Exhibit 27

UNITED STATES DISTRICT COURT
FOR THE DISTRICT OF SOUTH CAROLINA COLUMBIA DIVISION

The South Carolina State Conference of the NAACP, *et al.* *Plaintiffs*, v. Alexander, *et al.* *Defendants*.	No. 3-21-cv-03302-JMC-TJH-RMG

EXPERT REPORT

Kosuke Imai, Ph.D.

April 4, 2022

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I. INTRODUCTION AND SCOPE OF WORK

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

2. I have been asked by counsel representing the plaintiffs in this case to analyze relevant data and provide my expert opinions related to the role that race played in drawing certain districts in South Carolina's Congressional district plan (hereafter "the enacted plan"). To do so, I first conducted a "race-blind" simulation analysis of Districts 1 and 6 to examine how race played a role in determining the boundary of these two districts under the enacted plan.

3. Specifically, I simulate two separate sets of 10,000 alternative boundary lines between Districts 1 and 6 while adhering to other redistricting criteria. These criteria include those specified in the 2021 Guidelines and Criteria for Congressional and Legislative Redistricting adopted by the South Carolina House of Representatives Judiciary Committee and Redistricting Ad Hoc Committee as well as in the 2021 Redistricting Guidelines adopted by the South Carolina Senate Judiciary Committee (hereafter "the South Carolina guidelines"). The first set simulates the entire district boundary of the two districts whereas the second set simulates only the boundary within Charleston County. These localized race-blind simulation analyses allow me to determine whether and to what extent the enacted plan's inclusion or exclusion of Black voters in Districts 1 and 6 played a role in determining the boundary of these two districts beyond the purpose of adhering to the traditional redistricting criteria, including those specified in the South Carolina guidelines.

4. My second simulation analysis addresses the possibility that race was considered for compliance with the Voting Rights Act (VRA) when drawing the enacted plan. Specifically, I simulate 10,000 alternative statewide plans such that District 6 under each simulated plan has the overall Black voting age population (BVAP) proportion between 45% and 50% while adhering

to other redistricting criteria, including those specified in the South Carolina guidelines.[1] This statewide simulation analysis allows me to determine whether and to what extent the enacted plan's inclusion or exclusion of Black voters played a role in drawing Districts 1, 2, and 5 that surround District 6 beyond the purpose of compliance with the VRA and the traditional redistricting criteria, including those specified in the South Carolina guidelines.

5. I ensured that my simulated plans are generally at least as compliant with the South Carolina guidelines as the enacted plan, on average. To do this, whenever necessary, I instructed the simulation algorithm to split fewer than or an equal number of counties and municipalities in comparison to the enacted plan, on average. In addition, following the enacted plan, I instructed the simulation algorithm to have no incumbency pairing. Thus, these two simulation analyses allow me to determine how race would be treated in districting plans if the districts were drawn under the specified conditions while adhering to other traditional redistricting principles, including those in the South Carolina guidelines.

II. SUMMARY OF OPINIONS

6. My localized race-blind redistricting simulation analysis of Districts 1 and 6 shows that the enacted plan draws their boundary line such that a disproportionately large number of Black voters, particularly those who live in Charleston County, are placed into District 6, leading to an unusually low BVAP proportion in District 1. This simulation analysis demonstrates that race played a significant role beyond the purpose of adhering to the traditional redistricting criteria, including those specified in the South Carolina guidelines.

7. My statewide simulation analysis with the VRA constraint shows that compliance with the VRA cannot explain the above key finding of my localized race-blind simulation analysis: race was a significant factor in drawing the boundary between Districts 1 and 6 under the enacted plan. In addition, this statewide simulation analysis with the VRA constraint demonstrates that the enacted plan unnecessarily cracks Black voters who live in Richland County into Districts 2

1. In this report, I define BVAP as people who are at least 18 years old and any part Black per the Census definition.

and 6 while also cracking Black voters who live in Sumter County into Districts 5 and 6. Thus, my analysis shows that race also played a significant role in determining the boundaries between District 6 and its other surrounding districts (i.e., Districts 2 and 5) of the enacted plan, beyond the purpose of complying with the VRA and other traditional redistricting criteria, including those specified in the South Carolina guidelines.

III. QUALIFICATIONS, EXPERIENCE, AND COMPENSATION

8. I am trained as a political scientist (Ph.D. in 2003, Harvard) and a statistician (MA in 2002, Harvard). I have published more than 70 articles in peer reviewed journals, including premier political science journals (e.g., *American Journal of Political Science*, *American Political Science Review*, *Political Analysis*), statistics journals (e.g., *Biometrika*, *Journal of the American Statistical Association*, *Journal of the Royal Statistical Society*), and general science journals (e.g., *Lancet*, *Nature Human Behavior*, *Science Advances*). My work has been widely cited across a diverse set of disciplines. For each of the past four years, Clarivate Analytics, which tracks citation counts in academic journals, has named me as a highly cited researcher in the cross-field category for producing "multiple highly cited papers that rank in the top 1% by citations for field and year in Web of Science."

9. I started my academic career at Princeton University, where I played a leading role in building interdisciplinary data science communities and programs on campus. I was the founding director of Princeton's Program in Statistics and Machine Learning from 2013 to 2017. In 2018, I moved to Harvard, where I am Professor jointly appointed in the Department of Government and the Department of Statistics, the first such appointment in the history of the university. Outside of universities, between 2017 and 2019, I served as the president of the Society for Political Methodology, a premier academic organization of more than one thousand researchers worldwide who conduct methodological research in political science. My introductory statistics textbook for social scientists, *Quantitative Social Science: An Introduction* (Princeton University Press, 2017), has been widely adopted at major research universities in the United States and beyond.

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

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

12. I have also developed an open-source software package titled `redist` that allows researchers and policy makers to implement the cutting-edge simulation methods developed by us and others (Kenny et al. 2020). This software package can be installed for free on any personal computer with a Windows, Mac, or Linux operating system. According to a website that tracks the download statistics of R packages, our software package has been downloaded about 30,000 times since 2016.[2]

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

14. Previously, I have submitted my expert reports, based on redistricting simulation analyses, to the Congressional and General Assembly redistricting cases in Ohio (*League of Women Voters of Ohio et al. v. Ohio Redistricting Commission et al.* The Supreme Court of Ohio, No. 2021–1449; *League of Women Voters of Ohio et al. v. Ohio Redistricting Commission et*

2. https://ipub.com/dev-corner/apps/r-package-downloads/ (accessed on January 17, 2022)

al. The Supreme Court of Ohio, No. 2021–1193; *League of Women Voters of Ohio et al. v. Frank LaRose et al.* The Supreme Court of Ohio, No. 2022–0303). In both cases, the Ohio Supreme court heavily relied upon my analyses in its decisions (*League of Women Voters of Ohio v. Ohio Redistricting Commission*, Slip Opinion No. 2022-Ohio-65; *Adams v. DeWine*, Slip Opinion No. 2022-Ohio-89). I have also submitted expert reports, which utilize redistricting simulation analyses, to the Alabama Congressional redistricting case in the United States District Court Northern District of Alabama Southern Division (*Milligan et al. v. Merrill et al.* No. 2:2021cv01530), the Pennsylvania State House redistricting case in the Supreme Court of Pennsylvania (*Benninghoff v. 2021 Legislative Reapportionment Commission* No. 11 MM 2022), and the Kentucky State House and Congressional redistricting cases (*Graham et al. v. Adams et al.* Commonwealth of Kentucky Franklin Circuit Court Division, No. 22-CI-00047). I have also submitted an expert report on the South Carolina State House redistricting plan in this case.

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

16. I am being compensated at a rate of $450 per hour. My compensation does not depend in any way on the outcome of the case or on the opinions and testimony that I provide.

IV. METHODOLOGY

17. I conducted simulation analyses to help evaluate whether the enacted plan was drawn using race as a significant factor. Redistricting simulation algorithms generate a representative sample of all possible plans that satisfy a specified set of criteria. These criteria may, for example, include requiring a certain degree of population equality, avoiding pairing of incumbents, drawing compact districts, and limiting the number of counties being split. The resulting simulated plans represent a set of alternative plans that are compliant with these redistricting criteria. One can then evaluate the properties of a proposed plan by comparing it against the simulated plans. If the proposed plan unusually treats particular racial groups in a certain way *when compared to* the ensemble of simulated plans, this serves as empirical evidence that the proposed plan was likely drawn using race as a significant factor.

18. Furthermore, statistical theory allows us to quantify the degree to which the proposed plan is extreme in terms of racial composition, relative to the ensemble of simulated plans. For example, we can estimate the probability of a race-blind simulated plan packing Black people into a district at least as much as a proposed plan does. If this probability is small, then the proposed plan is a statistical outlier because the enacted plan is highly unlikely to come from the race-blind distribution that is used to generate the simulated plans.

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

A. Simulation Setup

20. My race-blind local simulation analysis focuses on the boundary between Districts 1 and 6. I conducted a race-blind simulation analysis by generating, without consideration of race, a total of 10,000 alternative district boundaries with the following properties, which are based on the South Carolina guidelines and traditional redistricting principles:

- all relevant districts are geographically contiguous
- all relevant districts do not exceed an overall population deviation of $\pm$ 0.1%[3]
- no incumbent is paired with another incumbent

3. This maximal deviation is measured with respect to the ideal population of a congressional district in South Carolina, which is the total population divided by seven, i.e., about 730 people. Although this deviation is greater than what the South Carolina guidelines require, it is an appropriate threshold for my simulation analysis of VTD-level data given that the average VTD population in South Carolina is 2,257. One could further reduce the population deviation of each simulated plan by moving census blocks located on the district boundaries from one district to another, but such adjustments would not materially alter the conclusions of my analysis because the findings are based on patterns of certain Black voting age population of much greater magnitude.

- all relevant districts are on average at least as compact as the enacted plan (Appendix C)
- the number of split counties is on average no greater than the corresponding number under the enacted plan (see Appendix D)
- the number of split municipalities is on average no greater than the corresponding number under the enacted plan (see Appendix E)
- no race or partisan information was used

In addition, I also generated a separate set of 10,000 alternative district boundaries within Charleston County while keeping the rest of the district boundary identical to the one in the enacted plan. These simulated districts have the same properties as those described above.

21. These race-blind simulated plans were generated by only considering the above criteria, using the merge-split type simulation algorithm with the enacted plan as a starting plan (E. A. Autry et al. 2021; Carter et al. 2019; briefly described in Appendix B). Importantly, the simulation procedure does not use the information about race at all, and hence I call this a "race-blind" simulation analysis. I provide the detailed information about my simulation procedure in Appendix B. These localized race-blind simulation analyses enable me to examine whether and to what extent race was used as a significant factor in determining the boundary between Districts 1 and 6 beyond the purpose of adhering to the above traditional redistricting criteria.

22. I also conducted a separate simulation analysis on the statewide map, which generates a total of 10,000 alternative plans with the following properties, which are based on the South Carolina guidelines and traditional redistricting principles:

- all districts are geographically contiguous
- all districts do not exceed an overall population deviation of $\pm$ 0.1%
- no incumbent is paired with another incumbent
- the overall BVAP proportion of District 6 is kept between 45% and 50%[4]
- all districts are on average at least as compact as the enacted plan (Appendix C)

4. This range was chosen so that it generally matches with the corresponding BVAP proportion under the enacted plan, which is 46.9%.

- the number of split counties under the simulated plans is on average no greater than the corresponding number under the enacted plan (see Appendix D)
- the number of split municipalities under the simulated plans is on average no greater than the corresponding number under the enacted plan (see Appendix E)
- no partisan information was used

These simulated plans were generated using the same merge-split type simulation algorithm. I provide the detailed information about my simulation procedure in Appendix B. This statewide simulation analysis allows me to determine whether and to what extent race was considered as a significant factor in determining the relevant district boundaries of the enacted plan beyond the purpose of compliance with the VRA and the traditional redistricting criteria, including those specified in the South Carolina guidelines.

23. Like the enacted plan, all of my simulated plans do not pair an incumbent in the same district. Therefore, I name each simulated district by first identifying the incumbent that resides in the simulated district, and naming the simulated district by the district number of that incumbent's district assignment in the enacted plan. This renaming procedure allows me to compare each enacted district with a comparable simulated district, even though the two districts often do not cover the same geographic area.

24. For both the localized and statewide simulation analyses, I can easily generate additional plans by running the algorithm longer, but for the purpose of my analysis, 10,000 simulated plans for each county will yield statistically precise conclusions. In other words, generating more than 10,000 plans, while possible, will not materially affect the conclusions of my analysis.

B. Description of Redistricting Simulation Software

25. In my analysis, I used the two open-source software packages for redistricting analysis, `redist` (Kenny et al. 2020) and `redistmetrics` (Kenny et al. 2022), which implement a variety of redistricting simulation algorithms as well as other evaluation methods and metrics. My collaborators and I have developed these software packages, so that other researchers and the general public can implement these state-of-the-art methods on their own. I supplemented these

packages with code written primarily to account for the redistricting rules, criteria, and guidelines that are specific to South Carolina. All of my analyses were conducted on a personal computer. Indeed, all of my analysis code can be replicated by running my code on any personal computer once the required software packages, which are also freely available and open-source, are installed.

V. LOCALIZED RACE-BLIND SIMULATION ANALYSIS

26. Using the redistricting simulation methodology described above, I evaluated empirical evidence regarding whether and to what extent race was a significant factor in drawing the relevant districts under the enacted plan beyond the traditional redistricting criteria including those specified in the South Carolina guidelines. Specifically, I simulated two separate sets of 10,000 alternative district boundaries between Districts 1 and 6, using the localized race-blind simulation procedures described in Section IV. The first set simulates the entire district boundary between these two districts while the second set simulates the part of the district boundary that is located within Charleston County.

A. The Boundary between Districts 1 and 6

27. I first show the results of my race-blind simulation analysis that generates 10,000 alternative boundaries between Districts 1 and 6. The left map of Figure 1 shows the precinct-level BVAP in these two districts where a precinct with a greater number of black voters is shaded with a darker color. The right map of the figure displays, for each precinct, the proportion of the 10,000 race-blind simulated plans that assign it to District 1 instead of District 6. A precinct shaded by a darker color means that it is more likely to belong to District 1 under the race-blind simulated plans.

28. The examination of these two maps show that the district boundary of the enacted plan is highly unusual in comparison to the race-blind simulated plans. Specifically, as shown in the left map, the enacted plan splits Charleston County by including a large number of Black voters who live in the western part of the city of Charleston as well as the city of North Charleston into District 6 (indicated by precincts shaded with relatively dark orange color), while assigning

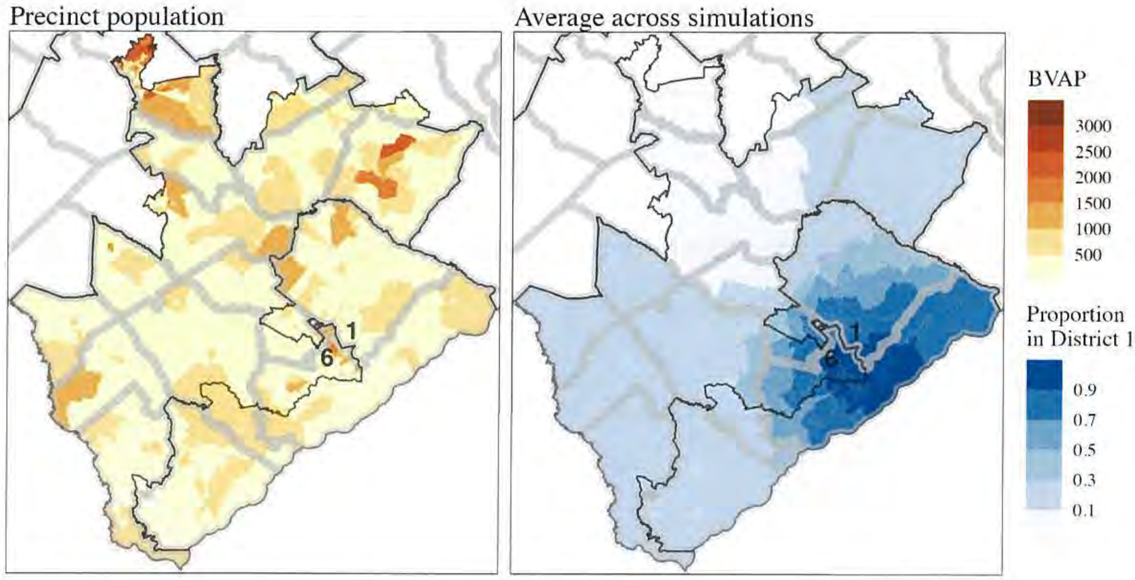

Figure 1: The Boundary between Districts 1 and 6. The left map shows the VTD-level Black voting-age population (BVAP) with the boundary between Districts 1 and 6 demarcated by a solid black line. A VTD with a darker orange color has a greater number of Black voters. The grey lines represent county boundaries. In the right map, each precinct is shaded by the proportion of 10,000 race-blind simulated plans that assign it to District 1. A precinct with a darker blue color is more likely to belong to District 1 under the race-blind simulated plans.

the eastern part of the city of Charleston where few Black voters live to District 1. The right map shows, however, that most of the race-blind simulated plans assign these precincts to District 1 instead of District 6, as indicated by dark blue shade.

29. As a result of this unusual district boundary, the BVAP proportion of District 1 under the enacted plan is only 17.4%, which is much lower than the race-blind simulated plans. As shown in Figure 2, none of my 10,000 race-blind simulated plans (grey histogram) has a lower BVAP proportion for District 1 than the enacted plan (red line). The average difference in the BVAP proportion of District 1 between the enacted and race-blind simulated plans is about 5.8 percentage points, which corresponds to 3.1 standard deviations of the simulated plans. In other words, the enacted plan places a disproportionately large number of Black voters into District 6, lowering the BVAP proportion of District 1.

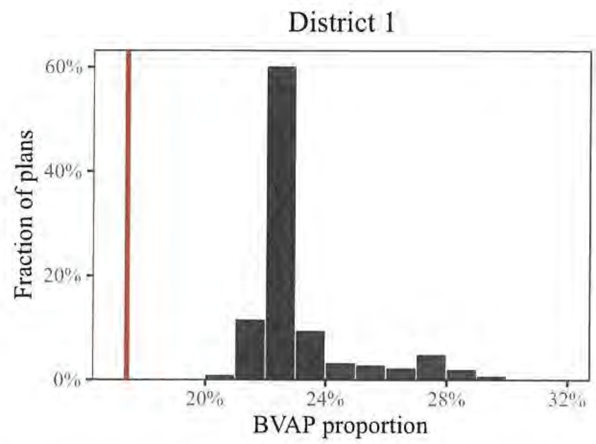

Figure 2: Histogram represents the distribution of the Black voting-age population (BVAP) proportion for District 1, across 10,000 race-blind simulated plans. The red line indicates the corresponding BVAP number under the enacted plan (red vertical line). None of the race-blind simulated plans has a lower BVAP proportion for District 1 than the enacted plan.

B. Charleston County

30. Next, I conduct another race-blind simulation analysis within Charleston County, which contains parts of Districts 1 and 6 under the enacted plan. In this race-blind simulation analysis, I keep the rest of these two districts unchanged from the enacted plan. This means that the only difference between the enacted and simulated plans is how Charleston County is split between Districts 1 and 6. The resulting simulated plans therefore preserve much of these two districts as defined under the enacted plan.

31. The findings are similar to those discussed above. As mentioned earlier (see the left map of Figure 1), the enacted plan splits Charleston County by placing a disproportionately large number of Black voters into District 6, while assigning relatively few Black voters to District 1. As a result, within Charleston County, the BVAP proportion of District 6 (32.1%) is 21.4 percentage points higher than that of District 1 (10.7%).

32. I examine whether this gap in the within-county BVAP under the enacted and race-blind simulated plans is statistically significant by comparing the enacted plan with the 10,000 localized race-blind simulated plans. The gray histogram in Figure 3 represents the distribution

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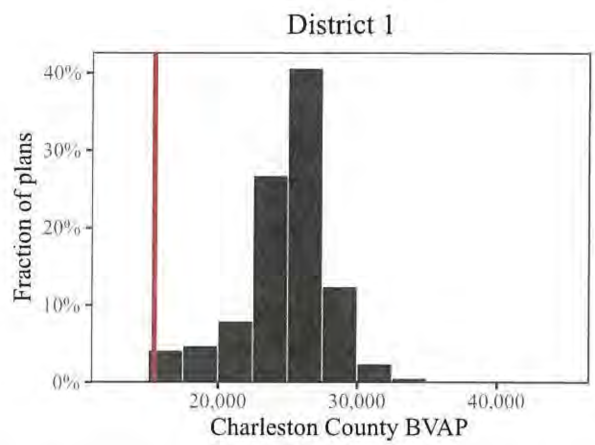

Figure 3: Histogram represents the distribution of the Black voting-age population (BVAP), across 10,000 race-blind simulated plans, who live in Charleston County and are assigned to District 1. The red line indicates the corresponding BVAP number under the enacted plan.

of Black voters who live in Charleston County and are assigned to District 1. The red vertical line indicates the corresponding BVAP number under the enacted plan. The figure shows that District 1 under the enacted plan contains about 15,400 Black voters who live in Charleston County, while across my 10,000 race-blind simulated plans, District 1 has approximately 24,900 black voters on average. This difference of 9,500 voters, which corresponds to 2.9 standard deviations of the simulated distribution, is statistically significant. In fact, only 0.2% of the 10,000 race-blind simulated plans place fewer Black voters from Charleston County into District 1 than the enacted plan.

33. In sum, my localized race-blind simulation analysis of Charleston County reaches the same conclusion as my other race-blind simulation analysis that a disproportionately large number of Black voters who live in the county are included into District 6, lowering the BVAP proportion of District 1.

VI. STATEWIDE SIMULATION ANALYSIS WITH THE VRA CONSTRAINT

34. I also conducted a statewide simulation analysis to address the possibility that race was considered in drawing the district boundaries of the enacted plan in order to comply with

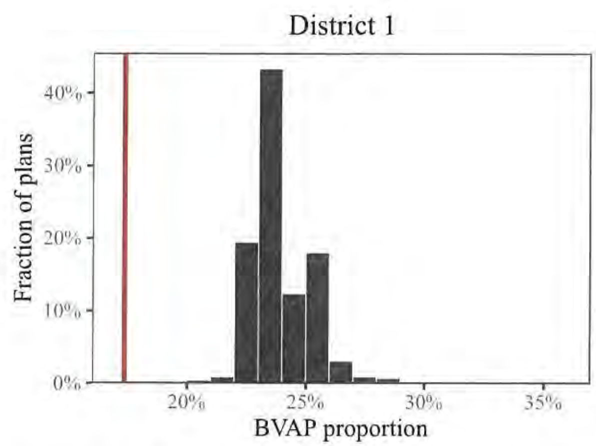

Figure 4: BVAP Proportion in District 1. Histogram represents the distribution of the Black voting-age population (BVAP) proportion, across 10,000 statewide simulated plans with the VRA constraint, within District 1. The red line indicates the corresponding BVAP proportion under the enacted plan.

the VRA. As explained in Section IV.A, I simulated 10,000 alternative plans that keep the overall BVAP proportion of District 6 between 45% and 50% while adhering to other traditional redistricting principles, including those specified in the South Carolina guidelines. Using these simulated plans, I investigate whether and to what extent race was used as a significant factor, beyond the purpose of compliance with the VRA and other redistricting criteria. I specifically examine the district boundaries in Charleston, Richland, and Sumter Counties, which correspond to the boundaries between District 6 and Districts 1, 2, and 5, respectively.

A. Charleston County (District 1)

35. I begin by comparing the BVAP proportion of District 1 under the enacted plan with the corresponding number under the simulated plans. Figure 4 shows that the BVAP proportion of District 1 is unusually low under the enacted plan (red vertical line; 17.4%) in comparison to the 10,000 simulated plans with the VRA constraint (grey histogram). On average, the BVAP proportion of District 1 under the enacted plan is 6.5 percentage points (4.5 standard deviations of the simulated distribution) lower than the corresponding number under the simulated plans. Indeed, no simulated plan has a lower BVAP proportion for District 1 than the enacted plan, implying that the enacted plan is a statistical outlier in this regard. This finding is consistent with that under the

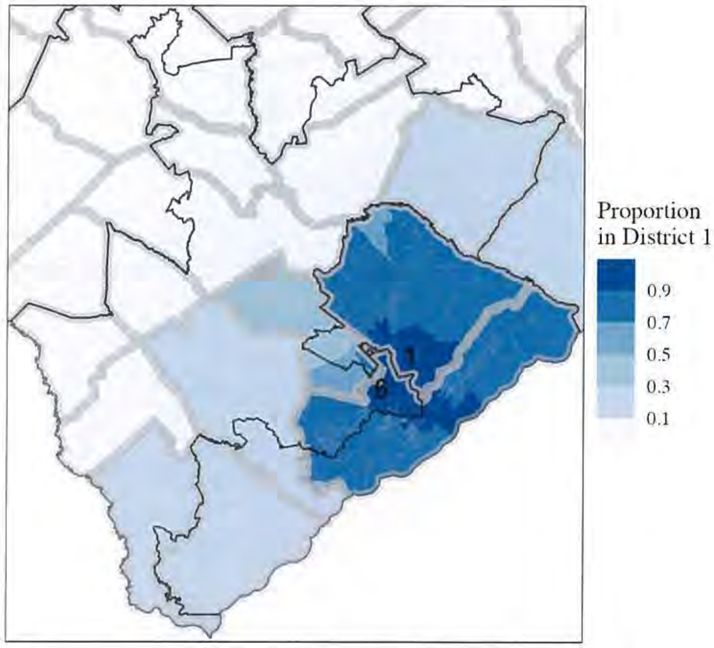

Figure 5: The Boundary of District 1 and 6 in the Statewide Simulation with the Voting Rights Act (VRA) Constraint. In the map, each precinct is shaded by the proportion of 10,000 simulated plans under the VRA constraint that assign it to District 1. A precinct with a darker blue color is more likely to belong to District 1 under the enacted plan. The solid black line demarcates the district boundaries of the enacted plan. The grey lines represent county boundaries.

localized race-blind simulation (shown in Figure 2). Thus, keeping the BVAP proportion of District 6 between 45% and 50% does not materially change the conclusion that the BVAP proportion of District 1 is unusually low.

36. I next show that the unusually low BVAP proportion of District 1 is at least in part due to the way the district boundary is drawn within Charleston County. Figure 5 presents the proportion of the 10,000 simulated plans under the VRA constraint that assign each precinct to District 1. The finding is consistent with that of my localized race-blind simulation analyses shown in Section V (shown in the right map of Figure 1). The way in which the enacted plan splits Charleston County by placing a disproportionately large number of Black voters into District 6 is highly unusual in comparison to the simulated plans. In particular, under the simulated plans, the city of North Charleston where many Black voters live is much more likely to be part of District 1 than District 6 (as indicated by dark blue precincts).

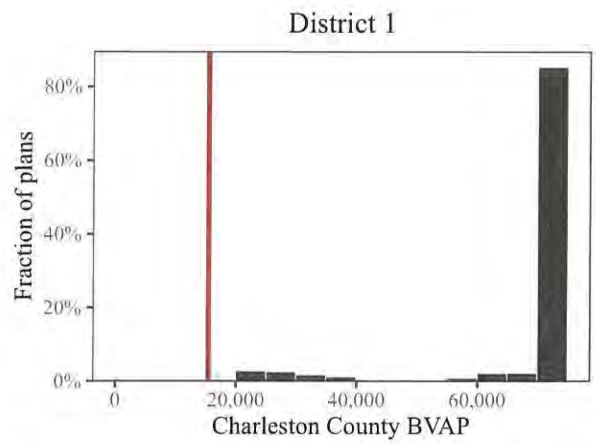

Figure 6: Histogram represents the distribution of the Black voting-age population (BVAP), across 10,000 statewide simulated plans with the VRA constraint, who live in Charleston County and are assigned to District 1. The red line indicates the corresponding BVAP number under the enacted plan.

37. The histogram in Figure 6 further demonstrates this fact by showing the distribution of BVAP who live in Charleston County and are assigned to District 1 under the simulated plans with the VRA constraint. The red vertical line indicates the corresponding number under the enacted plan. Under the simulated plans, a much greater number of Black voters who live in Charleston County are assigned to District 1 in comparison to the enacted plan. In fact, a large spike around 74,600 implies that a vast majority of simulated plans (76.3%) assign the entire county to District 1. In contrast, the enacted plan only places about 15,400 Black voters in District 1, lowering its BVAP proportion. Indeed, only 0.27% of the 10,000 simulated plans places fewer Black voters into District 1 than the enacted plan.

38. In sum, my statewide simulation analysis with the VRA constraint shows that the BVAP proportion of District 1 under the enacted plan is unusually low in part due to the way in which Charleston County is split. This finding implies that race was used as a significant factor in determining the boundary between Districts 1 and 6, especially in Charleston County, beyond the purpose of complying with the VRA and the traditional redistricting criteria.

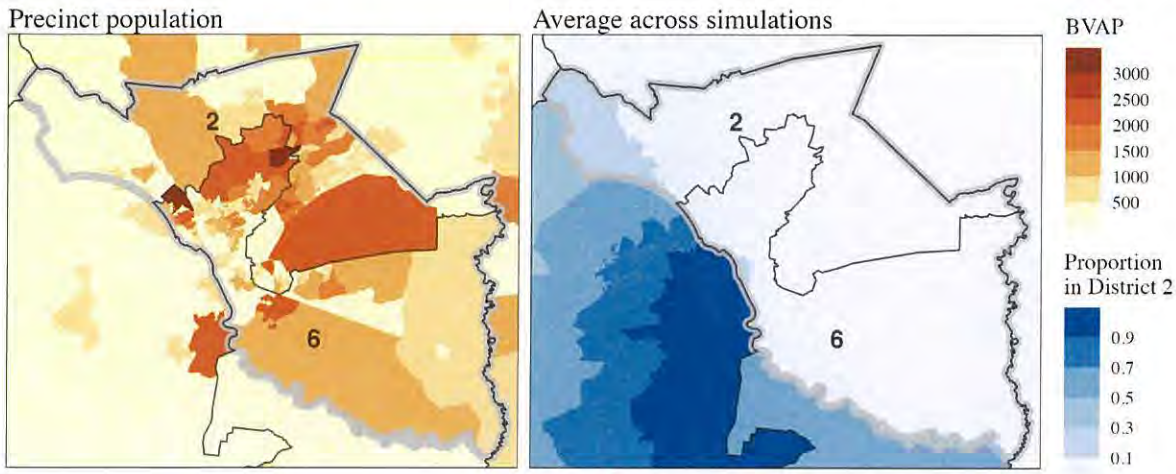

Figure 7: Analysis of Richland County in the Statewide Simulation with the Voting Rights Act (VRA) Constraint. Under the enacted plan, this county consists of Districts 2 and 6, which are demarcated by solid black lines. The grey lines represent county boundaries. The left map shows the precinct-level Black voting-age population (BVAP). In the right map, the districts are shaded by the proportion of 10,000 race-blind simulated plans with the VRA constraint that assign each precinct to District 2. The vast majority of the simulated plans do not include Richland County in District 2.

B. Richland County (District 2)

39. Next, I examine the district boundary in Richland County using the same set of 10,000 statewide simulated plans with the VRA constraint. As shown in the left map of Figure 7, the enacted plan splits this county by including the northern part of the city of Columbia and its environs where a relatively large number of Black voters live into District 6 while assigning the rest of the county to District 2. In other words, the enacted plan cracks Black voters who live in this county into Districts 2 and 6. As a result, within this county, the BVAP proportion of District 6 is 55.4% while that of District 2 is at 37.1%.

40. The enacted plan's decision to crack Black voters by splitting Richland County into Districts 2 and 6, however, is highly unusual when compared to the simulated plans. The right map of Figure 7 shows that many of the simulated plans do not include Richland County in

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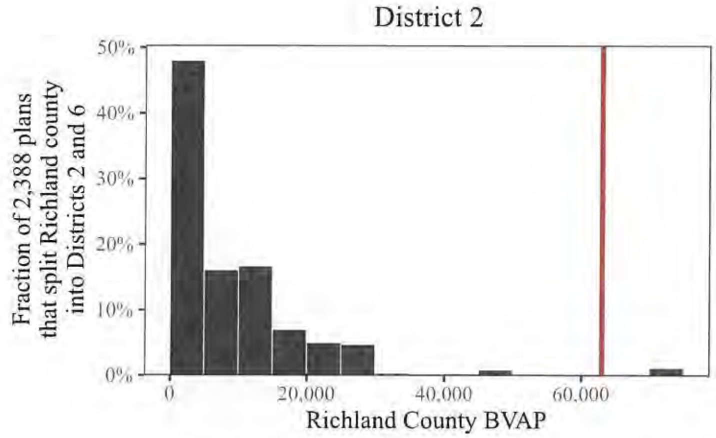

Figure 8: The distribution of Black voting-age population (BVAP) across the subset of plans in which Richland county is split only into Districts 2 and 6. The plans come from statewide plans simulated with the VRA constraint.

District 2 at all (as indicated by light blue color). In fact, 39.4% of the simulated plans do not split Richland County at all and all of these simulated plans assign the entire county to District 6. Even when some simulated plans assign a part of Richland County to District 2, they tend to include the northwestern corner of the county, where very few Black voters live (as indicated by slightly darker blue color), rather than cracking Black voters like the enacted plan does.

41. Although about 23.9% of the simulated plans do divide Richland County into Districts 2 and 6, they do so in a way that is different from the enacted plan. Figure 8 demonstrates this fact by presenting the distribution of BVAP in District 2 among these 2,387 simulated plans that split Richland County into Districts 2 and 6. The grey histogram in the figure shows that these simulated plans place much fewer Black voters in District 2 than the enacted plan. In fact, only 1% of these simulated plans include a greater number of Black voters in District 2 than the enacted plan. The average difference is about 53,900 voters, which corresponds to 4.8 standard deviations of simulated distribution, and is statistically significant. The results are similar even when we include all simulated plans that assign at least some part of Richland County to District 2. Among those simulated plans, only 0.6% of them place a greater number of Black voters who live in Richland County into District 2.

42. Thus, my statewide simulation analysis with the VRA constraint shows that the

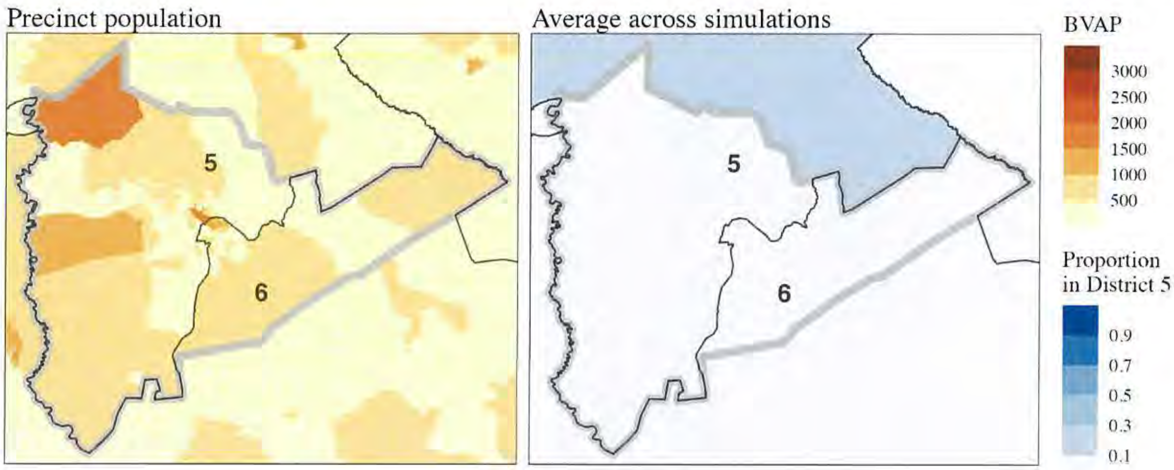

Figure 9: Analysis of Sumter County in the Statewide Simulation with the Voting Rights Act (VRA) Constraint. Under the enacted plan, this county consists of Districts 5 and 6, which are demarcated by solid black lines. The grey lines represent county boundaries. The left map shows the precinct-level Black voting-age population (BVAP). In the right map, the districts are shaded by the proportion of 10,000 race-blind simulated plans with the VRA constraint that assign each precinct to District 5. The vast majority of the simulated plans do not include Sumter County in District 5.

enacted plan unnecessarily cracks Black voters who live in Richland County into Districts 2 and 6. The finding implies that the unusual boundary between Districts 2 and 6 under the enacted plan can neither be explained by compliance with the VRA nor the traditional redistricting criteria.

C. Sumter County (District 5)

43. Finally, I examine the district boundary of Sumter County using the same set of 10,000 statewide simulated plans with the VRA constraint. As shown in the left map of Figure 9, the enacted plan divides Sumter County into Districts 5 and 6 by splitting the city of Sumter, thereby cracking Black voters who live in that area. As a result, about 64% of Black voters who live in Sumter County belong to District 5 while the remaining 36% are assigned to District 6. In contrast, the right map of the figure shows that under the simulated plans with the VRA constraint, no part of Sumter County is likely to belong to District 5 (as indicated by light blue color). Indeed,

Table 1: Frequency of Pairings of Districts in Sumter County in Statewide VRA Simulation. Only shows combination that appear in 1 percent or more of the 10,000 simulated plans.

Pairings	Frequency
District 6	90.3%
District 6, District 7	4.5%
District 5	2.4%
District 5, District 6	1.2%

only 6.9% of the simulated plans split Sumter County into multiple districts. Like Richland County, therefore, this shows that it is unnecessary to crack Black voters by splitting Sumter County in order to comply with the VRA.

44. Table 1 further shows the relative frequency of district pairings that occur within Sumter County. The enacted plan's decision to split Sumter County into Districts 5 and 6 is highly unusual. In fact, only 1.2% of the 10,000 simulated plans split Sumter County into Districts 5 and 6, like the enacted plan does. In contrast, a vast majority of the simulated plans assign the entirety of Sumter County to a single district (2.4% for District 5 and 90.3% for District 6) without splitting the county.

45. Thus, my statewide simulation analysis with the VRA constraint shows that the enacted plan cracks Black voters who live in Sumter County into Districts 5 and 6. The finding implies that the unusual boundary between Districts 5 and 6 can neither be explained by compliance with the VRA constraint nor the traditional redistricting criteria.

Pursuant to 28 U.S.C. § 1746, I hereby declare under penalty of perjury that the forgoing is true and correct:

Executed, this day, April 4, 2022, in Cambridge, Massachusetts.

Kosuke Imai, Ph.D.

VII. APPENDIX

A. Introduction to Redistricting Simulation

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

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

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

49. In addition, the algorithms ensure that all of the sampled plans (a) are geographi-

5. Declaration of Dr. Jonathan C. Mattingly, Common Cause v. Lewis (2019); Testimony of Dr. Jowei Chen, Common Cause v. Lewis (2019); Testimony of Dr. Pegden, Common Cause v. Lewis (2019); Expert Report of Jonathan Mattingly on the North Carolina State Legislature, Rucho v. Common Cause (2019); Expert Report of Jowei Chen, Rucho v. Common Cause (2019); Amicus Brief of Mathematicians, Law Professors, and Students in Support of Appellees and Affirmance, Rucho v. Common Cause (2019); Brief of Amici Curaiae Professors Wesley Pegden, Jonathan Rodden, and Samuel S.-H. Wang in Support of Appellees, Rucho v. Common Cause (2019); Intervenor's Memo, Ohio A. Philip Randolph Inst. et al. v. Larry Householder (2019); Expert Report of Jowei Chen, League of Women Voters of Michigan v. Benson (2019). Expert Report of Kosuke Imai, League of Women Voters of Ohio et al. v. Ohio Redistricting Commission et al. (2021). Expert Report of Kosuke Imai, Milligan et al. v. Merrill et al. (2021).

cally contiguous, and (b) have a population which deviates by no more than a specified amount from a target population.

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

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

52. The MCMC algorithms (E. Autry et al. 2020; E. A. Autry et al. 2021; Carter et al. 2019) also form districts by drawing a random spanning tree and splitting it. Unlike the SMC algorithm, however, these algorithms do not draw redistricting plans from scratch. Instead, the MCMC algorithms start with an existing plan and modify it, merging a random pair of districts and then splitting them a new way.

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

B. Implementation Details

54. I conducted three different simulations. For all simulations, I used the merge-split type MCMC algorithm, as described above and implemented in the open-source R package `redist` my collaborators and I developed (Kenny et al. 2020). To name simulated districts, we simulate plans that do not pair two or more incumbents in the same district, using the incumbency constraint whenever necessary.

55. In the first set of simulations involving Districts 1 and 6, I take the precincts that were assigned to District 1 and 6 in the enacted plan and simulate plans that split this area into two congressional districts. This means that districts 2–5 and 7 are not modified. In the Charleston County simulation, I freeze the district assignments of Districts 1 and 6 outside Charleston County as they are in the enacted plan. This means that only the district boundary within the county is simulated while the remaining parts of the relevant districts outside of the county remain unaltered. In the statewide simulation, I do not freeze any districts and simulate plans with 7 congressional districts. Unlike the other two simulations, I use data on race to target specific districts, which I describe below.

56. For each simulation, I generated a total of 10,000 alternative plans by instructing the algorithm so that the resulting simulated plans adhere to the set of redistricting criteria listed in Section IV. Thus, my simulated plans are at least as compliant with these criteria as the enacted plan. Specifically, the 10,000 plans are obtained for each simulation as follows. First, I generated a total of 110,000 to 132,000 plans separately obtained from 10 to 12 parallel Markov chains, each with 11,000 plans. All simulations start the Markov chain with the enacted plan. Second, I discarded the first 1,000 iterations of each Markov chain, a procedure commonly called burn-in, so that initial values do not affect results. Third, in some simulations, I removed plans that still had incumbency pairings so that like the enacted plan all the simulated plans have no incumbency pairing. In the statewide simulation with a VRA constraint, I removed plans in which District 6's BVAP was below 45%. Both of these removals tend to be no more than a trivial proportion of the simulated plans, because of the constraints already encoded in the algorithm. Fourth, I take the

last 100,000 of the remaining plans. Finally, I kept every 10th plan from these 100,000 plans, a procedure commonly called thinning, resulting in 10,000 simulated plans for each analysis. Below I give the details of the algorithmic inputs for each simulation analysis.

57. Every simulation has a set of constraints so that the resulting simulated plans are compliant with the specified set of redistricting criteria listed in Section IV. Greater values of these strengths generally means that the algorithm is more strongly instructed to sample plans that conform to the selected criterion of interest. The simulations have a default compactness constraint of strength 1. Below, we list additional constraints that are unique to each simulation analysis.

- *Localized District 1 and 6 Simulation*: A soft county split avoidance constraint of strength 0.4, and an incumbency pairing avoidance constraint of strength 1.
- *Localized Charleston County Simulation*: A constraint avoiding splitting municipalities, with a strength of 0.3. The compactness constraint was raised to 1.07.
- *Statewide VRA Simulation*: A custom constraint that penalizes plans in which District 6's BVAP is outside the range of 0.45–0.5. This constraint is given a strength of 8. An incumbency pairing avoidance constraint with a strength of 8 is also added. Finally, there is a soft county split avoid constraint of strength 0.95, and a hierarchical county split constraint that effectively limits the number of counties split to 6.

C. Compactness of the Simulated Districts

58. I measured compactness with the standard metric of Polsby-Popper score (Figure 10) and the faction of edges kept (Figure 11). According to these measures, the simulated plans are on average at least as compact as the enacted plan.

D. County Splits of the Simulated Districts

59. Figure 12 shows that the number of counties split under the simulated plans (grey histograms) is no greater than that under the enacted plan (red vertical line). The Charleston County simulation is not shown because it only varies the boundary within a single county, so its county splits will be the same as the enacted plan.

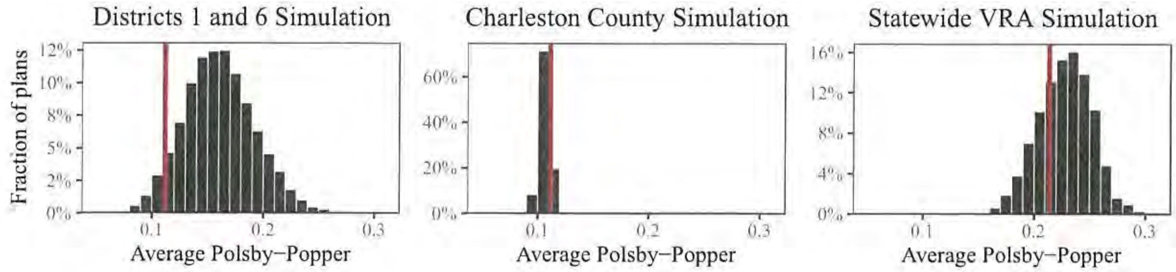

Figure 10: Compactness of Simulations Measured by the Polsby Popper Score. The measure computes the average of the district-level Polsby Popper score for each simulated district. In the Districts 1 and 6 simulation and the Charleston County simulation, there are 2 districts. In the statewide VRA district, there are 7 districts. The histogram represents the compactness of simulated plans while the vertical red line represents the enacted plan. A greater value indicates a more compact redistricting plan.

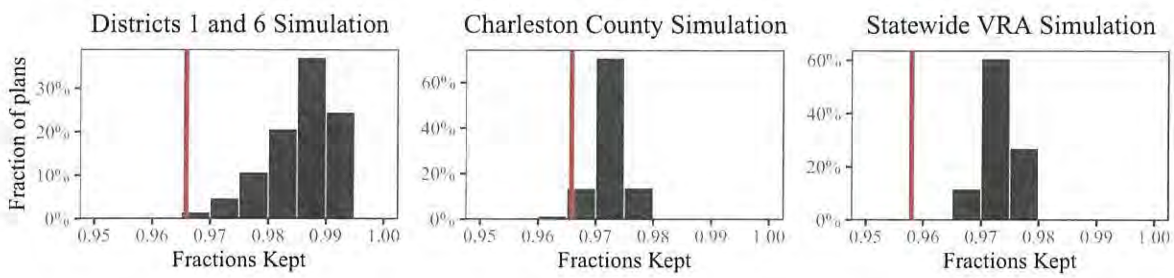

Figure 11: Compactness of Simulations Measured by the Fraction of Edges Kept. The measure computes the fraction of edges kept for each simulated district. The histogram represents the compactness of simulated plans while the vertical red line represents the enacted plan. A greater value indicates a more compact redistricting plan.

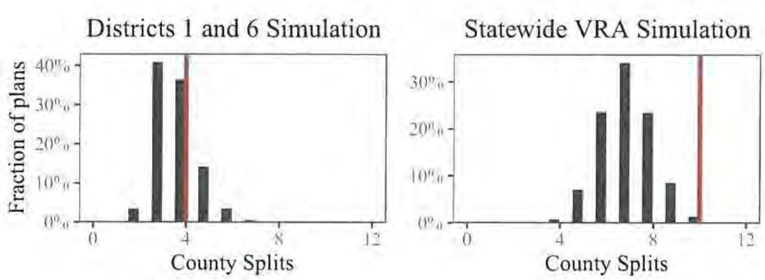

Figure 12: County splits in simulation. The histogram shows the distribution of the number of split counties under the simulated plans while the red vertical line shows the enacted plan. On average, the simulated plans split fewer number of counties than the enacted plan.

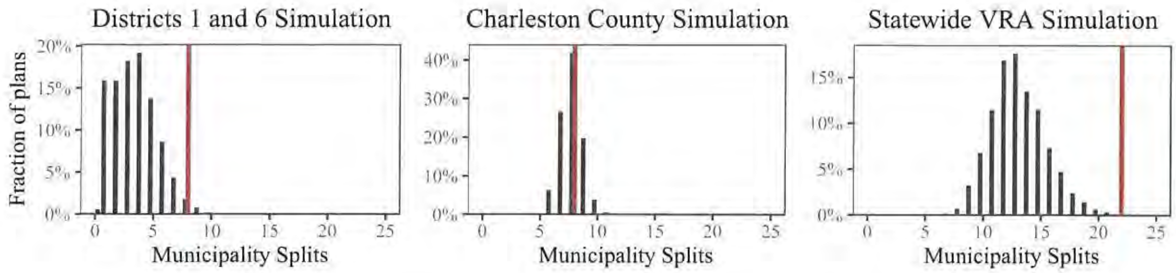

Figure 13: Municipality splits in simulation. The histogram shows the distribution of the number of split municipalities under the simulated plans while the red vertical line shows the enacted plan. On average, the simulated plans split fewer number of municipalities than the enacted plan.

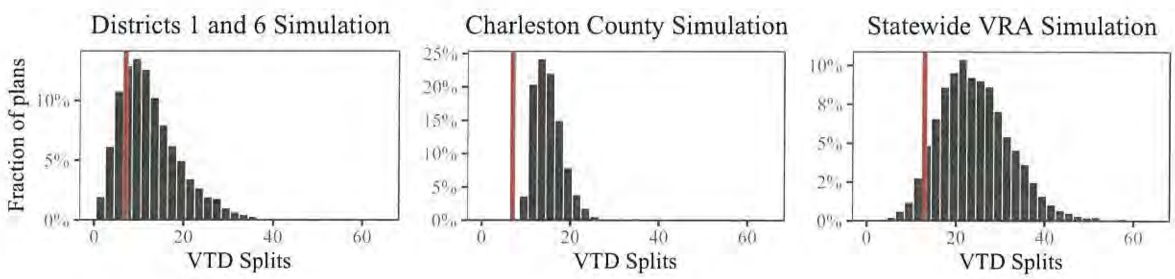

Figure 14: Precinct or Voting Tabulation District (VTD) splits in the simulation. The histogram shows the distribution of the number of split VTDs under the simulated plans while the red vertical line shows the enacted plan.

E. Municipality Splits of the Simulated Districts

60. Figure 13 shows that the number of municipalities split under the simulated plans (grey histograms) is no greater than that under the enacted plan (red vertical line).

F. Precinct Splits of the Simulated Districts

61. Figure 14 show that the number of split precincts or voting tabulation districts (VTDs) among the simulated plans (grey histogram) is generally compatible with that of the enacted plan (vertical red line) but tends to be somewhat higher on average. This is in part due to the fact that many municipalities split VTDs, implying that there often is a direct trade-off between municipality and precinct splits.

G. Data Sources

G.1. Data Acquisition

62. The 2020 Census Block shapefiles, 2020 Census Place shapefiles, total population by race and ethnicity, and voting age population by race and ethnicity directly were acquired from the Census FTP portal. In this report, when reporting the black voting age population, I count voters in the Census that are any-part black as black.

63. The VTD block assignment files and Census Place block assignment files were acquired from the Census website.

64. The incumbent addresses were acquired from the Redistricting Data Hub and subsequently modified based on public information and records (e.g., South Carolina State Election Commission filings, South Carolina property records) and input from plaintiffs' counsel. These addresses were then geocoded to census blocks.

65. The passed Congressional plan was acquired from the South Carolina House of Representatives Redistricting 2021 website.

66. The 2020 Census place block assignment files (for city and town boundaries) were obtained from the Census website.

G.2. Data Processing

67. For datasets that were on the 2020 census block level (total population, voting age population, VTD assignment, incumbent addresses, congressional district assignment, and census place assignment), these datasets were joined to the 2020 Census block shapefile.

G.3. Data Aggregation

68. The full block-level dataset was aggregated up to the level of the 2020 voting districts, taking into account (a) discontiguities in voting districts (b) splits of voting districts by the proposed Congressional plan and (c) splits of voting districts by cities and towns.

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EXHIBIT A

Curriculum Vitae

Kosuke Imai

Curriculum Vitae

March 2022

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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

Books

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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.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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.

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

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

Invited Contributions

1. Imai, Kosuke. (2022). "Causal Diagrams and Social Science Research." *Probabilistic and Causal Inference: The Works of Judea Pearl.* Geffner, Hector and Dechter, Rina and Halpern, Joseph Y. (eds). Association for Computing Machinery and Morgan & Claypool, pp. 647–654.

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

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

4. 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.

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

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

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

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

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

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

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

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

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

14. 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.

15. 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. Ham, Dae Woong, Kosuke Imai, and Lucas Janson. "Using Machine Learning to Test Causal Hypotheses in Conjoint Analysis."

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

3. 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."

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

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

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

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

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

9. 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."

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

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

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

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

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

Publications in Japanese

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

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

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

Statistical Software

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

External Research Grants

Principal and Co-Principal Investigator

1. National Science Foundation (2022-2025). "Collaborative Research: Understanding the Evolution of Political Campaign Advertisements over the Last Century." (Accountable Institutions and Behavior Program, SES–2148928). Principal Investigator (with Michael Crespin and Bryce Dietrich) $538,484.

2. 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.

3. 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.

4. 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.

5. 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

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

7. 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.

8. 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

9. 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.

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

11. 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.

12. 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.

13. 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.

14. 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.

15. 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.

16. 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.

17. 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). To be Postdoctoral Fellow, Princeton Unviersity, followed by Assistant Professor, Department of Political Science, Boston University

4. Ambarish Chattopadhyay (Statistics). To be Postdoctoral Fellow, Stanford University
5. Shusei Eshima (Government)
6. Georgina Evans (Government). To be Research Scientist, Google Brain
7. Dae Woong Ham (Statistics)
8. Zeyang Jia (Statistics)
9. Christopher T. Kenny (Government)
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. Michael Lingzhe Li (Ph.D. in 2021, Operations Research, MIT). Postdoctoral Fellow, MIT. To be Assistant Professor, Technology and Operations Management Unit, Harvard Business School
2. Alexander Tarr (Ph.D. in 2021, Department of Electrical and Computer Engineering, Princeton University; Dissertation Committee Chair)
3. 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
4. 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

5. Erik Wang (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political and Social Change, Australian National University
6. Diana Stanescu (Ph.D. in 2020, Department of Politics, Princeton University). Postdoctoral Fellow, Stanford University
7. Nicole Pashley (Ph.D. in 2020, Department of Statistics, Harvard University). Assistant Professor, Department of Statistics, Rutgers University
8. Asya Magazinnik (Ph.D. in 2020, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Massachusetts Institute of Technology
9. Max Goplerud (Ph.D. in 2020, Department of Government, Harvard University). Assistant Professor, Department of Political Science, University of Pittsburgh
10. Naoki Egami (Ph.D. in 2020, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, Columbia University
11. Brandon de la Cuesta (Ph.D. in 2019, Department of Politics, Princeton University). Postdoctoral Fellow, Center on Global Poverty and Development, Stanford University
12. Yang-Yang Zhou (Ph.D. in 2019, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, University of British Columbia
13. Winston Chou (Ph.D. in 2019, Department of Politics, Princeton University). Senior Data Scientist at Apple
14. 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
15. Benjamin Fifield (Ph.D. in 2018, Department of Politics, Princeton University; Dissertation Committee Chair). Data Scientist, American Civil Liberties Union
16. Tyler Pratt. (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Yale University
17. Romain Ferrali (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Aix-Marseille School of Economics
18. Julia Morse (Ph.D. in 2017, Woodrow Wilson School, Princeton University). Assistant Professor, Department of Political Science, University of California, Santa Barbara
19. Yuki Shiraito (Ph.D. in 2017, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, University of Michigan
20. Carlos Velasco Rivera (Ph.D. in 2016, Department of Politics, Princeton University). Research Scientist, Facebook
21. 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

22. Graeme Blair (Ph.D. in 2016, Department of Politics, Princeton University). Assistant Professor, University of California, Los Angeles
23. Jaquilyn R. Waddell Boie (Ph.D. in 2015, Department of Politics, Princeton University). Private consultant
24. Scott Abramson (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, University of Rochester
25. Michael Barber (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Brigham Young University
26. In Song Kim (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Massachusetts Institute of Technology
27. Alex Ruder (Ph.D. in 2014, Department of Politics, Princeton University). Principal Advisor, Federal Reserve Bank of Atlanta
28. Meredith Wilf (Ph.D. in 2014, Department of Politics, Princeton University). Senior Director, Capital Rx
29. Will Bullock. (Ph.D. candidate, Department of Politics, Princeton University). Senior Researcher, Facebook
30. Teppei Yamamoto (Ph.D. in 2011, Department of Politics, Princeton University; Dissertation Committee Chair). Associate Professor, Department of Political Science, Massachusetts Institute of Technology
31. Dustin Tingley (Ph.D. in 2010, Department of Politics, Princeton University). Professor, Department of Government, Harvard University
32. Aaron Strauss (Ph.D. in 2009, Department of Politics, Princeton University). Former Executive Director, Analyst Institute
33. 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
34. 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

Mmeber, Senior Lecturer Search Committee (2021-2022)

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 Review Committee member, Department of Political Science, University of Rochester (2022)

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.

Expert Reports

1. Milligan *et al.* *v.* Merrill *et al.* United States District Court for the Northern District of Alabama, Case No. 2:2021cv01530

2. League of Women Voters of Ohio *et al.* *v.* Ohio Redistricting Commission *et al.* The Supreme Court of Ohio, Case No. 2021–1449

3. League of Women Voters of Ohio *et al.* *v.* Ohio Redistricting Commission *et al.* The Supreme Court of Ohio, Case No. 2021–1193

4. League of Women Voters of Ohio *et al.* *v.* Frank LaRose *et al.* The Supreme Court of Ohio, Case No. 2022–0303

5. The South Carolina State Conference of the NAACP, *et al.* *v.* McMaster, *et al.* United States District Court for the District of South Carolina Columbia Division, Case No. 3-21-cv-03302-JMC-TJH-RMG

6. Benninghoff *v.* 2021 Legislative Reapportionment Commission. The Supreme Court of Pennsylvania, Case No. 11 MM 2022

7. Graham *et al.* *v.* Adams *et al.* Commonwealth of Kentucky Franklin Circuit Court Division, Case No. 22-CI-00047