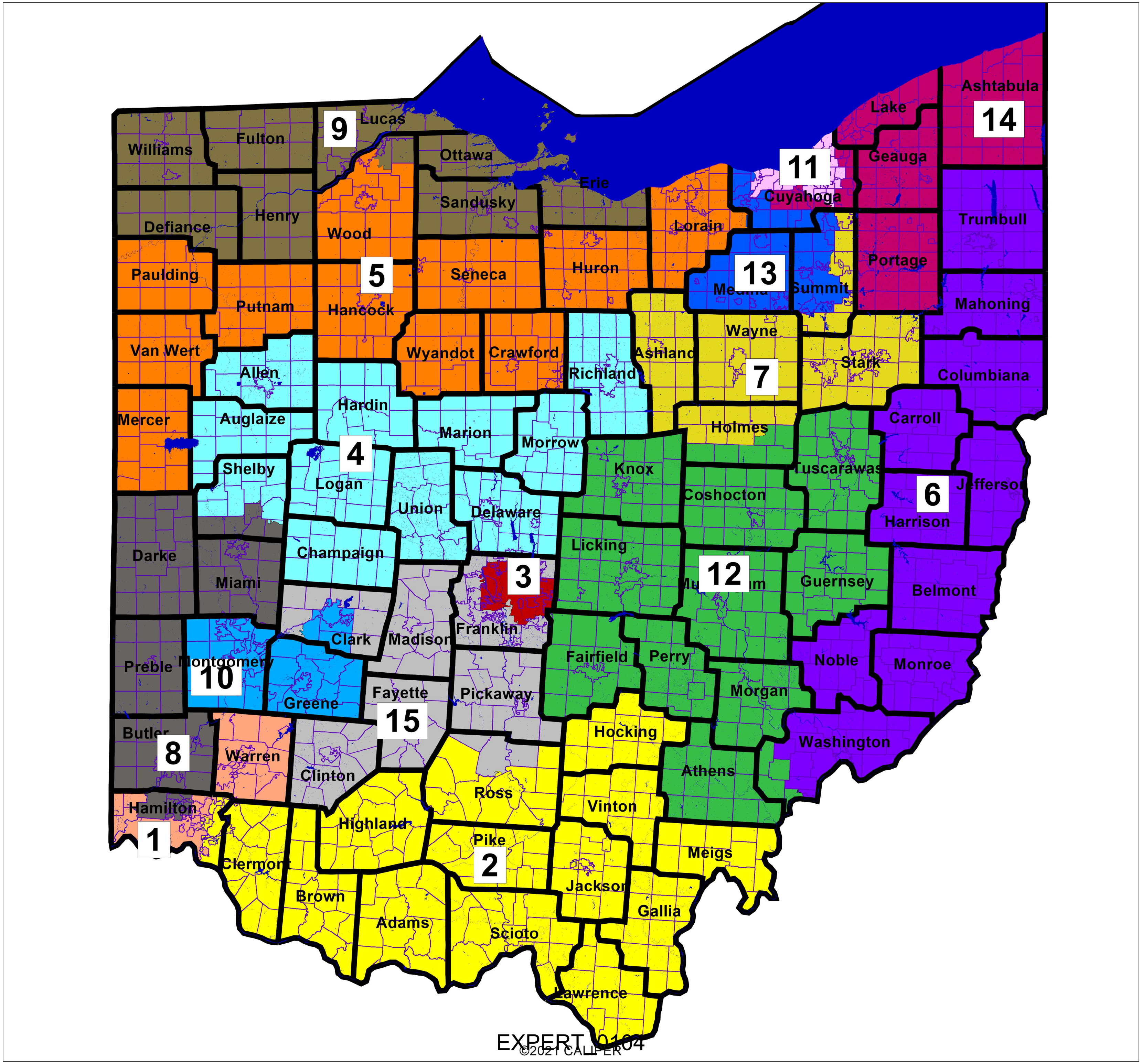

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Exhibit B

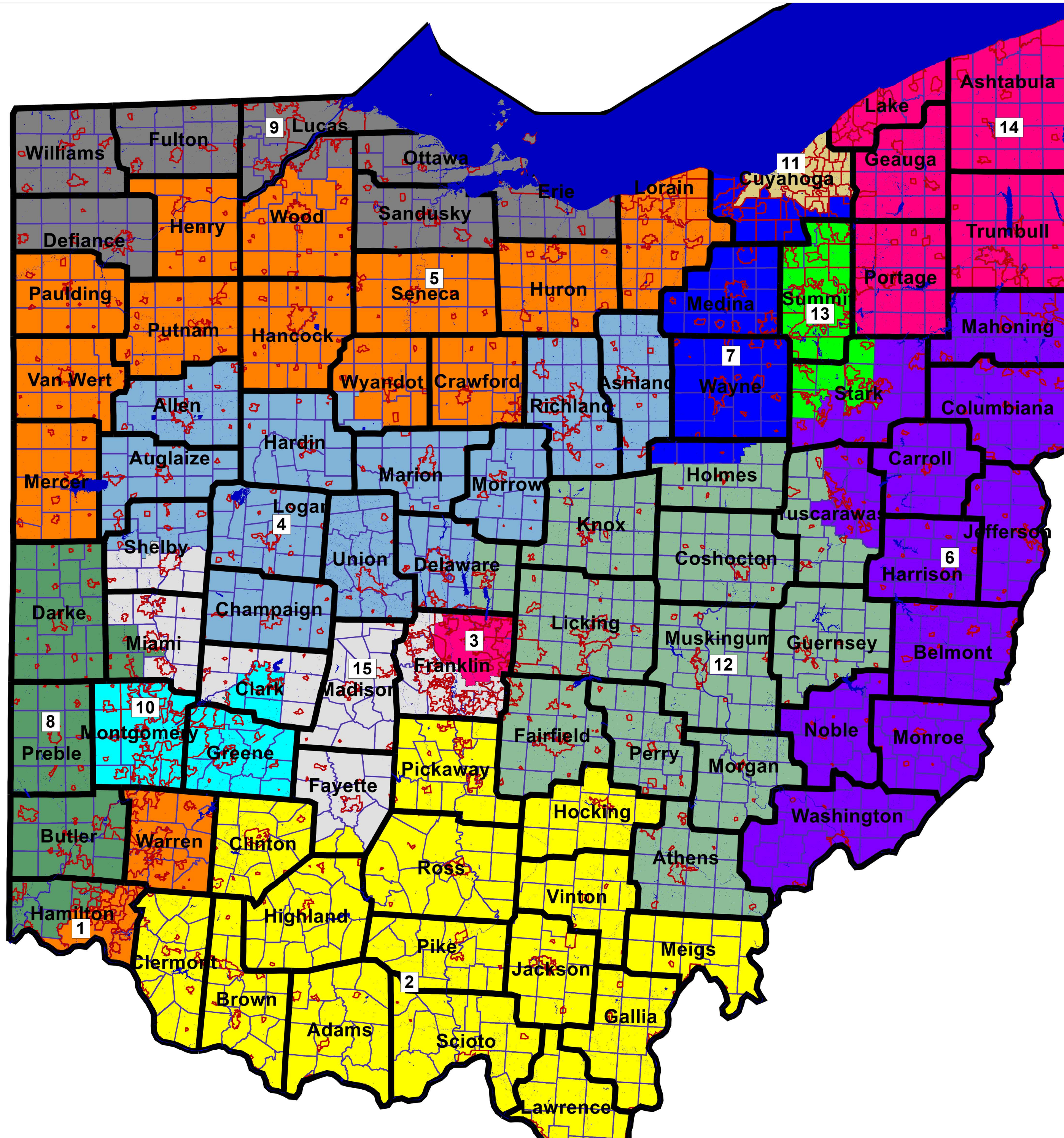

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Exhibit C

Brown/Galonski Congressional District Proposal

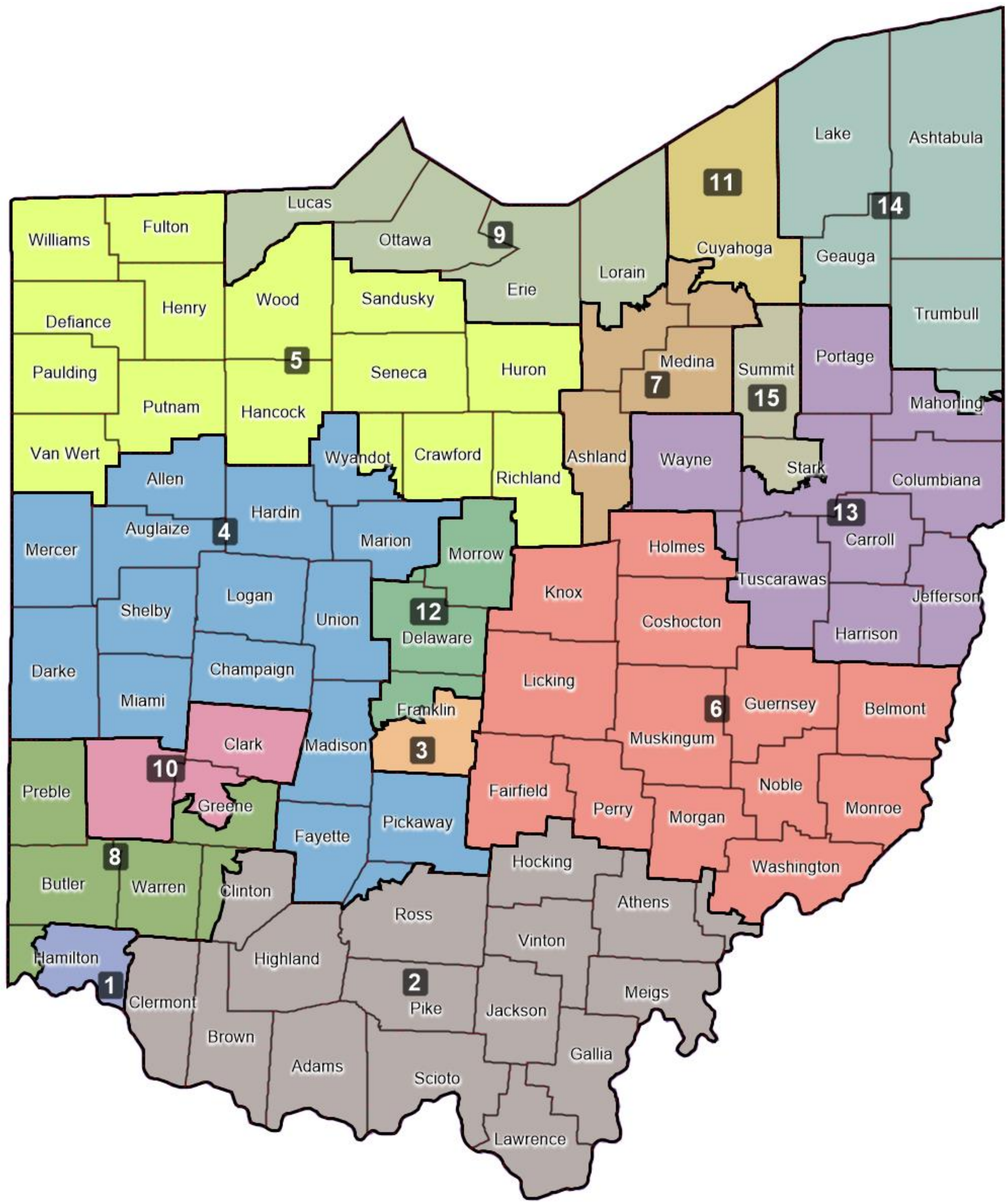


Exhibit D

Proposed Sub SB 237 Map

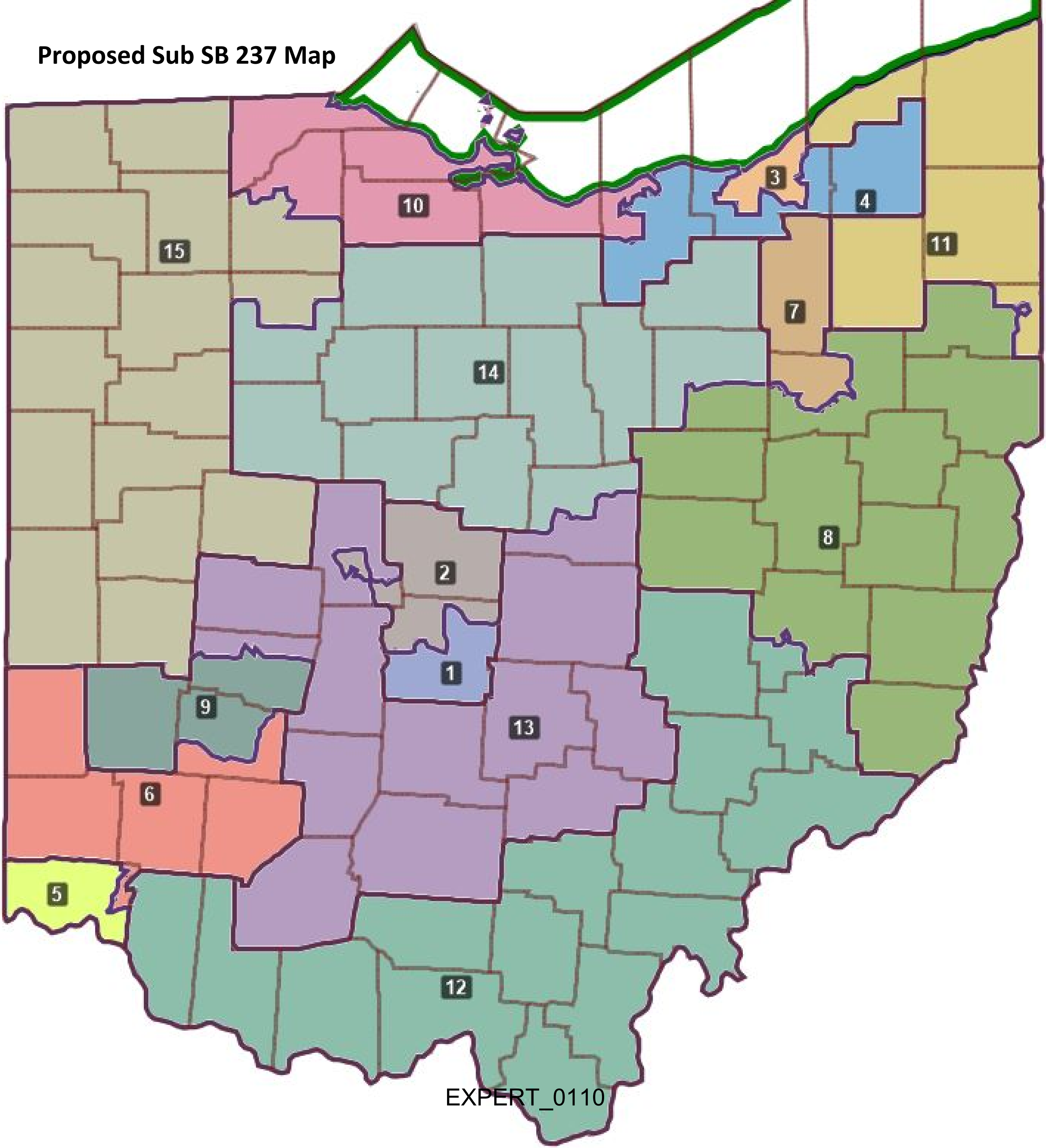
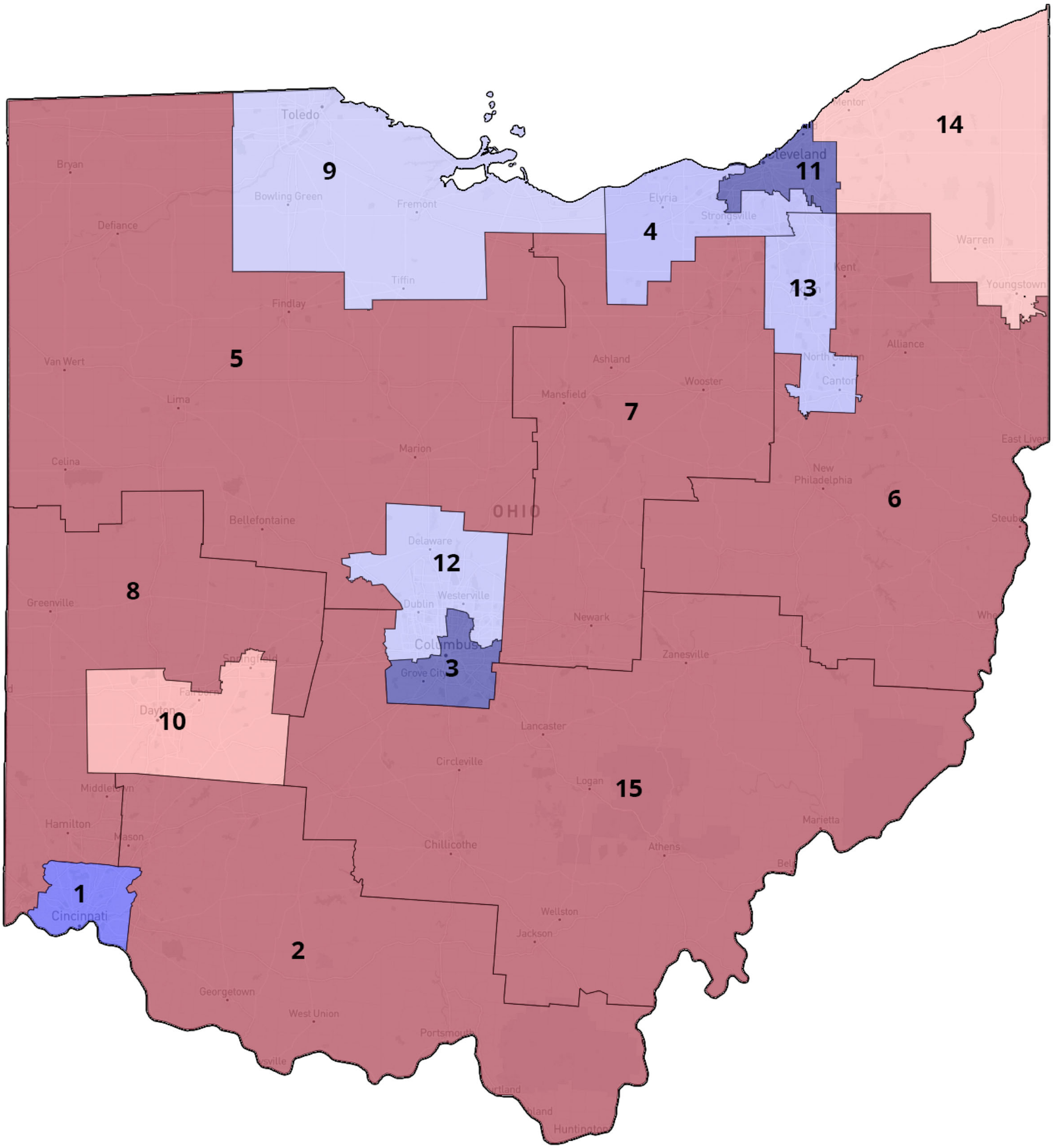


Exhibit E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Westerville
Dublin
Columbus
Grove City
Mentor
Cleveland
Elyria
Strongsville
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Youngstown
Kent
Alliance
Ashland
Wooster
Mansfield
North Canton
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New Philadelphia
Newark
Zanesville
Lancaster
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Logan
Marietta
Athens
Chillicothe
Wellston
Jackson
Georgetown
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Middletown
Hamilton
Mason
Cincinnati
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Exhibit F

Democratic Amendments to Strigari March 1, 2022 Map

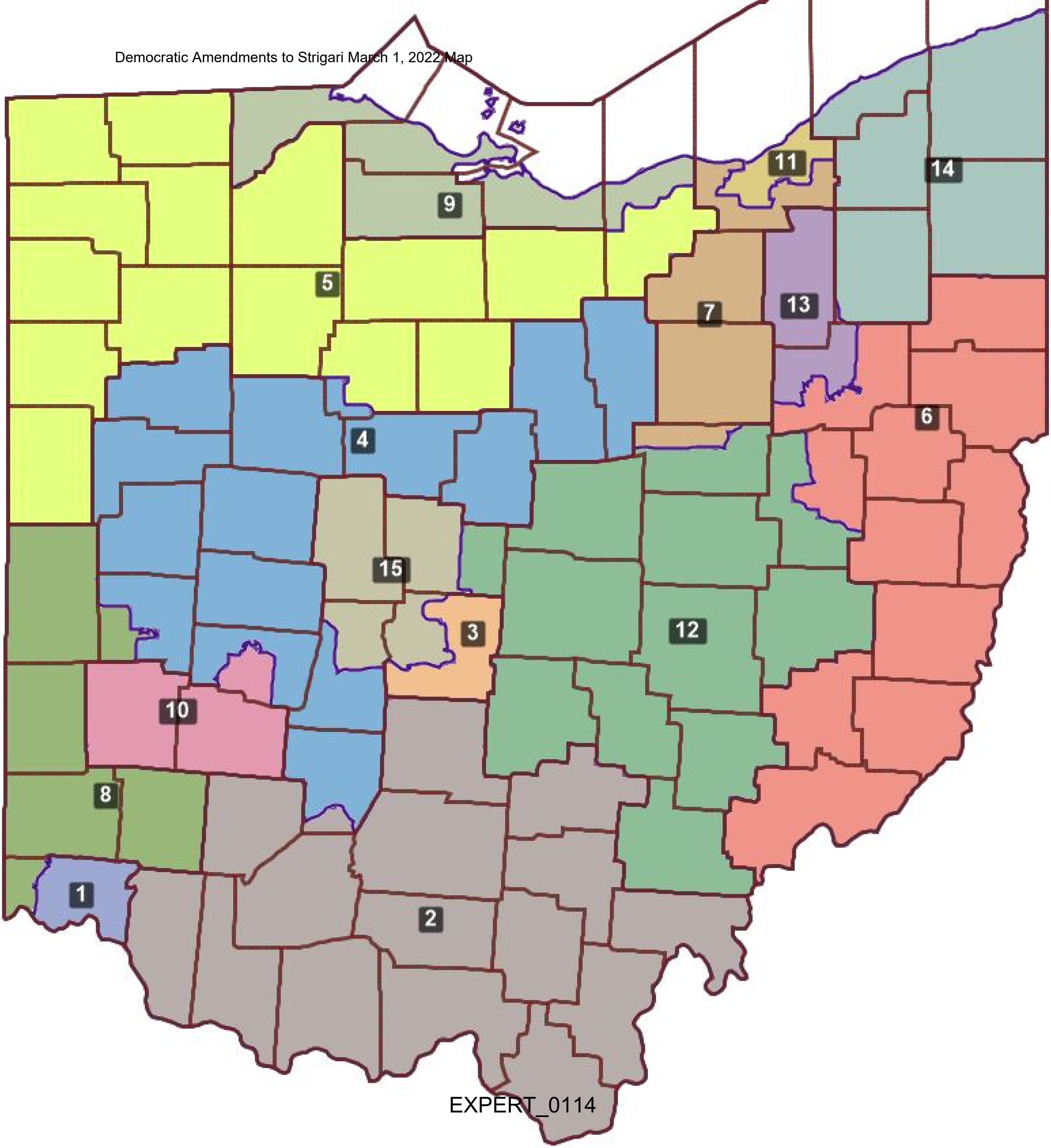

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Exhibit G

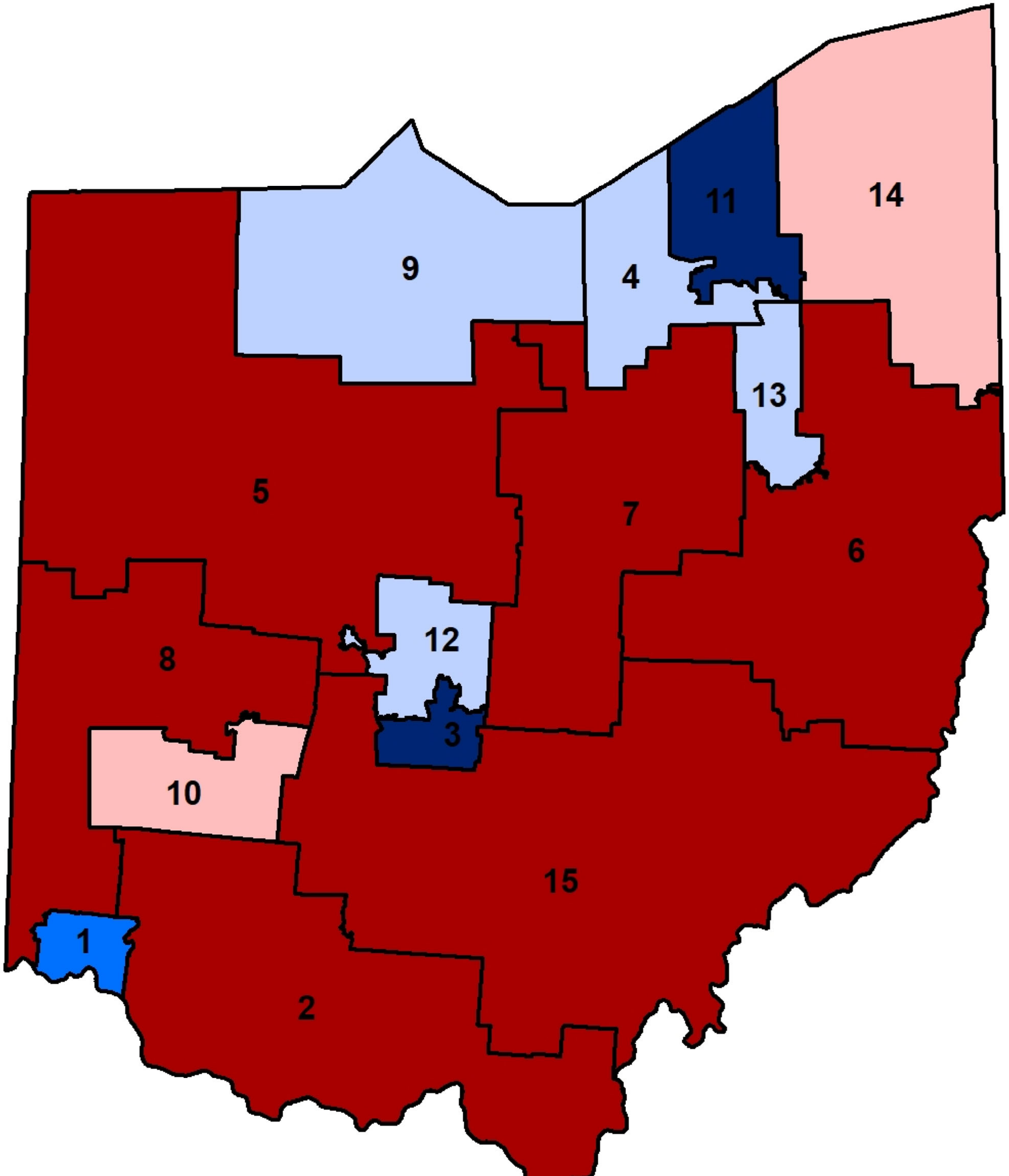
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Exhibit H

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Email: jrodden@stanford.edu
Homepage: http://www.jonathanrodden.com

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.

Peer Reviewed Journal Articles

Who Registers? Village Networks, Household Dynamics, and Voter Registration in Rural Uganda, 2021, *Comparative Political Studies* forthcoming (with Romain Ferrali, Guy Grossman, and Melina Platas).

Partisan Dislocation: A Precinct-Level Measure of Representation and Gerrymandering, 2021, *Political Analysis* forthcoming (with Daryl DeFord Nick Eubank).

Who is my Neighbor? The Spatial Efficiency of Partisanship, 2020, *Statistics and Public Policy* 7(1):87-100 (with Nick Eubank).

Handgun Ownership and Suicide in California, 2020, *New England Journal of Medicine* 382:2220-2229 (with David M. Studdert, Yifan Zhang, Sonja A. Swanson, Lea Prince, Erin E. Holsinger, Matthew J. Spittal, Garen J. Wintemute, and Matthew Miller).

Viral Voting: Social Networks and Political Participation, 2020, *Quarterly Journal of Political Science* (with Nick Eubank, Guy Grossman, and Melina Platas).

It Takes a Village: Peer Effects and Externalities in Technology Adoption, 2020, *American Journal of Political Science* (with Romain Ferrali, Guy Grossman, and Melina Platas). Winner, 2020 Best Conference Paper Award, American Political Science Association Network Section.

Assembly of the LongSHOT Cohort: Public Record Linkage on a Grand Scale, 2019, *Injury Prevention* (with Yifan Zhang, Erin Holsinger, Lea Prince, Sonja Swanson, Matthew Miller, Garen Wintemute, and David Studdert).

Crowdsourcing Accountability: ICT for Service Delivery, 2018, *World Development* 112: 74-87 (with Guy Grossman and Melina Platas).

Geography, Uncertainty, and Polarization, 2018, *Political Science Research and Methods* doi:10.1017/psrm.2018.12 (with Nolan McCarty, Boris Shor, Chris Tausanovitch, and Chris Warshaw).

Handgun Acquisitions in California after Two Mass Shootings, 2017, *Annals of Internal Medicine* 166(10):698-706. (with David Studdert, Yifan Zhang, Rob Hyndman, and Garen Wintemute).

Cutting Through the Thicket: Redistricting Simulations and the Detection of Partisan Gerrymanders, 2015, *Election Law Journal* 14,4:1-15 (with Jowei Chen).

The Achilles Heel of Plurality Systems: Geography and Representation in Multi-Party Democracies, 2015, *American Journal of Political Science* 59,4: 789-805 (with Ernesto Calvo). Winner, Michael Wallerstein Award for best paper in political economy, American Political Science Association.

Why has U.S. Policy Uncertainty Risen Since 1960?, 2014, *American Economic Review: Papers and Proceedings* May 2014 (with Nicholas Bloom, Brandice Canes-Wrone, Scott Baker, and Steven Davis).

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

How Should We Measure District-Level Public Opinion on Individual Issues?, 2012, *Journal of Politics* 74, 1: 203-219 (with Chris Warshaw).

Representation and Redistribution in Federations, 2011, *Proceedings of the National Academy of Sciences* 108, 21:8601-8604 (with Tiberiu Dragu).

Dual Accountability and the Nationalization of Party Competition: Evidence from Four Federatons, 2011, *Party Politics* 17, 5: 629-653 (with Erik Wibbels).

The Geographic Distribution of Political Preferences, 2010, *Annual Review of Political Science* 13: 297–340.

Fiscal Decentralization and the Business Cycle: An Empirical Study of Seven Federations, 2009, *Economics and Politics* 22,1: 37–67 (with Erik Wibbels).

Getting into the Game: Legislative Bargaining, Distributive Politics, and EU Enlargement, 2009, *Public Finance and Management* 9, 4 (with Deniz Aksoy).

The Strength of Issues: Using Multiple Measures to Gauge Preference Stability, Ideological Constraint, and Issue Voting, 2008. *American Political Science Review* 102, 2: 215–232 (with Stephen Ansolabehere and James Snyder).

Does Religion Distract the Poor? Income and Issue Voting Around the World, 2008, *Comparative Political Studies* 41, 4: 437–476 (with Ana Lorena De La O).

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).

Distributive Politics in a Federation: Electoral Strategies, Legislative Bargaining, and Government Coalitions, 2004, *Dados* 47, 3 (with Marta Arretche, in Portuguese).

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).

Reviving Leviathan: Fiscal Federalism and the Growth of Government, 2003, *International Organization* 57 (Fall), 695–729.

Beyond the Fiction of Federalism: Macroeconomic Management in Multi-tiered Systems, 2003, *World Politics* 54, 4 (July): 494–531 (with Erik Wibbels).

The Dilemma of Fiscal Federalism: Grants and Fiscal Performance around the World, 2002, *American Journal of Political Science* 46(3): 670–687.

Strength in Numbers: Representation and Redistribution in the European Union, 2002, *European Union Politics* 3, 2: 151–175.

Does Federalism Preserve Markets? *Virginia Law Review* 83, 7 (with Susan Rose-Ackerman). Spanish version, 1999, in *Quorum* 68.

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.

Market Discipline and U.S. Federalism, 2012, in Peter Conti-Brown and David A. Skeel, Jr., eds, *When States Go Broke: The Origins, Context, and Solutions for the American States in Fiscal Crisis*, Cambridge University Press.

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.

Back to the Future: Endogenous Institutions and Comparative Politics, 2009, in Mark Lichbach and Alan Zuckerman, eds., *Comparative Politics: Rationality, Culture, and Structure* (Second Edition), Cambridge University Press.

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.

Globalization and Fiscal Decentralization, (with Geoffrey Garrett), 2003, in Miles Kahler and David Lake, eds., *Governance in a Global Economy: Political Authority in Transition*, Princeton University Press: 87-109. (Updated version, 2007, in David Cameron, Gustav Ranis, and Annalisa Zinn, eds., *Globalization and Self-Determination: Is the Nation-State under Siege?* Routledge.)

Introduction and Overview (Chapter 1), 2003, in Rodden et al., *Fiscal Decentralization and the Challenge of Hard Budget Constraints* (see above).

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.

On the Migration of Fiscal Sovereignty, 2004, *PS: Political Science and Politics* July, 2004: 427–431.

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

IN THE SUPREME COURT OF OHIO

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

EXHIBITS TO COMPLAINT – VOLUME 2 OF 2

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Counsel for Relators

IN THE SUPREME COURT OF OHIO

Regina Adams, *et al.* **Relators,** **v.** **Governor Mike DeWine, *et al.*** **Respondents.**	**Case No. ______________________** 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.

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 Enacted 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.

3. 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 which has already announced his retirement. All of 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 majority-Democratic districts. The other two districts with Democratic incumbents have been dramatically reconfigured, both now with Republican majorities.

4. 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.

II. QUALIFICATIONS

5. 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.

6. 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."

7. 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.

8. 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.

9. 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

10. 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] Since the General Assembly has not as of this writing made block assignment files or electronic files of its redistricting plan available to the public, I relied upon a block assignment file extracted from a public web archive that creates block assignment files from map images.[3] 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."[4] 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.

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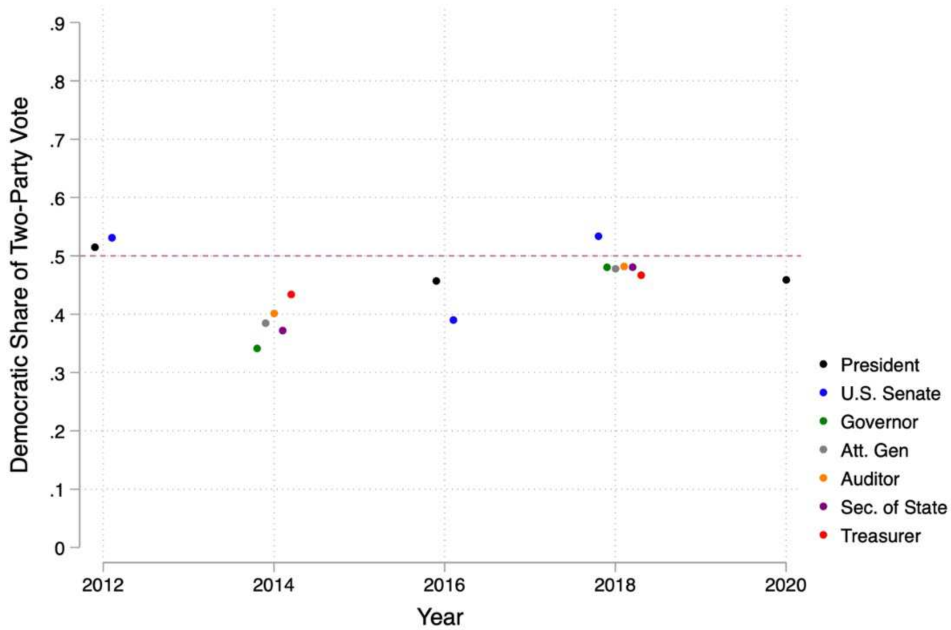
[1] https://alarm-redist.github.io/posts/2021-08-10-census-2020/.
[2] https://redistricting.ohio.gov/maps.
[3] https://davesredistricting.org.
[4] https://www.redistricting.ohio.gov/resources.

congressional districts.[5] I also used geographic boundary files of communities of Columbus, Ohio from the City of Columbus GIS department.[6] For the analysis conducted in this report, I use three software packages: Stata, Maptitude for Redistricting, and ArcGIS Pro.

IV. THE PARTISANSHIP OF THE 2021 CONGRESSIONAL PLAN

11. I have been asked to determine whether the 2021 Congressional Plan favors one of the two parties 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.

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



12. 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.

13. 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 of the statewide general elections from 2012 to 2020, the

[5] https://docs.google.com/spreadsheets/d/17yr9mcAtuUdNjI9NEPYKxXsEldzzQ2ZaDwEAbnPRyS4/edit?pref=2&pli=1#gid=1641247082.
[6] https://opendata.columbus.gov/datasets/c4b483507f374e62bd705450e116e017/explore

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.

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%**

14. Next, in order to gain an initial understanding of which party's candidate is likely to win each seat under the 2021 Congressional Plan, I use precinct-level data from recent elections, and aggregate the results within the district boundaries enacted by the legislature. 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, 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.

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

15. 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.

16. 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.

17. The district-level aggregated statewide election results displayed on the right-hand side of Table 2 are extremely reliable predictors of actual congressional election results. There were five general elections for Ohio's 16 seats 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.

18. If the same pattern continues, and the statewide aggregates continue to perfectly predict congressional outcomes, the Democrats can anticipate winning only 3 of 15 seats throughout the decade. 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.[7]

19. 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. 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.

20. Based on the statewide vote shares in Table 2, without any consideration of incumbency, one might get the mistaken impression that there are additional "competitive" seats in the Enacted Plan. Above all, one might imagine that District 1, with its roughly 52 percent Republican vote share, is a competitive seat. However, note that in the previous cycle the district had a slightly higher 54 percent Republican vote share in statewide races. The incumbent, Steve Chabot, very consistently outperformed his party's district vote share in statewide races, winning easily with, on average, around 58 percent of the vote. In other words, Representative Chabot enjoyed an incumbency advantage of around four percentage points. Much of the district remains unchanged, including parts of Cincinnati, its western suburbs, and Warren County, so there is no reason to anticipate that this advantage will suddenly disappear.

21. The remaining seats are even less competitive. For instance, the Republican vote share in statewide races 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. Once again, as with District 1, the incumbent enjoyed a sizable incumbency advantage, and again, there is no reason to anticipate that it will suddenly disappear. One simply cannot characterize District 10 in the Enacted Plan as competitive. The same can be said about

[7] 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.

Districts 14 and 15—districts with Republican incumbents where the Republican vote share hovers around 54 percent.

V. PUTTING THE 2021 CONGRESSIONAL PLAN IN PERSPECTIVE

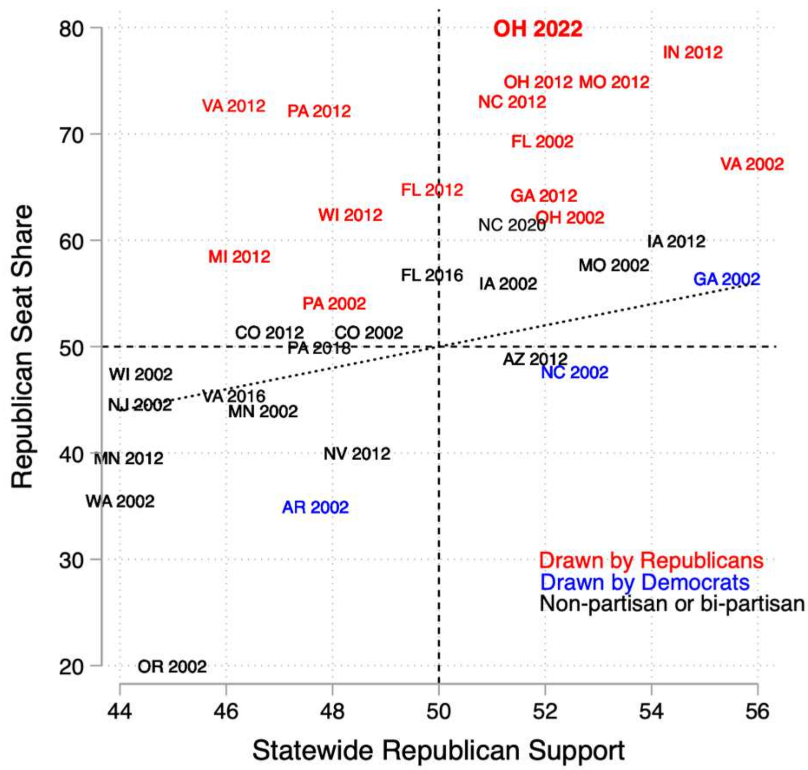
22. In any two-party democracy, it is not normal for a party with an average of 53.2 percent of the vote to receive 80 percent of the seats. In fact, even in the United States, which has maintained the idiosyncratic practice of allowing incumbent partisan majorities to draw their own districts without 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.[8] Next, for each redistricting cycle, I calculate the share of all congressional seats won by Republican candidates.

23. In Figure 2, 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.[9] 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 2, in order to focus on states most similar to Ohio and facilitate legibility, I zoom in on a group of the most evenly divided states, where statewide partisanship is between 44 and 56 percent. I also include a graph that includes all the states in the appendix.

[8] 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 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.

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

Figure 2: Vote Shares in Statewide Elections and Seat Shares in Congressional Elections, Evenly Divided States With Four or More Districts, 2000 and 2020 Redistricting Cycles



24. For the most part, districts drawn by courts, divided legislatures, and independent commissions come closer to proportionality than those drawn by legislators. 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 2. 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 2, 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.

25. 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 data marker titled "Ohio 2022" is the anticipated seat share, calculated as described above at 80 percent, for the 2021 Congressional Plan.

26. As can be visualized in Figure 2, 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.[10]

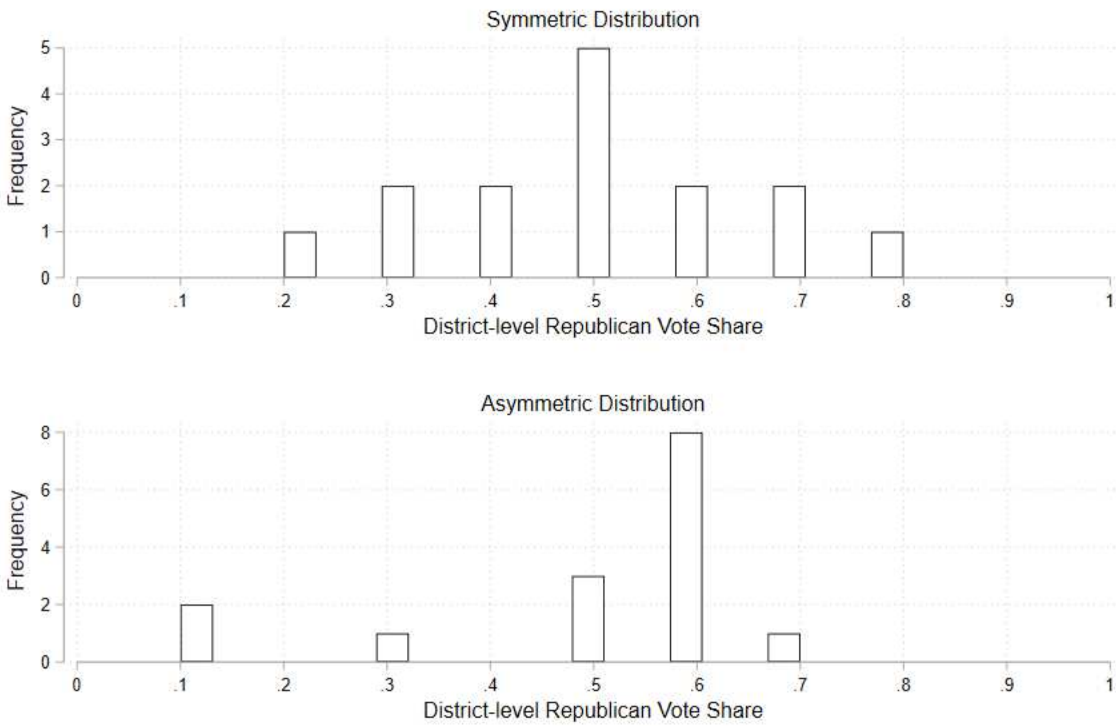
27. When attempting to assess the impact of a redistricting plan on the relative advantage or disadvantage it provides to the parties, it is important to go beyond simply calculating the difference between a party's statewide support and its seat share. For many realistic scenarios in which partisans are distributed across districts without political manipulation of the district 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 3 below.

Table 3: 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

[10] 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.

Figure 3: Distribution of Vote Shares Across Districts in Two Redistricting Plans in Hypothetical State

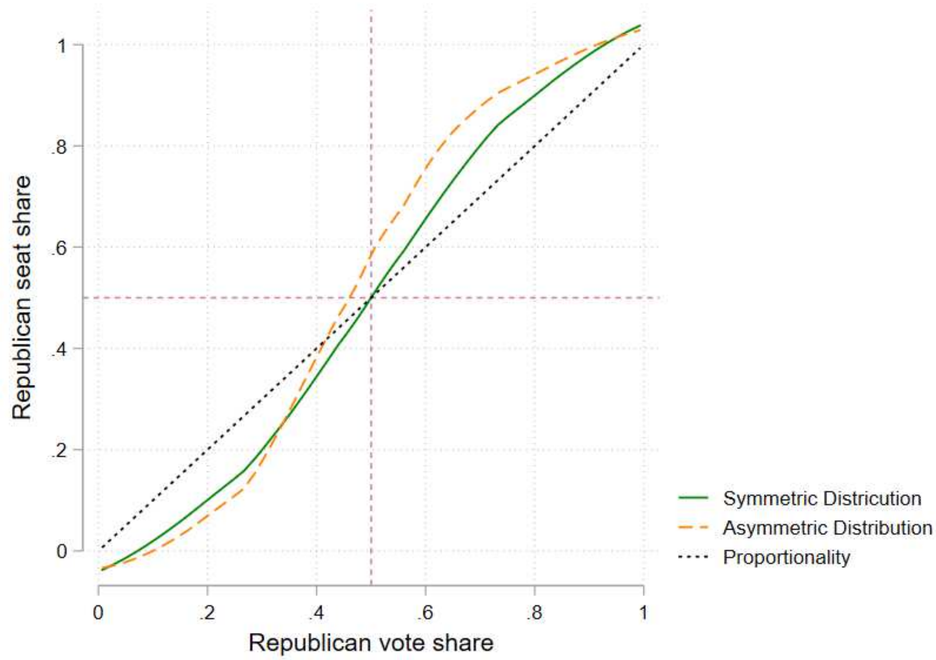


28. In this example, there are 75 Democrats and 75 Republicans. Under normal circumstances, each party can expect to win 5 districts, but 5 districts are toss-ups containing even numbers of Democrats and Republicans.

29. The top panel of Figure 3 uses a histogram—a simple visual display of the data from Table 3—to display the distribution of expected vote shares of the parties across districts in this hypothetical state, with its symmetric distribution of partisanship.

30. 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.

Figure 4: Hypothetical symmetric vote-seat curve



31. How do these alternative scenarios affect the seat share? The result of these simulated scenarios is displayed with the green line in Figure 4. 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.

32. The green line in Figure 4 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 4. 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.

33. 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 4, 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.

34. 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 by the Republican Party. In this example, provided numerically on the right-hand side of Table 3 (labeled as "Example 2"), and visually with a histogram in the lower panel of Figure 3, 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.

35. 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 4. 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.

36. 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.[11] 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).

37. More recently, Nicholas Stephanopoulos and Eric McGhee have adapted this concept to the context of redistricting and gerrymandering in the United States.[12] 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

[11] Ron Johnston. 2002. "Manipulating Maps and Winning Elections: Measuring the Impact of Malapportionment and Gerrymandering." *Political Geography* 21: pages 1-31.
[12] See Nicholas Stephanopoulos and Eric McGhee. 2015. "Partisan Gerrymandering and the Efficiency Gap." *University of Chicago Law Review* 82,831.

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, 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.

Table 4: 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

38. Table 4 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.

39. 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.

40. 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 3.

41. 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 2 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.

42. 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.

43. 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.[13]

44. In addition to the efficiency gap, another approach to measuring partisan asymmetry is to calculate so-called electoral bias.[14] This approach flows directly from the vote-seat curves in

[13] 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.

[14] 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 4 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.

45. 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 4 above: a 50 percent vote share on the horizontal axis corresponds to a 60 percent seat share on the vertical axis.

46. 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.

47. 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 affidavit 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.[15]

48. 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.

[15] 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.

49. In any case, whether we pursue 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?

50. 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.

51. 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 supposedly 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.[16]

52. The legislature has redrawn District 1 to include many of the suburban and rural areas that had previously been in 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.

53. In all the other districts with Republican incumbents, safe margins have been maintained so that incumbents are likely to survive even a significant statewide swing toward the

[16] 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.

Democratic Party.

54. 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 Marcy 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. Tim Ryan, who has announced that he is running for the U.S. Senate, was the incumbent in District 13, which has been completely reconfigured as a predominantly rural, safe Republican district in the Enacted Plan.

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

55. 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 higher proportions of votes for more progressive candidates.[17] 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 3 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.

56. However, the larger implication 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, 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

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

single district as possible. The legislature has pursued each of these strategies to prevent the emergence of majority-Democratic districts in Ohio.

57. 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 Republicans far more than anything that can be explained by residential geography alone. Recall the striking difference between the black and red data markers in Figure 2 above, indicating that with similar levels of partisanship, districts drawn by Republican legislators 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.[18]

58. In order to verify that the extreme pro-Republican bias described above was not forced upon the legislature by the Ohio Constitution or residential geography of Ohio, it is useful to conduct a simple exercise: we can examine the congressional maps submitted by Democrats and other groups in 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 their map and, if they comply with the Constitution, 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.

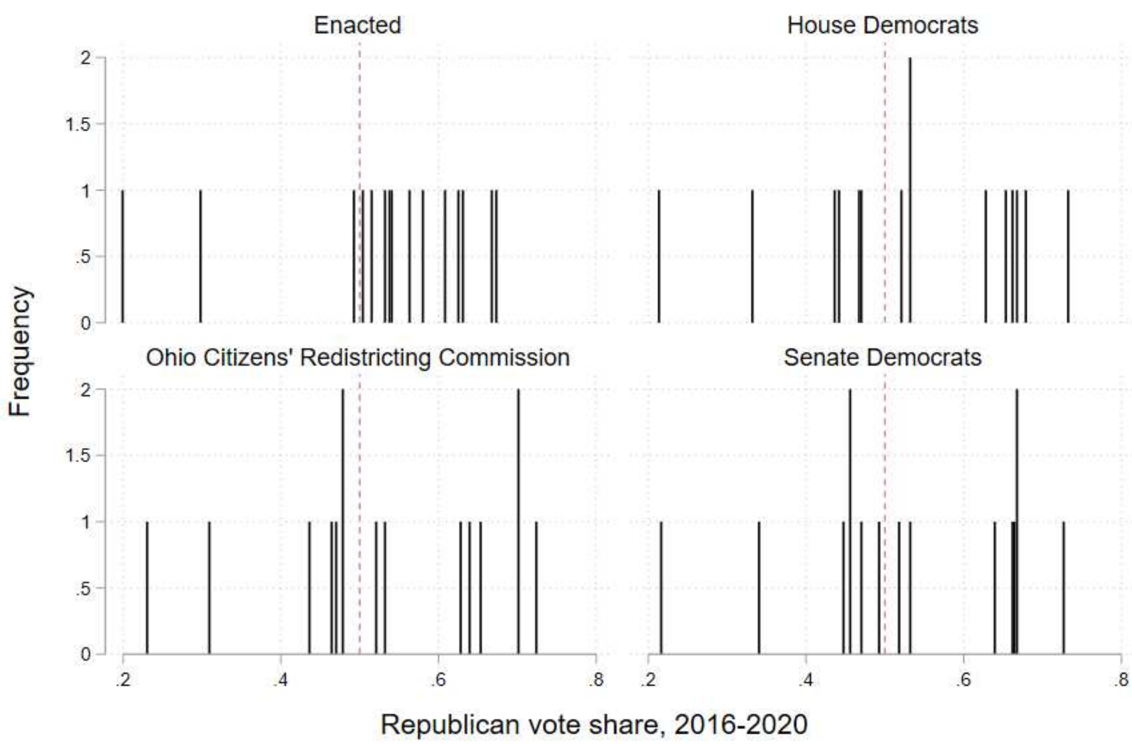
59. Figure 5 provides histograms of the composite vote share of statewide Republican candidates from 2016 to 2020—the same measure used extensively above—aggregated to boundaries of proposed congressional districts. The top left panel represents the enacted districts. The panels on the right represent districts proposed by the House (top) and Senate (bottom) Democrats, attached as Exhibits C and B, respectively. In the lower left-hand corner, I include a districting plan submitted by a group called the Ohio Citizens Redistricting Committee (OCRC), attached as Exhibit D.

60. Note that all the graphs 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

[18] 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.

1 above), while the House plan falls short by one seat. In other words, if these maps were included in Figure 3 above, they would be on, or slightly below, the dotted line of proportionality, much like the court-drawn maps in Figure 3.

Figure 5: Histograms of Enacted and Alternative Maps



61. 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. In all, it is a textbook case of a map that creates an extremely efficient distribution of support for one party and an inefficient distribution 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.

62. What accounts for these large differences in the efficiency of support for the two parties in the different maps? Above all, the answer lies in the treatment of urban areas.

63. 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, like North College Hill and Mount Healthy, 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.

Figure 6: Partisanship and the Enacted Plan's Districts, Hamilton County and Surroundings

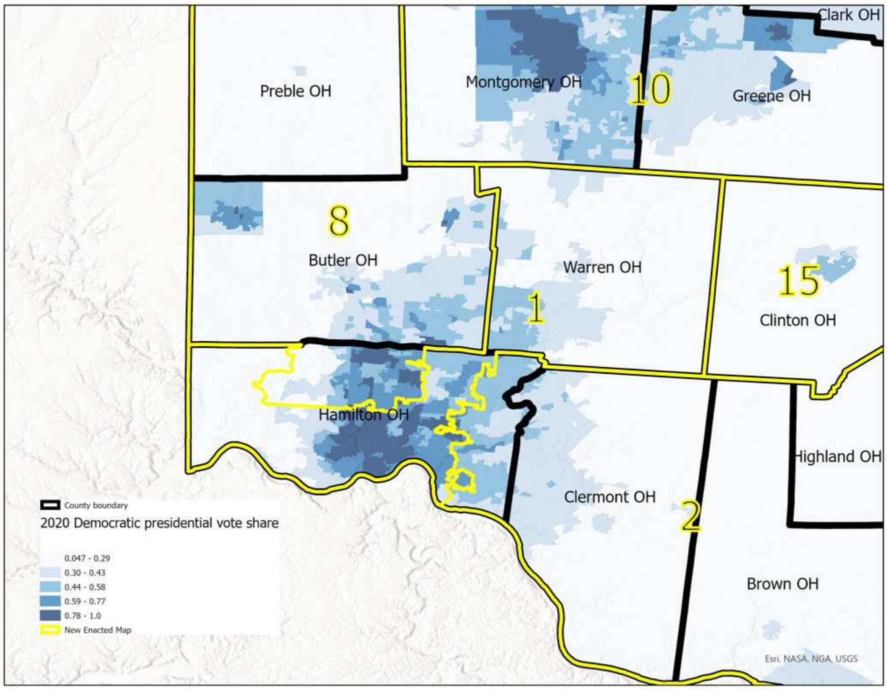
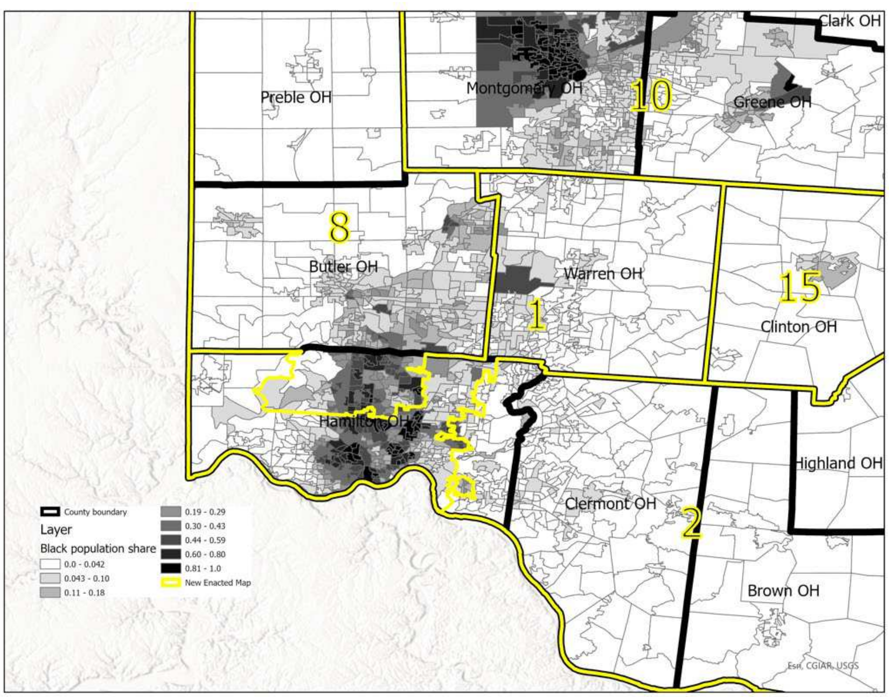


Figure 7: Race and the Enacted Plan's Districts, Hamilton County and Surroundings



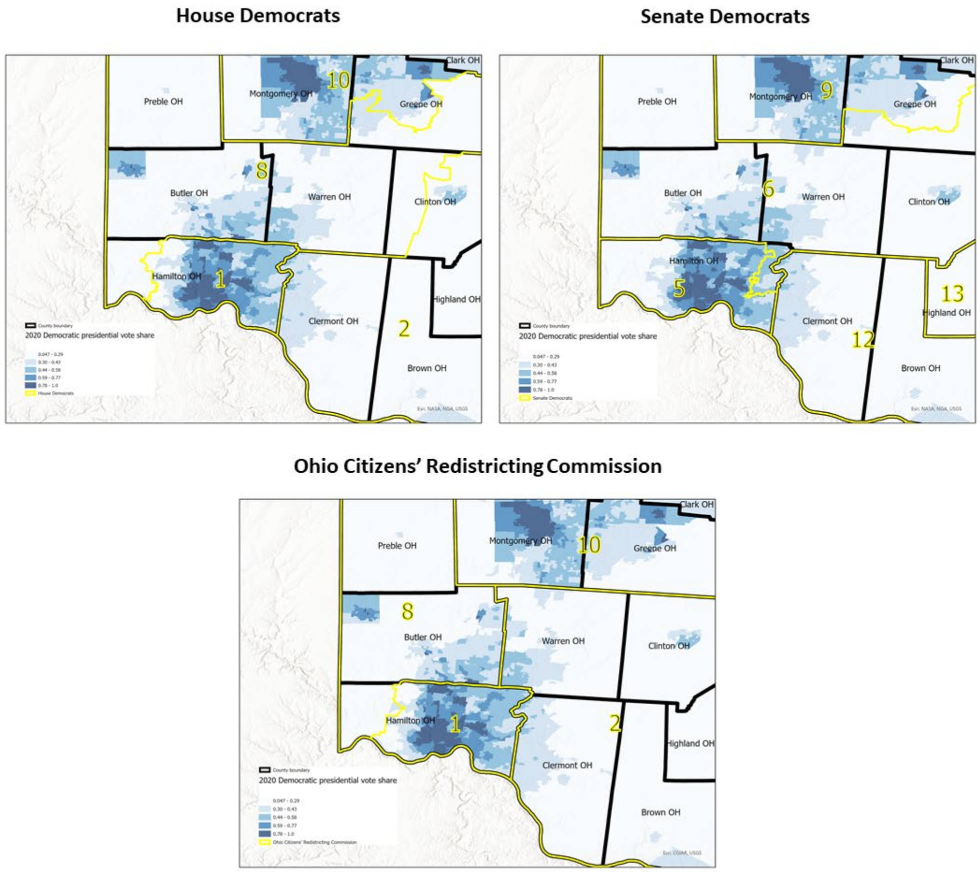
64. However, the Enacted Plan traverses the Hamilton County boundary in *three* different places in order to overwhelm Cincinnati's Democratic population with a sufficient number of exurban and rural Republicans. The entire urban, Black population of Northern Hamilton County is carved out from its urban surroundings and combined with a rural Republican district, District 8, whose northern boundary is 85 miles away. Second, instead of being combined with its immediate inner-ring suburbs, Cincinnati is combined with rural Warren County via a very narrow corridor in District 1. Finally, Cincinnati's eastern suburbs are extracted and combined with District 2, which is extremely rural and Republican.

65. This can be visualized in Figure 6, which overlays the Enacted Plan on a map of partisanship, from precinct-level results of the 2020 presidential election. Figure 7 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.

66. 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.

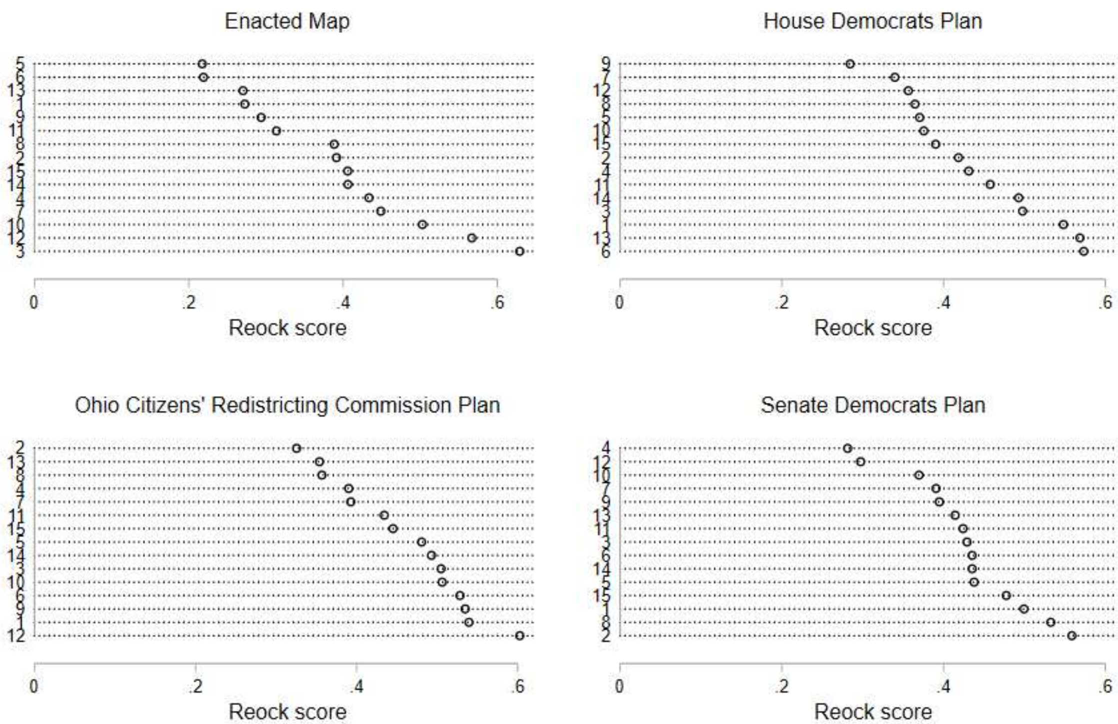
67. The arrangement of these plans can be seen in Figure 8. Clearly, it is quite straightforward to draw a district that is compact, minimizes splits, and keeps the Black community together. Notably, these arrangements all produce a majority-Democratic district (56.5 percent for the House Democrats' plan, 55.4 percent for the Senate Democrats' plan, and 56.4 percent for the OCRC plan).

Figure 8: Partisanship and Districts of Alternative Plans, Hamilton County and Surroundings



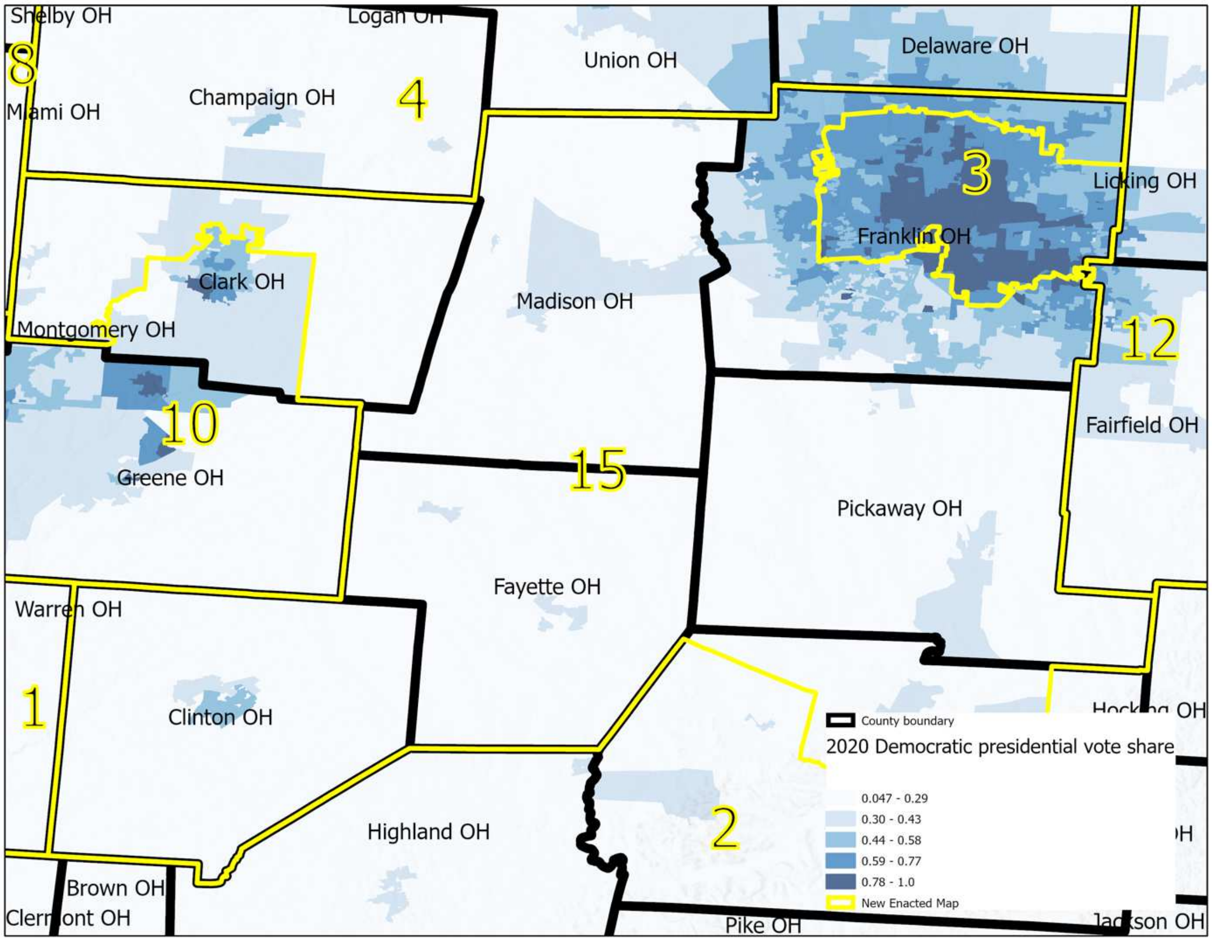
68. These alternative plans are also more compact than the Enacted Plan, both in the areas in and around Hamilton County and (as discussed below) plan-wide. Higher Reock score values indicate greater compactness. The Reock score for the General Assembly's District 1 was .27. The Reock score for District 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 9 below.

Figure 9: Reock Scores for Enacted and Alternative Plans



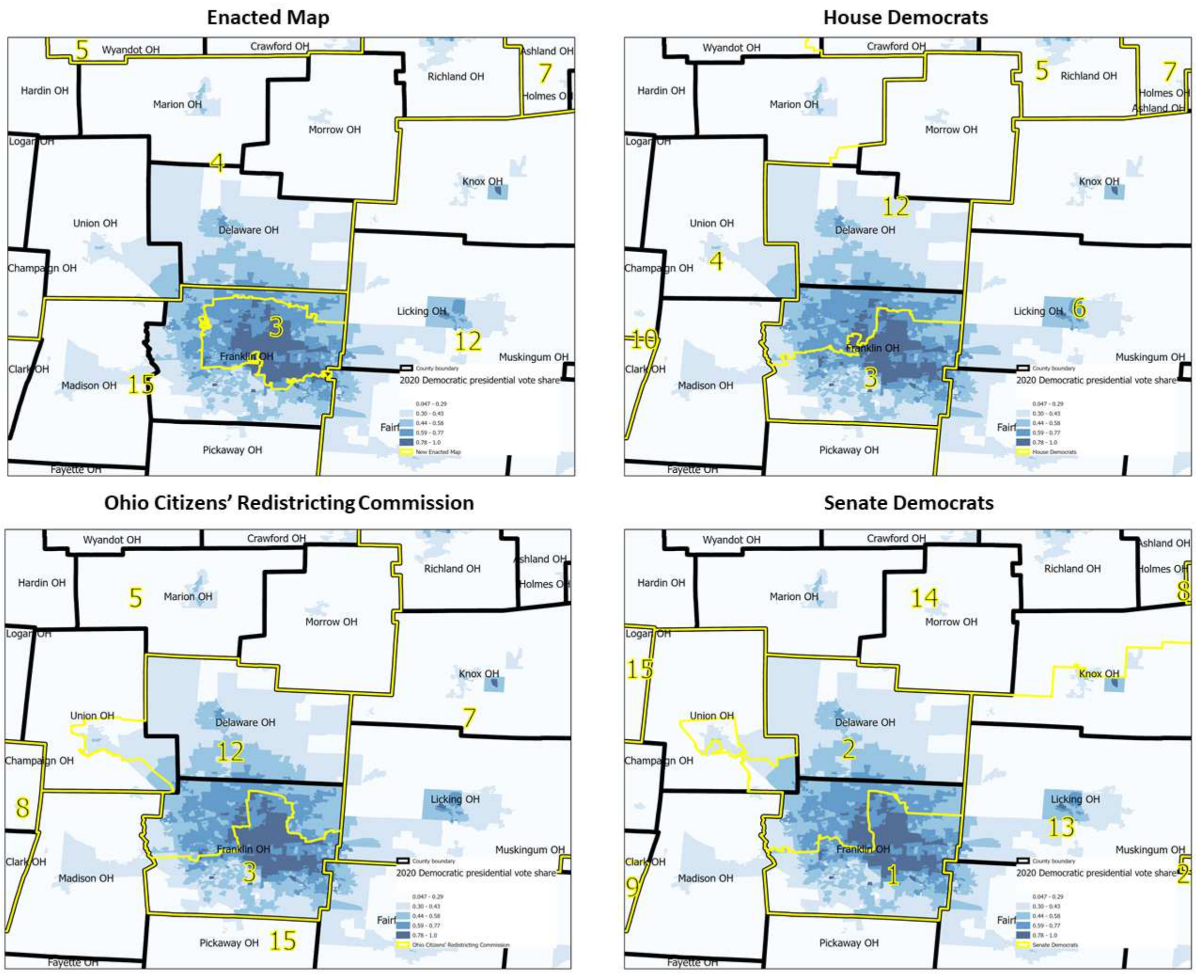
69. Next, consider the Columbus area in Franklin County. The city of Columbus is larger than a unit of congressional representation, so it must be split. In Cincinnati, it was possible to maneuver to avoid the creation of a Democratic district that would have otherwise emerged. But in Columbus, the number of Democratic voters was simply too large to pursue that strategy. 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 10).

Figure 10: Partisanship and Enacted Districts, Columbus and Surroundings



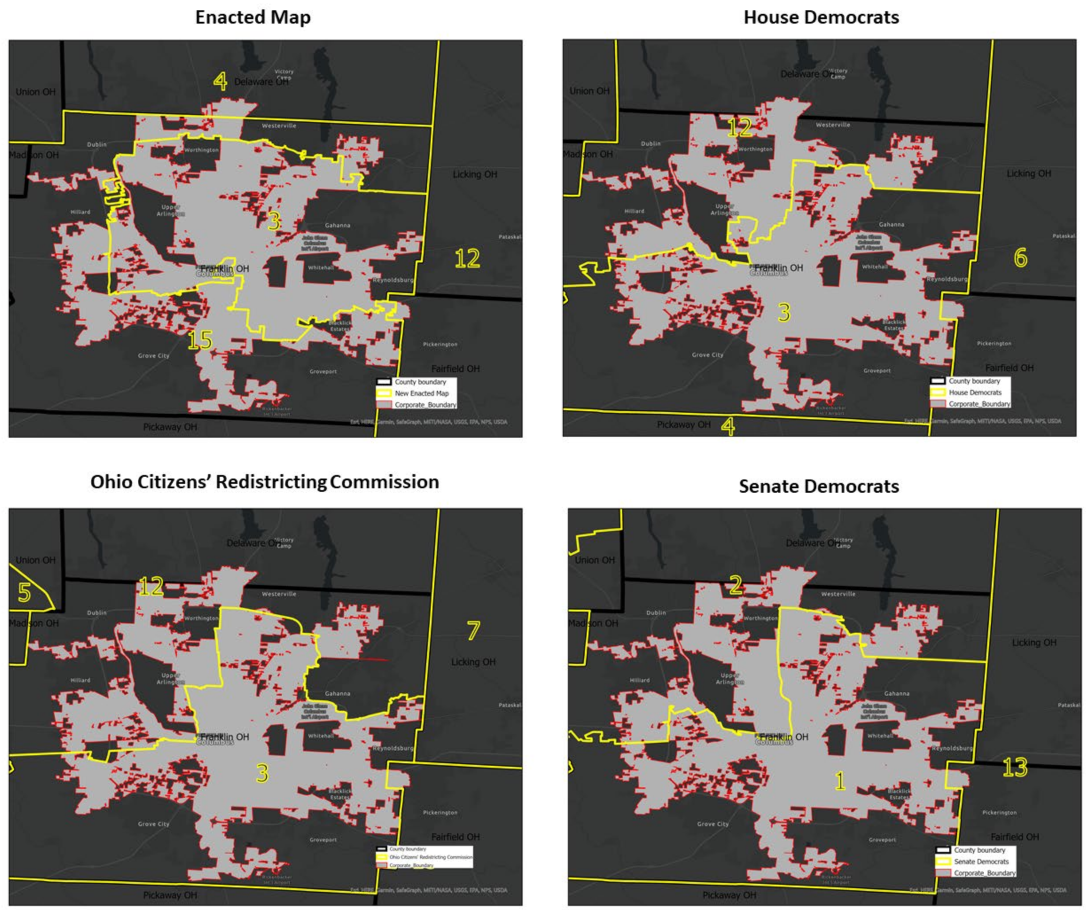
70. In contrast, the alternative plans split Columbus with a line that runs from west to east (see Figure 11). This arrangement creates a compact southern Columbus district that includes much of the city and its southern suburbs, and a relatively compact northern Columbus district that is able to include all of 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 11: Partisanship and Enacted and Alternative Districts, Columbus and Surroundings



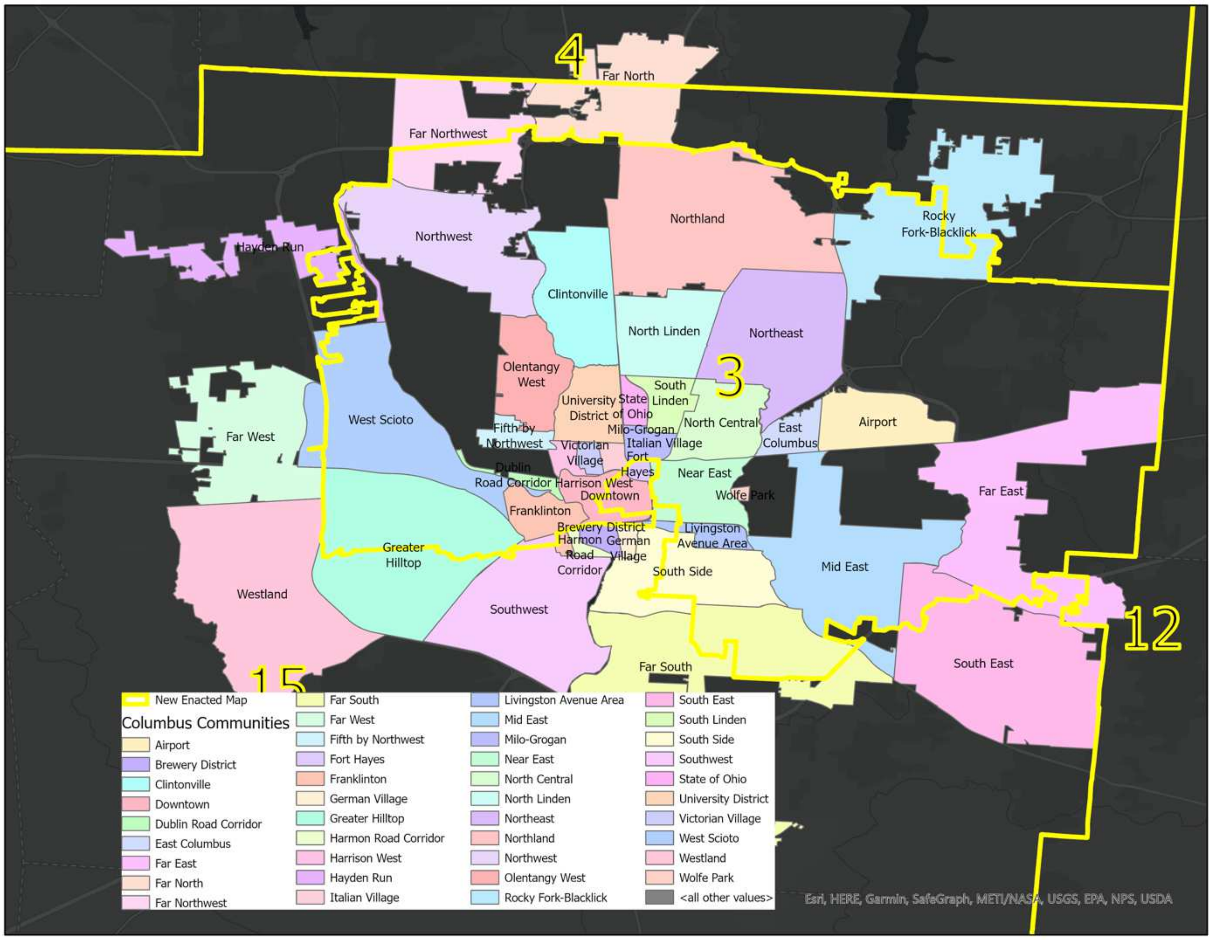
71. The Enacted Plan produces several non-contiguous chunks of Columbus that are removed from the city and placed in largely rural District 15. Figure 12 features the Columbus Corporate Boundary and its interaction with the Enacted Plan as well as the alternative plans. In the Enacted Plan, there are 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 12: The Boundary of the City of Columbus and Boundaries of the Enacted Plan and Alternative Plans



72. 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 13 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.

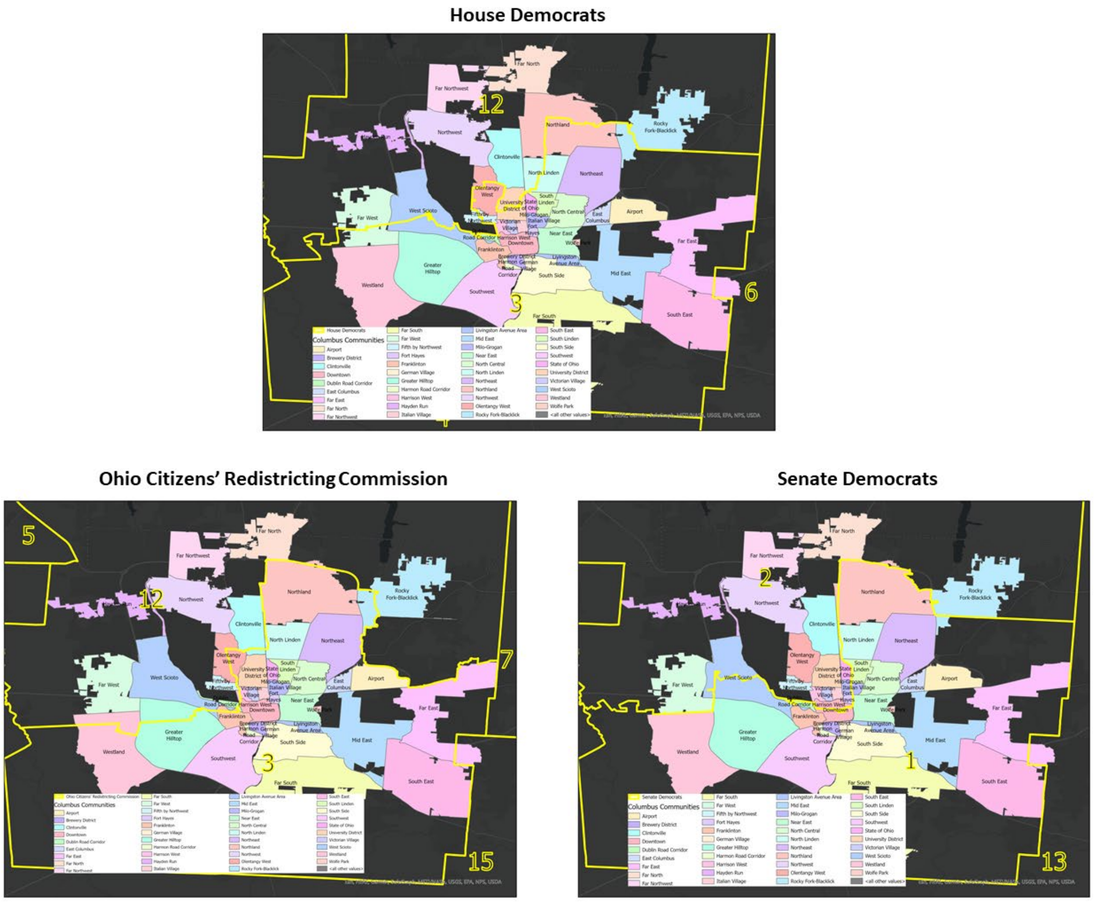
Figure 13: The Boundary of the Communities of the City of Columbus and Boundaries of the Enacted Plan



73. 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 14).[19]

[19] 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 14: The Boundary of the Communities of the City of Columbus and Boundaries of the Alternative Plans



74. 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 15 and 16).

Figure 15: Partisanship and the Boundaries of the Enacted Plan, Northeast Ohio

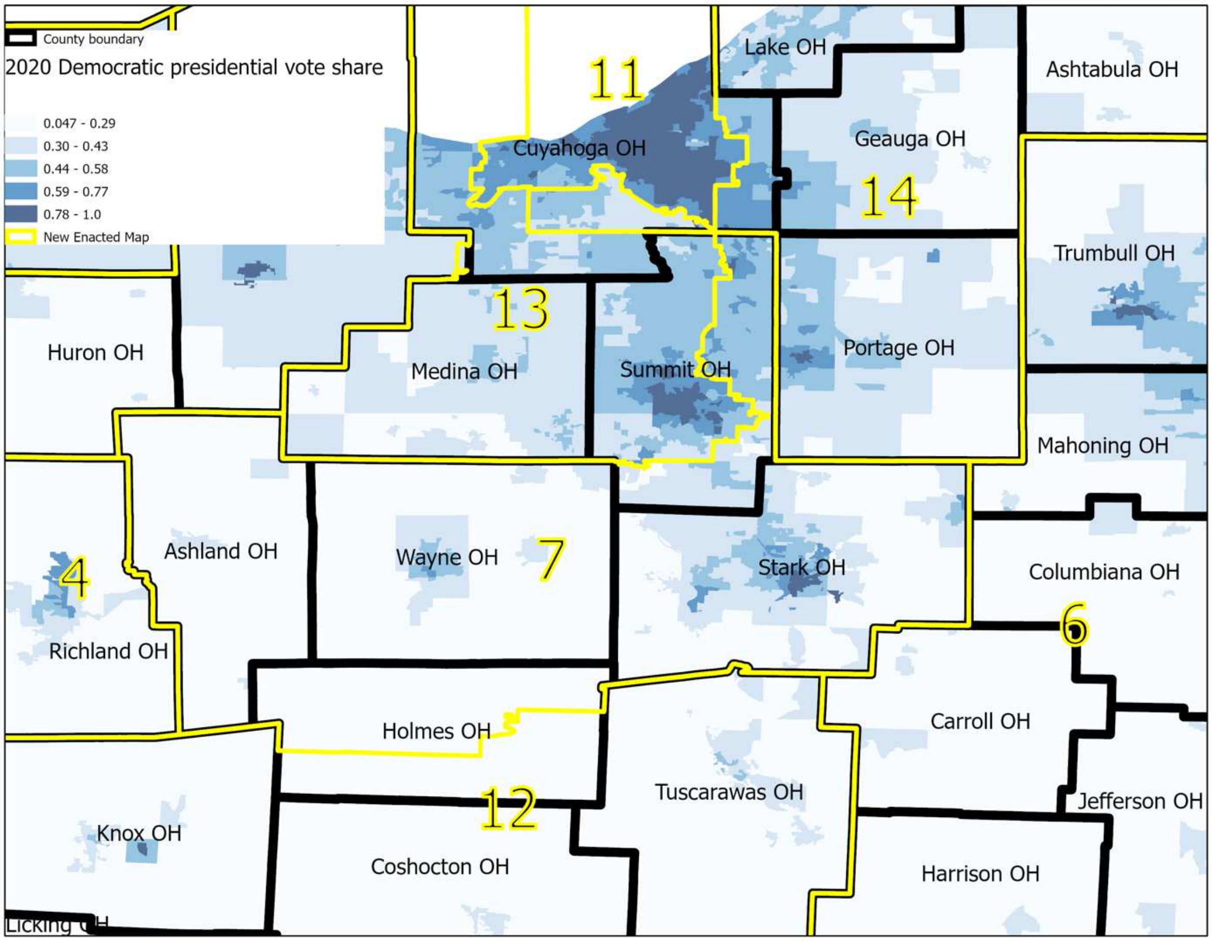
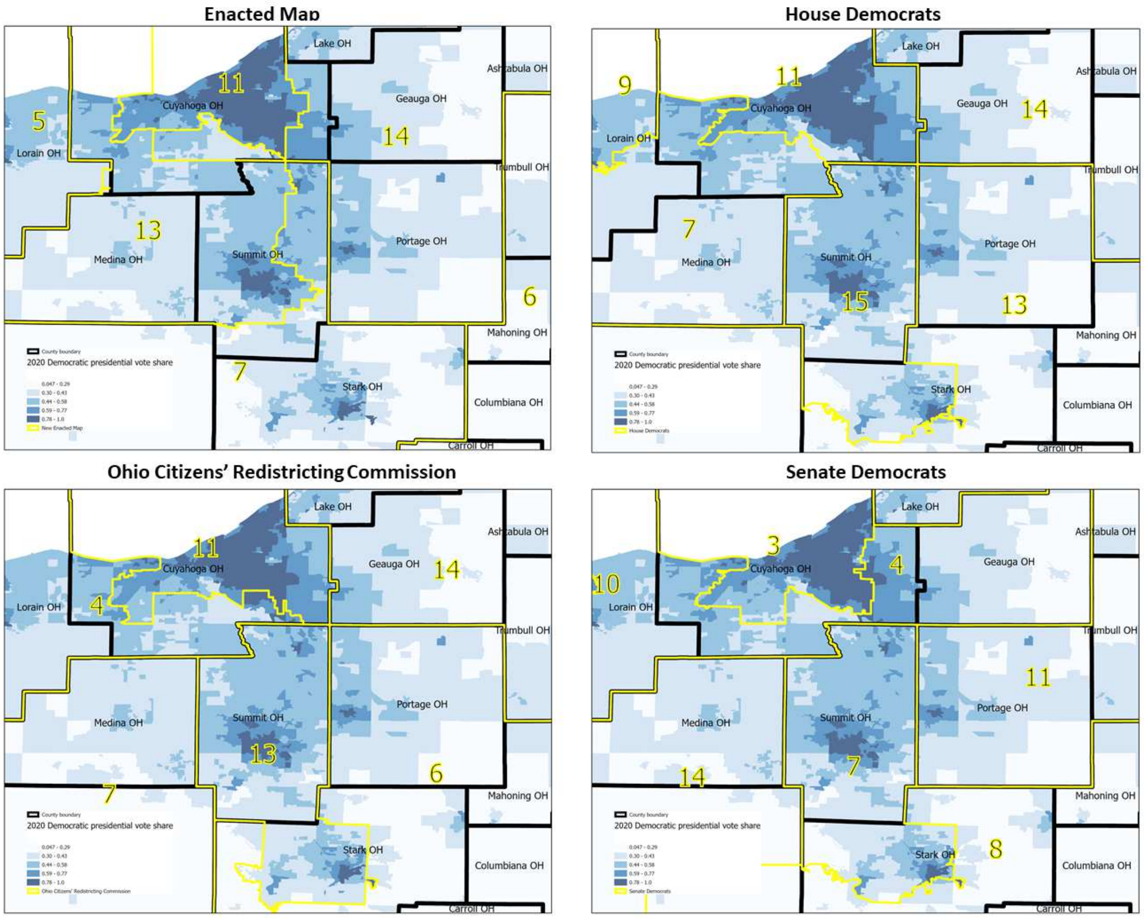


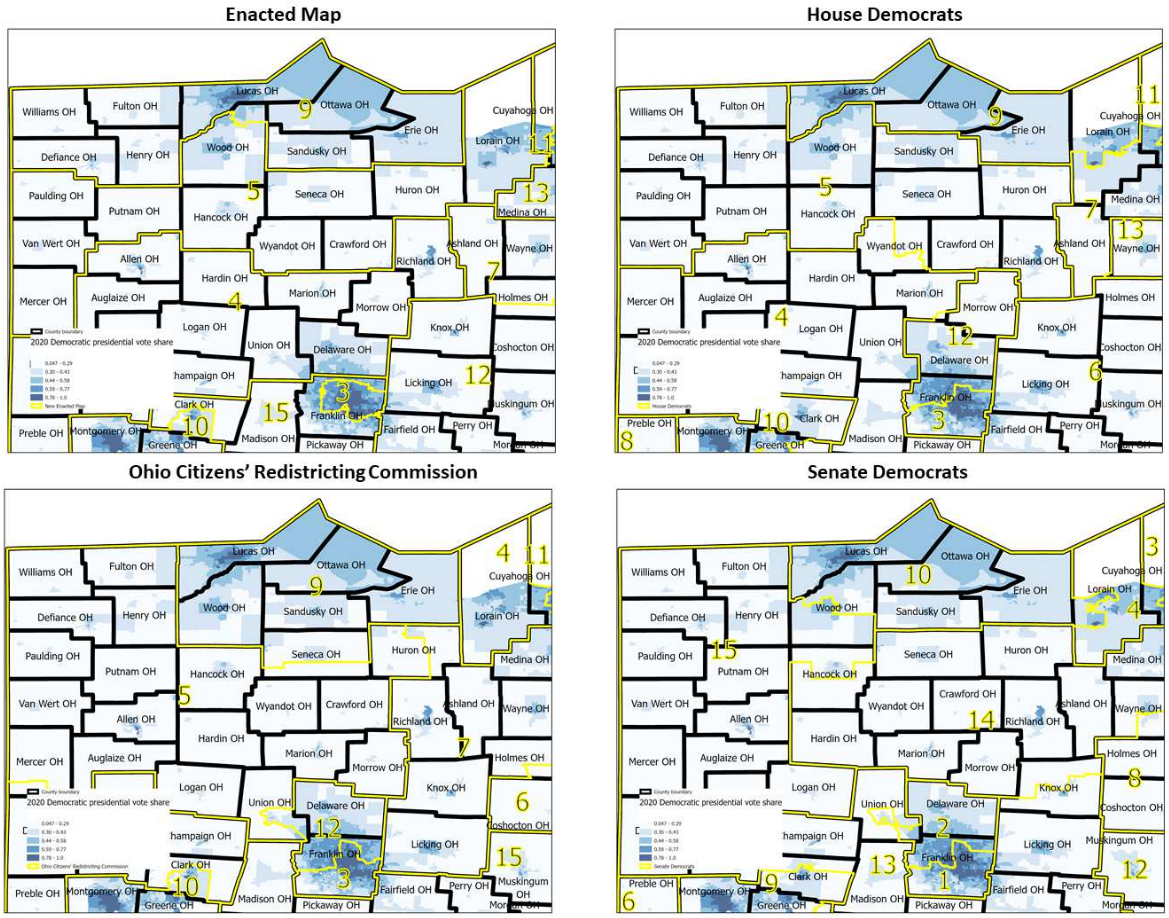
Figure 16: Partisanship and the Boundaries of the Enacted and Alternative Plans, Northeast Ohio



75. 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 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.

76. Finally, consider Northwest Ohio. The Enacted plan and the three alternative plans are depicted in Figure 17. 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 to the Western 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 the Indiana border.

Figure 17: Partisanship and the Boundaries of the Enacted and Alternative Plans, Northwest Ohio



77. 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.

78. 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.

79. 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.

80. 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 any townships, while producing 15 city splits. 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.

81. 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 5. 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.

Table 5: 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

82. As described above, and as explained further elsewhere,[20] 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

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

non-compact districts are forced upon district-drawers by natural geography and the specific rules governing the redistricting process in a state.

83. For this reason, one should approach average, plan-wide compactness scores like those in Table 5 with caution—especially for cross-state comparisons. However, the discussion above demonstrates that the extreme favorability of the General Assembly's maps 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.

VIII. CONCLUSION

84. 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 that 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 General Assembly sacrificed compactness, introduced unnecessary splits to urban counties, and divided a number of urban and suburban communities, including minority communities, throughout the state.

85. I have read the Complaint filed in this action and affirm that the factual allegations contained in paragraphs 2, 4, 13, 14, 61, 98-100, 116-24, and 126-30 are true.

Jonathan Rodden

Jonathan Rodden

Sworn to before me this 22nd day of November 2021.

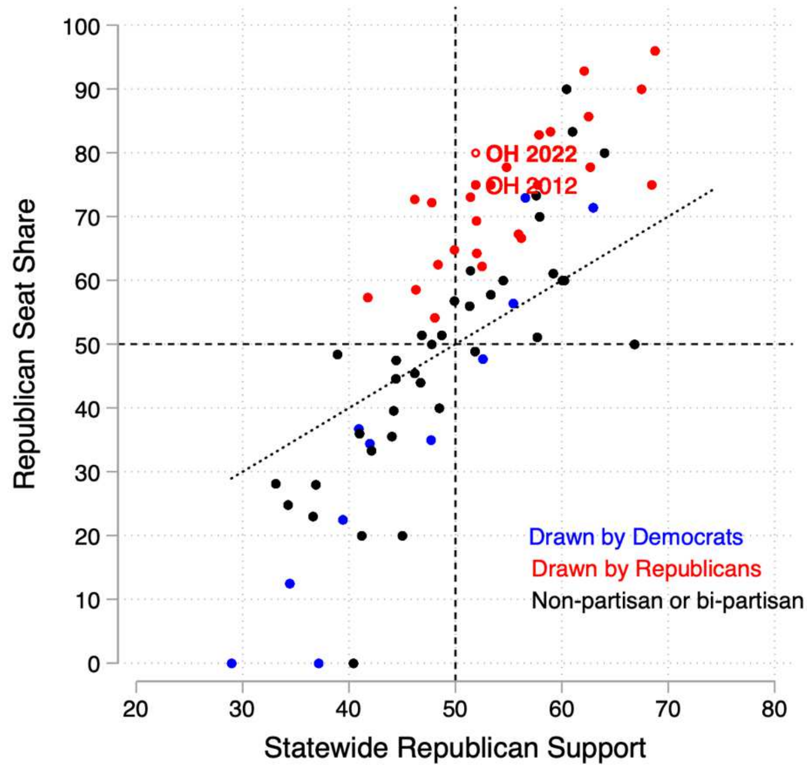
(See Attached Notarize.com Certificate for Notarization)

Notary Public

My commission expires 06/03/2025

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)
Marysville City, Union County
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, Elyria 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: 15, all cities.

House Democratic Plan

Mack CDP, also splits Green Township, Hamilton County; only count once as Township split
Union Township, Clinton County
Liberty Township, Clinton County
Buckskin Township, Ross County
Concord Township, Ross County
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
Lake Township, Ashland County
Seven Hills City, Cuyahoga County
North Ridgeville City, Lorain County
Beavercreek City, Greene County
Canton Township, Stark County
Poland Township, Mahoning County

Total splits: 19 total splits, 13 are townships

Ohio Citizens Redistricting Commission Plan

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

JURAT

State/Commonwealth of _____ TEXAS _____)
)
☐ City ☑ County of _____ Comal _____)

On ___ 11/22/2021 ___, before me, _____ Lauren Peterson _____ ,
Date *Notary Name*

the foregoing instrument was subscribed and sworn (or affirmed) before me by:

_____ Jonathan Rodden _____.
Name of Affiant(s)

☐ Personally known to me **-- OR --**

☐ Proved to me on the basis of the oath of _____ N/A _____ **-- OR --**
Name of Credible Witness

☑ Proved to me on the basis of satisfactory evidence: _____ driver_license _____
Type of ID Presented

NOTARY PUBLIC
STATE OF TEXAS
Lauren Peterson
ID NUMBER
12499352-4
COMMISSION EXPIRES
June 3, 2025

WITNESS my hand and official seal. Lauren Peterson

Notary Public Signature: _____

Notary Name: _____ Lauren Peterson _____
Notary Commission Number: __ 12499352-4 __
Notary Commission Expires: __ 06/03/2025 __
Notarized online using audio-video communication

DESCRIPTION OF ATTACHED DOCUMENT

Title or Type of Document: _ Ohio Congressional Redistricting- Expert Affidavit ___

Document Date: _____ 11/22/2021 _____

Number of Pages (including notarial certificate): ___ 39 ___

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Exhibit A

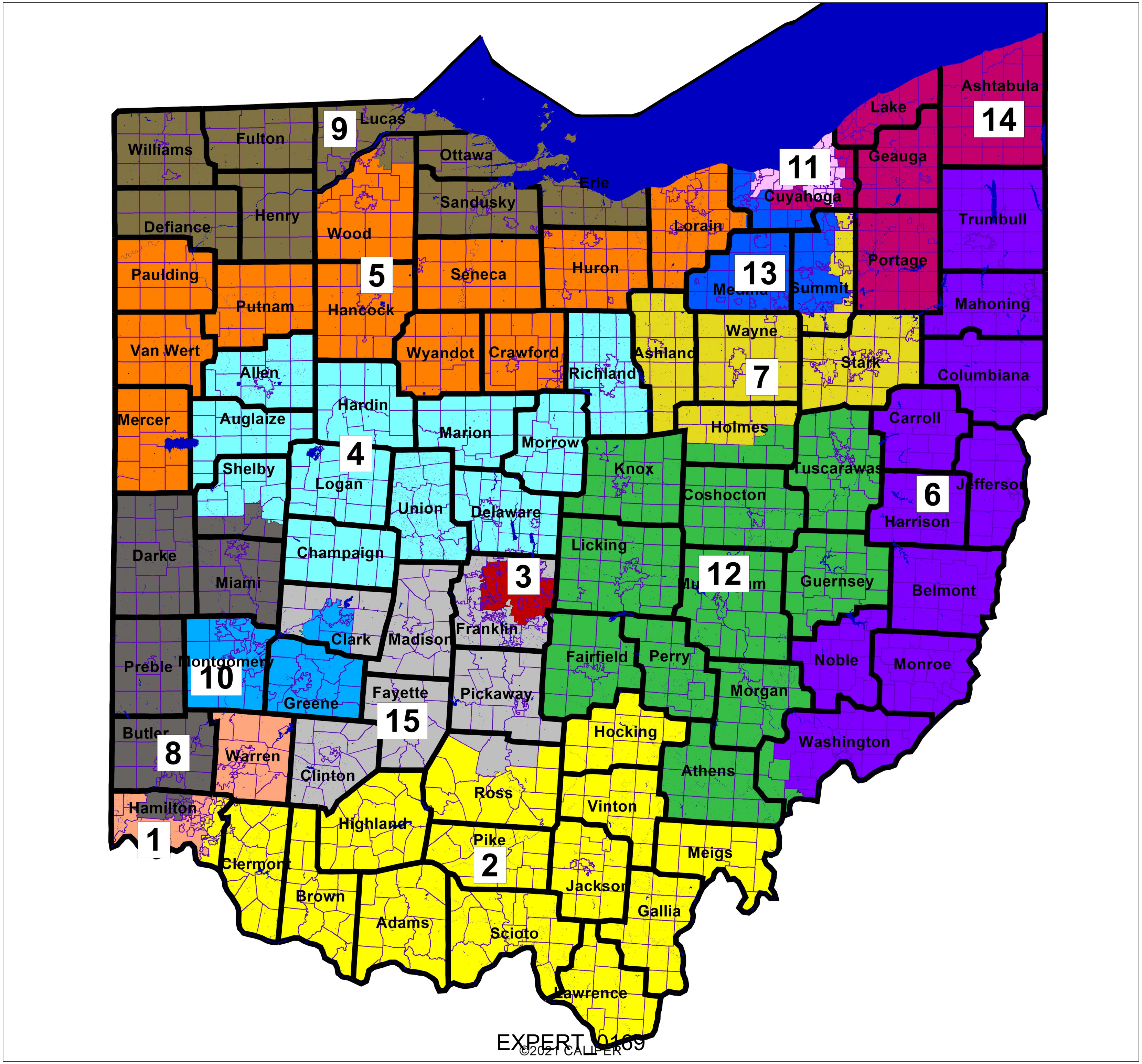

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Exhibit B

Proposed Sub SB 237 Map

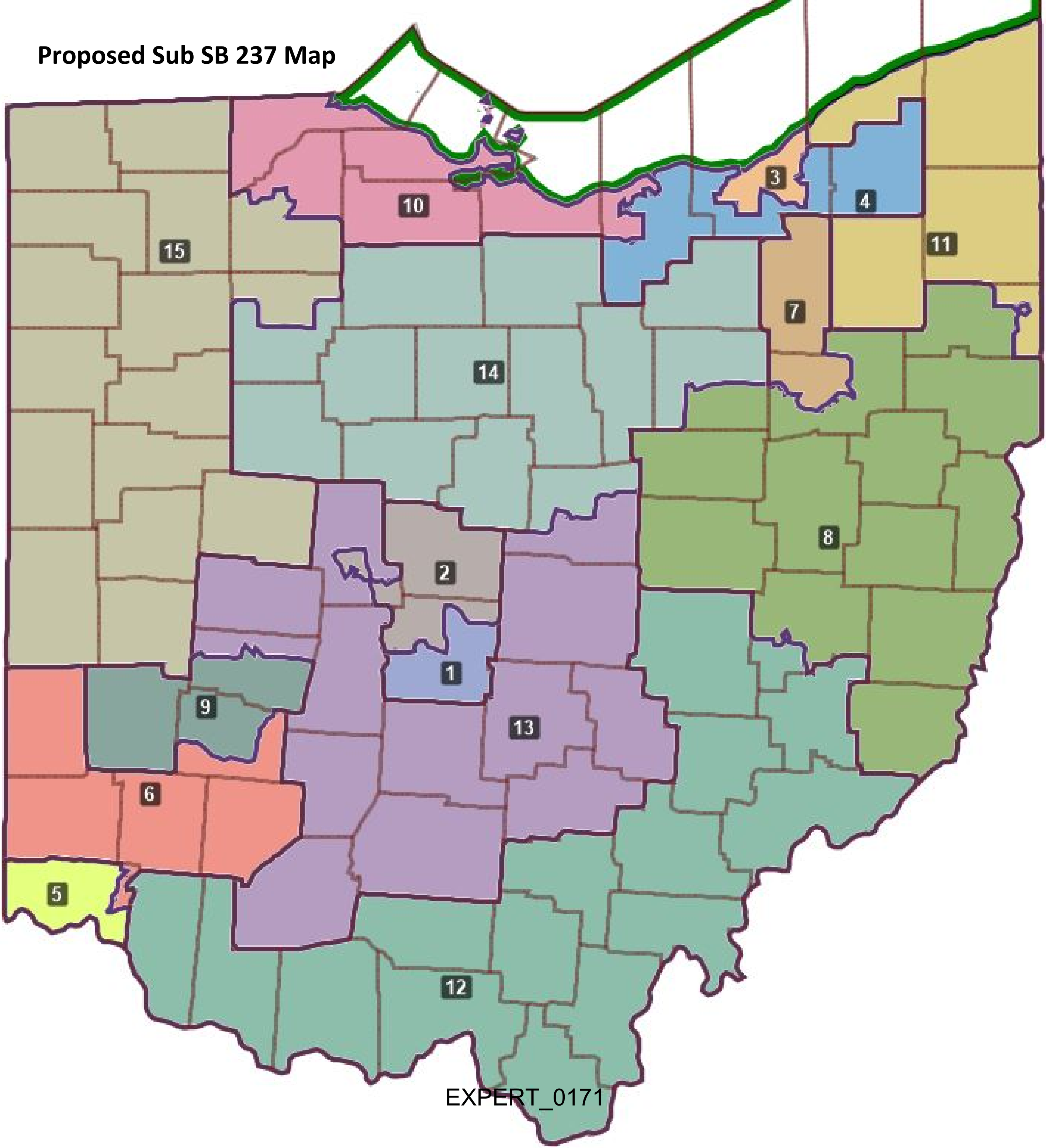

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Exhibit C

Brown/Galonski Congressional District Proposal

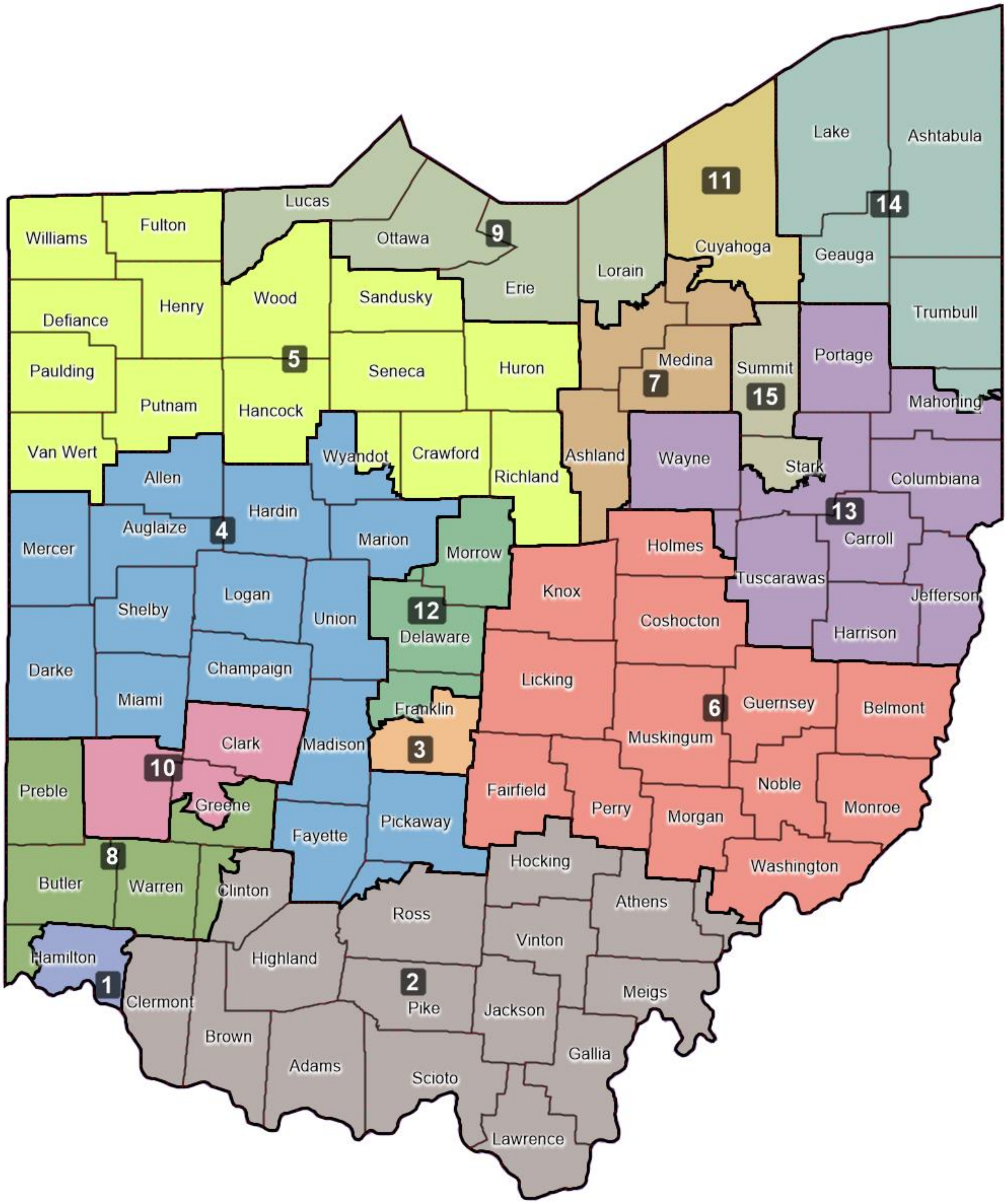
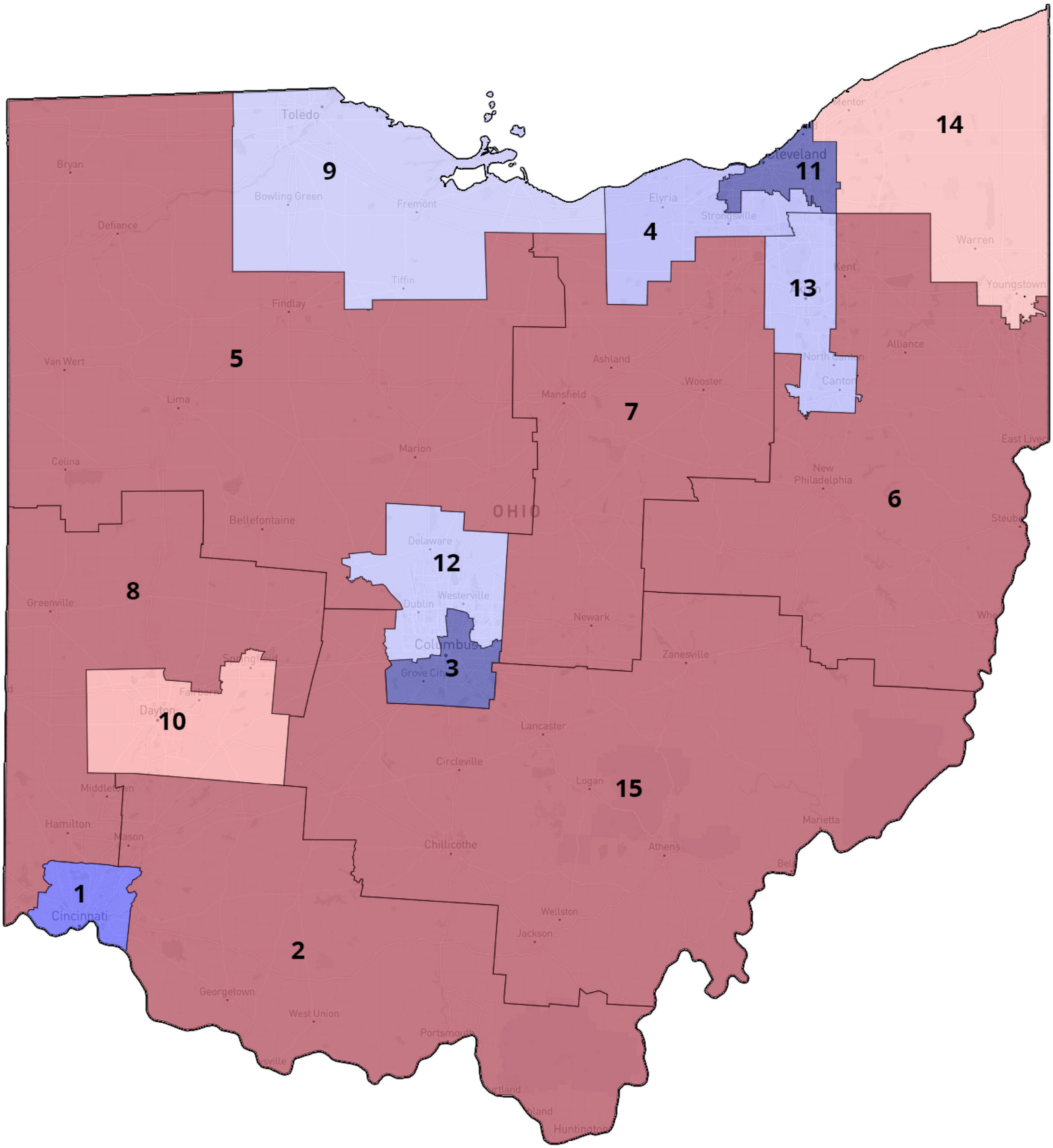


Exhibit D



Toledo
9
Bowling Green
Fremont
Tiffin
Findlay
Bryan
Defiance
Van Wert
Lima
Celina
5
Marion
OHIO
Bellefontaine
Elyria
Strongsville
4
Cleveland
11
Mentor
14
Warren
Youngstown
Kent
13
Alliance
North Canton
Canton
Ashland
Wooster
Mansfield
7
East Liver
New Philadelphia
6
Delaware
12
Westerville
Dublin
Columbus
Grove City
3
Newark
Zanesville
Greenville
8
Springfield
Fairborn
Dayton
10
Middletown
Hamilton
Mason
1
Cincinnati
2
Georgetown
West Union
Portsmouth
Lancaster
Circleville
Logan
15
Chillicothe
Athens
Marietta
Wellston
Jackson
Huntington

EXPERT_0175

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

EXPERT_0177

IN THE SUPREME COURT OF OHIO

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

EVIDENCE TO MOTION TO ENFORCE COURT'S ORDER
(Affidavit of Dr. Christopher Warshaw)

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warshaw@email.gwu.edu (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
March 06, 2022 17:09:34 -8:00 [56BE908CE6AF] [96.27.183.41]
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.,	
Petitioners	**Case No. 2021-1449**
v.	**Original Action Pursuant to Ohio Const., Art. XI**
OHIO REDISTRICTING COMMISSION, 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 03/06/2022, 2022.

Christopher Warshaw
Signed on 2022/03/06 17:09:34 -8:00
Christopher Warshaw

Sworn and subscribed before me this ___ day of 03/06/2022, 2022.

Signed on 2022/03/06 17:09:34 -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 2022/03/06 18:09:34 PST 56BE908CE6AF

Notarial act performed by audio-visual communication

EXPERT_0181

EXHIBIT A

An Evaluation of the Partisan Bias in Ohio's Enacted March 2, 2022 Congressional Districting Plan

Christopher Warshaw*

March 6, 2022

*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, March 2 plan in Ohio, I examined:
  - GIS Files with the 2012-2020 Ohio Congressional plan and the enacted plan): I obtained the 2012-2020 plan from the state website, the original plan from Counsel in this case, and the March 2 enacted plan from the Ohio Redistricting Commission's website
  - 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]
  - 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 PlanScore 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.
- 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.

1. See https://dataverse.harvard.edu/dataverse/electionscience.

– 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 this case, as well as six other redistricting-related cases and several Census-related cases (see my CV for a current list). 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

This report examines whether the Ohio Redistricting Commission's March 2 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 passed without bipartisan support 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, March 2 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, March 2 map. Second, I use a composite of previous statewide election results between 2016-2020 to analyze the new map.[2] Third, I complement this approach using the open source PlanScore.org website, which is a project of the Campaign Legal Center.[3] 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.[4] 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. Finally, I analyze the compactness of the districts in the enacted plan.

All of these analyses indicate an extreme level of pro-Republican bias in Ohio's enacted, March 2 Congressional plan. There are 10 strongly Republican districts, 2 strongly Democratic districts, and 3 potentially competitive districts, two of which lean toward Republicans. In the average election, Republicans are likely to get about 55% of the statewide vote and about 75-80% of the seats in Ohio's congressional delegation. Thus, the plan clearly unduly favors the Republican party. Moreover, it favors Republicans nearly as much as the Commission's initial, enacted plan did.

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 just as extreme. On the new map, Democrats would only win 20% (3) of the seats using the precinct-level results of the 2020 congressional election while Republicans would win 80% (12) of the seats.

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.[5] However, he would have only won 27% (4) of the Congressional districts under the March 2 plan. In the 2018 gubernatorial

2. These include the following elections: 2016 Presidential, 2016 Senate, 2018 Senate, 2018 gubernatorial, 2018 attorney's general, 2018 Secretary of State, 2018 Auditor, 2018 Treasurer, and 2020 Presidential.

3. I am on the social science advisory board of Plan Score, but do not have any role in PlanScore's evaluation of individual maps.

4. See `https://planscore.campaignlegal.org/models/data/2021D/` for more details.

5. Following standard convention, throughout my analysis I focus on two-party vote shares.

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 33% of the districts under the enacted, March 2 plan. In the 2016 presidential election, Democrat Hillary Clinton received about 46% of the two-party vote. But she would too have only won 27% of the revised plan's seats.

Based on all the available statewide elections in Ohio between 2016-2020, I find that the enacted, March 2 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 28% of the seats.[6]

I reach the same conclusion using the predictive model on the PlanScore website. It indicates that the enacted, March 2 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 76% of the seats in Ohio's Congressional delegation (and Democrats would win 24% of the seats).[7] Based on generally accepted Political Science metrics (the Efficiency Gap and the Declination), PlanScore indicates that Ohio's enacted, March 2 plan would have historically extreme levels of pro-Republican bias. In fact, the pro-Republican bias in Ohio's Congressional plan is larger than 96% of previous plans in the United States from 1972-2020.

Overall, this analysis indicates that the Commission's 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 map has an extreme level of bias in favor of the Republican party. Moreover, the March 2 plan is almost as biased in favor of Republicans as the Commission's original, enacted plan that I evaluated in my report on November 30, 2021.

The rest of this report proceeds as follows. First, I provide a brief overview of par-

6. There are a variety of ways we could aggregate previous statewide elections to create a composite index (see the discussion on p. 7-8 of my January 25th report in the parallel case about the constitutionality of the state legislative plans in Ohio). In my main analysis, I weight the composite scores to give each election cycle equal weight in the index. This ensures that the composite index is not overly influenced by whatever election year happens to have the most elections (2018 in the case of Ohio). This is important because much of the uncertainty in projecting future elections comes from variation across electoral cycles rather than across contests within cycles. So, in my view, it is useful to not disproportionately weight the index toward any particular election year. In the appendix, however, I show that I reach similar conclusions using a composite index that weights each statewide contest equally (rather than each year equally).

7. This is a probabilistic estimate based on 1000 simulations of possible elections using a model of the elections between 2012-2020.

tisan gerrymandering and how social scientists measure the degree of partisan bias in a districting plan. I then provide a systematic evaluation of the partisan fairness of Ohio's enacted, March 2 congressional districting plan. Finally, I discuss the compactness of the districts on the Commission's plan.

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% 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 described in my November 30th report.[8] I utilize these approaches to quantify the partisan fairness of

8. These metrics are described in depth on pp. 6-13 of my November 30, 2021 report on the Commission's original enacted congressional plan. Note that the exact calculation methods for the efficiency gap and declination differ slightly across sources. To calculate the efficiency gap I use the formula:

$$EG = S_D^{margin} - 2 * V_D^{margin} \tag{1}$$

the Commission's enacted congressional plan.

5 Partisan Bias in Ohio's Enacted, March 2 Congressional Map

In this section, I will provide a more systematic evaluation of the partisan fairness of Ohio's enacted, March 2 congressional districting plan (see Figure 1 for a map of the 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. I compare the Commission's March 2 plan to the 2012-2020 plan and the original enacted plan from November.

Figure 1: Map of Enacted, March 2 Congressional Districts from PlanScore.org

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, March 2 map to estimate the various metrics. This approach implicitly assumes that future elections will look like the 2020 election. These endogenous elections are likely to be an excellent predictor of future voting patterns in congressional

where S_D^{margin} is the Democratic Party's seat margin (the seat share minus 0.5) and V_D^{margin} is the Democratic Party's vote margin (McGhee 2017, 11-12). I use the declination formula discussed in Warrington (2018, 42).

elections. Based on these results, Republicans would win 57% of the votes, but 80% of the seats on the March 2 plan. In other words, Republicans would win 23 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%
Commission's Original, 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%
Commission's Enacted March 2 Plan			
Republican Seat Share	80%		
Efficiency Gap	-16%	91%	96%
Declination	-.61	92%	95%
Mean-Median Diff	-3%	36%	70%
Symmetry Bias	-17%	91%	93%
Average		77%	89%

Table 1: Partisan bias metrics for Congressional plan based on 2020 Congressional election results re-aggregated onto enacted, March 2 map

The average efficiency gap of the enacted, March 2 plan based on the precinct-level 2020 House results is -16% in a pro-Republican direction (see Table 1). This is more extreme than 91% of previous Congressional plans nationwide over the past five decades (1972-2020) and more pro-Republican than over 96% of previous plans. The plan is more pro-Republican than 95% of prior plans in the country using the declination metric. The other metrics also show that Ohio's enacted, March 2 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 89% of previous plans (which is nearly identical to the Commission's original, enacted plan).

5.2 Composite of previous statewide elections

Next, I use a composite of previous statewide election results between 2016-2020 re-aggregated to the enacted, March 2 map. 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.

		2016-2020 Composite	
Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Republican Seat Share	74%		
Efficiency Gap	-16%	90%	96%
Declination	-.56	89%	93%
Mean-Median Diff	-3%	39%	71%
Symmetry Bias	-17%	91%	93%
Average		77%	88%
Commission's Original, Enacted Plan			
Republican Seat Share	76%		
Efficiency Gap	-18%	93%	97%
Declination	-.59	92%	95%
Mean-Median Diff	-2%	24%	63%
Symmetry Bias	-10%	69%	83%
Average		70%	85%
Commission's Enacted March 2 Plan			
Republican Seat Share	72%		
Efficiency Gap	-14%	86%	94%
Declination	-.44	81%	88%
Mean-Median Diff	-1%	17%	59%
Symmetry	-11%	73%	84%
Average		70%	85%

Table 2: Composite bias metrics for enacted, March 2 Congressional plan based on statewide elections

When I average across these statewide elections from 2016-2020, Democrats win 45% of the votes and 28% of the seats (see Table 2). The average efficiency gap of the enacted, March 2 plan based on these previous election results is -14%. This is more extreme than 86% of previous plans and more pro-Republican than 94% of previous plans. The plan is also more pro-Republican than 88% of previous plans using the declination metric. The mean-median and symmetry also show that Ohio's 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.[9]

9. In the Appendix, I show that I reach very similar results if I average previous elections across

5.3 PlanScore

Third, I evaluate the enacted, March 2 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.[10] It then calculates various partisan bias metrics. In this case, PlanScore provides estimates of the efficiency gap and declination.[11]

PlanScore also indicates that the Congressional plan has a substantial pro-Republican bias (Table 3). According to PlanScore, the enacted, March 2 plan has a pro-Republican efficiency gap of 13%. The plan favors Republicans in 99% of the scenarios estimated by PlanScore.[12] Moreover, it is more extreme than 91% of previous plans and more pro-Republican than 97% 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%
Commission's Original, Enacted Plan				
Republican Seat Share	79%			
Efficiency Gap	-16%	99%	97%	97%
Declination	-.58	99%	95%	98%
Average		99%	96%	98%
Commission's Enacted March 2 Plan				
Republican Seat Share	76%			
Efficiency Gap	-13%	99%	91%	97%
Declination	-.47	98%	90%	95%
Average		99%	91%	96%

Table 3: PlanScore partisan bias metrics for enacted, March 2 Congressional plan

contests rather than weighting each year equally.

10. See `https://planscore.campaignlegal.org/models/data/2021D/` for more details.

11. 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%.

12. See `https://planscore.campaignlegal.org/plan.html?20220303T200000.374167789Z`

6 Competitiveness of Districts

In this section, I use a variety of approaches to estimate the number of competitive districts in both the 2012-20 congressional plan, the original enacted plan, and the March 2 plan (see Table 4). My analysis indicates that the enacted, March 2 plan has just one more competitive district than the 2012-2020 plan.

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	3	3	2	5	2
Commission's Original Plan	3	3	5	4	2	4	3.5
Commission's March 2 Plan	3	2	4	4	2	4	3

Table 4: 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 4, 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 March 2 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 4, 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 2016-2020. 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).[13] I then examine the number of districts that would have been won at least once by each party. This approach indicates there was 1 competitive district on the 2012-20 plan and 2 competitive districts on the enacted March 2 plan.

Next, I use a composite of the 2016-2020 statewide election results to estimate the number of competitive districts. Once again, in column 3 of Table 4, 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 4 competitive districts on the March 2 plan.

13. 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.

Lastly, I use PlanScore to estimate the potential competitiveness of individual districts on the enacted, March 2 plan. In column 4 of Table 4, 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, March 2 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 4, 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, March 2 plan. In column 6 of Table 4, 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, March 2 plan.

Finally, column 7 of Table 4 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 March 2 plan.

Moreover, it is important to note that the fact that there are about three potentially competitive districts on the enacted, March 2 plan does not mean that each party has a 50-50 chance at winning these districts. In fact, Republicans are favored in two of these districts. We can see this using each of the predictive approaches I've used in this report that are summarized in Table 5. The table shows that only one of the three competitive districts (shown in grey) slightly leans toward Democrats. So Republicans are likely to win at least two of these districts in the average election. 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, 12 of the 15 districts on the enacted plan lean toward Republicans.

	Projected Democratic Vote Share			
District	House 2020	Composite (2016-2020)	PlanScore	Average Dem. Share
1	0.50	0.51	0.52	0.51
2	0.25	0.29	0.25	0.26
3	0.69	0.69	0.69	0.69
4	0.29	0.31	0.30	0.30
5	0.34	0.37	0.34	0.35
6	0.34	0.39	0.33	0.36
7	0.41	0.44	0.43	0.43
8	0.37	0.37	0.37	0.37
9	0.47	0.49	0.46	0.47
10	0.42	0.46	0.46	0.45
11	0.78	0.79	0.75	0.78
12	0.31	0.35	0.32	0.33
13	0.49	0.51	0.49	0.49
14	0.40	0.43	0.40	0.41
15	0.43	0.45	0.44	0.44

Table 5: Democratic Vote Share Projections for Each District on Commission's March 2 Plan using a Variety of Methods. Competitive districts in grey, Democratic districts in blue, and Republican districts in red.

7 Compactness

In this section, I examine the compactness of the districts on the Commission's March 2 plan. I focus on two commonly used compactness metrics to evaluate the compactness of the plans. First, the Reock Score is the ratio of the area of the district to the area of a minimum bounding circle that encloses the district's geometry. Second, the Polsby-Popper measure is the ratio of the area of the district to the area of a circle whose circumference is equal to the perimeter of the district (See Figure 2 for illustrations of each metric from Ansolabehere and Palmer (2016, 751)). Each of these metrics falls within the range of [0,1] and a score closer to 1 indicates a more compact district.

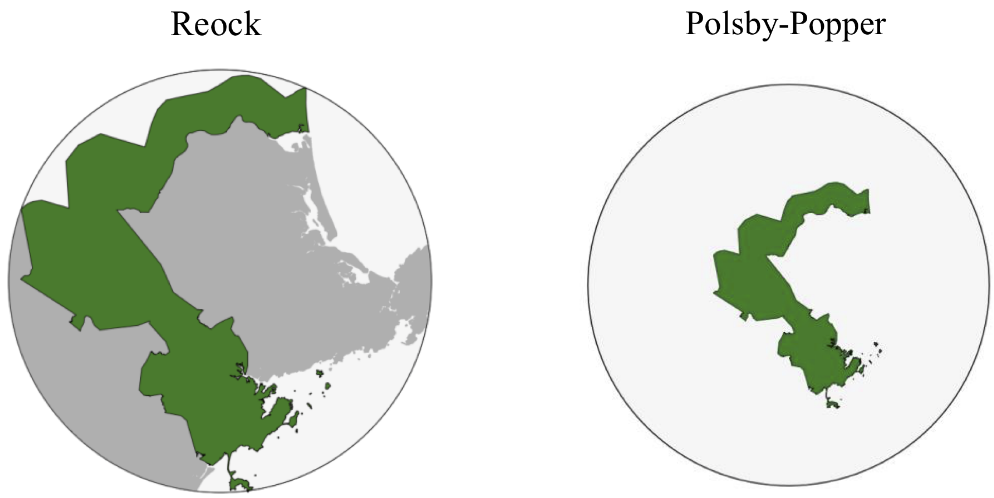

Figure 2: Illustration of Compactness Measures from Ansolabehere and Palmer (2016)

Table 6 shows the compactness metrics for the Commission's enacted, March 2 plan.[14] The districts vary widely in their compactness levels.

District	Reock	Polsby-Popper
1	0.31	0.25
2	0.49	0.31
3	0.69	0.51
4	0.37	0.31
5	0.23	0.20
6	0.29	0.22
7	0.33	0.22
8	0.29	0.28
9	0.27	0.27
10	0.51	0.44
11	0.46	0.40
12	0.59	0.31
13	0.41	0.27
14	0.48	0.65
15	0.28	0.14
Mean	0.40	0.32

Table 6: Compactness Metrics for Districts on Commission's Enacted, March 2 Plan. Higher scores indicate higher levels of compactness.

District 15 receives the lowest compactness scores. Its Reock score is 0.28 and its Polsby-Popper score is 0.14. Both of these scores rank in the bottom quintile of the compactness scores for all congressional districts over the past 200 years (see Figure 3 which shows the distribution of compactness measures for all congressional districts from

14. The compactness scores were calculated in the software program, R, using the `redistmetrics` package.

1789-2013 from Ansolabehere and Palmer (2016)).[15] They also rank in the bottom quintile of the compactness scores for congressional districts around the country in the 2020 cycle. Figure 4 shows how district 15's Reock score compares to other districts around the country in 2020, illustrating that it is an outlier in its level of non-compactness.[16]

			Percentile				
Measure	Mean	SD	10%	25%	50%	75%	90%
Reock	0.405	0.110	0.260	0.326	0.408	0.481	0.546
Polsby-Popper	0.293	0.158	0.080	0.178	0.287	0.400	0.511

Figure 3: Distribution of Compactness Measures for All Congressional Districts from Ansolabehere and Palmer (2016)

District 1 also receives relatively low compactness scores. Its Reock score is 0.31 and its Polsby-Popper score is 0.25. Its Reock score is in the bottom quartile for all congressional districts over the past 200 years (see Figure 3), and its Polsby-Popper is well below the average for all congressional districts over the past two centuries. Moreover, Figure 4 shows that its Reock score is in the bottom tercile of the compactness scores for congressional districts around the country in the 2020 cycle.

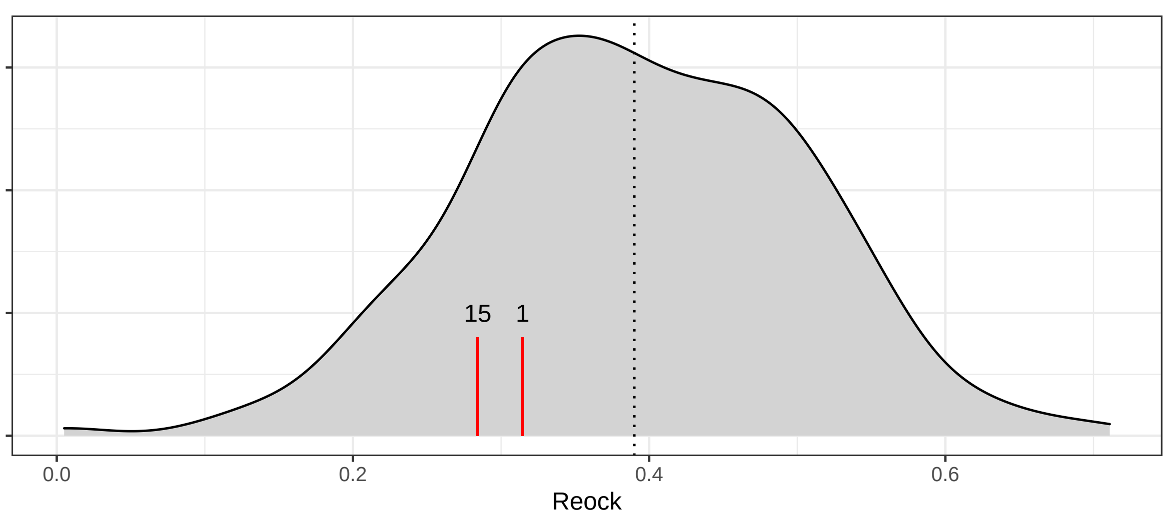

Figure 4: Comparison of District 1 and 15's Reock Score to All 435 Congressional Districts in 2020. Higher scores indicate higher levels of compactness. The dotted line shows the average Reock score of districts in 2020.

15. It includes data on 9,276 different districts and 34,996 district-Congress dyads (i.e. the Congressional elections each district was used for).

16. The Reock scores for all 435 districts in use in 2020 were calculated using PlanScore.org.

8 Conclusion

Overall, there is a substantial Republican bias in the translation of votes to seats in the newly enacted, March 2 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. It is also nearly as unfair as the original, enacted plan. Moreover, the new map does not contain significantly more competitive districts than the 2012-2020 plan and has fewer than the original, enacted plan. Overall, the Commission's March 2 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	-16%	91%	96%
Declination	-.57	89%	93%
Mean-Median Diff	-3%	41%	72%
Symmetry	-22%	97%	98%
Average		80%	90%
Enacted Plan			
Efficiency Gap	-17%	93%	97%
Declination	-.55	88%	93%
Mean-Median Diff	-2%	19%	61%
Symmetry	-12%	78%	86%
Average		70%	84%
March 2 Plan			
Efficiency Gap	-12%	82%	93%
Declination	-.36	74%	83%
Mean-Median Diff	-1%	16%	59%
Symmetry	-14%	84%	89%
Average		64%	81%

Table A1: Composite partisan bias metrics for Congressional plan based on all elections from 2016-2020, averaging across contests rather than across years

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Research

Publications

Book

"Dynamic Democracy: Public Opinion, Elections, and Policy Making in the American States." Forthcoming. University of Chicago Press. (with Devin Caughey)

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(Invited to revise and resubmit at the *American Political Science Review*)

"Partisan Polarization in the Mass Public in South Korea and the United States"

"How Partisanship in Cities Influences Housing Policy" (with Justin de Benedictis-Kessner and Dan Jones)

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"Electoral Accountability for Ideological Extremism in American Elections" (with Devin Caughey)

"Gerrymandering in Local Governments" (with Yamil Valez)

"When Mass Opinion Goes to the Ballot Box: A National Assessment of State Level Issue Opinion and Ballot Initiative Results" (with Jonathan Robinson and John Sides)

"Inequalities in Participation, Voting, and Representation in Local Governments" (with Justin de Benedictis-Kessner and John Sides)

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"The Supreme Court is deciding a gerrymandering case. Here's the social science that the Justices need to know." *Washington Post*, Monkey Cage. June 1, 2019.

"New research shows just how badly a citizenship question would hurt the 2020 Census." *Washington Post*, Monkey Cage. April 22, 2019. (with Matt Barreto, Matthew A. Baum, Bryce J. Dietrich, Rebecca Goldstein, and Maya Sen)

"G.O.P. Senators Might Not Realize It, but Not One State Supports the Health Bill." *New York Times*. June 14, 2017. (with David Broockman)

Invited Talks

2021-2022: American University

2020-2021: University of Maryland; Stony Brook University

2019-2020: Princeton; UC Berkeley

2018-2019: Stanford; Northeast Political Methodology Meeting at NYU; University of Maryland

2017-2018: USC PIPE Symposium on Studying Subnational Policy Making; BYU; University of Chicago Conference on Political Polarization

2016-2017: University of Virginia; UCLA

2015-2016: Washington University in St. Louis; Texas A&M; Arizona State University Conference on Campaigns, Elections and Representation

2014-2015: Yale; Columbia; Duke

2013-2014: Princeton; Boston University; Rochester University

2012-2013: MIT American Politics Conference; Columbia Representation Conference; Princeton Media & Politics Conference; Annual Meeting of the Society for Political Methodology

Grants

Russell Sage Foundation, 2019-2021 ($119,475)

GW UFF, 2019-2020 ($14,433)

MIT Elections Lab, 2019-2020 ($14,000)

Jeptha H. and Emily V. Wade Award, 2014-2016 ($59,686)

MIT Energy Institute (MITEI) Seed Grant, 2014-2016 ($137,147)

MIT SHASS Research Fund, 2012-2014 ($8,734)

Software

dgo: Dynamic Estimation of Group-Level Opinion. 2017. R package. `https://CRAN.R-project.org/package=dgo`. (with James Dunham and Devin Caughey)

Awards and Honors

OVPR Early Career Scholar at George Washington University, 2019.

APSA award for best journal article on State Politics & Policy in 2016.

Award for best paper on State Politics & Policy at the 2014 American Political Science Conference.

Graduate Fellowship, Dept. of Political Science, Stanford University, 2006-2012

David A. Wells Prize in Political Economy for Best Undergraduate Economics Thesis, Williams College, 2002

Phi Beta Kappa, Williams College, 2002

Teaching Experience

Instructor:

Measurement Models (Graduate-level) (GW), 2020

Political Representation (Graduate-level) (GW), 2019

Elections (GW), 2018, 2019, 2021

Multi-level and Panel Models (Graduate-level) (GW), 2017, 2018, 2019, 2021

Public Opinion (GW), 2017

American Political Institutions (Graduate-level) (MIT), 2014, 2016

Public Opinion and Elections (MIT), 2016

Energy Policy (MIT), 2013

Democracy in America (MIT), 2013, 2014

Constitutional Law & Judicial Politics (MIT), 2013, 2015

Making Public Policy (MIT), 2012, 2014

Teaching Assistant:

Introduction to American Law (Stanford University), 2010

Judicial Politics and Constitutional Law (Stanford University), 2009

Political Economy of Energy Policy (Stanford University), 2008

Introduction to International Relations (Stanford University), 2008

Introduction to Public Policy (Stanford University), 2007

Introduction to Econometrics (Williams College), 2002

Graduate Advising

George Washington University:

Alex Beck (Dissertation committee chair)

Dickson Su (Dissertation committee chair)

Kerry Synan (Dissertation committee co-chair)

Jared Heern (Dissertation committee member)

Colin Emrich (Graduates in 2021, Dissertation committee member)

Massachusetts Institute of Technology:

Leah Stokes (Graduated in 2015, Dissertation committee member)

Krista Loose (2016, Dissertation committee member)

Tom O'Grady (2017, Dissertation committee member)

Justin de Benedictis-Kessner (2017, Dissertation committee member)

Alex Copulsky (2017, Masters thesis committee member)

James Dunham (2018, Dissertation committee member)

Parrish Bergquist (2018, Dissertation committee member)

Meg Goldberg (2019, Dissertation committee member)

University Service

George Washington University:

Member, Academic Program Review Committee, Sociology Dept., 2021

Coordinator, Graduate Political Science Admissions Committee, 2019-2020

Coordinator, American Politics Workshop, 2018-2020

Member, Methods Exam Committee, 2017-2020

Member, Graduate Political Science Admissions Committee, 2018-2019

Massachusetts Institute of Technology:

Member, Energy Education Task Force, 2012-2017

Parking and Transit Committee, 2013-2017

Member, Graduate Political Science Admissions Committee, 2013-2015

Faculty Fellow, Burchard Scholars, 2013-2015

Stanford University (as graduate student):

President, Stanford Environmental Law Society, 2009-2010

Executive Board Member, Stanford Environmental Law Society 2008-2010

Member, University Committee on Graduate Studies, 2007-2009

Member, University Library Committee, 2007-2008

President, Political Science Graduate Students Association, 2007-2008

Professional Service

Reviewer: American Political Science Review, American Journal of Political Science, Journal of Politics, Political Analysis, Political Behavior, Econometrica, Quarterly Journal of Political Science, Legislative Studies Quarterly, Political Research Quarterly, American Politics Research, British Journal of Political Science, Journal of Law and Courts, Public Opinion Quarterly, Political Science Research and Methods, State Politics and Policy Quarterly, Journal of Experimental Political Science, Nature Climate Change, Urban Affairs Review, Journal of Health Politics, Policy and Law, Perspectives on Politics, Review of Economics and Statistics, Cambridge University Press

Member, Best Dissertation Committee, Urban Politics Section of the American Political Science Assoc., 2021

Member, Program Committee, Midwest Political Science Association Conference, 2020

Lead Organizer, Local Political Economy APSA Pre-Conference at George Washington University, 2019

Member, Planning Committee, Cooperative Congressional Election Study (CCES), 2018

Member, Best Paper Committee, State Politics Section of the American Political Science Assoc., 2018

Editorial Board, Journal of Politics, 2017-18

Executive Committee, Urban Politics Section of the American Political Science Association, 2015-2017

Organizing Committee, Conference on Ideal Point Models at MIT, http://idealpoint.tahk.us, 2015

Member, Best Paper Committee, Urban Politics Section of the American Political Science Assoc., 2015

Consulting

Partisan Gerrymandering:

Expert, *League of Women Voters of Michigan* vs *Michigan Independent Citizens Redistricting Commission* (2022), State House Districts

Expert, *League of Women Voters of Ohio* v. *Ohio Redistricting Commission* (2021), Congressional districts

Expert, *League of Women Voters of Ohio* v. *Ohio Redistricting Commission* (2021), State Legislative Districts

Expert, *League of Women Voters* vs. *Kent County Apportionment Commission* (2021)

Expert, *APRI et al.* v. *v. Smith et al.* (2018-2019)

Expert, *League of Women Voters of Michigan* v. *Johnson* (2018-2019)

Expert, *League of Women Voters of Pennsylvania* v. *the Commonwealth of Pennsylvania* (2017-18)

Census:

Expert, *La Union del Pueblo Entero , et al.* v. *Trump*, Effect of Excluding Undocumented Immigrants from Census on Apportionment (2020)

Expert, *Common Cause et al.* v. *Trump*, Effect of Excluding Undocumented Immigrants from Census on Apportionment (2020)

Expert, *State of New York* v. *Trump*, Effect of Excluding Undocumented Immigrants from Census on Apportionment (2020)

Expert, *New York Immigration Coalition* v. *US Dept of Commerce* & *State of NY* v. *US Dept of Commerce*, Effects of Undercount on Census due to Citizenship Question (2018)

Policy Reports:

Consultant, *Abell Foundation*, Report on Potential Institutional Reforms for Baltimore's City Elections

Community Service

PlanScore: Social Science Advisory Team (2020-2021)

Sierra Club: National Board of Directors (2009-2015)

Last updated: February 27, 2022

IN THE SUPREME COURT OF OHIO

League of Women Voters of Ohio, ***et al.*** **Relators,** **v.** **Governor Michael DeWine,** ***et al.*** **Respondents.**	**Case No. ______________** Original Action Filed Pursuant to Ohio Constitution, Article XIX, Section 3(A)

EXHIBITS TO COMPLAINT - VOLUME 1 OF 3

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Joshua González (PHV 25424-2021)*
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EXHIBIT 1

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.

Signed on 2021/11/30 08:13:08 -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 2021/11/30 09:13:08 PST 0C271766C922

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

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).

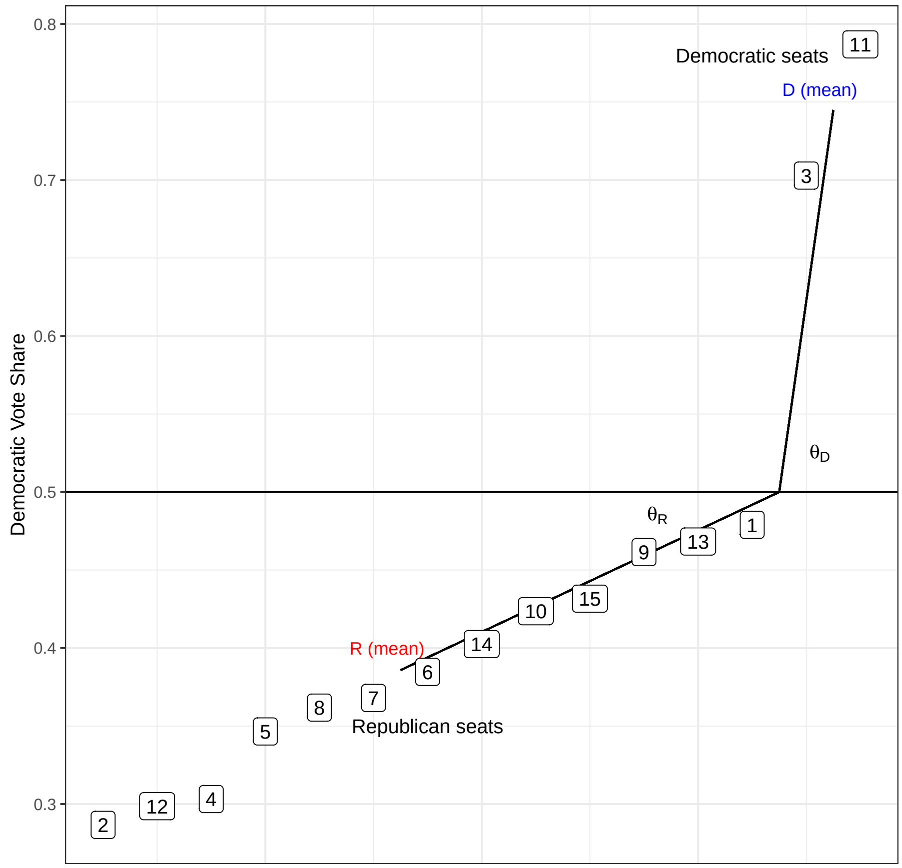

Figure 1: Plot illustrating declination based on votes in 2020 Congressional election re-aggregated to new plan

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: $\delta = 2^*$ $(\theta_R$ - $\theta_D)$ / π.

14. This adjustment uses this equation: $\hat{\delta} = \delta$ * ln(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).

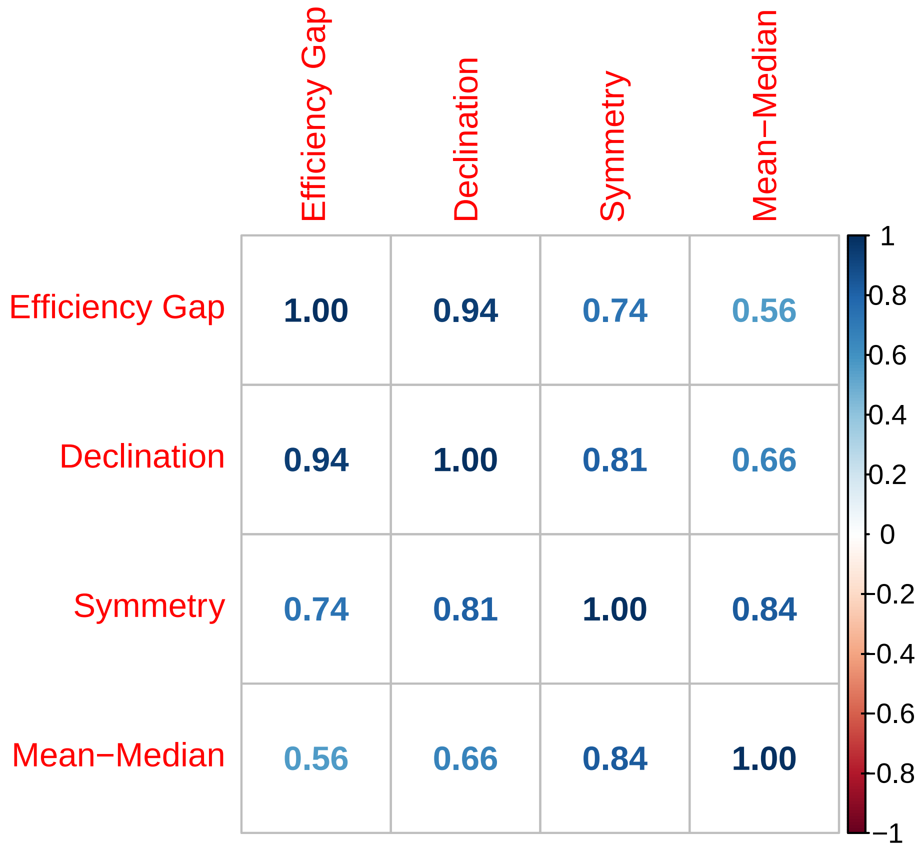

Figure 2: Correlation between measures of partisan bias in states.

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)."

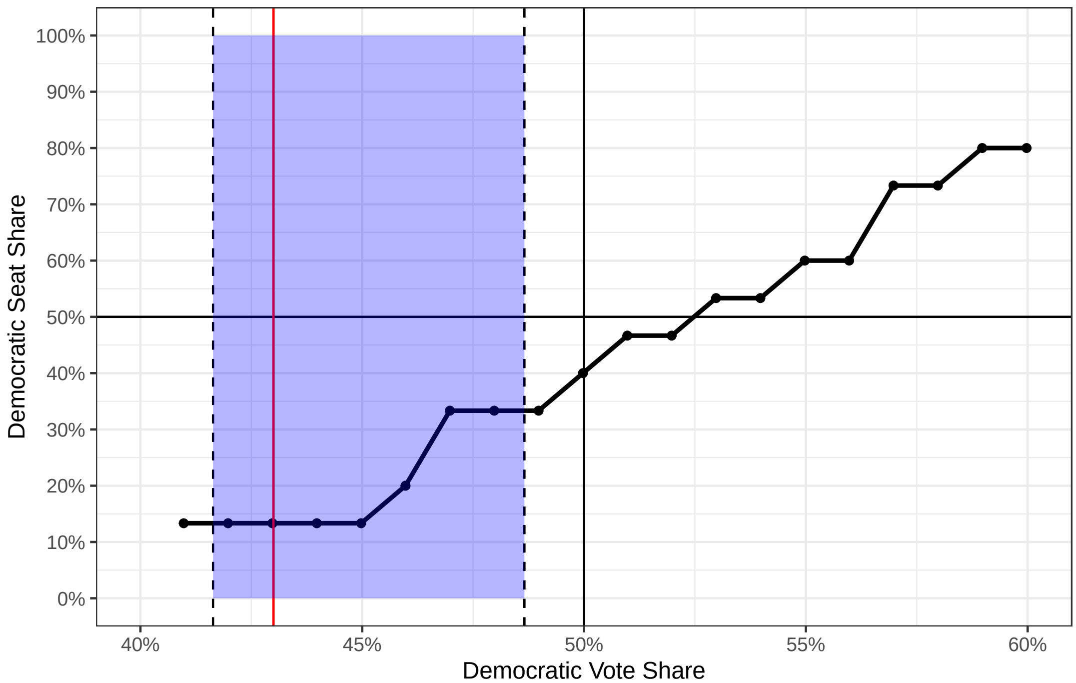

Figure 3: Vote-seat curve in Ohio using uniform swings in 2020 election results re-aggregated using enacted plan. The shaded area shows the range between the minimum and maximum Democratic statewide vote share in congressional elections from 2012-2020. The red line shows the actual Democratic statewide 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

CERTIFICATE OF SERVICE

I, Freda J. Levenson, hereby certify that on this 25th day of April 2022, I caused a true and correct copy of the foregoing to be served by email upon the counsel below:

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