Written Testimony about the League of Women Voters of Ohio Petitioners Congressional Map

Freda J. Levenson

February 23, 2022

1. On February 22, 2022 Dr. Imai submitted a Congressional district plan to the Ohio Redistricting Commission website ("the submitted plan"). Below, I set forth (a) the overall partisan composition of the submitted plan, (b) the overall compactness of the submitted plan, and (c) compliance with the federal Voting Rights Act.
2. In his evaluation of the partisan composition of the submitted plan, Dr. Imai used the method discussed on page 6 of his expert Affidavit (attached as Exhibit A) submitted on January 25th, 2022 in LWV of Ohio et al v. Ohio Redistricting Commission (Case No 2021-1193), and the election set discussed on page 4. The election set included all statewide elections for the period 2016-2020.
3. Using this approach, the overall partisan balance of the submitted map is 5.89 Democratic seats, and 9.11 Republican seats.
4. Table 1 sets forth the average two-party Republican and Democratic voteshares across the nine elections in the election set for each district. The first column ("District") indicates the number of each district in the map. The second column ("Average Democratic Voteshare") provides the average two-party voteshare for the Democratic candidate in each of the nine statewide elections between 2016 and 2020. The third column ("Average Republican Voteshare") provides the average two-party voteshare for the Republican candidate in each of the nine statewide elections during that period.
5. The districts in the submitted plan are compact. Two standard scoring methods, Polsby-Popper and Reock, provide the following compactness scores: The minimum Polsby-Popper and Reock scores across all 15 districts, respectively, are .264 and .321. The average Polsby-Popper and Reock scores across all 15 districts, respectively, are .384 and .432.
6. Table 2 sets forth the Reock and Polsby-Popper scores for each district. The first column ("District") indicates the number of each district in the map. The second column ("Polsby-Popper Score") gives the Polsby-Popper score of that district. The third column ("Reock Score") gives the Reock score of that district.
7. Finally, the map is compliant with the federal Voting Rights Act. The standards for compliance with the Voting Rights Act were discussed by Dr. Lisa Handley in her expert affidavit submitted December 10th, 2021 (attached as Exhibit B) in LWV of Ohio et al v. Ohio Redistricting Commission (Case No 2021-1449). Her report states on page 5 that to comply with the federal Voting Rights Act, a district with a minimum of 42% any-part Black Voting Age Population or higher should be drawn in the area of Cuyahoga County. The corresponding district in the submitted map, CD 11, has an any-part Black Voting Age Population percentage of 44.7%.

Table 1:

District	Average Democratic Voteshare	Average Republican Voteshare
1	56.5%	43.5%
2	33.4%	66.6%
3	66.0%	34.0%
4	34.4%	65.6%
5	25.8%	74.2%
6	35.5%	64.5%
7	45.6%	54.4%
8	33.1%	66.9%
9	55.7%	44.3%
10	46.1%	53.9%
11	80.4%	19.6%
12	53.9%	46.1%
13	54.6%	45.4%
14	46.9%	53.1%
15	38.1%	61.9%

Table 2:

District	Polsby-Popper Score	Reock Score
1	0.471	0.563
2	0.344	0.489
3	0.468	0.505
4	0.264	0.453
5	0.354	0.364
6	0.303	0.354
7	0.335	0.366
8	0.343	0.417
9	0.328	0.321
10	0.517	0.542
11	0.375	0.357
12	0.371	0.374
13	0.421	0.409
14	0.442	0.447
15	0.428	0.514

EXHIBIT A

IN THE SUPREME COURT OF OHIO

League of Women Voters of Ohio,
A. Phillip Randolph Institute of Ohio,
Tom Harry,
Tracy Beavers,
Valerie Lee,
Iris Meltzer,
Sherry Rose,
Bonnie Bishop

Relators,

v.

Ohio Redistricting Commission,
Michael DeWine,
Frank LaRose,
Keith Faber,
Matt Huffman,
Robert R. Cupp,
Vernon Sykes,
Emilia S. Sykes

Respondents.

Case No. 2021-1193
Original Action Pursuant to
Ohio Const., Art. XI

EXPERT REPORT

Kosuke Imai, Ph.D.

January 25, 2022

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

2. I have been asked by counsel representing the Relators in this case to analyze relevant data and provide my expert opinions related to whether Ohio's recently revised state House districting plan (hereafter the "revised plan") meets the criteria in Article XI, Section 6 of Ohio's Constitution. More specifically, I have been asked to statistically analyze the revised plan's compliance with Article XI, Sections 6(A) and 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. My analysis yields the following findings:

- The Commission's methodology of measuring district-level partisan lean is susceptible to inaccuracies. Classification into Republican-leaning versus Democratic-leaning districts based on the 50% threshold ignores the varying strength of partisanship across districts. The revised plan contains 12 districts whose Democratic vote shares are within one percentage point above the 50% threshold, based on the 2016–2020 election set used by the Commission. Out of these 12 "Democratic-leaning" districts, 9 districts have the Democratic vote share less than a half percentage point above the 50% threshold. The Commission's methodology classifies all of these toss-up districts as Democratic-leaning, grossly overestimating the total number of Democratic-leaning districts under the revised plan.

- The Commission's methodology is highly sensitive to its choice of elections to include for analysis. Removing any one election out of the 2016–2020 election set used by the Commission yields increases the total number of Republican-leaning districts under the revised plan by 6 to 12 percentage points. The preferred methodology, which I used in my initial expert report as well as in this report, overcomes this problem of the Commission's methodology by computing the fraction of elections that are expected to be won by each party as a measure of partisanship under a given redistricting plan.

- The revised plan exhibits a significant partisan bias in favor of the Republican party. The magnitude of bias is still much greater under the revised plan than *any* of my 5,000 simulated plans, according to the expected number of Republican seats as well as several other standard partisan bias metrics used in the academic literature.

- The revised plan fails to meet the proportionality criteria, making it almost certain for the Republican party to win disproportionately more seats relative to their statewide vote share. The degree of disproportionality is still much greater under the revised plan than *any* of my 5,000 simulated plans.

III. METHODOLOGY TO EVALUATE THE REVISED PLAN

A. The Problem of the Commission's Methodology

4. In its Section 8(C)(2) Statement, the Commission evaluates the partisan bias of the revised plan by computing the number of Republican-leaning and Democratic-leaning districts based on the 9 statewide elections from 2016 to 2020. The Commission concludes in the statement that the revised plan "contains 57 Republican-leaning House districts. This corresponds to approximately 57% of the total number of house districts."

5. To calculate the number of Republican-leaning districts, the Commission first computes, for each precinct in the state, the total number of Republican votes and Democratic votes, tallied across the 2016–2020 statewide elections. Then, the Commission classifies a district as "Republican-leaning" if the total number of Republican votes exceeds the total number of Democratic votes, and as "Democratic-leaning" otherwise.

6. This methodology of measuring district-level partisan lean is susceptible to inaccuracies. Consider two hypothetical districts: District A, with a Republican vote share of 50.1%,

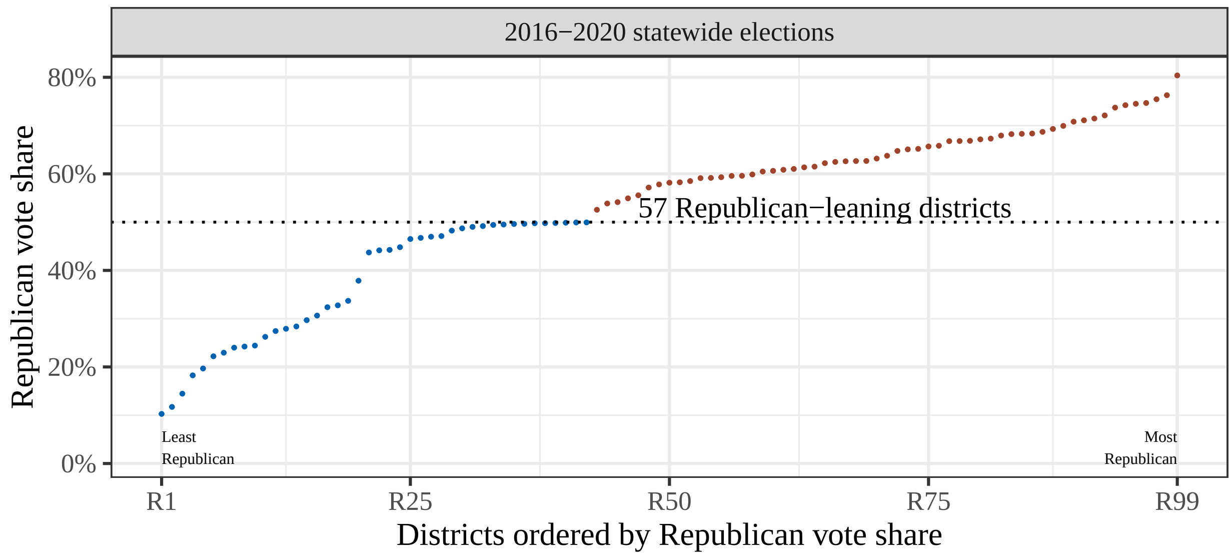

Figure 1: Republican votes shares calculated for the revised plan, computed by adding votes across the 9 statewide elections from 2016-2020.

and District B, with a Republican vote share of 49.9%, under the Commission's calculation of vote share. Since the Republican vote shares of these two districts differ only by 0.2 percentage points, they essentially have the same partisan lean. According to the Commission's methodology, however, District A would be considered "Republican-leaning" while District B would be classified as "Democratic-leaning." In other words, the Commission treats these two toss-up districts in the exactly same way as two lopsided districts, one with the Republican vote share of 100% and another which has the Democratic vote share of 100%.

7. This methodological deficiency biases the Commission's evaluation of the revised plan. Figure 1 shows the Republican vote shares, based on the 2016–2020 elections, of all 99 House districts under the revised plan. In this plot, the districts of the revised plan are ordered by the magnitude of their Republican vote share with the leftmost dot indicating the least Republican district and the rightmost dot representing the most Republican district. This means that district R1 has the lowest Republican vote share while district R99 is has the highest Republican vote share. (To be clear, the R1 through R99 district identifiers do not correspond to the House district numbers in the revised plan.)

8. There are 12 districts whose Republican vote share lies within one percentage point

below the 50% threshold (indicated by a group of blue dots right below the dotted horizontal line). And, 9 out of these 12 districts are within a half percentage point below the threshold. According to the Commission's methodology, these toss-up districts are all classified as "Democratic-leaning" districts. In contrast, there is no toss-up district whose Republican vote share is just above the 50% threshold. Among the districts that are considered by the Commission as "Republican-leaning" (i.e., those above the 50% line), the lowest Republican vote share is 52.6%, representing more than a 5 percentage point lead over Democrats. In other words, using the Commissions' own numbers, a shift in election results by just one percentage point towards the Republicans could lead to as many as 12 more Republican-won seats. By counting what are really toss-up districts as "Democratic-leaning" in this way, the Commission's methodology grossly overestimates the number of Democratic-leaning districts under the revised plan.

B. A Preferred Methodology

9. I now present a preferred methodology that overcomes the problem of the Commission's methodology explained above. This methodology was used in my initial expert report to this Court to evaluate the enacted plan. Specifically, for any given district of a redistricting plan, I first determine the likely winner based on the vote totals for each statewide election. I then average this number across all the statewide elections, arriving at the fraction of elections in which Republican candidates are expected to win this district (Tallying this number across districts yields the expected number of Republican seats under a redistricting plan).

10. This preferred methodology is based on the key observation that toss-up districts, unlike safe districts, are sometimes won by Republican candidates and other times won by Democrats, depending on elections. Thus, the fraction of elections, for which the Republican party receives more than 50% of votes, represents a superior measure of district-level partisan lean. In fact, political methodologists advocate evaluating redistricting plans by averaging across elections (Gelman and King 1994; Katz, King, and Rosenblatt 2020).

11. Table 1 illustrates the preferred methodology by presenting the proportions of statewide elections that are likely to be won by Republican candidates (based on the 2016–2020

District number	Rep. vote share	Rep. fraction of elections won
Classified by the Commission as "Democratic-leaning"		
52	49.94%	44.44%
23	49.93%	33.33%
27	49.88%	33.33%
10	49.82%	55.56%
15	49.78%	33.33%
Classified by the Commission as "Republican-leaning"		
76	52.55%	88.89%
56	53.86%	88.89%
94	54.14%	88.89%
35	54.92%	88.89%
53	55.56%	88.89%

Table 1: Districts classified by the Commission as "Democratic-leaning" and "Republican-leaning" whose Republican vote shares, based on the 2016-2020 statewide elections, are the closest to the 50% threshold (five districts each). The fraction of elections won represents the proportion of 9 statewide elections, for which the Republican vote share exceeds 50% for that district.

election set) for five districts classified by the Commission as "Democratic-leaning" and another set of five districts considered by the Commission as "Republican-leaning" districts. These two sets of districts were selected because their Republican vote shares are closest to 50% among the "Democratic-leaning" and "Republican-leaning" districts, respectively.

12. District 52 of the revised plan has a Republican vote share of 49.94%, which is less than one tenth of one percentage point shy of the 50% threshold. The Commission's methodology classifies this district as "Democratic-leaning," but based on the vote shares from each of the 2016–2020 statewide elections, this district would have been won by Republican candidates in 4 out of 9 elections (and by Democratic candidates in the remaining 5 elections). So, District 52 is clearly a toss-up district. Similarly, the other four "Democratic-leaning" districts in the table have the Republican vote share that is less than a quarter of one percentage point below of the 50% threshold. Republican candidates would have won these "Democratic-leaning" districts in 3 to 5 out of 9 elections, implying that they are toss-up districts and could often be won by Republican candidates.

13. The revised plan contains a total of 12 districts, whose Democratic vote share is

between 50% and 51% (5 of which are included in Table 1). The Commission's methodology considers all of these districts as "Democratic-leaning." The preferred methodology, however, reveals that the Republican party would have won about 6 out of these 12 districts when averaging across the 2016–2020 statewide elections.

14. In contrast, five "Republican-leaning" districts in Table 1 exceed the 50% threshold by a greater margin, ranging from 2.6 to 5.6 percentage points (Recall that these districts were selected because they have the lowest Republican vote share among all of the 57 "Republican-leaning" districts). Given the large margin, these districts are expected to be much safer than the five "Democratic-leaning" districts listed in the table. Indeed, the fraction of elections won by the Republican party for these districts is much higher, reaching 88.9% (8 out of 9 elections). Thus, the preferred methodology is able to more accurately measure the varying magnitude of partisan lean than the Commission's methodology.

15. Finally, I demonstrate that the preferred methodology is much less sensitive to the choice of election set used for analysis than the Commission's methodology. To do this, I conduct a so-called *leave-one-out* analysis by removing one election out of the 2016-2020 election set used by the Commission and applying their methodology to the remaining election data. This type of leave-one-out analysis is often used in statistics to examine the robustness of methodology. Since there exist a total number of 9 statewide elections in this set, repeating this procedure yields 9 different estimates of the number of "Republican-leaning" districts under the revised plan. I then compare these results to the Commission's official result based on all of the 9 statewide elections. If the Commission's methodology is not sensitive to the choice of election set used, then removing one election should not greatly affect the resulting estimate. I conduct the same analysis using the preferred methodology and investigate the sensitivity of each methodology to the choice of election set.

16. The left plot of Figure 2 shows that the Commission's methodology is highly sensitive to the choice of election set. When any one election is removed, the total number of "Republican-leaning" districts under the revised plan is much greater than the result based on

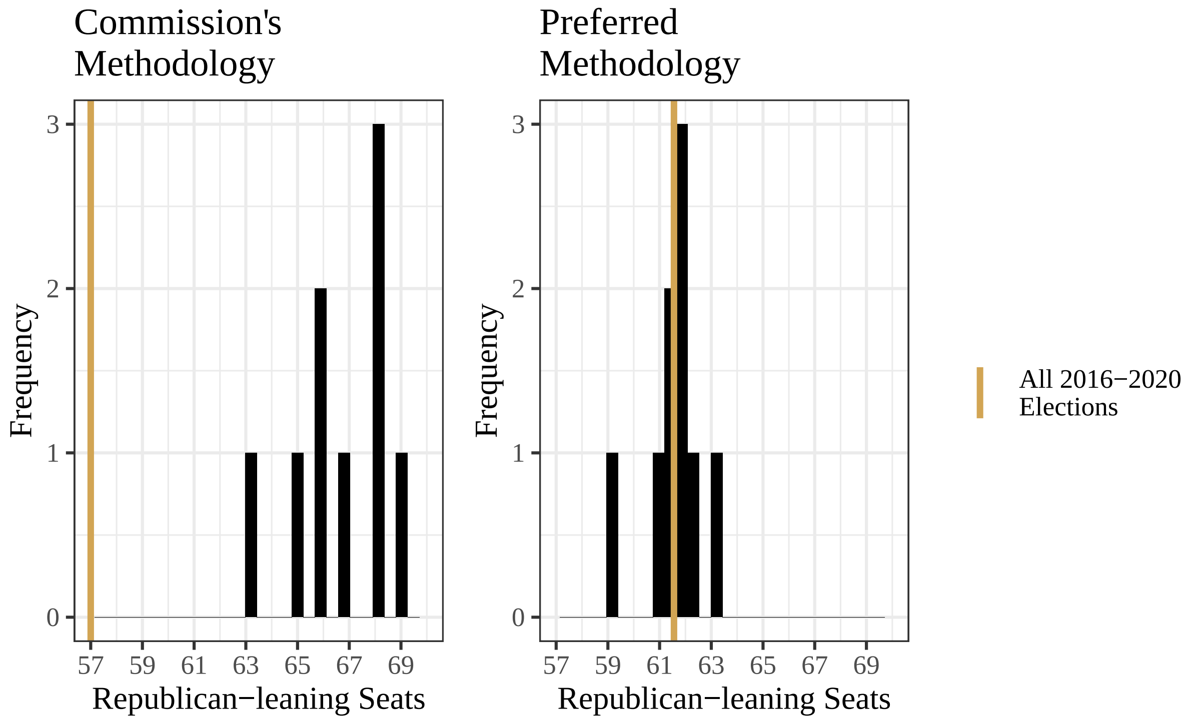

Figure 2: Comparison of election calculations for counting Republican-leaning seats for the 9 statewide elections for 2016-2020, leaving one election out for each calculation.

all 9 statewide elections. Indeed, according to the leave-one-out analysis, the total number of "Republican-leaning" districts ranges from 63 to 69, while the Commission's result based on all 9 statewide elections is only 57 districts. Thus, removing any single election from the 2016–2020 election set increases the total number of Republican-leaning districts by 6 to 12 percentage points. Thus, the Commission's approach is not only sensitive to which elections are included but also grossly underestimates the total number of "Republican-leaning" districts.

17. In contrast, the right plot of Figure 2 shows that the preferred methodology is less sensitive to the choice of election set used. The total number of expected Republican seats under the revised plan ranges from 59.2 to 63.1 with the estimate based on all 9 statewide elections located in the middle of the leave-one-out distribution. Indeed, under the preferred methodology, leaving out one election could only have only a modest effect on expected seat share corresponding to no more than one-ninth of the partisan lean scoring for each district. This and other analyses

presented above demonstrate the advantages of the preferred methodology over the Commission's methodology.

IV. COMPARISON OF THE REVISED PLAN WITH THE SIMULATED PLANS

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

19. I evaluate the revised plan's compliance with Sections 6(A) and 6(B) by comparing it with the same set of 5,000 simulated plans used in my initial report. Recall that these simulated plans are equally or more compliant with Sections 3, 4, and 6(c) than the enacted plan (see the initial report for details). As done in my initial report and my analysis above, I present the evaluation of the revised plan based on a total of 9 statewide elections from 2016 to 2020, which were used by the Commission. My analysis shows that the revised plan still has worse partisan bias and proportionality scores than any of my 5,000 simulated plans.

A. Compliance with Section 6(A)

20. Figure 3 presents the results regarding the enacted plan's compliance with Section 6(A). As detailed in my initial report, the compliance with Section 6(A) was measured based on four partisan bias metrics that are commonly used in the political science literature. The exact formula for these metrics differs slightly across sources, and I rely on the methods described in Stephanopoulos and McGhee 2015 and Katz, King, and Rosenblatt 2020. I adjusted the sign of each metric so that a smaller value implies less partisan bias with a positive value representing a bias towards the Republican party.

21. When compared to my 5,000 simulated plans (black histogram), the revised plan (yellow vertical line) is a clear outlier favoring the Republican party. Indeed, the revised map is more biased towards the Republican party than any of 5,000 simulated plans for all four partisan

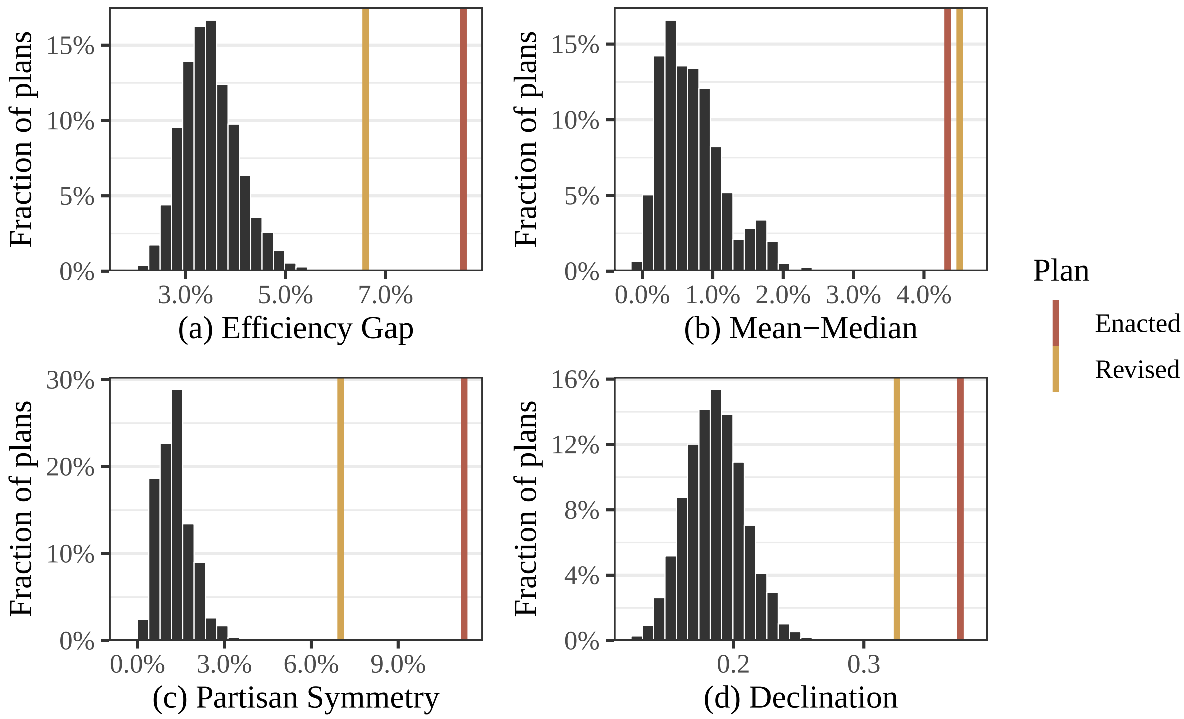

Figure 3: Four partisan bias measures calculated for the 5,000 simulated House redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the revised plan (yellow) and the enacted plan (red). For each measure, larger values (towards the right) correspond to more Republican-favoring plans.

bias metrics I considered. With the exception of the mean-median metric, the revised plan somewhat improves upon the enacted plan. This improvement, however, is too small to make the revised plan comparable to the simulated plans in terms of partisan bias.

22. Under the revised plan, the efficiency gap score is still more than 5 standard deviations greater than the corresponding score under the average simulated plan. Similarly, the revised plan yields the values of mean-median, partisan symmetry, and declination metrics that are over 8, 9, and 6 standard deviations greater than the average simulated plan, respectively. These statistically significant results imply that the revised plan is substantially biased towards the Republican party when compared to the simulated plans.

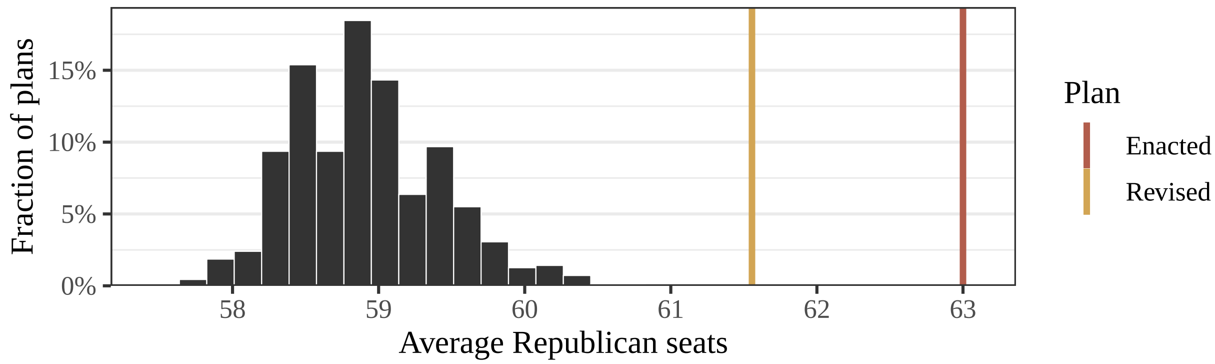

Figure 4: Average number of Repulican seats calculated for the 5,000 simulated House redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the revised plan (yellow) and the enacted plan (red).

B. Compliance with Section 6(B)

23. I next present the results regarding the plans' compliance with Section 6(B). I use the proportionality metric to examine whether or not the statewide seat share of each party corresponds closely to its statewide vote share under each plan. As I show below, the revised plan is a clear outlier relative to the simulated plans. That is, all of my 5,000 simulated plans are more compliant with Section 6(B) than the revised plan.

24. Following my initial report, I next compare the expected number of Republican seats under the revised plan with that under the same 5,000 simulated plans. The calculation of the expected number of Republican seats is based on the preferred methodology explained above. Figure 4 shows that under the revised plan, the Republican party is expected to win 61.6 seats, which is about 2.7 seats higher than the average simulated plan of 58.9 seats. Indeed, none of my 5,000 simulated plans awards that many seats to Republicans. The difference between the revised plan and the average simulated plan exceeds 5 standard deviations of the simulated plans and is therefore statistically significant. Although the revised plan awards, on average, about 1.4 fewer seat to Republicans than the enacted plan, the revised plan is still much more favorable to the Republican than any of the 5,000 simulated plans.

25. This discrepancy is reflected in the proportionality metric, which is shown in Figure 5. A value of zero for this measure implies complete proportionality, while positive values indicate

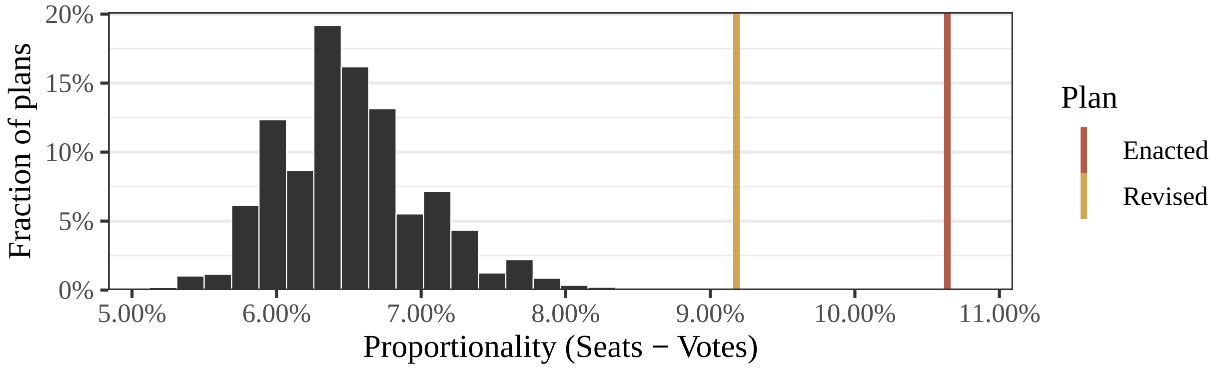

Figure 5: Corresponding proportionality measure calculated for the 5,000 simulated House redistricting plans computed by averaging across the 9 statewide elections from 2016 to 2020. Overlaid are the values for the revised plan (yellow) and the enacted plan (red).

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 revised plan has a proportionality score of 9.2%, implying that the Republican party would receive an average of 9.2% more seats under the revised 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 revised plan. The difference between the revised plan and the average simulated plan is more than 5 standard deviations of the simulated plans and therefore is statistically significant. Although the revised plan improves upon the enacted plan (red) by about 1.5 percentage points, the revised plan is still much more favorable towards the Republican party than any of the 5,000 simulated plans.

V. APPENDIX

A. References

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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.

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

EXHIBIT A

Curriculum Vitae

Kosuke Imai

Curriculum Vitae

January 2022

Contact Information

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Education

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

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

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

Positions

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

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

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

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

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

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

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

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

Honors and Awards

1. Invited to read "Experimental Evaluation of Computer-Assisted Human Decision-Making: Application to Pretrial Risk Assessment Instrument." before the Royal Statistical Society Research Section, London (2022).

2. *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, 2021).

3. *Excellence in Mentoring Award*, awarded by the Society for Political Methodology (2021).

4. *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).

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. Olivella, Santiago, Tyler Pratt, and Kosuke Imai. "Dynamic Stochastic Blockmodel Regression for Social Networks: Application to International Conflicts." *Journal of the American Statistical Association*, Forthcoming.

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

3. 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.

4. 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.

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

6. de la Cuesta, Brandon, Naoki Egami, and Kosuke Imai. (2022). "Experimental Design and Statistical Inference for Conjoint Analysis: The Essential Role of Population Distribution." *Political Analysis*, Vol. 30, No. 1 (January), pp. 19–45.

7. 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.

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68. 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.

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Invited Contributions

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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.

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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.

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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. Goplerud, Max, Kosuke Imai, Nicole E. Pashley. "Estimating Heterogeneous Causal Effects of High-Dimensional Treatments: Application to Conjoint Analysis."

2. Malani, Anup, Phoebe Holtzman, Kosuke Imai, Cynthia Kinnan, Morgen Miller, Shailender Swaminathan, Alessandra Voena, Bartosz Woda, and Gabriella Conti. "Effect of Health Insurance in India: A Randomized Controlled Trial."

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

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

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

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

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

8. 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."

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

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

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

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

13. 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.

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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.

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

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

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

External Research Grants

Principal Investigator

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

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

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

4. The Alfred P. Sloan Foundation (2020–2022). "Causal Inference with Complex Treatment Regimes: Design, Identification, Estimation, and Heterogeneity." (Economics Program; 2020–13946) Co-Principal Investigator (with Francesca Dominici and Jose Zubizarreta) $996,299

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

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

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

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

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

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

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

12. National Science Foundation, (2009–2012). "Statistical Analysis of Causal Mechanisms: Identification, Inference, and Sensitivity Analysis," (Methodology, Measurement, and Statistics Program and Political Science Program; SES–0918968). Principal Investigator. $97,574.

13. National Science Foundation, (2009–2011). "Collaborative Research: The Measurement and Identification of Media Priming Effects in Political Science," (Methodology, Measurement, and Statistics Program and Political Science Program; SES–0849715). Principal Investigator (with Nicholas Valentino). $317,126.

14. National Science Foundation, (2008–2009). "New Statistical Methods for Randomized Experiments in Political Science and Public Policy," (Political Science Program; SES–0752050). Principal Investigator. $52,565.

15. National Science Foundation, (2006–2009). "Collaborative Research: Generalized Propensity Score Methods," (Methodology, Measurement and Statistics Program; SES–0550873). Principal Investigator (with Donald B. Rubin and David A. van Dyk). $460,000.

16. The Telecommunications Advancement Foundation, (2004). "Analyzing the Effects of Party Webpages on Political Opinions and Voting Behavior," Principal Investigator (with Naoko Taniguchi and Yusaku Horiuchi). $12,000.

Adviser and Statistical Consultant

1. National Science Foundation (2016–2017). "Doctoral Dissertation Research: Crossing Africa's Arbitrary Borders: How Refugees Shape National Boundaries by Challenging Them." (Political Science Program, SES–1560636). Principal Investigator and Adviser for Co-PI Yang-Yang Zhou's Dissertation Research. $18,900.

2. Institute of Education Sciences (2012–2014). "Academic and Behavioral Consequences of Visible Security Measures in Schools" (R305A120181). Statistical Consultant (Emily Tanner-Smith, Principal Investigator). $351,228.

3. National Science Foundation (2013–2014). "Doctoral Dissertation Research: Open Trade for Sale: Lobbying by Productive Exporting Firm" (Political Science Program, SES–1264090). Principal Investigator and Adviser for Co-PI In Song Kim's Dissertation Research. $22,540.

4. National Science Foundation (2012–2013). "Doctoral Dissertation Research: The Politics of Location in Resource Rent Distribution and the Projection of Power in Africa" (Political Science Program, SES–1260754). Principal Investigator and Adviser for Co-PI Graeme Blair's Dissertation Research. $17,640.

Invited Short Courses and Outreach Lectures

1. Short Course on Causal Inference and Statistics – Department of Political Science, Rice University, 2009; Institute of Political Science, Academia Sinica, 2014.

2. Short Course on Causal Inference and Identification, The Empirical Implications of Theoretical Models (EITM) Summer Institute – Harris School of Public Policy, University of Chicago, 2011; Department of Politics, Princeton University, 2012.

3. Short Course on Causal Mediation Analysis – Summer Graduate Seminar, Institute of Statistical Mathematics, Tokyo Japan, 2010; Society for Research on Educational Effectiveness Conference, Washington DC, Fall 2011, Spring 2012, Spring 2015; Inter-American Development Bank, 2012; Center for Education Research, University of Wisconsin, Madison, 2012; Bobst Center for Peace and Justice, Princeton University, 2014; Graduate School of Education, University of Pennsylvania, 2014; EITM Summer Institute, Duke University, 2014; Center for Lifespan Psychology, Max Planck Institute for Human Development, 2015; School of Communication Research, University of Amsterdam, 2015; Uppsala University, 2016

4. Short Course on Covariate Balancing Propensity Score – Society for Research on Educational Effectiveness Conference, Washington DC, Spring 2013; Uppsala University, 2016

5. Short Course on Matching Methods for Causal Inference – Institute of Behavioral Science, University of Colorado, Boulder, 2009; Department of Political Science, Duke University, 2013.

6. Lecture on Statistics and Social Sciences – New Jersey Japanese School, 2011, 2016; Kaisei Academy, 2012, 2014; Princeton University Wilson College, 2012; University of Tokyo, 2014

Selected Presentations

1. Distinguished speaker, Harvard College Summer Program for Undergraduates in Data Science, 2021.
2. Keynote speaker, Kansas-Western Missouri Chapter of the American Statistical Association, 2021.
3. Invited plenary panelist, Association for Computing Machinery Conference on Fairness, Accountability, and Transparency (ACM FAccT) 2021.
4. Keynote speaker, Taiwan Political Science Association, 2020.
5. Keynote speaker, Boston Japanese Researchers Forum, Massachusetts Institute of Technology, 2020.
6. Keynote speaker, Causal Mediation Analysis Training Workshop, Mailman School of Public Health, Columbia University, 2020.
7. Keynote speaker, Special Workshop on Evidence-based Policy Making. World Economic Forum, Centre for the Fourth Industrial Revolution, Japan, 2020.
8. Distinguished speaker, Institute for Data, Systems, and Society. Massachusetts Institute of Technology, 2019.
9. Keynote speaker, The Harvard Experimental Political Science Graduate Student Conference, Harvard University, 2019.
10. Invited speaker, Beyond Curve Fitting: Causation, Counterfactuals, and Imagination-based AI. Association for the Advancement of Artificial Intelligence, Spring Symposium, Stanford University, 2019.
11. Inaugural speaker, Causal Inference Seminar, Departments of Biostatistics and Statistics, Boston University, 2019.
12. Keynote speaker, The Second Latin American Political Methodology Meeting, Universidad de los Andes (Department of Political Science), 2018.
13. Keynote speaker, The First Latin American Political Methodology Meeting, Pontifical Catholic University of Chile (Department of Political Science), 2017.
14. Keynote speaker, Workshop on Uncovering Causal Mechanisms, University of Munich (Department of Economics), 2016.
15. Keynote speaker, The National Quality Registry Research Conference, Stockholm, 2016.

16. Keynote speaker, The UK-Causal Inference Meeting, University of Bristol (School of Mathematics), 2015.
17. Keynote speaker, The UP-STAT Conference, the Upstate Chapters of the American Statistical Association, 2015.
18. Keynote speaker, The Winter Conference in Statistics, Swedish Statistical Society and Umeå University (Department of Mathematics and Mathematical Statistics), 2015.
19. Inaugural invited speaker, The International Methods Colloquium, Rice University, 2015.
20. Invited speaker, The International Meeting on Experimental and Behavioral Social Sciences, University of Oxford (Nuffield College), 2014.
21. Keynote speaker, The Annual Conference of Australian Society for Quantitative Political Science, University of Sydney, 2013.
22. Keynote speaker, The Graduate Student Conference on Experiments in Interactive Decision Making, Princeton University. 2008.

Conferences Organized

1. The Asian Political Methodology Meetings (January 2014, 2015, 2016, 2017, 2018; co-organizer)
2. The Experimental Research Workshop (September 2012; co-organizer)
3. The 12th World Meeting of the International Society for Bayesian Analysis (June 2012; a member of the organizing committee)
4. Conference on Causal Inference and the Study of Conflict and State Building (May 2012; organizer)
5. The 28th Annual Society for Political Methodology Summer Meeting (July 2011; host)
6. Conference on New Methodologies and their Applications in Comparative Politics and International Relations (February 2011; co-organizer)

Teaching

Courses Taught at Harvard

1. Stat 286/Gov 2003 Causal Inference (formally Stat 186/Gov 2002): introduction to causal inference
2. Gov 2003 Topics in Quantitative Methodology: causal inference, applied Bayesian statistics, machine learning

Courses Taught at Princeton

1. POL 245 Visualizing Data: exploratory data analysis, graphical statistics, data visualization
2. POL 345 Quantitative Analysis and Politics: a first course in quantitative social science
3. POL 451 Statistical Methods in Political Science: basic probability and statistical theory, their applications in the social sciences
4. POL 502 Mathematics for Political Science: real analysis, linear algebra, calculus
5. POL 571 Quantitative Analysis I: probability theory, statistical theory, linear models
6. POL 572 Quantitative Analysis II: intermediate applied statistics
7. POL 573 Quantitative Analysis III: advanced applied statistics
8. POL 574 Quantitative Analysis IV: advanced applied statistics with various topics including Bayesian statistics and causal inference
9. Reading Courses: basic mathematical probability and statistics, applied bayesian statistics, spatial statistics

Advising

Current Students

1. Soubhik Barari (Government)
2. Adam Breuer (Computer Science and Government). To be Assistant Professor, Department of Government and Department of Computer Science, Dartmouth College
3. Jacob Brown (Government)
4. Ambarish Chattopadhyay (Statistics)
5. Shusei Eshima (Government)
6. Georgina Evans (Government)
7. Dae Woong Ham (Statistics)
8. Christopher T. Kenny (Government)
9. Michael Lingzhe Li (MIT, Operations Research Center)
10. Jialu Li (Government)
11. Cory McCartan (Statistics)
12. Sayumi Miyano (Princeton, Politics)
13. Sun Young Park (Government)
14. Casey Petroff (Political Economy and Government)

15. Averell Schmidt (Kennedy School)
16. Sooahn Shin (Government)
17. Tyler Simko (Government)
18. Soichiro Yamauchi (Government)
19. Yi Zhang (Statistics)

Current Postdocs

1. Eli Ben-Michael
2. Evan Rosenman

Former Students

1. Alexander Tarr (Ph.D. in 2021, Department of Electrical and Computer Engineering, Princeton University; Dissertation Committee Chair)
2. Connor Jerzak (Ph.D. in 2021, Department of Government, Harvard University). Postdoctoral Fellow, Linkoping University. To be Assistant Professor, Department of Government, University of Texas, Austin
3. Shiro Kuriwaki (Ph.D. in 2021, Department of Government, Harvard University). Postdoctoral Fellow, Stanford University. To be Assistant Professor, Department of Political Science, Yale University
4. Erik Wang (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political and Social Change, Australian National University
5. Diana Stanescu (Ph.D. in 2020, Department of Politics, Princeton University). Postdoctoral Fellow, Stanford University
6. Nicole Pashley (Ph.D. in 2020, Department of Statistics, Harvard University). Assistant Professor, Department of Statistics, Rutgers University
7. Asya Magazinnik (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Massachusetts Institute of Technology
8. Max Goplerud (Ph.D. in 2020, Department of Government, Harvard University). Assistant Professor, Department of Political Science, University of Pittsburgh
9. Naoki Egami (Ph.D. in 2020, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, Columbia University
10. Brandon de la Cuesta (Ph.D. in 2019, Department of Politics, Princeton University). Postdoctoral Fellow, Center on Global Poverty and Development, Stanford University
11. Yang-Yang Zhou (Ph.D. in 2019, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, University of British Columbia

12. Winston Chou (Ph.D. in 2019, Department of Politics, Princeton University). Senior Data Scientist at Apple
13. Ted Enamorado (Ph.D. in 2019, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, Washington University in St. Louis
14. Benjamin Fifield (Ph.D. in 2018, Department of Politics, Princeton University; Dissertation Committee Chair). Data Scientist, American Civil Liberties Union
15. Tyler Pratt. (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Yale University
16. Romain Ferrali (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Aix-Marseille School of Economics
17. Julia Morse (Ph.D. in 2017, Woodrow Wilson School, Princeton University). Assistant Professor, Department of Political Science, University of California, Santa Barbara
18. Yuki Shiraito (Ph.D. in 2017, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, University of Michigan
19. Carlos Velasco Rivera (Ph.D. in 2016, Department of Politics, Princeton University). Research Scientist, Facebook
20. Gabriel Lopez Moctezuma (Ph.D. in 2016, Department of Politics, Princeton University). Assistant Professor, Division of the Humanities and Social Sciences, California Institute of Technology
21. Graeme Blair (Ph.D. in 2016, Department of Politics, Princeton University). Assistant Professor, University of California, Los Angeles
22. Jaquilyn R. Waddell Boie (Ph.D. in 2015, Department of Politics, Princeton University). Private consultant
23. Scott Abramson (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, University of Rochester
24. Michael Barber (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Brigham Young University
25. In Song Kim (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Massachusetts Institute of Technology
26. Alex Ruder (Ph.D. in 2014, Department of Politics, Princeton University). Senior Community Economic Development Advisor, Federal Reserve Bank of Atlanta
27. Meredith Wilf (Ph.D. in 2014, Department of Politics, Princeton University). Senior Director, Capital Rx
28. Will Bullock. (Ph.D. candidate, Department of Politics, Princeton University). Senior Researcher, Facebook

29. Teppei Yamamoto (Ph.D. in 2011, Department of Politics, Princeton University; Dissertation Committee Chair). Associate Professor, Department of Political Science, Massachusetts Institute of Technology

30. Dustin Tingley (Ph.D. in 2010, Department of Politics, Princeton University). Professor, Department of Government, Harvard University

31. Aaron Strauss (Ph.D. in 2009, Department of Politics, Princeton University). Former Executive Director, Analyst Institute

32. Samir Soneji (Ph.D. in 2008, Office of Population Research, Princeton University; Dissertation Committee Chair). Associate Professor, Department of Health Behavior at the Gillings School of Global Public Health, University of North Carolina, Chapel Hill

33. Ying Lu (Ph.D. in 2005, Woodrow Wilson School, Princeton University; Dissertation Committee Chair). Associate Professor, Steinhardt School of Culture, Education, and Human Development, New York University

Former Predocs and Postdocs

1. Zhichao Jiang (Postdoctoral Fellow, 2016–2019). Assistant Professor, Department of Biostatistics and Epidemiology, School of Public Health and Health Sciences, University of Massachusetts, Amherst

2. Adeline Lo (Postdoctoral Fellow, 2016–2019). Assistant Professor, Department of Political Science, University of Wisconsin, Madison

3. Yunkyu Sohn (Postdoctoral Fellow, 2016–2018). Assistant Professor, School of Political Science and Economics, Waseda University

4. Xiaolin Yang (Postdoctoral Fellow, 2015–2017). Research Scientist, Amazon

5. Santiago Olivella (Postdoctoral Fellow, 2015–2016). Associate Professor, Department of Political Science, University of North Carolina

6. Drew Dimmery (Predoctoral Fellow, 2015–2016). Research Scientist, Facebook

7. James Lo (Postdoctoral Fellow, 2014–2016). Assistant Professor, Department of Political Science, University of Southern California

8. Steven Liao (Predoctoral Fellow, 2014–2015). Assistant Professor, Department of Political Science, University of California, Riverside

9. Michael Higgins (Postdoctoral Fellow, 2013–2015). Associate Professor, Department of Statistics, Kansas State University

10. Kentaro Hirose (Postdoctoral Fellow, 2012–2015). Assistant Professor, Waseda Institute for Advanced Studies

11. Chad Hazlett (Predoctoral Fellow, 2013–2014). Associate Professor, Departments of Political Science and Statistics, University of California, Los Angeles

12. Florian Hollenbach (Predoctoral Fellow, 2013–2014). Associate Professor, Department of International Economics, Government and Business at the Copenhagen Business School

13. Marc Ratkovic (Predoctoral and Postdoctoral Fellow, 2010–2012). Assistant Professor, Department of Politics, Princeton University

Editorial and Referee Service

Co-editor for *Journal of Causal Inference* (2014 – present)

Associate editor for *American Journal of Political Science* (2014 – 2019), *Journal of Business & Economic Statistics* (2015 – 2024), *Journal of Causal Inference* (2011 – 2014), *Journal of Experimental Political Science* (2013 – 2017), *Observational Studies* (2014 – present), *Political Analysis* (2014 – 2017).

Editorial board member for *Asian Journal of Comparative Politics* (2014 – present), *Journal of Educational and Behavioral Statistics* (2011 – present), *Journal of Politics* (2007 – 2008, 2019–2020), *Journal of Research on Educational Effectiveness* (2014 – 2016), *Political Analysis* (2010 – 2013), *Political Science Research and Methods* (2019 – present).

Guest editor for *Political Analysis* virtual issue on causal inference (2011).

Referee for *ACM Computing Surveys*, *American Economic Journal: Applied Economics*, *American Economic Review: Insights*, *American Journal of Epidemiology*, *American Journal of Evaluation*, *American Journal of Political Science*, *American Political Science Review*, *American Politics Research*, *American Sociological Review*, *Annals of Applied Statistics*, *Annals of Statistics*, *Annals of the Institute of Statistical Mathematics*, *Biometrics*, *Biometrika*, *Biostatistics*, *BMC Medical Research Methodology*, *British Journal of Mathematical and Statistical Psychology*, *British Journal of Political Science*, *Canadian Journal of Statistics*, *Chapman & Hall/CRC Press*, *Child Development*, *Communications for Statistical Applications and Methods*, *Computational Statistics and Data Analysis*, *Electoral Studies*, *Econometrica*, *Econometrics*, *Empirical Economics*, *Environmental Management*, *Epidemiology*, *European Union Politics*, *IEEE Transactions on Information Theory*, *International Journal of Biostatistics*, *International Journal of Epidemiology*, *International Journal of Public Opinion Research*, *International Migration Review*, John Wiley & Sons, *Journal of Applied Econometrics*, *Journal of Applied Statistics*, *Journal of Biopharmaceutical Statistics*, *Journal of Business and Economic Statistics*, *Journal of Causal Inference*, *Journal of Computational and Graphical Statistics*, *Journal of Conflict Resolution*, *Journal of Consulting and Clinical Psychology*, *Journal of Econometrics*, *Journal of Educational and Behavioral Statistics*, *Journal of Empirical Legal Studies*, *Journal of Multivariate Analysis*, *Journal of Official Statistics*, *Journal of Peace Research*, *Journal of Politics*, *Journal of Research on Educational Effectiveness*,*Journal of Statistical Planning and Inference*, *Journal of Statistical Software*, *Journal of Survey Statistics and Methodology*, *Journal of the American Statistical Association (Case Studies and Applications; Theory and Methods)*, *Journal of the Japanese and International Economies*, *Journal of the Japan Statistical Society*, *Journal of the Royal Statistical Society (Series A; Series B; Series C)*, *Law & Social Inquiry*, *Legislative Studies Quarterly*, *Management Science*, Multivariate Behavioral Research, National Science Foundation (Economics; Methodology, Measurement, and Statistics; Political Science), Natural Sciences and Engineering Research Council of Canada, *Nature Machine Intelligence*, *NeuroImage*, *Osteoporosis International*, *Oxford Bulletin of Economics and Statistics*, *Pharmaceutical Statistics*, *Pharmacoepidemiology and Drug Safety*, *PLOS One*, *Policy and Internet*, *Political Analysis*, *Political Behavior*, *Political Communication*, *Political Research Quarterly*, *Political Science Research and Methods*, *Population Health Metrics*, *Population Studies*, *Prevention Science*, *Proceedings of the National Academy of Sciences*, Princeton University Press, *Psychological Methods*, *Psychometrika*, *Public Opinion Quarterly*, *Quarterly Journal of Economics*, *Quarterly Journal of Political Science*, *Review of Economics and Statistics*, Routledge, Sage Publications, *Scandinavian Journal of Statistics*, *Science*, Sloan Foundation, Springer, *Sociological Methodology*, *Sociological Methods & Research*, *Statistical Methodology*, *Statistical Methods and Applications*, *Statistical Methods in Medical Research*, *Statistical Science*, *Statistica Sinica*, *Statistics & Probability Letters*, *Statistics in Medicine*, *Systems Biology*, U.S.-Israel Binational Science Foundation, *Value in Health*, *World Politics*.

University and Departmental Committees

Harvard University

Department of Government

- Member, Curriculum and Educational Policy Committee (2020–2021)
- Member, Second-year Progress Committee (2019–2020)
- Member, Graduate Placement Committee (2019–2020)
- Member, Graduate Admissions Committee (2018–2019)
- Member, Graduate Poster Session Committee (2018–2019)

Department of Statistics

- Chair, Senior Faculty Search Committee (2021–2022)
- Member, Junior Faculty Search Committee (2018–2019)
- Member, Second-year Progress Committee (2018–2019, 2020–2021)

Princeton University

University

- Executive Committee Member, Program in Statistics and Machine Learning (2013–2018)
- Executive Committee Member, Committee for Statistical Studies (2011-2018)
- Member, Organizing Committee, Retreat on Data and Information Science at Princeton (2016)
- Member, Council of the Princeton University Community (2015)
- Member, Search Committee for the Dean of College (2015)
- Member, Committee on the Library and Computing (2013–2016)
- Member, Committee on the Fund for Experimental Social Science (2013–2018)
- Member, Personally Identifiable Research Data Group (2012–2018)
- Member, Research Computing Advisory Group (2013–2018)
- Member, Task Force on Statistics and Machine Learning (2014–2015)

Department of Politics

Chair, Department Committee on Research and Computing (2012–2018)

Chair, Formal and Quantitative Methods Junior Search Committee (2012–2013, 2014–2015, 2016–2017)

Chair, Reappointment Committee (2015–2016)

Member, Diversity Initiative Committee (2014–2015)

Member, American Politics Junior Search Committee (2012–2014)

Member, Department Chair's Advisory Committee (2010–2013, 2015–2016)

Member, Department Priority Committee (2012–2013, 2014–2015, 2016–2017)

Member, Formal and Quantitative Methods Curriculum Committee (2005–2006)

Member, Formal and Quantitative Methods Junior Search Committee (2009–2010, 2015–2016)

Member, Formal and Quantitative Methods Postdoc Search Committee (2009–2018)

Member, Graduate Admissions Committee (2012–2013)

Member, Reappointment Committee (2014–2016)

Member, Space Committee (2014–2016)

Member, Undergraduate Curriculum Committee (2014–2015)

Member, Undergraduate Exam Committee (2007–2008)

Member, Undergraduate Thesis Prize Committee (2005–2006, 2008–2011)

Center for Statistics and Machine Learning

Executive Committee Member (2016–2018)

Member, Search Committee (2015–2017)

Services to the Profession

National Academies of Sciences, Engineering, and Medicine

Committee on National Statistics, Division of Behavioral and Social Sciences and Education, Panel on the Review and Evaluation of the 2014 Survey of Income and Program Participation Content and Design (2014–2017)

National Science Foundation

Proposal Review Panel (2020)

The Society for Political Methodology

President (2017–2019)

Vice President and President Elect (2015–2017)

Annual Meeting Committee, Chair (2011)

Career Award Committee (2015–2017)

Program Committee for Annual Meeting (2012), Chair (2011)

Graduate Student Selection Committee for the Annual Meeting (2005), Chair (2011)

Miller Prize Selection Committee (2010–2011)

Statistical Software Award Committee (2009–2010)

Emerging Scholar Award Committee (2013)

American Statistical Association

Journal of Educational and Behavioral Statistics Management Committee (2016 – present)

Others

External Expert, Department of Methodology, London School of Economics and Political Science (2017)

Memberships

American Political Science Association; American Statistical Association; Midwest Political Science Association; The Society for Political Methodology.

CERTIFICATE OF SERVICE

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

Bridget C. Coontz, bridget.coontz@ohioago.gov
Julie M. Pfeiffer, julie.pfeiffer@ohioago.gov
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Counsel for Respondents House Speaker Robert R. Cupp and Senate President Matt Huffman

Erik Clark, ejclark@organlegal.com

Counsel for Respondent Ohio Redistricting Commission

/s/ Freda J. Levenson
Freda J. Levenson (0045916)
Counsel for Relators

EXHIBIT B

Affidavit of Dr. Lisa Handley

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

Summary.

1. I was retained by counsel for Relators in this matter to conduct a district-specific, functional analysis of voting patterns by race in Cuyahoga County, where there is a significant Black population and it is possible to draw a majority Black congressional district. My task was to ascertain the Black voting age population ("BVAP") necessary to provide Black voters with an opportunity to elect their candidates of choice based on the participation rates and voting patterns by race in recent elections.[1] This affidavit reports the results of my analysis of voting patterns in Cuyahoga County, including recent congressional elections in the 11th Congressional District.
2. A district-specific, functional analysis is required to determine whether a district is likely to provide minority voters with an opportunity to elect their candidates of choice. There is no single universal or statewide demographic target that can be applied for Black voters to elect their candidates of choice – the population needed to create an "effective minority district" varies by location and depends upon the participation rates and voting patterns of Black and white voters in that specific area.
3. An analysis of voting patterns is required to estimate voter participation rates by race, as well as the level of support from Black and white voters for each of the candidates competing in the examined elections. This information can then be used to calculate the Black population concentration required for the Black voters' preferred candidates to win election to office in a specific district. Drawing districts informed by this percentage avoids creating districts that either fail to provide Black voters with the opportunity to elect their candidates of choice or unnecessarily pack minority voters into districts to reduce the number of minority opportunity districts.
4. In *Ohio APRI v. Householder*, I submitted a report concluding that the previous 11th Congressional District of Ohio would be an effective minority district with 45% Black BVAP. 373 F.Supp.3d 978 (S.D. Ohio, May 3, 2019). As summarized by the court, I

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

concluded: "[W]ith a 45% BVAP in District 11, African-American voters would have a realistic opportunity to elect their candidate of choice with a 'comfortable margin.' In fact, even with a BVAP as low as 40%, African-American voters would have elected the Black-preferred candidate in the elections studied. [I] concluded that there is no need to draw a majority African-American District 11 in order to allow African-American voters to elect their candidate of choice there." *Id*. at 1044-46.

5. In this report, I shift the focus of my analysis from residents of the 11th Congressional District to residents of Cuyahoga County more broadly and I update the elections analyzed to include those held since I submitted my 2018 report. My reason for studying voting patterns in Cuyahoga County in its entirety is the recognition that the congressional district boundaries will change – no longer including all of the same voters as the current Congressional District 11 – and Congressional District 11 is likely to be redrawn to fall entirely within Cuyahoga County as a consequence of recent amendments to the Ohio Constitution.[2]
6. The results of this updated analysis of voting patterns in Cuyahoga County are consistent with my previous findings: a majority Black district is not required to provide Black voters with a realistic opportunity to elect candidates of their choice to Congress in this area of Ohio. My estimates of participation rates and voting patterns by race in Cuyahoga County has led me to conclude, on the basis of the most challenging election for a Black-preferred candidate to win in Cuyahoga County that I examined (the 2014 gubernatorial election), a 42% BVAP district would offer Black voters an effective opportunity to elect their preferred candidates to Congress.

Professional Experience.

7. I have over thirty-five years of experience as a voting rights and redistricting expert. I have advised scores of jurisdictions and other clients on minority voting rights and redistricting-related issues. I have served as an expert in dozens of voting rights cases. My clients have included state and local jurisdictions, independent redistricting

[2] The Ohio State Constitution was amended in 2018 to specify that if the general assembly draws the congressional plan, the assembly "shall not unduly split governmental units, giving preference to keeping whole, in the order named, counties, then townships and municipal corporations." Article XIX Section 1.(C)(3)(b) of the Ohio Constitution.

commissions (Arizona, Colorado, Michigan), the U.S. Department of Justice, national civil rights organizations, and such international organizations as the United Nations.

8. I have been actively involved in researching, writing, and teaching on subjects relating to voting rights, including minority representation, electoral system design, and redistricting. I co-authored a book, *Minority Representation and the Quest for Voting Equality* (Cambridge University Press, 1992) and co-edited a volume, *Redistricting in Comparative Perspective* (Oxford University Press, 2008), on these subjects. In addition, my research on these topics has appeared in peer-reviewed journals such as *Journal of Politics*, *Legislative Studies Quarterly*, *American Politics Quarterly*, *Journal of Law and Politics*, and *Law and Policy*, as well as law reviews (e.g., *North Carolina Law Review*) and a number of edited books. I hold a Ph.D. in political science from The George Washington University.
9. I have been a principal of Frontier International Electoral Consulting since co-founding the company in 1998. Frontier IEC specializes in providing electoral assistance in transitional democracies and post-conflict countries. In addition, I am a Visiting Research Academic at Oxford Brookes University in Oxford, United Kingdom. Attached to the end of this report as Appendix B is a copy of my *curriculum vitae*.

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

10. The Black voting age population (BVAP) percentage needed to elect Black-preferred candidates is calculated by taking into account the relative participation rates of Black and white Ohioans, as well as the expected level of Black support for the Black-preferred candidates (their "cohesiveness") in an area, and the expected level of white voters' "crossover" voting for the Black-preferred candidates. This requires constructing a database that combines demographic information and election results, then analyzing the data for patterns. These patterns are then used to produce estimates of participation rates and voting patterns by race.
11. **Database.** To analyze voting patterns in Ohio requires a database that combines election returns and population data by race (or registration or turnout by race if this information is available). To build this dataset in this instance, 2016, 2018, and 2020 precinct-level shapefiles were acquired from the Voting and Election Science Team. These shapefiles

were joined to precinct-level election returns from the Ohio Secretary of State's office, which were processed and cleaned by OpenElections. In addition, 2012 and 2014 election returns pro-rated to the 2010 voting district ("VTD") level, were acquired from Bill Cooper, who submitted an expert affidavit in *LWVO v. Ohio Redistricting Commission*, 2021-1193. The 2020 Census Block shapefiles, and total and voting age population by race and ethnicity, were obtained from the Census FTP portal. The election returns data was disaggregated down to the level of the 2020 Census block and, for the 2016, 2018, and 2020 election cycles separately, re-aggregated up to the level of the voting precincts used in those years, accounting for precincts split by congressional districts. For the 2012 and 2014 election cycles, the block-level election results were re-aggregated up to the level of the 2010 VTDs, taking into account splits of VTDs by congressional districts.

12. **Elections Analyzed.** I analyzed all recent statewide Ohio general elections held in 2016, 2018, and 2020 to estimate voting patterns by race in Cuyahoga County. This included contests for U.S. President, U.S. Senate, Governor, Attorney General, Secretary of State, Treasurer, and Auditor. I also examined the 2014 general election contests for Governor and Secretary of State,[3] as well as the 2012 election contests for U.S. President and U.S. Senate. In addition, I analyzed the 2016, 2018, and 2020 general elections for U.S. Congress in District 11.

13. **Primary Elections.** As is usually the case in the United States, there is a two-stage election process in Ohio – a primary election and a general election. Black-preferred candidates must win both elections to gain office. The overwhelming majority of Black voters in Ohio vote in the Democratic primary rather than the Republican primary. As a consequence, it is not possible to estimate Black voting behavior in Republican primaries and, in any case, Black voters' candidates of choice are found in Democratic primaries. In the past ten years, there were two statewide Democratic primaries that included African American candidates: the 2018 Democratic primary for Governor and the 2016 Democratic primary for U.S. Senate. I analyzed both of these elections. (Although both contests included African American candidates, these candidates were not, in fact, the candidates preferred by Black voters.) In addition, I analyzed recent Democratic primaries for Congressional District 11.

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

There were no contested primaries for the congressional seats in 2016 or 2018, but the district had a primary in 2020. There was also a special Democratic primary held in Congressional District 11 in August 2021 when President Biden appointed the incumbent, Rep. Marcia Fudge, as Secretary of the U.S. Department of Housing and Urban Development.[4]

14. The results of the 2016 elections reported here vary slightly from those in my *Ohio APRI v. Householder* report. There are two reasons for this. First, this analysis incorporates all Cuyahoga County precincts, not simply those precincts that fall within the prior boundaries of Congressional District 11. (Congressional District 11 previously included Summit County precincts – these were included in the analysis for my *Ohio APRI v. Householder* report but are excluded here from the countywide analysis; they are, however, included in the congressional elections analyzed.) Second, my *Ohio APRI v. Householder* report relies on 2010 census data, whereas my analysis in this report uses 2020 census data to determine the demographic composition of the precincts for 2016.

15. **Racial Bloc Voting Analysis.** Direct information on how Black and white voters cast their votes is not available; voters' race is not included in their voter registration in Ohio and the race of the voter is not, of course, obtainable from a ballot. To estimate vote choices by race, I used three standard statistical techniques: homogeneous precinct analysis, ecological regression, and ecological inference.

16. Two of these analytic procedures – homogeneous precinct analysis and ecological regression – were employed by the plaintiffs' expert in *Thornburg v. Gingles*, 478 U.S. 30 (1986), and have the benefit of the Supreme Court's approval in that case, and other courts' approval in most subsequent voting rights cases. The third technique, ecological inference, was developed after the *Gingles* decision, and was designed, in part, to address the issue of out-of-bounds estimates (estimates that exceed 100 percent or are less than zero percent), which can arise in ecological regression analysis. Ecological inference analysis has been introduced and accepted in numerous federal and state court proceedings.

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[4] The precinct election results for the November 2021 general election have yet to be released by the Secretary of State so I have been unable to analyze the 2021 general election for Congressional District 11.

17. *Homogeneous precinct* ("HP") analysis is the simplest technique: it involves comparing the percentage of votes received by each of the candidates in precincts that are racially homogeneous. The general practice is to label a precinct as homogeneous if at least 90 percent of the voting age population is composed of a single race. In fact, the homogeneous results reported are not estimates – they are the actual precinct results. However, most voters in Ohio do not reside in homogeneous precincts, and voters who reside in homogeneous precincts may not be representative of voters who live in more integrated precincts. For this reason, I refer to these percentages as estimates.

18. The second statistical technique I employed, *ecological regression* ("ER"), uses information from all precincts, not simply the homogeneous ones, to derive estimates of the voting behavior of Black and white Ohioans. If there is a strong linear relationship across precincts between the percentage of Blacks (or whites) and the percentage of votes cast for a given candidate, this relationship can be used to estimate the percentage of Blacks and whites voting for each of the candidates in the election contest being examined.

19. The third technique, *ecological inference* ("EI"), was developed by Professor Gary King. This approach also uses information from all precincts but, unlike ecological regression, it does not rely on an assumption of linearity. Instead, it incorporates maximum likelihood statistics to produce estimates of voting patterns by race. In addition, it utilizes the method of bounds, which uses more of the available information from the precinct returns and provides more information about the voting behavior being estimated.[5] The method of bounds also precludes the estimates from exceeding the possible limits. However, unlike ecological regression, EI does not guarantee that the candidate estimates add to 100 percent of each racial group in the elections examined.

20. In addition, I utilized a more recently developed version of ecological inference which I have labeled "EI RxC" in the summary tables found in Appendix A. EI RxC expands the

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

analysis so that differences in the relative rates of minority and white turnout can be taken into account in deriving the estimates of minority and white support for the candidates.

21. Estimates using all four methodological approaches (homogeneous precinct analysis, ecological regression, and the two approaches to ecological inference) are reported in the summary racial bloc voting tables for Cuyahoga County found in Appendix A.

22. **Equalizing Black and white turnout.** Because Black Ohioans who are eligible to vote often turn out to vote at lower rates than white Ohioans (this is consistently the case in Cuyahoga County in recent elections, as indicated by the summary table of voting patterns found in Appendix A), the BVAP needed to ensure that Black voters comprise at least half of the voters in an election is often higher than 50 percent. Once I estimated the respective turnout rates of Black and white voters using the statistical techniques described above, I could mathematically calculate the percentage needed to equalize minority and white voters.[6] But equalizing turnout is only the first step in the process – it does not take into account the voting patterns of Black and white voters. If voting is

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

Let

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

Therefore,

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

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

$$M(A) = (1 - M)B$$
$$M(A) = B - M(B)$$
$$M(A) + M(B) = B$$
$$M(A + B) = B$$
$$M = B/(A+B)$$

Thus, for example, if 39.3% of the black population turned out and 48.3% of the white population turned out, B= .483 and A = .393, and M = .483/ (.393+.483) = .483/.876 = .5513, therefore a black VAP of 55.1% would produce an equal number of black and white voters. (For a more in-depth discussion of equalizing turnout see Kimball Brace, Bernard Grofman, Lisa Handley and Richard Niemi, "Minority Voting Equality: The 65 Percent Rule in Theory and Practice," *Law and Policy*, 10 (1), January 1988.)

racially polarized but a significant number of white voters typically "crossover" to vote for Black voters' preferred candidate, it may be that white crossover voting can compensate for depressed Black turnout relative to white turnout. If this is the case, Black voters need not make up at least 50 percent of the voters in an election for the Black-preferred candidate to win.

23. **Incorporating Minority Cohesion and White Crossover Voting.** Even if Black voters are turning out at lower rates than whites, and voting is racially polarized, if a relatively consistent percentage of white voters support Black-preferred candidates, these candidates can be elected despite the lower Black turnout. This is especially true if Black voters are very cohesive in supporting their preferred candidates. A district-specific, functional analysis should take into account not only differences in the turnout rates of Black and white voters, but also voting patterns by race.[7]

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

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

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

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

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

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

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

Cuyahoga County and Congressional District 11

26. Table 1, below, incorporates the estimates of turnout and votes by race reported in the summary table for Cuyahoga County found in Appendix A,[8] and calculates the percentage of the vote the candidate preferred by Black voters would receive in a district with a given BVAP. The BVAP percentages considered are 35, 40, 45, 50, and 55%. Looking down the last few columns of Table 1, it is apparent that the Black-preferred candidate would win all but one of the 13 statewide general election contests considered in a district with a BVAP of 40%. Moreover, the Black-preferred candidate would win the three congressional general election contests in landslides.
27. Only the 2014 Governor's race would require a district with more than a 40% BVAP for the candidate of choice of Black voters to win. More precisely, the percent BVAP needed for the Black-preferred candidate to win the 2014 Governor's race is 41.4%. This is because the white incumbent (John Kasich) received more support from white voters in Cuyahoga County than any other Republican in the elections I examined.
28. In every general election since 2018, the Black-preferred candidate would receive at least 67% of the vote – and as much as 73% (75% in a congressional contest)– in a 40% BVAP district.
29. Primary elections are more challenging for Black-preferred candidates, but only when there are more than two or three candidates competing. For example, in the 2018 Democratic primary for Governor, six candidates ran for the nomination. The 2021 Special Primary for Congressional District 11 drew 13 candidates, although only two received more than 2% of the vote.
30. On the basis of my analysis of voting patterns in statewide elections over the past decade, and an examination of recent congressional contests, I conclude that a district with a 42% BVAP is likely to provide Black voters with a realistic opportunity to elect their candidates of choice in a newly drawn congressional district located within Cuyahoga County. This is because the election contest that proved the most challenging for the candidate of choice of Black voters to win was the 2014 Governor contest and the percent BVAP needed for the Black-preferred candidate to win this election is 41.4%.

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

31. A congressional district that is less than majority Black provides Black voters with an opportunity to elect their candidates of choice in Cuyahoga County because, although Black voters in the county usually turn out to vote at lower rates than white voters, Black voters are very cohesive in supporting their preferred candidates, and white voters vote for these Black-preferred candidates in sufficient percentages for the candidate of choice of the Black voters to prevail.

Table 1: Percent Black VAP Needed to Win Election in Cuyahoga County and Congressional District 11

Cuyahoga County Percent Black VAP needed to win	race of B-P candidate	turnout rate for office and percent vote for black-preferred candidates						percent of vote B-P cand would have received if district was 55% black VAP	percent of vote B-P cand would have received if district was 50% black VAP	percent of vote B-P cand would have received if district was 45% black VAP	percent of vote B-P cand would have received if district was 40% black VAP	percent of vote B-P cand would have received if district was 35% black VAP
		Black votes			White votes							
		votes cast for office	B-P	all others	votes cast for office	B-P	all others					
GENERAL ELECTIONS												
2020 President	W	54.1	97.1	2.9	75.3	53.2	46.8	73.7	71.6	69.5	67.4	65.4
2018 Governor	W	46.2	96.1	3.9	58.2	52.9	47.1	74.2	72.0	69.9	67.9	65.8
2018 Treasurer	AA	45.8	98.1	1.9	56.0	51.9	48.1	75.0	72.7	70.4	68.2	66.0
2018 Attorney General	W	45.5	97.7	2.3	57.2	56.4	43.6	76.8	74.7	72.7	70.7	68.8
2018 Auditor	W	45.2	95.9	4.1	55.9	52.7	47.3	74.2	72.0	69.9	67.8	65.8
2018 Secretary State	W	45.7	96.8	3.2	56.7	54.2	45.8	75.3	73.2	71.1	69.1	67.1
2018 U.S. Senate	W	45.9	98.3	1.7	57.9	60.4	39.6	79.1	77.2	75.3	73.5	71.7
2016 President	W	63.8	97.8	2.2	65.9	47.9	52.1	74.9	72.4	70.0	67.5	65.0
2016 U.S. Senate	W	59.9	93.9	6.1	64.4	36.2	63.8	66.9	64.0	61.1	58.3	55.5
2014 Governor	W	30.4	88.0	12.0	41.2	30.2	69.8	57.6	54.7	52.0	49.3	46.6
2014 Secretary State	AA	32.1	97.8	2.2	40.3	40.7	59.3	68.9	66.0	63.2	60.5	57.8
2012 President	AA	71.6	99.0	1.0	65.7	53.9	46.1	79.7	77.4	75.2	72.9	70.6
2012 U.S. Senate	W	66.3	98.7	1.3	62.6	57.4	42.6	80.7	78.6	76.6	74.5	72.4
DEMOCRATIC PRIMARIES												
2018 Governor	W	17.8	51.0	49.0	15.4	31.4	68.6	42.9	41.9	40.9	39.9	38.9
2016 U.S. Senate	W	30.3	69.2	30.8	16.2	55.8	44.2	65.1	64.5	63.9	63.2	62.5
CONGRESSIONAL DISTRICT 11												
2020 General	AA	53.6	97.4	2.6	71.6	61.2	38.8	78.5	76.7	75.0	73.3	71.6
2018 General	AA	47.2	98.0	2.0	58.7	62.7	37.3	80.2	78.4	76.7	75.0	73.4
2016 General	AA	62.0	98.0	2.0	60.0	53.4	46.6	78.3	76.1	73.8	71.6	69.3
2020 Dem Primary	AA	16.2	93.0	7.0	22.8	88.6	11.4	90.6	90.4	90.2	90.0	89.8
2021 Special Primary	AA	18.0	48.6	51.4	21.8	53.2	46.8	50.9	51.1	51.3	51.6	51.8

Cuyahoga County, Ohio			Estimates for Black Voters				Estimates for White Voters			
	Party	Race	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
General Elections										
2020 General										
U.S. President										
Joseph Biden	D	W/AA*	95.8	100.6	98.4	97.1	50.3	48.9	50.1	53.2
Donald Trump	R	W/W	3.3	-1.6	1.2	1.7	48.8	49.9	48.7	46.0
others			0.9	1.0	1.0	1.2	1.0	1.1	1.2	0.8
votes for office			*57.1*	*50.5*	*54.1*	*54.1*	*79.9*	*73.2*	*75.3*	*75.3*
2018 General										
Governor										
Richard Cordray	D	W/W	94.8	99.7	97.5	96.1	48.9	48.9	49.8	52.9
Mike Dewine	R	W/W	3.6	-1.6	1.2	1.8	48.9	48.3	47.3	45.0
others			1.7	1.9	1.7	2.1	2.2	2.7	2.5	2.1
votes for office			*48.6*	*42.7*	*46.2*	*46.2*	*63.2*	*55.7*	*58.2*	*58.2*
Treasurer										
Rob Richardson	D	AA	97.2	103.0	99.2	98.1	47.6	48.0	49.4	51.9
Robert Sprague	R	W	2.8	-3.0	0.8	1.9	52.4	52.0	50.6	48.1
votes for office			*48.0*	*42.4*	*45.8*	*45.8*	*60.7*	*53.6*	*56.0*	*56.0*
Attorney General										
Steve Dettelbach	D	W	96.2	101.4	98.7	97.7	51.9	52.5	53.8	56.4
Dave Yost	R	W	3.8	-1.4	1.4	2.3	48.1	47.4	46.2	43.6
votes for office			*47.8*	*42.0*	*45.5*	*45.5*	*62.1*	*54.8*	*57.2*	*57.2*
Auditor										
Zack Space	D	W	95.0	100.3	97.7	95.9	48.5	48.5	49.6	52.7
Keith Faber	R	W	2.3	-3.1	0.7	1.4	47.4	46.7	45.2	43.0
Robert Coogan	Lib	W	2.7	2.8	2.5	2.7	4.1	4.8	4.6	4.3
votes for office			*47.3*	*41.8*	*45.2*	*45.2*	*60.6*	*53.5*	*55.9*	*55.9*
Secretary of State										
Kathleen Clyde	D	W	95.8	101.0	98.4	96.8	49.9	50.2	51.2	54.2
Frank LaRose	R	W	3.0	-2.3	0.9	1.6	48.0	47.3	46.0	43.8
Dustin Nanna	Lib	W	1.2	1.3	1.3	1.5	2.1	2.5	2.4	2.0
votes for office			*47.9*	*42.3*	*45.7*	*45.7*	*61.5*	*54.3*	*56.7*	*56.7*

Cuyahoga County, Ohio			Estimates for Black Voters				Estimates for White Voters			
	Party	Race	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
2018 General (cont)										
U.S. Senate										
Sherrod Brown	D	W	97.8	102.6	99.3	98.3	55.9	56.5	57.8	60.4
Jim Renacci	R	W	2.2	-2.7	0.6	1.7	44.1	43.5	42.3	39.6
votes for office			*48.3*	*42.5*	*45.9*	*45.9*	*62.8*	*55.4*	*57.9*	*57.9*
2016 General										
U.S. President										
Hillary Clinton	D	W	97.3	103.0	99.3	97.8	45.9	45.1	46.2	47.9
Donald Trump	R	W	1.7	-9.8	0.6	1.1	50.1	50.2	48.8	47.7
others			1.0	0.8	0.9	1.1	4.1	4.8	4.7	4.4
votes for office			*67.1*	*61.3*	*63.8*	*63.8*	*72.5*	*63.4*	*65.9*	*65.9*
U.S. Senate										
Ted Strickland	D	W	91.6	97.5	95.0	93.9	35.1	33.9	34.2	36.2
Rob Portman	R	W	4.6	-1.8	1.5	1.7	60.4	60.7	60.0	59.1
others			3.8	4.3	4.0	4.3	4.5	5.4	5.2	4.7
votes for office			*62.9*	*57.2*	*59.9*	*59.9*	*71.1*	*62.1*	*64.4*	*64.4*
2014 General										
Governor										
Edward FitzGerald	D	W	85.1	89.8	88.2	88.0	29.2	29.2	28.4	30.2
Joh Kasich	R	W	14.9	10.2	11.9	12.0	70.8	70.8	71.7	69.8
votes for office			*31.3*	*27.4*	*30.4*	*30.4*	*42.8*	*37.9*	*41.2*	*41.2*
Secretary of State										
Nina Turner	D	AA	97.2	103.2	98.8	97.8	38.1	38.9	39.2	40.7
Jon Husted	R	W	2.8	-3.2	1.3	2.2	61.9	61.0	60.8	59.3
votes for office			*32.5*	*29.0*	*32.1*	*32.1*	*41.6*	*36.9*	*40.3*	*40.3*
2012 General										
U.S. President										
Barack Obama	D	AA	99.1	104.5	99.4	99.0	51.6	53.3	54.6	53.9
Mitt Romney	R	W	0.9	-4.5	0.4	1.0	48.4	46.7	45.4	46.1
votes for office			*73.2*	*69.7*	*71.6*	*71.6*	*70.2*	*64.3*	*65.7*	*65.7*

Cuyahoga County, Ohio			Estimates for Black Voters				Estimates for White Voters			
	Party	**Race**	**HP**	**ER**	**EI 2x2**	**EI RxC**	**HP**	**ER**	**EI 2x2**	**EI RxC**
2012 General (cont)										
U.S. Senate										
Sherrod Brown	D	W	98.2	103.1	99.4	98.7	55.2	56.6	57.4	57.4
Josh Mandel	R	W	1.8	-3.2	0.6	1.3	44.8	43.4	42.6	42.6
votes for office			*67.5*	*64.4*	*66.3*	*66.3*	*66.5*	*60.8*	*62.6*	*62.6*
Democratic Primaries										
2018 Primary										
Governor										
Richard Cordray	D	W/W	43.0	39.5	42.0	41.2	58.3	59.5	61.8	60.7
Dennis Kucinich	D	W/AA*	50.5	53.3	51.2	51.0	34.1	33.0	31.5	31.4
Bill O'Neill	D	W/AA*	29.0	3.3	3.1	3.3	1.5	1.3	1.3	1.5
Paul Ray	D	W/W	0.7	0.7	0.7	1.0	0.5	0.5	0.6	0.6
Joe Schiavoni	D	W/W	1.8	1.8	1.8	2.2	5.3	5.5	4.9	5.2
Larry Ealy	D	AA/W	1.2	1.4	1.0	1.3	0.3	0.2	0.4	0.6
votes for office			*17.5*	*14.9*	*17.8*	*17.8*	*14.4*	*12.9*	*15.4*	*15.4*
2016 Primary										
U.S. Senator										
Kelli Prather	D	AA	12.4	13.4	13.0	13.4	10.4	11.5	11.3	10.3
P.G. Sittenfeld	D	W	17.5	15.9	16.4	17.4	31.8	32.1	32.4	33.9
Ted Strickland	D	W	70.1	70.7	70.7	69.2	57.8	56.4	56.3	55.8
votes for office			*29.4*	*27.9*	*30.3*	*30.3*	*16.6*	*14.1*	*16.2*	*16.2*

Congressional District 11				Estimates for Black Voters				Estimates for White Voters			
	Party	Race	Vote	HP	ER	EI 2x2	EI RxC	HP	ER	EI 2x2	EI RxC
2016 General											
Marcia Fudge	D	AA	80.3	96.4	100.4	98.6	98.0	42.0	51.5	53.7	53.4
Beverly Goldstein	R	W	19.8	3.6	-0.4	1.4	2.0	58.0	48.5	46.3	46.6
votes for office				*62.8*	*58.9*	*62.0*		*69.6*	*57.6*	*60.0*	
2018 General											
Marcia Fudge	D	AA	82.2	97.5	100.6	99.2	98.0	46.7	57.5	59.4	62.7
Beverly Goldstein	R	W	17.8	2.5	-0.6	0.7	2.0	53.4	42.5	40.6	37.3
votes for office				*48.4*	*43.7*	*47.2*		*64.8*	*55.5*	*58.7*	
2020 General											
Marcia Fudge	D	AA	80.1	95.5	98.9	97.6	97.4	44.7	55.5	57.4	61.2
Laverne Gore	R	AA	20	4.5	1.1	2.4	2.6	55.3	44.6	3.6	38.8
votes for office				*54.9*	*49.8*	*53.6*		*78.5*	*70.0*	*71.6*	
2020 Democratic Primary											
Marcia Fudge	D	AA	90.5	93.1	92.6	93.9	93.0	87.2	85.3	86.7	88.6
Others	D		9.5	6.9	7.3	6.1	7.0	12.8	14.7	13.2	11.4
votes for office				*16.7*	*13.4*	*16.2*		*15.9*	*17.4*	*22.8*	
2021 Special Primary											
Shontel Brown	D	AA	50.1	49.3	48.0	49.6	48.6	52.9	49.7	52.1	53.2
Nina Turner	D	AA	44.6	44.7	45.8	44.5	45.3	37.1	44.4	43.3	41.9
Others	D		5.3	6.0	6.1	5.7	6.1	10.0	5.8	4.6	4.9
Turnout/VAP				*18.4*	*15.1*	*18.0*		*11.8*	*14.6*	*21.8*	
2021 Special General											
Shontel Brown	D	AA	78.8								
Laverne Gore	R	AA	21.2								
votes for office											

Lisa R. Handley

CURRICULUM VITAE

Professional Experience

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

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

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

Education

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

Present Employment

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

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

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

U.S. Clients since 2000

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

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

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

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

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

Arkansas: expert witness for Plaintiffs in Jeffers v. Beebe

Colorado: Colorado Redistricting Board (redistricting consultation)

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

Florida: State Senate (redistricting consultation)

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

Louisiana: Louisiana Legislative Black Caucus (expert witness testimony)

Massachusetts: State Senate (redistricting consultation)

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

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

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

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

New York: State Assembly (redistricting consultation)

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

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

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

Pennsylvania: Senate Democratic Caucus (redistricting consultation)

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

Vermont: Secretary of State (redistricting consultation)

International Clients since 2000

United Nations

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

International Foundation for Election Systems (IFES)

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

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

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

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

Publications

***Books**:*

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

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

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

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

***Academic Journal Articles**:*

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Chapters in Edited Volumes:

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

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

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

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

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

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

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

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

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

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

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

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

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

Electronic Publication:

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

Additional Writings of Note:

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

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

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

Recent Court Cases

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

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

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

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

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

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

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

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

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

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

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

Contact Information

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CERTIFICATE OF SERVICE

I, Freda J. Levenson, hereby certify that on this 10th day of December, 2021, I caused a true and correct copy of the foregoing document to be served by email upon the counsel listed below:

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/s/ Freda J. Levenson
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Counsel for Relators