Political Analysis, 9:3

Estimating Voter Preference Distributions from Individual-Level Voting Data

Jeffrey B. Lewis
Politics Department, Princeton University, Princeton, NJ 08544-1012
e-mail: jblewis@princeton.edu

This paper presents a method for inferring the distribution of voter ideal points on a single dimension from individual-level binary choice data. The statistical model and estimation technique draw heavily on the psychometric literature on test taking and, in particular, on the work of Bock and Aitkin (1981) and are similar to several recent methods of estimating legislative ideal points (Londregan 2000; Bailey 2001). I present Monte Carlo results validating the method. The method is then applied to determining the partisan and ideological basis of support for presidential candidates in 1992 and to U.S. mass and congressional partisan realignment on abortion policy since 1973.

1 Introduction

OVER THE LAST decade great strides have been made in the empirical application of spatial models of policy preferences. Developments such as Poole and Rosenthal's NOMINATE (1985, 1997) and Heckman–Snyder (1997) scores, and the application of these estimators to roll-call voting in the U.S. Congress have greatly increased our understanding of legislative behavior.[1] While progress has been made in the mapping of legislative preferences, similar progress has not been made in the mapping of voter preferences. While locating legislators is critical to understanding the workings of legislatures, we would also like to know how voter preferences and legislator preferences are linked [see Gerber and Lewis (2000) for an application to this question]. In this paper, drawing on standard models of test-taking from the psychometrics literature, I present a method of inferring the distribution of voters' spatial preferences in each of a number of predetermined voter groups that is consistent even when the number of observed choices (votes) is small.

The method is similar to the random coefficient models recently presented by Londregan (2000b, pp. 248–255), Bailey (2001), and Jackman (2000). In these models, the authors are

Author's note: This research was supported by the Woodrow Wilson School of Public and International Affairs, Princeton University, and the Rockefeller Center for Public Policy, Dartmouth College. Thanks go to Liz Gerber, Simon Jackman, and David Epstein for comments on drafts of this paper presented at the 1998 American Political Science Association Meetings and 1999 Midwest Political Science Association Meetings. I thank Brian Stults for comments and research assistance. All ancillary materials are available at the *Political Analysis* web site.

[1] An excellent example of these advances is the "committee outlier" literature; see Groseclose (1994) or Londregan and Snyder (1994).

P1: FIC
lewis June 1, 2001 14:2

able to generate consistent estimates of some model parameters from data sets in which there are a very small number of legislators (Londregan) or a very small number of observed votes (Bailey or Jackman). Like Bailey (2001) and Jackman (2000), the model developed here is consistent when the number of observed votes is small, however, it differs from those methods in that it allows direct and consistent estimation of preference means and variances across any number of predetermined voter groups.

I present two brief empirical examples. In the first example, the estimator is applied to individual-level voting data and used to probe the ideological and partisan basis of support for H. Ross Perot and other candidates in the 1992 presidential election. In the second, the method is applied to congressional roll call and survey data and used to track partisan realignment on abortion in the United States since 1973.

The empirical estimation of voter ideal points has lagged behind the estimation of legislative ideal points because of both methodological and data limitations. As described below, the data that we generally have for voters are not amenable to estimation techniques that are applied to roll-call voting such as Heckman–Snyder or Poole–Rosenthal. Not only do we tend to observe far fewer bits of data from which to infer each voter's preferences, but voter behavior appears to be more stochastic than legislator behavior. Putting aside the possibility that the stochastic nature of the observed behavior of voters means that they have no political preferences (Converse and Markus 1979), at the very least, the amount of information about voter preferences that can be gleaned from a particular vote or answer to a particular survey item is less for members of the public than for members of the legislature. Thus, not only do we observe relatively few choices for each voter, but each choice may well contain less information about each voter's ideal point.

In this paper, I show how these limitations can be overcome if the analyst's quantities of interest are features of the distribution of ideal points and not the individual ideal points themselves.[2] In many instances, one does not need to know the ideal point of any particular voter. For example, one might want to compare the location of the median voter across a set of legislative districts or measure the preference heterogeneity of those districts. Similarly, one may want to know if ticket-splitting voters are more moderate than those voting straight tickets. Focusing on the distribution of ideal points within subsets of the sample avoids the statistical inconsistency that generally plagues ideal-point estimation when very few choices are observed for each actor.

In general, the "actions" of voters that we observe are answers to survey questions. The method described below can be used to model these answers. However, the model was developed specifically for a relatively rare, but very interesting data source—actual individual-level ballots. The method can also be used to study legislative voting data. Examples using each of these data sources are presented below. More generally, the method is appropriate in many situations in which the analyst needs to infer intergroup differences along some underlying dimension from a small number of individual-level binary choice items. For example, in experimental settings, the method could be used to infer mean and variance differences between treatment and control groups where the variable of interest is indicated by a series of observed binary items.

The rest of the paper is laid out as follows. In the next section, I describe the general problem of inferring spatial locations (of, for example, legislators) from observations on

[2]See also Lord (1962), Mislevy (1984), and Mislevy et al. (1992) for discussions of this general approach in the context of test-taking.

binary items (roll-call votes). In Section 3, I develop a model for estimating the distribution of voter preferences within each of a number of predetermined groups from these data. Section 4 presents Monte Carlo results validating the method. In Section 5, I present two applications. In the first, I apply the method to inferring the partisan and ideological basis of support for H. Ross Perot in the 1992 presidential election. In the second, I apply the method to mass and congressional partisan alignment on abortion. Section 6 concludes. Readers more interested in the application of the model than its derivation, estimation, and statistical properties may wish to focus on the first part of Section 3 and Section 5.

2 Spatial Models of Legislators' Preferences or Spatial Locations

Models of roll-call voting in legislatures are an obvious place to start in any consideration of recovering spatial positions from binary choice data. Over the last 20 years there have been great advances in the methods for mapping legislators in policy spaces based on their roll-call voting records. However, almost all existing models of roll-call voting have desirable statistical properties only as the number of observed votes grows large. In a legislative setting, this is not particularly problematic because, for most legislatures, the number of recorded votes is indeed quite large.

Table 1 lists a number of techniques that have been used to estimate legislators' spatial locations or ideal points. In discussing the methods, I use the terms "location" and "ideal point" interchangeably. While some of these models are explicitly designed to place legislators in a multidimensional space, others are restricted to a single dimension. A few can be extended to multiple dimensions only with a great increase in computational cost (for example, Rasch models and random-effects models).

The most important statistical issue is the consistency of the estimated ideal points. The problem is most easily seen from a maximum-likelihood (ML) perspective. Supposing that an ML estimator for each of the ideal point models could be written, it would have the form $L(\boldsymbol{V} \mid \boldsymbol{\tau}, \boldsymbol{\Theta})$, where $\mathbf{V}$ is a $n_L \times n_v$ matrix of observed votes (the data), $\boldsymbol{\tau}$ is a vector of parameters describing characteristics of the proposals, and $\boldsymbol{\Theta}$ is a vector of parameters describing the ideal points. Suppose that each of the n_v proposals to be voted on has one or more elements of $\boldsymbol{\tau}$ associated with it and that $\boldsymbol{\Theta}$ is a vector of n_L ideal points. Consider the ML estimators for $\boldsymbol{\tau}$ and $\boldsymbol{\Theta}$ as the size of the data matrix increases: as the number of legislators n_L grows, so does the size of $\boldsymbol{\Theta}$. Similarly, as n_v grows, so does the size of $\boldsymbol{\tau}$. This proliferation of parameters as the sample size increases is well-known to undermine the standard consistency results for ML estimators (Neyman and Scott 1948).

One way around this problem has been to show that estimates of $\boldsymbol{\Theta}$ will be consistent under a so-called "triple" asymptotic condition (Haberman 1977). In these cases, $\boldsymbol{\Theta}$ can be consistently estimated if the following three conditions hold: (1) the number of roll calls goes to infinity, (2) the number of legislators goes to infinity, and (3) the ratio of votes to legislators goes to infinity. In other words, these estimators will work if you have a large legislature that takes a lot of roll-call votes. Poole and Rosenthal's NOMINATE procedure is consistent under these conditions (Londregan 2000a). In cases where the number of observed choice items is small, these consistency conditions are not met.

In cases where the triple asymptotic condition seems unlikely to hold, several alternative solutions have been presented. The first is to specify the model in such a way that there exists a sufficient statistic (S) for $\boldsymbol{\tau}$. In this case the likelihood can be

Table 1 Methods of estimating legislator/voter locations or ideal points

Method	*Estimator type*	*Consistent as*	*Citation/example*
Vote index	NP	n/a	ADA score
Guttman scaling	NP	n/a	Anderson et al., 1966
Heckman–Snyder scores	GLS	$n_v \to \infty$	Heckman and Snyder (1997)
NOMINATE scores	ML	$n_v, n_L, \frac{n_v}{n_L} \to \infty$	Poole and Rosenthal (1997)
Random proposal models	MML	$n_v \to \infty$	Londregan (2000b, pp. 248–255)
Rasch models	CML	$n_v \to \infty$	Ladha (1991)
Covariate models	ML	$n_L \to \infty$	Peltzman (1985)
Random-effects covariate models	MML	$n_v, n_L \to \infty$	Bailey (2001)
Fully-Bayesian random-effects models	MCMC	$n_v, n_L \to \infty$	Jackman (2000)
Nonmetric Optimal Classification	NP	n/a	Poole (2000)

NP = Nonparametric, GLS = Generalized Least Squares, ML = Maximum Likelihood, CML = Conditional Maximum Likelihood, MML = Marginal Maximum Likelihood, MCMC = Markov Chain Monte Carlo, n_L = Number of legislators/voters, and n_v = Number of votes.

reformulated as

$$L(\boldsymbol{V} \mid \boldsymbol{\Theta}, \boldsymbol{\tau}) = \prod_l L_c(\mathbf{V}_l \mid \boldsymbol{\Theta}, S_l) g(S_l \mid \boldsymbol{\tau}).$$

Since the corresponding log likelihood,

$$\ln L(\boldsymbol{V} \mid \boldsymbol{\Theta}, \boldsymbol{\tau}) = \sum_l (\ln L_c(\mathbf{V}_l \mid \boldsymbol{\Theta}, S_l) + \ln g(S_l \mid \boldsymbol{\tau})),$$

is additively separable in $\boldsymbol{\Theta}$ and $\boldsymbol{\tau}$, the value that maximizes $L(\cdot)$ over $\boldsymbol{\Theta}$ will be the same as the value that maximizes $L_c(\cdot)$ over $\boldsymbol{\Theta}$. Assuming that $L_c(\cdot)$ meets the usual conditions for consistent ML estimation, we see that we can get consistent estimates of $\boldsymbol{\Theta}$ as n_v grows large by maximizing the likelihood of $\boldsymbol{\Theta}$ conditional on S. This method is referred to as conditional ML. Both the Heckman–Snyder and the (one-parameter) Rasch-type models take this approach. From the standpoint of estimating voter preferences, these models are not satisfactory because they are consistent only as the number of votes grows large.

The above approaches can all be put under the general heading of fixed-effects models. That is, they treat all of the vote characteristics and the ideal-point parameters as fixed constants to be estimated. Another approach would be to treat the set of proposals as a draw from some distribution, $g(\tau)$. The likelihood of $L(\boldsymbol{V} \mid \boldsymbol{\Theta})$ can then be written

$$L(\boldsymbol{V} \mid \boldsymbol{\Theta}) = \prod_l \int L(\mathbf{V}_l \mid \boldsymbol{\Theta}, \tau) dG(\tau). \tag{1}$$

Integrating out the nuisance parameters ($\boldsymbol{\tau}$) and maximizing (1) over $\boldsymbol{\Theta}$ yields the marginal ML. Londregan's (2000) random-coefficient model takes this approach. Londregan presents a model in which $g(\tau)$ is conditioned on a set of proposer-specific covariates (e.g., party of the proposer). This use of auxiliary information weakens the importance of the arbitrary distributional assumption, g. The coefficients on the covariates are also of direct substantive interest. The model is consistent as the number of votes grows large. Since Londregan's method still requires the number of proposals to grow large, it is not appropriate for the problem at hand, but it does suggest a possible course.

Rather than using auxiliary information to help identify the distribution of proposal characteristics, we could parameterize the ideal points using covariates. This is quite common in the literature. The most common form of the "covariate" models are those in which the legislators' ideal points are assumed to be a deterministic linear function of a set of covariates,

$$\theta_l = \mathbf{X}_l \boldsymbol{\lambda}$$

where θ_l is legislator l's ideal point and $\mathbf{X}_l$ is a vector of observed legislator attributes (e.g., party, constituency characteristics, or previous occupation). These deterministic models are commonly used (at least implicitly) in models of both legislative voting and candidate elections [Krehbiel and Rivers' (1988) paper is a particularly nice example of this approach]. Generally these models involve running a probit or logit regression of a single roll call or vote choice on a vector of covariates. The ideal points can then be estimated as $\mathbf{X}_l \hat{\boldsymbol{\lambda}}$. While these models can be applied to situations in which many decisions are observed, the estimated ideal points are consistent with a single observed roll call as the number of voters or legislators grows large.

One problem with the deterministic covariate model is that it is restrictive to assume that the ideal points can be written as a deterministic function of a set of covariates. Drawing on work in the psychometrics of test taking, Bailey (2001) generalizes the deterministic covariate model by assuming that the ideal points are a linear function of a set of covariates and a legislator-specific random shock,

$$\theta_l = \mathbf{X}_\mathbf{l} \boldsymbol{\lambda} + \epsilon_l$$

Bailey's model can be thought of as a mirror image of Londregan's. Bailey treats $\boldsymbol{\tau}$ as a set of fixed effects to be estimated and integrates over the random θ,

$$L(\mathbf{V} \mid \boldsymbol{\tau}, \boldsymbol{\lambda}) = \prod_l \int L(\mathbf{V}_l \mid \theta, \boldsymbol{\tau}) dG(\theta \mid \mathbf{X}, \boldsymbol{\lambda})$$

Having assumed a distribution for ϵ, Bailey can then consistently estimate the *distribution* of legislator ideal points as the number of legislators grows large. To find a particular legislator's ideal point, the *a posteriori* expectation $\mathrm{E}(\theta_l \mid \mathbf{V}, \boldsymbol{\lambda}, \boldsymbol{\tau})$ can be estimated using the estimated $\hat{\boldsymbol{\lambda}}$ and $\hat{\boldsymbol{\tau}}$ in place of $\boldsymbol{\lambda}$ and $\boldsymbol{\tau}$. The consistency of these estimates requires that the number of legislators and the number of roll calls grows large.

Jackman's (2000) MCMC estimator is similar to Bailey's except that no covariates are included.[3] Here again, individual ideal points are consistent as the number of legislators and roll calls grows large. Either of these models could be used to infer posterior distributions of voter preferences. Because I am interested in the distribution of voter ideal points and not

[3]MCMC approaches to similar models have also been presented in the test-taking literature (e.g., Patz and Junker 1999).

each individual's ideal point, the random-effects models are promising. However, neither of these two models is well suited to estimating more general intergroup differences in the distribution of preferences. Bailey models only mean differences across groups. Jackman assumes that all legislators are drawn from a common prior distribution, and the MCMC estimator is not attractive when the number of observations is very large.

3 Inferring Ideal-Point Means and Variances from Individual-Level Binary Choice Data

In this section, I derive a random-effects model appropriate to individual-level proposition voting and similar data. The model allows the estimation of the mean and variance of the distribution of voter ideal points along a single dimension across any number of predetermined voter groups. If the number of voter groups is held constant, the estimated group means and variances can be consistently estimated as the number of voters grows large. The model is derived in the usual way from a simple spatial model in which voters have quadratic preferences. By parameterizing not only the mean but also the variance of the ideal-point distribution across groups, the estimator below extends a general class of two-parameter Rasch item response models (see Bock and Aitkin 1981) that have been adapted to legislative settings by Bailey (2001) and Londregan (2000b). Because the data sets to which the method is applied are quite large—in one example presented below $N = 2.8$ million—special attention is paid to techniques that can be used to reduce the computational burden.

3.1 *A Simple Spatial Model*

I begin with the standard spatial model of voting (Hotelling 1929; Downs 1957; Black 1958; Hinich and Enelow 1984). In the spatial model, it is assumed that policy choices can be represented by points in Euclidean space. Each voter is assumed to have a most preferred policy position, θ, in a one-dimensional space. A voter's utility for various policy alternatives is defined by a function of the distance between the position of the alternative and the voter's ideal point. Following the usual convention in the literature, I assume that this function is a simple quadratic. To introduce uncertainty into the vote choice, I assume that voters' utilities for various alternatives are not determined solely by their spatial positions but are also determined by an additive idiosyncratic shock ϵ. Thus, the utility for a voter at θ from the implementation of a policy A is

$$U(\theta, A) = -(\theta - A)^2 + \epsilon$$

where, by assumption, $\epsilon \sim N(0, \sigma)$ and i.i.d. across alternatives.

The difference between the utility provided by any two alternatives A and B is

$$\begin{aligned} U(\theta, A) - U(\theta, B) &= -(\theta - A)^2 + (\theta - B)^2 + \epsilon_A - \epsilon_B \\ &= (B^2 - A^2) + 2(A - B)\theta - (\epsilon_B - \epsilon_A) \end{aligned}$$

Assuming sincere voting in the sense that voters vote for the alternative that they prefer, the probability that a voter with ideal point θ votes for alternative A over alternative B is

$$\text{Prob(Vote for } A \mid \theta) = \text{Prob}((B^2 - A^2) + 2(A - B)\theta > (\epsilon_B - \epsilon_A))$$

Because $\epsilon \sim N(0, \sigma)$, $\epsilon_B - \epsilon_A \sim N(0, \sqrt{2}\sigma)$, Letting V_{lk} represent voter l's choice on the kth policy question (hereafter "item" or "proposition"), $\{A_k, B_k\}$, where $V_{lk} = 1$ denotes the choice of A_k and $V_{lk} = 0$ denotes the choice of B_k, and letting $\alpha_k = (B_k^2 - A_k^2)/\sqrt{2}\sigma$ and $\beta_k = 2(A_k - B_k)/\sqrt{2}\sigma$, we find the familiar probit model,

$$\text{Prob}(V_{lk} = v_{lk}) = \Phi(\alpha_k + \beta_k\theta_l)^{v_{lk}}(1 - \Phi(\alpha_k + \beta_k\theta_l))^{(1-v_{lk})}$$

where β is the probit "slope" which reflects the degree to which the probability of voting for a particular item is a function of the underlying dimension. Similarly, α is the probit "intercept." While these parameters were explicity derived from the spatial model, it should be noted that α may also reflect a valence component. That is, if, *ceteris paribus*, one proposition gets more votes than another because of its inherently higher quality or valence, this greater support will be reflected in a larger estimated α.[4] If θ was observed for each voter, then the proposition parameters, $(\boldsymbol{\alpha}, \boldsymbol{\beta})$, could be estimated from a set of observed votes by standard ML techniques. If votes are independent (conditional on θ) across voters and propositions, we could then maximize

$$\prod_{l=1}^{N}\prod_{k=1}^{K}\Phi(\alpha_k + \beta_k\theta_l)^{v_{lk}}(1 - \Phi(\alpha_k + \beta_k\theta_l))^{(1-v_{lk})}$$

with respect to $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. However, $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_N)$ is not observed. While it would be possible to maximize the above likelihood with respect to $\boldsymbol{\theta}$ (in addition to $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$), these estimates would not have desirable statistical properties due to the proliferation of parameters problem described in Section 2.

Instead, I treat θ as a random quantity drawn from a known family of distributions allowing the distributions to vary across groups. Assume that there are G distinct groups, $g = 1, \ldots, G$, in the electorate. Among each group the distribution of ideal points is assumed to be normal, with a mean μ_g and standard deviation σ_g That is,

$$\theta_g \sim N(\mu_g, \sigma_g)$$

The joint likelihood can be written

$$L(\mathbf{V}, \boldsymbol{\theta} \mid \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\mu}, \boldsymbol{\sigma}) = \prod_{l}\prod_{k}\Phi(\alpha_k + \beta_k\theta)^{v_{lk}}(1 - \Phi(\alpha_k + \beta_k\theta))^{(1-v_{lk})}\phi(\theta \mid \mu_{g(l)}, \sigma_{g(l)})$$

where $g(l)$ is a function returning the group affiliation of voter l. Integrating out over the unobserved $\boldsymbol{\theta}$, we find the marginal ML,

$$L(\mathbf{V} \mid \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\mu}, \boldsymbol{\sigma}) = \prod_{l}\int\prod_{k}\Phi(\alpha_k + \beta_k\theta)^{v_{lk}}(1 - \Phi(\alpha_k + \beta_k\theta))^{(1-v_{lk})}\phi(\theta|\mu_{g(l)}, \sigma_{g(l)})\, d\theta$$

The maximization of this likelihood yields consistent estimators of the proposition parameters and the group means and standard deviations. As the number of parameters and subscripts is a bit unwieldy, I provide Table 2, listing each parameter, variable, and index.

[4] Londregan (2000a) explicitly incorporates a similar valence effect in his model of voting in small legislatures.

Table 2 Index, parameter, and variable definitions

Quantity/index	*Symbol*
Voters	$l = 1, 2, \ldots, N$
Items (propositions)	$k = 1, 2, \ldots, K$
Groups	$g = 1, 2, \ldots, G$
Vote patterns	$i = 1, 2, \ldots, I$
Item intercepts	$\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_K)$
Item slopes	$\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_K)$
Group means	$\boldsymbol{\mu} = (\mu_1, \mu_2, \ldots, \mu_G)$
Group standard deviations	$\boldsymbol{\sigma} = (\sigma_1, \sigma_2, \ldots, \sigma_G)$
Votes pattern i in group g	$\mathbf{V}_{ig} = (V_{ig1}, V_{ig2}, \ldots, V_{igK})$
Number of voters in group g casting pattern i	c_{ig}
Ideal point of voter l	θ_l

3.2 *Estimating the Model*

To simplify the estimation of the model, I follow Bock and Aitkin (1981) in grouping the data into patterns[5] and in employing an EM algorithm to overcome computational problems related to the direct maximization of the likelihood presented above. Grouping of the data is the first computational savings that can be achieved. All we know about each voter is the pattern of votes that she casts across the K items and the group to which she belongs. Any two voters casting the same pattern of votes and belonging to the same group are interchangeable and thus must make the same contribution to the likelihood. Following this logic, we can group the data by their patterns of votes and group membership. Letting i index patterns of votes, define V_{ig} to be the ith vote pattern in group g. Similarly define c_{ig} to be the number of voters in group g casting pattern V_{ig}. The likelihood can then be reformed as

$$\prod_i \prod_g \left[\int \prod_k \Phi(\alpha_k + \beta_k\theta)^{V_{igk}} \left[1 - \Phi(\alpha_k + \beta_k\theta)\right]^{(1-V_{igk})} \phi(\theta \mid \mu_g, \sigma_g) d\theta \right]^{c_{ig}}$$

Taking logs and letting $Z = (\theta - \mu_g)/\sigma_g$, the log likelihood can be written

$$\sum_i \sum_g c_{ig} \ln\biggl(\int \prod_k \Phi(\alpha_k + \beta_k(\mu_g + \sigma_g Z))^{V_{igk}} \times \left[1 - \Phi(\alpha_k + \beta_k(\mu_g + \sigma_g Z))\right]^{(1-V_{igk})} \phi(Z)\, d\theta \biggr) \tag{2}$$

where ϕ is now the standard normal density function.

The integral in Eq. (2) cannot be solved analytically and is numerically approximated by Gauss–Hermite quadrature (see Stroud and Secrest 1966).

[5]Londregan (2000) also points out this possibility in a different context.

Though Eq. (2) can be maximized directly, greater numerical efficiencies can be achieved through the application of an EM algorithm (Dempster et al. 1977). A full description of the application of the EM algorithm to this problem is given by Lewis (2001). One drawback of the EM algorithm in contrast to direct maximization using standard techniques is that there is no straightforward way to estimate the standard errors of the estimates. Once estimates are arrived at, the standard errors are calculated by using gradient or Hessian-based estimators derived from the full log-likelihood function.

3.3 *Model Identification*

As is true of many methods of inferring an underlying dimension from a set of indicators, the scale of the underlying ideal point (θ) distribution is not uniquely defined. For example, if each group's standard deviation (σ) is multiplied by any positive constant κ and each β and μ is multiplied by $1/\kappa$, the log likelihood [Eq. (2)] is unchanged. Similarly, if a constant amount, C, is added to each group mean (μ), the same log likelihood is maintained by subtracting $\beta_k C$ from each α_k ($k = 1, \ldots, K$). To establish the scale of the ideal-point distribution, I set $\mu_1 = 0$ and $\sigma_1 = 1$. This involves no loss of generality. After the estimation, linear transformations of the parameters (and associated measures of uncertainty) can be applied to achieve a more convenient scale if necessary (as in Section 5.1). Additionally, the direction of the scale is undefined; every solution to maximization of Eq. (2) has a reflected solution in which each of the β's and μ's is multiplied by -1.

Given a choice of scale and direction for the ideal points (θ), the other parameters are identified if more than one item is observed ($K > 1$). To see that the model is unidentified with only one item, note that each group in this case has two free parameters that can be used to describe its distribution of vote patterns,[6] but each group's members are distributed over only two possible vote patterns, (1) or (0). Since one group parameter is sufficient for the group's distribution over the two outcomes (holding the other parameters fixed), the model is not identified with only one item. With two items, the number of potential patterns per group exceeds the number of free parameters for each group and the model is identified.

4 Monte Carlo Results

In inferring legislator ideal points from roll-call voting data, it is typically the case that a large number of votes are observed for each member. Recent U.S. Congresses have taken more than 600 hundred roll-call votes per session from which one can infer legislators' positions. The method developed above is designed to provide estimates of features of the distribution of preferences within and across groups when the number of observed vote choices is small. However, a question remains: Exactly how small can "small" be? Figure 1 presents the results of a series of Monte Carlo experiments that address this question.

In these experiments, the number of groups is held fixed at five and the observations are assumed to be evenly distributed among the five groups.[7] The total number of voters (N) is held fixed at 2500. Table 3 shows the values of the parameters. Notice that the slopes include both positive and negative values. That is, in some cases, the more "liberal" voters

[6] The free parameters are α_1 and β_1 for group 1 and μ_g and σ_g for groups $g = (2, \ldots, G)$.

[7] Five hundred trials were run for each number of items from 2 to 12. Abstentions are randomly distributed and make up 10% of all vote decisions.

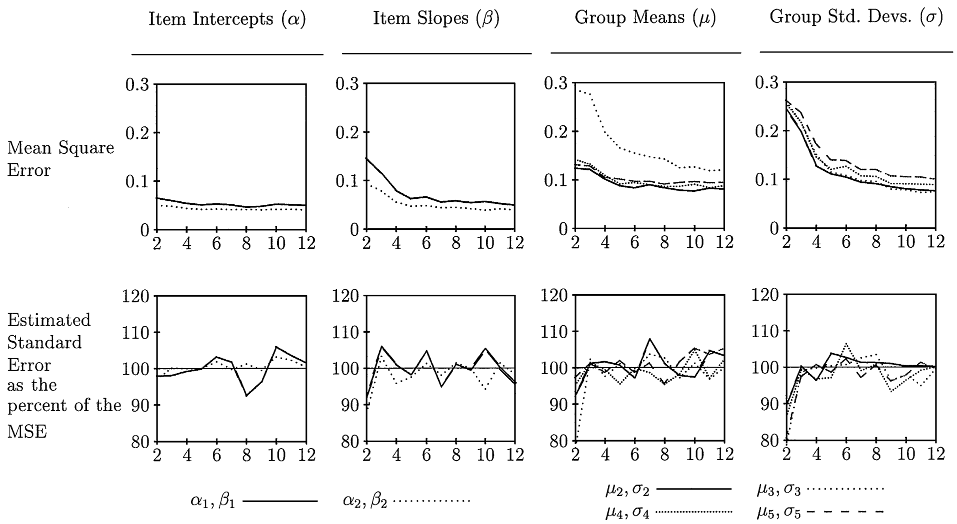


Fig. 1 Parameter estimates as a function of the number of items. Results of Monte Carlo experiments in which the number of items is varied from 2 to 12. Notice that improvements in MSE and standard error accuracy come quickly at first but diminish as the number of items grows beyond six. Observe, further, that the largest group mean ($\alpha_3 = 1.7$) has the largest MSE.

are more likely to vote for a particular item, and in other instances, they are more likely to vote against. Similarly, some groups have mean positions of less than zero and others have means above zero.

The top row in Fig. 1 graphs the observed (root) mean square errors (MSEs) of the estimates of various parameters of the model as a function of the number of observed items. The first two panels report the MSEs for the estimated intercepts (α's) and slopes (β's) associated with items 1 and 2. Interestingly, the quality of the estimated intercepts is relatively unaffected by the addition of more observed items, though the MSEs do decrease as more items are included. The quality of the slope estimates is more dramatically improved by additional items. The MSE of $\hat{\beta}_1$ is cut nearly in half as the number of items is increased from 2 to 12.

The addition of items has a much more dramatic effect on the estimated group parameters (μ's and σ's). This is not surprising because additional items directly affect the estimates of μ's and σ's, whereas they only indirectly affect the other α's and β's (through their effects on the μ's and the σ's). With only three items, it is particularly difficult to gauge reliably the variance of the distribution of voters within each group (σ). The MSE begins to level off with as few as 6 or 7 items, and very little is gained by moving from 10 to 12 items.

μ_3 is particularly unreliably estimated when the number of observed items is small. This results from the large (absolute) value of μ_3 and the ratios of α_1 to β_1 and α_2 to β_2, which are close to 0. To see this, note that the negative of the ratio of α to β gives the value of

Table 3 Parameter values used in the Monte Carlo experiments

Intercepts	$\boldsymbol{\alpha} = (0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.3, 0.8, 0.4, -0.2, 0.5, 0.1)$
Slopes	$\boldsymbol{\beta} = (0.7, 0.5, -0.5, 1.0, -1.2, -0.3, -0.7, 0.4, 0.8, 0.3, 0.7, 0.5)$
Group means	$\boldsymbol{\alpha} = (0.0, 0.3, 1.7, 0.4, -0.2)$
Group standard deviations	$\boldsymbol{\sigma} = (1.0, 1.0, 0.8, 1.2, 1.4)$

the ideal point (θ) for a voter who will vote yes or no on that item with equal probability. For group 3, whose ideal-point distribution has a mean of 1.7 and a standard deviation of 0.8, less than 1% of the group has even a 50/50 chance of voting no on item 1 or 2, and the average member would vote no only 12 or 17% of the time.[8] When the outcomes within a group are so lopsided, it becomes difficult to tell exactly where the group mean actually falls because changes in the mean have a relatively small effect on the share of votes cast for and against. This result is similar to that found in simple probit models, and it holds not only when support for an item is very lopsided within a particular group but also when support for a particular item is lopsided or polarizing across all groups.

The bottom row in Fig. 1 graphs the average ratio of the estimated standard errors to the observed MSEs of the parameter estimates against the number of observed items. Beyond the reliability of the estimates, it would also be reassuring to know the point at which the estimated uncertainty of the estimates is a good proxy for their true uncertainty. These panels address this question. For the intercepts and slopes, the estimated standard errors are a reasonable reflection of the uncertainty in the estimates with any number of observed items. The average estimated standard error is never more than 10% away from the observed MSE. Because the estimated standard errors are found to be too large (more than 100%) for some numbers of items and too small (less than 100%) for other numbers of items, it seems reasonable to conclude that much of the variation found in these panels is due to running only 500 trials for each number of items.

The estimated standard errors of the group means and variances understate the true sampling uncertainty with only two items. In this case, the estimated standard errors were on average less than 80% as large as the true sampling uncertainty. However, with three or more items much more reasonable standard error estimates were achieved—always within 10% of the true sampling uncertainty.

In terms of the reliability of the estimates and our ability to measure that reliability, the answer to the question, "How small can a *small* number of items be?" seems to be about six. Additional items increase the reliability of the estimates but offer relatively little additional advantage—at least for the set of parameter values considered here. However, because the parameters of lopsided items or very extreme groups are harder to estimate, more items may be required in those situations.

In other experiments, I find that reasonable estimates are made with as few as 200 observations per group and as few as 5 points of quadrature. The estimated group parameters are also found to be fairly robust to violations of the assumed independence between the observed items (votes) and to mild violations of the assumed normal distribution of preferences within each group (see Lewis 2001).

5 Two Applications: Support for Perot and Partisan Relignment on Abortion

In this section, I apply the method to three data sets addressing two important substantive questions in political science. The first application is to individual-level voting data from Los Angeles County. This analysis attempts to uncover, in a way fuller than is typically possible using survey data the partisan and policy preference bases of support for presidential candidates in the 1992 election. The second application revisits Adams (1997) by mapping the evolution of partisan preferences on abortion in the United States since *Roe v. Wade* in 1973. In this application the method is applied to roll-call voting

[8] The probability of a voter located at 1.7 voting against item 1 is $1 - \Phi(0 + 0.7(1.7)) = 0.117$, and that for item 2 is $1 - \Phi(0.1 + 0.5(1.7)) = 0.171$.

data from the U.S. House and to survey data from the General Social Science Survey (GSS).

5.1 *Sources of Support for Presidential Candidates in Los Angeles, 1992*

The 1992 presidential election is particularly interesting because of the presence of H. Ross Perot. Perot gained 19.0% of the vote nationwide (and 17.8% in Los Angeles County), more than any third-party candidate since Theodore Roosevelt in 1912. Much has been written about this election and about the consequences and meaning of Perot's candidacy. Using survey data or aggregated election returns, scholars have sought to determine Perot's effects on turnout (Lacy and Burden 1999; Knack 1997; Southwell and Everest 1998). Other scholars have tried to determine whether Perot disproportionately took votes from Clinton or from Bush (Alvarez and Nagler 1995; Abramson et al. 1995). Still others have investigated whether Perot reflected a protest against the major-party choices or a real preference for his platform (Owen and Dennis 1996; Holian et al. 1997; Ceaser and Busch 1993). More generally, it has been argued that 1992 was a particularly nonideological election that was largely a referendum on Bush's handling of the economy or the character of the candidates [see Thorson and Stambough (1995) and Abrams and Butkiewicz (1995) and references therein].

Rather than looking at survey or aggregated election returns, I consider the policy and partisan bases of support for 1992 presidential candidates using a data set of individual marked ballots (see Table 4). The advantage of these data is that they reflect the actual voting behavior of a very large number of voters across all candidate races as well as their revealed preferences on real policy questions (ballot propositions). The drawback of these data is that they come from only one county and contain no demographic covariates. However, I argue that the ability of these data to map the preferences of groups of voters that would be too small to consider using survey data and that would require heroic ecological inferences using aggregate data overshadows the loss of generality inherent in data from a single (though very large) locality. For a complete description of how these data are created and processed, see Lewis (2001).

To determine the partisan and ideological basis of support for the various presidential candidates, I apply the method described in Section 3 to voting on the 12 ballot propositions. These include a number of highly polarizing and high-profile questions such as term limits

Table 4 Support for presidential candidates in Los Angeles County by votes cast in other federal offices, 1992

	Straight Republican	*Split*	*Straight Democrat*	*Minor party*	*President only*	*Total*
Clinton	3.69	44.14	90.46	28.15	46.86	52.55
Bush	79.03	27.51	2.18	8.82	28.87	29.05
Perot	17.01	27.14	7.19	56.83	23.26	17.75
Other	0.26	1.20	0.17	6.19	1.01	0.65
Total	100	100	100	100	100	100
N	587,142	1,085,442	1,016,111	18,598	45,390	2,752,683
Percent	21.33	39.43	36.91	0.68	1.65	100

"Straight Democrat" and "Straight Republican" voters are those that voted a straight ticket across the two US Senate elections and a US House election. "Minor party" voters supported two minor party candidates across the two US Senate elections and a US house election. President only voters abstained in the other three federal elections.

and welfare reform. They also include more mundane questions such as whether to continue the collection of certain road tolls 35 years in the future, bread-and-butter tax and spending issues such as school bonds and tax reform, and social questions such as physician-assisted suicide. In this estimation, the groups of voters were defined by their presidential vote and voter type ({Staight-Democrat, Split, Straight-Republican, Minor Party, President Only} × {Clinton, Bush, Perot, Other}). Estimates of the mean and variance of the preference distribution within each of these 20 groups are made. I then draw inferences about the partisan and ideological composition of the supporters of each presidential candidate from these estimates.

The estimated item parameters (α's and β's) are listed in Table 5. The issue space has been normalized so that Clinton-voting straight-Democrats have a mean position of -1 and Bush-voting straight-Republicans have a mean position of 1. Thus, higher ideal points are associated with conservative positions and lower ideal points are associated with liberal positions. The most ideologically polarizing propositions (largest absolute β's) are associated with the two bonds, welfare reform, tax reform, term limits, and the reorganization of the Office of the Legislative Analyst. All of the effects are in the expected directions. Conservatives were less likely to support the bond issues, progressive tax reform, and reorganizing the Legislative Analyst's office and they were more likely to support welfare reform and term limits. Other measures such as the snack tax repeal, single-payer health care, and assisted suicide were much less ideologically polarizing.

The "cutpoint" column shows the location of the voter who is expected to be indifferent between voting for or against a given proposition. Most of the cutpoints fall between the straight-Democratic and the straight-Republican means (that is, between -1 and 1), meaning that for most of the propositions the average Republican partisan and Democratic partisan had opposing preferences. The three cutpoints that fall outside the $(-1, 1)$ interval had strong valence components, and voting on them was relatively unrelated to the ideological dimension. Overall, the item parameters reflect the fact that tax and spending issues are at the heart of the main dimension of political competition in the United States.

Table 5 Estimated item parameters α and β

Proposition	*Description*	*Intercept* (α)	*Slope* (β)	*Cutpoint* ($-\alpha/\beta$)
155	School bonds	0.17	−0.90	0.19
156	Rail bonds	0.08	−0.89	0.09
157	Allow toll roads	−0.57	−0.26	−2.19
158	Reorganize the office of the state analyst	−0.25	−0.67	−0.37
160	Property tax exemption	0.10	−0.20	0.50
161	Assisted suicide	−0.13	−0.15	−0.87
162	Alter state employee retirement fund	−0.02	−0.29	−0.07
163	Repeal sales tax on food	0.40	0.04	−10.00
164	Congressional term limits	0.27	0.36	−0.75
165	Welfare and budget reform	−0.15	0.41	0.37
166	Single−payer healthcare	−0.47	−0.15	−3.13
167	Progressive tax reform	−0.29	−0.44	−0.66

Maximum standard errors of $\hat{\alpha}$ and $\hat{\beta}$ are 0.01. The average standard error for $\hat{\alpha}$ and $\hat{\beta}$ are <0.005. $N = 2,795,083$.

Table 6 Means and variances of the ideological positions of various Los Angeles County voter types, 1992

		Straight Republican	*Split*	*Straight Democrat*	*Minor party*	*President only*	*Total*
Clinton	$\hat{\mu}$	0.42	−0.30	−1.00	−0.09	−0.44	−0.74
	$\hat{\sigma}$	0.95	1.07	1.24	0.96	1.19	1.23
Bush	$\hat{\mu}$	1.00	0.50	−0.19	0.39	0.37	0.77
	$\hat{\sigma}$	1.13	1.03	1.00	0.92	1.09	1.13
Perot	$\hat{\mu}$	0.87	0.36	−0.24	0.35	0.24	0.38
	$\hat{\sigma}$	1.01	0.95	1.02	0.91	1.08	1.03
Other	$\hat{\mu}$	1.29	0.56	−0.90	−0.32	−0.20	0.41
	$\hat{\sigma}$	1.15	1.44	1.37	1.20	1.21	1.49
Total	$\hat{\mu}$	0.96	0.11	−0.93	0.19	−0.05	−0.09
	$\hat{\sigma}$	1.11	1.10	1.24	0.97	1.20	1.36

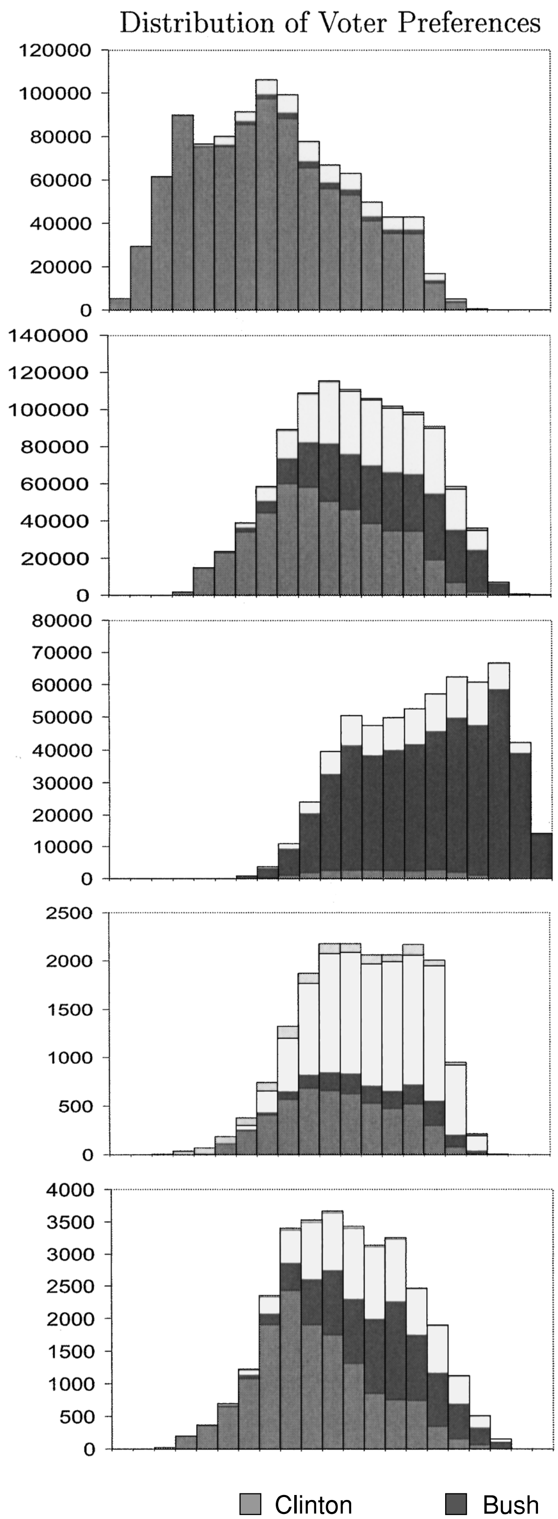
"Straight-Democratic voters" voted Democrat for both US Senate races and US House of Representatives. "Straight-Republican voters" voted Republican for both US Senate races and US House of Representatives. "Minor-party voters" voted for two minor party candidates across the two Senate races and US house of Representatives. President only voters abstained in the other federal offices, though they voted on at least one proposition in addition to a Presidential candidate. The average standard error of μ is 0.02 and for σ is 0.01.

Table 6 summarizes the main results of the analysis. Here we see the means and standard deviations of the ideal-point distributions within each group of voters. Interestingly, those splitting their tickets across the Senate and House races are on average located about halfway between the straight-ticket-voting Democrats and Republicans. Supporters of Perot were more ideologically concentrated than voters for Clinton and Bush and centered much closer to the Bush average than the Clinton average.

A graphical representation of the distribution of voters across partisan types and presidential vote choice is given in Fig. 2. The figure shows the distribution of expected *a posteriori* ideal-point estimates for voters of each partisan type (see Lewis 2001). Each of the histogram bars is shaded to reflect the proportion of voters in that interval that supported each of the presidential candidates. The histograms reveal some additional detail that is not found in Table 6. Consider, for example, the second panel in Fig. 2. It illustrates Clinton's advantage over Bush among those relatively independent voters who split their tickets at the federal legislative level. While Clinton won a plurality of the liberals and centrists among this group, Perot won the center right, and Bush managed to win only among the relatively few voters on the extreme right.

The last two panels in Fig. 2 demonstrate a real advantage of ballot data over survey or aggregate data. Because the "sample" of voters is so large, I am able to render nuanced and detailed mappings of the preferences and voting choices of very small groups in the electorate. Those voting for other minor party candidates or voting only for president represent 0.68 and 1.65% of LA voters, respectively. In a usual survey sample of 2000, one would expect to find only 14 minor-party and 33 president-only respondents. Even a sample of 10,000 would on average contain fewer than 200 respondents among these two groups—far too few to break down by presidential vote choice and policy preference. In contrast, the ballot data include nearly 64,000 voters in these two groups.

Taken in total, this analysis shows that there were important policy and partisan considerations in the 1992 presidential that are manifest not only in the votes for Clinton and



Straight-Democratic voters ($N =$ 1,016,111): These voters are mostly drawn from the left side of the voter distribution and vote overwhelmingly for Clinton. Democrats of all ideological bents stuck with Clinton. Nearly all defections were to Perot and were drawn from the center and right.

Split-party voters ($N = 1{,}085{,}442$): These voters are drawn from the center to right of the preference distribution. Among splitters support for Perot is greatest in those from the center and right. Perot outpolled Bush among those in the center to left of this group and outpolled Clinton on those on the right.

Straight-Republican voters ($N =$ 587,142): These voters are mostly drawn from the right. Support for Perot among these voters was stronger than among Democratic voters. Perot drew support from the full spectrum of Republicans.

Minor-party voters ($N = 18{,}500$): Voters who supported at least two minor-party candidates in U.S. Senate or U.S. House elections were drawn predominantly from the right, though some came from the left as well, reflecting the diversity of third-party alternatives. Support for Perot was the greatest among this group.

President-only voters ($N = 45{,}390$): These voters were drawn predominantly from the center of the preference distribution. Voters in this group mostly favored Bush on the right and Clinton on the left. Interestingly, Perot support was largest on the center-left and far-right.

Fig. 2 Histograms of expected *a posteriori* ideal points by voter type.

Bush but also in the votes for Perot. Partisan effects were revealed by the fact that, holding policy position constant, straight-ticket voters (across the federal legislative offices) were more likely to vote for Clinton and Bush than those more independent voters who split their tickets at the federal legislative level. Within each partisan group, moving to the left increased the relative advantage of Clinton over Bush. Similarly, for each partisan group, Perot runs best among those in the center or center-right of the policy space. These sorts of inferences would be difficult to make with confidence using survey data and very difficult to make at all using aggregated voting data.

5.2 *Party Alignment on Abortion Since* Roe v. Wade

A persistent question in American politics is how certain policy positions come to be associated with particular political parties. The classic realignment models of Key (1955) or Burnham (1979) suggest that when a new salient issue appears on the agenda, preferences on that issue often cut across preexisting partisan cleavages. However, as the issue becomes sufficiently salient, the parties will quickly realign in such a way that they take opposing positions on the issue. This realignment could result either from parties staking positions on the new issue in hopes of increasing their electoral prospects or from one or the other party being taken over by an insurgent group promoting a particular position on the new issue. According to these theories, the new partisan alignment is manifest in "critical elections" in which large shifts in traditional voting patterns are observed.

In contrast to the models that predict swift and punctuated change, Carmines and Stimson (1989) suggest that partisan realignments are not marked by critical elections but, rather, evolve slowly over time. Adams (1997) presents a very interesting illustration of this theory of issue evolution. Adams traces the changes in partisan preferences on abortion policy in the mass public and in the Congress since its emergence on the national political landscape following the landmark *Roe v. Wade* Supreme Court decision in 1973. Using additive scales based on roll call votes and survey questions, Adams (1997) tracks mean partisan preferences in the Congress and the public, concluding that "the two major parties in the United States are not the same two parties that existed just over 20 years ago when it comes to abortion .... The shift is gradual, with no single election precipitating change, and the process runs from elites to masses" (p. 735).

In what follows, I revisit and update through 2000 Adam's analysis of the evolution of the abortion issue in the U.S. House and in the mass public applying the statistical model developed in Section 3. The method allows me to paint a fuller picture of the distribution of preferences within and between the two parties over time. The method is well suited to this question because relatively few votes on abortion are cast in each Congress and, indeed, over the 1973 to 2000 period. The method is similarly well suited to the available survey data that is based on six binary items. Both the mass public and the congressional analyses illustrate the ability of the model to extract information about the distribution of preferences within and between partisan groups from a small number of observed survey responses or votes.

5.2.1 Abortion Policy Preferences in the U.S. House

To measure the abortion policy preferences of legislators, I collected roll calls related to abortion in the U.S. House from the 93rd through the 106th Congresses (1973–2000).[9]

[9] A list of the roll calls used and a description of how they were selected is given in Lewis (2001).

As shown in Table 7, the number of votes ranges from a low of 4 to a high of 21. The scaling of roll calls over time introduces additional questions of identification. Scalings made using votes from one Congress are not comparable to those made in another. To place different Congresses in the same space, identifying restrictions must be made. In fixed-effects models in which each member's ideal point is estimated, such as NOMINATE, identification of a common issue space is achieved by fixing each legislator's location over time.[10] With the model developed here, individual ideal points are not estimated and, thus, cannot be constrained in this way. Alternatively, identification over time can be achieved if identical votes were taken in each legislature. This is implicitly what is being assumed when interest group rating scores are compared over time. Given that today's roll calls determine tomorrow's status quos, it seems unlikely that one observes the same set of alternatives and status quos in Congress after Congress. In the end, without nailing down the location of (at least some of) the members of the legislature or the characteristics of the observed choices, direct comparisons between years cannot be made. Fortunately, in this case, we are interested mainly in differences between the distribution of the Democrats and Republicans in each Congress. Issue evolution suggests that parties will slowly come to be associated with opposing positions along an issue but does not predict exactly what those positions will be. Thus, it is sufficient to identify the partisan distributions relative to one another and not their absolute positions. To this end, I have constrained the mean and standard deviation of the Democratic ideal-point distribution to be 0 and 1, respectively, in each Congress. Using the positions of outspoken pro-life and pro-choice members in the earlier Congresses and positions of pro-life and pro-choice interest groups in the later Congresses, I define the direction of the scale such that larger (more positive) values reflect more pro-life positions.

Table 7 summarizes the results of the analysis. The second and third columns give the mean and standard deviation of the Republican ideal-point distribution in each Congress. Consistent with Adams, I find that in every Congress the average Republican is more pro-life than the average Democrat. The Republicans were more heterogeneous in their abortion policy preferences than Democrats in the 95th to the 102nd Congresses and have been more homogeneous since. While the means and standard deviations cannot be directly compared across time, it is possible to use these estimates to create an intertemporally comparable measure of party divergence. The fourth column in Table 7 shows where in the distribution of Republican members the median Democrat would fall.[11] For example, in the 105th Congress only 1% of Republicans held a more pro-choice position than the median Democrat, whereas in the 95th Congress 28% of Republicans were more pro-choice than the median Democrat. With the exception of the 102nd Congress, the parties have been considerably more polarized since the 100th Congress than they were previously. While the degree of polarization has bounced around considerably, the parties have remained highly polarized for the last four Congresses.[12]

Some evidence that Democrats have become more pro-choice while Republicans have become more pro-life is found in the average cutpoints. The average cutpoint was to the left of the average Democrat through the 95th Congress and has been to the right of the

[10]In some versions of NOMINATE this assumption is weakened to allow members to move over time in a limited way. However, identification is still achieved by constraining members' positions over time.

[11]Since the distribution of legislator preferences is assumed to be normal, the median and mean Democrat have the same position of 0 in each Congress. The position of 0 in the Republican distribution is calculated as $100\Phi((0-\mu_R)/\sigma_R)$.

[12]Some of the variability over time is probably attributable to differences in abortion questions that appeared in each Congress.

Table 7 Partisan preferences over abortion policy in the US House, 1973–2000

Congress	*Republican mean*	*Republican standard deviation*	*Median Democrat's Republican Percentile*	*Average cutpoint* $(-\beta/\alpha)$	*Average absolute* β	*No. of Roll-calls*
93	0.97	0.72	9	−0.28	2.51	9
94	0.02	0.87	49	−0.41	5.54	4
95	0.62	1.08	28	−0.09	2.82	20
96	1.63	1.06	6	0.41	3.48	10
97	1.50	1.14	9	0.41	4.26	4
98	0.55	1.09	31	0.21	3.80	5
99	0.72	1.14	26	0.17	3.19	5
100	1.72	1.30	9	0.40	5.28	4
101	1.79	1.15	6	1.53	2.59	8
102	0.40	1.22	37	0.37	3.49	16
103	1.91	0.73	1	1.00	4.03	15
104	1.92	0.77	1	1.19	3.18	20
105	2.17	0.91	1	0.59	3.65	20
106	1.80	0.81	1	0.83	3.65	21

Democrat means and standard deviation are set to 0 and 1 respectively for each Congress. Larger (more positive) values reflect more pro-life positions. The "Median Democrat's Republican Percentile" column shows where in the Republican distribution the median Democrat would fall. Average standard errors are: 0.10 for the Republican mean, 0.11 for the Republican standard deviation, 0.25 for β, 0.20 for α, 0.06 for the cutpoints, and 2.2 for the median Democrat's Republican percentile. The standard errors for the cutpoints and median Democrat's Republican percentile are calculated by the delta method.

average Democrat ever since. While it is not possible to know whether the Democrats have remained fixed over time and the proposals voted on have generated cutpoints increasingly farther to the pro-life side, as may have resulted from the Republican takeover of the House in the 104th Congress, or whether the average cutpoint has remained relatively constant over time and the Democrats have become more pro-choice relative to those cutpoints, it seems reasonable to assume that both trends are probably at work.

Figure 3 presents a graphical display of the results of the analysis. Each panel graphs the *a posteriori* distribution of ideal points for each party.[13] The panels also indicate the location of each roll-call cutpoint by dashes at the top and bottom of the panels. Vertical lines at the top of the panels show roll calls where an "aye" would move policy in the pro-life position. Vertical lines at the bottom of the panel show cutpoints for roll calls where an "aye" would move policy in the pro-choice direction. These graphs illustrate the increasing divergence of the Democrats and Republicans over the period as the well as movement of the cutpoints in a pro-life direction over time.

5.2.2 Abortion Policy Preferences in the U.S. Mass Public

Figure 3 largely confirms Adams' conclusion of a slow evolution of partisan realignment on abortion policy between 1973, when the partisan delegations were relatively overlapping,

[13] Formulas for calculating the posterior distribution over the discrete approximation to the normal prior are given by Lewis (2001). The graph panels are kernel density plots that smooth this discrete distribution. The plots use normal kernels and 51 points of support in the distribution of X_q.

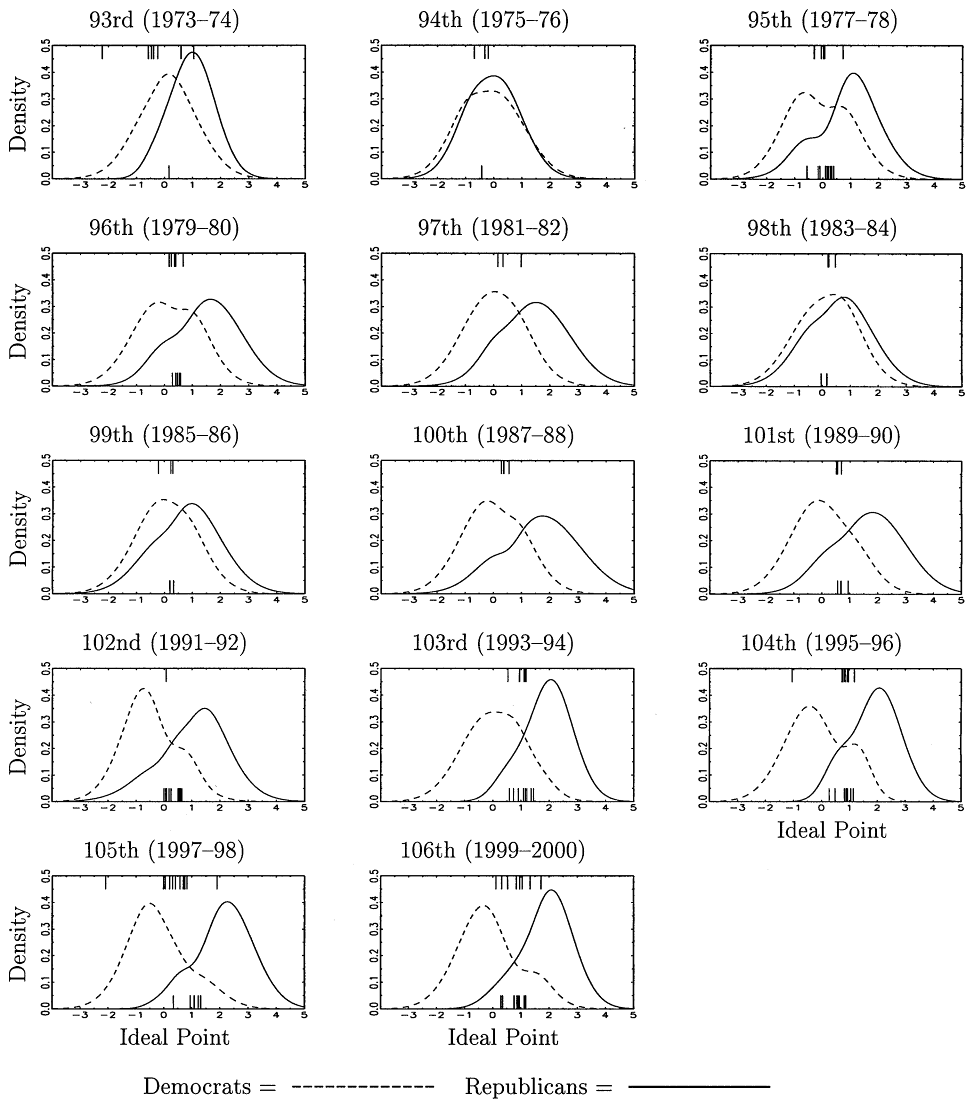


Fig. 3 Distribution of abortion preferences in the U.S. House by party, 1973–2000. Increasingly pro-life positions are found by moving from the left to the right in each panel. The vertical lines at the top and bottom of each panel show the cutpoints for abortion roll calls taken in that Congress. Vertical lines on the top show motions to change policy in the pro-life direction. Vertical lines at the bottom show motions to change policy in the pro-choice direction.

to 2000, when there was considerably less overlap. To answer the question of whether a similar pattern arises in the mass public, I employ the GSS, which has asked the same battery of six binary questions about the conditions under which abortion should be legal in at least 1 year of every 2-year period between 1973 and 1998. Because the same questions were asked on each survey, I constrain the item parameters (α and β) for each question to be fixed over time. This creates estimates of the partisan means and standard deviations that can be compared across time and avoids some of the indeterminacy in the congressional results presented above.

Table 8 Analysis of the abortion items on the General Social Science Survey, 1973–1998

Allow abortion if	α	β	*Cutpoint* $(-\alpha/\beta)$
In the case of rape (ABRAPE)	−1.85 (0.05)	1.64 (0.04)	1.12 (0.04)
Woman's health is in danger (ABHLTH)	−2.34 (0.04)	1.43 (0.05)	1.64 (0.05)
Woman is unmarried (ABSINGLE)	0.59 (0.08)	3.08 (0.12)	−0.19 (0.03)
Married woman wants no more children (ABNOMORE)	0.62 (0.08)	2.95 (0.11)	−0.21 (0.03)
Fetus will have birth defect (ABDEFECT)	−1.65 (0.04)	1.51 (0.05)	1.09 (0.04)
Woman is poor (ABPOOR)	0.29 (0.07)	2.86 (0.11)	−0.10 (0.03)

The underlying dimension is constructed such that larger (more positive) values reflect increasingly pro-life positions. Standard errors are given in parentheses. The standard errors for the cutpoints are calculated by the delta method.

Table 8 presents the estimated item parameters for each of the six abortion questions. As above, the issue scale is defined such that increasingly positive values are associated with increasingly pro-life positions. The order of the cutpoints comports with expectations. The cutpoints on the question of whether to allow abortion if the mother's health is endangered by the pregnancy is farthest out in the pro-life direction. That is, responding "no" to this question divides the most pro-life respondents from the rest of the public. On the other hand, allowing abortion in cases where the woman is poor or simply wants no more children divides voters farther into the pro-choice end of the scale.

Table 9 presents the main results of the analysis of the survey responses. Because the same questions were asked in each 2-year period, the estimated means and standard deviations are

Table 9 Partisan preferences over abortion policy in the US public, 1973–1998

	Democrats		*Republicans*		*Independents*		*Median Democrat's Republican Percentile*
Years	*Mean*	*Standard deviation*	*Mean*	*Standard deviation*	*Mean*	*Standard deviation*	
1973–74	0.00	1.00	−0.18	1.00	−0.29	1.07	57
1975–76	0.05	1.05	−0.16	1.10	−0.32	1.09	58
1977–78	−0.05	0.98	−0.30	1.02	−0.22	1.15	60
1979–80	0.00	1.09	−0.16	1.12	−0.08	1.12	56
1981–82	0.11	1.00	0.03	1.13	−0.11	1.11	53
1983–84	0.17	0.98	0.02	1.03	0.06	1.19	56
1985–86	0.12	1.07	0.21	1.02	0.12	1.22	46
1987–88	0.17	1.09	0.12	1.19	0.11	1.14	52
1989–90	0.02	1.12	0.18	1.05	−0.01	1.13	44
1991–92	0.03	0.99	0.08	1.10	0.18	1.05	48
1993–94	−0.33	1.11	0.24	1.23	0.10	1.19	32
1995–96	−0.26	1.06	0.22	1.18	0.14	1.02	34
1997–98	0.19	1.16	0.35	1.33	0.08	1.15	45

Democrat means and standard deviation are set to 0 and 1 respectively for each two-year period. Larger (more positive) values reflect more pro-life positions. The "Median Democrat's Republican Percentile" column shows where in the Republican distribution the median Democrat would fall. Average standard errors are 0.04 for the estimated means, 0.06 for the estimated standard deviation, and 1.7 for the median Democrat's Republican percentile. The standard deviation of the median Democrat's Republican percentile is calculated by the delta method.

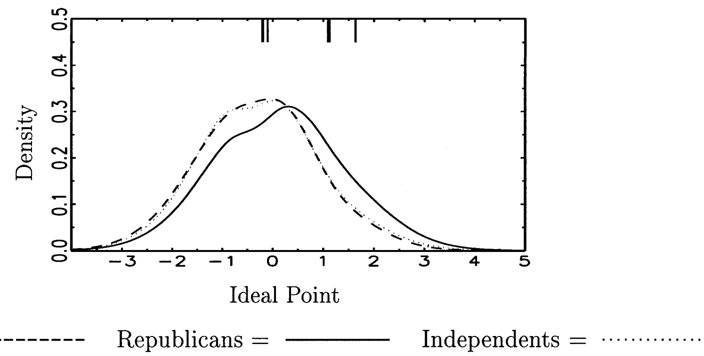


Fig. 4 Distribution of Abortion Preferences in the U.S. Public by Party Identification, 1993–1994 is the 2-year period with the largest mass-level partisan polarization on abortion. Increasingly pro-life positions are found by moving from the left to the right. The vertical lines in each panel show the cutpoints for the six abortion question asked in every survey. These cutpoints are held constant over time.

comparable across time. The scale is normalized by setting the mean and standard deviation of the Democratic distribution to be 0 and 1, respectively, in 1973–1974. Consistent with Adams, I find that Republican identifiers are more pro-choice than Democratic identifiers into the early 1980s and more pro-life since. Republicans have been becoming increasingly pro-life over the period, as have Independents. Democrats have become somewhat more pro-choice over time. Interestingly, the within-party variations have increased over time for both Democratic and Republican identifiers. This finding is inconsistent with the notion of partisan sorting over time. I again measure the degree of overlap in the partisan distributions by the percentile rank that the median Democrat would hold in the Republican distribution. Over time, the polarization first decreased as the Democratic median moved toward the median of the Republican party from the pro-life side (1973–1984) and then increased as the Democratic median moved away from the Republican median toward a more pro-choice position. However, the degree of partisan overlap has remained much larger in the mass public than in the Congress. At no time was the median Democrat even in the bottom (or top) quartile of the Republican preference distribution. In contrast, we saw above that the median Democrat has been in the first percentile of the Republican distribution for the last 8 years.

Figure 4 shows the *a posteriori* distribution of abortion policy preferences in the mass public by partisan identification during the 2-year period with the greatest degree of partisan polarization. The vertical lines at the top of the panels show the cutpoints for each of the six survey items. Unlike the congressional preference distributions presented in Fig. 3, here we find much less partisan differentiation even in the most polarized period.

Overall, the findings are fairly consistent with Adams (1997). Congressional party delegations have become largely polarized on abortion since 1973. While the mass analysis reflects the general mean trends characterized by Adams, the distribution presented in Fig. 4 suggests that Adams may have somewhat overstated the degree of mass realignment.

6 Conclusion

By developing a model that directly estimates features of the distribution of groups of voter ideal points as opposed to separately estimating each individual voter's ideal point, the usual problems associated with estimating ideal points when the number of observed choice items is small is overcome. In particular, consistent estimates of the means and variances of the preference distribution within a set of predetermined voter groups are obtained. Other features of the distribution as well as *a posteriori* estimates of the individual ideal points can also be obtained.

Monte Carlo experiments demonstrate the efficacy of the model even with as few as six observed choice items per voter. The model is also robust to modest violations of its distributional and item independence assumptions.

By applying the method to understanding support for presidential candidates in 1992, we gained insight into the partisan and ideological basis of support for each of the candidates using individual ballot data that could not have come from survey or aggregate data with the same level of detail or confidence. Similarly, revisiting Adams (1997), a more nuanced picture of the evolution of partisan preferences on abortion policy since 1973 was painted.

The empirical applications demonstrate the efficacy of the method when applied to a wide variety of data that share the common characteristic that preferences are indicated by a small number of binary choice items. Beyond its use in spatial models of policy preference, the method provides a general way of making efficient inferences about intergroup differences from a small set of binary indicators and thus may have application well beyond the examples presented here.

References

Abrams, B. A., and J. L. Butkiewicz. 1995. "The Influence of State-Level Economic-Conditions on the 1992 US Presidential-Election." *Public Choice* 85(1):1–10.

Abramson, Paul R., John H. Aldrich, Phillip Paolino, and David W. Rohde. 1995. "3rd-Party and Independent Candidates in American Politics—Wallace, Anderson and Perot." *Political Science Quarterly* 110(3):349–367.

Adams, Greg D. 1997. "Abortion: Evidence of an Issue Evolution." *American Journal of Political Science* 41(3):718–737.

Alvarez, R. Michael, and Jonathan Nagler. 1995. "Economics Issues and the Perot Candidacy—Voter Choice in the 1992 Presidential-Election." *American Journal of Political Science* 39(3):714–744.

Bailey, Michael. 2001. "Ideal Point Estimation with a Small Number of Votes." *Political Analysis* 9(3):192–210.

Black, Duncan. 1958. *The Theory of Committees and Elections*. Cambridge, England: Cambridge University Press.

Bock, R. Darrell, and Murray Aitken. 1981. "Marginal Maximum Likelihood Estimation of Item Parameters: Application of the EM Algorithm." *Psychometrika* 46(4):443–459.

Burnham, Walter Dean. 1979. *Critical Elections and the Mainsprings of American Politics*. New York: W. W. Norton.

Carmines, Edward O., and James A. Stimson. 1989. *Issue Evolution: Race and the Transformation of American Politics*. Princeton, NJ: Princeton University Press.

Ceaser, James W., and Andrew Busch. 1993. *Upside Down and Inside Out: The 1992 Elections and American Politics*. Boulder, CO: Rowman & Littlefield.

Converse, Phillip, and Gregory A. Markus. 1979. "Ca Plus Change . . . The New CPS Election Study Panel." *American Political Science Review* 73(1):32–49.

Dempster, A. P., N. M. Laird, and D. B. Rubin. 1977. "Maximum Likelihood Estimation from Incomplete Data via the EM Algorithm." *Journal of the Royal Statistical Society, Series B* 39(1):1–38.

Downs, Anthony. 1957. *An Economic Theory of Democracy*. New York: Harper & Row.

Gerber, Elisabeth R., and Jeffrey B. Lewis. 2000. "Representing Heterogeneous Districts," Presented at the 2000 American Political Science Association Meetings, Washington, DC.

Groseclose, Timothy J. 1994. "The Committee Outlier Debate: A Review and a Reexamination of Some of the Evidence." *Public Choice* 80:265–273.

Haberman, Shelby J. 1977. "Maximum Likelihood Estimation in Exponential Response Model." *Annals of Statistics* 6(5):815–841.

Heckman, James J., and James M. Snyder. 1997. "Linear Probability Models of the Demand for Attributes with an Empirical Application to Estimating the Preferences of Legislators." *Rand Journal of Economics* 28:S142–S169.

Hinich, Melvin J., and James M. Enelow. 1984. *The Spatial Theory of Voting: An Introduction*. Cambridge, England: Cambridge University Press.

Holian, D. B., T. B. Krebs, and M. H. Walsh. 1997. "Constituency Opinion, Ross Perot, and Roll-Call Behavior in the US House: The Case of the NAFTA." *Legislative Studies Quarterly* 22(3):369–392.

Hotelling, H. 1929. "Stability in Competition." *Economic Journal* 39:41–57.

Jackman, Simon. 2000. "Estimation and Inference Are Missing Data Problems." *Political Analysis* 8(4):307–332.

Key, V. O. 1955. "A Theory of Critical Elections." *Journal of Politics* 17(1):3–18.

Knack, S. 1997. "The Reappearing American Voter: Why Did Turnout Rise in '92?" *Electoral Studies* 16(1):17–32.

Lacy, Dean, and Barry C. Burden. 1999. "The Vote-Stealing and Turnout Effects of Ross Perot in the 1992 US "presidential." *American Journal of Political Science* 43(1):233–255.

Lahda, Krishna K. 1991. "A Spatial Model of Legislative Voting with Perceptual Error." *Public Choice* 68:151–174.

Lewis, Jeffrey B. 2001. "Technical Appendix and Ancillary Materials for 'Estimating Voter Preference Distributions from Individual-Level Voting Data.' " Available at the *Political Analysis* web site.

Londregan, John. 2000a. "Estimating Legislators' Preferred Points." *Political Analysis* 8:35–56.

Londregan, John B. 2000b. *Legislative Institutions and Ideology in Chile*. Cambridge, England: Cambridge University Press.

Londregan, John, and James M. Snyder. 1994. "Comparing Committee and Floor Preferences." *Legislative Studies Quarterly* 19(2):233–265.

Lord, Fredrick M. 1962. "Estimating Norms by Item-Sampling." *Educational and Psychological Measurement* 22(2):259–267.

Mislevy, Robert J. 1984. "Estimating Latent Distributions." *Psychometrika* 49(3):359–381.

Mislevy, Robert J., Albert E. Beaton, Bruce Kaplan, and Kathleen M. Sheehan. 1992. "Estimating Population Characteristics from Sparse Matrix Samples of Item Responses." *Journal of Educational Measurement* 29(2):144–161.

Neyman, J., and Elizabeth L. Scott. 1948. "Consistent Estimates Based on Partially Consistent Observations." *Econometrics* 16(1):1–32.

Owen, D., and J. Dennis. 1996. "Anti-Partyism in the USA and Support for Ross Perot." *European Journal of Political Research* 29(3):383–400.

Patz, Richard J., and Brian W. Junker. 1999. "A Straightforward Approach to Markov Chain Monte Carlo Methods for Item Response Models." *Journal of Educational and Behavioral Statistics* 24(2):146–178.

Peltzman, Sam. 1985. "Constituent Interest and Congressional Voting." *Journal of Law & Politics* 27:181–210.

Poole, Keith T. 2000. "Nonparametric Unfolding of Binary Choice Data." *Political Analysis* 8(3):211–237.

Poole, Keith T., and Howard Rosenthal. 1997. *Congress: A Political-Economic History of Roll Call Voting*. Oxford: Oxford University Press.

Southwell, P. L., and M. J. Everest. 1998. "The Electoral Consequences of Alienation: Nonvoting and Protest Voting in the 1992 Presidential Race." *Social Science Journal* 35(1):43–51.

Stroud, A. H., and Don Secrest. 1966. *Gaussian Quadrature Formulas*. Englewood Cliffs, NJ: Prentice–Hall.

Thorson, G. R., and S. J. Stambough. 1995. "Anti-incumbency and the 1992 Elections—The Changing Face of Presidential Coattails." *Journal of Politics* 57(1):210–220.