IN THE UNITED STATES DISTRICT COURT NORTHERN DISTRICT OF ALABAMA SOUTHERN DIVISION

Milligan *et al.*

Plaintiffs,

v.

Merrill *et al.*

Defendents.

EXPERT REPORT

Kosuke Imai, Ph.D.

December 10, 2021

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I. INTRODUCTION AND SCOPE OF WORK

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

2. I have been asked by counsel representing the plaintiffs in this case to analyze relevant data and provide my expert opinions related to the role that race played in drawing Alabama's congressional district plan (HB1). To do so, I simulated two sets of 10,000 possible Alabama congressional districting plans that adhere to other redistricting considerations. The simulations allow me to determine whether and to what extent the Alabama legislature's inclusion or exclusion of Black voters in Districts 2 and 7 in HB1 is consistent with the likelihood of particular outcomes in the simulated plans that are generated without consideration of race.[1]

3. These simulated plans are at least as compact as the enacted plan and have fewer than or an equal number of county splits. Like the enacted plan, none of these simulated plans pair incumbents. The first set of 10,000 alternative plans were generated without any consideration of race. I call them "race-blind" simulated plans. These race-blind simulations allow me to determine how race would be treated in districting plans if the districts were drawn without using any consideration of race. I also generated the second set of 10,000 alternative plans that have one majority-minority district (MMD) but otherwise followed the same criteria as the race-blind simulation procedure used for the first set. They were referred to as "one-MMD" simulated plans. These one-MMD simulations allow me to examine how the racial composition of the other districts would look if the districts were drawn with the constraint of including one MMD but otherwise not considering race at all.

II. SUMMARY OF OPINIONS

1. My analysis focused on Districts 2 and 7, the districts with the highest proportion of Black voters, where the role of race was most apparent. Other types of analysis may uncover similar evidence in Districts 1 and 3, but the simulations run here focus on the predominance of race in Districts 2 and 7.

4. The comparison of the race-blind simulated plans with the enacted plan yields the following findings: The enacted plan draws Black voters who live in Jefferson and Montgomery Counties into District 7 at a rate not present in the race-blind simulated plans. Indeed, the enacted plan is a clear statistical outlier in this regard when compared to the ensemble of the race-blind simulated plans. As a result of the enacted plan including an unusually large number of Black voters into District 7, the Black voting age population (BVAP) proportion of District 2 is much lower than a vast majority of the simulated plans.[2]

5. The comparison of the one-MMD simulated plans with the enacted plan yields the following findings: The enacted plan sweeps about 39,000 Black voters who live in Montgomery County into District 7 in the ways that render it a statistical outlier when compared to the simulated plans. In contrast, about 90% of the one-MMD simulated plans include fewer than 4,000 Black voters from Montgomery in the MMD, and instead include most Black voters from Montgomery in other districts. As a result of packing Black voters who live in Montgomery into District 7 in the enacted plan, the district with the second highest BVAP proportion (i.e., District 2) has a BVAP of only 30.1%. In contrast, a large proportion of the one-MMD simulated plans avoid packing Black voters into the MMD and the district with the second highest BVAP proportion achieves, on average, 4.4 percentage points or higher BVAP proportion than the enacted plan. This difference is statistically significant using the conventional standard.

6. My simulation analyses, therefore, provide evidence that race was a significant factor in drawing the enacted plan.

III. QUALIFICATIONS, EXPERIENCE, AND COMPENSATION

7. I am trained as a political scientist (Ph.D. in 2003, Harvard) and a statistician (MA in 2002, Harvard). I have published more than 60 articles in peer reviewed journals, including premier political science journals (e.g., *American Journal of Political Science*, *American Political Science Review*, *Political Science*), statistics journals (e.g., *Biometrika*, *Journal of the American*

2. I define BVAP as people who are some part Black per the Census definition.

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."

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

9. 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.

10. 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).

11. I have also developed an open-source software package titled `redist` that allows

researchers and policy makers to implement the cutting-edge simulation methods developed by us and others (Kenny et al. 2020). This software package can be installed for free on any personal computer with Windows, Mac, or Linux operating system. According to a website that tracks the download statistics of R packages, our software package has been downloaded about 30,000 times since 2016 with an increasing download rate.[3]

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

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

14. 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

15. I conducted simulation analyses to help evaluate whether the enacted plan was drawn using race as a primary 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 the state could have drawn while being 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 predominant factor.

3. https://ipub.com/dev-corner/apps/r-package-downloads/ (accessed on December 6, 2021)

16. 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 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.

17. A primary advantage of the simulation-based approach, over other traditional methods, is its ability to account for the political and geographic features that are specific to each state, including spatial distribution of voters and configuration of administrative boundaries. Simulation methods can also incorporate each state's redistricting rules. These state-specific features limit the types of redistricting plans that can be drawn, making comparison across states 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 Alabama's administrative boundaries, political realities, and legal requirements. Appendix A provides a brief introduction to redistricting simulation.

A. Simulation Setup

18. For the purposes of my analyses, I have ensured that all of my simulated plans have the following properties:

- there are a total of seven geographically contiguous districts
- all districts do not exceed an overall population deviation of $\pm$ 0.5%
- districts are more compact than the enacted plan on average
- fewer than or equal to the number of county boundaries split under the enacted plan
- no more than one incumbent is placed in each district[4]
- no partisan information is used for simulation

19. I provide an overview of my simulation procedure while leaving the detailed infor-

4. I exclude Representative Mo Brooks who has announced his candidacy for the United States Senate from the list of incumbents.

mation about the simulation algorithms to Appendix B. I generated two sets of 10,000 simulated plans. The first set is generated by only considering the above criteria, using the Sequential Monte Carlo (SMC) simulation algorithm (McCartan and Imai 2020; Kenny et al. 2021; briefly described in Appendix B). Importantly, the simulation procedure does not use the information about race at all. I call this "race-blind" simulation analysis.

20. The second set of simulated plans also satisfy the above criteria, but use the information about race to create one majority-minority district (MMD). At the request of counsel for plaintiffs, the MMD is drawn as a district with the proportion of Black voting age population (BVAP) between 50% and 51%. I use the short-burst Markov chain Monte Carlo (MCMC) algorithm (Cannon et al. 2020; briefly described in Appendix B) to find different MMDs by running this algorithm multiple times. Then, for each simulated MMD, I use the same race-blind simulation procedure as the one used for the race-blind simulation analysis to generate the remaining six districts. Specifically, I run the SMC algorithm on the rest of the state without using any information about race. Each of the resulting simulated plans, therefore, has one MMD and the remaining districts created in the race-blind fashion. I call this "one-MMD" simulation analysis.

21. Neither of my two simulation analyses use any partisan information. Lastly, Appendix E.1 provides the detailed information about data sources used in my analysis.

B. Description of Redistricting Simulation Software

22. In my analysis, I use the open-source software package for redistricting analysis `redist` (Kenny et al. 2020), which implements a variety of redistricting simulation algorithms as well as other evaluation methods. My collaborators and I have written the code for this software package, so that other researchers and the general public can implement these state-of-the-art methods on their own. I supplement this package with code written primarily to account for the redistricting rules and criteria that are specific to Alabama. All of my analyses are conducted on a laptop. Indeed, all of my analysis code can be run on any personal computer once the required software packages, which are also freely available and open-source, are installed.

V. EVALUATION OF THE ENACTED PLAN

23. Using the redistricting simulation methodology described above, I evaluate evidence regarding whether race was a primary factor in drawing the enacted plan. This is done by instructing the algorithms to adhere to all of the other redistricting rules and then comparing how the enacted plan treats race to the treatment of race in the resulting simulated plans. Specifically, I simulated two sets of 10,000 alternative plans ("race-blind" and "one-MMD"), using the simulation procedure described in Section IV.

24. In Appendix C, I show that the simulated plans are on average at least as compact as the enacted plan based on the standard compactness measures. For example, virtually all of the race-blind simulated plans are more compact than the enacted plan. Appendix D shows that most of the simulated plans have fewer than or equal to the number of county splits the enacted plan does. Indeed, almost all of the race-blind simulated plans split at most four counties while the enacted plan splits six counties. As mentioned above, all simulated plans have at most one incumbent located in any given district. This allows me to number the districts of each simulated plan according to the incumbents contained in them.

25. I can easily generate additional plans by running the algorithm longer, but for the purpose of my analysis, 10,000 simulated plans for each set 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.

A. Race-blind Simulation Analysis

26. I start with the evaluation of the enacted plan based on the race-blind simulation analysis. I show that the way in which the enacted plan deviates from the simulated plans implies that race was a predominant factor in drawing the district boundaries of the enacted plan.

A.1. Outlier Analysis of Districts 2 and 7

27. I first conduct an outlier analysis of District 7, which is the sole MMD under the enacted plan. This analysis examines how extreme the BVAP proportion of District 7 is under the enacted plan when compared to that under the race-blind simulated plans. Figure 1 presents

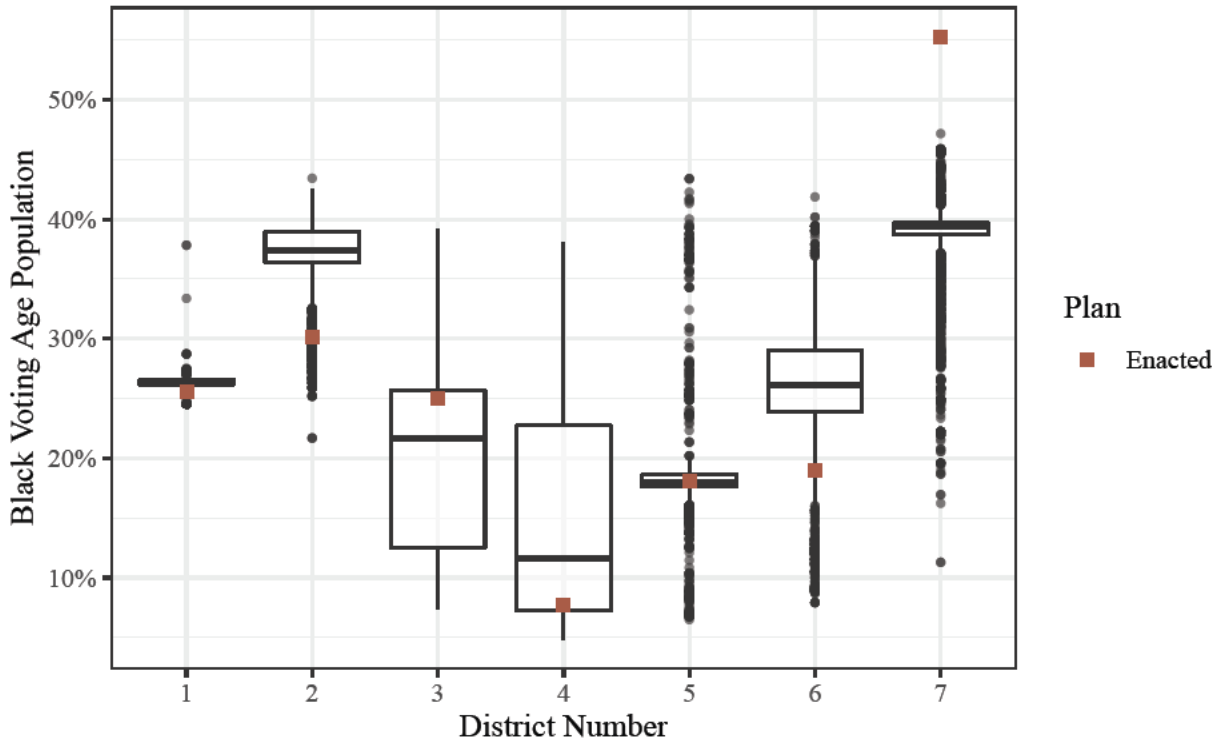

Figure 1: Proportion of Black voting age population (BVAP) for each district of the enacted plan (represented by the red square) compared to the distribution of BVAP proportion for the corresponding district under the simulated plans (represented by a boxplot). District 7 of the enacted plan is a clear outlier.

the distribution of the BVAP proportion for each district under the simulated plans (boxplot) with the red square representing the BVAP proportion for the corresponding district under the enacted plan (matched based on the incumbent location). Note that in a boxplot, the "box" contains 50% of the data points (those from 25 percentile to 75 percentile to be exact) with the horizontal line indicating the median value whereas the vertical lines coming out of the box, called "whiskers", indicate the range, which contains most data. Any data points that are beyond these whiskers are considered as outliers.

28. For the BVAP proportion of District 7, the enacted plan is a clear outlier, including many more Black people than the corresponding district of the simulated plans. In fact, none of my 10,000 simulated plans has a district that has anywhere near as high a BVAP percentage as District 7 of the enacted plan. In other words, the enacted plan considers race beyond what is required

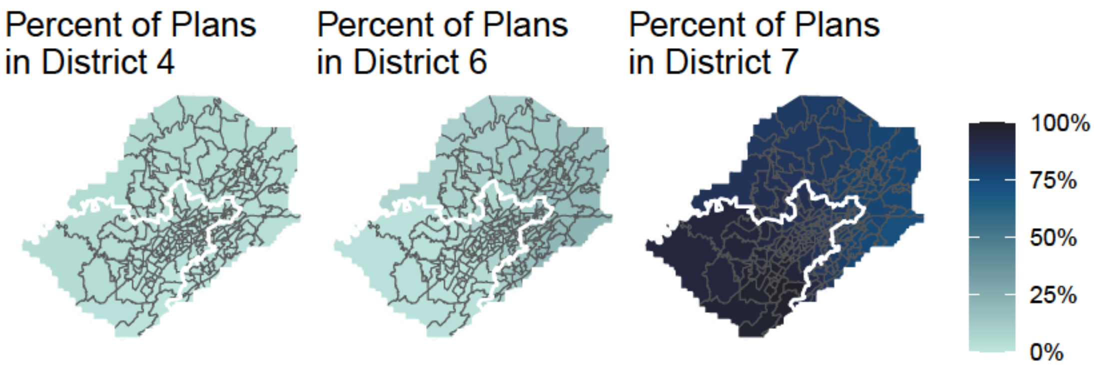

Figure 2: Precinct assignments to Districts 4 (left plot), 6 (middle plot), and 7 (right) across the simulated plans within Jefferson County. Darker colors indicate precincts that are often assigned to that district in simulated plans, while lighter colors indicate precincts that are less likely to be included in that district. The white line represents the district boundary of the enacted plan.

to satisfy the other redistricting criteria. Given the extent to which the BVAP of District 7 is an outlier, I conclude that race was a predominant factor" in drawing the district.

29. As a result of the high percentage of BVAP in District 7, the BVAP of District 2 under the enacted plan, which is 30.1%, is much lower than that under a vast majority of the simulated plans. Most simulated plans achieve a BVAP between 36.4% and 38.9% for this district.

A.2. Analysis of Jefferson County

30. I next analyze Jefferson County, where the city of Birmingham is located. The enacted plan splits this county by including a large part of Birmingham into District 7 while assigning the rest of the county to District 6. I examine how this decision differs from the way in which the simulated plans treat Jefferson County. First, unlike the enacted plan, more than half of the simulated plans (53.3%) do not split Jefferson County at all. These simulated plans include the entire county as part of District 7.

31. Second, the way in which the enacted plan splits Jefferson County is highly unusual. Figure 2 presents the proportion of simulated plans that assign each precinct from Jefferson County to Districts 4 (left), 6 (middle), and 7 (right). Darker colors indicate precincts that are likely to be assigned to each district under the simulated plans, whereas lighter colors represent the ones that tend to be part of other districts. As discussed above, the figure shows that the whole Jefferson

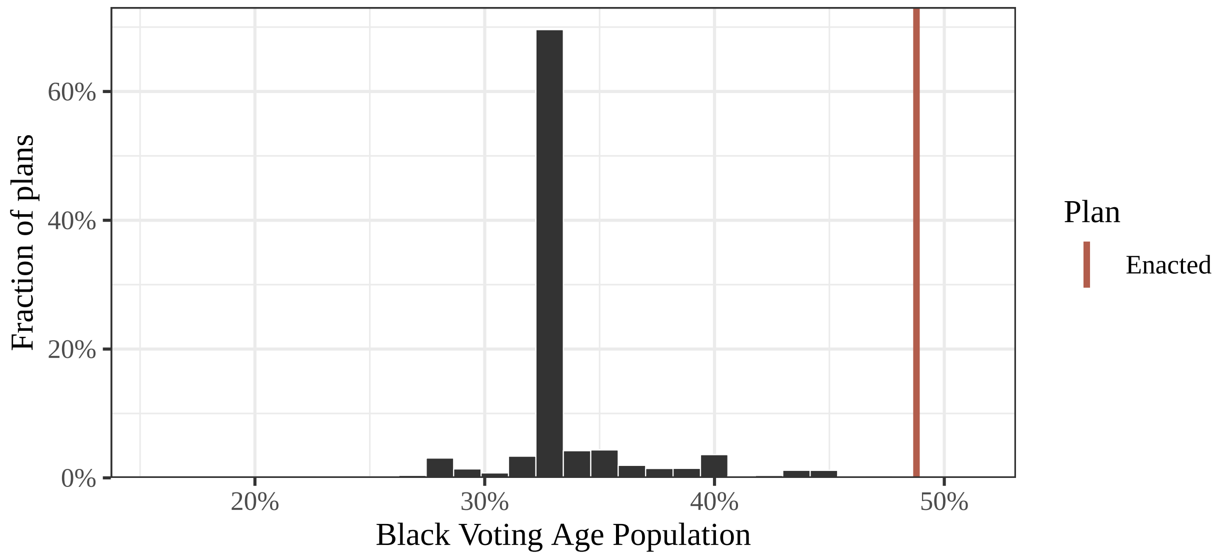

Figure 3: Comparison of Black Voting Age Population percent within Jefferson County and District 7 between simulated plans (black bars) and the enacted plan (red line).

County is usually part of District 7, indicated by the fact that the entire county is colored dark in the right map. Even when split, the simulated plans tend to assign much of the county to District 7. This pattern is in sharp contrast to the way in which the enacted plan splits Jefferson County — it groups precincts where more Black Alabamians reside and includes them into District 7 while assigning the rest of the county to District 6.

32. The examination of the BVAP within Jefferson County also confirms that the enacted plan is an outlier with respect to how it packs many Black residents of Jefferson County into District 7. Figure 3 presents the distribution of BVAP proportions within both Jefferson County and District 7 across simulated plans and compares it against the enacted plan (red line). The enacted plan is a clear outlier in that it packs many more Black residents of Jefferson County into District 7 than 9,992 of the 10,000 simulated plans. In other words, only 0.08% of simulated plans pack as many Black residents of Jefferson County into District 7 as the enacted plan.

A.3. Analysis of Montgomery County

33. In addition to Jefferson, Montgomery is another key county where many Black Alabamians live. The enacted plan splits this county into Districts 2 and 7. Importantly, the enacted plan divides the city of Montgomery into those two districts. I examine how often Montgomery

County is split in the simulated plans to determine whether the decision to split Montgomery County in the enacted plan was likely to occur in order to satisfy other redistricting criteria. I find that over 97% of the simulated plans do not split Montgomery County at all. Indeed, about 94% of these simulated plans assign the entire Montgomery County to Districts 2 or 6 rather than District 7. It is clear that the enacted plan packs Black voters who live in the western part of the city of Montgomery into District 7 while leaving District 2 with fewer Black voters.

34. Based on these findings, it is my opinion that the enacted plan splits Montgomery County in a way that includes a disproportionate number of Black people into District 7, even though doing so was unnecessary to satisfy the other redistricting criteria.

B. <u>One-MMD Simulation Analysis</u>

35. I next conduct the one-MMD simulation analysis. As described in Section IV, this simulation procedure first uses a simulation algorithm to find an MMD with the BVAP proportion of 50–51% and then runs another simulation algorithm on the rest of the state without using any information about race. Like in the race-blind simulation, I created a total of 10,000 plans (see Appendix B for details).

B.1. Analysis of the Majority-Minority District

36. I find that all of the simulated plans use Birmingham as part of the MMD. In fact, many of the simulated plans split Jefferson County and incorporate the city of Birmingham into the MMD in a similar way to the enacted plan. In addition, all of the simulated plans split Tuscaloosa County and within this county draw district boundaries similar to those in the enacted plan.

37. The key difference between the enacted plan and simulated plans is how Montgomery County is treated. The enacted plan packs an unnecessarily large number of Black voters into the MMD, i.e., District 7, when compared to the simulated plans. Specifically, the enacted plan splits the City of Montgomery into two and includes its western part along with its northern and southern environs into the MMD. In contrast, a majority (62.2%) of the simulated plans do not split Montgomery County at all and instead assign the whole county to a non-MMD. Moreover, even in 37.8% of the simulated plans that split Montgomery County, a much smaller part of the

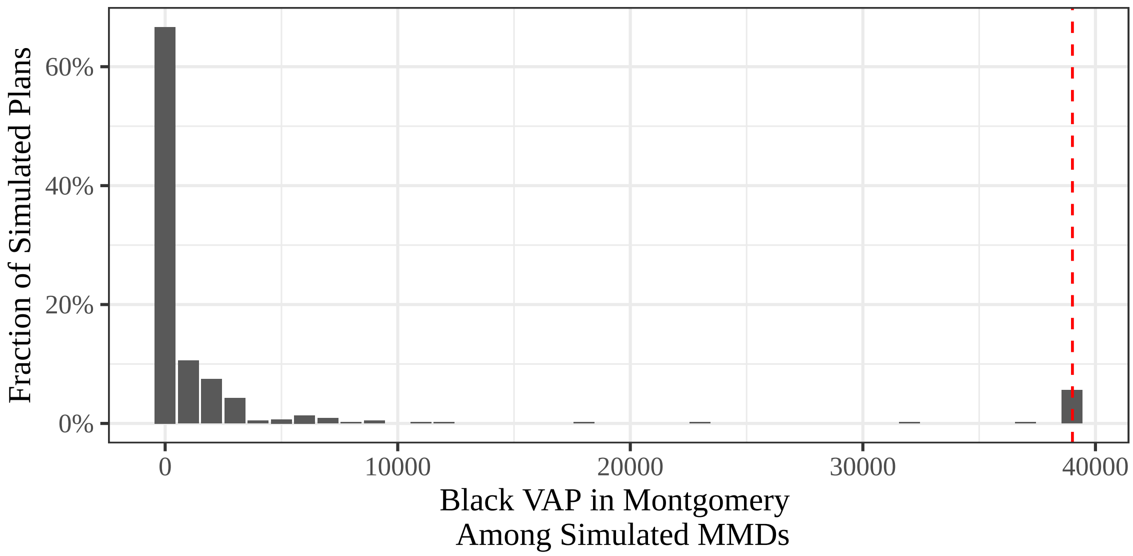

Figure 4: Black voting age population (BVAP) in Montgomery among each simulated majority-minority district (MMD). The enacted plan (red) places considerably more Black population in Montgomery than most simulated MMDs.

county's population gets assigned to the MMD.

38. Figure 4 shows the distribution of the BVAP in Montgomery County that is assigned to the MMD across the simulated plans. The enacted plan (red dashed line) assigns about 39,000 Black residents of voting age to the MMD. In contrast, the simulated plans include a much smaller percentage of BVAP of Montgomery County in the MMD. The distribution for the simulated plans is highly skewed with a large spike at zero because a majority of the simulated plans do not assign any part of Montgomery County to the MMD and instead keep Montgomery County as a whole. And, even when the MMD incorporates a part of Montgomery County in 37.8% of the simulated plans, it includes much less than 4,000 Black residents of voting age most of the time as opposed to 39,000 in the enacted plan.

39. Figure 5 shows which parts of Montgomery County, if any, are likely to be included in the MMD under the simulated plans. In this map, a precinct with darker shade means that it is part of the MMD in a greater number of simulated plans. Consistent with the finding above, most of Montgomery County has almost zero chance of being part of the MMD. The only area that is somewhat likely to be included in the MMD is the western edge of the City of Montgomery. But,

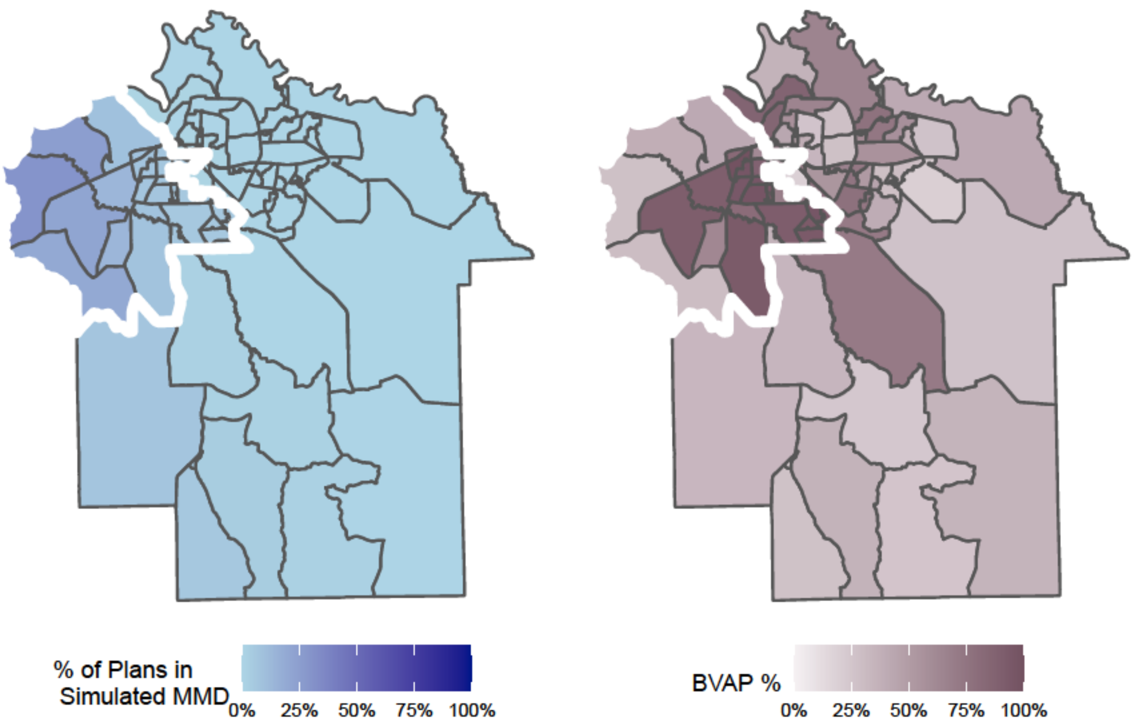

Figure 5: The fraction of times that each Montgomery precinct was assigned to a simulated majority-minority district compared to the enacted plan (white) on left, and the black voting age population share of each precinct in Montgomery county on right.

this area is much smaller than the area that is part of the MMD under the enacted plan as delineated by the white line.

40. In sum, the above analysis demonstrates that the enacted plan places Black voters who live in Montgomery County into District 7 in a manner that suggests race was a predominant factor in drawing district boundaries. In contrast, most of the simulated plans place none or few of these voters in the MMD.

B.2. Analysis of the Second Highest BVAP District

41. The consequence of packing Black voters who live in Montgomery County into the MMD is that it leaves fewer Black voters for other districts. Figure 6 shows the distribution of BVAP proportion for the district that has the second highest BVAP proportion under each simulated plan. Note that under more than 90% of the simulated plans, District 2 has the second highest BVAP proportion. When compared to the enacted plan (represented by the red dashed line), under

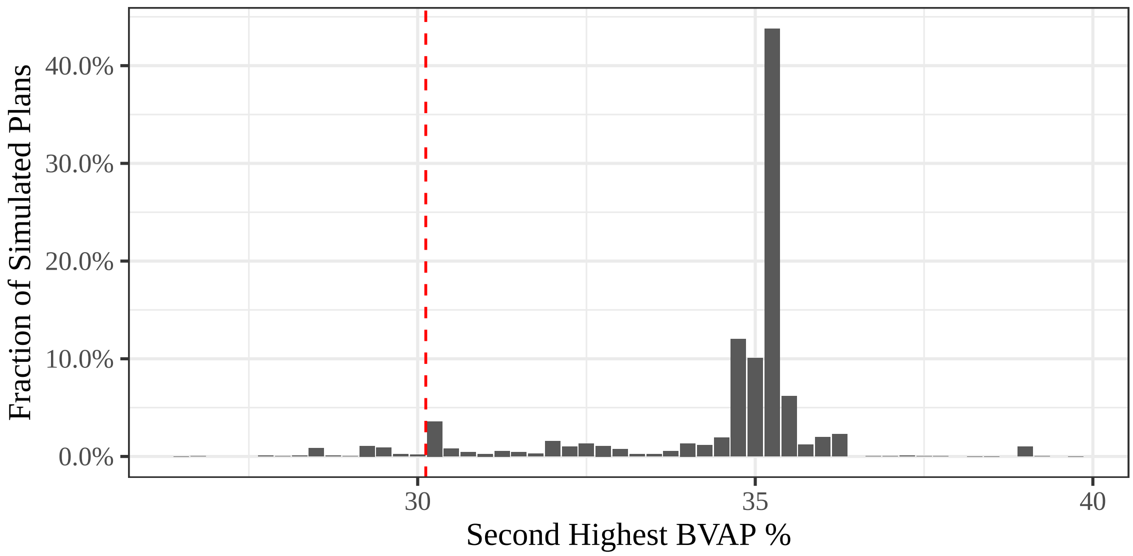

Figure 6: The second highest Black voting age population (BVAP) proportion (after the simulated majority-minority district) in each simulated plan. The vast majority of simulated plans have greater BVAP than the enacted (red).

the simulated plans, this district has a much higher BVAP proportion with the maximum value of 39.7%. Although all of non-MMD districts were generated without using any information about race, the simulation plan has, on average, the second highest district-level BVAP proportion at 34.5%, which is 4.4 percentage point higher than the corresponding BVAP proportion under the enacted plan (30.1%). Only 3.7% of the simulated plans have the second highest district-level BVAP proportion to be less than the one for the enacted plan (30.1%).

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

Executed, this day, December 10, 2021, in Cambridge, Massachusetts.

Kosuke Imai, Ph.D.

VI. APPENDIX

A. Introduction to Redistricting Simulation

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

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

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

4. In addition, the algorithms ensure that all of the sampled plans (a) are geographically contiguous, and (b) have a population which deviates by no more than a specified amount

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

from a target population.

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

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

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

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

B. Implementation Details

B.1. Race-blind simulation analysis

9. In my race-blind simulation analysis, I use the SMC algorithm for a couple of reasons. First, unlike the MCMC algorithms, the SMC algorithm generates nearly independent samples, leading to a diverse set of redistricting plans that satisfy the specified constraints. Second, the SMC algorithm avoids splitting political subdivision boundaries where possible, an important consideration in the case of Alabama.

10. Article II(b) of the Reapportionment Committee Redistricting Guidelines (hereafter *the Guidelines*) states "Congressional districts shall have minimal population deviation." I selected the population deviation threshold of 0.5% given the fact that our primary unit of analysis is voting districts (VTD), the smallest geographical unit for which the election results are available. Although this means that the total population is not exactly equalized across the Congressional districts in my simulated plans, this level of population deviation (i.e., about 3,500 people) is too small to qualitatively change the conclusions of my analyses.

11. Article II(h) of the Guidelines require districts to be "contiguous and reasonably compact". The SMC algorithm I use is designed to generate contiguous and relatively compact districts. Figure 7 of Appendix C shows that most of the simulated plans are more compact than the enacted plan according to the Polsby-Popper measure (Polsby and Popper 1991), which is a common metric of compactness used in the academic literature.

12. Article II(j)(iv) of the Guidelines call for minimizing the number of counties within each district. To achieve this, I instructed the algorithm to reduce the number of county splits. I do this in two ways. The first is instruct the algorithm to draw boundaries along county boundaries where feasible, which mechanically limits the maximum number of possible county spits. To further reduce the number of county splits, I also impose a small penalty against splitting counties into the probability distribution that governs the sampling process. The mathematical formulation of this constraint is $C_{\text{splits}} n_{\text{splits}}$, where n_{splits} is the number of splits for a given plan or portion of a plan and C_{splits} is a parameter, which controls the strength of the constraint. I set $C_{\text{splits}} = 1$, which is balanced with the incumbency constraint (discussed in the next paragraph) as the maximum integer

value without sacrificing the sampling efficiency and sample diversity. Figure 9 of Appendix D shows that the simulated plans have fewer or equal number of county splits than the enacted plan, which splits a total of 6 counties.

13. Article II(j)(i) of the Guidelines state that "Contests between incumbents will be avoided whenever possible." Indeed, the enacted plan includes no more than one incumbent in each district. I follow this decision and ensure that all simulated plans have the same property. This is achieved by adding a penalty to any sampled districts which pair incumbents, similar to the penalty used for reducing splits. The mathematical formulation of this constraint is analogous to that for splits, $C_{\text{pair}} n_{\text{pair}}$, where n_{pair} is the number of incumbents paired for a given plan or portion of a plan and again C_{pair} is a parameter which controls the strength of the constraint. I set $C_{\text{pair}} = 2$ to ensure that I can sample plans without incumbent pairings in a reasonable portion of the original sample. This value is balanced with C_{splits} to ensure that the final sample is diverse. As this is probability-based, I sample 50,000 plans and reject those which still pair incumbents. Of the remaining plans, I take the first 10,000 which do not pair any incumbents and do not split any counties more than once. My list of incumbents does not include Representative Mo Brooks of the fifth Congressional district who plans to run for the Senate.

B.2. One-MMD simulation analysis

14. The one-MMD simulation analysis proceeds in two steps. First, I run the short-burst algorithm (Cannon et al. 2020) based on the merge-split type MCMC algorithm (Autry et al. 2020; Carter et al. 2019). I designed the algorithm so that it will find one majority-minority district (MMD) with the BVAP proportion between 50% and 51%, as instructed by counsel for the plaintiffs. Additionally, I instructed the algorithm to seek MMDs with few county splits. I do both by using the following mathematical criterion: $I_{\text{MMD}} - 0.2 f_{\text{splits}}$, where I_{MMD} is an indicator variable (1 if the plan has an MMD between 50 and 51% BVAP, 0 otherwise) for whether or not there is an MMD in the plan, and f_{splits} is the fraction of counties that are split. In the enacted plan, there is one MMD and 6 (out of 67) counties are split, creating a score of 0.982. Since within the MMD itself, there are 3 county splits (Jefferson, Tuscaloosa, and Montgomery), I seek an MMD

with 3 or fewer county splits. I instructed the short-burst algorithm to seek a score of 0.985, which would indicate plans that have an MMD and the limited number of county splits.

15. While this algorithm seeks plans that meet the score, I run it more times than the required number of plans so that I will have enough plans to analyze even in rare cases where the algorithm fails to converge. Specifically, I run this algorithm 650 times, from which 444 plans successfully meet this score, have no incumbent pairs, and create an MMD with 3 or fewer county splits. Once I obtain 444 MMDs with the desirable characteristics, I run the race-blind analysis on the rest of the state. Next, I simulate 10,000 plans created using these MMDs. To do this, I take each simulated MMD and use the Sequential Monte Carlo (SMC) simulation algorithm (McCartan and Imai 2020; Kenny et al. 2021) to generate the remaining districts in the rest of the state without using race information. I use the same constraints as in the earlier race-blind analysis in the SMC algorithm, to reduce the likelihood of incumbent pairs and limit the number of county splits. I place a slightly higher weight on each constraint, i.e., $C_{\text{splits}} = 3$, than in the race-blind analysis, because part of the map has already been accounted for in the creation of the MMD. Half of the county splits in the enacted map, i.e., 3 out of 6, come from the single MMD, so this makes for realistic comparison maps.

I aim to create 10,000 sample plans, and I again oversample so that I can remove maps from the analysis that do not meet the specified criteria above. Simulation algorithms are probabilistic, and it is possible to create maps which do not meet the criteria even when there is a weight placed on them. By oversampling, I can remove the plans which do not meet the criteria and still reach the targeted sample size of 10,000. Specifically, I randomly sample 300 of the 444 created MMDs. For each of these simulated MMDs, I run a race-blind analysis on the rest of the state by taking 75 independent draws of the SMC algorithm.

Finally, I adjust for oversampling by removing ultimate plans that do not meet the criteria. For example, a very small number of simulated plans (<1%) create 7 county splits, which are dropped from the analysis. I also drop any simulated plan that contains an incumbent pair, and take 50 independent draws from 200 randomly selected starting points, for a total of 10,000 plans.

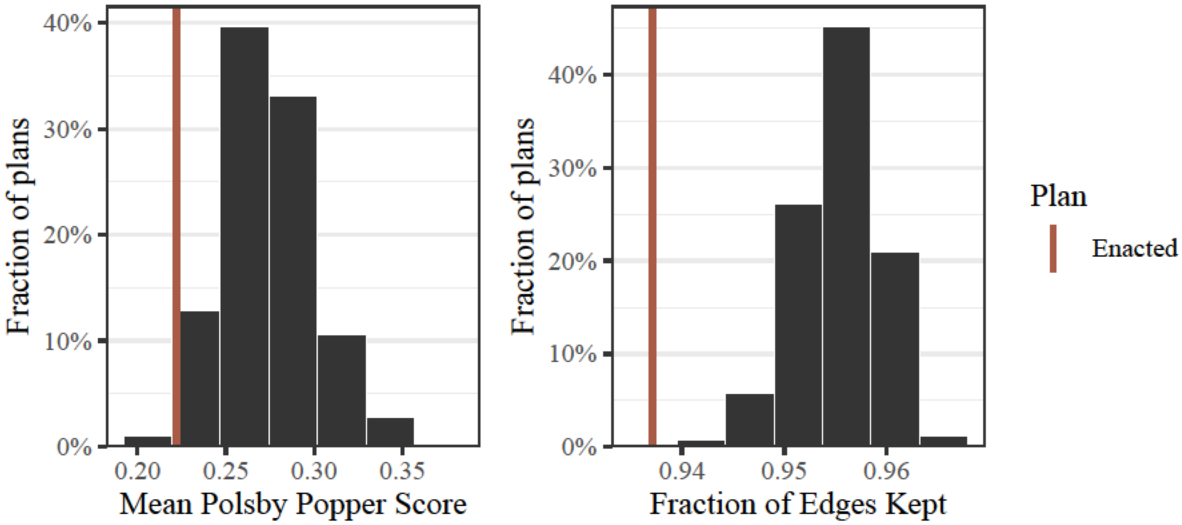

Figure 7: The compactness of the race-blind simulated plans according to two measures – the average Polsby-Popper compactness (left) and fraction of edges kept (right). In general, simulated plans are as compact or more compact than the enacted plan.

I take the same number of draws from each plan so that each of the generated MMDs has an equal weight in the final outcome.

C. Compactness of the Simulated Plans

16. I now show that the simulated plans are more compliant than the enacted plan. I use the average Polsby–Popper (Polsby and Popper 1991) and edge-removal (DeFord, Duchin, and Solomon 2021; McCartan and Imai 2020) scores, two commonly-used quantitative measures of district compactness. For the edge-removal compactness, I present the fraction of edge kept so that like the Polsby–Popper score, a greater value implies a higher level of compactness. Figure 7 shows that according to these two measures, almost all of the race-blind simulated plans are more compact the enacted plan.

17. Figure 8 also shows that according to the Polsby–Popper and edge-removal scores, almost all of the one-MMD simulated plans are more compact than the enacted plan.

D. County Splits of the Simulated Plans

18. Figure 9 compares the number of counties split between the race-blind simulated plans and the enacted plan (red). The race-blind simulated plans split fewer counties than the

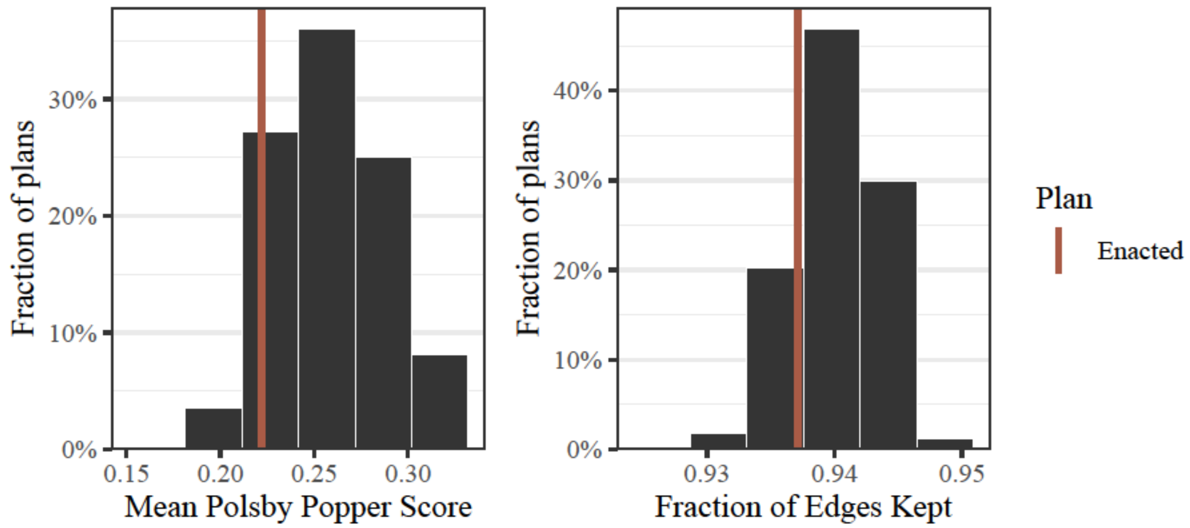

Figure 8: The compactness of the one-MMD simulated plans according to two measures – Polsby-Popper compactness (left) and fraction of edges kept (right). In general, simulated plans are as compact or more compact than the enacted plan.

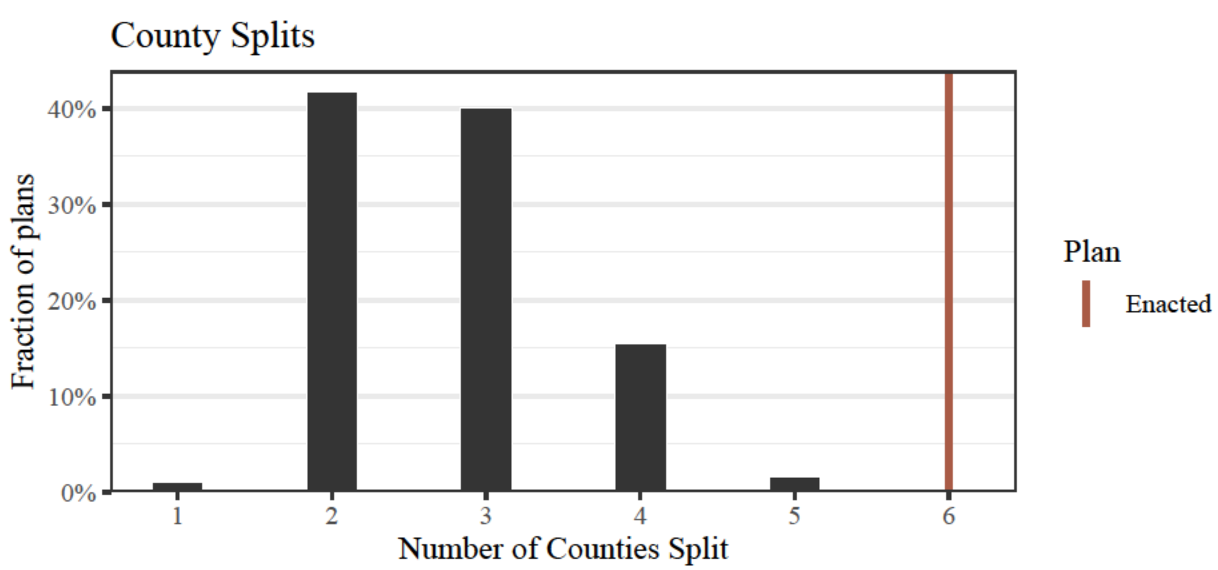

Figure 9: The number of counties split in the simulated plans (histogram) and in the enacted plan (red line). A county is deemed as split if any of its precincts are assigned to different districts. The left plot presents the total number of split counties while the right plot shows the number of counties that are split into more than two districts.

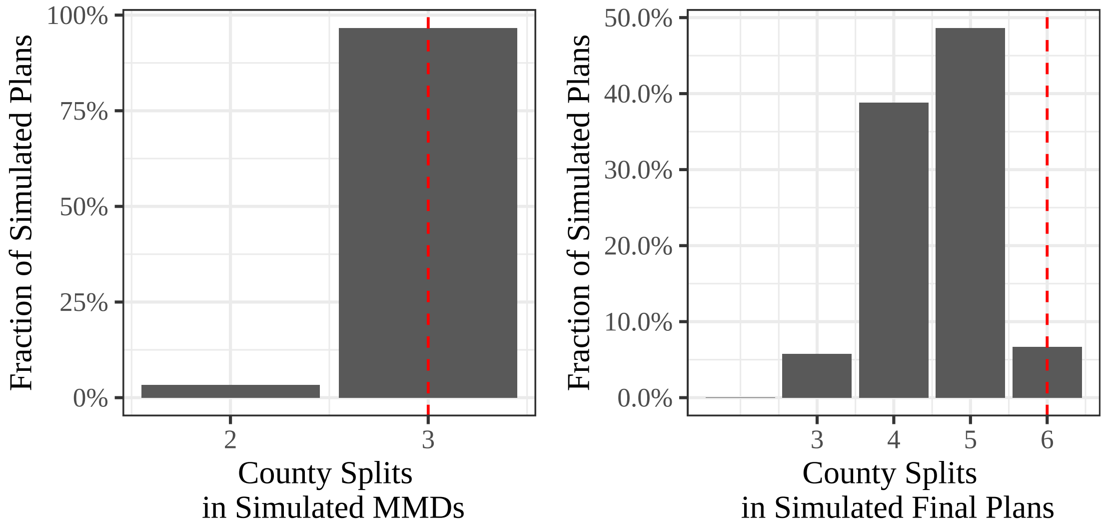

Figure 10: The number of county splits in each simulated majority-minority district (left) and in the complete simulated plans (right). All simulated plans used in the analysis have the same number or fewer splits than the enacted plan (red).

enacted plan.

19. For the one-MMD simulation analysis, Figure 10 presents the number of counties split within the MMD (left plot) and the total number of counties split (right plot). The figure shows that when compared to the enacted plan, all of the one-MMD simulated plans have fewer or equal number of county splits within the MMD and across all districts.

E. References and Materials Considered

E.1. Data Sources

20. The 2016, 2018, and 2020 precinct-level shapefiles came from the Voting and Election Science Team. Those shapefiles were joined to 2016, 2018, and 2020 precinct-level election returns from the Alabama Secretary of State's office, which were processed and cleaned by OpenElections.

21. The 2014 precinct-level election returns came from the Alabama Secretary of State's office, and, after cleaning, were joined those to the 2016 precinct-level shapefile acquired from the Voting and Election Science Team. Since absentee and provisional vote is reported at the county level, the county-level absentee and provisional votes for each candidate were distributed

to the precincts in the county, proportional to the share of the candidate's vote total in the county that was reported from each precinct.

22. The 2020 Census Block shapefiles, total population by race and ethnicity, and voting age population by race and ethnicity were obtained directly from the Census FTP portal. The VTD block assignment files, congressional district block assignment files, state house district block assignment files, and state senate district block assignment files came from the Census website. The draft congressional, state house, and state senate plans came from a member of the Alabama Permanent Legislative Committee on Reapportionment.

23. For datasets that were on the 2020 census block level (total population, voting age population, VTD assignment, congressional district assignment, state house district assignment, and state senate district assignment), these datasets were joined to the 2020 Census block shapefile.

24. For datasets that were not on the level of the census block (2014, 2016, 2017, 2018, and 2020 election returns – precinct), they were disaggregated down to the 2020 census block level. Then, they were joined to the 2020 Census block shapefile. The full block-level dataset was aggregated up to the level of the 2020 voting districts, taking into account (a) discontiguities in voting districts and (b) splits of voting districts by any of the implemented and proposed plans.

E.2. References

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EXHIBIT A

Curriculum Vitae

Kosuke Imai

Curriculum Vitae

November 2021

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Education

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

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

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

Positions

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

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

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

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

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

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

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

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

Honors and Awards

1. Invited to read "Experimental Evaluation of Computer-Assisted Human Decision-Making: Application to Pretrial Risk Assessment Instrument." before the Royal Statistical Society Research Section, London (2021).

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

3. *Statistical Software Award* for developing statistical software that makes a significant research contribution, for "fastLink: Fast Probabilistic Record Linkage," awarded by the Society for Political Methodology (2021).

4. *Highly Cited Researcher* (cross-field category) for "production of multiple highly cited papers that rank in the top 1% by citations for field and year in Web of Science," awarded by Clarivate Analytics (2018, 2019, 2020).

5. *President*, The Society for Political Methodology (2017–2019). *Vice President and President-elect* (2015–2017).

6. *Elected Fellow*, The Society for Political Methodology (2017).

7. *The Nils Petter Gleditsch Article of the Year Award* (2017), awarded by *Journal of Peace Research*.

8. *Statistical Software Award* for developing statistical software that makes a significant research contribution, for "mediation: R Package for Causal Mediation Analysis," awarded by the Society for Political Methodology (2015).

9. *Outstanding Reviewer Award* for Journal of Educational and Behavioral Statistics, given by the American Educational Research Association (2014).

10. *The Stanley Kelley, Jr. Teaching Award*, given by the Department of Politics, Princeton University (2013).

11. *Pi Sigma Alpha Award* for the best paper presented at the 2012 Midwest Political Science Association annual meeting, for "Explaining Support for Combatants during Wartime: A Survey Experiment in Afghanistan," awarded by the Midwest Political Science Association (2013).

12. Invited to read "Experimental Designs for Identifying Causal Mechanisms" before the Royal Statistical Society Research Section, London (2012).

13. Inaugural recipient of the *Emerging Scholar Award* for a young scholar making exceptional contributions to political methodology who is within ten years of their terminal degree, awarded by the Society for Political Methodology (2011).

14. *Political Analysis Editors' Choice Award* for an article providing an especially significant contribution to political methodology, for "Estimation of Heterogeneous Treatment Effects from Randomized Experiments, with Application to the Optimal Planning of the Get-out-the-vote Campaign," awarded by the Society for Political Methodology and Oxford University Press (2011).

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

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

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

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

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

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

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

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

Publications in English

Book

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

Stata version (2021) with Lori D. Bougher.

Tidyverse version (forthcoming) with Nora Webb Williams

Refereed Journal Articles

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

2. Imai, Kosuke, Zhichao Jiang, D. James Greiner, Ryan Halen, and Sooahn Shin. "Experimental Evaluation of Computer-Assisted Human Decision-Making: Application to Pretrial Risk Assessment Instrument." (with discussion) *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Forthcoming. To be read before the Royal Statistical Society.

3. Imai, Kosuke, In Song Kim, and Erik Wang. "Matching Methods for Causal Inference with Time-Series Cross-Sectional Data." *American Journal of Political Science*, Forthcoming.

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

5. de la Cuesta, Brandon, Naoki Egami, and Kosuke Imai."Experimental Design and Statistical Inference for Conjoint Analysis: The Essential Role of Population Distribution." *Political Analysis*, Forthcoming.

6. Kenny, Christopher T., Shiro Kuriwaki, Cory McCartan, Evan Rosenman, Tyler Simko, and Kosuke Imai. (2021). "The Use of Differential Privacy for Census Data and its Impact on Redistricting: The Case of the 2020 U.S. Census." *Science Advances*, Vol. 7, No. 7 (October), pp. 1-17.

7. Imai, Kosuke and James Lo. (2021). " Robustness of Empirical Evidence for the Democratic Peace: A Nonparametric Sensitivity Analysis." *International Organization*, Vol. 75, No. 3 (Summer), pp. 901–919.

8. Imai, Kosuke, Zhichao Jiang, and Anup Malani. (2021). "Causal Inference with Interference and Noncompliance in the Two-Stage Randomized Experiments." *Journal of the American Statistical Association*, Vol. 116, No. 534, pp. 632-644.

9. Imai, Kosuke, and In Song Kim. (2021). "On the Use of Two-way Fixed Effects Regression Models for Causal Inference with Panel Data." *Political Analysis*, Vol. 29, No. 3 (July), pp. 405–415.

10. Imai, Kosuke and Zhichao Jiang. (2020). "Identification and Sensitivity Analysis of Contagion Effects with Randomized Placebo-Controlled Trials." *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, Vol. 183, No. 4 (October), pp. 1637–1657.

11. Fifield, Benjamin, Michael Higgins, Kosuke Imai, and Alexander Tarr. (2020). "Automated Redistricting Simulation Using Markov Chain Monte Carlo." *Journal of Computational and Graphical Statistics*, Vol. 29, No. 4, pp. 715–728.

12. Fifield, Benjamin, Kosuke Imai, Jun Kawahara, and Christopher T. Kenny. (2020). "The Essential Role of Empirical Validation in Legislative Redistricting Simulation." *Statistics and Public Policy*, Vol. 7, No 1, pp. 52–68.

13. Ning, Yang, Sida Peng, and Kosuke Imai. (2020). "Robust Estimation of Causal Effects via High-Dimensional Covariate Balancing Propensity Score." *Biometrika*, Vol. 107, No. 3 (September), pp. 533—554.

14. Chou, Winston, Kosuke Imai, and Bryn Rosenfeld. (2020). "Sensitive Survey Questions with Auxiliary Information." *Sociological Methods & Research*, Vol. 49, No. 2 (May), pp. 418–454.

15. Imai, Kosuke, Gary King, and Carlos Velasco Rivera. (2020). "Do Nonpartisan Programmatic Policies Have Partisan Electoral Effects? Evidence from Two Large Scale Randomized Experiments." *Journal of Politics*, Vol. 82, No. 2 (April), pp. 714–730.

16. Zhao, Shandong, David A. van Dyk, and Kosuke Imai. (2020). "Propensity-Score Based Methods for Causal Inference in Observational Studies with Non-Binary Treatments." *Statistical Methods in Medical Research*, Vol. 29, No. 3 (March), pp. 709–727.

17. Lyall, Jason, Yang-Yang Zhou, and Kosuke Imai. (2020). "Can Economic Assistance Shape Combatant Support in Wartime? Experimental Evidence from Afghanistan." *American Political Science Review*, Vol. 114, No. 1 (February), pp. 126–143.

18. Kim, In Song, Steven Liao, and Kosuke Imai. (2020). "Measuring Trade Profile with Granular Product-level Trade Data." *American Journal of Political Science*, Vol. 64, No. 1 (January), pp. 102-117.

19. Enamorado, Ted and Kosuke Imai. (2019). "Validating Self-reported Turnout by Linking Public Opinion Surveys with Administrative Records." *Public Opinion Quarterly*, Vol. 83, No. 4 (Winter), pp. 723—748.

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

21. Egami, Naoki, and Kosuke Imai. "Causal Interaction in Factorial Experiments: Application to Conjoint Analysis." *Journal of the American Statistical Association*, Vol. 114, No. 526 (June), pp. 529-540.

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27. Imai, Kosuke, James Lo, and Jonathan Olmsted. (2016). "Fast Estimation of Ideal Points with Massive Data." *American Political Science Review*, Vol. 110, No. 4 (December), pp. 631–656.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

67. Imai, Kosuke, and David A. van Dyk. (2005). "A Bayesian Analysis of the Multinomial Probit Model Using Marginal Data Augmentation." *Journal of Econometrics*, Vol. 124, No. 2 (February), pp. 311–334.

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

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

Invited Contributions

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

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

3. de la Cuesta, Brandon and Kosuke Imai. (2016). "Misunderstandings about the Regression Discontinuity Design in the Study of Close Elections." *Annual Review of Political Science*, Vol. 19, pp. 375–396.

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

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

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

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

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

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

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

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

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

13. Imai, Kosuke, Gary King, and Clayton Nall. (2009). "Rejoinder: Matched Pairs and the Future of Cluster-Randomized Experiments." *Statistical Science*, Vol. 24, No. 1 (February), pp. 65–72.

14. Imai, Kosuke. (2003). "Review of Jeff Gill's *Bayesian Methods: A Social and Behavioral Sciences Approach*," *The Political Methodologist*, Vol. 11 No. 1, 9–10.

Refereed Conference Proceedings

1. Svyatkovskiy, Alexey, Kosuke Imai, Mary Kroeger, and Yuki Shiraito. (2016). "Large-scale text processing pipeline with Apache Spark," *IEEE International Conference on Big Data*, Washington, DC, pp. 3928-3935.

Other Publications and Manuscripts

1. Goldstein, Daniel, Kosuke Imai, Anja S. Göritz, and Peter M. Gollwitzer. (2008). "Nudging Turnout: Mere Measurement and Implementation Planning of Intentions to Vote."

2. Ho, Daniel E. and Kosuke Imai. (2004). " The Impact of Partisan Electoral Regulation: Ballot Effects from the California Alphabet Lottery, 1978–2002." Princeton Law & Public Affairs Paper No. 04-001; Harvard Public Law Working Paper No. 89.

3. Imai, Kosuke. (2003). "Essays on Political Methodology," *Ph.D. Thesis.* Department of Government, Harvard University.

4. Imai, Kosuke, and Jeremy M. Weinstein. (2000). "Measuring the Economic Impact of Civil War," Working Paper Series No. 51, Center for International Development, Harvard University.

Selected Manuscripts

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

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

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

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

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

6. Papadogeorgou, Georgia, Kosuke Imai, Jason Lyall, and Fan Li. "Causal Inference with Spatio-temporal Data: Estimating the Effects of Airstrikes on Insurgent Violence in Iraq."

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

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

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

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

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

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

Publications in Japanese

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

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

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

Statistical Software

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

External Research Grants

Principal Investigator

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

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

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

4. The Alfred P. Sloan Foundation (2020–2022). "Causal Inference with Complex Treatment Regimes: Design, Identification, Estimation, and Heterogeneity." (Economics Program;

2020–13946) Co-Principal Investigator (with Francesca Dominici and Jose Zubizarreta) $996,299

5. Facebook Research Grant (2018). $25,000.
6. National Science Foundation (2016–2021). "Collaborative Conference Proposal: Support for Conferences and Mentoring of Women and Underrepresented Groups in Political Methodology." (Methodology, Measurement and Statistics and Political Science Programs; SES–1628102) Principal Investigator (with Jeffrey Lewis) $312,322. Supplement (SES–1831370) $60,000.
7. The United States Agency for International Development (2015–2017). "Unemployment and Insurgent Violence in Afghanistan: Evidence from the Community Development Program." (AID–OAA–A–12–00096) Principal Investigator (with Jason Lyall) $188,037
8. The United States Institute of Peace (2015–2016). "Assessing the Links between Economic Interventions and Stability: An impact evaluation of vocational and skills training in Kandahar, Afghanistan," Principal Investigator (with David Haines, Jon Kurtz, and Jason Lyall) $144,494.
9. Amazon Web Services in Education Research Grant (2014). Principal Investigator (with Graeme Blair and Carlos Velasco Rivera) $3,000.
10. Development Bank of Latin America (CAF) (2013). "The Origins of Citizen Support for Narcos: An Empirical Investigation," Principal Investigator (with Graeme Blair, Fabiana Machado, and Carlos Velasco Rivera). $15,000.
11. The International Growth Centre (2011–2013). "Poverty, Militancy, and Citizen Demands in Natural Resource-Rich Regions: Randomized Evaluation of the Oil Profits Dividend Plan for the Niger Delta" (RA–2010–12–013). Principal Investigator (with Graeme Blair). $117,116.
12. National Science Foundation, (2009–2012). "Statistical Analysis of Causal Mechanisms: Identification, Inference, and Sensitivity Analysis," (Methodology, Measurement, and Statistics Program and Political Science Program; SES–0918968). Principal Investigator. $97,574.
13. National Science Foundation, (2009–2011). "Collaborative Research: The Measurement and Identification of Media Priming Effects in Political Science," (Methodology, Measurement, and Statistics Program and Political Science Program; SES–0849715). Principal Investigator (with Nicholas Valentino). $317,126.
14. National Science Foundation, (2008–2009). "New Statistical Methods for Randomized Experiments in Political Science and Public Policy," (Political Science Program; SES–0752050). Principal Investigator. $52,565.
15. National Science Foundation, (2006–2009). "Collaborative Research: Generalized Propensity Score Methods," (Methodology, Measurement and Statistics Program; SES–0550873). Principal Investigator (with Donald B. Rubin and David A. van Dyk). $460,000.
16. The Telecommunications Advancement Foundation, (2004). "Analyzing the Effects of Party Webpages on Political Opinions and Voting Behavior," Principal Investigator (with Naoko Taniguchi and Yusaku Horiuchi). $12,000.

Adviser and Statistical Consultant

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

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

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

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

Invited Short Courses and Outreach Lectures

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

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

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

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

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

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

Selected Presentations

1. Distinguished speaker, Harvard College Summer Program for Undergraduates in Data Science, 2021.
2. Keynote speaker, Kansas-Western Missouri Chapter of the American Statistical Association, 2021.
3. Invited plenary panelist, Association for Computing Machinery Conference on Fairness, Accountability, and Transparency (ACM FAccT) 2021.
4. Keynote speaker, Taiwan Political Science Association, 2020.
5. Keynote speaker, Boston Japanese Researchers Forum, Massachusetts Institute of Technology, 2020.
6. Keynote speaker, Causal Mediation Analysis Training Workshop, Mailman School of Public Health, Columbia University, 2020.
7. Keynote speaker, Special Workshop on Evidence-based Policy Making. World Economic Forum, Centre for the Fourth Industrial Revolution, Japan, 2020.
8. Distinguished speaker, Institute for Data, Systems, and Society. Massachusetts Institute of Technology, 2019.
9. Keynote speaker, The Harvard Experimental Political Science Graduate Student Conference, Harvard University, 2019.
10. Invited speaker, Beyond Curve Fitting: Causation, Counterfactuals, and Imagination-based AI. Association for the Advancement of Artificial Intelligence, Spring Symposium, Stanford University, 2019.
11. Inaugural speaker, Causal Inference Seminar, Departments of Biostatistics and Statistics, Boston University, 2019.
12. Keynote speaker, The Second Latin American Political Methodology Meeting, Universidad de los Andes (Department of Political Science), 2018.
13. Keynote speaker, The First Latin American Political Methodology Meeting, Pontifical Catholic University of Chile (Department of Political Science), 2017.
14. Keynote speaker, Workshop on Uncovering Causal Mechanisms, University of Munich (Department of Economics), 2016.
15. Keynote speaker, The National Quality Registry Research Conference, Stockholm, 2016.
16. Keynote speaker, The UK-Causal Inference Meeting, University of Bristol (School of Mathematics), 2015.
17. Keynote speaker, The UP-STAT Conference, the Upstate Chapters of the American Statistical Association, 2015.
18. Keynote speaker, The Winter Conference in Statistics, Swedish Statistical Society and Umeå University (Department of Mathematics and Mathematical Statistics), 2015.

19. Inaugural invited speaker, The International Methods Colloquium, Rice University, 2015.
20. Invited speaker, The International Meeting on Experimental and Behavioral Social Sciences, University of Oxford (Nuffield College), 2014.
21. Keynote speaker, The Annual Conference of Australian Society for Quantitative Political Science, University of Sydney, 2013.
22. Keynote speaker, The Graduate Student Conference on Experiments in Interactive Decision Making, Princeton University. 2008.

Conferences Organized

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

Teaching

Courses Taught at Harvard

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

Courses Taught at Princeton

1. POL 245 Visualizing Data: exploratory data analysis, graphical statistics, data visualization
2. POL 345 Quantitative Analysis and Politics: a first course in quantitative social science
3. POL 451 Statistical Methods in Political Science: basic probability and statistical theory, their applications in the social sciences
4. POL 502 Mathematics for Political Science: real analysis, linear algebra, calculus
5. POL 571 Quantitative Analysis I: probability theory, statistical theory, linear models
6. POL 572 Quantitative Analysis II: intermediate applied statistics

7. POL 573 Quantitative Analysis III: advanced applied statistics

8. POL 574 Quantitative Analysis IV: advanced applied statistics with various topics including Bayesian statistics and causal inference

9. Reading Courses: basic mathematical probability and statistics, applied bayesian statistics, spatial statistics

Advising

Current Students

1. Soubhik Barari (Government)

2. Adam Breuer (Computer Science and Government). To be Assistant Professor, Department of Government and Department of Computer Science, Dartmouth College

3. Jacob Brown (Government)

4. Ambarish Chattopadhyay (Statistics)

5. Shusei Eshima (Government)

6. Georgina Evans (Government)

7. Dae Woong Ham (Statistics)

8. Christopher T. Kenny (Government)

9. Michael Lingzhe Li (MIT, Operations Research Center)

10. Jialu Li (Government)

11. Cory McCartan (Statistics)

12. Sayumi Miyano (Princeton, Politics)

13. Sun Young Park (Government)

14. Casey Petroff (Political Economy and Government)

15. Averell Schmidt (Kennedy School)

16. Sooahn Shin (Government)

17. Tyler Simko (Government)

18. Soichiro Yamauchi (Government)

19. Yi Zhang (Statistics)

Current Postdocs

1. Eli Ben-Michael

2. Evan Rosenman

Former Students

1. Alexander Tarr (Ph.D. in 2021, Department of Electrical and Computer Engineering, Princeton University; Dissertation Committee Chair)

2. Connor Jerzak (Ph.D. in 2021, Department of Government, Harvard University). Postdoctoral Fellow, Linkoping University. To be Assistant Professor, Department of Government, University of Texas, Austin

3. Shiro Kuriwaki (Ph.D. in 2021, Department of Government, Harvard University). Postdoctoral Fellow, Stanford University. To be Assistant Professor, Department of Political Science, Yale University

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

5. Diana Stanescu (Ph.D. in 2020, Department of Politics, Princeton University). Postdoctoral Fellow, Stanford University

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

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

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

9. Naoki Egami (Ph.D. in 2020, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, Columbia University

10. Brandon de la Cuesta (Ph.D. in 2019, Department of Politics, Princeton University). Postdoctoral Fellow, Center on Global Poverty and Development, Stanford University

11. Yang-Yang Zhou (Ph.D. in 2019, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, University of British Columbia

12. Winston Chou (Ph.D. in 2019, Department of Politics, Princeton University). Senior Data Scientist at Apple

13. Ted Enamorado (Ph.D. in 2019, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, Washington University in St. Louis

14. Benjamin Fifield (Ph.D. in 2018, Department of Politics, Princeton University; Dissertation Committee Chair). Data Scientist, American Civil Liberties Union

15. Tyler Pratt. (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Department of Political Science, Yale University

16. Romain Ferrali (Ph.D. in 2018, Department of Politics, Princeton University). Assistant Professor, Aix-Marseille School of Economics

17. Julia Morse (Ph.D. in 2017, Woodrow Wilson School, Princeton University). Assistant Professor, Department of Political Science, University of California, Santa Barbara

18. Yuki Shiraito (Ph.D. in 2017, Department of Politics, Princeton University; Dissertation Committee Chair). Assistant Professor, Department of Political Science, University of Michigan

19. Carlos Velasco Rivera (Ph.D. in 2016, Department of Politics, Princeton University). Research Scientist, Facebook

20. Gabriel Lopez Moctezuma (Ph.D. in 2016, Department of Politics, Princeton University). Assistant Professor, Division of the Humanities and Social Sciences, California Institute of Technology

21. Graeme Blair (Ph.D. in 2016, Department of Politics, Princeton University). Assistant Professor, University of California, Los Angeles

22. Jaquilyn R. Waddell Boie (Ph.D. in 2015, Department of Politics, Princeton University). Private consultant

23. Scott Abramson (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, University of Rochester

24. Michael Barber (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Brigham Young University

25. In Song Kim (Ph.D. in 2014, Department of Politics, Princeton University). Associate Professor, Department of Political Science, Massachusetts Institute of Technology

26. Alex Ruder (Ph.D. in 2014, Department of Politics, Princeton University). Senior Community Economic Development Advisor, Federal Reserve Bank of Atlanta

27. Meredith Wilf (Ph.D. in 2014, Department of Politics, Princeton University). Senior Director, Capital Rx

28. Will Bullock. (Ph.D. candidate, Department of Politics, Princeton University). Senior Researcher, Facebook

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

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

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

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

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

Former Predocs and Postdocs

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

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

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

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

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

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

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

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

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

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

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

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

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

Editorial and Referee Service

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

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

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

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

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

University and Departmental Committees

Harvard University

Department of Government

Member, Curriculum and Educational Policy Committee (2020–2021)

Member, Second-year Progress Committee (2019–2020)

Member, Graduate Placement Committee (2019–2020)

Member, Graduate Admissions Committee (2018–2019)

Member, Graduate Poster Session Committee (2018–2019)

Department of Statistics

Chair, Senior Faculty Search Committee (2021–2022)

Member, Junior Faculty Search Committee (2018–2019)

Member, Second-year Progress Committee (2018–2019, 2020–2021)

Princeton University

University

Executive Committee Member, Program in Statistics and Machine Learning (2013–2018)

Executive Committee Member, Committee for Statistical Studies (2011-2018)

Member, Organizing Committee, Retreat on Data and Information Science at Princeton (2016)

Member, Council of the Princeton University Community (2015)

Member, Search Committee for the Dean of College (2015)

Member, Committee on the Library and Computing (2013–2016)

Member, Committee on the Fund for Experimental Social Science (2013–2018)

Member, Personally Identifiable Research Data Group (2012–2018)

Member, Research Computing Advisory Group (2013–2018)

Member, Task Force on Statistics and Machine Learning (2014–2015)

Department of Politics

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

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

Chair, Reappointment Committee (2015–2016)

Member, Diversity Initiative Committee (2014–2015)

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

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

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

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

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

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

Member, Graduate Admissions Committee (2012–2013)
Member, Reappointment Committee (2014–2016)
Member, Space Committee (2014–2016)
Member, Undergraduate Curriculum Committee (2014–2015)
Member, Undergraduate Exam Committee (2007–2008)
Member, Undergraduate Thesis Prize Committee (2005–2006, 2008–2011)

Center for Statistics and Machine Learning

Executive Committee Member (2016–2018)
Member, Search Committee (2015–2017)

Services to the Profession

National Academies of Sciences, Engineering, and Medicine

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

National Science Foundation

Proposal Review Panel (2020)

The Society for Political Methodology

President (2017–2019)
Vice President and President Elect (2015–2017)
Annual Meeting Committee, Chair (2011)
Career Award Committee (2015–2017)
Program Committee for Annual Meeting (2012), Chair (2011)
Graduate Student Selection Committee for the Annual Meeting (2005), Chair (2011)
Miller Prize Selection Committee (2010–2011)
Statistical Software Award Committee (2009–2010)
Emerging Scholar Award Committee (2013)

American Statistical Association

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

Others

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

Memberships

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