IN THE SUPREME COURT OF OHIO

THE OHIO ORGANIZING COLLABORATIVE, *et al.*, *Relators*, *v.* OHIO REDISTRICTING COMMISSION, *et al.*, *Respondents*.	:	Case No. 2021-1210 **APPORTIONMENT CASE** Filed pursuant to S.Ct.Prac.R. 14.03(A) and Section 9 of Article XI of the Ohio Constitution to challenge a plan of apportionment promulgated pursuant to Article XI.

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AFFIDAVIT OF DANIELLE STEWART

(affidavits of additional expert witnesses)

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. 2021-1193

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Affidavit of Kosuke Imai.pdf

DocVerify ID:	F28E1E3D-C0A8-4D4A-A864-16B12998E5F9
Created:	October 22, 2021 11:32:30 -8:00
Pages:	1
Remote Notary:	Yes / State: OH

E-Signature Summary

E-Signature 1: Kosuke Imai (KI)
October 22, 2021 12:01:57 -8:00 [CE102AED8522] [140.247.116.184]
imai@harvard.edu (Principal)

E-Signature Notary: Theresa M Sabo (TMS)
October 22, 2021 12:01:57 -8:00 [D88C9F804C9B] [74.142.214.254]
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I, Theresa M Sabo, did witness the participants named above electronically sign this document.

Notarial act performed by audio-visual communication

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, et al.,

Relators,

v.

OHIO REDISTRICTING COMMISSION, et al.,

Respondents.

Case No. 2021-1193

Original Action 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 sates 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 10/22/2021 ,2021.

Kosuke Imai
Signed on 2021/10/22 12:01:57 -8:00

Kosuke Imai

Sworn and subscribed before me this 10/22/2021 day of __________, 2021

NOTARY PUBLIC
STATE OF OHIO
Theresa Michelle Sabo
Commission # 2016-re-619622
Electronic Notary Public
State of Ohio
My Comm Exp. Nov 28, 2021
Notary Stamp 2021/10/22 12:01:57 PST D88C9F804C9B

Signed on 2021/10/22 12:01:57 -8:00

EXHIBIT A

Table of Contents

EXPERT REPORT

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 recently enacted state legislative districting plan (hereafter the "enacted plan") meets the criteria in Article XI, Section 6 of Ohio's Constitution. More specifically, I have been asked:

- To statistically analyze the enacted plan's compliance with Article XI, Section 6(A) by comparing it against other alternative plans that are as or more compliant with other relevant requirements of Article XI.
- To statistically analyze the enacted plan's compliance with Article XI, Section 6(B) by comparing it against other alternative plans that are as or more compliant with other relevant requirements of Article XI.

II. SUMMARY OF OPINIONS

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

- The enacted plan exhibits a significant partisan bias in favor of the Republican party. The magnitude of bias is much greater under the enacted plan than *any* of my 5,000 simulated plans, according to several standard metrics used in the academic literature.
- The enacted plan fails to meet the proportionality criteria of Section 6(B), making it almost certain for the Republican party to win disproportionately more seats relative to their statewide vote share. The degree of disproportionality is much greater under the enacted plan than *any* of my 5,000 simulated plans.

- In several counties including Hamilton, Franklin, and Cuyahoga, the enacted plan packs a disproportionately large number of Democratic voters in some districts while turning other districts into safe Republican seats.

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 three 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 more than 25,000 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 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 Sections 6(A) and 6(B). 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

1. https://ipub.com/dev-corner/apps/r-package-downloads/ (accessed on September 24, 2021)

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. For the purposes of my analyses, I have assumed that the enacted plan is compliant with Sections 3 and 4. I have further ensured that all my simulated plans are equally or more compliant with Sections 3 and 4 than the enacted plan. My simulation procedure achieves this, in part, by exactly following many of the county-level decisions made by Respondents in creating the enacted plan. Appendix B provides detailed information about this process. For all simulations, I ensure districts fall within a 5% deviation from population parity, pursuant to Section 3(B)(1).

15. Section 6(A) states that no plan should be drawn "primarily to favor or disfavor a political party." One can ensure that a plan is compliant with this provision by drawing district boundaries in a way that does not favor or disfavor one political party. Accordingly, when instructing the algorithm to build districts, I apply a party-neutral constraint that places a smaller weight on the likelihood of creating districts that have vote shares for each party too far from 50%. The weight continuously increases as the two-party vote share of a district approaches a 50-50 split, which receives the greatest weight. Appendix C presents the exact formula of this constraint, which

mirrors the way other constraints are imposed on simulation algorithms (Herschlag et al. 2020a).

16. This constraint is designed to discourage "packing," which represents a common feature of gerrymandering (Owen and Grofman 1988; Best et al. 2018; Buzas and Warrington 2021). The boundaries of these packed districts are drawn so that they contain an excessive number of voters from one party, leading to that party disproportionately wasting votes (McGhee 2014; Stephanopoulos and McGhee 2015, 2018). Similarly, the constraint discourages "cracking" to the extent that a group of voters, which could form a majority in a district, is split into small groups across multiple districts.

17. This constraint is party-neutral, encouraging districts that maximize the voting power of each voter equally regardless of their partisanship. In other words, switching the party labels produces identical weights, and hence the same simulation results.

18. Lastly, in the generation of simulated plans, the algorithm does not use any of the partisan bias evaluation metrics discussed in Section B. Rather, such metrics are used to evaluate the resulting set of simulated plans once they are generated, in order to determine compliance with Section 6(A). The algorithm also does not use the proportionality criteria. Instead, I will use this criteria to evaluate the plan's compliance with Section 6(B) based on simulated plans. This separation between algorithmic constraints and evaluation metrics is critical in order to ensure fair evaluation of the enacted and simulated plans.

B. Metrics Used to Measure Bias

19. To measure compliance with Sections 6(A) and 6(B) in the set of simulated plans generated by the algorithm, the enacted plan, and the Democratic caucus plan, 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 September 23, 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.

20. To represent compliance with Section 6(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

21. To measure compliance with Section 6(B), I use the proportionality metric, which is defined as the difference between the Republican seat share and the Republican vote share in statewide elections. According to the 13 statewide elections from 2012 to 2020 for which the election results are available at the precinct level (see Appendix G.1 for the list of these elections), the Republican vote share is 53.9% of the votes cast for two major parties when weighting each statewide contest equally. This percentage is essentially identical to the corresponding number (54%), which is reported by the Commission in its Article XI, Section 8(C)(2) Statement. This number reduces to 53.1% if I use the raw percentage of votes rather than the two-party votes. This suggests that my analysis based on two-party vote is more favorable to the enacted map when evaluating its compliance with Section 6(B) than if I used the raw percentage of votes. For each redistricting plan, I compute the average number of Republican seats won using these past statewide elections.

22. I compute the proportionality metric used to measure compliance with Section 6(B) as follows. First, consider the House of Representatives. Given a redistricting plan, I first determine likely winners of all districts based on the vote totals for each statewide election. This gives the total number of expected Republican seats won in each statewide election given the plan. I then average this number across all the statewide elections, arriving at the average number of seats Republican candidates are expected to win. Dividing this by the total number of House districts, which is 99, gives the average expected Republican seat share for the plan. Subtracting from this seat share the statewide Republican vote share for the election yields a measure of proportionality. The same procedure is applied to the Senate. The only difference is that the total number of Senate districts is 33 since the Ohio constitution requires each Senate district to consist of three House districts.

23. When this measure is positive, it means Republicans win more seats on average than their share of votes, and vice versa for Democrats when it is negative. Calculating the number of seats across elections is important, from both a legal and social scientific perspective: political scientists advocate evaluating redistricting plans by averaging across elections (Gelman and King 1994; Katz, King, and Rosenblatt 2020), and Section 6(B) of Article XI of the Ohio Constitution explicitly mandates evaluation on the basis of the statewide elections during the past 10 years.

C. Description of Redistricting Simulation Software

24. 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. I conducted all of my analyses 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.

D. An Example Simulated Plan

25. Figure 21 of Appendix D shows a sample redistricting plan for the House generated using my algorithm. The plan scores the median value according to the proportionality measure described above. Republicans are expected to win an average of 58.9 seats under this simulated plan, using the 9 statewide election results from 2016, 2018, and 2020.

26. Similarly, Figure 22 of Appendix D shows a sample redistricting plan for the Senate generated using my algorithm. The plan also scores the median value according to the proportionality measure. Republicans are expected to win an average of 19.6 seats under this simulated plan, again using the 9 statewide election results from 2016, 2018, and 2020.

V. STATEWIDE EVALUATION OF THE ENACTED PLAN

27. Using the methodology described above, I evaluated the enacted plan's compliance with Article XI Sections 6(A) and 6(B). At the instruction of counsel for the Relators, I also

evaluated the compliance of the Democratic caucus plan, with Sections 6(A) and 6(B). Appendix G.1 provides the detailed information about data sources.

28. I simulated 5,000 alternative House of Representatives plans and 5,000 alternative Senate plans, using the simulation procedure described in Section IV. As explained in Appendix B, every simulated plan is at least as compliant with Sections 3 and 4 as the enacted plan, which I am assuming is compliant with those provisions for the purpose of this analysis. Appendix E also shows that the simulated plans are as compact as the enacted plan, pursuant to Section 6(c).

29. 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.

30. Below, I present the results of two evaluations based on different sets of statewide election results. First, I follow the Commission's approach and use a total of 9 statewide elections from 2016, 2018, and 2020 (see Section A). My analysis shows that the enacted plan has worse partisan bias and proportionality scores than any of my 5,000 simulated plans. Second, to give the Commission the benefit of the doubt, I repeat the same evaluation using a more complete set of statewide election results by adding the available election results from 2012 and 2014 (see Section B). I show that using this more complete set of statewide elections does not affect my substantive conclusions.

A. Evaluation Using the Commission's Approach

31. I begin by evaluating the enacted plan's compliance with Sections 6(A) and 6(B), using the Commission's approach. In its Article XI, Section 8(C)(2) Statement, the Commission used only a total of 9 statewide elections from 2016, 2018, and 2020 to compute the expected Republican seat share under the enacted plan. This Commission's approach is not ideal given that Article XI, Section 6(B) states that the statewide voter preferences should be measured using the statewide election results during the last ten years. Nevertheless, I first follow the Commission's approach and evaluate the enacted plan's compliance using this particular subset of statewide elec-

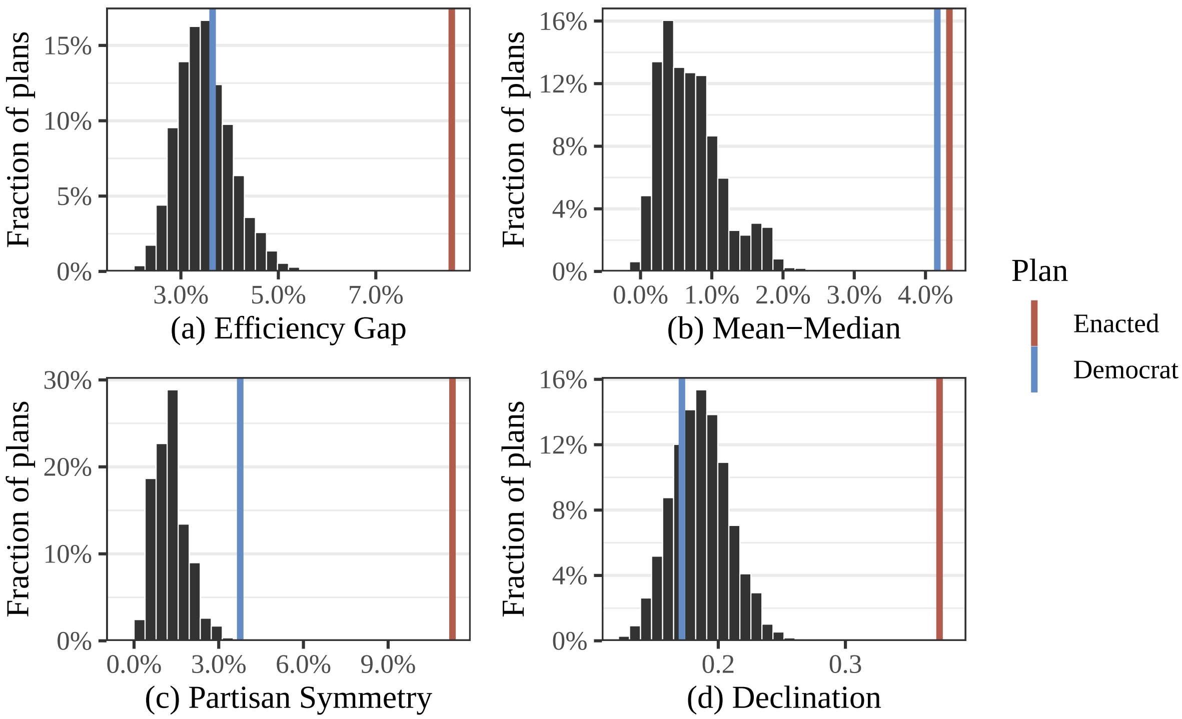

Figure 1: Four partisan bias measures calculated for the 5,000 simulated House redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic caucus plan (blue). For each measure, larger values (towards the right) correspond to more Republican-favoring plans.

tion results.

A.1. Compliance with Section 6(A)

32. I first present the results regarding the enacted plan's compliance with Section 6(A) for the House (Figure 1) and Senate (Figure 2). We adjusted the sign of each metric so that a smaller value implies less partisan bias. Recall that the simulated plans follow several of the map-drawing decisions established by the enacted plan (see Appendix B). Despite this constraint, when compared to these simulated plans (black histogram), the enacted plan (red vertical line) is a clear outlier favoring the Republican party for both the House and Senate. Indeed, the enacted map is more biased than any of 5,000 simulated plans for all four partisan bias metrics I considered.

33. For the House, the efficiency gap, which captures both cracking and packing, is 8.6% for the enacted map, whereas the average efficiency gap for the simulated plans is only 3.4%.

This implies that the enacted plan wastes over 110,000 more Democratic votes on average than the simulated plans, and over 110,000 fewer Republican votes. As shown in Figure 1(a), the enacted map is a clear outlier according to this metric.

34. 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. Figure 1(b) shows that in terms of the mean-median gap, the enacted plan is also a clear outlier relative to the simulated plans.

35. Partisan symmetry is based on the idea that each party should receive half of the seats if they each receive 50% of votes. Figure 1(c) shows that the enacted plan scores 11.3% on this metric while the simulated plans score 1.2%, on average. This suggests that under the enacted plan, the Republican party would gain roughly 22 more seats than the Democrats, for a hypothetical tied election. In contrast, the simulated plans would give only 2 more seats to the Republican party than the Democrats in the same situation. Again, the enacted plan is a clear outlier according to this metric.

36. Lastly, the declination represents another measure of asymmetry in the vote distribution. As shown in Figure 7(d), the enacted plan also scores worse on this metric than any of the 5,000 simulated plans.

37. The Democratic caucus plan (blue vertical line) scores better than the enacted plan across all partisan bias metrics with the exception of the mean-median metric, for which both plans perform poorly. In addition, this plan is an outlier for the mean-median and partisan symmetry metrics, while it does as well for the other two metrics as most of the simulated plans.

38. For the Senate, my simulation analysis uses the House districts of the enacted plan, which I found to be biased as shown above. Furthermore, as explained in Appendix B, the simulated plans follow additional map-drawing decisions established by the enacted plan. Despite this constraint, Figure 2 shows that the enacted plan is extreme relative to the simulated plans according to all four partisan bias metrics. For example, as shown in Figure 2(a), the efficiency gap of the enacted plan is 10.5% whereas the simulated plans score 3.5% on average for this metric. Like the

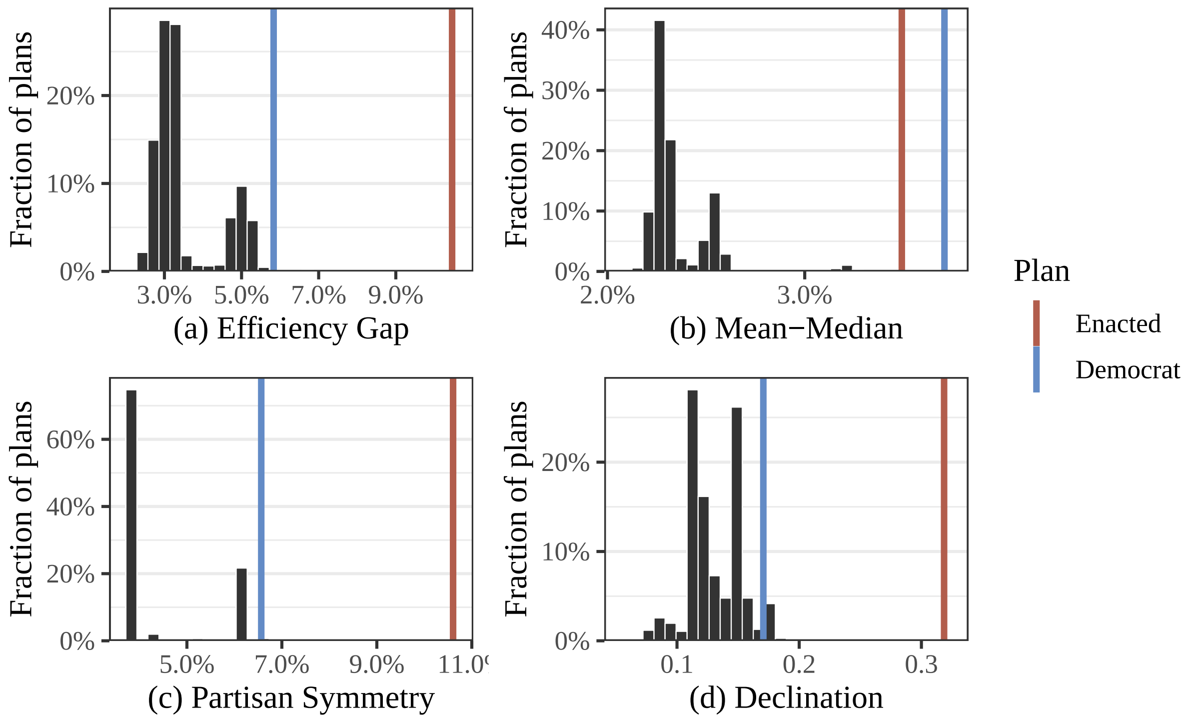

Figure 2: Four partisan bias measures calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic caucus plan (blue). For each measure, larger values (towards the right) correspond to more Republican-favoring plans.

House, all of the 5,000 simulated plans have a lower (better) partisan bias score than the enacted plan across all four metrics considered here.

39. For the Senate, the Democratic caucus plan is also an outlier for all partisan bias metrics. But, it has better scores than the enacted plan with the exception of the mean-median metric.

A.2. Compliance with Section 6(B)

40. I next present the results regarding the plans' compliance with Section 6(B), using the Commission's approach. Section 6(B) states that "the statewide proportion of districts whose voters, based on statewide state and federal partisan general election results during the last ten years, favor each political party shall correspond closely to the statewide preferences of the voters of Ohio." Therefore, I use the proportionality metric to examine whether or not the statewide

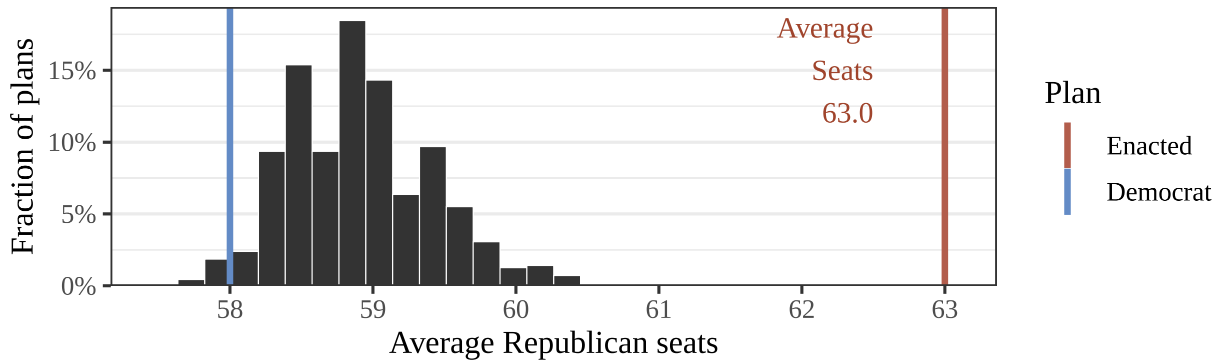

Figure 3: Average number of Repulican seats calculated for the 5,000 simulated House redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

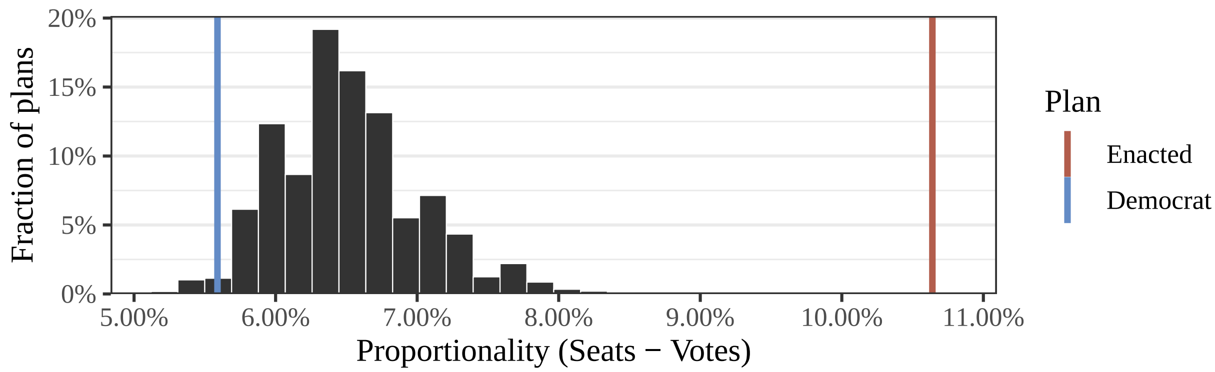

Figure 4: Corresponding proportionality measure calculated for the 5,000 simulated House redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

seat share of each party corresponds closely to its statewide vote share under each plan. As I show below, for both the House and Senate, the enacted plan is a clear outlier relative to the simulated plans. That is, although the simulated plans follow several of the map-drawing decisions established in the enacted plan, all of my 5,000 simulated plans are more compliant with Section 6(B) than the enacted plan.

41. For the House, Figure 3 shows that under the enacted plan, the Republican party is expected to win 63.0 seats, which is about 4 seats higher than the average simulated plan of 58.9 seats. None of my 5,000 simulated plans awards that many seats to Republicans. Under the Democratic caucus plan, the Republican party earns less seats than most of the simulated plans.

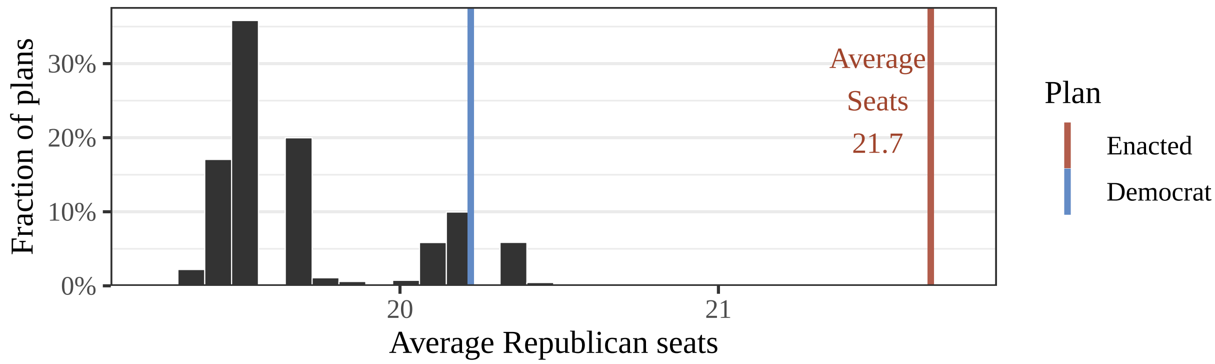

Figure 5: Average number of Repulican seats calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

42. This discrepancy is reflected in the proportionality metric, which is shown in Figure 4. A value of zero for this measure implies complete proportionality, while positive values indicate that Republicans win a larger share of seats than vote share, on average. A smaller value indicates a plan's better compliance with Section 6(B). The enacted plan has a proportionality score of 10.6%, implying that the Republican party would receive an average of 10.6% more seats under the enacted plan than under a proportional plan where the vote share is equal to the seat share. In contrast, under the simulated plans, the average proportionality score is only 6.5%. Indeed, all simulated plans score better than the enacted plan. It is worth noting that the Democratic caucus plan even outperforms most of the simulated plan.

43. For the Senate, the substantive conclusion is similar despite the fact that the simulated plans are based on the House districts of the enacted plan and follow several additional map-drawing decisions made by the Respondents. Figure 5 shows that the enacted plan favors the Republican party to a large degree and is a clear outlier. Under the enacted plan, the Republican party is expected to win 21.7 seats on average, which is much greater than any of my 5,000 simulated plans. On average, the simulated plans would award Republicans 19.7 seats, which is about 2 seats fewer than the enacted plan. The Democratic caucus plan awards fewer expected Republican seats than the enacted plan, but it tends to be more favorable to the Republican party than many of my simulated plans.

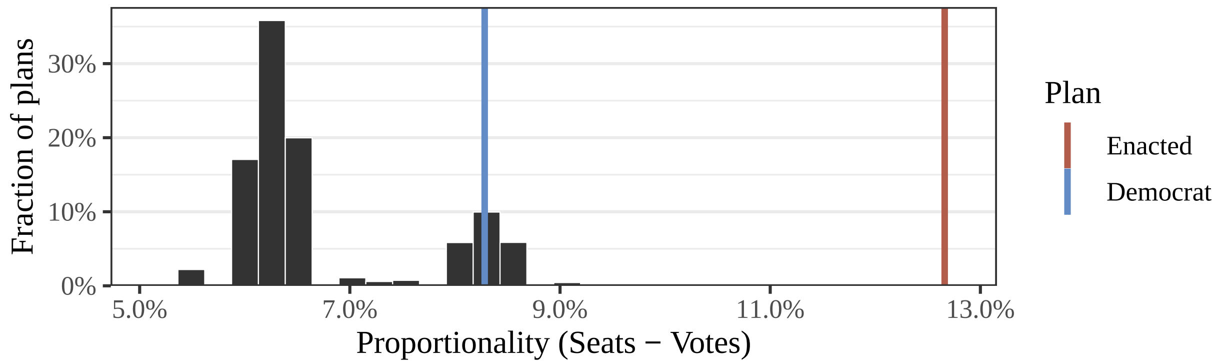

Figure 6: Corresponding proportionality measure calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

44. As for the proportionality criteria of Section 6(B), all of my 5,000 simulated Senate plans have smaller (better) proportionality scores than the enacted plan. The enacted plan has a deviation from proportionality that is nearly double the average simulated plan, giving Republicans 12.7% more seats on average above the proportional outcome. In contrast, the simulated plans would give Republicans only 6.7% more seats on average above the proportional outcome. The Democratic caucus plan performs better than the enacted plan but scores worse than most of my simulated plans.

B. Evaluation Using the 13 Statewide Election Results

45. To give the Commission the benefit of the doubt, I conducted an additional evaluation by supplementing these 9 elections with 4 additional statewide elections from 2012 and 2014 (see Appendix G.1 for the list of these 13 statewide elections). I show that the use of these additional statewide elections does not alter my substantive conclusions. My analysis demonstrates that regardless of which set of elections I use, for both the House and Senate, the enacted plan is a clear outlier relative to the simulated plans, according to all four partisan bias metrics. The enacted plan also has worse proportionality scores than any of the 5,000 simulated plans.

B.1. Compliance with Section 6(A)

46. For the House, the efficiency gap is 8.23% for the enacted map, whereas the average efficiency gap for the simulated plans is only 3.80%. This implies that the enacted plan wastes

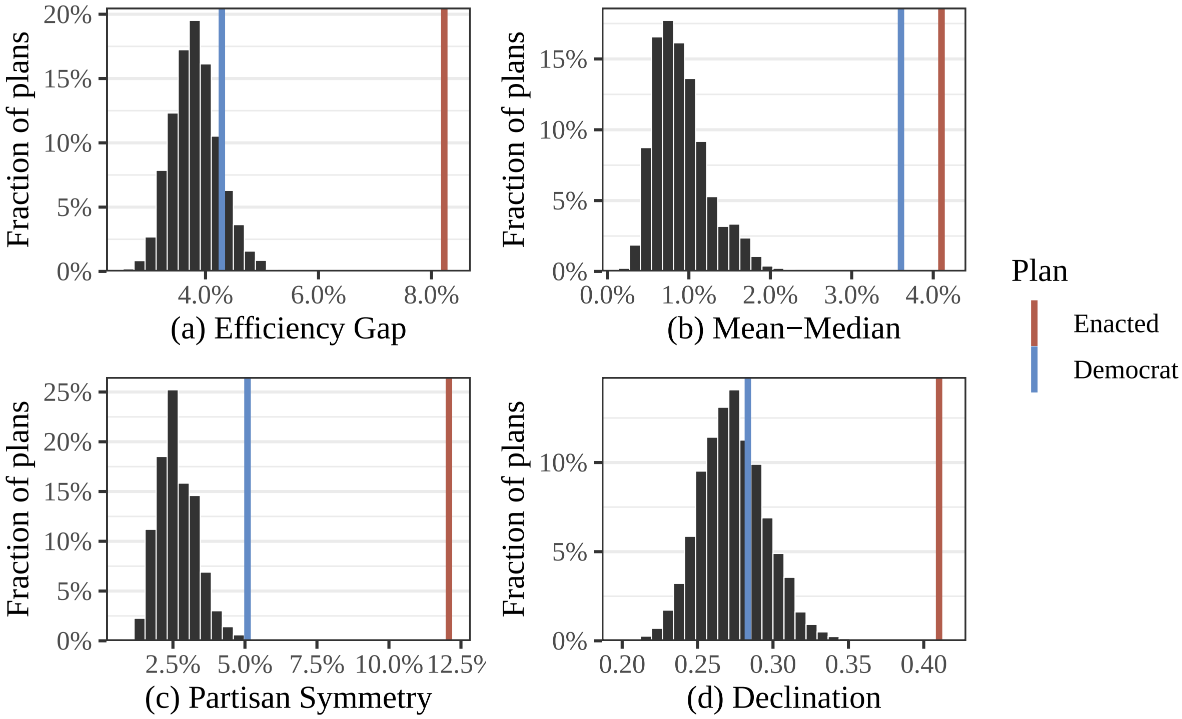

Figure 7: Four partisan bias measures calculated for the 5,000 simulated House of Representatives redistricting plans, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the three comparison plans. For each measure, larger values (towards the right) correspond to more Republican-favoring plans.

over 100,000 more Democratic votes on average than the simulated plans, and over 100,000 fewer Republican votes. As shown in Figure 7(a), the enacted map is a clear outlier according to this metric. Figure 7(b) shows that in terms of the mean-median gap, the enacted plan is also extreme relative to the simulated plans.

47. In addition, Figure 7(c) shows that the enacted plan scores 12.1% on the partisan symmetry metric while the simulated plans score 2.6%, on average. This suggests that under the enacted plan, the Republican party would gain roughly 24 more seats than the Democrats, for a hypothetical tied election. Again, the enacted plan is a clear outlier according to this metric. Finally, as shown in Figure 7(d), the enacted plan also scores worse on the declination metric than any of the 5,000 simulated plans.

48. For the House, the Democratic caucus plan (blue line) has better scores than the

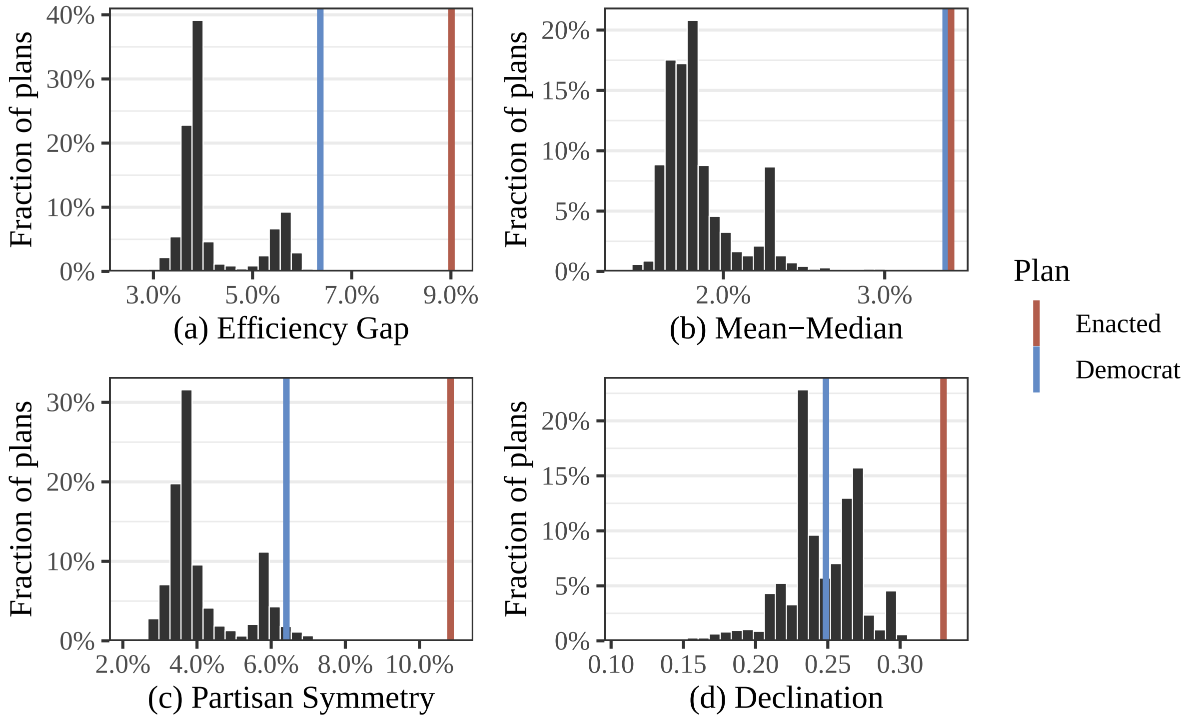

Figure 8: Four partisan bias measures calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 13 statewide elections, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the Democratic caucus plan (blue). For each measure, larger values (towards the right) correspond to more Republican-favoring plans.

enacted plan for all four partisan bias metrics. Indeed, the Democratic caucus plan does as well for the efficiency gap and declination metrics as many of the simulated plans. Like the enacted plan, however, the Democratic caucus plan is an outlier for the mean-median and partisan symmetry metrics.

49. For the Senate, the results also remain essentially unaffected by the decision to use this more complete set of statewide election results. Although my simulated Senate plans are based on the House districts of the enacted plan, Figure 8 shows that the enacted plan is extreme relative to the simulated plans according to all four partisan bias metrics. For example, as shown in Figure 8(a), the efficiency gap of the enacted plan is 9.0% whereas the simulated plans score 3.9% on average for this metric. Like the House, all of the 5,000 simulated plans have a lower (better) partisan bias score than the enacted plan across all four metrics considered here.

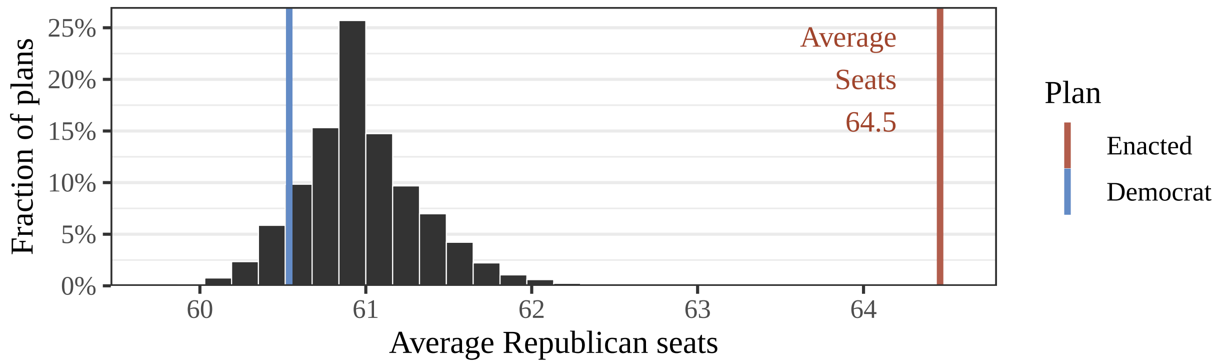

Figure 9: Average number of Repulican seats calculated for the 5,000 simulated House of Representatives redistricting plans, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the three comparison plans.

50. For the Senate, the Democratic caucus plan is also an outlier for all the partisan metrics with the exception of declination. But, the Democratic caucus plan has better scores than the enacted plan though for the mean-median metric, both plans perform about the same.

B.2. Compliance with Section 6(B)

51. The results for the enacted plan's compliance with Section 6(B) also do not change when using this more complete set of statewide elections. For the House, across the simulated plans, Republicans are expected to earn 60.9 seats on average as shown in Figure 9. In comparison, under the enacted plan Republicans would earn an average of 64.5 seats, as indicated by the red vertical line. Thus, the enacted plan gives a roughly 4 seat advantage to Republicans on average when compared to the simulated plans. Indeed, none of the simulated plans came even close to awarding this many average seats to Republican candidates.

52. In terms of the proportionality criteria of Section 6(B), the enacted plan has an average proportionality score of about 0.11, implying that the Republican party would receive an average of 11% more seats under the enacted plan than under a proportional plan where the vote share is equal to the seat share. Again, all 5,000 simulated plans had smaller (better) proportionality scores. The enacted plan also achieves a worse proportionality score than the Democratic caucus plan, which, unlike the enacted plan, is not an outlier.

53. Under the Democratic caucus plan, the Republican party would be expected to win

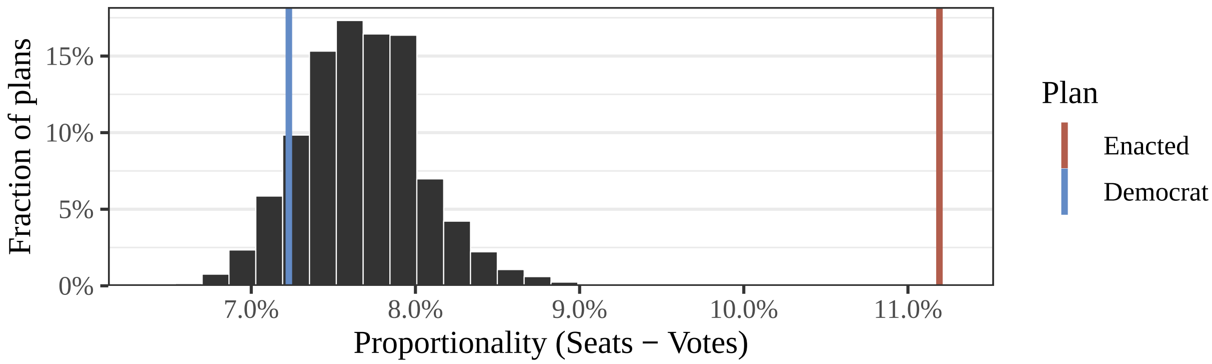

Figure 10: Corresponding proportionality measure calculated for the 5,000 simulated House of Representatives redistricting plans, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the three comparison plans.

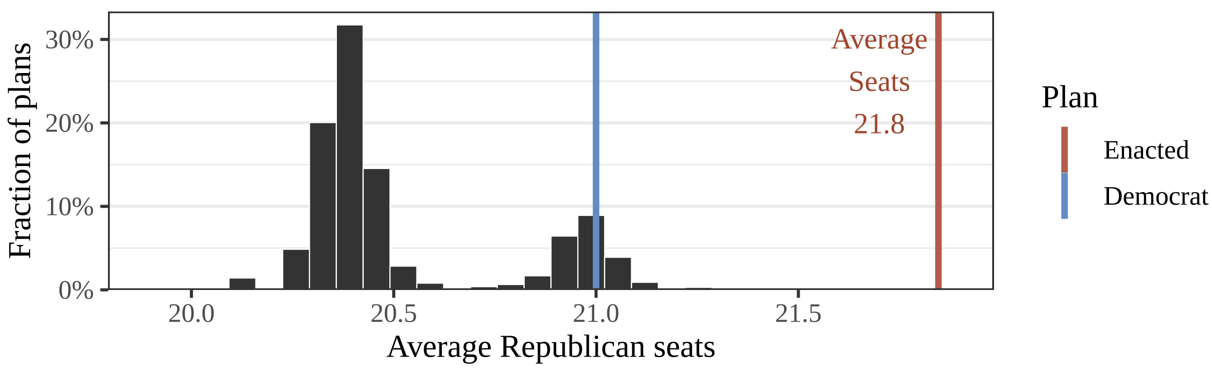

Figure 11: Average number of Repulican seats calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 13 statewide elections, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

about the same number of seats as many of the simulated plans. Accordingly, the Democratic caucus plan performs as well on the proportionality metric as many of the simulated plans.

54. For the Senate, the results also remain unaffected. Figure 11 shows that the enacted plan is the most favorable to the Republican party and is a clear outlier when compared to the simulated plans. Indeed, no simulated plan awards more seats to Republicans than the enacted plan. Republicans earn an average of 20.5 seats among the sampled plans, whereas the enacted map gives Republicans 21.8 seats on average.

55. As shown in Figure 12, the enacted plan has an average proportionality score of about 12.3%, which implies that the Republican party will receive about 12.3% more seats on

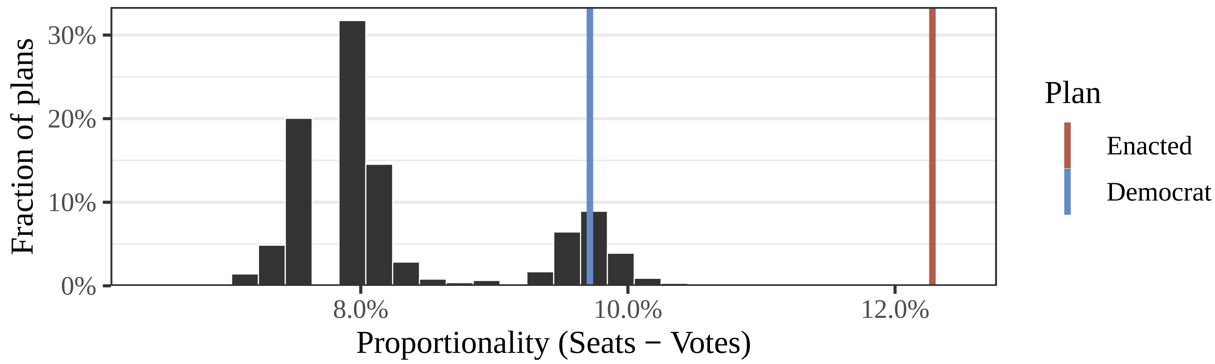

Figure 12: Corresponding proportionality measure calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 13 statewide elections, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

average under the enacted plan than under proportionality. As with the House simulations, all 5,000 simulated plans had better proportionality scores, with a mean proportionality score giving about 8.3% more seats on average to Republicans above the proportional outcome. The Democratic caucus plan has a better score than the enacted plan, though it has a worse score than most of the simulated plans.

VI. DETAILED LOCAL ANALYSIS OF COUNTY CLUSTERS

56. 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 House and Senate districts in Hamilton, Franklin, and Cuyahoga-Summit-Geauga counties. My analysis of these counties shows that for both the House and Senate, the enacted plan packs a disproportionately large number of Democratic voters into some districts while turning other districts into Republican safe seats. The results shown in this section are based on the 13 statewide elections.

A. Hamilton County

A.1. House of Representatives

57. For the House districts, I began by calculating, for each precinct, the average two-party vote share of the district to which that precinct is assigned under the enacted plan. I also performed the same calculation under each simulated plan and then averaged these vote shares

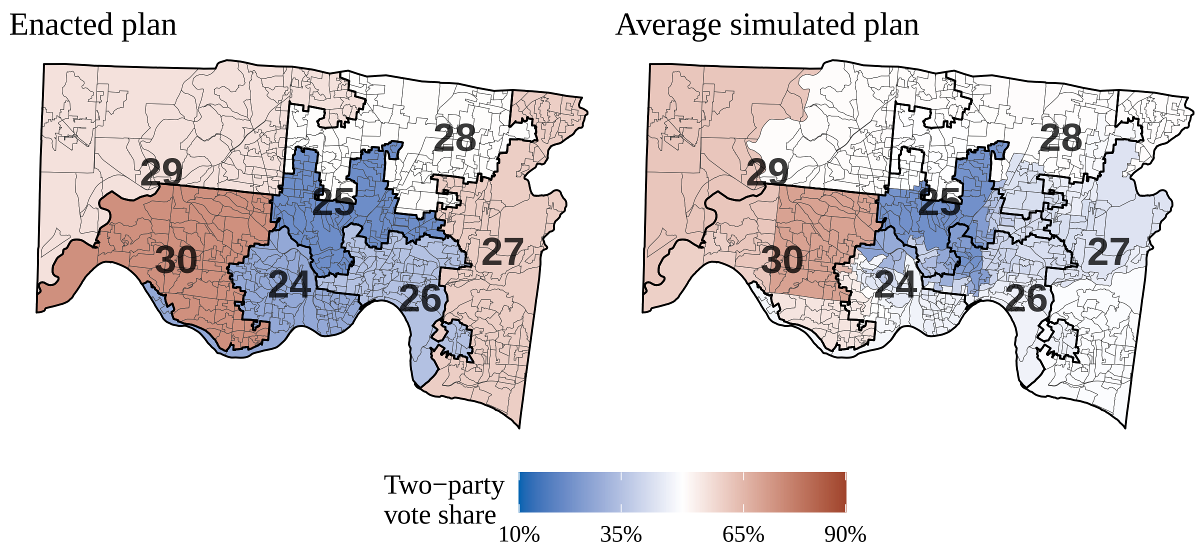

Figure 13: House districts in Hamilton county. The left and right maps show the average two-party vote share for each district under the enacted and average simulated plan, respectively. The enacted plan packs Democratic voters into districts 24, 25, and 26, turning districts 27, 29, and 30 into Republican safe seats. In contrast, under the average simulated plan, more voters live in competitive districts.

across all of the simulated plans. For example, precinct 061031AMM of Cincinnati lies within district 25 of the enacted map, which has an average Republican two-party vote share of 21.77%. 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 38.92%, which is 17.16% higher than under the enacted plan. So, based on the representative set of simulated plans that have less partisan bias, precinct 061031AMM is packed into a more Democratic district under the enacted plan than would otherwise be expected.

58. Figure 13 shows the average vote share (averaged across the statewide contests) for each precinct under the enacted plan (left plot) and under the average simulated plan (right). Under the enacted plan, Democratic areas are packed into even-more Democratic districts, turning competitive and Republican-leaning areas into safe Republican seats. This is especially apparent along the southern border, with packed Democratic districts 24 and 26 allowing districts 27 and 30 to be shored up to safe Republican seats. In addition, more voters belong to competitive districts

under the average simulation plan than under the enacted plan. This is indicated by a much larger white area under the average simulated plan than under the enacted plan.

59. A closer look at each district reveals the packing and cracking of Democratic voters under the enacted map. For reference, I also include a map of two-party vote share for each precinct in Figure 24 of Appendix F. Consider enacted district 25 as an example. This district stretches into the Democratic-leaning area at its north west corner, making this district much more Democratic than the average simulated plan. In fact, most voters in this area would belong to competitive districts under the average simulation plan as indicated by its white color in the average simulated map. Similarly, the enacted plan packs district 24 with Democratic voters who, under the average simulated plan, would live in more competitive districts (again indicated by white color) under the average simulated plan. Yet another example is enacted district 29, which grabs a heavily Democratic area at its north east area. This cracking is possible without leading to a loss of Republican seat because the western side of this district is heavily Republican.

60. As a result, the enacted plan yields 3.3 Republican seats in Hamilton county, on average. Of the 5,000 simulated plans, more than 99.5% yield a lower average of Republican seats, with the average simulated plan leading to only 2.3 Republican seats. In other words, the enacted plan's packing of Democratic voters apparent in Figure 13 allows Republicans to gain an average of 1 seat in Hamilton County alone, out of 7 total.

A.2. Senate

61. My analysis reaches the same conclusion for the Senate. The enacted plan creates a total of 3 Senate districts out of 9 House districts in Hamilton and Warren counties. To be compliant with Sections 4(B)(1) and 4(B)(2), there are only 6 possible ways draw district boundaries from the House districts in the enacted plan (see Appendix B).

62. Figure 14 presents all of these plans along with the district-level average vote share under each plan. The enacted map (top left plot) packs a large number of Democratic voters into one district, which has 72.4% Democratic two-party vote share. At the same time, the enacted plan has two safe expected seats for Republicans with an average Democratic two-party vote share

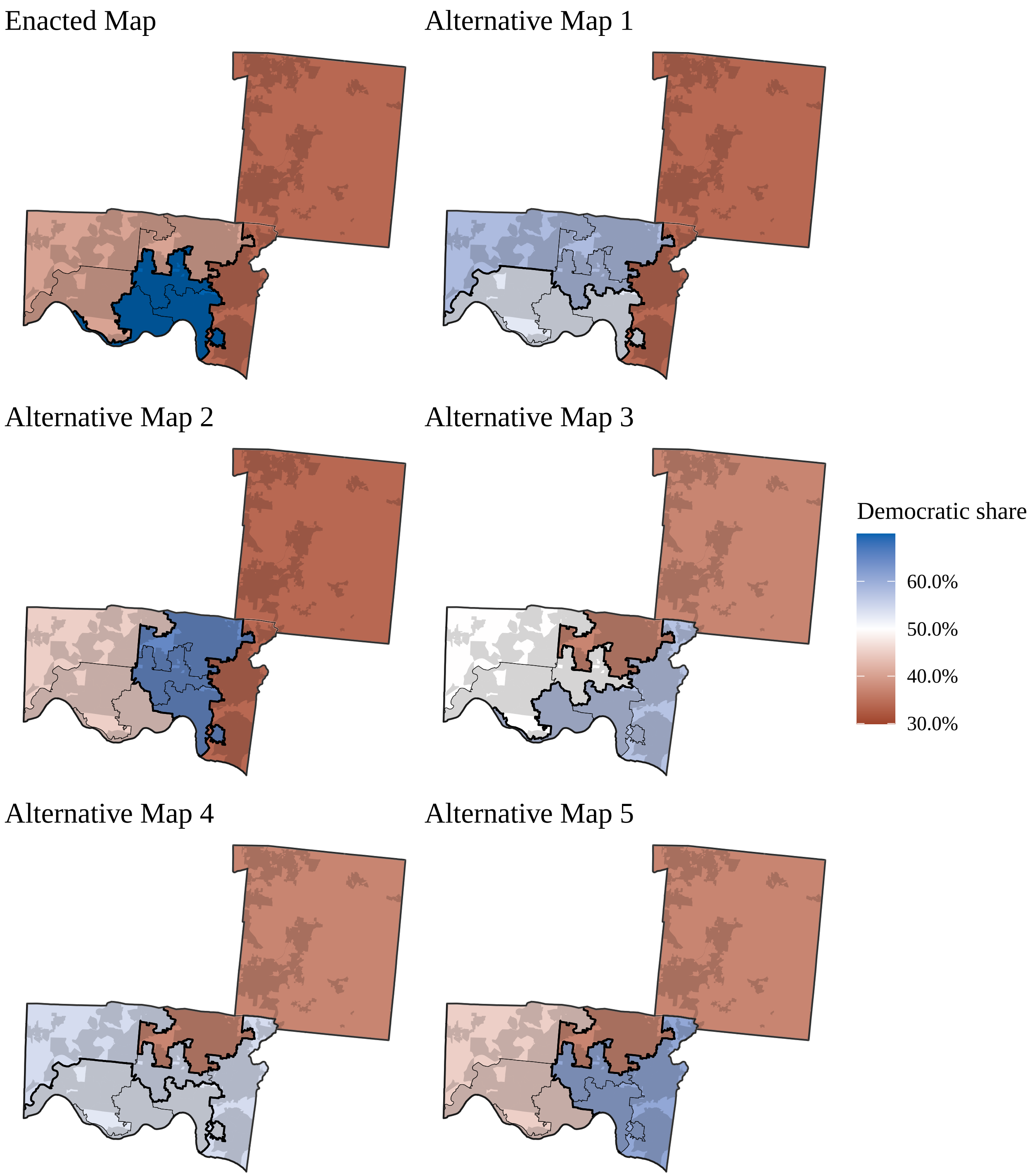

Figure 14: The 6 possible Senate districts in the Hamilton and Warren county cluster. The enacted plan is the top left plan. The enacted plan (top left) packs a disproportionately large number of Democratic voters into one district, creating two safe Republican districts. In contrast, the other plans create more competitive districts.

of 34.0% and 40.3%. In contrast, the other alternative plans do not have such a packed district. In particular, Alternative Map 3 (right middle plot) has one competitive district (Democratic vote-share of 49.9%) along with one Democratic (57.2%) and one Republican district (37.1%). This shows that the enacted plan unnecessarily packs Democratic voters into one district and is the most favorable to the Republican party among all possible plans in this area.

B. Franklin County

B.1. House of Representatives

63. Analogous to Figure 13, Figure 15 shows the average vote share (averaged across the statewide contests) for each precinct under the enacted plan (left plot) and under the average simulated plan (right plot) for Franklin county. Just like in Hamilton county, the enacted plan packs Democratic voters into a small number of districts (i.e., districts 1, 2, 3, and 7), allowing for the creation of two Republican seats in districts 10 and 12, and a third slightly Republican-leaning seat in district 4. For most of the areas of Franklin county which belong to Republican districts under the enacted plan, the average simulated plan would have placed them in more competitive or slightly Democratic-leaning districts.

64. This packing strategy can be seen clearly in the precinct-level vote shares as well, which are shown in Figure 25 of Appendix F. Districts 3 and 4 serve as illustrative examples. The boundary between the districts exactly follows the boudnary between the heavily-Democratic area around Columbus and the Republican-leaning area outside. A similar pattern is seen on the boundary of districts 4 and 9. The right plot of Figure 15 confirms that this boundary pattern is unusual, relative to the simulated plans: the average simulated district 4 is around five points more Democratic than the enacted district 4.

65. The net result of this packing is that the enacted plan yields 3.4 Republican seats in Franklin county, on average. Of the 5,000 simulated plans, all yield a lower average of Republican seats, with the average simulated plan leading to only 3.0 Republican seats. In other words, the enacted plan's packing of Democratic voters apparent in Figure 15 allows Republicans to gain an average of nearly half a seat in Franklin county, out of 12 total.

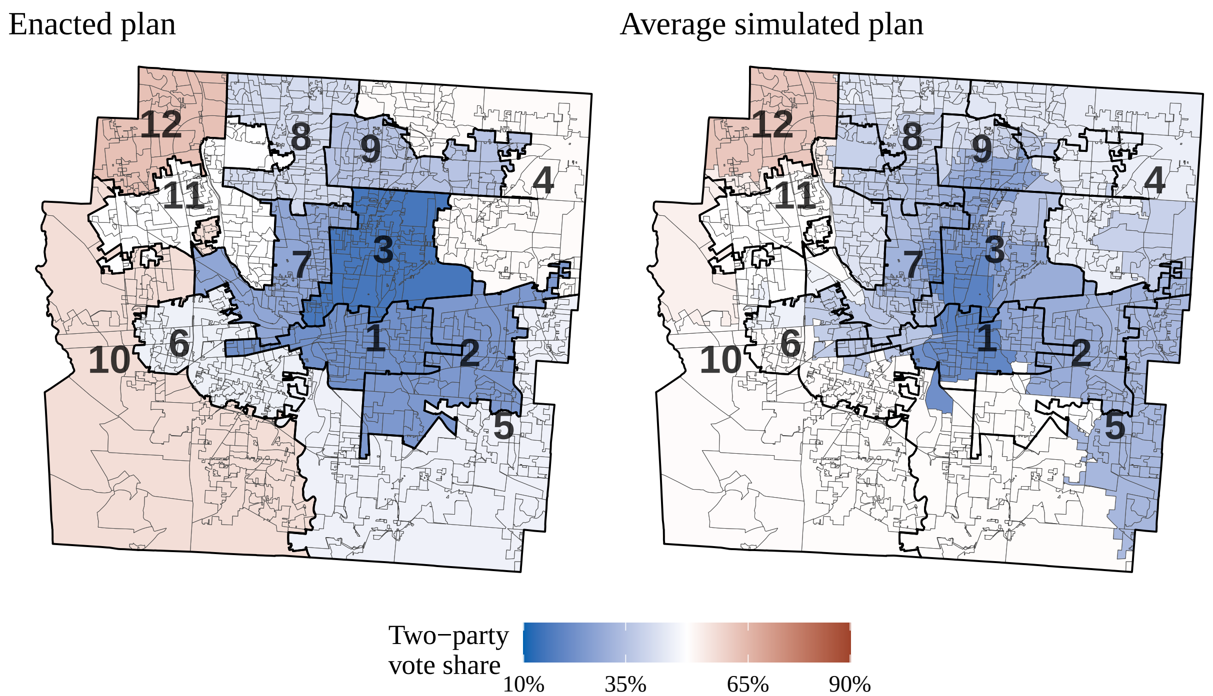

Figure 15: House districts in Franklin county. The left and right maps show the average two-party vote share for each district under the enacted and average simulated plan, respectively. The enacted plan packs Democratic voters into districts 1, 2, 3, and 7, turning districts 10 and 12 into Republican seats. In contrast, under the average simulated plan, more voters live in competitive districts.

B.2. Senate

66. For the Senate, as explained in Appendix B, my Senate analysis uses the House districts of the enacted plan. Since each Senate district consists of three House districts, the number of all possible Senate plans that satisfy Article XI Section 4(B) is relatively small. Thus, I used the algorithm of Fifield, Imai, et al. 2020 to enumerate all possible compliant plans. The algorithm found a total of 153 such compliant districting plans within this county cluster.

67. Panel (a) of Figure 16 presents each plan's two-party vote shares for the most Republican district (vertical axis) and the second most Republican district (horizontal axis). The plot clearly shows that the enacted plan, represented by the solid red square, chooses the combination of one safe Republican district and one competitive district. Panel (b) of the same figure shows that the enacted plan gives the best chance of electing two Republicans by packing the maximum

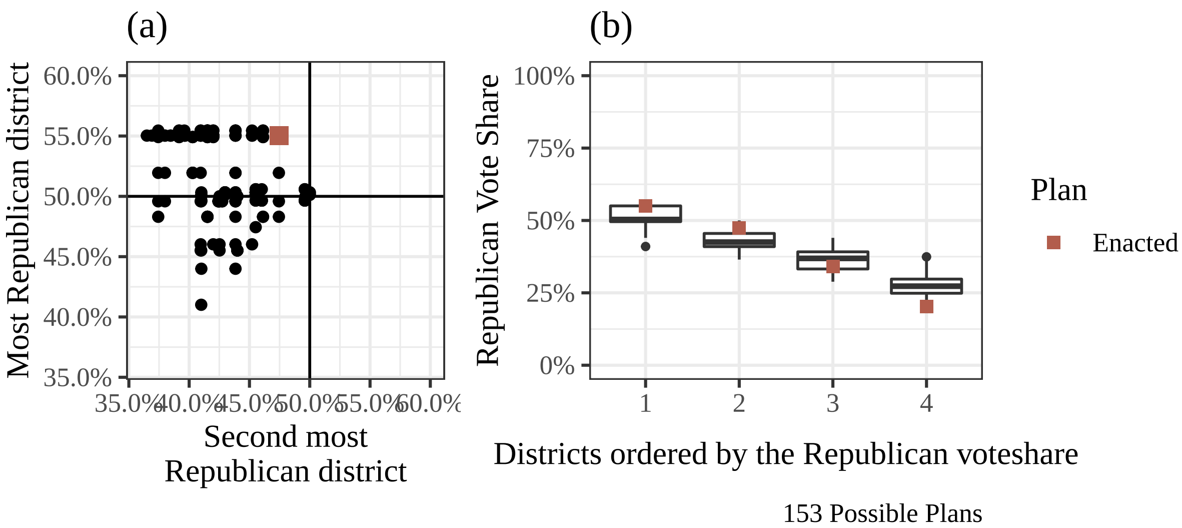

Figure 16: Comparison of simulated districts in Franklin and Union counties with the enacted districts. In panel (a), the vertical axis indicates the most Republican district and the horizontal axis indicates the next most Republican district. In panel (b), the districts are ordered horizontally by the Republican two-party vote share. The vertical axis indicates the Republican two-party vote share in that district.

number of Democratic voters into the most Democratic district. This shows that among all possible compliant plans in this county cluster, the enacted plan is the most favorable to the Republican party.

C. Cuyahoga, Summit, and Geauga Counties

C.1. House of Representatives

68. Figure 17 shows a similar pattern to Figures 13 and 15. The enacted plan creates additional Republican seats by concentrating Democrats and drawing district borders along partisan boundaries. In Cuyahoga, Summit, and Geauga counties, this is most apparent in districts 17 and 31, which under the simulated plans are generally more competitive or even Democratic-leaning, but which are Republican seats under the enacted plan.

69. This is achieved for enacted district 17 in part by having the boundary between districts 17 and 22 follow a partisan divide at a town boundary, as is visible at the precinct level in Figure 26 of Appendix F. In district 31, the enacted plan follows the western border of Akron exactly, and separates Akron proper from the towns of Norton and Barberton to its southwest.

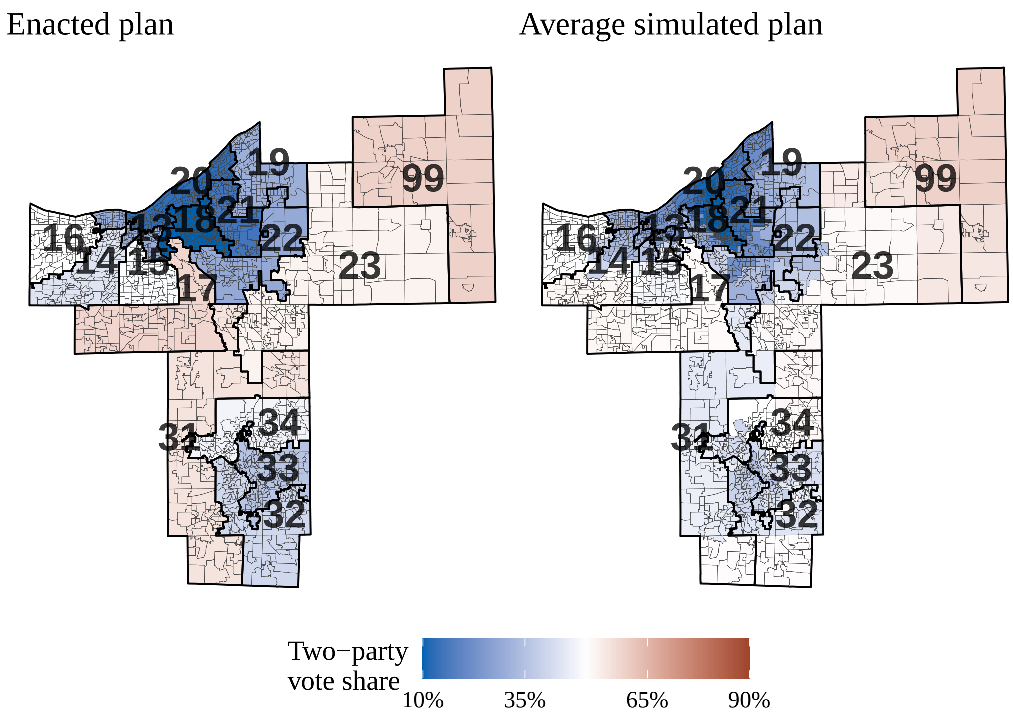

Figure 17: House districts in Cuyahoga, Summit, and Geauga counties. The left and right maps show the average two-party vote share for each district under the enacted and average simulated plan, respectively. The enacted plan packs Democratic voters in Cleveland districts, shoring up Republican vote shares in districts 17 and 31.

With the simulated plans, Norton and Barberton are more likely to be included with at least part of Akron, and consequently district 31 leans slightly Democratic.

70. In total, the enacted plan yields 6.3 Republican seats in these three counties, on average. Of the 5,000 simulated plans, all yield a lower average of Republican seats, with the average simulated plan leading to 5.4 Republican seats.

C.2. Senate

71. Like the Franklin county cluster, I used the enumeration algorithm to identify all possible compliant Senate plans within the Cuyahoga-Summit-Geauga county cluster. There are a total of 27 such plans in this case. Panel (a) of Figure 18 presents each plan's vote share for the most Republican district (vertical axis) and the second most Republican district (horizontal axis). The panel shows that the enacted plan chooses the districts, which are most favorable to the Republican party. Specifically, it chooses one safe district and one competitive district. Panel

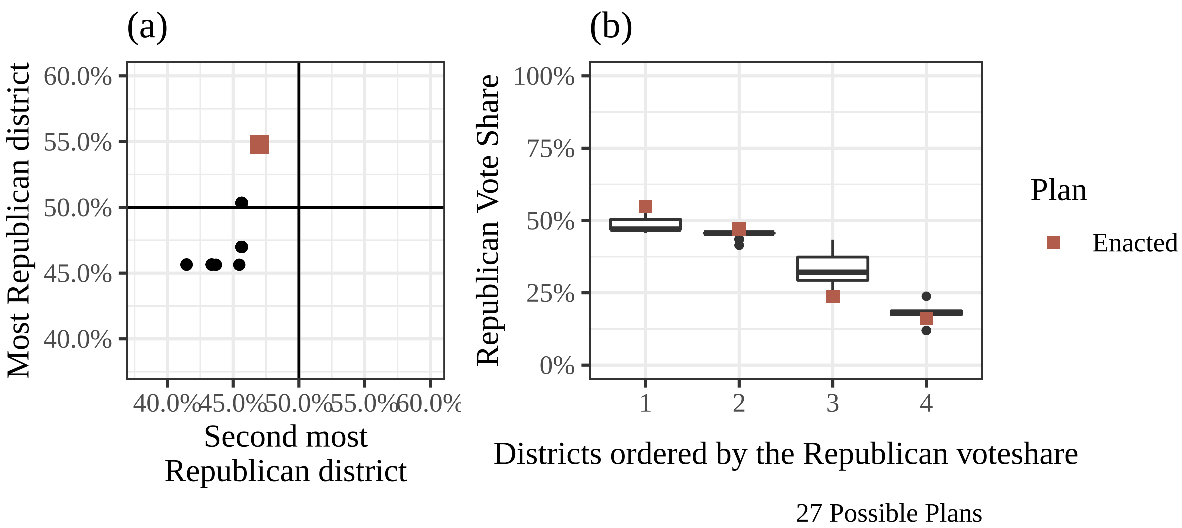

Figure 18: Comparison of simulated districts in Cuyahoga, Summit, and Geauga counties with the enacted districts. In panel (a), the vertical axis indicates the most Republican district and the horizontal axis indicates the next most Republican district. In panel (b), the districts are ordered horizontally by the Republican two-party vote share. The vertical axis indicates the Republican two-party vote share in that district.

(b) of the figure presents the Republican vote share across the districts that are ordered by the magnitude of their Republican vote shares. The enacted plan packs Democratic voters into the most Democratic districts, making the other two districts most Republican leaning possible. Again, among all compliant plans in this county cluster, the enacted plan is the most favorable to the Republican party.

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 Ohio and elsewhere, including Michigan, North Carolina, and Pennsylvania.[2]

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

2. 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. These two guarantees are precisely those required by Article XI, § 03(B)(3) and § 03(B)(1), respectively.

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. Incorporating Article XI Sections 3 and 4 into the Algorithm

9. For the House of Representative plans, I follow the exact decisions made by Respondents under the enacted plan in creating clusters of counties, each of which contains a certain number of whole House districts. I simulate redistricting plans independently within each of these county clusters and combine them across the clusters to generate statewide plans.

10. For the Senate, my analysis is dependent on the House district boundaries in the enacted plan (Recall that a Senate district consists of exactly three House districts). I again follow the exact decisions made by Respondents in creating clusters of counties, each of which contains a certain number of whole Senate districts. Like the House of Representatives, I conduct a simulation analysis independently within each county cluster and then combine the results to generate statewide plans.

11. This process ensures that my simulated House and Senate plans are at least as compliant with Sections 3 and 4 as the enacted plan, which I am assuming is compliant with these provisions. I now explain this process in detail separately for the House and the Senate.

B.1. The House of Representatives

12. In drawing a redistricting plan for the House of Representatives, a multitude of constraints must be satisfied. We begin by classifying a total of 88 counties in Ohio into three categories based on their population according to Article XI Section 3(C) of the constitution: 3(C)(1), 3(C)(2), and 3(C)(3) counties, which are colored using green, blue, and yellow, respectively, in Figure 19.

13. There are a total of twenty-two 3(C)(1) counties. According to § 3(C)(1), each of these large counties should be "divided into as many house of representative districts as it has as it has whole ratios of representation." In addition, the article stipulates that "Any fraction of the population in excess of a whole ratio shall be a part of only one adjoining house of representatives district." There are many possible ways to choose the adjoining district when spilling over an excess fraction of the population from each of 3(C)(1) county into neighboring counties. The enacted map makes certain choices about how to allocate excess population from 3(C)(1) counties

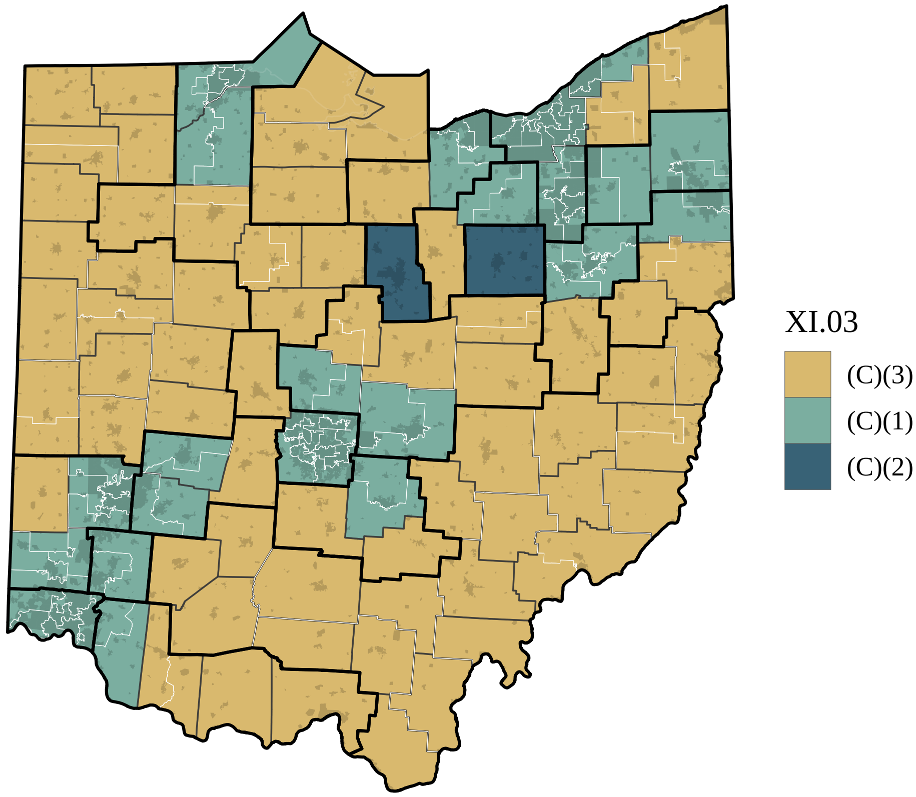

Figure 19: Ohio counties, colored by the subsection of Article XI.03 which they are subject to. Gray lines are county borders, and white lines are the district borders of the plan enacted by Respondents. Thick black lines demarcate independent county clusters used in simulation.

into neighboring counties. We follow these decisions of the enacted plan by starting with each 3(C)(1) county and selecting the minimal set of adjacent counties that contain whole districts in the enacted plan. These minimal sets of adjacent counties that contain whole districts sometimes include counties smaller than the ratio of representation, and we ensure that each of these counties is not split more than once, as required by § 3(C)(3). This results in 18 non-overlapping clusters of counties, as shown in Table 1. These clusters are demarcated in Figure 19 using the solid black boundary lines.

14. These clusters are determined by starting with each 3(C)(1) county and selecting the minimal set of adjacent counties so that no district in the enacted plan crossed their borders. For example, according to the enacted plan, all seven districts in Hamilton county lie entirely within the county, so Hamilton county is its own cluster. In contrast, in the enacted plan, one of the districts in Lorain county spills into Huron county (but goes no further), and so Lorain and Huron

Table 1: The clusters of counties that contain whole districts according to the enacted plan.

Counties	Districts
Franklin and Union	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, and 12
Cuyahoga, Summit, Lake, Geauga, and Ashtabula	13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 31, 32, 33, 34, 56, 57, and 99
Hamilton	24, 25, 26, 27, 28, 29, and 30
Butler, Montgomery, and Preble	35, 36, 37, 38, 39, 44, 45, and 46
Lucas, Wood, Hancock, Putnam, Wyandot, Crawford, and Marion	40, 41, 42, 43, 76, 83, and 87
Stark and Tuscarawas	47, 48, 49, and 50
Portage and Trumbull	64, 65, and 72
Lorain and Huron	51, 52, and 53
Warren	54 and 55
Mahoning, Columbiana, and Carroll	58, 59, and 79
Licking, Delaware, Morrow, Knox, Holmes, and Coshocton	60, 61, 68, 69, and 98
Clermont, Brown, Adams, and Scioto	62, 63, and 90
Fairfield, Pickaway, and Hocking	73 and 74
Medina and Ashland	66 and 67
Clark, Greene, and Madison	70, 71, and 75
Williams, Fulton, Defiance, Henry, Paulding, Van Wert, Mercer, Allen, Auglaize, Hardin, Logan, Champaign, Shelby, Darke, and Miami	80, 81, 82, 84, 85, and 86
Ottawa, Erie, Sandusky, and Seneca	88 and 89
Clinton, Fayette, Highland, Ross, Pike, Vinton, Jackson, Lawrence, Gallia, Meigs, Athens, Perry, Morgan, Washington, Monroe, Noble, Belmont, Jefferson, Harrison, Guernsey, and Muskingum	91, 92, 93, 94, 95, 96, and 97

form a cluster.

15. In addition, there are two 3(C)(2) counties—Richland and Wayne—whose population falls between 95% and 105% of the target population. The enacted plan complies with § 3(C)(2) and assigns one district to each of these two counties. My analysis treats these two counties in the same way, and therefore no simulation is required.

16. Lastly, under the enacted plan, the remainder of the state (i.e., the entire state minus two 3(C)(2) counties and 19 clusters) is divided into three contiguous sets of counties, which consist of a subset of 3(C)(3) counties (see Figure 19). The list of counties that belong to each of these remaining clusters is given in the final three rows of Table 1. Per § 3(C)(3), these counties should not be split more than once. Occasionally, the algorithm will by chance split one of these counties more than once. I discard these simulations, leaving only those which are fully compliant with § 3(C)(3).

17. The enacted plan has no violation of § 3(C)(1). To ensure perfect compliance with this provision, I instruct the algorithm to follow the enacted plan and avoid creating districts that cross certain county boundaries. These boundaries are borders between Delaware and Licking, Delaware and Knox, Licking and Knox, Butler and Montgomery, Greene and Clark, Geauga and Cuyahoga, Lake and Cuyahoga, Summit and Cuyahoga, and Geauga and Lake counties. Preserving these boundaries is needed to guarantee that my simulated plans do not violate § 3(C)(1), and make the same choice as the enacted plan in terms of county splits.

18. Another important set of choices is which municipalities or townships to split, pursuant to § 3(D)(2) and § 3(D)(3). I ensured that the simulated plans complied with § 3(D)(2) and § 3(D)(3) as much as or more than the enacted plan by instructing the algorithm to avoid splitting any municipalities or townships smaller than the ratio of representation, except for those split by Respondents in the enacted plan. There are at least eleven instances in which the enacted plan splits municipalities or townships. They are the cities of Cleveland, Columbus, Cincinnati, Toledo, Akron, Dayton, Solon, and New Albany (the largest contiguous portion lying within Franklin county), and the townships of Jackson (in Franklin County), Copley, and Nimishillen. The algo-

Table 2: The clusters of counties that are consistent with the enacted plan. These clusters avoid violations of XI.04.

Districts	Counties
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	Franklin, Union
35, 36, 37, 38, 39, 80	Montgomery, Butler*, Preble, Miami*, Darke*
24, 25, 26, 27, 28, 29, 30, 54, 55	Hamilton, Warren
13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 31	Cuyahoga, Summit*, Geauga*
32, 33, 34, 40, 41, 42, 44, 45, 46, 47, 48, 49, 51, 52, 53, 56, 57, 99, 64, 65, 72, 70, 71, 75	Summit*, Lucas*, Butler*, Lorain, Huron, Lake, Ashtabula*, Trumbull, Portage, Clark, Greene, Madison
43, 50, 58, 59, 60, 61, 62, 63, 66, 67, 68, 69, 73, 74, 76, 77, 78, 79, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98	All remaining counties and partial counties

rithm is allowed to split these municipalities or townships along the specific district lines adopted in the enacted plan. None of these municipalities or townships are between 50% and 100% of ratio of representation and therefore do not violate § 3(D)(2).

B.2. The Senate

19. Like my analysis of the enacted plan for the House of Representatives described above, I follow many of the decisions made by Respondents in creating the enacted plan for the Senate. I begin my analysis of the enacted Senate plan by using the enacted House plan (recall that each Senate district should consist of exactly three House districts).

20. Given the enacted House plan, I consider the restrictions the Ohio constitution imposes on the construction of Senate districts. Specifically, § 4(B)(1) states that a large county, which contains at least one whole Senate ratio of representation, should contain as many whole Senate districts as possible, and any excess fraction should be part of only one adjoining Senate district. In addition, § 4(B)(2) demands that a small county, which contains less than one Senate ratio of representation but more than one House ratio of representation, should not be split into multiple Senate districts.

21. As done for my House analysis, I follow the exact decisions made by Respondents in creating the cluster of counties that contain a certain number of whole Senate districts without spilling into an adjacent county. Table 2 presents the list of such county clusters used in the enacted plan along with their Senate districts. These clusters are colored in Figure 20. We conduct separate simulation analyses within each of the following county clusters—Franklin (red), Cuyahoga-Summit-Geauga (CSG; yellow), Hamilton (purple), Montgomery-Butler-Preble-Miami-Darke (MBPMD; orange). In the figure, the "Determined" county clusters (dark blue) refer to the House districts which can only be in one Senate district to be compliant. No simulation is necessary for any of these "Determined" clusters because we follow the enacted Senate district that was adopted. Finally, the "Remainder" county cluster (white) represents the rest of counties that need not be grouped to be compliant with the Section 4 constraints. Like other county clusters, we conduct separate simulations within this cluster.

C. Implementation details

22. 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, the SMC algorithm continues to perform accurately in large states with many districts, a critical feature for the Ohio House of Representatives districts.

23. The mathematical function I used to discourage packed districts mirrors the way other constraints are imposed on simulation algorithms (e.g., Herschlag et al. 2020a) and is given by $C(|x_d - 0.5||x_r - 0.5|)^p$ where x_d and x_r represent the two-party vote share for Democrats and Republican (averaged across the statewide elections used in my analysis), and C is a parameter controlling the strength of the constraint. This mathematical function is completely symmetric between the two parties—switching the party labels produces the exact same value. The values of $p = 0.15$ (House) and $p = 1.5$ (Senate) were selected for the exponent based on my experience implementing similar constraints for the Voting Rights Act compliance, and by simulation experi-

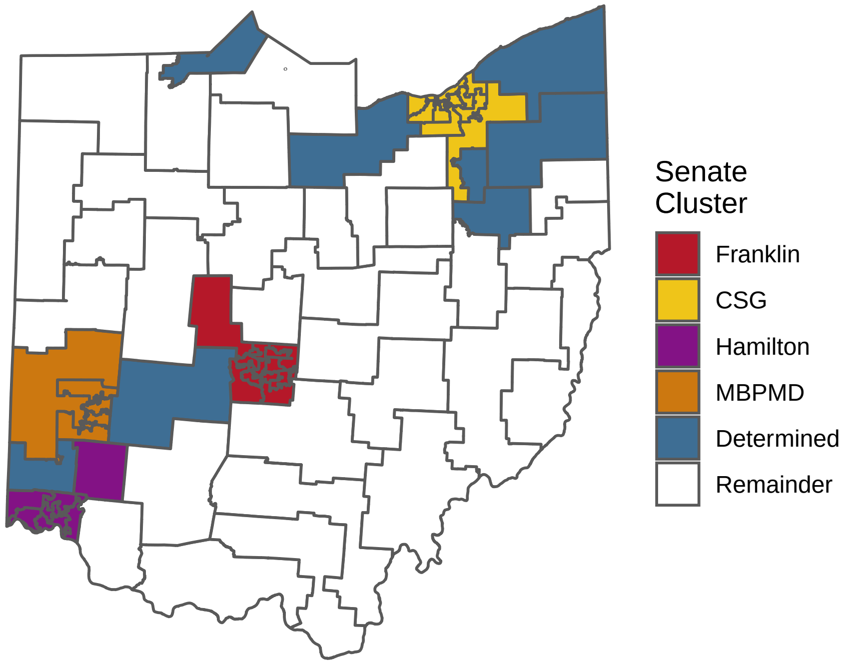

Figure 20: County clusters for the Senate implied by the decisions made to create the enacted House plan ensuring that no violations of Article XI Section 4(B)(1) or 4(B)(2). 'Determined' refers to the clusters, which there is only one compliant districting, whereas 'Remainder' refers to the rest of counties that need not be grouped to comply with the Section 4 constraints.

ments on this data. As a result, it is impossible for this constraint to favor one party over another. Note that for the Senate, removing this additional constraint yields substantively similar results.

24. I allowed the value of C to vary between 5 and 100 for each cluster simulation. Variance across clusters is necessary because each cluster has a different number and configuration of districts, and these affect how well the constraint function binds. Within the 5 to 100 range, I chose the maximum value which still maintained the accuracy of the algorithm, according to several diagnostic measures. Specifically, I increased the value of C in increments of 5, until either the resampling efficiency at any stage of the iteration fell below 1%, or the diversity of the sample, as measured by the pairwise variation of information distance between 100 randomly selected plans, was below 0.35–0.40. More detail about these diagnostic measures may be found in the

original SMC algorithm paper (McCartan and Imai 2020).

C.1. The House of Representatives

25. For the House plans, I run the algorithm independently within each county cluster and then combine the results to obtain a statewide plan. Thus, my analysis will examine how each cluster can be divided into the fixed number of districts in different ways, and how this drawing process affects each plan's compliance with Sections 6(A) and 6(B).

26. In Hamilton county, I ensured that there be one district whose majority of voting age population identify themselves in any part as Black. I made this decision based on the affidavit of Dr. Lisa Handley, which I reviewed. To accomplish this, I used a Voting Rights Act constraint and tuned it so that at least 75% of simulated plans in Hamilton county had one such majority-minority district (MMD). This constraint may be written mathematically as $\sqrt{\max(x_b - 0.51, 0)}$, where x_b is the share of a district's VAP that is Black. This is a common way to formulate the VRA constraint (Herschlag et al. 2020b).

27. Because this county uses both partisan bias and VRA constraints, which interact with one another, I employed a different rule in selecting the value of C for Hamilton county. I first adjusted the strength of the VRA constraint until at least 75% of simulated plans had one or more MMDs. Then, I increased the value of C in increments of 5 until the diversity of the sample reached 0.2. After generating redistricting plans in Hamilton county, I discarded the simulated plans that do not have at least one such MMD so that my simulated plans are perfectly compliant with this requirement.

C.2. The Senate

28. Simulating the Senate plans proceeds similarly, using the House districts of the enacted plan rather than precincts as geographical units. Simulating redistricting plans independently within each of these county clusters ensures that the combined statewide plans are in compliance with § 4(B)(1) and § 4(B)(2). After conducting a simulation analysis within each county cluster, I then combine the simulated plans from each cluster to create statewide plans. As with the House district simulation approach, I sample districts using 5% population bounds in accordance with

§ 3(B)(1). This guarantees that all 3 district plans are achievable in terms of the total statewide population. I also apply our party-neutral constraint, increasing its strength incrementally until the stopping criteria is met, as done in the House simulation. Per instruction of counsel for the Relators, I do not impose a VRA constraint.

D. An Example Simulated Plan

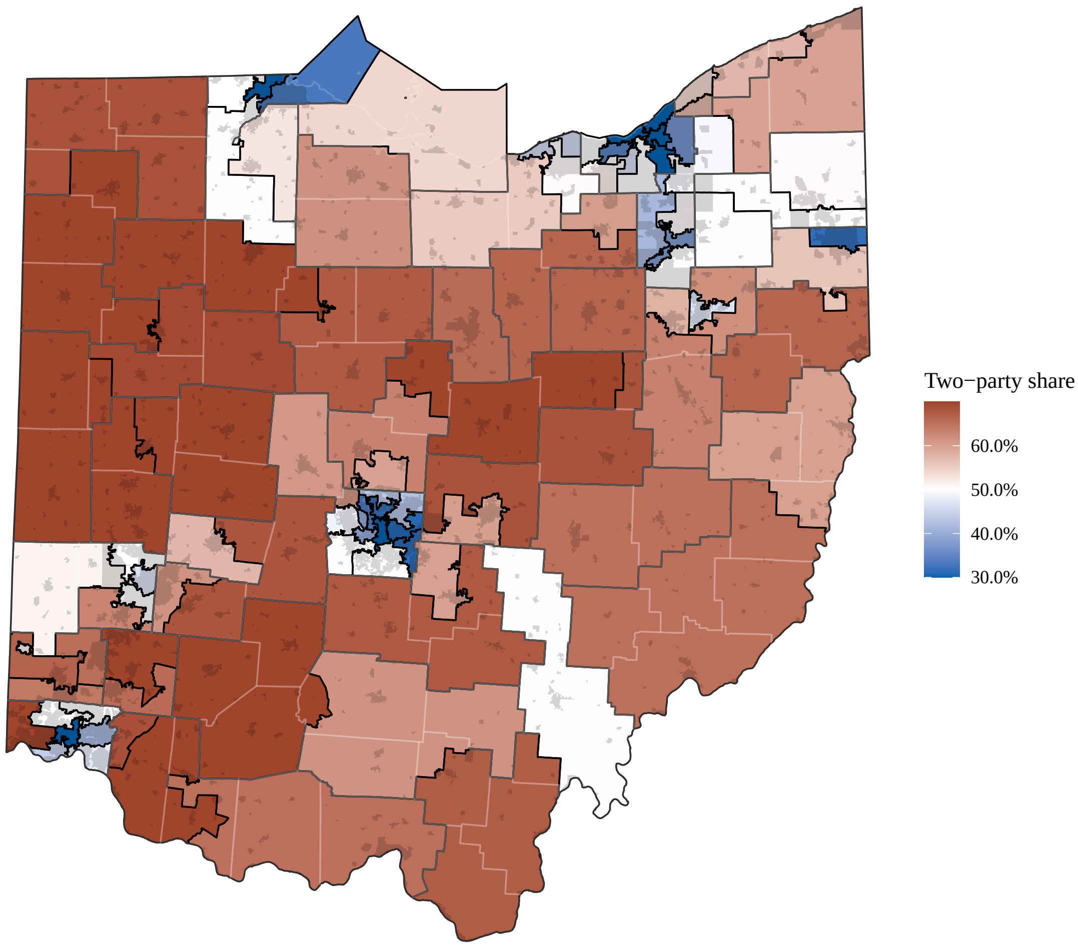

Figure 21: An example simulated redistricting plan for the House, with districts colored by their average two-party vote share.

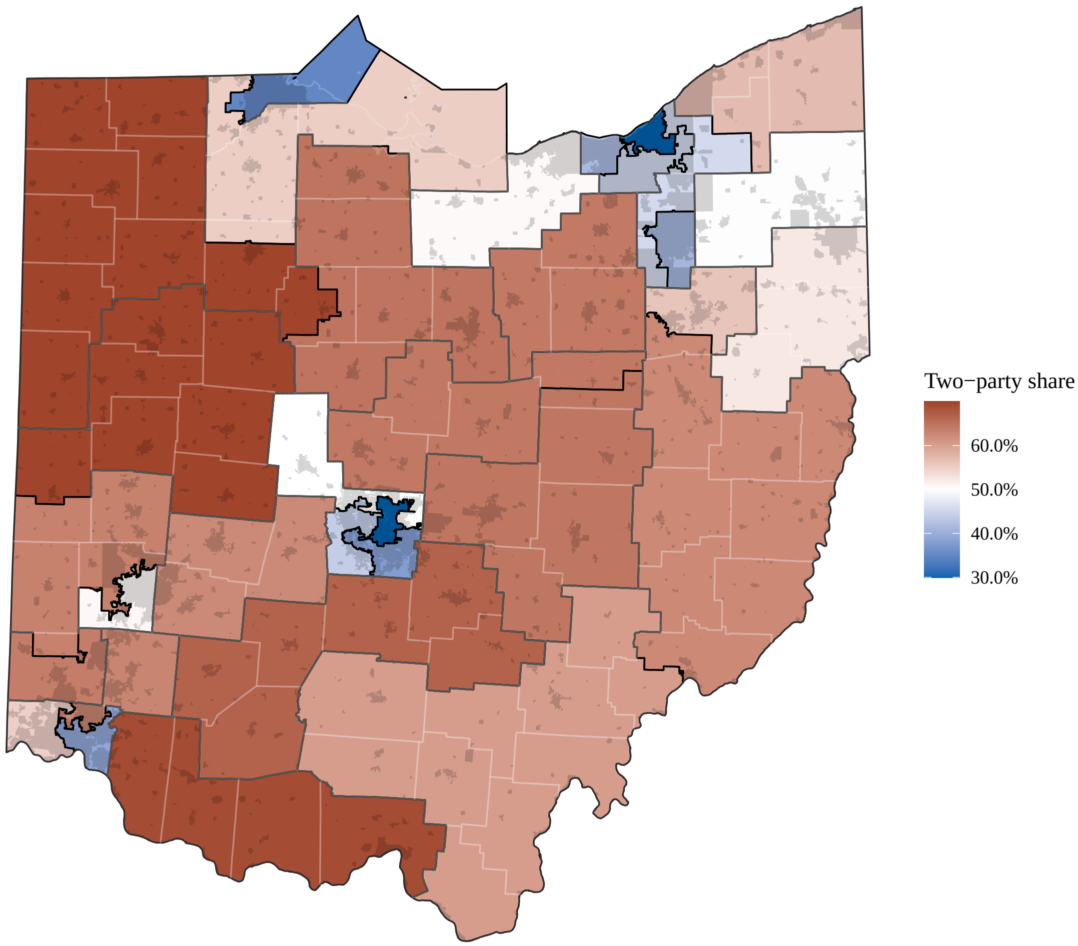

Figure 22: An example simulated redistricting plan for the Senate, with districts colored by their average two-party vote share.

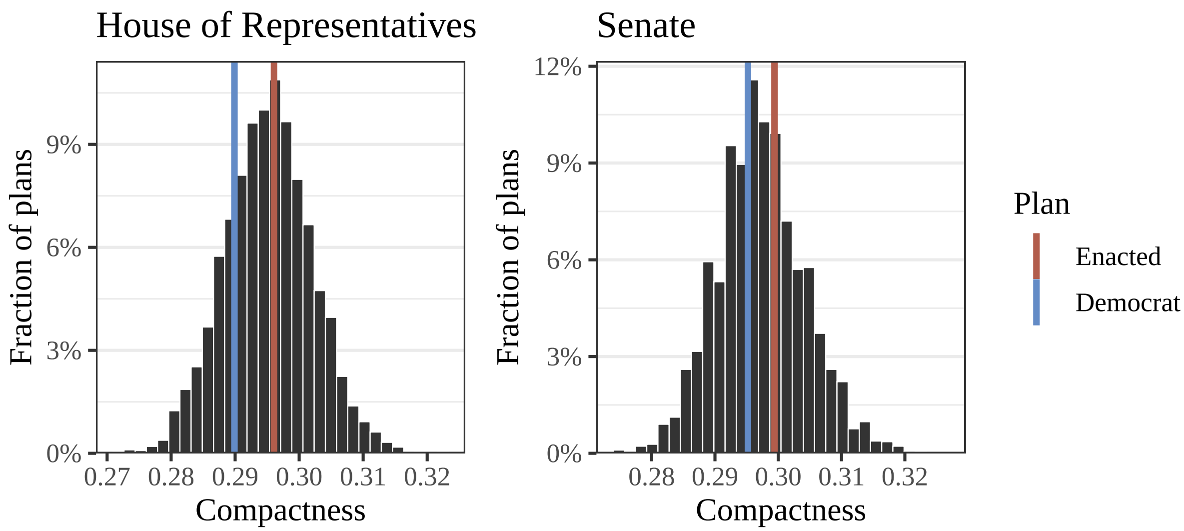

Figure 23: Polsby–Popper compactness scores for the simulated redistricting plans. Overlaid are scores for the enacted (red) and the Democratic caucus plan (blue). Larger values indicate more compact districts.

E. Compliance with Section 6(C)

29. The results in Section V show that the simulated plans and the Democratic caucus plan are much more compliant with Sections 6(A) and 6(B) than the enacted plan. I now show that this superior compliance is achieved without sacrificing compliance with Section 6(C), which requires districts to be compact. I use the Polsby–Popper score, a commonly-used quantitative measure of district compactness (Polsby and Popper 1991).

30. Figure 23 shows that the enacted plan and the Democratic caucus plan are both as compact as the simulated plans, on average. The result clearly implies that it is possible to be more compliant with Sections 6(A) and 6(B) without sacrificing the compliance with Section 6(C).

F. Vote Share for Precincts

31. Figure 24 presents the two-party vote share for precincts of Hamilton county. Figure 25 presents the two-party vote share for precincts of Franklin county. Figure 26 presents the two-party vote share for precincts of Cuyahoga, Summit, and Geauga Counties.

G. References and Materials Considered

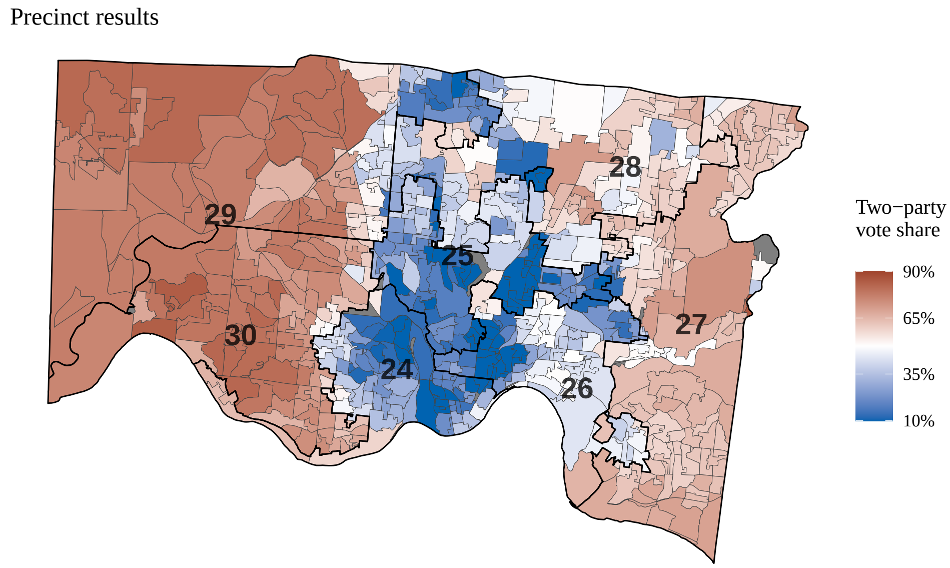

Figure 24: Vote shares for the precincts of Hamilton county.

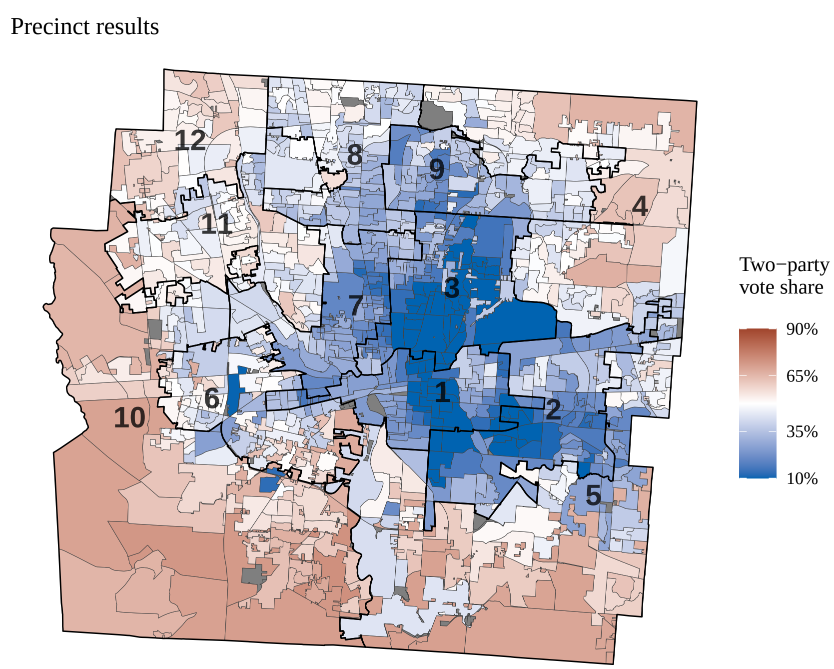

Figure 25: Vote shares for the precincts of Franklin county.

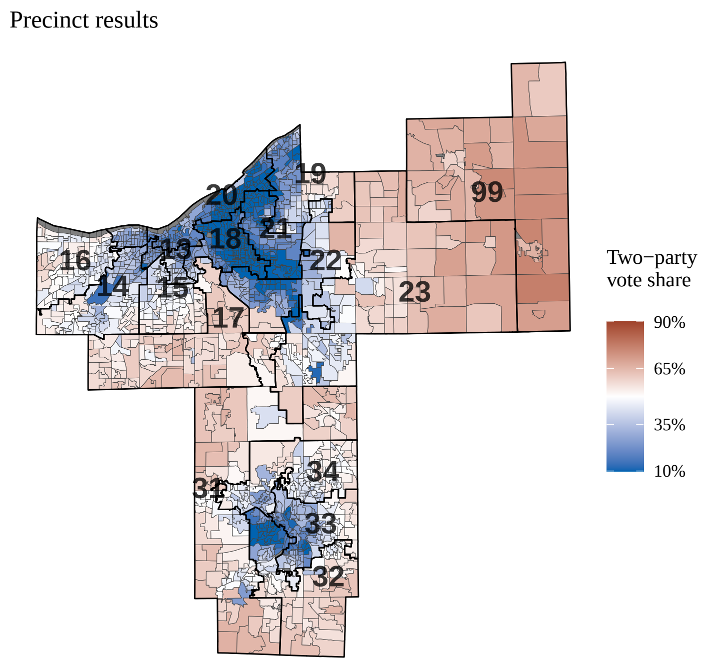

Figure 26: Vote shares for the precincts of Cuyahoga, Summit, and Geauga counties.

G.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)

- 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), VTD block assignment files, lower general assembly district block assignment files, and upper general assembly district 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 and the House and Senate Democratic Caucuses plan data were obtained from the Ohio Redistricting Commission website, as block assignment files.

Data Processing

- The datasets that were on the 2020 census block level (total population, voting age population, Census place assignment, VTD assignment, lower GA district assignment, upper GA district assignment, Democratic proposed plans, enacted plans) 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 upper and lower General Assembly plans.

- 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 muncipality 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 of Expert Report

Kosuke Imai

Curriculum Vitae

October 2021

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Education

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

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

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

Positions

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

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

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

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

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

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

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

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

Honors and Awards

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

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

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

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

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

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

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

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

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

Publications in English

Book

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

Stata version (2021) with Lori D. Bougher.

Tidyverse version (forthcoming) with Nora Webb Williams

Refereed Journal Articles

1. 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.

2. 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.

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

4. 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.

5. 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.

6. 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.

7. 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.

8. 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.

9. 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.

10. 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.

11. 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.

12. 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.

13. 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.

14. 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.

15. 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.

16. 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.

17. 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.

18. 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.

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

20. 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.

21. 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.

22. 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.

23. 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.

24. 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.

25. 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.

26. 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.

27. 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.

28. 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.

29. 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.

30. 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)

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

32. 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.

33. 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.

34. 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.

35. 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.

36. 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.

37. 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).

38. 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.

39. 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.

40. 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.

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

42. 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.

43. 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)

44. 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)

45. 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.

46. 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.

47. 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.

48. 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)

49. 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.

50. 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.

51. 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.

52. 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.

53. 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.

54. 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.

55. 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.

56. 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.

57. 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.

58. 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.

59. 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.

60. 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.

61. 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.

62. 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.

63. 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.

64. 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.

65. 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.

66. 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.

67. 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.

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

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

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

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

5. 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."

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

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

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

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

10. Fan, Jianqing, Kosuke Imai, Han Liu, Yang Ning, and Xiaolin Yang. "Improving Covariate Balancing Propensity Score: A Doubly Robust and Efficient Approach."

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. 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. Diana Stanescu (Ph.D. in 2020, Department of Politics, Princeton University). Postdoctoral Fellow, U.S.-Japan Program, Harvard University

5. Erik Wang (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political and Social Change, Australian National University

6. Asya Magazinnik (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Massachusetts Institute of Technology

7. Max Goplerud (Ph.D. in 2020, Department of Government, Harvard University). Assistant Professor, Department of Political Science, University of Pittsburgh

8. Nicole Pashley (Ph.D. in 2020, Department of Statistics, Harvard University). Assistant Professor, Department of Statistics, Rutgers University

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). Postdoctoral Fellow, New York University, Abu Dhabi

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). Assistant Professor, Graduate School of Public and International Affairs, University of Pittsburgh

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). Executive Director, Analyst Institute

32. Samir Soneji (Ph.D. in 2008, Office of Population Research, Princeton University; Dissertation Committee Chair). Associate Professor, Dartmouth Institute for Health Policy & Clinical Practice, Geisel School of Medicine, Dartmouth College

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). Assistant 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). Assistant 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). Assistant Professor, Departments of Political Science and Statistics, University of California, Los Angeles
12. Florian Hollenbach (Predoctoral Fellow, 2013–2014). Assistant Professor, Department of Political Science, Texas A&M University
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

KI_071

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.

CERTIFICATE OF SERVICE

I, Freda J. Levenson, hereby certify that on October 22, 2021, I caused a true and correct copy of the following documents to be served by email upon the counsel listed below:

1. **Affidavit of Dr. Kosuke Imai**
2. **Exhibit A - Dr. Kosuke Imai Expert Report (pages 1 - 73)**

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Counsel for Respondent Ohio Redistricting Commission

/s/ Freda J. Levenson

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, *et al.*, *Relators*, *v.* OHIO REDISTRICTING COMMISSION, *et al.*, *Respondents*.	Case No. 2021-1193

AFFIDAVIT OF DR. LISA HANDLEY

EVIDENCE OF RELATORS – DR. LISA HANDLEY EXPERT REPORT

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Robert D. Fram (PHV 25414-2021)
Donald Brown** (PHV 25480-2021)
Joshua González (PHV 25424-2021)
Juliana Goldrosen (PHV 25193-2021)
David Denuyl (PHV 25452-2021)
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Affidavit of Lisa Handley.pdf

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E-Signature Summary

E-Signature 1: Lisa Handley (LH)
October 22, 2021 07:01:47 -8:00 [6826B49E8098] [71.191.84.32]
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I, Theresa M Sabo, did witness the participants named above electronically sign this document.

Notarial act performed by audio-visual communication

IN THE SUPREME COURT OF OHIO

LEAGUE OF WOMEN VOTERS OF OHIO, et al.,	
Relators	**Case No. 2021-1193**
v.	**Original Action Pursuant to Ohio Const., Art. XI**
OHIO REDISTRICTING COMMISSION, et al.,	
Respondents.	

AFFIDAVIT OF LISA HANDLEY

Franklin County
/ss
State of Ohio

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

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

FURTHER AFFIANT SAYETH NAUGHT.

Executed on 10/22/2021, 2021.

Lisa Handley
Signed on 2021/10/22 07:01:47 -8:00
Lisa Handley

Sworn and subscribed before me this 10/22/2021 day of ____________, 2021.

Signed on 2021/10/22 07:01:47 -8:00
Notary Public

NOTARY PUBLIC
STATE OF OHIO
Theresa Michelle Sabo
Commission # 2016-re-619622
Electronic Notary Public
State of Ohio
My Comm Exp. Nov 28, 2021
Notary Stamp 2021/10/22 07:01:47 PST F15204A411DA

EXHIBIT A

Draft Affidavit of Dr. Lisa Handley

PROVIDING BLACKVOTERS WITH AN OPPORTUNITY TO ELECT: A DISTRICT-SPECIFIC, FUNCTIONAL ANALYSIS OF OHIO VOTING BY RACE

Summary.

1. I was retained by counsel for Relators in this matter to conduct a district-specific, functional analysis of voting patterns by race in areas of Ohio with significant Black populations to ascertain the Black voting age population necessary to provide Black voters with an opportunity to elect their candidates of choice in state legislative elections.[1]
2. A district-specific, functional analysis is required to determine whether a district is likely to provide minority voters with an opportunity to elect their candidates of choice. There is no single universal or statewide demographic target that can be applied for Black voters to elect their candidates of choice – the population needed to create an "effective minority district" varies by location and depends upon the participation rates and voting patterns of Black and white voters in that specific area.
3. An analysis of voting patterns is required to estimate voter participation rates by race, as well as the level of support from Black and white voters for each of the candidates competing in the examined elections. This information can then be used to calculate the Black population concentration required for the Black voters' preferred candidates to win election to office in a specific district. Drawing districts informed by this percentage avoids creating districts that either fail to provide Black voters with the opportunity to elect their candidates of choice or unnecessarily pack minority voters into districts to reduce the number of minority opportunity districts.
4. My analysis of voting patterns in recent statewide and state legislative elections indicate that voting in Hamilton County is consistently racially polarized. For example, in every one of the 13 statewide general elections analyzed, Black voters provided overwhelming support for their preferred candidates and white voters strongly favored the opponents of these candidates. Incorporating the estimates of turnout and votes by race produced by the racial bloc voting analysis, I calculated the Black voting age population that would be

[1] I am being compensated at a rate of $300 per hour.

needed for the Black-preferred candidate to win each of these racially polarized elections. This analysis led me to conclude that a district with a 50 percent Black voting age population would be sufficient to provide Black voters with an opportunity to elect their candidates of choice in the Cincinnati area of Hamilton County.

Professional Experience.

5. I have over thirty-five years of experience as a voting rights and redistricting expert. I have advised scores of jurisdictions and other clients on minority voting rights and redistricting-related issues. I have served as an expert in dozens of voting rights cases. My clients have included state and local jurisdictions, independent redistricting commissions (Arizona, Colorado, Michigan), the U.S. Department of Justice, national civil rights organizations, and such international organizations as the United Nations.
6. I have been actively involved in researching, writing, and teaching on subjects relating to voting rights, including minority representation, electoral system design, and redistricting. I co-authored a book, *Minority Representation and the Quest for Voting Equality* (Cambridge University Press, 1992) and co-edited a volume, *Redistricting in Comparative Perspective* (Oxford University Press, 2008), on these subjects. In addition, my research on these topics has appeared in peer-reviewed journals such as *Journal of Politics*, *Legislative Studies Quarterly*, *American Politics Quarterly*, *Journal of Law and Politics*, and *Law and Policy,* as well as law reviews (e.g., *North Carolina Law Review*) and a number of edited books. I hold a Ph.D. in political science from The George Washington University.
7. I have been a principal of Frontier International Electoral Consulting since co-founding the company in 1998. Frontier IEC specializes in providing electoral assistance in transitional democracies and post-conflict countries. In addition, I am a Visiting Research Academic at Oxford Brookes University in Oxford, United Kingdom. Attached to the end of this report is a copy of my *curriculum vitae*.

Calculating the Black Voting Age Population Needed to Elect Black-Preferred Candidates.

8. The Black voting age population (BVAP) percentage needed to elect Black-preferred candidates is calculated by taking into account the relative participation rates of Black and white Ohioans, as well as the expected level of Black support for the Black-preferred candidates (their "cohesiveness"), and the expected level of white voters' "crossover" voting for the Black-preferred candidates. This analysis requires constructing a database that combines demographic information and election results, then analyzes the data for patterns and uses these patterns to produce estimates of participation rates and voting patterns by race.

9. **Database.** To analyze voting patterns in Ohio requires a database that combines election returns and population data by race (or registration or turnout by race if this information is available). To build this dataset in this instance, 2016, 2018, and 2020 precinct-level shapefiles were acquired from the Voting and Election Science Team. These shapefiles were joined to precinct-level election returns from the Ohio Secretary of State's office, which were processed and cleaned by OpenElections. In addition, 2012 and 2014 election returns pro-rated to the 2010 voting district ("VTD") level, were acquired from Bill Cooper. The 2020 Census Block shapefiles, and total and voting age population by race and ethnicity, were obtained from the Census FTP portal. The election returns data was disaggregated down to the level of the 2020 Census block and, for the 2016, 2018, and 2020 election cycles separately, re-aggregated up to the level of the voting precincts used in those years, accounting for splits of precincts by state house and senate districts. For the 2012 and 2014 election cycles, the block-level election results were re-aggregated up to the level of the 2010 VTDs, taking into account splits of VTDs by state legislative districts.

10. **Elections Analyzed.** Using these data, I analyzed all statewide contested elections held between 2012 and 2020 for which I had data: the 2020 Presidential election; the 2018 elections for U.S. Senate, Governor, Attorney General, Secretary of State, Treasurer, and Auditor; the 2016 elections for President and U.S. Senate; the 2014 elections for Governor and Secretary of State;[2] and the 2012 elections for President and U.S. Senate. Only three of these elections included Black candidates: Barack Obama in the 2012 Presidential election;

[2] Data on the other statewide elections held in 2014 (Attorney General, Treasurer, and Auditor) was not readily available. No minority candidates competed in these three statewide election contests.

Nina Turner, the Democratic candidate for Secretary of State in 2014; and Rob Richardson, the Democratic candidate for Treasurer in 2018.[3] In addition to these statewide contests, I analyzed recent state legislative contests in select areas of the State, as described below.

11. **Primary Elections.** As is usually the case in the United States, there is a two-stage election process in Ohio – a primary election and a general election. Black-preferred candidates must win both elections to gain office. The overwhelming majority of Black voters in Ohio vote in the Democratic primary rather than the Republican primary. As a consequence, it is not possible to estimate Black voting behavior in Republican primaries and, in any case, Black voters' candidates of choice are found in Democratic primaries. In the past ten years, there were two statewide Democratic primaries that included African American candidates: the 2018 Democratic primary for Governor and the 2016 Democratic primary for U.S. Senate. I analyzed both of these elections. (Although both contests included African American candidates, these candidates were not, in fact, the candidates preferred by Black voters.) In addition, I analyzed recent Democratic primaries for state legislative office in areas of the state with significant Black populations.
12. **Racial Bloc Voting Analysis.** Direct information on how Black and white voters cast their votes is not available; voters' race is not included in their voter registration in Ohio and the race of the voter is not, of course, obtainable from a ballot. To estimate vote choices by race, I used three standard statistical techniques: homogeneous precinct analysis, ecological regression, and ecological inference.
13. Two of these analytic procedures – homogeneous precinct analysis and ecological regression – were employed by the plaintiffs' expert in *Thornburg v. Gingles*, 478 U.S. 30 (1986), and have the benefit of the Supreme Court's approval in that case, and other courts' approval in most subsequent voting rights cases. The third technique, ecological inference, was developed after the *Gingles* decision, and was designed, in part, to address the issue of out-of-bounds estimates (estimates that exceed 100 percent or are less than

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[3] The three elections that included Black candidates are more probative in the context of determining if voting is racially polarized than contests in which all of the candidates are white. This is because it is not sufficient for Black voters to be able to elect their candidates of choice only if these candidates are white. On the other hand, it is important to recognize that not all Black candidates are the preferred candidates of Black voters.

zero percent), which can arise in ecological regression analysis. Ecological inference analysis has been introduced and accepted in numerous federal and state court proceedings.

14. Homogeneous precinct (HP) analysis is the simplest technique: it involves comparing the percentage of votes received by each of the candidates in precincts that are racially homogeneous. The general practice is to label a precinct as homogeneous if at least 90 percent of the voting age population is composed of a single race. In fact, the homogeneous results reported are not estimates – they are the actual precinct results. However, most voters in Ohio do not reside in homogeneous precincts, and voters who reside in homogeneous precincts may not be representative of voters who live in more integrated precincts. For this reason, I refer to these percentages as estimates.
15. The second statistical technique I employed, ecological regression (ER), uses information from all of the precincts, not simply the homogeneous ones, to derive estimates of the voting behavior of Black and white Ohioans. If there is a strong linear relationship across precincts between the percentage of Blacks (or whites) and the percentage of votes cast for a given candidate, this relationship can be used to estimate the percentage of Blacks and whites voting for each of the candidates in the election contest being examined.
16. The third technique, ecological inference (EI), was developed by Professor Gary King. This approach also uses information from all precincts but, unlike ecological regression, it does not rely on an assumption of linearity. Instead, it incorporates maximum likelihood statistics to produce estimates of voting patterns by race. In addition, it utilizes the method of bounds, which uses more of the available information from the precinct returns and provides more information about the voting behavior being estimated.[4] The method of bounds also precludes the estimates from exceeding the possible limits. (Ecological regression can produce estimates of less than 0 percent or more than 100 percent of the voters supporting a given candidate, especially when voting is very

[4] The following is an example of how the method of bounds works: if a given precinct has 100 voters, of which 75 are Black and 25 are white, and the Black candidate received 80 votes, then at least 55 of the Black voters voted for the Black candidate and at most all 75 did. (The method of bounds is less useful for calculating estimates for white voters, as anywhere between none of the whites and all of the whites could have voted for the candidate.) These bounds are used when calculating EI estimates but not when using ecological regression.

polarized.) However, unlike ecological regression, EI does not guarantee that the candidate estimates add to 100 percent of each racial group in the elections examined.

17. In addition, I utilized a more recently developed version of ecological inference which I have labeled "EI RxC" in the summary tables found in the Appendix. EI RxC expands the analysis so that differences in the relative rates of minority and white turnout can be taken into account in deriving the estimates of minority and white support for the candidates.
18. Estimates using all four methodological approaches, homogeneous precinct analysis, ecological regression, and the two approaches to ecological inference, are reported in the summary racial bloc voting table included in the Appendix.
19. **Equalizing Black and white turnout.** Because Black Ohioans who are eligible to vote often turn out to vote at lower rates than white Ohioans (this is consistently the case in Hamilton County, as indicated by the summary table of voting patterns in Hamilton County found in the Appendix), the Black voting age population ("BVAP") needed to ensure that Black voters comprise at least half of the voters in an election is often higher than 50 percent. Once I estimated the respective turnout rates of Black and white voters using the statistical techniques described above, I could mathematically calculate the percentage needed to equalize minority and white voters.[5] But equalizing turnout is only

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[5] The equalizing percentage is calculated mathematically by solving the following equation:

Let

M	=	the proportion of the district's voting age population that is Black
W = 1-M	=	the proportion of the district's voting age population that is white
A	=	the proportion of the Black voting age population that turned out to vote
B	=	the proportion of the white voting age population that turned out to vote

Therefore,

M(A)	=	the proportion of the population that is Black and turned out to vote (1)
(1-M)B	=	the proportion of total population that is white and turned out to vote (2)

To find the value of M that is needed for (1) and (2) to be equal, (1) and (2) are set as equal and we solve for M algebraically:

$$
\begin{aligned}
M(A) &= (1 - M) B \\
M(A) &= B - M(B) \\
M(A) + M(B) &= B \\
M(A + B) &= B \\
M &= B/(A+B)
\end{aligned}
$$

Thus, for example, if 39.3% of the black population turned out and 48.3% of the white population turned out, B= .483 and A = .393, and M = .483/ (.393+.483) = .483/.876 = .5513, therefore a the first step in the process – is does not take into account the voting patterns of Black and white voters. If voting is racially polarized but a significant number of white voters typically "crossover" to vote for Black voters' preferred candidate, it may be the case that this crossover voting can compensate for depressed Black turnout relative to white turnout. If this is the case, Black voters need not make up at least 50 percent of the voters in an election for the Black-preferred candidate to win.

20. **Incorporating Minority Cohesion and White Crossover Voting.** Even if Black voters are turning out at lower rates than whites, and voting is racially polarized, if a relatively consistent percentage of white voters support Black-preferred candidates, these candidates can be elected despite the lower Black turnout. This is especially true if Black voters are very cohesive in supporting their preferred candidates. A district-specific, functional analysis should take into account not only differences in the turnout rates of Black and white voters, but also voting patterns by race.[6]

21. To illustrate this mathematically, consider a district that has 1000 persons of voting age, 50% of who are Black and 50% of who are white. Let us begin by assuming that Black turnout is lower than white turnout in a two-candidate general election. In our hypothetical election example, 42% of the Black voting age population (VAP) turn out to vote and 60% of the white VAP vote. This means that, for our illustrative election, there are 210 Black voters and 300 white voters. Further suppose that 96% of the Black voters supported their candidate of choice and 25% of the white voters cast their votes for this candidate (with the other 75% supporting her opponent in the election contest). Thus, in our example, Black voters cast 200 of their 210 votes for the Black-preferred candidate and their other 8 votes for her opponent; white voters cast 75 of their 300 votes for the Black-preferred candidate and 225 votes for their preferred candidate:

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black VAP of 55.1% would produce an equal number of black and white voters. (For a more in-depth discussion of equalizing turnout see Kimball Brace, Bernard Grofman, Lisa Handley and Richard Niemi, "Minority Voting Equality: The 65 Percent Rule in Theory and Practice," *Law and Policy*, 10 (1), January 1988.)

[6] For an in-depth discussion of this approach to creating effective minority districts, see Bernard Grofman, Lisa Handley and David Lublin, "Drawing Effective Minority Districts: A Conceptual Framework and Some Empirical Evidence," *North Carolina Law Review*, volume 79 (5), June 2001.

	VAP	turnout	voters	support for Black-preferred candidate	votes for Black-preferred candidate	support for white-preferred candidate	votes for white-preferred candidate
Black	500	0.42	210	0.96	202	0.04	8
White	500	0.60	300	0.25	75	0.75	225
			510		277		233

The candidate of choice of Black voters would receive a total of 277 votes (202 from Black voters and 75 from white voters), while the candidate preferred by white voters would receive only 233 votes (8 from Black voters and 225 from white voters). The Black-preferred candidate would win the election with 55.4% (277/500) of the vote in this hypothetical 50% Black VAP district. And the Black-preferred candidate would be successful despite the fact that the election was racially polarized and that Blacks turned out to vote at a lower rate than whites.

22. The candidate of choice of Black voters would still win the election by a very small margin (50.9%) in a district that is 45% Black with these same voting patterns:

	VAP	turnout	voters	support for Black-preferred candidate	votes for Black-preferred candidate	support for white-preferred candidate	votes for white-preferred candidate
Black	450	0.42	189	0.96	181	0.04	8
White	550	0.60	330	0.25	83	0.75	248
			519		264		255

In a district with a 40% BVAP, however, the Black-preferred candidate would garner only 47.5% of the vote. [7]

[7] In the illustrative examples, VAP and voting patterns are known and the equation solves for percentage of votes received by the Black-preferred candidate. In determining the percentage of Black VAP needed to provide Black voters with an opportunity to elect their candidates of choice, voting patterns and the percentage of votes are known and we are solving for the VAP needed to produce at least 50 percent of the votes for the Black-preferred candidate.

Hamilton County

23. My analysis of voting patterns in recent elections in Hamilton County indicate that voting is consistently racially polarized – in every one of the 13 statewide general elections analyzed, Black voters voted overwhelmingly for their preferred candidate and white voters strongly favored the opponent of this candidate. For example, in the 2018 election contest for State Treasurer (the most recent statewide election contest to include a Black candidate), at least 94. 5% of Black voters supported African American Rob Richardson. (The percentage estimates vary depending on the statistical approach used.) However at least 61.8% of white voters cast their vote for his opponent, Robert Sprague. The Appendix provides a table for Hamilton County indicating the estimates for Black and white voters for all 13 of the statewide elections, using the four approaches discussed above, as well as the two recent statewide Democratic primaries that included African American candidates.
24. Table 1, below, incorporates the estimates of turnout and votes by race reported in the Appendix,[8] and calculates the percent BVAP needed for the Black-preferred candidate to win the election. An important election to examine is the 2014 contest for Secretary of State, which included a Black candidate, Nina Turner, who was strongly supported by Black voters. The EI estimates for turnout (labeled "votes cast for office") are 29.0% for Black residents of voting age and 46.4% for voting age white residents. Black voters were very cohesive in their support for Turner – 95.5% of Black voters cast a vote for her according to the EI estimate. In addition, 25.6% of White voters supported Turner. Using these estimates, I calculated the percentage of vote she would have received if a district had a 35% BVAP (43.2%), a 40% BVAP (46.2%), a 45% BVAP (49.3%), a 50% BVAP (52.5%) and a 55% BVAP (55.9%). It is not until the district has a 50% BVAP that Turner wins the election.

[8] The EI estimate that controls for differential turnout – labeled "EI RxC" in the summary racial bloc voting results table – was used to calculate the percent Black VAP needed to win.

25. This exercise was repeated for all 13 general elections analyzed.[9] Looking down the columns of Table 1, it is apparent that the Black-preferred candidate would fail to win several contests if the district was 35%, 40% or 45% BVAP. It is only at 50% BVAP that the Black-preferred candidate wins all but one election, the 2014 contest for Governor won by popular Republican incumbent, John Kasich.

26. Recent state legislative elections (2016, 2018, and 2020) in Hamilton County are less useful for determining the BVAP needed to elect Black voters' candidates of choice. Two of the seven state house districts in Hamilton County do not have a sufficient number of Black voters to analyze voting patterns by race (State House Districts 27 and 30). There were no contested elections in a third Hamilton County state house district, State House District 31, in 2018 or 2020 and in 2016 voting in this district was not polarized. Voting in State House District 28 was polarized in 2016, 2018 and 2020; in State House District 29 voting was polarized in 2018 and the election was uncontested in both 2016 and 2020. Voting in majority Black State House District 32 was not polarized in 2016 or 2018 and the Black incumbent, Catherine Ingram, was unopposed in 2020. Recent election contests in the other majority Black house district, State House 33, may have been polarized (the ER and EI estimates indicate it was, but the EI RxC estimates suggests it was not), but the candidate preferred by Black voters easily won with approximately 75 percent of the vote in 2016, 2018 and 2020. Recent state senate elections in Hamilton County yielded similar results. In the 2016 and 2020 elections in State Senate District 8 voting was racially polarized and the candidate preferred by Black voters was easily defeated. The state senate election in State Senate District 9 in 2018 was not polarized and Black candidate Cecil Thomas easily won with over 76 percent of the vote. The BVAP needed for the candidate to win the racially polarized state legislative elections varies widely, from less than 35 to over 60 percent.[10]

27. On the basis of my analysis of statewide elections over the past decade, and an examination of recent state legislative contests, I conclude that a district with a 50 percent

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[9] Neither of the statewide Democratic primaries that I analyzed were racially polarized in Hamilton County. Therefore, it is the general election that is determinative to the success of Black-preferred candidates.

[10] If voting is not racially polarized, calculating a percent Black VAP needed to win produces nonsense since a 0 percent BVAP district would still elect the Black-preferred candidate.

Black population is sufficient to provide Black voters with an opportunity to elect their candidates of choice in the Cincinnati area of Hamilton County.

Table 1: Percent Black VAP Needed to Win Election in Hamilton County

Hamilton County Percent Black VAP needed to win	race of B-P candidate	turnout rate for office and percent vote for black-preferred candidates						percent of vote B-P cand would have received if district was 55% black VAP	percent of vote B-P cand would have received if district was 50% black VAP	percent of vote B-P cand would have received if district was 45% black VAP	percent of vote B-P cand would have received if district was 40% black VAP	percent of vote B-P cand would have received if district was 35% black VAP	comments
		Black votes			White votes								
		votes cast for office	B-P	all others	votes cast for office	B-P	all others						
GENERAL ELECTIONS													
2020 President	W	48.3	94.0	6.0	81.3	44.0	56.0	65.0	62.6	60.4	58.2	56.1	polarized
2018 Governor	W	37.1	94.0	6.0	66.3	39.7	60.3	61.8	59.2	56.8	54.5	52.3	polarized
2018 Treasurer	AA	37.5	96.8	3.2	64.3	38.2	61.8	62.6	59.8	57.1	54.6	52.2	polarized
2018 Attorney General	W	37.2	96.6	3.4	65.5	41.7	58.3	64.2	61.6	59.1	56.8	54.6	polarized
2018 Auditor	W	37.3	94.1	5.9	64.4	36.7	63.3	60.5	57.8	55.2	52.7	50.3	polarized
2018 Secretary State	W	37.4	94.9	5.1	65.1	40.4	59.6	62.9	60.3	57.8	55.5	53.3	polarized
2018 U.S. Senate	W	37.6	96.6	3.4	65.7	46.3	53.7	67.0	64.6	62.3	60.2	58.1	polarized
2016 President	W	50.9	96.1	3.9	74.5	35.9	64.1	63.3	60.3	57.5	54.7	52.1	polarized
2016 U.S. Senate	W	49.1	92.8	7.2	74.3	23.2	76.8	54.3	50.9	47.6	44.5	41.5	polarized
2014 Governor	W	27.8	93.9	6.1	47.6	22.8	77.2	52.4	49.0	45.8	42.7	39.8	polarized
2014 Secretary State	AA	29.0	95.5	4.5	46.4	25.6	74.4	55.9	52.5	49.3	46.2	43.2	polarized
2012 President	AA	65.5	97.9	2.1	73.0	35.6	64.4	68.2	65.1	62.0	58.9	55.9	polarized
2012 U.S. Senate	W	63.7	97.9	2.1	70.1	38.7	61.3	69.9	66.9	63.9	61.0	58.1	polarized
DEMOCRATIC PRIMARIES													
2018 Governor	W	12.2	55.5	44.5	10.0	70.4	29.6	61.5	62.2	63.0	63.7	64.5	not polarized (6 cand)
2016 U.S. Senate	W	30.2	44.9	55.1	11.1	50.3	49.7	46.1	46.4	46.6	46.8	47.1	not polarized (3 cand)

Appendix

County: Hamilton			Estimates for Black Voters				Estimates for White Voters			
	Party	Race	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
General Elections										
2020 General										
U.S. President										
Joseph Biden	D	W/AA*		106.8	95.4	94.0	33.4	36.5	40.3	44.0
Donald Trump	R	W/W		-8.1	2.7	3.3	65.0	61.8	58.0	55.0
others				1.3	1.5	2.7	1.6	1.7	1.5	1.0
votes for office				*45.3*	*48.3*	*48.3*	*82.9*	*80.7*	*81.3*	*81.3*
2018 General										
Governor										
Richard Cordray	D	W/W	93.2	106.4	96.9	94.0	29.7	32.1	36.7	39.7
Mike Dewine	R	W/W	5.7	-8.5	2.9	2.7	67.6	64.8	60.6	58.2
others			1.1	2.2	2.0	3.3	2.7	3.1	3.0	2.1
votes for office			*48.5*	*34.9*	*37.1*	*37.1*	*66.9*	*65.5*	*66.3*	*66.3*
Treasurer										
Rob Richardson	D	AA	94.5	109.7	97.1	96.8	29.0	31.2	35.7	38.2
Robert Sprague	R	W	5.5	-9.5	3.0	3.2	71.0	68.8	64.3	61.8
votes for office			*48.5*	*35.3*	*37.5*	*37.5*	*65.0*	*63.6*	*64.3*	*64.3*
Attorney General										
Steve Dettelbach	D	W	94.4	109.2	97.2	96.6	31.8	34.4	38.7	41.7
Dave Yost	R	W	5.6	-9.2	2.8	3.4	68.2	65.6	61.3	58.3
votes for office			*48.5*	*35.0*	*37.2*	*37.2*	*66.1*	*64.7*	*65.5*	*65.5*
Auditor										
Zack Space	D	W	93.6	106.8	96.8	94.1	27.4	29.5	33.1	36.7
Keith Faber	R	W	4.8	-10.2	2.8	2.4	67.5	64.9	60.0	57.8
Robert Coogan	Lib	W	1.6	3.4	3.2	3.5	5.1	5.6	5.6	5.5
votes for office			*48.1*	*35.0*	*37.3*	*37.3*	*65.1*	*63.7*	*64.4*	*64.4*
Secretary of State										
Kathleen Clyde	D	W	94.2	108.1	97.2	94.9	30.3	32.9	36.8	40.4
Frank LaRose	R	W	4.5	-9.6	2.8	2.5	67.2	64.5	59.9	57.6
Dustin Nanna	Lib	W	1.3	1.6	3.2	2.6	2.4	2.7	2.7	2.0
votes for office			*48.5*	*35.5*	*37.4*	*37.4*	*65.7*	*64.3*	*65.1*	*65.1*

County: Hamilton			Estimates for Black Voters				Estimates for White Voters			
	Party	Race	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
2018 General (cont)										
U.S. Senate										
Sherrod Brown	D	W	95.8	109.6	97.5	96.6	36.2	38.9	43.5	46.3
Jim Renacci	R	W	4.2	-9.6	2.5	3.4	63.8	61.1	56.5	53.7
votes for office			*48.2*	*35.2*	*37.6*	*37.6*	*66.2*	*64.8*	*65.7*	*65.7*
2016 General										
U.S. President										
Hillary Clinton	D	W	95.2	108.3	96.5	96.1	28.2	29.8	33.5	35.9
Donald Trump	R	W	3.5	-9.7	2.9	1.8	67.1	64.6	60.2	58.9
others			1.3	1.4	1.1	2.2	4.7	5.6	57.0	5.2
votes for office			*65.9*	*49.6*	*50.9*	*50.9*	*76.9*	*74.2*	*74.5*	*74.5*
U.S. Senate										
Ted Strickland	D	W	90.1	100.5	94.7	92.8	18.8	18.4	20.1	23.2
Rob Portman	R	W	7.5	-5.3	4.4	1.9	77.9	78.0	75.3	74.2
others			2.4	4.8	4.5	5.2	3.3	3.6	3.6	2.7
votes for office			*63.4*	*47.2*	*49.1*	*49.1*	*76.5*	*74.0*	*74.3*	*74.3*
Democratic Primaries										
2018 Primary										
Governor										
Richard Cordray	D	W/W	56.5	54.1	55.6	55.5	69.5	69.1	70.3	70.4
Dennis Kucinich	D	W/AA*	19.5	21.6	21.3	21.6	17.4	18.5	18.9	17.9
Bill O'Neill	D	W/AA*	10.5	12.1	11.3	11.2	3.4	2.8	2.4	2.6
Paul Ray	D	W/W	4.8	3.5	0.6	2.9	1.2	1.1	1.4	1.5
Joe Schiavoni	D	W/W	4.7	5.3	4.0	6.4	7.9	8.2	7.6	6.6
Larry Ealy	D	AA/W	3.9	3.4	1.9	2.4	0.6	0.2	0.5	1.1
votes for office			*10.0*	*9.9*	*12.2*	*12.2*	*7.0*	*7.2*	*10.0*	*10.0*
2016 Primary										
U.S. Senator										
Kelli Prather	D	AA	18.8	23.1	22.5	21.1	12.6	11.9	11.5	7.2
P.G. Sittenfeld	D	W	27.2	32.8	33.8	34.0	35.1	36.7	38.8	42.6
Ted Strickland	D	W	54.0	44.1	43.9	44.9	52.4	51.3	49.6	50.3
votes for office			*26.2*	*27.2*	*30.2*	*30.2*	*9.8*	*9.4*	*11.1*	*11.1*

Lisa R. Handley
CURRICULUM VITAE

Professional Experience

Dr. Handley has over thirty years of experience in the areas of redistricting and voting rights, both as a practitioner and an academician, and is recognized nationally and internationally as an expert on these subjects. She has advised numerous clients on redistricting and has served as an expert in dozens of redistricting and voting rights court cases. Her clients have included the U.S. Department of Justice, civil rights organizations, independent redistricting commissions and scores of state and local jurisdictions. Internationally, Dr. Handley has provided electoral assistance in more than a dozen countries, serving as a consultant on electoral system design and redistricting for the United Nations, UNDP, IFES, and International IDEA. In addition, Dr. Handley served as Chairman of the Electoral Boundaries Commission in the Cayman Islands.

Dr. Handley has been actively involved in research, writing and teaching on the subjects of redistricting and voting rights. She has co-written a book, Minority Representation and the Quest for Voting Equality (Cambridge University Press, 1992) and co-edited a volume (Redistricting in Comparative Perspective, Oxford University Press, 2008) on these subjects. Her research has also appeared in peer-reviewed journals such as *Journal of Politics*, *Legislative Studies Quarterly*, *American Politics Quarterly*, *Journal of Law and Politics*, and *Law and Policy,* as well as law reviews and edited books. She has taught political science undergraduate and graduate courses related to these subjects at several universities including the University of Virginia and George Washington University. Dr. Handley is a Visiting Research Academic at Oxford Brookes University in the United Kingdom.

Dr. Handley is the President of Frontier International Consulting, a consulting firm that specializes in providing electoral assistance in transitional and post-conflict democracies. She also works as an independent election consultant both in the United States and internationally.

Education

Ph.D. The George Washington University, Political Science, 1991

Present Employment

President, Frontier International Electoral Consulting LLC (since co-founding company in 1998).

Senior International Electoral Consultant Technical assistance for clients such as the UN, UNDP and IFES on electoral system design and boundary delimitation

Visiting Research Academic, Centre for Development and Emergency Practice (CENDEP), Oxford Brookes University

U.S. Clients since 2000

American Civil Liberties Union (expert testimony in Ohio partisan gerrymander challenge and challenge to Commerce Department inclusion of citizenship question on 2020 census form)

Lawyers Committee for Civil Rights Under Law (expert testimony in challenges to statewide judicial elections in Texas and Alabama)

US Department of Justice (expert witness testimony in several Section 2 and Section 5 cases)

Alaska: Alaska Redistricting Board (redistricting consultation, expert witness testimony)

Arizona: Arizona Independent Redistricting Board (redistricting consultation, expert witness)

Arkansas: expert witness for Plaintiffs in Jeffers v. Beebe

Colorado: Colorado Redistricting Board (redistricting consultation)

Connecticut: State Senate and State House of Representatives (redistricting consultation)

Florida: State Senate (redistricting consultation)

Kansas: State Senate and House Legislative Services (redistricting consultation)

Louisiana: Louisiana Legislative Black Caucus (expert witness testimony)

Massachusetts: State Senate (redistricting consultation)

Maryland: Attorney General (redistricting consultation, expert witness testimony)

Miami-Dade County, Florida: County Attorney (redistricting consultation)

Nassau County, New York: Redistricting Commission (redistricting consulting)

New Mexico: State House (redistricting consultation, expert witness testimony)

New York: State Assembly (redistricting consultation)

New York City: Redistricting Commission and Charter Commission (redistricting consultation and Section 5 submission assistance)

New York State Court: Expert to the Special Master (drew congressional lines for state court)

Ohio: State Democratic Party (redistricting litigation support, expert witness testimony)

Pennsylvania: Senate Democratic Caucus (redistricting consultation)

Rhode Island: State Senate and State House (litigation support, expert witness testimony)

Vermont: Secretary of State (redistricting consultation)

International Clients since 2000

United Nations

- Afghanistan – electoral system design and district delimitation expert
- Bangladesh (UNDP) – redistricting expert
- Sierra Leone (UNDP) – redistricting expert
- Liberia (UNMIL, UN peacekeeping mission) – redistricting expert
- Democratic Republic of the Congo (MONUC, UN peacekeeping mission) – election feasibility mission, electoral system design and redistricting expert
- Kenya (UN) – electoral system design and redistricting expert
- Haiti (UN) – election feasibility mission, electoral system design and redistricting expert
- Zimbabwe (UNDP) – redistricting expert
- Lead Writer on the topic of boundary delimitation (redistricting) for ACE (Joint UN, IFES and IDEA project on the Administration and Cost of Elections Project)

International Foundation for Election Systems (IFES)

- Afghanistan – district delimitation expert
- Sudan – redistricting expert
- Kosovo – electoral system design and redistricting expert
- Nigeria – redistricting expert
- Nepal – redistricting expert
- Georgia – electoral system design and district delimitation expert
- Yemen – redistricting expert
- Lebanon – electoral system design and redistricting expert
- Malaysia – electoral system design and redistricting expert
- Myanmar – electoral system design and redistricting expert
- Ukraine – electoral system design and redistricting expert
- Pakistan – consultant for developing redistricting software
- Principal consultant for the Delimitation Equity Project – conducted research, wrote reference manual and developed training curriculum
- Writer on electoral boundary delimitation (redistricting), Elections Standards Project
- Training – developed training curriculum and conducted training workshops on electoral boundary delimitation (redistricting) in Azerbaijan and Jamaica

International Institute for Democracy and Electoral Assistance (International IDEA):

- Consultant on electoral dispute resolution systems
- Technology consultant on use of GIS for electoral district delimitation
- Training – developed training material and conducted training workshop on electoral boundary delimitation (redistricting) for African election officials (Mauritius)
- Curriculum development – boundary delimitation curriculum for the BRIDGE Project

Other international clients have included The Cayman Islands; the Australian Election Commission; the Boundary Commission of British Columbia, Canada; and the Global Justice Project for Iraq.

Publications

Books:

Does Torture Prevention Work? Liverpool University Press, 2016 (served as editor and author, with Richard Carver)

Comparative Redistricting in Perspective, Oxford University Press, 2008 (first editor, with Bernard Grofman).

Delimitation Equity Project: Resource Guide, Center for Transitional and Post-Conflict Governance at IFES and USAID publication, 2006 (lead author).

Minority Representation and the Quest for Voting Equality, Cambridge University Press, 1992 (with Bernard Grofman and Richard Niemi).

Academic Journal Articles:

"Drawing Electoral Districts to Promote Minority Representation" Representation, forthcoming, published online DOI:10.1080/00344893.2020.1815076.

"Evaluating national preventive mechanisms: a conceptual model," Journal of Human Rights Practice, Volume 12 (2), July 2020 (with Richard Carver).

"Minority Success in Non-Majority Minority Districts: Finding the 'Sweet Spot'," Journal of Race, Ethnicity and Politics, forthcoming (with David Lublin, Thomas Brunell and Bernard Grofman).

"Has the Voting Rights Act Outlived its Usefulness: In a Word, "No," Legislative Studies Quarterly, volume 34 (4), November 2009 (with David Lublin, Thomas Brunell and Bernard Grofman).

"Delimitation Consulting in the US and Elsewhere," Zeitschrift für Politikberatung, volume 1 (3/4), 2008 (with Peter Schrott).

"Drawing Effective Minority Districts: A Conceptual Framework and Some Empirical Evidence," North Carolina Law Review, volume 79 (5), June 2001 (with Bernard Grofman and David Lublin).

"A Guide to 2000 Redistricting Tools and Technology" in The Real Y2K Problem: Census 2000 Data and Redistricting Technology, edited by Nathaniel Persily, New York: Brennan Center, 2000.

"1990s Issues in Voting Rights," Mississippi Law Journal, 65 (2), Winter 1995 (with Bernard Grofman).

"Minority Turnout and the Creation of Majority-Minority Districts," American Politics Quarterly, 23 (2), April 1995 (with Kimball Brace, Richard Niemi and Harold Stanley).

"Identifying and Remedying Racial Gerrymandering," Journal of Law and Politics, 8 (2), Winter 1992 (with Bernard Grofman).

"The Impact of the Voting Rights Act on Minority Representation in Southern State Legislatures," Legislative Studies Quarterly, 16 (1), February 1991 (with Bernard Grofman).

"Minority Population Proportion and Black and Hispanic Congressional Success in the 1970s and 1980s," American Politics Quarterly, 17 (4), October 1989 (with Bernard Grofman).

"Black Representation: Making Sense of Electoral Geography at Different Levels of Government," Legislative Studies Quarterly, 14 (2), May 1989 (with Bernard Grofman).

"Minority Voting Equality: The 65 Percent Rule in Theory and Practice," Law and Policy, 10 (1), January 1988 (with Kimball Brace, Bernard Grofman and Richard Niemi).

"Does Redistricting Aimed to Help Blacks Necessarily Help Republicans?" Journal of Politics, 49 (1), February 1987 (with Kimball Brace and Bernard Grofman).

Chapters in Edited Volumes:

“Effective torture prevention,” Research Handbook on Torture, Sir Malcolm Evans and Jens Modvig (eds), Cheltenham: Edward Elgar, 2020 (with Richard Carver).

“Redistricting” in Oxford Handbook of Electoral Systems, Erik Herron Robert Pekkanen and Matthew Shugart (eds), Oxford: Oxford University Press, 2018.

“Role of the Courts in the Electoral Boundary Delimitation Process,” in International Election Remedies, John Hardin Young (ed.), Chicago: American Bar Association Press, 2017.

“One Person, One Vote, Different Values: Comparing Delimitation Practices in India, Canada, the United Kingdom, and the United States,” in Fixing Electoral Boundaries in India, edited by Mohd. Sanjeer Alam and K.C. Sivaramakrishman, New Delhi: Oxford University Press, 2015.

“Delimiting Electoral Boundaries in Post-Conflict Settings,” in Comparative Redistricting in Perspective, edited by Lisa Handley and Bernard Grofman, Oxford: Oxford University Press, 2008.

“A Comparative Survey of Structures and Criteria for Boundary Delimitation,” in Comparative Redistricting in Perspective, edited by Lisa Handley and Bernard Grofman, Oxford: Oxford University Press, 2008.

“Drawing Effective Minority Districts: A Conceptual Model,” in Voting Rights and Minority Representation, edited by David Bositis, published by the Joint Center for Political and Economic Studies, Washington DC, and University Press of America, New York, 2006.

"Electing Minority-Preferred Candidates to Legislative Office: The Relationship Between Minority Percentages in Districts and the Election of Minority-Preferred Candidates," in Race and Redistricting in the 1990s, edited by Bernard Grofman; New York: Agathon Press, 1998 (with Bernard Grofman and Wayne Arden).

"Estimating the Impact of Voting-Rights-Related Districting on Democratic Strength in the U.S. House of Representatives," in Race and Redistricting in the 1990s, edited by Bernard Grofman; New York: Agathon Press, 1998 (with Bernard Grofman).

"Voting Rights in the 1990s: An Overview," in Race and Redistricting in the 1990s, edited by Bernard Grofman; New York: Agathon Press, 1998 (with Bernard Grofman and Wayne Arden).

"Racial Context, the 1968 Wallace Vote and Southern Presidential Dealignment: Evidence from North Carolina and Elsewhere," in Spatial and Contextual Models in Political Research, edited by Munroe Eagles; Taylor and Francis Publishing Co., 1995 (with Bernard Grofman).

"The Impact of the Voting Rights Act on Minority Representation: Black Officeholding in Southern State Legislatures and Congressional Delegations," in The Quiet Revolution: The Impact of the Voting Rights Act in the South, 1965-1990, eds. Chandler Davidson and Bernard Grofman, Princeton University Press, 1994 (with Bernard Grofman).

"Preconditions for Black and Hispanic Congressional Success," in United States Electoral Systems: Their Impact on Women and Minorities, eds. Wilma Rule and Joseph Zimmerman, Greenwood Press, 1992 (with Bernard Grofman).

Electronic Publication:

"Boundary Delimitation" Topic Area for the Administration and Cost of Elections (ACE) Project, 1998. Published by the ACE Project on the ACE website (www.aceproject.org).

Additional Writings of Note:

Amicus brief presented to the US Supreme Court in Gill v. Whitford, Brief of Political Science Professors as Amici Curiae, 2017 (one of many social scientists to sign brief)

Amicus brief presented to the US Supreme Court in Shelby County v. Holder, Brief of Historians and Social Scientists as Amici Curiae, 2013 (one of several dozen historians and social scientists to sign brief)

Amicus brief presented to the US Supreme Court in Bartlett v. Strickland, 2008 (with Nathaniel Persily, Bernard Grofman, Bruce Cain, and Theodore Arrington).

Recent Court Cases

In the past ten years, Dr. Handley has served as an testifying expert or expert consultant in the following cases:

Ohio Philip Randolph Institute v. Larry Householder (2019) – partisan gerrymander challenge to Ohio congressional districts; testifying expert for ACLU on minority voting patterns

State of New York v. U.S. Department of Commerce/ New York Immigration Coalition v. U.S. Department of Commerce (2018-2019) – challenge to inclusion of citizenship question on 2020 census form; testifying expert on behalf of ACLU

U.S. v. City of Eastpointe (settled 2019) – minority vote dilution challenge to City of Eastpointe, Michigan, at-large city council election system; testifying expert on behalf of U.S. Department of Justice

Alabama NAACP v. State of Alabama (decided 2020) – minority vote dilution challenge to Alabama statewide judicial election system; testifying expert on behalf of Lawyers Committee for Civil Rights Under Law

Lopez v. Abbott (2017-2018) – minority vote dilution challenge to Texas statewide judicial election system; testifying expert on behalf of Lawyers Committee for Civil Rights Under Law

Personhuballuah v. Alcorn (2015-2017) – racial gerrymandering challenge to Virginia congressional districts; expert for the Attorney General and Governor of the State of Virginia; written testimony on behalf of Governor

Perry v. Perez (2014) – Texas congressional and state house districts (Section 2 case before federal court in San Antonio, Texas; testifying expert for the U.S. Department of Justice)

Jeffers v. Beebe (2012) – Arkansas state house districts (testifying expert for the Plaintiffs)

State of Texas v. U.S. (2011-2012) – Texas congressional and state house districts (Section 5 case before the Circuit Court of the District of Columbia; testifying expert for the U.S. Department of Justice)

In RE 2011 Redistricting Cases (2011-2012) – State legislative districts for State of Alaska (testifying expert for the Alaska Redistricting Board)

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CERTIFICATE OF SERVICE

I, Freda J. Levenson, hereby certify that on October 22, 2021, I caused a true and correct copy of the following documents to be served by email upon the counsel listed below:

1. **Affidavit of Dr. Lisa Handley**
2. **Report and Exhibits of Dr. Lisa Handley (pages 1 - 23)**

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/s/ Freda J. Levenson

IN THE SUPREME COURT OF OHIO

BRIA BENNETT, *et al.*, *Relators*, *v.* OHIO REDISTRICTING COMMISSION, *et al.*, *Respondents*.	Case No. 2021-1198

EVIDENCE OF BENNETT RELATORS

(Expert Affidavit of Dr. Jonathan Rodden & Exhibits)

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Secretary of State Frank LaRose, and
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Bria Bennett et al.

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House Speaker Robert Cupp

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House Minority Leader Emilia Sykes

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Dave Yost

Counsel for Respondent
Ohio Redistricting Commission

IN THE SUPREME COURT OF OHIO

Bria Bennett, *et al.*, **Relators,** **v.** **Ohio Redistricting Commission, *et al.*,** **Respondents.**	**Case No. 2021-1198** Original Action Filed Pursuant to Ohio Constitution, Article XI, Section 9(A) *[Apportionment Case Pursuant to S. Ct. Prac. R. 14.03]*

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 State House of Representatives and Ohio Senate, adopted by the Ohio Redistricting Commission on September 16, 2021, and attached as Exhibit A ("2021 Commission Plan"), addresses the standard set forth in Article XI, Section 6(B), namely, that "[t]he statewide proportion of districts whose voters, based on statewide state and federal partisan general election results during the last ten years, favor each political party shall correspond closely to the statewide preferences of the voters of Ohio."

2. I demonstrate that this "partisan proportionality" standard was clearly not met by the map adopted by the Ohio Redistricting Commission.

3. Furthermore, I have been asked to examine whether the partisan composition of the Commission's maps may have been a result of the Commission's need to satisfy other requirements of the Ohio Constitution: specifically, the requirements to avoid county and municipal splits, laid out in Article XI, Sections 3 and 4, and to attempt to draw compact districts, as set forth in Article XI, Section 6(C).

4. In order to answer this question, I do two things. First, I examine several additional maps that were available to the Commission, and to the public, prior to September 15. Second, I create my own alternative redistricting maps for the Ohio House and Senate, abiding by the rules set forth in the Ohio Constitution. I demonstrate that my alternative redistricting maps, like each of the alternative plans available to the Commission, were able to abide by the "partisan proportionality" requirement more closely while also abiding by the strict rules of

the Ohio Constitution regarding county and municipality splits, and while creating districts with similar or better compactness scores than those drawn by the Commission.

5. I was also asked to conduct a careful examination of the key geographic regions where the likely partisan outcomes associated with the 2021 Commission Plan were notably different from those of the alternative maps. In most instances, the alternative plans are more respectful of traditional redistricting criteria than the 2021 Commission Plan. Moreover, in some metro areas, the Commission's plan clearly achieves a lower anticipated Democratic seat share than the alternative plans by breaking up urban and suburban Democratic communities, including Black communities, and embedding them in districts where exurban and rural whites make up majorities. Moreover, some of the Commission's specific splits of urban counties are especially well-crafted to reduce the overall Democratic seat share in a region. And relative to the alternative plans, the Commission's plan often packs Democratic voters into overwhelmingly Democratic urban districts, which allows the Commission to carve out additional suburban and exurban districts with comfortable Republican majorities.

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 G.

7. In my current academic work, I conduct research on the relationship between the patterns of political representation, geographic location of demographic and partisan groups, and the drawing of electoral districts. I have published papers using statistical methods to assess political geography, balloting, and representation in a variety of academic journals including *Statistics and Public Policy, Proceedings of the National Academy of Science*, *American Economic Review Papers and Proceedings*, the *Journal of Economic Perspectives*, the *Virginia Law Review*, the *American Journal of Political Science*, the *British Journal of Political Science*, the *Annual Review of Political Science*, and the *Journal of Politics.* One of these papers was selected by the American Political Science Association as the winner of the Michael Wallerstein Award for the best paper on political economy published in the last year, and another received an award from the American Political Science Association section on social networks. In 2021, I received a John Simon Guggenheim Memorial Foundation Fellowship, and received the Martha Derthick Award of the American Political Science Association for "the best book published at least ten years ago that has made a lasting contribution to the study of federalism and intergovernmental relations."

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

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

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

III. DATA SOURCES

11. I have collected statewide election data for 2012 to 2020 from the Ohio Secretary of State. I also accessed precinct-level election results from the Ohio Secretary of State for statewide elections from 2016 to 2020 that were matched to 2020 Ohio vote tabulation districts by a team at Harvard University called the Algorithm-Assisted Redistricting Methodology Project.[1] Additionally, I accessed the proposed and adopted Ohio redistricting plans uploaded to the web page of the Ohio Redistricting Commission, true copies of which are attached as Exhibits A, C, D, and E.[2] For the analysis conducted in this report, I use three software packages: Stata, Maptitude for Redistricting, and ArcGIS Pro. In creating my maps,

[1] https://alarm-redist.github.io/posts/2021-08-10-census-2020/
[2] https://redistricting.ohio.gov/maps

I used the same U.S. Census redistricting data used by the Ohio Redistricting Commission, as archived in the "Ohio University Common and Unified Redistricting Database."[3]

IV. MEASURING PARTISAN PROPORTIONALITY

12. The Ohio Constitution instructs the Commission to use "statewide state and federal partisan general election results during the last ten years" to ascertain the "statewide preferences of the voters of Ohio" and attempt to draw a map in which the "statewide proportion of districts whose voters favor each party shall correspond closely" to those "statewide preferences."

13. As further discussed below, the only reasonable way to implement this notion of "statewide preferences," as ascertained from past elections to anticipated future seat shares, is via the proportion of votes received by the candidates for the two parties. That is to say, if a party won 50 percent of the average statewide vote in the relevant elections, a proposed map should favor that party—aggregating the results of those same elections—in somewhere very close to 50 percent of the seats.

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

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

[3] https://www.redistricting.ohio.gov/resources

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

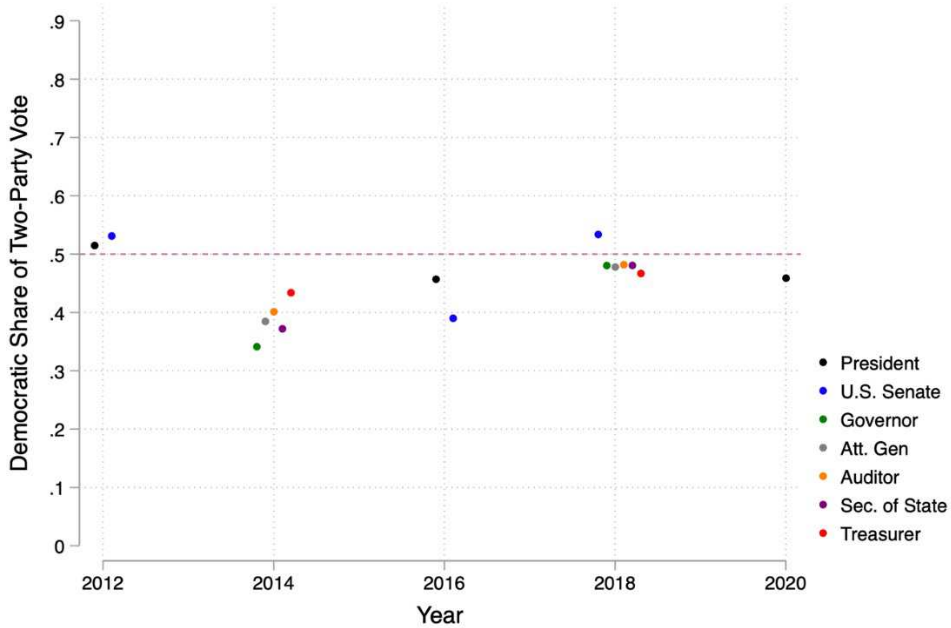


Table 1: Statewide General Election Outcomes, Ohio, 2012-2020

	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%**

16. Determining the proportion of districts that favor each party, based on consideration of the relevant elections identified in Article XI, Section 6, requires an aggregation of the precinct-level results of these past elections to the boundaries of a map's proposed districts. However, precinct-level election results linked with geo-spatial boundaries were not available for the 2012 and 2014 elections, as the Commission itself acknowledged in its Article XI, Section 8(C)(2) Statement, attached as Exhibit F. Thus, Table 1 also sets forth that the two-party Democratic vote share in the 2016, 2018, and 2020 general elections was around 47 percent.

17. Accordingly, using the full statewide election results from 2012 to 2020, the statewide preferences of Ohio voters must be translated into state legislative maps in which 45.9 percent of seats favor Democrats and 54.1 percent of seats favor Republicans. Since there are 99 seats in the Ohio House of Representatives, a statewide vote share of 45.9 percent would be associated with 45.44 Democratic seats, which rounds down to 45 seats. Similarly, a 45.9 percent vote share would be associated with about 15.15 Democratic seats in the 33-member Ohio Senate, which rounds down to 15 seats.

18. I have aggregated the precinct-level results of each election from 2016 to 2020 included in Table 1 to the level of the districts in the 2021 Commission Plan. For each district, I calculate the average Democratic share of the votes received by the candidates of the two major parties across each of these elections. I then ascertain the number of districts in which this quantity is greater than 50 percent. Using this technique, I determine that the 2021 Commission Plan

produced 37 majority-Democratic House seats and 62 majority-Republican House seats, as shown in Table 2 below. In the Senate, the 2021 Commission Plan produced 10 majority-Democratic Senate seats and 23 majority-Republican seats. This is a gap of 8 House seats and 5 Senate seats between the Democratic-leaning seats produced by the 2021 Commission Plan and the seat share that would be proportionate to the statewide Democratic vote share.

19. Notably, the partisanship of the Commission's maps is not very different from that of the current maps, adopted in 2011 and attached as Exhibit B. The current breakdown of the General Assembly under the 2011 maps is as follows: 35 Democrats and 64 Republicans in the House; 8 Democrats and 25 Republicans in the Senate.

20. In addition to this examination of seats above and below the 50 percent cut-point, it is also useful to examine how many of the Democratic- and Republican-leaning seats are razor-thin majorities, and how many are more comfortable majorities. I count the number of seats where the average Democratic share of the vote for the two major parties was less than 48 percent—let us call these expected Republican seats. And I count the number of seats where the average Democratic share of the vote for the two major parties was greater than 52 percent—let us call these expected Democratic seats. Finally, I count the number of seats that we might call "toss-ups," where the average Democratic vote share was between 48 percent and 52 percent.

21. As set forth in Table 2 below, in the 2021 Commission Plan, all of the majority-Republican House seats are greater than 52 percent Republican. Of the 37 majority-Democratic seats, only 32 are greater than 52 percent Democratic. All 5 of the toss-up seats are slim Democratic majorities. As set forth in Table 3, in the Commission's Senate plan, there are 21 expected Republican seats, 9 expected Democratic seats, and 3 toss-ups, of which 1 is a slim Democratic majority and 2 are slim Republican majorities. As explained further below, by generating a large number of seats with comfortable Republican majorities, the Commission has generated plans that would provide the Republican Party with a majority of seats even in the event of a comfortable Democratic statewide victory.

22. In its Article XI, Section 8(C)(2) Statement, the Commission explained its ostensible attempt to comply with the "partisan proportionality" requirement in the Ohio Constitution. In this statement, the Ohio Redistricting Commission offers an unsound implementation of the constitutional requirement, suggesting that in addition to the vote share, an equally reasonable way to measure "statewide preferences" is by calculating the share of all elections in the last decade in which each party received more votes than the other party. This is a flawed way of characterizing voter preferences in general, but especially when the purpose is to evaluate seat shares. With this interpretation, a party that always wins 50.01 percent of the vote in general elections would be viewed as having 100 percent of the "statewide preference," entitling it to draw a map that gave itself all the seats, a patently absurd outcome.

23. Consider, for example, a situation in which the United States adopted Ohio's constitutional amendment for U.S. House of Representatives districts. The only nationwide elections are presidential elections, for which Democratic candidates have won a majority of the popular vote in each election since 2004, although many of these elections were extremely close. By the Commission's logic, voters preferred Democratic candidates 100 percent of the time, and

would therefore be entitled to 100 percent of the seats in Congress. Similarly, the Commission's measurement would suggest that Minnesota voters prefer 100 percent of their elected officials to be Democrats, simply because Democrats have won 100 percent of the statewide partisan races in the past decade—even though those elections were relatively close, and control of the state legislature in Minnesota has been closely divided throughout that period. The same would be true in California, even though more than 6 million people in that state voted for former President Donald Trump in the 2020 presidential election. This is simply not a tenable methodology for determining voter preferences.

24. In the vast academic literature on voter preferences and seats, I have never encountered the notion that the seat share should correspond to the share of past elections in which a party "won," or received a plurality of votes. Perhaps the foundational work in this literature is a paper published in 1950 by Kendall and Stuart,[4] exploring the vote share in each election as a measure of voter preferences and examining the transformation of those votes to seats in the British Parliament. Then, Gudgin and Taylor published a book in 1979 that explored the geography of voter preferences, as ultimately expressed through vote shares in specific elections, and the transformation of those votes to seats.[5] Next, a variety of books and articles by Ronald Johnston and collaborators, and more recently, Gary King and collaborators, further developed these insights about preferences, votes, and seats.[6] A recent analytical review of the resulting literature is provided in a 2020 article by Katz, King, and Rosenblatt.[7]

25. In this entire literature, the basic starting point is to conceptualize vote shares in specific elections as indicators of voter preferences. These works explore how the geography of preferences, combined with the specific electoral districting plan, combine to translate votes into seats in the legislature. All of this literature shares a basic normative notion that 50 percent of the votes should translate into 50 percent of the seats, and that in a two-party system, there should be symmetry in the way a redistricting plan treats the two parties.

26. Partisan symmetry means that if the two parties' vote shares were reversed, their seat shares would be similarly reversed. For instance, imagine a redistricting plan in which Party A, if it received 52 percent of the votes, could anticipate 55 percent of the seats, due the fact that it was victorious in several of the most competitive seats. Partisan symmetry means that an electoral wave in favor of Party B, such that Party B now received 52 percent of the votes, would also provide Party B with a similar 55 percent seat share. However, if Party A can manipulate the redistricting process to produce partisan asymmetry, it might produce an unusually large number of seats with comfortable, but not overwhelming, majorities for Party

[4] M. Kendall and A. Stuart, 1950, "The Law of Cubic Proportion in Election Results," *British Journal of Sociology* 1,3:183,96.
[5] Gudgin G, PJ Taylor PJ. 1979*, Seats, Votes, and the Spatial Organisation of Elections*. London: Pion.
[6] See PJ Taylor Ronald Johnston, 1979*, Geography of Elections*. London: Croom Helm; and Robert Browning and Gary King, 1987, "Seats, Votes, and Gerrymandering: Estimating Representation and Bias in State Legislative Redistricting." *Law and Policy* 9,3:305-322.
[7] J. Katz, G. King, and E. Rosenblatt, 2020, "Theoretical Foundations and Empirical Evaluations of Partisan Fairness in District-Based Democracies," *American Political Science Review* 114,1: 164-178.

A, thus building a levy to withstand a wave in favor of Party B. In the asymmetric scenario, then, 52 percent of the vote for Party B would be insufficient to provide it with a legislative majority.

27. This literature on partisan proportionality and, relatedly, partisan symmetry, does sometimes examine multiple elections in order to examine the impact of different vote shares and different geographies of support over time on the transformation of votes to seats, but the starting point remains that vote share is the means to determine partisan preference. At no point in this literature do scholars conceptualize the notion of partisan proportionality or symmetry as pertaining to the relationship between the seat share and the number of overall pluralities achieved over a period of time.

28. In short, the notion of proportionality employed by academics is no different from that employed by pundits, politicians, and the mass public: it pertains to the relationship between the vote share and the seat share. Surely this is also the notion invoked by the Ohio Constitution.

29. Thus, the Commission was tasked with attempting to draw a map in which around 54 percent of the seats are anticipated to produce Republican majorities. Instead, they have drawn a House map where Republicans can expect comfortable majorities in 63 percent of the seats. And they have drawn a Senate map in which Republicans can expect majorities in a stunning 70 percent of seats.

30. Neither the academic literature nor common usage in political discourse could suggest that this result "closely corresponds" to the "statewide preferences" of voters. In fact, the lack of correspondence between votes and seats is even more profound than suggested by the simple statewide averages discussed thus far. As mentioned above, an important focus of the academic literature on votes and seats is the notion of "symmetry." In a two-party system, what would happen to the seat shares if the vote shares of the two parties reversed?

31. Fortunately, recent Ohio electoral history gives us an opportunity to examine just that scenario. In 2018, the Republican candidate for Treasurer, Robert Sprague, won 53.3 percent of the two-party vote. If we aggregate the precinct-level votes in the 2018 Treasurer election to match the 2021 Commission's Ohio House of Representatives districts, Mr. Sprague would win majorities in 64 percent of the districts. That is to say, based on the 2018 votes for Treasurer, the Republican seat share is more than 10 percentage points higher than the Republican vote share.

32. On the same day, November 6, 2018, on the same ballot, the Democratic candidate for U.S. Senate, Sherrod Brown, received slightly more votes than Mr. Sprague, ending up with 53.4 percent of the two-party vote. Yet if we aggregate these U.S. Senate votes up to match the 2021 Commission's House districts, Senator Brown would receive majorities in only 49.5 percent of the seats. With relatively similar statewide victories of just over 53 percent, these two candidates' vote shares translate to dramatically different outcomes in terms of seats in the 2021 Commission House map. The Republican candidate's 53.3 percent win translates to a supermajority of seats, while the Democratic candidate's slightly *higher* 53.4 percent win translates to a *minority* of seats.

33. This example reveals the troubling extent to which the 2021 Commission Plan falls short of any notion of correspondence between voters' preferences and legislative seats. Because so many of the Republican majorities in districts drawn by the Commission are comfortable, even if the Democrats win a comfortable majority of votes—on the order of 53.4 percent—they still cannot expect to serve in the legislative majority.

V. COMPARING THE COMMISSION'S MAPS TO ALTERNATIVE MAPS

34. It is clearly the case that the 2021 Commission did not adopt maps in which the party seat share closely corresponds with the vote share in relevant statewide elections under any reasonable interpretation of the Ohio Constitution's partisan fairness requirement. But one might imagine that the partisan composition of the Commission's maps was a function of constraints imposed by other constitutional requirements related to traditional redistricting principles that the Commission understood to be more important. Perhaps the Commission *attempted* to abide by Article XI, Section 6(B), but the job was simply too difficult.

35. In fact, the next line after the "partisan proportionality" clause dictates that the Commission "shall attempt" to draw compact districts. One might wonder whether the Commission found it difficult to achieve partisan proportionality because of a tension between that goal and the additional goal of drawing compact districts. Moreover, the Constitution requires that the Commission use entire counties, municipal corporations, and townships as the building blocks of districts to the extent possible. Counties with population greater than that which is sufficient for a single district must spill over into only a single additional district. The Commission must also endeavor not to split counties more than once, and not to split more than one municipality per district. Conceivably, efforts to abide by requirements like these could make it difficult for a map-drawer to achieve partisan proportionality despite a concerted effort to do so.

36. A simple and effective way to examine such assumptions is to analyze other maps that were made available to the Commission before it finalized its own maps. Did those maps come closer to achieving partisan proportionality while abiding by the same rules and achieving similar benchmarks with respect to the traditional redistricting principles emphasized in the Constitution? If so, one cannot accept the claim that the Commission was forced by restrictive rules into drawing maps with a large advantage for one party.

37. Specifically, I examined a map introduced by Senator Sykes on September 2, attached as Exhibit C, and another map introduced by Senator Sykes on September 15, attached as Exhibit H. An additional map was proposed by a group called the "Ohio Citizens Redistricting Commission" and is attached as Exhibit E. Based on my review and to the best of my knowledge, with the possible exception of the Sykes September 2 map, discussed further below, these maps are materially compliant with the line-drawing rules explained above, as set forth in Article XI, Sections 3 and 4 of the Ohio Constitution.

38. In addition to examining maps produced by others, I have produced my own redistricting plan for the Ohio House and Senate. By drawing my own maps, I was able to gain a full appreciation for the challenges and trade-offs associated with the Ohio Constitution's

redistricting rules, and can explain how I resolved them, and with what implications for partisanship and respect for traditional redistricting criteria.

39. My approach was to begin by creating a complete plan for the House of Representatives and then assemble groups of three House districts in order to produce a Senate plan. However, this approach ran into a roadblock since most reasonable configurations of House districts cannot produce a valid Senate plan. Article XI, Section 4(B)(2) of the Ohio Constitution states that "Counties having less than one senate ratio of representation, but at least one house of representatives ratio of representation, shall be part of only one senate district." In Northeast Ohio, it is extremely difficult to comply with Section 4(B)(2) in conjunction with the immediately preceding 4(B)(1), which states that "a county having at least one whole senate ratio of representation shall have as many senate districts wholly within the boundaries of the county as it has whole senate ratios of representation. Any fraction of the population in excess of a whole ratio shall be a part of only one adjoining senate district."

40. This is complex in Northeast Ohio because both Cuyahoga and Summit Counties have well beyond the population of a single extra house district that must find a home in an adjoining district, and many surrounding House districts are unavailable as partners because of the prohibition on splits of medium-sized counties and the position of all relevant counties in the corner of the state. A rather unsatisfactory way to solve this problem is to severely under-represent the people of Northeast Ohio, over-populating virtually every district in this part of the state as close as possible to the 5 percent constraint, and under-populating many districts throughout the rest of the state. I came to the conclusion that this is the only way to configure districts in the House of Representatives in a way that allows for Senate districts that *strictly* comply with Article XI, Section 4 in Northeast Ohio. I thus configured House districts in Northeast Ohio with a sole focus on finding an arrangement that would yield valid Senate districts.

41. This same basic approach, with dramatic over-population of Cuyahoga and other Northeast Ohio districts, was also taken in the 2021 Commission Plan, the Citizens' Commission Plan, and the Sykes 9/15 Plan. It is not entirely clear, however, that the Ohio Constitution *requires* this unusual type of harm to the voters of Northeast Ohio, since Article XI, Section 4(B)(3) instructs the commission to "commit the fewest possible violations" in the event that "it is not possible to draw representative districts that comply with all of the requirements of this article." The Sykes map of September 2, 2021 does not strictly comply with Article XI, Section 4, because it splits Trumbull County (between districts 1 and 18), even though it is in the population range of counties for which splits should usually be avoided. The Sykes 9/2 map is, thus, a useful reference point as a map that takes a slightly different approach to interpreting Article XI, Section 4: one that purchases fair representation for Northeast Ohio at the rather minute cost of a single county split. In contrast, the Sykes 9/15 plan removes the offending county split and reconfigures both the House and Senate maps to under-represent Northeast Ohio.

42. After resolving the dilemma of Northeast Ohio, my approach was to follow the rules laid out by the Ohio Constitution, beginning with House districts, and, within the strict constraints regarding municipal and county splits, also attempt to maximize compactness and minimize county splits. These goals are sometimes in conflict. In some regions of Ohio, the population

sizes and geographic arrangement of counties mean that in order to keep counties together, one must tolerate some non-compact districts. In general, since the Constitution calls for the use of entire counties as building blocks for districts whenever possible, my approach was to prioritize the minimization of county splits when drawing (and refining) first my House and then my Senate plan, while also trying to make decisions that facilitated a relatively compact set of districts for any given region.

43. After achieving these things, I considered an additional factor in metro areas. I attempted to avoid drawing districts that excessively packed members of one of the parties in a way that would undermine their representation. Moreover, when drawing district lines, I attempted to avoid splitting groups of geographically proximate co-partisans in a way that would prevent them from forming a majority.

44. I did not deviate from the application of traditional redistricting principles in order to help or harm one of the political parties. For instance, in Toledo, it is possible to further "unpack" urban Democrats and produce an additional majority-Democratic district, but this would have created a rather non-compact district that would have also intentionally split geographically proximate Republican communities. Elsewhere, in a couple of places it is possible within the rules of the Ohio Constitution to string together far-flung Democratic industrial and college towns. I avoided drawing districts in this manner. Rather, within the confines of the constitutional rules and the application of traditional redistricting criteria, I simply made a conscious effort to avoid drawing districts that would have the effect of clearly packing or cracking geographically proximate co-partisans.

45. I paid no attention to racial data when drawing my maps. However, after completing my redistricting plans, I checked for compliance with the Voting Rights Act as follows. First, I used precinct-level data on race and partisanship, using the same statewide general election races detailed in Table 1 above and, using ecological inference, ascertained whether racially polarized voting was present within each of Ohio's major metropolitan counties. Next, in counties where racially polarized voting was present, I made sure that, under my alternative Senate and House plans, candidates of choice for Black voters in statewide elections had indeed been victorious in the relevant districts in my redistricting plan. In each metro area with a large Black community and clear evidence of racially polarized voting—specifically Akron, Cincinnati, Dayton, and Toledo—this was clearly the case. I thus did not make any changes to my alternative plans to ensure compliance with the Voting Rights Act.

46. For my maps, attached as Exhibit I, for each of the alternative maps presented to the Commission, and for the Commission's proposed maps (attached as Exhibit D), I have produced compactness scores for the districts to assess the maps' compliance with Article XI, Section 6(C). I have included Reock, Polsby-Popper, and Convex Hull compactness measures, each of which takes a somewhat different approach to the notion of district compactness.

47. Although the Ohio Constitution does not specify the optimal number of county splits, I have also calculated the number of county splits generated by each plan. I define a county split in the same way as the Ohio Constitution. For example, Franklin County is not considered to be split in a House of Representatives plan if 11 districts are formed that fit completely within

the county, and no fragment of any district spills over the county boundary. Moreover, a county that is kept intact but joined together with other "split" counties is not considered a split county. A county is only considered to be split if some part—but not all—of its territory is joined with territory from another county in the formation of a district.

Table 2: Summary Information, Ohio House of Representative Plans Submitted to Ohio Redistricting Commission

	Commission 9/15	Commission 9/9	Sykes 9/2	Sykes 9/15	Citizens 9/10	Rodden
Average compactness scores						
(Higher scores = more compact)						
Reock	0.40	0.40	0.40	0.39	0.40	0.41
Polsby-Popper	0.30	0.30	0.31	0.29	0.34	0.36
Area/Convex Hull	0.74	0.73	0.74	0.72	0.76	0.79
Number of split counties	33	33	30	33	43	32
# of seats with average two-party Democratic vote share >.5	37	32	44	42	43	43
Expressed as percentage of seats	37.4%	32.3%	44.4%	42.4%	43.4%	43.4%
# of seats with average two-party Republican vote share >.5	62	67	55	57	56	56
Expressed as percentage of seats	62.6%	67.7%	55.6%	57.6%	56.6%	56.6%
Distance from proportional seat allocation (seats)	8	13	1	3	2	2
Expressed as percentage of seats	8.1%	13.1%	1.0%	3.0%	2.0%	2.0%

# of seats with average two-party Democratic vote share >.52	32	31	41	38	42	40
Expressed as a percentage of seats	32.3%	31.3%	41.4%	38.4%	42.4%	40.4%
# of seats with average two-party Democratic vote share <.48	62	63	54	54	54	56
Expressed as percentage of seats	62.6%	63.6%	54.5%	54.5%	54.5%	56.6%
# of seats with average two-party Democratic vote share between .48 and .52	5	5	4	6	3	3
Expressed as percentage of seats	5.1%	5.1%	4.0%	6.1%	3.0%	3.0%

48. In Table 2, I provide compactness scores and information on county splits for each of the Ohio House of Representatives plans I analyzed. Next, using the same technique described above, I include the number of majority-Democratic districts, majority-Republican districts, expected Democratic districts, expected Republican districts, and toss-up districts that would be produced by each plan.

49. First, in terms of compactness, Senator Sykes' initial plan was slightly more compact than the Commission's final September 15 plan, but his revised plan, after reconfiguring Northeast Ohio, was slightly less compact. The plan produced by the Citizens' Commission was on average more compact according to both the Polsby-Popper and Convex Hull scores. The House map I produced was more compact by every measure than those produced by the Commission, Senator Sykes, and the Citizens' Commission.

50. The Commission's House of Representatives Plan splits 33 counties. The Citizens' Commission splits a greater number of counties (43) than does the Ohio Redistricting Commission's, while Senator Sykes' original plan splits fewer counties (only 30), and his revised plan is similar to the Commission's on this dimension. Likewise, my alternative plan splits 32 counties.

51. Next, let us examine the partisan outcomes associated with these alternative plans. The relevant information is also contained in Table 2. The initial plan submitted by Senator Sykes came very close to achieving partisan proportionality. It produced 44 majority-Democratic seats and 55 majority-Republican seats—a difference from proportionality of only 1 seat. My alternative plan, as well as the plan produced by the Citizens' Commission, produced 43 Democratic seats and 56 Republican seats—a difference from proportionality of only 2 seats. Senator Sykes's revised plan produced 42 majority-Democratic seats—a difference from proportionality of 3 seats. Again, in contrast to my alternative plan and these other plans, which came very close to achieving partisan proportionality, the Ohio Redistricting Commission's final plan deviated 8 seats from true proportionality.

52. In short, the plans introduced by Senator Sykes and the Citizens' Redistricting Commission are relatively similar to the Commission's Plan in their deference to traditional redistricting criteria emphasized in the Ohio Constitution—and my alternative plan is more compact on average—but each of these plans also comes much closer to achieving the required partisan proportionality. This indicates that the failure of the 2021 Commission Plan to achieve partisan proportionality and its overall favorability to Republicans were intentional choices, rather than natural outgrowths of other constraints.

53. Next, let us undertake a similar comparison of the Ohio Redistricting Commission's Senate maps with these alternative maps. The key information is contained in Table 3. Once again, the plans presented by Senator Sykes demonstrated a similar level of average compactness to the Commission's plan on each of the three metrics I considered. And again, my alternative plan, along with the plan produced by the Citizens' Commission, were clearly more compact than the Commission plan. Relative to the Commission's Senate map, my alternative map split 2 additional counties, the Sykes maps split 3 additional counties, and the Citizens' map split 5 additional counties.

54. The Commission's Senate map produced only 10 majority-Democratic seats, and 23 majority-Republican seats. In contrast, both the original Sykes Senate map and the Citizens' Commission Senate map produced 14 Democratic seats and 19 Republican seats. The revised Sykes map produced 13 Democratic seats and 20 Republican seats. My alternative map produced 15 Democratic seats and 18 Republican seats. Recall that the target set forth by the Constitution was 15 Democratic seats, meaning that 2 of these plans came within a single seat of the target, and 1 achieved proportionality. Again, as with the House of Representatives, these alternative maps demonstrate that, for the Senate as well, it is possible to abide both by the Ohio Constitution's traditional redistricting requirements as well as its partisan proportionality requirement. The fact that the Commission's map so strongly favors the Republican Party is the result of discretionary choices made by the Commission and reflects that the Commission did not attempt to achieve partisan proportionality.

Table 3: Summary Information, Ohio Senate Plans Submitted to Ohio Redistricting Commission

	Commission 9/15	Commission 9/9	Sykes 9/2	Sykes 9/15	Citizens 9/10	Rodden
Average compactness scores						
(Higher scores = more compact)						
Reock	0.39	0.39	0.39	0.38	0.43	0.44
Polsby-Popper	0.31	0.31	0.31	0.31	0.37	0.37
Area/Convex Hull	0.73	0.72	0.73	0.74	0.78	0.78
Number of split counties	13	13	16	16	18	15

# of seats with average two-party Democratic vote share >.5	10	9	14	13	14	15
Expressed as percentage of seats	30.3%	27.3%	42.4%	42.4%	42.4%	45.5%
# of seats with average two-party Republican vote share >.5	23	24	19	20	19	18
Expressed as percentage of seats	69.7%	72.7%	57.6%	60.6%	57.6%	54.5%
Distance from proportional seat allocation (seats)	5	6	1	2	1	0
Expressed as percentage of seats	15.2%	18.2%	3.0%	6.1%	3.0%	0
# of seats with average two-party Democratic vote share >.52	9	8	13	12	12	12
Expressed as a percentage of seats	9.1%	8.1%	13.1%	12.1%	12.1%	12.1%
# of seats with average two-party Democratic vote share <.48	21	21	18	19	18	18
Expressed as percentage of seats	63.6%	63.6%	54.5%	57.6%	54.5%	54.5%
# of seats with average two-party Democratic vote share between .48 and .52	3	4	2	2	3	3
Expressed as percentage of seats	3.0%	4.0%	2.0%	2.0%	3.0%	3.0%

VI. WHY DID THE OHIO REDISTRICTING COMMISSION FALL SO FAR SHORT OF PROPORTIONALITY?

55. It is clear that the 2021 Commission Plan produces outcomes that are at odds with the partisan fairness required by the Ohio Constitution, while alternative plans achieve near-proportional outcomes. Next, it is useful to gain a better understanding of how this happened by examining the specific choices that led to such striking differences in the partisanship of the Commission's maps relative to the alternative maps. This section examines the differences between the maps in more detail, focusing first on aggregate data, and then drilling down into the individual regions where different outcomes are notable.

The Geographic Distribution of Partisanship Across Districts

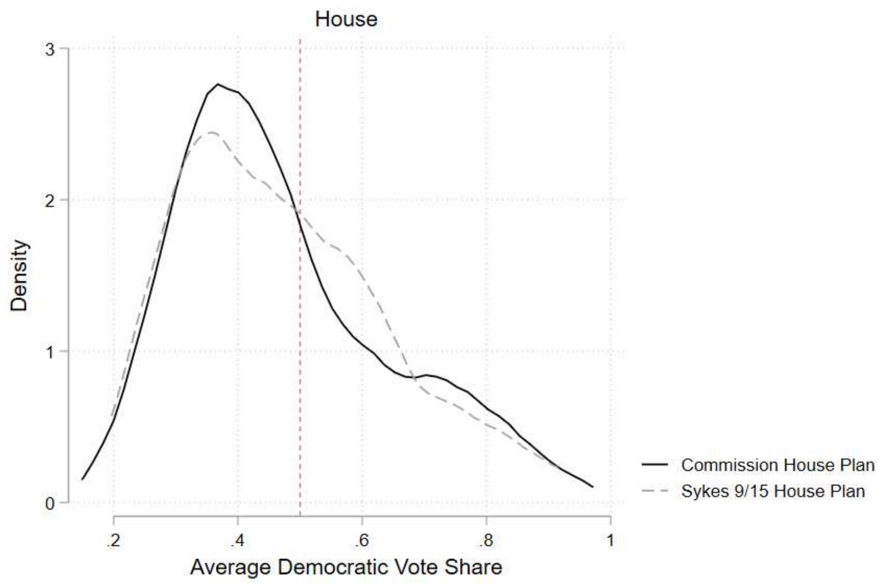
56. In order to gain a better appreciation for the way in which the maps drawn by the Commission differ from the more proportional alternative maps presented by Senator Sykes and the Citizens' Commission, and in this report, it is useful to look at how the different maps diverged in addressing the geographic distribution of partisanship across districts.

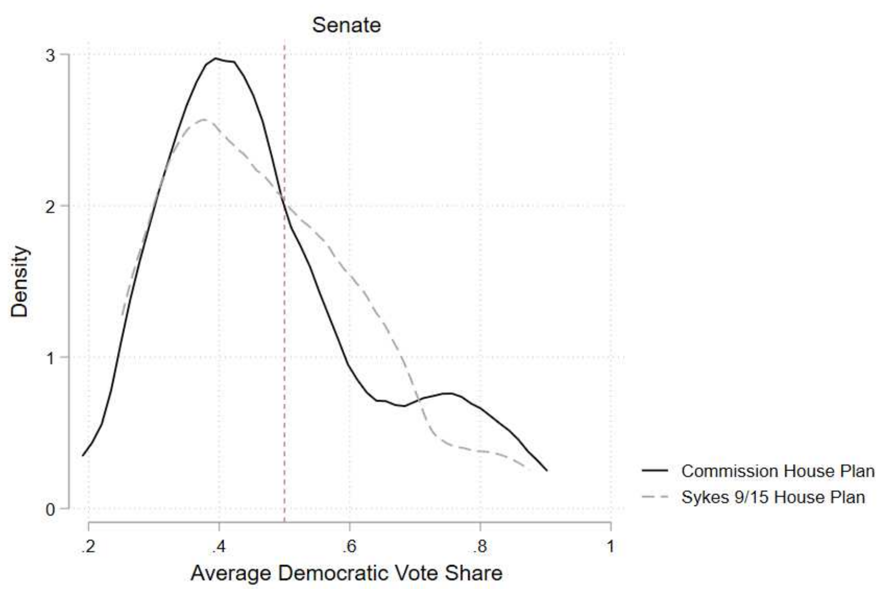
57. To do this, I present a kernel density—which is simply a smoothed histogram—that displays the distribution of the Democratic vote share across districts for each proposed redistricting plan. Figure 2 does this first for the House plans (in the top panel), and then for Senate plans (in the bottom panel). The bold line captures the distribution of Democratic vote share across the districts in the Commission's maps, and the dashed gray line captures the same thing for the Sykes 9/15 maps. The distributions for the Sykes 9/2 maps as well as the Citizens' Commission maps, as well as my own maps, look very similar to the gray dashed lines, so, for ease of exposition, I do not include them.

58. The basic shape of the kernel density in Figure 2 is one that I have written about elsewhere.[8] Democratic voters tend to be highly concentrated in the urban core of large cities, while Republican voters are concentrated in sprawling rural areas, and suburban areas are heterogeneous and competitive. Inner-ring suburban areas usually lean toward Democrats, and as one moves to the outer-ring suburbs, the Republican vote share increases. In recent years, Democratic majorities have been spilling further out into the suburbs, and in cities like Columbus, now reach to the distant outer suburbs and even some exurbs.

[8] See Jonathan Rodden, 2010 "The Geographic Distribution of Political Preferences," *Annual Review of Political Science* 13:297-340; Jonathan Rodden, 2019, *Why Cities Lose: The Deep Roots of the Urban-Rural Political Divide.* New York: Basic Books.

Figure 2: Distribution of Average Democratic Vote Shares Across Proposed Districts





59. The concentration of some Democratic voters in some very urban areas means that it is often impossible to avoid drawing electoral districts that are extremely Democratic. As a result, both the Commission's map and the alternative maps produce distributions with a long right tail. All of the districts in the right tail of the distributions in Figure 2 are in very urban areas.

60. It should also be noted that in Ohio, many rural areas are also now extremely Republican, and it can be difficult to avoid drawing rural districts that are not overwhelmingly Republican. This phenomenon is only occasionally tempered by the presence of an isolated college town like Oxford or Yellow Springs, which might, for example, turn an otherwise 80 percent Republican area into a 70 percent Republican area. While the left tail of the distribution is not quite as long as the right tail, it also includes a large number of landslide Republican districts.

61. The *overall shape* of the distribution—driven by Ohio's political geography—is similar for both the Commission's plan and the alternative plans. That is to say, both have long right tails composed of urban, Democratic districts, and both produce similar numbers of rural, highly Republican districts, as demonstrated by the fact that, on the left side of the graph, the dashed line and solid line are right on top of one another.

62. It is clear that Ohio's political geography necessitates some solidly Democratic and solidly Republican districts, but map-drawers have considerable flexibility in the middle of the distribution, and with the extent of packing of Democrats in cities. In Figure 2, we can see that the shape of the distribution of partisanship across districts in the Commission's plan is distinctive in the districts that are neither solidly Republican nor solidly Democratic. This is apparent as we move to the right on the graph and enter the territory of comfortable, but not landslide, Republican victories. The Commission's maps produce a far larger number of such districts. And then, once we cross the 50 percent threshold, there is a dramatic reversal. The Commission's maps produce far *fewer* districts with Democratic majorities. Finally, the maps are also different when we move further to the right, where the black line is above the gray dashed line, indicating that the Commission's maps produce a larger number of landslide Democratic districts—what is known in the literature as "packing."

63. How did the Commission and these alternative groups of map-drawers produce maps with such starkly different partisan outcomes, given that they were working within the constraints of the same political geography and the same rather restrictive rules? To find the answer, we must examine Ohio's cities and their surroundings. The differences between the black and gray lines in Figure 2 is driven by choices made in and around cities. In particular, the Commission's maps produced notably fewer majority-Democratic districts in the regions around Akron, Cincinnati, Cleveland, Columbus, and Dayton.

Franklin County Area

64. Consider Franklin County and its surroundings. Figure 3 displays this region, with yellow lines corresponding to the districts drawn in the 2021 Commission House map. Colors go from light blue to dark blue as the precinct-level 2020 presidential Democratic vote share increases. From Figure 3, one can see how the Commission's district boundaries correspond to partisanship.

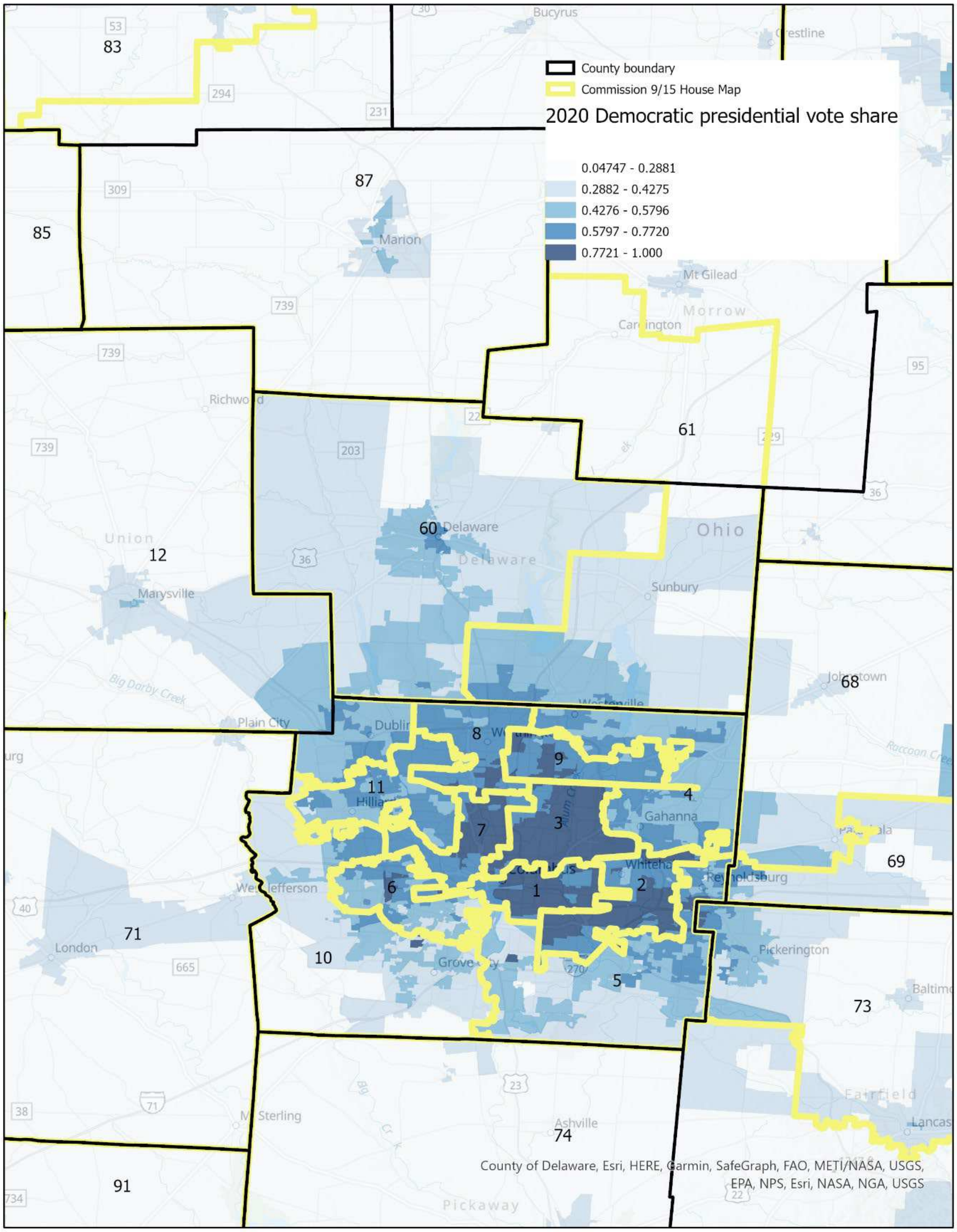
65. Several things are noteworthy about the Commission's map. First, as Franklin County has become more Democratic over time, and as Democratic dominance has spilled over from the urban core to suburban areas, there is now only one possible area for the construction of a comfortable majority-Republican district—in the southwest corner. District 10 in the

Commission's map pulls together all of the most Republican exurban parts of Franklin County in order to carve out such a district. This district runs almost the entire length of Franklin County, from the southern border almost to the northern border, stopping just short of the more Democratic-leaning suburban areas in the northwest corner of the county.

66. Second, in the northwest corner of the county, Dublin—especially the part in Franklin County closest to Ohio State University—is an educated suburban community that has been drifting toward the Democratic Party in recent years. It is one of the most Democratic border-adjacent communities in Franklin County. However, instead of connecting it with surrounding Democratic-leaning communities, the Commission map splits Franklin County in the northwest corner to extract Dublin from the rest of Franklin County, combining Dublin with relatively rural Union County. In doing so, the Commission map thus extracts a growing Democratic community and embeds it in a district with numerically greater rural Republicans. Given its population of 1,323,807, Franklin County could easily accommodate 11 districts without a split. Instead, the Commission chose to create 9 under-populated districts and extract a relatively large chunk of Democratic voters from the county, preventing those voters from contributing to an additional Democratic district.

67. Finally, there is a group of growing, increasingly Democratic-leaning Columbus suburbs hugging the southern border of Delaware County, and a corridor of Democratic-leaning precincts connecting to the relatively Democratic town of Delaware. If we use decade averages, these suburbs appear to be Republican leaning. However, they have moved sharply toward the Democratic Party in recent years, and in the 2020 Presidential Election, a majority of voters in these suburbs voted for the Democratic candidate. Using the most recent election results, these areas would easily correspond to a compact majority-Democratic district. Instead, the Commission's districts split those increasingly Democratic voters in half with a north-south dividing line, thus preventing a majority-Democratic district from emerging in that area, instead producing 2 very comfortable Republican districts. This is a classic example of what is known in the literature on gerrymandering as "cracking."

Figure 3: Franklin County and Surroundings; Partisanship and the Commission's House Boundaries



68. It is useful to contrast the Commission's plan with the alternative plans that exhibited greater statewide proportionality. Beginning with the Commission's plan, followed by my own alternative plan (referred to as the "my plan" or the "Rodden plan"), the Sykes 9/15 plan, and the Citizens' Commission plan, Figure 4 simply displays the districts with Democratic majorities in blue and Republican majorities in red, using averages over all statewide elections from 2012 to 2020. Similar maps will be presented below for other regions, where highly competitive districts, with average Democratic vote share between 48 percent and 52 percent will be displayed with separate colors, but none of the districts displayed in Figure 4 are in that range.

69. In Franklin County and the surrounding area, the Commission's plan produces 10 majority-Democratic House districts. In Figure 4, we can see that the Rodden plan, along with the Citizens' Commission plan, produces 11 majority-Democratic districts, while the Sykes plan produces 12.

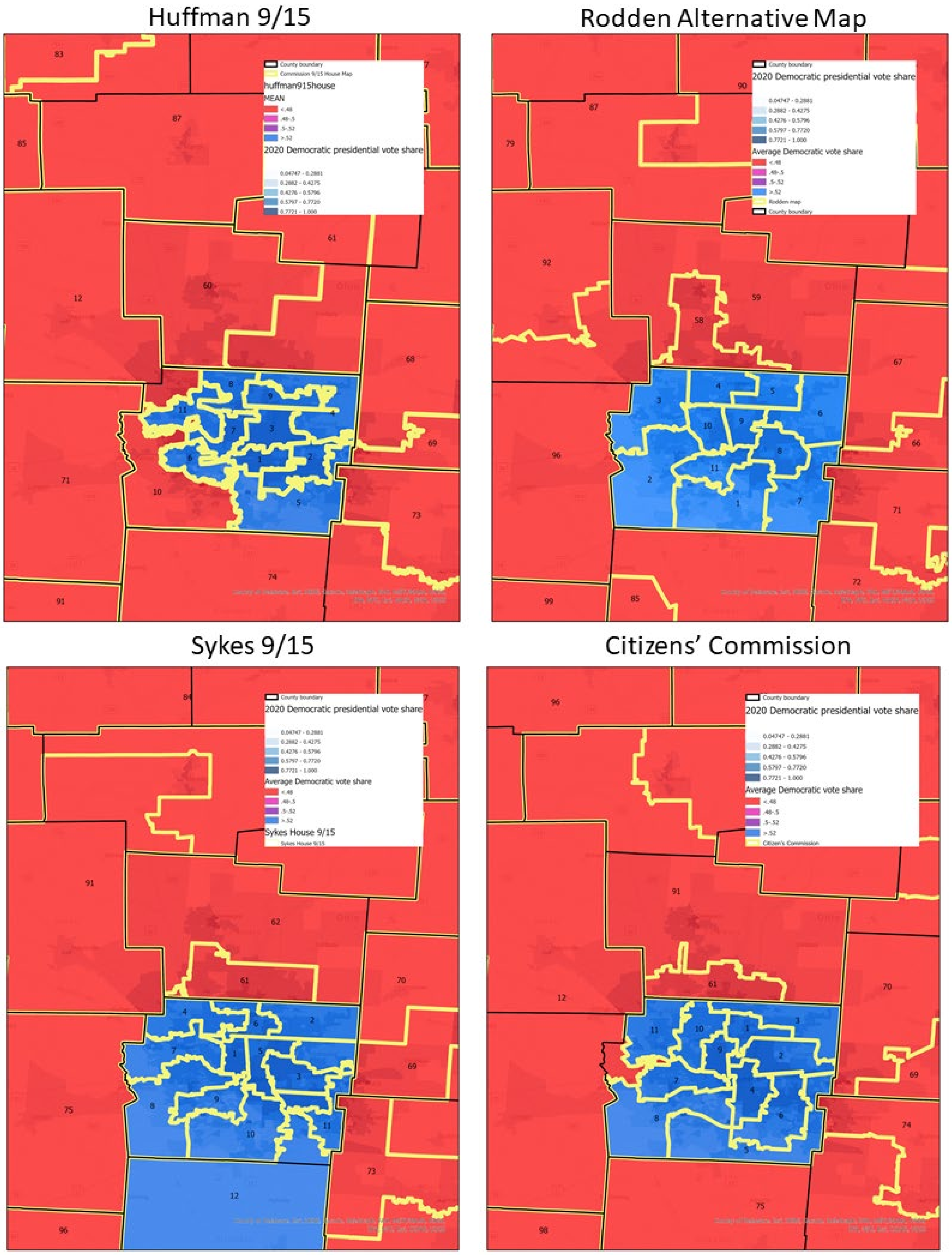
70. Let us now examine the choices made in the alternative maps that produced additional Democratic-leaning Franklin-County districts. First, those drawing alternative maps simply avoided making a special effort to carve out a Republican district in the southwest. For instance, my plan included a relatively compact district in the southwest corner of the county, but I made no effort to keep Democratic-leaning Columbus districts out in order to craft a Republican-leaning district.

71. Second, since they did not attempt to carve out a Republican district, the alternative plans engaged in less packing of Democrats into highly non-competitive districts. While the Commission's plan produced 4 Franklin-County districts where the Democratic vote share was above 75 percent, each of the alternative plans each produced only 2 such districts.

72. Third, the alternative plans took different approaches to splitting the county. As described above, my approach was to keep counties whole whenever possible. Since it was possible to avoid splitting Franklin County, I did not introduce a split. Like the Commission's plan, the Sykes plan did include a split, and it generated a district that combined some Franklin County precincts that favor Democrats with some rural Republican precincts in a surrounding county (Pickaway). But Pickaway is a smaller county than Union, such that while the Commission's split produced a comfortable Republican district in the northwest, the Sykes plan's split produced a competitive but Democratic-leaning district in the south. The Citizens' Commission did not produce systematically underpopulated districts in Franklin County and, as a result, required a much smaller split fragment of Franklin County.

73. Fourth, note that each of the alternative plans produced a compact district in southern Delaware County by keeping the growing Columbus suburbs together rather than splitting them in half. These districts are colored red in Figure 4, which is based on average vote shares over the last decade. However, if one focuses on the 2020 presidential election, these districts are majority-Democratic. Joseph Biden received around 51 percent of the vote in district 61 in both configurations.

Figure 4: Franklin County and Surroundings; Party Majorities Associated with House Boundaries of Four Redistricting Plans



74. Finally, it is worth noting that the districts in my plan are more compact than those created by the Commission. If we leave aside Delaware County and focus only on the districts of Franklin County, the average compactness of my districts, according to the Polsby-Popper score, was .39, while the score for the Commission's plan was .19. The score for the Sykes plan was .25, and that for the Citizens' plan was .30. The average Reock score for my plan was .47, while the score for the Commission's plan was .37. The scores for the Sykes and Citizens' plans were .40 and .37 respectively.

Hamilton County Area

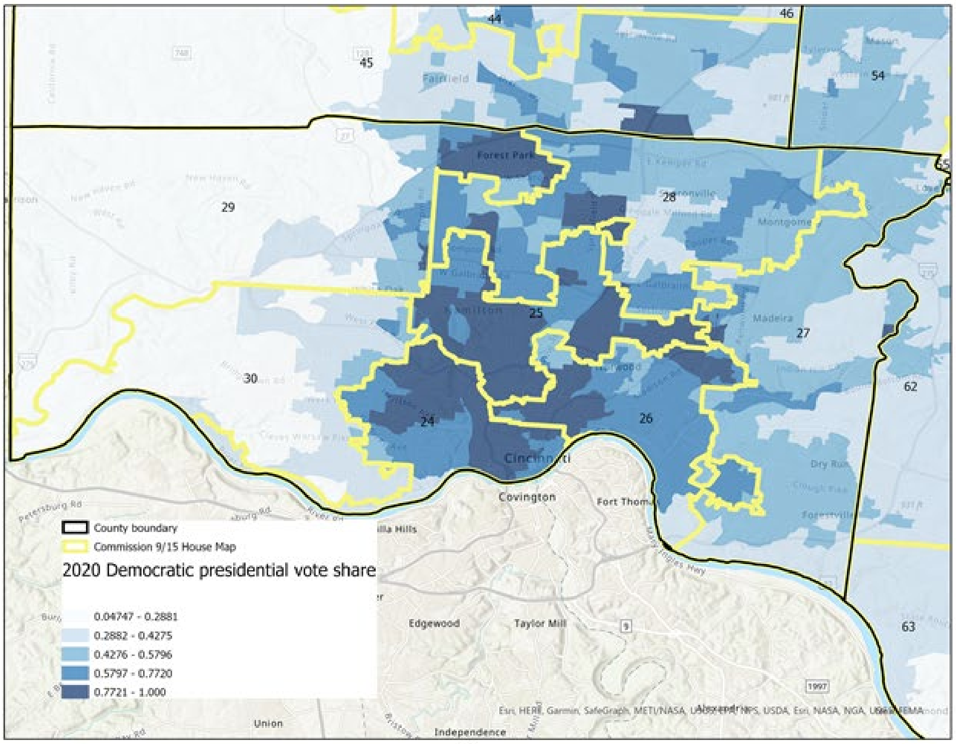
75. Next, let us examine the Cincinnati area. Again, it is useful to get the lay of the land by viewing a precinct-level map of partisanship, superimposing the Commission's districts. It is also useful to understand the arrangement of race, which is highly correlated with voting behavior in metro Cincinnati. Figure 5 demonstrates that there is a north-south swath of Black voters in the middle of Hamilton County. These communities vote in large numbers for Democratic candidates. However, there are also Democratic-leaning suburban communities on the east side of Cincinnati that are not predominantly Black.

76. On the west side of Hamilton County, a majority-white, Republican-leaning district will emerge in the outer-ring suburbs and exurbs of Cincinnati in almost any configuration. However, the Commission has crafted a *second* majority-Republican district by keeping both districts as small as possible (within the 5 percent population deviation constraint) and reaching into Forest Park City—a majority-Black and overwhelmingly Democratic area, and surrounding precincts, in order to assemble sufficient population to produce an additional majority-Republican district. As discussed further below, this maneuver led to the creation of a relatively non-compact set of Hamilton County districts.

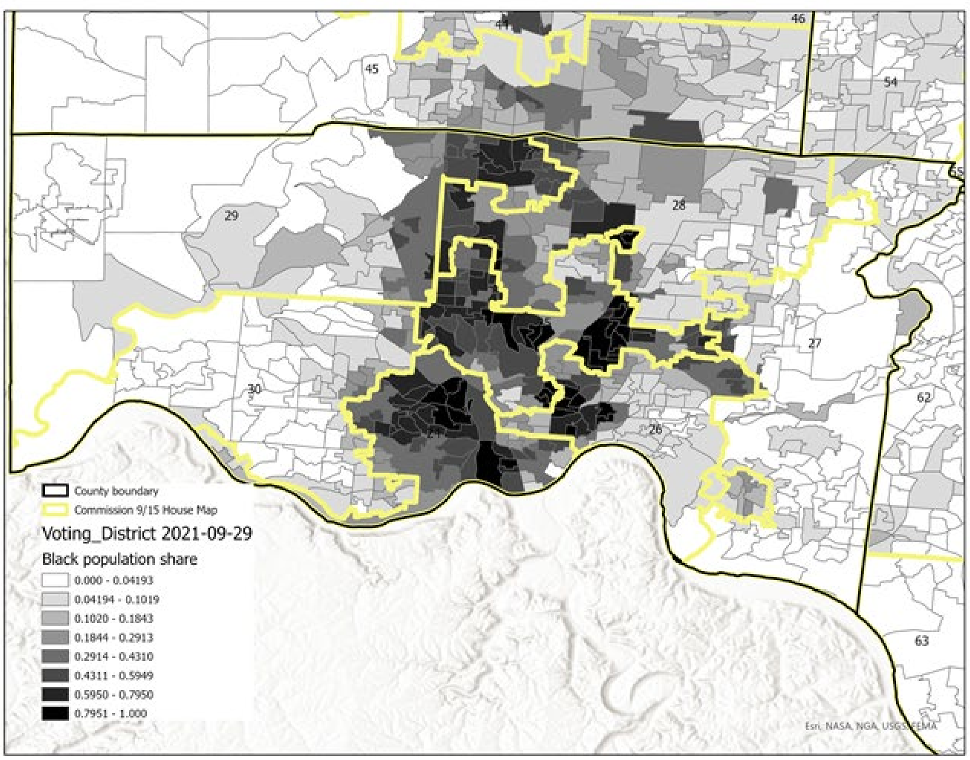
77. Moreover, by carefully avoiding Democratic neighborhoods, the Commission's plan also extracted a Republican-leaning district in Cincinnati's eastern suburbs (District 27). In addition, in the northern suburbs, District 28 in the Commission's plan, while Democratic leaning, is within reach for Republican candidates, with an average Democratic vote share of around 52 percent.

Figure 5: Hamilton County and Surroundings; Partisanship, Race, and the Commission's House Boundaries

Partisanship

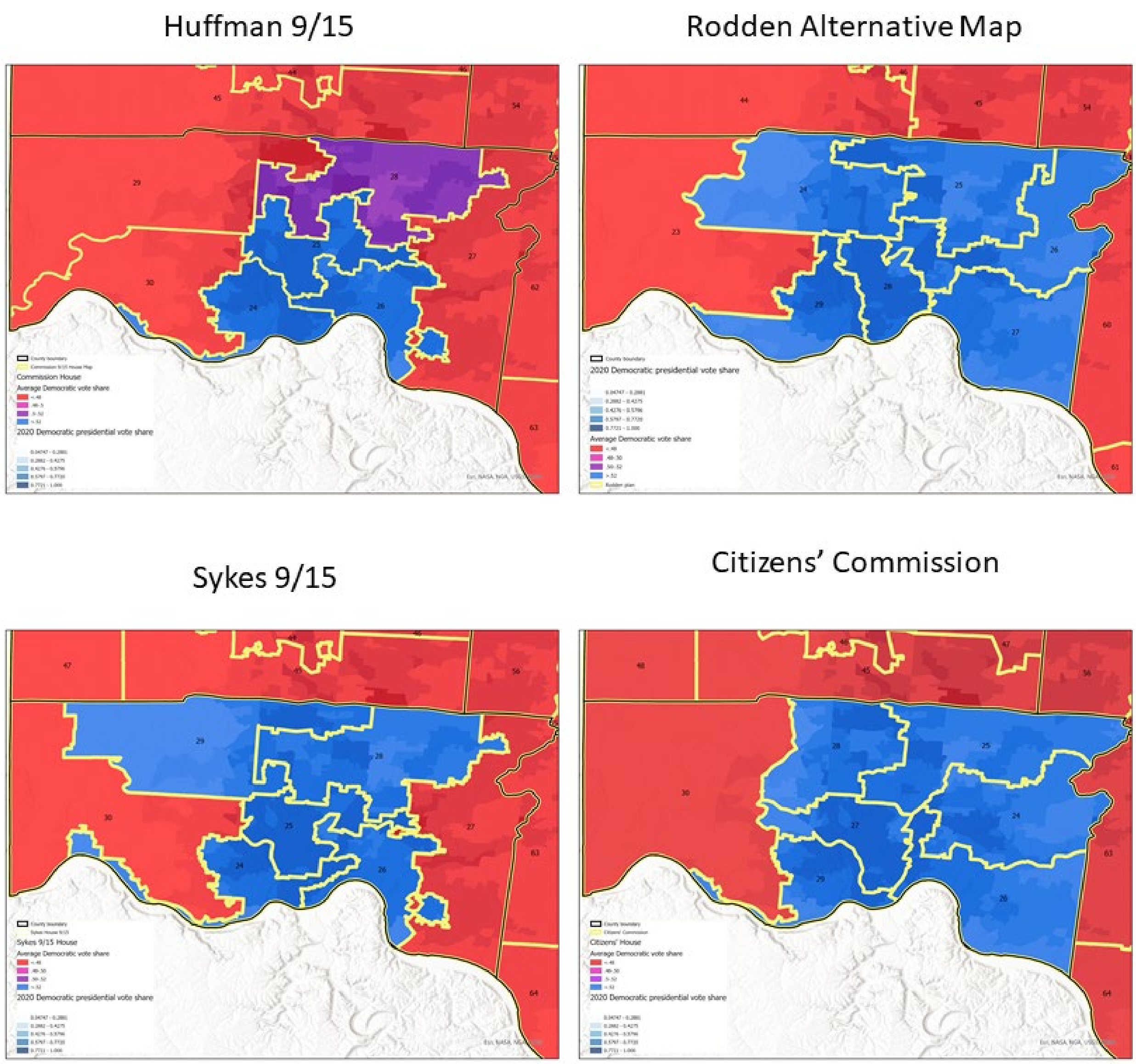


Race



78. Next, let us examine the alternative plans. Like the Commission's map, each of the alternative maps avoided splitting Hamilton County, which wholly contains 7 districts in each map. The Commission's map produced 3 Republican districts and 4 Democratic districts, 1 of which was relatively competitive. My plan, along with the Citizens' plan, produced a 6-1 breakdown, and the Sykes plan produced a 5-2 breakdown, both in favor of the Democrats.

Figure 6: Hamilton County and Surroundings; Party Majorities Associated with House Boundaries of Four Redistricting Plans



79. What accounts for these differences? Above all, these alternative plans made no efforts to craft a second Republican district in the suburbs by cracking Black neighborhoods in the northern part of the county, leaving them with only a single exurban Republican-leaning district. Second, by adopting an east-west rather than north-south orientation for the boundaries on the east side of the county, my plan, along with the Citizens' plan, did not craft an eastern Republican-leaning district.

80. Finally, as with Franklin County, the plans that exhibited greater statewide partisan proportionality were also the most compact in Hamilton County. My plan and the Citizens' Commission plan, both with 6-1 Democratic margins, were the most compact plans in Hamilton County. The average Polsby-Popper score for the Citizens' plan was .31, and for my plan it was .26. The Commission's plan and the Sykes plan each had scores of .17. The story is similar for the Reock score. The average for my plan was .43, and for the Citizens' plan it was .41, while for the two more Republican-leaning plans (the Commission's plan and the Sykes plan), the scores were .32 and .34 respectively.

Montgomery County Area

81. Next, let us move a few miles to the north and examine the Dayton area. In the Commission's House plan, only 1 of 5 Montgomery-based seats (number 38) has a clear Democratic majority, while an additional seat (number 36) was essentially a tie, with an average Democratic vote share of 50.03 percent. The other 3 seats had comfortable Republican majorities.

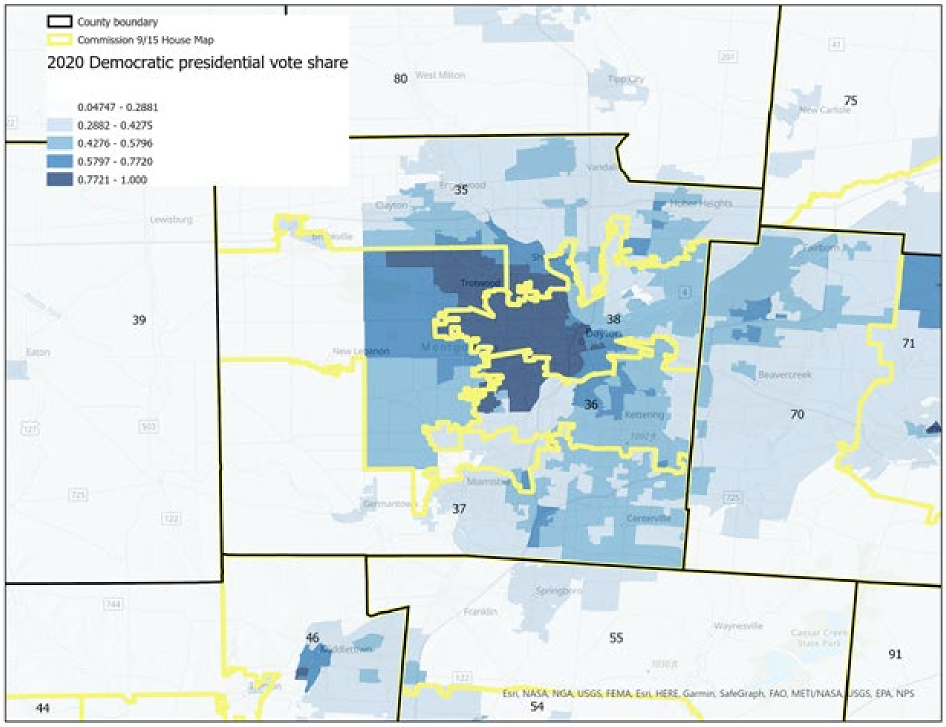
82. In my plan, there were 3 majority-Democratic seats, although 1 of them was a marginal seat, with an average Democratic vote share of 51.5 percent. Likewise, both the Sykes and Citizens' Commission plans produced 3 majority-Democratic seats. In order to see how the Commission's plan produced such a surprisingly pro-Republican outcome, let us once again examine how the Commission's districts interact with the partisan and racial geography of the county.

83. In Figure 7, the Commission's House district boundaries are superimposed on maps of partisanship and race in the Montgomery County area. The Commission's plan takes the relatively compact Black community of metropolitan Dayton, which votes overwhelmingly for Democratic candidates, and scatters it across 4 separate districts. The district with the largest Black community—number 38—is a majority-Democratic district. In fact, it is a super-majority Democratic district, where on average, Democrats win 69 percent of the vote. However, all of the other fragments of Dayton's Black community are combined with sufficient numbers of surrounding white, suburban populations in the 4 other Montgomery districts to generate 1 true toss-up (District 36) and 3 districts with comfortable Republican majorities.

84. A key part of this approach was to extract the Black community of Trotwood and other areas on the west side of Dayton and combine them with far-flung, rural Preble County to the west. Considerable care and craft seem to have gone into this effort to break up Black areas of metropolitan Dayton in a way that prevents the emergence of majority-Democratic districts.

Figure 7: Montgomery County and Surroundings; Partisanship, Race, and the Commission's House Boundaries

Partisanship



Race

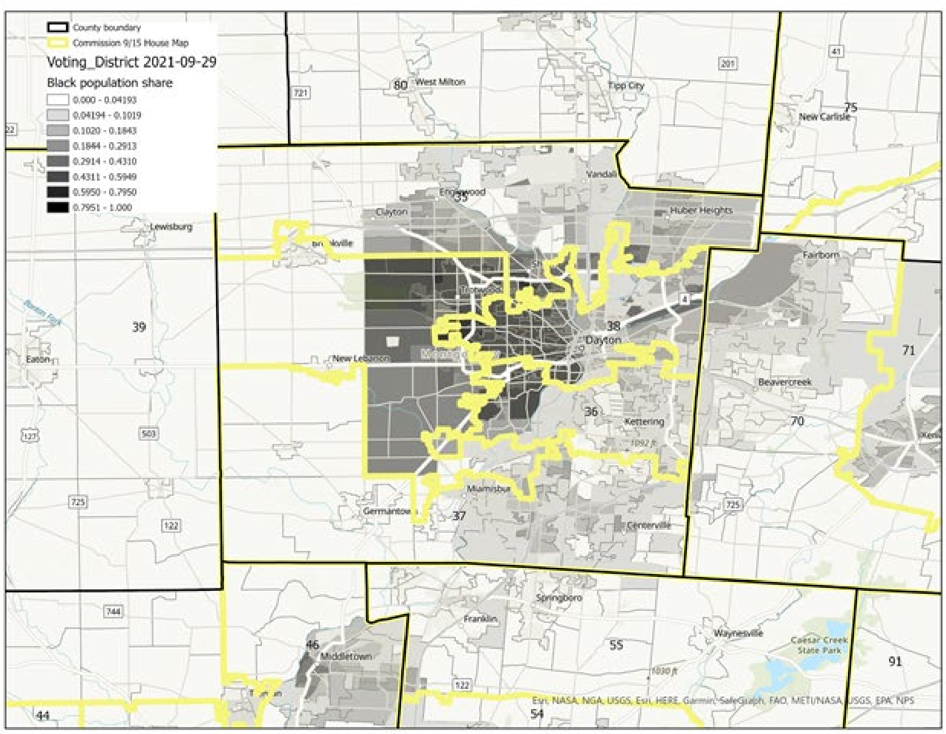
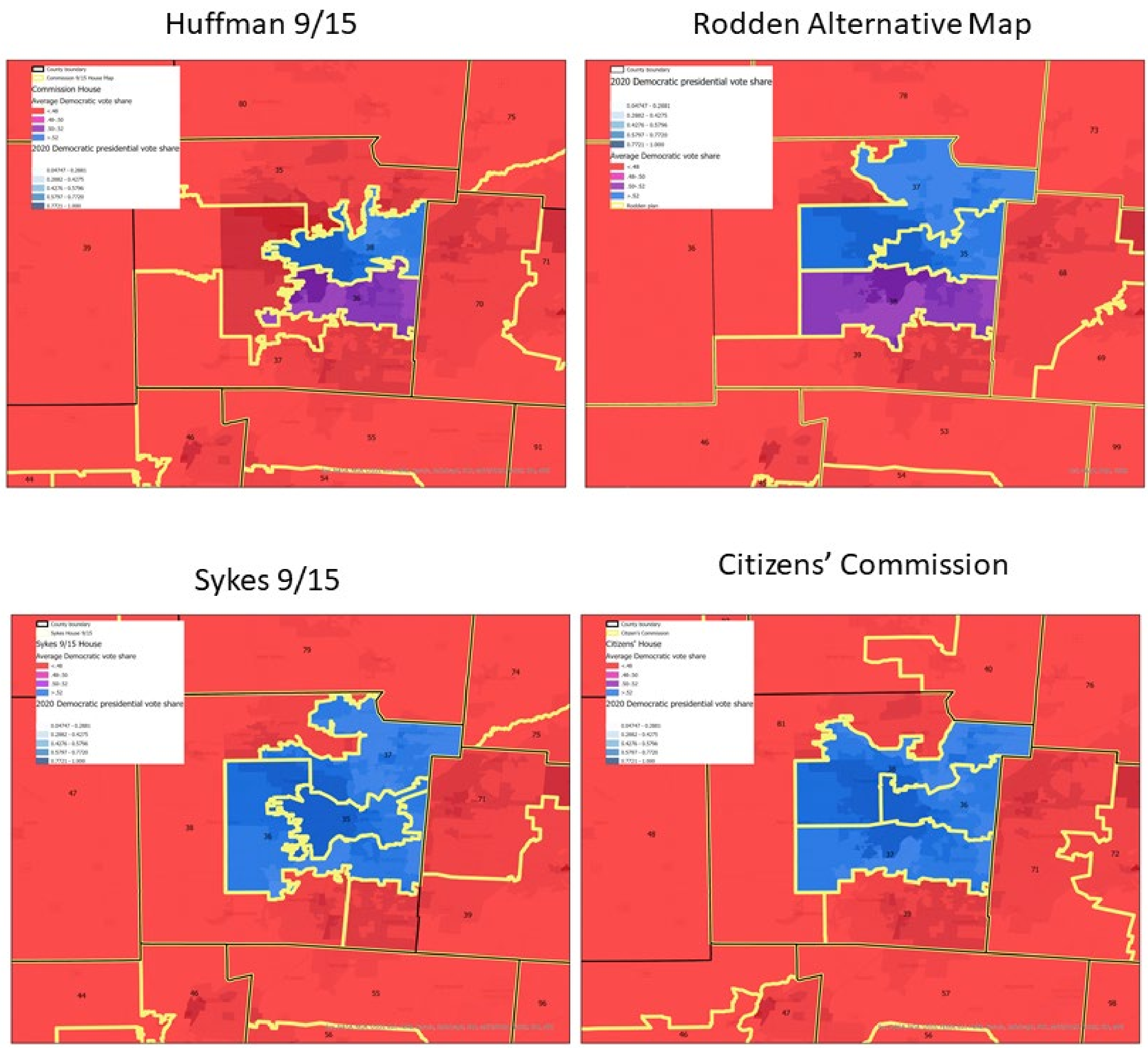


Figure 8: Montgomery County and Surroundings; Party Majorities Associated with House Boundaries of Four Redistricting Plans



85. Again, in order to appreciate the partisan impact of the Commission's approach to scattering the Dayton Black community across multiple districts, it is useful to examine the alternative maps. Following the same format as above, Figure 8 provides maps that facilitate comparison of the Commission's plan with the alternative plans.

86. Simply by keeping Dayton-area communities together, my map produced a relatively compact, very Democratic central Dayton district, as well as a Democratic-leaning northern suburban district, and a competitive but Democratic-leaning suburban district to the south. My plan also includes a Republican-leaning exurban district to the South, and a western exurban district that, like the Commission's district, combines with Preble County. A notable difference, however, is that my plan does not extract western Dayton-area Black communities in order to place them in a predominantly rural district. The configuration is different, but the same overall structure is present in the Citizens' plan. The Sykes plan has some similarities, but it is less compact, and combines parts of the Southern and western suburbs.

87. Once again, my plan and the plan produced by the Citizens' Commission, were substantially more compact according to the Polsby-Popper score, with average scores of .27 and .29 respectively for the Montgomery districts. The average score of the Commission's plan was .15, and the Sykes plan was .13. The four plans were less distinctive, however, according to the Reock score—all were bunched together with scores ranging from .37 to .39.

Northeast Ohio

88. Next, let us examine Northeast Ohio. As described above, all of the mapmakers faced difficult constraints associated with the strict rules for the construction of Senate districts, and these rules had implications for House districts as well. Each of the redistricting plans considered here ended up with the same basic solution: they drew consistently under-populated districts in Cuyahoga County, and indeed throughout the northeastern part of the state, and included a district that combines parts of several counties. Also, in each plan, it was necessary to create a district that kept Canton, Ohio whole.

89. In spite of these constraints, the Commission's plan ended up with a very different partisan outcome than the alternative plans. If we consider Northeast Ohio to be the area contained in Figure 9, the Commission's House plan includes 14 districts with average Democratic vote shares above 52 percent, and an additional 4 districts with very slim Democratic majorities, for a total of 18 majority-Democratic districts. As mentioned above, the Commission's House plan does not include any bare-majority Republican districts, in Northeast Ohio or anywhere else. Under the Commission's plan, 18 is perhaps the upper limit of districts that might be competitive for Democratic candidates.

90. In my plan, there are 17 districts with an average Democratic vote share above 52 percent, and 2 additional districts with Democratic vote shares between 50 and 52 percent, so that overall, there are 19 Democratic-leaning districts. The Sykes plan includes 17 districts with average Democratic majorities greater than 52 percent, 2 districts with slim Democratic-majorities, and 2 districts with slim Republican majorities, for a total of 19 Democratic-leaning districts, and 21 districts that could be at least competitive for Democratic candidates. The House plan produced by the Citizens' Commission produced 19 districts with average Democratic vote shares greater than 52 percent, and 2 additional districts with slim Republican majorities, again producing 21 districts that could be competitive for Democratic candidates.

91. To understand the sources of these differences, let us proceed through the region, guided by the image of the Commission's district boundaries superimposed on precinct-level election results (Figure 9), and images capturing the partisan outcomes produced by the Commission's maps and the alternative maps (Figure 10).

Figure 9: Northeast Ohio; Partisanship and the Commission's House Boundaries

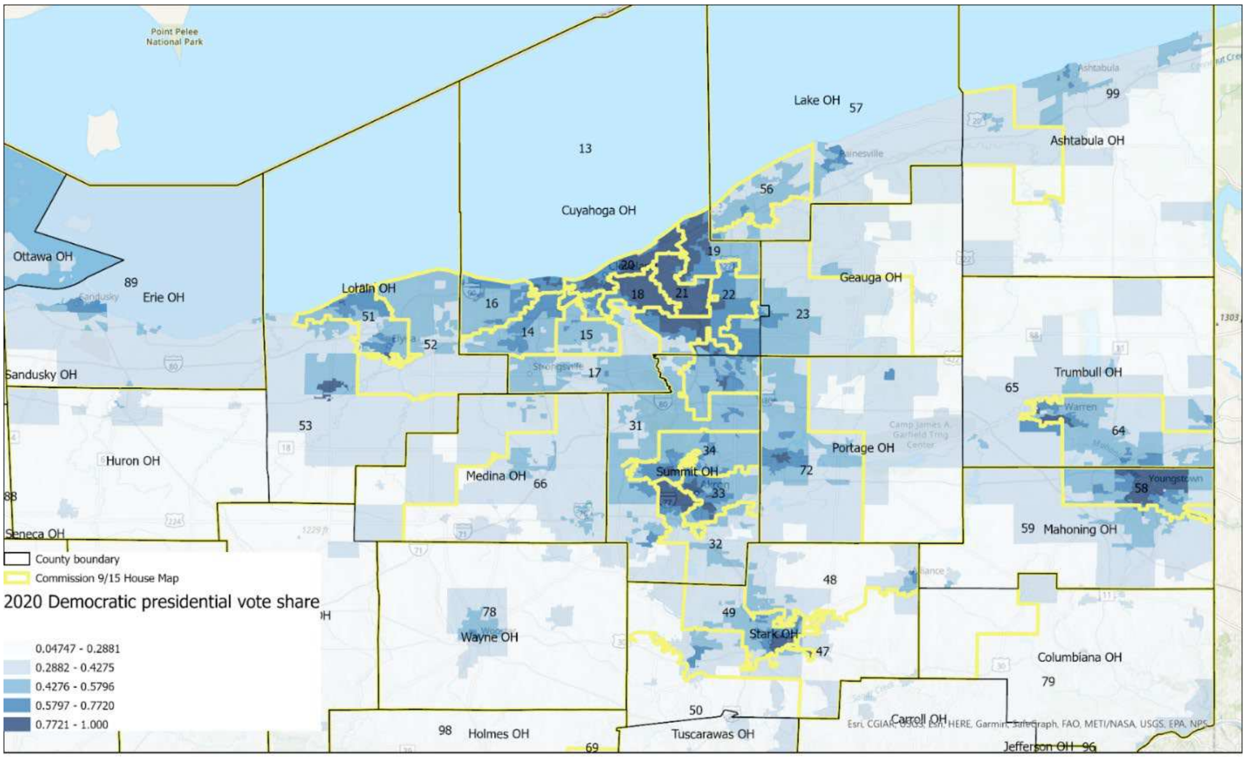
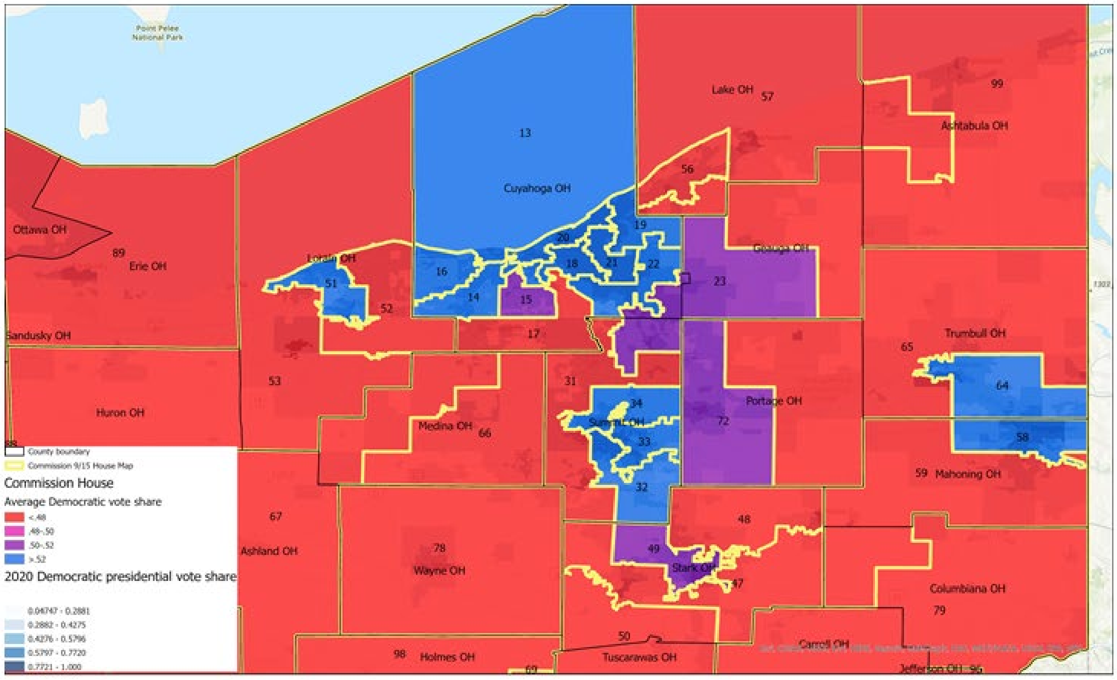


Figure 10a: Northeast Ohio; Party Majorities Associated with House Boundaries of the Commission's Plan and the Rodden Alternative Plan

Huffman 9/15



Rodden Alternative Map

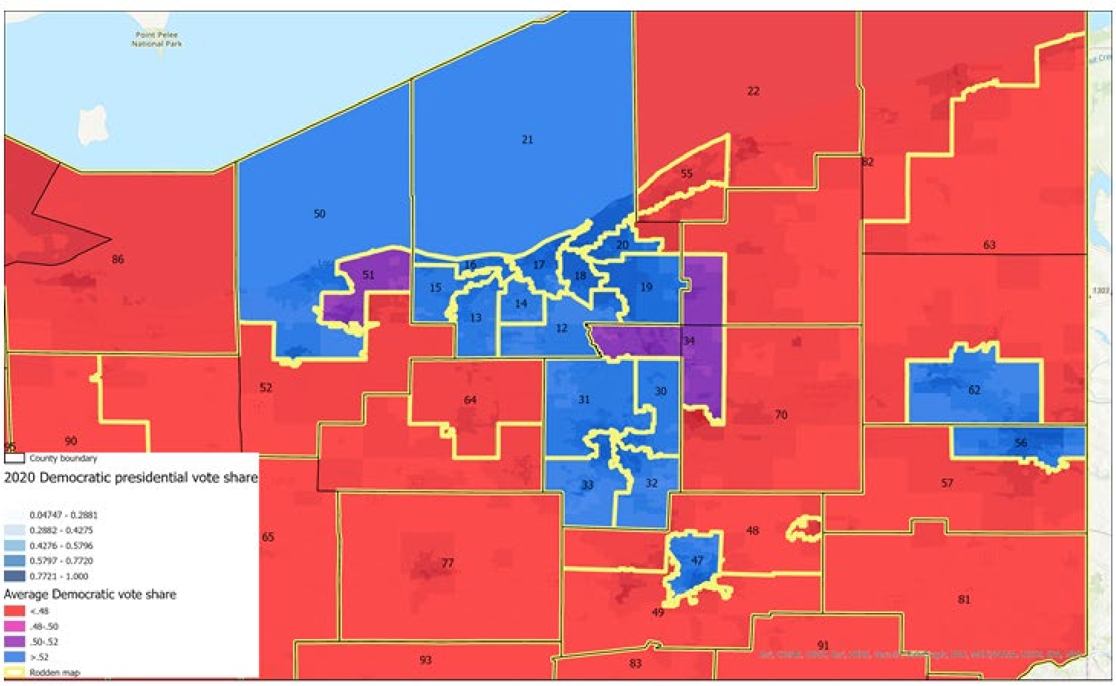
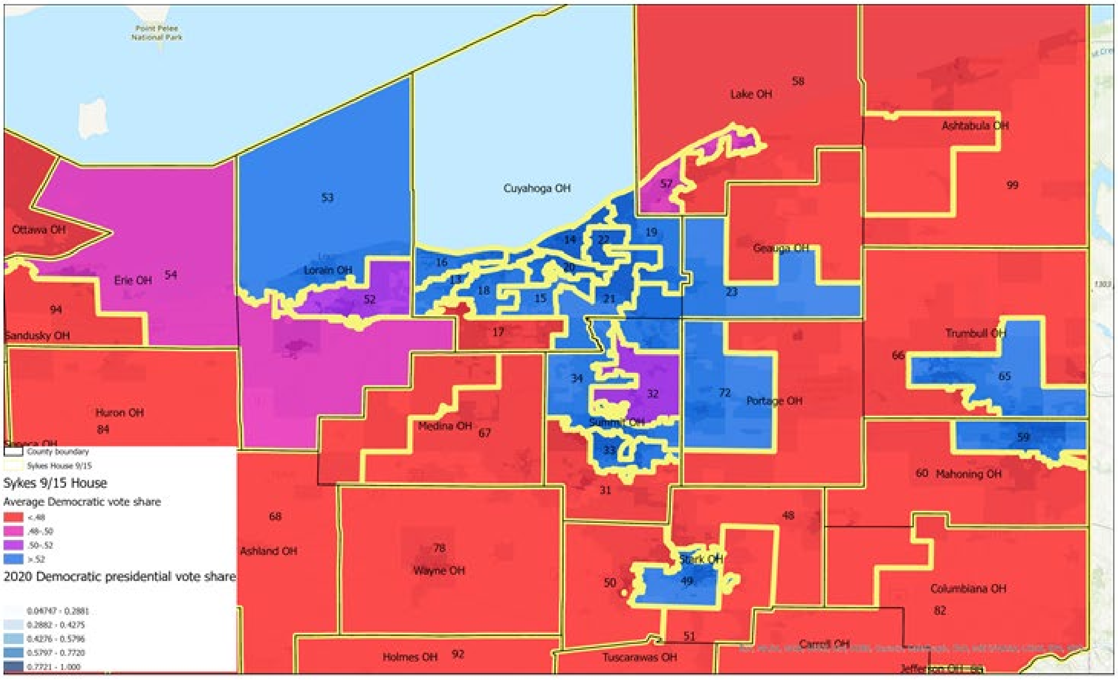
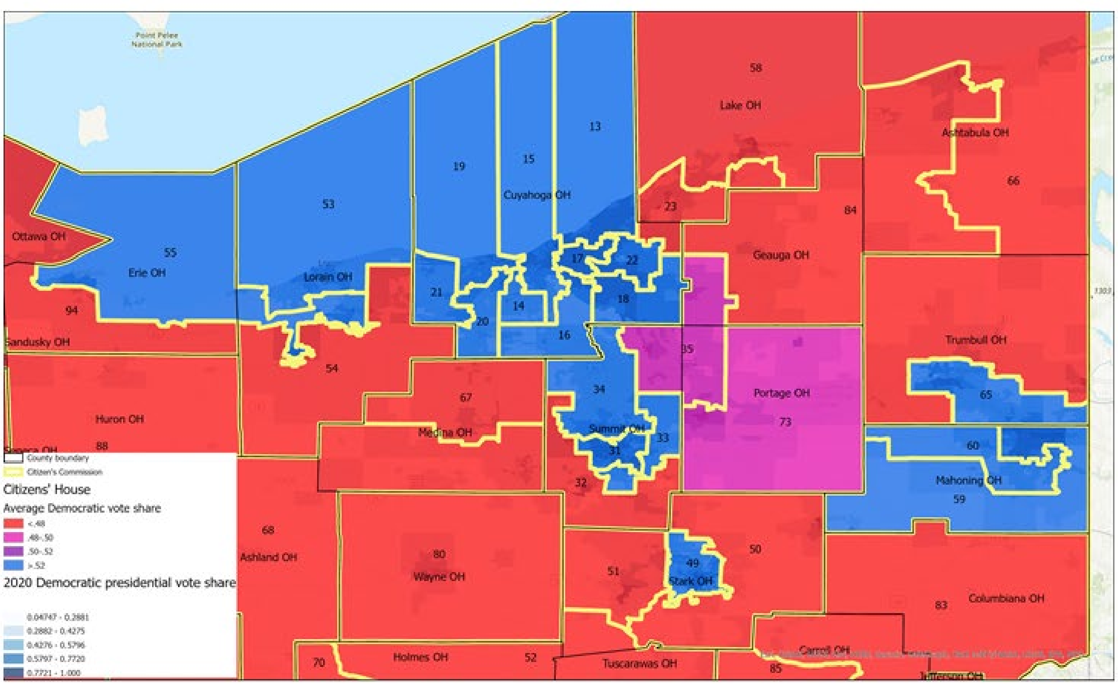


Figure 10b: Northeast Ohio; Party Majorities Associated with House Boundaries of the Sykes 9/15 and Citizens' Commission Plans

Sykes 9/15



Citizens' Commission



92. I begin with the county of Lorain. There are long-standing Democratic strongholds in each of the old industrial towns along the lake between the Sandusky Bay and Cleveland, including Lorain and Elyria, both of which are in Lorain County. Slightly to the southwest of Elyria is the small Democratic stronghold of Oberlin. Combined with their Republican suburban and rural surroundings, these towns make Erie and Lorain extremely competitive. Democrat Richard Cordray won Lorain County in the 2018 gubernatorial election by 6,578 votes, and all other statewide Democrats also won Lorain County that year, but Donald Trump won Lorain County by 3,853 votes in the 2020 presidential election. In Erie County, while Trump won by over 4,000 votes in 2020, Republican Governor DeWine received only 83 more votes than Cordray.

93. In this region, the Commission's plan produced only a single, very Democratic seat, with an average Democratic vote share of 63 percent, surrounded by comfortably Republican seats. This was achieved by combining the cities of Lorain and Elyria into a single district, numbered 51. When drawing districts in Lorain County, I avoided this packing strategy. Rather, I drew separate Lorain (50) and Elyria (51) districts. The Sykes map also created separate Lorain (53) and Elyria-based (52) districts. In both my map and the Sykes map, the Lorain-based district ends up comfortably Democratic, while the Elyria seat is Democratic-leaning but quite competitive. The Sykes approach also creates a competitive Republican-leaning district that includes Sandusky and Oberlin. In general, the Sykes plan makes this section of the Lake Erie coastline quite competitive relative to the Commission's plan. The Citizens' Commission plan produces 2 comfortably Democratic seats, by creating a Lorain-centric district, numbered 53, as well as an elongated coastal district that pulls together Elyria, Oberlin, and Sandusky.

94. Next, in Cuyahoga County, the Commission's plan carved out a comfortable Republican district along the southern border of the county, numbered 17, as well as a competitive Parma-based district, numbered 15. Looking at Figure 9, one can see that district 17 was drawn so as to pull together Republican-leaning communities in the outer suburbs. Using all of the elections since 2016, District 15 has an average Democratic vote share of 51.7 percent, but it should be noted that Donald Trump won majorities in this district in both 2016 and 2020. In addition, the district that combines Cuyahoga, Geauga, and Summit counties is essentially a toss-up, with an average Democratic vote share of 50.1 percent. In short, this plan creates 3 districts that are either comfortable or quite competitive for Republican candidates.

95. As described above, my approach to Cuyahoga County was to pay no attention to partisanship, but rather, to focus on generating a House plan that would enable a valid Senate plan. This required careful efforts to avoid splitting municipalities, while creating districts that were as close as possible to the 5 percent population deviation threshold. Those efforts did not yield a majority-Republican district in southern Cuyahoga County. The same was true of the Citizens' plan, but the Sykes 9/15 plan did produce one such district.

96. As in other metro areas examined above, an important part of the reason for the difference between the Commission's plan and the alternative plans in Cuyahoga County is that the Commission produces 6 districts with Democratic majorities higher than 70 percent, while each of the alternative plans produces only 4 such highly packed districts.

97. Next, let us turn to Summit County. The Commission's plan produces 3 comfortable Democratic districts and 1 comfortable Republican district. My plan divided most of the county into 4 relatively compact quadrants, which generated 4 Democratic-leaning districts. The Sykes plan and Citizens' Commission plans also produced 3 majority-Democratic districts and 1 majority-Republican district, but 1 of the majority-Democratic districts in the Sykes plan—number 32—is extremely competitive, with an average Democratic vote share of only 50.7 percent.

98. Next, each redistricting plan had a different approach to the city of Canton. In the Commission's plan, the Canton district, number 49, is quite competitive for Republican candidates, with an average Democratic vote share of 51 percent. In my plan, and in both the Sykes and Citizens' Commission plans, a more compact Canton-based district (numbered 47 in the Rodden plan and 49 in the others), produced more comfortable Democratic majorities (53.9 percent in the Rodden plan, 54.5 in the Sykes plan, and 54.1 percent in the Citizens' plan).

99. Finally, Mahoning County is evenly divided, with 1 majority-Democratic districts and 1 majority-Republican district in the Commission's plan, in the Rodden plan, and in the Sykes plan. The population of Mahoning County makes it possible to draw 2 House districts that fall completely within Mahoning County. My plan, as well as the Citizens' Commission plan, were able to achieve this. Note that the configuration adopted by the Citizens' Commission plan led to the creation of 2 majority-Democratic districts rather than only 1.

100. As with the other metro areas examined above, in Northeast Ohio, my alternative plan, as well as the plans introduced by Senator Sykes and the Citizens' Commission produced a larger number of majority-Democratic districts than did the Commission's plan—thus pushing the overall plan in the direction of statewide partisan proportionality. This was not achieved by abandoning the application of traditional redistricting principles. By avoiding a split of Mahoning County, my plan and the Citizens' Commission plan contained 1 fewer county split in Northeast Ohio than did the Commission's plan. There is no evidence that the specific county splits and mergers selected in the Sykes or Citizens' Commission plans did greater violence to specific communities of interest than did the Commission's plan. As in the other parts of Ohio explored above, my alternative map was more compact on average than the Commission's map. The average Polsby-Popper score for my map, as well as the Citizens' map, in the districts of Northeast Ohio was .35. The score for the Commission's plan was .30, and that for the Sykes plan was .27. The average Reock scores were closer together. The average score for my plan was .41, the Citizens' Commission and the Ohio Redistricting Commission were both .39, and Sykes plan was .37.

Summary of Case Studies

101. This tour around Ohio's metropolitan areas helps explain how the Commission managed to produce so many Republican-majority districts relative to the statewide vote share. For the most part, they followed the strategy of packing and cracking the supporters of their opponents. In each metropolitan area discussed above, the Commission generated a set of extremely Democratic districts in urban core areas, leaving fewer Democrats to contribute to potential Democratic majorities in other districts. As demonstrated by the alternative maps,

it was always possible to abide by traditional redistricting principles and draw compact districts that did not produce nearly as many extremely Democratic districts. Packing occurred not just in dense neighborhoods in large cities. Another example of packing is in Lorain County, where two Democratic cities were stuffed into the same district.

102. Second, when possible, the Commission's maps attempted to prevent geographically proximate groups of Democrats from joining together to form a district. In the Cincinnati and Dayton metro areas, for instance, this involved splitting proximate suburban Black communities and scattering them across majority-Republican districts that were largely exurban and even rural. As demonstrated by the alternative plans, these choices were not driven by constitutional rules, traditional redistricting principles, or geographic constraints. Rather, they were driven by discretionary choices.

103. Third, while keeping proximate groups of Democrats apart, when possible, the Commission's plans always attempted to string together groups of proximate Republicans to carve out majority-Republican districts within urban counties. Often, this involved a configuration based on long, narrow strips hugging the county boundary in sparsely populated exurban areas. Examples include District 10 in southwest Franklin County, District 27 in eastern Hamilton County, District 39 outside of Dayton, and District 17 in southern Cuyahoga County. District 31 in Summit County follows the Republican-leaning exurbs almost all the way around Akron.

104. Additionally, the Commission was careful in its use of county splits near cities. In Franklin County, for example, the Commission created a series of under-populated but extremely Democratic districts, freeing up voters to combine with a neighboring rural, Republican county, thus minimizing the Democratic seats produced in the Columbus area.

105. These case studies demonstrated that it is not always necessary to draw bizarre-shaped districts in order to pursue the cracking and packing maneuvers that produce surprisingly pro-Republican outcomes. However, it is telling that in each metro area my maps were, on average, more compact than those produced by the Commission according to the Polsby-Popper measure, and in most cases, according to the Reock measure as well. The same was true of the maps produced by the Citizens' Commission. Recall from Tables 2 and 3 above that when considered as a whole, my maps and those produced by the Citizens' Commission were more compact by every measure than those produced by the Ohio Redistricting Commission.

106. Overall, the contrast between the Commission's map and the alternative maps allows us to rule out the claim that the surprisingly large number of anticipated Republican seats associated with the Commission's plan were somehow driven by the confluence of Ohio's political geography, the requirements of the Ohio Constitution, and a focus on traditional redistricting principles. Indeed, we have seen that three very different alternative plans came very close to overall partisan proportionality, while abiding by the rules of the Ohio Constitution and often hewing more closely to traditional redistricting principles.

VII. CONCLUSION

107. Under no reasonable statistical method or definition do the Ohio State House of Representatives and Senate maps adopted by the Ohio Redistricting Commission achieve partisan proportionality.

108. The Commission's plan favors Republicans for reasons other than compliance with traditional redistricting principles and the Ohio Constitution's other requirements, as demonstrated by maps that I have prepared myself, as well as alternative maps presented to the Commission. These alternative maps achieve far greater partisan proportionality and are relatively similar, indeed in many cases better, according to traditional redistricting principles.

Jonathan Andrew Rodden

Jonathan Rodden

STATE OF FLORIDA COUNTY OF Duval

Sworn to before me this 22nd day of October 2021. by Jonathan Andrew Rodden

Provided Identification: Passport

Richard T Schnell

Notary Public Richard T Schnell

Notarized online using audio-video communication

NOTARY PUBLIC • STATE OF FLORIDA

RICHARD T SCHNELL
Notary Public - State of Florida
Commission # HH 29895
Expires on August 9, 2024

My commission expires 08/09/2024

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CERTIFICATE OF SERVICE

I, Derek Clinger, hereby certify that a copy of Evidence of Bennett Relators (Expert Affidavit of Dr. Jonathan Rodden) was served via email this 22nd day of October, 2021, upon the counsel listed below:

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Secretary of State Frank LaRose, and
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Dated: October 22, 2021

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Bria Bennett et al.

AFFIDAVIT OF DR. JONATHAN RODDEN – APPENDIX OF EXHIBITS

Index of Documents

ITEM	DESCRIPTION	BATES RANGE
A	2021 Commission Plan	RODDEN_0001 – 0003
B	2011 Adopted Plan	RODDEN_0004 – 0006
C	September 2, 2021 Ohio Senate Democratic Update	RODDEN_0007 – 0009
D	September 9, 2021 Ohio Senate President	RODDEN_0010 – 0012
E	Ohio Citizens' Redistricting Commission Plan	RODDEN_0013 – 0015
F	Article XI, Sec 8(C)(2) Statement	RODDEN_0016 – 0018
G	Curriculum Vitae of Dr. Jonathan Rodden	RODDEN_0019 – 0027
H	September 15, 2021 House& Senate Dem Caucus	RODDEN_0028 – 0030
I	Rodden Alternative Plan	RODDEN_0031 – 0033

Exhibit A

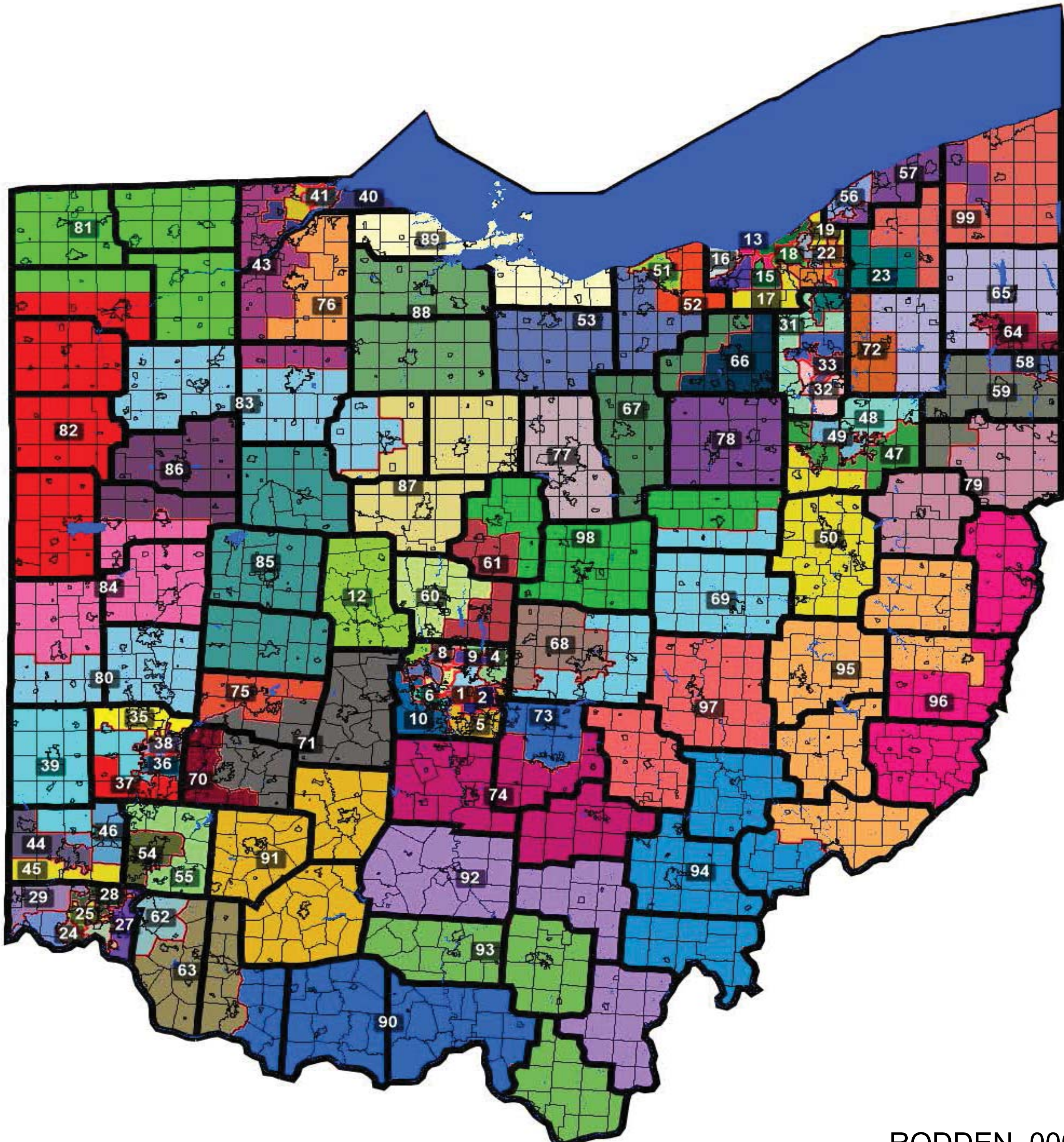
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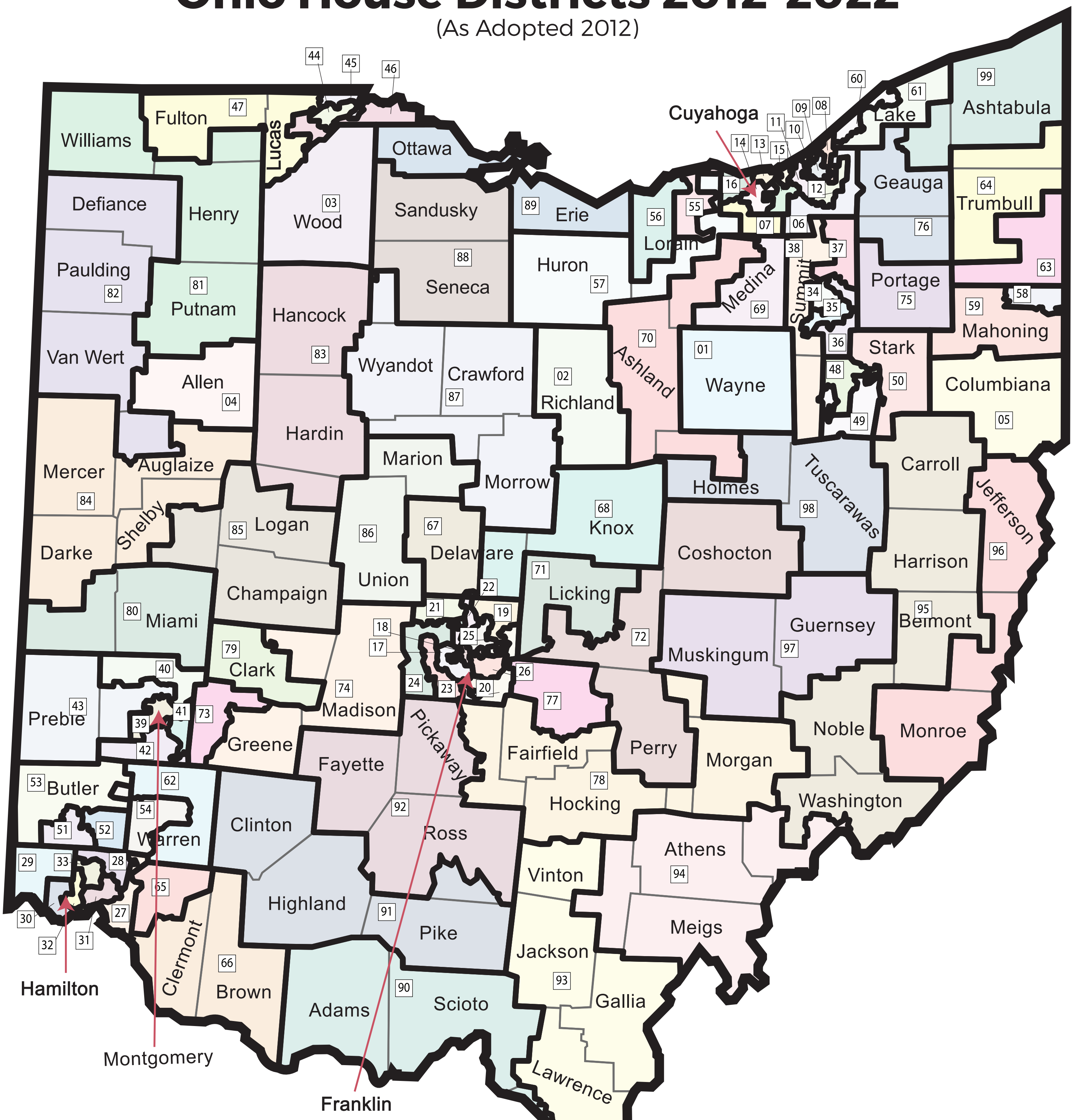
Exhibit B

Frank LaRose

Ohio Secretary of State

Ohio House Districts 2012-2022

(As Adopted 2012)



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

Last Revised 02/2018

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Frank LaRose
Ohio Secretary of State

Ohio Senate Districts 2012-2022

(As Adopted 2012)

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

Last Revised 02/2018

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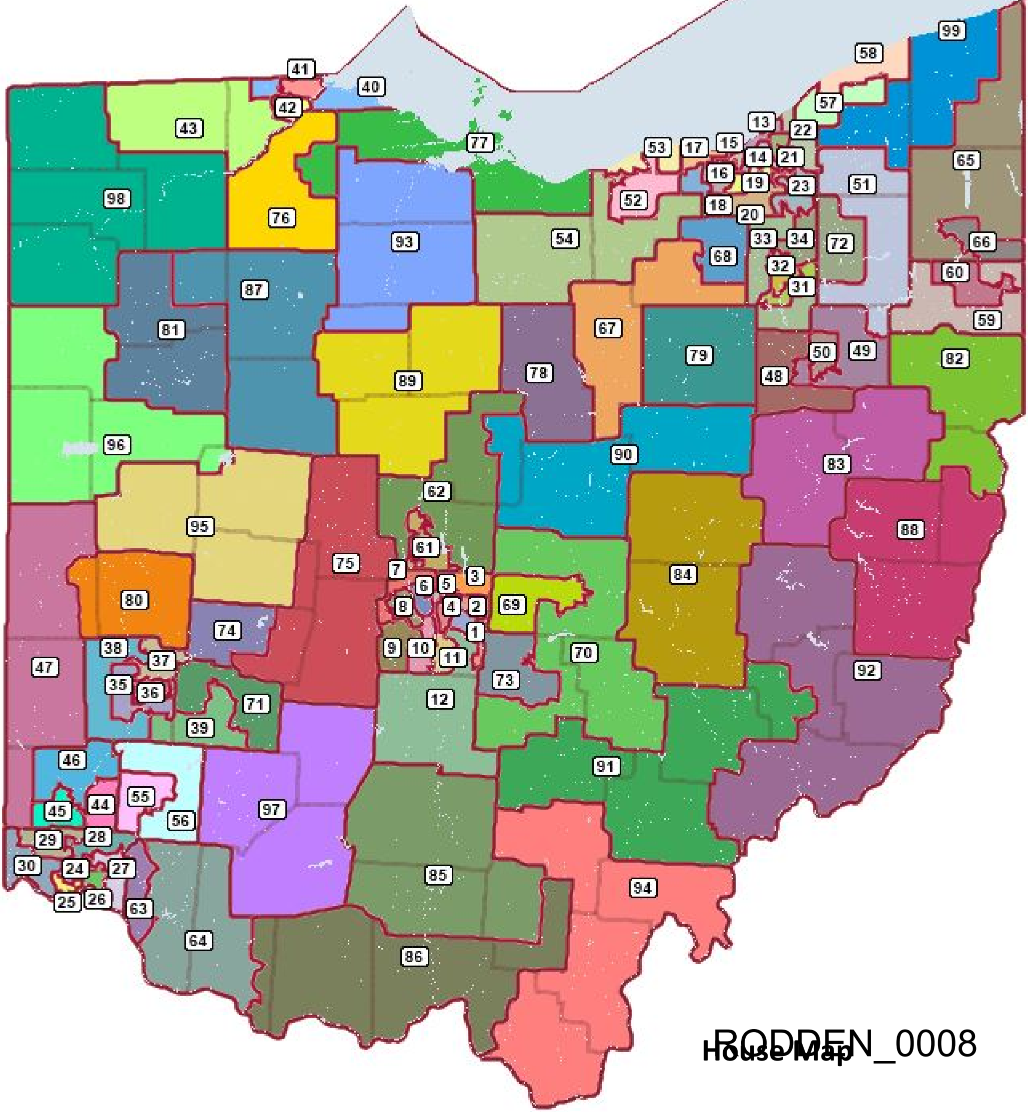
Exhibit C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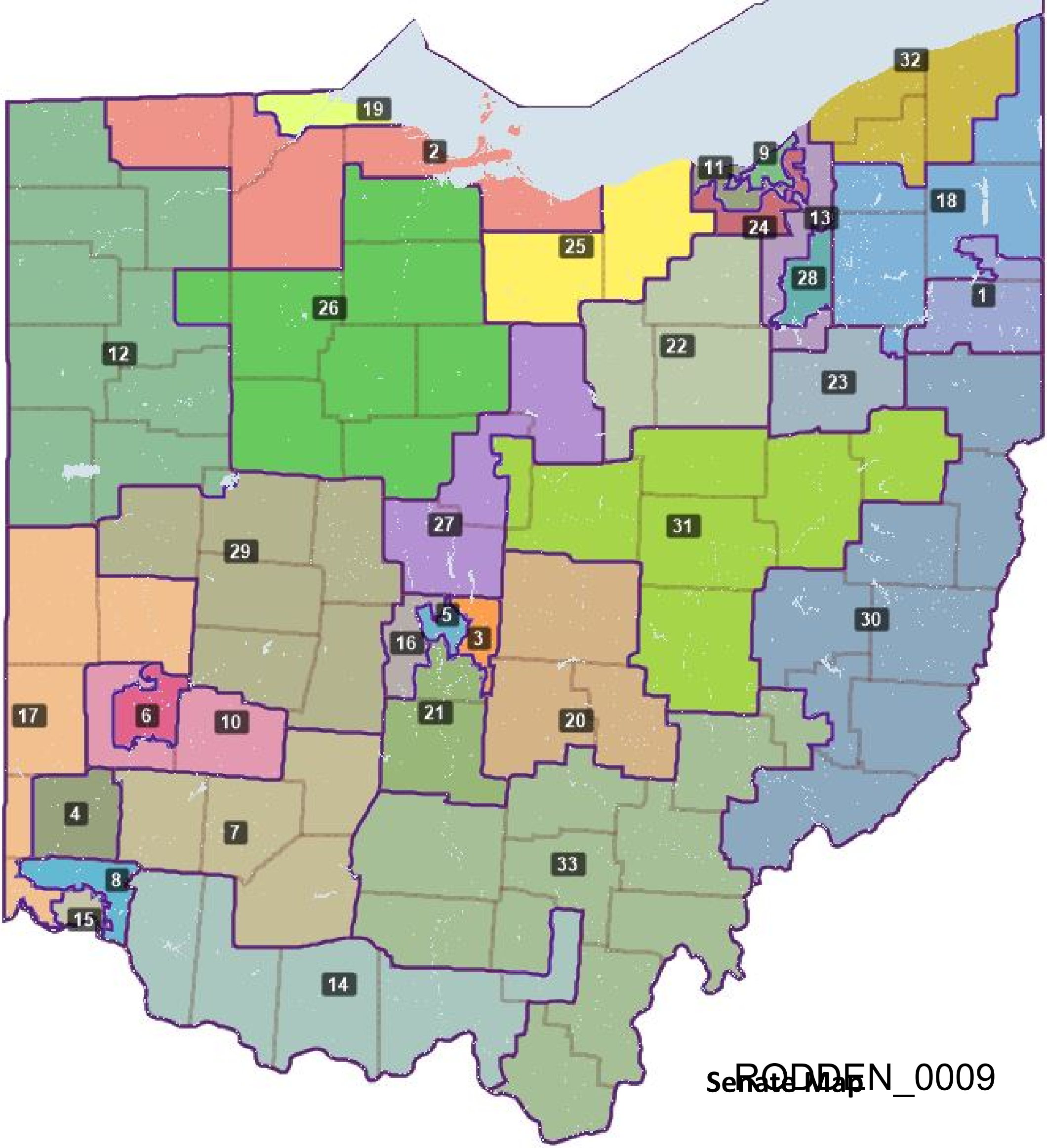
House Map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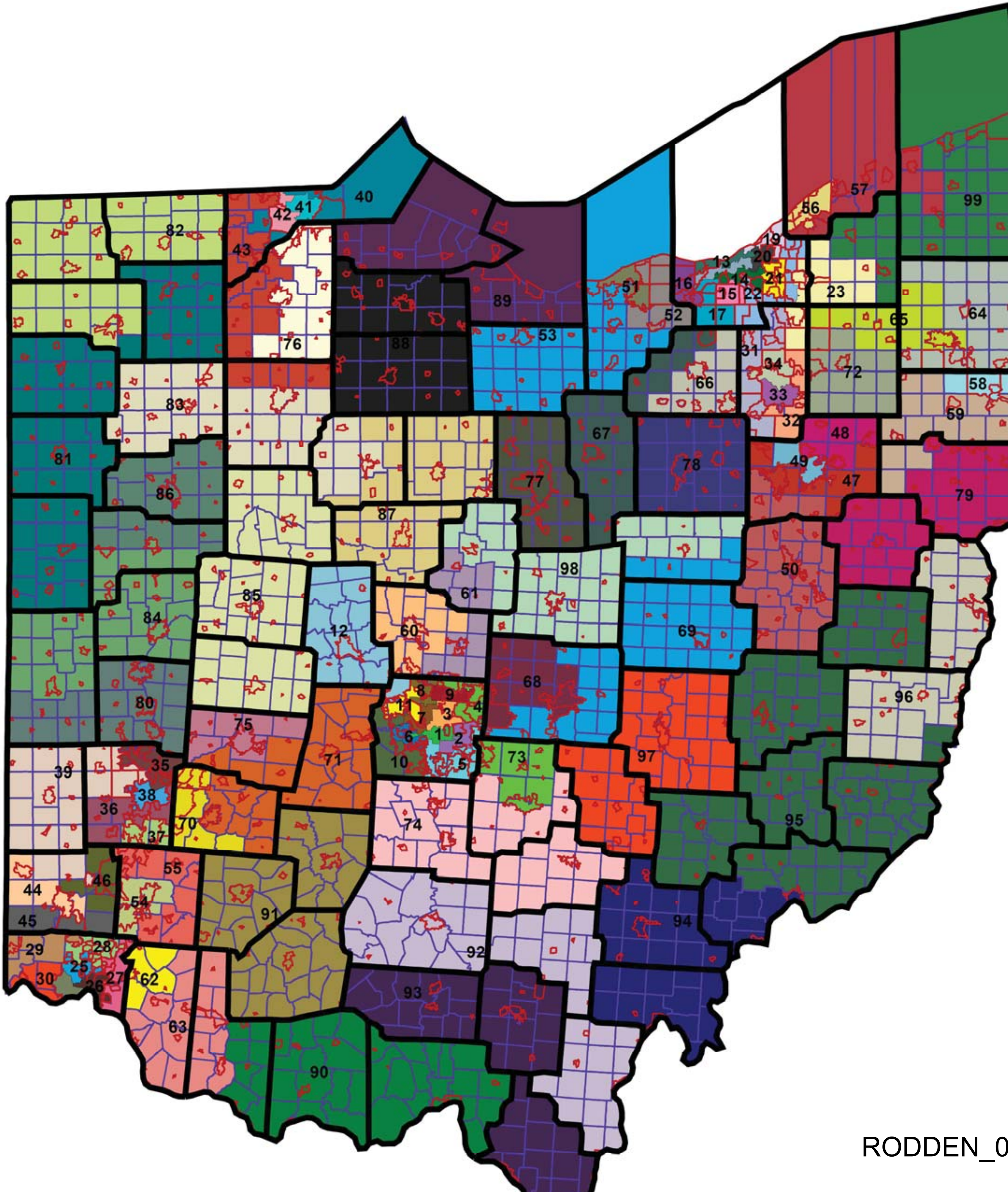
Senate Map

Exhibit D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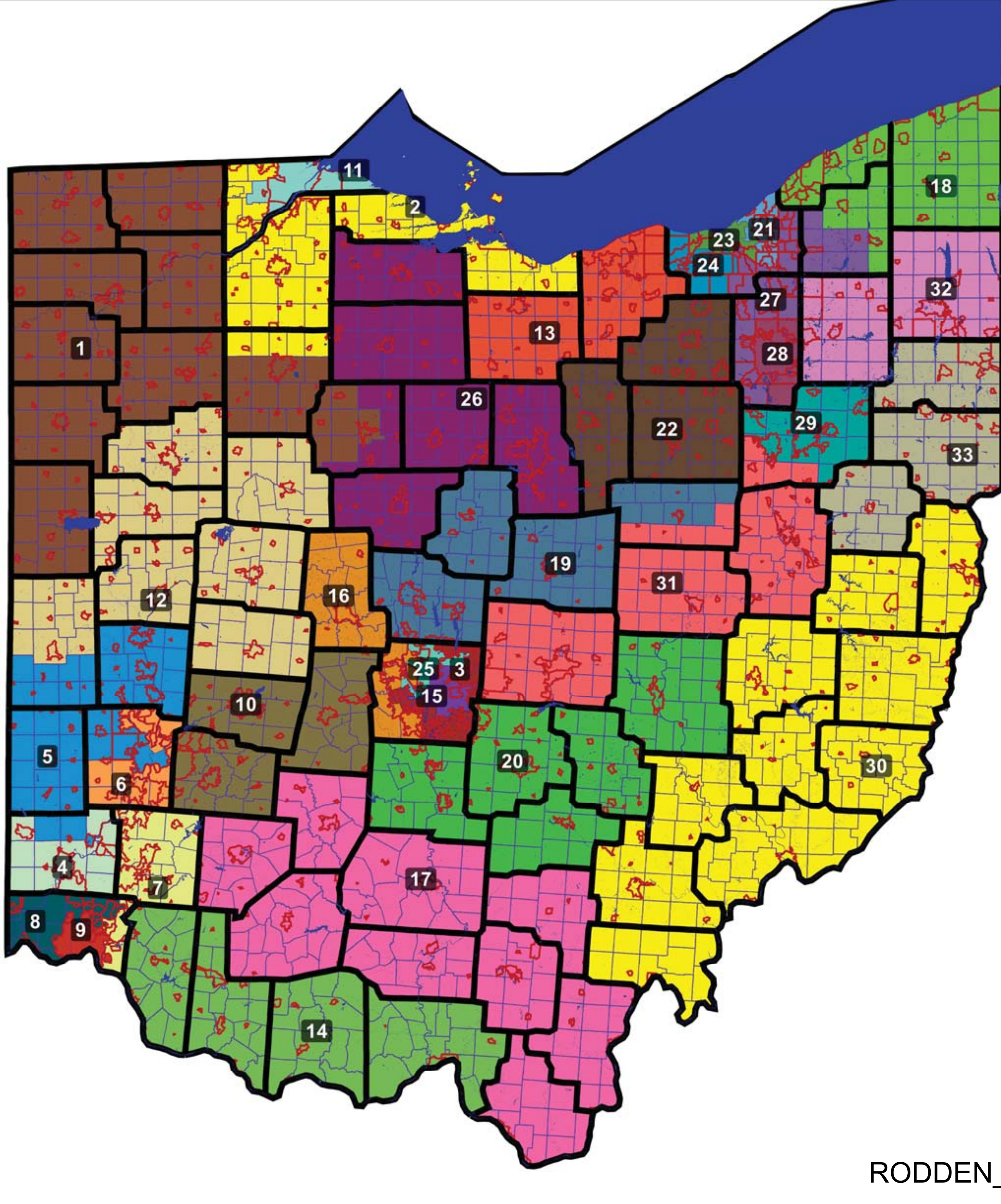
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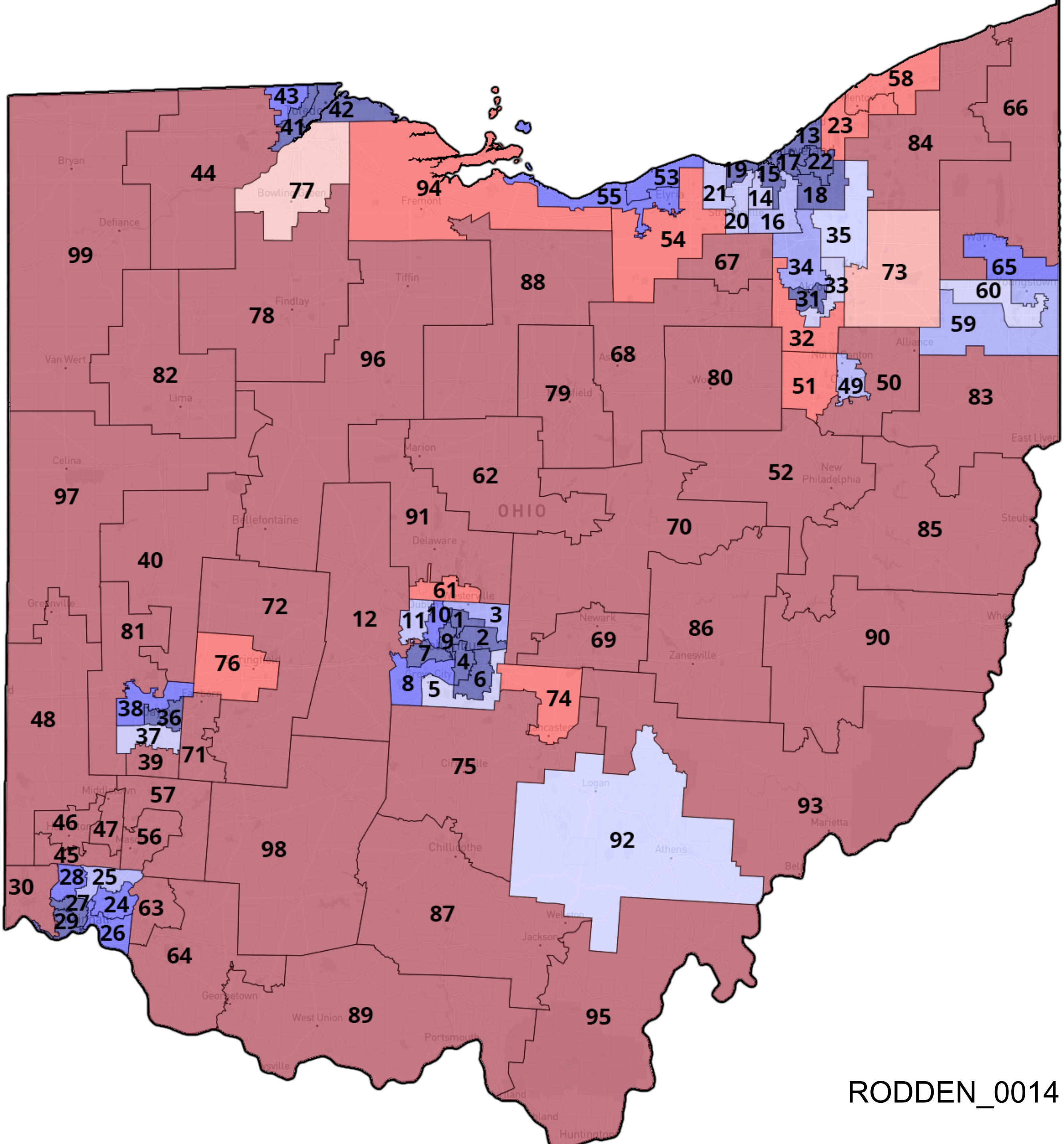
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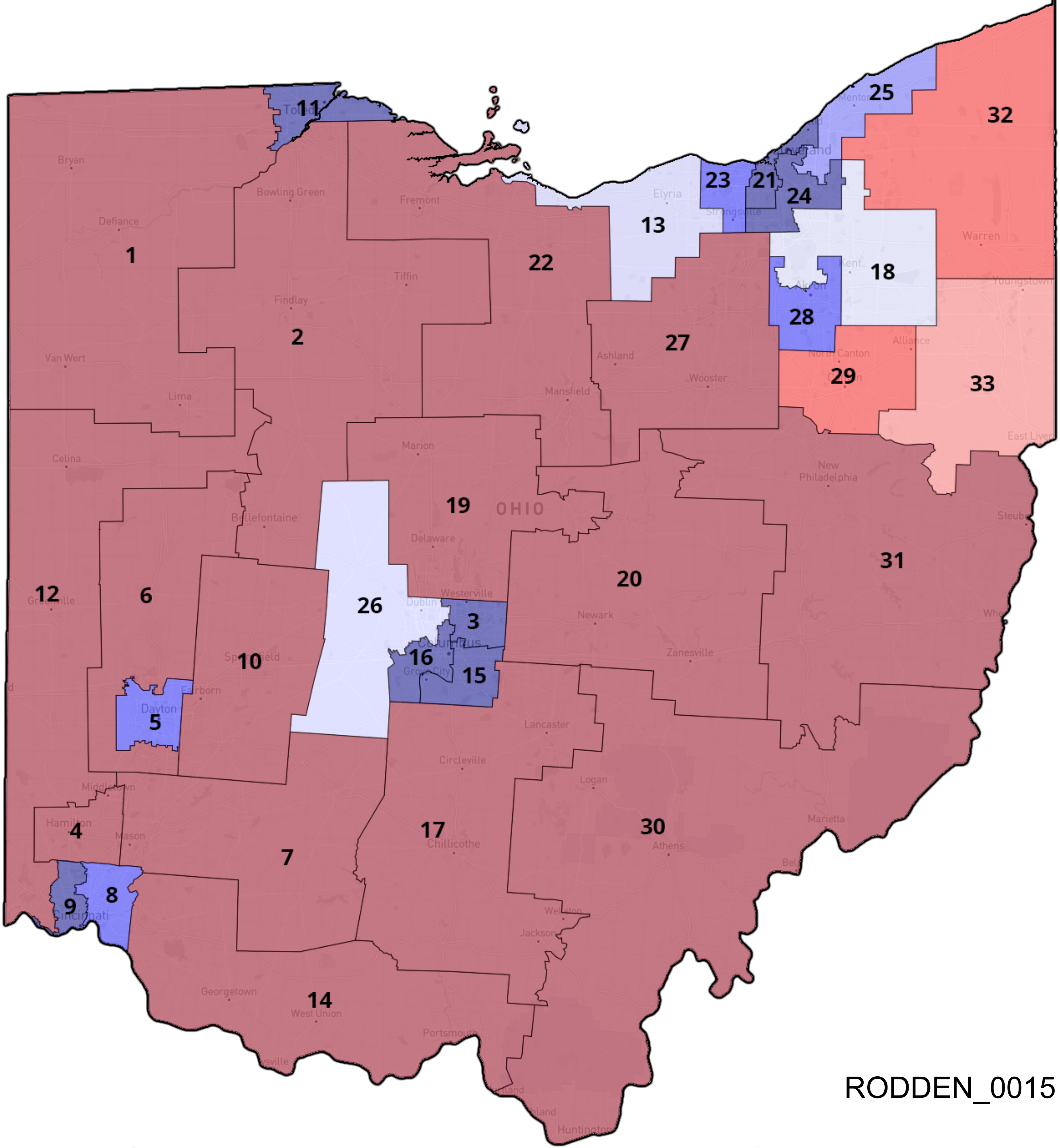
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Exhibit F

Article XI, Section 8(C)(2) Statement

Pursuant to Article XI, Section 8(C)(2) of the Ohio Constitution, the Ohio Redistricting Commission issues the following statement:

The Commission determined that the statewide preferences of the voters of Ohio predominately favor Republican candidates.

The Commission considered statewide state and federal partisan general election results during the last ten years. There were sixteen such contests. When considering the results of each of those elections, the Commission determined that Republican candidates won thirteen out of sixteen of those elections resulting in a statewide proportion of voters favoring statewide Republican candidates of 81% and a statewide proportion of voters favoring statewide Democratic candidates of 19%. When considering the number of votes cast in each of those elections for Republican and Democratic candidates, the statewide proportion of voters favoring statewide Republican candidates is 54% and the statewide proportion of voters favoring statewide Democratic candidates is 46%. Thus, the statewide proportion of voters favoring statewide Republican candidates is between 54% and 81% and the statewide proportion of voters favoring statewide Democratic candidates is between 19% and 46%. The Commission obtained publicly available geographic data for statewide partisan elections in 2016, 2018, and 2020. Publicly available geographic data for those elections was not available for elections in 2012 and 2014. Using this data, the Commission adopted the final general assembly district plan, which contains 85 districts (64.4%) favoring Republican candidates and 47 districts (35.6%) favoring Democratic candidates out of a total of 132 districts. Accordingly, the statewide proportion of districts whose voters favor each political party corresponds closely to the statewide preferences of the voters of Ohio.

The final general assembly district plan adopted by the Commission complies with all of the mandatory requirements of Article XI, Sections 2, 3, 4, 5, and 7 of the Ohio Constitution. The Commission's attempt to meet the aspirational standards of Article XI, Section 6 of the Ohio Constitution did not result in any violation of the mandatory requirements of Article XI, Sections 2, 3 ,4, 5, and 7 of the Ohio Constitution.

Exhibit G

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United States Citizen.

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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).

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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).

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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.

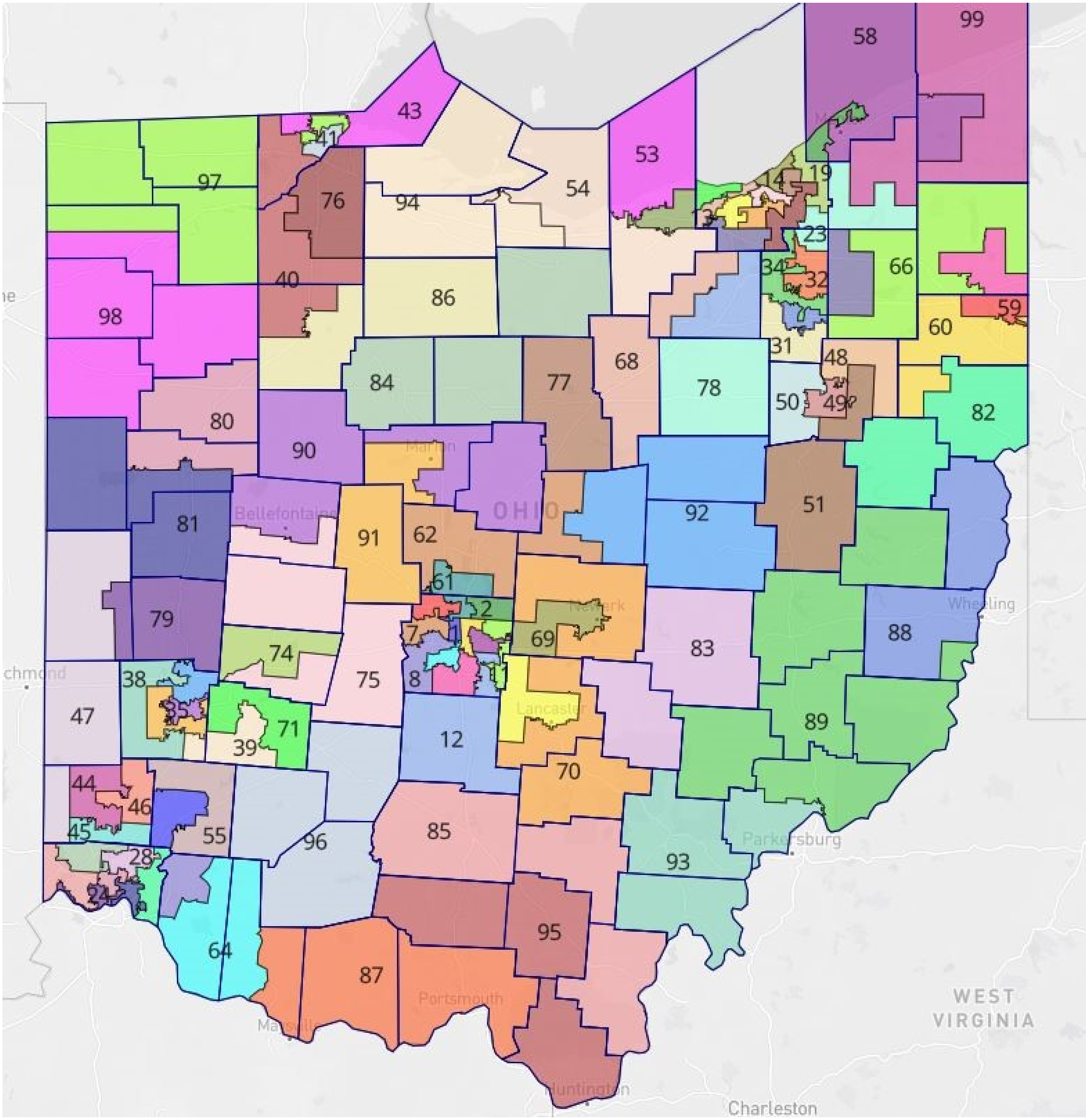
2006–2009: World Bank, Independent Evaluations Group. Undertook evaluations of World Bank decentralization and safety net programs.

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

Exhibit H



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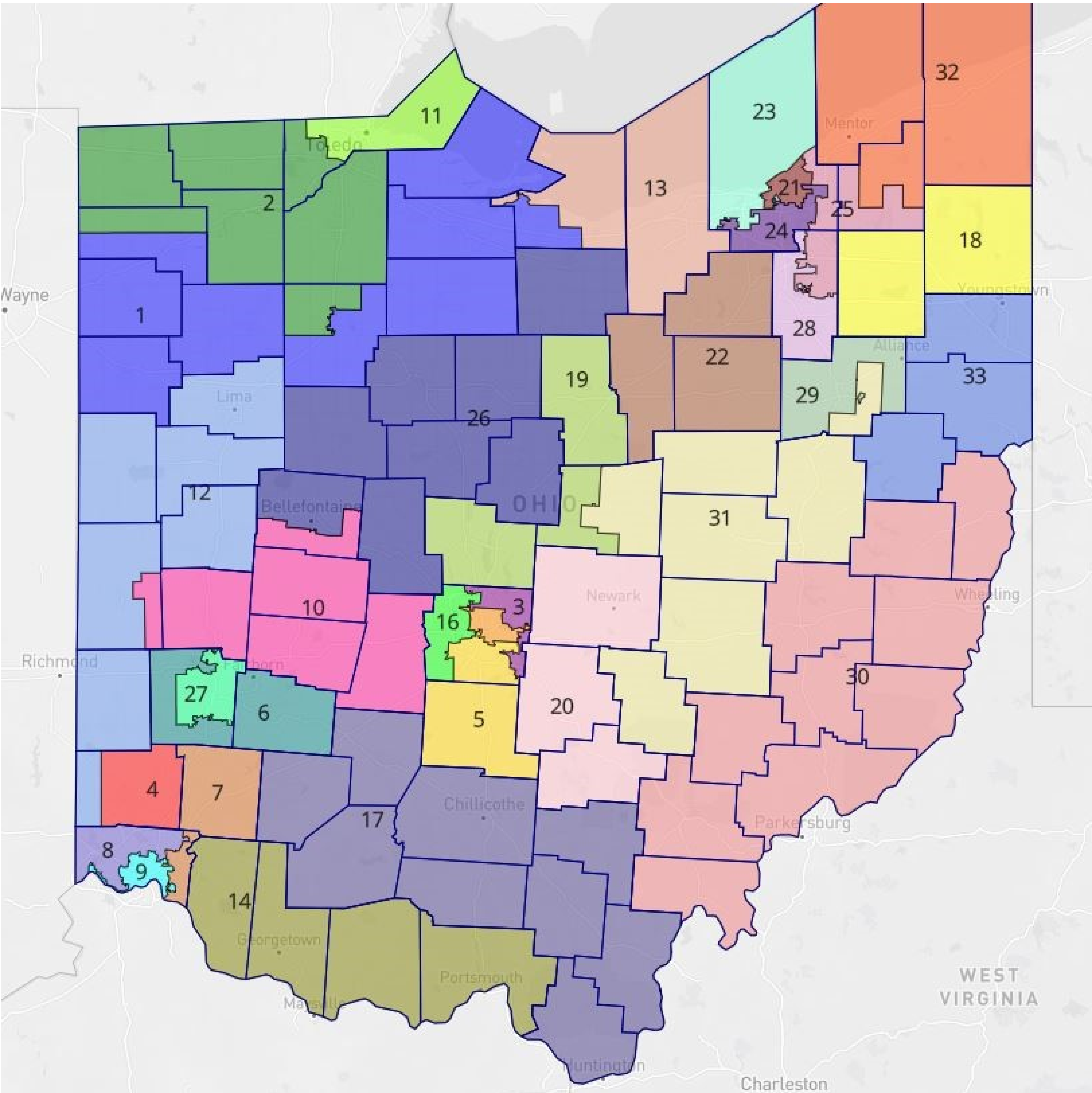

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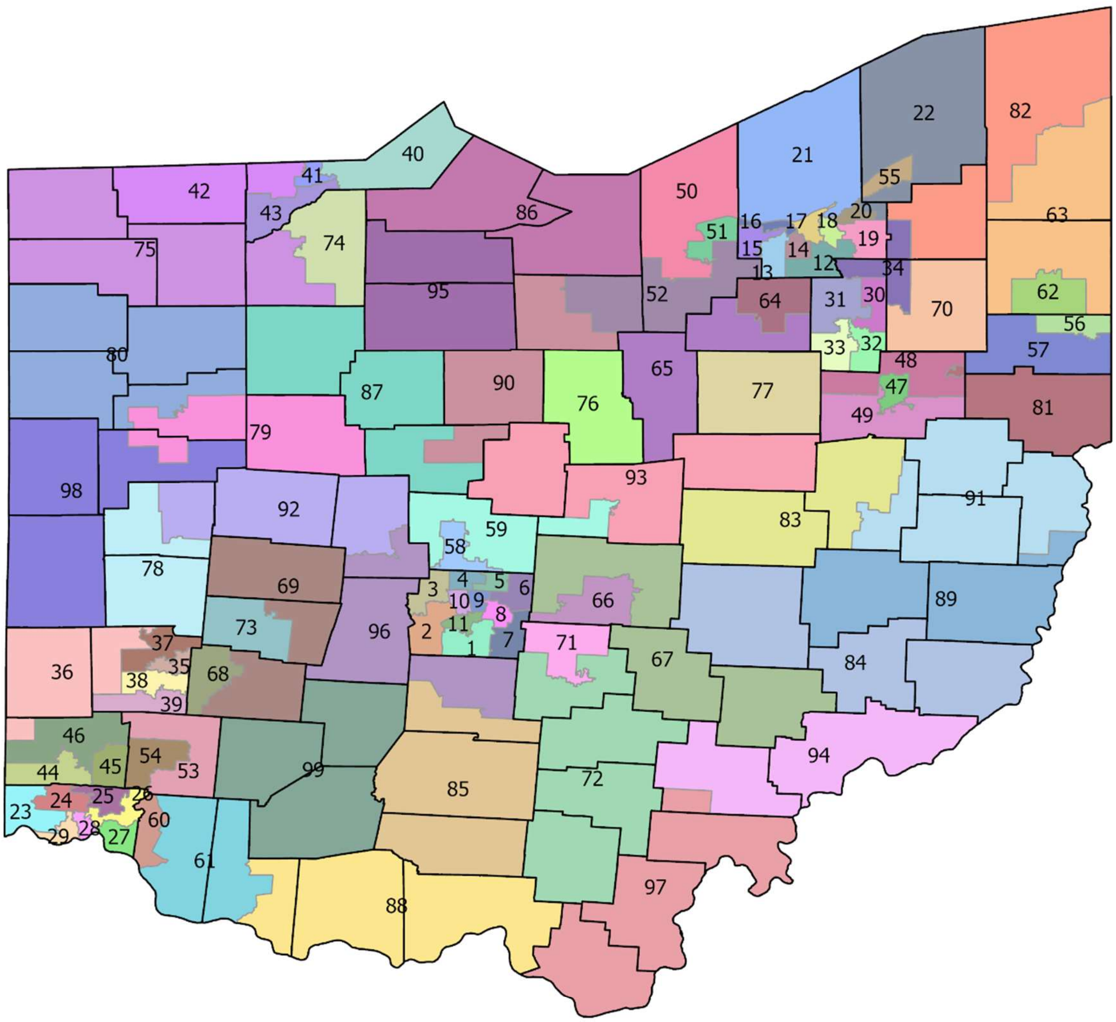
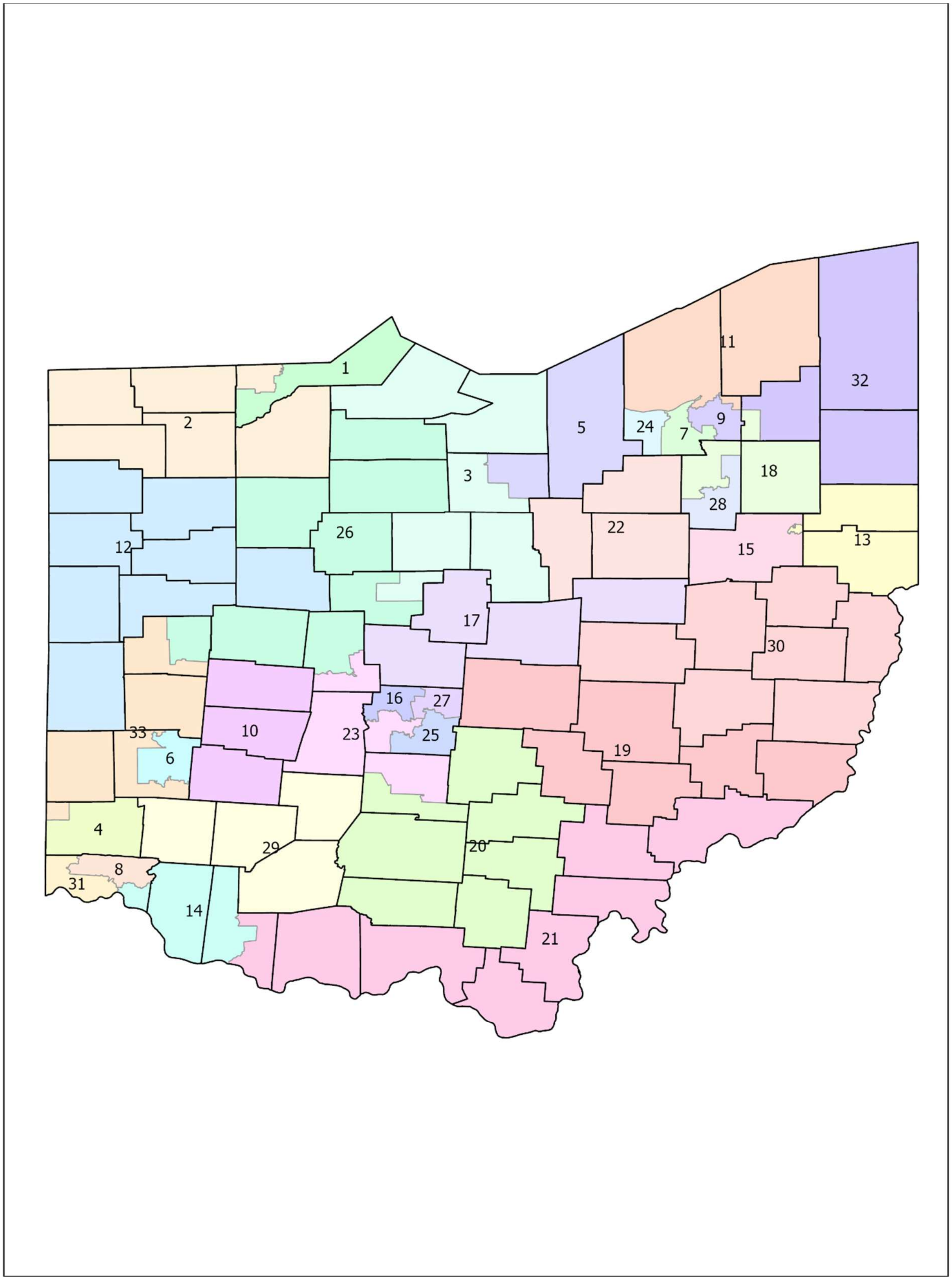
Exhibit I

Rodden Alternative House Plan



Rodden Alternative Senate Plan



CERTIFICATE OF SERVICE

I, Danielle L. Stewart, hereby certify that on October 22, 2021, I caused a true and correct copy of the following documents to be served by email upon the counsel listed below:

1. **Affidavit of Danielle Stewart (affidavits of additional expert witnesses)**

2. **Expert report of Kosuke Imai, Ph.D.**

3. **Affidavit of Dr. Lisa Handley**

4. **Affidavit of Dr. Jonathan Rodden**

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Dated: October 22, 2021

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