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

(Affidavit of Jyoti Jasrasaria & Exhibits)

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<u>Affidavit of Jyoti Jasrasaria</u>

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

1. In the above-captioned case, the Ohio Supreme Court has entered an order providing that parties shall file any evidence they intend to present no later than Friday, October 22, 2021.
2. I am an attorney at law, and I serve as legal counsel to the Relators in this action.
3. Document 1 is a true and correct copy of the expert affidavit of Dr. Christopher Warshaw, submitted in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1193, on September 23, 2021.
4. Document 2 is a true and correct copy of the expert affidavit of William S. Cooper, submitted in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1193, on September 23, 2021.
5. Document 3 is a true and correct copy of the expert affidavit of Professor Michael S. Latner, submitted in *The Ohio Organizing Collective, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1210, on September 27, 2021.
6. Document 4 is a true and correct copy of the expert affidavit of Professor Michael S. Latner, served in *The Ohio Organizing Collective, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1210, on October 22, 2021.

7. Document 5 is a true and correct copy of the expert affidavit of Dr. Lisa Handley, served in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1193, on October 22, 2021.

8. Document 6 is a true and correct copy of the expert affidavit of Professor Kosuke Imai, served in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1193, on October 22, 2021.

9. The Index at the beginning of the Appendix gives a description of each document and states where it appears in the Appendix.

Jyoti Jasrasaria

Jyoti Jasrasaria

Signed at Madison, Madison, Florida.

City, County, State

Sworn to and subscribed before me this 22nd day of October, 2021

Provided a Ohio Driver's License

Notary's Comission Number: HH18136

Comission Expiration Date 07/06/2024

Ketina K. Glover

Notary Public

KETINA K GLOVER
Notary Public - State of Florida
Commission # HH18136
Expires on July 6, 2024

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Online Notary Ketina K. Glover

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CERTIFICATE OF SERVICE

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

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AFFIDAVIT OF JYOTI JASRASARIA – APPENDIX OF EXHIBITS

Index of Documents

ITEM	DESCRIPTION	BATES RANGE
1	Expert affidavit of Dr. Christopher Warshaw, submitted in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1193, on September 23, 2021	EXPERT_0001 – 0059
2	Expert affidavit of William S. Cooper, submitted in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1193, on September 23, 2021	EXPERT_0060 – 0131
3	Expert affidavit of Professor Michael S. Latner, submitted in *The Ohio Organizing Collective, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1210, on September 27, 2021	EXPERT_0132 – 0157
4	Expert affidavit of Professor Michael S. Latner, served in *The Ohio Organizing Collective, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1210, on October 22, 2021	EXPERT_0158 – 0212
5	Expert affidavit of Dr. Lisa Handley, served in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1193, on October 22, 2021	EXPERT_0213 – 0243
6	Expert affidavit of Professor Kosuke Imai, served in *League of Women Voters, et al. v. Ohio Redistricting Commission, et al.*, Ohio Supreme Court Case No. 2021-1193, on October 22, 2021	EXPERT_0244 – 0324

Warshaw Affidavit.pdf

DocVerify ID:	DBFE2537-827C-47D0-9584-70B76BDA0A11
Created:	September 23, 2021 07:10:09 -8:00
Pages:	1
Remote Notary:	Yes / State: OH

E-Signature Summary

E-Signature 1: Christopher Warshaw (CW)
September 23, 2021 08:33:15 -8:00 [BDE06C6B6751] [69.143.174.137]
warshaw@email.gwu.edu (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
September 23, 2021 08:33:15 -8:00 [FCBE739C4315] [23.28.168.121]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

IN THE SUPREME COURT OF OHIO

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

AFFIDAVIT OF CHRISTOPHER WARSHAW

Franklin County
/ss
State of Ohio

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

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

FURTHER AFFIANT SAYETH NAUGHT.

Executed on 09/23/2021, 2021.

Signed on 2021/09/23 08:33:15 -8:00
Christopher Warshaw

Sworn and subscribed before me this ____ day of 09/23/2021, 2021.

Theresa Michelle Sabo
Commission # 2016-re-619622
Electronic Notary Public
State of Ohio
My Comm Exp. Nov 28, 2021
Notary Stamp 2021/09/23 08:33:15 PST FCBE739C4315

Notary Public
Signed on 2021/09/23 08:33:15 -8:00

EXPERT_0002

Exhibit A

An Evaluation of the Partisan Bias in Ohio's Enacted State Legislative Districting Plan

Christopher Warshaw*

September 23, 2021

*Associate Professor, Department of Political Science, George Washington University. warshaw@gwu.edu. Note that the analyses and views in this report are my own, and do not represent the views of George Washington University.

Contents

1 Introduction

My name is Christopher Warshaw. I am an Associate Professor of Political Science at George Washington University. Previously, I was an Associate Professor at the Massachusetts Institute of Technology from July 2016 - July 2017, and an Assistant Professor at MIT from July 2012 - July 2016.

I have been asked by counsel representing the plaintiffs in this case to analyze relevant data and provide my expert opinions about whether Ohio's enacted state legislative districting plan meets the criteria in Article XI, Section 6 of Ohio's Constitution. More specifically, I have been asked:

- To evaluate whether the plan meets the requirement of Article XI, Section 6(B) 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 [] correspond[s] closely to the statewide preferences of the voters of Ohio."

- To evaluate whether the plan appears to meet the requirement of Article XI, Section 6(A) that "No general assembly district plan shall be drawn primarily to favor or disfavor a political party" based on a variety of standard academic metrics typically used to assess the degree of partisan bias in a districting plan.

- To examine the consequences of the enacted redistricting plans on the representation that Ohio residents receive in state government.

2 Qualifications, Publications and Compensation

My Ph.D. is in Political Science, from Stanford University, where my graduate training included courses in political science and statistics. I also have a J.D. from Stanford Law School. My academic research focuses on public opinion, representation, elections, and polarization in American Politics. I have written multiple papers that focus on elections and two papers that focus specifically on partisan gerrymandering. I also have a forthcoming book that includes an extensive analysis on the causes and consequences of partisan gerrymandering in state governments.

My curriculum vitae is attached to this report. All publications that I have authored and published appear in my curriculum vitae. My work is published or forthcoming in peer-reviewed journals such as: the *American Political Science Review*, the *American Journal of Political Science*, the *Journal of Politics*, *Political Analysis*, *Political Science Research and Methods*, the *British Journal of Political Science*, *Political Behavior*, *Science*

Advances, the *Election Law Journal*, *Nature Energy*, *Public Choice*, and edited volumes from Cambridge University Press and Oxford University Press. My book entitled *Dynamic Democracy in the American States* is forthcoming from the University of Chicago Press. My non-academic writing has been published in the *New York Times* and the *Washington Post*. My work has also been discussed in the *Economist* and many other prominent media outlets.

My opinions in this case are based on the knowledge I have amassed over my education, training and experience, including a detailed review of the relevant academic literature. They also follow from statistical analysis of the following data:

- In order to calculate partisan bias in state legislative elections, I examined:
  - Precinct-level data on recent Ohio elections: I use precinct-level data on Ohio's statewide elections between 2016-20 from the Voting and Election Science Team (University of Florida, Wichita State University). I obtained these data from the Harvard Dataverse.[1] As far as I know, there are no publicly available datasets with precinct-level returns from 2012-14 that are linked to precinct boundaries (e.g., shapefiles). For these elections, I obtained data via the ACLU that their expert Bill Cooper put together.[2]
  - A large canonical data set on candidacies and results in state legislative elections: I obtained results from 1972-2020 collected by Carl Klarner and a large team of collaborators. The results from 1972-2012 are based on data maintained by the Inter-university Consortium for Political and Social Research (ICPSR) (Klarner et al. 2013). The data from 2013-2020 were collected by Klarner.
  - Data on presidential election returns in state legislative districts: For elections between 1972 and 1991, I used data on county-level presidential election returns from 1972-1988 collected by the Inter-university Consortium for Political and Social Research (ICPSR 2006) and mapped these returns to state legislative districts. For elections between 1992 and 2001, I used data on presidential

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

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

election returns in the 2000 election collected by McDonald (2014) and Wright et al. (2009). For elections between 2002 and 2011, I used data on the 2004 and 2008 presidential elections collected by Rogers (2017). For elections between 2012 and 2020, I used data on presidential election returns for the 2012 and 2016 elections from the DailyKos website.

  - Information on who controlled each redistricting plan in state legislative elections: (e.g., Democrats, Republicans, or a Commission) from 1972-2012 assembled by Stephanopoulos (2018).
  - The Plan Score website: PlanScore is a project of the nonpartisan Campaign Legal Center (CLC) that enables people to score proposed maps for their partisan, demographic, racial, and geometric features. I am on the social science advisory team for PlanScore.

- In order to examine the effect of gerrymandering in state legislative elections on representation in state government, I examined:
  - Well established estimates of the ideology of state legislators based on their roll call votes developed by Professors Nolan McCarty and Boris Shor (Shor and McCarty 2011).[3]
  - Estimates of the policy liberalism of state governments based on approximately 180 policies using a model I developed in a co-authored paper which was published in the *American Journal of Political Science* (Caughey and Warshaw 2016) and that we extended for our book *Dynamic Democracy in the American States*.

I have previously provided expert reports in three redistricting-related cases: *League of Women Voters of Pennsylvania v. Commonwealth of Pennsylvania*, No. 159 MM 2017, *League of Women Voters of Michigan* v. *Johnson*, 17-14148 (E.D. Mich), and *APRI et al.* v. *Smith et al.*, No. 18-cv-357 (S.D. Ohio). In addition, I have provided expert testimony and reports in several cases related to the U.S. Census: *State of New York et al.* v. *United States Department of Commerce*, 18-cv-2921 (SDNY), *New York* v. *Trump*; *Common Cause* v. *Trump*, 20-cv-2023 (D.D.C.), and *La Union Del Pueblo Entero (LUPE)* v. *Trump*, 19-2710 (D. Md.).

I am being compensated at a rate of $325 per hour. The opinions in this report are my own, and do not represent the views of George Washington University.

3. These scores were downloaded from the Harvard Dataverse website, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GZJOT3.

3 Summary

This report examines whether Ohio's enacted state legislative maps meet the criteria in the Ohio Constitution. Article XI, Section 6 of Ohio's Constitution requires that the Redistricting Commission "attempt to draw a general assembly district plan" that meets the following standards related to partisan fairness. Section 6(A) prohibits a district plan from being "drawn primarily to favor or disfavor a political party." 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."

My report provides evidence relevant to evaluating both of these criteria. Ohio's Constitutional criteria requiring districting plans refrain from benefiting a particular political party are related to a long-line of Political Science literature on democratic representation. The relationship between the distribution of partisan support in the electorate and the partisan composition of the government—what Powell (2004) calls "vote–seat representation"—is a critical link in the longer representational chain between citizens' preferences and governments' policies. If the relationship between votes and seats systematically advantages one party over another, then some citizens will enjoy more influence—more "voice"—over political outcomes than others (Caughey, Tausanovitch, and Warshaw 2017).

I use two complementary methodologies to evaluate whether Ohio's state legislative plans meet the requirements of Article XI, Section 6 in its Constitution. First, I use a composite of previous statewide election results between 2012-2020. This approach is based directly on the text of Article XI, Section 6(B), which states that "statewide state and federal partisan general election results during the last ten years" shall be used to evaluate whether a plan meets the Constitution's proportionality requirement. However, this approach has some methodological weaknesses. Therefore, I complement this approach using additional approaches from the open source PlanScore.org website, which is a project of the Campaign Legal Center.[4] PlanScore uses a statistical model to estimate district-level vote shares for a new map based on the relationship between presidential election results and legislative results between 2012-2020.[5] Based on these two approaches, I characterize the bias in Ohio's plans based on both simple proportionality and a large set of established metrics of partisan fairness. I also place the bias in Ohio's plans into historical perspective.

4. I am on the social science advisory board of Plan Score, but I am not compensated by Campaign Legal Center nor do I have any role in PlanScore's evaluation of individual maps.

5. See https://planscore.campaignlegal.org/models/data/2021B/ for more details.

All of these analyses indicate an extreme level of pro-Republican bias in Ohio's enacted state house and state senate plans. In the 2020 presidential election, Democrat Joe Biden received about 46% of the two-party vote.[6] However, he would have only won 35% of the state house districts and 33% of the state senate districts in the enacted plan. In the 2018 gubernatorial election, Democrat Richard Cordray did a little bit better. He received about 48% of the two-party vote. Yet again, however, he would have only won 37% of the state house districts and 36% of the state senate districts under the enacted plan. In the 2018 Senate election, Democratic Senator Sherrod Brown did even better. He received about 53% of the two-party vote. But he would still have won less than half of the state house districts and just over half the state senate districts under the enacted plan.

Based on all the available statewide elections in Ohio between 2012-2020, I find that the enacted state house and state senate plans lead to a much higher Republican share of the seats than their share of the statewide vote. Indeed, across the 16 statewide elections, the Democrats' statewide two-party vote share averaged about 45.5%, but they are only likely to win about 33% of the seats in the state house and 31-32% of the seats in the state senate.[7]

We reach the same conclusion using the predictive model on the PlanScore website. It indicates that the enacted plans favor Republican candidates in 97-99% of scenarios. Even though Republicans only get about 56% of the statewide vote in recent elections, PlanScore analysis indicates that Republicans are expected to win 71% of the seats in Ohio's state senate and 68% of the seats in Ohio's state house. Thus, the plans have a pro-Republican proportionality bias of 15% and 12%. Based on generally accepted Political Science metrics (the Efficiency Gap and the Declination), PlanScore indicates that Ohio's enacted plan would have historically extreme levels of pro-Republican bias. In fact, the pro-Republican bias in Ohio's enacted state senate plan is larger than 91% of previous plans, and the bias in Ohio's state house plan is larger than 90% of previous plans.

Overall, this analysis indicates that the enacted plan appears to be drawn to favor one political party based on a variety of metrics, and the two-parties' seat shares do not correspond closely to their vote shares.

The rest of this report proceeds as follows. First, I provide an overview of partisan gerrymandering and how social scientists measure the degree of partisan bias in a districting plan. Second, I trace the levels of partisan bias in Ohio's state legislative plans over the

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

7. I weight the composite scores to give each election cycle equal weight in the index. The seat-level projections are based on the 13 statewide elections where I have precinct-level data. In these elections, the Democrats' statewide two-party vote share averaged 45%.

past fifty years. Third, I evaluate the enacted plans and compare them to the 2012-2020 map. Finally, I show the consequences of partisan gerrymandering for the representation that citizens of Ohio receive in its state government.

4 Background on Partisan Gerrymandering

The goal of partisan gerrymandering is to create legislative districts that are as "efficient" as possible in translating a party's vote share into seat share (McGhee 2014, 2017; Caughey, Tausanovitch, and Warshaw 2017). In practice, this entails drawing districts in which the supporters of the advantaged party constitute either a slim majority (e.g., 55% of the two-party vote) or a small minority (e.g., 20%). The former is achieved by "cracking" local opposing-party majorities across multiple districts and the latter by "packing" them into a few overwhelming strongholds. In a "cracked" district, the disadvantaged party narrowly loses, while in a "packed" district, the disadvantaged party wins overwhelmingly (Buzas and Warrington 2021). The resulting *asymmetry* or *advantage* in the efficiency of the vote–seat relationships of the two parties lies at the core of normative critiques of partisan gerrymandering. Asymmetries in the translation of votes to seats "offer a party a means of increasing its margin of control over policy without winning more votes from the public" (McGhee 2014).

In addition to creating a plan that skews the vote-seat curve toward their party, the advantaged party also often seeks to build a map that is *insulated* against changes in the public's preferences. This type of unresponsive map enables the advantaged party to continue to win the majority of seats even in the face of large gains in the disadvantaged party's statewide vote share. It ensures that the gerrymander is durable over multiple election cycles.

There are a number of approaches that have been proposed to measure partisan advantage in a districting plan. These approaches focus on asymmetries in the efficiency of the vote–seat relationships of the two parties. In recent years, at least 10 different approaches have been proposed (McGhee 2017). While no measure is perfect, much of the recent literature has focused on a handful of related approaches. The results of these metrics sometimes diverge in states where one party dominates elections. But they generally all yield similar substantive results in competitive states (see Stephanopoulos and McGhee 2018, 556). In the analysis that follows, I use a number of these metrics to examine the proposed plans as well as the trajectory of partisan gerrymandering in Ohio and the nation as a whole.[8]

8. For historical elections, I use data on the results of legislative elections over the past few decades. For

4.1 Proportionality

Arguably, the simplest metric of partisan bias in a districting plan is whether each party's share of the seats is proportional to its share of the votes. Ohio has embedded this simple metric in Section 6(B) of its Constitution, which 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." We can thus calculate the proportionality of a districting plan using the following equation:

$$Proportionality = S - V \tag{1}$$

where S is the Democratic seat share and V is the Democratic vote share in statewide elections.

We can illustrate the proportionality metric by reference to Ohio's state house elections in 2020. In this election, the Democratic candidate won about 46% of the statewide two-party vote in the presidential race. But Democrats won only 35% of the state house seats in Ohio. This led to a pro-Republican bias in the proportionality metric of about 11%.

It is worth briefly comparing my definition of the proportionality metric to the one used by the Commission in their Article XI, Section 8(C)(2) Statement.[9] In that Statement, the Commission defined the statewide preferences of the voters of Ohio largely based on the percentage of statewide elections won by Republicans over the past ten years rather than Republicans' vote share in those elections.[10] I do not know of a single academic

all legislative elections that were contested between two major party candidates, I use the raw vote totals to calculate various metrics that measure the degree of partisan gerrymandering. For legislative elections that are uncontested (i.e., those that lacked either a Democratic or Republican candidate), we do not directly observe the number of people that support each party's candidate. In these cases, it is necessary to estimate the two-party vote share because "determining the degree of packing and cracking requires knowing how many people in each district support each party" (Stephanopoulos and McGhee 2015, 865). Using publicly available data and statistical models, I estimate the two-party vote share in each district based on previous and future elections in that district as well as the results in similar districts elsewhere. This is similar to the approach used in a variety of other studies that estimate these gerrymandering metrics (e.g., Gelman and King 1994a; Stephanopoulos and McGhee 2015; Brennan Center 2017; Jackman 2017; McGhee 2018; Warrington 2018b) The details of this calculation for uncontested races are described in further detail in the Appendix and in Stephanopoulos and Warshaw (2020). I then use this information to estimate the gerrymandering metrics discussed below for congressional elections between 1972 to 2020. I start the analysis in 1972 since those are the first districting plans drawn after the Supreme Court cases stemming from *Baker v. Carr* ended malapportionment and established the principle of one-person, one-vote.

9. `https://www.redistricting.ohio.gov/assets/organizations/redistricting-commission/events/commission-meeting-september-15-2021-76/article-xi-sec-8c2-statement.pdf`.

10. "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

book, article, or paper that defines voters' statewide preferences in this way. Moreover, the Commission's definition makes little logical sense. It implies that if Republicans had won each statewide election with 50.1% of the vote, the statewide proportion of voters favoring Republican candidates is 100%. Thus, Republicans would be entitled to win 100% of the legislative seats. Based on the academic literature, it makes much more sense to read the requirements that the proportion of districts correspond to the statewide preferences of voters to imply that Republicans are entitled to 50.1% of the legislative seats if they win 50.1% of the votes.

In much of this report, I focus on proportionality since it is explicitly discussed in Article XI, Section 6(B) of the Constitution. But there are at least two important limitations associated with using proportionality as the sole metric of whether a districting plan is "drawn primarily to favor or disfavor a political party" (Article XI, Section 6(A)). One is that historically there tends to be a winner's bonus in legislative elections. This means that a party that wins 55% of the votes tends to win about 60% of the seats (Stephanopoulos and McGhee 2015, 854). As I discuss below, however, Ohio's map is very disproportionate even after taking into consideration this winner's bonus. Another limitation is that the proportionality metric "looks more favorably than the [other metrics] on parties that win a majority of seats with a minority of votes—a situation many feel ought to be punished more aggressively—and otherwise requires more sacrifice from a majority party than is typical in American elections" (McGhee 2017). As a result of these limitations, academics tend to supplement the proportionality metric with a number of other approaches to characterize partisan bias in districting plans that favors a particular political party. I will now discuss these other approaches.

4.2 Efficiency Gap

Both cracked and packed districts "waste" more votes of the disadvantaged party than of the advantaged one (McGhee 2014; Stephanopoulos and McGhee 2015).[11] This suggests that gerrymandering can be measured based on asymmetries in the number of wasted votes for each party. The *efficiency gap* (EG) focuses squarely on the number of each party's wasted votes in each election. It is defined as "the difference between the parties' respective wasted votes, divided by the total number of votes cast in the election"

resulting in a statewide proportion of voters favoring statewide Republican candidates of 81%..."

11. The authors of the efficiency gap use the term "waste" or "wasted" to describe votes for the losing party and votes for the winning party in excess of what is needed to win an election. Since the term is used by the efficiency gap authors, I use it here when discussing the efficiency gap.

(Stephanopoulos and McGhee 2015, 831; see also McGhee 2014, 2017).[12] All of the losing party's votes are wasted if they lose the election. When a party wins an election, the wasted votes are those above the 50%+1 needed to win.

If we adopt the convention that positive values of the efficiency gap imply a Democratic advantage in the districting process and negative ones imply a Republican advantage, the efficiency gap can be written mathematically as:

$$EG = \frac{W_R}{n} - \frac{W_D}{n} \tag{2}$$

where W_R are wasted votes for Republicans, W_D are wasted votes for Democrats, and n is the total number of votes in each state.

Table 1 provides a simple example about how to calculate the efficiency gap with three districts where the same number of people vote in each district. In this example, Democrats win a majority of the statewide vote, but they only win 1/3 seats. In the first district, they win the district with 75/100 votes. This means that they only wasted the 24 votes that were unnecessary to win a majority of the vote in this district. But they lose the other two districts and thus waste all 40 of their votes in those districts. In all, they waste 104 votes. Republicans, on the other hand, waste all 25 of their votes in the first district. But they only waste the 9 votes unnecessary to win a majority in the two districts they win. In all, they only waste 43 votes. This implies a pro-Republican efficiency gap of $\frac{43}{300}$ - $\frac{104}{300}$= -20%.

Table 1: Illustrative Example of Efficiency Gap

District	Democratic Votes	Republican Votes
1	75	25
2	40	60
3	40	60
Total	155 (52%)	145 (48%)
Wasted	104	43

12. The efficiency gap calculations here focus on wasted votes in *legislative elections* since these results directly capture voters' preferences in these elections. However, we might also calculate the efficiency gap using district-level results from presidential elections or other statewide races. These have the "advantage of being (mostly) unaffected by district-level candidate characteristics" (Stephanopoulos and McGhee 2015, 868). This feature is particularly useful for simulating efficiency gaps from randomly generated districting plans since candidate characteristics are clearly influenced by the final districting plan. Presidential elections or other statewide races are less closely tied, however, to voters' preferences in legislative races given the district lines that actually exist. In practice, though, both legislative races and other statewide races produce similar efficiency gap results for modern elections where voters are well sorted by party and ideology. Indeed, the data indicate that the correlation between efficiency gap estimates based on congressional elections and presidential elections is approximately 0.8 for elections held after 2000 and about 0.9 for elections held after the 2011 redistricting cycle.

In order to account for unequal population or turnout across districts, the efficiency gap formula in equation 2 can be rewritten as:

$$EG = S_D^{margin} - 2 * V_D^{margin} \tag{3}$$

where S_D^{margin} is the Democratic Party's seat margin (the seat share minus 0.5) and V_D^{margin} is is the Democratic Party's vote margin. V_D^{margin} is calculated by aggregating the raw votes for Democratic candidates across all districts, dividing by the total raw vote cast across all districts, and subtracting 0.5 (McGhee 2017, 11-12). In the example above, this equation also provides an efficiency gap of -20% in favor of Republicans. But it could lead to a slightly different estimate of the efficiency gap if districts are malapportioned or there is unequal turnout across districts.[13] In the case of Ohio's state house, equation 3 implies there was a pro-Republican efficiency gap of approximately 10.5% in 2012 and 9.9% in 2020.

The efficiency gap mathematically captures the packing and cracking that are at the heart of partisan gerrymanders (Buzas and Warrington 2021). It measures the extra seats one party wins over and above what would be expected if neither party were advantaged in the translation of votes to seats (i.e., if they had the same number of wasted votes). A key advantage of the efficiency gap over other measures of partisan bias is that it can be calculated directly from observed election returns even when the parties' statewide vote shares are not equal.

4.3 Mean-median Gap

Another metric that some scholars have proposed to measure partisan bias in a districting plan is the *mean-median gap*: the difference between a party's vote share in the median district and their average vote share across all districts. If the party wins more votes in the median district than in the average district, they have an advantage in the translation of votes to seats (Krasno et al. 2018; Best et al. 2017; Wang 2016). In statistics, comparing a dataset's mean and median is a common statistical analysis used to assess skews in the data and detect asymmetries (Brennan Center 2017). The mean-median difference is very easy to apply (Wang 2016). It is possible, however, for packing and cracking to occur without any change in the mean-median difference. That is, a party could gain seats in the

13. In general, the two formulations of the efficiency gap formula yield very similar results. Because Democrats tend to win lower-turnout districts, however, the turnout adjusted version of the efficiency gap in equation 3 tends to produce results that suggest about a 2% smaller disadvantage for Democrats than the version in Equation 2 (see McGhee 2018).

legislature without the mean-median gap changing (McGhee 2017).[14] It is also sensitive to the outcome in the median district (Warrington 2018b). In addition, the mean-median difference lacks a straightforward interpretation in terms of the number of seats that a party gains through gerrymandering. Finally, the assumptions of the mean-median gap are less tenable in less electorally competitive states.

District	Democratic Vote Share
6	25.6 %
4	30.2 %
7	30.2 %
8	31 %
5	32 %
15	36.6 %
16	36.8 %
2	38.9 %
14	39.9 %
10	41.6 %
12	43.1 %
1	46.3 %
13	53.9 %
9	63.1 %
3	70.8 %
11	80.1 %
Mean	43.8%
Median	39.4%

Table 2: Results in 2020 Ohio Congressional Elections

Table 2 illustrates the mean-median approach using the district-level election results in the 2020 Ohio congressional elections. It indicates that many Democratic voters were packed into just 4 districts where the Democratic candidates won by overwhelming margins. The remaining Democratic voters were cracked across the other districts. This table shows the disproportionate percentage of the statewide vote that Democrats would have needed to win a majority of Ohio's congressional seats in 2020. Across all districts, Democrats won an average of 43.8% of the vote. But they only won 39.4% in the median district. This translated into a pro-Republican mean-median difference of 4.4%.

14. As McGhee (2017), notes, "If the median equals the win/loss threshold–i.e., a vote share of 0.5–then when a seat changes hands, the median will also change and the median- mean difference will reflect that change. But if the median is anything other than 0.5, seats can change hands without any change in the median and so without any change in the median-mean difference." See also Buzas and Warrington (2021) who make a similar point using simulated packing and cracking.

4.4 Symmetry in the Vote-Seat Curve Across Parties

Basic fairness suggests that in a two-party system each party should receive the same share of seats for identical shares of votes. The *symmetry* idea is easiest to understand at an aggregate vote share of 0.5—a party that receives half the vote ought to receive half the seats—but a similar logic can apply across the "seats- votes curve" that traces out how seat shares change as vote shares rise and fall. For example, if a party receives a vote share of 0.57 and a seat share of 0.64, the opposing party should also expect to receive a seat share of 0.64 if it were to receive a vote share of 0.57. An unbiased system means that for V share of the votes a party should receive S share of the seats, and this should be true for all parties and vote percentages (Niemi and Deegan 1978; Gelman and King 1994a; McGhee 2014; Katz, King, and Rosenblatt 2020).

Gelman and King (1994a, 536) propose two ways to measure partisan bias in the symmetry of the vote-seat curve. First, it can be measured using counter-factual election results in a range of statewide vote shares between .45 and .55. Across this range of vote shares, each party should receive the same number of seats. Symmetry captures any departures from the standard that each party should receive the same seat share across this range of plausible vote shares. For example, if partisan bias is -0.05, this means that the Democrats receive 5% fewer seats in the legislature than they should under the symmetry standard (and the Republicans receive 5% more seats than they should).

To illustrate the symmetry metric, Table 3 calculates what each party's share of the seats would have been in Ohio's 2020 state house elections across a range of statewide vote shares from 45%-55%. It shows that Democrats only received 36% of the seats in most of the scenarios where they received less than 50% of the votes. This might not have been problematic under the symmetry standard if Republicans also only received 36% of the seats when they received less than 50% of the votes. However, Table 3 shows that Republicans still would have received half of the seats even when they won a minority of the votes. Across this range of statewide vote shares from 45%-55%, Democrats receive an average of 40% of the seats (and Republicans win 60%). This implies a partisan bias of 10% using the symmetry metric. That is, Republicans won 10 percentage points more of the seats than they would have won if the seat-vote curve was symmetric between the two parties.

The symmetry metric is closely related to the efficiency gap. In the special case where each party receives half of the statewide vote, the symmetry and the efficiency gap metrics are mathematically identical (Stephanopoulos and McGhee 2015, 856). More generally, the symmetry and efficiency gap yield very similar substantive results when each party's statewide vote share is close to 50% (as is the case in Ohio). When elections are uncompet-

Dem. Vote Share	Dem. Seat Share	Rep. Vote Share	Rep. Seat Share
45%	34%	55%	66%
46%	35%	54%	65%
47%	36%	53%	64%
48%	36%	52%	64%
49%	38%	51%	62%
50%	40%	50%	60%
51%	40%	49%	60%
52%	43%	48%	57%
53%	44%	47%	56%
54%	48%	46%	52%
55%	51%	45%	49%
Mean Seat Share	41%		59%
Bias	-9%		9%

Table 3: Symmetry Calculations for 2020's State House Elections

itive, however, and one party wins a large percentage of the statewide vote, the efficiency gap and these symmetry metrics are less correlated with one another (Stephanopoulos and McGhee 2015, 857).

A weakness of the symmetry approach is that it requires the analyst to calculate counterfactual elections. This approach has both conceptual and empirical limitations. At a conceptual level, it is not clear that it aligns perfectly with the usual definition of a gerrymander. Indeed, "when observers assert that a district plan is a gerrymander, they usually mean that it systematically benefits a party (and harms its opponent) in actual elections. They do not mean that a plan would advantage a party in the hypothetical event of a tied election, or if the parties' vote shares flipped" (857). At an empirical level, in order to generate symmetry metrics, we need to simulate counter-factual elections by shifting the actual vote share in each district a uniform amount (McGhee 2014).[15] In general, this uniform swing assumption seems reasonable based on past election results (though is probably less reasonable in less competitive states). Moreover, it has been widely used in past studies of redistricting. But there is no way to conclusively validate the uniform swing assumption for any particular election.

An important strength, however, of the symmetry approach is that it is based on the shape of the seats-votes curve and not any particular point on it. As a result, it is relatively immune to shifts in party performance (McGhee 2014). For instance, the bias toward

15. In principle, the uniform swing election could be relaxed, and swings could be estimated on a district-by-district basis. But this is rarely done in practice since it would require a much more complicated statistical model, and probably would not improve estimates of symmetry very much.

Republicans in Ohio's symmetry metric was very similar in 2012-2020. Moreover, the symmetry approach has been very widely used in previous studies of gerrymandering and redistricting (Gelman and King 1994a; McGhee 2014). Overall, the symmetry approach is useful for assessing partisan advantage in the districting process.

4.5 Declination

Another measure of asymmetries in redistricting plans is called *declination* (Warrington 2018b, 2018a). The declination metric treats asymmetry in the vote distribution as indicative of partisan bias in a districting plan (Warrington 2018a). If all the districts in a plan are lined up from the least Democratic to the most Democratic, the mid-point of the line formed by one party's seats should be about as far from the 50 percent threshold for victory on average as the other party's (McGhee 2018).

Declination suggests that when there is no gerrymandering, the angles of the lines (θ_D and θ_R) between the mean across all districts and the point on the 50% line between the mass of points representing each party will be roughly equal. When they deviate from each other, the smaller angle (θ_R in the case of Ohio) will generally identify the favored party. To capture this idea, declination takes the difference between those two angles (θ_D and θ_R) and divides by $\pi/2$ to convert the result from radians to fractions of 90 degrees.[16] This produces a number between -1 and 1. As calculated here, positive values favor Democrats and negative values favor Republicans.[17] Warrington (2018b) suggests a further adjustment to account for differences in the number of seats across legislative chambers. I use this adjusted declination estimate in the analysis that follows.[18]

4.6 Comparison of Partisan Bias Measures

All of the measures of partisan advantage discussed in the previous sections are closely related both theoretically and empirically (McGhee 2017; Stephanopoulos and McGhee 2018). Broadly speaking, all of the metrics consider how votes between the two parties are distributed across districts (Warrington 2018a). For example, the efficiency gap is mathematically equivalent to partisan bias in tied statewide elections (Stephanopoulos

16. This equation is: $\delta = 2^* \ (\theta_R \text{ - } \theta_D) \ / \ \pi$.

17. In order to validate my estimates of declination, I compare my estimates to the ones presented in Warrington (2018b). I find that my declination estimates are nearly identical to the estimates originally developed by Warrington in the appendix to his article. In fact, the correlation between the declination values that I calculate and those in Warrington (2018b) is .94 for the U.S. House (note that Warrington does not estimate declination values for state senate elections). Small differences between the declination estimates likely stem from minor differences in how we impute vote shares in uncontested races.

18. This adjustment uses this equation: $\hat{\delta} = \delta \ * \ \ln(\text{seats}) \ / \ 2$

and McGhee 2018). Also, the median-mean difference is similar to the symmetry metric, since any perfectly symmetric seats-votes curve will also have the same mean and median (McGhee 2017).

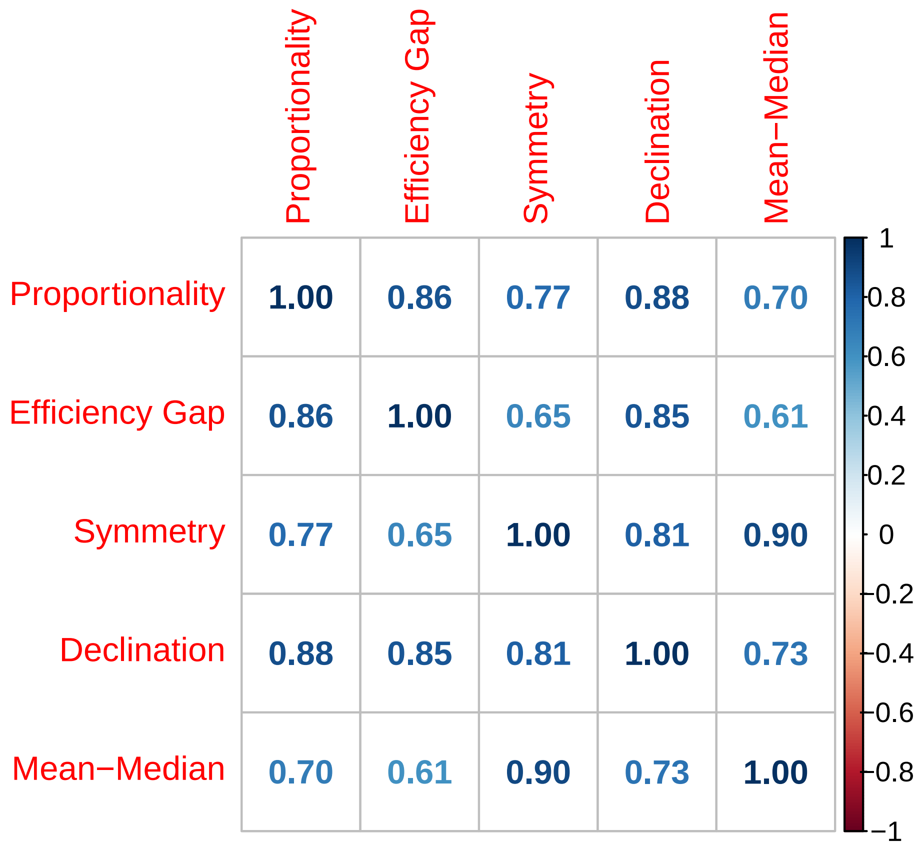

Figure 1: Correlation between measures of partisan bias in states.

Second, each of the concepts are closely related empirically, particularly in states with competitive elections. Figure 1 shows the correlation between each measure. The various measures have high correlations with one another.[19] Moreover, most of the variation in the metrics can be summarized on a single latent dimension (Stephanopoulos and McGhee 2018; Stephanopoulos and Warshaw 2020). So, overall, while there may be occasional

19. While each measure is highly correlated with one another, the efficiency gap and declination measures are particularly closed related and the symmetry and mean-median measures are very closely related. This could be because the efficiency gap and the declination consider the seats actually won by each party, while the symmetry metric and the mean-median difference do not (Stephanopoulos and McGhee 2018, 1557).

cases where the metrics disagree about the amount of bias in a particular plan, the various metrics usually yield similar results for the degree of partisan bias in a districting plan (Nagle 2015).

In the case of Ohio, all the metrics indicate that Republicans had a large advantage in the districting process in Ohio since the 2011 plan went into place, and that the new plan would further cement this advantage. The fact that all the metrics are in agreement in Ohio strengthens our confidence that the new plan is a partisan gerrymander designed to favor a particular political party.

4.7 The Responsiveness of a Legislative Districting Plan to Changes in Voters' Preferences

The responsiveness of a map indicates how many seats change hands as vote shares rise and fall. Thus, it can be thought of as the slope of the seats-votes curve across a range of vote shares (McGhee 2014). An unresponsive map ensures that the bias in a districting plan toward the advantaged party is insulated against changes in voters' preferences, and thus is durable across multiple election cycles. In addition to serving as an indicator of the durability of a gerrymander, some scholars have suggested that responsiveness is another metric to measure gerrymandering itself (Cox and Katz 1999). There are a couple of approaches we might use to measure the responsiveness of a districting plan.

First, we could simply look at the number of competitive districts. In general, a plan with more competitive elections is likely to be more responsive to changes in voters' preferences than a plan with fewer competitive elections (McGhee 2014). Uncompetitive districts tend to protect incumbents and lock in the gerrymandering party's electoral advantage (Tufte 1973; Gelman and King 1994a). Following past work, I measure whether a district was competitive in an election based on whether the winning party received less than 55% of the two-party vote (Jacobson and Carson 2015, 91). Based on this definition, only 16% of the district in Ohio's state house plan were competitive in 2012 and just 13% were competitive in 2020.

Second, we could directly measure the responsiveness of the vote-seat curve to counterfactual changes in each party's statewide vote share. Gelman and King (1994a, 535) propose a technique that measures responsiveness based on uniform swings in the two parties' counterfactual vote shares. Specifically, they propose varying each party's vote shares in the average district between 45% and 55% and then measuring the degree to which this change in vote share leads to a change in seat share. In responsive systems, a 10% change in vote share from 45% to 55% will generally lead to a change in seat share of

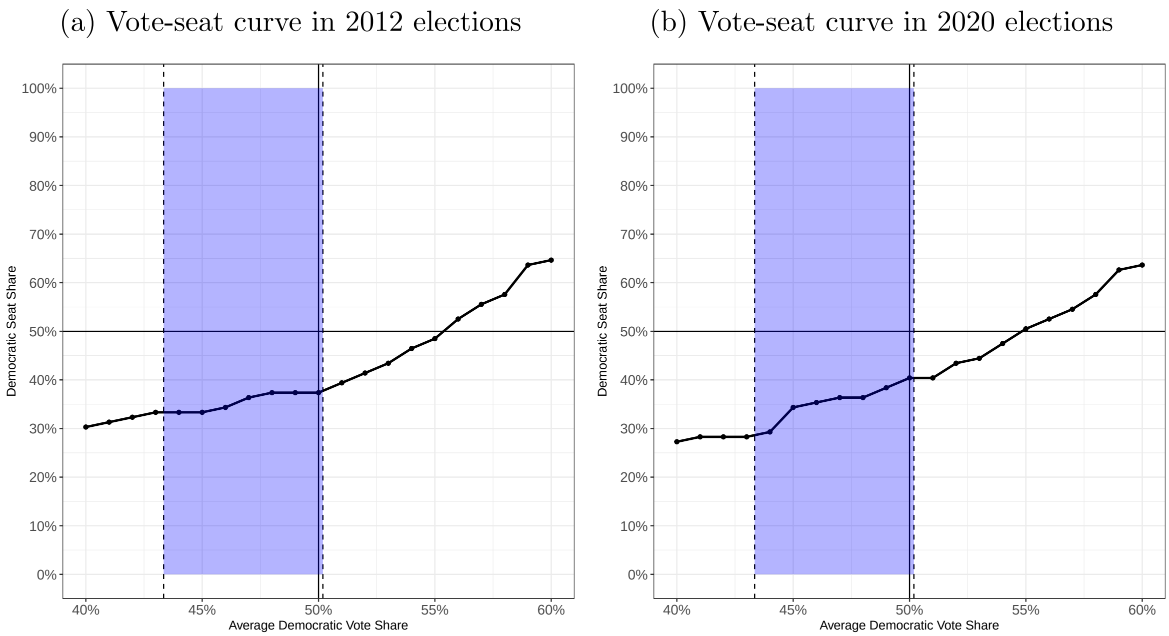

Figure 2: Vote-seat curve in Ohio using uniform swings in 2012 and 2020 election results. The shaded area shows the range between the minimum and maximum Democratic statewide vote share in state house elections from 2012-2020.

around 20%. In an unresponsive system, there could be little or no change in seat share from a 10% change in vote share.

To illustrate the concept of responsiveness, Figure 2 shows the vote-seat curve in Ohio generated by applying uniform swings in the 2012 and 2020 election results.[20] Specifically, I apply a uniform swing in the actual election results until I achieve an average Democratic vote share of 40%. Then I steadily increase the average Democratic vote share until it reaches 60%. Figure 2 indicates that the vote-seat curves in Ohio in 2012 and 2020 were extremely unresponsive to changes in voters' preferences. In fact, Republicans win 50% or more of the seats across all of the range of actual election swings over the past decade.

4.8 Partisan Control of the Redistricting Process and Gerrymandering

While many factors could influence the degree of partisan advantage in the districting process,[21] there is a wide body of evidence from previous studies that control of the re-

20. The layout of this chart is adapted from charts of responsiveness in Royden, Li, and Rudensky (2018).

21. Partisan advantage in the districting process can differ across states for reasons unrelated to the drawing of district lines, such as variation in how different demographic groups are distributed across geographic space (Chen and Rodden 2013). It can also be affected by the intentional drawing of district

districting process has a large effect on partisan advantage in subsequent elections carried out under a given plan. Cox and Katz (2002) show that Democratic control of the redistricting process in many states during the 1960s led to a lasting partisan advantage for Democrats in House elections. More generally, Gelman and King (1994b) find that the party in control of redistricting shifts outcomes in its favor, and that "the effect is substantial and fades only very gradually over the following 10 years" (543). This result has been confirmed in numerous recent articles. McGhee (2014) finds that "parties seek to use redistricting to shift bias in their favor and that they are successful in these efforts" (74).[22] Finally, Stephanopoulos (2018) shows that partisan control of the districting process has a substantial effect on the efficiency gap.[23]

5 Historical Analysis of Partisan Bias in Ohio's Legislative Districts

In this section, I provide an historical overview of the partisan bias in Ohio's state legislative districts over the past 50 years. Figure 3 shows trends in the proportionality bias in Ohio's state legislative districts between 1972 and 2020.[24] It indicates that the 2011 redistricting plan led to a large Republican advantage in Ohio state legislative elections.

In the state house elections in 2012, Democratic candidates won 50.2% of the statewide vote, but they won only 39.4% of Ohio's state house seats. This led to a pro-Republican proportionality bias, for instance, of approximately -11%. The results in the next few state house elections were fairly similar to those in 2012. Democrats won 45.1% of the votes, but only 35.4% of the seats in the 2020 state house elections. Thus, Ohio's state house had a pro-Republican proportionality bias approximately 10% in 2020.

The state senate is similar. Over the 2015-2022 period when the previous map was fully in place, Democrats controlled about 27% of the seats and the state senate had a pro-Republican proportionality bias of about -16%.[25] Democrats only controlled 24% of the seats after the state senate election in 2020, despite winning nearly 45% of the

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lines to accomplish goals other than maximizing partisan seat share, such as ensuring the representation of racial minorities (e.g., Brace, Grofman, and Handley 1987).

22. McGhee (2014) finds that partisan control affects the districting process using both the Gelman and King (1994b) measure of partisan symmetry and the efficiency gap as outcome variables.

23. He shows that states with unified Republican control have about 5 percentage points more pro-Republican efficiency gaps than states with split control, and states with unified Democratic control have about 3 percentage points more pro-Democratic efficiency gaps than states with split control.

24. Note that detailed nationwide data on state legislative elections in 2020 is not yet available.

25. If we also include 2012 when only half the seats were elected under the 2012-2020 map, Democrats controlled about 28% of the seats over the course of the decade.

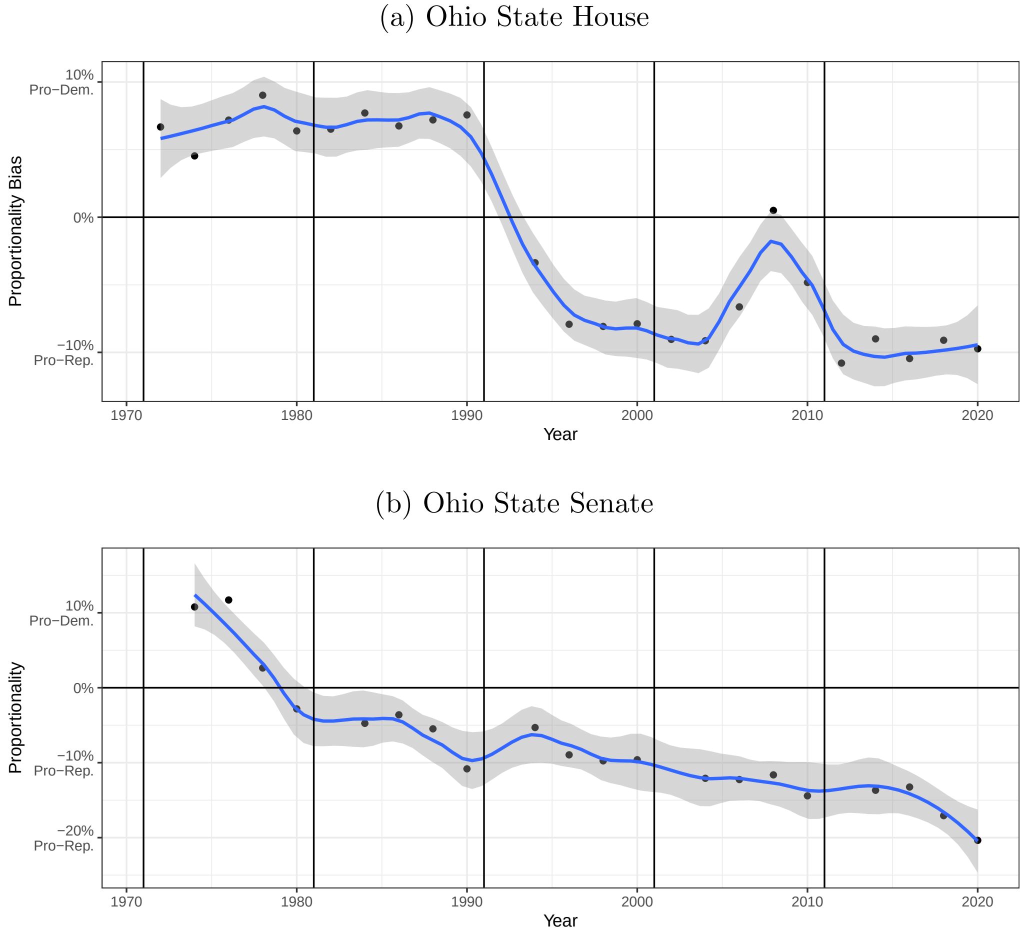

Figure 3: Historical Trajectory of the Proportionality in Ohio. Each vertical line shows the demarcation between decennial redistricting plans. The blue line shows the moving average and the grey bar is a confidence interval. The dots represent the proportionality bias in each year in Ohio.

statewide vote.

We see similar levels of pro-Republican bias using other metrics of partisan bias. Figures 5 and 6 compare Ohio to other states using a variety of different metrics. Each dot in the charts represents a particular state's partisan advantage for state house and state senate elections in that state that year. Overall, Ohio's state house election in 2012 (when the last districting plan went into place) had a larger pro-Republican bias in its Efficiency Gap than 95.9% of the state house elections over the past five decades, and it had a larger absolute bias than 87% of previous plans. Figures 5 and 6 also show that the pro-Republican bias in Ohio's state legislative plans was very durable and stable across the 2012-2020 period.

Turning to other metrics of partisan bias in districting plans, Ohio's 2012 elections

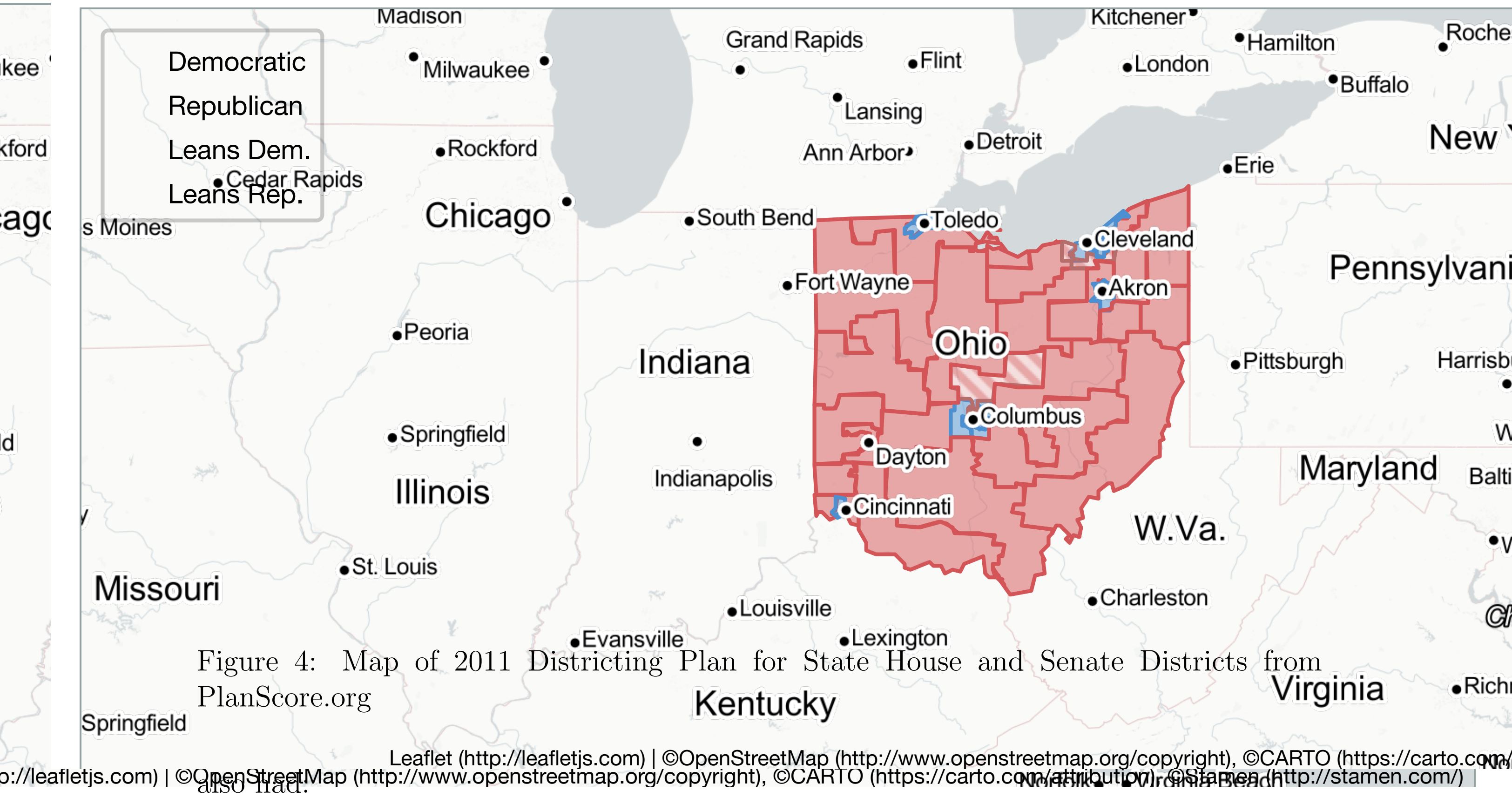

Figure 4: Map of 2011 Districting Plan for State House and Senate Districts from PlanScore.org

also had:

- A more extreme declination value than 88.1% of previous state house elections and a larger pro-Republican bias in its declination than 94.7% of the previous elections.

- A more extreme difference between the mean and median district than 87.2% of previous state house elections and a larger pro-Republican bias than in 90.3% of previous elections.

- A more extreme symmetry metric than 89.1% of previous state house elections and a larger pro-Republican bias in its declination than 93.4% of the previous elections.

Likewise, Ohio's state senate results in the first election after its 2011 plan fully went into place in 2014 had a larger absolute Efficiency Gap than 65.7% of previous state senate elections, and it had a larger pro-Republican bias than 83% of the state senate elections over the past five decades. Using other metrics of partisan bias in districting plans, it also had:

- A more extreme declination value than 80.5% of previous state senate elections and a larger pro-Republican bias in its declination than 90.5% of the previous elections.

- A more extreme difference between the mean and median district than 88.8% of previous state senate elections and also a larger pro-Republican bias in the difference between the mean and median district than 90% of previous elections.

- A more extreme symmetry metric than 98.8% of previous state house elections and a larger pro-Republican bias in its declination than 99% of the previous elections.

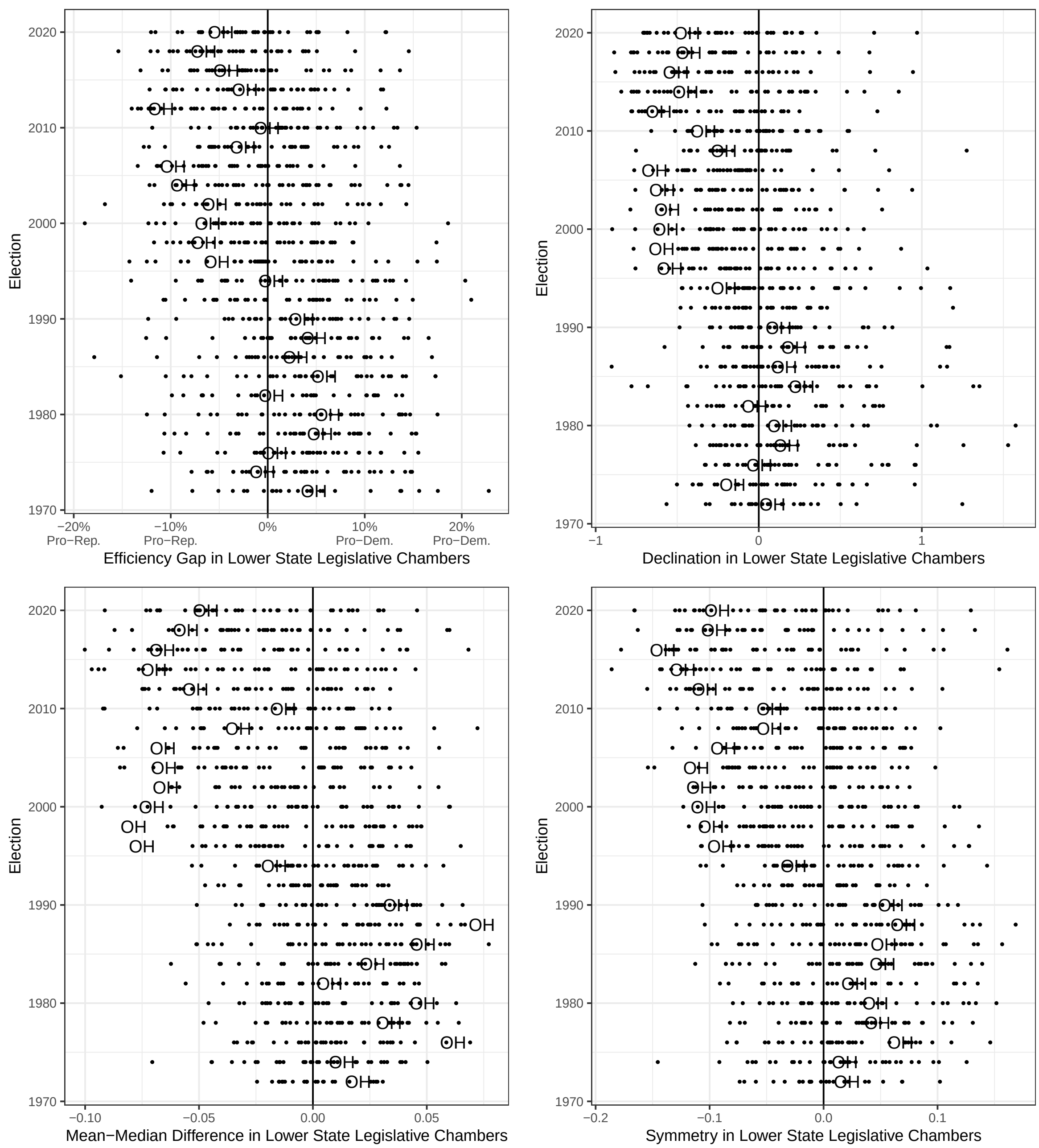

Figure 5: Partisan Advantage in Ohio's State House Relative to Other States. The dots represent the metrics in individual states. The metrics in Ohio are labelled to distinguish them from other states. Negative values are pro-Republican and positive values are pro-Democratic.

Overall, this evidence indicates that Ohio's state legislative plans during the 2012-2020 period has a historically extreme level of pro-Republican bias. The next section will examine whether the state Commission's enacted plans reduce this bias and are likely to yield legislative results that are proportional to the statewide vote and not designed to

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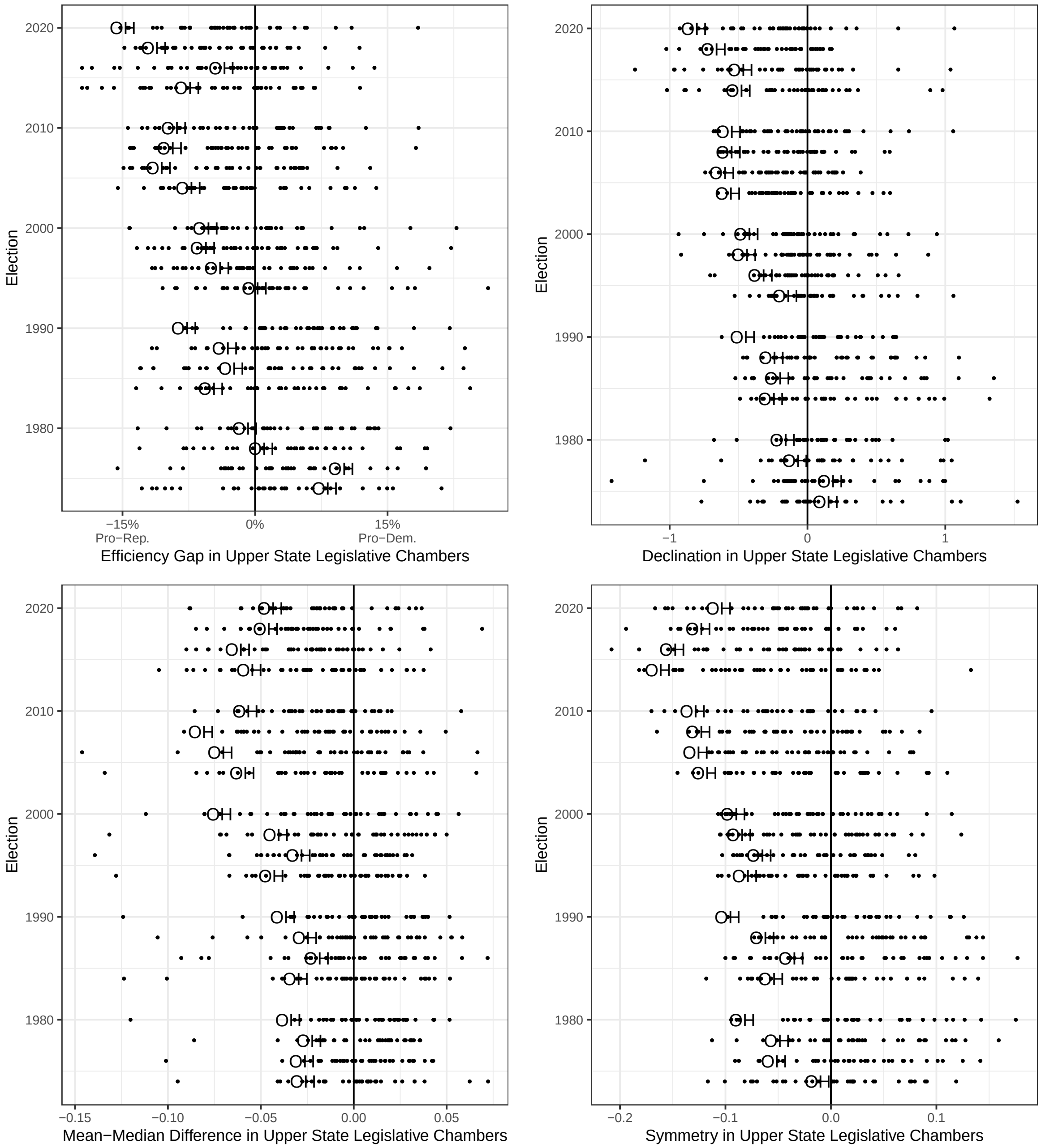

Figure 6: Partisan Advantage in Ohio's State Senate Relative to Other States. The dots represent the metrics in individual states. The metrics in Ohio are labelled to distinguish them from other states. Negative values are pro-Republican and positive values are pro-Democratic.

favor a political party as Article XI, Section 6 of Ohio's Constitution requires.

6 Partisan Bias in Ohio's Enacted State Legislative Districting Plans

In this section, I will provide a comprehensive evaluation of the partisan fairness of Ohio's enacted state legislative districting plan (see Figure 7 for maps of the enacted plans).

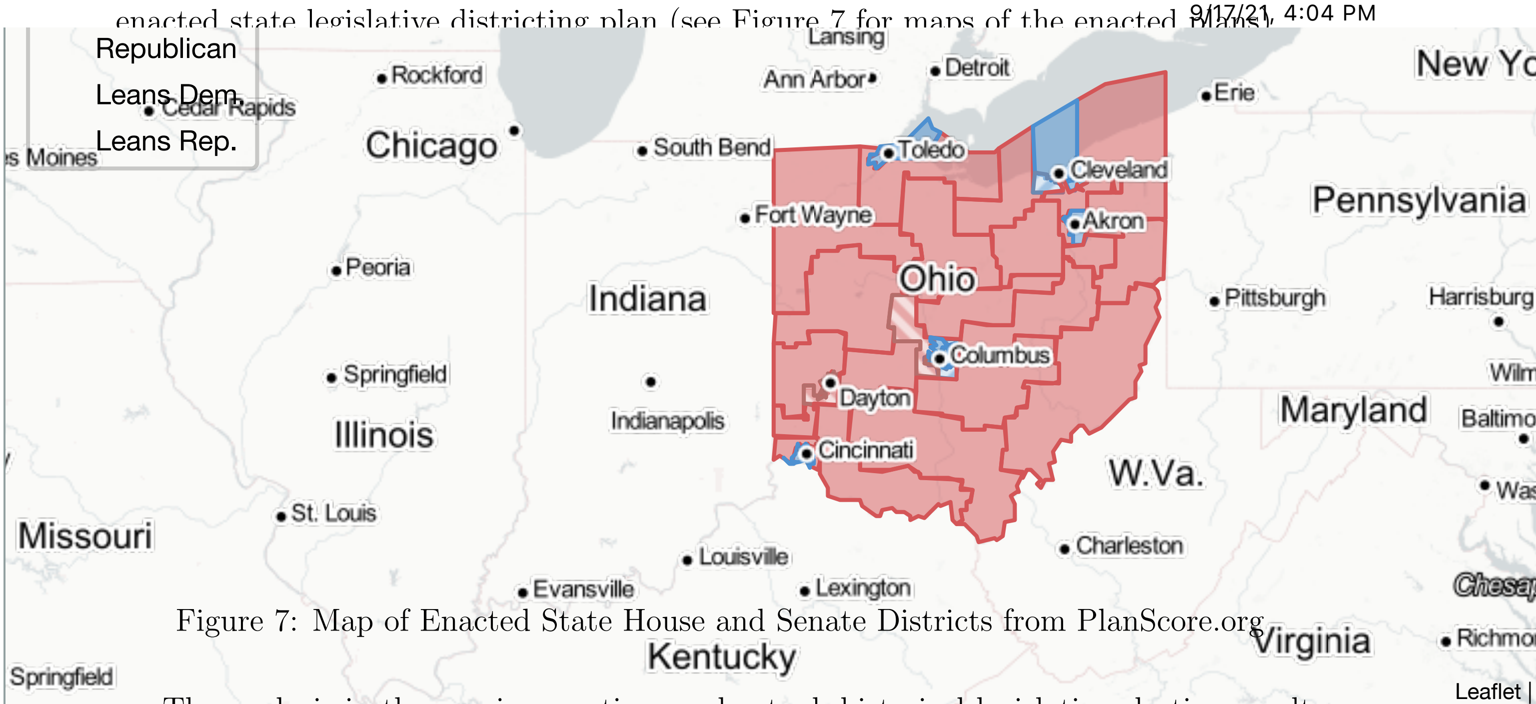

Figure 7: Map of Enacted State House and Senate Districts from PlanScore.org

The analysis in the previous section used actual, historical legislative election results to estimate the partisan fairness of Ohio's past state legislative district plans. In order to evaluate the enacted plans, however, we need to predict future election results on this map. Unfortunately, there is no way to know, with certainty, the results of future elections. I use two complementary methodologies to predict future legislative elections in Ohio and generate the various metrics I discussed earlier.

First, I use a composite of previous statewide election results between 2012-2020.[26] This approach is based on the approach discussed in Article XI, Section 6 of Ohio's Constitution, which states that the "statewide state and federal partisan general election results during the last ten years" shall be used to determine the proportion of voters supporting each party. I aggregate these election results to estimate the Democratic and Republican vote shares in each district of the enacted state legislative plans.[27] This

District	Candidate Scenario	Pop. 2020	Non-Hisp. Black CVAP 2019	Hispanic CVAP 2019	Non-Hisp. Asian CVAP 2019	Chance of 1+ Flips†	Chance of Democratic Win	Pr Vote
1	Open Seat	350,024	1.2%	4.3%	0.5%	No	<1%	26% D
2	Open Seat	348,100	4.3%	3.8%	1.1%	No	6%	42% D
3	Open Seat	346,752	16.3%	3.0%	2.7%	Yes	69%	53% D
4	Open Seat	368,937	8.5%	2.2%	2.5%	No	3%	37% D
5	Open Seat	361,734	12.8%	1.2%	1.0%	No	1%	35% D
6	Open Seat	362,205	18.8%	1.9%	1.8%	Yes	44%	49% D
7	Open Seat	358,613	4.8%	1.7%	3.5%	No	3%	38% D
8	Open Seat	342,721	16.0%	1.5%	1.6%	No	9%	43% D
9	Open Seat	371,642	39.2%	1.8%	1.5%	No	>99%	70% D
10	Open Seat	347,786	8.2%	2.0%	1.6%	No	20%	47% D
11	Open Seat	342,626	22.7%	6.0%	1.0%	No	94%	59% D

Pop 202
15,49
17,55
14,10
14,50
16,73
15,51
15,17
15,18
20,99
13,23
14,32
13,76

26. These elections include the 2012 Presidential election, the 2012 Senate election, the 2014 gubernatorial election, the 2014 Secretary of State election, the 2016 Presidential election, the 2016 Senate election, the 2018 Senate election, the 2018 gubernatorial election, the 2018 attorney's general election, the 2018 Secretary of State election, the 2018 Auditor election, the 2018 Treasurer, and the 2020 Presidential election. Geographic data on the other three statewide elections in 2014 is not readily available. But this probably doesn't affect my results much since these elections were similar to the average of the 2014 gubernatorial and Secretary of State elections.

27. I weight the composite scores to give each election cycle equal weight in the index.

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approach implicitly assumes that future election results will look like the average of these recent statewide elections.

Second, I evaluate the enacted plans using a more sophisticated, predictive model from the PlanScore.org website. PlanScore uses a statistical model of the relationship between districts' latent partisanship and election outcomes. This enables it to estimate district-level vote shares for a new map and the corresponding partisan gerrymandering metrics.[28] Based on these two approaches, I characterize the bias in Ohio's plan using each of the metrics discussed above. I also place the bias in Ohio's plan into historical perspective.

Both of these approaches indicate that the enacted plan is just as biased, if not even more biased, than the 2012-2020 plan. Moreover, the enacted plan has an extreme level of partisan bias compared to other plans over the past 50 years. Overall, the enacted plan appears to violate both Article XI, Section 6(A) and (B) of Ohio's Constitution. It violates Section 6(A) by appearing to being drawn to favor on political party based on a variety of metrics. It violates Section 6(B) because the two-parties' seat shares do not correspond closely to their vote shares.

6.1 Analysis based on Proportionality Metric

First, I evaluate the enacted plans based on the proportionality metric embedded in the State's Constitution. Table 4 shows the proportionality of the enacted state Senate plans using both the composite of recent statewide elections and the PlanScore predictive model. The top two rows show the results for the current 2012-2020 plan. They indicate that this plan is estimated to lead Democrats to get 13-14% fewer seats than votes. Thus, this plan clearly fails the proportionality test established by Ohio's Constitution. The next two rows show the proportionality of the Commission's enacted map for 2022-2030. This map too is predicted to lead Democrats to get 14-15% fewer seats than votes. Thus, it too fails the proportionality test established by the Constitution.

Plan	Modeling Approach	Dem. Voteshare	Dem. Seatshare	Proportionality Bias	More Biased than % of Plans	More Pro-Rep. than % of Plans
2012-2020 Plan	2012-20 Composite	45%	32%	-13%	68%	86%
2012-2020 Plan	PlanScore	44%	30%	-14%	70%	87%
Commission's Plan	2012-20 Composite	45%	31%	-14%	69%	87%
Commission's Plan	PlanScore	44%	29%	-15%	73%	89%

Table 4: Proportionality metrics for State Senate plan

28. See `https://planscore.campaignlegal.org/models/data/2021B/` for more details.

Figure 5 shows the proportionality for the enacted state House plans. Once again, the top two rows show the results for the current 2012-2020 plan. They indicate that this plan is estimated to lead Democrats to get 12-13% fewer seats than votes. Thus, this plan violates the proportionality requirements set forth in Ohio's Constitution. The next two rows show the proportionality of the Commission's enacted map for 2022-2030. This map too is predicted to lead Democrats to get about 12% fewer seats than votes. As a result, it too fails the proportionality test established by the Constitution.

Plan	Modeling Approach	Dem. Voteshare	Dem. Seatshare	Proportionality Bias	More Biased than % of Plans	More Pro-Rep. than % of Plans
2012-2020 Plan	2012-20 Composite	45%	33%	-12%	68%	88%
2012-2020 Plan	PlanScore	44%	31%	-13%	72%	89%
Commission's Plan	2012-20 Composite	45%	33%	-12%	66%	86%
Commission's Plan	PlanScore	44%	32%	-12%	68%	88%

Table 5: Proportionality metrics for State House plan

6.2 Evaluation using Additional Partisan Bias Metrics

In this section, I evaluate the Commission's enacted plans using the other metrics I discussed earlier (Tables 6 and 7). These metrics further support the conclusion that Ohio's enacted plan violates Article XI, Section 6(A) of Ohio's Constitution because they are drawn to favor a particular political party.

First, I use the composite of previous statewide election results to estimate the various metrics. For the state Senate, the average efficiency gap of the enacted plan based on these previous election results is -9%. This is more extreme than 73% of previous plans and more pro-Republican than 86% of previous plans. The other metrics also show that Ohio's enacted plan has a substantial pro-Republican bias. When we average across all four metrics, the plan is more extreme than 77% of previous plans and more pro-Republican than 86% of previous plans.

For the state House, average efficiency gap of the enacted plan based on these previous election results is -7%. This is more extreme than 65% of previous plans and more pro-Republican than 85% of previous plans. The other metrics also show that Ohio's enacted plan has a large pro-Republican bias. When we average across all four metrics, the plan is more extreme than 75% of previous plans and more pro-Republican than 87% of previous plans.

Next, I use the PlanScore website to evaluate the enacted state legislative plan. PlanScore uses a statistical model to predict the results of each district in the enacted

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Efficiency Gap	-8%	70%	85%
Mean-Median Diff	-3%	68%	76%
Declination	-.40	72%	84%
Symmetry	-12%	92%	94%
Average		76%	85%
Commission's Enacted Plan			
Efficiency Gap	-9%	73%	86%
Mean-Median Diff	-4%	71%	78%
Declination	-.44	75%	86%
Symmetry	-11%	88%	92%
Average		77%	86%

Table 6: Additional partisan bias metrics for State Senate plan based on composite election results

Metric	Value	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan			
Efficiency Gap	-7%	70%	88%
Mean-Median Diff	-4%	75%	83%
Declination	-0.58	86%	93%
Symmetry	-9%	82%	88%
Average		78%	88%
Commission's Enacted Plan			
Efficiency Gap	-7%	65%	85%
Mean-Median Diff	-3%	61%	77%
Declination	-.50	82%	91%
Symmetry	-11%	91%	94%
Average		75%	87%

Table 7: Composite partisan bias metrics for State House plan

plan based on relationship between past legislative elections over the past decade and recent presidential election results.[29] It then calculates various partisan bias metrics. In this case, PlanScore provides estimates of the efficiency gap and declination.[30]

The efficiency gap and declination metrics estimated by PlanScore are very similar to my estimates based on a composite of recent election results. Across these two metrics, the enacted state Senate plan favors Republicans in 99% of PlanScore's scenarios (Table

29. The model is described in more detail on this web page: `https://planscore.campaignlegal.org/models/data/2021B/`.

30. The partisan symmetry and mean-median difference scores are only shown when the parties' statewide vote shares fall between 45% and 55% because outside this range the metrics' assumptions are less plausible (McGhee 2017, 9). In the PlanScore model, the Democrats' two-party vote share is just below 45%.

8).[31] It is more extreme than 80% of previous plans and more pro-Republican than 91% of previous plans.

Metric	Value	Favors Rep's in this % of Scenarios	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan				
Efficiency Gap	-8%	97%	72%	85%
Declination	-.38	99%	75%	87%
Average		98%	74%	86%
Commission's Enacted Plan				
Efficiency Gap	-9%	98%	80%	92%
Declination	-.46	99%	80%	90%
Average		99%	80%	91%

Table 8: PlanScore partisan bias metrics for state senate plan

PlanScore indicates that the enacted state House plan also has a substantial pro-Republican bias. The state House plan favors Republicans in 98% of the scenarios estimated by PlanScore (Table 9).[32] Moreover, it is more extreme than 75% of previous plans and more pro-Republican than 90% of previous plans.

Metric	Value	Favors Rep's in this % of Scenarios	More Biased than this % Historical Plans	More Pro-Republican than this % Historical Plans
2012-2020 Plan				
Efficiency Gap	-8%	97%	75%	91%
Declination	-.54	99%	87%	95%
Average		98%	81%	93%
Commission's Enacted Plan				
Efficiency Gap	-6.5%	97%	68%	90%
Declination	-.47	99%	81%	90%
Average		98%	75%	90%

Table 9: PlanScore partisan bias metrics for state house plan

31. See `https://planscore.campaignlegal.org/plan.html?20210917T195933.527730209Z`
32. See `https://planscore.campaignlegal.org/plan.html?20210917T195948.683202507Z`

6.3 The Responsiveness of Ohio's Enacted State Legislative Plan to Changes in Voters' Preferences

As I discussed earlier, the responsiveness of a map indicates how many seats change hands as vote shares rise and fall. An unresponsive map ensures that the bias in a districting plan toward the advantaged party is insulated against changes in voters' preferences, and thus is durable across multiple election cycles. In addition to serving as an indicator of the durability of a gerrymander, some scholars have suggested that responsiveness is another metric to measure gerrymandering itself (Cox and Katz 1999). There are a couple of approaches we might use to measure the responsiveness of a districting plan.

I evaluate the responsiveness based on the number of competitive districts. I use slightly different approaches to define a competitive district in the composite election results and the PlanScore predictive model. In the composite election results, I define it based on whether the winning party received less than 55% of the two-party vote (Jacobson and Carson 2015, 91). In the PlanScore results, I define it based on whether there is at least a 50% probability that each party will win a district over a decade-long redistricting cycle.[33] I find that the Commission's enacted plans lead to a small number of competitive districts. In both plans, approximately 20% of the districts would be competitive.

	2012-20 Composite	**PlanScore**
2012-2020 Plan	18%	21%
Commission's Enacted Plan	16%	21%

Table 10: Competitiveness metrics for State Senate plan

	2012-20 Composite	**PlanScore**
2012-2020 Plan	17%	22%
Commission's Enacted Plan	18%	21%

Table 11: Competitiveness metrics for State House plan

33. In general, however, these definitions are similar. There is roughly a 50% probability that each party will win a district over a decade-long redistricting cycle when the expected two-party vote share is between 45-55%.

7 Partisan Gerrymandering & Representation in State Government

In the previous section, I have shown that Ohio's enacted districting plans is likely to lead to a substantial partisan advantage for Republicans in state legislative elections. Now, I turn to the effects of this partisan advantage for the representation that citizens of Ohio receive in state government. A bias in the translation of votes to seats diminishes the ability of voters in Ohio to elect representatives of their choice. Specifically, it reduces the representation of Democratic voters. The polarization in state legislatures means that representatives in state legislatures nearly always vote the party line. So gerrymandering leads Democrats to be less likely to have their views represented in state government. This means that they have little, if any, voice on important issues in Ohio's state government.

7.1 Polarization in State Legislatures

Earlier, we saw that the Congress has become extremely polarized in recent years. In this section, we will examine polarization in state legislatures over the past two decades.

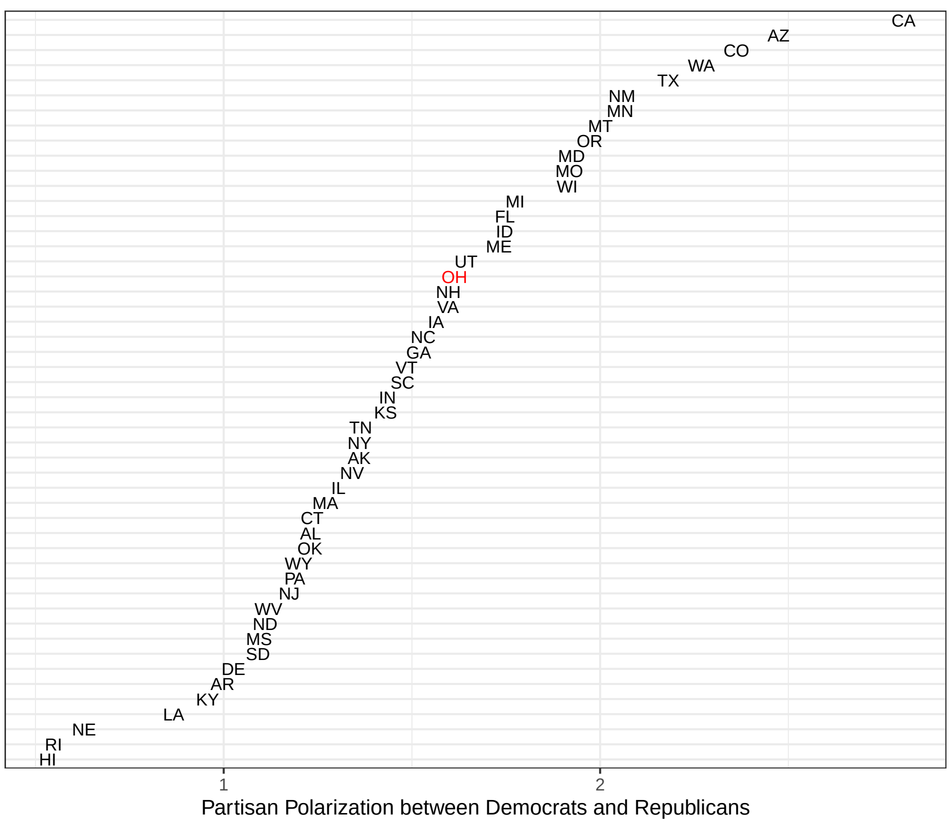

Figure 8: Polarization in Lower State Legislative Chambers in each State from 2001-2018.

Although an individual state legislator may cast hundreds or even thousands of roll call votes, their voting behavior can usually be parsimoniously summarized in terms of a single left–right score, their estimated ideology (Shor and McCarty 2011; Poole and Rosenthal 1997). Using roll-call records from all fifty state legislatures, Shor and McCarty (2011) have estimated the ideology of the members of every state legislature in each session between 1995 and 2018.[34] These estimated ideology scores summarize the ideological differences between different legislators, as expressed in their roll-call votes for and against legislative proposals.

Figure 8 (above) shows that state legislatures have become quite polarized in recent years. This chart shows the difference between the ideology scores of the median Democratic and Republican in each state's lower legislative chamber from 2001-2018. It indicates that the median Republican is over one standard deviation more conservative than the median Democrat in nearly every state legislature. This is even true of legislators that represent similar, or even identical, constituencies (Shor and McCarty 2011; Fowler and Hall 2017; Caughey, Tausanovitch, and Warshaw 2017).

In Ohio, the median Republican is about 1.5 standard deviations more conservative than the median Democrat. Figure 9 shows the average ideology of Democrats and Republicans in the Ohio state house over the past 20 years. It also shows the ideology of every individual member. This figure indicates that there is a large difference between the roll call voting patterns of Democrats and Republicans in Ohio. Moreover, Republican state legislators in Ohio are always more conservative than Democratic state legislators.

34. Shor and McCarty (2011) use data from the National Political Awareness Test, a survey of legislators run by Project Vote Smart, in order to make comparisons between legislators across different states. Each legislator is assigned an ideology score based on all roll call votes using a statistical model that takes advantage of the similarities between the coalitions that emerge on different votes, rather than by subjective judgements of the individual votes.

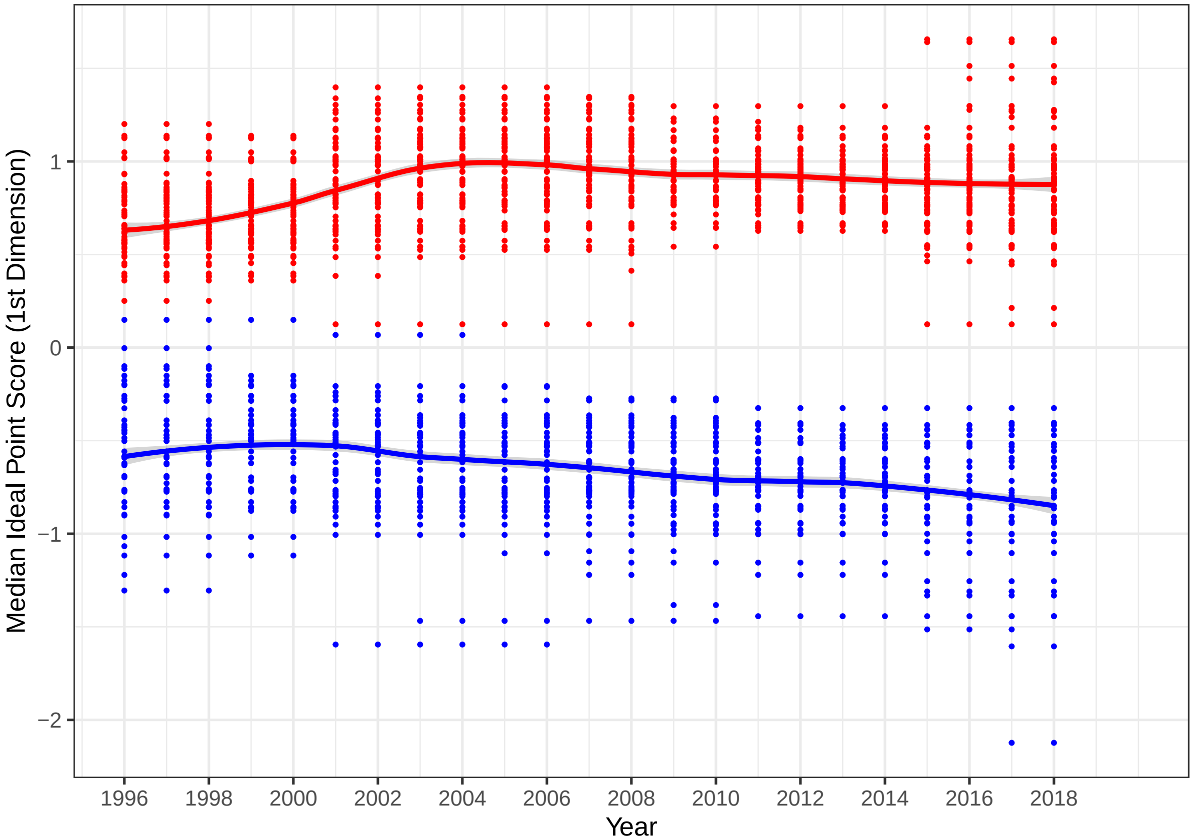

Figure 9: Average Ideology of Dem.'s and Rep's in Ohio State House

7.2 Gerrymandering and Roll Call Voting in State Legislatures

We know that partisan advantages in the translation of votes to seats give one party a larger seat share than they would have received without any advantage in the efficiency gap.[35] We also know that Republicans take much more conservative roll call positions than Democrats in state legislatures (Shor and McCarty 2011). Putting these facts together leads to the clear expectation that changes in the partisan bias of a districting plan should lead to changes in the position of the median voter in state legislatures. But the magnitude of changes in the position of the median voter is not clear *a priori*. This depends on whether additional members of the majority party tend to be moderate (because they are winning closer districts) or typical for their party (when parties are polarized). As the seat share of the majority party grows, the median voter will be closer to the center of the majority party. At the same time, the center itself may be moving depending on the positions of the new members.

35. This section is adapted from a peer-reviewed paper published in the *Election Law Journal* that I wrote with several co-authors (Caughey, Tausanovitch, and Warshaw 2017).

Table 12: The Effect of the Efficiency Gap on the Median Ideology in State Lower Chambers

	Dependent variable:	
	Median Ideology in State House	
	(1)	(2)
Efficiency Gap_{t-1}	-0.038^{***}	-0.038^{***}
	(0.007)	(0.007)
Republican Presidential Share		0.032^{***}
		(0.008)
Lagged Outcome	0.382^{***}	0.333^{***}
	(0.080)	(0.081)
Constant	0.805^{***}	2.244^{***}
	(0.191)	(0.360)
Year FEs	X	X
State FEs	X	X
Lagged Outcome Variable	X	X
Observations	339	339
R^2	0.859	0.869
Adjusted R^2	0.832	0.843
Note:	*p<0.1; **p<0.05; ***p<0.01	

In my published work, I have shown that a pro-Republican bias in the efficiency gap leads to more conservative median ideology scores of state legislators in lower chambers (Caughey, Tausanovitch, and Warshaw 2017; Caughey and Warshaw 2022). I reproduce that analysis here in Table 12 using the Efficiency Gap measures developed for this report and the ideology measures of state legislators developed by Shor and McCarty (2011).[36] The first column shows the results of a model that include fixed effects (FEs) for state as well as year and a lagged outcome variable. The second column adds a control for the results of most recent presidential election.[37] The estimates indicate that state-years in which the efficiency gap was more pro-Republican than average for that state also

36. Note that I obtain similar substantive findings using the mean-median and declination measures in this analysis as well as in the analysis in the next section on the effect of gerrymandering on state policy.

37. These specifications capture the relationship between the efficiency gap and legislative roll call voting patterns within states net of national trends, eliminating the influence of time-invariant state-specific confounders. It also includes a lagged outcome variable to control for states' recent policy history. In column (2), we add the Republican presidential vote in the previous presidential election. This controls for variation in the position of the median voter in the state. Not surprisingly, we find that states that are more Republican in presidential elections also have a more conservative state house. The effect of the efficiency gap, however, is essentially identical here to the model in column (2).

tended to have more conservative roll call voting behavior in the state house. Across both regression specifications, a one percentage point pro-Republican shift in the efficiency gap moves the median ideology scores in the state house 0.04 standard deviations to the right. These estimates suggest, for example, that the median ideology of the Ohio state house, which had about a 10% pro-Republican efficiency gap in 2012, would shift nearly half a standard deviation to the left if it adopted a districting plan with no efficiency advantage for either party.

7.3 The Efficiency Gap and Policy Outputs in State Legislatures

Next, I examine the effect of the efficiency gap on state policy conservatism. In my published work, co-authors and I have shown that the partisan composition of state legislatures has an important effect on policy (Caughey, Xu, and Warshaw 2017; Caughey and Warshaw 2022). I have also shown that partisan bias in districting can skew policy in favor of the advantaged party (Caughey, Tausanovitch, and Warshaw 2017; Caughey and Warshaw 2022).

Table 13: The Effect of the Efficiency Gap on State Policy Conservatism, 1972-2014

	Dependent variable:	
	State Policy Conservatism	
	(1)	(2)
Efficiency Gap_{t-1}	-0.003***	-0.003***
	(0.001)	(0.001)
Republican Governor_{t-1}	0.022**	0.023***
	(0.009)	(0.008)
Republican Presidential Share		−0.005***
		(0.001)
Lagged Outcome	0.933***	0.904***
	(0.019)	(0.021)
Year FEs	X	X
State FEs	X	X
Lagged Outcome Variable	X	X
Observations	814	814
R^2	0.991	0.992
Adjusted R^2	0.991	0.991
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 13 reproduces these results using regression specifications analogous to those in

Table 12. It indicates that a one percentage point pro-Republican shift in the efficiency gap increases state policy conservatism by 0.003 standard deviations. This means that a 10 percentage point increase in the efficiency gap would increase policy conservatism by 0.03 standard deviations, which is equivalent to about a percentage point increase in the percentage of conservative policies in a state. This effect is similar to the effect of a shift of one percentage point in the composition of the vote for president (column 2) and is larger than the effect of a governor's partisanship.

7.4 Summary of Gerrymandering & Representation in State Government

Overall, the analyses in this section show that partisan bias in districting plans has large consequences for state government. States with pro-Republican bias in their districting plans have 1) more conservative state legislatures and 2) more conservative policy outcomes (and conversely for states with pro-Democratic districting plans).

8 Conclusion

Overall, there is a substantial and durable Republican bias in the translation of votes to seats in the enacted state legislative plans in Ohio.

- <u>The statewide proportion of districts whose voters favor each political party in Ohio's enacted state legislative districting plans do not correspond closely to the statewide preferences of the voters of Ohio.</u> Based on a variety of different analyses, I find that Republicans are likely to get a much larger share of the seats in the enacted maps than their share of the statewide vote.

- <u>The plans appear to be drawn to favor the Republican Party.</u> Based on a variety of metrics, the pro-Republican bias in Ohio's state legislative districting plans is very large relative to other states over the past 50 years. The pro-Republican bias in Ohio's plan cannot solely be a function of geography. This suggests that the plan was drawn to favor legislative candidates from the Republican Party.

- <u>The pro-Republican advantage in state legislative elections in Ohio causes Democratic voters whose votes are wasted to be effectively shut out of the political process.</u> Due to the growing polarization in Congress and state legislatures, there is a large difference between the roll call voting behavior of Democrats and Republicans. A representative from one party increasingly does not represent the views of a constituent of the opposite party. Thus, Democratic voters whose votes are wasted are unlikely to see their preferences represented by policymakers.

References

Best, Robin E, Shawn J Donahue, Jonathan Krasno, Daniel B Magleby, and Michael D McDonald. 2017. "Considering the Prospects for Establishing a Packing Gerrymandering Standard." *Election Law Journal: Rules, Politics, and Policy.*

Brace, Kimball, Bernard Grofman, and Lisa Handley. 1987. "Does Redistricting Aimed to Help Blacks Necessarily Help Republicans?" *Journal of Politics* 49 (1): 169–185.

Brennan Center. 2017. *Extreme Maps.* `https://www.brennancenter.org/publication/extreme-maps`.

Buzas, Jeffrey S, and Gregory S Warrington. 2021. "Simulated packing and cracking." *Election Law Journal: Rules, Politics, and Policy.*

Campagna, Janet, and Bernard Grofman. 1990. "Party control and partisan bias in 1980s congressional redistricting." *The Journal of Politics* 52 (4): 1242–1257.

Caughey, Devin, Chris Tausanovitch, and Christopher Warshaw. 2017. "Partisan Gerrymandering and the Political Process: Effects on Roll-Call Voting and State Policies." *Election Law Journal* 16 (4).

Caughey, Devin, and Christopher Warshaw. 2016. "The Dynamics of State Policy Liberalism, 1936–2014." *American Journal of Political Science* 60 (4): 899–913.

———. 2022. *Dynamic Democracy: Citizens, Politicians, and Policymaking in the American States.* University of Chicago Press.

Caughey, Devin, Yiqing Xu, and Christopher Warshaw. 2017. "Incremental democracy: The policy effects of partisan control of state government." *The Journal of Politics* 79 (4): 1342–1358.

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

Cox, Gary W., and Jonathan N. Katz. 1999. "The reapportionment revolution and bias in US congressional elections." *American Journal of Political Science:* 812–841.

———. 2002. *Elbridge Gerry's Salamander: The Electoral Consequences of the Reapportionment Revolution.* New York: Cambridge University Press.

Dunham, James, Devin Caughey, and Christopher Warshaw. 2016. *dgo: Dynamic Estimation of Group-Level Opinion. R package version 0.2.3.* https://jamesdunham.github.io/dgo/.

Fowler, Anthony, and Andrew Hall. 2017. "Long Term Consequences of Elections." *British Journal of Political Science* 47 (2): 351–372.

Gelman, Andrew, and Gary King. 1994a. "A unified method of evaluating electoral systems and redistricting plans." *American Journal of Political Science* 38 (2): 514–554.

———. 1994b. "Enhancing Democracy Through Legislative Redistricting." *American Political Science Review* 88 (03): 541–559.

ICPSR. 2006. *State Legislative Election Returns in the United States, 1968-1989.*

Jackman, Simon. 2015. *Assessing the Current Wisconsin State Legislative Districting Plan.* Expert Analysis by Political Scientist, Stanford, CA: Stanford University.

———. 2017. *Assessing the Current North Carolina Congressional Districting Plan.* Expert Analysis by Political Scientist, Stanford, CA: Stanford University.

Jacobson, Gary C. 2015. "It's nothing personal: The decline of the incumbency advantage in US House elections." *The Journal of Politics* 77 (3): 861–873.

Jacobson, Gary C, and Jamie L Carson. 2015. *The politics of congressional elections.* Rowman & Littlefield.

Kastellec, Jonathan P, Andrew Gelman, and Jamie P Chandler. 2008. "Predicting and dissecting the seats-votes curve in the 2006 US House election." *PS: Political Science & Politics* 41 (1): 139–145.

Katz, Jonathan N, Gary King, and Elizabeth Rosenblatt. 2020. "Theoretical foundations and empirical evaluations of partisan fairness in district-based democracies." *American Political Science Review* 114 (1): 164–178.

King, Gary, and Andrew Gelman. 1991. "Systemic consequences of incumbency advantage in US House elections." *American Journal of Political Science:* 110–138.

Klarner, Carl, William Berry, Thomas Carsey, Malcolm Jewell, Richard Niemi, Lynda Powell, and James Snyder. 2013. *State Legislative Election Returns (1967–2010).* ICPSR34297-v1. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2013-01-11. doi:10.3886/ICPSR34297.v1.

Kollman, K., A. Hicken, D. Caramani, D. Backer, and D. Lublin. 2017. *Constituency-level elections archive [data file and codebook].* Ann Arbor, MI: Center for Political Studies, University of Michigan.

Krasno, Jonathan S, Daniel Magleby, Michael D McDonald, Shawn Donahue, and Robin E Best. 2018. "Can Gerrymanders Be Detected? An Examination of Wisconsin's State Assembly." *American Politics Research.*

McDonald, Michael P. 2014. "Presidential vote within state legislative districts." *State Politics & Policy Quarterly* 14 (2): 196–204.

McGhee, Eric. 2014. "Measuring Partisan Bias in Single-Member District Electoral Systems." *Legislative Studies Quarterly* 39 (1): 55–85.

———. 2017. "Measuring Efficiency in Redistricting." *Election Law Journal: Rules, Politics, and Policy.*

———. 2018. *Assessing California's Redistricting Commission: Effects on Partisan Fairness and Competitiveness.* Report from the Public Policy Institute of California. Available at `http://www.ppic.org/publication/assessing-californias-redistricting-commission-effects-on-partisan-fairness-and-competitiveness/`.

MIT Election and Data Science Lab. 2017. *U.S. House 1976–2016.* Available on the Harvard Dataverse at `http://dx.doi.org/10.7910/DVN/IG0UN2`.

Nagle, John F. 2015. "Measures of partisan bias for legislating fair elections." *Election Law Journal* 14 (4): 346–360.

Niemi, Richard G, and John Deegan. 1978. "A theory of political districting." *American Political Science Review* 72 (4): 1304–1323.

Poole, Keith T., and Howard Rosenthal. 1997. *Congress: A Political-Economic History of Roll Call Voting.* New York: Oxford UP.

Powell, G. Bingham, Jr. 2004. "Political Representation in Comparative Politics." *Annual Review of Political Science* 7:273–296.

Rogers, Steven. 2017. "Electoral Accountability for State Legislative Roll Calls and Ideological Representation." *American Political Science Review* 111 (3): 555–571.

Royden, Laura, Michael Li, and Yurij Rudensky. 2018. *Extreme Gerrymandering & the 2018 Midterm.*

Shor, Boris, and Nolan McCarty. 2011. "The Ideological Mapping of American Legislatures." *American Political Science Review* 105 (3): 530–551.

Stephanopoulos, Nicholas. 2018. "The Causes and Consequences of Gerrymandering." *William and Mary Law Review* 59.

Stephanopoulos, Nicholas O, and Christopher Warshaw. 2020. "The impact of partisan gerrymandering on political parties." *Legislative Studies Quarterly* 45 (4): 609–643.

Stephanopoulos, Nicholas O., and Eric M. McGhee. 2015. "Partisan Gerrymandering and the Efficiency Gap." *University of Chicago Law Review* 82 (2): 831–900.

———. 2018. "The measure of a metric: The debate over quantifying partisan gerrymandering." *Stan. L. Rev.* 70:1503.

Tufte, Edward R. 1973. "The relationship between seats and votes in two-party systems." *American Political Science Review* 67 (2): 540–554.

Wang, Samuel. 2016. "Three Tests for Practical Evaluation of Partisan Gerrymandering." *Stan. L. Rev.* 68:1263–1597.

Warrington, Gregory S. 2018a. "Introduction to the declination function for gerrymanders." *arXiv preprint arXiv:1803.04799.*

———. 2018b. "Quantifying Gerrymandering Using the Vote Distribution." *Election Law Journal* 17 (1): 39–57.

Wright, Gerald, Tracy Osborn, Jon Winburn, and Jennifer Hayes Clark. 2009. "Patterns of representation in the American states and Congress." In *annual conference on State Politics and Policy, Chapel Hill, NC.*

Supplementary Appendix

A Measurement Model for Uncontested Races

A factor that complicates the computation of the Efficiency Gap (as well as any other measure of partisan bias) is that many seats are uncontested. As Stephanopoulos and McGhee (2015, 865) put it, "Since gerrymanders redistribute voters in order to pack and crack the opposition, determining the degree of packing and cracking requires knowing how many people in each district support each party."[38] In uncontested races, however, it is not possible to calculate a two-party vote share. Thus, we have no way of knowing based on the election returns alone how many people supported each party.

As a result, we need some strategy to impute the two-party vote shares in these districts in order to estimate the Efficiency Gap. There are a variety of potential approaches to address this problem. The simplest strategy is to simply assume that the winning candidate receives 75% of the vote and the losing candidate receives 25% of the vote. Many political science studies have adopted this approach (e.g., Gelman and King 1994a; Kastellec, Gelman, and Chandler 2008).[39] However, Kastellec, Gelman, and Chandler (2008) point out that "there is no way to know whether the losing candidate would have actually received 25% of the vote. For example, in a heavily Democratic district in Philadelphia, this probably over-estimates the vote share a Republican candidate would have gotten. In contrast, it might under-estimate the Republican vote share in a more suburban, swing district."

A more sophisticated strategy to address uncontested races is to estimate the two-party vote share in district$_i$ based on previous and future elections in that district as well as the results in similar districts elsewhere. A variety of recent analyses have used this approach. The Brennan Center's recent report uses a variant of this approach for its estimates of Efficiency Gaps between 1992-2016 (Brennan Center 2017, 16).[40] This

38. A variety of other scholars have noted this problem. For instance, Campagna and Grofman (1990, 1247) note that "One key issue [for studies of redistricting] is how to handle uncontested seats. [One needs] to avoid using 100% as the vote share for a party in an uncontested seat (which, for Congress, tends to bloat ... vote share)."

39. Kastellec, Gelman, and Chandler (2008) justify this strategy by noting that King and Gelman (1991) and Gelman and King (1994a) examined the "vote shares received in the last election before a district became uncontested and the first election after a district became uncontested. The average of these values was about 0.75 for the incumbent party and represents the average 'effective support' for the party in uncontested races."

40. Brennan Center (2017, 16) states that 'For districts without both a Democrat and Republican running in the general election, we estimated the vote share both parties would have received in a contested two-party election based on the prior election's House results, the most recent district-level

strategy is also used by the Public Policy Institute of California for its estimates of the Efficiency Gap over the last decade (McGhee 2018), and by Professor Simon Jackman in his expert reports for litigation in Wisconsin and North Carolina (Jackman 2015, 2017). One downside of this approach, however, is that it relies on less transparent assumptions than the simpler strategy described above.

Unfortunately, there are no publicly available, published estimates of the Efficiency Gap that span the past four decades for all three legislative chambers, including congressional, state house, and state senate districts. As a result, I build my own estimates using both approaches described above for imputing uncontested districts. That is, I build one set of Efficiency Gap estimates based on the assumption that the winning party receives 75% of the vote in uncontested districts and another version using a model that imputes the vote shares in uncontested districts based on previous and future elections in that district as well as the results in similar districts elsewhere. I use the latter estimates in the main body of the report. But it is important to note that the substantive results in the report are robust to the precise details of how we calculate the Efficiency Gap.

A.1 Overview of Data

A.1.1 Congressional Districts

For congressional districts, the foundation of my analysis was congressional election results from 1972-2018 collected by the Constituency-Level Elections Archive (CLEA) (Kollman et al. 2017). The results from 1972-1990 are based on data collected and maintained by the Inter-university Consortium for Political and Social Research (ICPSR) and adjusted by CLEA. The data from 1992-2018 are based on data collected by CLEA from the Office of the Clerk at the House of the Representatives. I supplemented this dataset with election results collected by the MIT Election and Data Science Lab (MIT Election and Data Science Lab 2017). I used data on presidential election returns and incumbency status in Congressional elections collected by Professor Gary Jacobson (University of California, San Diego). This dataset has been used in many Political Science studies and has canonical status in the political science profession (Jacobson 2015). I group elections by decade and estimate the Efficiency Gap for each state's plan in each election year.

Presidential results using totals calculated and compiled by Daily Kos Elections for both 2012 and 2016, a district's Cook Partisan Voter Index, and the winning candidate's incumbency status."

A.1.2 State Legislative Districts

For state legislative districts, the foundation for my analysis was a large canonical data set on candidacies and results in state legislative elections from 1972-2018 collected by Carl Klarner and a large team of collaborators. The results from 1972-2012 are based on data maintained by the Inter-university Consortium for Political and Social Research (ICPSR) (Klarner et al. 2013). I obtained data from 2013-2018 directly from Klarner. I obtained Ohio's returns in 2020 directly from the state government's website.

I used a variety of sources of data on presidential election returns in state legislative districts. For elections between 1972 and 1991, I used data on county-level election returns from 1972-1988 collected by the Inter-university Consortium for Political and Social Research (ICPSR 2006) and mapped these returns to state legislative districts in order to estimate presidential, senate, and governor election results by state legislative district. For elections between 1992 and 2001, I used data on presidential election returns in the 2000 election collected by McDonald (2014) and Wright et al. (2009). For elections between 2002 and 2011, I used data on the 2004 and 2008 presidential elections collected by Rogers (2017). For elections between 2012 and 2018, I used data on presidential election returns for the 2012 and 2016 elections from the DailyKos website.

I group each state's elections based on its redistricting plan using data from Carl Klarner. In most cases, redistricting plans are constant over the course of a decade. However, a handful of states have redistricted mid-decade for various reasons. In general, I drop these states from my analysis. I also drop state legislative elections from my analysis where I am unable to match to data on presidential vote share. I also drop state senate elections in the first cycle after a redistricting from my analysis because it is not clear whether each district in the chamber is using the post-redistricting map.

Many state legislative elections are conducted in multimember districts. Previous studies have dropped the bulk of these districts from their analyses (e.g., Jackman 2015). However, I include multimember districts in my analysis of the Efficiency Gap in state legislative elections. For multimember districts with posts, I treat each post as if it's a separate district. For multimember systems without posts, I match each winner with a maximum of one loser of the opposite party, and assume that they ran against each other in a post election. Specifically, I match the worst-performing winner with the best-performing loser of the opposite party, and then the next-worst performing winner with the second-best performing loser of the opposite party, etc. If there are more winners than losers, then there will be some "uncontested" races.

Finally, if only a portion of a state legislative chambers were elected in a particular year, I group these elections with the most recent previous election in each district in

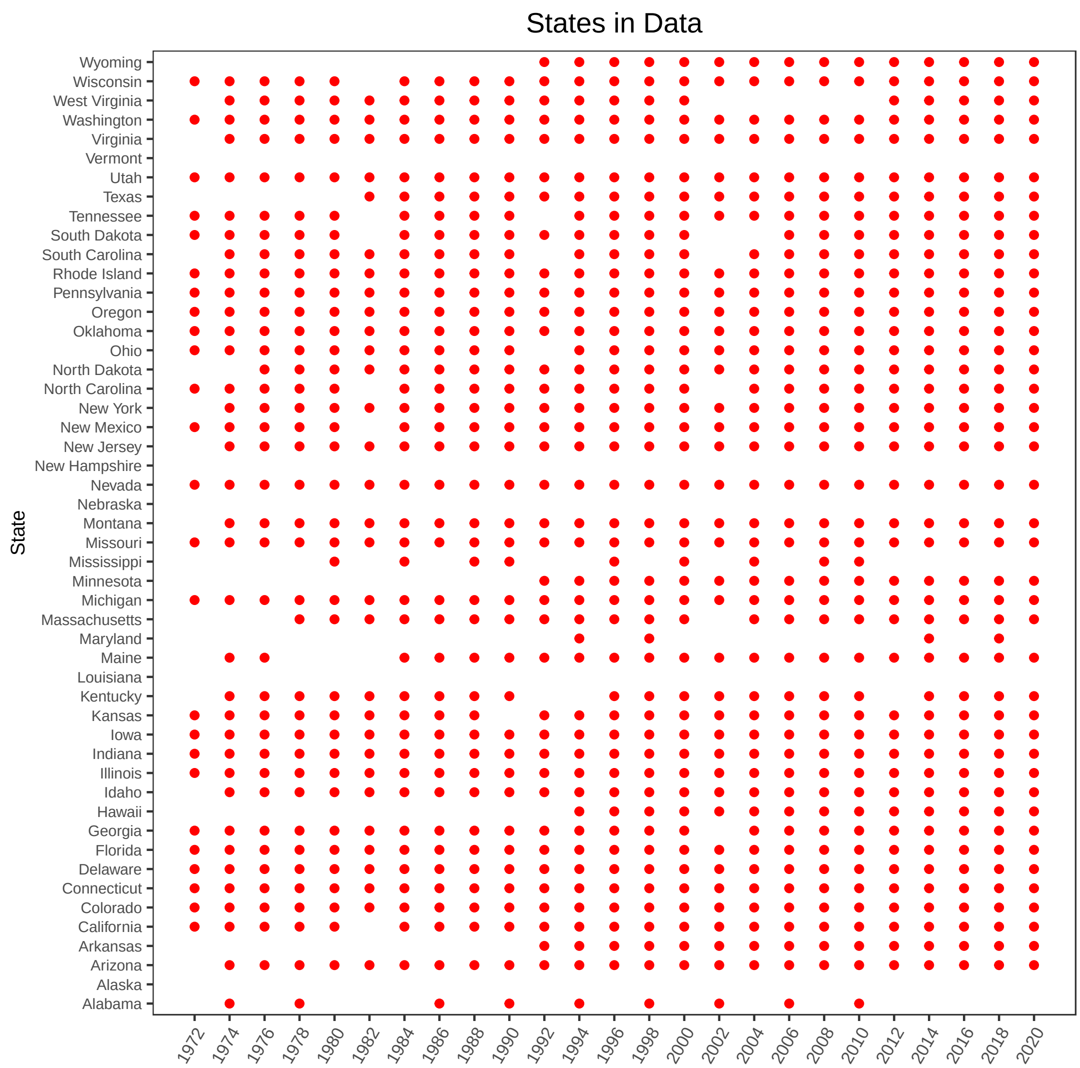

Figure A1: States and election cycles where I estimate the Efficiency Gap in State House Districts.

order to calculate each party's seat share, vote share, the number of wasted votes, the Efficiency Gap, and other statistics.

Figure A1 (above) shows the states and election cycles where I estimate an efficiency gap for state house districts. Overall, I have estimated the Efficiency Gap for 896 of the 1123 (80%) state house election years in partisan legislatures between 1972 and 2016.[41] This is substantially more than previous analyses of gerrymandering in state legislatures using the Efficiency Gap (e.g., Stephanopoulos and McGhee 2015; Jackman 2015).

41. I have dropped state-years for the following reasons. First, I drop state-years where I am unable to match presidential election results to state legislative districts. Second, I drop state-years that precede a mid-decade redistricting.

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A.2 Details of Statistical Models

This section presents the details of the statistical models that I use to impute uncontested races.

1. First, I estimate the Efficiency Gap assuming that the winner in uncontested races receives 75% of the vote and the loser receives 25% of the vote. I estimate the statewide Democratic vote share by assuming that turnout in each district was equal and simply taking the average of the two-party vote shares in each district.

2. Second, I estimate the Efficiency Gap using a statistical model to impute both the vote share and turnout in uncontested districts. This model is closely related to the imputation strategy for uncontested districts adopted by previous studies of the Efficiency Gap (Stephanopoulos and McGhee 2015; Jackman 2015, 2017; Brennan Center 2017; McGhee 2018).

    - In order to estimate the vote shares in uncontested districts, I model the proportion of the two-party vote received by the Democrat ($p_{d,t}$) in each district (d) using a binomial model.

    $$s^v_{d,t} \sim \text{Binomial}(n^v_{d,t},\ p^v_{d,t}), \tag{4}$$

    where d indexes districts and t indexes elections. $n^v_{d,t}$ is set to 2000[42] and $s^v_{d,t}$ is the two-party vote share multiplied by 2000. For uncontested races, we set $n^v_{d,t}$ and $s^v_{d,t}$ to zero. We then model p as a function of: previous and future results in that district, each district's presidential vote share, whether there is an incumbent running, and if so, their party, and the region (congressional districts) or state (state legislative districts) that the district is in. For state legislative races, I also include the Democrats' vote share in governors and senate races during the 1970s and 1980s as a predictor since state legislative races during this period were less nationalized than in more recent decades. More formally, for congressional districts, we model

    $$p^v_{d,t} = \Phi(\gamma_t + \ p^v_{d,t-1} + \beta_1 * pvote_{d,t} + \beta_2 * incumbency_{d,t} + \alpha^{region}_{s[d]}) \tag{5}$$

42. This number is set for computational efficiency. However, it could be arbitrarily set to some other number, and this would not affect the model results.

where *pvote* is the percentage of the two-party presidential vote received by the Democratic candidate in each district; *incumbency* is a factor equal to 1 if there is a Democratic incumbent, 0 if there is no incumbent, and -1 if there is a Republican incumbent; regions are based on economic regions defined by the Bureau of Economic Advisors; and the normal CDF Φ maps p to the $(0, 1)$ interval. I estimate the model separately each decennial redistricting period (i.e., years ending in 02 - 12) using the `dgmrp` function in the `dgo` package in R (Dunham, Caughey, and Warshaw 2016).[43] The mean estimate of Democratic vote share in uncontested congressional races won by Democrats is 71% and the average estimate of Democratic vote share in uncontested races won by Republicans is 31%.[44]

- In order to estimate the turnout in uncontested congressional districts, I model the proportion of the population ($p_{d,t}$) that votes in each district (d) using a similar binomial model.

$$s^t_{d,t} \sim \text{Binomial}(n^t_{d,t},\ p^t_{d,t}), \tag{6}$$

where $n^t_{d,t}$ is set to 2000 and $s^t_{d,t}$ is the proportion of the population that voted for either the Democratic or Republican candidate multiplied by 2000. For districts with uncontested races, we set $n^t_{d,t}$ and $s^t_{d,t}$ to zero. We then model p as a function of: previous and future results in that district, whether there is an incumbent running, and if so, their party, and the region that the district is in. More formally, we model

$$p^t_{d,t} = \Phi(\gamma_t + \ p^t_{d,t-1} + \beta_1 * incumbency_{d,t} + \alpha^{region}_{s[d]}) \tag{7}$$

where *incumbency* is a factor equal to 1 if there is a Democratic incumbent, 0 if there is no incumbent, and -1 if there is a Republican incumbent; regions are based on economic regions defined by the Bureau of Economic Advisors; and the normal CDF Φ maps p to the $(0, 1)$ interval. I estimate the model separately each decennial redistricting period (i.e., years ending in 02 - 12)

43. Due to data limitations, for both the models of turnout and vote share in congressional elections, I do not split apart states' plans due to mid-decade redistrictings. In recent decades, however, only a handful of states have conducted mid-decade redistrictings. For state legislative districts, I drop elections from districting plans established prior to a mid-decade redistricting.

44. These estimates are very similar to those of Stephanopoulos and McGhee (2015, 866). Based on a similar approach, they estimate a "mean Democratic vote share [in uncontested races] of 70 percent," and for uncontested Republicans, they estimate "a mean Democratic vote share of 32 percent."

using the `dgmrp` function in the `dgo` package in R (Dunham, Caughey, and Warshaw 2016).

- In order to estimate the turnout in uncontested state legislative districts, I take the average of the turnout in district$_d$ in other presidential or midterm years in a given decade. If no data on district$_d$ is available, I take the average of turnout in year$_t$ elsewhere in the state. I use this simpler approach due to the unavailability of population data for state legislative districts.
- Finally, for uncontested congressional and state legislative districts, I estimate the number of Democratic votes in each district by multiplying the estimated, imputed Democratic vote share ($p^v_{d,t}$) by the estimate of the total turnout. For contested districts, I use the actual number of Democratic votes and total votes in each district. Combining these approaches, I estimate the statewide Democratic vote share by simply summing the Democratic votes in each district and dividing by the total number of votes.

Now that we know voters' two-party preferences in contested districts and we have estimates of their preferences in uncontested districts, we are finally in position to estimate the partisan advantage in the congressional and state legislative districting process during each state-year. I estimate the efficiency gap in all states for each election between 1972 to 2016 using equation 3.[45]

In the discussion of congressional districts in the main body of the report, I focus on states with more than 6 congressional seats. I omit smaller states for two reasons. First, these states contribute less to the overall distribution of seats in Congress (Stephanopoulos and McGhee 2015, 868). Second, the Efficiency Gap in smaller states tends to be more volatile and thus less informative about partisan bias. For example, in a state with only three seats, a change in the winner of one seat could cause a huge shift in their Efficiency Gap.

A.3 Validation

Prior to examining our results, it is useful to validate my measures of the Efficiency Gap to make sure that it aligns closely with alternative modeling approaches for uncontested races. In fact, Figure A2 shows that the precise method used to impute uncontested congressional races makes relatively little difference for estimates of the Efficiency Gap.

45. I start the analysis in 1972 since those are the first districting plans drawn after the Supreme Court cases stemming from *Baker v. Carr* ended malapportionment and established the principle of one-person, one-vote.

- The correlation between estimates of the Efficiency Gap for congressional districts I calculated using the Bayesian method described above and a simpler approach that assumes the winner in uncontested races received 75% of the two-party vote is 0.95.

- The correlation between my estimates of the Efficiency Gap for congressional districts and estimates for 1992-2016 developed by the Brennan Center is 0.95.

- The correlation between my estimates of the Efficiency Gap for congressional districts and estimates for 2002-2016 developed by the Public Policy Institute of California is 0.98.

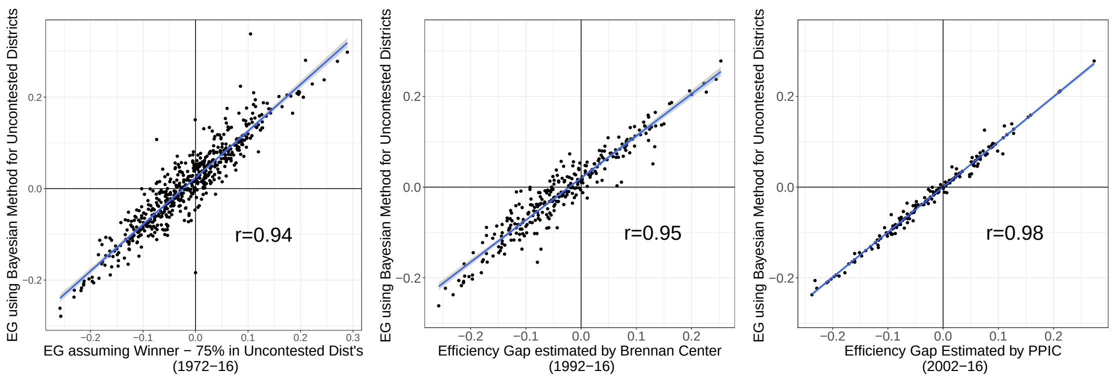

Figure A2: Validation of the Efficiency Gap Measure for Congressional Elections

I also find very high correlations between my estimates of the Efficiency Gap in state house districts and other modeling approaches for estimating the Efficiency Gap.

- The correlation between estimates of the Efficiency Gap for congressional districts I calculated using the Bayesian method described above and a simpler approach that assumes the winner in uncontested races received 75% of the two-party vote is 0.84.

- The correlation between my estimates of the Efficiency Gap for congressional districts and estimates for 1972-2014 developed by Jackman (2015) is 0.91.[46]

- I also find very high correlations between my estimates of the Efficiency Gap and the declination measures discussed in the main body of the report.

46. It is important to note that my methodology for estimating the Efficiency Gap differs from Jackman (2015)'s approach in three relatively minor ways which slightly attenuates the correlation between our measures. First, I adjust for unequal turnout across districts. If I do not adjust for differences in turnout, my Efficiency Gap estimates have a 0.96 correlation with Jackman's estimates. Second, I use presidential vote share as a predictor of state legislative elections throughout the entire time period to estimate uncontested districts. Finally, I include states with multimember districts in my analysis.

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Academic Employment

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Massachusetts Institute of Technology, Cambridge, MA

Associate Professor of Political Science (without tenure), 2016 - 2017

Assistant Professor of Political Science, 2012 - 2016

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Stanford University, Ph.D., Political Science, 2012

Fields: American Politics, Comparative Politics, and Political Methodology (Statistics)

Stanford Law School, Juris Doctorate, 2011

Williams College, B.A., *magna cum laude*, 2002

Research Interests

American Politics, Representation, Elections, Public Opinion, State & Local Politics, Environmental Politics and Policy, Statistical Methodology

Research

Publications

Book

"Dynamic Democracy: Citizens, Politicians, and Policymaking in the American States." Forthcoming. University of Chicago Press. (with Devin Caughey)

Peer Reviewed Articles

24. "The Effect of Television Advertising in United States Elections." Forthcoming. *American Political Science Review*. (with John Sides and Lynn Vavreck).

23. "Using Screeners to Measure Respondent Attention on Self-Administered Surveys: Which Items and How Many?" 2021. *Political Science Research and Methods*. 9(2): 430–437. (with Adam Berinsky, Michele Margolis, and Mike Sances)
22. "The Impact of Partisan Gerrymandering on Political Parties." 2020. *Legislative Studies Quarterly*. 45(4): 609-643. (with Nicholas Stephanopoulos)
21. "Fatalities from COVID-19 are reducing Americans' support for Republicans at every level of federal office." 2020. *Science Advances*. (with Lynn Vavreck and Ryan Baxter-King)
20. "Accountability for the Local Economy at All Levels of Government in United States Elections." 2020. *American Political Science Review*. 114(3): 660-676. (with Justin de Benedictis-Kessner)
19. "Politics in Forgotten Governments: The Partisan Composition of County Legislatures and County Fiscal Policies." 2020. *Journal of Politics*. 82(2): 460-475. (with Justin de Benedictis-Kessner)
18. "On the Representativeness of Primary Electorates." 2020. *British Journal of Political Science*. 50(2): 677-685. (with John Sides, Chris Tausanovitch, and Lynn Vavreck)
17. "Geography, Uncertainty, and Polarization." 2019. *Political Science Research and Methods*. 7(4): 775-794. (with Nolan McCarty, Jonathan Rodden, Boris Shor, and Chris Tausanovitch)
16. "Policy Ideology in European Mass Publics, 1981–2016." 2019. *American Political Science Review*. 113(3): 674-693. (with Devin Caughey and Tom O'Grady).
15. "Does Global Warming Increase Public Concern About Climate Change?" 2019. *Journal of Politics*. 81(2): 686-691. (with Parrish Bergquist)
14. "Local Elections and Representation in the United States." 2019. *Annual Review of Political Science*. 22(1): 461-479.
13. "The Ideological Nationalization of Party Constituencies in the American States". 2018. *Public Choice*. Keith Poole Symposium. 176(1-2): 133-151. (with James Dunham and Devin Caughey)
12. "Policy Preferences and Policy Change: Dynamic Responsiveness in the American States, 1936-2014." 2018. *American Political Science Review*. 112(2): 249-266. (with Devin Caughey)
11. "Does the Ideological Proximity Between Candidates and Voters Affect Voting in U.S. House Elections?" 2018. *Political Behavior*. 40(1): 223-245. (with Chris Tausanovitch)
10. "Partisan Gerrymandering and the Political Process: Effects on Roll-Call Voting and State Policies." *Election Law Journal.* December, 2017. 16(4): 453-469. Symposium on Partisan Gerrymandering and the Efficiency Gap. (with Devin Caughey and Chris Tausanovitch)
9. "Incremental Democracy: The Policy Effects of Partisan Control of State Government." 2017. *Journal of Politics*. 79(4): 1342-1358. (with Devin Caughey and Yiqing Xu)
8. "Renewable energy policy design and framing influences public support in the United States." 2017. *Nature Energy*. 2(17107). (with Leah Stokes)
7. "Estimating Candidates' Political Orientation in a Polarized Congress." 2017. *Political Analysis*. 25(2): 167-187. (with Chris Tausanovitch)
6. "The Dynamics of State Policy Liberalism, 1936-2014." 2016. *American Journal of Political Science*. 60(4): 899-913. (with Devin Caughey)
5. "Mayoral Partisanship and Municipal Fiscal Policy." 2016. *Journal of Politics*. 78(4): 1124-1138. (with Justin de Benedictis-Kessner)

4. "Dynamic Estimation of Latent Opinion Using a Hierarchical Group-Level IRT Model." 2015. *Political Analysis*. 23(2): 197-211. (with Devin Caughey)
3. "Representation in Municipal Government." 2014. *American Political Science Review*. 108(3): 605-641. (with Chris Tausanovitch)
2. "Measuring Constituent Policy Preferences in Congress, State Legislatures and Cities." 2013. *Journal of Politics*. 75(2): 330-342. (with Chris Tausanovitch)
1. "How Should We Measure District-Level Public Opinion on Individual Issues?" 2012. *Journal of Politics*. 74(1): 203-219. (with Jonathan Rodden)

Editor Reviewed Articles in Journals and Law Reviews

4. "A preference for constant costs." 2020. *Nature Climate Change*. News & Views. 10: 978–979
3. "Public Opinion in Subnational Politics." 2019. *Journal of Politics*. 81(1): 352-363. Editor reviewed for Symposium on Subnational Policymaking. (with Devin Caughey)
2. "Spatial variation in messaging effects." 2018. *Nature Climate Change*. News & Views. April, 2018.
1. "Business as Usual? Analyzing the Doctrinal Development of Environmental Standing Doctrine since 1976." 2011. *Harvard Law and Policy Review*. Volume 5.2. (with Gregory Wannier).

Book Chapters

5. "Elections and Parties in Environmental Politics." 2020. *Handbook on U.S. Environmental Policy*. David Konisky, ed. (with Parrish Bergquist)
4. "Latent Constructs in Public Opinion." 2018. *Oxford Handbook on Polling and Polling Methods*. R. Michael Alvarez and Lonna Atkeson, ed. Oxford: Oxford University Press.
3. "The Application of Big Data in Surveys to the Study of Elections, Public Opinion, and Representation." 2016. *Data Analytics in Social Science, Government, and Industry*. R. Michael Alvarez, ed. Cambridge: Cambridge University Press.
2. "The Political Economy of Expropriation and Privatization in the Oil Sector." 2012. *Oil and Governance: State-Owned Enterprises and the World Energy Supply*. David G. Victor, David Hults, and Mark Thurber, eds. Cambridge: Cambridge University Press.
1. "Democratization and Countermajoritarian Institutions: The Role of Power and Constitutional Design In Self-Enforcing Democracy." 2012. *Comparative Constitutional Design*. Cambridge: Cambridge University Press. (with Susan Alberts and Barry R. Weingast).

Policy Reports

1. "Reforming Baltimore's Mayoral Elections." 2020. Abell Foundation Report.
`https://www.abell.org/publications/reforming-baltimores-mayoral-elections`

Articles Under Review

"The Effect of Fox News Channel on U.S. Elections: 2000-2020" (with Elliott Ash, Sergio Galletta, and Matteo Pinna)

"Moderates" (with Anthony Fowler, Seth Hill, Jeff Lewis, Chris Tausanovitch, Lynn Vavreck)

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

Works in Progress

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

"Gerrymandering in Local Governments" (with Laura Royden)

"Partisan Selection in City Councils" (with Justin de Benedictis-Kessner and Dan Jones)

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

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

"The Ideology of State Party Platforms " (with Justin Phillips and Gerald Gamm)

Non-Academic Writing

"Here are six big takeaways from the 2020 elections." *Washington Post*. November 7, 2020. (with Emily Thorson)

"TV ads still win elections. And Democrats are buying a lot more of them." *Washington Post*. October 28, 2020. (with John Sides and Lynn Vavreck)

"How Local Covid Deaths Are Affecting Vote Choice." *New York Times*. July 28, 2020. (with Lynn Vavreck)

"Allowing Only Older Americans to Vote by Mail Leads to Severe Racial Disparities." *Election Law Blog*. July 1, 2020.

"A coronavirus recession would hurt all kinds of Republican candidates – not just Trump." *Washington Post*, Monkey Cage. March 18, 2020. (with Justin de Benedictis-Kessner).

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

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

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

Invited Talks

2020-2021: University of Maryland; Stony Brook University

2019-2020: Princeton; UC Berkeley

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

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

2016-2017: University of Virginia; UCLA

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

2014-2015: Yale; Columbia; Duke

2013-2014: Princeton; Boston University; Rochester University

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

Grants

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

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

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

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

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

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

Software

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

Awards and Honors

OVPR Early Career Scholar at George Washington University, 2019.

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

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

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

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

Phi Beta Kappa, Williams College, 2002

Teaching Experience

Instructor:

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

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

Elections (GW), 2018, 2019

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

Public Opinion (GW), 2017

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

Public Opinion and Elections (MIT), 2016

Energy Policy (MIT), 2013

Democracy in America (MIT), 2013, 2014

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

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Teaching Assistant:

Introduction to American Law (Stanford University), 2010

Judicial Politics and Constitutional Law (Stanford University), 2009

Political Economy of Energy Policy (Stanford University), 2008

Introduction to International Relations (Stanford University), 2008

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Graduate Advising

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Massachusetts Institute of Technology:

Leah Stokes (Graduated in 2015, Dissertation committee member)

Krista Loose (2016, Dissertation committee member)

Tom O'Grady (2017, Dissertation committee member)

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

Alex Copulsky (2017, Masters thesis committee member)

James Dunham (2018, Dissertation committee member)

Parrish Bergquist (2018, Dissertation committee member)

Meg Goldberg (2019, Dissertation committee member)

University Service

George Washington University:

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

Coordinator, Graduate Political Science Admissions Committee, 2019-2020

Coordinator, American Politics Workshop, 2018-2020

Member, Methods Exam Committee, 2017-2020

Member, Graduate Political Science Admissions Committee, 2018-2019

Massachusetts Institute of Technology:

Member, Energy Education Task Force, 2012-2017

Parking and Transit Committee, 2013-2017

Member, Graduate Political Science Admissions Committee, 2013-2015

Faculty Fellow, Burchard Scholars, 2013-2015

Stanford University (as graduate student):

President, Stanford Environmental Law Society, 2009-2010

Executive Board Member, Stanford Environmental Law Society 2008-2010

Member, University Committee on Graduate Studies, 2007-2009

Member, University Library Committee, 2007-2008

President, Political Science Graduate Students Association, 2007-2008

Professional Service

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

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

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

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

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

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

Editorial Board, Journal of Politics, 2017-18

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

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

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

Consulting

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

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

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

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

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

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

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

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

Community Service

PlanScore: Leadership Team (2020-2021)

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

Last updated: September 23, 2021

Affidavit of Bill Cooper.pdf

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Created:	September 22, 2021 16:18:02 -8:00
Pages:	7
Remote Notary:	Yes / State: OH

E-Signature Summary

E-Signature 1: William S.Cooper (WSC)
September 22, 2021 16:37:36 -8:00 [C0B37E35774A] [76.77.160.155]
bcooper@msn.com (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
September 22, 2021 16:37:36 -8:00 [DF9F5EAE7674] [23.28.168.121]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

EXPERT_0060

AFFIDAVIT OF WILLIAM S. COOPER

STATE OF OHIO)

) SS:

COUNTY OF FRANKLIN)

Affiant William S. Cooper, having been first duly cautioned and sworn, deposes and states as follows:

I am over the age of 18 and fully competent to testify to the statements and facts contained herein, and I have personal knowledge of all of them.

A. Redistricting Experience

1. I have a B.A. in Economics from Davidson College. As a private consultant, I have been retained as a demographic and redistricting expert for the Plaintiffs. I am compensated at a rate of $150 per hour, and my compensation is not contingent on the outcome of this litigation.

2. I have qualified at trial as an expert witness on redistricting and demographics in approximately 45 voting rights cases litigated in 18 states.

3. One of those lawsuits was *Ohio A. Philip Randolph Institute v. Smith,* in the United States District Court for the Southern District of Ohio. I served as a

redistricting expert for the plaintiffs and was qualified as an expert and testified at trial in March of 2019.

4. Six of those 45 lawsuits resulted in changes to state legislative boundaries that were favorable to the plaintiffs: In the 1990s – *Rural West Tennessee African-American Affairs v. McWherter*; In the 2000s – *Old Person v. Cooney* and *Bone Shirt v. Hazeltine*. In the 2010s – *Alabama Legislative Black Caucus v. Alabama* and *Thomas v. Bryant.* Approximately 30 of the 45 cases led to changes in local election district plans.

5. In the 2010s, I developed nine state legislative plans (Alabama, Connecticut, Florida, Georgia, Kentucky, Mississippi, South Carolina, Texas, and Virginia) and about 150 local redistricting plans – primarily for organizations working to protect minority voting rights. In addition, I prepared congressional plans for clients in nine states (Alabama, Florida, Georgia, Louisiana, Maryland, Ohio, Pennsylvania, South Carolina, and Virginia).

6. I have been retained as expert and consultant by both civil rights plaintiffs and governments.

7. I currently serve as a redistricting consultant to the San Juan County, Utah Commission and the Wenatchee, Washington City Council.

8. For additional historical information on my redistricting experience, see Exhibit A attached to this report.

B. Purpose of Affidavit

9. The attorneys for the plaintiffs in this lawsuit have asked me to analyze partisan balance in the legislative plans (House and Senate) adopted by the Ohio Redistricting Commission ("the Commission") on September 16, 2021.

10. I was also asked by the plaintiffs' attorneys to analyze partisan balance in the final Democratic Caucus House and Senate plans that were submitted to the Commission prior to the September 16, 2021 vote.

11. In addition, the attorneys asked me to examine partisan balance in several legislative plans prepared by Ohio voters[1] in advance of the September 15, 2021 Commission deadline.

B. Methodology

12. For the purpose of this affidavit, I define contemporary partisan balance using a mean average composite Democratic percentage score based on head-to-

[1] I selected four sets of legislative plans prepared by the general public prior to the adoption of the Commission's legislative plans.

Two sets were submitted to the Commission (Tim Clarke) and (Ohio Citizens Redistricting Commission) -- available at: https://www.redistricting.ohio.gov/maps.

Two sets were submitted to the Ohio Fair Districts competition: (Pranav Padmanabhan) and (Paul Nieves) -- available at: https://www.fairdistrictsohio.org/mappingwinners.

head contests combining 2018 and 2020[2] – for 2018: US Senate (Brown-Renacci), Governor (Cordray- DeWine), Treasurer (Richardson -Sprague) and for 2020: President (Biden-Trump).

13. I define majority as 50%+ 1.

14. For the 2020 election, I disaggregated 2020 VTD-level election results to the 2020 census block level based on voting age population, as reported in the OCURD database.[3] For the 2018 election, I disaggregated 2020 VTD-level election results to the 2020 census block level, as reported in data prepared by VEST.[4]

15. I used Caliper Corporation's *Maptitude for Redistricting 2021* GIS software in the preparation of this affidavit. *Maptitude* is used by many local and state governing bodies across the country for redistricting and other types of demographic analysis

C. Findings

(i) Partisan Balance

16. The Commission plans fall far short of meeting the state constitutional mandate to approximate the statewide 2012 to 2020 partisan vote share (45%

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[2] I am in the process of supplementing my partisan balance analysis with additional analysis to include data from the 2012-2016 elections.

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

[4] https://redistrictingdatahub.org/dataset/2018-oh-election-data-projected-to-2020-vtds/

Democratic). The Adopted House Plan contains **38 composite majority-Democratic districts (38.4%)** and the Adopted Senate Plan contains **12 composite majority-Democratic districts (33.4%)**. (Exhibit B-1 and B-2).

17. By contrast, the Democratic Caucus House Plan submitted to the Commission contains **44 composite majority-Democratic districts (44.4%)** and the Democratic Caucus Senate Plan submitted to the Commission contains **14 composite majority-Democratic districts (42.4%)**. (Exhibit C-1 and C-2).

18. All four of the citizen House plans I examined are superior to the Adopted House Plan in terms of composite partisan balance. The mean average House plan score for the four plans is **43 composite majority-Democratic districts (43.4%)**. See Exhibit D-1 *(Tim Clarke*); Exhibit E-1 (*Ohio Citizens Redistricting Commission*); Exhibit F-1 (*Pranav Padmanabhan*); Exhibit G-1 (*Paul Nieves*).

19. All four of the citizen Senate plans I examined are superior to the Adopted Senate Plan in terms of partisan balance. The mean average Senate plan score for the four plans is **14 composite majority-Democratic districts (43.2%).** See Exhibit D-2 *(Tim Clarke*); Exhibit E-2 (*Ohio Citizens Redistricting Commission*); Exhibit F-2 (*Pranav Padmanabhan*); Exhibit G-2 (*Paul Nieves*).

(ii) Traditional Redistricting Principles

20. Adherence to traditional redistricting principles, such as compactness and preservation of jurisdictional and precinct boundaries, does not support the

Commission's decision to adopt legislative plans that weigh heavily in favor of Republican candidates.

21. The Adopted House Plan scores a mean average of .40 on the Reock compactness measure[5] and .30 on the Polsby-Popper measure[6]. The Adopted Senate Plan has a mean average of .39 Reock score and a .31 Polsby-Popper score. (Exhibits H-1 and H-2) **Legislative plans can be drawn as compact or more compact without the skewed partisan bias found in the adopted plans**.

22. The Adopted House Plan contains 72 unique county/district splits, while splitting populated areas in 87 VTDs. (Exhibits I-1 and I-2) **Legislative plans with similar – or better – county and VTD split metrics can be drawn without the skewed partisan bias found in the adopted plans.**

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[5] "The Reock test is an area-based measure that compares each district to a circle, which is considered to be the most compact shape possible. For each district, the Reock test computes the ratio of the area of the district to the area of the minimum enclosing circle for the district. The measure is always between 0 and 1, with 1 being the most compact. The Reock test computes one number for each district and the minimum, maximum, mean and standard deviation for the plan." *Maptitude For Redistricting* software documentation (authored by the Caliper Corporation).

[6] The Polsby-Popper test computes the ratio of the district area to the area of a circle with the same perimeter: 4pArea/ (Perimeter2). The measure is always between 0 and 1, with 1 being the most compact. The Polsby-Popper test computes one number for each district and the minimum, maximum, mean and standard deviation for the plan. *Maptitude For Redistricting* software documentation (authored by the Caliper Corporation).

23. The Adopted House Plan pairs 3 sets of incumbents and the Adopted Senate Plan pairs 3 sets of incumbents. **Legislative plans with the same number, similar – or fewer –incumbent conflicts can be drawn without the skewed partisan balance found in the adopted plans.**

FURTHER AFFIANT SAYETH NAUGHT.

Executed on September 22 , 2021

C0B37E35774A

Signed on 2021/09/22 16:37:36 -8:00

William S. Cooper

09/22/2021

Sworn to and subscribed before me this day of September 2021

DF9F5EAE7674

Signed on 2021/09/22 16:37:36 -8:00

N

My commission expires

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 2021/09/22 16:37:36 PST DF9F5EAE7674

June 30, 2021

William S. Cooper
P.O. Box 16066
Bristol, VA 24209
276-669-8567
bcooper@msn.com

<u>Summary of Redistricting Work</u>

I have a B.A. in Economics from Davidson College in Davidson, North Carolina.

Since 1986, I have prepared proposed redistricting maps of approximately 750 jurisdictions for Section 2 litigation, Section 5 comment letters, and for use in other efforts to promote compliance with the Voting Rights Act of 1965. I have analyzed and prepared election plans in over 100 of these jurisdictions for two or more of the decennial censuses – either as part of concurrent legislative reapportionments or, retrospectively, in relation to litigation involving many of the cases listed below.

From 1986 to 2020, I have prepared election plans for Section 2 litigation in Alabama, Connecticut, Florida, Georgia, Louisiana, Maryland, Mississippi, Missouri, Montana, Nebraska, New Jersey, New York, North Carolina, Ohio, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Washington, and Wyoming.

<u>Post-2010 Redistricting Experience</u>

Since the release of the 2010 Census in February 2011, I have developed statewide legislative plans on behalf of clients in nine states (Alabama, Connecticut, Florida, Georgia, Kentucky, Mississippi, South Carolina, Texas, and Virginia), as well as over 150 local redistricting plans in approximately 30 states – primarily for groups working to protect minority voting rights. In addition, I have prepared congressional plans for clients in eight states (Alabama, Florida, Georgia, Louisiana, Maryland, Ohio, Pennsylvania, South Carolina, and Virginia).

In March 2011, I was retained by the Sussex County, Virginia Board of Supervisors and the Bolivar County, Mississippi Board of Supervisors to draft new district plans based on the 2010 Census. In the summer of 2011, both counties received Section 5 preclearance from the U.S. Department of Justice (DOJ).

Also in 2011, I was retained by way of a subcontract with Olmedillo X5 LLC to assist with redistricting for the Miami-Dade County, Florida Board of Commissioners and the Miami-Dade, Florida School Board. Final plans were adopted in late 2011 following public hearings.

In the fall of 2011, I was retained by the City of Grenada, Mississippi to provide redistricting services. The ward plan I developed received DOJ preclearance in March 2012.

In 2012 and 2013, I served as a redistricting consultant to the Tunica County, Mississippi Board of Supervisors and the Claiborne County, Mississippi Board of Supervisors.

In *Montes v. City of Yakima* (E.D. Wash. Feb. 17, 2015) the court adopted, as a remedy for the Voting Rights Act Section 2 violation, a seven single-member district plan that I developed for the Latino plaintiffs. I served as the expert for the Plaintiffs in the liability and remedy phases of the case.

In *Pope v. Albany County* (N.D.N.Y. Mar. 24, 2015), the court approved, as a remedy for a Section 2 violation, a plan drawn by the defendants, creating a new Black-majority district. I served as the expert for the Plaintiffs in the liability and remedy phases of the case.

In 2016, two redistricting plans that I developed on behalf of the plaintiffs for consent decrees in Section 2 lawsuits in Georgia were adopted (*NAACP v. Fayette County, Georgia* and *NAACP v. Emanuel County, Georgia)*.

In 2016, two federal courts granted summary judgment to the plaintiffs based in part on my *Gingles 1* testimony: *Navajo Nation v. San Juan County, Utah* (C.D. Utah 2016) and NAACP v. *Ferguson-Florissant School District, Missouri* (E. D. Mo. August 22, 2016).

Also in 2016, based in part on my analysis, the City of Pasco, Washington admitted to a Section 2 violation. As a result, in *Glatt v. City of Pasco* (E.D. Wash. Jan. 27, 2017), the court ordered a plan that created three Latino majority single-member districts in a 6 district, 1 at-large plan.

In 2018, I served as the redistricting consultant to the Governor Wolf interveners at the remedial stage of *League of Women Voters, et al. v. Commonwealth of Pennsylvania*.

In August 2018, the Wenatchee City Council adopted a hybrid election plan that I developed – five single-member districts with two members at-large. The Wenatchee election plan is the first plan adopted under the Washington Voting Rights Acts of 2018.

In February 2019, a federal court ruled in favor of the plaintiffs in a Section 2 case regarding Senate District 22 in Mississippi, based in part on my *Gingles* 1 testimony in *Thomas v. Bryant (S.D. Ms. Feb 16, 2019).*

In the summer of 2019, I developed redistricting plans for the Grand County (Utah) Change of Form of Government Study Committee.

In the fall of 2019, a redistricting plan I developed for a consent decree involving the Jefferson County, Alabama Board of Education was adopted *Traci Jones, et al. v. Jefferson County Board of Education, et al*.

In May 2020, a federal court ruled in favor of the plaintiffs in a Section 2 case in *NAACP et al. v. East Ramapo Central School District, NY,* based in part on my *Gingles* 1 testimony. In October 2020, the federal court adopted a consent decree plan I developed for elections to be held in February 2021.

In May and June of 2020, I served as a consultant to the City of Quincy, Florida – the Defendant in a Section 2 lawsuit filed by two Anglo voters (*Baroody v. City of Quincy*). The federal court for the Northern District of Florida ruled in favor of the Defendants. The Plaintiffs voluntarily dismissed the case.

In the summer of 2020, I provided technical redistricting assistance to the City of Chestertown, Maryland.

I am currently a redistricting consultant and expert for the plaintiffs in *Jayla Allen v. Waller County, Texas.* I testified remotely at trial in October 2020.

Since 2011, I have served as a redistricting and demographic consultant to the Massachusetts-based Prison Policy Initiative for a nationwide project to end prison-based gerrymandering. I have analyzed proposed and adopted election plans in about 25 states as part of my work.

In 2018 (Utah) and again in 2020 (Arizona), I have provided technical assistance to the Rural Utah Project for voter registration efforts on the Navajo Nation Reservation.

<u>Post-2010 Demographics Experience</u>

My trial testimony in Section 2 lawsuits usually includes presentations of U.S. Census data with charts, tables, and/or maps to demonstrate socioeconomic disparities between non-Hispanic Whites and racial or ethnic minorities.

I served as a demographic expert for plaintiffs in four state-level voting cases related to the Covid-19 pandemic (South Carolina, Alabama, and Louisiana) and state court in North Carolina.

I have also served as an expert witness on demographics in non-voting trials. For example, in an April 2017 opinion in *Stout v. Jefferson County Board of Education* (Case no.2:65-cv-00396-MHH), a school desegregation case involving the City of Gardendale, Ala., the court made extensive reference to my testimony.

I provide technical demographic and mapping assistance to the Food Research and Action Center (FRAC) in Washington D.C and their constituent organizations around the country. Most of my work with FRAC involves the Summer Food Program and Child and Adult Care Food Program. Both programs provide nutritional assistance to school-age children who are eligible for free and reduced price meals. As part of this project, I developed an online interactive map to determine site eligibility for the two programs that has been in continuous use by community organizations and school districts around the country since 2003. The map is updated annually with new data from a Special Tabulation of the American Community Survey prepared by the U.S. Census Bureau for the Food and Nutrition Service of the U.S. Department of Agriculture.

<u>Historical Redistricting Experience</u>

In the 1980s and 1990s, I developed voting plans in about 400 state and local jurisdictions – primarily in the South and Rocky Mountain West. During the 2000s and 2010s, I prepared draft election plans involving about 350 state and local jurisdictions in 25 states. Most of these plans were prepared at the request of local citizens' groups, national organizations such as the NAACP, tribal governments, and for Section 2 or Section 5 litigation.

Election plans I developed for governments in two counties – Sussex County, Virginia and Webster County, Mississippi – were adopted and precleared in 2002 by the U.S. Department of Justice. A ward plan I prepared for the City of Grenada, Mississippi was precleared in August 2005. A county supervisors' plan I produced for Bolivar County, Mississippi was precleared in January 2006.

In August 2005, a federal court ordered the State of South Dakota to remedy a

Section 2 voting rights violation and adopt a state legislative plan I developed (*Bone Shirt v. Hazeltine*).

A county council plan I developed for Native American plaintiffs in a Section 2 lawsuit (*Blackmoon v. Charles Mix County*) was adopted by Charles Mix County, South Dakota in November 2005. A plan I drafted for Latino plaintiffs in Bethlehem, Pennsylvania (*Pennsylvania Statewide Latino Coalition v. Bethlehem Area School District*) was adopted in March 2009. Plans I developed for minority plaintiffs in Columbus County, North Carolina and Montezuma- Cortez School District in Colorado were adopted in 2009.

Since 1986, I have testified at trial as an expert witness on redistricting and demographics in federal courts in the following voting rights cases (approximate most recent testimony dates are in parentheses). I also filed declarations and was deposed in most of these cases.

Alabama
Chestnut v Merrill (2019)
Alabama State Conference of the NAACP v. Alabama (2018)
Alabama Legislative Black Caucus et al. v. Alabama et al. (2013)

Colorado
Cuthair v. Montezuma-Cortez School Board (1997)

Florida
Baroody v. City of Quincy (2020)

Georgia
Cofield v. City of LaGrange (1996)
Love v. Deal (1995)
Askew v. City of Rome (1995)
Woodard v. Lumber City (1989)

Louisiana
Terrebonne Parish NAACP v. Jindal, et al. (2017)
Wilson v. Town of St. Francisville (1996)
Reno v. Bossier Parish (1995)
Knight v. McKeithen (1994)

Maryland
Cane v. Worcester County (1994

Mississippi

Thomas v. Bryant (2019)
Fairley v. Hattiesburg (2014)
Boddie v. Cleveland School District (2010)
Fairley v. Hattiesburg (2008)
Boddie v. Cleveland (2003)
Jamison v. City of Tupelo (2006)
Smith v. Clark (2002)
NAACP v. Fordice (1999)
Addy v Newton County (1995)
Ewing v. Monroe County (1995)
Gunn v. Chickasaw County (1995)
Nichols v. Okolona (1995)

Montana
Old Person v. Brown (on remand) (2001)
Old Person v. Cooney (1998)

Missouri
Missouri NAACP v. Ferguson-Florissant School District (2016)

Nebraska
Stabler v. Thurston County (1995)

New York
NAACP v. East Ramapo Central School District (2020)
Pope v. County of Albany (2015)
Arbor Hills Concerned Citizens v. Albany County (2003)

Ohio
A. Philip Randolph Institute, et al. v. Ryan (2019)

South Carolina
Smith v. Beasley (1996)

South Dakota
Bone Shirt v. Hazeltine (2004)
Cottier v. City of Martin (2004)

Tennessee
Cousins v. McWherter (1994)
Rural West Tennessee African American Affairs Council v. McWherter (1993)

Texas
Jayla Allen v. Waller County, Texas

Utah
*Navajo Nation v. San Juan County (2017),*brief testimony –11 declarations, 2 depositions

Virginia
Smith v. Brunswick County (1991)
Henderson v. Richmond County (1988)
McDaniel v. Mehfoud (1988)
White v. *Daniel (1989)*

Wyoming
Large v. Fremont County (2007)

In addition, I have filed expert declarations or been deposed in the following cases that did not require trial testimony. The dates listed indicate the deposition date or date of last declaration or supplemental declaration:

Alabama
People First of Alabama v. Merrill (2020), Covid-19 demographics only
Alabama State NAACP v. City of Pleasant Grove (2019)
James v. Jefferson County Board of Education (2019)
Voketz v. City of Decatur (2018)

Arkansas
*Mays v. Thurston (2020)***--** Covid-19 demographics only)

Connecticut
NAACP v. Merrill (2020)

Florida
Calvin v. Jefferson County (2016)
Thompson v. Glades County (2001)
Johnson v. DeSoto County (1999)
Burton v. City of Belle Glade (1997)

Georgia
Dwight v. Kemp (2018)
Georgia NAACP et al. v. Gwinnett County, GA (2018
Georgia State Conference NAACP et al v. Georgia (2018)
Georgia State Conference NAACP, et al. v. Fayette County (2015)
Knighton v. Dougherty County (2002)
Johnson v. Miller (1998)
Jones v. Cook County (1993)

Kentucky
Herbert v. Kentucky State Board of Elections (2013)

Louisiana
Power Coalition for Equity and Justice v. Edwards (2020), Covid-19 demographics only
Johnson v. Ardoin (2019
NAACP v. St. Landry Parish Council (2005)
Prejean v. Foster (1998)
Rodney v. McKeithen (1993)

Maryland
Benisek v. Lamone (2017)
Fletcher v. Lamone (2011)

Mississippi
Partee v. Coahoma County (2015)
Figgs v. Quitman County (2015)
West v. Natchez (2015)
Williams v. Bolivar County (2005)
Houston v. Lafayette County (2002)
Clark v. Calhoun County (on remand)(1993)
Teague v. Attala County (on remand)(1993)
Wilson v. Clarksdale (1992)
Stanfield v. Lee County(1991)

Montana
Alden v. Rosebud County (2000)

North Carolina
Lewis v. Alamance County (1991)
Gause v. Brunswick County (1992)
Webster v. Person County (1992)

Rhode Island
Davidson v. City of Cranston (2015)

South Carolina
Thomas v. Andino (2020), Covid-19 demographics only
Vander Linden v. Campbell (1996

South Dakota
Kirkie v. Buffalo County (2004
Emery v. Hunt (1999)

Tennessee
NAACP v. Frost, et al. (2003)

Virginia
Moon v. Beyer (1990)

Washington
Glatt v. City of Pasco (2016)
Montes v. City of Yakima (2014

\# # #

Exhibit B-1

Adopted House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	115498	-3688	-3.09%	81.78%	83.93%	81.21%	78.79%	81.43%
2	117559	-1627	-1.37%	77.35%	80.63%	78.15%	77.08%	78.30%
3	114104	-5082	-4.26%	84.79%	88.30%	86.50%	85.24%	86.21%
4	114500	-4686	-3.93%	58.76%	59.16%	54.67%	51.50%	56.02%
5	116735	-2451	-2.06%	55.27%	60.91%	56.91%	54.94%	57.01%
6	115517	-3669	-3.08%	53.57%	61.59%	57.78%	55.40%	57.08%
7	115170	-4016	-3.37%	79.01%	80.80%	78.18%	74.69%	78.17%
8	115189	-3997	-3.35%	68.08%	68.42%	64.31%	60.89%	65.43%
9	120997	1811	1.52%	70.44%	72.74%	69.51%	67.54%	70.06%
10	113326	-5860	-4.92%	46.30%	51.96%	49.14%	44.32%	47.93%
11	114236	-4950	-4.15%	61.12%	61.28%	56.45%	52.17%	57.76%
12	113760	-5426	-4.55%	44.52%	46.48%	41.38%	38.42%	42.70%
13	124554	5368	4.50%	70.81%	77.19%	73.50%	72.16%	73.42%
14	125064	5878	4.93%	55.94%	64.52%	58.71%	57.83%	59.25%
15	125088	5902	4.95%	48.45%	58.91%	52.66%	51.82%	52.96%
16	121879	2693	2.26%	56.80%	59.88%	54.24%	51.72%	55.66%
17	124819	5633	4.73%	44.51%	50.13%	44.39%	41.92%	45.24%
18	123226	4040	3.39%	89.91%	93.24%	91.22%	91.68%	91.51%
19	124679	5493	4.61%	73.58%	76.86%	72.47%	71.81%	73.68%
20	125098	5912	4.96%	86.01%	90.28%	88.06%	87.42%	87.94%
21	122023	2837	2.38%	87.77%	89.18%	86.85%	85.84%	87.41%
22	124633	5447	4.57%	73.46%	77.56%	73.51%	73.05%	74.39%
23	122775	3589	3.01%	52.10%	56.21%	50.64%	48.93%	51.97%
24	123469	4283	3.59%	75.26%	76.88%	73.51%	72.50%	74.54%
25	123568	4382	3.68%	82.45%	83.12%	80.56%	79.70%	81.46%
26	124802	5616	4.71%	71.28%	72.23%	68.63%	66.61%	69.69%
27	116286	-2900	-2.43%	50.19%	48.59%	44.04%	41.84%	46.16%
28	114050	-5136	-4.31%	57.06%	57.22%	52.84%	51.56%	54.67%
29	114653	-4533	-3.80%	45.89%	49.98%	45.44%	45.21%	46.63%
30	113811	-5375	-4.51%	31.85%	34.83%	28.47%	27.48%	30.66%
31	124467	5281	4.43%	46.75%	52.22%	47.98%	45.24%	48.05%
32	122679	3493	2.93%	55.57%	64.13%	61.61%	59.94%	60.31%
33	123791	4605	3.86%	62.53%	69.48%	66.93%	65.64%	66.15%
34	121807	2621	2.20%	56.82%	61.10%	56.94%	54.66%	57.38%
35	121171	1985	1.67%	46.01%	52.29%	45.44%	45.53%	47.32%
36	114991	-4195	-3.52%	53.15%	57.32%	50.93%	50.50%	52.97%
37	125125	5939	4.98%	41.49%	44.46%	37.65%	36.73%	40.08%
38	122075	2889	2.42%	68.59%	74.20%	69.85%	69.97%	70.65%
39	116366	-2820	-2.37%	36.56%	45.53%	40.22%	39.79%	40.52%
40	113280	-5906	-4.96%	50.73%	61.65%	55.46%	52.13%	54.99%
41	113996	-5190	-4.35%	75.69%	82.25%	78.92%	77.43%	78.57%
42	115350	-3836	-3.22%	66.82%	73.90%	69.02%	66.21%	68.99%

Adopted House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
43	115804	-3382	-2.84%	43.67%	51.60%	44.51%	41.07%	45.21%
44	123473	4287	3.60%	38.92%	43.76%	39.90%	38.81%	40.35%
45	123472	4286	3.60%	40.98%	41.96%	38.07%	37.01%	39.50%
46	121992	2806	2.35%	36.19%	39.47%	35.68%	34.74%	36.52%
47	115745	-3441	-2.89%	36.08%	47.69%	42.60%	41.93%	42.08%
48	113975	-5211	-4.37%	38.78%	45.95%	40.86%	39.86%	41.36%
49	124555	5369	4.50%	50.14%	55.81%	51.57%	50.67%	52.05%
50	113841	-5345	-4.48%	28.96%	42.75%	36.72%	36.79%	36.31%
51	125115	5929	4.97%	57.35%	69.81%	64.38%	63.58%	63.78%
52	124642	5456	4.58%	44.85%	52.50%	45.68%	43.90%	46.73%
53	121772	2586	2.17%	37.76%	52.19%	45.30%	44.01%	44.81%
54	121704	2518	2.11%	41.03%	41.00%	36.84%	35.60%	38.62%
55	120633	1447	1.21%	28.24%	31.16%	26.77%	26.13%	28.07%
56	124454	5268	4.42%	44.99%	54.35%	46.79%	46.15%	48.07%
57	124671	5485	4.60%	40.26%	49.36%	42.54%	41.72%	43.47%
58	116292	-2894	-2.43%	61.03%	72.74%	69.05%	68.37%	67.80%
59	123105	3919	3.29%	38.36%	49.68%	45.11%	42.77%	43.98%
60	113964	-5222	-4.38%	45.08%	46.53%	41.55%	38.67%	42.96%
61	113860	-5326	-4.47%	45.41%	47.03%	42.23%	39.29%	43.49%
62	124425	5239	4.40%	34.66%	37.02%	32.81%	31.91%	34.10%
63	113544	-5642	-4.73%	24.65%	31.08%	26.93%	26.39%	27.26%
64	124731	5545	4.65%	51.11%	63.35%	58.62%	57.61%	57.67%
65	117025	-2161	-1.81%	33.32%	47.62%	42.57%	40.53%	41.01%
66	116342	-2844	-2.39%	38.63%	44.87%	39.60%	38.30%	40.35%
67	118575	-611	-0.51%	32.24%	42.64%	36.30%	35.50%	36.67%
68	115385	-3801	-3.19%	36.98%	43.86%	38.49%	37.05%	39.10%
69	114369	-4817	-4.04%	29.74%	39.65%	34.00%	33.18%	34.14%
70	116643	-2543	-2.13%	40.88%	43.52%	36.33%	36.12%	39.21%
71	115026	-4160	-3.49%	33.11%	41.94%	34.75%	34.33%	36.03%
72	122012	2826	2.37%	48.32%	56.58%	52.62%	50.75%	52.07%
73	123971	4785	4.01%	41.68%	47.57%	41.87%	40.09%	42.80%
74	121539	2353	1.97%	26.49%	38.51%	32.41%	30.80%	32.05%
75	116122	-3064	-2.57%	40.02%	51.06%	41.82%	42.46%	43.84%
76	116323	-2863	-2.40%	47.40%	56.87%	49.46%	46.53%	50.07%
77	124936	5750	4.82%	29.84%	40.43%	34.32%	33.70%	34.57%
78	116894	-2292	-1.92%	31.19%	38.91%	34.77%	33.69%	34.64%
79	117815	-1371	-1.15%	26.85%	39.26%	33.88%	32.94%	33.23%
80	124211	5025	4.22%	25.95%	34.13%	26.72%	26.12%	28.23%
81	113487	-5699	-4.78%	27.89%	40.69%	30.15%	29.48%	32.05%
82	122541	3355	2.81%	22.99%	31.86%	25.39%	25.29%	26.38%
83	113996	-5190	-4.35%	25.78%	35.93%	26.60%	23.77%	28.02%
84	118816	-370	-0.31%	18.59%	29.04%	21.72%	21.00%	22.59%

Adopted House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
85	115560	-3626	-3.04%	23.67%	34.84%	27.91%	26.13%	28.14%
86	114486	-4700	-3.94%	28.01%	38.41%	29.01%	29.52%	31.24%
87	113433	-5753	-4.83%	27.23%	39.62%	33.17%	31.90%	32.98%
88	113965	-5221	-4.38%	34.39%	48.34%	38.85%	36.90%	39.62%
89	115986	-3200	-2.68%	41.87%	53.81%	47.57%	44.69%	46.99%
90	115793	-3393	-2.85%	25.21%	39.99%	33.49%	33.62%	33.08%
91	114286	-4900	-4.11%	22.01%	31.12%	25.67%	25.08%	25.97%
92	119113	-73	-0.06%	28.38%	42.07%	35.47%	35.03%	35.24%
93	117981	-1205	-1.01%	25.44%	40.23%	33.25%	33.51%	33.10%
94	122131	2945	2.47%	39.58%	53.12%	47.60%	47.04%	46.83%
95	124027	4841	4.06%	26.79%	41.30%	32.57%	34.33%	33.74%
96	124223	5037	4.23%	28.91%	47.56%	37.35%	41.09%	38.72%
97	121818	2632	2.21%	28.55%	42.07%	33.99%	34.02%	34.66%
98	113571	-5615	-4.71%	24.42%	33.78%	29.04%	27.98%	28.81%
99	125112	5926	4.97%	35.91%	47.33%	40.44%	39.99%	40.92%
Total	**11,799,448**		**9.94%**					

Exhibit B-2

Adopted Senate

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	350024	-7535	-2.11%	25.49%	35.97%	27.27%	26.06%	28.70%
2	348113	-9446	-2.64%	44.20%	53.92%	47.02%	43.94%	47.27%
3	346752	-10807	-3.02%	56.30%	60.29%	56.11%	53.52%	56.56%
4	368937	11378	3.18%	38.78%	41.69%	37.84%	36.81%	38.78%
5	361748	4189	1.17%	36.02%	43.99%	37.43%	37.12%	38.64%
6	362191	4632	1.30%	52.41%	56.46%	50.42%	49.96%	52.31%
7	358623	1064	0.30%	39.84%	40.56%	36.21%	34.77%	37.85%
8	342514	-15045	-4.21%	44.77%	47.17%	42.02%	41.20%	43.79%
9	371839	14280	3.99%	76.40%	77.47%	74.33%	73.00%	75.30%
10	347791	-9768	-2.73%	38.09%	45.28%	37.47%	37.45%	39.57%
11	342626	-14933	-4.18%	62.88%	71.47%	66.50%	63.87%	66.18%
12	348862	-8697	-2.43%	23.22%	33.91%	26.04%	25.39%	27.14%
13	371529	13970	3.91%	45.86%	57.09%	50.60%	49.29%	50.71%
14	353762	-3797	-1.06%	28.69%	36.05%	31.20%	30.69%	31.66%
15	347161	-10398	-2.91%	81.24%	84.17%	81.80%	80.17%	81.85%
16	341322	-16237	-4.54%	50.95%	53.63%	49.33%	45.30%	49.80%
17	351380	-6179	-1.73%	25.28%	37.86%	31.51%	31.25%	31.48%
18	374237	16678	4.66%	40.70%	50.55%	43.46%	42.80%	44.38%
19	341395	-16164	-4.52%	39.42%	43.24%	38.45%	35.96%	39.27%
20	367328	9769	2.73%	32.52%	42.85%	36.28%	35.13%	36.69%
21	371335	13776	3.85%	78.36%	81.43%	77.89%	77.17%	78.71%
22	351811	-5748	-1.61%	34.28%	42.35%	37.07%	35.99%	37.42%
23	372878	15319	4.28%	81.88%	86.86%	84.25%	83.74%	84.18%
24	372031	14472	4.05%	53.92%	61.02%	55.14%	53.65%	55.93%
25	351356	-6203	-1.73%	72.17%	73.70%	70.31%	67.30%	70.87%
26	352334	-5225	-1.46%	30.55%	42.82%	35.47%	34.22%	35.76%
27	372061	14502	4.06%	47.84%	52.92%	47.71%	45.44%	48.48%
28	368277	10718	3.00%	58.00%	64.40%	61.21%	59.42%	60.76%
29	354275	-3284	-0.92%	41.48%	49.64%	44.82%	43.96%	44.97%
30	370381	12822	3.59%	31.53%	47.30%	39.13%	40.80%	39.69%
31	343595	-13964	-3.91%	32.00%	42.15%	36.48%	35.73%	36.59%
32	363768	6209	1.74%	44.21%	55.90%	51.34%	49.68%	50.28%
33	357212	-347	-0.10%	41.11%	53.07%	48.56%	47.02%	47.44%
Total	**11,799,448**		**9.20%**					

Exhibit C-1

Democratic Caucus House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	113314	-5872	-4.93%	80.89%	82.06%	79.59%	76.22%	79.69%
2	113317	-5869	-4.92%	61.50%	62.17%	58.04%	55.15%	59.21%
3	113371	-5815	-4.88%	76.60%	78.84%	75.72%	73.98%	76.28%
4	113395	-5791	-4.86%	62.19%	61.97%	57.15%	53.24%	58.64%
5	113398	-5788	-4.86%	84.15%	87.61%	85.72%	84.78%	85.56%
6	113302	-5884	-4.94%	70.17%	71.46%	68.04%	65.75%	68.86%
7	113242	-5944	-4.99%	59.87%	60.28%	55.48%	51.31%	56.73%
8	113326	-5860	-4.92%	56.47%	61.68%	58.06%	54.57%	57.69%
9	113345	-5841	-4.90%	60.50%	68.12%	64.64%	62.02%	63.82%
10	113272	-5914	-4.96%	54.22%	61.17%	58.57%	54.36%	57.08%
11	124868	5682	4.77%	60.61%	62.66%	58.41%	55.95%	59.41%
12	124196	5010	4.20%	51.41%	60.14%	56.29%	54.78%	55.66%
13	122665	3479	2.92%	62.34%	68.70%	63.87%	62.22%	64.28%
14	123152	3966	3.33%	90.75%	93.17%	91.14%	91.22%	91.57%
15	124739	5553	4.66%	52.60%	62.51%	56.60%	55.95%	56.91%
16	123088	3902	3.27%	64.21%	66.32%	61.43%	58.92%	62.72%
17	125002	5816	4.88%	47.14%	53.04%	47.48%	45.23%	48.22%
18	125125	5939	4.98%	55.97%	65.67%	59.85%	59.70%	60.30%
19	122602	3416	2.87%	69.23%	72.42%	67.65%	66.71%	69.00%
20	123965	4779	4.01%	80.55%	87.29%	84.68%	84.89%	84.35%
21	123174	3988	3.35%	71.47%	75.45%	71.55%	70.77%	72.31%
22	122477	3291	2.76%	87.79%	89.07%	86.76%	85.60%	87.31%
23	123608	4422	3.71%	53.45%	57.67%	52.17%	50.58%	53.47%
24	124278	5092	4.27%	70.87%	73.39%	69.71%	69.26%	70.81%
25	113281	-5905	-4.95%	86.53%	87.55%	85.38%	84.40%	85.97%
26	113236	-5950	-4.99%	69.45%	69.79%	66.00%	63.67%	67.23%
27	122969	3783	3.17%	50.44%	49.00%	44.45%	42.28%	46.54%
28	118318	-868	-0.73%	59.46%	59.32%	55.17%	53.81%	56.94%
29	115434	-3752	-3.15%	55.36%	58.18%	53.82%	53.83%	55.30%
30	123123	3937	3.30%	29.59%	32.94%	26.75%	25.68%	28.74%
31	124857	5671	4.76%	42.55%	51.38%	48.06%	45.42%	46.86%
32	123719	4533	3.80%	52.99%	56.65%	51.98%	49.70%	52.83%
33	124276	5090	4.27%	69.01%	76.40%	74.59%	73.39%	73.35%
34	123335	4149	3.48%	57.64%	62.17%	58.24%	56.33%	58.60%
35	114134	-5052	-4.24%	72.67%	77.99%	73.69%	74.07%	74.60%
36	116227	-2959	-2.48%	55.32%	60.04%	54.09%	53.75%	55.80%
37	120132	946	0.79%	52.41%	58.23%	52.13%	52.25%	53.75%
38	125134	5948	4.99%	35.69%	41.90%	34.87%	34.33%	36.70%
39	114924	-4262	-3.58%	41.49%	44.41%	37.19%	36.67%	39.94%
40	113587	-5599	-4.70%	41.61%	50.93%	43.69%	40.19%	44.11%
41	113767	-5419	-4.55%	76.08%	81.57%	77.99%	76.18%	77.95%
42	113530	-5656	-4.75%	62.69%	71.64%	66.33%	63.60%	66.07%

Democratic Caucus House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
43	123306	4120	3.46%	51.78%	60.58%	54.63%	51.19%	54.54%
44	116641	-2545	-2.14%	32.67%	37.03%	33.04%	32.13%	33.72%
45	118121	-1065	-0.89%	42.34%	43.08%	39.20%	38.10%	40.68%
46	122121	2935	2.46%	36.18%	39.47%	35.67%	34.73%	36.51%
47	120154	968	0.81%	24.75%	35.17%	28.41%	28.17%	29.12%
48	115936	-3250	-2.73%	38.32%	45.39%	40.41%	39.41%	40.88%
49	113513	-5673	-4.76%	50.03%	59.61%	55.53%	54.87%	55.01%
50	115252	-3934	-3.30%	38.59%	46.73%	41.65%	40.79%	41.94%
51	123415	4229	3.55%	29.80%	43.27%	37.29%	37.18%	36.89%
52	122559	3373	2.83%	49.10%	58.51%	51.67%	50.44%	52.43%
53	125112	5926	4.97%	52.69%	62.65%	57.12%	55.63%	57.03%
54	116782	-2404	-2.02%	43.87%	55.81%	49.94%	48.28%	49.48%
55	120633	1447	1.21%	28.24%	31.16%	26.77%	26.13%	28.07%
56	121704	2518	2.11%	41.03%	41.00%	36.84%	35.60%	38.62%
57	124786	5600	4.70%	47.28%	56.62%	49.42%	49.02%	50.59%
58	125108	5922	4.97%	37.89%	47.14%	39.91%	38.84%	40.94%
59	116273	-2913	-2.44%	61.03%	72.74%	69.05%	68.37%	67.80%
60	123124	3938	3.30%	38.36%	49.69%	45.12%	42.78%	43.99%
61	115920	-3266	-2.74%	50.88%	49.86%	44.94%	41.54%	46.81%
62	116803	-2383	-2.00%	38.29%	42.11%	37.24%	34.98%	38.16%
63	124425	5239	4.40%	34.66%	37.02%	32.81%	31.91%	34.10%
64	113544	-5642	-4.73%	24.65%	31.08%	26.93%	26.39%	27.26%
65	124630	5444	4.57%	50.73%	63.10%	58.38%	57.31%	57.38%
66	124142	4956	4.16%	33.65%	47.53%	42.66%	40.71%	41.14%
67	116342	-2844	-2.39%	38.63%	44.87%	39.60%	38.30%	40.35%
68	118575	-611	-0.51%	32.24%	42.64%	36.30%	35.50%	36.67%
69	122017	2831	2.38%	41.03%	47.39%	42.21%	40.85%	42.87%
70	121099	1913	1.61%	25.80%	36.94%	30.88%	29.51%	30.78%
71	114724	-4462	-3.74%	42.31%	45.70%	38.42%	38.56%	41.25%
72	114996	-4190	-3.52%	49.57%	57.74%	53.69%	51.77%	53.19%
73	122374	3188	2.67%	42.20%	47.57%	42.01%	40.28%	43.01%
74	116122	-3064	-2.57%	40.02%	51.06%	41.82%	42.46%	43.84%
75	113325	-5861	-4.92%	26.89%	36.63%	30.04%	28.45%	30.50%
76	114226	-4960	-4.16%	47.91%	56.66%	49.23%	46.33%	50.03%
77	124936	5750	4.82%	29.84%	40.43%	34.32%	33.70%	34.57%
78	116894	-2292	-1.92%	31.19%	38.91%	34.77%	33.69%	34.64%
79	114974	-4212	-3.53%	26.88%	34.84%	27.58%	26.86%	29.04%
80	114502	-4684	-3.93%	28.01%	38.41%	29.01%	29.51%	31.23%
81	124884	5698	4.78%	18.08%	27.88%	20.80%	20.12%	21.72%
82	117815	-1371	-1.15%	26.85%	39.26%	33.88%	32.94%	33.23%
83	121818	2632	2.21%	28.55%	42.07%	33.99%	34.02%	34.66%
84	122490	3304	2.77%	26.45%	40.25%	32.57%	31.52%	32.70%

Democratic Caucus House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
85	119113	-73	-0.06%	28.38%	42.07%	35.47%	35.03%	35.24%
86	115100	-4086	-3.43%	32.58%	43.34%	33.84%	30.78%	35.13%
87	115793	-3393	-2.85%	25.21%	39.99%	33.49%	33.62%	33.08%
88	123941	4755	3.99%	29.19%	46.24%	36.19%	39.62%	37.81%
89	124663	5477	4.60%	24.50%	41.41%	32.51%	34.23%	33.16%
90	115483	-3703	-3.11%	23.09%	34.37%	28.16%	26.26%	27.97%
91	113548	-5638	-4.73%	33.71%	40.83%	35.51%	33.90%	35.99%
92	124957	5771	4.84%	24.84%	35.83%	30.44%	29.93%	30.26%
93	121777	2591	2.17%	42.09%	54.52%	49.04%	48.82%	48.62%
94	123393	4207	3.53%	37.20%	50.73%	43.06%	39.85%	42.71%
95	117981	-1205	-1.01%	25.44%	40.23%	33.25%	33.51%	33.10%
96	114286	-4900	-4.11%	22.01%	31.12%	25.67%	25.08%	25.97%
97	113487	-5699	-4.78%	27.89%	40.69%	30.15%	29.48%	32.05%
98	114464	-4722	-3.96%	23.08%	33.27%	25.62%	25.47%	26.86%
99	125141	5955	5.00%	37.00%	48.18%	41.44%	40.96%	41.90%
Total	**11,799,448**		**9.99%**					

Exhibit C-2

Democratic Caucus Senate

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	352957	-4602	-1.29%	31.17%	42.85%	34.58%	32.43%	35.26%
2	341300	-16259	-4.55%	39.15%	49.62%	41.27%	38.85%	42.22%
3	351487	-6072	-1.70%	63.64%	65.03%	61.06%	58.50%	62.06%
4	356883	-676	-0.19%	37.31%	40.09%	36.21%	35.21%	37.21%
5	350813	-6746	-1.89%	54.84%	62.57%	59.26%	56.49%	58.29%
6	354782	-2777	-0.78%	39.74%	43.97%	36.80%	36.48%	39.25%
7	365306	7747	2.17%	40.12%	40.86%	36.51%	35.06%	38.14%
8	356875	-684	-0.19%	47.43%	49.57%	44.60%	43.79%	46.35%
9	350795	-6764	-1.89%	75.13%	76.60%	73.38%	72.02%	74.29%
10	344421	-13138	-3.67%	30.92%	40.53%	32.87%	32.29%	34.15%
11	350603	-6956	-1.95%	62.37%	70.43%	65.39%	62.70%	65.22%
12	359540	1981	0.55%	23.25%	33.47%	25.77%	25.61%	27.02%
13	364453	6894	1.93%	48.52%	58.92%	52.84%	51.37%	52.91%
14	353762	-3797	-1.06%	28.69%	36.05%	31.20%	30.69%	31.66%
15	340083	-17476	-4.89%	80.41%	82.56%	80.03%	77.89%	80.22%
16	339963	-17596	-4.92%	59.74%	61.26%	56.76%	52.87%	57.66%
17	351380	-6179	-1.73%	25.28%	37.86%	31.51%	31.25%	31.48%
18	363768	6209	1.74%	44.21%	55.90%	51.34%	49.68%	50.28%
19	357659	100	0.03%	40.16%	44.43%	39.20%	36.98%	40.19%
20	365490	7931	2.22%	36.21%	43.85%	38.26%	36.77%	38.77%
21	369594	12035	3.37%	86.56%	89.79%	87.48%	87.05%	87.72%
22	351811	-5748	-1.61%	34.28%	42.35%	37.07%	35.99%	37.42%
23	370878	13319	3.72%	61.23%	66.89%	61.76%	60.18%	62.51%
24	372915	15356	4.29%	56.96%	63.65%	58.61%	57.39%	59.15%
25	369929	12370	3.46%	58.23%	61.98%	57.03%	55.39%	58.16%
26	351521	-6038	-1.69%	27.56%	38.41%	31.98%	30.45%	32.10%
27	350493	-7066	-1.98%	58.88%	64.20%	58.64%	58.65%	60.09%
28	372468	14909	4.17%	55.34%	62.47%	59.37%	57.45%	58.66%
29	344701	-12858	-3.60%	41.60%	49.67%	44.88%	44.05%	45.05%
30	370381	12822	3.59%	31.53%	47.30%	39.13%	40.80%	39.69%
31	370190	12631	3.53%	27.88%	40.68%	34.15%	33.98%	34.17%
32	375035	17476	4.89%	40.70%	50.52%	43.45%	42.77%	44.36%
33	357212	-347	-0.10%	41.11%	53.07%	48.56%	47.02%	47.44%
Total	**11,799,448**		**9.81%**					

Exhibit D-1

Tim Clarke House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	114725	-4461	-3.74%	56.13%	57.33%	48.92%	52.89%	53.82%
2	113846	-5340	-4.48%	64.90%	65.19%	57.50%	60.79%	62.10%
3	114732	-4454	-3.74%	60.74%	61.27%	53.99%	57.00%	58.25%
4	114822	-4364	-3.66%	55.81%	59.58%	52.35%	55.43%	55.79%
5	115194	-3992	-3.35%	66.22%	66.64%	57.78%	62.14%	63.20%
6	113995	-5191	-4.36%	78.13%	81.28%	77.83%	79.03%	79.07%
7	114947	-4239	-3.56%	79.93%	82.94%	79.59%	80.39%	80.71%
8	114461	-4725	-3.96%	81.44%	83.02%	77.67%	80.55%	80.67%
9	113913	-5273	-4.42%	75.65%	79.32%	73.57%	76.35%	76.22%
10	114819	-4367	-3.66%	63.36%	67.06%	61.81%	63.50%	63.94%
11	116322	-2864	-2.40%	50.72%	57.99%	50.75%	55.25%	53.68%
12	124466	5280	4.43%	55.10%	59.42%	51.49%	53.73%	54.93%
13	125135	5949	4.99%	69.76%	74.27%	68.24%	69.94%	70.55%
14	124896	5710	4.79%	51.51%	58.75%	51.45%	52.95%	53.67%
15	125088	5902	4.95%	48.45%	58.91%	51.82%	52.66%	52.96%
16	124988	5802	4.87%	52.52%	57.00%	49.72%	51.66%	52.73%
17	124312	5126	4.30%	82.21%	88.56%	86.42%	86.04%	85.81%
18	124834	5648	4.74%	89.54%	92.54%	90.10%	90.69%	90.72%
19	124320	5134	4.31%	85.57%	87.26%	83.48%	84.74%	85.26%
20	125117	5931	4.98%	80.26%	85.00%	81.74%	81.76%	82.19%
21	125023	5837	4.90%	73.72%	77.71%	73.04%	73.43%	74.48%
22	123849	4663	3.91%	29.72%	33.11%	25.83%	26.90%	28.89%
23	116045	-3141	-2.64%	52.50%	54.60%	49.93%	50.06%	51.77%
24	120009	823	0.69%	56.46%	55.89%	50.29%	51.80%	53.61%
25	117112	-2074	-1.74%	72.07%	74.58%	70.18%	70.85%	71.92%
26	115227	-3959	-3.32%	79.81%	81.82%	78.37%	79.21%	79.80%
27	116817	-2369	-1.99%	74.72%	74.58%	68.85%	71.24%	72.35%
28	121580	2394	2.01%	54.32%	53.61%	47.11%	49.07%	51.03%
29	123580	4394	3.69%	52.76%	56.48%	49.36%	51.44%	52.51%
30	123464	4278	3.59%	57.22%	66.35%	61.84%	63.76%	62.29%
31	123753	4567	3.83%	53.24%	57.84%	51.40%	53.62%	54.02%
32	122285	3099	2.60%	66.08%	72.72%	69.10%	70.47%	69.59%
33	124767	5581	4.68%	38.46%	46.76%	40.11%	42.29%	41.91%
34	119214	28	0.02%	53.20%	59.33%	53.38%	53.16%	54.77%
35	118009	-1177	-0.99%	69.16%	75.48%	71.43%	70.91%	71.75%
36	122890	3704	3.11%	53.35%	57.67%	51.03%	51.57%	53.40%
37	113816	-5370	-4.51%	43.32%	45.78%	37.98%	38.93%	41.50%
38	116913	-2273	-1.91%	34.68%	42.54%	35.99%	36.73%	37.48%
39	117062	-2124	-1.78%	47.26%	54.28%	44.47%	47.81%	48.45%
40	117630	-1556	-1.31%	60.05%	68.47%	59.51%	62.83%	62.72%
41	117484	-1702	-1.43%	75.87%	82.00%	76.85%	78.49%	78.30%
42	119467	281	0.24%	47.60%	60.46%	50.65%	53.78%	53.13%

Tim Clarke House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
43	115855	-3331	-2.79%	31.08%	36.41%	32.05%	32.61%	33.04%
44	117579	-1607	-1.35%	38.64%	42.15%	37.23%	37.96%	39.00%
45	123449	4263	3.58%	41.25%	41.38%	36.13%	37.65%	39.10%
46	114688	-4498	-3.77%	37.20%	45.81%	39.97%	40.78%	40.94%
47	119726	540	0.45%	50.24%	59.64%	54.79%	55.49%	55.04%
48	124889	5703	4.78%	38.19%	45.69%	39.58%	40.56%	41.01%
49	118032	-1154	-0.97%	52.99%	62.86%	55.95%	57.44%	57.31%
50	115008	-4178	-3.51%	52.19%	62.35%	54.83%	56.11%	56.37%
51	118452	-734	-0.62%	39.18%	50.40%	41.79%	43.60%	43.74%
52	120807	1621	1.36%	41.73%	41.80%	36.32%	37.58%	39.36%
53	121530	2344	1.97%	27.05%	30.04%	25.11%	25.70%	26.97%
54	124562	5376	4.51%	48.54%	56.62%	48.54%	49.46%	50.79%
55	124679	5493	4.61%	40.35%	48.93%	41.08%	41.96%	43.08%
56	113584	-5602	-4.70%	47.89%	59.82%	53.38%	55.33%	54.11%
57	115030	-4156	-3.49%	50.36%	61.27%	56.23%	57.31%	56.29%
58	115397	-3789	-3.18%	50.26%	49.57%	41.32%	44.73%	46.47%
59	117720	-1466	-1.23%	41.70%	44.12%	36.75%	39.10%	40.42%
60	118762	-424	-0.36%	35.28%	37.48%	32.36%	33.30%	34.61%
61	119207	21	0.02%	24.54%	30.91%	26.21%	26.73%	27.10%
62	124312	5126	4.30%	51.09%	63.87%	57.89%	59.04%	57.97%
63	116221	-2965	-2.49%	35.05%	48.94%	41.97%	43.45%	42.35%
64	114406	-4780	-4.01%	38.66%	47.23%	40.02%	41.23%	41.79%
65	120511	1325	1.11%	32.39%	40.40%	33.93%	34.83%	35.39%
66	119369	183	0.15%	39.89%	46.37%	39.77%	41.26%	41.82%
67	115458	-3728	-3.13%	41.15%	43.76%	36.36%	36.58%	39.46%
68	120573	1387	1.16%	48.51%	56.91%	50.82%	52.82%	52.27%
69	122470	3284	2.76%	42.31%	47.50%	40.24%	42.02%	43.02%
70	116122	-3064	-2.57%	40.02%	51.06%	42.46%	41.82%	43.84%
71	122787	3601	3.02%	47.01%	56.14%	45.92%	48.83%	49.47%
72	124936	5750	4.82%	29.84%	40.43%	33.70%	34.32%	34.57%
73	116894	-2292	-1.92%	31.19%	38.91%	33.69%	34.77%	34.64%
74	118558	-628	-0.53%	26.87%	35.18%	27.11%	27.87%	29.25%
75	117531	-1655	-1.39%	27.26%	37.47%	28.75%	28.33%	30.46%
76	117427	-1759	-1.48%	27.15%	38.96%	32.54%	33.62%	33.07%
77	118212	-974	-0.82%	36.90%	47.20%	39.71%	40.27%	41.02%
78	119984	798	0.67%	28.15%	41.94%	35.97%	36.07%	35.53%
79	117402	-1784	-1.50%	24.40%	37.88%	30.00%	30.69%	30.74%
80	119557	371	0.31%	29.63%	43.99%	36.66%	37.05%	36.83%
81	117182	-2004	-1.68%	24.79%	37.12%	25.71%	26.87%	28.62%
82	115561	-3625	-3.04%	27.44%	36.96%	25.25%	28.30%	29.49%
83	115793	-3393	-2.85%	25.21%	39.99%	33.62%	33.49%	33.08%
84	117663	-1523	-1.28%	29.15%	45.79%	39.24%	35.93%	37.52%

Tim Clarke House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
85	119179	-7	-0.01%	27.19%	38.92%	31.97%	33.35%	32.86%
86	121871	2685	2.25%	27.59%	36.61%	30.24%	31.56%	31.50%
87	117100	-2086	-1.75%	45.90%	58.72%	52.03%	52.78%	52.36%
88	115837	-3349	-2.81%	26.68%	42.43%	35.68%	33.15%	34.49%
89	123426	4240	3.56%	34.41%	48.54%	36.93%	38.92%	39.70%
90	118814	-372	-0.31%	33.73%	47.41%	39.30%	40.52%	40.24%
91	120570	1384	1.16%	47.43%	57.23%	51.62%	53.23%	52.38%
92	120113	927	0.78%	24.60%	38.03%	31.15%	31.12%	31.23%
93	115349	-3837	-3.22%	18.26%	28.38%	20.79%	20.43%	21.97%
94	114405	-4781	-4.01%	30.75%	39.42%	32.23%	31.95%	33.59%
95	123310	4124	3.46%	21.66%	31.57%	23.72%	25.39%	25.58%
96	119273	87	0.07%	22.65%	35.29%	28.97%	28.69%	28.90%
97	118311	-875	-0.73%	28.59%	36.89%	28.98%	31.41%	31.47%
98	119952	766	0.64%	22.71%	35.64%	29.59%	29.95%	29.47%
99	123125	3939	3.30%	26.26%	36.59%	28.69%	28.77%	30.08%
Total	**11,799,448**		**9.69%**					

Exhibit D-2

Tim Clarke Senate

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	355868	10054	2.81%	26.13%	36.89%	27.97%	26.56%	29.39%
2	365680	1228	0.34%	42.88%	54.88%	47.01%	44.33%	47.28%
3	343674	-8854	-2.48%	71.23%	73.26%	70.02%	68.25%	70.69%
4	356883	-14842	-4.15%	37.31%	40.09%	36.21%	35.21%	37.21%
5	346078	-1905	-0.53%	32.31%	39.23%	32.37%	31.89%	33.95%
6	360113	-6259	-1.75%	57.63%	63.08%	57.38%	57.40%	58.88%
7	362346	-936	-0.26%	41.64%	42.93%	38.75%	37.56%	40.22%
8	357778	13408	3.75%	55.55%	57.85%	53.19%	51.86%	54.61%
9	352852	-12660	-3.54%	60.94%	62.02%	58.04%	57.01%	59.50%
10	345985	-14878	-4.16%	37.36%	44.48%	36.58%	36.79%	38.80%
11	352176	16474	4.61%	59.11%	66.59%	61.15%	58.36%	61.30%
12	359399	-3971	-1.11%	25.21%	34.69%	27.18%	26.49%	28.39%
13	351492	3248	0.91%	47.66%	58.12%	51.95%	50.39%	52.03%
14	353762	-3797	-1.06%	28.69%	36.05%	31.20%	30.69%	31.66%
15	343568	-3427	-0.96%	73.61%	75.37%	71.91%	68.50%	72.35%
16	343393	-1918	-0.54%	59.15%	60.89%	56.55%	53.08%	57.42%
17	359622	-10188	-2.85%	25.65%	39.27%	32.73%	32.50%	32.54%
18	374264	14744	4.12%	53.55%	60.90%	54.77%	54.00%	55.81%
19	351428	-15633	-4.37%	40.98%	44.15%	39.11%	36.28%	40.13%
20	356972	-16409	-4.59%	37.37%	48.02%	41.83%	40.73%	41.99%
21	373466	17375	4.86%	85.76%	89.13%	86.80%	86.18%	86.97%
22	351811	-4994	-1.40%	34.28%	42.35%	37.07%	35.99%	37.42%
23	375193	16633	4.65%	59.51%	66.16%	61.22%	60.29%	61.79%
24	374497	16713	4.67%	58.32%	63.69%	58.37%	56.58%	59.24%
25	351711	16463	4.60%	53.68%	60.75%	57.32%	54.72%	56.62%
26	362929	14378	4.02%	30.28%	42.21%	36.00%	34.95%	35.86%
27	370797	-5748	-1.61%	54.22%	59.81%	55.75%	53.71%	55.87%
28	367625	-4267	-1.19%	49.16%	57.14%	53.38%	51.54%	52.80%
29	359303	10176	2.85%	41.23%	49.53%	44.67%	43.86%	44.82%
30	353484	-13806	-3.86%	27.99%	43.42%	35.05%	36.99%	35.86%
31	360513	-7197	-2.01%	30.66%	39.86%	34.39%	33.42%	34.58%
32	358745	14013	3.92%	40.97%	53.30%	47.57%	46.47%	47.08%
33	346041	-13217	-3.70%	41.86%	53.69%	49.19%	47.63%	48.09%
Total	**11,799,448**		**9.45%**					

Exhibit E-1

Ohio Citizens Redistricting Commission House

District	Population	Deviation	% Deviation	Trump-Biden	Renacci-Brown	Dewine-Cordray	Sprague-Richardson	4- Election Composite
1	116195	-2991	-2.51%	72.86%	75.7%	72.61%	70.93%	73.01%
2	117795	-1391	-1.17%	71.11%	72.9%	69.64%	67.84%	70.37%
3	114715	-4471	-3.75%	59.95%	60.1%	55.79%	52.70%	57.14%
4	113852	-5334	-4.48%	82.97%	85.9%	83.73%	82.22%	83.71%
5	124669	5483	4.60%	53.43%	58.3%	55.05%	51.45%	54.54%
6	115611	-3575	-3.00%	68.54%	73.4%	70.44%	69.06%	70.35%
7	116226	-2960	-2.48%	63.85%	67.7%	64.07%	60.84%	64.12%
8	122253	3067	2.57%	55.23%	63.4%	59.98%	56.75%	58.83%
9	117162	-2024	-1.70%	81.07%	82.6%	80.15%	76.92%	80.19%
10	124414	5228	4.39%	65.43%	64.9%	60.25%	56.12%	61.68%
11	124449	5263	4.42%	58.65%	59.0%	54.12%	50.30%	55.51%
12	123074	3888	3.26%	35.40%	40.5%	35.80%	33.43%	36.28%
13	124826	5640	4.73%	86.18%	88.7%	85.80%	86.18%	86.72%
14	125140	5954	5.00%	49.96%	60.8%	54.77%	54.12%	54.91%
15	124968	5782	4.85%	65.61%	73.6%	69.22%	67.95%	69.10%
16	125024	5838	4.90%	53.79%	59.3%	54.22%	52.71%	55.00%
17	124611	5425	4.55%	91.00%	92.8%	91.03%	90.70%	91.39%
18	124637	5451	4.57%	79.93%	82.0%	78.80%	78.63%	79.83%
19	124790	5604	4.70%	68.20%	72.3%	67.76%	65.71%	68.48%
20	124936	5750	4.82%	51.56%	59.3%	53.51%	52.53%	54.24%
21	124466	5280	4.43%	55.10%	59.4%	53.73%	51.49%	54.93%
22	124364	5178	4.34%	76.59%	79.3%	75.41%	74.00%	76.33%
23	124750	5564	4.67%	45.09%	53.1%	45.97%	44.86%	47.25%
24	124421	5235	4.39%	62.20%	62.9%	58.83%	57.22%	60.28%
25	124842	5656	4.75%	58.67%	57.8%	53.82%	52.22%	55.63%
26	121704	2518	2.11%	63.15%	62.3%	58.36%	56.06%	59.98%
27	115205	-3981	-3.34%	77.77%	79.3%	76.37%	75.39%	77.20%
28	116284	-2902	-2.43%	59.23%	61.6%	57.36%	57.28%	58.86%
29	113410	-5776	-4.85%	66.57%	69.1%	64.66%	64.03%	66.09%
30	114773	-4413	-3.70%	27.22%	30.6%	24.63%	23.65%	26.54%
31	117262	-1924	-1.61%	76.50%	82.4%	80.73%	80.23%	79.95%
32	122161	2975	2.50%	42.07%	50.5%	47.21%	44.46%	46.06%
33	113869	-5317	-4.46%	51.47%	58.3%	54.57%	52.58%	54.24%
34	123343	4157	3.49%	56.14%	60.8%	56.33%	54.08%	56.83%
35	124037	4851	4.07%	51.91%	54.8%	49.62%	47.52%	50.96%
36	121041	1855	1.56%	63.10%	69.4%	64.46%	64.58%	65.38%
37	114535	-4651	-3.90%	55.05%	59.2%	53.11%	52.63%	55.00%
38	120078	892	0.75%	59.68%	65.5%	59.85%	60.08%	61.28%
39	122332	3146	2.64%	43.12%	45.8%	38.97%	38.09%	41.48%
40	114430	-4756	-3.99%	22.60%	31.6%	24.99%	23.77%	25.74%
41	123848	4662	3.91%	66.81%	74.1%	69.31%	66.76%	69.24%
42	125100	5914	4.96%	63.59%	73.7%	69.08%	66.86%	68.31%

Ohio Citizens Redistricting Commission House

District	Population	Deviation	% Deviation	Trump-Biden	Renacci-Brown	Dewine-Cordray	Sprague-Richardson	4- Election Composite
43	125085	5899	4.95%	56.25%	63.7%	57.91%	54.51%	58.08%
44	122840	3654	3.07%	35.97%	46.4%	37.94%	35.62%	38.98%
45	113579	-5607	-4.70%	42.22%	43.2%	39.28%	38.24%	40.73%
46	113453	-5733	-4.81%	32.61%	37.2%	33.21%	32.34%	33.83%
47	115685	-3501	-2.94%	38.75%	41.2%	37.36%	36.31%	38.41%
48	117398	-1788	-1.50%	25.83%	35.6%	29.41%	28.98%	29.94%
49	119639	453	0.38%	52.84%	59.1%	54.63%	53.86%	55.10%
50	123441	4255	3.57%	33.30%	43.0%	37.95%	36.96%	37.80%
51	124655	5469	4.59%	39.06%	47.6%	42.62%	41.88%	42.79%
52	121163	1977	1.66%	26.61%	38.5%	32.72%	32.70%	32.63%
53	123543	4357	3.66%	52.91%	62.9%	57.33%	55.89%	57.26%
54	113276	-5910	-4.96%	40.71%	50.7%	43.42%	41.90%	44.19%
55	123988	4802	4.03%	53.22%	64.0%	58.65%	57.15%	58.26%
56	123512	4326	3.63%	40.85%	40.8%	36.74%	35.52%	38.49%
57	118825	-361	-0.30%	27.83%	30.9%	26.40%	25.77%	27.71%
58	124908	5722	4.80%	42.05%	51.5%	44.27%	43.64%	45.36%
59	113818	-5368	-4.50%	50.25%	60.8%	56.69%	55.55%	55.82%
60	114796	-4390	-3.68%	47.99%	60.2%	55.87%	53.98%	54.52%
61	114457	-4729	-3.97%	51.11%	50.1%	45.07%	41.67%	46.98%
62	113840	-5346	-4.49%	28.54%	39.4%	34.21%	32.72%	33.73%
63	122488	3302	2.77%	34.95%	37.3%	33.03%	32.11%	34.34%
64	114614	-4572	-3.84%	24.29%	30.5%	26.45%	25.86%	26.78%
65	121935	2749	2.31%	51.87%	64.4%	59.69%	58.73%	58.66%
66	124615	5429	4.56%	34.90%	48.9%	43.15%	41.58%	42.13%
67	120308	1122	0.94%	38.92%	46.8%	40.94%	39.74%	41.61%
68	114609	-4577	-3.84%	31.72%	40.4%	34.74%	33.87%	35.18%
69	113494	-5692	-4.78%	35.75%	43.9%	38.28%	37.03%	38.73%
70	114070	-5116	-4.29%	31.00%	38.8%	33.98%	32.56%	34.07%
71	113413	-5773	-4.84%	41.24%	43.9%	36.68%	36.44%	39.55%
72	115706	-3480	-2.92%	31.66%	41.7%	33.58%	33.56%	35.12%
73	124923	5737	4.81%	42.30%	53.8%	49.92%	47.92%	48.49%
74	116348	-2838	-2.38%	42.08%	48.1%	42.34%	40.58%	43.27%
75	114358	-4828	-4.05%	26.78%	37.5%	31.52%	29.72%	31.37%
76	113562	-5624	-4.72%	40.47%	51.0%	41.87%	42.55%	43.96%
77	113541	-5645	-4.74%	48.37%	56.7%	49.46%	46.56%	50.26%
78	123965	4779	4.01%	29.63%	39.8%	30.54%	27.07%	31.77%
79	124936	5750	4.82%	29.84%	40.4%	34.32%	33.70%	34.57%
80	116894	-2292	-1.92%	31.19%	38.9%	34.77%	33.69%	34.64%
81	114538	-4648	-3.90%	28.21%	35.8%	28.74%	28.08%	30.21%
82	122106	2920	2.45%	26.95%	37.7%	28.31%	28.96%	30.48%
83	115728	-3458	-2.90%	26.82%	38.7%	33.51%	32.46%	32.88%
84	125022	5836	4.90%	36.51%	46.4%	39.52%	38.84%	40.31%

Ohio Citizens Redistricting Commission House

District	Population	Deviation	% Deviation	Trump-Biden	Renacci-Brown	Dewine-Cordray	Sprague-Richardson	4- Election Composite
85	113824	-5362	-4.50%	27.92%	44.5%	36.05%	38.41%	36.71%
86	113586	-5600	-4.70%	29.32%	42.6%	34.24%	34.50%	35.17%
87	116665	-2521	-2.12%	29.27%	44.2%	37.37%	37.19%	37.02%
88	113928	-5258	-4.41%	27.44%	41.8%	34.30%	33.15%	34.18%
89	116660	-2526	-2.12%	25.45%	40.4%	33.84%	34.05%	33.44%
90	115375	-3811	-3.20%	26.36%	44.0%	34.32%	36.68%	35.33%
91	113629	-5557	-4.66%	38.82%	42.8%	37.73%	35.52%	38.73%
92	113391	-5795	-4.86%	43.01%	58.0%	53.46%	52.19%	51.67%
93	113769	-5417	-4.54%	26.54%	40.6%	32.19%	33.57%	33.22%
94	113701	-5485	-4.60%	37.45%	50.6%	43.13%	40.01%	42.81%
95	116593	-2593	-2.18%	24.54%	37.7%	30.78%	31.00%	31.00%
96	121281	2095	1.76%	25.92%	38.8%	30.01%	28.24%	30.74%
97	121417	2231	1.87%	17.71%	27.9%	19.64%	19.74%	21.24%
98	114286	-4900	-4.11%	22.01%	31.1%	25.67%	25.08%	25.97%
99	122667	3481	2.92%	26.52%	36.9%	29.15%	28.93%	30.38%
Total	**11,799,448**		**9.96%**					

Exhibit E-2

Ohio Citizens Redistricting Commission Senate

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	367613	10054	2.81%	30.07%	40.52%	31.98%	31.28%	33.46%
2	358787	1228	0.34%	34.45%	45.06%	36.64%	33.85%	37.50%
3	348705	-8854	-2.48%	67.23%	68.70%	65.07%	62.84%	65.96%
4	342717	-14842	-4.15%	38.14%	40.77%	36.87%	35.87%	37.91%
5	355654	-1905	-0.53%	59.08%	64.41%	58.80%	58.76%	60.26%
6	351300	-6259	-1.75%	31.89%	38.27%	31.47%	30.53%	33.04%
7	356623	-936	-0.26%	30.91%	34.60%	30.01%	29.17%	31.17%
8	370967	13408	3.75%	61.38%	61.04%	57.03%	55.19%	58.66%
9	344899	-12660	-3.54%	67.30%	69.61%	65.80%	65.24%	66.99%
10	342681	-14878	-4.16%	37.69%	45.15%	37.10%	37.22%	39.29%
11	374033	16474	4.61%	61.73%	69.86%	64.73%	61.96%	64.57%
12	353588	-3971	-1.11%	23.53%	31.17%	24.36%	23.93%	25.75%
13	360807	3248	0.91%	48.79%	59.15%	53.04%	51.59%	53.14%
14	353762	-3797	-1.06%	28.69%	36.05%	31.20%	30.69%	31.66%
15	354132	-3427	-0.96%	67.39%	71.81%	69.01%	66.80%	68.75%
16	355641	-1918	-0.54%	67.15%	72.44%	69.34%	66.09%	68.76%
17	347371	-10188	-2.85%	32.97%	43.31%	37.17%	35.87%	37.33%
18	372303	14744	4.12%	50.60%	56.63%	52.08%	49.95%	52.32%
19	341926	-15633	-4.37%	40.53%	44.71%	39.67%	37.13%	40.51%
20	341150	-16409	-4.59%	32.08%	41.67%	35.53%	34.68%	35.99%
21	374934	17375	4.86%	67.29%	74.93%	70.63%	70.24%	70.77%
22	352565	-4994	-1.40%	31.83%	44.59%	37.54%	35.86%	37.45%
23	374192	16633	4.65%	58.55%	63.91%	58.60%	56.79%	59.46%
24	374272	16713	4.67%	74.11%	77.79%	74.45%	73.88%	75.06%
25	374022	16463	4.60%	54.72%	61.99%	56.08%	54.94%	56.93%
26	371937	14378	4.02%	54.10%	56.18%	51.50%	47.87%	52.41%
27	351811	-5748	-1.61%	34.28%	42.35%	37.07%	35.99%	37.42%
28	353292	-4267	-1.19%	54.17%	61.74%	58.73%	56.92%	57.89%
29	367735	10176	2.85%	40.90%	49.26%	44.38%	43.56%	44.52%
30	343753	-13806	-3.86%	30.85%	45.27%	38.55%	38.75%	38.36%
31	350362	-7197	-2.01%	26.99%	42.48%	34.44%	36.08%	35.00%
32	371572	14013	3.92%	40.75%	52.90%	47.13%	46.03%	46.70%
33	344342	-13217	-3.70%	41.86%	53.70%	49.25%	47.69%	48.13%
Total	**11,799,448**		**9.45%**					

Exhibit F-1

Pranav Padmanabhan House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	122732	3546	2.98%	76.64%	82.9%	79.83%	78.22%	79.41%
2	123621	4435	3.72%	55.25%	65.8%	59.70%	56.48%	59.30%
3	119872	686	0.58%	58.23%	65.1%	59.51%	56.26%	59.76%
4	120616	1430	1.20%	38.30%	48.4%	40.94%	38.19%	41.45%
5	119399	213	0.18%	47.32%	56.6%	49.08%	46.19%	49.79%
6	123393	4207	3.53%	37.20%	50.7%	43.06%	39.85%	42.71%
7	121856	2670	2.24%	27.96%	40.0%	30.65%	30.19%	32.20%
8	116867	-2319	-1.95%	27.42%	38.1%	28.73%	29.30%	30.90%
9	114233	-4953	-4.16%	27.30%	37.4%	28.62%	24.90%	29.54%
10	124905	5719	4.80%	18.12%	27.4%	19.77%	19.94%	21.31%
11	120751	1565	1.31%	26.33%	34.4%	27.05%	26.37%	28.53%
12	122109	2923	2.45%	19.36%	30.0%	22.90%	22.30%	23.63%
13	113647	-5539	-4.65%	82.88%	86.5%	83.18%	83.97%	84.12%
14	115166	-4020	-3.37%	50.13%	56.6%	50.24%	49.88%	51.72%
15	124406	5220	4.38%	38.29%	44.9%	37.81%	37.63%	39.66%
16	122378	3192	2.68%	43.12%	45.8%	38.97%	38.09%	41.48%
17	115011	-4175	-3.50%	45.58%	48.2%	41.13%	40.59%	43.88%
18	114667	-4519	-3.79%	38.82%	44.7%	37.11%	37.62%	39.56%
19	120172	986	0.83%	39.75%	42.0%	38.13%	37.00%	39.21%
20	119035	-151	-0.13%	38.42%	42.0%	37.81%	37.07%	38.82%
21	119069	-117	-0.10%	34.40%	39.3%	35.73%	34.64%	36.01%
22	116777	-2409	-2.02%	66.36%	67.6%	63.99%	63.58%	65.38%
23	121580	2394	2.01%	52.16%	53.2%	48.61%	47.42%	50.35%
24	117145	-2041	-1.71%	29.35%	32.6%	26.66%	25.70%	28.57%
25	123062	3876	3.25%	64.14%	66.7%	61.93%	61.30%	63.51%
26	120171	985	0.83%	84.78%	86.1%	83.96%	83.04%	84.48%
27	115011	-4175	-3.50%	72.18%	72.6%	69.10%	66.88%	70.19%
28	118374	-812	-0.68%	47.69%	46.2%	41.75%	39.72%	43.85%
29	121210	2024	1.70%	38.15%	40.0%	35.59%	34.40%	37.03%
30	117991	-1195	-1.00%	28.65%	32.7%	28.81%	27.78%	29.48%
31	114790	-4396	-3.69%	27.19%	40.2%	32.30%	31.83%	32.88%
32	124936	5750	4.82%	29.84%	40.4%	34.32%	33.70%	34.57%
33	117667	-1519	-1.27%	28.17%	41.1%	32.42%	30.94%	33.15%
34	115516	-3670	-3.08%	23.96%	34.3%	27.41%	26.04%	27.92%
35	121063	1877	1.57%	39.95%	50.6%	41.36%	42.05%	43.49%
36	120851	1665	1.40%	26.22%	37.2%	31.67%	30.32%	31.36%
37	124286	5100	4.28%	41.57%	41.7%	37.49%	36.27%	39.26%
38	118051	-1135	-0.95%	27.43%	30.3%	25.94%	25.30%	27.24%
39	114748	-4438	-3.72%	21.16%	30.2%	24.69%	24.75%	25.19%
40	115723	-3463	-2.91%	26.01%	42.0%	35.49%	35.49%	34.74%
41	115031	-4155	-3.49%	24.57%	38.6%	31.79%	31.87%	31.72%
42	115373	-3813	-3.20%	40.42%	54.7%	49.83%	48.83%	48.44%

Pranav Padmanabhan House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
43	124815	5629	4.72%	80.34%	84.1%	81.70%	80.89%	81.76%
44	114619	-4567	-3.83%	80.58%	82.5%	79.68%	77.37%	80.02%
45	119129	-57	-0.05%	74.69%	77.5%	74.57%	73.42%	75.05%
46	115573	-3613	-3.03%	80.31%	81.3%	78.78%	75.49%	78.98%
47	117066	-2120	-1.78%	62.91%	63.7%	59.04%	54.75%	60.09%
48	124774	5588	4.69%	53.23%	57.5%	53.66%	50.42%	53.71%
49	119871	685	0.57%	27.75%	37.9%	32.47%	30.82%	32.25%
50	116614	-2572	-2.16%	50.81%	49.8%	44.87%	41.45%	46.74%
51	125018	5832	4.89%	41.94%	44.6%	39.64%	37.60%	40.94%
52	117953	-1233	-1.03%	65.82%	72.9%	69.65%	67.09%	68.85%
53	124663	5477	4.60%	50.96%	57.9%	55.25%	51.72%	53.96%
54	114783	-4403	-3.69%	32.05%	43.0%	36.89%	35.22%	36.80%
55	115475	-3711	-3.11%	59.68%	59.9%	55.45%	52.28%	56.82%
56	119299	113	0.09%	67.45%	68.4%	64.67%	61.78%	65.57%
57	117477	-1709	-1.43%	60.92%	60.9%	56.11%	52.37%	57.58%
58	121736	2550	2.14%	41.08%	47.4%	42.24%	40.88%	42.90%
59	119504	318	0.27%	26.65%	35.8%	30.79%	29.32%	30.63%
60	123022	3836	3.22%	28.60%	41.9%	33.70%	33.93%	34.54%
61	113657	-5529	-4.64%	90.90%	93.3%	91.27%	91.46%	91.74%
62	121992	2806	2.35%	81.72%	87.4%	84.70%	85.14%	84.75%
63	117621	-1565	-1.31%	72.94%	81.4%	78.16%	77.19%	77.42%
64	113728	-5458	-4.58%	67.23%	71.2%	66.61%	64.52%	67.40%
65	115609	-3577	-3.00%	53.87%	58.8%	52.95%	50.90%	54.13%
66	122375	3189	2.68%	47.40%	53.8%	48.03%	46.02%	48.80%
67	122475	3289	2.76%	75.89%	79.5%	75.64%	75.20%	76.55%
68	116497	-2689	-2.26%	84.81%	86.7%	84.03%	82.76%	84.57%
69	116777	-2409	-2.02%	75.65%	79.2%	75.04%	74.62%	76.12%
70	122640	3454	2.90%	49.03%	58.4%	51.54%	50.31%	52.32%
71	120153	967	0.81%	53.28%	63.2%	57.66%	56.23%	57.59%
72	121660	2474	2.08%	43.77%	55.8%	49.89%	48.20%	49.40%
73	113368	-5818	-4.88%	48.92%	59.8%	53.57%	52.89%	53.79%
74	119697	511	0.43%	51.21%	54.9%	49.18%	47.00%	50.57%
75	123524	4338	3.64%	39.94%	48.4%	41.42%	40.46%	42.55%
76	119167	-19	-0.02%	26.60%	40.6%	32.26%	34.02%	33.37%
77	120236	1050	0.88%	25.23%	39.8%	32.88%	31.89%	32.46%
78	122487	3301	2.77%	42.30%	47.5%	42.02%	40.24%	43.01%
79	116253	-2933	-2.46%	43.94%	55.1%	51.34%	49.40%	49.95%
80	116924	-2262	-1.90%	50.31%	54.6%	49.48%	47.36%	50.43%
81	117088	-2098	-1.76%	51.67%	56.6%	51.95%	49.92%	52.54%
82	114720	-4466	-3.75%	55.91%	61.8%	58.67%	56.06%	58.12%
83	122892	3706	3.11%	75.66%	81.6%	79.99%	79.32%	79.15%
84	114342	-4844	-4.06%	42.51%	51.5%	47.94%	45.55%	46.86%

Pranav Padmanabhan House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
85	124638	5452	4.57%	33.38%	42.5%	37.42%	36.37%	37.42%
86	125130	5944	4.99%	51.33%	58.7%	54.24%	53.48%	54.43%
87	125085	5899	4.95%	39.00%	47.6%	42.62%	41.88%	42.78%
88	122059	2873	2.41%	40.52%	47.8%	42.33%	40.92%	42.88%
89	123280	4094	3.43%	27.30%	36.4%	30.51%	30.03%	31.05%
90	116894	-2292	-1.92%	31.19%	38.9%	34.77%	33.69%	34.64%
91	116790	-2396	-2.01%	26.90%	39.4%	33.45%	33.11%	33.22%
92	124543	5357	4.49%	28.33%	43.0%	36.47%	36.83%	36.15%
93	116833	-2353	-1.97%	29.80%	47.2%	37.22%	40.51%	38.69%
94	118178	-1008	-0.85%	33.89%	48.0%	42.34%	40.79%	41.24%
95	118246	-940	-0.79%	39.86%	50.5%	43.58%	42.84%	44.19%
96	118905	-281	-0.24%	44.34%	53.8%	46.48%	46.10%	47.68%
97	113318	-5868	-4.92%	39.93%	51.3%	46.75%	44.44%	45.61%
98	115296	-3890	-3.26%	61.17%	72.8%	69.15%	68.49%	67.91%
99	119719	533	0.45%	51.38%	63.8%	59.02%	57.97%	58.05%
Total	**11,799,448**		**9.91%**					

Exhibit F-2

Pranav Padmanabhan Senate

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	366225	8666	2.42%	61.87%	69.99%	64.88%	62.11%	64.71%
2	363408	5849	1.64%	40.73%	51.76%	44.24%	41.28%	44.50%
3	352956	-4603	-1.29%	27.57%	38.52%	29.36%	28.18%	30.91%
4	367765	10206	2.85%	21.21%	30.50%	23.14%	22.79%	24.41%
5	353219	-4340	-1.21%	55.11%	61.24%	55.58%	55.66%	56.90%
6	352056	-5503	-1.54%	42.70%	46.30%	39.17%	38.82%	41.75%
7	358276	717	0.20%	37.51%	41.02%	37.19%	36.20%	37.98%
8	355502	-2057	-0.58%	48.57%	50.64%	45.84%	45.04%	47.53%
9	358244	685	0.19%	73.66%	75.24%	71.83%	70.48%	72.80%
10	357575	16	0.00%	38.54%	40.11%	35.87%	34.38%	37.22%
11	357393	-166	-0.05%	28.44%	40.56%	33.06%	32.21%	33.57%
12	357430	-129	-0.04%	29.92%	40.74%	33.47%	32.80%	34.23%
13	357085	-474	-0.13%	30.51%	34.26%	29.65%	28.99%	30.85%
14	346127	-11432	-3.20%	30.26%	45.31%	39.22%	38.94%	38.43%
15	358563	1004	0.28%	78.43%	81.27%	78.52%	77.07%	78.82%
16	354793	-2766	-0.77%	65.02%	67.78%	64.09%	60.48%	64.34%
17	361503	3944	1.10%	40.89%	44.57%	39.51%	37.02%	40.50%
18	357394	-165	-0.05%	48.91%	57.32%	53.34%	50.72%	52.58%
19	354876	-2683	-0.75%	62.54%	62.95%	58.61%	55.35%	59.86%
20	364262	6703	1.87%	32.12%	41.62%	35.59%	34.67%	36.00%
21	353270	-4289	-1.20%	81.95%	87.73%	85.11%	85.07%	84.97%
22	351712	-5847	-1.64%	56.00%	61.24%	55.84%	53.81%	56.73%
23	355749	-1810	-0.51%	78.88%	81.91%	78.43%	77.70%	79.23%
24	364453	6894	1.93%	48.52%	58.92%	52.84%	51.37%	52.91%
25	356589	-970	-0.27%	46.68%	53.92%	47.65%	46.25%	48.62%
26	361890	4331	1.21%	31.65%	42.76%	35.87%	35.52%	36.45%
27	350265	-7294	-2.04%	48.95%	55.46%	50.90%	48.86%	51.04%
28	351954	-5605	-1.57%	56.22%	63.56%	60.70%	58.77%	59.81%
29	374853	17294	4.84%	40.59%	49.05%	44.17%	43.34%	44.29%
30	362233	4674	1.31%	33.58%	41.55%	36.40%	35.36%	36.72%
31	358166	607	0.17%	28.35%	43.26%	35.76%	36.85%	36.06%
32	355329	-2230	-0.62%	39.45%	50.78%	44.16%	43.27%	44.42%
33	348333	-9226	-2.58%	49.80%	61.57%	57.13%	55.76%	56.07%
Total	**11,799,448**		**8.04%**					

Exhibit G-1

Paul Nieves House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	122777	3591	3.01%	51.81%	60.3%	56.71%	54.05%	55.72%
2	118506	-680	-0.57%	55.15%	61.5%	58.81%	54.41%	57.47%
3	118958	-228	-0.19%	70.88%	73.5%	69.78%	68.39%	70.63%
4	115230	-3956	-3.32%	66.01%	69.3%	65.88%	62.44%	65.91%
5	120144	958	0.80%	74.33%	74.5%	70.99%	67.15%	71.75%
6	124205	5019	4.21%	58.09%	58.5%	53.64%	49.75%	54.99%
7	119811	625	0.52%	67.53%	67.9%	63.72%	60.22%	64.83%
8	122622	3436	2.88%	58.86%	59.1%	54.59%	51.35%	55.98%
9	119971	785	0.66%	73.63%	76.3%	73.53%	71.79%	73.82%
10	118611	-575	-0.48%	82.70%	85.4%	83.05%	81.57%	83.17%
11	122972	3786	3.18%	71.12%	75.5%	73.07%	71.82%	72.89%
12	114287	-4899	-4.11%	77.15%	80.4%	76.30%	76.04%	77.46%
13	113655	-5531	-4.64%	86.10%	88.5%	86.19%	85.51%	86.58%
14	113351	-5835	-4.90%	86.59%	88.5%	85.91%	85.43%	86.61%
15	113352	-5834	-4.89%	57.02%	60.6%	55.08%	53.15%	56.46%
16	115419	-3767	-3.16%	87.71%	91.4%	89.36%	88.54%	89.26%
17	113934	-5252	-4.41%	77.87%	84.2%	80.83%	81.31%	81.06%
18	115970	-3216	-2.70%	68.01%	77.0%	72.81%	72.53%	72.58%
19	113476	-5710	-4.79%	48.92%	59.8%	53.58%	52.91%	53.80%
20	123088	3902	3.27%	64.21%	66.3%	61.43%	58.92%	62.72%
21	114532	-4654	-3.90%	54.66%	62.1%	56.43%	54.72%	56.97%
22	113753	-5433	-4.56%	44.91%	50.9%	45.08%	42.90%	45.94%
23	121919	2733	2.29%	47.25%	51.3%	46.78%	46.55%	47.96%
24	119149	-37	-0.03%	32.04%	35.1%	28.70%	27.79%	30.91%
25	115605	-3581	-3.00%	75.53%	76.0%	73.09%	72.29%	74.22%
26	118975	-211	-0.18%	78.88%	80.5%	77.37%	76.67%	78.36%
27	115565	-3621	-3.04%	78.14%	80.0%	77.35%	75.68%	77.79%
28	122838	3652	3.06%	58.07%	56.7%	52.20%	49.69%	54.15%
29	116588	-2598	-2.18%	50.35%	49.8%	45.14%	43.31%	47.16%
30	121517	2331	1.96%	50.21%	59.6%	56.38%	54.63%	55.19%
31	118405	-781	-0.66%	76.01%	79.8%	77.78%	76.53%	77.52%
32	114351	-4835	-4.06%	45.23%	52.3%	48.88%	46.10%	48.12%
33	123305	4119	3.46%	52.94%	56.7%	51.63%	49.60%	52.72%
34	123247	4061	3.41%	45.64%	53.3%	48.00%	46.31%	48.32%
35	113542	-5644	-4.74%	75.52%	79.2%	75.42%	75.75%	76.46%
36	115536	-3650	-3.06%	37.28%	43.3%	36.60%	35.98%	38.30%
37	118653	-533	-0.45%	50.86%	56.9%	50.46%	50.61%	52.20%
38	118805	-381	-0.32%	47.26%	49.4%	42.49%	41.60%	45.18%
39	116202	-2984	-2.50%	49.70%	56.8%	49.92%	50.29%	51.66%
40	122537	3351	2.81%	36.81%	40.7%	33.04%	33.10%	35.91%
41	119054	-132	-0.11%	54.94%	66.8%	60.94%	57.77%	60.11%
42	116212	-2974	-2.50%	57.53%	63.9%	58.30%	54.98%	58.69%

Paul Nieves House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
43	117063	-2123	-1.78%	77.20%	82.8%	79.34%	77.82%	79.28%
44	121663	2477	2.08%	40.35%	50.2%	42.99%	40.11%	43.41%
45	124983	5797	4.86%	40.49%	47.1%	41.99%	40.96%	42.63%
46	125009	5823	4.89%	51.02%	60.1%	55.82%	55.45%	55.59%
47	124861	5675	4.76%	32.47%	42.7%	37.56%	36.49%	37.29%
48	114938	-4248	-3.56%	41.01%	49.4%	42.57%	41.68%	43.67%
49	117665	-1521	-1.28%	45.07%	54.7%	47.08%	46.44%	48.31%
50	124133	4947	4.15%	50.52%	49.5%	44.55%	41.15%	46.43%
51	124941	5755	4.83%	35.82%	41.3%	36.39%	34.37%	36.98%
52	120153	967	0.81%	53.28%	63.2%	57.66%	56.23%	57.59%
53	116068	-3118	-2.62%	49.57%	58.7%	51.84%	50.63%	52.69%
54	114452	-4734	-3.97%	38.42%	52.5%	45.62%	44.26%	45.19%
55	122073	2887	2.42%	38.19%	45.1%	39.70%	38.46%	40.37%
56	115328	-3858	-3.24%	24.63%	36.2%	29.39%	28.92%	29.79%
57	120198	1012	0.85%	28.15%	30.8%	26.43%	25.74%	27.77%
58	122139	2953	2.48%	40.37%	40.9%	36.66%	35.51%	38.35%
59	118762	-424	-0.36%	35.28%	37.5%	33.30%	32.36%	34.61%
60	119207	21	0.02%	24.54%	30.9%	26.73%	26.21%	27.10%
61	121606	2420	2.03%	41.64%	41.5%	37.83%	36.33%	39.33%
62	119113	-73	-0.06%	40.05%	43.3%	39.18%	38.48%	40.25%
63	124169	4983	4.18%	28.29%	34.1%	30.17%	29.55%	30.52%
64	118349	-837	-0.70%	24.81%	35.6%	28.55%	28.34%	29.33%
65	120065	879	0.74%	27.49%	35.6%	28.11%	27.51%	29.68%
66	124710	5524	4.63%	39.29%	50.2%	41.09%	41.52%	43.03%
67	121856	2670	2.24%	27.96%	40.0%	30.65%	30.19%	32.20%
68	116894	-2292	-1.92%	31.19%	38.9%	34.77%	33.69%	34.64%
69	124936	5750	4.82%	29.84%	40.4%	34.32%	33.70%	34.57%
70	115986	-3200	-2.68%	41.87%	53.8%	47.57%	44.69%	46.99%
71	113965	-5221	-4.38%	34.39%	48.3%	38.85%	36.90%	39.62%
72	118137	-1049	-0.88%	47.67%	56.3%	48.90%	46.01%	49.72%
73	117955	-1231	-1.03%	27.31%	40.0%	33.16%	31.00%	32.87%
74	123482	4296	3.60%	26.50%	36.7%	27.34%	24.35%	28.73%
75	116973	-2213	-1.86%	28.84%	39.3%	29.91%	30.45%	32.11%
76	114368	-4818	-4.04%	17.54%	26.7%	19.43%	19.47%	20.79%
77	113307	-5879	-4.93%	22.33%	32.6%	26.06%	24.60%	26.41%
78	120675	1489	1.25%	31.17%	37.3%	32.30%	30.16%	32.72%
79	116736	-2450	-2.06%	49.30%	57.3%	53.42%	51.49%	52.88%
80	118301	-885	-0.74%	36.48%	45.1%	39.23%	37.47%	39.56%
81	119725	539	0.45%	36.77%	48.9%	42.10%	41.69%	42.38%
82	115707	-3479	-2.92%	39.65%	53.7%	48.73%	47.09%	47.28%
83	122319	3133	2.63%	51.36%	64.0%	59.28%	57.99%	58.16%
84	119460	274	0.23%	60.29%	70.7%	66.93%	66.04%	65.99%

Paul Nieves House

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
85	117414	-1772	-1.49%	32.90%	44.6%	39.52%	37.53%	38.63%
86	122817	3631	3.05%	28.57%	42.8%	35.67%	36.88%	35.99%
87	119984	798	0.67%	28.15%	41.9%	36.07%	35.97%	35.53%
88	119273	87	0.07%	22.65%	35.3%	28.69%	28.97%	28.90%
89	120735	1549	1.30%	41.17%	47.5%	42.28%	40.86%	42.94%
90	120505	1319	1.11%	26.62%	35.8%	30.79%	29.40%	30.65%
91	121818	2632	2.21%	28.55%	42.1%	33.99%	34.02%	34.66%
92	122282	3096	2.60%	25.51%	44.8%	34.33%	37.30%	35.49%
93	122202	3016	2.53%	42.00%	54.0%	48.23%	48.46%	48.18%
94	121440	2254	1.89%	42.35%	47.6%	42.12%	40.33%	43.10%
95	124070	4884	4.10%	26.06%	38.6%	32.29%	30.71%	31.92%
96	123279	4093	3.43%	22.33%	31.9%	26.32%	25.84%	26.59%
97	122307	3121	2.62%	28.86%	43.9%	36.88%	36.65%	36.58%
98	122470	3284	2.76%	24.57%	38.1%	31.39%	31.47%	31.37%
99	115793	-3393	-2.85%	25.21%	40.0%	33.49%	33.62%	33.08%
Total	**11,799,448**		**9.82%**					

Exhibit G-2

Paul Nieves Senate

District	Population	Deviation	% Deviation	Biden-Trump	Brown-Renacci	Cordray-Dewine	Richardson-Sprague-	4- Election Dem Composite
1	353197	-4362	-1.22%	24.57%	35.06%	26.45%	26.48%	28.14%
2	363282	5723	1.60%	38.01%	47.66%	39.64%	36.68%	40.50%
3	356513	-1046	-0.29%	58.04%	64.01%	60.80%	57.22%	60.02%
4	364888	7329	2.05%	36.78%	39.65%	35.77%	34.78%	36.75%
5	347731	-9828	-2.75%	53.12%	58.82%	53.16%	53.07%	54.54%
6	357544	-15	0.00%	44.12%	48.01%	40.82%	40.62%	43.39%
7	365616	8057	2.25%	30.81%	34.75%	30.11%	29.30%	31.24%
8	357656	97	0.03%	43.05%	45.14%	39.91%	38.90%	41.75%
9	350145	-7414	-2.07%	77.36%	78.59%	75.70%	74.66%	76.58%
10	363124	5565	1.56%	30.48%	40.44%	32.54%	32.40%	33.97%
11	352329	-5230	-1.46%	62.36%	70.38%	65.34%	62.63%	65.18%
12	351937	-5622	-1.57%	26.99%	36.52%	30.43%	28.50%	30.61%
13	350591	-6968	-1.95%	44.34%	56.27%	50.08%	48.11%	49.70%
14	360807	3248	0.91%	40.78%	43.41%	39.18%	37.61%	40.25%
15	360541	2982	0.83%	74.63%	77.98%	75.14%	73.77%	75.38%
16	364160	6601	1.85%	66.26%	66.95%	62.77%	59.04%	63.75%
17	360570	3011	0.84%	26.18%	40.58%	33.82%	33.82%	33.60%
18	350744	-6815	-1.91%	41.51%	51.68%	46.73%	44.97%	46.22%
19	366726	9167	2.56%	59.46%	59.80%	55.51%	52.67%	56.86%
20	367328	9769	2.73%	32.52%	42.85%	36.28%	35.13%	36.69%
21	345323	-12236	-3.42%	77.95%	84.47%	81.32%	81.14%	81.22%
22	356151	-1408	-0.39%	27.53%	39.01%	33.52%	33.20%	33.32%
23	353688	-3871	-1.08%	56.74%	62.78%	57.09%	55.20%	57.95%
24	340581	-16978	-4.75%	50.55%	57.06%	51.25%	49.59%	52.11%
25	341293	-16266	-4.55%	83.32%	85.89%	82.91%	82.44%	83.64%
26	354229	-3330	-0.93%	29.61%	41.69%	34.23%	33.23%	34.69%
27	368625	11066	3.09%	45.74%	51.94%	46.66%	44.98%	47.33%
28	354273	-3286	-0.92%	56.08%	63.32%	60.46%	58.53%	59.60%
29	374853	17294	4.84%	40.59%	49.05%	44.17%	43.34%	44.29%
30	367301	9742	2.72%	31.86%	47.30%	39.48%	40.95%	39.90%
31	366181	8622	2.41%	34.47%	41.44%	36.41%	34.77%	36.77%
32	352328	-5231	-1.46%	41.19%	51.13%	44.04%	43.38%	44.93%
33	359193	1634	0.46%	47.17%	58.86%	54.31%	52.89%	53.31%
Total	**11,799,448**		**9.59%**					

User:
Plan Name: adopted_House_9_15_vtd
Plan Type: Senate

Exhibit H-1

Measures of Compactness Report

Wednesday, September 22, 2021 8:28 AM

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.20	0.08
Max	0.63	0.78
Mean	0.40	0.30
Std. Dev.	0.10	0.15

District	Reock	Polsby-Popper
1	0.22	0.20
2	0.24	0.12
3	0.46	0.33
4	0.39	0.14
5	0.36	0.15
6	0.44	0.14
7	0.39	0.14
8	0.46	0.22
9	0.27	0.16
10	0.37	0.14
11	0.40	0.09

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.20	0.08
Max	0.63	0.78
Mean	0.40	0.30
Std. Dev.	0.10	0.15

District	Reock	Polsby-Popper
12	0.43	0.44
13	0.43	0.44
14	0.35	0.30
15	0.51	0.49
16	0.51	0.41
17	0.38	0.30
18	0.44	0.19
19	0.43	0.27
20	0.20	0.17
21	0.40	0.24
22	0.38	0.16
23	0.38	0.25
24	0.23	0.13
25	0.41	0.12

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.20	0.08
Max	0.63	0.78
Mean	0.40	0.30
Std. Dev.	0.10	0.15

District	Reock	Polsby-Popper
26	0.38	0.14
27	0.28	0.14
28	0.39	0.13
29	0.33	0.31
30	0.37	0.23
31	0.25	0.13
32	0.38	0.18
33	0.39	0.12
34	0.37	0.17
35	0.30	0.16
36	0.38	0.12
37	0.33	0.23
38	0.38	0.08
39	0.54	0.18

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.20	0.08
Max	0.63	0.78
Mean	0.40	0.30
Std. Dev.	0.10	0.15

District	Reock	Polsby-Popper
40	0.23	0.18
41	0.56	0.34
42	0.47	0.25
43	0.26	0.16
44	0.33	0.23
45	0.24	0.22
46	0.52	0.27
47	0.29	0.09
48	0.51	0.20
49	0.33	0.10
50	0.45	0.42
51	0.36	0.15
52	0.46	0.21
53	0.27	0.24

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.20	0.08
Max	0.63	0.78
Mean	0.40	0.30
Std. Dev.	0.10	0.15

District	Reock	Polsby-Popper
54	0.48	0.37
55	0.40	0.28
56	0.31	0.32
57	0.46	0.29
58	0.38	0.36
59	0.40	0.30
60	0.59	0.53
61	0.38	0.31
62	0.46	0.47
63	0.59	0.55
64	0.39	0.32
65	0.41	0.30
66	0.40	0.47
67	0.23	0.26

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.20	0.08
Max	0.63	0.78
Mean	0.40	0.30
Std. Dev.	0.10	0.15

District	Reock	Polsby-Popper
68	0.56	0.33
69	0.25	0.20
70	0.38	0.34
71	0.41	0.32
72	0.36	0.51
73	0.54	0.45
74	0.40	0.34
75	0.32	0.40
76	0.40	0.33
77	0.48	0.58
78	0.63	0.78
79	0.41	0.42
80	0.39	0.48
81	0.50	0.61

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.20	0.08
Max	0.63	0.78
Mean	0.40	0.30
Std. Dev.	0.10	0.15

District	Reock	Polsby-Popper
82	0.35	0.46
83	0.33	0.34
84	0.42	0.41
85	0.47	0.55
86	0.52	0.49
87	0.51	0.44
88	0.58	0.71
89	0.42	0.50
90	0.39	0.38
91	0.54	0.58
92	0.27	0.23
93	0.29	0.26
94	0.50	0.32
95	0.38	0.28

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.20	0.08
Max	0.63	0.78
Mean	0.40	0.30
Std. Dev.	0.10	0.15

District	Reock	Polsby-Popper
96	0.27	0.27
97	0.51	0.45
98	0.28	0.27
99	0.35	0.31

Measures of Compactness Summary

Reock	The measure is always between 0 and 1, with 1 being the most compact.
Polsby-Popper	The measure is always between 0 and 1, with 1 being the most compact.

Exhibit H-2

User:
Plan Name: adopted_Senate_9_15_vtd
Plan Type: Senate

Measures of Compactness Report

Wednesday, September 22, 2021 8:30 AM

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.26	0.06
Max	0.59	0.65
Mean	0.39	0.31
Std. Dev.	0.09	0.15

District	Reock	Polsby-Popper
1	0.42	0.33
2	0.33	0.24
3	0.33	0.06
4	0.51	0.35
5	0.48	0.20
6	0.41	0.10
7	0.33	0.24
8	0.35	0.18
9	0.33	0.09
10	0.45	0.53
11	0.28	0.32

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.26	0.06
Max	0.59	0.65
Mean	0.39	0.31
Std. Dev.	0.09	0.15

District	Reock	Polsby-Popper
12	0.51	0.43
13	0.32	0.39
14	0.30	0.33
15	0.39	0.16
16	0.26	0.20
17	0.39	0.32
18	0.59	0.65
19	0.27	0.29
20	0.37	0.38
21	0.44	0.21
22	0.49	0.53
23	0.46	0.43
24	0.44	0.41
25	0.30	0.09

	Reock	Polsby-Popper
Sum	N/A	N/A
Min	0.26	0.06
Max	0.59	0.65
Mean	0.39	0.31
Std. Dev.	0.09	0.15

District	Reock	Polsby-Popper
26	0.42	0.31
27	0.27	0.12
28	0.49	0.36
29	0.55	0.39
30	0.31	0.31
31	0.30	0.29
32	0.44	0.55
33	0.45	0.51

Measures of Compactness Summary

Reock	The measure is always between 0 and 1, with 1 being the most compact.
Polsby-Popper	The measure is always between 0 and 1, with 1 being the most compact.

Exhibit I-1

User:
Plan Name: **adopted_House_9_15_vtd**
Plan Type: **Senate**

Political Subdivison Splits Between Districts

Wednesday, September 22, 2021 8:33 AM

Split Counts

Number of subdivisions split into more than one district:		Number of splits involving no population:	
County	35	County	0
Voting District	110	Voting District	31

Number of times a subdivision is split into multiple districts:

County	72
Voting District	118

County	Voting District	District	Population
Split Counties:			
Ashtabula OH		57	16,522
Ashtabula OH		99	81,052
Auglaize OH		84	34,142
Auglaize OH		86	12,280
Belmont OH		95	20,908
Belmont OH		96	45,589
Brown OH		63	29,368
Brown OH		90	14,308
Butler OH		39	21,420
Butler OH		44	123,473
Butler OH		45	123,472
Butler OH		46	121,992
Clark OH		71	19,879
Clark OH		75	116,122
Clermont OH		62	124,425
Clermont OH		63	84,176
Columbiana OH		59	10,783
Columbiana OH		79	91,094
Cuyahoga OH		13	124,554
Cuyahoga OH		14	125,064
Cuyahoga OH		15	125,088
Cuyahoga OH		16	121,879
Cuyahoga OH		17	124,819
Cuyahoga OH		18	123,226
Cuyahoga OH		19	124,679
Cuyahoga OH		20	125,098
Cuyahoga OH		21	122,023
Cuyahoga OH		22	124,633
Cuyahoga OH		23	23,754
Darke OH		80	15,437
Darke OH		84	36,444
Defiance OH		81	6,010
Defiance OH		82	32,276

County	Voting District	District	Population
Delaware OH		60	113,964
Delaware OH		61	100,160
Fairfield OH		73	123,971
Fairfield OH		74	34,950
Franklin OH		1	115,498
Franklin OH		2	117,559
Franklin OH		3	114,104
Franklin OH		4	114,500
Franklin OH		5	116,735
Franklin OH		6	115,517
Franklin OH		7	115,170
Franklin OH		8	115,189
Franklin OH		9	120,997
Franklin OH		10	113,326
Franklin OH		11	114,236
Franklin OH		12	50,976
Geauga OH		23	51,337
Geauga OH		99	44,060
Greene OH		70	116,643
Greene OH		71	51,323
Hamilton OH		24	123,469
Hamilton OH		25	123,568
Hamilton OH		26	124,802
Hamilton OH		27	116,286
Hamilton OH		28	114,050
Hamilton OH		29	114,653
Hamilton OH		30	113,811
Hancock OH		43	11,226
Hancock OH		83	63,694
Holmes OH		69	14,623
Holmes OH		98	29,600
Lake OH		56	124,454
Lake OH		57	108,149
Licking OH		68	115,385
Licking OH		69	63,134
Lorain OH		51	125,115
Lorain OH		52	124,642
Lorain OH		53	63,207
Lucas OH		40	113,280
Lucas OH		41	113,996
Lucas OH		42	115,350
Lucas OH		43	88,653
Mahoning OH		58	116,292
Mahoning OH		59	112,322
Medina OH		66	116,342
Medina OH		67	66,128
Montgomery OH		35	121,171

EXPERT_0116

County	Voting District	District	Population
Montgomery OH		36	114,991
Montgomery OH		37	125,125
Montgomery OH		38	122,075
Montgomery OH		39	53,947
Morrow OH		61	13,700
Morrow OH		98	21,250
Portage OH		65	39,779
Portage OH		72	122,012
Stark OH		47	115,745
Stark OH		48	113,975
Stark OH		49	124,555
Stark OH		50	20,578
Summit OH		23	47,684
Summit OH		31	124,467
Summit OH		32	122,679
Summit OH		33	123,791
Summit OH		34	121,807
Trumbull OH		64	124,731
Trumbull OH		65	77,246
Warren OH		54	121,704
Warren OH		55	120,633
Washington OH		94	23,688
Washington OH		95	36,083
Wood OH		43	15,925
Wood OH		76	116,323
Wyandot OH		83	15,851
Wyandot OH		87	6,049
Split VTDs:			
Auglaize OH	DUCHOUQUET E	84	2
Auglaize OH	DUCHOUQUET E	86	1,863
Auglaize OH	DUCHOUQUET W	84	703
Auglaize OH	DUCHOUQUET W	86	451
Auglaize OH	MOULTON	84	0
Auglaize OH	MOULTON	86	1,585
Auglaize OH	NOBLE	84	16
Auglaize OH	NOBLE	86	1,199
Auglaize OH	WAPAKONETA 2B	84	1,221
Auglaize OH	WAPAKONETA 2B	86	0
Butler OH	HANOVER TWP 7	44	1,309
Butler OH	HANOVER TWP 7	45	6
Butler OH	MADISON TWP 5	39	249
Butler OH	MADISON TWP 5	46	298
Butler OH	ROSS TWP 4	44	5
Butler OH	ROSS TWP 4	45	1,328
Butler OH	ST. CLAIR TWP 1	39	1
Butler OH	ST. CLAIR TWP 1	46	1,452
Butler OH	ST. CLAIR TWP 2	39	251

EXPERT_0117

County	Voting District	District	Population
Butler OH	ST. CLAIR TWP 2	44	0
Butler OH	ST. CLAIR TWP 2	46	275
Butler OH	ST. CLAIR TWP 5	44	828
Butler OH	ST. CLAIR TWP 5	46	122
Clark OH	MR-1	71	1,657
Clark OH	MR-1	75	0
Clermont OH	BATAVIA TWP H	62	0
Clermont OH	BATAVIA TWP H	63	1,046
Cuyahoga OH	CLEVELAND-09-H	18	114
Cuyahoga OH	CLEVELAND-09-H	20	724
Cuyahoga OH	CLEVELAND-09-I	18	288
Cuyahoga OH	CLEVELAND-09-I	20	353
Cuyahoga OH	CLEVELAND-09-K	18	423
Cuyahoga OH	CLEVELAND-09-K	20	194
Cuyahoga OH	CLEVELAND-11-A	13	851
Cuyahoga OH	CLEVELAND-11-A	14	378
Cuyahoga OH	UNIVERSITY HEIGHTS-00-D	19	1,269
Cuyahoga OH	UNIVERSITY HEIGHTS-00-D	21	6
Fairfield OH	BLOOM B	73	0
Fairfield OH	BLOOM B	74	1,655
Fairfield OH	VIOLET D	73	1,503
Fairfield OH	VIOLET D	74	0
Franklin OH	BLENDON-B	4	499
Franklin OH	BLENDON-B	9	3
Franklin OH	BLENDON-C	4	1,091
Franklin OH	BLENDON-C	9	530
Franklin OH	BLENDON-D	4	1,950
Franklin OH	BLENDON-D	9	39
Franklin OH	BROWN-B	10	692
Franklin OH	BROWN-B	11	250
Franklin OH	CLINTON-A	3	1,392
Franklin OH	CLINTON-A	7	121
Franklin OH	CLINTON-A	8	0
Franklin OH	COLS 37-C	5	3,242
Franklin OH	COLS 37-C	10	52
Franklin OH	FRANKLIN-C	6	1,294
Franklin OH	FRANKLIN-C	7	17
Franklin OH	FRANKLIN-D	1	0
Franklin OH	FRANKLIN-D	5	27
Franklin OH	FRANKLIN-D	6	1,541
Franklin OH	HAMILTON-A	2	0
Franklin OH	HAMILTON-A	5	1,351
Franklin OH	JACKSON-A	5	0
Franklin OH	JACKSON-A	6	77
Franklin OH	JACKSON-A	10	1,060

County	Voting District	District	Population
Franklin OH	JEFFERSON-H	2	52
Franklin OH	JEFFERSON-H	4	1,736
Franklin OH	JEFFERSON-H	5	34
Franklin OH	MADISON-C	2	15
Franklin OH	MADISON-C	5	1,405
Franklin OH	MADISON-D	2	0
Franklin OH	MADISON-D	5	2,027
Franklin OH	NEW ALBANY-A	4	1,535
Franklin OH	NEW ALBANY-A	9	30
Franklin OH	NORWICH-A	7	6
Franklin OH	NORWICH-A	10	1,151
Franklin OH	NORWICH-A	11	115
Franklin OH	PERRY-B	8	28
Franklin OH	PERRY-B	11	1,149
Franklin OH	PERRY-C	7	309
Franklin OH	PERRY-C	8	221
Franklin OH	PERRY-C	11	34
Franklin OH	PLAIN-A	4	405
Franklin OH	PLAIN-A	9	60
Franklin OH	PRAIRIE-C	6	662
Franklin OH	PRAIRIE-C	10	480
Franklin OH	PRAIRIE-E	6	3
Franklin OH	PRAIRIE-E	10	1,550
Franklin OH	PRAIRIE-K	6	35
Franklin OH	PRAIRIE-K	10	633
Franklin OH	SHARON-A	4	3
Franklin OH	SHARON-A	8	796
Franklin OH	SHARON-A	9	57
Franklin OH	TRURO-A	2	17
Franklin OH	TRURO-A	5	155
Franklin OH	WASHINGTON-A	11	8
Franklin OH	WASHINGTON-A	12	985
Hamilton OH	DELHI A	24	9
Hamilton OH	DELHI A	30	2,005
Hamilton OH	NORWOOD 4-C	25	0
Hamilton OH	NORWOOD 4-C	26	1,572
Hamilton OH	WHITEWATER A	29	1,865
Hamilton OH	WHITEWATER A	30	0
Hancock OH	ALLEN TWP WEST-VAN BUREN	43	1,475
Hancock OH	ALLEN TWP WEST-VAN BUREN	83	0
Licking OH	HARRISON TWP A	68	7
Licking OH	HARRISON TWP A	69	1,484
Licking OH	MADISON TWP A	68	10
Licking OH	MADISON TWP A	69	1,906
Licking OH	PATASKALA 1-B	68	2,795

County	Voting District	District	Population
Licking OH	PATASKALA 1-B	69	15
Lorain OH	CARLISLE TWP #1	51	6
Lorain OH	CARLISLE TWP #1	52	897
Lorain OH	CARLISLE TWP #2	51	20
Lorain OH	CARLISLE TWP #2	52	1,943
Lorain OH	EATON TWP #1	51	9
Lorain OH	EATON TWP #1	52	1,763
Lorain OH	GRAFTON TWP #1	52	0
Lorain OH	GRAFTON TWP #1	53	1,496
Lorain OH	GRAFTON VILL #1/#2	52	1,128
Lorain OH	GRAFTON VILL #1/#2	53	6
Lucas OH	MAUMEE 1	40	1,452
Lucas OH	MAUMEE 1	43	0
Lucas OH	SYLVANIA TOWNSHIP A	42	123
Lucas OH	SYLVANIA TOWNSHIP A	43	1,515
Medina OH	YORK TWP A	66	36
Medina OH	YORK TWP A	67	1,180
Montgomery OH	CLAY-B	35	1,088
Montgomery OH	CLAY-B	39	13
Montgomery OH	CLAY-C	35	1,613
Montgomery OH	CLAY-C	39	0
Montgomery OH	DAYTON 3-B	35	9
Montgomery OH	DAYTON 3-B	38	1,064
Montgomery OH	JEFFERSON-B	36	251
Montgomery OH	JEFFERSON-B	39	1,667
Montgomery OH	JEFFERSON-C	36	63
Montgomery OH	JEFFERSON-C	39	1,439
Montgomery OH	MIAMI-C	37	470
Montgomery OH	MIAMI-C	39	1,051
Montgomery OH	MIAMI-G	36	0
Montgomery OH	MIAMI-G	37	1,561
Montgomery OH	RIVERSIDE-B	35	373
Montgomery OH	RIVERSIDE-B	38	1,821
Montgomery OH	TROTWOOD 4-A	38	18
Montgomery OH	TROTWOOD 4-A	39	1,426
Montgomery OH	TROTWOOD 4-C	38	153
Montgomery OH	TROTWOOD 4-C	39	1,176
Stark OH	CANTON TWP 1	47	1,560
Stark OH	CANTON TWP 1	49	58
Stark OH	CANTON TWP 6	47	1,710
Stark OH	CANTON TWP 6	49	33
Stark OH	JACKSON TWP 1	47	42
Stark OH	JACKSON TWP 1	49	1,987
Stark OH	NIMISHILLEN TWP 1	47	36
Stark OH	NIMISHILLEN TWP 1	48	1,121
Stark OH	NIMISHILLEN TWP 2	47	54
Stark OH	NIMISHILLEN TWP 2	48	959

County	Voting District	District	Population
Stark OH	OSNABURG TWP 3	47	1,611
Stark OH	OSNABURG TWP 3	49	0
Stark OH	PERRY TWP 4	47	1,826
Stark OH	PERRY TWP 4	50	106
Stark OH	PIKE TWP 3	47	0
Stark OH	PIKE TWP 3	50	1,138
Stark OH	PLAIN TWP 12	48	1,106
Stark OH	PLAIN TWP 12	49	17
Stark OH	PLAIN TWP 2	48	792
Stark OH	PLAIN TWP 2	49	978
Stark OH	PLAIN TWP 23	48	421
Stark OH	PLAIN TWP 23	49	937
Stark OH	PLAIN TWP 25	48	1,137
Stark OH	PLAIN TWP 25	49	0
Stark OH	PLAIN TWP 4	48	903
Stark OH	PLAIN TWP 4	49	134
Stark OH	PLAIN TWP 6	48	749
Stark OH	PLAIN TWP 6	49	141
Stark OH	TUSCARAWAS TWP 2	47	200
Stark OH	TUSCARAWAS TWP 2	50	1,617
Stark OH	WASHINGTON TWP 1	47	1,621
Stark OH	WASHINGTON TWP 1	48	57
Summit OH	BATH TWP A	31	1,190
Summit OH	BATH TWP A	34	0
Summit OH	BATH TWP D	31	1,065
Summit OH	BATH TWP D	34	96
Summit OH	COVENTRY TWP A	32	1,414
Summit OH	COVENTRY TWP A	33	18
Summit OH	COVENTRY TWP D	32	1,228
Summit OH	COVENTRY TWP D	33	13
Summit OH	COVENTRY TWP E	31	63
Summit OH	COVENTRY TWP E	32	1,168
Summit OH	HUDSON 2-A	23	0
Summit OH	HUDSON 2-A	31	1,472
Summit OH	NEW FRANKLIN 1-C	31	1,052
Summit OH	NEW FRANKLIN 1-C	32	0
Summit OH	NEW FRANKLIN 4-A	31	1,101
Summit OH	NEW FRANKLIN 4-A	32	0
Summit OH	SAGAMORE HILLS TWP I	23	48
Summit OH	SAGAMORE HILLS TWP I	31	719
Summit OH	SPRINGFIELD TWP A	32	1,665
Summit OH	SPRINGFIELD TWP A	33	0
Summit OH	TWINSBURG TWP C	23	1,149
Summit OH	TWINSBURG TWP C	31	15
Trumbull OH	WARREN TWP B	64	44
Trumbull OH	WARREN TWP B	65	1,182
Trumbull OH	WARREN TWP D	64	14

County	Voting District	District	Population
Trumbull OH	WARREN TWP D	65	1,246
Trumbull OH	WARREN TWP E	64	6
Trumbull OH	WARREN TWP E	65	1,239
Trumbull OH	WARREN TWP F	64	102
Trumbull OH	WARREN TWP F	65	911
Warren OH	DEERFIELD TWP E	54	1,131
Warren OH	DEERFIELD TWP E	55	0
Warren OH	DEERFIELD TWP Z	54	1,418
Warren OH	DEERFIELD TWP Z	55	0
Warren OH	HAMILTON TWP A	54	0
Warren OH	HAMILTON TWP A	55	818
Warren OH	HAMILTON TWP F	54	0
Warren OH	HAMILTON TWP F	55	1,286
Warren OH	HAMILTON TWP U	54	2
Warren OH	HAMILTON TWP U	55	1,049
Warren OH	TURTLECREEK TWP A	54	1,578
Warren OH	TURTLECREEK TWP A	55	372
Warren OH	TURTLECREEK TWP L	54	979
Warren OH	TURTLECREEK TWP L	55	860
Washington OH	Warren NE	94	1,120
Washington OH	Warren NE	95	40
Wood OH	MIDDLETON TWP NORTH	43	2,565
Wood OH	MIDDLETON TWP NORTH	76	124
Wood OH	PLAIN TWP	43	1,559
Wood OH	PLAIN TWP	76	66

Exhibit I-2

User:
Plan Name: **adopted_Senate_9_15_vtd**
Plan Type: **Senate**

Political Subdivison Splits Between Districts

Wednesday, September 22, 2021 8:32 AM

Split Counts

Number of subdivisions split into more than one district:		Number of splits involving no population:	
County	13	County	0
Voting District	45	Voting District	9

Number of times a subdivision is split into multiple districts:

County	18
Voting District	45

County	Voting District	District	Population
Split Counties:			
Butler OH		4	368,937
Butler OH		5	21,420
Cuyahoga OH		21	371,335
Cuyahoga OH		23	372,878
Cuyahoga OH		24	372,031
Cuyahoga OH		27	148,573
Darke OH		5	15,437
Darke OH		12	36,444
Franklin OH		3	346,752
Franklin OH		15	347,161
Franklin OH		16	278,538
Franklin OH		25	351,356
Geauga OH		18	44,060
Geauga OH		27	51,337
Hamilton OH		7	116,286
Hamilton OH		8	342,514
Hamilton OH		9	371,839
Hancock OH		1	63,694
Hancock OH		2	11,226
Holmes OH		19	29,600
Holmes OH		31	14,623
Lucas OH		2	88,653
Lucas OH		11	342,626
Montgomery OH		5	175,118
Montgomery OH		6	362,191
Stark OH		29	354,275
Stark OH		31	20,578
Summit OH		27	172,151
Summit OH		28	368,277
Wyandot OH		1	15,851
Wyandot OH		26	6,049
Split VTDs:			
Butler OH	MADISON TWP 5	4	298

County	Voting District	District	Population
Butler OH	MADISON TWP 5	5	249
Butler OH	ST. CLAIR TWP 1	4	1,452
Butler OH	ST. CLAIR TWP 1	5	1
Butler OH	ST. CLAIR TWP 2	4	275
Butler OH	ST. CLAIR TWP 2	5	251
Cuyahoga OH	CLEVELAND-11-A	23	851
Cuyahoga OH	CLEVELAND-11-A	24	378
Franklin OH	BLENDON-B	3	499
Franklin OH	BLENDON-B	25	3
Franklin OH	BLENDON-C	3	1,091
Franklin OH	BLENDON-C	25	530
Franklin OH	BLENDON-D	3	1,950
Franklin OH	BLENDON-D	25	39
Franklin OH	CLINTON-A	15	1,392
Franklin OH	CLINTON-A	25	121
Franklin OH	COLS 37-C	3	3,242
Franklin OH	COLS 37-C	16	52
Franklin OH	FRANKLIN-C	3	1,294
Franklin OH	FRANKLIN-C	25	17
Franklin OH	FRANKLIN-D	3	1,568
Franklin OH	FRANKLIN-D	15	0
Franklin OH	HAMILTON-A	3	1,351
Franklin OH	HAMILTON-A	15	0
Franklin OH	JACKSON-A	3	77
Franklin OH	JACKSON-A	16	1,060
Franklin OH	JEFFERSON-H	3	1,770
Franklin OH	JEFFERSON-H	15	52
Franklin OH	MADISON-C	3	1,405
Franklin OH	MADISON-C	15	15
Franklin OH	MADISON-D	3	2,027
Franklin OH	MADISON-D	15	0
Franklin OH	NEW ALBANY-A	3	1,535
Franklin OH	NEW ALBANY-A	25	30
Franklin OH	NORWICH-A	16	1,266
Franklin OH	NORWICH-A	25	6
Franklin OH	PERRY-B	16	1,149
Franklin OH	PERRY-B	25	28
Franklin OH	PERRY-C	16	34
Franklin OH	PERRY-C	25	530
Franklin OH	PLAIN-A	3	405
Franklin OH	PLAIN-A	25	60
Franklin OH	PRAIRIE-C	3	662
Franklin OH	PRAIRIE-C	16	480
Franklin OH	PRAIRIE-E	3	3
Franklin OH	PRAIRIE-E	16	1,550
Franklin OH	PRAIRIE-K	3	35
Franklin OH	PRAIRIE-K	16	633

County	Voting District	District	Population
Franklin OH	SHARON-A	3	3
Franklin OH	SHARON-A	25	853
Franklin OH	TRURO-A	3	155
Franklin OH	TRURO-A	15	17
Hamilton OH	DELHI A	8	2,005
Hamilton OH	DELHI A	9	9
Hancock OH	ALLEN TWP WEST-VAN BUREN	1	0
Hancock OH	ALLEN TWP WEST-VAN BUREN	2	1,475
Lucas OH	MAUMEE 1	2	0
Lucas OH	MAUMEE 1	11	1,452
Lucas OH	SYLVANIA TOWNSHIP A	2	1,515
Lucas OH	SYLVANIA TOWNSHIP A	11	123
Montgomery OH	DAYTON 3-B	5	9
Montgomery OH	DAYTON 3-B	6	1,064
Montgomery OH	JEFFERSON-B	5	1,667
Montgomery OH	JEFFERSON-B	6	251
Montgomery OH	JEFFERSON-C	5	1,439
Montgomery OH	JEFFERSON-C	6	63
Montgomery OH	MIAMI-C	5	1,051
Montgomery OH	MIAMI-C	6	470
Montgomery OH	RIVERSIDE-B	5	373
Montgomery OH	RIVERSIDE-B	6	1,821
Montgomery OH	TROTWOOD 4-A	5	1,426
Montgomery OH	TROTWOOD 4-A	6	18
Montgomery OH	TROTWOOD 4-C	5	1,176
Montgomery OH	TROTWOOD 4-C	6	153
Stark OH	PERRY TWP 4	29	1,826
Stark OH	PERRY TWP 4	31	106
Stark OH	PIKE TWP 3	29	0
Stark OH	PIKE TWP 3	31	1,138
Stark OH	TUSCARAWAS TWP 2	29	200
Stark OH	TUSCARAWAS TWP 2	31	1,617
Summit OH	BATH TWP A	27	1,190
Summit OH	BATH TWP A	28	0
Summit OH	BATH TWP D	27	1,065
Summit OH	BATH TWP D	28	96
Summit OH	COVENTRY TWP E	27	63
Summit OH	COVENTRY TWP E	28	1,168
Summit OH	NEW FRANKLIN 1-C	27	1,052
Summit OH	NEW FRANKLIN 1-C	28	0
Summit OH	NEW FRANKLIN 4-A	27	1,101
Summit OH	NEW FRANKLIN 4-A	28	0

Exhibit 10

8.27.21 Written Testimony of Collin Marozzi

ACLU
AMERICAN CIVIL LIBERTIES UNION
FOUNDATION
Ohio

TO: The Ohio Redistricting Commission

FROM: Collin Marozzi, Policy Strategist, ACLU of Ohio

DATE: August 27, 2021

RE: General Assembly District Map Plan – Interested Party Testimony

My name is Collin Marozzi and I am a Policy Strategist at the American Civil Liberties Union of Ohio. Thank you to The Ohio Redistricting Commission (The Commission) for this opportunity to testify. With approximately eight million members, activists, and supporters nationwide -- and over 200,000 members, supporters, and activists representing all of Ohio's 88 counties, the American Civil Liberties Union (ACLU) is a nationwide organization that advances its mission of defending the principles of liberty and equality embodied in our Constitution and civil rights laws. Here in Ohio, this includes extensive work to safeguard our democracy and the right to vote, including fair and equal maps and representation.

As the Commission turns, for the first time in Ohio's history, to the task of drawing fair and representative maps, we remind you of the need to comply with the following:

First, Ohio's 2020 Census data reveals several trends that make the composition of the state of Ohio noticeably different than in 2010. The majority of Ohio's counties shrunk in population — in most rural areas, and city centers like Cleveland and Toledo. Meanwhile, the population has boomed in Ohio's capital and the suburbs surrounding Columbus. Population has also grown in the Cincinnati metropolitan area.

The Columbus and Cincinnati urban and suburban regions made up for population losses elsewhere. Franklin County grew by more than 160,000 people — a 13.8% increase. Neighboring Delaware, and Union counties both grew by more than 20%. However, Ohio's total population grew by only 2.3% — more slowly than the rest of the nation, resulting in the loss of a Congressional seat. The fact is, if not for sizable population growth in Ohio's minority communities, the state would have ended the decade smaller than it started it. The Commission must account for these demographic shifts when drawing new maps.

Ohio's stagnating population should incentivize this Commission to create fair and representative districts, and end the blight that gerrymandering has inflicted on the people of Ohio. According to public testimony given to this Commission, the people of Ohio feel left behind; victims of a gerrymandered system that perpetuates partisan extremism, stifles competitive elections, and emboldens legislators to neglect their constituents. Chris Warshaw, Associate Professor at George Washington University, wrote on the effects gerrymandering has on political attitudes and his research found data that “suggests that partisan gerrymandering not only distorts the link between elections and the legislature, it undermines Americans’ faith in democracy itself.[1]” In light of witness testimony, it is evident Ohioans’ faith in their government and representation needs to be restored.

Next, we want to focus the attention of The Commission on its obligation to comply with Article XI, Section 6 of the Ohio Constitution[2]. The new requirements in Article XI, Section 6, were passed through ballot measure Issue 1 in 2015[3], with overwhelming public support, winning over 71% of the vote.

Not only does the Ohio Constitution mandate compliance with Section 6. Compliance with Section 6 is the only way to ensure The Commission's legitimacy in the eyes of Ohio voters. Compliance with the population and jurisdiction splitting rules in Sections 3 and 4 is not the ultimate goal, but only the means to an end. Creating a General Assembly map that complies with the Standards prescribed in Section 6 is the ultimate goal. The end product of this Commission must be a map that provides for proportional partisan representation, and that doesn’t primarily favor one political party over another. In this era of intentional extreme partisan gerrymanders, Ohio’s Section 6(a) provides our citizens with an essential safeguard by removing any one political party’s desired outcome from this process.

In addition, Section 6(b) mandates that The Commission draw a General Assembly map in which the statewide proportion of districts reflects the statewide partisan vote share over the last decade[4]. In 2015, millions of Ohioans supported Issue 1, not because it called for a 10% allowable variance in Ohio’s ratio of representation, and not because it created a procedure for determining incumbency following senate boundary line changes. The millions of Ohioans who supported Issue 1 did so because it promised to deliver fair, proportional, and bipartisan districts. Fulfilling that promise should be the goal of this Commission.

We compiled data from all statewide partisan elections between 2012-2020. This data provides not only a close look into the statewide partisan preferences of Ohio voters, but also demonstrates how far our current map deviates from the essential protections of Section 6(b). In 2020, Republicans received just over half of the votes for statewide partisan races (53.3%), but won nearly two-thirds of the State House seats (64.6%) and more than three-fourths of state senate seats (75.8%). This level of variance violates the new rules established in Section 6(b), as the current map has afforded Republicans disproportionate representation in both the State House and State Senate in every election since 2012. In fact, over the past decade, Ohio Republicans have never had less than a 6 percentage point advantage in the state house and a

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[1] *APRI v. Householder* , 18-cv-357 (S.D. Ohio), Trial Ex. P571 (Dr. Chris Warshaw Report) at 10 (hereinafter Trial Ex. 571).

[2] Ohio Const. art. XI § 6.

[3] Ballotpedia, *Ohio Bipartisan Redistricting Commission Amendment, Issue 1 (2015)*, https://ballotpedia.org/Ohio_Bipartisan_Redistricting_Commission_Amendment,_Issue_1_(2015) (last visited Aug. 24, 2021).

[4] Ohio Const. art. XI § 6 (“That 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.”).

10 percentage point advantage in the state senate. Since 2014, the statewide vote share for Republicans has dropped, while their share of seats in the General Assembly has grown.

Tables 1 and 2, at the bottom of my testimony, demonstrates the discrepancy in statewide election vote totals and the allocation of General Assembly seats over the past ten years. Section 6(b) requires this Commission to create a General Assembly map with minimal variance between the vote share for all statewide partisan elections, and legislative seats. We look forward to finally ending an era where the representation in the General Assembly does not reflect the will of Ohio voters.

Lastly, we remind The Commission of Article XI, Section 1(c), which charges The Commission to seek public input on the proposed plan[5]. Because meaningful public input requires community members to first critically analyze the proposed map, we ask that The Commission share the proposed map in a form that supports public interaction, such as in a machine-readable electronic ESRI shapefile format, or, if shapefiles are not available, in a .csv-format Block Equivalency file. Meaningful public input also requires adequate time between a map's introduction and the constitutionally required public hearings. Adequate time is needed to conduct a thorough review and analysis before informed comments can be submitted to the Commission. We ask the Commission to allow for days - not hours - between a map's introduction, and the subsequent hearings.

Thank you to all Commissioners for your service in this vital task for our democracy, and I'm happy to answer any questions.

Table 1: Average vote share for statewide candidates and share of the state house and state senate in Ohio, 2012-2020[6]

year	Rep. vote share - all statewide candidates	Dem. vote share - all statewide candidates	Other vote share - all statewide candidates	Rep. share of state house	Dem. share of state house	Rep. share of state senate	Dem. share of state senate
2012	46.2%	50.7%	3.10%	60.6%	39.4%	69.7%	30.3%
2014	59.7%	37.7%	2.54%	65.7%	34.3%	69.7%	30.3%
2016	54.8%	40.4%	4.78%	66.7%	33.3%	72.7%	27.3%

5 Ohio Const. art. XI § 1.

6 https://www.ohiosos.gov/elections/election-results-and-data/?__cf_chl_jschl_tk__=pmd_Z8hLRrkFGR7A8ZSjsE1sG.zEeeGlfOO2aCcqvCZHvgw-1629835990-0-gqNtZGzNAjujcnBszQkR

2018	51.2%	46.9%	1.88%	61.6%	38.4%	72.7%	27.3%
2020	53.3%	45.2%	1.49%	64.6%	35.4%	75.8%	24.2%
Avg.	**53.04%**	**44.18%**	**2.76%**	**63.84%**	**36.16%**	**72.12%**	**27.88%**

Table 2: Electoral vote totals and vote share by year and contest for all statewide partisan contests[7]

Year	**Contest**	**Dem. Votes**	**Rep. Votes**	**Other Votes**	**Rep. Vote %**	**Dem. Vote %**
2012	President	2827709	2661439	91791	47.7%	50.7%
2012	Senate	2762766	2435744	250618	44.7%	50.7%
2014	Governor	1009359	1944848	101706	63.6%	33.0%
2014	Auditor	1149305	1711927	143363	57.0%	38.3%
2014	SoS	1074475	1811020	141292	59.8%	35.5%
2014	Treasurer	1323325	1724060	0	56.6%	43.4%
2014	Attorney General	1178426	1882048	0	61.5%	38.5%
2016	President	2394164	2841005	261318	51.7%	43.6%
2016	Senate	1996908	3118567	258689	58.0%	37.2%
2018	Governor	2067847	2231917	129818	50.4%	46.7%

[7] https://www.ohiosos.gov/elections/election-results-and-data/?__cf_chl_jschl_tk__=pmd_Z8hLRrkFGR7A8ZSjsE1sG.zEeeGlfOO2aCcqyCZHvgw-1629835990-0-gqNtZGzNAjujcnBszQkR

2018	Auditor	2006204	2152769	175790	49.7%	46.3%
2018	SoS	2049944	2210356	103471	50.7%	47.0%
2018	Treasurer	2022016	2304444	0	53.3%	46.7%
2018	Attorney General	2084593	2272440	0	52.2%	47.8%
2020	President	2679165	3154834	88203	53.3%	45.2%

IN THE SUPREME COURT OF OHIO

THE OHIO ORGANIZING COLLABORATIVE, *et al.*, *Relators*, *v.* OHIO REDISTRICTING COMMISSION, *et al.*, *Respondents.*	: : : : : : : : : : :	**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.

AFFIDAVIT OF MICHAEL S. LATNER

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

1. I am a Professor in the Political Science Department at California Polytechnic State University. My research focuses on representation, electoral system design, and statistical methods in elections and in designing electoral districts. I have extensive experience with redistricting and have specialized in analyzing electoral district maps for compliance with constitutional and statutory requirements, which includes analysis of partisan advantage present in district maps. Over the past two decades, I have analyzed the properties of various types of electoral systems across the globe, the 2011 redistricting cycle on representation in Congress, the

causes and consequences of redistricting across state legislatures, and have conducted numerous analyses of the ways that electoral rules have shaped electoral outcomes in state and local elections in the United States. A copy of my curriculum vitae is attached as Exhibit A.

2. I teach courses in Voting Rights and Representation; Campaigns and Elections; Political Participation; Democracy, Design and Public Policy; and Quantitative Methods in political analysis. In the last ten years I have given dozens of speeches, interviews, and presentations on quantitative political analysis of electoral districts and how to analyze partisan advantage. I have also written and contributed to peer reviewed papers and books on the topic of electoral district maps, including:

- *Gerrymandering the States: Partisanship, Race, and the Transformation of American Federalism*, with Alex Keena, Anthony J. McGann, and Charles Anthony Smith, 2021. Cambridge University Press.
- "Common Forms of Gerrymandering in the United States" *Decisions*, with Alex Keena, Anthony J. McGann, and Charles Anthony Smith, (vol 32, Dec. 2019).
- "Diagnosing Electoral Integrity" in *Electoral Integrity in America: Securing Democracy*, (eds. Pippa Norris, Sarah Cameron, Thomas Wynter), 2018. Oxford University Press.
- *Gerrymandering in America: The House of Representatives, The Supreme Court, and the Future of Political Sovereignty*, with Alex Keena, Anthony J. McGann, and Charles Anthony Smith, 2016. Cambridge University Press.

- "A Discernable and Manageable Standard for Partisan Gerrymandering" with Alex Keena, Anthony J. McGann, and Charles Anthony Smith, *Election Law Journal*, 14, 4, 2015.
- "The Calculus of Consensus Democracy: Rethinking Patterns of Democracy without Veto Players," with Anthony J. McGann, *Comparative Political Studies*, 46, 7, 2013.
- "Mapping the Consequences of Electoral Reform" with Kyle Roach, *California Journal of Politics and Policy*, 3, 1, 2011.
- "Geographical Representation under Proportional Representation: The Cases of Israel and The Netherlands" with Anthony J. McGann, *Electoral Studies*, 24, 4, 2005.

3. I have been invited as an expert to speak at several universities on the topic of redistricting and gerrymandering, including the University of California Hastings School of Law and Emory University School of Law. My first co-authored book on the topic, *Gerrymandering in America*, which has received over 100 academic citations, was also cited for our measures of the magnitude of partisan bias produced in the 2011 redistricting cycle in an amicus brief by political science professors submitted to the Supreme Court of the United States in *Gill v. Whitford*, 138 S. Ct. 1916 (2018). *See* Brief for Political Science Professors as Amici Curiae 3. This portion of the amicus brief was cited by Justice Elena Kagan in her concurrence. *See* 138 S. Ct. at 1941.

4. I am familiar with and have studied Article XI of the Ohio Constitution.

5. I have been asked by the relators to analyze the General Assembly district plan adopted on September 16, 2021 (the "Enacted Plan") by the Ohio Redistricting Commission (the

"Commission"), and to analyze whether it complies with Article XI of the Ohio Constitution. To conduct this analysis, I rely on total population data from the 2010 and 2020 Decennial Census, data on citizen voting age population (CVAP) from the 2018 and 2019 American Community Survey 5-year estimates, and election data from the Voting and Election Science Team (VEST) datahub[1], unless otherwise noted. These data, including shapefile data, are publicly available through several repositories and mapping projects.[2]

ANALYSIS UNDER ARTICLE XI, SECTION 6(A) & (B)

6. Section 6(A) of Article XI requires the Commission to attempt to draw districts meeting the standard that: "No general assembly district plan shall be drawn primarily to favor or disfavor a political party." Section 6(B) requires the Commission to attempt to draw districts meeting the standard 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."[3]

Section 6(B) – Proportionality

7. The Ohio Constitution imposes a *proportionality* requirement. There are several statistical measures[4] to estimate proportionality, which is a principal scientifically accepted definition of the degree to which an electoral system reflects the statewide preferences of voters.[5]

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[1] https://dataverse.harvard.edu/dataverse/electionscience

[2] I obtained data from the following:
Redistricting Data Hub: https://redistrictingdatahub.org/data/about-our-data/#pl
Dave's Redistricting App: https://davesredistricting.org/

[3] Section 6(C) requires that General assembly districts be compact.

[4] Taagepera, R. *Predicting party sizes: the logic of simple electoral systems.* (2007) Oxford University Press.

[5] Indeed, interest in the relationship between votes cast and seats won can be traced back to the origins of election science. See, for example, John Stuart Mill, "Of True and False Democracy: Representation of All and Representation of the Majority Only" in *Considerations on Representative Government* (1861). For a more recent treatment, see Matthew Shugart and Rein Taagepera, "The Number of Parties and Proportionality: Two Key Tools for Analysis" in *Votes from Seats: Logical Models of Electoral Systems.* (2017, Cambridge University Press).

In democratic electoral systems, the number of seats won by political parties in a parliament or assembly should correspond with or be broadly proportionate to the number of votes cast in support of those parties.[6]

8. A simple illustration demonstrates the principle of proportionality and how disproportionality can emerge in an election. Imagine a 5-seat assembly, with 100 voters in each district and two parties (A and B) competing for seats. In districts 1-3, Party B narrowly squeaks out 51 percent/49 percent victories, but loses badly to Party A in districts 4 and 5, where Party A voters are heavily concentrated. Looking at the state as a whole, more residents actually support Party A (59 percent to 41 percent), but because Party B has more efficiently distributed voters it wins 60 percent of the assembly seats, violating the principle of majority rule. The difference between the percentage of votes (41 percent) and the percentage of seats (60 percent) won by Party B is the level of disproportionality in this election: 19 points.

Table 1. How Disproportionality Emerges

District	Party A votes	Party B votes	Party A seats	Party B seats
1	49	51	0	1
2	49	51	0	1
3	49	51	0	1
4	75	25	1	0
<u>5</u>	<u>75</u>	<u>25</u>	<u>1</u>	<u>0</u>
Statewide	59%	41%	40%	60%

9. Although there are various ways to measure proportionality, Section 6(B) specifies a particular one. Under Section 6(B), the Commission must attempt to draw a map where "[t]he statewide proportion of districts whose voters, based on statewide state and federal

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[6] David Farrell (2001) *Electoral Systems. A Comparative Introduction.* London: Palgrave; G. Bingham Powell *Elections as Instruments of Democracy: Majoritarian and Proportional Visions*. Yale University Press, 2000. Arend Lijphart (1994) *Electoral Systems and Party Systems. A Study of Twenty-Seven Democracies 1945–1990*. Oxford University Press; Michael Gallagher, "Proportionality, Disproportionality, and Electoral Systems" *Electoral Studies,* (1991), 10, 1; Douglas Rae (1967) *The Political Consequences of Electoral Laws.* New Haven, CT/London: Yale University Press.

partisan general election results during the last ten years, favor each political party correspond[s] closely to the statewide preferences of the voters of Ohio." Accordingly, I tailored my analysis to determine whether the Enacted Plan comports with Section 6(B).

10. I obtained Voting and Election Science Team (VEST) data, which provides the most comprehensive, composite precinct-level data and is regularly used by many other social scientists and public mapping projects, to project seats won for each party under the Enacted Plan and compared them with statewide composite voter preferences. While data on statewide voter preferences is available for the 2012, 2014, 2016, 2018, and 2020 elections, precinct-level VEST data is available only for the elections in 2016, 2018, and 2020. I am not aware of any other source for precinct-level data for the 2012 and 2014 elections. Due to these data limitations, I projected seats won based on data from 2016, 2018, and 2020, and I compared these seats won with statewide composite voter preferences drawn from the 2012, 2014, 2016, 2018, and 2020 elections.

11. The average results of statewide Democratic and Republican vote shares from 2012 through 2020 are 45.9 percent and 54.1 percent, respectively. *See* Table 2. Therefore, under Section 6(B), the statewide proportion of districts whose voters favor each political party should "correspond closely" to 45.9 percent for Democrats and 54.1 percent for Republicans. Since there are 99 seats in the Ohio House of Representatives and 33 seats in the Ohio Senate, this corresponds with 45 Democratic seats and 54 Republican seats in the House and 15 Democratic seats and 18 Republican seats in the Senate.

Table 2. Estimating Statewide Vote Share

Race	D votes	R votes	D share	R share
2012 Pres	2,827,709	2,661,439	51.5%	48.5%
2012 Sen	2,762,766	2,435,744	53.1%	46.9%
2014 Gov	1,009,359	1,944,848	34.2%	65.8%
2014 AG	1,178,426	1,882,048	38.5%	61.5%
2014 Audit	1,149,305	1,711,927	40.2%	59.8%
2014 SOS	1,074,475	1,811,020	37.2%	62.8%
2014 Treas	1,323,325	1,724,060	43.4%	56.6%
2016 Pres	2,394,164	2,841,005	45.7%	54.3%
2016 Sen	1,996,908	3,118,567	39.0%	61.0%
2018 Gov	2,070,046	2,235,825	48.1%	51.9%
2018 Sen	2,358,508	2,057,559	53.4%	46.6%
2018 AG	2,086,715	2,276,414	47.8%	52.2%
2018 Audit	2,008,295	2,156,663	48.2%	52.2%
2018 SOS	2,052,098	2,214,173	48.1%	51.9%
2018 Treas	2,024,194	2,308,425	46.7%	52.2%
2020 Pres	2,679,165	3,154,834	45.9%	54.1%
Composite (2016-2020)	2,261,349	2,614,419	46.4%	53.6%
Composite (2012-2020)	1,937,216	2,283,416	45.9%	54.1%

12. I conclude that the Enacted Plan violates Section 6(B) because it violates the proportionality requirement. According to the composite data, 64 of 99 House seats (that is, 64.6 percent) and 24 of 33 Senate seats (that is, 72.2 percent) favor Republicans (I do not leave out any “toss-up” districts). In other words, the plan is expected to give the Republican Party approximately 67 percent of the seats in both houses of the General Assembly—a veto-proof majority—even though only 54 percent of votes cast in statewide elections over the past decade favored Republican candidates. The average disproportionality for the Enacted Plan is estimated to be 11 points for the House and 19 points for the Senate.

13. This is higher than the levels of disproportionality observed in 2014, 2016, and 2020 in the House under the prior decade's legislative plan. It is also higher than the levels of disproportionality observed in 2012, 2014 and 2018 in the Senate. *See* Figure 1. Figure 1 displays the difference between vote and seat shares for the Republican Party over the last decade of House and Senate elections. There is a clear history of disproportionality in Ohio elections, and actually two occurrences (2012 House, 2018 Senate) where a minority of voters produced victories in a majority of seats. Further, in 2012, 2016, and 2020, in mostly Republican-favored districts, the Senate elections exhibited massive disproportionality.

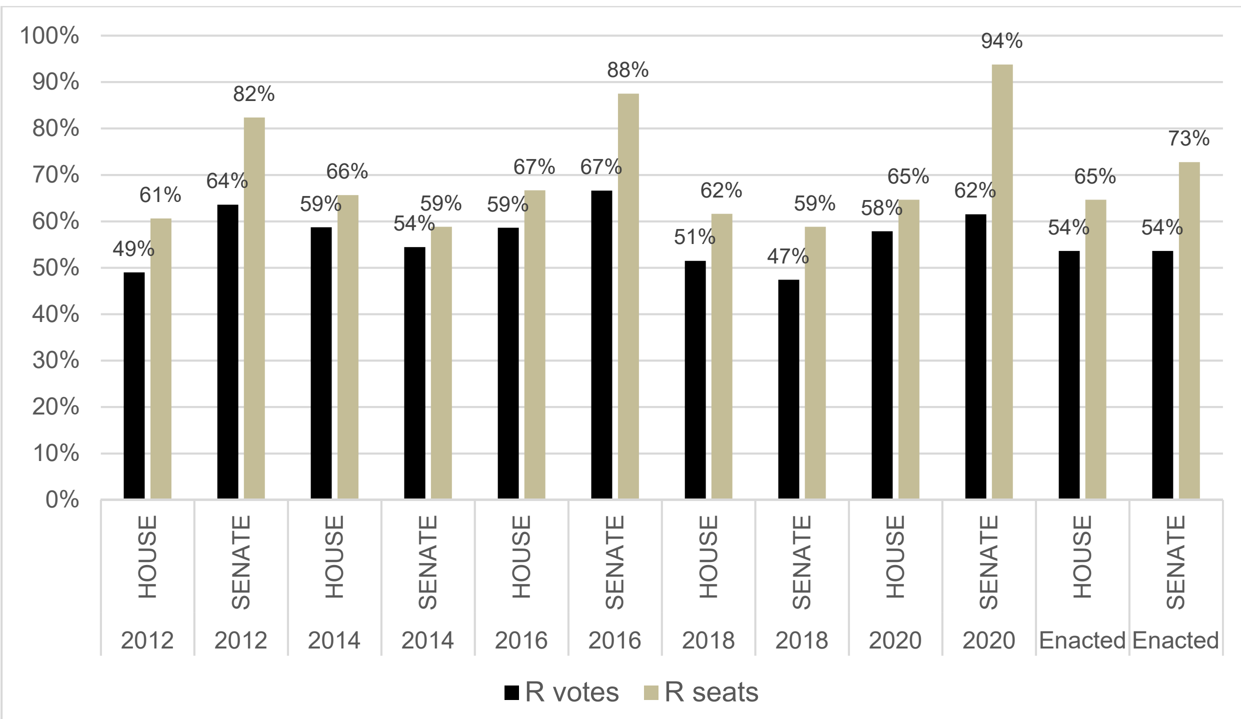

Figure 1. Differences in Republican vote and seat shares, 2012-2020, and estimated differences in the House and Senate enacted plans. Historical data retrieved from the Ohio Secretary of State Election Results repository.

14. I have been asked to review the Article XI, Section 8(C)(2) Statement issued by the Commission (the "Statement"). Section 8(C)(2) required the Commission to "include a statement explaining [1] what the commission determined to be the statewide preferences of the

voters of Ohio and [2] the manner in which the statewide proportion of districts in the plan whose voters, based on statewide state and federal partisan general election results during the last ten years, favor each political party corresponds closely to those preferences," as described in Section 6(B).

15. The Statement indicates that the Commission calculated the statewide preferences of the voters in Ohio in two ways: by calculating (1) the number of statewide state and federal partisan elections won by Republican and Democratic candidates, respectively, over the last ten years; and (2) the number of votes cast for Republican and Democratic candidates, respectively, in statewide state and federal partisan elections over the last ten years. According to the Commission's calculation, Republican candidates won 13 out of 16 statewide state and federal partisan elections, or 81 percent of such elections, while Democratic candidates won 3 out of 16 such elections, or 19 percent. As for votes cast by voters, the Commission found, as I did above, that the average statewide proportion of voters favoring Republican candidates during that period was 54 percent and the statewide proportion of voters favoring Democratic candidates was 46 percent. On this basis, the Commission concluded that "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%."

16. The Commission stated that it adopted a plan that contains 85 House and Senate districts (64.4 percent) favoring Republican candidates and 47 House and Senate districts (35.6 percent) favoring Democratic candidates out of a total of 132 General Assembly districts.[7] Because 64.4 percent is between 54 percent and 81 percent, the Commission concluded that "the

[7] The aggregate results from the composite data I use project 89 seats favoring Republicans and 44 favoring Democrats. Four House districts (15, 23, 36, 72) are within 0.005 of the majority two-party vote share. My seat allocation estimates are functions of whichever party receives the most votes in those districts according to the composite data.

statewide proportion of districts whose voters favor each political party corresponds closely to the statewide preferences of the voters of Ohio."

17. Neither election science nor any reasonable definition of the phrase "statewide preferences of the voters of Ohio" supports the Commission's conclusion or its determination of the statewide preferences of the voters of Ohio.

18. As noted, Section 6(B) indicates that the benchmark for proportionality should be the "statewide preferences of the *voters* in Ohio." The Commission's approach—which looks not to votes cast but statewide offices won—lacks a basis in Section 6(B)'s text.

19. Moreover, although there are several accepted statistical measures to estimate proportionality, not a single such measure of which I am aware leaves votes cast out of the equation. For good reason: to say that the ultimate outcome of a statewide election reflects statewide preferences of the voters is to disregard all the voters who cast a vote for the candidates who did not win. It fails to account for any factors that shape the conversion of votes to seats from election to election, which is the question we are asked to evaluate. Under the Commission's logic, if the Republican Party won five statewide elections with 50.1 percent of the vote and the Democrats won zero elections over the same time period, that would mean that the statewide preference of the voters of Ohio is to elect Republicans to 100 percent of the districts in the State. Thus, under the Commission's logic, the election margins are irrelevant and the 49.9 percent of votes not cast for Republican candidates are literally discounted.

20. The scientific evaluation of proportionality in elections is a function of how closely the statewide proportion of votes cast for parties corresponds to the proportion of assembly seats that those parties receive. The vote tallies from statewide races are an appropriate source for determining proportionality in newly enacted plans because these elections are not

impacted by districting choices, have been consistently contested by candidates from the two major parties, provide voters the same candidate choice across the entirety of the state, and generally feature higher voter turnout. In other words, they allow for a consistent, statewide measure of voter preference. To understand the proportion of General Assembly seats won under an adopted district plan, the statewide votes cast for the two major party candidates are tallied within each adopted district, which allows for a consistent determination of the proportion of assembly seats that each party receives under the Enacted Plan.

21. Accordingly, I conclude that the Enacted Plan violates proportionality as defined in Section 6(B) and that the Commission's 8(C)(2) statement indicating the statewide preferences of voters in Ohio was mistaken.

<u>Section 6(A): Favor or Disfavor of a Political Party</u>

22. I have also analyzed the Enacted Plan to determine if it comports with Section 6(A), which requires that the Commission attempt to adopt a map that is not primarily drawn to favor or disfavor a political party. The metric I adopt for this analysis is partisan symmetry, the most broadly accepted metric used by political scientists to measure partisan bias. The principle of partisan symmetry requires that a districting system award the same number of seats to each party's candidates for the same share of statewide votes they receive. Originally developed by Andrew Gelman and Gary King, the measure has a long history of peer-reviewed scientific application.[8]

[8] Andrew Gelman and Gary King, "Estimating Incumbency Advantage Without Bias" American Journal of Political Science, Vol. 34, No. 4, pp. 1142-1164, November 1990 , Available at SSRN: https://ssrn.com/abstract=1084180; Bernard Grofman and Gary King, "The Future of Partisan Symmetry as a Judicial Test for Partisan Gerrymandering after *LULAC v Perry*" Election Law Journal, 6,1,2007. Available at https://gking.harvard.edu/files/jp.pdf

23. Partisan symmetry differs from proportionality, which I discussed above, in fundamental ways. In a two-party system, the principle of partisan symmetry requires that the number of seats won by a party when it receives a certain percentage of the vote will be the same for each party, while proportionality, as discussed, requires a close correlation of seats won to proportion of ballots cast. The question posed by a partisan symmetry analysis is how many more (or less) seats does Party A get for, say, 54 percent of the statewide vote, compared to what Party B gets for 54 percent of the vote. So, whereas proportionality focuses purely on the aggregation effects of voters' preferences, symmetry estimates the effect on party seats when voters change partisan support.

24. Scientifically accepted measures of partisan symmetry follow logically from the principle that an electoral system should treat voters from both parties equally regardless of which party they choose, and that the party that wins the most votes should win the most seats.[9]

25. Figure 2 below assesses the partisan symmetry of the Enacted Plan. It charts the more competitive House districts (***i.e.***, the 45th to 75th most competitive House Districts) from most to least Republican in support. The top of the transparent portion of the bars reflects the estimate of support for Republicans in each district with the statewide average estimate of 54 percent support.

26. With that estimated statewide level of support, Republicans would win nearly two-thirds of House seats, i.e., 64 seats. But if there is an eight-point uniform swing in support toward Democrats across the districts, so that they have 54 percent support statewide, represented by the black portion of each bar *only* (i.e., subtract the transparent portion), you can see that Democrats are likely to win fewer seats (15 fewer seats, to be precise) with the same

[9] Anthony J McGann, Charles Anthony Smith, Michael Latner, Alex Keena, "A Discernable and Manageable Standard for Partisan Gerrymandering" *Election Law Journal*, 14, 4, 2015

level of support that won Republicans 64 seats. In other words, if the Republicans receive 54 percent of the vote, they would enjoy a supermajority, but if the Democrats receive 54 percent of the vote, they would not even win a majority of seats. This means the plan is asymmetric within a range of foreseeable statewide election outcomes.

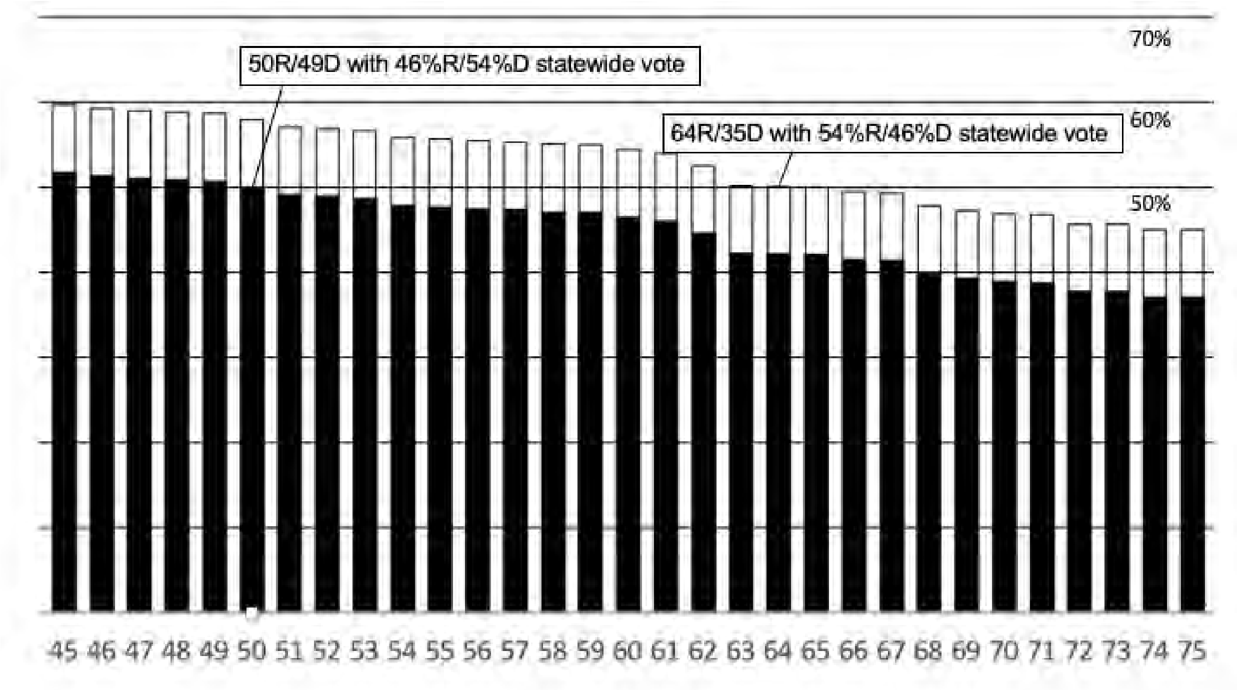

Figure 2. The distribution of party support across districts in the enacted House map demonstrates asymmetry: Republicans receive 64 seats with 54 percent statewide support, while Democrats receive 49 seats with 54 percent statewide support.

27. To test the robustness of these findings, I calculate partisan symmetry and responsiveness for the Enacted Plan, which, instead of assuming uniform vote swing across districts, imputes random "noise" (up to 5 points) to reflect the idiosyncrasies and perturbations that occur in actual elections over time. *See* Table 3. The procedure also allows me to calculate confidence intervals to provide estimates of statistical significance:

Table 3: Symmetry and Responsiveness of the Enacted Plan

Enacted Plan	Asymmetry	95% Conf.		Responsiveness	95% Conf.
House Plan	-15.39	+/-5.87		2.13	+/-0.62
Senate Plan	-17.34	+/-10.48		2.5	+/-1.12

28. These calculations show that the Enacted House Plan substantially and significantly discriminates against Democratic voters (negative numbers indicate Republican advantage). For statewide vote shares ranging from 45 percent to 55 percent, within the swing of actual Ohio voting patterns, the Republican Party picks up an average 15 percent more seats than Democrats for the same vote share, under the enacted House map. Similarly, the enacted Senate map substantially and significantly discriminates against Democratic voters. For statewide vote shares ranging from 45 percent to 55 percent, within the swing of actual Ohio voting patterns, the Republican Party picks up an average 17 percent more seats than Democrats for the same vote share, under the enacted Senate map.

29. Responsiveness scores represent the estimated increase in seat share that follows from a one percent increase in party vote share. If the responsiveness scores are less than one it indicates little change as state support shifts from one party to another; a classic incumbent protection gerrymander. By comparison, districts in states like South Dakota (3.8, 4.4) and Hawaii (4.1, 5.4)[10] were quite responsive over the last decade, reflecting more of a "winner take all" aspect in their plans. Hyper-responsive plans are less likely to be durable gerrymanders, because the map-drawing party spreads its advantage too thin across too many districts, making it vulnerable to a statewide shift in party support (scholars refer to such plans as

[10] *Gerrymandering the States*, pp.198-201

"dummymanders").[11] The observed responsiveness estimates for the enacted Ohio maps reflect a durable, "seat maximizing" gerrymander.

30. One final question that I explore concerns the origins of and the discretionary choices that contributed to the bias in the Enacted Plan. In order to identify the sources of asymmetry in partisan support in these maps, I compared the level of partisan support in adjacent districts to look for evidence of partisan "packing" or "cracking" of voters. A comprehensive analysis of racially polarized voting at the precinct level, along with estimates of alternative districting options, would be necessary to ensure Voting Rights Act compliance of the Enacted Plan and is beyond the scope of this affidavit. But a simple comparison of district partisan and racial composition reveals important patterns about how district-level allocations of populations into districts yields bias in the statewide maps.

31. It appears that the selection of counties for splitting and joining together territories in a district, especially when splitting more populated counties into multiple districts contributes to bias in the Enacted Plan. Indeed, there is evidence that these discretionary choices have been used for packing and cracking throughout the state. For example, Democratic voters are packed into House districts 1-3 (Senate district 15), including what will now be a 53 percent voting age Black population in district 2. House districts 10 and 11 select municipalities in a manner to create two safe seats, one for each party. These district boundary configurations create the opportunity for a fairly safe Republican seat to be put together in Senate district 16.

32. In Cuyahoga County, packing Democratic and African-American voters into House districts 18, 20, and 21 yields a safe Republican district 17. Similarly, the configuration of House districts 41 and 42 in Lucas County opens up a safer district 43 for Republicans, and the

[11] Bernard Grofman and Thomas Brunell, "The Art of the Dummymander" in *Redistricting in the New Millennium* (2005). Lexington Books. Lantham, MD.

choice of aggregation of these House seats into Senate seats also packs Democrats into Senate districts 21 and 23. In Summit County, Democratic voters are similarly concentrated into House district 33, and by splitting two regions of Akron into a district, Democratic voters are wrapped up in House districts 34 and 32 in a manner that leaves district 31 a safer Republican seat.

33. In Hamilton County, I observe that House districts 24 and 25 are packed with 71 percent and 78 percent Democratic voters, respectively, with high proportions (41 percent and 52 percent, respectively) of voting age African-Americans, while adjacent House districts 27, 29 and 30 are safely Republican. Senate aggregation also creates a packed Senate district 9. Similarly, in Montgomery County I observe that House district 38 is packed with 67 percent Democratic voters, which creates safe Republican seats in adjoining House districts 35 and 39, and a toss-up district 36. Below I display the partisan lean underlying these Montgomery area districts for the Enacted House Plan (Figure 3) and a Citizens' Redistricting Commission "Unity Map" submission (Figure 4). Whereas Republicans could expect to win 3 of 7 seats in and around Hamilton County and could win 4 of 5 in Montgomery County under the Enacted Plan, a comparison plan indicates that Republicans could expect to win one seat in Hamilton County and two Montgomery County seats.

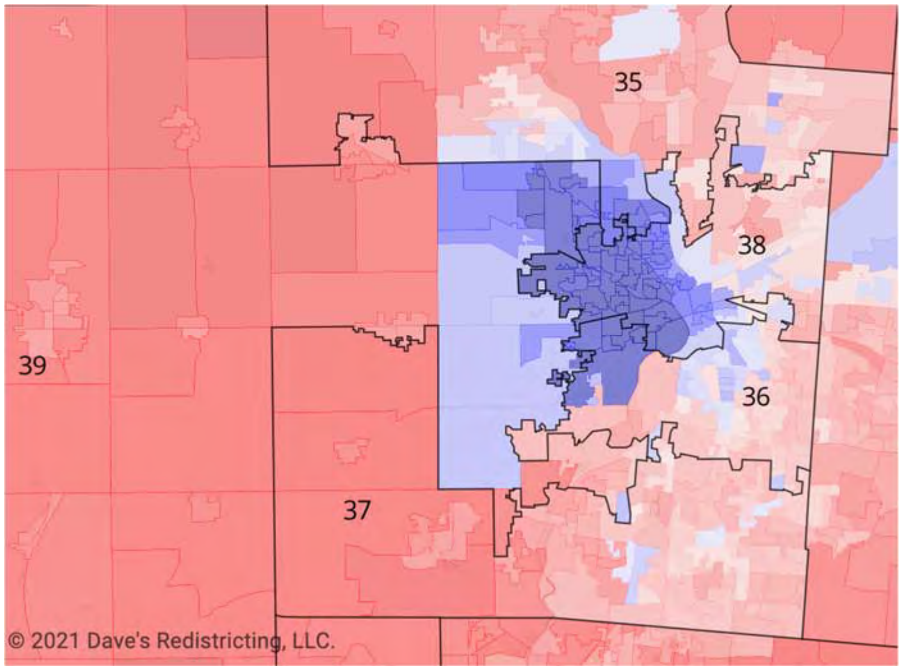

Figure 3. Enacted Plan, Montgomery County area.

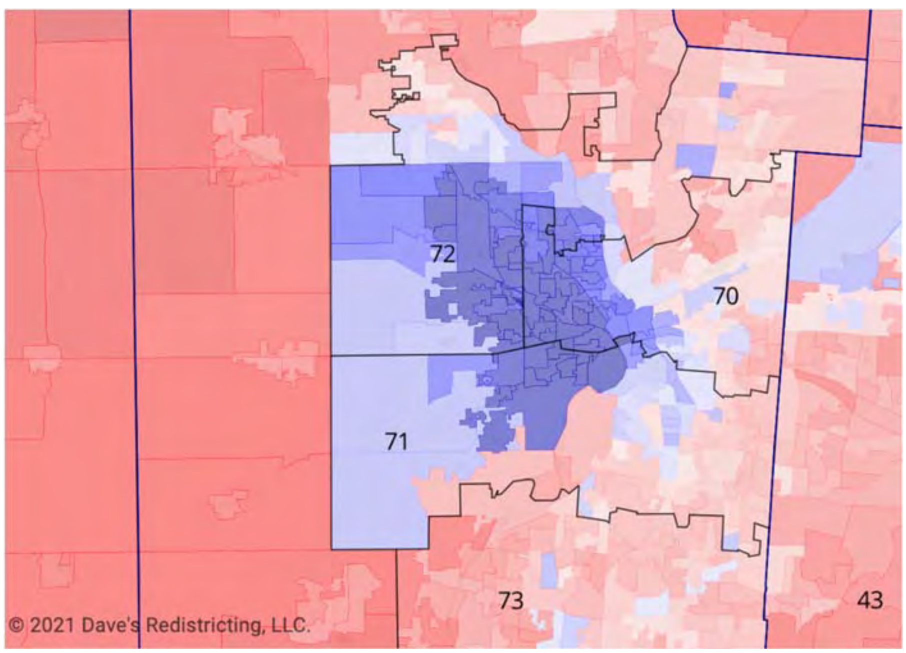

Figure 4. Comparison House Plan (submitted by Geoff Wise)
of Montgomery area districts

34. Many district boundaries in the Enacted Plan conform to partisan precincts in a precise manner, which indicates that the Commission relied on the partisan makeup of the

districts when drawing district boundaries and attempted to draw districts to favor one political party over the other. My analysis indicates that the Commission succeeded.

35. Both the House and Senate maps are biased in favor of the Republican Party, and asymmetries in partisan support across districts establish this bias. My analysis demonstrated that the 15-seat asymmetrical advantage that Republican voters enjoy over Democrats as a result of this plan would allow a minority of Republican voters to elect a majority of seats in the General Assembly. Similarly, it would enable a narrow majority of Republican voters to elect a supermajority of seats in the General Assembly. By the same token, the Enacted Plan greatly disadvantages and burdens citizens who vote for Democratic candidates, as they must band together and persuade more citizens to join their cause to obtain a level of political power comparable to that enjoyed by Republicans under the same plan. In short, the Commission's plan treats Ohio citizens differently based on their political party preference or political associations and does not give their votes equal weight, thereby violating the core principle of political equality. Accordingly, I conclude that the Enacted Plan is in clear violation of the anti-partisan gerrymandering provisions of the Ohio Constitution.

Michael S. Latner

Michael S. Latner

ACKNOWLEDGMENT

A notary public or other officer completing this certificate verifies only the identity of the individual who signed the document to which this certificate is attached, and not the truthfulness, accuracy, or validity of that document.

State of Virginia
County of Hanover)

On 09/27/2021 before me, Andrew Ray Yon

appeared Michael S. Latner, who proved to me on the basis of satisfactory evidence to be the person(s) whose name(s) is/are subscribed to the within instrument and acknowledged to me that he/she/they executed the same in his/her/their authorized capacity(ies), and that by his/her/their signature(s) on the instrument the person(s), or the entity upon behalf of which the person(s) acted, executed the instrument.

I certify under PENALTY OF PERJURY under the laws of the State of Virginia that the foregoing paragraph is true and correct.

COMMONWEALTH OF VIRGINIA
N
ELECTRONIC NOTARY PUBLIC

Andrew Ray Yon
REGISTRATION NUMBER
7759341
COMMISSION EXPIRES
August 31, 2022

WITNESS my hand and official seal.

Signature **(Seal)**

My commission expires 08/31/2022

Notarized online using audio-video communication

Executed in Hanover County, VA

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Notarize

Exhibit A

to Affidavit of Michael S. Latner

Michael Steven Latner

mlatner@calpoly.edu, @mlatner, mikelatner.com

Appointments

Union of Concerned Scientists
- 2019- Senior Fellow
- 2018-2019 Kendall Science Fellow

California Polytechnic State University, San Luis Obispo
- 2019-Professor of Political Science
- 2014-2018 Associate Professor of Political Science
- 2008-2014 Assistant Professor of Political Science
- 2007-2008 Lecturer in Political Science

University of Southern California
- 2006-2007 Teaching Fellow

University of California, Irvine
- 2005-2007 Lecturer

Field Research Corporation
- 1996-2000 Project Manager, Senior Survey Supervisor

Education

Ph.D., Political Science, University of California at Irvine, 2008
M.A., Political Science, University of California at Irvine, 2004
B.A., Political Science, California State University Chico, 1995
A.A., Butte Community College, Oroville, CA, 1993

Books

Gerrymandering the States: Partisanship, Race, and the Transformation of American Federalism with Anthony J. McGann, Charles Anthony Smith, and Alex Keena., Cambridge University Press, 2021. https://www.cambridge.org/core/books/gerrymandering-the-states/27FBE0280F339E739758A29DF7CD74A2#fndtn-information

Gerrymandering in America: The House of Representatives, The Supreme Court, and the Future of Popular Sovereignty with Anthony J. McGann, Charles Anthony Smith, and Alex Keena., Cambridge University Press, 2016.
https://www.cambridge.org/core/books/gerrymandering-in-america/C2A9A40879A353AC7484B49834CB54E4

Peer-Reviewed Publications

"Common Forms of Gerrymandering in the United States" *Decisions*, (32) with Alex Keena,Anthony J. McGann, and Charles Anthony Smith. (2019)
https://journals.kozminski.edu.pl/pub/5797

Our Unhealthy Democracy: How Voting Restrictions Harm Public Health—and What We Can Do about It, policy paper published by Union of Concerned Scientists, Center for Science and Democracy, October 2019, https://www.ucsusa.org/resources/our-unhealthy-democracy

"Diagnosing Electoral Integrity" chapter in *Electoral Integrity in America: Securing Democracy,* Pippa Norris, Sarah Cameron and Thomas Wynter (eds.), Oxford University Press, 2018.
https://www.electoralintegrityproject.com/electoral-integrity-in-america/

Building a Healthier Democracy: The Link Between Voting Rights and Environmental Justice, Union of Concerned Scientists research report, September 2018 https://www.ucsusa.org/sites/default/files/attach/2018/09/building-a-healthier-democracy-report.pdf

"Measuring Legislative Behavior: An Exploration of Digitaldemocracy.org" with Alexander M., Dekhtyar, Foaad Khosmood, Nicole Angelini, and Andrew Voorhees, *California Journal of Politics and Policy,* vol 9, issue 3, 2017. https://doi.org/10.5070/P2cjpp9336921

"Darwinian Democracy? How evolutionary theory informs constitutional design" chapter in *Handbook of Biology and Politics,* Steven Peterson and Albert Somit (eds.), Edward Elgar Publishing, 2017.
https://www.elgaronline.com/view/9781783476268.00037.xml

"A Discernable and Manageable Standard for Partisan Gerrymandering" with Anthony J. McGann, Charles Anthony Smith, and Alex Keena. December, 2015., *Election Law Journal: Rules, Politics, and Policy*. 14(4): 295-311.
https://doi.org/10.1089/elj.2015.0312

"The Calculus of Consensus Democracy: Rethinking *Patterns of Democracy* without veto players" with Anthony J. McGann, *Comparative Political Studies,* 2013, Vol 46, pp. 823-850, http://dx.doi.org/10.1177/0010414012463883

"Mapping the Consequences of Electoral Reform" with Kyle Roach, in *California Journal of Politics and Policy,* 2011, vol 3, issue 1. https://escholarship.org/uc/item/9mv9b480

"Geographical Representation Under Proportional Representation: The Cases of Israel andThe Netherlands," with Anthony McGann, *Electoral Studies,* 2005, vol 24, issue 4.
https://www.sciencedirect.com/science/article/pii/S0261379405000247

Recent Technical/Research Consultation Papers

The 2020 Randolph W. Thrower Symposium, Emory School of Law, Panel III: Violations and Enforcement: Identifying and Rectifying Campaign and Election Violations:
https://law.emory.edu/academics/journals/emory-law-journal-symposium.html

Securing Fair Elections: Challenges to Voting in Georgia and the United States (2019), co-author, Scholars Strategy Network,
https://scholars.org/sites/scholars/files/12.10.19_Securing_Fair_Elections_Report_FINAL.pdf

"Possible Results of Proportional-voting Systems for Seattle Port Commission Elections" with Jack Santucci, June 30th 2018, prepared for More Equitable Democracy

City of Pismo Beach Digital Engagement Strategy, 2015, prepared for the City of Pismo Beach

"Building a Healthier Democracy" presentation at National Advisory Board meeting, Union of Concerned Scientists, New York, New York, September 2018

Guest, Data-Driven Strategies to Promote Youth Turnout, Massachusetts Institute of

Technology, August 28-29, 2018

Census Counts 2020 Taskforce https://censuscounts.org

Presenter, Redistricting and Election Law Panel, American Political Science Association annual meeting, Boston, Massachusetts,
August 2018

"Feminist Messaging in the 2018 Congressional Elections" presented at the Cal Poly Alumni retreat, Lair of the Golden Bear, June 2018

Presenter and Discussant, Midwestern Political Science Association annual meeting, Chicago, Illinois, April 2018

Presenter and Discussant, Voting in 2018 and Beyond: Ensuring Access and Accountability of the Ballot in America, Hastings Constitutional Law Quarterly 2018 Symposium

"Diagnosing Electoral Integrity" Electoral Integrity Project pre-APSA workshop, San Francisco, California, August 2017

Presenter, American Political Science Association annual meeting, San Francisco, California, August 2017

"Will the Revolution be Digitized?" presented at the Cal Poly Alumni retreat, Lair of the Golden Bear, June 2017

Discussant and Chair, Western Political Science Association annual meeting, San Diego, California, April 2017

Chair, Discussant, and Presenter, American Political Science Association annual meeting, San Francisco, California, August 2015

Fellowships, Awards, and Professional Recognition

Kendall Science Fellow (Voting Rights), Union of Concerned Scientists, 2018-2019
Faculty Scholar, Institute for Advanced Technology and Public Policy, 2015-present
Research Scholarship and Creative Activity Grant for California Redistricting Project, 2016
Common Cause Redistricting Research Competition, 3rd Place, 2015
Gold Medal, California Mid-State Fair Home Brewing Competition, Milk Stout, 2014
Wilma Rule Award, Californians for Electoral Reform, 2013
CA State Faculty Support Grant, 2009-10

(pre-doctoral)
2003 U.C. Regents Pre-Dissertation Fellowship
2003 Summer research award, School of Social Sciences
2001 Summer research fellowship for ICPSR, University of Michigan
2000-01 William Podlich Fellow, Center for the Study of Democracy, U.C. Irvine
1995 Charles McCall Award, California State University Social Science Research Council

Election Consulting/Management
Susan Funk for Atascadero City Council 2018
Jimmy Paulding for SLO County Supervisor 2018
Aaron Gomez for San Luis Obispo City Council 2016
Dawn Ortiz-Legg for State Assembly 2016
Eric Michielssen for SLO County Supervisor 2016
Len Colamarino for Atascadero City Council 2014
Jim Patterson for SLO County Supervisor 2012
Brian Sturtevant for Atascadero City Council 2010
John Graham for Congress, 2004
John McCain for President, 2000

Recent Non-peer reviewed professional publications/news articles/blogs
A compilation of my media publications can be found at mikelatner.com

Current Teaching Rotation
POLS 590 MPP Graduate Writing Seminar (Fall section)
POLS 568 Democracy, Design and Public Policy
POLS 560 Quantitative Methods
POLS 445 Voting Rights and Representation
POLS 375 California Politics
POLS 317 Campaigns and Elections
POLS 316 Political Participation
POLS 112 American and California Government

Other Courses Taught
POLS 470 Evolutionary Perspectives in Political Science
Metropolitan Inequality (USC)
California Politics (UCI)
The American Political System (UCI)

University service
Quantitative Reasoning assessment committee, 2016-
Academic Senate Instruction Committee, 2014-2017

CLA Assessment Committee 2018
CLA Commencement, College Marshall, 2013-2016, 2018

POLS Phi Beta Kappa Supervisor, 2018
POLS Curriculum Committee, 2011-2016
POLS MPP Committee, 2007-
POLS Assessment Committee, 2008, 2009, 2011-2016, 2018
POLS Alumni Advisory Board, 2007-

Political Science Club, 2009
POLS Paper Awards Committee, 2009, 2011, 2012
POLS Guest Speaker Committee 2007-2009

IN THE SUPREME COURT OF OHIO

THE OHIO ORGANIZING COLLABORATIVE, *et al.*,	:	Case No. 2021-1210
Relators,	:	**APPORTIONMENT CASE**
v.	:	
OHIO REDISTRICTING COMMISSION, *et al.*,	:	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.
Respondents.	:	

AFFIDAVIT AND EXPERT REPORT OF MICHAEL S. LATNER

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

1. I am a Professor in the Political Science Department at California Polytechnic State University. My research focuses on representation, electoral system design, and statistical methods in elections and in designing electoral districts. I have extensive experience with redistricting and have specialized in analyzing electoral district maps for compliance with constitutional and statutory requirements, which includes analysis of partisan advantage present in district maps. I have been retained to give my opinions concerning the General Assembly district plan adopted by the Ohio Redistricting Commission in September 2021. A table of the contents of my opinions appears below.

TABLE OF CONTENTS

BACKGROUND & QUALIFICATIONS

2. As I averred in my prior affidavit attached to the relators' complaint in this apportionment case. Over the past two decades, I have analyzed the properties of various types of electoral systems across the globe, the impact of the 2011 redistricting cycle on representation in Congress, the causes and consequences of redistricting across state legislatures, and have conducted numerous analyses of the ways that electoral rules have shaped electoral outcomes in state and local elections in the United States. A copy of my curriculum vitae is attached as Exhibit A.

3. I teach courses in Voting Rights and Representation; Campaigns and Elections; Political Participation; Democracy, Design and Public Policy; and Quantitative Methods in Political Analysis. I also serve as a voting rights Senior Fellow at the Union of Concerned Scientists' Center for Science and Democracy, one of the nation's largest non-partisan science advocacy organizations. In the last ten years I have given dozens of speeches, interviews, and presentations on quantitative political analysis of electoral districts and how to analyze partisan advantage. I have also written and contributed to peer reviewed papers and books on the topic of electoral district maps, a list of which is included on my curriculum vitae.

4. I have been invited as an expert to speak at several universities on the topic of redistricting and gerrymandering, including the University of California Hastings School of Law and Emory University School of Law. My first co-authored book on the topic, *Gerrymandering in America*, which has received over 100 academic citations, was also cited for our measures of the magnitude of partisan bias produced in the 2011 redistricting cycle in an amicus brief by political science professors submitted to the United States Supreme Court in *Gill v. Whitford*, 138 S. Ct. 1916 (2018). *See* Brief for Political Science Professors as Amici Curiae 3. This

portion of the amicus brief was cited by Justice Elena Kagan in her concurrence. ***See*** 138 S. Ct. at 1941.

5. I am familiar with and have studied Article XI of the Ohio Constitution.

6. As noted, I have been asked by the relators to analyze the General Assembly district plan adopted on September 16, 2021 (the "Enacted Plan") by the Ohio Redistricting Commission (the "Commission"), and to analyze whether it complies with Article XI of the Ohio Constitution. To conduct this analysis, I rely on total population data from the 2010 and 2020 Decennial Census and 2016-2020 election data from the Voting and Election Science Team (VEST) datahub,[1] unless otherwise noted. These data, including shapefile data, are publicly available through several repositories and mapping projects.[2] I have also reviewed several other plans for comparison, including the Republican caucus plan introduced by the Commission on September 9, 2021, the Democratic caucus plan, and maps from the Ohio Citizens' Redistricting Commission.

7. I am receiving compensation for my study and testimony at an hourly rate of $250 per hour. My compensation is in no way dependent on the outcome of the dispute.

SUMMARY OF MY OPINIONS

8. The Enacted Plan systematically disfavors Democratic voters by drawing the boundaries for House and Senate districts in an asymmetric manner that minimizes the number of legislative seats that Democrats can win with a given percentage of statewide votes, while retaining a larger number of seats that Republican can reliably win with same percentage of statewide votes. This disparate treatment of voters based on party preference has the effect of

[1] https://dataverse.harvard.edu/dataverse/electionscience.

[2] I obtained data from the following:
Redistricting Data Hub: https://redistrictingdatahub.org/data/about-our-data/#pl.
Dave's Redistricting App: https://davesredistricting.org/.

entrenching a veto-proof supermajority in both chambers of the legislature. It gives Ohio voters highly unequal ability to alter or reform their government by electing candidates who support their policy positions. Put simply, the Enacted Plan has the effect of giving Republican voters more weight and thus more power to elect candidates and influence policy than it provides Democratic voters.

9. The Enacted Plan shows that the person or persons who drew the House and Senate maps intended to treat Ohio citizens differently because of their voting history, political associations and affiliations, and to burden voters who vote for Democratic candidates because of those political associations and affiliations. The House and Senate district maps favor Republicans for reasons other than adherence to Article XI's requirements and Ohio's political geography. Rather, the maps reflect discretionary choices that the map drawers made to increase Republican voters' advantage over Democratic voters. The highly asymmetric and disproportionate benefits that accrue to Republican voters under these maps did not occur by chance or accident.

10. The proportion of House and Senate districts in the Enacted Plan that favor or disfavor a political party or that party's voters, based on statewide state and federal partisan general election results during the last ten years, does not correspond, much less correspond closely, to the statewide preferences of the voters of Ohio. To the contrary, the Enacted Plan disproportionately favors Republican voters relative to the statewide preferences of Ohio voters. The person or persons who drew the Enacted Plan could have produced more proportionate maps while also adhering to the other requirements of Article XI.

Overview of Partisan Gerrymandering

11. Partisan gerrymandering occurs when members of a political party in control of redistricting manipulate the geographic boundaries of electoral districts in a manner that systemically advantages their party. The goal of partisan gerrymandering is to secure an advantage in future elections in good and bad election cycles alike. Effectively gerrymandered districts can give one party control of a state legislature or a congressional delegation for a full decade, even in swing states that have a closely split electorate, where both parties can win statewide depending on political winds.

12. There are two main techniques employed in gerrymandering: "packing," which wastes votes by unnecessarily concentrating the constituents of the disfavored party into a small handful of districts, and "cracking," which splits constituents of the disfavored party across several districts where they cannot form an electoral majority.[3] In both instances, the votes for the disfavored party are wasted and the votes for the favored party are strategically distributed to create seemingly close contests in a large number of districts that nonetheless have been drawn to produce reliable electoral majorities.[4]

13. A partisan gerrymander generates what is called "partisan bias." Partisan bias is the difference between the share of seats that a party receives for a given vote share, and the seat share that the other party would receive for the same vote share. A biased map enables the advantaged party to win seats in the legislature with a smaller vote share than what the disadvantaged party needs.

[3] Bernard Grofman and Cervas, Jonathan, (2020), "The Terminology of Districting". Available at SSRN: https://ssrn.com/abstract=3540444, p.14.
[4] ***Ibid***.

14. The harms caused by partisan gerrymandering are well documented. Recent research provides empirical evidence that voters' associational rights are diminished: partisan bias in districting plans is associated with the disfavored party contesting fewer districts, with candidates for the disadvantaged party having weaker resumes, and with lower donor support.[5] Conversely, the favored party need not put resources into contesting packed districts, allowing for efficient political expenditures. In other words, gerrymandering severely shrinks the geography, and the number of communities, where meaningful inter-party political competition takes place.

15. The bias that is manifested through partisan gerrymandering also has negative policy and social consequences. When the ideological representation of individual districts is distorted, that distortion shapes the composition of legislatures and the policies that they produce.[6] In turn, research has shown that social policy and health outcomes are impacted by legislative bias, with biased legislatures exhibiting less responsiveness to the health needs of statewide constituencies.[7] Because government policies typically apply statewide, it is the entire population that is potentially harmed by gerrymandering. For example, gerrymandered state legislatures have gone further in enacting restrictive election laws that potentially impact all voters within a state, and they were less likely to expand voting opportunities amid the COVID-19 pandemic.[8]

16. Partisan gerrymandering is a fundamental assault on the principle of democracy. It replaces rule by the people with rule by entrenched partisan interests that choose district

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[5] Stephanopoulos, Nicholas and Warshaw, Chris, (2019). "The Impact of Partisan Gerrymandering on Political Parties" Available at SSRN: https://ssrn.com/abstract=3330695 or http://dx.doi.org/10.2139/ssrn.3330695

[6] Caughey, Devin, Chris Tausanovitch, and Christopher Warshaw.(2017) "Partisan Gerrymandering and the Political Process: Effects on Roll-Call Voting and State Policies." *Election Law Journal: Rules, Politics, and Policy* 16, no. 4 (December 2017): 453–469.

[7] *Gerrymandering the States*, Ch.6.

[8] *Ibid.*

boundaries and empower certain constituencies at the expense of others. In other words, it gives unequal voting power to voters based on party association and preference. Partisan gerrymandering can effectively determine electoral outcomes, in spite of changes in voter support and variable turnout. In addition to the harms it causes to democracy, gerrymandering causes direct, material harm to voters in the form of distorted policy outcomes. Finally, by protecting politicians from accountability, gerrymandering contributes to the erosion of support for democratic government and the rule of law, fueling the rise of authoritarian governance.[9] Accordingly, the overwhelming—if not unanimous—consensus among political scientists is that a system that provides for minority rule or creates unequal voting rights is no longer a democracy or a government instituted for the equal protection and benefit of its citizens.

ANALYSIS AND OPINIONS

I. The Proportion of Districts in the Enacted Plan That Favor a Political Party Does Not Correspond with the Statewide Preferences of the Voters of Ohio

17. The people of Ohio have enshrined proportionality as a constitutional requirement for drawing assembly districts. As a general matter, the principle of proportionality means that the number of seats won by political parties in a parliament or assembly should correspond with or be broadly proportionate to the number of votes cast in support of those parties.[10]

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[9] Ozan O. Varol, (2015). "Stealth Authoritarianism", 100 *Iowa L. Rev.* 1673; https://ilr.law.uiowa.edu/print/volume-100-issue-4/stealth-authoritarianism/.

[10] Douglas Rae (1967) *The Political Consequences of Electoral Laws.* New Haven, CT/London: Yale University Press; Michael Gallagher, "Proportionality, Disproportionality, and Electoral Systems" *Electoral Studies,* (1991), 10, 1; Arend Lijphart (1994) *Electoral Systems and Party Systems. A Study of Twenty-Seven Democracies 1945–1990*. Oxford University Press; G. Bingham Powell (2000) *Elections as Instruments of Democracy: Majoritarian and Proportional Visions*. Yale University Press; David Farrell (2001) *Electoral Systems. A Comparative Introduction.* London: Palgrave.

Proportionality is a scientifically accepted concept that can be measured by the degree to which an electoral system or district scheme reflects the statewide preferences of voters.[11]

18. Broadly speaking, political scientists assess the proportionality of an electoral district map by comparing how the proportion of votes cast for a party relates to the proportion of seats that the party would be expected to win. A simple illustration demonstrates the principle of proportionality and how it can emerge in an election. Imagine a 5-seat state assembly, with 100 voters in each district and two parties (A and B) competing for seats. In an election, Party B wins narrow 51 percent/49 percent victories in districts 1, 2 and 3, but loses badly in districts 4 and 5, where Party A voters are heavily concentrated. Looking at the state as a whole, Party A is preferred by a 59 percent majority of voters, but Party B has won 60 percent of the assembly seats. See Table 1. Since the number of seats won by Party A does not correspond closely to the statewide voter preferences, the map is not proportional, and actually violates the principle of majority rule in this case. The difference between the percentage of votes (41 percent) and the percentage of seats (60 percent) won by Party B is the level of disproportionality in this election: 19 points.

[11] Interest in the relationship between votes cast and seats won can be traced back to the origins of election science. See, for example, John Stuart Mill, "Of True and False Democracy: Representation of All and Representation of the Majority Only" in *Considerations on Representative Government* (1861). For a more recent treatment, see Matthew Shugart and Rein Taagepera, "The Number of Parties and Proportionality: Two Key Tools for Analysis" in *Votes from Seats: Logical Models of Electoral Systems.* (2017, Cambridge University Press).

TABLE 1

How Disproportionality Emerges

Differences between the proportion of votes and seats won produce disproportionality.

SEATS	PARTY A VOTES	PARTY B VOTES	PARTY A SEATS	PARTY B SEATS
1	49	51	0	1
2	49	51	0	1
3	49	51	0	1
4	75	25	1	0
5	75	25	1	0
Statewide	59%	41%	40%	60%

Table 1. Disproportionality Illustration

19. Although there are various ways to measure proportionality,[12] Section 6(B) of the Ohio Constitution specifies a particular one. Under Section 6(B), the Commission must draw a map where "[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 correspond[s] closely to the statewide preferences of the voters of Ohio." Accordingly, I tailored my analysis to determine whether the Enacted Plan comports with Section 6(B).

20. My analysis proceeds in four steps. First, I calculate the statewide preferences of the voters of Ohio, based on statewide state and federal partisan general election results during the last ten years. Second, I calculate the statewide proportion of districts whose voters favor each political party, based on the same set of statewide elections for which data is publicly available. I do this for the House, the Senate, and for the General Assembly as a whole. Then, to

[12] Taagepera, R. *Predicting Party Sizes: The Logic of Simple Electoral Systems.* (2007) Oxford University Press.

determine whether the two figures "closely correspond" to each other, I calculate the difference between those two figures. Finally, I compare that difference to both to the previous legislative map and to other maps submitted to the Commission.

21. I start by calculating the statewide preferences of the voters of Ohio based on statewide state and federal partisan general election results during the last ten years. I find that the average results of statewide Democratic and Republican vote shares from 2012 through 2020 are 45.9 percent and 54.1 percent, respectively. See Table 2.

TABLE 2

Statewide Preferences of Ohio Voters

RACE	DEMOCRATIC VOTES	REPUBLICAN VOTES	DEMOCRATIC SHARE	REPUBLICAN SHARE
2012 Presidential	2,827,709	2,661,439	51.5%	48.5%
2012 Senate	2,762,766	2,435,744	53.1%	46.9%
2014 Governor	1,009,359	1,944,848	34.2%	65.8%
2014 Attorney General	1,178,426	1,882,048	38.5%	61.5%
2014 Auditor	1,149,305	1,711,927	40.2%	59.8%
2014 Secretary of State	1,074,475	1,811,020	37.2%	62.8%
2014 Treasurer	1,323,325	1,724,060	43.4%	56.6%
2016 Presidential	2,394,164	2,841,005	45.7%	54.3%
2016 Senate	1,996,908	3,118,567	39.0%	61.0%
2018 Governor	2,070,046	2,235,825	48.1%	51.9%
2018 Senate	2,358,508	2,057,559	53.4%	46.6%
2018 Attorney General	2,086,715	2,276,414	47.8%	52.2%
2018 Auditor	2,008,295	2,156,663	48.2%	51.8%
2018 Secretary of State	2,052,098	2,214,273	48.1%	51.9%
2018 Treasurer	2,024,194	2,308,425	46.7%	53.3%
2020 Presidential	2,679,165	3,154,834	45.9%	54.1%
Sum of votes	30,995,458	36,534,651	45.9 %	54.1%
Divided by number of races	16	16		
Composite (2012-2020)	1,937,216	2,283,416	45.9%	54.1%

Table 2. Statewide Preferences of Ohio Voters

22. Next, using 2016-2020 precinct-level election data from the Voting and Election Science Team (VEST),[13] (the only years for which I was able to obtain publicly available precinct-level results), I determined the statewide composite: 46.4 percent Democratic and 53.6 percent Republican. I then calculate the statewide proportion of districts whose voters favor each political party. The composite precinct votes were assigned to districts to calculate average district-level vote shares, which determined seat shares. I allocated a district to a political party whenever that party has an average two-party vote share above 50 percent. Four House Districts (15, 23, 36, 72) are within 0.5 percent of the majority two-party vote share. I allocated these seats to the party that receives a majority despite the tight margins.

A. Analysis of the Proportionality of the House Map in the Enacted Plan

23. Applying this method, the enacted House district map yields 64 districts for Republicans (64.6 percent of districts) and 35 seats for Democrats (35.4 percent of districts). See Table 3. By contrast, under a proportionate map, 54 seats (54.1 percent) should favor Republicans and 45 seats (45.9 percent) should favor Democrats. Given that the composite results from 2016-2020 are slightly more favorable to Democrats, the disproportionality would be even more pronounced if the analysis was limited to those years rather than 2012-2020.

[13] VEST provides the most comprehensive, composite precinct-level data and is regularly used by social scientists and public mapping projects. While data on statewide voter preferences is available for the 2012, 2014, 2016, 2018, and 2020 elections, precinct-level VEST data is available only for the elections in 2016, 2018, and 2020. I am not aware of any other source for precinct-level data for the 2012 and 2014 elections. Due to these data limitations, I projected seats won based on data from 2016, 2018, and 2020, and I compared these seats won with statewide composite voter preferences drawn from the 2012, 2014, 2016, 2018, and 2020 elections.

TABLE 3

Estimated Seat Shares for Enacted Plan

	REPUBLICAN	DEMOCRATIC
Statewide vote	54.1%	45.9%
Enacted House seats	64	35
Enacted House seat share	64.6%	35.4%
Enacted Senate seats	24	9
Enacted Senate seat share	72.7%	27.3%

Table 3. Estimated Seat Shares for Enacted Plan

24. To determine whether the parties' statewide vote share "corresponds closely" with the seat share in the House, I look to the difference in relative seat share between Democrats and Republicans and the difference in actual number of seats. Here, the difference in relative seat share is 11 percent: 65 percent of the House seats favor Republicans, even though only 54 percent of votes cast were for Republicans. That translates to 10 additional seats that favor Republicans in the House as compared to a fully proportionate map.

25. The Commission was presented with other plans that featured less disproportionality and were materially compliant with Article XI.[14] The Ohio Citizens' Redistricting Commission ("OCRC") House map, for example, has a near proportional allocation of seats (55.6 percent of seats favor Republicans with 54.1 percent of the vote). The OCRC map

[14] Specifically, I examined the extent to which the district boundaries split counties, municipalities and townships, and did not observe deviations from the priorities as laid out in Sections 3 and 4. While the numbering of the OCRC districts is not ordered in the same format as the Enacted Plan, the county- and municipal-level criteria appear to have been met.

demonstrates that the Commission could have introduced and enacted a more proportionate map if it had attempted to do so.

26. The enacted House map is also less proportional than last decade's legislative map, which was enacted before the Ohio Constitution was amended to expressly require proportionality. My published research on the consequences of gerrymandering in state legislatures demonstrates that Ohio enacted some of the most biased districting plans in the country in 2011.[15] The average historical disproportionality for the House over the last decade is approximately 9 percent. See Figure 1.

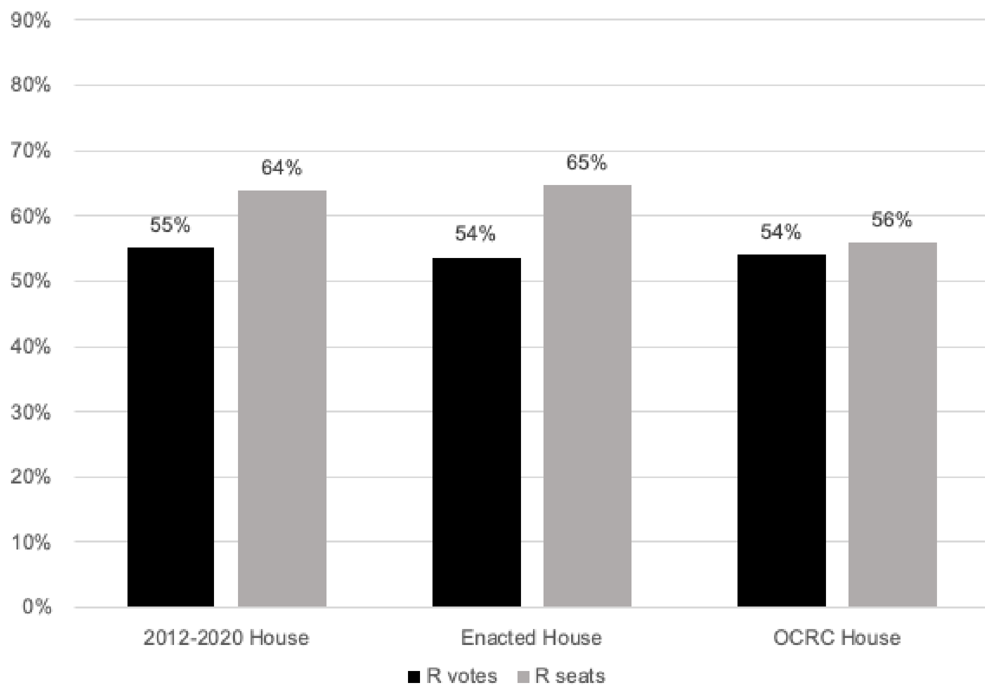

Figure 1. Disproportionality in 2012-2020, Enacted, and OCRC House Maps

27. Accordingly, I conclude that the statewide proportion of districts in the enacted House map whose voters favor each political party does not correspond, much less correspond closely, to the statewide preferences of the voters of Ohio.

[15] *Gerrymandering in America*, pp. 88-94; *Gerrymandering the States*, pp. 191-207.

B. Analysis of the Proportionality of the Senate Map in the Enacted Plan

28. I also analyzed the enacted Senate map for similar evidence of disproportionality, and arrived at a similar conclusion: the Senate map fails to meet Section 6(B)'s proportionality requirement.

29. There are 33 seats in the Ohio Senate. Elections are staggered so that 16 or 17 members are elected in every even-year election. Under Section 6(B), 18 seats (54.1 percent) should favor Republicans, while 15 seats (45.9 percent) should favor Democrats. Under the enacted map, however, 24 seats (73 percent) favor Republicans and 9 seats favor Democrats (27 percent). See Figure 2. The difference between the Republican statewide vote share and Republican seat share in the Senate is 19 percent, which translates into six additional seats that favor Republicans in the Senate.

30. As with the enacted House map, the Commission was presented with other maps that featured less disproportionality. The OCRC Senate map has a disproportionality of just 1 percent: 55 percent of Senate seats favor Republicans for a 54.1 vote share. Had the Commission attempted to comply with Section 6(B), it could have introduced and passed a substantially more proportional map.

31. From a historical perspective, the enacted Senate map is also more disproportionate than the 2012-2020 Senate map. The average historical disproportionality for the Senate over the last decade is approximately 17 percent. See Figure 2. At 19 percent, the enacted Senate map's projected disproportionality is worse than the 17 percent average level of disproportionality measured in last decade's Senate map

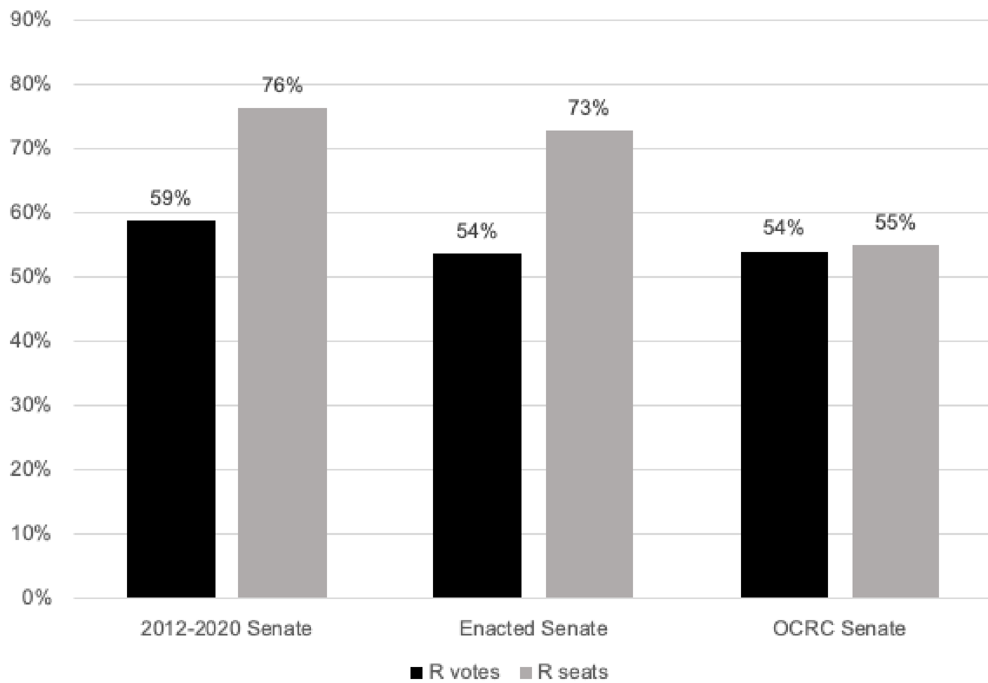

Figure 2. Disproportionality in 2012-2020, Enacted, and OCRC Senate Maps

32. Accordingly, I conclude that the statewide proportion of districts in the enacted Senate map whose voters favor each political party does not correspond, much less correspond closely, to the statewide preferences of the voters of Ohio.

C. Analysis of the Proportionality of the Enacted Plan as a Whole.

33. Finally, I combined the two preceding analyses to determine the proportionality of the Enacted Plan as a whole. There are 132 General Assembly districts in Ohio and, in the Enacted Plan, 88 favor the Republican Party (67 percent) and 44 favor the Democratic Party (33 percent). Under Section 6(B), 71 seats (54.1 percent) should favor Republicans, while 61 seats (45.9 percent) should favor Democrats. This level of disproportionality is unusually high by any standard.[16]

[16] Matthew Shugart and Rein Taagepera (2017), p.69. For example, proportionality for the U.S. House of Representatives is typically within 5 percent of vote shares.

34. Accordingly, I conclude that the statewide proportion of districts in the Enacted Plan whose voters favor each political party does not correspond, much less correspond closely, to the statewide preferences of the voters of Ohio.

D. Analysis of the Commission's 8(C)(2) Statement.

35. I have also been asked to review the Article XI, Section 8(C)(2) Statement issued by the Commission (the "Statement"). Section 8(C)(2) required the Commission to "include a statement explaining what the commission determined to be the statewide preferences of the voters of Ohio and the manner in which the statewide proportion of districts in the plan whose voters, based on statewide state and federal partisan general election results during the last ten years, favor each political party corresponds closely to those preferences," as described in Section 6(B).

36. The Statement indicates that the Commission calculated the statewide preferences of the voters in Ohio by calculating two numbers: (1) the number of statewide state and federal partisan elections won by Republican and Democratic candidates, respectively, over the last ten years; and (2) the number of votes cast for Republican and Democratic candidates, respectively, in statewide state and federal partisan elections over the last ten years. According to the Commission's calculations, Republican candidates won 13 out of 16 statewide state and federal partisan elections, or 81 percent of such elections, while Democratic candidates won 3 out of 16 such elections, or 19 percent. As for votes cast by voters, the Commission found, as I did above, that the average statewide proportion of voters favoring Republican candidates during that period was 54 percent and the statewide proportion of voters favoring Democratic candidates was 46 percent. On this basis, the Commission concluded that "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%."

37. The Commission stated that it adopted a plan that contains 85 House and Senate districts (64.4 percent) favoring Republican candidates and 47 House and Senate districts (35.6 percent) favoring Democratic candidates out of a total of 132 General Assembly districts.[17] Because 64.4 percent is between 54 percent and 81 percent, the Commission concluded that "the statewide proportion of districts whose voters favor each political party corresponds closely to the statewide preferences of the voters of Ohio."

38. Neither election science nor any reasonable definition of the phrase "statewide preferences of the voters of Ohio" supports the Commission's conclusion that the Enacted Plan is proportional.

39. As noted, Section 6(B) indicates that the benchmark for proportionality should be the "statewide preferences of the *voters* in Ohio." The Commission's approach—which included a measure that looks not to votes cast but statewide offices won—lacks a basis in Section 6(B)'s text.

40. Moreover, although there are several accepted statistical measures to estimate proportionality,[18] not a single such measure of which I am aware leaves votes cast out of the equation. For good reason: to say that the ultimate *outcome* of a statewide election reflects the statewide preferences of the voters is to disregard all the *voters* who cast a vote for the candidates who did not win. Also, it ignores differential turnout from election to election. If the Republican Party won five statewide elections with 50.1 percent of the vote and the Democrats won zero elections over the same time period, under the Commission's proportionality logic, that

[17] The composite data I use project 88 seats favoring Republicans and 44 favoring Democrats. Minor differences in the attribution of precincts to districts, used to estimate seat shares, can result in seats being attributed to different parties in very competitive districts. That said, even using the Commission's seat shares, the disproportionality of the Enacted Plan remains substantially high relative to comparison plans.
[18] Matthew Shugart and Rein Taagepera, (2017), Ch. 4

would mean that the statewide preference of the voters of Ohio is to elect Republicans to 100 percent of the districts in the state. Thus, under the Commission's reasoning, the election margins are irrelevant, and the 49.9 percent of votes not cast for Republican candidates are literally discounted. Because the Commission relied upon an invalid measure of proportionality to conclude that the Enacted Plan is proportional, and because the Enacted Plan lacks proportionality when assessed under valid measures, the Commission's Section 8(C)(2) statement should not be credited.

E. Conclusions About the Proportionality of the Enacted Plan

41. I conclude that the Enacted Plan violates Section 6(B) because the proportion of districts in the enacted plan that favor the Republican Party does not correspond closely with the statewide preferences of the voters of Ohio. The plan can be expected to provide the Republican Party approximately 67 percent of the seats in both chambers of the General Assembly—a veto-proof majority—even though only 54 percent of votes cast in statewide elections over the past decade favored Republican candidates. The average disproportionality for the Enacted Plan is estimated to be 11 percent for the House and 19 percent for the Senate. This is a high enough level of disproportionality to allow a party to win majority control over the General Assembly with a minority of votes, as has been demonstrated in two elections in the last decade. It is also significantly higher than other plans presented to the Commission, and higher than the average disproportionality seen in last decade's maps that were not subject to proportionality or other partisan fairness requirements.

II. The Enacted Plan Favors Republican Voters and Disfavors Democratic Voters

42. I have analyzed the Enacted Plan and conclude that it discriminates against voters who support the Democratic Party, to the advantage of voters who support the Republican Party.

I use statistical, comparative, and geographic analysis to determine whether the Enacted Plan favors or disfavors one party's voters over others. First, I determine the degree to which the Enacted Plan exhibits asymmetry in the allocation of seats for votes. Second, I compare asymmetries across two comparison plans: the plan proposed by the state Democratic Caucus, and a "unity" map proposed by OCRC. These other plans are useful for two reasons: (1) because, as mentioned, they are materially compliant with the Ohio Constitution; and (2) because they were presented to the Commission during the map-drawing process and could have been introduced. Accordingly, analysis of these plans helps establish whether the Commission could have drawn a less biased plan. Third, I analyze the geography of boundary choices in the Enacted Plan and the aggregation of House districts into Senate districts to identify the source of bias and the sorting of populations in the Enacted Plan. Fourth, I evaluate the amendments that were made to the plan between the time it was introduced and the time it was passed to determine whether those amendments feature a partisan bias. Finally, I look to whether Section 6(C)'s compactness requirement could explain the partisan bias in the Enacted Plan.

A. Partisan Asymmetry Analysis

1. Partisan Symmetry Overview

43. The primary metric I adopt in this section is partisan symmetry, a broadly accepted metric used by political scientists to measure partisan bias.[19] The principle of partisan symmetry requires that a districting system award the same number of seats to each party's

[19] Barry Burden and Corwin Smidt, "Evaluating Legislative Districts Using Measures of Partisan Bias and Simulations, *Sage Open*, 10, 4, 2020; https://doi.org/10.1177/2158244020981054; Anthony J McGann, Charles Anthony Smith, Michael Latner, Alex Keena, "A Discernable and Manageable Standard for Partisan Gerrymandering" *Election Law Journal*, 14, 4, 2015; John F. Nagle. "Measures of Partisan Bias for Legislating Fair Elections", *Election Law Journal*: 2015. pp. 346-360.http://doi.org/10.1089/elj.2015.0311.

candidates for the same share of statewide votes they receive. Originally developed by Andrew Gelman and Gary King, the measure has a long history of peer-reviewed scientific application.[20]

44. Partisan symmetry differs from proportionality, which I discussed above, in fundamental ways. In a two-party system, the principle of partisan symmetry requires that the number of seats won by a party when it receives a certain percentage of the statewide vote will be the same for each party, while the principle of proportionality requires that the number of seats won by a party correspond with or be proportionate to the number of votes cast in support of those parties. The question posed by a partisan symmetry analysis, in other words, is how many more (or fewer) seats does one party get for some share of the statewide vote as compared to what another party gets for that same statewide vote share.

45. Scientifically accepted measures of partisan symmetry follow logically from the principle that an electoral system should treat voters equally regardless of with which party they choose to associate, and that the party that wins the most votes should win the most seats.[21] I estimate symmetry in two ways: (1) a simple numeric formula (*S*) that can be calculated by hand,[22] and (2) a computational model of symmetry with statistical confidence intervals. The computational symmetry models estimate symmetry in the seats-votes function across a range of vote shares, while *S* measures symmetry in the distribution of support for parties across the districts that each party wins.

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[20]E.R.Tufte, (1973). "The relationship between seats and votes in two-party systems." Bernard Grofman and Gary King, "The Future of Partisan Symmetry as a Judicial Test for Partisan Gerrymandering after *LULAC v Perry*" *Election Law Journal*, 6,1,2007. Available at https://gking.harvard.edu/files/jp.pdf; *American Political Science Review*, 67, 540–554; Andrew Gelman and Gary King, "Estimating Incumbency Advantage Without Bias" *American Journal of Political Science*, Vol. 34, No. 4, pp. 1142-1164, November 1990, Available at SSRN: https://ssrn.com/abstract=1084180; Available at https://gking.harvard.edu/files/jp.pdf*American Political Science Review*, 67, 540–554.
[21] McGann, et.al., "A Discernable and Manageable Standard for Partisan Gerrymandering".
[22] This metric was first developed by Anthony McGann, during the writing of *Gerrymandering the States,* p. 30.

46. To calculate the simple measure of symmetry, *S*, I take the districts that are 5 percent above or below the statewide average of party support, and determine what proportion of those districts favor Democrats and what proportion favor Republicans. That is, a plan's bias under *S* equals the proportion of seats with Democratic vote share above five percent of the Democratic average minus the proportion of seats with Republican vote share above five percent of the Republican average. Put simply, *S* tells you whether a districting plan creates more Republican or Democratic leaning districts relative to the party's statewide average. A negative value for *S* means Republicans are advantaged while a positive value means Democrats are advantaged. In this report, simple *S* symmetry is charted graphically in the form of histograms. See, e.g., Figure 3. A symmetrical plan would show similar distributions of districts on either side of the vertical line denoting the average vote share; an asymmetrical plan would give the favored party more districts past the line denoting the average vote share for the party.

47. For the computational models, I calculate partisan symmetry for the plans, but instead of assuming uniform vote swing across districts, I impute random "noise" (up to five points) in 1,000 simulations of district vote distributions to reflect the idiosyncrasies and perturbations that occur in real elections over time. The procedure also allows me to calculate confidence intervals to provide estimates of statistical significance. In this report, the computational model is charted as a seats/votes S-curve function. See, e.g., Figure 3.

2. Partisan Symmetry in the House Map

48. Table 4 below shows the two measures of symmetry for the enacted House, Democratic Caucus, and the OCRC maps. Once again, I use available 2016-2020 precinct-level election data from the Voting and Election Science Team (VEST) for the calculations.

49. Both measures of symmetry show an approximate 15 percent seat advantage for Republican voters under the Enacted Plan. Moreover, the enacted House map is two to three

times as biased as comparison maps. When compared to historic measures, this level of bias suggests that the enacted House map is more biased than nearly three-quarters of state legislative maps drawn in the 2011 redistricting cycle.[23] The computational model also shows that this bias is substantial and statistically significant at the 95 percent confidence level. See Table 4.

TABLE 4

Symmetry in Enacted House and Comparison Maps

	SIMPLE S	ASYMMETRY	(95% CONFIDENCE)
Enacted House	−15	−15.39	(5.87)
Democratic House	−4	−6.37	(5.64)
OCRC House	−5	−8.11	(5.35)

Table 4. Symmetry in Enacted House and Comparison Maps

50. The extent of asymmetry in the enacted House map suggests that if Democrats were to win the same vote share as the Republicans average, 54 percent, they would still not win majority control of the Ohio House. As Table 5 shows, subtracting 8 percent from the Republican vote share in each district and giving it to Democrats yields 49 seats under the Enacted Plan, one seat short of a majority. By contrast, with 54 percent of the vote share, Republicans are expected to win a 64-seat veto-proof supermajority.

[23] Historical measures are found in *Gerrymandering the States*, pp.198-201.

TABLE 5

Seats and Seat Share for Both Parties Receiving 54 Percent of the Statewide Vote*

	STATE VOTE SHARE	SEATS	SEAT SHARE
Democratic voters	54%	49	49%
Republican voters	54%	64	65%

*Under uniform vote swing in each district.

Table 5. Seats and Seat Share for Both Parties Receiving 54 Percent of the Statewide Vote

51. The next set of graphs illustrate the two symmetry scores and provide a straightforward way of observing asymmetries in districting plans. The logic of symmetry requires that districting plans allocate district seats in equal numbers to parties with comparable levels of district-level support. That is, a histogram of a symmetric plan looks the same on both sides of the statewide party vote share average. In terms of a seats/votes function, the curve of seats won to votes won should intersect at the 50 percent point (50 percent of seats for 50 percent of votes).

52. Figure 3 provides a hypothetical example of what a perfectly symmetric (and proportional) districting plan looks like. In the figure, there are six competitive districts, with Party A winning between 45 and 55 percent of the vote. On either side of the six-seat column, there are five districts where Party A wins between 55 and 65 percent, and five districts where Party B wins between 55 and 65 percent, and so on. Both parties receive an equal share of districts (38 percent) 5 percent or more above their statewide average (50 percent). The symmetric distribution of districts necessarily produces a symmetric seats-votes function, as shown in the panel on the right. You can see that if Party A wins 60 percent of the vote, it

receives 71 percent of the seats, but Party B also receives 71 percent of seats with 60 percent of the vote.[24]

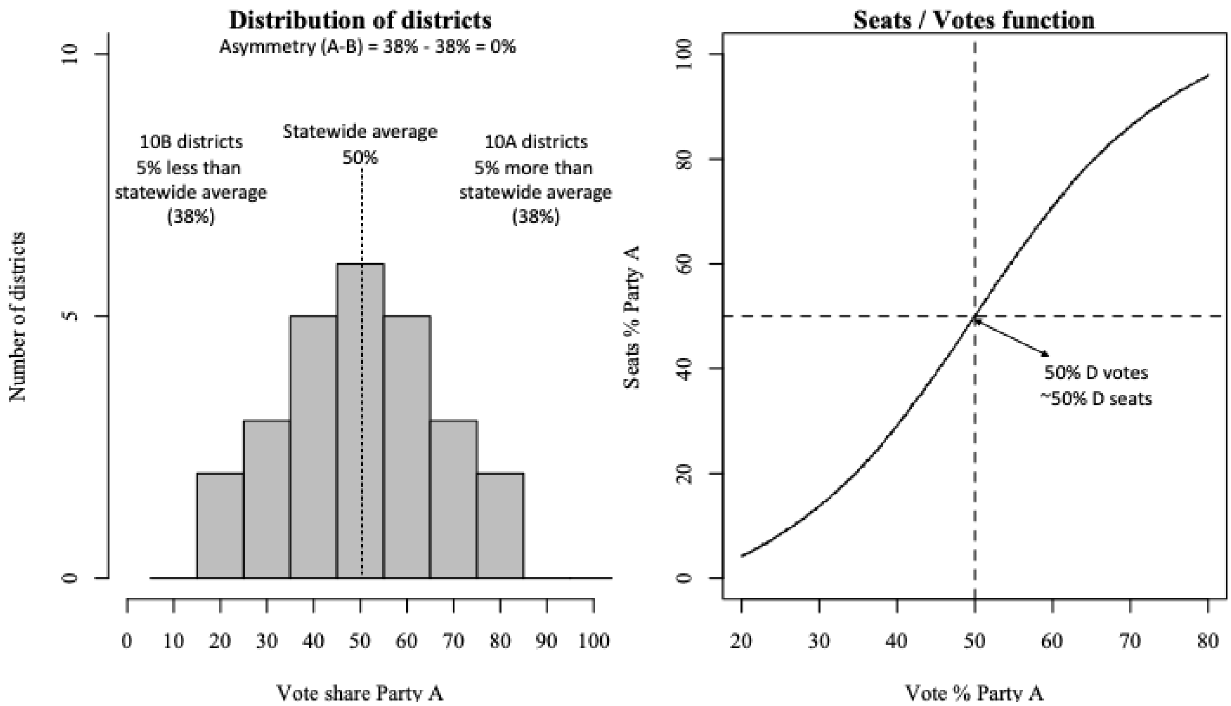

Figure 3. Hypothetical Symmetric Plan

53. For the enacted House map, Figure 4 illustrates the Simple *S* calculation, showing how the distribution of districts is skewed in favor of Republican voters. The histogram shows that Republicans win 47 percent of seats with more than 5 percent of their statewide vote share, compared to 32 percent of Democratic seats, an asymmetry of 15 percent. In fact, Republican voters have been drawn into 30 districts where they are expected to form 55-65 percent of the electorate. Democratic voters reach about half of that number with an equivalent range of support. Further, Democratic voters have been drawn into far more packed districts where they are expected to form more than 75 percent or of the electorate (visible on the far right of the

[24] Note also that the histogram need not be centered on 50 percent of the vote to be symmetric. The median district might have Party A winning, say, 70 percent of the vote (in a state dominated by Party A), but that would produce an identical seats-votes function: if there was a 20-point swing away from Party A and it only won 50 percent of the vote, it would still receive 50 percent of the seats.

histogram). Republican voters have been drawn into only one district where they are expected to form more than 75 percent of the electorate. Overall, the seats/votes function also demonstrates this bias. With 50 percent of the Democratic vote share, Democratic candidates are expected to yield only 42 percent of House seats on average, under the Enacted Plan.

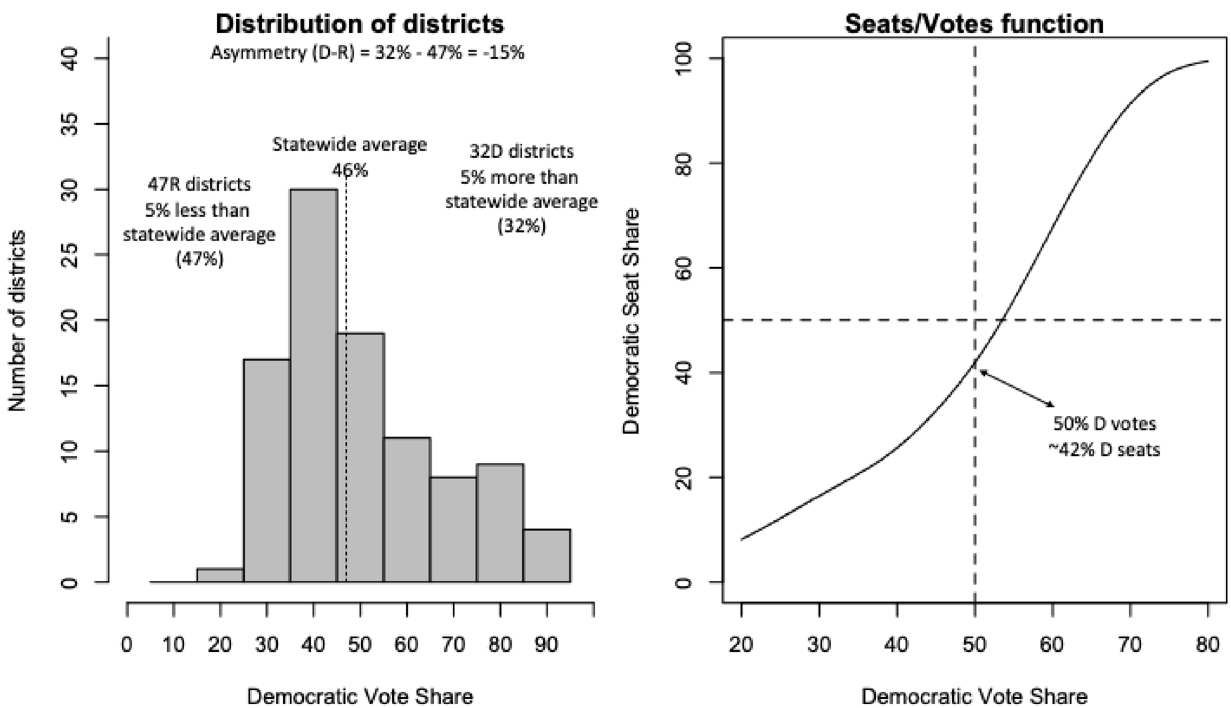

Figure 4. Histogram and Seats/Votes Function Under the Enacted House Map

54. For comparison, the histogram in Figure 5 shows that the OCRC map is visibly more symmetric. Democrats win more than twice as many districts in the 55-65 percent range. The overall asymmetry is reduced, with the proportion of seats won by Democrats and Republicans with five percent or more of their statewide support only differing by five percent (42 percent and 47 percent, respectively).

55. As shown in the seats/votes function, Democrats are much closer to winning a majority of seats with a majority of the statewide vote. The plan still deviates in favor of

Republicans at more extreme vote swings (Republicans would gain more than 75 percent of seats with 60 percent of the vote, compared to a 60 percent seat share for Democrats), but the results are far more symmetric and closer to proportional for the 45-55 percent vote range where elections in Ohio typically occur.

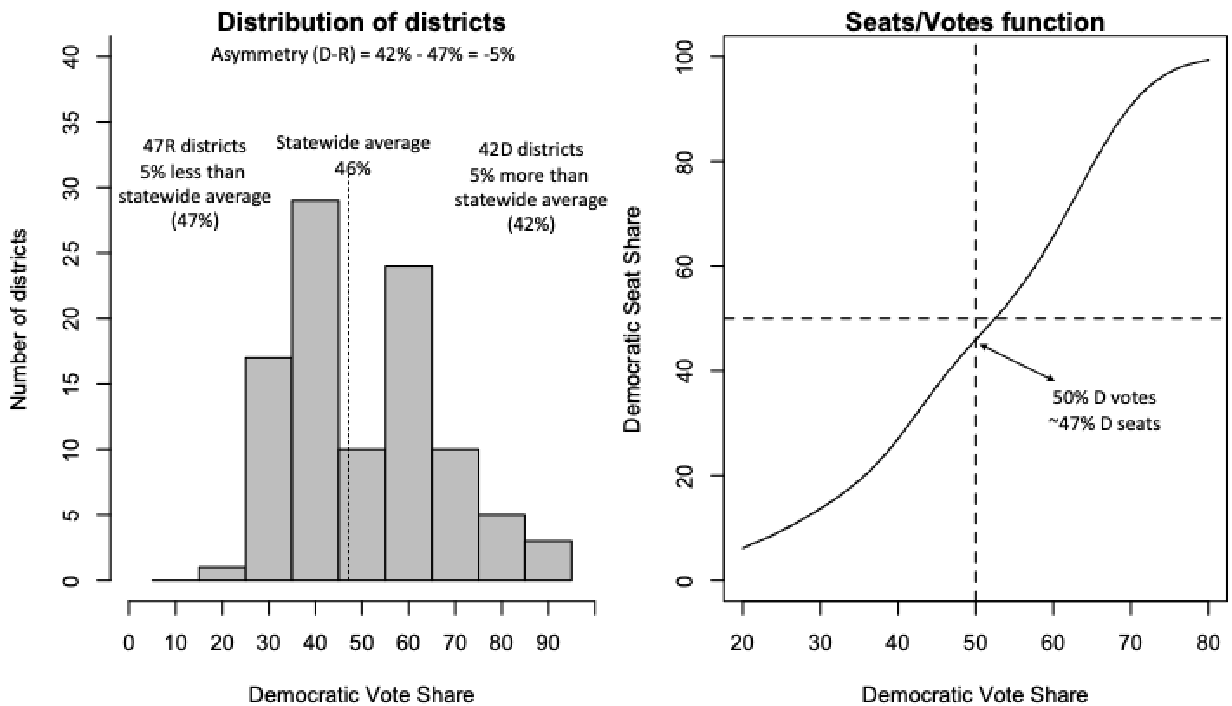

Figure 5. Histogram and Seats/Votes Function Under the OCRC House Map

56. Other professional nonpartisan redistricting assessment groups have also measured bias in the enacted House map and have likewise concluded that it is biased in favor of Republican voters. PlanScore,[25] a project of the nonpartisan Campaign Legal Center that allows people to score the partisan, demographic, racial, and geometric features of districting maps, estimates that the enacted House map favors Republicans in over 90 percent of plausible election

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[25] PlanScore, Ohio State House: https://planscore.campaignlegal.org/plan.html?20210927T160848.177071909Z. Note that this page is incorrectly labeled "State Senate" but the figures are for the State House. PlanScore limits the calculation of symmetry scores to what they consider competitive plans. One reason the computational symmetry model I employ provides statistical confidence intervals is to reduce the likelihood of making false inferences from uncompetitive plans. At any rate, Ohio partisan vote shares are competitive, with historic vote shares typically falling within the 45-55 percent range.

districting scenarios, and that it exhibits extreme bias by historical standards. Similarly, the Princeton Gerrymandering Project, directed by Professor Sam Wang, who has been influential in developing metrics of partisan bias,[26] gives the enacted House map a grade of "F" on fairness, based on simulations that assess symmetry and changes in partisan support.[27]

3. Partisan Symmetry in the Senate Map

57. My analysis of the enacted Senate map demonstrates that, rather than attenuating partisan bias by balancing out the bias of underlying House districts, the aggregation of three House districts into each of 33 Senate districts builds off of and further exacerbates the bias in the enacted House map.

58. Like the 2011 House map, the Senate map implemented after the 2010 Census was among the most biased state legislative plans produced in the last redistricting cycle.[28] The newly enacted Senate map is also substantially and significantly biased against Democratic voters. See Table 6. The symmetry measures indicate a 15 to 17 percent seat advantage for Republican voters. For comparison, neither the Democratic Caucus nor the OCRC Senate maps show statistically significant levels of asymmetry. In other words, there were less biased options available for designing a Senate map, and the Enacted Plan incorporated politically motivated choices.

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[26] Sam S.H Wang, (2016), "Three Practical Tests for Gerrymandering: Application to Maryland and Wisconsin." *Election Law Journal*; DOI: 10.1089/elj.2016.0387.
[27] Princeton Gerrymandering Project, Ohio Final House Map: https://gerrymander.princeton.edu/redistricting-report-card?planId=rec1ovrNKW7xjVsKb. This is a source of information that is generally and widely relied upon by political scientists who study partisan bias in electoral maps.
[28] *Gerrymandering the States*, pp.198-201.

TABLE 6

Symmetry in Enacted Senate and Comparison Maps

	SIMPLE S	ASYMMETRY	(95% CONFIDENCE)
Enacted Senate	−15	−17.34	(10.48)
Democratic Senate	−12	−8.34	(9.52)
OCRC Senate	−9	−6.48	(9.22)

Table 6. Symmetry in Enacted Senate and Comparison Maps

59. Table 7 simulates a uniform swing of eight percent in favor of Democrats, so that they receive 54 percent of the statewide vote, and compares it with the performance of Republicans under a 54 percent Republican statewide vote share. The Democratic Party would win 18 seats with 54 percent of the vote, narrowly exceeding the 17 seats needed for a majority. With the same vote share, Republicans would control 24 seats, nearly three quarters of Senate seats.

TABLE 7

Senate Seats and Seat Share for Both Parties Receiving 54 Percent of the Statewide Vote*

	STATE VOTE SHARE	SEATS	SEAT SHARE
Democratic voters	54%	18	55%
Republican voters	54%	24	73%

*Under uniform vote swing in each district.

Table 7. Senate Seats and Seat Share for Both Parties Receiving 54 Percent of the Statewide Vote

60. This level of Republican advantage in seat share suggests that, under the enacted Senate map, if a bare majority (50 percent plus one vote) of Ohio voters supported Democratic

candidates in future elections, Democrats would likely not win a 17-seat bare majority in the Senate. See Figure 6. This is a consequence of the skewed allocation of seats that can be observed in a histogram of the enacted Senate map. Whereas Republicans are expected to win 14 of 33 Senate districts with five percent or more of their statewide vote share, Democrats only obtain nine of 33 districts, a 15 percent difference in favor of Republicans. And similar to the enacted House map, there are three Senate districts (15, 21, 23) that Democrats are winning by higher than a 75 percent margin, with no comparably lopsided victories for Republicans, because their voters have been distributed more efficiently by the Commission.

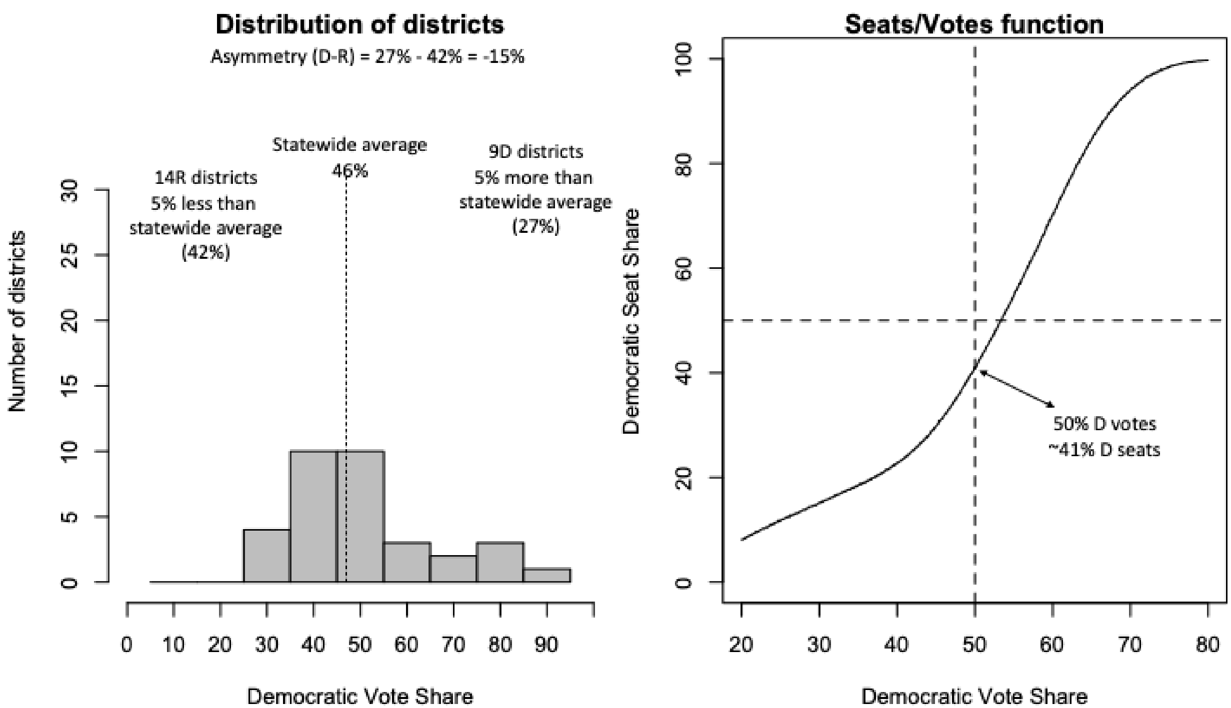


Figure 6. Histogram and Seats/Votes Function Under the Enacted Senate Map

61. For comparison, graphing the distribution of districts by Democratic vote share and the seats/votes function of the OCRC Senate map illustrates its greater symmetry, and demonstrates that drawing a more symmetric map was possible. Democrats win more seats with

55-75 percent of the two-party vote, and correspondingly fewer Democratic districts are packed with 75 percent or higher Democratic voters. See Figure 7.

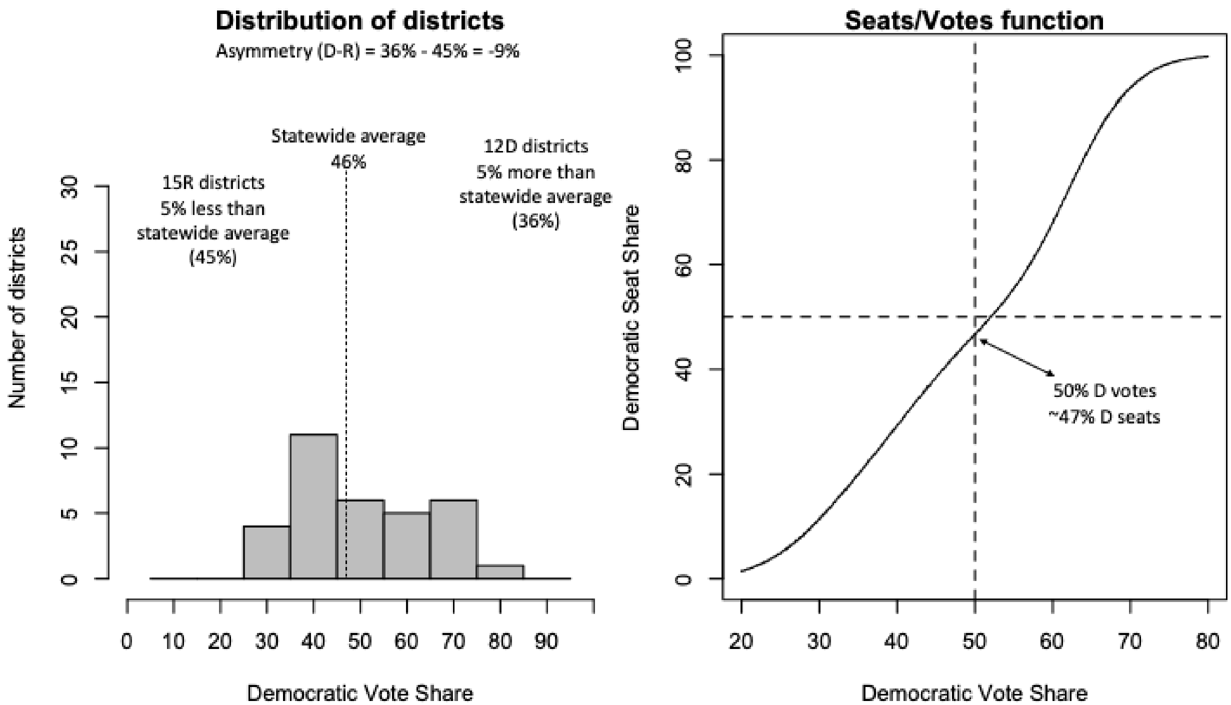


Figure 7. Histogram and Seats/Votes Function Under OCRC Senate Map

62. The foregoing analysis establishes that the Enacted Plan is biased in favor of Republicans.

B. District Boundary Analysis

1. District Boundary Overview

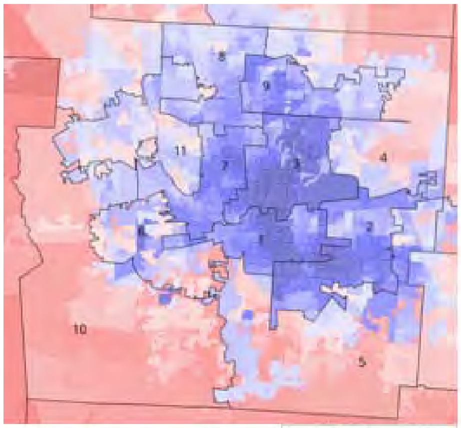
63. In order to identify the sources of asymmetry in partisan support in these maps, I compare the level of partisan support across adjacent districts and similar counties to look for evidence of partisan "packing" or "cracking" of voters. I find that in the most populous, heavily Democratic counties, adjacent districts in the Enacted Plan are drawn to maximize the number of seats that Republicans win. In mid-size and smaller counties, district design provides a decisive advantage to Republican voters. Similarly, House districts are aggregated into Senate districts in a manner that dilutes the voting power of Democratic voters. I conclude that the Enacted Plan

unnecessarily packs Democratic voters into uncompetitive districts in order to create more reliably winnable Republican districts, in a durable, seat-maximizing Republican gerrymander. More than six House districts and more than two Senate districts would need to be redrawn in order to remedy this gerrymander.

2. Precinct and District Border Analysis in the House Map

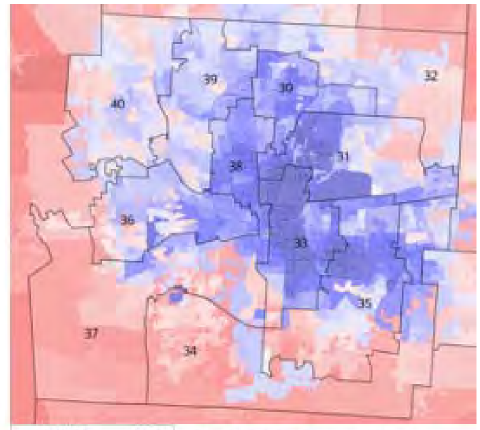
64. The selection of counties for splitting and joining together territories into districts can contribute to partisan bias. There is evidence that these discretionary choices in the Enacted Plan have been used for packing and cracking throughout the state. Using the composite 2016-2020 data, several examples illustrate these properties of the Enacted Plan through geographic and comparative analysis.

65. Figure 8a displays maps and district Democratic vote shares for the 12 districts carved out of Franklin County for the Enacted Plan and the OCRC plan. Democratic support is concentrated in central Columbus, where both maps locate four heavily Democratic districts. However, the Enacted Plan's Columbus districts (1, 2, 3, and 7) are a minimum 75 percent Democratic, while the OCRC districts do a better job of including suburban areas that help to balance the partisan vote concentration. The Enacted Plan's packing of Columbus districts yields two Republican seats by keeping district 10 out of Columbus and allocating the remainder of Franklin County's population to district 12 (upper left quadrant) and joining it with Union County.



Enacted Franklin County House Districts

District	Mean
3	85.7%
1	80.6%
2	77.3%
7	75.3%
9	68.2%
8	63.3%
11	55.8%
5	54.7%
6	54.5%
4	54.2%
10	45.3%
12	39.2%



OCRC Franklin County House Districts

District	Mean
33	84.3%
38	77.7%
30	72.0%
35	71.0%
31	69.2%
36	60.8%
39	59.9%
32	55.0%
37	54.5%
40	53.4%
34	52.6%
41	31.9%

Figure 8a. Districts 3, 1, 2 and 7 Pack Democratic Voters

66. In Figure 8b, the visible concentration of Democratic voters in a few districts creates an opportunity for Republicans to pick up an extra seat in Franklin County. This contributes to the asymmetry of the plan by carving out an additional Republican seat in a Democratic stronghold. While the Enacted Plan may appear more proportional ***within*** the county, the plan's asymmetry (and disproportionality) results from a lack of Democratic seats being carved out of the smaller counties where Republicans dominate.

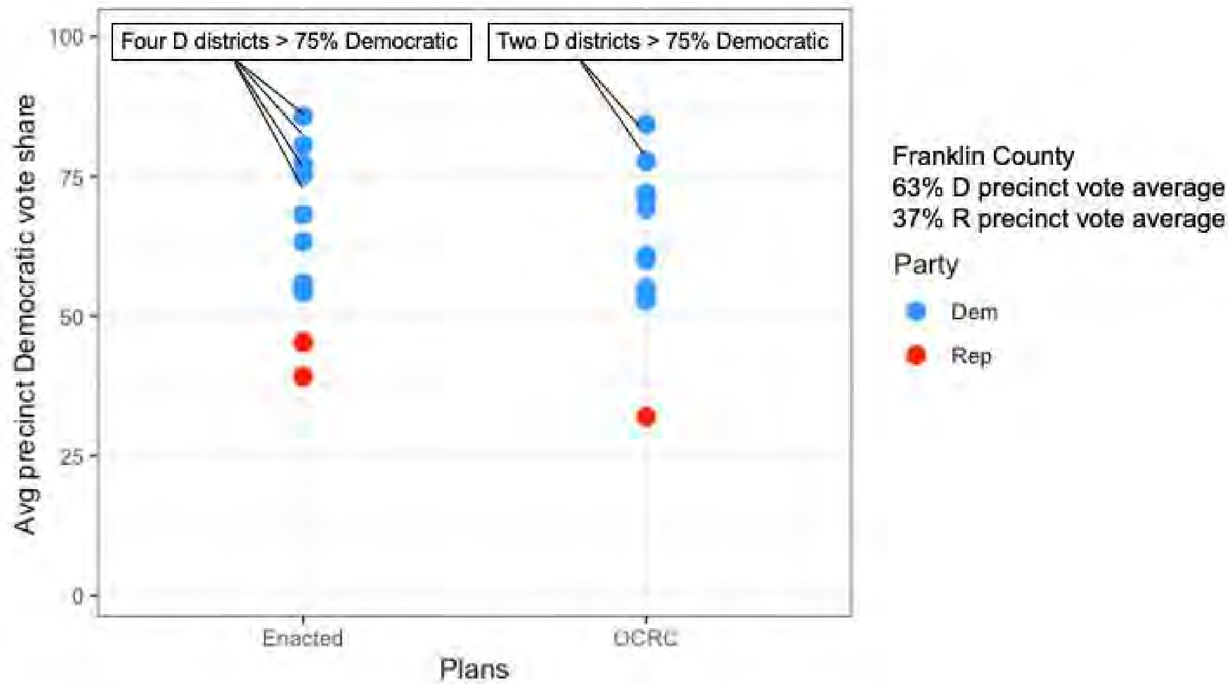
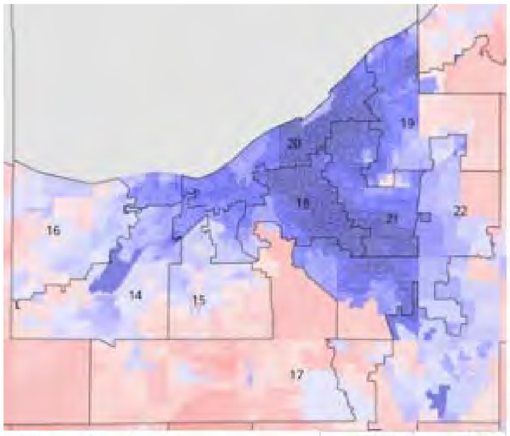


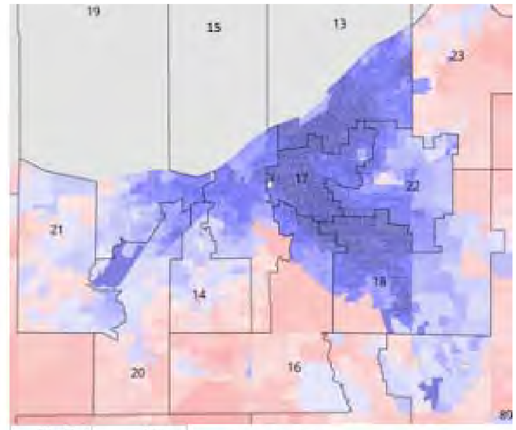
Figure 8b. Packing Democratic Voters Generates Additional Republican Seat in Franklin County

67. There is a similar pattern in the even more Democratic Cuyahoga County. See Figure 9a. Once again, while both plans carve heavily Democratic districts out of central Cleveland, the Enacted Plan's Cleveland and adjacent districts, specifically 18, 20, and 21, are packed with more Democratic voters, and that difference, however subtle, creates an opportunity to draw two highly competitive seats, 15 and 23, that lean Republican.



Enacted Cuyahoga County House Districts

District	Mean
18	91.1%
20	88.3%
21	88.1%
22	73.4%
19	72.7%
13	71.1%
14	57.2%
16	53.2%
23	49.8%
15	49.7%
17	42.8%



OCRC Cuyahoga County House Districts

District	Mean
17	92.5%
13	87.9%
18	79.9%
22	74.3%
15	69.3%
19	66.5%
16	56.2%
20	54.2%
21	52.4%
14	51.8%
23	44.5%

Figure 9a. Districts 18, 20, 21 Pack Democratic Voters

68. While it would require some relaxation of compactness requirements, and possibly a change in the Commission's county splitting rules, to create competitive districts in Cleveland, packing voters in the manner that the enacted House map does is not necessary to create a fair statewide districting plan. In these most populous counties, we repeatedly find a pattern with the Enacted Plan placing urban voters, and primarily voters of color, into slightly more concentrated districts. See Figure 9b. The cumulative impact of these tactics across counties is to generate a substantial seat advantage in the General Assembly in favor of Republicans.

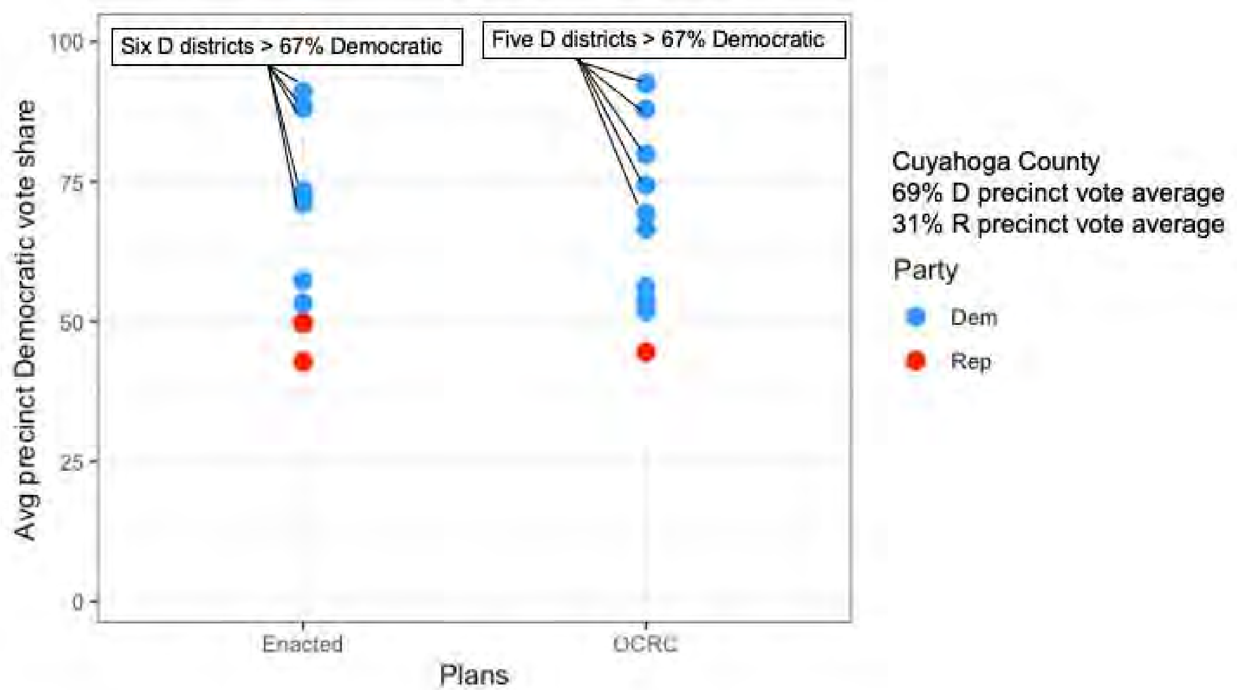
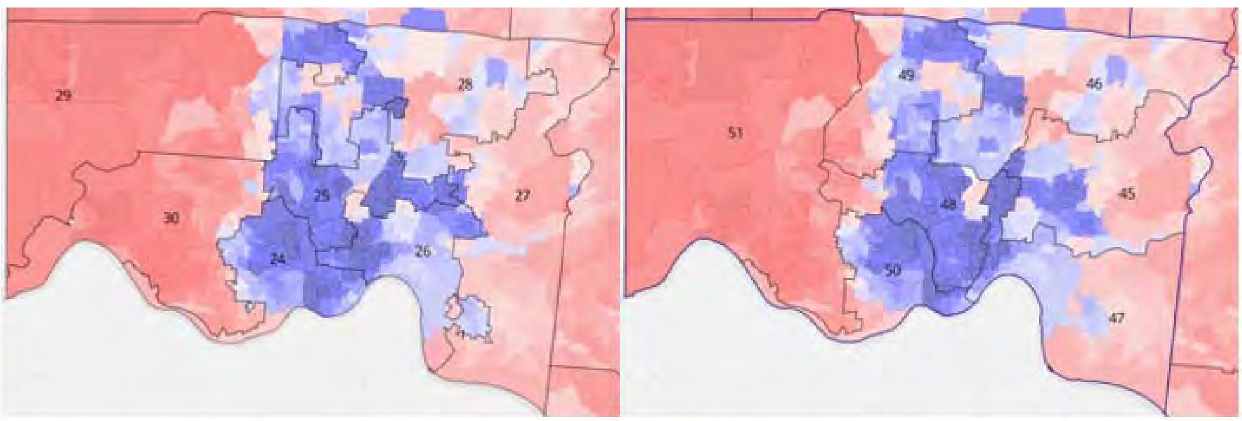


Figure 9b. Packing Democratic Voters Generates Additional Republican Seat in Cuyahoga County

69. Figure 10a illustrates the maps and district vote shares for the Enacted and OCRC House maps for districts with populations in Hamilton County. In the enacted House map, districts 24, 25, and 26 contain large shares of Cincinnati voters. These districts are uncompetitive, packing Democrats in a manner that creates three reliable Republican seats on the eastern and western borders of the county. One of those, district 29, carves out the highly Democratic city of Forest Park (top center), submerging it with the rural western half of the county. The OCRC map has four districts that are close to the county average Democratic vote share of 56 percent, compared to only one such district, 28, in the enacted House map.

70. Figure 10b shows the disparity more clearly. The enacted House map concentrates Cincinnati voters into three packed, Democratic supermajorities, which have an expected Democratic vote share of more than 67 percent. This frees up more suburban voters that the Commission used to create two more competitive, but reliably Republican districts. Specifically, the comparison to the OCRC map shows how central and southern Cincinnati voters are packed into districts 24 and 25 in a manner that dilutes the weight of their votes relative to alternatives. While it is also true that the only Republican district in the OCRC plan is uncompetitive, it does accurately reflect the politics of the rural western half of the county, and overall, more OCRC districts are closer to the county average.



Enacted Hamilton County House Districts

District	Mean
25	80.8%
24	74.6%
26	67.5%
28	53.5%
29	46.7%
27	44.0%
30	28.4%

OCRC Hamilton County House Districts

District	Mean
48	77.3%
50	65.8%
49	59.1%
47	56.7%
45	56.3%
46	53.5%
51	24.2%

Figure 10a. Districts 25, 24, and 26 Pack Democratic Voters

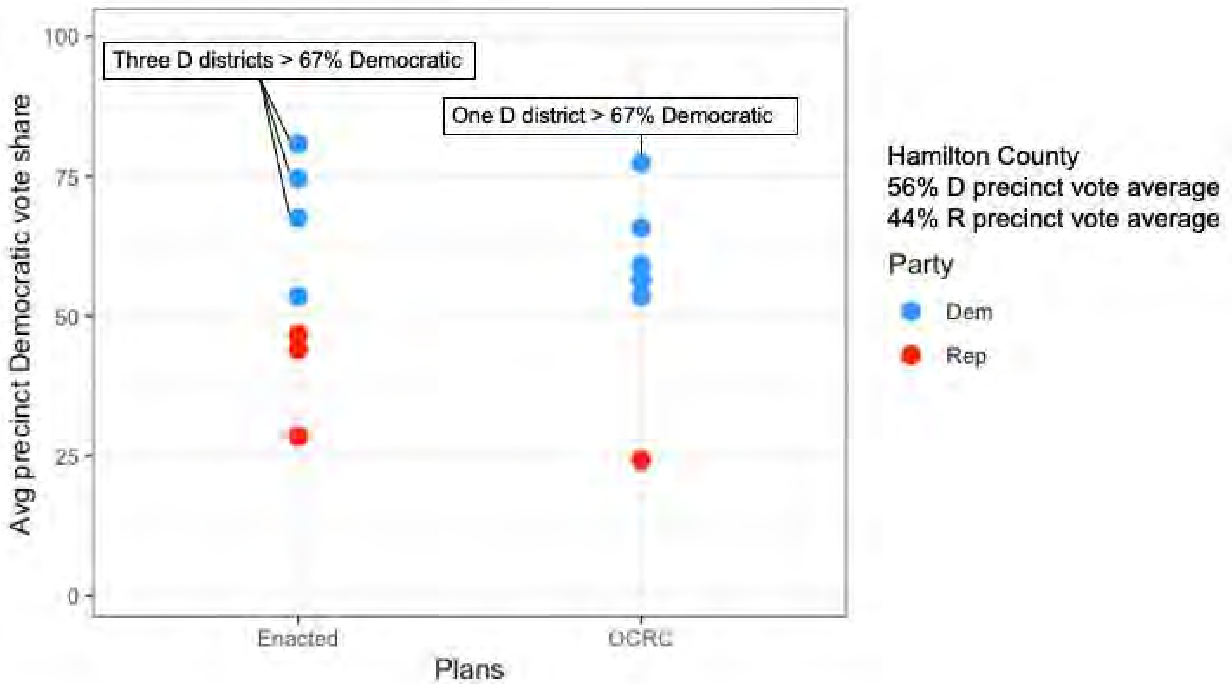
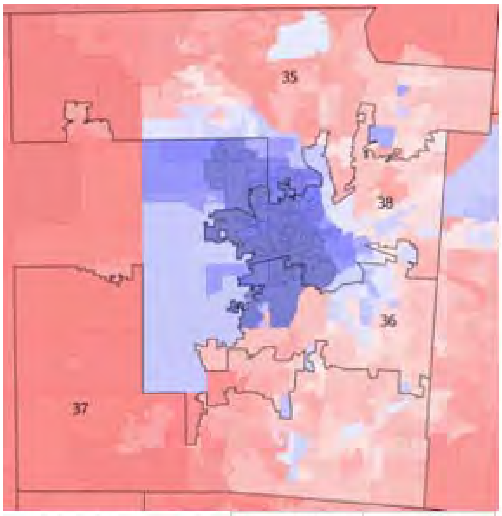


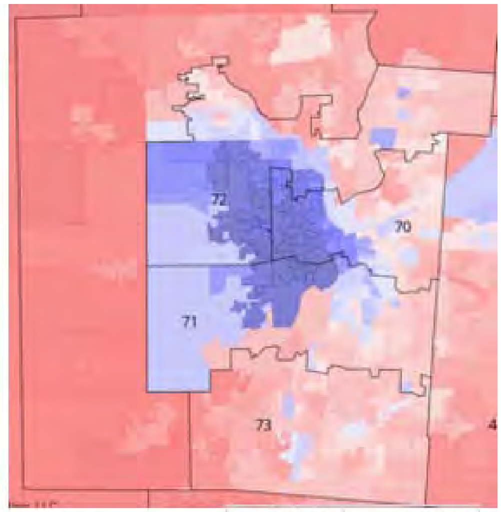
Figure 10b. Packing Democratic Voters Generates Two Additional Republican Seats in Hamilton County

71. Once again, there is a similar pattern in the five districts carved out of Montgomery County, shown in Figure 11a. District 38 in the enacted House map concentrates much of the population of central Dayton into a 71 percent Democratic "sink," while district 39 takes up the western suburbs of Montgomery County and combines them with adjacent Preble County to create a 66 percent Republican district.



Enacted Montgomery County House Districts

District	Mean
38	71.7%
36	50.7%
35	45.0%
37	37.5%
39	34.1%



OCRC Montgomery County House Districts

District	Mean
70	63.7%
72	59.6%
71	53.4%
73	39.0%
69	26.8%

Figure 11a. District 38 in Dayton Packed with Democratic Voters

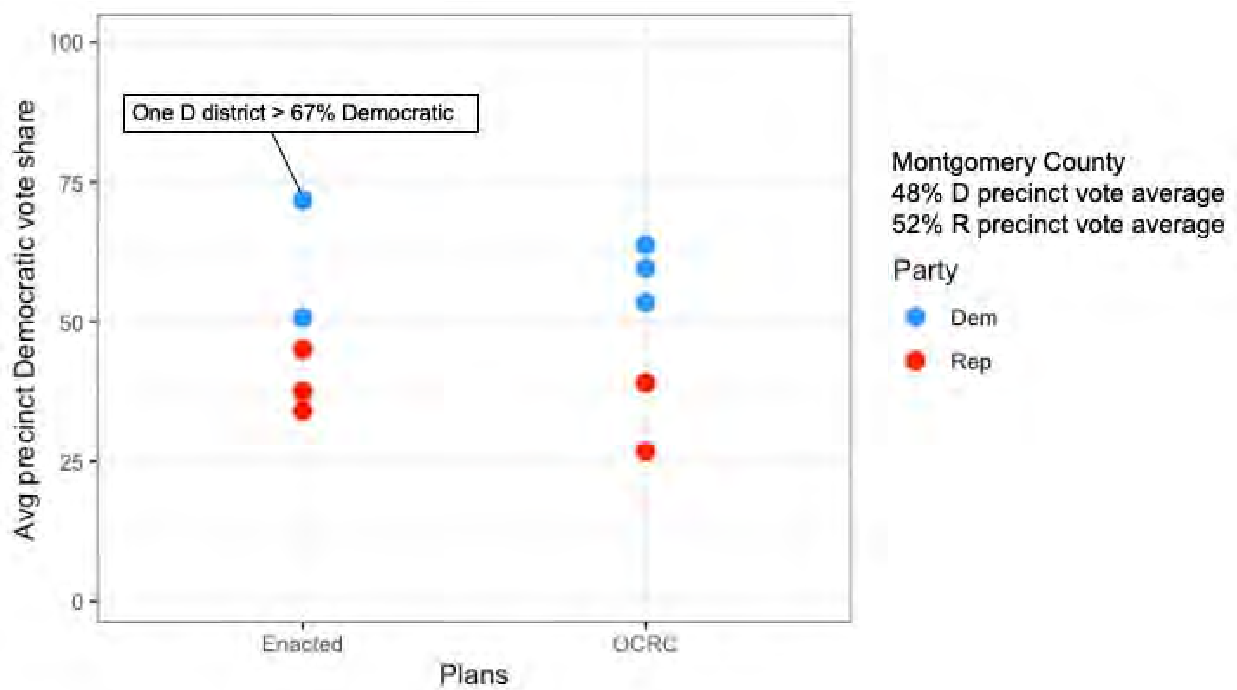
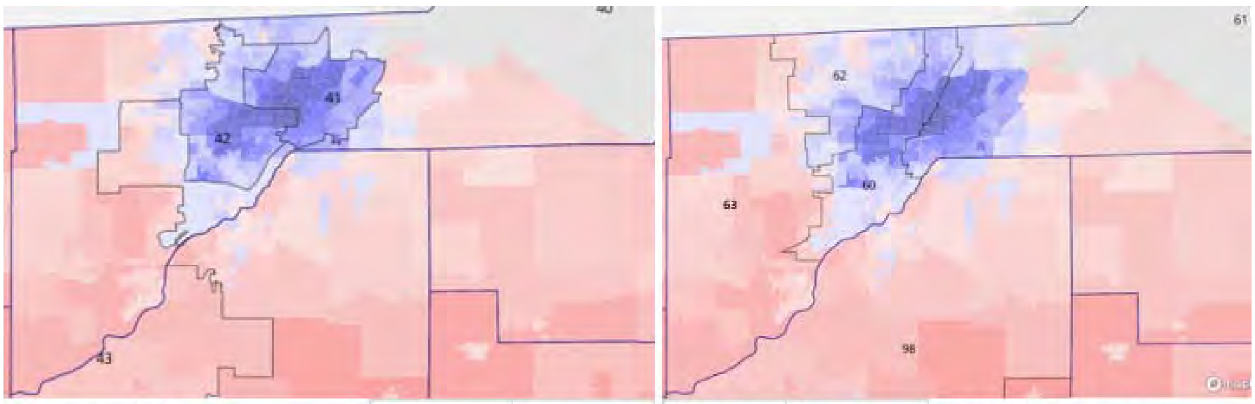


Figure 11b. Packing Democratic Voters Generates Additional Republican Seat in Montgomery County

Figure 12a shows the geographic pattern of districts in Lucas County. Once again, there is evidence that the Enacted Plan uses a "sink," district 41, to pack Toledo voters into a 77 percent Democratic district. This enabled the Commission to create a competitive district 40 that wraps around Toledo in a meandering patter and takes in different communities around the county, and District 43 which combines Toledo's suburban Democratic voters with rural voters in Hancock County more than 60 miles away.



Enacted Lucas County House Districts

District	Mean
41	77.4%
42	67.4%
40	51.9%
43	41.4%

District	Mean
60	69.7%
61	68.8%
62	55.0%
63	34.3%

OCRC Lucas County House Districts

Figure 12a. District 41 Packs Democratic Voters

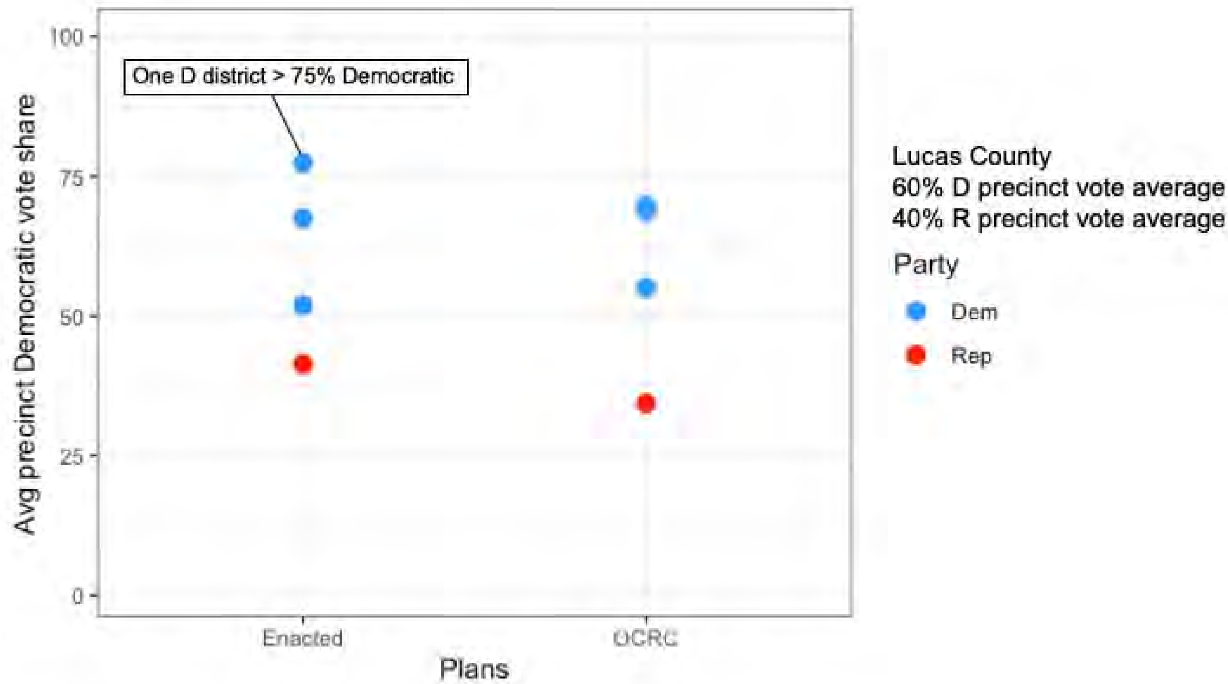


Figure 12b. Packed Democratic Voters Creates Competitive District in Lucas County

72. Generalizing, the few additional seats drawn in large, heavily Democratic counties, combined with a disproportionate number of pro-Republican districts drawn out of mid-size counties, generates most of the bias in the enacted House map. Tables 8a and 8b show the Republican vote and seat shares for the lower, middle, and upper 33 districts by the county populations from which they are drawn. These tables reflect not only the considerable urban-rural partisan divide in the state, but also the impact of choices regarding what populations are selected to construct districts.

73. Republicans earn 38 percent of votes from districts in the most populous counties and receive 27 percent of seats, a difference of 11 percent. See Table 8a. However, in districts from the least populated counties, the seat-to-vote difference is nearly three times as large, 29 percent in favor of Republicans. And in the more competitive middle third of districts,

Republicans win 71 percent of seats with 54 percent of the vote, a 17 percent difference favoring their party.

TABLE 8A

District Vote/Seat Shares by County (population)

Republicans win a disproportionate share of seats in the middle and lower third of districts, far outweighing their relative disadvantage in more populous counties.

	LOWER THIRD	MIDDLE THIRD	UPPER THIRD
Republican vote share	68%	54%	38%
Republican seat share	97%	71%	27%
Difference	29%	17%	−11%

Table 8a. Disproportionality of Seats Won by County Size in Enacted Map

74. In the OCRC House map, differences between vote and seat shares are more balanced between counties. Specifically, Republicans win fewer seats (15 percent) in the largest counties with approximately the same vote share (39 percent) as the enacted House map, which helps to balance out their winning all of the seats in the lower third of counties. There is relatively little difference (3 percent) between the vote and seat shares that parties win in the districts drawn from mid-size counties under the OCRC plan. See Table 8b. This demonstrates once again that the choice of district boundaries was a partisan one in the Enacted Plan.

TABLE 8B

District Vote/Seat Shares by County (population)

The OCRC plan exhibits more balance in the selection of district boundaries within and between counties.

	LOWER THIRD	MIDDLE THIRD	UPPER THIRD
Republican vote share	66%	55%	39%
Republican seat share	100%	58%	15%
Difference	34%	3%	−24%

Table 8b. More Proportionality of Seats Won by County Size

75. District boundaries in the enacted House map carve up partisan precincts and counties in a precise manner, indicating that the Commission relied on the partisan makeup of the districts when drawing district boundaries and attempted to draw districts to favor one political party over the other. My analysis indicates that the Commission succeeded.

3. Precinct and District Border Analysis in the Senate Map

76. My analysis of the enacted Senate map reveals that House districts were aggregated (three House districts to one Senate district) in a manner that largely preserves the bias generated in the enacted House map. As Figure 13a shows, the most Democratic House seats are largely incorporated into the most Democratic Senate seats. This reflects a decision to pack Democratic voters into districts that dilute the strength of their votes relative to Republican voters. For example, Senate district 15 packs together House districts 1-3, creating an opportunity to put together a reliably Republican Senate district 16. In Figure 13a, the average Senate Democratic vote share points is marked with the label "Sen." Under the enacted Senate

map, the competitiveness of Democratic Senate seats quickly dissipates, observed as the change in the slope of the points after the 50 percent line is reached.

77. The enacted Senate map submerges seven Democratic House seats into Republican Senate seats, compared to two Republican district seats into Democratic Senate seats. This is another way of generating or maintaining asymmetry, as a larger proportion of Democratic voters are being put into Senate districts where they are a minority relative to Republican voters. Figure 13b, which graphs the OCRC House-to Senate seats, shows that it is possible to make more balanced decisions regarding the allocation of House seats into Senate districts. The OCRC map has a more symmetric balance of competitive Republican and Democratic Senate seats. Whereas the enacted Senate map submerges seven Democratic House seats into six Republican Senate seats, but only two Republican House seats into two Democratic Senate seats, the OCRC plan submerges six and four seats, respectively. Further, with three Senate districts containing 75 percent or more Democratic voters, compared to one under the OCRC plan, the comparison of the two plans demonstrates that the Enacted Plan concentrates more Democrats into uncompetitive districts than is necessary, diluting their voting strength relative to Ohio voters who support Republican candidates.

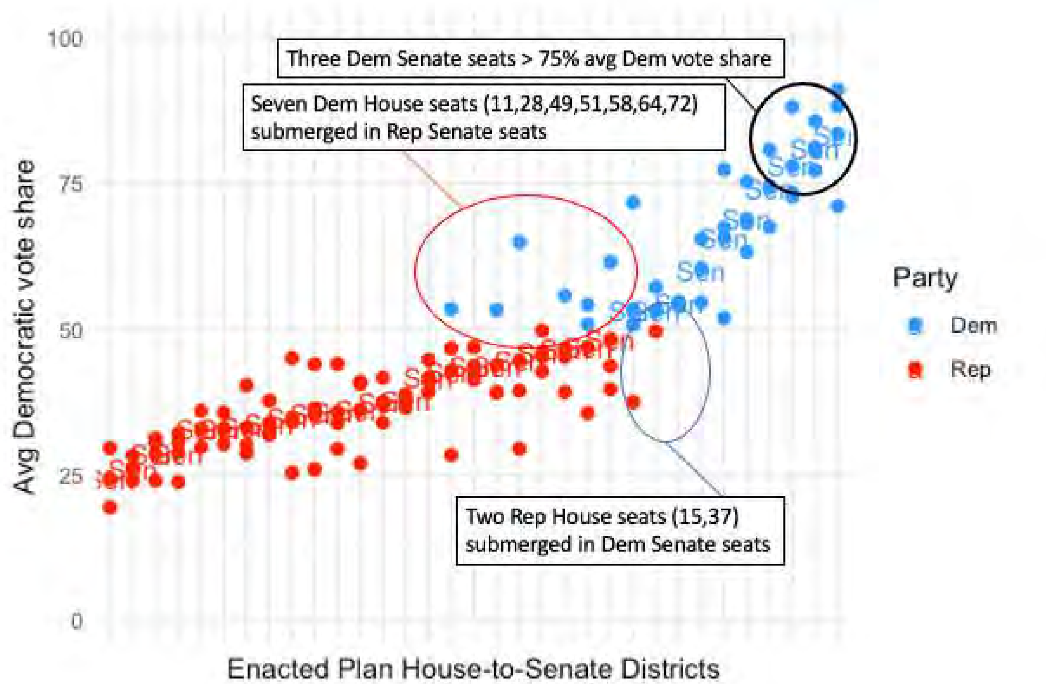


Figure 13a. Enacted Senate Map Maintains House Map Bias by Submerging Democratic House Districts into Republican Senate Seats

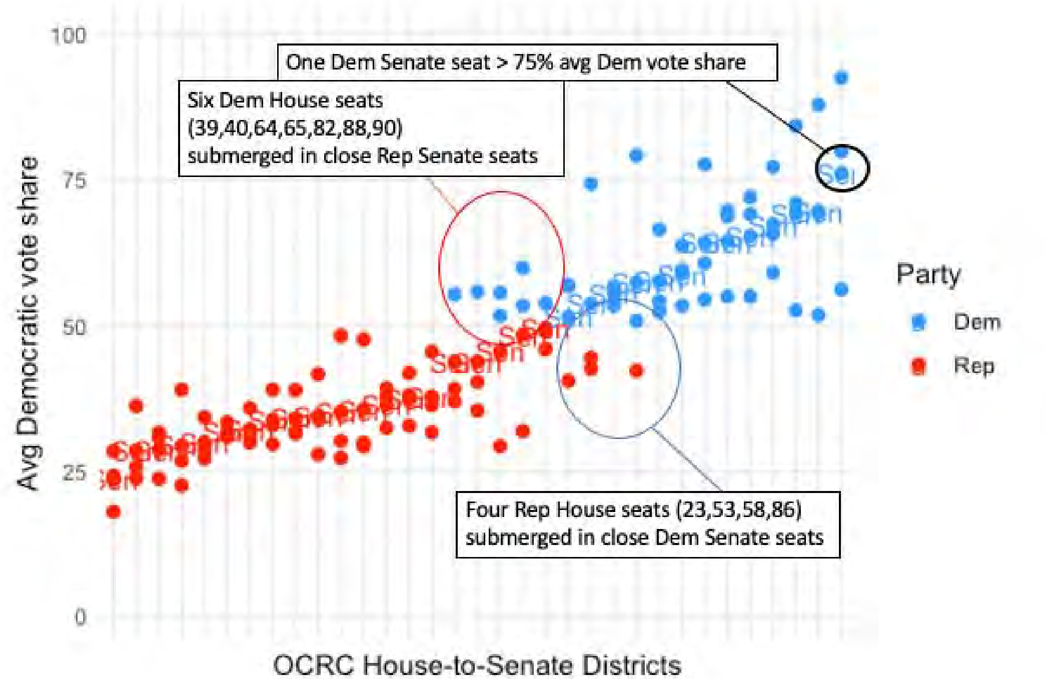


Figure 13b. OCRC Senate Map Balances Submerging Republican and Democratic House Districts into Senate Seats

C. Amendment Analysis

78. I examined the original plan submitted to the Commission by Ray DiRossi that the Commission introduced and found the following changes made to the Enacted Plan between the plan's introduction and passage. The overall impact of these amendments appears to have been to give up a few Democratic seats in order to reinforce the capacity for Republicans to retain a supermajority advantage by bolstering their support in House districts 17, 39, 65, and 94.

79. In the amendments, four House districts shifted from reliably Republican (districts 32, 64) or competitive Republican (districts 36, 72) to reliable or competitive Democratic districts. In turn, four fairly competitive Republican House districts (districts 17, 39, 65, and 94) were made more reliably Republican. Heavily Democratic districts 18 and 22 were made even less competitive (91 and 73 percent, respectively). Two heavily Republican districts, districts 81 and 82, were rearranged to be even more heavily Republican (76 and 75 percent, respectively), and two heavily Democratic districts (14 and 38) became somewhat less so (69 and 57 percent, respectively).

D. Compactness Analysis

80. I also looked to whether the map's bias could be explained by the Commission's attempt to draw compact districts. Under Section 6(C), the Commission is required to attempt to draw districts that are compact, or not irregularly shaped. However, the enacted plan is no more compact than the comparison plans.

81. There is no scientific consensus over how to measure "irregularity" in district shapes. It is a complex, multidimensional phenomena rather than a coherent scientific or legal concept. The distinction between compact and uncompact districts is thus more like the

distinction between art and pornography, in that you "know it when you see it."[29] The utility of analyzing compactness in districting decisions is that comparative analysis can reveal whether mapmakers sacrificed compactness in order to achieve other goals, or vice versa.

82. In the case of the Enacted Plan, whether one uses common compactness metrics such as Reock (the area of the district divided by the area of the smallest circle encompassing the district), Polsby-Popper (a function that divides the area of a district by its perimeter), convex hull (the area of a district divided by the convex hull of the district boundaries), or an index based on a combination of measures, the Enacted Plan districts are no more compact than the comparison plans. For example, using both conventional measures and composite indices, the Enacted House districts are less compact on average (Reock = .38, Polsby-Popper = .30, Kaufman et.al. = 29) compared to the OCRC districts (.39, .54, 56, respectively).

83. Because the Enacted Plan is no more compact than the comparison plans, I conclude that the bias observed in the Enacted Plan is not a result of the Commission trying to achieve greater district compactness. Indeed, it is possible to draw a General Assembly plan that is both more fair and at least equally compact.

E. Conclusions About the Partisan Bias Inherent in the Enacted Plan

84. Both the House and Senate maps are biased in favor of Republican voters, as demonstrated by the significant asymmetries in partisan support across districts in both enacted maps. My analysis shows that the 15-seat asymmetrical advantage that Republican voters enjoy over Democrats as a result of this plan would allow a minority of Republican voters to elect a

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[29] Aaron Kaufman, Gary King, and Mayya Komisarchik. 2021. "How to Measure Legislative District Compactness If You Only Know it When You See It." American Journal of Political Science, 65, 3, Pp. 533-550. Publisher's Version Copy at https://j.mp/2Fs3ESc. The characterization of pornography comes from Justice Potter Stewart, *Jacobellis v. Ohio*, 378 U.S. 184, 197 (1964).

majority of seats in the General Assembly. Similarly, it would enable a narrow majority of Republican voters to elect a supermajority of seats in the General Assembly. By the same token, the Enacted Plan greatly disadvantages and burdens citizens who vote for Democratic candidates, as they cannot obtain the same level of political power as Republicans, even with the same number of votes. In short, the Commission's plan treats Ohio citizens differently based on their political party preference or political associations and does not give their votes equal weight or representation, thereby violating the core principles of political equality and procedural justice.

Michael S. Latner

Michael S. Latner

Exhibit A

to Affidavit of Michael S. Latner

Michael Steven Latner

mlatner@calpoly.edu, @mlatner, mikelatner.com

Appointments

Union of Concerned Scientists

2019- Senior Fellow

2018-2019 Kendall Science Fellow

California Polytechnic State University, San Luis Obispo

2019-Professor of Political Science

2014-2018 Associate Professor of Political Science

2008-2014 Assistant Professor of Political Science

2007-2008 Lecturer in Political Science

University of Southern California

2006-2007 Teaching Fellow

University of California, Irvine

2005-2007 Lecturer

Field Research Corporation

1996-2000 Project Manager, Senior Survey Supervisor

Education

Ph.D., Political Science, University of California at Irvine, 2008
M.A., Political Science, University of California at Irvine, 2004
B.A., Political Science, California State University Chico, 1995
A.A., Butte Community College, Oroville, CA, 1993

Books

Gerrymandering the States: Partisanship, Race, and the Transformation of American Federalism with Anthony J. McGann, Charles Anthony Smith, and Alex Keena., Cambridge University Press, 2021. https://www.cambridge.org/core/books/gerrymandering-the-states/27FBE0280F339E739758A29DF7CD74A2#fndtn-information

Gerrymandering in America: The House of Representatives, The Supreme Court, and the Future of Popular Sovereignty with Anthony J. McGann, Charles Anthony Smith, and Alex Keena., Cambridge University Press, 2016. https://www.cambridge.org/core/books/gerrymandering-in-america/C2A9A40879A353AC7484B49834CB54E4

Peer-Reviewed Publications

"Common Forms of Gerrymandering in the United States" *Decisions*, (32) with Alex Keena,Anthony J. McGann, and Charles Anthony Smith. (2019) https://journals.kozminski.edu.pl/pub/5797

Our Unhealthy Democracy: How Voting Restrictions Harm Public Health—and What We Can Do about It, policy paper published by Union of Concerned Scientists, Center for Science and Democracy, October 2019, https://www.ucsusa.org/resources/our-unhealthy-democracy

"Diagnosing Electoral Integrity" chapter in *Electoral Integrity in America: Securing Democracy,* Pippa Norris, Sarah Cameron and Thomas Wynter (eds.), Oxford University Press, 2018. https://www.electoralintegrityproject.com/electoral-integrity-in-america/

Building a Healthier Democracy: The Link Between Voting Rights and Environmental Justice, Union of Concerned Scientists research report, September 2018 https://www.ucsusa.org/sites/default/files/attach/2018/09/building-a-healthier-democracy-report.pdf

"Measuring Legislative Behavior: An Exploration of Digitaldemocracy.org" with Alexander M., Dekhtyar, Foaad Khosmood, Nicole Angelini, and Andrew Voorhees, *California Journal of Politics and Policy,* vol 9, issue 3, 2017. https://doi.org/10.5070/P2cjpp9336921

"Darwinian Democracy? How evolutionary theory informs constitutional design" chapter in *Handbook of Biology and Politics,* Steven Peterson and Albert Somit (eds.), Edward Elgar Publishing, 2017.
https://www.elgaronline.com/view/9781783476268.00037.xml

"A Discernable and Manageable Standard for Partisan Gerrymandering" with Anthony J. McGann, Charles Anthony Smith, and Alex Keena. December, 2015., *Election Law Journal: Rules, Politics, and Policy*. 14(4): 295-311.
https://doi.org/10.1089/elj.2015.0312

"The Calculus of Consensus Democracy: Rethinking *Patterns of Democracy* without veto players" with Anthony J. McGann, *Comparative Political Studies,* 2013, Vol 46, pp. 823-850, http://dx.doi.org/10.1177/0010414012463883

"Mapping the Consequences of Electoral Reform" with Kyle Roach, in *California Journal of Politics and Policy,* 2011, vol 3, issue 1. https://escholarship.org/uc/item/9mv9b480

"Geographical Representation Under Proportional Representation: The Cases of Israel andThe Netherlands," with Anthony McGann, *Electoral Studies,* 2005, vol 24, issue 4.
https://www.sciencedirect.com/science/article/pii/S0261379405000247

Recent Technical/Research Consultation Papers

The 2020 Randolph W. Thrower Symposium, Emory School of Law, Panel III: Violations and Enforcement: Identifying and Rectifying Campaign and Election Violations:
https://law.emory.edu/academics/journals/emory-law-journal-symposium.html

Securing Fair Elections: Challenges to Voting in Georgia and the United States (2019), co-author, Scholars Strategy Network,
https://scholars.org/sites/scholars/files/12.10.19_Securing_Fair_Elections_Report_FINAL.pdf

"Possible Results of Proportional-voting Systems for Seattle Port Commission Elections" with Jack Santucci, June 30th 2018, prepared for More Equitable Democracy

City of Pismo Beach Digital Engagement Strategy, 2015, prepared for the City of Pismo Beach

"Building a Healthier Democracy" presentation at National Advisory Board meeting, Union of Concerned Scientists, New York, New York, September 2018

Guest, Data-Driven Strategies to Promote Youth Turnout, Massachusetts Institute of

Technology, August 28-29, 2018

Census Counts 2020 Taskforce https://censuscounts.org

Presenter, Redistricting and Election Law Panel, American Political Science Association annual meeting, Boston, Massachusetts,
August 2018

"Feminist Messaging in the 2018 Congressional Elections" presented at the Cal Poly Alumni retreat, Lair of the Golden Bear, June 2018

Presenter and Discussant, Midwestern Political Science Association annual meeting, Chicago, Illinois, April 2018

Presenter and Discussant, Voting in 2018 and Beyond: Ensuring Access and Accountability of the Ballot in America, Hastings Constitutional Law Quarterly 2018 Symposium

"Diagnosing Electoral Integrity" Electoral Integrity Project pre-APSA workshop, San Francisco, California, August 2017

Presenter, American Political Science Association annual meeting, San Francisco, California, August 2017

"Will the Revolution be Digitized?" presented at the Cal Poly Alumni retreat, Lair of the Golden Bear, June 2017

Discussant and Chair, Western Political Science Association annual meeting, San Diego, California, April 2017

Chair, Discussant, and Presenter, American Political Science Association annual meeting, San Francisco, California, August 2015

Fellowships, Awards, and Professional Recognition
Kendall Science Fellow (Voting Rights), Union of Concerned Scientists, 2018-2019
Faculty Scholar, Institute for Advanced Technology and Public Policy, 2015-present
Research Scholarship and Creative Activity Grant for California Redistricting Project, 2016
Common Cause Redistricting Research Competition, 3rd Place, 2015
Gold Medal, California Mid-State Fair Home Brewing Competition, Milk Stout, 2014
Wilma Rule Award, Californians for Electoral Reform, 2013
CA State Faculty Support Grant, 2009-10

(pre-doctoral)
2003 U.C. Regents Pre-Dissertation Fellowship
2003 Summer research award, School of Social Sciences
2001 Summer research fellowship for ICPSR, University of Michigan
2000-01 William Podlich Fellow, Center for the Study of Democracy, U.C. Irvine
1995 Charles McCall Award, California State University Social Science Research Council

Election Consulting/Management
Susan Funk for Atascadero City Council 2018
Jimmy Paulding for SLO County Supervisor 2018
Aaron Gomez for San Luis Obispo City Council 2016
Dawn Ortiz-Legg for State Assembly 2016
Eric Michielssen for SLO County Supervisor 2016
Len Colamarino for Atascadero City Council 2014
Jim Patterson for SLO County Supervisor 2012
Brian Sturtevant for Atascadero City Council 2010
John Graham for Congress, 2004
John McCain for President, 2000

Recent Non-peer reviewed professional publications/news articles/blogs
A compilation of my media publications can be found at mikelatner.com

Current Teaching Rotation
POLS 590 MPP Graduate Writing Seminar (Fall section)
POLS 568 Democracy, Design and Public Policy
POLS 560 Quantitative Methods
POLS 445 Voting Rights and Representation
POLS 375 California Politics
POLS 317 Campaigns and Elections
POLS 316 Political Participation
POLS 112 American and California Government

Other Courses Taught
POLS 470 Evolutionary Perspectives in Political Science
Metropolitan Inequality (USC)
California Politics (UCI)
The American Political System (UCI)

University service
Quantitative Reasoning assessment committee, 2016-
Academic Senate Instruction Committee, 2014-2017

CLA Assessment Committee 2018
CLA Commencement, College Marshall, 2013-2016, 2018

POLS Phi Beta Kappa Supervisor, 2018
POLS Curriculum Committee, 2011-2016
POLS MPP Committee, 2007-
POLS Assessment Committee, 2008, 2009, 2011-2016, 2018
POLS Alumni Advisory Board, 2007-

Political Science Club, 2009
POLS Paper Awards Committee, 2009, 2011, 2012
POLS Guest Speaker Committee 2007-2009

ACKNOWLEDGMENT

A notary public or other officer completing this certificate verifies only the identity of the individual who signed the document to which this certificate is attached, and not the truthfulness, accuracy, or validity of that document.

State of Texas
County of Bexar)

On 10/22/2021 before me, Jose Aaron Gutierrez Banda

appeared Michael S Latner, who proved to me on the basis of satisfactory evidence to be the person(s) whose name(~~s~~) is/~~are~~ subscribed to the within instrument and acknowledged to me that he/~~she/they~~ executed the same in his/~~her/their~~ authorized capacity(~~ies~~), and that by his/~~her/their~~ signature(~~s~~) on the instrument the person(~~s~~), or the entity upon behalf of which the person(~~s~~) acted, executed the instrument.

I certify under PENALTY OF PERJURY under the laws of the State of Texas that the foregoing paragraph is true and correct.

WITNESS my hand and official seal.

NOTARY PUBLIC
STATE OF TEXAS
Jose Aaron Gutierrez Banda
ID NUMBER
13290519-6
COMMISSION EXPIRES
February 2, 2025

Signature Jose Aaron Gutierrez Banda **(Seal)**

Notarized online using audio-video 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

AFFIDAVIT OF DR. LISA HANDLEY

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***Pro Hac Vice Motion Pending*

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Counsel for Respondent
Ohio Redistricting Commission

Affidavit of Lisa Handley.pdf

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Created:	October 22, 2021 05:55:51 -8:00
Pages:	1
Remote Notary:	Yes / State: OH

E-Signature Summary

E-Signature 1: Lisa Handley (LH)
October 22, 2021 07:01:47 -8:00 [6826B49E8098] [71.191.84.32]
lrhandley@aol.com (Principal) (Personally Known)

E-Signature Notary: Theresa M Sabo (TMS)
October 22, 2021 07:01:47 -8:00 [F15204A411DA] [23.28.168.121]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

EXPERT_0216

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
6826849E8098

Lisa Handley

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

F15204A411DA
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

[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

[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

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

AFFIDAVIT OF DR. KOSUKE IMAI

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Affidavit of Kosuke Imai.pdf

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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]
tess.sabo@gmail.com
I, Theresa M Sabo, did witness the participants named above electronically sign this document.

EXPERT_0247

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
CE102AED8522
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

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-

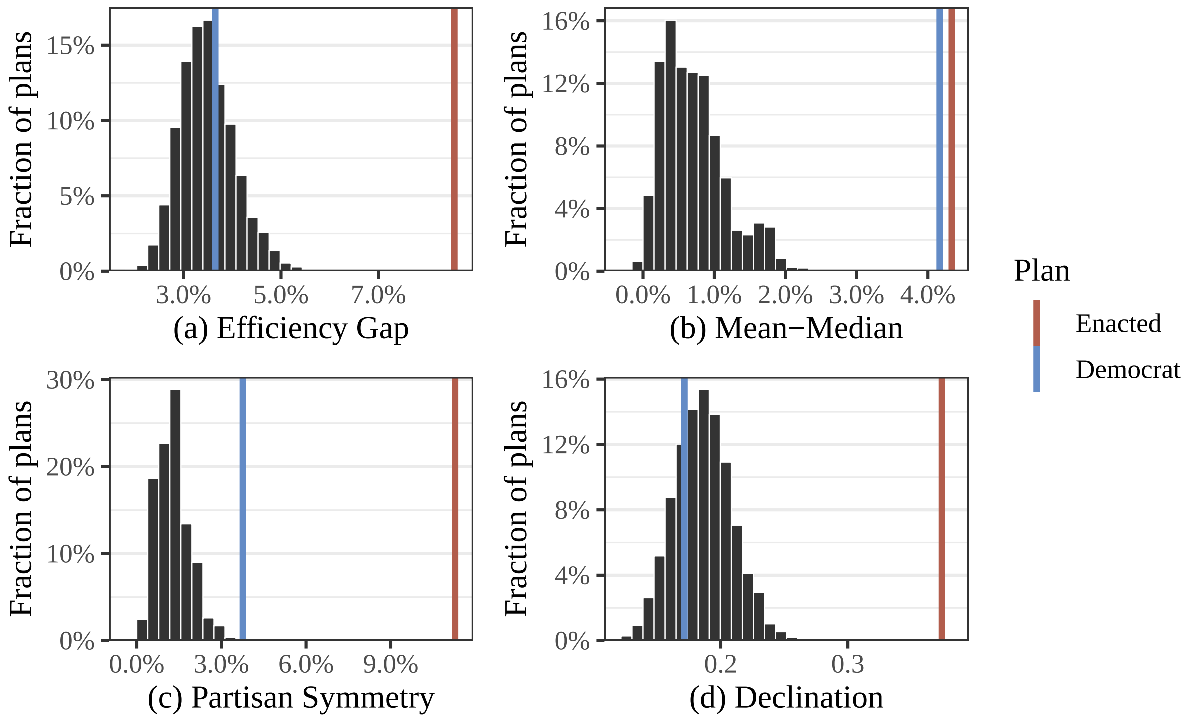

Figure 1: Four partisan bias measures calculated for the 5,000 simulated House redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic caucus plan (blue). For each measure, larger values (towards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

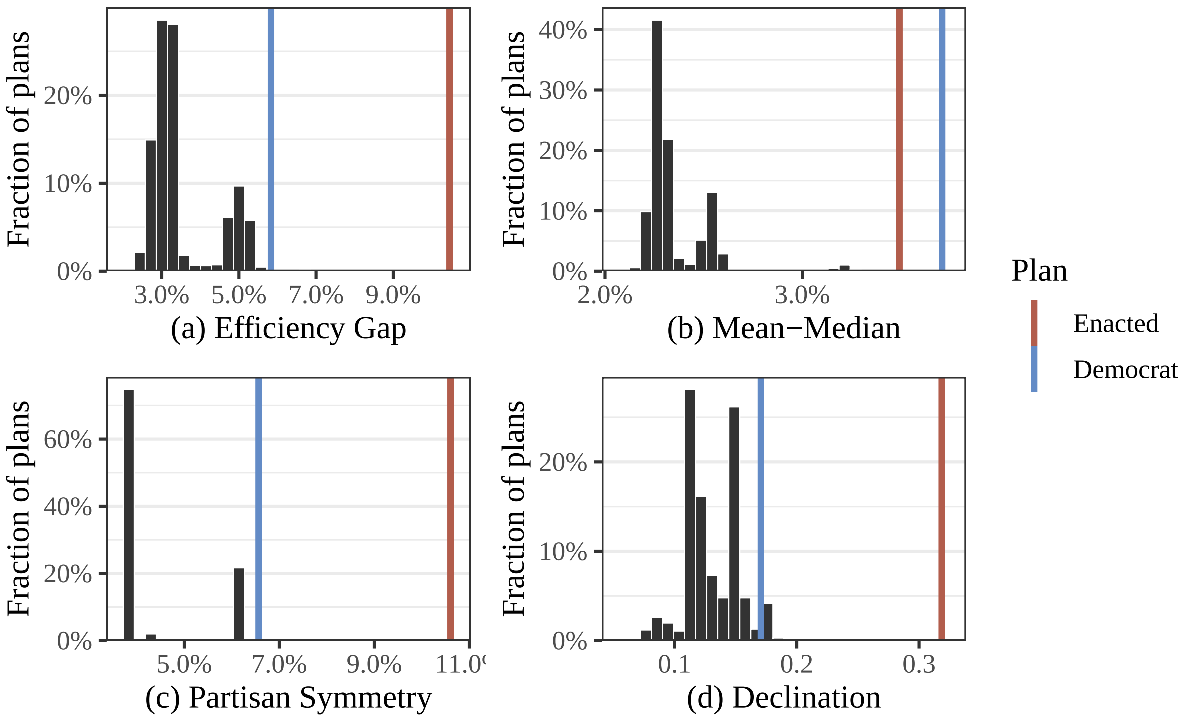

Figure 2: Four partisan bias measures calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic caucus plan (blue). For each measure, larger values (towards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

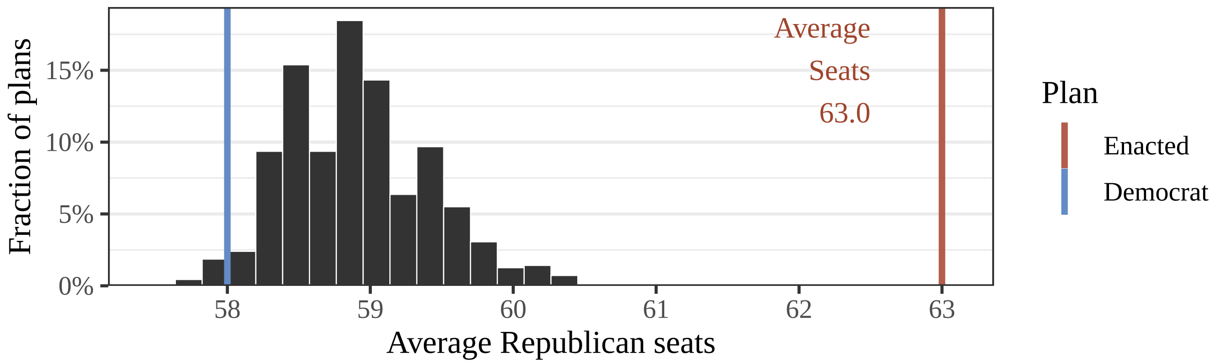

Figure 3: Average number of Repulican seats calculated for the 5,000 simulated House redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

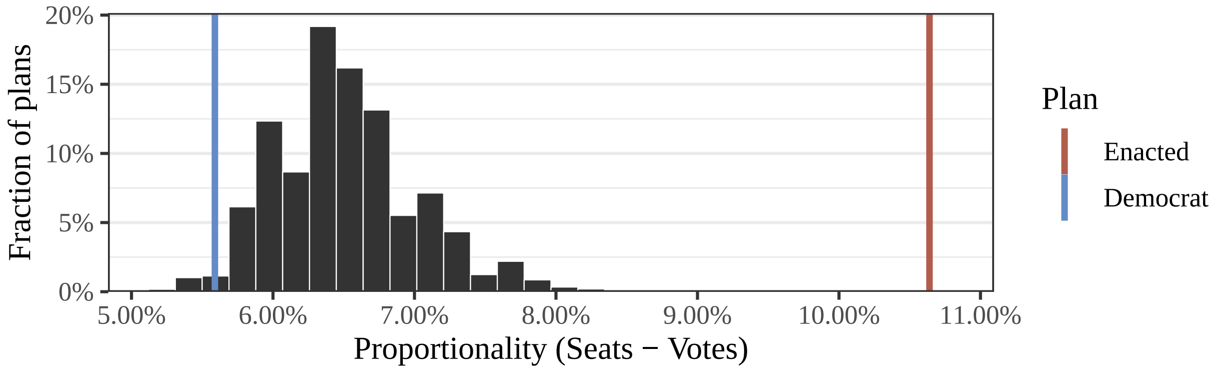

Figure 4: Corresponding proportionality measure calculated for the 5,000 simulated House redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

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.

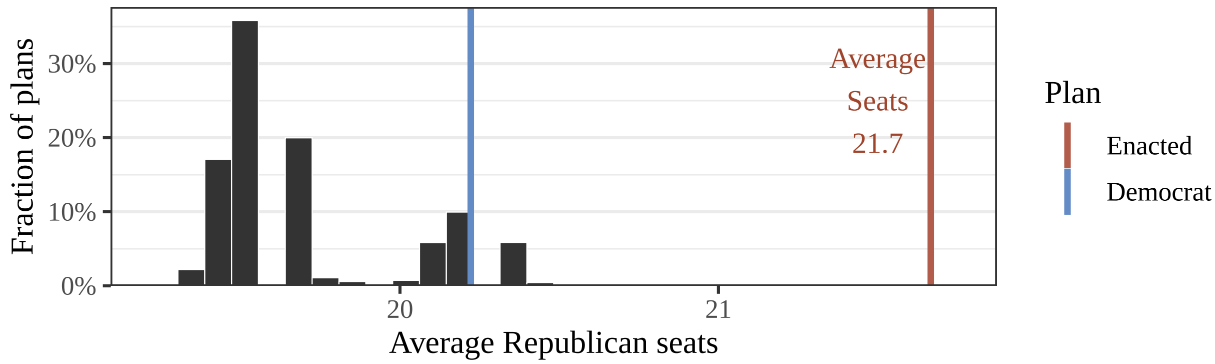

Figure 5: Average number of Repulican seats calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

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.

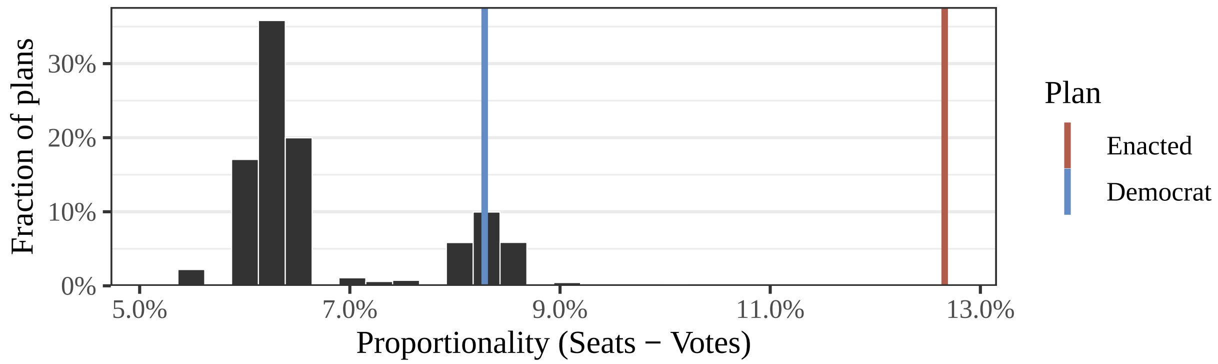

Figure 6: Corresponding proportionality measure calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

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

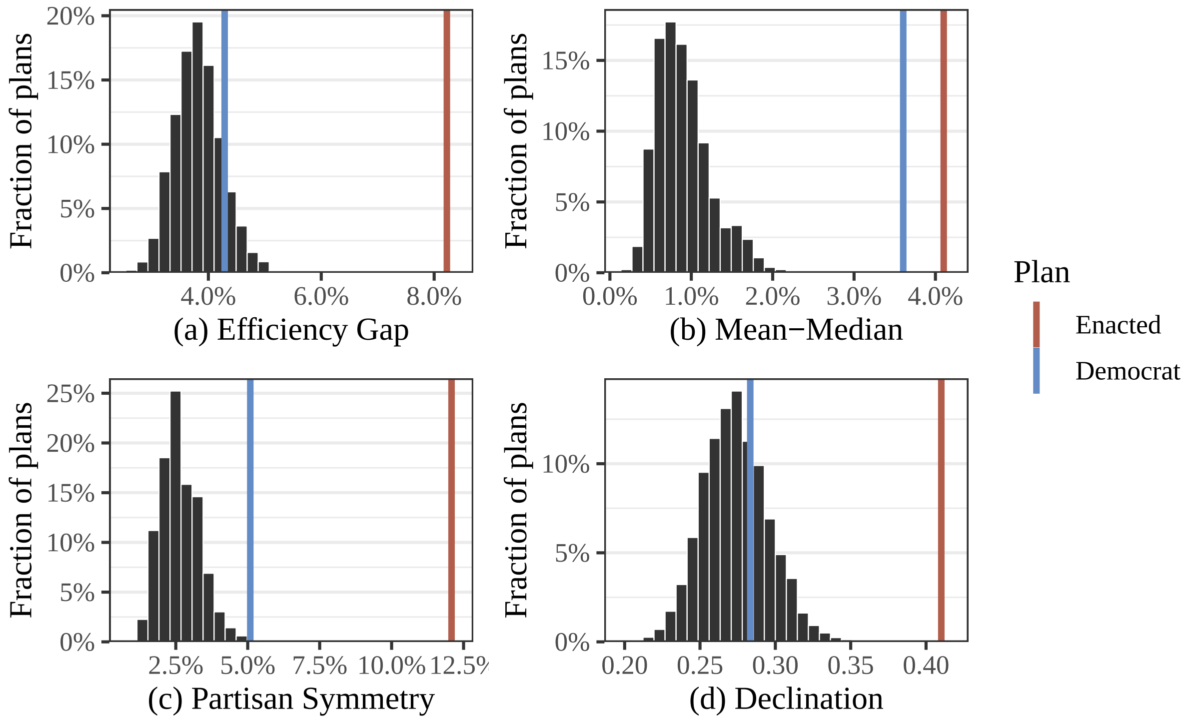

Figure 7: Four partisan bias measures calculated for the 5,000 simulated House of Representatives redistricting plans, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the three comparison plans. For each measure, larger values (towards the right) correspond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

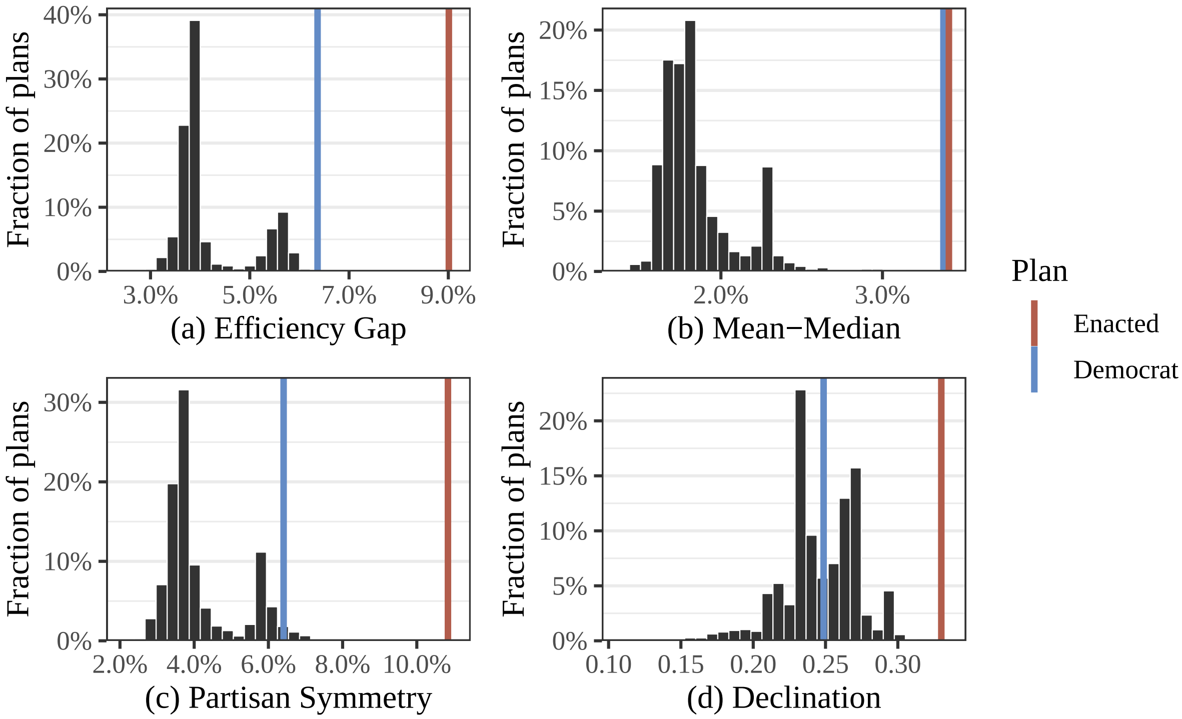

Figure 8: Four partisan bias measures calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 13 statewide elections, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the Democratic caucus plan (blue). For each measure,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

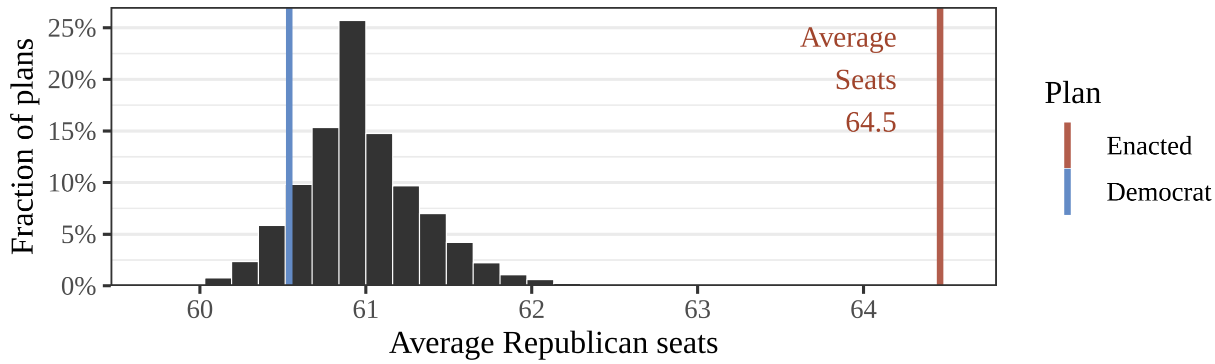

Figure 9: Average number of Repulican seats calculated for the 5,000 simulated House of Representatives redistricting plans, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the three comparison plans.

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

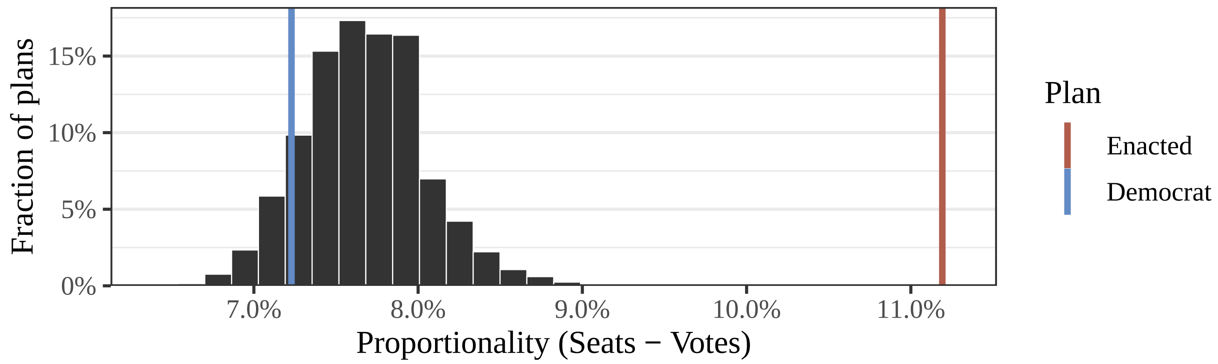

Figure 10: Corresponding proportionality measure calculated for the 5,000 simulated House of Representatives redistricting plans, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the three comparison plans.

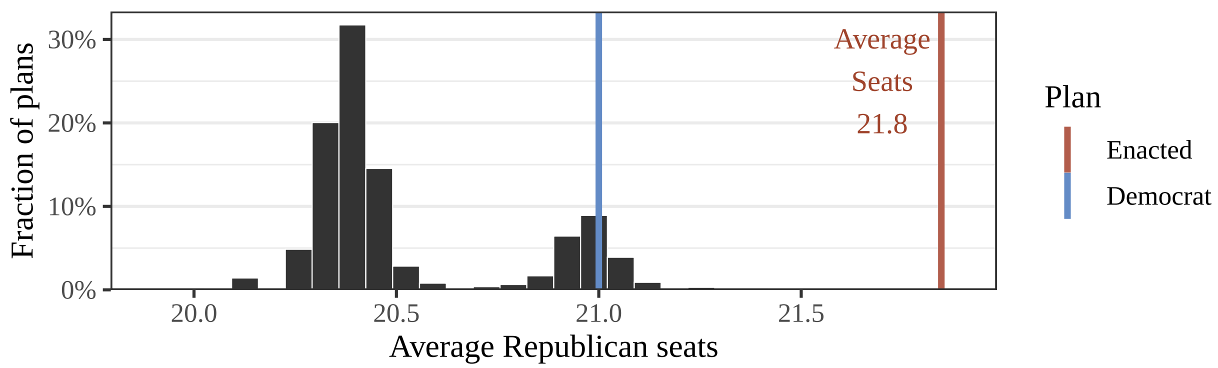

Figure 11: Average number of Repulican seats calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 13 statewide elections, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

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

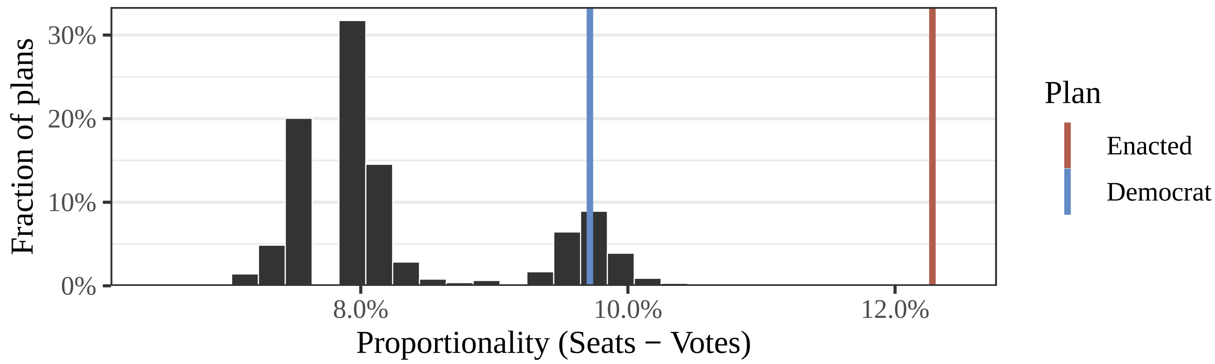

Figure 12: Corresponding proportionality measure calculated for the 5,000 simulated Senate redistricting plans computed by averaging across the 13 statewide elections, using an alternative method of calculation. Overlaid are the values for the enacted plan (red) and the Democratic plan (blue).

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

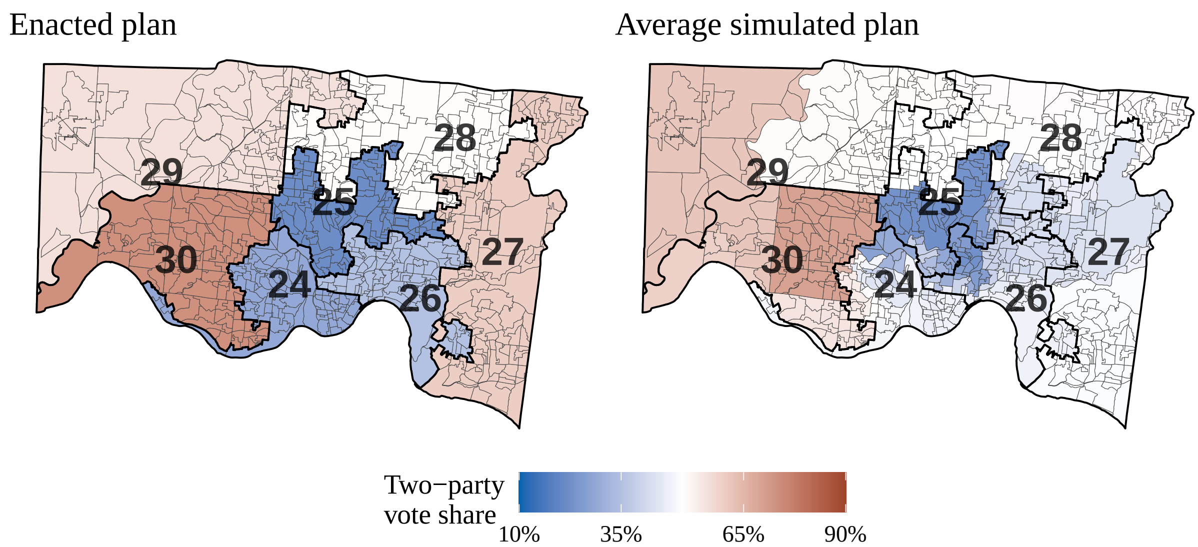

Figure 13: House districts in Hamilton county. The left and right maps show the average two-party vote share for each district under the enacted and average simulated plan, respectively. The enacted plan packs Democratic voters into districts 24, 25, and 26, turning districts 27, 29, and 30 into Republican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

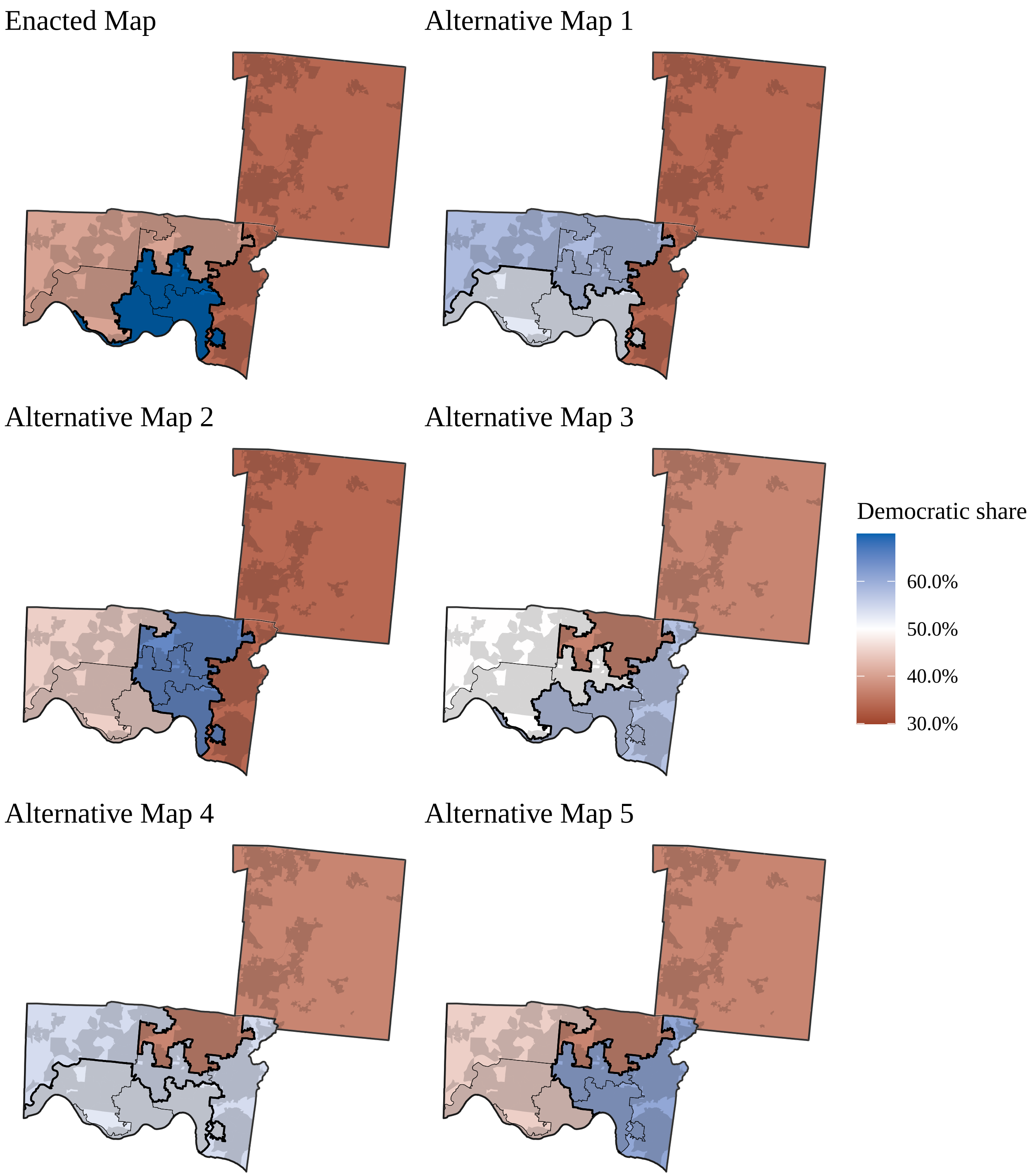

Figure 14: The 6 possible Senate districts in the Hamilton and Warren county cluster. The enacted plan is the top left plan. The enacted plan (top left) packs a disproportionately large number of Democratic voters into one district, creating two safe Republican districts. In contrast, the other plans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

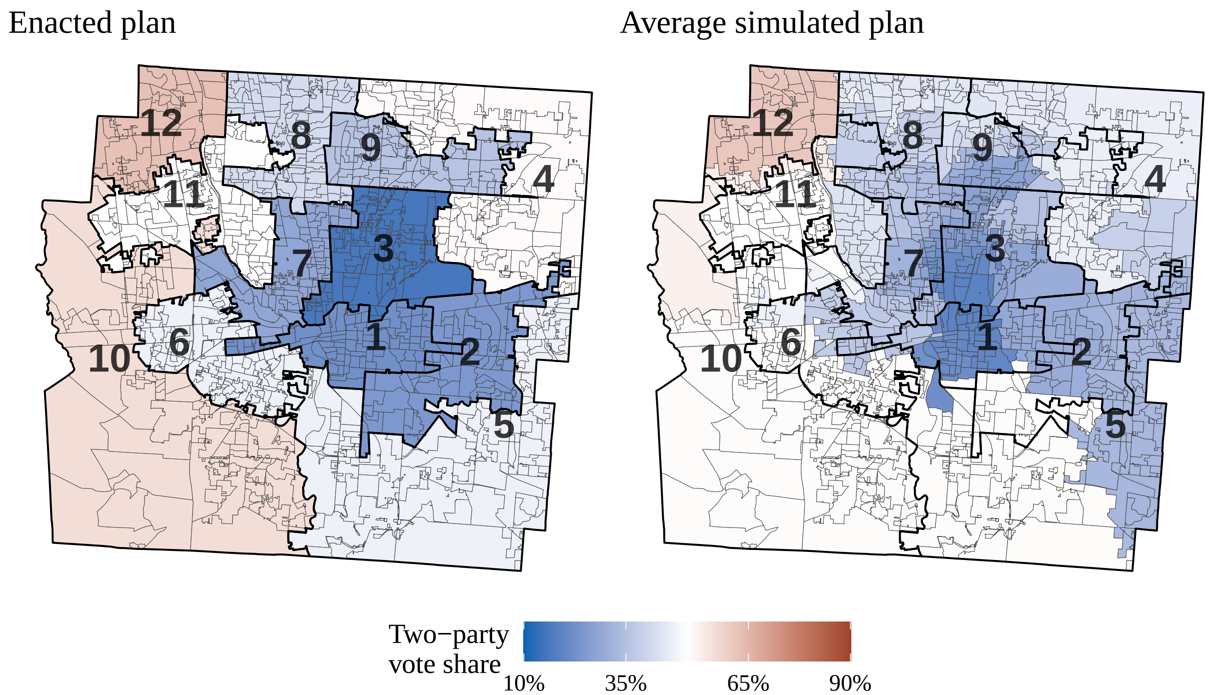

Figure 15: House districts in Franklin county. The left and right maps show the average two-party vote share for each district under the enacted and average simulated plan, respectively. The enacted plan packs Democratic voters into districts 1, 2, 3, and 7, turning districts 10 and 12 into Republican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

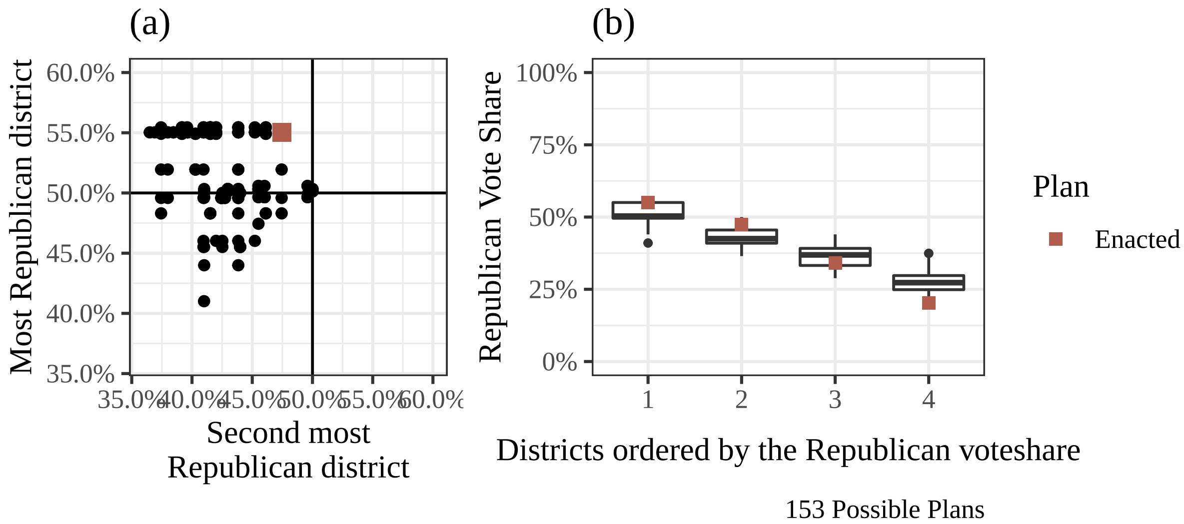

Figure 16: Comparison of simulated districts in Franklin and Union counties with the enacted districts. In panel (a), the vertical axis indicates the most Republican district and the horizontal axis indicates the next most Republican district. In panel (b), the districts are ordered horizontally by the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

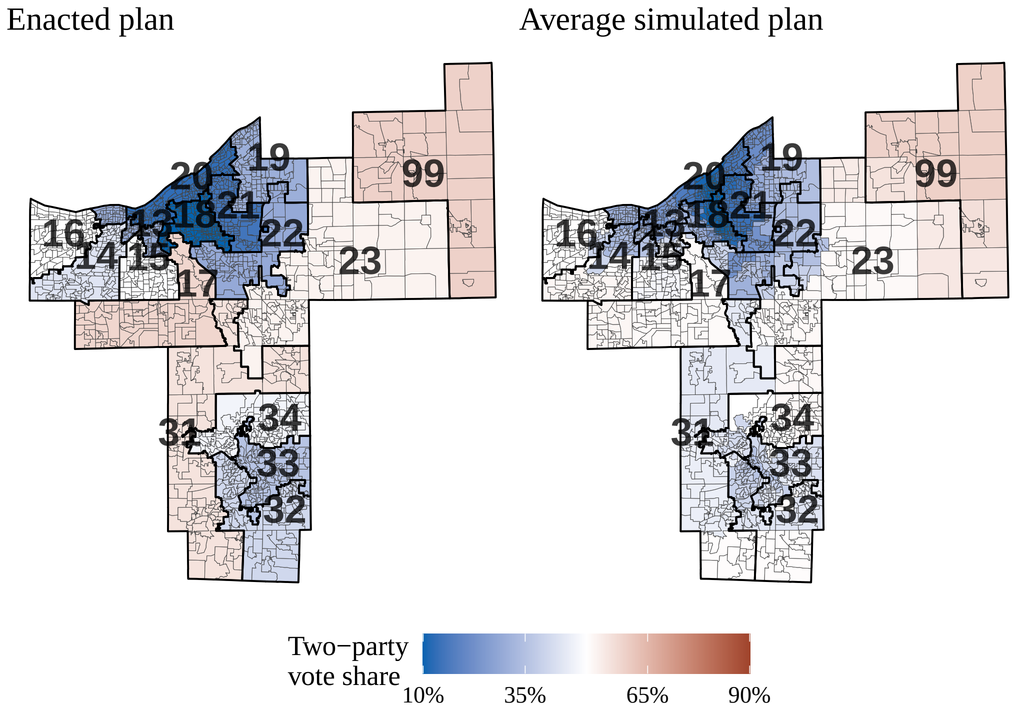

Figure 17: House districts in Cuyahoga, Summit, and Geauga counties. The left and right maps show the average two-party vote share for each district under the enacted and average simulated plan, respectively. The enacted plan packs Democratic voters in Cleveland districts, shoring up Republican vote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

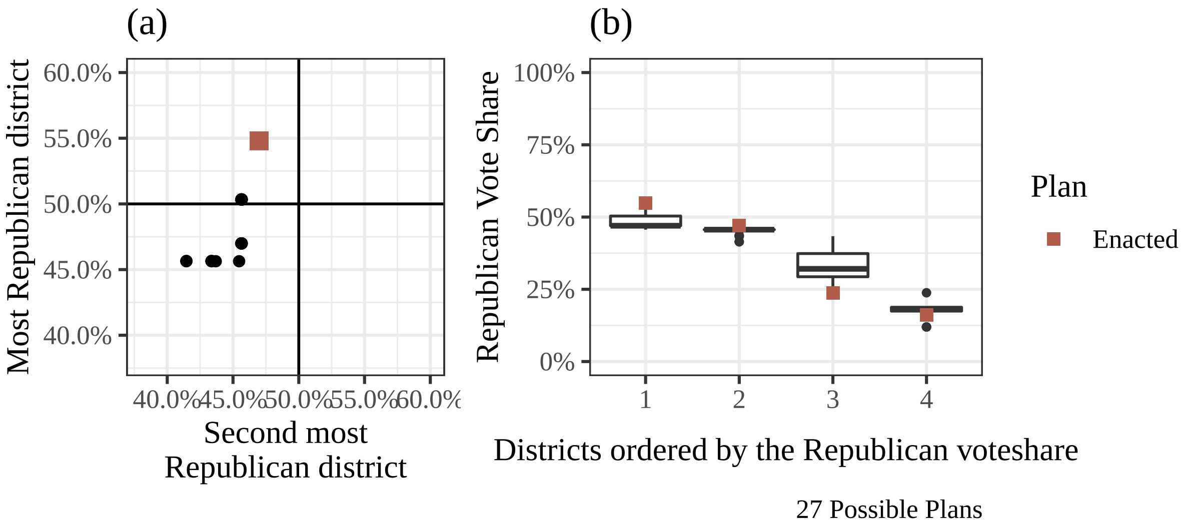

Figure 18: Comparison of simulated districts in Cuyahoga, Summit, and Geauga counties with the enacted districts. In panel (a), the vertical axis indicates the most Republican district and the horizontal axis indicates the next most Republican district. In panel (b), the districts are ordered horizontally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

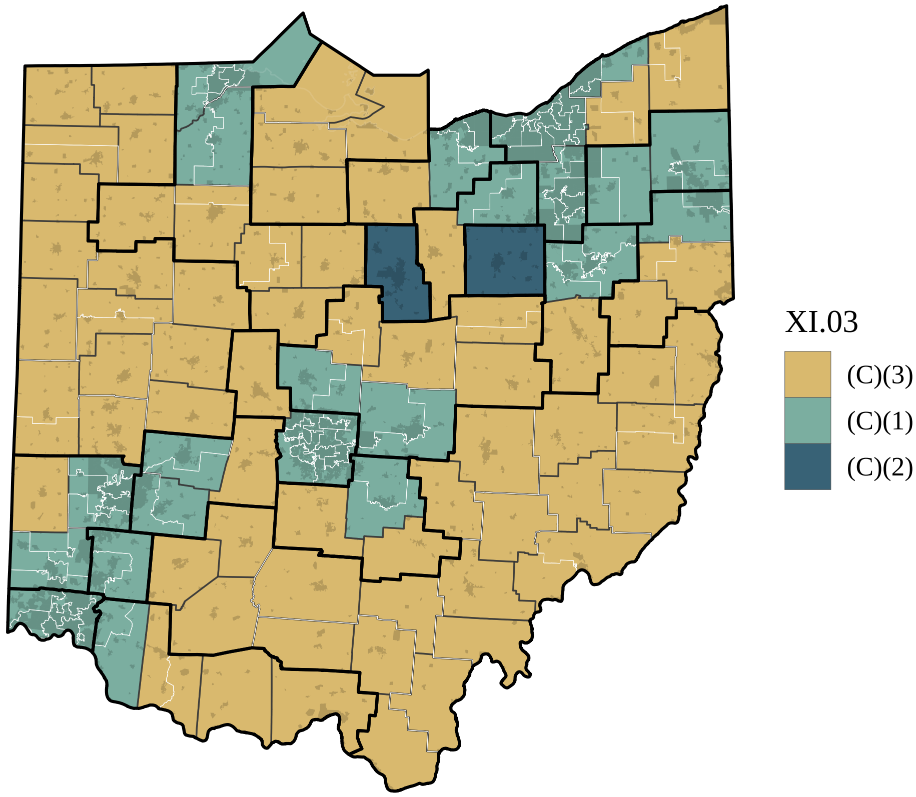

Figure 19: Ohio counties, colored by the subsection of Article XI.03 which they are subject to. Gray lines are county borders, and white lines are the district borders of the plan enacted by Respondents. Thick black lines demarcate independent county clusters used in simulation.

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-

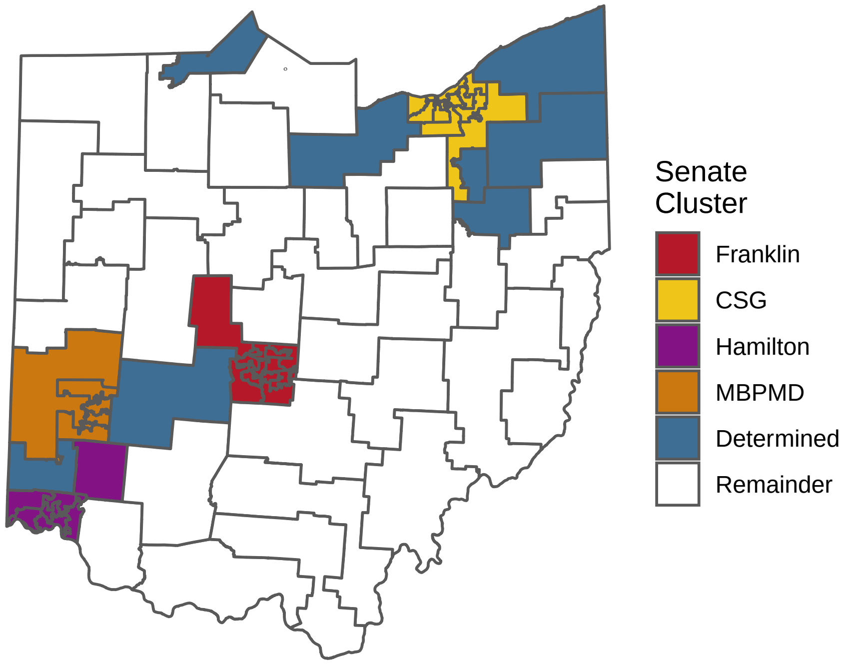

Figure 20: County clusters for the Senate implied by the decisions made to create the enacted House plan ensuring that no violations of Article XI Section 4(B)(1) or 4(B)(2). 'Determined' refers to the clusters, which there is only one compliant districting, whereas 'Remainder' refers to the rest of 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

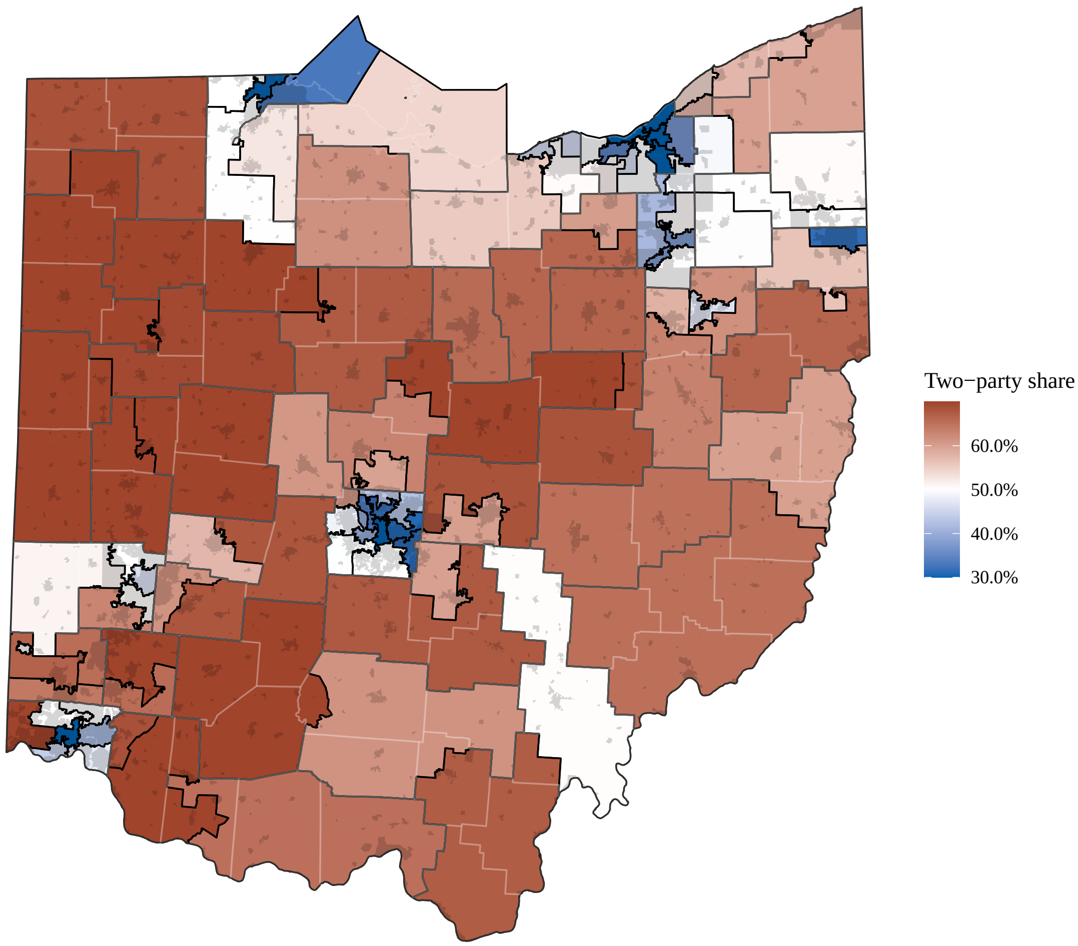

Figure 21: An example simulated redistricting plan for the House, with districts colored by their average two-party vote share.

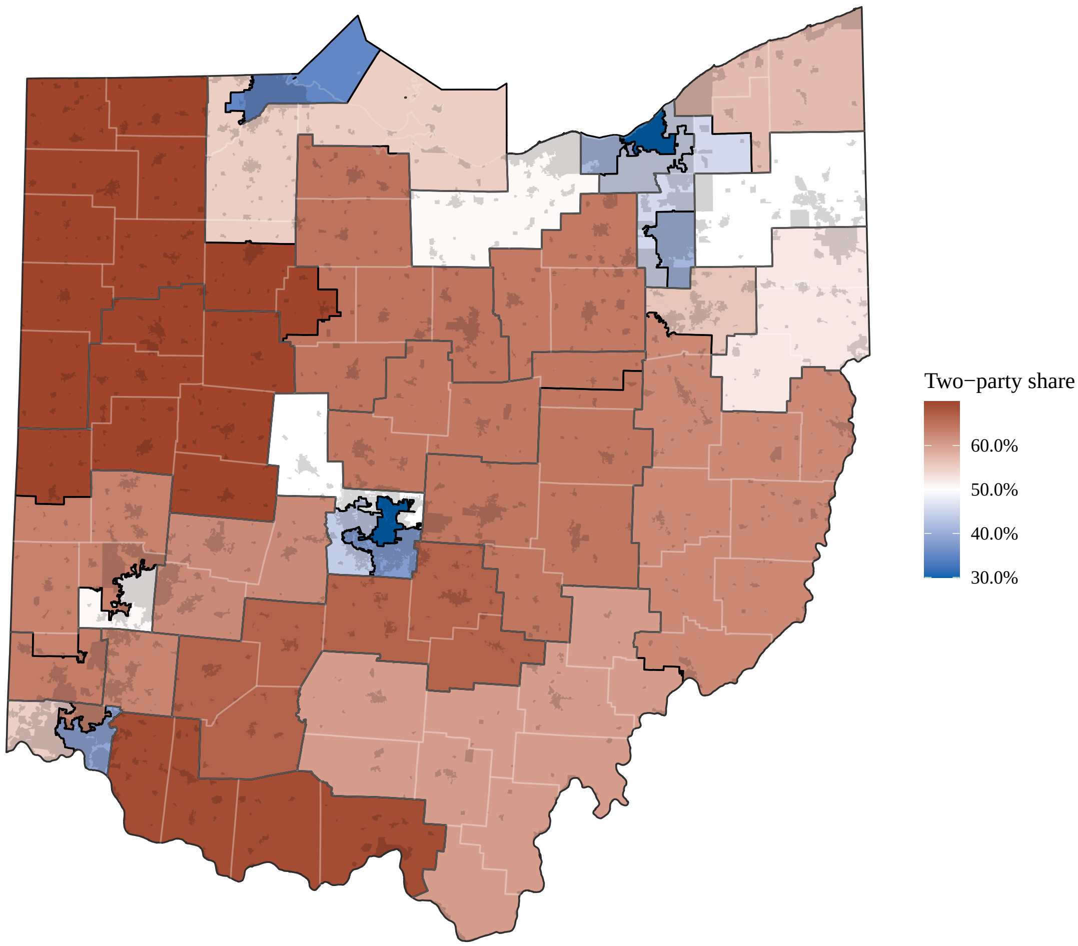

Figure 22: An example simulated redistricting plan for the Senate, with districts colored by their average two-party vote share.

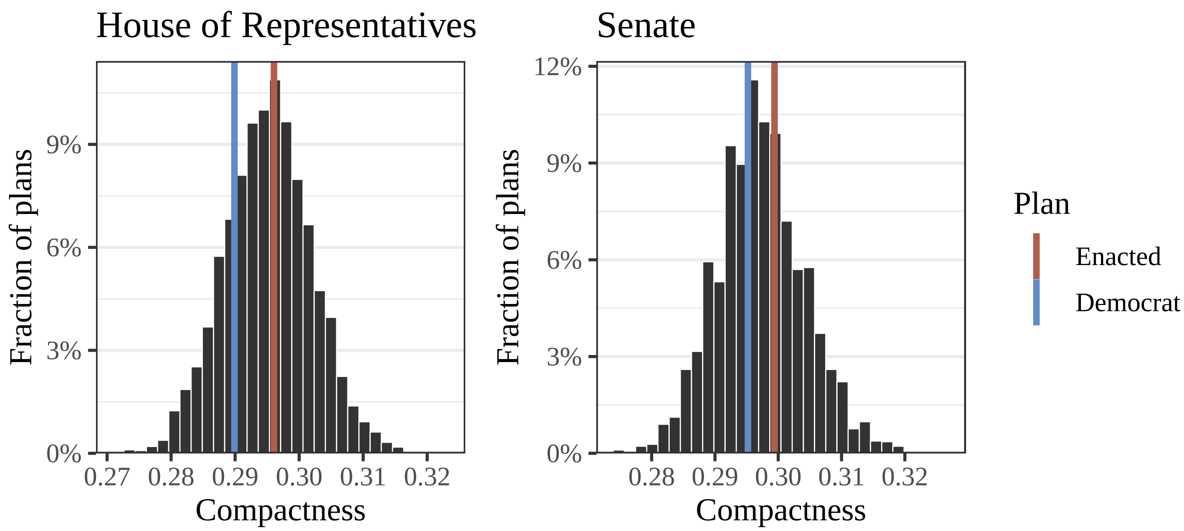

Figure 23: Polsby–Popper compactness scores for the simulated redistricting plans. Overlaid are scores for the enacted (red) and the Democratic caucus plan (blue). Larger values indicate more compact districts.

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

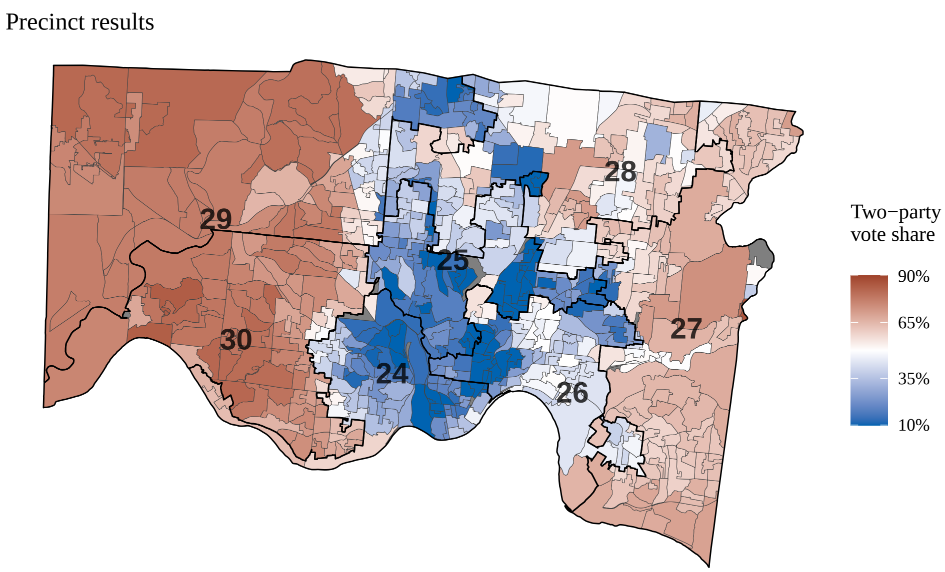

Figure 24: Vote shares for the precincts of Hamilton county.

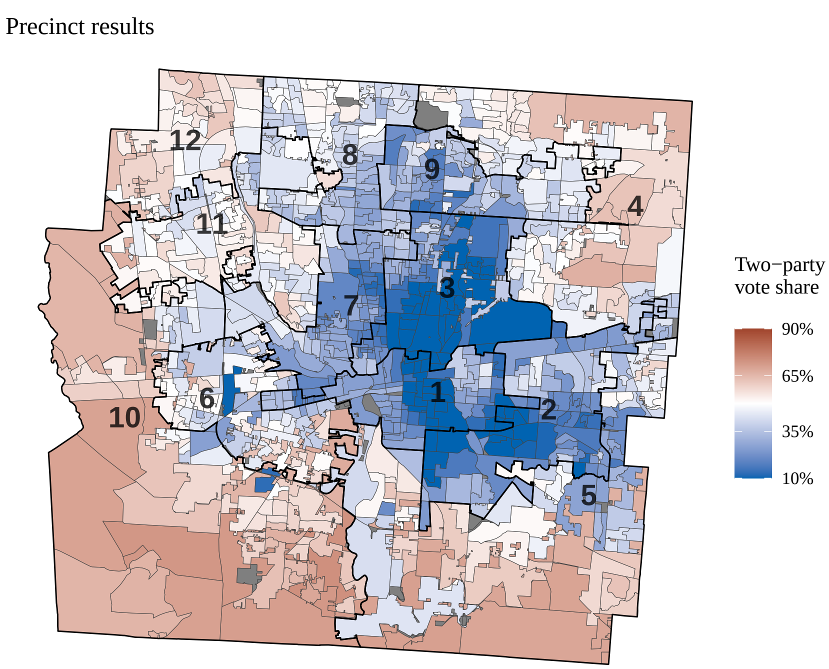

Figure 25: Vote shares for the precincts of Franklin county.

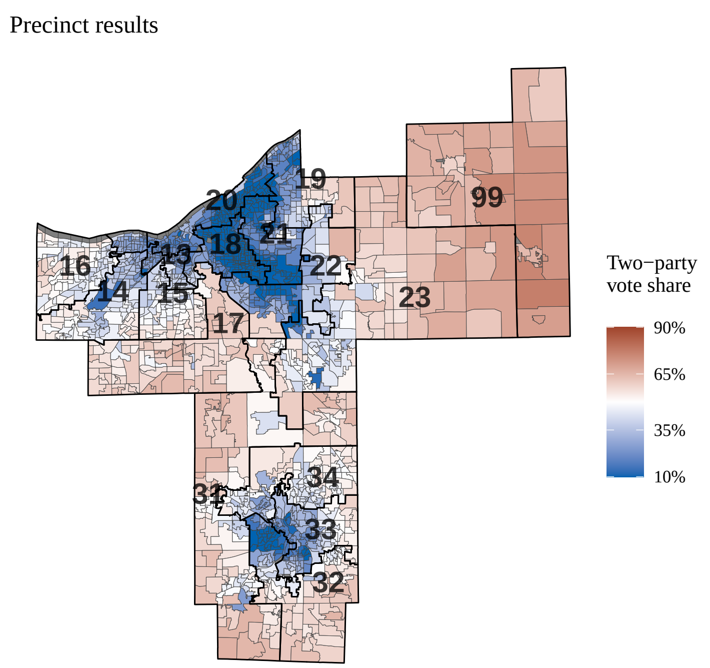

Figure 26: Vote shares for the precincts of Cuyahoga, Summit, and Geauga counties.

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.

G.2. References

Autry, Eric, Daniel Carter, Gregory Herschlag, Zach Hunter, and Jonathan Mattingly. 2020. "Multi-scale merge-split Markov chain Monte Carlo for Redistricting." *arXiv preprint arXiv:2008.08054.*

Best, Robin E., Shawn J. Donahue, Jonathan Krasno, Daniel B. Magleby, and Michael D. McDonald. 2018. "Considering the Prospects for Establishing a Packing Gerrymandering Standard." *Election Law Journal: Rules, Politics, and Policy* 17 (1): 1–20.

Buzas, Jeffrey S., and Gregory S. Warrington. 2021. "Simulated Packing and Cracking." *Election Law Journal,* https://doi.org/10.1089/elj.2020.0673.

Carter, Daniel, Gregory Herschlag, Zach Hunter, and Jonathan Mattingly. 2019. "A Merge-Split Proposal for Reversible Monte Carlo Markov Chain Sampling of Redistricting Plans." *arXiv preprint arXiv:1911.01503.*

DeFord, Daryl, Moon Duchin, and Justin Solomon. 2021. "Recombination: A Family of Markov Chains for Redistricting." Https://hdsr.mitpress.mit.edu/pub/1ds8ptxu, *Harvard Data Science Review* (March 31, 2021). https://doi.org/10.1162/99608f92.eb30390f. https://hdsr.mitpress.mit.edu/pub/1ds8ptxu.

Doucet, Arnaud, Nando de Freitas, and Neil Gordon. 2001. *Sequential Monte Carlo methods in practice.* New York: Springer.

Fifield, Benjamin, Michael Higgins, Kosuke Imai, and Alexander Tarr. 2020. "Automated Redistricting Simulation Using Markov Chain Monte Carlo." *Journal of Computational and Graphical Statistics* 29 (4): 715–728.

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

Gelman, Andrew, and Gary King. 1994. "A unified method of evaluating electoral systems and redistricting plans." *American Journal of Political Science,* 514–554.

Gilks, Walter R., Sylvia Richardson, and David J. Spiegelhalter. 1996. *Markov chain Monte Carlo in Practice.* London: Chapman & Hall.

Herschlag, Gregory, Han Sung Kang, Justin Luo, Christy Vaughn Graves, Sachet Bangia, Robert Ravier, and Jonathan C Mattingly. 2020a. "Quantifying Gerrymandering in North Carolina" [in eng]. *Statistics and Public Policy* 7 (1): 30–38. ISSN: 2330-443X.

———. 2020b. "Quantifying gerrymandering in North Carolina: Supplemental Appendix." *Statistics and Public Policy* 7 (1): 30–38.

Imai, Kosuke, and Kabir Khanna. 2016. "Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Record." *Political Analysis* 24 (2): 263–272.

Imai, Kosuke, Ying Lu, and Aaron Strauss. 2008. "Bayesian and Likelihood Inference for 2×2 Ecological Tables: An Incomplete Data Approach." *Political Analysis* 16 (1): 41–69.

Katz, Jonathan N, Gary King, and Elizabeth Rosenblatt. 2020. "Theoretical foundations and empirical evaluations of partisan fairness in district-based democracies." *American Political Science Review* 114 (1): 164–178.

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

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

McCartan, Cory, and Kosuke Imai. 2020. "Sequential Monte Carlo for sampling balanced and compact redistricting plans." *arXiv preprint arXiv:2008.06131.*

McGhee, Eric. 2014. "Measuring Partisan Bias in Single-Member District Electoral Systems." *Legislative Studies Quarterly* 39 (1): 55–85.

Owen, Guillermo, and Bernard Grofman. 1988. "Optimal Partisan Gerrymandering." *Political Geography Quarterly* 7 (1): 5–22.

Polsby, Daniel D, and Robert D Popper. 1991. "The third criterion: Compactness as a procedural safeguard against partisan gerrymandering." *Yale Law & Policy Review* 9 (2): 301–353.

Stephanopoulos, Nicholas O., and Eric M. McGhee. 2015. "Partisan Gerrymandering and the Efficiency Gap." *University of Chicago Law Review* 82 (2): 831–900.

———. 2018. "The Measure of a Metric: The Debate over Quantifying Partisan Gerrymandering." *Stanford Law Review* 70:1503–1568.

Exhibit A of Expert Report

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Curriculum Vitae

October 2021

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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.

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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). Post-doctoral Fellow. To be Assistant Professor, Department of Government, University of Texas, Austin

3. Shiro Kuriwaki (Ph.D. in 2021, Department of Government, Harvard University). Post-doctoral Fellow, Stanford University. To be Assistant Professor, Department of Political Science, Yale University

4. 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

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