Methodological Issues in Bridging Ideal Points in Disparate Institutions in a Data Sparse Environment*

Boris Shor[†], Nolan McCarty[‡], Christopher Berry[§]

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Abstract

In earlier work, we created Congressional common space scores for multiple state legislatures using bridge actors who served in both institutions. Here, we employ simulations to explore the general issues involved in bridging institutions in data-sparse environments, where only a few bridge actors exist to allow inter-institutional comparisons. We find that only a few such bridges are necessary to improve ideal point estimates of rescaled legislative chambers.

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[†]Harris School of Public Policy Studies, University of Chicago; bshor@uchicago.edu

[‡]Woodrow Wilson School of Public and International Affairs, Princeton University; nmccarty@princeton.edu

[§]Harris School of Public Policy Studies, University of Chicago; crberry@uchicago.edu

1 Introduction

The need for comparable preference estimates across political institutions is hardly new. The existing literature includes, for example, efforts to produce common ideological scales for the US House and Senate (Poole and Rosenthal 1997; Groseclose, Levitt and Snyder 1999), for presidents and Congress (McCarty and Poole 1995), for presidents, senators, and Supreme Court justices (Bailey and Chang 2001; Bailey, Kamoie and Maltzman 2005), and for Supreme Court and Court of Appeals justices (Epstein et al. 2005). Indeed, connecting overlapping generations of political actors within a single institution over time presents similar challenges of estimating comparable ideal points for actors whose choices are not observed simultaneously (Poole and Rosenthal 1997; Martin and Quinn 2002).

All of the efforts to place multiple institutions in a common space rely, in varying ways, on bridge actors. These are political actors who make choices that can be construed as votes in more than one institutional setting. Common examples of bridge actors include members of Congress who serve multiple terms, members who migrate from the House to the Senate, solicitor generals who advocate for one side in front of the Supreme Court, and presidents who express views on congressional bills.

Poole (2005) (chapter 6) provides an overview of methods for estimating a common spatial map across institutions using bridge actors. He suggests two approaches. The first, which we call "linear mapping," extracts spatial maps for the two institutions separately and then connects them by regressing the two sets of coordinates for the bridge actors. The latter, which we call "pooled scaling," combines the roll call matrices across institutions into one large matrix. Using bridge actors as the "glue," one executes the scaling simultaneously for all the legislators across all chambers.

Canonical applications are employed in what we call data-rich environments. That is, there are a great many bridge actors or bridge roll calls that allow us to bridge institutions. Combined with the assumption that individual ideology is consistent, a multitude of such individuals gives us great precision in mapping ideal points from one chamber to another.

Think, for example, of the great many US House representatives who go on to become senators. Luckily, we are able to capture these bridge actors because of the very good data we have on roll calls going back to 1787, and leverage them to create common space Congressional scores for all of American history.

However, as ideal point analysis is extended beyond the US Congress, data necessarily becomes far more sparse. This is for two reasons. First, bridge actors across wider institutional gulfs are far rarer than, for example, "graduating" representatives. Second, data on roll calls and legislators in Congress is almost unique in its completeness over time.

For example, in previous work (Shor, McCarty and Berry 2008), we collected roll call data on over 40 states over approximately a decade. Our bridge actors are state legislators who later went on to serve in Congress. States vary in the number of these bridge actors that serve in Congress, because of size, a party/electoral system that encourages such moves, and the incumbency advantage. However, only a few states have more than a handful of these individuals elected to Congress *after* they served in the state legislature in the past decade.

2 Simulation Setup

We conduct a Monte Carlo analysis of the performance of NOMINATE and item response model ideal point estimation techniques (Jackman 2000; Martin and Quinn 2002; Clinton, Jackman and Rivers 2004; Jackman 2004) under a variety of theoretical conditions. First, we simulate roll call votes for two separate chambers bridged by a small number of legislators. Chamber 1 is the larger chamber (think of it as a stand-in for Congress), while Chamber 2 is the smaller chamber (think of it as a state legislature). The goal is to rescale Chamber 2 scores into the same scale as Chamber 1.

We vary a number of parameters including the number of bridges, the size of the chambers, the party proportions, and the mean and variance of true ideological positions. We run this simulation for a large number of iterations. Thus, for each set of parameters, we create many unique sets of legislators and roll call "votes." We then estimate ideal points for each simulation from the "revealed" vote decisions of the legislators we create.

The comparison of the estimated ideal points with the known true ideal points of these individuals gives us a barometer on how well we are doing, even under potentially adverse conditions. The measure of improvement is the difference in the root mean squared error for using some bridging technique versus only "naive" within-chamber scores (averaged over the iterations). In other words, how much better are we doing by not ignoring the necessity for rescaling?

2.1 Data Generating Process

The simulation's parameters are set to create two chambers in two polar opposite scenarios. In the first scenario, which we call "equal," is the nightmare for the mapping approach. Here, both chambers have Democrats and Republicans (and their bridges) drawn from the exact same distribution. Democrats come from a distribution of ideal points distributed $N \backsim (-0.5, 0.1)$, and Republicans $N \backsim (0.5, 0.1)$ (see the left-hand side of figure 1). It is a very hard case for mapping because, quite simply, no rescaling is necessary. In fact, because of the noise we introduce, bridges will vary because of pure randomness and any information we draw from them is pointless. The standard here should be that mapping not do too much damage to recovering estimates of true ideal points.

The second scenario, which we entitle "extreme," is the best case for bridging. Here, both chambers are drawn from quite different distributions, such that the second chamber is substantially more conservative than the first. Democrats in chamber 1 come from a distribution of ideal points distributed $N \backsim (-0.5, 0.1)$, and Republicans $N \backsim (0.5, 0.1)$. Democrats in chamber 2 come from a distribution of ideal points distributed $N \backsim (0.25, 0.1)$, and Republicans $N \backsim (0.75, 0.1)$ (see the right-hand side of figure 1).

The problem here is quite intuitive – ideal point estimation performed solely within Chamber 2 can not "tell" that it is substantially more conservative than Chamber 1. Because any scaling technique performed solely within each of these different chambers can not recover the true scale, bridging should do very well here. The identifying assumption here is that our bridge actors are exactly identical in both chambers. The relation between their two within-chamber scores, then, helps us to scale the second chamber correctly.

2.2 Mapping Procedure

We begin by estimating ideal points from the roll calls created by our data generating process via NOMINATE. Chamber 1 scores are left as is, because they will be used as the common space into which Chamber 2 will be projected. The estimated ideal points are shown as density curves in the second column in figures 3 and 4 (the first column shows the true ideal points which are created with a very slight amount of noise in our DGP).

The mapping procedure is simple: we regress the Chamber 1 scores for our bridge actors on their Chamber 2 scores. These regressions produce a set of intercept and slope coefficients mapping scores from intra-Chamber 2 space to Chamber 1 common space. These coefficients are summarized in figure 2.

Since we know the true values of the generated ideal points, we can measure how well the mapping procedure does in recovering the intercept and slope. Recall that in the "equal" scenario, both chambers are exactly alike. Thus, a perfect rescaling of Chamber 2 into Chamber 1 space should have a 0 intercept and a slope of 1. The left hand side of figure 2 shows that this is nearly the case. Intercepts center around 0, while slopes seem to center around 0.9.

These coefficients are used to generate predicted scores for the non-bridge legislators in Chamber 2. These predicted scores in common space are plotted as density curves in column three of figures 3 and 4.

The comparison of the true, raw, and mapped scores are to be found in the final column of figures 3 and 4.

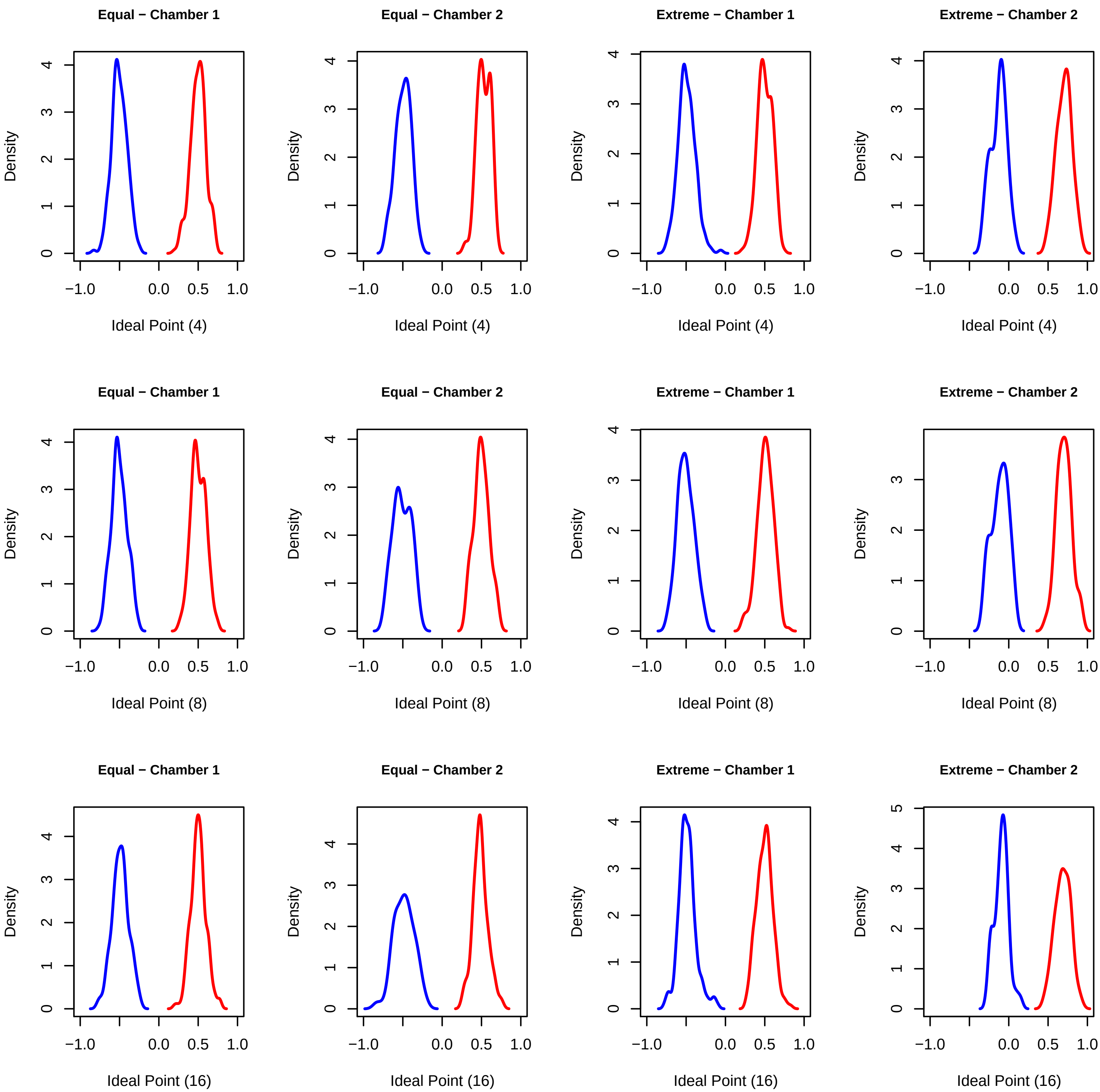

Figure 1: *Chamber 1: 200 Democrats, 200 Republicans. Chamber 2: 50 Democrats, 50 Republicans. 4, 8, and 16 bridge actors. 250 votes per chamber, 250 simulations.*

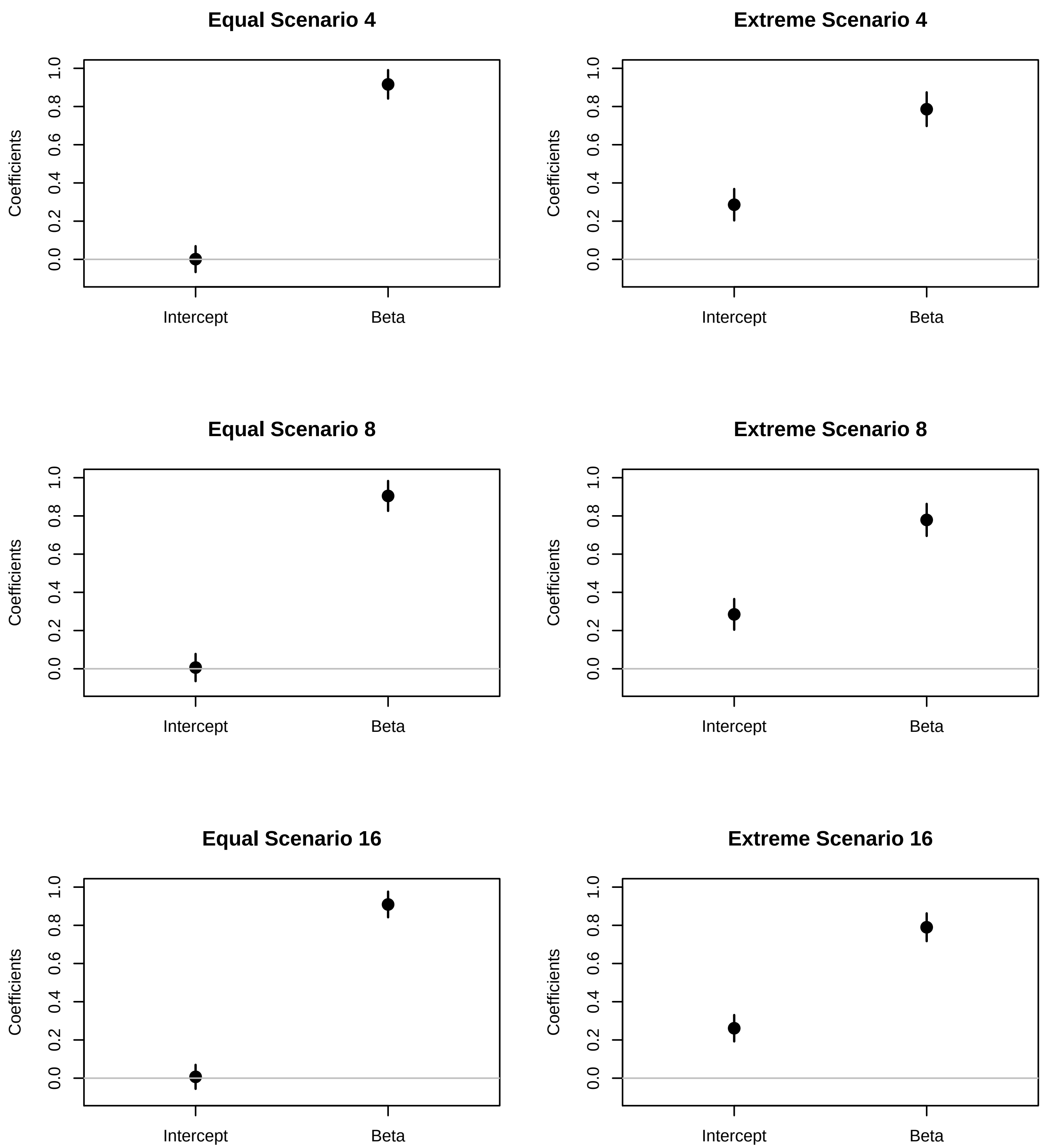

Figure 2: *Plot of estimated coefficients from mapping equations. Chamber 1: 200 Democrats, 200 Republicans. Chamber 2: 50 Democrats, 50 Republicans. 4, 8, and 16 bridge actors. 250 votes per chamber, 250 simulations.*

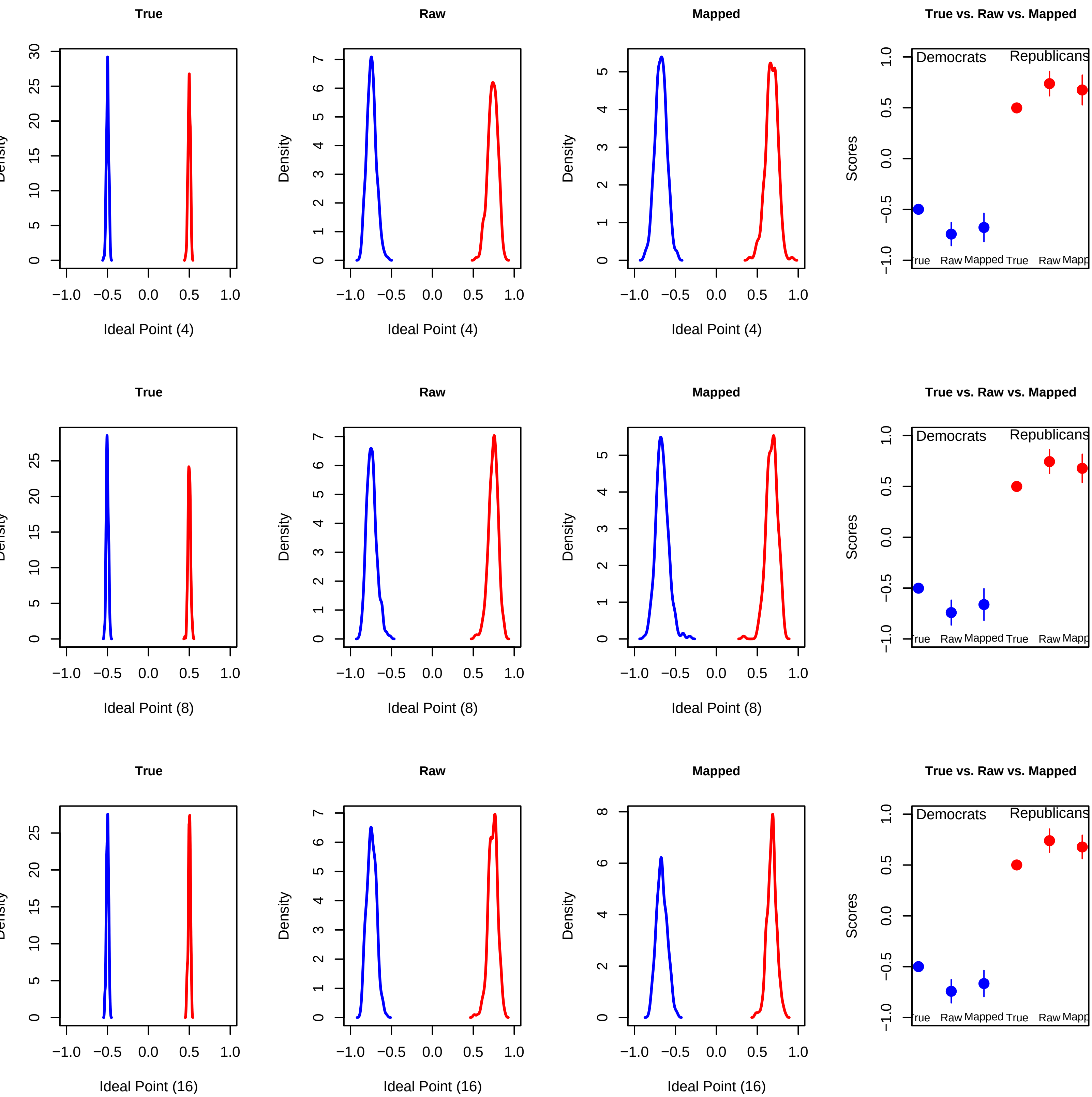

Figure 3: *Density plot of true, "naive" (raw), and mapped ideal points for the "equal" chamber scenario. Chamber 2: 50 Democrats, 50 Republicans. 4, 8, and 16 bridge actors. 250 votes per chamber, 250 simulations.*

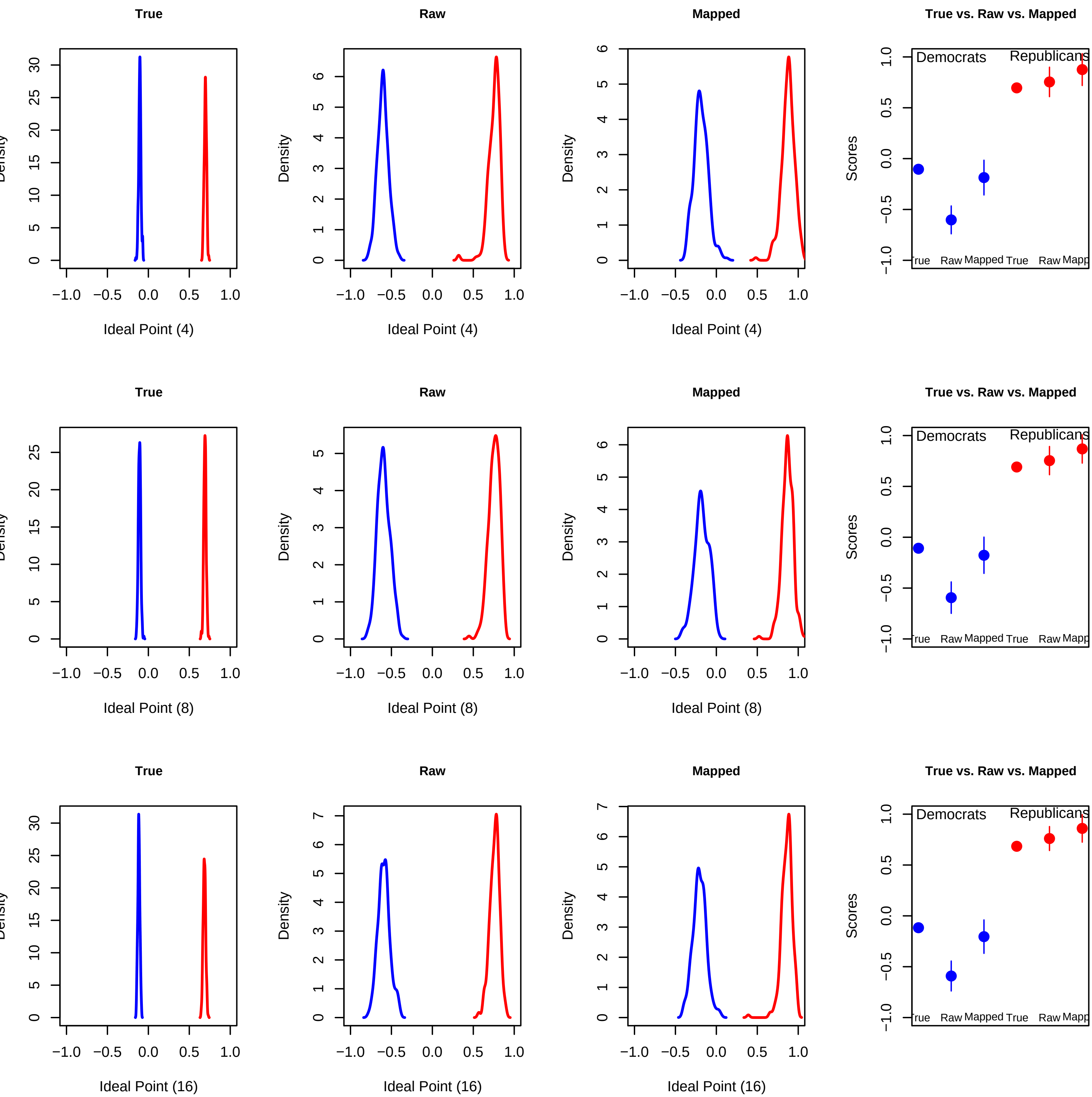

Figure 4: *Density plot of true, "naive" (raw), and mapped ideal points for the "extreme" chamber scenario. Chamber 2: 50 Democrats, 50 Republicans. 4, 8, and 16 bridge actors. 250 votes per chamber, 250 simulations.*

3 Varying Data Generating Process Parameters

3.1 Ideological Consistency Assumption

In our simulations, we make bridge actors have identical ideology across both chambers. We justify this because we think it most likely that political elites combine coherent belief systems (Converse 1964) and ideological intensity (Poole 2003). Issue positions are related, even if philosophically (or logically) such positions may not necessarily hang together. These interrelationships are anchored by the ardent passion of ideologues. Second, parties structure voting agendas in legislatures and constrain individual ideological drift (Jenkins 2000). In the electoral arena, parties weed out nonconformists as they develop and promote candidates. The ideological constancy of members of Congress, for example, has been empirically studied extensively and research has largely confirmed the consistency assumption. Poole and Rosenthal (1991) and Poole (2003) argue that ideological change in Congress at least has been almost entirely driven by conversion.

In future simulations for this paper, we examine the consequences when this assumption is weakened.

3.2 Sufficiency of Bridging Observations

Even if bridge actors are in fact ideologically consistent as they move from one chamber to another, how many are enough? Previous attempts at creating common space scores, like those bringing together House and Senate, have enjoyed large amounts of bridge actors. But we do not yet have a good methodological rules of thumb of how few bridges are necessary. This is important because as bridging gets applied in new areas, we are likely to see substantially fewer numbers of bridges.

Our basic finding is that a low number of bridge actors does not harm the overall fitness of estimated ideal points. A simple illustration shows how few bridge actors are necessary to recover true ideal points.

Figure 5 shows how the linear mapping procedure works with four, eight, and sixteen bridge actors. The plots on the right show the root mean squared error improvement plotted against the "naive" RMSE measure for chamber 2 (the one we are trying to put into chamber 1 common space) for each of the 250 individual simulations. The black dots represent instances of the "extreme" scenario, while those of the white dots represent the "equal" scenario. The horizontal line divides the simulation results into two regions: the top half represents improvement over the "naive" results, while the bottom half represents unwanted deterioration. The left hand plots summarize the bridging improvement over all the simulations.

As expected, when chambers differ greatly, linear mapping does very well. This is true no matter how many bridge actors were present. The one change with additional bridge actors is the slight reduction in the variance of how much improvement was obtained given how bad the situation was to begin with (the cloud of dots is tighter).

What is surprising is how little the procedure harms the recovered estimates when chambers are exactly identical. While some of the simulations do show deterioration in the overall fit, they are very few. The mean improvement is positive, and even one standard deviation below the mean is positive as well, even for as few as four bridges.

We repeat the exercise in Figure 6 for pooling rather than linear mapping. As before, both scenarios show marked improvement in fit when compared to the "naive" unbridged fit benchmark. On the other hand, three important differences stand out. First, the average amount of improvement appears to be smaller for pooling than mapping. Second, the variance of the improvement is much greater for pooling than mapping (and, unlike mapping, a small number of simulations show deterioration in fit). Finally, the average amount of improvement for the "extreme" scenario is about the same as that for the "equal" scenario.

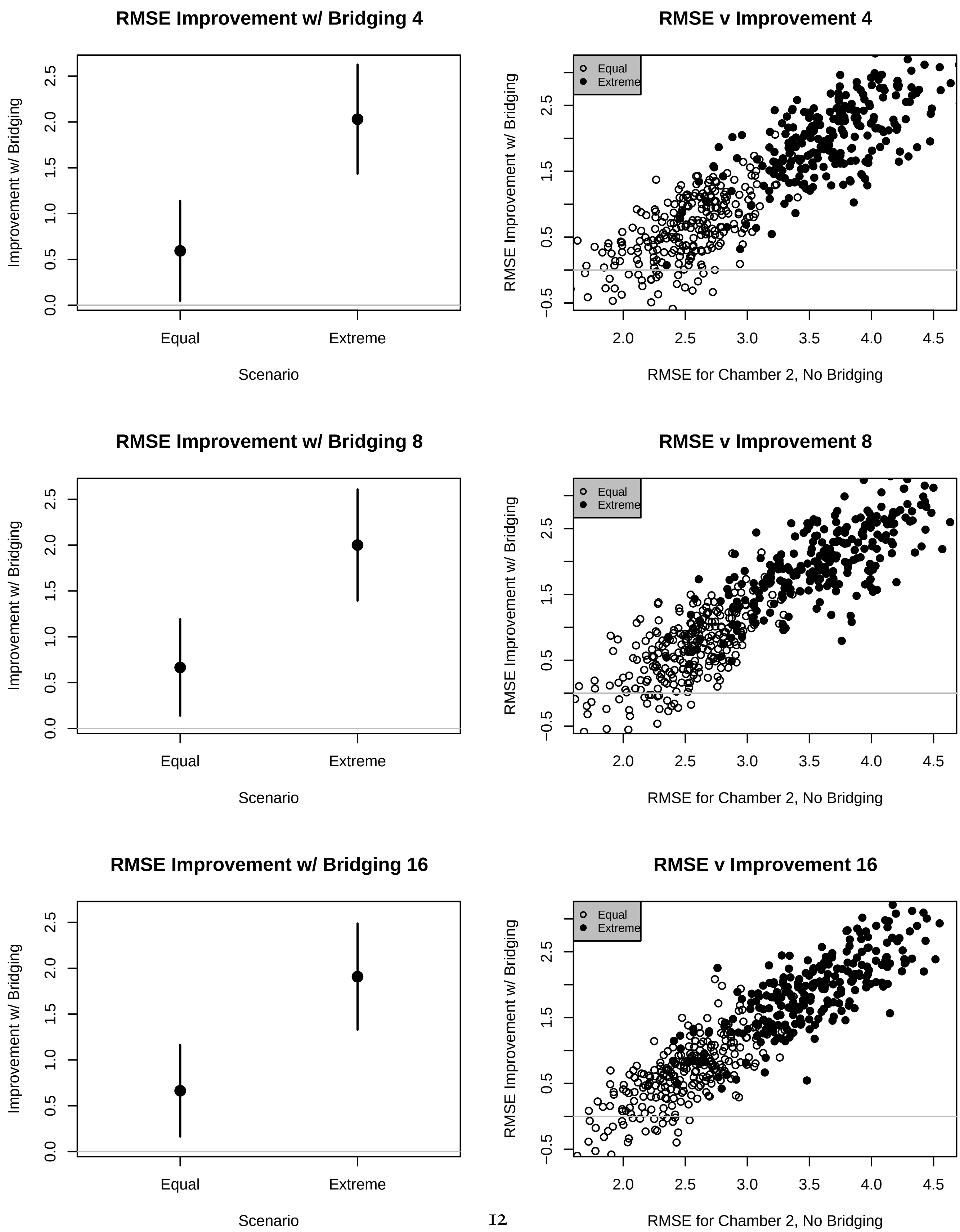

Figure 5: *Improvement in the performance of ideal point estimates recovering true ideal points with 4-16 bridge actors. Improvement is measured as the difference in the RMSE for using linear mapping, relative to not bridging at all. Comparisons are made between the recovered ideal points and the true ideal points generated by the DGP.*

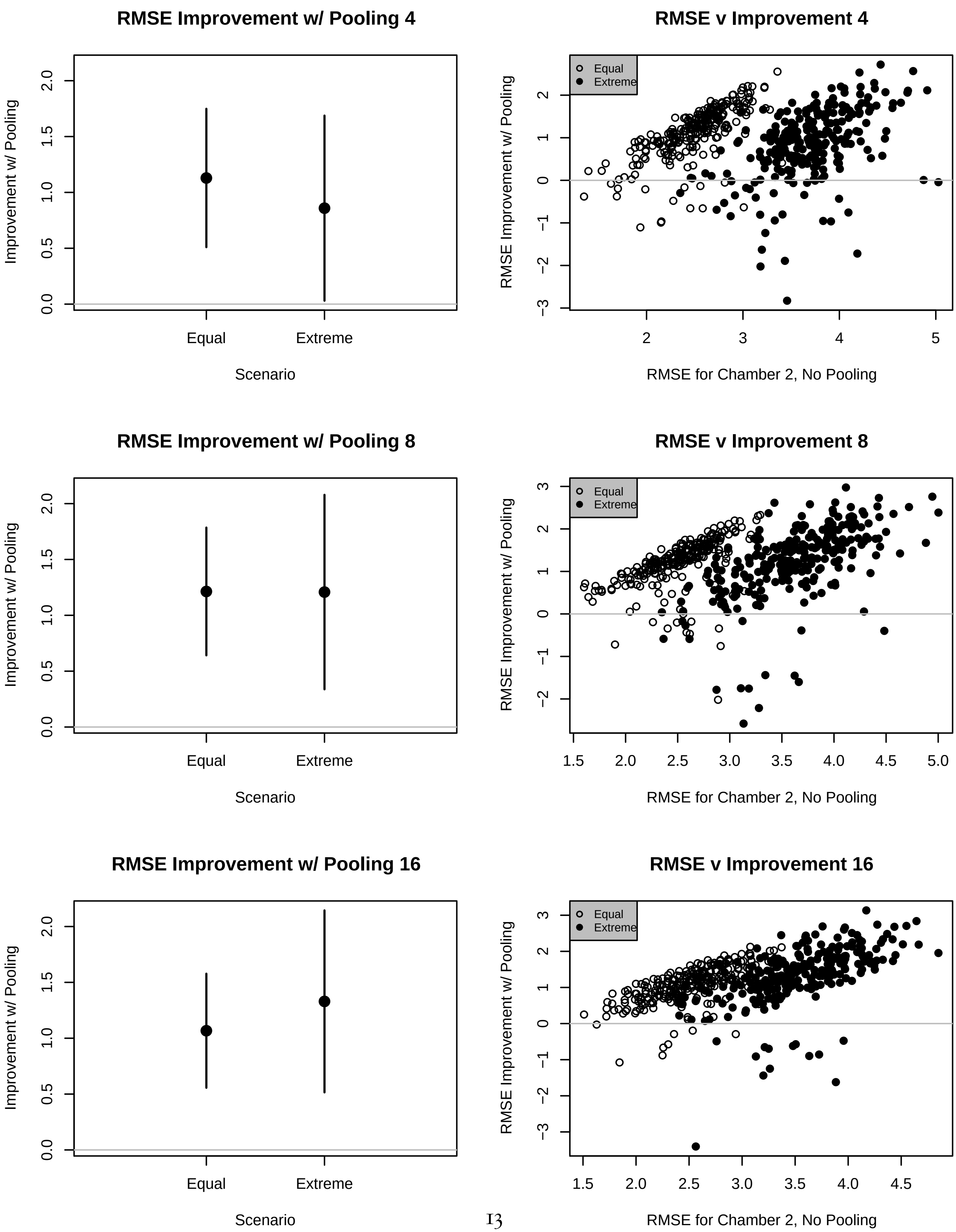

Figure 6: *Improvement in the performance of ideal point estimates recovering true ideal points with 4-16 bridge actors using pooling, relative to not bridging at all. Comparisons are made between the recovered ideal points and the true ideal points generated by the DGP.*

4 Mapping vs. Pooling

Poole (2005) suggests two approaches for making a valid inter-institutional common space: a regression-based approach we call "linear mapping," and a "big matrix" based approach we call pooled scaling.

While in principle, the two methods should produce largely similar results for data-rich environments, we do not know their relative performance when the number of bridge actors is small.[1]

It is of course entirely possible to employ pooled scaling and create a massive "super legislature" consisting of all state and Congressional legislators voting on every roll call across time. Naturally such an approach is extremely computing intensive[2] Are there any gains from doing so?

Figure 7 suggests the answer is "it depends." If the two chambers are identical, pooling offers a better fit. On the other hand, if the two chambers differ substantially, mapping gives less biased results on average. Given the substantial differences we uncover amongst the states in (Shor, McCarty and Berry 2008), the latter appears more likely, at least between state legislatures.

[1]In practice, the vast size of a matrix containing all votes and legislators for all available time for all the scaled legislatures means it is computationally challenging to do the latter all at once.

[2]Though we can do better by randomly sampling some smaller number of votes from each state.

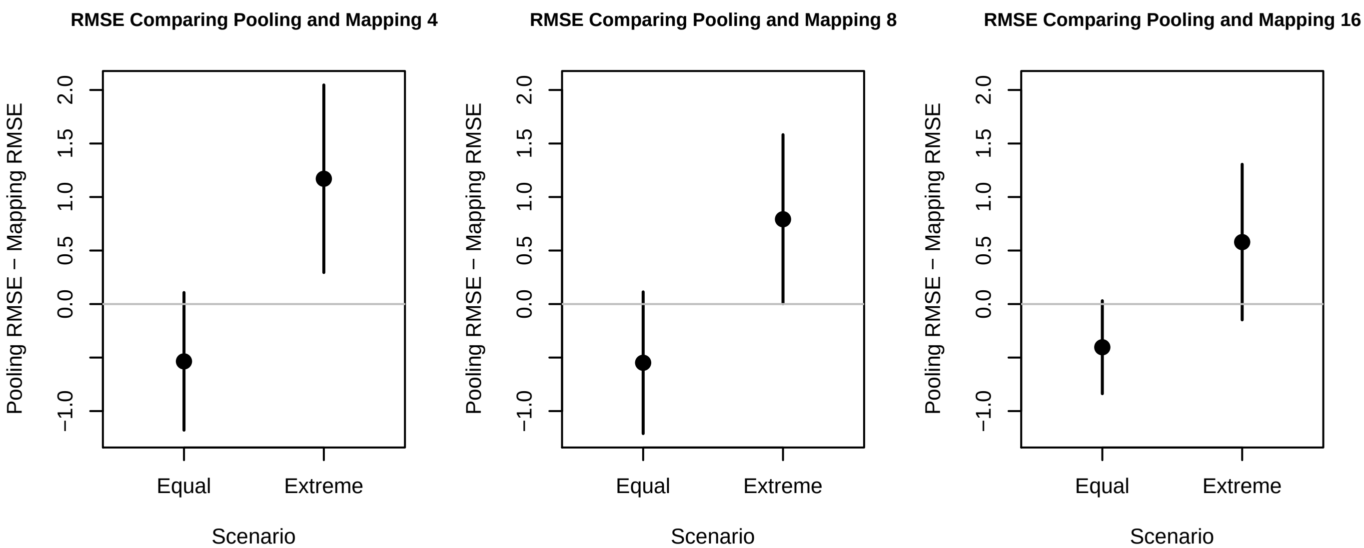

Figure 7: *Comparison of fit improvement of mapping relative to pooling. Zero indicates no difference, positive numbers indicate average superiority of mapping to pooling, and negative numbers are the opposite. The dot is the mean improvement in the simulations, the line is 1 sd above and below.*

5 Varying Estimation Techniques

We employ both NOMINATE and a one dimensional Bayesian item response model (Jackman 2000; Martin and Quinn 2002; Clinton, Jackman and Rivers 2004; Jackman 2004) based on Markov Chain Monte Carlo (MCMC) methods.[3] However, estimates of ideal points via both methods correlate extremely highly, confirming suspicions that both scaling techniques yield similar results in data-rich environments.

6 Conclusion

The most surprising finding coming out of these simulations is how few bridge actors are needed to successfully recover common space ideal points. If substantiated, this finding should embolden scholars to attempt to bridge broad institutional divides on the basis of only a few bridges.

The potential downside of doing so appears minimal. Even when we simulate two *identical* chambers, both of our bridging techniques do very little harm and on average even improve fit. However, when chambers are quite different, bridging brings the promise of substantial improvements in reducing bias. Assuming large differences in institutions and preferences in chambers bridged by very few individuals, we are more likely to be in the latter world rather than the former.

[3]See also Bafumi et al. (2005) for a discussion of the practical issues involved in this estimation strategy.

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