Measuring Bias and Uncertainty in DW-NOMINATE Ideal Point Estimates via the Parametric Bootstrap

Preliminary Draft, please do not cite without permission

Royce Carroll	Jeffrey B. Lewis	James Lo	Keith T. Poole
Rice	UCLA	UCLA	UCSD

Howard Rosenthal

NYU

September 4, 2008

ABSTRACT

DW-NOMINATE scores for the U.S. Congress are widely used measures of legislators' ideological locations over time. These scores have been used in a large number of studies in political science and closely related fields. In this paper we extend the work of Lewis and Poole (2004) on the parametric bootstrap to DW-NOMINATE and obtain standard errors for the legislator ideal points. These standard errors are in the range of one to four percent of the range of DW-NOMINATE coordinates.

1. INTRODUCTION

This paper presents a method for obtaining standard errors for the legislator parameters estimated by DW-NOMINATE. We extend the method developed by Lewis and Poole (2004) in which they use the parametric bootstrap (Efron, 1979; Efron and Tibshirani, 1993) to obtain standard errors and other measures of estimation uncertainty for W-NOMINATE (Poole and Rosenthal, 1985, 1991, 1997) and the Quadratic-Normal (QN) scaling procedure (Poole, 2001).

Because of the sheer size of the matrices being analyzed by DW-NOMINATE it is not practical to invert the information matrix or the analytical Hessian matrix directly. Consequently, traditional DW-NOMINATE computed only conditional standard errors. For example, the standard errors for a legislator were computed with the roll call parameters held fixed. This is possible to do because each legislator's parameters are independent of every other legislator's parameters. Although it is straightforward to compute these conditional standard errors, its likely that they substantially understate the full unconditionally sampling variability of the estimates. Indeed, we find that the conditional standard errors are 25 percent smaller on average than the unconditional standard errors that we derive here.

In the next section we outline the DW-NOMINATE model and briefly discuss the history of its development. In section 3 we discuss the application of the parametric bootstrap to DW-NOMINATE. In section 4 we show basic descriptive statistics of our results and we conclude in section 5.

2. A BRIEF HISTORY OF NOMINATE

The acronym DW-NOMINATE stands for dynamic, weighted, nominal three-step estimation. It is a FORTRAN program that estimates a probabilistic model of binary choice of legislators in a Parliamentary setting over time. The basic choice model is the random utility model developed by McFadden (1976). In the random utility model, a legislator's overall utility for voting Yea is the sum of a deterministic utility and a random error. Specifically, legislator

i's utility for the yea outcome on roll call j in legislative session t is

$$\mathrm{U}_{ijyt} = u_{ijyt} + \epsilon_{ijyt}. \tag{1}$$

where u_{ijyt} is the deterministic portion of the utility function and ϵ_{ijyt} is the stochastic or random portion of the utility function. It is standard to work with the difference between the utilities of yea and nay,

$$U_{ijyt} - U_{ijnt} = u_{ijyt} - u_{ijnt} + \epsilon_{ijyt} - \epsilon_{ijnt}.$$

Given the probability density for function $\epsilon_{ijyt} - \epsilon_{ijnt}$ the probability of a Yea vote by legislator i is

$$\mathrm{Pr}_i(Vote = Yea) = \mathrm{Pr}(U_{ijyt} - U_{ijnt} > 0) = \mathrm{Pr}(\epsilon_{ijnt} - \epsilon_{ijyt} < u_{ijyt} - u_{ijnt}). \tag{2}$$

The "NOMINATE model", as it has come to be known, uses the normal density function as the deterministic utility function. The original one-dimensional NOMINATE (Poole and Rosenthal, 1983, 1985, 1987a,b) used "logit" error for the stochastic portion of the utility function. Technically, ϵ_{ijyt} and ϵ_{ijnt} are a random sample of size two from the log of the inverse exponential distribution; that is:

$$f(\epsilon) = e^{-\epsilon} e^{-e^{-\epsilon}}$$

where $-\infty < \epsilon < \infty$.

Dhrymes (1978) shows that the probability distribution of $\epsilon_{ijnt} - \epsilon_{ijyt}$ is:

$$f(z) = \frac{e^{-z}}{(1 + e^{-z})^2}$$

where $z = \epsilon_{ijnt} - \epsilon_{ijyt}$ and $-\infty < z < \infty$. This is the logit distribution. The probability the legislator votes Yea is

$$\mathrm{Pr}_i(Vote = Yea) = \int_{-\infty}^{u_{ijyt} - u_{ijnt}} \frac{e^{-z}}{(1 + e^{-z})^2} dz = \frac{e^{u_{ijyt}}}{e^{u_{ijyt}} + e^{u_{ijnt}}}. \tag{3}$$

The log of the inverse exponential distribution and the logit distribution are unimodal but not symmetric. However, neither distribution is badly skewed and the logit distribution function is reasonably close to the normal distribution function. The advantage of the logit approach is that the probabilities are formulas. In contrast, with a normal error model the probabilities must be computed with some sort of series approximation. Given the computing resources of the early 1980s the logit model was far easier to estimate.

This early approach was extended to D-NOMINATE which was developed from 1986 to 1989. D-NOMINATE was multidimensional and could analyze more than one legislature at a time. Two modifications to D-NOMINATE were made when McCarty, Poole, and Rosenthal (1997) developed DW-NOMINATE. DW-NOMINATE is based on normally distributed errors rather than logit errors, and it uses the W-NOMINATE weighted distance model.

Although DW-NOMINATE, like D-NOMINATE, was designed to deal with the U. S. House and Senate, it can be used to analyze any voting body that meets in a series of legislative terms over time; for example, U. S. state legislatures, the United Nations, or the European Parliament. For our purposes, a “Legislative Term” is any distinct meeting of a voting body. In the U.S. context, we define a term to be one “Congress”, generally a two year period. DW-NOMINATE as structured requires that terms be indexed by integers. Future work could adapt the program to measure time by date, etc.

Let T be the number of legislative terms (Congresses, Parliaments, etc.) that are indexed by $t = 1, ..., T$; s denote the number of policy dimensions ($k = 1, ..., s$); p_t denote the number of legislators in legislative session t ($i = 1, ..., p_t$); q_t denote the number of roll call votes in legislative Session t ($j = 1, ..., q_t$); and T_i denote the number of Legislative Terms in which legislator i served ($t = 1, ..., T_i$). To allow for spatial movement over time, the legislator ideal points are treated as being polynomial functions of time; namely, legislator i's coordinate on dimension k at time t is given by:

$$X_{ikt} = \chi_{ik0} + \chi_{ik1}T_{t1} + \chi_{ik2}T_{t2} + ... + \chi_{ikv}T_{tv} \tag{4}$$

where v is the degree of the polynomial, the χ's are the coefficients of the polynomial, and the time-specific terms – the T's – are Legendre polynomials. Specifically, the first three terms of a Legendre polynomial representation of time are

$$T_{t1} = -1 + (t-1)\frac{2}{T-1}, \tag{5}$$

$$T_{t2} = \frac{3T_{t1}^2 - 1}{2}, \tag{6}$$

and

$$T_{t3} = \frac{5T_{t1}^3 - 3T_{t1}}{2}. \tag{7}$$

Legendre polynomials are orthogonal on the interval [-1,+1]. This is convenient because DW-NOMINATE scales the legislators and roll call midpoints to be in the unit hypersphere (more on this below). The orthogonality of the Legendre polynomials is a continuous property, but even with discrete data the linear and quadratic terms will be orthogonal. If ordinary powers of time were used instead, that is, t, t^2, t^3, and so on, these would be correlated.

The two roll call outcome points associated with Yea and Nay on the kth dimension at time t can be written in terms of their midpoint and the distance between them; namely,

$$O_{jkyt} = Z_{jkyt} - \delta_{jkt}$$

and

$$O_{jknt} = Z_{jkyt} + \delta_{jkt}$$

where the midpoint is

$$Z_{jkt} = \frac{O_{jkyt} + O_{jknt}}{2}$$

and δ_{jkt} is half the signed distance (δ_{jkt} can be negative) between the Yea and Nay points on the kth dimension; that is

$$\delta_{jkt} = \frac{O_{jkyt} - O_{jknt}}{2}.$$

Legislator i's utility for the Yea outcome on roll call j in Legislative Session t is

$$U_{ijyt} = u_{ijyt} + \epsilon_{ijyt} = \beta e^{-\frac{1}{2}\sum_{k=1}^{s} w_k^2 d_{ijkyt}^2} + \epsilon_{ijyt} \tag{8}$$

where

$$d_{ijkyt}^2 = (X_{ikt} - O_{jkyt})^2$$

and the w_k are the salience weights. Because the stochastic portion of the utility function is normally distributed with constant variance, β is proportional to $\frac{1}{\sigma^2}$ where

$$\epsilon_{ijnt} - \epsilon_{ijyt} \sim N(0, \sigma^2).$$

Hence the probability that legislator i votes Yea on the jth roll call in Legislative Session t is similar to that shown for the logit approach except that the normal distribution cumulative distribution function is substituted for the logistic;

$$\text{Pr}_i(Vote = Yea) = \Phi\left(u_{ijyt} - u_{ijnt}\right) = \Phi\left(\beta\left\{e^{-\frac{1}{2}\sum_{k=1}^{s} w_k^2 d_{ijkyt}^2} - e^{-\frac{1}{2}\sum_{k=1}^{s} w_k^2 d_{ijknt}^2}\right\}\right). \tag{9}$$

The natural log of the likelihood function is

$$\mathcal{L} = \sum_{t=1}^{T}\sum_{i=1}^{p_t}\sum_{j=1}^{q_t}\sum_{\tau=1}^{2} C_{ij\tau t} \ln P_{ij\tau t} \tag{10}$$

where τ is the index for Yea and Nay, $P_{ij\tau t}$ is the probability of voting for choice τ (yea or nay) as given by equation (9), and $C_{ij\tau t} = 1$ if the legislator's actual choice is τ and zero otherwise. Note that if a legislator did not vote on a roll call then $C_{ijyt} = C_{ijnt} = 0$.

The total number of parameters is at most

$$2s\sum_{t=1}^{T} q_t + sp(v+1) + s$$

where $2s\sum_{t=1}^{T} q_t$ is the number of roll call parameters, $sp(v+1)$ is the maximum possible number of legislator parameters — that is, all p legislators serve in at least $v+1$ legislative terms so that the $v+1$ χ_{ik}'s can be estimated for each member — and the last term represents β and w_2 through w_s that must be estimated (the weight on the first dimension can be set equal to 1). In practice v is usually set to 0 — the constant model where the legislator's ideal point is the same in every legislative Session in which she serves — or v is set to 1 — the linear model in which legislators are allowed to follow a straight line trajectory through the space over time. In their original D-NOMINATE work on the U.S. House and Senate, Poole and Rosenthal (1991; 1997; 2001; 2007) found that the linear model in two dimensions was the best combination of explanatory power and parsimony.

The spatial model outlined above has no natural metric. The metric used by DW-NOMINATE is established by requiring the constant point of the legislator's ideal point polynomial as well as the the midpoints of the roll call outcomes (Z_{jt}'s) to lie within a unit hypersphere. These constraints are similar to those used in D-NOMINATE (Poole and Rosenthal, 1997).

DW-NOMINATE like its predecessor D-NOMINATE does not generate its own parameter starting values because of the sheer size of the roll call data set being analyzed. Good starting values are crucial to reliably performing this complex non-linear estimation. In their development of D-NOMINATE Poole and Rosenthal experimented for over two years until they had a satisfactory solution to the problem. Essentially they began with what they thought was a sensible set of starting values and studied the estimated legislator coordinates by turning them into computer animations that could be played on a VHS video recorder. In these animations letter tokens and color for the estimated legislator coordinates were used to identify parties and regions of the United States.[1] Poole and Rosenthal then relied upon their knowledge of American political history to see if the output made visual sense.[2] If they saw anomalies they adjusted the output coordinates to correct for the anomalies and then used these adjusted coordinates as new starting values. At each step of this process the fit of the model increased but it was a relatively arduous task because the supercomputers of the 1980s were limited in their capabilities and the animations took about a week to make on the equipment at the Pittsburgh Supercomputer Center.

The upshot of what one of us has described as "Poole and Rosenthal were the outer loop of the estimation" is that the final coordinates from D-NOMINATE that were released to the larger research community in 1989-90 were about as close to the global maximum of the (constrained) likelihood function shown in equation (10) as was practicable given the computer resources of the time.

Consequently, when DW-NOMINATE was developed in 1996 it simply used for starts the D-NOMINATE coordinates along with patched-in W-NOMINATE coordinates for Congresses 100–105. The converged coordinates that maximized equation (10) were then checked against the D-NOMINATE coordinates both in terms of simple Pearson correlations along with the overall fit of the model for the common period of Congresses 1–99. DW-NOMINATE has a slightly higher overall fit (Poole and Rosenthal, 2007) and the Pearson correlations are

[1]Because DW-NOMINATE is a dynamic estimation, animations remain our preferred means for understanding the results and obtaining a rapid overview of the evolution of ideology in the political history of Congress. The most current animations, programmed in 2005, are on the web at voteworld.Berkeley.edu and voteview.ucsd.edu.

[2]For a short history of this see the discussion in Poole (1999; 2005).

all over 0.95 for dimensions one and two.

3. APPLYING THE PARAMETRIC BOOTSTRAP TO DW-NOMINATE

The parametric bootstrap is based in classical statistics. The parameters are treated as fixed constants to be estimated and consequently, they are not given probability distributions as in the Bayesian approach. Rather, the underlying probability model, with its parameters set equal to the maximum likelihood estimates, is used to generate repeated simulated samples. For each of these repeated samples, the model is refit, and the empirical distribution of these estimates across the pseudo-samples is used to estimate the relevant sampling distributions.

The parametric bootstrap is conceptually simple. In a maximum likelihood framework, the first step is to compute the likelihood function of the sample. The second step is to draw, for example, 1000 samples from the likelihood density and compute for each sample the maximum likelihood estimates of the parameters of interest. The sample variances computed from these 1000 values are the estimators of the variances of the parameters (Efron and Tibshirani, 1993).[3]

When the parametric bootstrap is applied to a scaling method such as DW-NOMINATE, the first step is to run the program to convergence and then calculate the probabilities for the observed choices. This produces a legislator by roll call matrix containing the estimated probabilities for the corresponding actual roll call choices of the legislators. Note that the product of these probabilities is the likelihood; that is:

$$\mathcal{L}(\hat{\theta}|Y) = \prod_{t=1}^{T}\prod_{i=1}^{p_t}\prod_{j=1}^{q_t}\prod_{\tau=1}^{2} \hat{P}_{ij\tau t}^{C_{ij\tau t}} \tag{11}$$

where $\hat{\theta}$ is the set of all the estimated ideal point, roll call, and utility function parameters, Y is the p by $\sum_{t=1}^{T} q_t$ matrix of roll calls for all Legislative Sessions with the number of non-missing entries equal to $\sum_{t=1}^{T}\sum_{i=1}^{p_t}\sum_{j=1}^{q_t}\sum_{\tau=1}^{2} C_{ij\tau t}$, $\hat{P}_{ij\tau t}$ is the estimated probability that legislator

[3]The parametric bootstrap assumes that the model has been correctly specified so that its assumptions are stronger than the nonparametric bootstrap. The non-parametric bootstrap is not readily applicable in this case because the data (roll call votes) are dependent across both members and roll calls (unconditionally).

i votes for choice t on the jth roll call in Legislative Session t as given by equation (9), and $C_{ij\tau t} = 1$ if the legislator's actual choice is t and zero otherwise.

To draw a random sample, we treat each estimated probability as a weighted coin and "flip" the coin. To do the "flip" we draw a number from a uniform distribution over zero to one — U(0,1) — and if the estimated probability is greater than or equal to the random draw, the sampled value is the observed choice. If the random draw is greater than the estimated probability, then the sampled value is the opposite of the observed choice; that is, if the observed choice is Yea then the sampled value is Nay. Note that this is equivalent to drawing a random sample of size one from $\sum_{t=1}^{T}\sum_{i=1}^{p_t}\sum_{j=1}^{q_t}\sum_{\tau=1}^{2} C_{ij\tau t}$ separate Bernoulli distributions with corresponding parameters $\hat{P}_{ij\tau t}$. In the context of a Bernoulli distribution the two outcomes are either "success" or "failure". Here a "success" is the observed choice and "failure" is the opposite choice.

The sample roll call matrix is then analyzed by DW-NOMINATE. This process is repeated n times and the variances of the legislator ideal points are calculated from the n bootstrap configurations. Technically, let π be a random draw from U(0,1). The sample rule is such that if the observed choice is Yea (Nay):

If $\pi \leq \hat{P}_{ij\tau t}$ then the sample value, $\hat{C}_{ij\tau t}$ is Yea(Nay). If $\pi \geq \hat{P}_{ij\tau t}$ then the sample value, $\hat{C}_{ij\tau t}$ is Nay(Yea).

This technique allows the underlying uncertainty to propagate through to all the estimated parameters. To see this, note that as $\hat{P}_{ij\tau t} \rightarrow 1$, then $\hat{C}_{ij\tau t} \rightarrow C_{ij\tau t}$, that is, sample choices become the observed choices so that the bootstrapped variances for the parameters of the model go to zero. If the fit of the model is poor, for example, if $\hat{P}_{ij\tau t}$ the are between 0.5 and 0.7, then the bootstrapped variances for the parameters will be large.

Applying the parametric bootstrap to DW-NOMINATE is not as easy as the application to W-NOMINATE and QN discussed in Lewis and Poole (2004). W-NOMINATE and QN are completely self-contained programs that generate their own starting values for the parameters. They read the sample roll call matrix and generate the estimated parameters for that bootstrap trial. Consequently, for each bootstrap run, new starting values can be computed; from the new starts, W-NOMINATE or QN can be run to convergence. This procedure leads to bootstrapped sets of parameters and the corresponding bootstrapped variances. In contrast, as we discussed above, DW-NOMINATE reads starting values for the parameters. Specifically for the two dimensional model, let $\tilde{X}$ be the $\sum_{t=1}^{T} p_t$ by s matrix of starting values for the legislators, let $\tilde{O}$ be the $\sum_{t=1}^{T} q_t$ by 2s matrix of starting values for the roll calls, $\tilde{w}_2$ be the starting value of the second dimension weight (recall that w_1 is set equal to 1), and $\tilde{\beta}$ be the starting value for the signal-to-noise parameter β. The steps in DW-NOMINATE are:

1. Read Y, $\tilde{X}$, $\tilde{O}$, $\tilde{w}_2$, and $\tilde{\beta}$
2. Estimate $\tilde{w}_2$, given $\tilde{X}$, $\tilde{O}$, and $\tilde{\beta}$
3. Estimate β, given $\tilde{X}$, $\tilde{O}$, and $\tilde{w}_2$
4. Estimate O given $\tilde{X}$, $\tilde{\beta}$, and $\tilde{w}_2$
5. Estimate X given O, β, and w_2
6. go to 2

Steps 1 to 6 are repeated until the improvement in geometric mean probability is less than 0.001. Typically, this is only about 3 to 5 iterations through the 6 steps.

Let h= 1,…,m be the number of bootstrap trials and let Y_h be the p by $\sum_{t=1}^{T} q_t$ matrix of roll calls for all legislative terms produced by the bootstrap draw procedure shown in equation (11). Let $\tilde{X}$, $\tilde{O}$, $\tilde{w}_2$, and $\tilde{\beta}$ be the actual starting values used to produce $\hat{\theta}$. Given the impossibility of programming the Poole-Rosenthal "outer loop", one possible approach is for step 1 to be:

1. Read Y_h, $\tilde{X}$, $\tilde{O}$, $\tilde{w}_2$, and $\tilde{\beta}$.

That is, use the same starting coordinates could be used for each bootstrap trial. However, because the DW-NOMINATE algorithm is not run to full convergence, we were concerned that the estimates from the bootstrap samples might depend in important ways on the starting values. In particular, the variability in the estimates obtained from the bootstrap samples might be attenuated by using a fixed set of starting values. To avoid this potential source of attenuation, we created new starting values for each bootstrap iteration by randomly perturbing the ML estimates. Specifically, we set:

$$\tilde{X}_h = \tilde{X} + \Psi$$

and

$$\tilde{Z}_h = \tilde{Z} + \Xi$$

where the $s\sum_{t=1}^{T} p_t$ elements of Ψ and the $s\sum_{t=1}^{T} q_t$ elements of Ξ were randomly drawn from a normal distribution with zero mean and constant variance, that is, N(0,σ^2). Note that we perturbed the midpoints of the outcomes. This was easier to implement computationally and is sufficient to produce dramatically different starting values for the roll calls depending upon how large σ^2 is. Consequently, at the h^{th} iteration step 1 is:

1. Read Y_h, $\tilde{X}_h$, $\tilde{O}_h$, $\tilde{w}_2$, and $\tilde{\beta}$

As it turns out, the magnitude of the estimated standard errors that we obtained using this starting value method do not substantially depend upon the value chosen for σ^2. Because the estimated standard errors remained stable as we increased σ^2 from 0 to 0.4, we are reasonably confident that the starting values are in no way driving the uncertainly estimates presented below.

One issue that we had to consider was the fact that the legislator and roll call coordinates are only identified up to an arbitrary rotation in the s-dimensional space. This will not be an important problem for us because DW-NOMINATE uses starting coordinates. Even though the starting coordinates are perturbed for each trial, because the perturbations are drawn from a mean zero symmetric distribution this is unlikely to introduce any arbitrary rotation in the final result.[4]

A more important issue is the interaction of the second dimension weight, w_2 , with the linear terms of the legislator polynomials; the χ_{ik1}'s. The only constraints used by DW-NOMINATE are that the constant point of the legislator — that is, the s by 1 vector χ_{i0} from

[4] We spot-checked this and found the rotation to be extremely small. Removing it would reduce our bootstrapped standard errors by a very tiny amount.

the s polynomials defined by equation (4) — and the midpoints of the roll call outcomes — the Z_{jt}'s — are within a unit hypersphere. Consequently, there is some interaction between w_2 and the linear terms for the legislators; the s by 1 vectors χ_{i1}. Namely, the legislators' time trends on the first dimension can all increase, the time trends on the second dimension can all increase a little, and the effect can be cancelled in terms of overall fit by increasing the size of w_2 to compensate. Let $\hat{X}$ be the $\sum_{t=1}^{T} p_t$ by s matrix of legislator coordinates estimated by DW-NOMINATE and let X_h be the $\sum_{t=1}^{T} p_t$ by s matrix of legislator coordinates estimated on the h^{th} bootstrap trial. We removed this effect by computing the regression

$$\hat{X} = X_h \Delta + \epsilon \tag{12}$$

where Δ is an s by s diagonal matrix. Because DW-NOMINATE always produces legislator coordinates with mean zero, we do not show a vector of intercepts in equation (12). To reduce notational clutter, we will simply use X_h to denote the h^{th} bootstrap trial with this correction taken into account.

The mean legislator ideal point on the k^{th} dimension at time t is:

$$\tilde{X}_{ikt} = \frac{\sum_{h=1}^{M} X_{hikt}}{m}$$

where X_{hikt} is the estimated coordinate on the h^{th} trial. The corresponding standard deviation is

$$\sigma_{X_{ikt}} = \sqrt{\frac{\sum_{h=1}^{M} (X_{hikt} - \hat{X}_{ikt})^2}{m-1}}.$$

We take a conservative approach and use the estimated coordinate, $\hat{X}_{ikt}$, rather than the mean of the bootstrap trials, $\tilde{X}_{ikt}$, as our "sample mean" in our calculation of the standard deviation. This inflates the standard deviations somewhat, but we feel it is better to err on the safe side and not underreport the standard deviations.

4. DW-NOMINATE STANDARD ERRORS AND AUXILIARY QUANTITIES OF INTEREST FOR THE UNITED STATES HOUSE AND SENATE, 1789 TO 2006

We applied the bootstrap procedure developed above to roll call votes taken in the United States House and Senate between the First Congress and the 109th Congress. The selection criteria for which members and roll calls to include in the analysis was the same as was used in Poole and Rosenthal (2007) and includes every roll call vote with at least 2.5 percent in the minority and every legislator casting more than 20 votes in any Congress. In total, locations are estimated for 35,739 Representative-Congress pairs and 8,644 Senator-Congress pairs covering 109 Congresses with 10,419 unique members of the House and 1,828 unique Senators. These estimates are based on 42,029 scalable roll call votes in the House with a total of 11,866,698 individual vote choices and 43,188 scalable roll call votes in the Senate with a total of 2,479,057 individual vote choices.

Each member's ideal point in each Congress is estimated along two dimensions. As described above, the constraints imposed on how each member's location can vary over time allow the estimated locations to be compared across Congresses. Previous research has demonstrated that the first dimension locations reveal standard left-right or economic cleavages, while the second dimension locations reflect social and sectional divisions. The importance of the second dimensions has waxed and waned throughout Senate history. Readers are encouraged to consult Poole and Rosenthal (2007) for a complete discussion of the DW-NOMINATE scores in the United States Congress. In what follows, we will assume a basic familiarity with NOMINATE scores and how they are commonly applied to the study of the United States Congress.

For the Senate, estimated first-dimension locations ranged from -1.252 (John Langdon, Jeffersonian, of New Hampshire in the 6th Congress) to 1.392 (James Ross, Federalist, of Pennsylvania in the 3rd Congress) with ninety percent of the estimated locations falling between -0.511 and 0.516. Second-dimension locations ranged from -1.482 (John McCain, Republican, of Arizona in the 109th Congress) to 1.475 (Richard Russell, Democrat, of Georgia, well known as a segregationist, in the 91st Congress) with ninety percent falling between -0.764 and 0.760. Estimates of first dimension locations in the House ranged from

-1.273 (Adam Clayton Powell, Democrat, of New York, a controversial African-American from Harlem, in the 79th Congress) to 1.586 (Harold Gross, Republican, of Iowa, well known as an isolationist conservative, in the 93rd Congress). Ninety percent of the first dimension locations fall between -0.545 and 0.587. Second dimension locations range from -1.691 (Frank Hook, Democrat, of Michigan in the 79th Congress) to 1.505 (John Shafer, Republican, of Wisconsin in the 68th Congress). Ninety percent of the second dimension locations fall between -0.833 and 0.928.

In the Senate, the average estimated standard error for first dimension locations was 0.05 and ninety percent of the first dimension standard errors fall between 0.02 and 0.10. The largest first dimension standard error was 0.41 and is associated with James Ross (Federalist) of Pennsylvania in the 3rd Congress. This large standard error is not unexpected given that Ross cast only 361 votes in his career, served at a time when the Senate had fewer than 35 members, and was located far from the middle of the dimension. The average second dimension standard error is 0.094. The largest second dimension standard error was 0.541 and is associated with Thaddeus Betts (Whig) of Connecticut in the 26th Congress. Betts cast only 44 votes in his career and served in a Senate with only 52 members. Overall, ninety percent of the second dimension standard errors fall between 0.042 and 0.166.

In the House, the average first-dimension standard error is 0.047. Ninety percent of the first dimension standard errors fall between 0.014 and 0.101. The largest first dimension standard error of 0.496 is associated with the estimated location of Harold Gross (R) of Iowa in the 93rd Congress. This large standard error results from the large (but uncertain) estimated linear trend in his estimated first-dimension location that moves him from 0.396 (with a standard error of 0.054) in the 81st Congress to 1.586 (0.496) by the 93rd Congress. The average House second-dimension standard error is 0.11 with 90 percent of the estimated standard errors falling between 0.037 and 0.235. The largest second dimension standard error, 0.738, is associated with the estimated second-dimension position of John Reid (D) of Missouri in the 37th Congress (Reid only cast 31 votes and only served in the 37th — the first two years of the Civil War).

Because of the substantially greater predictive power of the first dimension, it is unsurprising that first dimension locations are typically estimated with roughly twice the precision

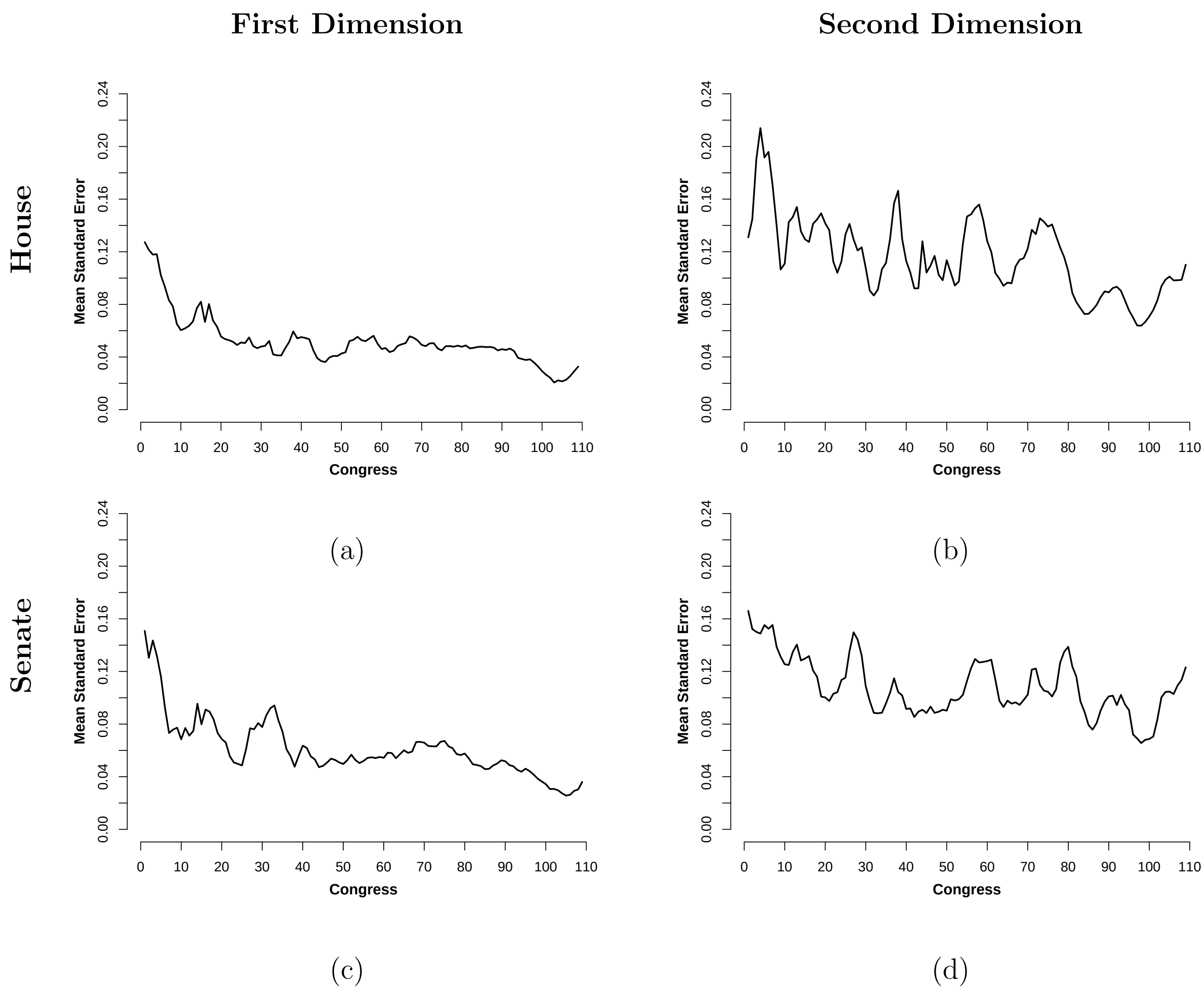


Figure 1: Mean DW-NOMINATE Standard Errors by Chamber and Dimension.

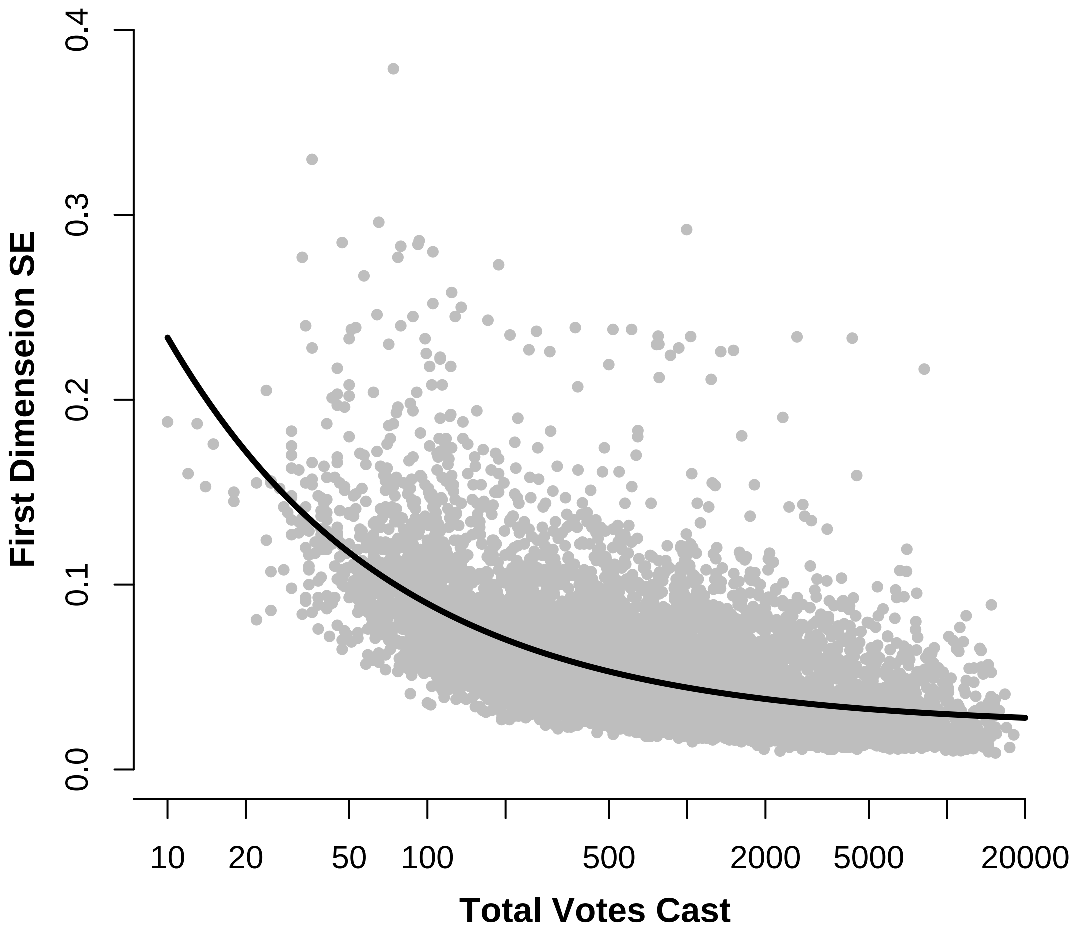


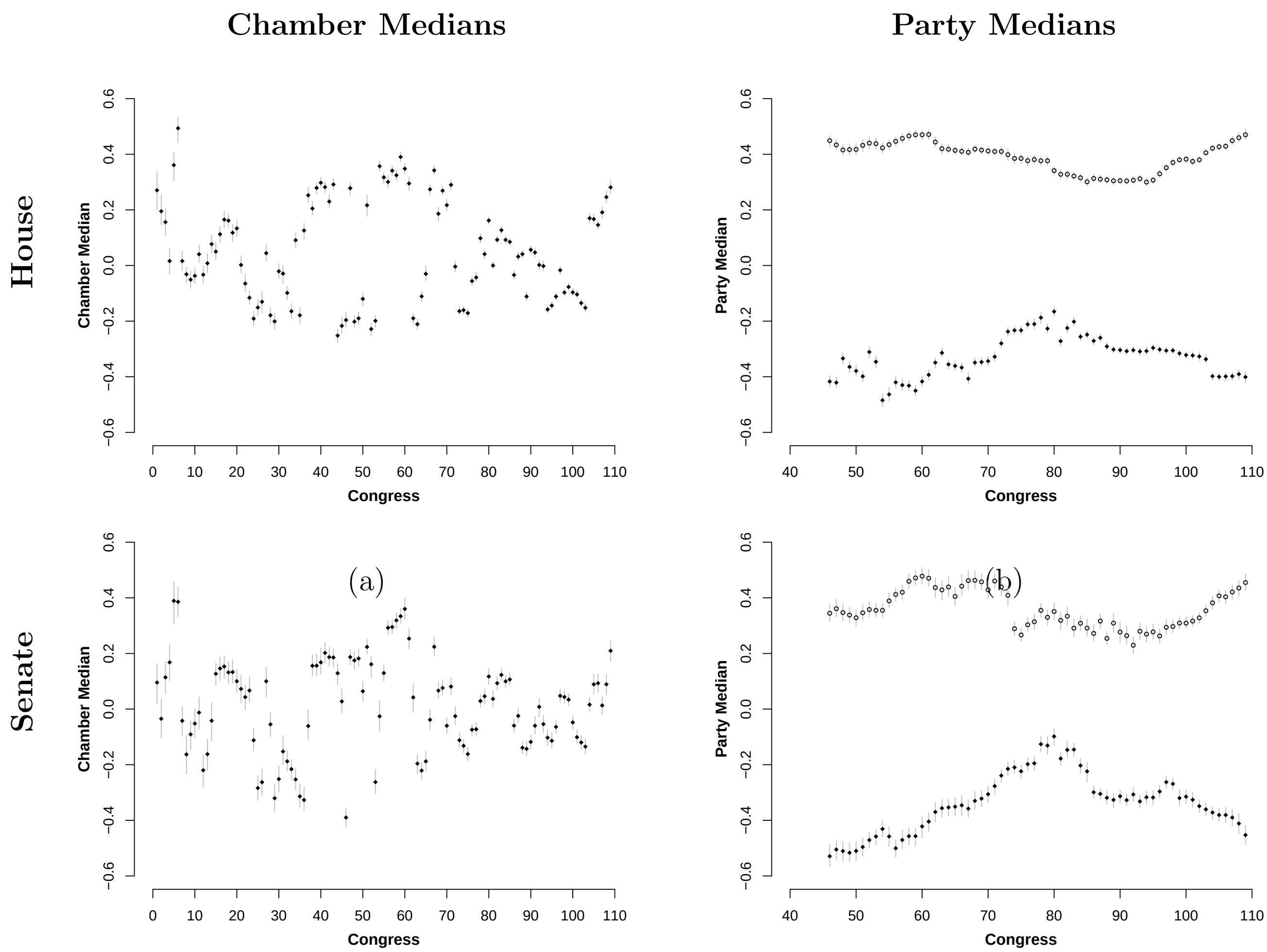
Figure 2: First dimension standard errors of legislators vs. number of votes for U.S. House of Representatives. *Standard errors shown are mean standard errors of legislators across all years of service. Fitted curve represents the best fit* $\frac{1}{\sqrt{N}}$ *line through the points, with* $R^2 = 0.36$.

as second dimension locations. Figures 1a and 1b plot the average standard errors for the first and second dimension locations respectively for the House and Figures 1c and 1d show the same information for the Senate. A scatterplot of all first dimension standard errors for the House is shown in Figure 2. Note that there is considerable variability over time. We are still investigating all of the factors that drive this variability. However, the historically small uncertainty associated with the first dimension locations of members of recent Congresses result at least in part from the relatively large size of the modern House and Senate, the large number of roll calls taken in recent Congresses in both chambers, and the large number of long serving members. In contrast, second dimension locations have been increasingly uncertain over past few decades. This lack of precision results from the declining salience of the second dimension (Poole and Rosenthal, 2007).

Figures 3a and 3c plot the locations of the floor medians for the House and Senate respectively, and Figures 3b and 3d show the Democrat and Republican Party medians since the end of Reconstruction (46th to 109th Congresses). One of the useful features of the bootstrap procedure is that it allows for easy calculation of standard errors and confidence intervals not only of individual members' locations, but for any function of those locations. The vertical line through each of the points plotted in Figures 3a to 3d represent the 95 percent confidence interval for the corresponding estimated median. Not surprisingly the medians are estimated with greater precisions than individual member locations and indeed are quite tightly estimated. Given that a good deal of scholarship turns on how the ideological composition of the House and Senate floor and party caucuses has varied over time as measured by DW-NOMINATE scores, it is comforting that that variation is not driven by estimation imprecision to any significant degree.

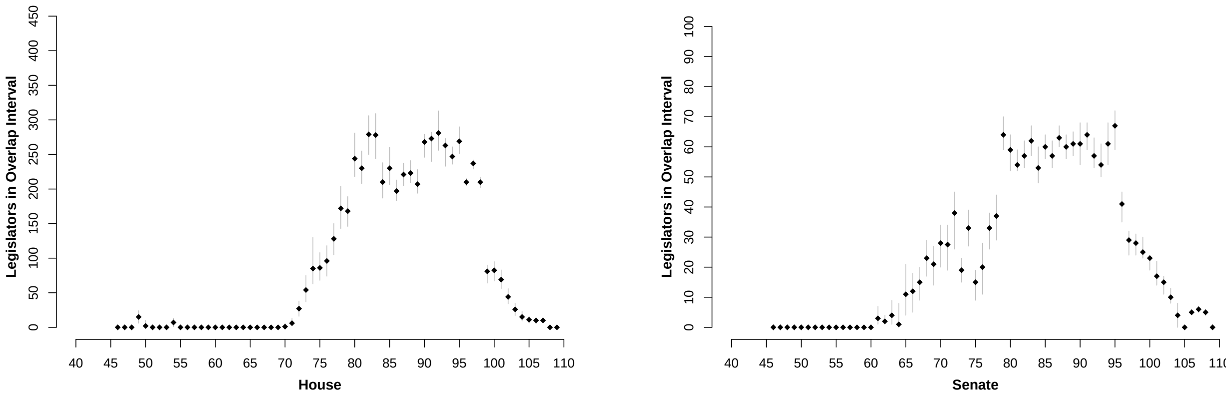
Another function of the ideal point estimates is the extent of ideological overlap between the two major parties. This measure has been used to study political polarization by Poole and Rosenthal (1997; 2001; 2007) and McCarty, Poole, and Rosenthal (2006). As Figure 4 shows, overlap is estimated with great precision.

Figures 5a and 5b show confidence ellipse for several prominent members of the 109th Congress. Figure 5a shows that then minority leader Nancy Pelosi (D-CA) is to the left of the Democratic caucus and her rival for party leader Steny Hoyer (D-MD) is to the right of



(c) (d)

Figure 3: Chamber and Party Median DW-NOMINATE scores by Chamber. *Chamber medians begin from the first Congress, while party medians begin from the 46th Congress dating back only to the joint existence of the modern Democratic (lower band) and Republican (upper band) parties. Lines from each point represent the empirical 95% confidence intervals of the estimates.*



House (a) **Senate** (b)

Figure 4: Overlap Intervals by Chamber from the 46th to the 109th Congresses. *Overlap intervals are computed as the number of legislators with ideal points lying between the most conservative Democrat and the most liberal Republican. Lines show 95% confidence intervals of the estimated overlap intervals.*

the caucus. Figure 5b reveals that Democrat Senate leader (Reid of NV) was significantly more moderate along the first dimension than the caucus that he leads and that he held a distinct position from the dimension-by-dimension Democratic median. Both Senator Hillary Clinton (D-NY) and Senator Barak Obama (D-IL) have confidence ellipses that overlap the center of the Democratic caucus (and each of these Senators has relatively large confidence ellipses due in part to their short tenure in the Senate). Interestingly, John McCain (R-AZ) despite his long service in the Senate is nevertheless quite imprecisely located in the 109th Congress.

McCain's move away from the Republican caucus is shown in Figure 6. Note that as he has moved farther away from his caucus, his position has become increasingly uncertain. Coming to a more complete understanding of this dynamic will be a focus of future work. The movement of the Senate median to the right in part reflects increased Republican membership following the elections of 1994 and 2002. The movement of the Republican median to the right reflects the increasing polarization of American politics. McCain's position has been very stable on the first dimension. McCain has frequently been a maverick. This has been

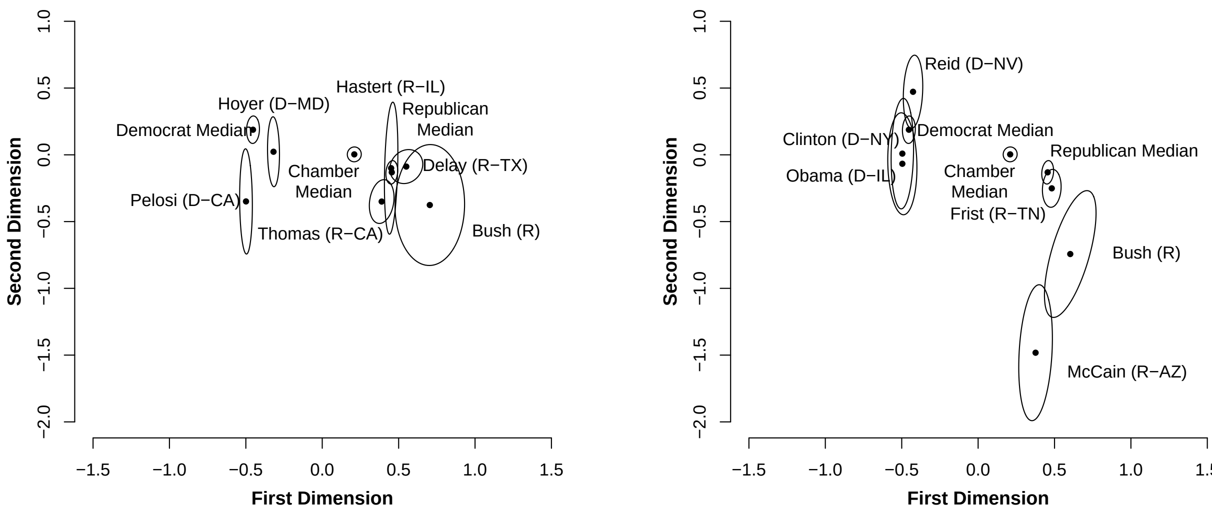


Figure 5: DW-NOMINATE scores in two dimensions of key members of the 109th Congress. *House results are shown on the left and Senate results are shown on the right. Ellipses are 95% confidence ellipsoids generated using R's ellipse package. The chamber and party medians have also been plotted. The estimates for President Bush are based on the votes selected by* Congressional Quarterly *to compute Bush's presidential support score.*

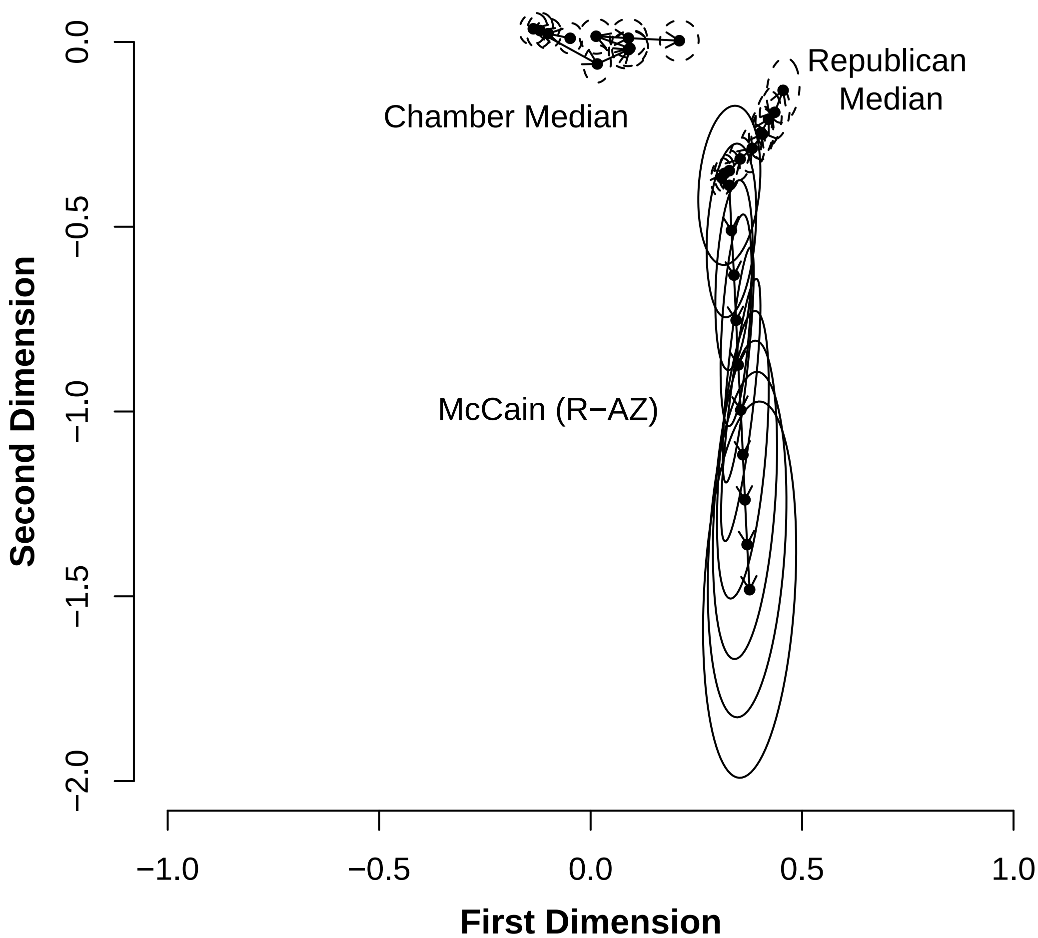


Figure 6: DW-NOMINATE shifts of McCain (R-AZ), Senate median, and Republican Senate median from the 100th to 109th Congress. *Ellipses are 95% confidence ellipsoids. Arrows point to a shift from one Congress to the next.*

picked up by his sharp movement on the second dimension, which, in recent years, has served mainly to pick up "odd" votes that fail to fit the liberal-conservative dimension. Finally, note that McCain's ellipses are smaller in the middle of his Senate career. This reflects the typical result in this setting that the estimates are more accurate near the center of a range of data.

5. CONCLUSION

Our results show that the parametric bootstrap is an effective method for obtaining standard errors for DW-NOMINATE. These standard errors are relatively small in magnitude and in the aggregate they reflect the well-known periods of Congressional history when roll call voting did not fit the spatial model (Poole and Rosenthal, 1997, 2007; Silbey, 1967)

References

Dhrymes, P. J. (1978). *Introductory Econometrics*. New York: Springer–Verlag.

Efron, B. (1979). Bootstrap methods: Another look at the jacknife. *Annals of Statistics 7*, 1–26.

Efron, B. and R. J. Tibshirani (1993). *An Introduction to the Bootstrap*. New York: Chapman and Hall.

Lewis, J. B. and K. T. Poole (2004). Measuring bias and uncertainty in ideal point estimates via the parametric bootstrap. *Political Analysis 12*(2), 105–127.

McCarty, N. M., K. T. Poole, and H. Rosenthal (1997). *Income Redistribution and the Realignment of American Politics*. Washington DC: SEI Press.

McCarty, N. M., K. T. Poole, and H. Rosenthal (2006). *Polarized America: The Dance of Ideology and Unequal Riches*. Cambridge, MA: MIT PRess.

McFadden, D. (1976). Quantal choice analysis: A survey. *Annals of Economic and Social Measurement 5*, 363–390.

Poole, K. T. (1999). Nominate: A short intellectual history. *The Political Methodologist 9*, 1–6.

Poole, K. T. (2001). The geometry of multidimensional quadratic utility in models of parliamentary roll call voting. *Political Analysis 9*, 211–226.

Poole, K. T. (2005). *Spatial Models of Parliamentary Voting*. Cambridge: Cambridge University Press.

Poole, K. T. and H. Rosenthal (1983). A spatial model for legislative roll call analysis. GSIA Working Paper No. 5-83-84.

Poole, K. T. and H. Rosenthal (1985). A spatial model for legislative roll call analysis. *American Journal of Political Science 29*, 357–84.

Poole, K. T. and H. Rosenthal (1987a). Analysis of congressional coalition patterns: A unidimensional spatial model. *Legislative Studies Quarterly 12*, 55–75.

Poole, K. T. and H. Rosenthal (1987b). The unidimensional congress, 1919-84. GSIA Working Paper No. 44-84-85.

Poole, K. T. and H. Rosenthal (1991). Patterns of congressional voting. *American Journal of Political Science 35*, 228–278.

Poole, K. T. and H. Rosenthal (1997). *Congress: A Political-Economic History of Roll Call Voting*. New York: Oxford University Press.

Poole, K. T. and H. Rosenthal (2001). D-nominate after 10 years: An update to congress: A political-economic history of roll call voting. *Legislative Studies Quarterly 26*, 5–29.

Poole, K. T. and H. Rosenthal (2007). *Ideology and Congress*. New Brunswick: Transaction Publishders.

Silbey, J. (1967). *The Shrine of Party*. Pittsburgh: University of Pittsburgh Press.