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Appendix: A Reasonable Bias Approach to Gerrymandering: Using Automated Plan Generation to Evaluate Redistricting Proposals

Bruce E. Cain

Wendy K. Tam Cho

Yan Y. Liu

Emily R. Zhang

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APPENDIX: A REASONABLE BIAS APPROACH TO GERRYMANDERING: USING AUTOMATED PLAN GENERATION TO EVALUATE REDISTRICTING PROPOSALS

BRUCE E. CAIN,* WENDY K. TAM CHO,** YAN Y. LIU,*** AND
EMILY R. ZHANG****

Here, we present our findings, analogous to those on the efficiency gap in Part I.B of our Article published in the print edition of the *William & Mary Law Review*, on the other measures of partisan fairness.¹

I. SEATS-VOTES BIAS

The graphs below are based on maps drawn from PEAR that improve upon the current Minnesota congressional plan on each of the following dimensions: competitiveness, responsiveness, proportional representation, and the efficiency gap. The red bars indicate the range of scores that the maps produce on each of those measures. The blue bars represent the seats-votes bias scores of the maps produced in each graph. Again, the purpose of this is to determine

* Professor of Political Science, Stanford University; Spence and Cleone Eccles Family Director of the Bill Lane Center for the American West.

** Professor in the Departments of Political Science, Statistics, Mathematics, Asian American Studies, and the College of Law at the University of Illinois at Urbana-Champaign; Senior Research Scientist at the National Center for Supercomputing Applications; Faculty in the Illinois Informatics Institute; Affiliate of the Cline Center for Democracy, the Cyber-GIS Center for Advanced Digital and Spatial Studies, the Computational Science and Engineering Program, and the Program on Law, Behavior, and Social Science.

*** Senior Research Programmer, National Center for Supercomputing Applications, and the Department of Geography and Geographic Information Science at the University of Illinois at Urbana-Champaign.

**** PhD candidate at the Department of Political Science at Stanford University; Stanford Law School, J.D. 2016.

1. See Cain et al., *A Reasonable Bias Approach to Gerrymandering: Using Automated Plan Generation to Evaluate Redistricting Proposals*, 59 WM & MARY L. REV. 1521, 1540-47 (2018).

whether the maps that score higher than the current redistricting map in Minnesota on each of the measures in the graphs also score high on seat-vote bias. Overlap in the bars suggests that the measures capture similar features of the map, while distance between the bars suggests that the measures tap different features of partisan unfairness.

Figure 1. Comparing Bias Against Other Measures

Figure 1a. Bias v. Competitiveness

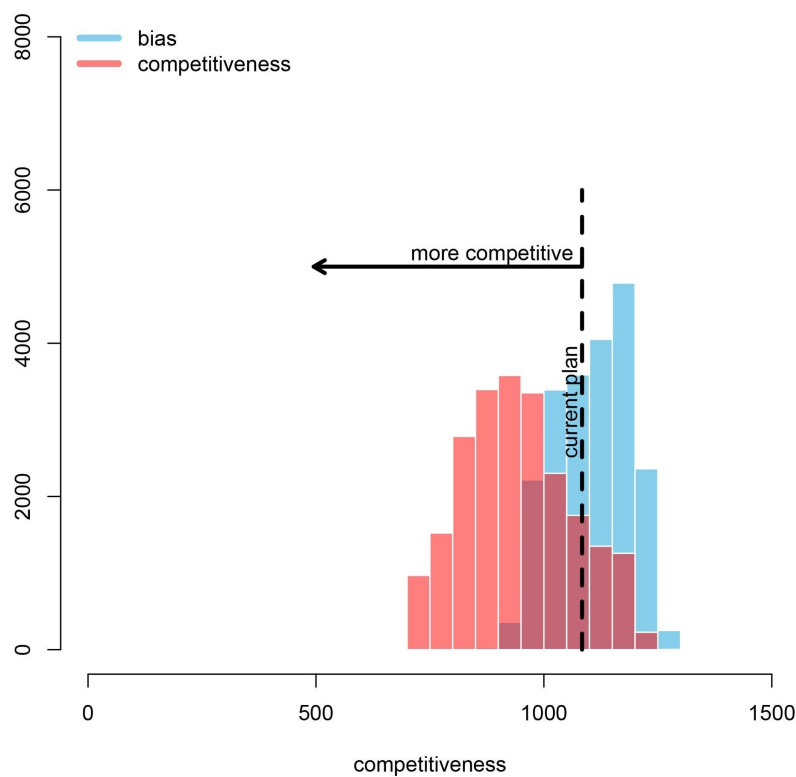


Figure 1b. Bias v. Responsiveness

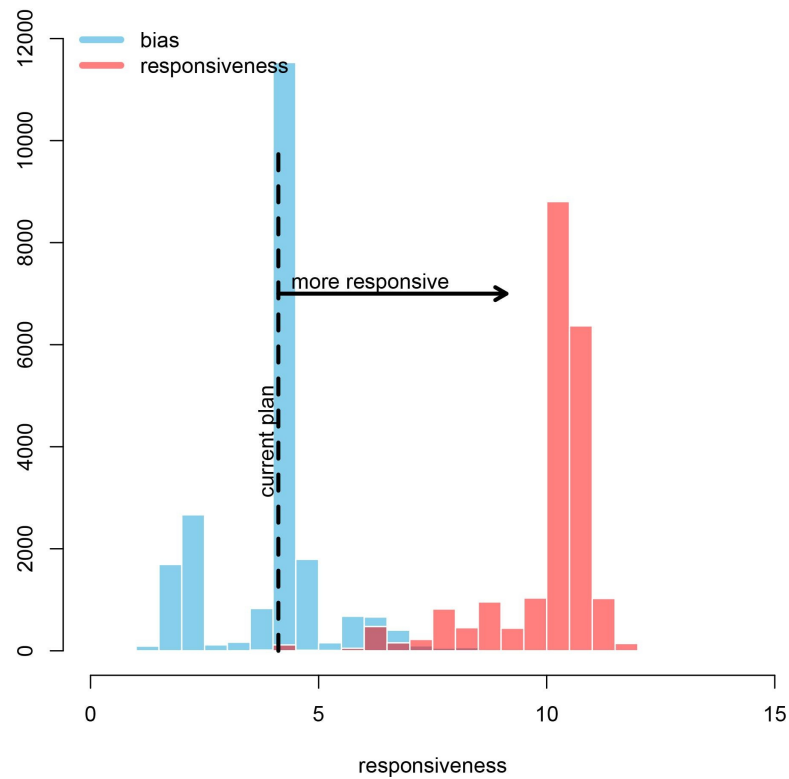


Figure 1c. Bias v. Proportional Representation

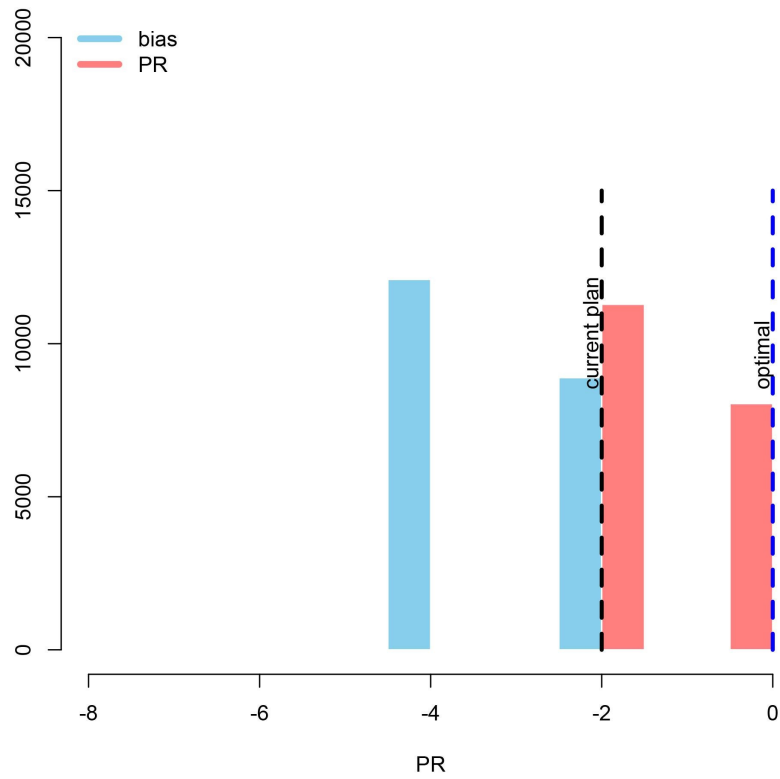
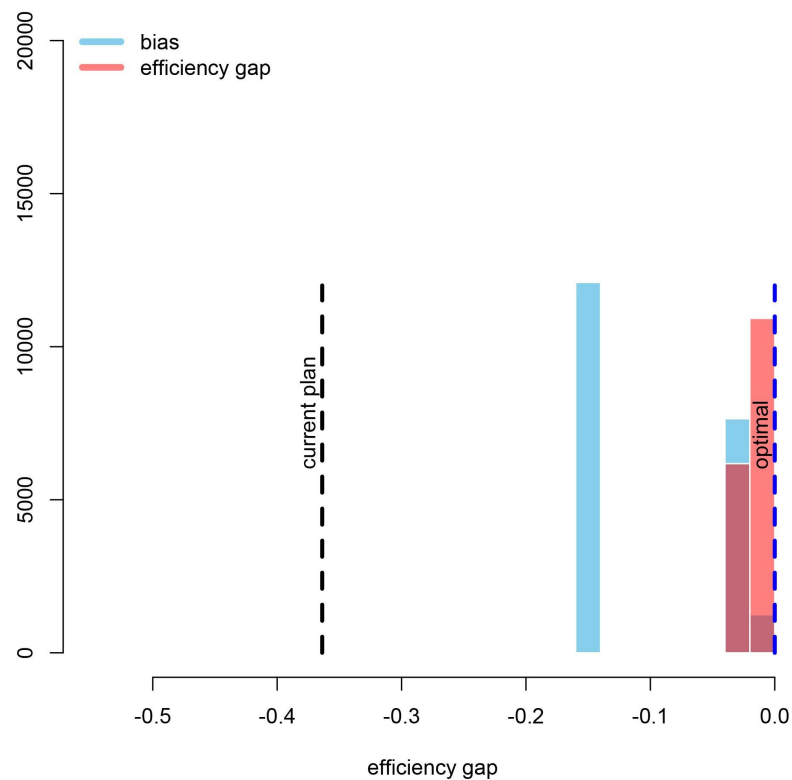


Figure 1d. Bias v. EG



Figures 1a and 1b are easy contrasts from one another, as are the bottom two. Seats-votes bias overlaps somewhat with competitiveness, as indicated in the first graph, whereas seats-votes bias does not overlap much at all with responsiveness. Seats-votes bias also does not seem to overlap much with proportional representation, while it does with the efficiency gap.

II. COMPETITIVENESS

We present the analogous findings for the measure of competitiveness below:

Figure 2. Comparing Competitiveness Against Other Measures

Figure 2a. Competitiveness v. Bias

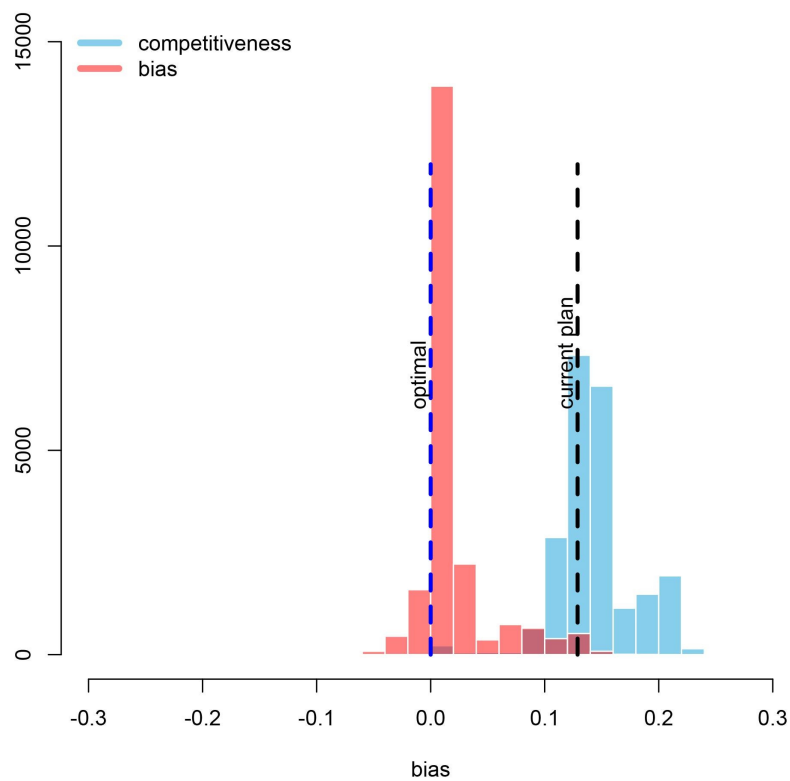


Figure 2b. Competitiveness v. Responsiveness

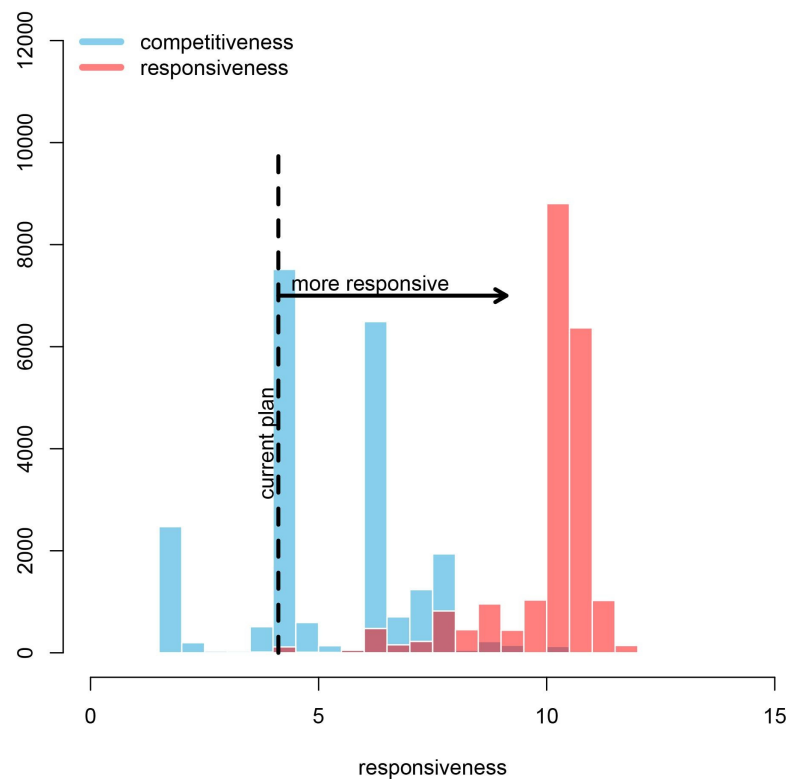
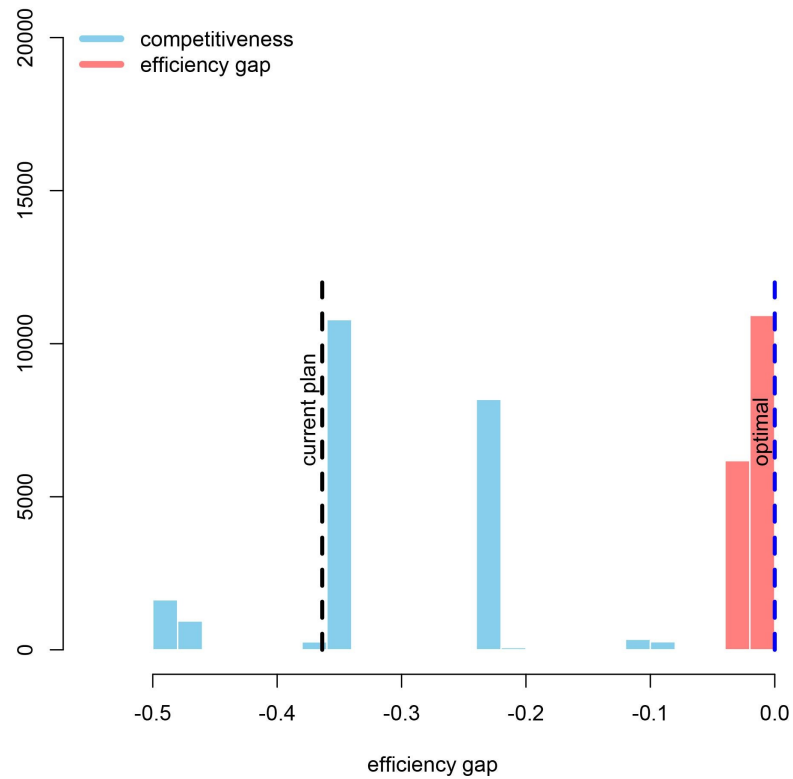


Figure 2c. Competitiveness v. EG

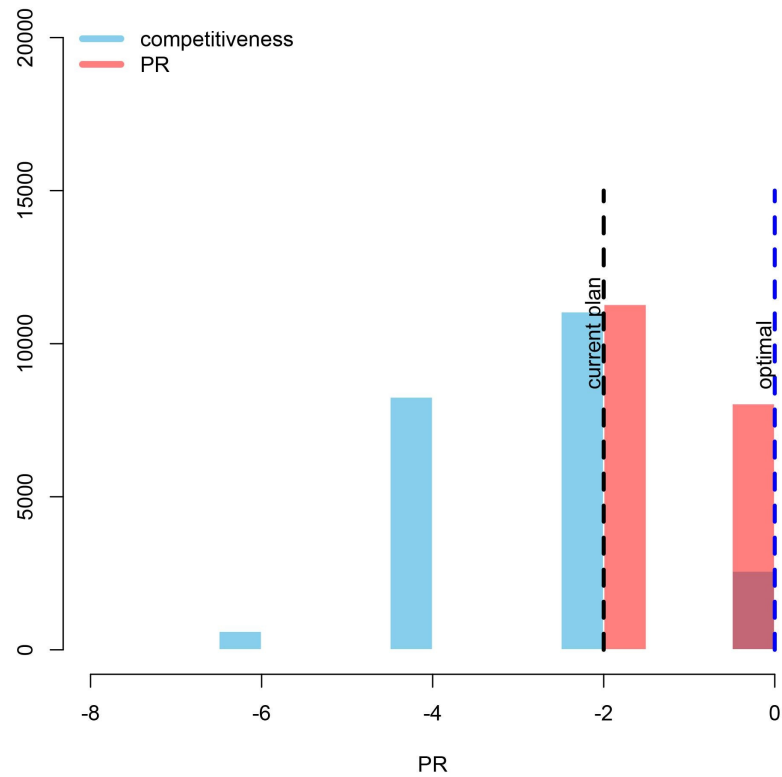


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Figure 2d. Competitiveness v. Proportional Representation

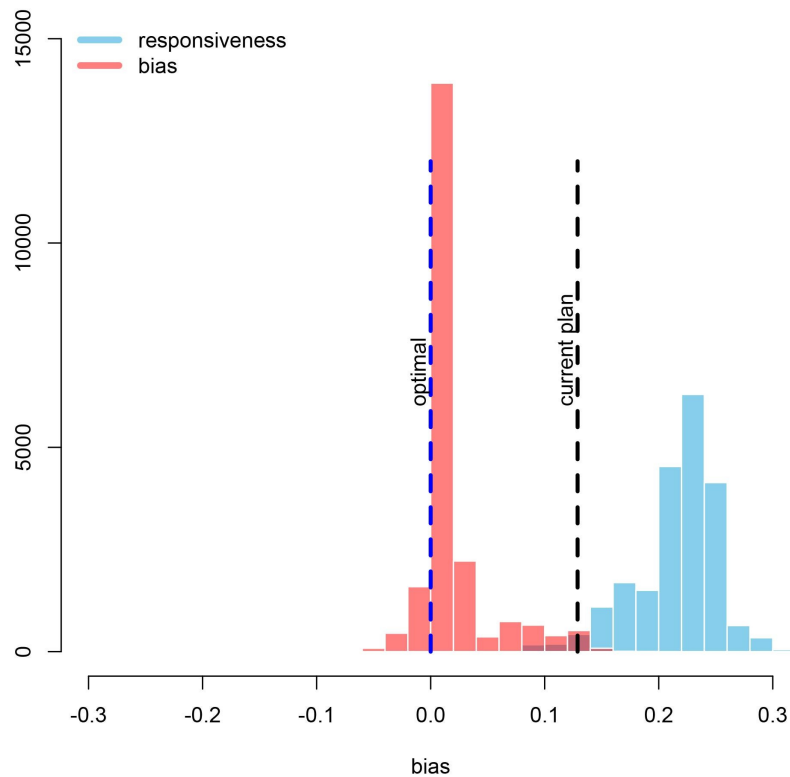


At this point, some of the results begin to seem familiar, as they are often mirror images of results we have already presented.

III. RESPONSIVENESS

Figure 3. Comparing Responsiveness Against Other Measures

Figure 3a. Responsiveness v. Bias



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Figure 3b. Responsiveness v. Competitiveness

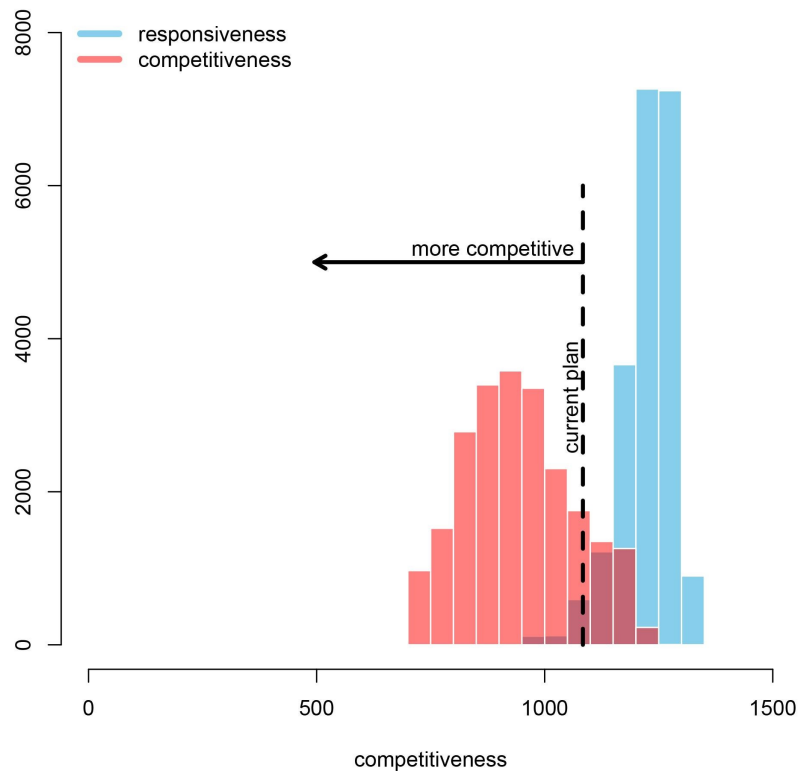
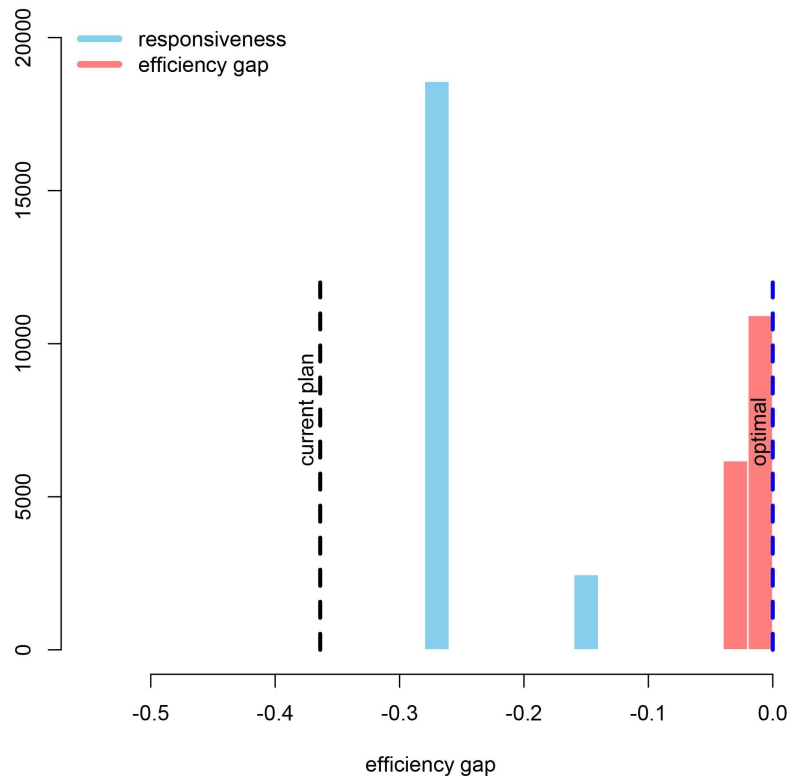


Figure 3c. Responsiveness v. EG

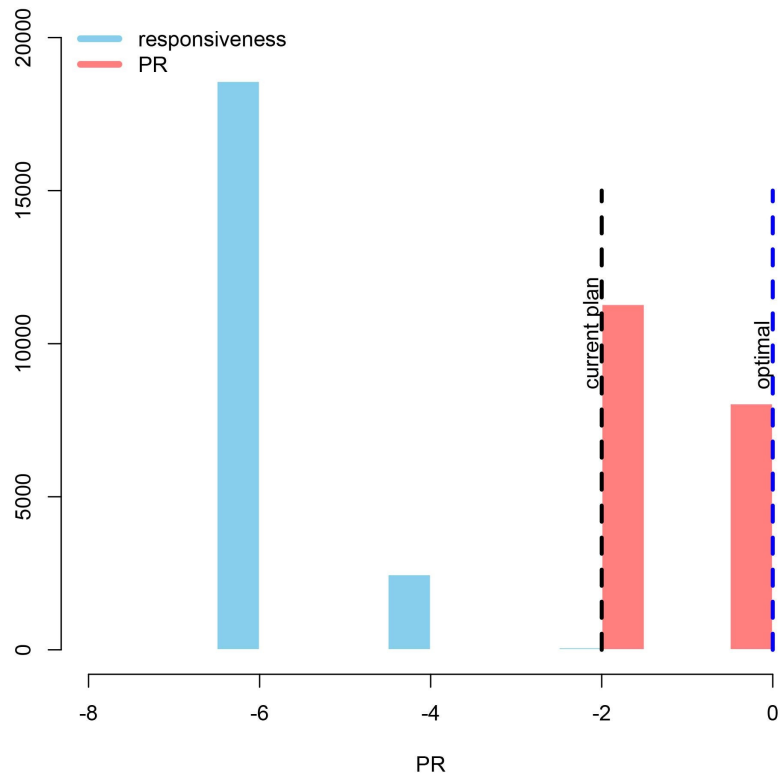


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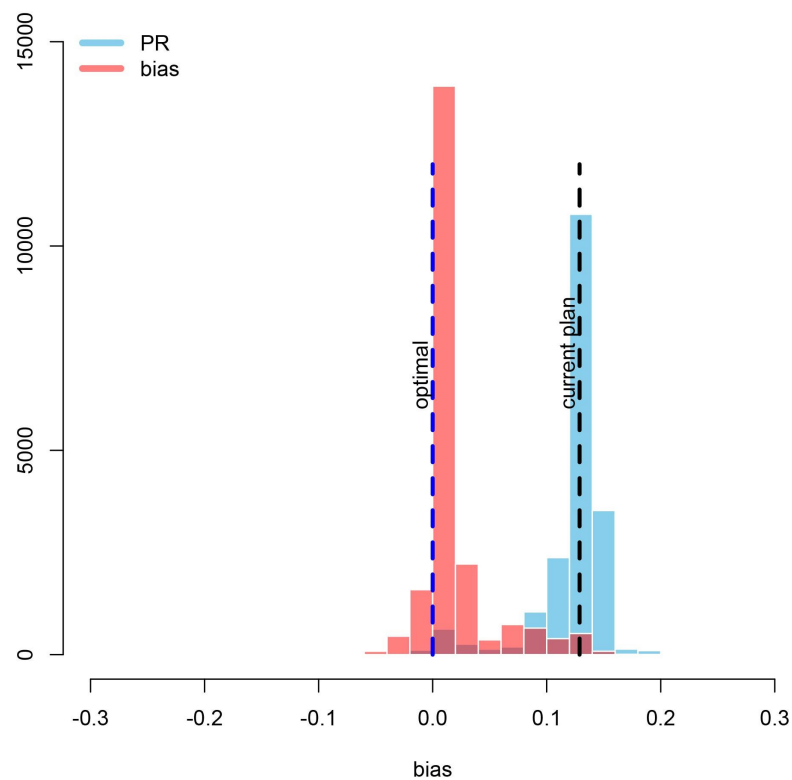
Figure 3d. Responsiveness v. Proportional Representation



IV. PROPORTIONAL REPRESENTATION

Figure 4. Comparing Proportional Representation Against Other Measures

Figure 4a. Proportional Representation v. Bias



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Figure 4b. Proportional Representation v. Competitiveness

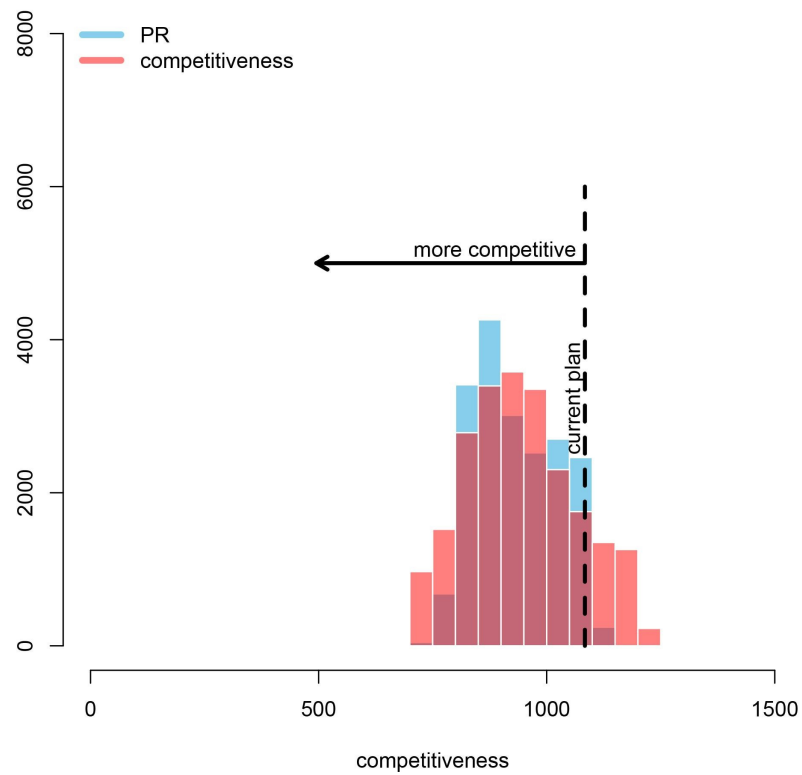
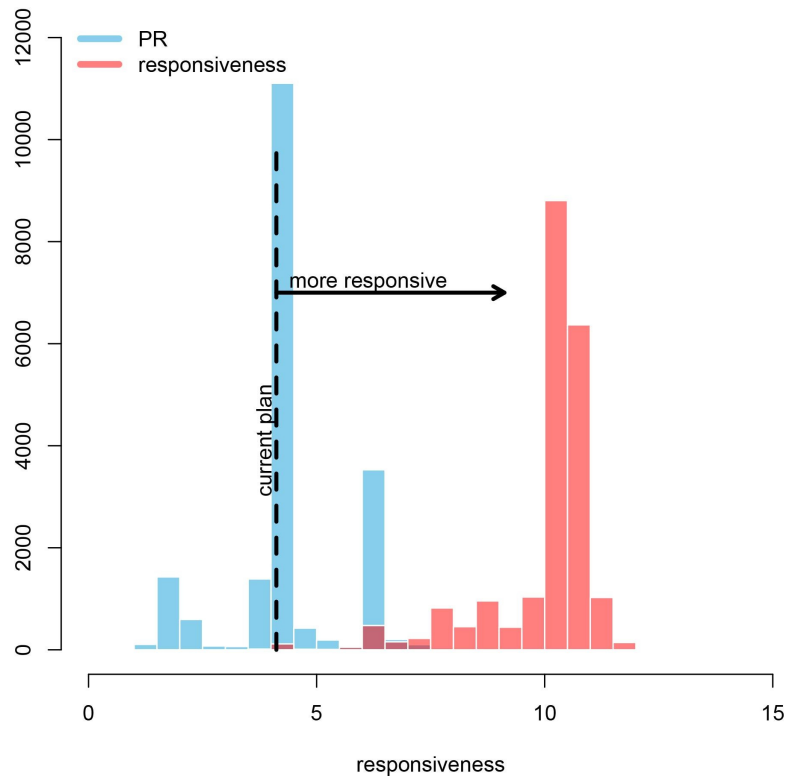


Figure 4c. Proportional Representation v. Responsiveness



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Figure 4d. Proportional Representation v. EG

