

Does Gerrymandering Cause Polarization?

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Abstract

It has now become fashionable to blame increasing levels of partisan conflict and polarization in Congress on the effects of partisan gerrymandering. In this paper, we attempt to assess whether there is a strong causal relationship between congressional districting and polarization. We find very little evidence for such a link. First, we show that congressional polarization is primarily a function of the differences in how Democrats and Republicans represent the same districts rather than a function of which districts each party represents or the distribution of constituency preferences. Second, we conduct a number of simulations to gauge the level of polarization under various “neutral” districting procedures. We find that the actual levels of polarization are not much higher than those produced by the simulations.

1. Introduction

Contemporary politics in the United States has been historically distinctive in at least two respects. The first is the ever increasing polarization of political elites. As McCarty, Poole, and Rosenthal (2006) have documented, partisan differences in voting behavior of U.S. House members and Senators have grown dramatically since the 1970s to levels not seen since the first part of the 20th century. The second distinction is the historically-low levels of competition in congressional elections. This is especially true of elections to the House of Representatives where 99 percent of incumbent members standing for reelection have been successful in the past two national elections.

Given the conjunction of these two patterns, it seems natural to draw a link. By far the most common link drawn by scholars and pundits alike is that the increased polarization of Congress is a direct result of the increasing ease of reelection. Presumably in an era of declining competition politicians no longer feel the need to reach out to moderate and independent voters to win elections. Instead politicians are free to pander to their ideological and partisan base. Politicians who do not pander may face primary challenges by ideologically purer candidates. In the 2004 Pennsylvania primary, Republican moderate Arlen Specter was unsuccessfully challenged by a candidate sponsored by the Club for Growth. In the 2006 Connecticut primary, Democratic moderate Joe Lieberman was successfully challenged by anti-war candidate Ned Lamont..

While such a link between increased polarization and declining competition makes sense, scholars have yet to establish a compelling causal relationship. Some

scholars (as well as the pundits) have hypothesized that the link between polarization and declining competition is rooted in the increasingly sophisticated techniques deployed during the congressional redistricting process that follows each decennial census. Pundits somewhat causally proclaim we are in “the age of gerrymandering” (Hulse, 2006). Many observers argue that the redistricting process increasingly produces districts that are homogeneous with respect to partisanship and voter ideology.¹ Consequently only conservative Republicans can win in conservative Republican districts just as liberal Democrats dominate liberal Democratic districts. Because redistricting no longer produces moderate, bipartisan, or heterogeneous districts, moderates cannot win election to the House.

This narrative is attractive not only because of analytical elegance, but because it suggests a single, perhaps even feasible, solution to what ails the American polity: take the politics out of redistricting. If neutral experts and judges drew districts rather than partisan politicians, districts would become heterogeneous and politically moderate. Appealing to independents would become the key to winning election, and polarization would become a thing of the past.

Unfortunately, although elegant in description and prescription, the story may not be true. There are a number of reasons to be skeptical on logical grounds. Certainly individual politicians desire more electoral security through the districting process. Yet it is not clear that these individual desires lead to more security for all politicians or that the resulting manipulation of districting exacerbates polarization. Despite the increased

¹ Carson et al., Eilperin (2006), Fiorina et al. (2004), Issacharoff (2004), Macedo et al. (2005), Theriault (2006), and Toobin (2003).

ingenuity and sophistication of gerrymanders, numerous constraints and obstacles remain to the using of redistricting as an “incumbency protection” plan. The requirements of equal size, compactness, and continuity reduce the scope of such manipulation. Because many states have relatively few districts, gerrymanderers often lack the degrees of freedom to create distorted districting plans. Some legal requirements such as majority-minority districts may exacerbate polarization. But such requirements would be adhered to under other districting mechanisms.

Politicians, moreover, generally have quite different incentives. Differential incentives lead to a more basic reason that gerrymandering does not necessarily generate safe seats. Consider the incentives of the partisan gerrymanderer. Here the majority party tries to maximize the number of seats it wins in future elections. Such a goal gives it the incentive to create as many districts where it constitutes the majority as possible. Doing so implies that the supporters of the minority party are packed into as few districts as possible. Ironically, this process leads to more electoral security (and presumably more extreme preferences) for the minority party and less for individual members of the majority party. Consequently, partisan gerrymandering leads to more competitive districts than non-competitive districts and has an ambiguous effect on polarization.

Not only does the theoretical case for a link between gerrymandering and polarization have holes, there is little empirical support for the claim. That the U.S. Senate has experienced an increase in polarization at the same time as the House suggests that gerrymandering plays at best a modest role. This fact has not deterred scholars from arguing either that gerrymandering-induced polarization from the House spilled over into the Senate (Eilpern (2006), Theriault (2006)) or that gerrymandering has an additional

contribution to polarization beyond the common factors that led to the increase of both the House and Senate. Neither in McCarty, Poole, and Rosenthal (2006) nor in the analysis that follows do we find much evidence for either of these claims.

To summarize, the primary findings of McCarty, Poole, and Rosenthal (2006, ch. 2) and the research reported in this paper are:

1. A very large fraction of the polarization in the House of Representatives is the result of within-district divergence between the voting records of Democratic and Republican members of Congress. In other words, for a given set of constituency characteristics, a Republican representative compiles an increasingly more conservative record than a Democrat does. The gerrymandering hypothesis cannot account for this form of polarization.
2. Some of the increase in polarization is due to an increase in the congruence between a district's characteristics and the party of its representative. Republicans are more likely to represent conservative districts and Democrats are more likely to represent liberal ones. Such an effect is consistent with the gerrymandering hypothesis but it is also consistent with a general geographic polarization of voters along ideological and partisan lines. Moreover, we find that the timing of this sorting effect is inconsistent with the gerrymandering story. It occurs in the 1980s and early 1990s, relatively early in the upswing of polarization. This is well before the most recent decline in electoral competition in the House. In particular, the larger increases in the sorting effect precede the 1994 elections when 34 Democratic incumbents were defeated and the Republicans enjoyed a 54 seat swing.

3. Using data on fixed geographic entities, we are able to compute the expected polarization following various districting procedures. The difference between the actual polarization and these simulated districting procedures allow us to establish estimates of the upper bound of the gerrymandering effect. This upper bound is very small and realistically can account, at most, for 10-15% of the increase in polarization since the 1970s. Because of constraints imposed by using county level data, this bound is almost certainly biased upward. But most damning, this upper bound does not increase substantially following redistricting as the gerrymandering hypothesis would suggest.

2. Preliminary Evidence

Despite the conventional wisdom that incumbency-protection gerrymanders have exacerbated partisanship and polarization in the U.S. House, there has been remarkably little systematic study of the issue. Carson, Crespin, Finochiarro, and Rohde (2003) find that members representing newly created or significantly redrawn districts have more extreme voting records than those representing districts that continue in their old form. Theriault (2006) conducts a similar analysis and reaches similar conclusions.² While suggestive, these studies fail to account for one important feature of the last three apportionment cycles. As McCarty, Poole, and Rosenthal (2006) report, the

² Unlike Carson et al, Theriault includes the type of redistricting plan (“incumbency-protection” or not) and type of redistricting institution (e.g. legislature or independent commission). Surprisingly, he finds that the use of commissions is associated with higher levels of polarization in newly drawn districts.

reapportionments since 1980 have shifted seats from the Northeast where polarization is moderate to the most polarized regions, the South and Southwest, while the relatively unpolarized Midwest has neither lost nor gained seats. Consequently, new congressional districts and those significantly redrawn are not a random sample of all districts, but are heavily concentrated in polarized regions. In any case, these effects have a very small aggregate effect on polarization. If we compute polarization for the 108th House weighting each state according to its seat share from the 1990s, polarization decreases only very slightly. In this paper, we measure polarization as the difference between the mean DW-NOMINATE score of House Republicans and the corresponding mean for the Democrats. For the 108th House, the measure is 0.867. The decrease brought about by re-weighting is only 0.003.

Another approach to establishing a link between polarization and gerrymandering is to demonstrate that congressional districts are more homogenous following reapportionments than before. Theriault (2006) does find that the number of congressional districts that a presidential candidate won by a large margin increased following the 1990 and 2000 reapportionments. He also notes, however, that the standard deviation of the presidential vote across congressional districts fell after the 1980 and 2000 reapportionments, suggesting less partisan packing of districts. The standard deviation increases a trivial amount following the 1990 round. So his findings are at best inconclusive.

McCarty, Poole, and Rosenthal (2006) look for direct evidence that the distribution of presidential voting is more bimodal in congressional districts than it is in other geographic boundaries not affected by political districting. They find, however,

that the distribution of presidential vote across congressional districts is very similar to the distribution of presidential vote across counties.³ Their figures are reproduced here as figure 1. Most district-level presidential vote margins are very similar to those of counties.

Insert Figure 1

These finding suggests that polarization of congressional districts cannot be much larger than that dictated by geographic sorting of voters.

3. Sources of Polarization

A little appreciated fact is that polarization in the U.S. Congress has two distinct manifestations. First, it can manifest itself in better *sorting* of legislators into districts so that Republicans are more likely to represent conservative districts and Democrats are more likely to represent liberal districts. The second manifestation is an increase in the *intra-district divergence* of the parties. The difference in the voting records of Republicans and Democrats representing the same (or very similar) district has increased. Both of these effects have increased the difference in mean or median voting scores of the two parties.

This distinction between sorting and intra-district divergence is illustrated graphically by examples shown in Figure 2. In both panels, we plot distributions of legislator ideal points against a hypothetical measure of district preferences. In panel a, the average Republican ideal point is much greater than the average Democratic ideal point because Republicans tend to represent all of the most conservative districts. But the

³ They do note an exception attributable to majority-minority districting.

difference between the Democrats and Republicans representing the moderate districts is quite small. In this scenario, polarization is primarily a product of sorting.

In panel b, some Democrats represent conservative districts while some Republicans represent liberal ones. But Republican representatives compile much more conservative voting records than a Democrat does for a given district preference. Consequently, polarization is due to intra-district divergence. Although we have constructed both panels such that the difference in party means is .9, the two panels show sharply distinct forms of representation.

To formalize sorting and intra-district divergence, note that we can write the difference in party means in NOMINATE (abbreviated *NOM*) as

$$E(NOM | R) - E(NOM | D) = \int \left[E(NOM | R, z) \frac{p(z)}{\bar{p}} - E(NOM | D, z) \frac{1-p(z)}{1-\bar{p}} \right] f(z) dz$$

where R and D represent Republican and Democratic representatives, z is a vector of district characteristics distributed by density function f and $p(\cdot)$ is the probability that a district with characteristics z elects a Republican member and \bar{p} is the average probability of electing a Republican. The difference between $E(NOM | R, z)$ and $E(NOM | D, z)$ reflects intra-district divergence while variation in $p(z)$ captures the sorting effect. When there is no sorting effect $p(z) = \bar{p}$ for all z . Thus, without a sorting effect,

$$E(NOM | R) - E(NOM | D) = \int [E(NOM | R, z) - E(NOM | D, z)] f(z) dz$$

The right-hand side of this equation is the average intra-district divergence between the parties. We abbreviate it as *AIDD*. When there is positive sorting such that more

conservative districts are more likely to elect Republicans, then

$E(NOM | R) - E(NOM | D) > AIDD$ with the difference due to sorting.⁴ Thus, we can decompose polarization measured as $E(NOM | R) - E(NOM | D)$ into the *AIDD* and sorting effects.

4. Estimating the AIDD and Sorting Effect

Estimating the *AIDD* is analogous to estimating the average treatment effect of the non-random assignment of party affiliations to representatives. There is a large literature discussing alternative methods of estimation this type of analysis. For now we assume that the assignment of party affiliations is based on observables in the vector z .⁵

If we assume linearity for the conditional mean functions,

i.e., $E(NOM | R, z) = \beta_1 + \beta_2 R + \beta_3 z$, we can estimate the *AIDD* as the OLS estimate of β_2 .

But following the suggestion of Wooldridge (2002), we include interactions of R with z in mean deviations to allow for some forms of non-linearity.⁶

Because these functional forms are somewhat restrictive, we also use matching estimators to calculate the *AIDD*. Intuitively, these estimators match observations from a control and treatment group that share similar characteristics z and then computes the

⁴ Before the 1970s, the “solid” Democratic south represents a negative sorting effect where many of the most conservative districts were the most likely to go Democratic.

⁵ An unobservable factor only affects the measurement of the *AIDD* if it affects the probability of assignment and voting record of the members asymmetrically across parties.

⁶ Mean deviating z before interacting with R insures that the *AIDD* is the coefficient on R .

average difference in x for the matched set. We use the bias-corrected estimator developed by Abadie and Imbens (2002) and implemented in STATA (Abadie, Drukker, Herr, and Imbens 2001).

To visualize the extent of sorting and divergence in actual data, we plot the DW-NOMINATE score for each member of the 108th (2003-2004) House of Representatives against the Bush vote in their districts in the 2004 election in Figure 3.⁷ The presence of both sorting and intra-district effects are evident. Clearly, Republican are overrepresented in districts that Bush won by large margins and are absent from those he lost big. But holding Bush's vote share constant, there is a large gap between Republican and Democrat NOMINATE scores. The loess lines plotted for each party show that the relationship between the NOMINATE score and the Bush vote is not exactly linear but the departure is not great. Importantly, $E(NOM | R, z) - E(NOM | D, z)$ does not vary much by z (the Bush vote). So estimating *AIDD* by OLS (under the maintained assumption that assignment of party affiliations is based on observables) seems reasonable. Matching estimates are generally less efficient but are not biased by the nonlinearities. One problem is that many of the Democratic districts do not match with any Republican districts. Many but not all of these are majority-minority districts. Because the inclusion of such "unmatched" districts may affect the matching estimates, we estimate the *AIDD* on districts whose propensity score for Republican representation lies between .1 and .9.⁸

⁷ Hereafter we abbreviate DW-NOMINATE to NOMINATE.

⁸ Crump, Hotz, Imbens and Mitnick (2006) argue for the appropriateness of trimming the observations where the propensity of treatment is less than α or greater than $1 - \alpha$. They

To show that the patterns are similar when additional conditioning variables are used, we plot the NOMINATE scores against fitted values from a regression on Bush vote, education levels, percent black and Hispanic, median income, and region in Figure 4. Again we find both sorting and intradistrict effects.

As discussed above, we estimate the sorting and intradistrict effect using both OLS and matching estimators.⁹ Table 1 reports the results for the 108th Congress. The first row lists the simple difference in party means (0.867) as the benchmark measure of polarization. The second row provides the estimate of intra-district divergence when we condition exclusively on the districts' presidential vote. The estimate of .667 suggests that 77% (.667/.867) of the contemporary level of polarization is accounted for by intra-

provide an algorithm for estimating the optimal α . In each biennial sample, we find that the optimal α to be slightly lower than .1. But the results are quite insensitive to the exact threshold. The results are also insensitive to the fact that the sample size changes from congress to congress. If instead of trimming at prespecified propensity levels, we generated samples in each congress of the n most competitive districts, the results would change very little. The propensity scores are based on probit estimates using the same covariates as the matching estimator.

⁹ The sample for Congress includes only those districts represented by a Democrat or a Republican. When deaths or retirements cause multiple members serve in the same district, we average the NOMINATE scores in the case of same party replacements, but discard opposite party replacements. Thus, the sample sizes are occasionally less than 435. It does not change our results if the replacements are treated as additional observations.

district differences with the remaining 23% (.200) due to sorting. The third row is an estimate based solely on matching districts based on presidential vote. This estimate is lower than that from OLS, but divergence is still the much larger component of polarization. In the next two rows we add additional control variables to the OLS and matching models. These include income, region, and the racial and ethnic composition of the district.¹⁰ The inclusion of these additional variables raises both the OLS and matching estimates. Based on the estimates from the more fully specified models, divergences account for closer to 80% of total polarization.

In Table 2, the analysis is repeated for the 107th House (2001-2002). These districts are based on districting following the 1990 Census. As suggested by the gerrymandering hypothesis, there is an increase in the overall level of polarization from the 107th House to the 108th of .021. In comparison of the models based exclusively on presidential vote and the fully specified matching model, the *AIDD* is larger in the 107th than the 108th. This suggests that the overall increase was due to a large increase in the sorting effect, consistent with the Gerrymandering hypothesis. But the fully-specified OLS model tells a different story. These results suggest the *AIDD* fell by .027, which is slightly more than the overall decline in polarization. This suggests that the sorting effect actually fell following reapportionment.

5. Does “Re”districting Cause Polarization?

¹⁰ Each district is matched to the four closest districts in terms of the covariates.

Observations are matched exactly on region. Varying the number of matches has little effect on the estimate.

Even if we accepted the finding of the matching estimates that there was an increase in the sorting effect from the 107th to the 108th, it does not follow that it resulted from gerrymandering. Such an increase could occur for a number of other reasons such as an increase in partisan voting in congressional elections (see Bartels 2000). Therefore, the gerrymandering hypothesis requires larger increases in the sorting effect following reapportionment than in other years. To test this implication, Tables 3 and 4 report estimates of the *AIDD* and sorting effects for each congressional term since the 1970s, based on the fully specified OLS and matching models respectively.

Both sets of estimates reveal that the sorting effect increased considerably over the 1990s between reapportionments. The matching estimates in table 4 indicate that sorting increased more in 1995-96 and 1997-98 than it did following redistricting. The average biennial increase over the 1990s was .018, only a bit lower than the post-districting increase. This is consistent with an extremely low causal effect of redistricting.

The patterns for the earlier rounds of districting provide only a little more support for a gerrymandering effect. The OLS results show that the sorting effects increased more during the redistricting that followed the 1980 and 1990 censuses than in the surrounding years.¹¹ The matching estimates also show an effect for 1980. But no such effect appears in the matching estimates for 1990.¹² Given that much of the discussion

¹¹ The Congress elected in the year of the census is not subject to reapportionment. Reapportionment and redistricting occur for the following Congress.

¹² It is important to note that even the largest of the year-to-year changes in the sorting

about gerrymandering has focused on the use of sophisticated computer programs to drawn boundaries, it is ironic that the largest effect we estimate occurred before the era of personal computing!

Even if we accepted the changes pre- and post-districting changes in sorting as the effect of gerrymandering, the effects are substantively quite small. Under this assumption, the gerrymandering effect is .07 for OLS and .06 for matching. Both of these represent less than 10% of the total level of polarization and less than 25% of the increase in polarization since 1973. If we “de-trended” these estimates by subtracting the increase average increases sorting effect since the last round of districting, the total effects would be even smaller.

Tables 4 and 5 do provide some evidence for at least one aspect of the gerrymandering hypothesis: that political competition falls after redistricting. Recall that the *AIDD* is estimated from those districts with estimated probabilities of electing a Republican of at least .1 but no more than .9. So the size of the sample used for estimating the *AIDD* is a rough measure of the number of competitive seats. The effects of redistricting are clear. The number of competitive districts fell by 92 in 1983 25 in 1993 and 42 in 2003. These declines are three out of the four largest and equal the total decline over the time period of the study. Surprisingly, such dramatic declines in electoral competition have had very little impact on polarization.

6. Does Districting Cause Polarization?

effect are not statistically significant given the level of estimation error of the *AIDD*.

Although we have demonstrated that the sorting effect does not increase much following redistricting, it is still possible that polarization is greater than it would be if the districting process were more politically neutral. In other words, *districting* might cause polarization even if *redistricting* does not. To explore this possibility, we conduct a number of simulations designed to predict what polarization would be under various districting plans. The first step in these simulations is to estimate $E(NOM | R, z)$ and $E(NOM | D, z)$. Given the results of the previous section, these can be adequately estimated by OLS. Second, we estimate the probability that a Republican wins in a district with characteristics z or $p(z)$. We use probit to estimate this function. To capture the effects of estimation error across the simulations, we estimate $E(NOM | R, z)$, $E(NOM | D, z)$, and $p(z)$ on a bootstrapped sample.

After we estimate these functions, we generate congressional districts from any smaller fixed geographic entities for which we can observe z . For data availability reasons, we use counties. After simulating an alternative districting plan, we compute \tilde{z} for each new district. We then generate election outcomes \tilde{R} or \tilde{D} using $p(\tilde{z})$ and compute NOMINATE scores for each simulated district using $E(NOM | \tilde{R}, \tilde{z})$ and $E(NOM | \tilde{D}, \tilde{z})$. Our simulated polarization measure is just the difference in means from the simulated data. We repeat this process 1000 times for each simulation experiment.

We now describe the various districting experiments.

6.1 Random Districting

Due to data limitations, our underlying geographical data is from U.S. counties. A major limitation of this data is that there is tremendous variation in size, ranging from Loving County, TX (pop 179) to Los Angeles CA (pop 9,545,829). In order to adjust for size differences and to rearrange these county units into new districts, we subdivide each county into 1000 person blocks (and eliminate counties with lower populations). Unfortunately, we do not consistently observe z at the sub-county levels so we must assume that each of these county blocks is identical. As we discuss below, this homogeneity assumption biases towards finding a gerrymandering effect. Thus, our county block data set contains 100 observations from a county with 100,000 people and 10 observations for a 10,000 person county. Using this procedure, we created 275,584 county blocks

Our first districting experiment simply randomly allocates (without replacement) the county blocks into 435 districts, ignoring all legal, political, and geographic constraints (including state boundaries). Obviously, this produces 435 districts that are ex ante drawn from the same distribution. Differences between districts will reflect only the random effects on the sampling process. Consequently, the simulated polarization will approximately equal the AIDD.¹³ Figure 5 plots the kernel estimate of the distribution of the simulated polarization scores across the 1000 iterations for the 108th House. For comparison purposes, the vertical line is the actual level of polarization in the 108th House. The mean value of polarization is 0.706 with 95% confidence interval of [.672, .743]. The results of all of the experiments are reported in Table 5.

¹³ Because the simulation experiments use OLS, it should mimic the AIDD estimated by OLS.

[Insert table 5 here]

In a second experiment, we simply add state boundaries to the experiment. Now districts are created from random sampling (without replacement) of county blocks within each state. Figure 6 shows the distribution of the simulated polarization measure across 1000 iterations. Simply adding state boundaries raise the mean simulated polarization to .769. This implies that almost 40% of the sorting effect (Polarization – AIDD) is the result of demographic and political variation across states. And no more than a .098 difference in party means can be accounted for by how voters are allocated within states.

There are many reasons, however, to believe that even this small estimated effect is much larger than the actual effect. The first reason has to do with the limitations of the county data. Our procedure assumes that counties are demographically and politically homogeneous. In states with large counties, this homogeneity assumption makes it more unlikely that the simulations will produce either very conservative or very liberal districts. Obviously, this reduces this reduces the chance of simulating high levels of polarization. The second reason why these random simulations overestimate the effects of gerrymandering is that they ignore a number of legal constraints on the districting process. Most importantly they ignore geographical constraints such as contiguity and compactness. One reason random districting produces relatively low polarization is that it allows for geographically implausible combinations such as Marin and San Diego counties in California. Finally, random districts violate reasonable for norms of representation. In the random districting scenario, all districts within a state are approximately microcosms of the state. Political and racial minorities have little

opportunity to elect representatives who share their preferences. Districting systems that take such representation seriously will necessarily produce more polarization than the random districting benchmark.

6.2 Geographical Constraints

Although there is little we can do about the effects of the homogeneity assumption, we can roughly estimate the effects of imposing contiguity and compactness requirements. Because of the coarseness of using county data, it is quite difficult to devise simulations of all districting plans that meet these requirements. Therefore, we use two different crude approximations. In the first, we rank order the county blocks within each state by longitude of the county center. Then on the basis of this ranking we divide the state into districts from North to South so that district 1 is composed of the most northern county blocks and district k is the most southern. The second experiment is the same as the first except that latitude is used. Both of these districting schemes satisfy contiguity and compactness, but of course they represent just two of the many that do so.

Figure 7 illustrates the distribution of simulated polarization measures for districting based on longitude. The mean polarization score is .822 which suggests a gerrymandering effect of at most .045. Although it is substantively small, this difference is statistically significant at conventional levels as only 4 of the 1000 simulation produce polarization scores exceeding the actual value. That is, even though the gerrymandering effect estimated using a simple geographic constraint is much smaller than the effect based only on purely random assignment within each state, the effect remains statistically

significant. The results for latitude (see table 5) (Figure 8) are quite similar with a mean polarization score of .814.

[Insert Figures 7 and 8]

6.3 Minority Representation

Another consideration that random districting ignores is the representation of racial minorities. The random districts are very majoritarian and are likely to produce few African-American or Hispanic representatives. To crudely, yet feasibly, capture, the effects of majority-minority districting plans, we generate districts on the basis of their racial composition. The districts with the largest African-American populations are placed in district 1, the second highest are placed into district 2, and so on.¹⁴

Figure 9 reveals the distribution of polarization estimates. The mean score is .829 and the p-value with respect to the actual level is .004. Again while the difference is statistically significant, substantively the effect is only slightly more than 10 percent of the increase in polarization since the 1970s. This result is hardly surprising. Given that African-Americans represent only roughly 15 percent of the population, packing this population into as few as congressional districts as possible can only explain so much of the national pattern of polarization. Simulations based on Hispanic population or African-American plus Hispanic population generate slightly lower polarization scores.

¹⁴ To actually implement a legally sound majority-minority districting plan, we would have to model the election of African-American representatives and then allocate county-blocks to maximize the number of African-American representatives.

[Insert Figure 9]

6.4 Political Representation

An undesirable feature of the randomized districting benchmark is that the districts are unrepresentative of diverse interests in each state. Each district is approximately a microcosm of the state so that conservative and liberal interests are not well represented.

To better capture districting plans that use political representation as a consideration, we conduct two simulations that produce districts representative of the partisan and ideological diversity in each state. The first experiment attempts to replicate each state's distribution of partisanship as measured by $p(z)$ ¹⁵. First, we use our probit estimates to calculate an estimate of $p(z)$ for each of the county blocks. We then rank the county blocks on the basis of these estimates where ties are broken randomly.¹⁶ Then we create k districts using the first $1/k$ percent of the blocks to form the first district, the second $1/k$ to form the second and so on. This procedure creates a distribution of Republican, Democrat, and independent districts that reflects the underlying distribution of partisanship of the county blocks.

It is important to note that the districts produced are quite different from what we would expect from incumbency-preserving gerrymanders. Under those plans,

¹⁵ Simulations based on presidential vote share yield quite similar results.

¹⁶ Because all blocks from the same county have identical estimates of $p(z)$, there are a large number of ties and therefore randomness in these simulations.

independent or swing districts (i.e. $p(z) \approx .5$) would be underrepresented. Alternatively, partisan representative districting produces many competitive districts.

A related criterion for politically representative districts is to produce districts which the distance from each representative's ideal point to those of her constituents is minimized. Unfortunately, we cannot implement this criterion directly because we do not observe the ideal point of voters or county blocks. We can instead rank county blocks on the basis of $E(NOM | z)$. However, $E(NOM | z)$ is very highly correlated with $p(z)$ so we do not report simulated districts based on it. We can alternatively rank on the basis of $E(NOM | z, R)$ or $E(NOM | z, D)$. Because we estimate $E(NOM | z, R)$ and $E(NOM | z, D)$ with OLS, the rank correlation of the estimates is 1. So we report only simulations based on $E(NOM | z, R)$. It is worth reiterating that, just as in the partisan case, this procedure produces moderate districts in the same proportion as moderate county blocks.

Figure 10 reveals the distribution of simulated polarization scores based on partisan representative districts. The mean score is .851, a mere .016 less than the actual level. But this difference is not statistically significant. More than 14% of the simulations produce polarization scores higher than the true level. So the effect is not statistically significant at conventional levels. As shown in Figure 11, the results for ideologically representative districts are almost identical. The mean is .853 and 17% of the simulations produce higher polarization scores than the actual level.

[Insert Figures 10 and 11]

Our simulation experiments also allow us an opportunity to evaluate again whether *redistricting* has an effect on polarization. If it does, the estimated polarizing effect of biased districting should have increased after the round of districting following

the 2000 Census. To test this hypothesis, we simulate the gerrymandering effect for the 107th House that preceded redistricting and compare to our simulations of the effect in the 108th House. Table 6 shows the simulated effect of districting for the 107th and 108th Houses for each of our experiments. Because the simulations are not statistically independent across congresses, it is difficult to assess the statistical significance of the differences. But the substantive insignificance is quite apparent. The largest differential is .013 for random districting by state. Most of the experiments account for a much lower or even a negative effect. The average effect across all of the simulations is just .004. Even if we were to accept the largest difference as the causal effect of the 2000 redistricting on polarization, it can only account for about 4% of the increase in polarization since the 1970s.

One might object to these results by arguing that the 2000 districting round had minimal effects because the sorting effect of gerrymandering is already so large that it could not have been increased by strategic districting. Casual inspection of Figures 3 and 4 seem to rule out this possibility as many conservative districts continue to be represented by Democrats just as many liberal districts continue to be represented by Republicans. But we can deal with this objection more systematically by estimating the predicted level of polarization under the counterfactual of perfect sorting using our estimates of $E(NOM | z, D)$, $E(NOM | z, R)$, and $p(z)$. To generate perfect sorting, we assign each district a Republican representative if its propensity for electing a Republican is greater than the average Republican propensity. We then impute NOMINATE scores for each district using this deterministic assignment and calculate the resulting polarization. This exercise reveals that polarization would be as high as .883 if districts

were perfectly sorted by party. Thus, the current sorting effect is only approximately half of its maximum value.

Conclusions

Despite a lack of direct evidence, partisan gerrymandering has become one of the prime suspects in the investigation into what killed moderation and bipartisanship in American politics. It seems only natural given that the circumstantial case seems so compelling. Politicians are observed engaging in raw power politics to draw districts for personal and partisan advantage. Simultaneously, electoral competitiveness declines in Congress. It seems reasonable to conclude that the two phenomena are related and that the consequence is greater polarization.

But in our search to uncover the smoking gun, the case has crumbled. Polarization is not primarily a phenomenon of how voters are sorted into districts. It is mostly the consequence of the different ways Democrats and Republicans would represent the same districts. Yes, the distribution of partisanship across districts is quite different now than it was in 1990, but most of the increase came unaided by redistricting. Finally, as our simulations demonstrate, the levels of polarization we observe are quite consistent with congressional districts representative of the states for which they are drawn. Thus, the scope of districting reform to eliminate polarization is extremely limited. Even if we eliminated districting all together and elected candidates statewide, we could only roll polarization back to the level of the mid-1990s.

Nothing we say should be interpreted as contentment with congressional districting as it is currently practiced. The protracted political and legal battles over the

boundaries cannot help but diminish the legitimacy of American democracy. And redistricting does appear to have a negative impact on electoral competition. There are many reasons to do something about gerrymandering. But reducing polarization is not one of them.

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| Table 1: Estimates of AIDD for 108th House (2003-2004) | | | | |
|--|-------------------------------|----------|-----------------|------------------|
| | Conditioning Variables | N | Estimate | 95% Conf. |
| Total Polarization | | 433 | .867 | [.833, .895] |
| OLS | Pres Vote | 278 | .667 | [.627, .708] |
| Matching | Pres Vote | 278 | .642 | [.601, .683] |
| OLS | +demo, region | 219 | .692 | [.646, .738] |
| Matching | +demo, region | 219 | .682 | [.645, .719] |

| Table 2: Estimates of AIDD for 107th House (2001-2002) | | | | |
|--|-------------------------------|----------|-----------------|------------------|
| | Conditioning Variables | N | Estimate | 95% Conf. |
| Total Polarization | | 434 | .846 | [.811, .879] |
| OLS | Pres Vote | 296 | .675 | [.638, .712] |
| Matching | Pres Vote | 296 | .659 | [.628, .690] |
| OLS | +demo, region | 261 | .665 | [.627, .704] |
| Matching | +demo, region | 261 | .683 | [.652, .716] |

Note: Total polarization is the difference in the Republican mean DW-NOMINATE score and the Democratic score. Observations where more than one party represented the district in the Congress are dropped, leading to total Ns below 435. In the matching regressions, observations with propensity score less than 0.1 or greater than .9 in magnitude are dropped. The OLS regressions are run for the same set of observations as used in the matching calculations.

| Table 3: AIDD and Sorting Based on OLS Estimates | | | | |
|--|--------------|-----------------------------------|---------|--|
| Congress | Polarization | Average Intra-District Divergence | Sorting | Number of Districts used to Compute AIDD |
| 108 th (2003-2004) | .867 | .692 | .175 | 219 |
| 107 th (2001-2002) | .846 | .665 | .181 | 261 |
| 106 th (1999-2000) | .826 | .677 | .149 | 285 |
| 105 th (1997-1998) | .816 | .673 | .143 | 280 |
| 104 th (1995-1996) | .790 | .656 | .134 | 281 |
| 103 rd (1993-1994) | .724 | .581 | .143 | 301 |
| 102 nd (1991-1992) | .680 | .569 | .111 | 326 |
| 101 st (1989-1990) | .663 | .568 | .095 | 310 |
| 100 th (1987-1988) | .662 | .551 | .111 | 301 |
| 99 th (1985-1986) | .660 | .555 | .105 | 294 |
| 98 th (1983-1984) | .635 | .533 | .102 | 320 |
| 97 th (1981-1982) | .607 | .556 | .057 | 412 |
| 96 th (1979-1980) | .586 | .515 | .071 | 402 |
| 95 th (1977-1978) | .563 | .497 | .066 | 395 |
| 94 th (1975-1976) | .577 | .507 | .070 | 398 |
| 93 rd (1973-1974) | .583 | .515 | .068 | 380 |

Note: Congresses that reflect the effects of reapportionment and redistricting are shaded.

| Congress | Polarization | Average Intra-District Divergence | Sorting | Number of Districts used to Compute AIDD |
|-------------------------------|--------------|-----------------------------------|---------|--|
| 108 th (2003-2004) | .867 | .682 | .185 | 219 |
| 107 th (2001-2002) | .846 | .683 | .163 | 261 |
| 106 th (1999-2000) | .826 | .677 | .150 | 285 |
| 105 th (1997-1998) | .816 | .667 | .149 | 280 |
| 104 th (1995-1996) | .790 | .665 | .125 | 281 |
| 103 rd (1993-1994) | .724 | .614 | .090 | 301 |
| 102 nd (1991-1992) | .680 | .582 | .098 | 326 |
| 101 st (1989-1990) | .663 | .553 | .110 | 310 |
| 100 th (1987-1988) | .662 | .549 | .113 | 301 |
| 99 th (1985-1986) | .660 | .547 | .113 | 294 |
| 98 th (1983-1984) | .635 | .529 | .106 | 320 |
| 97 th (1981-1982) | .607 | .547 | .060 | 412 |
| 96 th (1979-1980) | .586 | .512 | .074 | 402 |
| 95 th (1977-1978) | .563 | .490 | .073 | 395 |
| 94 th (1975-1976) | .577 | .506 | .071 | 398 |
| 93 rd (1973-1974) | .583 | .501 | .083 | 380 |

Note: Congresses that reflect the effects of reapportionment and redistricting are shaded.

Table 5: Simulation Results from the 108th (2003-2004) House

| Experiment | Mean | St. Dev | Min | Max | Pr > .867 |
|-------------------------------------|-------------|----------------|------------|------------|---------------------|
| Random | 0.706 | 0.018 | 0.646 | 0.755 | 0.000 |
| Random by State | 0.769 | 0.018 | 0.714 | 0.823 | 0.000 |
| By Longitude | 0.822 | 0.016 | 0.773 | 0.867 | 0.004 |
| By Latitude | 0.814 | 0.016 | 0.762 | 0.856 | 0.000 |
| Racially representative | 0.829 | 0.016 | 0.774 | 0.878 | 0.004 |
| Partisan representative | 0.851 | 0.015 | 0.796 | 0.897 | 0.146 |
| Ideologically representative | 0.853 | 0.015 | 0.798 | 0.898 | 0.171 |
| <i>Actual Polarization</i> | 0.867 | | | | |

| Table 6: Districting Effects Before and After Redistricting | | |
|--|---|---|
| Experiment | 107th House (2001-2002) | 108th House (2003-2004) |
| Random | .158 | .161 |
| Random by State | .085 | .098 |
| By Longitude | .042 | .045 |
| By Latitude | .050 | .053 |
| Racially representative | .041 | .038 |
| Partisan representative | .011 | .016 |
| Ideologically representative | .009 | .014 |
| <i>Actual polarization</i> | 0.846 | 0.867 |

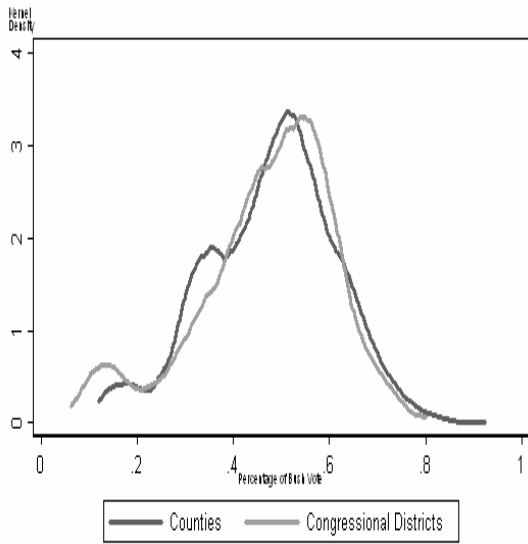


Figure 1A: Distribution of 2000 Bush Vote by Counties and Districts
 Note: Counties are weighted by population. Both densities estimated using bandwidth = .025

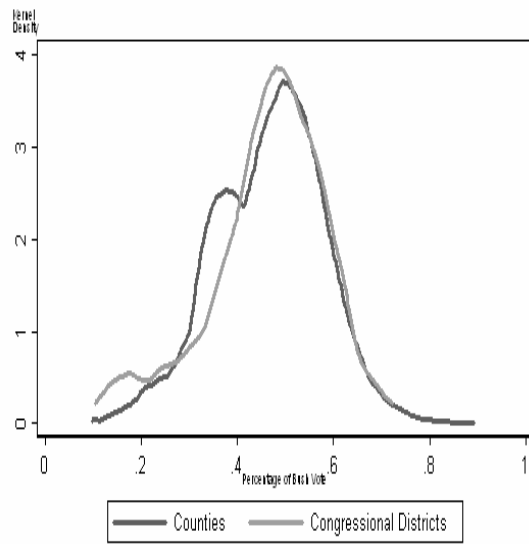


Figure 1B: Distribution of 1992 Bush Two-Party Vote by Counties and Districts
 Note: Counties are weighted by population. Both densities estimated using bandwidth = .025

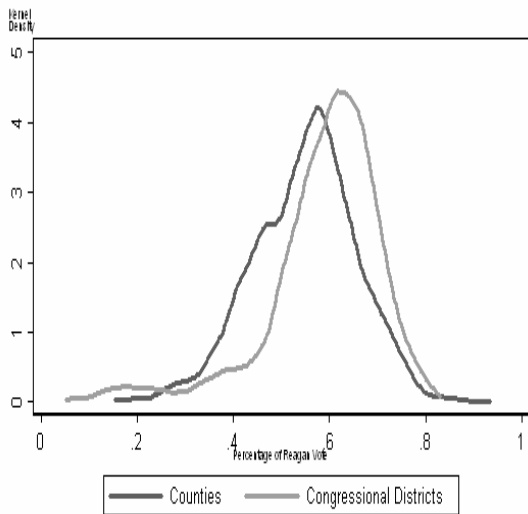


Figure 1C: Distribution of 1980 Reagan Two-Party Vote by Counties and Districts
 Note: Counties are weighted by population. Both densities estimated using bandwidth = .025

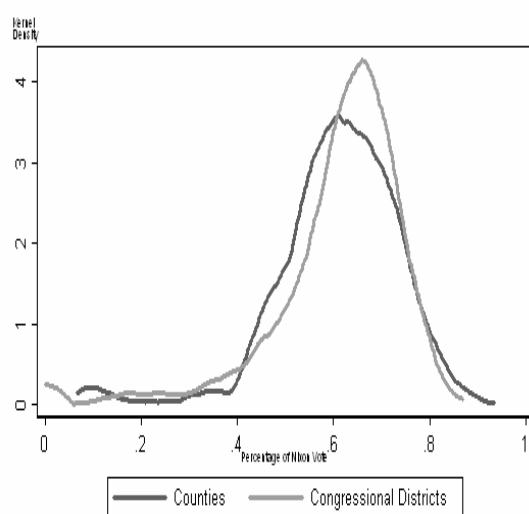


Figure 1D: Distribution of 1972 Nixon Two-Party Vote by Counties and Districts
 Note: Counties are weighted by population. Both densities estimated using bandwidth = .025

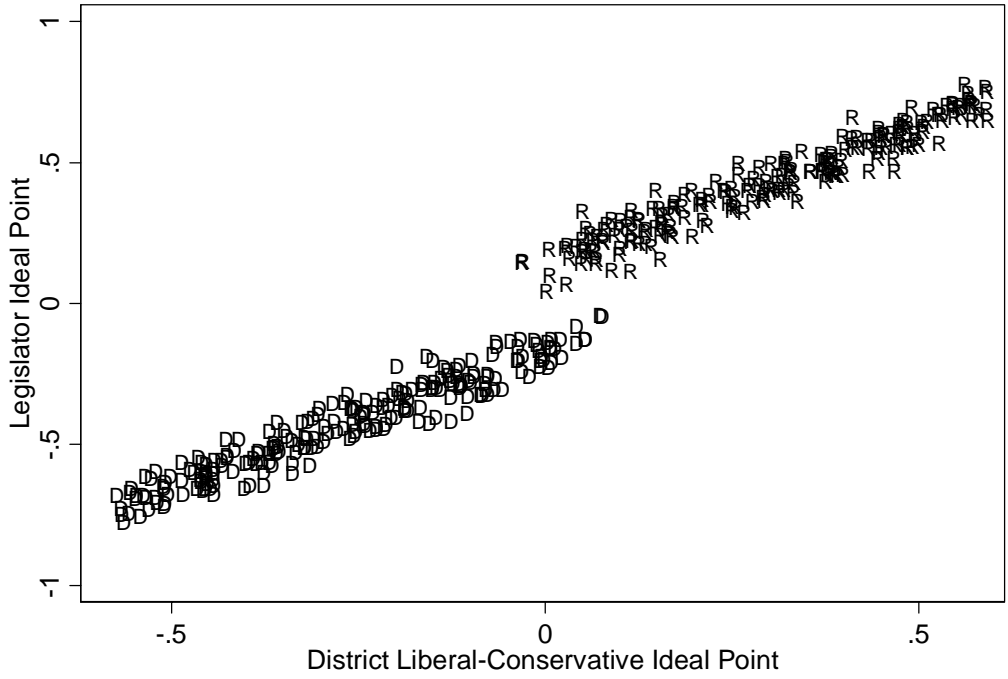


Figure 2A: Polarization from Sorting

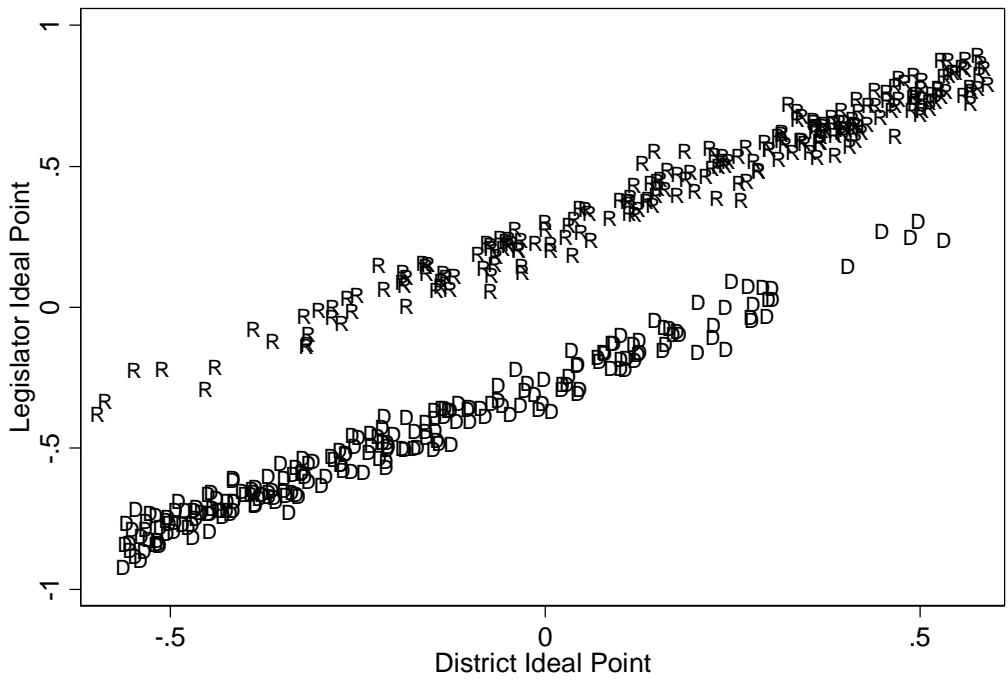


Figure 2B: Polarization from Intra-District Divergence

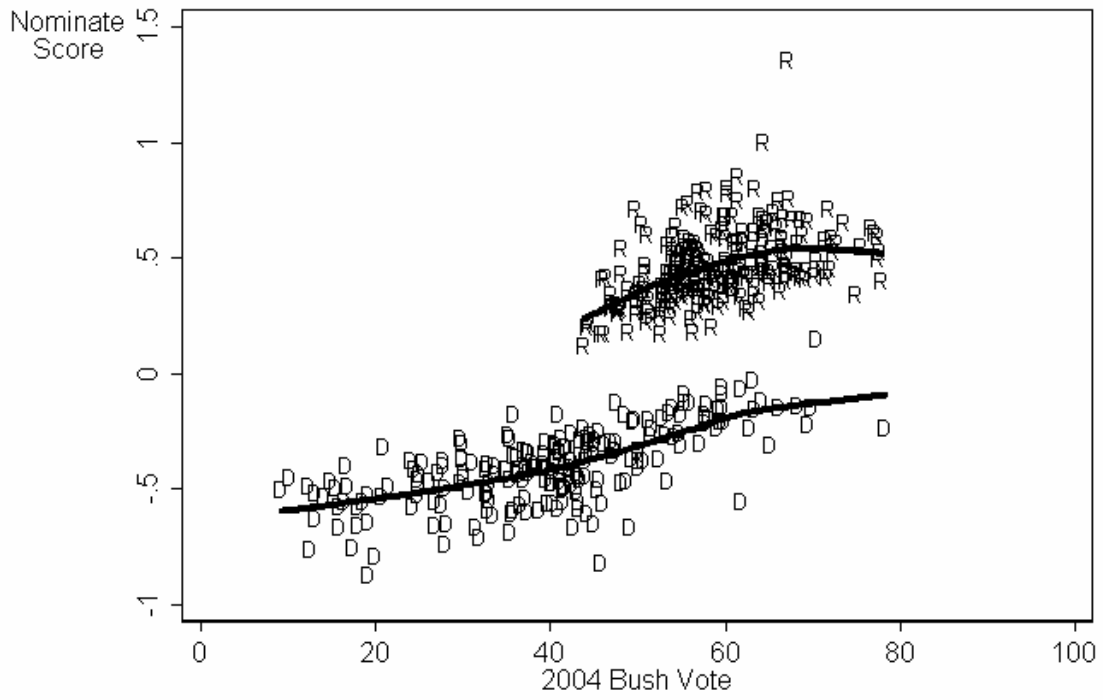


Figure 3: NOMINATE vs. Bush Vote, 108th House

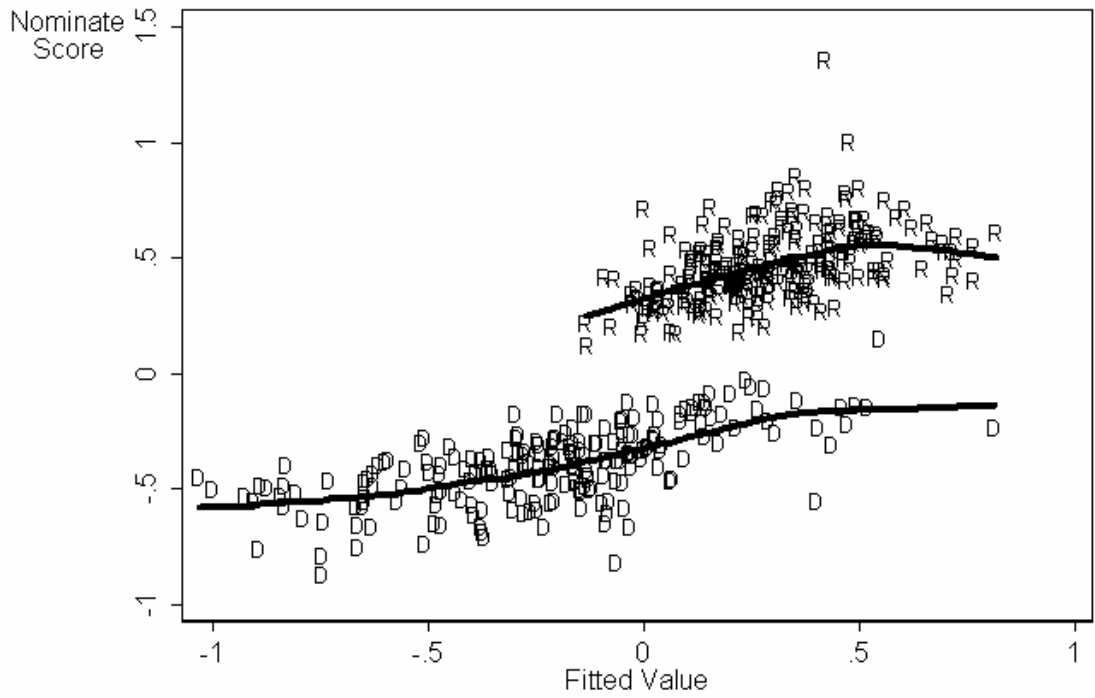


Figure 4: NOMINATE vs. Constituency Characteristics, 108th House

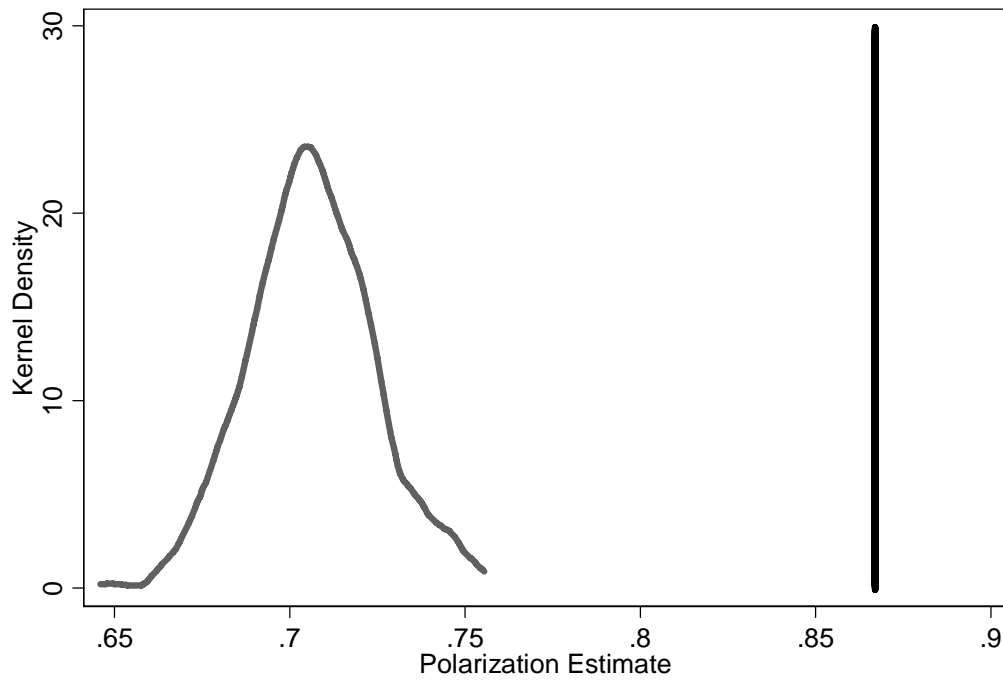


Figure 5: Bootstrap Estimates under Random Districting

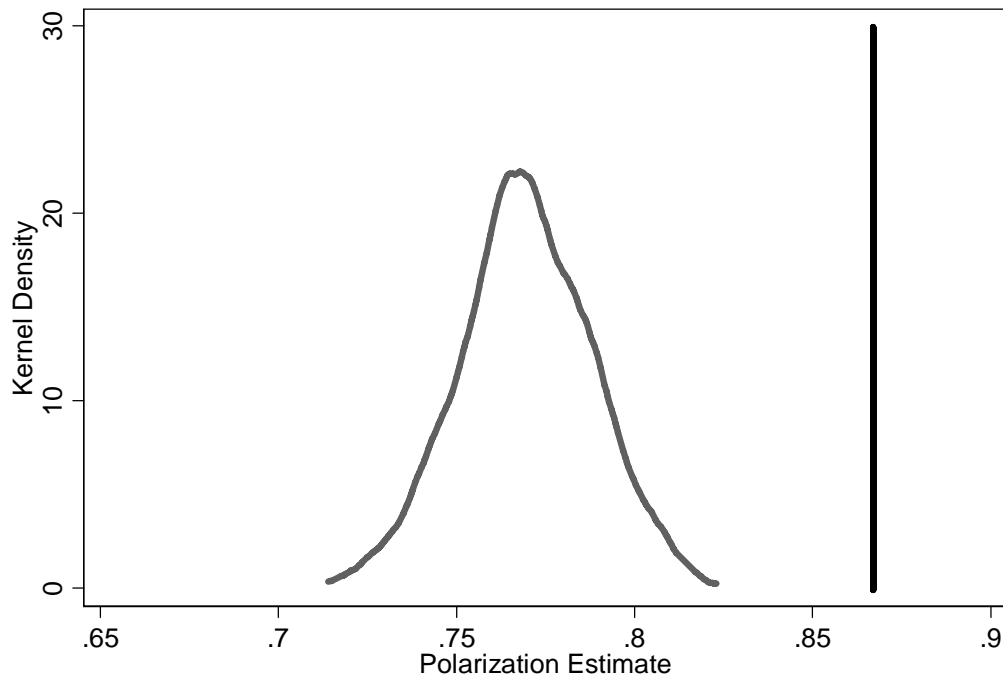


Figure 6: Bootstrap Estimates under Random Districting by State

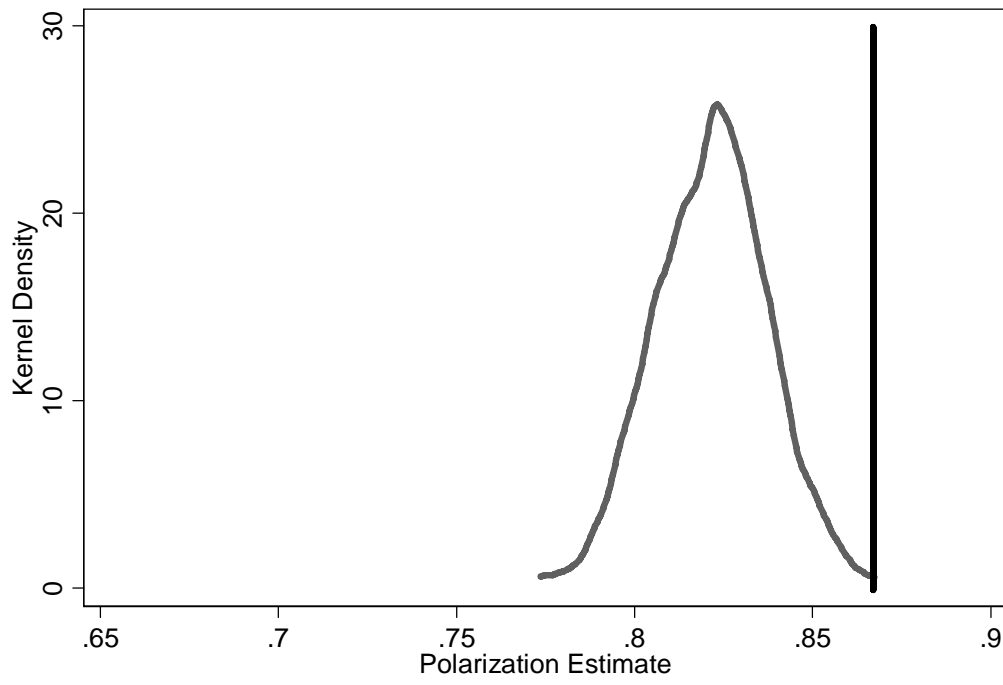


Figure 7: Bootstrap Estimates under Longitude Sorting

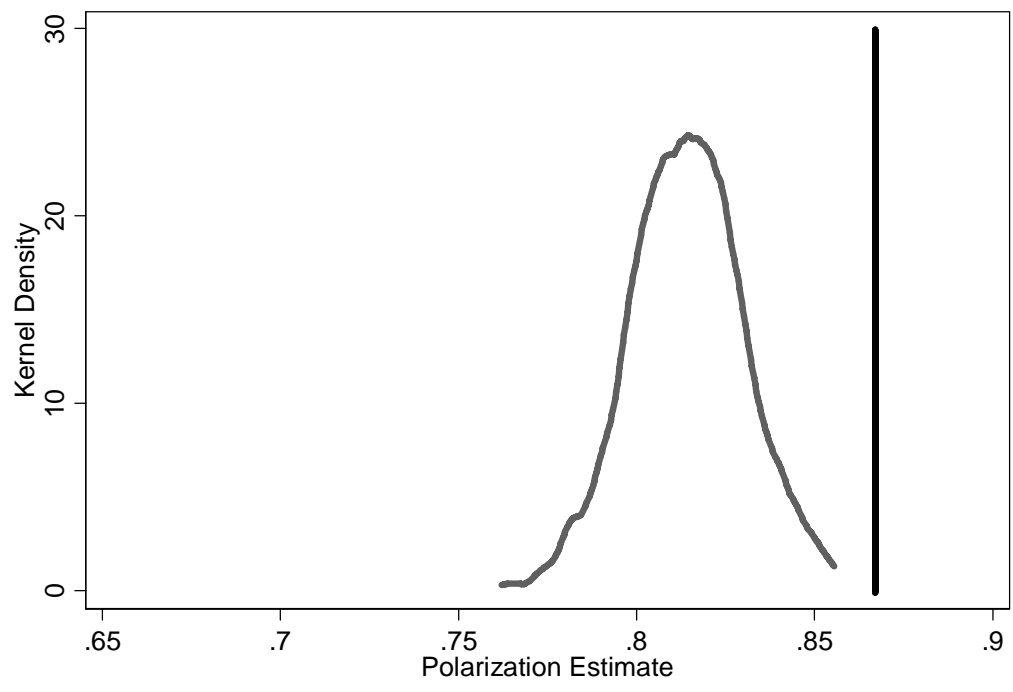


Figure 8: Bootstrap Estimates under Latitude Sorting

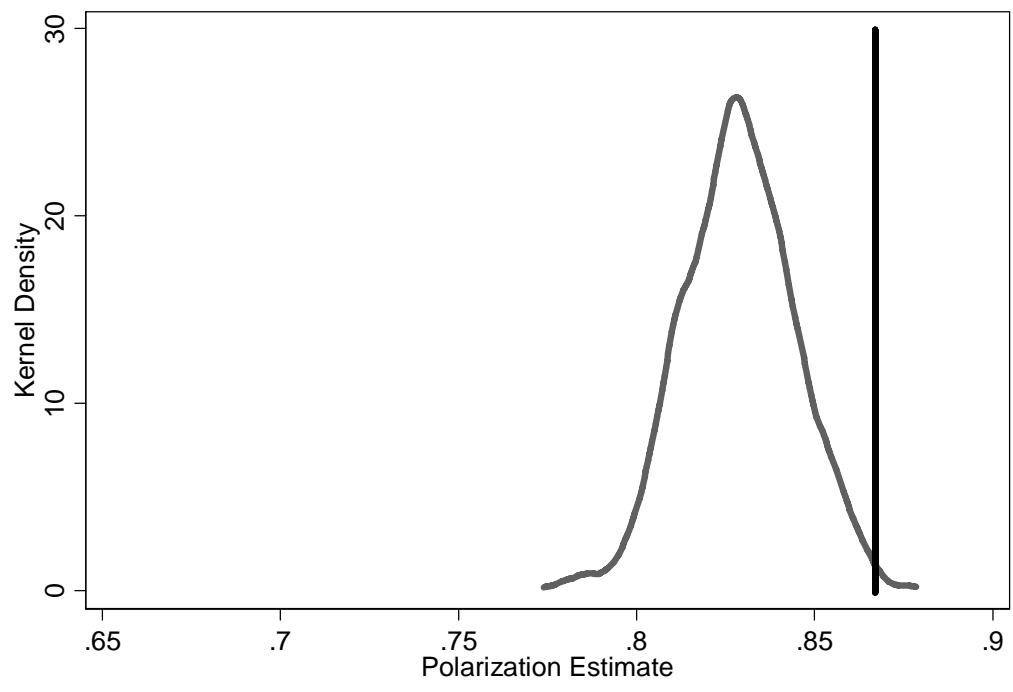


Figure 9: Bootstrap Estimates with Racially Representative Districts

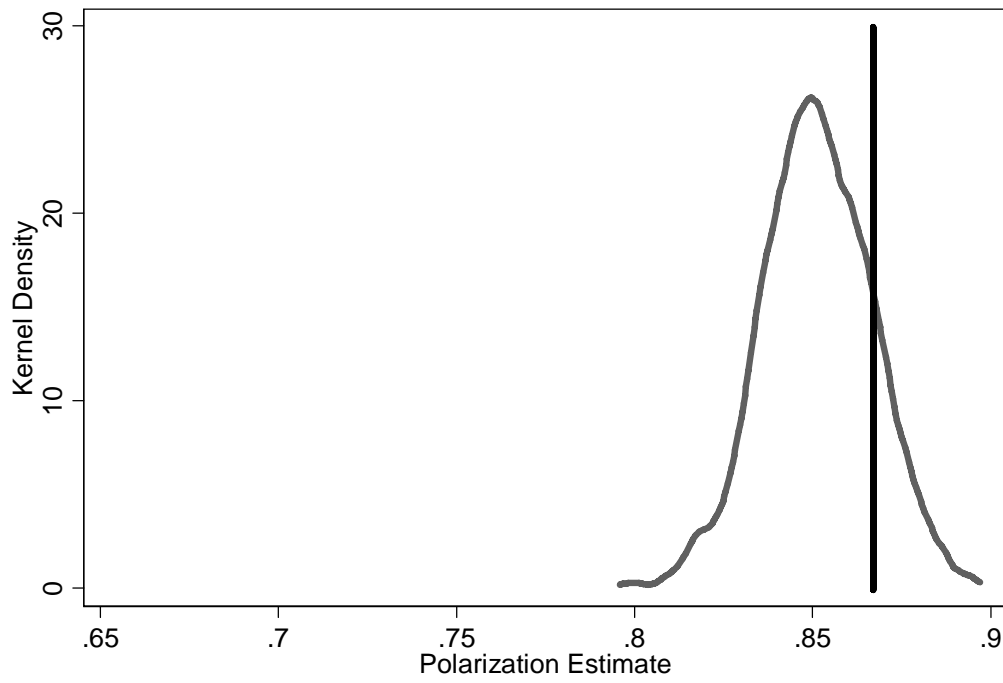


Figure 10: Bootstrap Estimates under Partisan Representative Districts

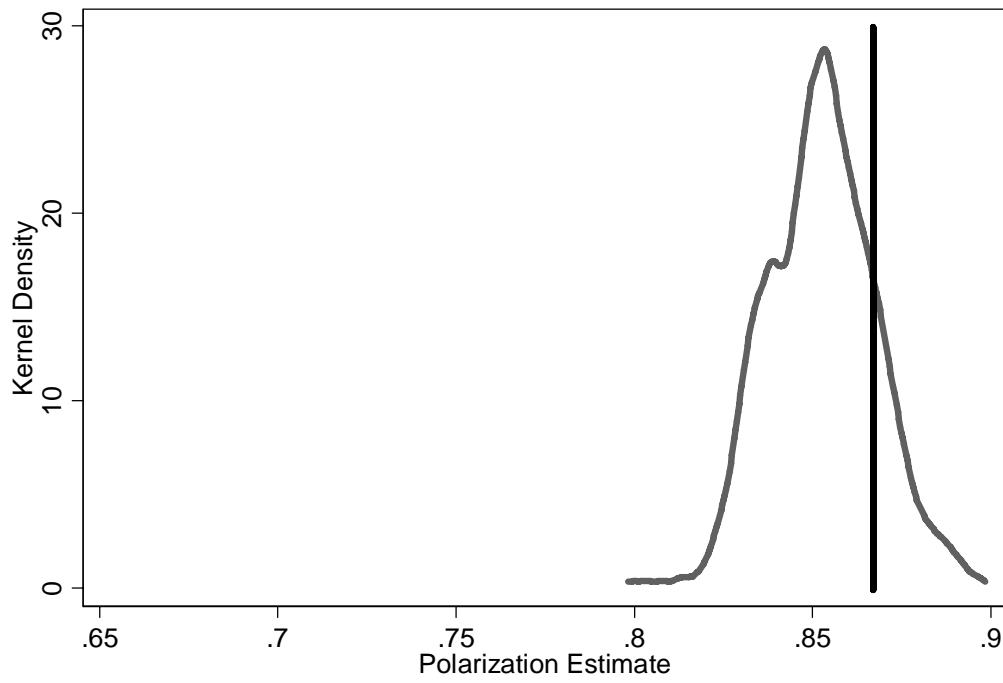


Figure 11: Bootstrap Estimates under Ideologically Representative Districts