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Unpredictable Voters in Ideal Point Estimation

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Ideal point estimators are typically based on an assumption that all legislators are equally responsive to modeled dimensions of legislative disagreement; however, particularistic constituency interests and idiosyncrasies of individual legislators introduce variation in the degree to which legislators cast votes predictably. I introduce a Bayesian heteroskedastic ideal point estimator and demonstrate by Monte Carlo simulation that it outperforms standard homoskedastic estimators at recovering the relative positions of legislators. In addition to providing a refinement of ideal point estimates, the heteroskedastic estimator recovers legislator-specific error variance parameters that describe the extent to which each legislator's voting behavior is *not* conditioned on the primary axes of disagreement in the legislature. Through applications to the roll call histories of the U.S. Congress, the E.U. Parliament, and the U.N. General Assembly, I demonstrate how to use the heteroskedastic estimator to study substantive questions related to legislative incentives for low-dimensional voting behavior as well as diagnose unmodeled dimensions and nonconstant ideal points.

1 Introduction

Ideal point estimators have revolutionized the empirical study of legislative behavior. These estimators (e.g., Poole and Rosenthal 1985, 1997; Poole 2000, 2001; Clinton, Jackman, and Rivers 2004a) provide two core summaries of roll call voting that are useful for researchers (Poole 2005). First, they provide ideal points that summarize legislators as having relative positions on a spatial axis (or axes). Second, they provide cutpoints (or cutlines) that summarize voting on each bill. Although these quantities can be recovered nonparametrically using optimal classification (OC) techniques (Poole 2000), additional information can be extracted from roll call data under parametric assumptions. In addition to legislator and bill location information, parametric estimators typically provide a discrimination parameter that indicates how powerfully ideal points predict votes on each bill.

This paper applies the logic of the bill discrimination parameter to legislators. Spatial voting models have almost always assumed that all voters are equally responsive to the spatial voting axis via an assumption of homoskedasticity in the latent voting model. But just as it is possible to learn both a cutpoint and a discrimination parameter for each bill, it is also possible to learn both an ideal point and the variance of the latent disturbance distribution for each legislator's votes. The variance of the latent vote distribution for

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an individual legislator captures the extent to which the dominant political axes—those which best capture voting behavior across the whole legislature—predict any particular legislator's voting. Estimating this parameter is not novel; however, there has been no previous discussion of its interpretation. Keith Poole has demonstrated a technique for estimating the variance of the error distribution σ_i^2 for each legislator i by conditional maximum likelihood under a quadratic loss, normal error (QN) specification of the spatial voting model (Poole 2001). His discussion treats these σ_i as a nuisance parameter rather than a quantity of interest, noting only that they are anti-correlated with classification success rates because larger errors in the random utility model lead to lower probabilities of correctly predicting a binary roll call vote. Here Poole left the problem, writing that "[c]learly the σ_i are capturing something beyond simple misclassification. This is an area for future research".

In Section 2 of this paper, I discuss several substantive sources of variation in legislators' responsiveness to the primary political axes, including particularistic constituency interests and idiosyncratic legislator preferences. These sources of heteroskedasticity cannot be effectively modeled by simply adding more dimensions to a homoskedastic estimator unless a large number of legislators are responsive to the *same* unmodeled factors. I then describe a Bayesian heteroskedastic ideal point estimator that can be either understood as a generalization of Jackman's (Jackman 2001) homoskedastic Bayesian estimator or a Bayesian implementation of Poole's QN estimator (Poole 2001). I use Monte Carlo simulation to assess how the number of legislators, the number of roll call votes, and the degree of true heteroskedasticity influence the degree to which the data-generating σ_i can be recovered. I find the heteroskedastic estimator outperforms the equivalent homoskedastic estimator for recovering ideal points, not only when there is substantial heteroskedasticity in the data generating process but even when the data-generating process is homoskedastic. In a technical appendix, I prove identifiability and give a detailed description of the Gibbs sampler.

In Section 3, I use a series of examples to show how the legislator-specific variance σ_i itself can help refine the summaries of legislative voting patterns provided by ideal point estimation. The heteroskedastic ideal point estimator explicitly measures which legislators are idiosyncratic in their voting. In the U.S. Congress, such unpredictable legislators have typically been referred to as "mavericks." I show that senators with maverick reputations are indeed spatially unpredictable. Scholars have argued that maverick behavior by legislators reflects a strategic response to marginal electoral incentives (Huitt 1961; Patterson 1961; Kirkpatrick and McLemore 1977; Shields 1985; Grose and Yoshinaka 2006); however, measuring maverick behavior has previously been difficult.[1] I also show that the concept of the unpredictable (or maverick) legislator is useful predictively. Republicans who defected from their party on the Iraq war authorization in 2002 were all either spatial moderates or spatially unpredictable based on their voting histories, making their defections

[1]Previous attempts to measure maverick legislative behavior have relied on rates of party voting (Patterson 1961; Shields 1985) or spatial model misclassification rates (Grose and Yoshinaka 2006). Unfortunately, party defection measures have systematic biases: moderates will always have higher rates of party defection. Switching from party defection to spatial misclassification does not make this problem go away: moderates have high rates of spatial misclassification because of the large number of cutting lines near the center of the chamber. Substantively, this is a problem because previous work has argued that legislators are adopting maverick behavior as a response to marginal (Patterson 1961) or uncertain (Grose and Yoshinaka 2006) electoral situations. But if measures of maverick behavior are conflated with moderation, these results may simply reflect the fact that moderates tend to come from marginal electoral districts or states. Distinguishing mavericks from moderates is important to understanding the relationship between electoral strategies and legislative behavior.

relatively probable compared to their co-partisans. Such unpredictability may reflect a lack of the constraints within the legislature that produce low-dimensional behavior for most legislators. I provide examples of particular legislators who faced changing circumstances —leaving party leadership or intense attention due to scandal—that coincided with sudden changes in the dimensionality of their voting behavior.

In addition to helping address these substantive questions, the heteroskedastic specification can be used diagnostically to assess legislature dimensionality and the validity of the constant ideal point assumption, which I demonstrate using data from the E.U. Parliament and the U.N. General Assembly. The heteroskedastic estimator improves on our ability to summarize legislative voting patterns using the spatial model by assessing the degree to which each legislator is responsive to the axis. This estimator is useful for helping scholars form a clearer understanding of the voting behavior that is captured by low-dimensional legislative models as well as that which is not.

2 Motivation and Specification

Ideal point estimation—like factor analytic techniques more generally—seeks to recover a small number of substantively meaningful dimensions of variation. This is useful for understanding legislative politics because it is often the case that a few dimensions of political disagreement strongly predict how legislators vote on any given roll call vote. In the United States, a left-right, primarily economic dimension explains most of the variation in legislative behavior (Poole and Rosenthal 1997). But legislators' left-right preferences are not the only factor motivating their behavior. One can estimate additional dimensions as well, each corresponding to different and decreasingly important sources of variation in the preferences of legislators. In the United States, an important second dimension arose largely along north-south regional lines during the civil rights era (Poole and Rosenthal 1997). In the E.U. Parliament, attitudes on European integration as well as domestic government-opposition dynamics predict voting behavior (Hix, Noury, and Roland 2006).

The process of adding dimensions to the estimator can be taken to its logical extreme: it is always possible to rationalize any roll call data as perfect spatial voting by employing a sufficient number of dimensions (Poole 2005). However, over-fitting the data this way is unenlightening. Beyond broad ideological conflicts about redistribution and regional, racial, ethnic, or religious divisions that divide entire societies, motivations for legislators to vote in particular ways become increasingly particularistic and decreasingly influential. Because there are many such factors, each exerting effects on only a few roll call votes or a few legislators, roll call data are incapable of revealing their influences on legislative behavior.[2] Such influences on voting preferences include particularistic interests of constituencies and idiosyncratic beliefs of legislators.

Particularistic interests of constituencies are a familiar influence on behavior in the U.S. Congress. One example is that most members of Congress have a strong preference for earmarked spending in their geographic constituency. Spatially, these ‘‘divide-the-dollar’’ policy preferences correspond to separate constituency-specific dimensions in which in-constituency legislators are at one position and every other legislator is located at another position. Although less starkly multidimensional, various forms of agriculture, industry, and resource extraction each tend to have a few strong advocates in Congress from places that will be disproportionately affected by policy decisions. Because these motivations are

[2] At least without the use of auxiliary information in addition to the roll call voting matrix.

important on small numbers of bills and require so many dimensions to capture the variation in preferences across legislators, they are not captured by low-dimensional spatial voting models. However, since some legislators care more than others about bringing home federal spending versus other priorities (Lee and Oppenheimer 1999), the strength of these incentives will vary in relative influence across legislators.

Idiosyncratic beliefs of legislators also come in various forms. Blanket opposition to congressional pork is a preference consistently acted upon by a few members of each Congress. Libertarians are often considered to be idiosyncratic in the United States, though it is only in a one-dimensional model that their votes will necessarily be difficult to predict. In general, adding additional dimensions to an ideal point estimator will not be substantively informative unless legislators are motivated by varying positions on dimensions that are frequently relevant to the roll call voting decisions of many legislators. To the extent that voting behavior is motivated instead by particularistic constituency concerns, idiosyncratic views held by only a small number of legislators, or other factors that are not broadly influential, adding dimensions will not be revealing. Nonetheless, in such cases, it is useful to know—for each legislator—how much is being left out by just estimating the major dimensions. Legislators who have many atypical influences will vote less predictably on the basis of the modeled axes.

2.1 *A Bayesian Heteroskedastic Ideal Point Estimator*

Parametric ideal point estimators are almost always based on random utility models describing a choice between "Yea" and "Nay" alternatives, but vary in their assumptions about the loss function for policies deviating from a legislator's ideal and the stochastic disturbances that capture all other influences on the vote choice. The NOMINATE family of estimators are based on policy preferences with gaussian loss, whereas most other estimators use quadratic loss. Some estimators are based on logistic disturbances (Poole and Rosenthal 1985; Bafumi et al. 2005), some on uniform disturbances (Heckman and Snyder 1997), and some on normal disturbances (Jackman 2001; Poole 2001). The quadratic loss, normal disturbance model has become especially popular in recent years, so I take that parametric form as my point of departure. This choice is one of expositional convenience: the logic of a heteroskedastic estimator can be applied to multiple functional forms (Poole 2005, 101).

I follow the notation used by Clinton, Jackman and Rivers (2004a, 356). Each legislator i has an ideal point $\mathbf{x_i}$ in $\mathbb{R}^d$, with quadratic loss for policies diverging from that location. A bill j is a vote between the status quo policy point $\boldsymbol{\psi}_\mathrm{j}$ and a proposed alternative $\boldsymbol{\zeta}_\mathrm{j}$. Thus, the decision of legislator i on roll call j is between a "Nay" vote with utility $U_i(\psi_j) = -\left\|\mathbf{x_i}-\boldsymbol{\psi}_\mathbf{j}\right\|^2+v_{ij}$ and a "Yea" vote with utility $U_i(\zeta_j) = -\left\|\mathbf{x_i}-\boldsymbol{\zeta}_\mathbf{j}\right\|^2+\eta_{ij}$, where v_{ij} and η_{ij} are components of the legislator's preferences for each alternative that are not captured by the modeled preference dimensions. A legislator will vote for the "Yea" alternative if and only if $U_i(\zeta_j) - U_i(\psi_j) > 0$, where

$$U_i(\zeta_j)-U_i(\psi_j) = \left\|\mathbf{x_i}-\boldsymbol{\psi}_\mathbf{j}\right\|^2-\left\|\mathbf{x_i}-\boldsymbol{\zeta}_\mathbf{j}\right\|^2+\eta_{ij}-v_{ij} = 2(\zeta_j-\psi_j)'\mathbf{x_i}+\boldsymbol{\psi}'_\mathbf{j}\boldsymbol{\psi}_\mathbf{j}-\boldsymbol{\zeta}'_\mathbf{j}\boldsymbol{\zeta}_\mathbf{j}+\eta_{ij}-v_{ij}.$$

To estimate the model, one must make an assumption about the distribution of the disturbances v_{ij} and η_{ij}. The standard assumption is that on any given bill, all legislators have disturbances drawn from the same distribution, but that each bill might have its own disturbance distribution $\eta_{ij} - v_{ij} \sim N(0, \sigma_j^2)$. For the reasons discussed above, I make a less restrictive assumption that the variance of these unmodeled components of the utility varies across legislators $\eta_{ij} - \nu_{ij} \sim N(0, \sigma_i^2\sigma_j^2)$. Collecting and relabeling unidentified terms, $\boldsymbol{\beta}_\mathbf{j} \equiv 2(\boldsymbol{\zeta}_\mathbf{j} - \boldsymbol{\psi}_\mathbf{j}) \big/ \sigma_j$ and $\alpha_j \equiv (\boldsymbol{\psi}'_\mathbf{j}\boldsymbol{\psi}_\mathbf{j} - \boldsymbol{\zeta}'_\mathbf{j}\boldsymbol{\zeta}_\mathbf{j}) \big/ \sigma_j$, it is possible to derive the probability of a "Yea" vote

$$P(y_{ij} = 1) = \Phi\left(\frac{\boldsymbol{\beta}'_\mathbf{j}\,\mathbf{x}_\mathbf{i} - \boldsymbol{\alpha}_\mathbf{j}}{\sigma_i}\right). \tag{1}$$

This equation has a natural interpretation as a heteroskedastic probit model for a legislator i's vote on bill j in which the regressors are the legislator's ideal point in each dimension and each legislator has a different σ_i characterizing the degree to which their ideal point predicts their choice. Unlike heteroskedastic probit applications where σ must be modeled from auxiliary information because only one binary choice is observed for each voter (Alvarez and Brehm 1995), here σ_i can be estimated for each legislator.[3]

Bafumi et al. (2005, 175) propose a "robust" ideal point estimator that has some similar properties to the heteroskedastic estimator. Their robust estimator limits the influence of individual roll call votes on legislators' ideal points by placing a floor and ceiling on the predicted probability of a "Yea" vote. By determining which legislators are most unpredictable, the heteroskedastic model similarly limits the influence of individual votes, but only for those legislators that are especially unpredictable. As the preceding discussion argues and forthcoming analysis demonstrates, there is real and meaningful variation in the degree to which individual legislators vote on the basis of the dominant spatial preference dimensions and modeling that heteroskedasticity reveals valuable information about legislative voting behavior.

In the technical appendix, I describe a Gibbs sampler for taking draws from the posterior distribution of the model parameters defined above given a matrix of roll call votes. Just as for ideal points, the fact that the σ_i are only relatively identified requires an appropriate identification constraint. For reasons described in the appendix, I normalize legislator errors σ_i such that their inverse mean is equal to 1.[4] Consequently, values of $\sigma_i > 1$ correspond to relatively unpredictable legislators. Throughout the analysis to follow, I use the following prior distributions. The prior distribution on the question parameters $\boldsymbol{\beta}_\mathbf{j}$ and α_j is $N(\mathbf{t_0}, \mathbf{T_0})$, where $\mathbf{t_0} = \mathbf{0}$ and $\mathbf{T_0} = \kappa\mathbf{I_n}$ with $\kappa = 25$ chosen to give a nearly uninformative distribution while preventing complete separation. On the legislators' ideal points $\mathbf{x_i}$, a $N(\mathbf{0}, \mathbf{I_n})$ prior defines the space of ideal points. For the legislator-specific variance, I use a conjugate inverse gamma prior, $\sigma_i^2 \sim \mathrm{IG}\left(\frac{c_0}{2}, \frac{d_0}{2}\right)$, which I choose to be improper and uninformative $c_0 = d_0 = 0$.

2.2 *Estimator Performance*

If the heteroskedastic estimator is to prove useful, it should have two properties. First, it should perform better than the homoskedastic model at recovering ideal points from

[3]Bafumi et al. (2005) parameterize a unidimensional ideal point estimator in a way that makes the symmetry between the bill discrimination parameter and the legislator-specific variance parameter especially clear:

$$P(y_{ij} = 1) = f(\text{Discrimination}_j \cdot (\text{Ideal Point}_i - \text{Cutpoint}_j)). \tag{2}$$

In this parameterization, one can write the heteroskedastic model in terms of both bill-specific discrimination parameters and legislator-specific discrimination parameters:

$$P(y_{ij} = 1) = f(\text{Discrimination}_i \cdot \text{Discrimination}_j \cdot (\text{Ideal Point}_i - \text{Cutpoint}_j)) \tag{3}$$

[4]The renormalization of the σ_i identifies the model, even in the absence of an informative prior. Other identification schemes might identify the model more elegantly.

roll call data generated by a heteroskedastic process. Ideally, it should perform no worse when the data-generating process is actually homoskedastic. Second, it should recover the relative values of σ_i with sufficient precision in realistic data sets to make meaningful inferences. In the only previous work that estimates a legislator-specific variance parameter, Poole (2001) reports Monte Carlo simulation results for the recovery of the ideal points from generated data, but does not compare homoskedastic and heteroskedastic estimators or evaluate success at recovering legislator-specific variances. Given the limitations of binary data and the already heavy parameterization of this class of models, some skepticism about a new ideal point estimator with yet more parameters is warranted (Haberman 1977; Londregan 2000). There are two important questions. First, how closely does the estimator recover the relative values of the ideal points and legislator-specific variances? Second, does the posterior sample adequately reflect the true uncertainty of the estimates such that we avoid making over-confident inferences about the relative values of ideal points and legislator-specific variances?

For the following Monte Carlo simulations, I begin by generating profiles of data generating parameters. I draw legislator ideal points x_i, α_j, and β_j from their prior distributions and $1/\sigma_i$ from a uniform distribution $U(1-\delta, 1+\delta)$. I simulate data with $\delta = 0, 0.25, 0.5$. The highest value of δ approximates estimates from recent sessions of the U.S. House. I also vary the number of legislators n and the number of roll call votes m across values of 10, 32, 100, and 320. For each of the 48 intersections of these parameters, I simulate 50 roll call matrices. I then compute mean posterior estimates for $\mathbf{x}$ and $\boldsymbol{\sigma}$ using both the homoskedastic estimator and the heteroskedastic estimator (both implemented in MCMCpack, Martin and Quinn 2009) on each simulated roll call matrix. This range of parameters includes performance evaluations relevant to small chambers like the U.S. Supreme Court as well as short-lived "legislatures" like public opinion surveys. To allow many replications, I use brief simulations: a 1000 iteration burn-in from starting values generated by the factor analytic model described by Heckman and Snyder (1997) followed by a 1000 iteration sample. Given these short samples, Monte Carlo error will lead to some underestimation of estimator performance.[5]

In Table 1, I report statistics relevant to assessing the quality of mean posterior estimates. I use Kendall's τ statistic to evaluate the degree to which the estimators recover the correct relative ordering of legislators in $\mathbf{x}$ and $\boldsymbol{\sigma}$. The τ statistic is simply the fraction of pairwise comparisons between legislators that are in the correct direction minus the fraction that are in the incorrect direction. First, I report the mean correlation (across the 50 simulations) of the data-generating ideal points with the mean posterior ideal points recovered by the homoskedastic estimator (τ_1). Second, I report the mean correlation of the data-generating ideal points with mean posterior ideal points from the heteroskedastic estimator (τ_2). Third, I report the mean correlation of the data-generating legislator-specific standard deviations with the mean posterior legislator-specific standard deviations (τ_3). Comparing τ_1 and τ_2 provides an evaluation of the relative performance of the homoskedastic and heteroskedastic estimators, whereas τ_3 provides an evaluation of the heteroskedastic estimator's ability to recover the legislator-specific variance parameter σ_i.

The heteroskedastic estimator slightly outperforms the homoskedastic estimator at recovering the relative positions of ideal points, even when the true data-generating process is homoskedastic. Both estimators are run on each simulated roll call matrix, so this comparison is based on identical roll call data. This slight advantage is "significant"

[5]Longer simulations yielded similar results.

Table 1 Kendall's τ statistics for the relationship between estimated and data-generating ideal points under the homoskedastic estimator (τ_1), between estimated and data-generating ideal points under the heteroskedastic estimator (τ_2), and between estimated and data-generating legislator-specific variances under the heteroskedastic estimator (τ_3)

		m = 10				*m = 32*				*m = 100*				*m = 320*		
$n = 10$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$
	τ_1	0.711	0.723	0.755	τ_1	0.873	0.891	0.862	τ_1	0.939	0.938	0.932	τ_1	0.977	0.968	0.965
	τ_2	0.747	0.740	0.774	τ_2	0.883	0.887	0.869	τ_2	0.940	0.939	0.948	τ_2	0.976	0.977	0.966
	τ_3		0.012	0.079	τ_3		0.016	0.177	τ_3		0.150	0.292	τ_3		0.261	0.479
$n = 32$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$
	τ_1	0.725	0.747	0.734	τ_1	0.881	0.873	0.873	τ_1	0.939	0.941	0.935	τ_1	0.965	0.966	0.965
	τ_2	0.763	0.777	0.758	τ_2	0.896	0.894	0.890	τ_2	0.954	0.948	0.943	τ_2	0.971	0.970	0.970
	τ_3		0.026	0.094	τ_3		0.117	0.257	τ_3		0.254	0.439	τ_3		0.397	0.587
$n = 100$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$
	τ_1	0.740	0.739	0.722	τ_1	0.879	0.882	0.875	τ_1	0.939	0.935	0.933	τ_1	0.968	0.965	0.959
	τ_2	0.765	0.773	0.754	τ_2	0.901	0.904	0.896	τ_2	0.950	0.947	0.946	τ_2	0.972	0.973	0.971
	τ_3		0.039	0.102	τ_3		0.145	0.265	τ_3		0.270	0.475	τ_3		0.434	0.638
$n = 320$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$		$\delta = 0$	$\delta = \frac{1}{4}$	$\delta = \frac{1}{2}$
	τ_1	0.730	0.744	0.742	τ_1	0.878	0.880	0.878	τ_1	0.939	0.939	0.932	τ_1	0.968	0.965	0.958
	τ_2	0.766	0.775	0.775	τ_2	0.901	0.902	0.900	τ_2	0.950	0.950	0.948	τ_2	0.973	0.973	0.972
	τ_3		0.047	0.104	τ_3		0.145	0.285	τ_3		0.285	0.488	τ_3		0.460	0.672

Note. The number of roll call votes m, the number of legislators m, and the degree of heteroskedasticity across legislators δ each vary across values similar to real roll call data. Each reported statistic is the mean of estimates on 50 simulated roll call matrices.

in the 50 simulations. On nearly every simulated roll call matrix, the heteroskedastic estimator performs slightly better than the homoskedastic estimator. Integrating over plausible values of σ_i appears to correct for random variation in legislators' realized votes. This performance gain grows only slightly with increasing true heteroskedasticity in the data-generating process. Surprisingly, the heteroskedastic estimator does better even when the roll call matrix is only 10×10, and moving from the homoskedastic to the heteroskedastic model increases the number of parameters from 30 to 40 (on 100 binary data points). The performance of both the homoskedastic or heteroskedastic estimators at recovering relative ideal points improves with larger numbers of roll call votes, but not with larger numbers of legislators.

It is far harder to recover relative values of σ_i than x_i. Success at recovering legislator-specific variances varies with the dimensions of the roll call matrix $n \times m$ and the degree of heteroskedasticity δ. The recovery of σ_i increases in quality primarily as the number of roll call votes increases and to a lesser extent as the number of legislators increases. Unsurprisingly, having a greater range of true legislator-specific variances improves the ability of the estimator to recover the relative levels of variance across legislators. The relative difficulty of recovering σ_i by comparison to x_i is analogous to the relatively difficulty of recovering the bill-specific latent slope β_j by comparison to the cut-point location $\frac{\alpha_j}{\beta_j}$.

These simulations suggest that for recovering ideal points, the heteroskedastic estimator is no worse than the homoskedastic estimator that is in general use across a range of roll call data. The estimates of legislator-specific variances themselves are unlikely to be useful in short legislatures with fewer than 100 votes (e.g., public opinion surveys). With a sufficient number of roll call votes, it is possible to recover these parameters somewhat reliably in very small legislatures (e.g., the U.S. Supreme Court). The most viable application is to national and super-national legislatures with hundreds of legislators and hundreds of roll call votes. A single Congress yields more roll call votes than the longest presented simulations for the Senate and both more legislators and more roll call votes for the House. In such cases, variation in the true σ_i can be recovered, though less reliably than variation in ideal points. In these large roll call matrices, the posterior intervals have very close to correct coverage, so inferences based on posterior simulations are reliable.[6]

3 Applications

The heteroskedasticity parameter σ_i has a number of possible uses as a direct object of study and as a diagnostic tool for better understanding the dimensions recovered by ideal point estimators. In this section, I describe several of these applications.[7]

[6]Relevant simulations available from the author upon request.

[7]A few initial anecdotes highlight the wide variety of information that can be extracted from the σ_i parameter. (1) In his early political career, Abraham Lincoln was a doctrinaire Whig. This made him among the more predictable voters in the 30th House (1847–48), his sole term in Congress ($\sigma_{1D} = 0.85$, $\sigma_{2D} = 0.94$). (2) Despite Lloyd Bentsen's skepticism about their similarity, John Kennedy and Dan Quayle were both among the most unpredictable senators in the chamber at the beginning of their respective careers and both became more doctrinaire the longer they were in the Senate. (3) Canon (1999) argues that John Conyers (D-MI) and John Lewis (D-GA) are exemplars of different styles of representation. According to Canon, Conyers has been an outspoken advocate of African-American interests and has frequently offered particularistic legislation with no chance of passage. Lewis has taken a different approach, usually speaking on behalf of his entire district rather than his African-American constituents. If Canon is correct that Conyers is motivated more by particularistic interests than Lewis, he ought to have a higher estimated σ_i. Consistent with this theory, Conyers has a greater σ_i than Lewis throughout their overlapping careers.

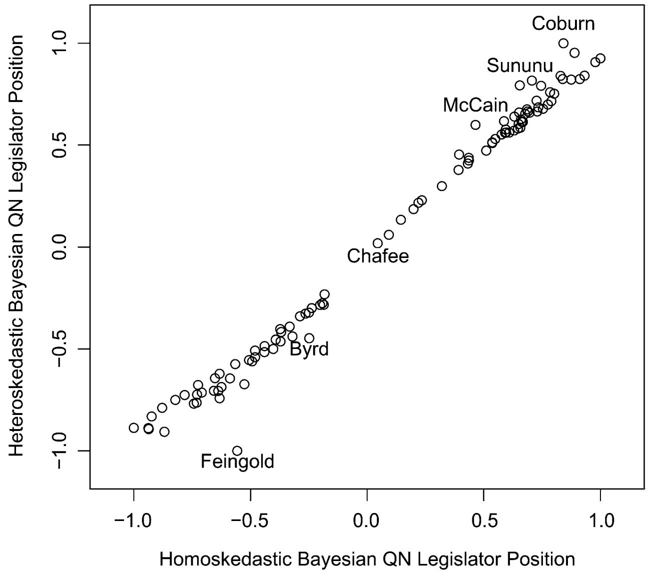

Fig. 1 Although most legislators ideal points change little, those with high σ_i are placed at more extreme positions by the heteroskedastic estimator than by the homoskedastic estimator.

3.1 *The Ideal Points of Unpredictable Legislators*

As Fig. 1 shows, using the heteroskedastic model instead of the homoskedastic model does not change estimated ideal points for most legislators.[8] However, the legislators with large estimated σ_i are estimated to have more extreme ideal points under the heteroskedastic estimator. This reflects a substantive advantage of the heteroskedastic model: it recognizes that not all deviations from the pole of extreme partisan voting reflect moderation, some reflect extreme positions on other political dimensions.

The clearest example of this effect in the 109th Senate is that the homoskedastic estimator places Russ Feingold (D-WI) in the middle of the Democratic party, ranked 21st most liberal out of 101 senators with a 95% high density interval (HDI) from 17th to 26th. In contrast, the heteroskedastic model indicates that he is probably the most liberal Democratic senator (1st; 95% HDI from 1st to 6th). A similar shift is evident for Tom Coburn at the other end of the political spectrum. The homoskedastic model assumes that all individuals make the same magnitude voting errors, so when senators like Feingold vote differently from ideologically similar senators, they are shifted towards the center, even if the reasons they deviated had nothing to do with the primary axis. The heteroskedastic model yields a more nuanced interpretation of the roll call data. Feingold has the highest estimated σ_i in the 109th Senate under one-dimensional (1D) model. He is very far left on the major axis that defines the 109th U.S. Senate, but sometimes votes differently from other senators on the left edge of the American political spectrum for reasons unrelated to the left-right preferences that motivate other Senators.

[8]This is not surprising given the structure of the estimator. Ordinary least squares (OLS) regression is unbiased even with heteroskedastic errors, and in essence the heteroskedastic model replaces conditional OLS regressions for x_i with conditional GLS regressions.

These results bear on questions such as the quadrennially popular “who is the most liberal/conservative senator?” (Clinton, Jackman, and Rivers 2004b). With respect to the 2008 election, we can assess whether John McCain is in fact a maverick and whether the way we answer that question influences whether we believe him to be a conservative or a moderate Republican in his legislative voting. Like Feingold and Coburn, McCain is more influenced than the average senator by factors other than the primary axis running through the Senate: his σ_i is among the highest in the chamber.[9] Whereas the homoskedastic estimator can only rationalize the resulting voting deviations as moderation, the heteroskedastic estimator identifies that his deviations are unrelated to his primary axis position because they do not match the deviations that most moderate Republican senators make.

Figure 1 shows that McCain’s location within the 109th Senate depends on which estimator one uses. Under the homoskedastic model, McCain’s median posterior rank places him as the 58th most liberal senator out of 101, with a 95% posterior interval from 55th to 60th. Under that model, McCain is clearly towards the moderate end of the Republican caucus. In contrast, under the heteroskedastic model, his median posterior rank moves rightward to 67th and his location within the caucus is far more uncertain—95% posterior interval from 60th through 80th—most of the central third of the Republican caucus. The heteroskedastic model tells us that because McCain is more influenced by factors other than the primary axis of the Senate than other legislators, we learn less about his location on that axis from his votes than we do for most legislators. It does not appear he is especially moderate compared to other Republicans on the primary axis that divides the U.S. Senate.

Such discrepancies turn out to only affect a few legislators in the U.S. Congress.[10] As is clear from Fig. 1, for secondary analyses using ideal point estimates as independent variables, the difference between the estimates of the two estimators is seldom going to be the analyst’s most serious problem. Relaxing the homoskedasticity assumption of previous models does not profoundly change ideal point estimates in the aggregate; however, it does significantly change the ideal point estimates of a few legislators whose behavior is not well approximated by the homoskedastic model.

3.2 *Were the Mavericks Who We Thought They Were?*

Although I have provided a theoretical argument for why the σ_i will capture the kinds of behaviors that are usually associated with mavericks—voting driven by factors orthogonal to those that influence most legislators—it is not obvious that popular usage of the term is actually in line with that definition. Are the legislators who are commonly called mavericks in fact those with high σ_i? One way to provide a check on the validity of σ_i as a measure of the existing concept of the maverick is by comparing estimated σ_i to recent media usage of the term. A list of mavericks can be generated by searching news databases for articles that refer to particular senators as mavericks during the 109th Congress,[11] and that list can then

[9]The other high-profile senators in the 2008 presidential election, Joseph Biden, Hillary Clinton, and Barack Obama, were all relatively predictable on the basis of the primary left-right axis.

[10]At most, a few legislators can have relatively high values of σ_i.

[11]I use a Lexis-Nexis search for all senators named mavericks in the New York Times or Washington Post during 2005 and 2006: search under “Major Papers” with “senator” as search term for the headline, lead and terms category and “maverick” in full text, with the particular newspapers specified as sources. Coding is straightforward, there were no cases in the sampled articles where it is ambiguous whether someone is being referred to as a maverick or as engaged in maverick behaviors.

Table 2 Estimated top five mavericks in the U.S. Senate for each of the last 30 completed sessions of Congress under a 2D model

Year	*Congress*	*1*		*2*		*3*		*4*		*5*	
1947	80	Langer	1.84 (0.18)	Johnson E	1.43 (0.18)	Williams J	1.40 (0.16)	Malone	1.38 (0.15)	Taylor G	1.33 (0.11)
1949	81	Langer	2.24 (0.22)	Williams J	1.40 (0.12)	Taylor G	1.35 (0.10)	Malone	1.32 (0.12)	Donnell	1.28 (0.11)
1951	82	Morse	1.43 (0.14)	Langer	1.39 (0.10)	Cordon	1.39 (0.14)	Long R	1.33 (0.13)	Robertson	1.31 (0.14)
1953	83	Langer	1.64 (0.17)	Williams J	1.57 (0.19)	Young	1.52 (0.17)	Fulbright	1.34 (0.13)	Kennedy	1.34 (0.13)
1955	84	Langer	2.03 (0.22)	Robertson	1.50 (0.23)	Williams J	1.45 (0.19)	McCarthy	1.40 (0.18)	Long	1.40 (0.19)
1957	85	Lausche	1.94 (0.22)	Langer	1.62 (0.15)	Malone	1.56 (0.14)	Douglas	1.50 (0.15)	Cooper	1.38 (0.14)
1959	86	Douglas	1.70 (0.15)	Lausche	1.66 (0.15)	Proxmire	1.62 (0.15)	Young S	1.51 (0.15)	Fulbright	1.38 (0.12)
1961	87	Proxmire	1.88 (0.18)	Lausche	1.71 (0.15)	Long R	1.65 (0.13)	Gruening	1.55 (0.14)	Douglas	1.51 (0.11)
1963	88	Morse	2.03 (0.16)	Proxmire	1.71 (0.15)	Lausche	1.36 (0.10)	Gore	1.35 (0.09)	Douglas	1.32 (0.10)
1965	89	Morse	2.22 (0.18)	Young S	1.61 (0.14)	Williams J	1.52 (0.12)	Lausche	1.51 (0.11)	Proxmire	1.49 (0.13)
1967	90	Morse	1.62 (0.11)	Proxmire	1.59 (0.13)	Williams J	1.49 (0.09)	Young S	1.36 (0.09)	Gruening	1.31 (0.08)
1969	91	Williams J	1.78 (0.12)	Proxmire	1.53 (0.12)	Cooper	1.30 (0.09)	Allen	1.27 (0.08)	Cook	1.27 (0.08)
1971	92	Cooper	1.47 (0.09)	Proxmire	1.39 (0.08)	Hatfield	1.38 (0.08)	Roth	1.33 (0.08)	Mansfieldm	1.32 (0.07)
1973	93	Proxmire	1.56 (0.09)	Metcalf	1.38 (0.07)	Roth	1.38 (0.08)	Hatfield	1.38 (0.08)	Biden	1.25 (0.06)
1975	94	Proxmire	1.49 (0.07)	Hatfield	1.46 (0.08)	Weicker	1.37 (0.06)	Roth	1.36 (0.07)	Biden	1.28 (0.05)
1977	95	Proxmire	1.47 (0.07)	Morgan	1.40 (0.07)	Durkin	1.33 (0.07)	Brooke	1.32 (0.06)	Metzenbaum	1.30 (0.07)
1979	96	Proxmire	2.04 (0.10)	Hatfield	1.43 (0.07)	Weicker	1.42 (0.06)	Bellmon	1.29 (0.06)	Stevenson	1.22 (0.06)
1981	97	Proxmire	1.95 (0.10)	Humphrey	1.46 (0.09)	Quayle	1.39 (0.08)	Weicker	1.28 (0.06)	Hatfield	1.24 (0.06)
1983	98	Proxmire	2.50 (0.17)	Humphrey	1.37 (0.08)	Quayle	1.33 (0.09)	Weicker	1.29 (0.07)	Rudman	1.26 (0.09)
1985	99	Proxmire	1.91 (0.11)	Zorinsky	1.43 (0.09)	Humphrey	1.38 (0.09)	Hatfield	1.29 (0.08)	Exon	1.25 (0.07)
1987	100	Proxmire	2.12 (0.13)	Hatfield	1.49 (0.09)	Conrad	1.44 (0.11)	Humphrey	1.38 (0.08)	Roth	1.32 (0.09)
1989	101	Humphrey	1.67 (0.13)	Hatfield	1.52 (0.12)	Pressler	1.51 (0.12)	Conrad	1.45 (0.11)	Byrd R	1.45 (0.12)
1991	102	Roth	1.46 (0.10)	Brown H	1.43 (0.11)	Smith R	1.32 (0.09)	Wellstone	1.32 (0.10)	Hollings	1.31 (0.10)
1993	103	Hatfield	1.63 (0.11)	Conrad	1.36 (0.10)	Byrd R	1.35 (0.08)	Deconcini	1.31 (0.10)	Roth	1.31 (0.09)
1995	104	Byrd R	1.73 (0.12)	Lieberman	1.38 (0.09)	Baucus	1.37 (0.10)	McCain	1.35 (0.08)	Hollings	1.34 (0.08)
1997	105	Byrd R	1.60 (0.13)	Faircloth	1.51 (0.11)	Hollings	1.46 (0.11)	Ford W	1.35 (0.10)	Shelby	1.30 (0.09)
1999	106	Voinovich	1.55 (0.11)	Feingold	1.49 (0.11)	Byrd R	1.39 (0.10)	Graham R	1.39 (0.10)	Fitzgerald	1.35 (0.09)
2001	107	Chafee	1.47 (0.13)	Byrd R	1.42 (0.13)	Voinovich	1.42 (0.11)	Fitzgerald	1.40 (0.10)	McCain	1.39 (0.14)
2003	108	Byrd R	1.52 (0.12)	Jeffords	1.39 (0.12)	Conrad	1.37 (0.11)	Hollings	1.35 (0.10)	Feingold	1.29 (0.10)
2005	109	Coburn	1.62 (0.13)	Ensign	1.32 (0.12)	Voinovich	1.32 (0.11)	Jeffords	1.30 (0.09)	Sununu	1.29 (0.10)

Table 3 Trends in mean party group posterior σ_i in the EU Parliament under 1D and 2D models (tabulated as σ_{1D} — σ_{2D})

EU Parliament	*1979–84*	*1984–89*	*1989–94*	*1994–99*	*1999–2004*
Anti-Europeans	—	—	—	1.216–1.044	1.553–1.105
Nonattached	1.029–1.032	1.029–1.016	1.068–1.018	1.079–1.011	1.242–1.045
Regionalists	1.029–1.027	1.057–1.027	1.079–1.014	1.065–1.002	—
Radical Right	—	1.034–1.012	1.144–1.022	—	—
French Gaullists	1.021–1.015	1.053–1.026	1.066–1.016	1.036–0.994	1.170–1.036
British Conservatives	1.030–1.020	1.012–0.957	1.009–1.054	—	—
Liberals	1.009–1.018	1.020–1.009	1.045–1.010	1.064–1.002	1.057–0.985
Radical Left	1.007–1.004	1.022–1.008	1.037–1.005	1.136–0.995	1.135–0.986
Italian Communists	—	—	1.009–0.998	—	—
Greens	—	—	1.055–0.986	1.260–0.972	1.050–0.940
Socialists	1.000–0.989	0.989–0.999	0.968–1.001	1.011–1.004	0.908–1.020
Christian Democrats	0.975–0.993	0.964–1.007	0.975–0.982	0.898–0.999	0.988–0.993
MEPs	548	637	597	721	696
Roll call votes	886	2135	2733	3740	5745

Note. The parliamentary groups that have been antagonistic to the E.U (top 4) have consistently and significantly higher σ_i than the other small party groups (middle 6) or the two major blocs (bottom 2).

be compared to the σ_i during those years. I compare those dubbed mavericks at least once[12] to all other senators. Those called a maverick by the press do in fact have higher σ_i on average; however, the difference is larger for σ_i estimated under a 1D model. In 1D, the average σ_i among mavericks is $\bar{\sigma}_m = 1.22$ against $\bar{\sigma}_{!m} = 1.01$ among other legislators (the 95% HDI on the difference of group means is (0.05, 0.38)). In 2D, $\bar{\sigma}_m = 1.09$, $\bar{\sigma}_{!m} = 1.01$, 95% HDI on the difference is (–0.02, 0.19). The 1D σ_i appears to be related to the existing concept of the maverick, whereas the 2D σ_i may be a more stringent standard than has been popularly applied. The press definition includes individuals who are off-diagonal: economically conservative and socially liberal or vice versa. Such individuals are relatively unpredictable under a 1D model, but not under a 2D model.[13]

A second way to assess whether the estimated σ_i are capturing behavior that fits general usage of the term "maverick" is to examine which legislators the measure identifies as being historically remarkable. Table 2 shows the top five Senate mavericks under a 2D model for the last 30 Congresses. Scholars of Congress will recognize many of the names on the list. One of the senators who appears repeatedly, William "Wild Bill" Langer (R-ND), had been removed from office as the governor of North Dakota after a felony conviction for fraud in 1934, an episode that led to Langer (temporarily) declaring North Dakota independent of the United States and barricading himself in the state house with a group of armed supporters. His popularity resilient, Langer was re-elected Governor in the following election and then elected to the Senate in 1940. Langer was sufficiently

[12]Senators Chafee, Coburn, Corzine, Feingold, Graham, Hagel, Lieberman, Lott, Lugar, McCain, B Nelson, G Smith, Specter, Voinovich, Warner.

[13]Sensitivity to the press standard of maverick-ness is limited by several factors and so a few caveats are in order. First, the standard being used by the *New York Times* and the *Washington Post* is surely applied unevenly, influences by many factors including whether a senator is high profile. Second, some patterns of unusual voting may be less obvious to the press or less newsworthy. Third, some senators may be getting credit for past behavior that no longer applies. Given these sources of error, the level of discrimination provided by the σ_i is encouraging.

controversial that the Senate Committee on Privileges and Elections recommended that Langer not be seated 13-3, but was overturned 52-30 by the full Senate. During his legislative career, Langer opposed Lend Lease, NATO, and the Marshall Plan. Unlike most Americans (senators included), Langer was no fan of Winston Churchill, "in 1951, when the former British Prime Minister visited the U.S. Langer sent a telegram to the pastor of Boston's Old North Church requesting that two lanterns be placed in the belfry to warn Americans that the British were coming (Robinson 1966; Gleen 1975)."

Also standing out in the list of historical mavericks in the Senate is William Proxmire (D-WI).

> *William Proxmire, a political maverick during 32 years in the Senate ... crusaded against government waste and irritated presidents and lawmakers from both parties because of his contempt for the mutual back-scratching most politicians engage in .... [H]e was best known for his Golden Fleece Awards, which he announced in monthly press releases to call attention to what he believed to be frivolous government spending .... When Mr. Proxmire set his mind to a task, he rarely relented until it was accomplished. For 19 years, he gave a speech on the floor nearly every morning the Senate was in session on behalf of the genocide treaty, more than 3,000 speeches in all (Severo 2005).*

Earlier in his career Proxmire was also consistently at or near the top of the list of maverick senators, all the way back to his first term after replacing Joseph McCarthy in the Senate. Presciently, Patterson (1961) begins an article on the Wisconsin state legislature: "Wisconsin has a well-known and well-deserved reputation for its political deviants, particularly in those its people have sent to the United States Senate—Old Bob LaFolette, Joseph McCarthy and now, perhaps, William Proxmire." Huitt (1961) wrote an entire article in the *American Political Science Review* on the unorthodox legislative style followed by Proxmire in his first term.[14] Huitt quotes Proxmire as expressing a desire to "be a senator like Wayne [Morse] and Paul [Douglas]" in 1958. Table 2 indicates that Proxmire succeeded in at least one regard: both the party-switcher Morse (R/I/D-OR) and the University of Chicago economist Douglas (D-IL) were consistently among the least predictable senators during Proxmire's early years in the Senate.

Like Proxmire in the Senate, Ron Paul's voting behavior is exceptional in the history of the U.S. House. In one dimension his σ_i has frequently been on the order of five times greater than the typical representative, indicating that his 1D ideal point is all but useless for predicting his voting behavior. Sometimes known to his constituents as "Dr. No", Paul is the most extreme libertarian there has been in the modern U.S. Congress.[15] He has the highest 1D σ_i in every Congress since he was elected to his current seat in 1996. However, as we would expect given his libertarian outlook, after moving to a 2D model that allows an off-diagonal, libertarian ideal point, Paul is no longer an extreme outlier in unpredictability, though he remains among the most unpredictable in the House.

[14]Early on, Proxmire's eccentricities were primarily legislative. Later in his career, he jogged to and from the Capitol in his work clothes every day Congress was in session.

[15]Paul votes against almost every spending bill and is in favor of the abolition of Social Security, Medicare, Medicaid, the IRS, the CIA, and the Federal Reserve. He voted against the Iraq war and supports a generally isolationist foreign policy. He favors repeal of federal drug laws and a return to the gold standard. He was the lone member of the House to vote against the Congressional Medals of Honor awarded to Pope John Paul II, Ronald Reagan, Rosa Parks, and Mother Theresa, arguing that the taxpayer should not have to pay the cost of minting the medals (but offering to pay for them himself). He was one of only 11 members of Congress to vote against Hurricane Katrina recovery funding for the gulf coast: "Is bailing out people that chose to live on the coastline a proper function of the federal government?" "Congressman Paul's Legislative Strategy? He'd Rather Say Not" Libby Copeland, *The Washington Post*, July 9, 2006.

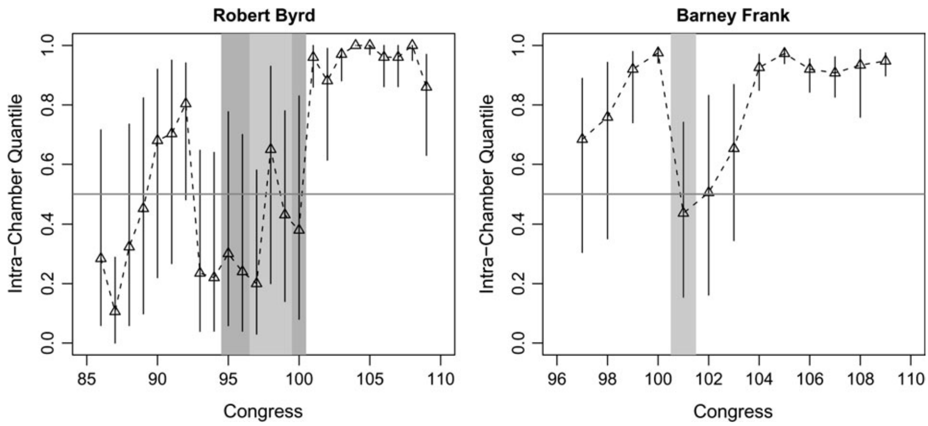

Fig. 2 The two plots depict intrachamber quantile of σ_i for individual legislators' careers. Majority (dark) and minority (light) leadership is indicated as a shaded region for Byrd, whereas a shaded region marks Frank's ethics investigation. In both cases, maverick voting behavior appears to have been suppressed for part of the legislator's career.

3.3 *Mavericks, Moderates, and the Iraq War Vote*

Only six Republican representatives and one Republican senator voted against the 2002 resolution authorizing the use of force in Iraq. Since about half of Democrats voted for the resolution, Republican votes against the bill were spatially anomalous: the cutting line was through the middle of the Democratic caucus. Under any spatial voting model, we expect to find that Republicans who voted against the authorization of force are moderates. Under the heteroskedastic model, we also expect to find some spatially unpredictable legislators, even if they have conservative ideal points. We can therefore evaluate whether the heteroskedastic model adds predictive power by looking at the ideal points and estimated variances of the seven Republican defectors.

The lone Senator, Lincoln Chafee (R-RI), was among the most liberal Republican senators for his entire tenure in the Senate, so his defection is plausible under any spatial model. In the House, the Republicans who voted against the resolution were John Duncan Jr. (R-TN), John Hostettler (R-IN), Amo Houghton (R-NY), Leach (R-IA), Connie Morella (R-MD), and Ron Paul (R-TX). The dissenters break equally into moderates and mavericks. Houghton, Morella, and Leach are moderates: each had ideal points near the center of the chamber throughout their careers and unremarkable values of σ_i. In contrast, Hostettler, Duncan, and Paul do not have moderate ideal points.[16] By ideal point, all are generally in the more conservative half of the Republican caucus. But each has also been a consistent maverick. In the session of Congress preceding the Iraq War vote (the 106th), the estimated σ_i for the 1D and 2D models (σ_{1D}, σ_{2D}) for Hostettler were (1.54, 1.71), for Duncan (1.64, 1.71), and for Paul (4.59, 1.84). With standard errors for these estimates of σ_i on the order of 0.1 and the distribution of $\boldsymbol{\sigma}$ for the chamber centered around 1 by the identification constraints on the model, each of these legislators were substantive and statistically significant mavericks before the Iraq war resolution ever came to a vote. Predictively, the heteroskedastic model captures the fact that these

[16]For Ron Paul, this depends on which ideal point estimator is used because different estimators respond to his highly nonspatial voting differently.

particular six legislators were all relatively likely among Republicans to oppose the war, but for varying reasons.

3.4 *Intrachamber Influences on Legislative Voting*

Some legislators become more or less predictable in their legislative voting in response to changes in their position with respect to their colleagues. In the first panel of Fig. 2, I plot σ_i over the Senate career of Robert C. Byrd (D-WV) under a 2D model (the equivalent plot for a 1D model is similar). Byrd maintained moderate levels of independent voting behavior over his early career and term as Majority and Minority Leader. Immediately upon giving up his Leadership position for the chair of the Appropriations Committee, he became sharply more unpredictable in his voting. It appears that this shift can be attributed to no longer having to represent his entire caucus. We can rule out agenda control as the mechanism by which Byrd avoided casting maverick votes because there is no difference between his behavior as minority and majority leader. Suppression of tendencies towards idiosyncratic voting while in leadership (or while seeking it) is by no means unique to Byrd, though few legislative leaders have such lengthy careers both before and after their stint in leadership. Trent Lott's σ_i rose sharply in the session of Congress after his ouster from the Republican Senate leadership. Tom DeLay had a very high σ_i until the Republican party took over Congress in 1995 and he became the Majority Whip, after which his voting became less idiosyncratic.

Party caucuses are not the only opportunity for legislators to influence one anothers behavior. In the second panel of Fig. 2, I plot σ_i for Barney Frank (D-MA). Frank exhibits a high and increasing σ_i early in his career. His voting then becomes much more predictable in the 101st Congress, followed by a recovery to his previous level of idiosyncrasy over the following three sessions and thereafter. The timing is unmistakable: Frank faced potential expulsion or censure from the House during the 101st Congress because of a scandal. The threat of formal punishment from the chamber appears to have induced Frank to temper his general legislative idiosyncrasy.

3.5 *Legislature Dimensionality*

In addition to revealing variation in voting behavior across legislators, the heteroskedastic model can also be a useful diagnostic tool. Just as heteroskedasticity can capture motivations that cannot be captured by a small number of spatial dimensions, it can also capture dimensions that were simply omitted. Examining legislators with large σ_i is analogous to examining units with large residuals in a regression model. If many legislators who are difficult to predict have some shared substantive attribute, it is likely that adding another dimension to the model is justified. This diagnostic function of the heteroskedastic model is quite useful when one is interested in a high-dimensional legislature like the E.U. Parliament. Hix, Noury, and Roland (2006, 2007) have demonstrated that the E.U. Parliament can be effectively modeled using spatial modeling techniques. They find a strong left-right first dimension throughout the history of the chamber; however, unlike the U.S. Congress, there are always important additional dimensions. One of the nontrivial additional dimensions is the conflict over European integration.

I applied the heteroskedastic estimator to the 1st–5th sessions of the E.U. Parliament, 1979–2004. In 1D and 2D models (Table 3), the most unpredictable legislators in each session of the European parliament tend to be anti-integration MEPs (e.g., Ian Paisley, Johanna-Christina Grund, Johannes Blokland, Rijk van Dam, Carl Lang, and Jean-Marie Le Pen). The fact that there is such a clearly identifiable pattern to which legislators are

Table 4 Top 10 mean posterior σ_i in the UNGA over the chamber's history

1946–53	*1954–69*	*1970–79*	*1980–88*	*1991–2000*	*2001–06*
Belgium 1.19	Cuba 1.48	India 1.33	Turkey 1.22	Mauritius 1.35	India 1.30
Turkey 1.18	Spain 1.18	Chile 1.31	West Germany 1.20	Pakistan 1.23	Sudan 1.29
Colombia 1.15	Israel 1.15	Israel 1.19	East Germany 1.18	Mongolia 1.18	Mauritania 1.18
Yugoslavia 1.13	Greece 1.12	Portugal 1.18	Iraq 1.16	India 1.11	Pakistan 1.15
France 1.11	Brazil 1.11	Saudi Arabia 1.17	Bhutan 1.14	Brunei 1.09	Venezuela 1.10
South Africa 1.11	France 1.08	Brazil 1.16	India 1.10	Nigeria 1.08	New Zealand 1.10
Australia 1.11	Ireland 1.08	Libya 1.12	Mauritius 1.09	Russia 1.07	Nigeria 1.09
India 1.09	Taiwan 1.07	Afghanistan 1.10	Romania 1.08	Turkey 1.06	Jordan 1.09
Argentina 1.07	South Africa 1.06	Cuba 1.08	Sri Lanka 1.08	Bhutan 1.05	Turkey 1.07
Ethiopia 1.07	Congo 1.06	Yemen 1.07	Syria 1.07	Monaco 1.05	Russia 1.07
Votes = 403	762	985	1289	705	363

hard to predict is a signal that the integration dimension of E.U. politics is missing from the low-dimensional models. This is consistent with the findings of Hix, Noury, and Roland (2007) that there are at least three important dimensions in the E.U. Parliament. Looking for this sort of substantive pattern in spatial errors across legislators provides another diagnostic tool to use along with existing approaches such as looking at changes in fraction of roll call votes correctly predicted and aggregate proportional reduction of error.

3.6 *Identifying Legislators with Changing Ideal Points*

One way that legislative behavior can be hard to predict is if the assumption of a constant ideal point fails. Although dramatic changes in voting preferences are rare for individual legislators in the U.S. Congress (with party switches being a notable exception; McCarty, Poole, and Rosenthal 2001), constant ideal points can fail dramatically in contexts like the U.N. General Assembly where "legislators" might undergo regime changes that radically alters their behavior. Voeten (2000) maps the evolution of UN General Assembly (UNGA) voting cleavages over the history of the institution using NOMINATE. I reanalyze this data to assess the extent to which there are countries whose voting behavior is hard to classify spatially. How to periodize the UNGA voting is not obvious because countries do not get voted into and out of the general assembly as legislators do in a legislature. I follow Voeten's periodization except that I split the 1970s and 1980s apart, unify the 1990s, and add an additional period to reflect new data.[17] Long periods are problematic because regime changes may result in sudden changes in ideal point that will lead to high spatial error as the model finds a compromise estimate that fits voting behavior poorly. To have large enough samples though, it is necessary to take periods on the order of a decade.[18]

[17]The periods are 1946–53, 1954–69, 1970–79, 1980–88, 1991–2000, 2000–06. The years 1989 and 1990 are omitted due to the rapid change in alignments and number of member states.

[18]As Voeten (2000) observes, some countries abstain more frequently than others. Ideal point estimators typically assume abstentions are missing at random (MAR) rather than indicative of indifference. It is likely that neither of these assumptions is correct, but better models for abstention require auxiliary information and a theory of what is driving abstention. Like Voeten, I assume MAR. Extreme values of σ_i cannot be estimated when there are many abstentions, so the results presented here may exclude countries that are not highly predictable on the basis of the primary axes in the UNGA, but abstain too frequently for the estimator to identify their unpredictability.

Table 4 lists the countries whose voting was least predictable under a 2D spatial model in each of the six historical periods. India appears at or near the top of the list throughout the history of the UN, perhaps reflecting its foundational role in the Non-Aligned Movement. Russia, with its unique political, geographic, and economic interests, has joined India as an idiosyncratic voter since the end of the Cold War. Israel and Turkey both have relatively nonspatial voting for much of the period under analysis. These countries are difficult to predict because they do not fall easily into any large voting bloc of similar nations, akin to the mavericks of the U.S. Congress. Such countries are poorly predicted by the spatial dimensions that predict most countries' votes because they have preferences that are unusual within the assembly.

Several of the countries listed—Cuba (1954–69), Chile (1970–79), and Portugal (1970–79)—appear unpredictable only in particular periods. These are failures of the constant ideal point assumption: political upheavals sharply changed their voting behavior, making them difficult to classify with a constant ideal point. Future analysis of the UNGA voting data might benefit from models that explicitly account for the possibility that regime changes will cause changes in ideal points. This might be accomplished by analysts exogenously creating "new countries" at the relevant regime changes, by applying a dynamic ideal point model (Martin and Quinn 2002) or perhaps ideally through the use of a (currently undeveloped) change-point ideal point estimator that estimates when units have changed their behavior.

4 Conclusion

Ideal point estimation can only identify those influences on legislative voting that affect many legislators on many votes. When scholars identify a legislature as having a certain number of dimensions, they are highlighting those few dimensions that influence large numbers of legislators and setting aside the wider variety of particularistic motivations that influence only a few. These motivations end up in the error term of the model. The heteroskedastic estimator helps scholars map out that error term. Improving our understanding of how the geometry of the spatial model maps onto the estimates we recover from roll call data is crucial to understanding how we should use that data to improve our understanding of the substance of legislative politics.

Explicitly accounting for heteroskedasticity is particularly important when there is an expectation of widely differential responsiveness. This is perhaps less of a worry for the legislatures that have been the traditional subjects of scaling models than for the newer applications of scaling models to the political preferences of citizens. Given the widely variable knowledge and interests of citizens, heteroskedasticity across survey respondents is especially important when scaling polling responses (Treier and Hillygus 2007) or scaling a mixed sample of citizens and legislators to form a common space for studying representation (Bafumi and Herron 2007). Although the methods presented here for use on roll call votes do not work reliably with the small number of responses available in public opinion surveys, resolving the underlying comparability problems is even more important for studying opinion and representation than it is for comparing legislators with similar levels and sources of political information.

5 Technical Appendix

5.1 *Identification*

To show identification analytically, I proceed by analogy from the homoskedastic model. Take the heteroskedastic model, $y^*_{ij} = \mathbf{x_i}\boldsymbol{\beta}_\mathbf{j} - \alpha_j + \epsilon_{ij}$ with $\epsilon ij \sim N(0, \sigma_i)$ and divide through by σ_i to make the errors homoskedastic:

$$\frac{y^*_{ij}}{\sigma_i} = \frac{\mathbf{x_i}\boldsymbol{\beta}_\mathbf{j}}{\sigma_i} - \frac{\alpha_j}{\sigma_i} + \epsilon'_{ij},$$

$$\epsilon'_{ij} \sim N(0, 1).$$

Because we observe only binary realizations of $y_{ij}*$ and $\sigma_i > 0$, this transformation has no effect on the likelihood. We can define new latent utility differences $y'^*_{ij} = \frac{y^*_{ij}}{\sigma_i}$ and new spatial positions $\mathbf{x'_i} = \frac{\mathbf{x_i}}{\sigma_i}$ by grouping unidentified parameters, yielding the expression:

$$y'^*_{ij} = \mathbf{x'_i}\boldsymbol{\beta}_\mathbf{j} - \frac{\alpha_j}{\sigma_i} + \epsilon'_{ij}.$$

The σ_i now appears as the "positions" $(\frac{1}{\sigma_i})$ for an additional spatial axis. If $\mathbf{x_i}$ is D dimensional, this is equivalent for purposes of identification to the $D + 1$ dimensional model without its intercept term. Thus, if the $D + 1$ dimensional homoskedastic model is identifiable, we have shown that the D dimensional heteroskedastic model is identifiable.

Rivers (2003) proves that to identify the homoskedastic multidimensional spatial model, four conditions must be met. Only the first three apply to the 1D case: the scale must be fixed with respect to additive invariance, with respect to multiplicative invariance and with respect to polarity. In multidimensional models, the axes must also be identified with respect to rotations of the space. The first two conditions are met here with appropriate priors and renormalization on the σ_i and the latter two by functional form.

We can rewrite the model as

$$y'^*_{ij} = \mathbf{x'_i}\,\boldsymbol{\beta}_\mathbf{j} - \alpha_j + \left(\frac{\sigma_i - 1}{\sigma_i}\right)\alpha_j + \epsilon'_{ij}.$$

The fraction $\frac{\sigma_i - 1}{\sigma_i} \to -\infty$ as $\sigma_i \to {}^{+}0$; however, any proper inverse-gamma prior on ${\sigma_i}^2$ has $P(\sigma_i^2) \to 0$ as $\sigma_i \to {}^{+}0$. Similarly, a proper inverse-gamma prior has $P(\sigma_i^2) \to 0$ as $\sigma_i \to \infty$. Thus, as the $N(\mathbf{t_0}, \mathbf{T_0})$ priors on the $\mathbf{x_i}$ identify the spatial scale with respect to multiplicative transforms, proper inverse-gamma priors on the ${\sigma_i}^2$ identify their scale with respect to multiplicative transformations.[19]

While we could rely on the prior distribution on the ${\sigma_i}^2$ to identify the scale with respect to additive transformations as well, we can use renormalization to eliminate additive invariance and simplify interpretation. By analogy to the identification condition $\sum_{i=1}^{n} \mathbf{x_i} = \mathbf{0}$ for ideal points[20] we can use the condition $\sum_{i=1}^{n}\left(\frac{\sigma_i - 1}{\sigma_i}\right) = 0$ for σ_i. This is equivalent to the condition $\frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{\sigma_i}\right) = 1$, leading to transparent comparisons with the homoskedastic error model.

[19]Poole (2001) observes that the σ_i are only identified "up to a multiplicative positive constant," but that this is not a problem because "we are interested primarily in how noisy legislators are relative to one another."
[20]This condition is suggested by Clinton, Jackman, and Rivers (2004a) and used in some of their estimations.

Finally, having ensured that the σ_i are identified with respect to multiplicative and additive transformations, we must ensure that they are identified with respect to polarity and with respect to rotation. The fact that the σ_i are always positive fixes their polarity. The nonidentification of the $\mathbf{x_i}$ under rotations is a product of their having identical priors and marginal likelihoods while being conditioned on $\boldsymbol{\beta}_\mathbf{j}$ that similarly have identical priors and marginal likelihoods. This allows rotations in the ideal point space that do not change the overall likelihood (Rivers 2003). The σ_i have a distinct prior distribution and marginal likelihood from the x_i and enter the equation in the form $\left(\frac{\sigma_i - 1}{\sigma_i}\right)$. The identification of the $\mathbf{x_i}$ is achieved by modifying the prior or the marginal likelihood (fixing certain item parameters to particular signs or constants) of each axis in such a way as to distinguish them from each other. Therefore, the identification condition for the σ_i relative to the spatial axes is already met by functional form.

5.2 *Estimation*

Simulating this model by Markov Chain Monte Carlo (MCMC) requires only a slight modification of the Clinton, Jackman, and Rivers (2004a) Gibbs sampler. First, we sample the latent utility differences for each bill for each legislator, conditional on the bill parameters, the legislator positions, and the legislator errors,

$$g(y_{ij}^*|y_{ij} = 0, \mathbf{x_i}, \boldsymbol{\beta}_\mathbf{j}, \alpha_j, \sigma_i) \sim N(\mathbf{x_i}\boldsymbol{\beta}_\mathbf{j} - \alpha_j, \sigma_i) I(y_{ij}^* < 0),$$

$$g(y_{ij}^*|y_{ij} = 1, \mathbf{x_i}, \boldsymbol{\beta}_\mathbf{j}, \alpha_j, \sigma_i) \sim N(\mathbf{x_i}\boldsymbol{\beta}_\mathbf{j} - \alpha_j, \sigma_i) I(y_{ij}^* \geqslant 0).$$

Second, we sample the bill parameters conditional on the latent utility differences and the legislator parameters. Let $\mathbf{X}^*$ be the $n \times (d+1)$ matrix of legislator positions with typical row $\mathbf{x_i}^* = (\mathbf{x_i}, -1)$ and $\mathbf{y_j}^*$ be the $n \times 1$ vector of latent utility differences for the jth bill. Also define $\boldsymbol{\Lambda}$ as the inverse variance matrix with $\boldsymbol{\Lambda}_\mathbf{ii} = 1/\sigma_i^2$ and $\boldsymbol{\Lambda}_\mathbf{ij} = 0 \ \forall \ i \neq j$.

$$g(\boldsymbol{\beta}_\mathbf{j}, \alpha_j | y_{ij}^*, \mathbf{x_i}, \sigma_i) \sim N\left(\left[\mathbf{X}^{*'}\boldsymbol{\Lambda}\mathbf{X}^* + \mathbf{T_0^{-1}}\right]^{-1}\left[\mathbf{X}^{*'}\boldsymbol{\Lambda}\mathbf{y}^* + \mathbf{T_0^{-1}t_0}\right], \left[\mathbf{X}^{*'}\boldsymbol{\Lambda}\mathbf{X}^* + \mathbf{T_0^{-1}}\right]^{-1}\right).$$

The variation in σ_i enters into the sampling of the $\boldsymbol{\beta}_\mathbf{j}$, α_j in a manner familiar from GLS techniques for weighted regression. Whereas in the canonical model this stage corresponds to sampling a "Bayesian regression" (Clinton, Jackman, and Rivers 2004a), in this model it corresponds to sampling a "weighted Bayesian regression" with known variance matrix. Substantively, this has the effect that the responses of legislators who make larger errors get lower weight in determining the question parameters. Under the constraint that $\sigma_i = 1 \ \forall \ i$, $\boldsymbol{\Lambda} = \mathbf{I_n}$ and the sampler becomes that of the homoskedastic model.

Third, we sample the legislator positions conditional on the latent utility differences, the bill parameters and the legislator errors. Let $w_{ij} = y_{ij}^* + \alpha_j = \mathbf{x_i}\boldsymbol{\beta}_\mathbf{j} + \epsilon_{ij}$ and $\mathbf{B}$ be the $m \times d$ matrix with rows given by $\boldsymbol{\beta}_\mathbf{j}$. Since the σ_i are constant across j, the variance matrix is just the identity matrix multiplied by a constant σ_i^2 and it can be factored from the matrix multiplication:[21]

[21] As before, under the constraint that $\sigma_i = 1 \ \forall \ i$ this formula is the same as in Clinton, Jackman, and Rivers (2004a).

$$g(\mathbf{x_i}|y^*_{ij}, \boldsymbol{\beta}_\mathbf{j}, \alpha_j, \sigma_i) \sim N\left(\left[\frac{1}{\sigma_i^2}\mathbf{B}'\mathbf{B}+\mathbf{V_i}^{-1}\right]^{-1}\left[\frac{1}{\sigma_i^2}\mathbf{B}'\mathbf{w_j}+\mathbf{V_i}^{-1}\mathbf{v_i}\right], \left[\frac{1}{\sigma_i^2}\mathbf{B}'\mathbf{B}+\mathbf{V_i}^{-1}\right]^{-1}\right).$$

Finally, we sample the legislator errors conditional on the latent utility differences, the bill parameters and the legislator positions. Let $e_{ij} = y^*_{ij} - \mathbf{x_i}\boldsymbol{\beta}_\mathbf{j} + \alpha_j$, collapse e_{ij} over j to form $\mathbf{e_i}$. Then define the sum of square errors for an individual i's votes as $\mathrm{SSE}_i = \mathbf{e_i}'\mathbf{e_i}$,

$$g(\sigma_i|y^*_{ij}, \boldsymbol{\beta}_\mathbf{j}, \alpha_j, \mathbf{x_i}) \sim \mathrm{IG}\left(\frac{c_0+m}{2}, \frac{d_0+\mathrm{SSE}_i}{2}\right). \tag{4}$$

In keeping with the identification conditions described above, I select an improper inverse gamma prior with mean at $\sigma_i = 1$ ($c_0 = d_0 = 0$) and renormalize at each iteration of the Gibbs sampler so that $\sum_i^n \frac{1}{\sigma_i} = n$.[22]

The four-stage Gibbs sampler described in the previous section allows us to sample from the posterior joint distribution of the bill and legislator parameters. Although the additional computational cost over previous models is minimal, this class of measurement models are all computationally intensive and are best estimated by dedicated code in a compiled language rather than using R or BUGS. I have modified C++ code written for the homoskedastic estimator by Martin and Quinn (2009) to fit this model. Simulation performance is similar to the homoskedastic estimator. A 1000 iteration sample on a recent session of the U.S. Senate with 100 voters and about 600 roll calls takes only a few minutes. Because of the large number of legislative sessions examined, most of the simulations in this paper have 3000 iterations of burn-in and 2000 iterations of sampling without thinning. A few of these simulations were replicated using simulations as long as 100,000 iterations, but no substantively important differences were observed.

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[22]The renormalization factor is seldom farther from 1 than ±0.02 after the first few iterations, so this has little effect on the shape of the simulated posterior distribution.

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