MATTHEW S. LEVENDUSKY
University of Pennsylvania
JEREMY C. POPE
Brigham Young University

Measuring Aggregate-Level Ideological Heterogeneity

Ideological heterogeneity is a key variable for the study of legislative and electoral politics. Scholars have long recognized that members with more ideologically heterogeneous constituencies behave differently than members with more homogeneous ones. Empirical tests of these theories, however, have typically been stymied by a lack of appropriate measures. We corrected this shortcoming by developing a measurement model for ideological heterogeneity, and we used our method to generate estimates for the 50 U.S. states and 435 congressional districts. Beyond the specific results presented here, a key contribution of our model is its flexibility: our technique can be used to produce similar estimates in a variety of contexts.

Ideological heterogeneity is a key explanatory variable for the study of legislative politics. Seminal works by Fenno (1978) and Fiorina (1974) have established that legislators who represent heterogeneous constituencies behave fundamentally differently than their counterparts with more homogeneous districts. These members have different "home styles" (Fenno 1978), roll-call voting records (Lewis and Gerber 2004), electoral coalition strategies (Bailey and Brady 1998),[1] electoral fortunes (Bond 1983; Fiorina 1974), patterns of position taking (Jones 2003), and campaign spending habits (Gronke 2000).

Scholars have typically operationalized ideological heterogeneity in one of two ways. They have measured constituency diversity by estimating the variance of survey responses to a liberal-conservative self-placement question aggregated at the state level (for example, see Bishin, Dow, and Adams 2006 and Jones 2003). More typically, scholars have operationalized ideological heterogeneity using demographic proxies, either aggregated into summary indices (Bond, Covington, and Fleisher 1985; Sullivan 1973) or disaggregated and used individually (Gronke 2000). Both approaches are suspect, because we do not know the measurement properties of these proxies—particularly their validity.

Until a valid measure of ideological heterogeneity exists, researchers may make only very limited progress in testing or extending the aforementioned theories. This article outlines our method for directly modeling ideological heterogeneity, which we used to generate estimates for the 50 U.S. states and 435 congressional districts. We focus here on elucidating a new measure, rather than resolving substantive debates about heterogeneity. That said, our off-the-shelf estimates [available from the authors' homepages at http://www.sas.upenn.edu/~mleven and http://politicalscience.byu.edu/faculty/jpope and the Appendix on the *Legislative Studies Quarterly* website: http://www.uiowa.edu/~lsq/Levendusky_Pope_Appendix.pdf] will allow scholars to test a wide variety of theories about ideological heterogeneity. Moreover, scholars interested in heterogeneity at *any* level, such as occurs in counties or state senate districts, can use our method to generate parallel estimates for the region of interest. This method should help scholars from many parts of American politics resolve theoretically relevant debates.

What Is Heterogeneity and Why Does It Matter?

What do scholars mean when they term a district "heterogeneous"? What makes a district heterogeneous or homogeneous? There are two general types of constituencies: consensual, where the electorate is not particularly diverse, and conflictual, where the electorate is relatively more diverse (Fiorina 1974). Diversity is essentially equivalent to heterogeneity—consensual districts are homogeneous; conflictual districts are heterogeneous. But to what dimension of diversity are we referring? Geographic (rural/urban)? Demographic (lines of race, class, and so on)? Something else (see Fenno 1978 and Fiorina 1974)? This article focuses on ideological diversity, which is arguably the most politically significant dimension of heterogeneity, because it shapes legislators' coalition-building efforts.

For legislators representing homogeneous districts, reelection-maximizing behavior is relatively straightforward. Their constituents are largely of one mind, so these legislators know how they must behave in order to be reelected. Members from more heterogeneous constituencies, by contrast, must juggle competing demands. In a constituency characterized by more ideological diversity, a challenger has more opportunities to appeal to disaffected groups and construct a coalition to defeat the incumbent. If more constituents fundamentally disagree about an issue, then more constituents will always be unhappy with any decision the legislator makes and may therefore be receptive to a potential challenger. When representing a heterogeneous district, a legislator must solve a more complex decision-making calculus, not only for roll-call votes, but for time and resource allocation (Fenno 1978; Fiorina 1974). Primary elections further complicate the calculus: candidates must cater to one set of voters in the primary election and another in the general (see, for example, Aranson and Ordeshook 1972, Coleman 1971, and Gerber and Morton 1998). Thus, ideological heterogeneity has a considerable impact on legislator behavior, and consequently we chose to focus our attention on this variable. That said, one advantage of our approach is that future scholars who are interested in another dimension of heterogeneity, such as geographic heterogeneity, can adapt our model to fit their needs.

But if ideological diversity is what heterogeneity is, why does it matter? Why do scholars need a new measure of it? In short, because many questions about how heterogeneity affects legislator behavior remain unanswered. Does heterogeneity shape a legislative member's roll-call voting record (Harden and Carsey 2008; Lewis and Gerber 2004)? Does it shape the factors that influence roll-call votes (Bailey and Brady 1998)? Does it affect the issues that members emphasize to constituents (Fenno 1978)? Does it inform patterns of position taking (Jones 2003)? The type of measure we develop here can be used to address these questions. Further, a new measure of ideological heterogeneity can shed light on questions about primary elections, polarization, and redistricting. For example, does the ideological homogeneity of primary constituencies (relative to general election constituencies) influence legislator behavior? Does considering within-state heterogeneity lead investigators to different conclusions about the divergence between "red" and "blue" states (Levendusky and Pope 2008)? Clearly, heterogeneity is a central concept in our understanding of legislative and electoral behavior. Our present contribution to these debates is to give scholars a tool for analyzing heterogeneity.

Measuring Heterogeneity

How can we operationalize ideological heterogeneity in an applied setting? We will use two measures throughout this article. First, we will use the variance of constituents' attitudes. This is a simple, straightforward measure of diversity: the higher the variance, the more diverse the constituents' attitudes are (Bishin, Dow, and Adams 2006; Fiorina 1974; Jones 2003).

Second, we will use a measure stemming from Fiorina's 1974 discussion of heterogeneity: the ideological distance between the primary "groups" in the district (see Fenno 1974, chap. 3, as well as Fenno 1978). Conflictual (heterogeneous) districts have multiple groups, none of which constitute a majority by themselves. The degree of ideological similarity between groups determines the degree of heterogeneity within the district (see also Shapiro et al. 1990). Here we interpreted these groups as being the political parties. Different scholars could emphasize other groups, but the partisan/ideological split of the district is the most relevant and politically interesting dynamic (Fiorina 1974).[2] We therefore chose the ideological distance between the Democratic Party and the Republican Party in each district as our secondary measure of district heterogeneity.

Previous efforts to measure ideological heterogeneity have typically relied on imperfect demographic proxy variables (Bond 1983; Bullock and Brady 1983; Patterson and Caldeira 1984; Sullivan 1973). Scholars have justified this choice by arguing that although demographics themselves are not explicitly political, they may provide the basis of political cleavages in elections (Bond, Covington, and Fleisher 1985, 516). While demographics and opinion are undoubtedly related at some level, equating state or district opinion diversity with demographic diversity requires a strong, untested assumption: more demographically diverse constituencies have citizens with more diverse attitudes (on average). If this assumption does not hold, then demographic variables will not validly estimate ideological heterogeneity. This untested assumption becomes particularly problematic in light of findings that demographics do not validly measure the average ideology of a state (Erikson, Wright, and McIver 1994; Kuklinski 1977).[3] If this same result extends to ideological heterogeneity, then this unreliable connection calls into question the results of previous work using demographic proxies.

Demographic proxies suffer from another problem: they assume that all diversity is equivalent and that groups should be equally diverse on all issues. A given constituency might be homogeneous on some issues but quite heterogeneous on others (Bishin 2009, especially chap. 6). As a result, a single demographic index misses the variation across issues. By contrast, our model can accommodate this sort of complexity; scholars can reestimate our model for different issues and different points in time, and further adapt the method to their own purposes. What we offer is a more flexible *method* for estimating heterogeneity.

As an alternative to demographic variables, some scholars have used opinion data to estimate the ideological heterogeneity of voters within a state. For example, some have calculated the standard deviation of various opinion items to make estimates (see Krasno 1994). This method is an improvement over using demographic items, but it too suffers from an important limitation: we cannot know the heterogeneity of constituents' opinions with certainty. Although we may have indicators of constituent opinion, we cannot directly observe such opinion and hence cannot know it definitively. Our estimates of opinion heterogeneity are necessarily contaminated with some unknown amount of measurement error, and our models should account for that fact. Much as this measurement error has been directly incorporated into theoretical and empirical tests at the microlevel (Achen 1975; Alvarez and Brehm 2002), it must play a role at the macrolevel—we need estimates of ideological heterogeneity and uncertainty estimates. Quantifying this uncertainty becomes particularly consequential when we wish to estimate the effect of ideological heterogeneity on political outcomes (such as election results, roll-call voting, and so on), given the pernicious effects of measurement error on regression coefficients. A key advantage of our method is that it allows us to account for the error in our measure in a systematic way, which in turn allows us to estimate correctly the relationship between preference heterogeneity and other political outcomes (for more on this point, see Treier and Jackman 2008). To overcome the limitations of past methods, we developed a model of ideological heterogeneity.

A Model of Heterogeneity

The first step in modeling ideological heterogeneity is to model the ideology of individual voters. This microlevel model builds on a simple proposition: each individual's ideology can be represented as a location on an underlying continuum. While we cannot observe that location directly (the scale is latent), we *can* observe multiple indicators of each individual's location on that underlying scale, namely, that person's responses to various survey items.

Given ordinal survey items, we modeled individuals' responses to policy preference items as a function of these underlying latent preferences using an ordinal item response model. Here, let $i = 1, 2, \ldots, N$ index individuals, and let $j = 1, 2, \ldots, J$ index items. Further, let $k = 1, 2, \ldots, K_j$ index the ordinal response categories for item j. We can write out the model as follows:

$$Pr[y_{ij} = 1] = \mathrm{F}(\tau_{j,1} - \alpha_j x_i)$$

$$Pr[y_{ij} = 2] = \mathrm{F}(\tau_{j,2} - \alpha_j x_i) - \mathrm{F}(\tau_{j,1} - \alpha_j x_i)$$

$$\ldots$$

$$Pr[y_{ij} = K_j] = 1 - \mathrm{F}(\tau_{j,Kj-1} - \alpha_j x_i).$$

Here, y_{ij} is respondent i's response to item j, x_i is respondent i's location on the latent dimension (her or his latent issue preference), α_j is a discrimination parameter indicating how much the responses to item j distinguish between more- and less-liberal respondents on the latent dimension, and $F(\cdot)$ is the cumulative distribution function for the logistic distribution. The τ_j parameters are a set of thresholds for each item, just as in a standard ordinal model. Because the thresholds must be ordered (i.e., $\tau_{j,k} > \tau_{j,k-1}$), we parameterize the thresholds as $\tau_{j,k} = \sum_{l=1}^{k} \delta_{j,l}$, and for $l \geq 2$, $\delta_{j,l}$ must be greater than 0. (For more detail on the standard item response model setup, see Johnson and Albert 1999).

Aside from these ordinal items, we used two additional types of data: data from binary (yes/no) items and continuous items. For the binary items, the model is $P(z_{ij} = 1) = \mathrm{F}(\beta_j\, x_i - \zeta_j)$, where z_{ij} is respondent i's response to item j, x_i is voter i's location on the latent trait (as before), $F(\cdot)$ is again the cumulative distribution function for the logistic distribution, and ζ_j and β_j are, respectively, the item difficulty (intercept) and item discrimination (slope) parameters for item j. (See Clinton, Jackman, and Rivers 2004b for more information on the standard binary item setup.)

For continuous items, the model is $c_{ij} \sim \mathrm{N}(\lambda_1 + \lambda_2 x_i, \omega_j^2)$, where c_{ij} is respondent i's response to item j, λ_1 and λ_2 are again difficulty and discrimination parameters, x_i is again the respondent i's location on the latent trait, and ω is an unknown variance to be estimated. (See Jackman 2004 for more explanation of this type of setup, especially how to combine multiple types of data in a single measurement model.)

Now that we have a model of individual-level ideology, we may transition to measuring ideological heterogeneity, that is, to estimating the variation in ideology *across* respondents. We first measured ideological diversity at the U.S. state level, because there is considerable interest in the ideological heterogeneity of the states and the relevant data are readily available. We stress, however, that our model is easily adaptable to other levels of geographic aggregation (for instance, to the congressional district level, as we demonstrate later in this article).

To study how ideological heterogeneity varies by state, we needed to make some assumptions about the distribution of ideology in each state. Here voters are indexed by $i = 1, 2, \ldots, N$ and arranged in states $m = 1, 2, \ldots, 50$ and parties $p = 1, 2, 3$, where 1, 2, and 3 correspond to the Democratic, Independent, and Republican parties, respectively.

$$x_i \sim N(\mu_{m[i],p[i]}, \sigma^2_{m[i],p[i]}),$$

where $m[i]$ indicates that voter i resides in state m and $p[i]$ indicates that voter i is in party p. We assumed that voters in each state and party are distributed normally; $\mu_{m,p}$ tells us where the "average" (mean) voter is located in state m and party p, and $\sigma^2_{m,p}$ measures the variation in party p in state m. So, for example, we assumed that Alabama Democrats follow a normal distribution with mean $\mu_{AL,Dem}$ and variance $\sigma^2_{AL,Dem}$, that Alabama Independents follow another normal distribution with mean $\mu_{AL,Ind}$ and variance $\sigma^2_{AL,Ind}$, and so forth. To find the distribution of voters in Alabama as a whole, we simply combined the three partisan distributions weighted by the fraction of respondents who identified with each party.[4] Varying these mean/variance parameters by state and party allows us to capture a great deal of heterogeneity across states. Our model reflects the fact that the Democratic Party in Massachusetts may not be the same as the Democratic Party in Alaska, but in both states, the Democrats are likely to be to the left of the Republicans. This type of model facilitates more accurate estimations of state-level ideological heterogeneity.

Our two measures of heterogeneity follow directly from this setup. First, our variance measure is simply σ^2_m, the variance of citizens' attitudes in a given state (the overall variance of citizens in a given state is the weighted average of the variance of each partisan subgroup). Second, our measure of the ideological distance between the partisan subgroups is $\mu_{m,\,Dem} - \mu_{m,\,Rep}$. The theoretical constructs of interest follow directly from our model estimation.

This model improves on related efforts in two important ways. First, despite our microlevel model's similarity to earlier efforts (Treier and Hillygus 2006; Treier and Jackman 2002), our focus is starkly different: we estimated state- and district-level variance parameters, whereas earlier works focused on individual voter ideologies (in our model, the x_i parameters). Second, our model extends earlier efforts pioneered by Lewis (2001) to measure ideological heterogeneity (see also Jessee 2005 and Lewis and Gerber 2004). Lewis's earlier model was limited because it used a unique but time-bound dataset (ballot image data from the 1992 election for Los Angeles county) and it considered only binary items. For this study, we generated heterogeneity estimates for all 50 states (and, as shown later, for the 435 congressional districts) using national survey data, and we considered a mix of indicators (binary, continuous, and ordinal). Our model is therefore more flexible and extendable, offering an important contribution to the literature in its own right.

The model we have outlined is relatively complex, with parameters for each voter, item, and state in the analysis, thus complicating traditional modes of inference. Happily, Bayesian techniques for estimation and inference are well suited to this type of problem (Clinton, Jackman, and Rivers 2004b), so we adopted them for this article. We provide the technical details of our approach in the online Appendix (http://www.uiowa.edu/~lsq/Levendusky_Pope_Appendix.pdf).

Heterogeneity at the District Level

Our primary focus here is on heterogeneity at the state level. Nonetheless, we also generated estimates at the congressional district level. To do so, we used the model as described, with one minor, simplifying change. The district level offers far fewer data than the state level, so we opted to estimate a less demanding model. We assumed $x_i \sim \mathrm{N}(\mu_{d[i]}, \sigma_{d[i]}^2)$, $d = 1, 2, \ldots 435$, where $d[i]$ indicates that respondent i is located in congressional district d. That is, we did not estimate separate distributions by party within each district. To ensure that this alternative model would not skew our picture of district heterogeneity (relative to that provided for the state level by the richer model), we reanalyzed the state data using the simpler model. All our substantive conclusions remained the same. We are therefore confident that the less demanding model does not hinder our analysis.

Data on Ideology

The primary data for this project came from the common content module of the Cooperative Congressional Election Study, better known as the CCES (Ansolabehere 2006).[5] The data from this survey do not constitute a random sample of the U.S. population (as would result from, say, a standard random-digit-dialing telephone survey) but instead come from the Internet panel of the Polimetrix Corporation (now called YouGov/Polimetrix). To generate data reflective of the U.S. population (rather than merely its online panel), Polimetrix uses a proprietary matching algorithm that matches CCES respondents to U.S. government data (for details of the sampling procedure, see Rivers 2006). The end result is that although the CCES sample is not a genuine random sample of the U.S. population, it should closely match the demographic makeup of the population.

Data quality becomes an obvious concern when researchers use a nonprobability sample (Malhotra and Krosnick 2007). This concern is particularly acute here because of the relative novelty of the Polimetrix sample matching procedure. Several recent studies, however, suggest that the CCES data closely resemble various other types of survey data collected during the same time frame (Ansolabehere and Persily 2008; Hill et al. 2007; Jacobson 2007; Vavreck and Rivers 2008). No doubt there is more work to be done to elucidate the strengths and weaknesses of these data, but these preliminary results are encouraging. The CCES may be far from perfect, but its large within-state sample sizes make our approach possible. We therefore accept any limitations of the CCES data as necessary evils, at least in the short term.

Scholars uneasy with the CCES should note two important points. First, our primary goal is to present a *method*, not a specific set of results. We therefore urge these scholars to look past the CCES data and focus on our general approach. Second, we also present results from the 2000 National Annenberg Election Study (NAES; for more details, see Romer et al. 2004) to demonstrate that our model can be used with different datasets from different points in time. (Readers interested in the details of our NAES analysis may refer to the online Appendix.)

We used the CCES data to estimate ideological diversity along the left-right economic dimension, which encompasses debates about taxes versus spending, the role of government versus market forces, and the like. We selected this dimension because it represents the principal division in contemporary American politics (Shafer and Claggett 1995) and should therefore be the most useful dimension of ideology for applied scholars. This is not, however, the only dimension relevant to contemporary American politics. To demonstrate the extendability and flexibility of our model, the Appendix presents estimates for the social dimension of ideology, which is concerned with debates about abortion, gay marriage, and school prayer, for example. Should other scholars wish to develop estimates for other dimensions, such as race issues or foreign policy, they can use our method to do so. Again, what we offer is a flexible and extendable *method* to measure diversity. We illustrate the method using a particular example, but our overall contribution is much broader.

To select the specific items used to measure ideology, we performed exploratory factor analysis on the set of ideological items included in the CCES. The factor analysis suggested that six items captured the economic dimension of respondent preferences: (1) whether or not social security funds should be invested in the stock market, (2) whether or not we should protect the environment at the expense of jobs, (3) whether the state government should increase taxes or cut spending, (4) whether or not our first step to balance the federal budget should be to cut domestic spending, and (5–6) how the respondent would have voted on two roll-call votes concerning cuts to capital gains taxes and an increase in the federal minimum wage. Dimensional analyses strongly suggest that these items are unidimensional; see the online Appendix for further details.

Our measures are estimates of operational ideology[6]—estimates of what respondents actually want government to do—as opposed to symbolic ideology, which concerns whether individuals identify as liberals or conservatives (Stimson 2004).[7] Measures of both operational and symbolic ideology are important for the study of politics, and scholars should pick the one that most closely matches their theoretical construct of interest (see the exchange generated by Berry et al. 2007). Scholars can download our estimates of variance, both the simple standard deviation and the party distance measures, from our websites. But we stress that, if these particular estimates are not appropriate for a given task, scholars can use the method outlined here to generate their own estimates of other quantities of interest.

Validating Our Measure

Before turning to a discussion of our results, we must establish that our model actually validly measures ideology. Recall that we estimated two parameters describing each state's ideology: a mean and a variance. Throughout this article, we focus on the variance parameter—our estimate of ideological heterogeneity—because that represents our major contribution to the literature. For our discussion of validity, however, we include a brief examination of the mean parameters, simply to demonstrate that our approach generates reasonable estimates. To assess validity, we correlated our measure of the average state ideology (the mean parameters) with several criterion variables that should be strongly related to the liberalism or conservatism of a state. We considered the average response in each state to the liberal-conservative self-identification question,[8] the average partisanship in the state, and the share of the state's (two-party) presidential vote going to the Democratic Party's nominee in 2004. Our estimates correlate strongly and sensibly with each of these criterion variables: –0.89, –0.75, and 0.73, respectively. These sensible results demonstrate that we have validly estimated average state ideology. (See the online Appendix for more discussion of our state mean parameters.)

A more realistic assessment of validity—as well as of the usefulness of our measure—requires that we assess the measure's correlation with variables related to (but distinct from) ideological heterogeneity. We assessed the relationship between our congressional district-level estimates of ideological heterogeneity and House member ideology. Extant theories predict that members representing more ideologically heterogeneous constituencies will take more extreme positions: in heterogeneous districts, legislators will be unconstrained by the overall median and more responsive to their party median (Bishin, Dow, and Adams 2006; Lewis and Gerber 2004) because they can construct multiple coalitions. As a result, legislators from more heterogeneous districts will take more extreme positions (see also Aranson and Ordeshook 1972 and Grofman and Owen 2006). Figure 1 depicts the relationship between our measure of ideological heterogeneity and each member's first-dimension DW-NOMINATE score (Poole and Rosenthal 1997).

Figure 1 shows strong support for our hypothesis. In both parties, more extreme members represent (on average) more heterogeneous constituencies, and the relationship is statistically significant. This finding suggests not only that our measure is a valid estimate of ideological heterogeneity, but also that it is useful for scholars who are interested in exploring the relationship between heterogeneity and related variables in legislative and electoral politics.

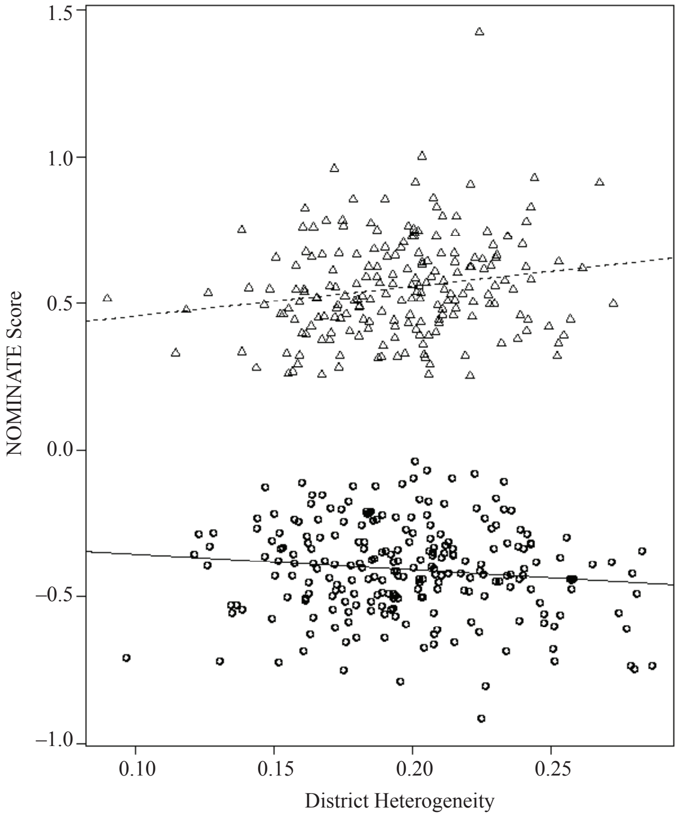
Results: Ideological Heterogeneity

What does our model imply about ideological heterogeneity across states? Figure 2 plots our estimates of ideological heterogeneity within each state (the σ_{state} parameters) and the within-state difference between the party means ($\mu_{state,\ Dem} - \mu_{state,\ Rep}$) for both the CCES and the NAES datasets. Scholars interested in the actual numeric estimates of state heterogeneity may refer to the Appendix table at the end of this article and to our websites, where they may download an Excel file containing the estimates.

As Figure 2 reveals, there is notable variation in how ideologically diverse voters are within a given state. Three findings in particular stand out. First, one might expect, ex ante, that less populous states would be more ideologically homogeneous, but this assumption is only weakly true. The correlation between (logged) state population and the within-state party distance is 0.2, and the correlation between (logged) state population and the within-state standard deviation is –0.07.[9] So there are some states with smaller populations that are relatively homogeneous (such as West Virginia, Utah, and Rhode Island), but some moderate- to large-sized states are also fairly homogeneous (for example, Massachusetts).[10]

Second, our two measures of state heterogeneity are not duplicates of one another, but there is a strong correlation between them,

FIGURE 1
District Heterogeneity and Member Extremity



Note: The measure of district extremity is the standard deviation measure developed in the article, member extremity is the member's first dimension DW-NOMINATE score. The circles (and solid line) depict districts represented by Democrats; the triangles (and dashed line) depict districts represented by Republicans.

suggesting that they tap into the same underlying theoretical concept of heterogeneity (the correlation between the two measures is 0.54). We do not take a strong stand as to which one is the "right" measure of heterogeneity for a given application—this is a decision that individual researchers should make for themselves with respect to their particular problems.

Third, drawing sharp distinctions between states is somewhat difficult. We can make relatively fine distinctions in the tails—the probability that Texas is more ideologically homogeneous than California on this dimension is approximately 1 (see Figure 2)—but in most cases, these sorts of distinctions fall short of traditional standards of statistical significance. For example, the probability that New Jersey is more homogeneous than Illinois is only 0.69 (using the σ_m^2 measure)—more likely than not, but far short of conventional standards for statistical significance.

One might be tempted to conclude that this limitation prevents our measure from being a useful estimate of state-level ideological heterogeneity. Such a conclusion would be erroneous, however. The fundamental difficulty here is *not* a lack of data (although obviously the more data we have, the finer the inferences we can draw; for example, we can draw finer inferences about California, which has more than 3,600 respondents, than we can about Vermont, which has 75 respondents). The real challenge is that most states have relatively similar levels of ideological heterogeneity. States are large, relatively diverse places, and, with some obvious exceptions, most states are simply not that different along this dimension, even in the raw data. Once we admit that survey measures contain noise that should be accounted for in measurement, we face the reality that making fine distinctions between states is frequently beyond our grasp.

An analogy from legislative politics is useful here. During the 2004 presidential campaign, *National Journal* claimed that John Kerry, the Democratic nominee, was the most liberal member of the U.S. Senate (Cohen 2004). But Clinton, Jackman, and Rivers (2004a) have demonstrated that this conclusion is untenable once one accounts for measurement error: Kerry is no more or less liberal than any number of his Democratic colleagues. The Clinton, Jackman, and Rivers method cannot distinguish between these senators because they all have very similar roll-call records. Despite this and other significant limitations,[11] however, scholars recognize that measures based on roll-call votes are useful tools for analyzing legislative politics. In our case, after we account for measurement error, distinguishing between more and less heterogeneous states is quite difficult, because citizens in many states are relatively similar ideologically. We cannot always draw sharp distinctions between states (paralleling Clinton, Jackman, and Rivers's finding about liberal senators). Nevertheless, our measure is an important contribution to the literature.

FIGURE 2
Estimates of Ideological Heterogeneity at the State Level

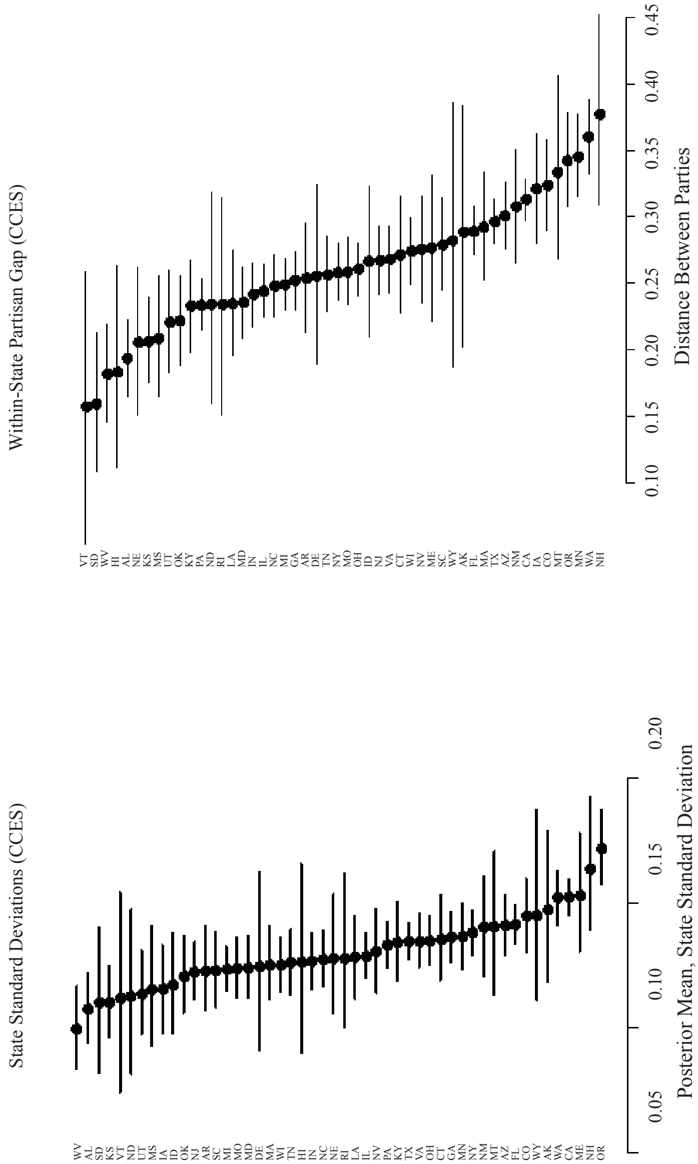
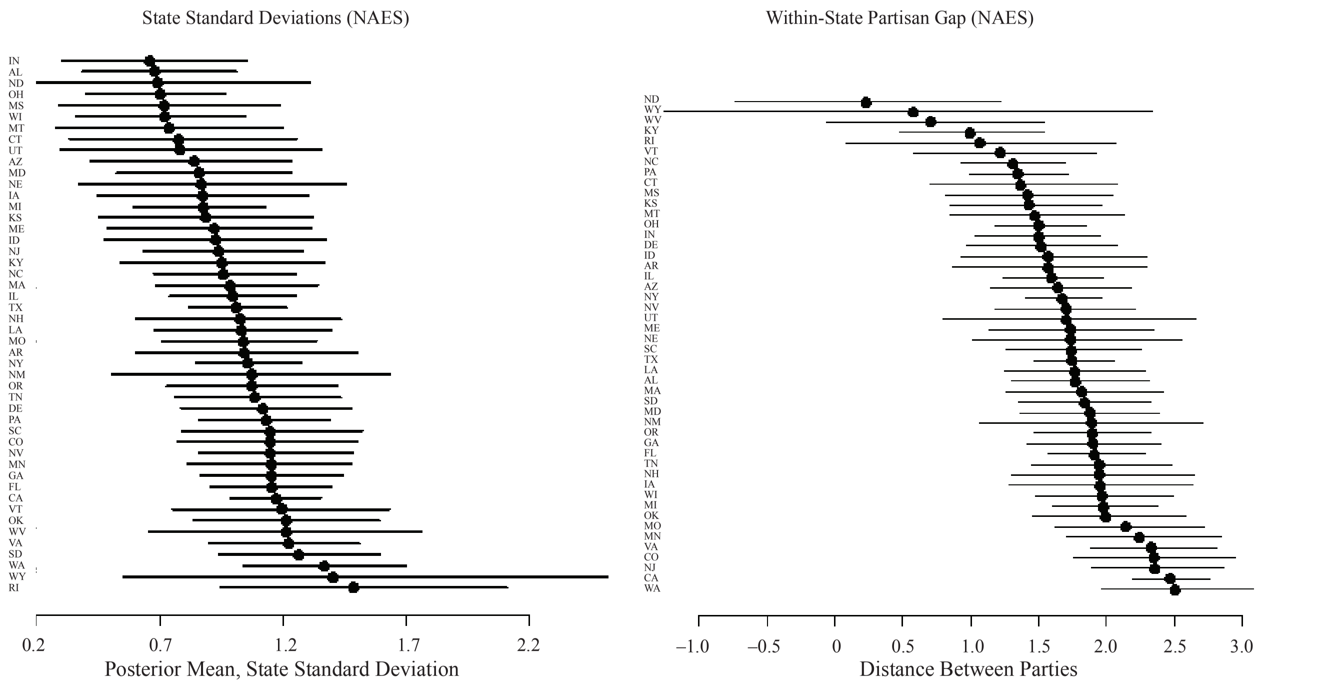


FIGURE 2 (continued)



Note: Entries are the posterior means and 95% highest posterior density intervals for our estimates of ideological heterogeneity within each state. The top two plots come from the CCES, the bottom two plots come from the 2000 NAES data. The left plot gives the results for the standard deviation measure; the right plot gives the results for the within-state party distance measure.

Do Demographics Predict Heterogeneity?

The results demonstrate that we can use survey data to validly measure ideological heterogeneity. But can demographic variables adequately proxy for ideological heterogeneity? While previous results provide grounds for skepticism (Erikson, Wright, and McIver 1994; Kuklinski 1977; Lewis and Gerber 2004), the literature has provided no definitive assessment of the relationship between opinion heterogeneity and demographics across states.

To develop such a test, we used a variety of demographic variables chosen by previous scholars to measure ideological heterogeneity (the online Appendix provides more details). Of particular interest here is the strength of the relationship between the Sullivan index (Sullivan 1973) and our survey-based measure of ideological heterogeneity. The Sullivan index measures diversity using a series of demographic variables, combining them into one summary value that "is nicely interpretable in probability terms, since it represents the proportion of characteristics upon which a randomly selected pair of individuals will differ" (Sullivan 1973, 70). This measure provides a straightforward way to assess the demographic diversity of a state and has been widely used in the applied literature as a proxy for ideological diversity (see, for example, Aistrup 2004, Bond 1983, Bond, Covington, and Fisher 1985, and Fiorina 1974). Table 1 reports the results of regressing our measures of state-level ideological heterogeneity on these demographic variables.

As Table 1 shows, these demographics jointly predict both measures of ideological heterogeneity. For instance, the *F*-test that all of the predictors are jointly 0 can be rejected at the $\alpha = .10$ level (one-tailed) for both measures of ideological heterogeneity. At first glance, this similarity might seem to support the use of demographic variables to proxy for opinion heterogeneity. But without a definitive model that can provide weights for the importance (and direction) of each demographic proxy, the demographic variables are less useful—we lack any theory for how to combine these indicators into a summary measure of heterogeneity. Further, the relationship between demographics and ideology could change over time, creating another difficulty for mapping from demographic to ideological heterogeneity. The individual correlations for our measure of opinion heterogeneity and any potential demographic proxy are never higher than 0.35. We can certainly conclude that individual demographics are *related* to ideological heterogeneity, but we are probably not justified in using them as a simple *proxy* for attitudinal heterogeneity.

TABLE 1
Demographics and Heterogeneity

Variable	Standard Deviation	Party Distance
Constant	0.14 (0.39)	–1.46 (1.26)
Log Proportion African American	–0.004 (0.003)	**–0.02** (0.01)
South	0.01 (0.04)	0.05 (0.13)
Log Median Income	–0.005 (0.03)	0.02 (0.10)
Log Proportion Foreign Born	–0.005 (0.005)	**–0.02** (0.01)
Log Proportion Urban	–0.008 (0.03)	0.10 (0.08)
Log Population Density	–0.004 (0.002)	–0.01 (0.007)
Log Total Population	**0.006** (0.003)	**0.03** (0.01)
Log Proportion Bachelor's Degree	0.07 (0.05)	0.13 (0.17)
Log Proportion Homeowners	–0.01 (0.05)	0.13 (0.15)
Log Union Membership	0.009 (0.006)	0.03 (0.02)
Log Proportion White Collar	–0.08 (0.07)	–0.09 (0.22)
Log Proportion African American × South	–0.001 (0.01)	0.001 (0.04)
Sullivan Index	0.06 (0.17)	0.17 (0.54)
R^2	0.35	0.40
N	50	50
F-statistic	1.48	1.85
p-value	0.17	0.07

Note: Regression results from predicting state-level heterogeneity measure (using Cooperative Congressional Election Study data) from demographic variables. Cell entries are OLS parameter estimates with associated standard errors in parentheses. Coefficients that can be statistically distinguished from 0 at conventional levels appear in **bold**.

The best existing summary measure—the Sullivan Index—fares no better than the individual indicators in terms of the strength of the relationship between demographic and ideological heterogeneity ($r = 0.28$ with the standard deviation measure, and $r = 0.21$ with the party distance measure). Our results make it clear that when actual opinion diversity measures are available, those should be used. Political science theories are typically written in terms of constituents' attitudinal diversity, not their demographic diversity, and our measures should reflect that fact. Our findings clarify that demographics are *not* good proxies for ideological diversity at the state level.[12]

Conclusion

This article provides a new approach to measuring ideological heterogeneity. We demonstrated our method using survey data to generate estimates for all 50 U.S. states and 435 congressional districts on the left-right economic dimension, estimates that are freely available on our websites (http://www.sas.upenn.edu/~mleven or http://politicalscience.byu.edu/faculty/jpope). We demonstrated not only that we can construct such a measure, but also that the measure is useful and important for applied researchers, because it is strongly related to substantively important topics in legislative and electoral politics.

Again, we wish to stress that our primary goal here was to outline a *method,* not a specific set of results. We do provide a set of estimates of ideological heterogeneity for the 50 U.S. states, but we emphasize that our contribution is much broader than this one set of results. Researchers wishing to focus on another dimension of ideology, such as attitudes regarding race or foreign policy, or those who want to examine symbolic ideology can utilize our method to do so. Likewise, scholars wishing to obtain estimates for other years, datasets, or even geographic areas can use our method. We hope other scholars will extend and further develop the tool provided here.

We think our measure holds tremendous potential for resolving a variety of substantive debates in the literature. While we leave these resolutions to future scholars, we note that many questions in the literature involve heterogeneity. For example, does heterogeneity affect roll-call votes (Harden and Carsey 2008)? The influences on legislator behavior (Bailey and Brady 1998)? A member's home style (Fenno 1978)? One could also use our measure to investigate the connections between heterogeneity and policymaking or interest group activity (Gray and Lowery 1993). Further, our measure can facilitate reassessment of the large literature on diversity and elections. Many scholars argue that members from more ideologically diverse districts will, all else being equal, have lower reelection margins, because challengers will be better able to construct winning coalitions in these diverse districts (Fenno 1978; Fiorina 1974; Sullivan 1973). Our measure gives scholars the tool needed to address these and other questions in future work.

Matthew S. Levendusky <mleven@sas.upenn.edu> *is Assistant Professor of Political Science, University of Pennsylvania, 208 South 37th Street, Philadelphia, PA 19104. Jeremy C. Pope* <jpope@byu.edu> *is Assistant Professor of Political Science and a research fellow in the Center for the Studies of Elections and Democracy, Brigham Young University, 745 Spencer W. Kimball Tower, Provo, UT 84602.*

APPENDIX
Parameter Estimates of Ideological Heterogeneity

State	CCES Standard Deviation	CCES Party Distance	CCES Variance, Raw Items	NAES Standard Deviation	NAES Party Distance	NAES Variance, Raw Items	Sullivan Index	NEP Variance, Libcon
AK	0.147	0.289	0.289	NA	NA	NA	0.580	0.561
AL	0.107	0.193	0.258	0.679	1.769	0.495	0.553	0.543
AR	0.122	0.254	0.269	1.044	1.568	0.672	0.538	0.678
AZ	0.141	0.301	0.298	0.839	1.640	0.581	0.619	0.556
CA	0.152	0.313	0.298	1.174	2.470	0.529	0.670	0.575
CO	0.145	0.324	0.298	1.148	2.351	0.530	0.590	0.553
CT	0.135	0.271	0.280	0.777	1.367	0.612	0.590	0.405
DE	0.124	0.255	0.275	1.118	1.516	0.624	0.576	0.433
FL	0.141	0.289	0.289	1.154	1.911	0.556	0.632	0.532
GA	0.136	0.252	0.286	1.152	1.901	0.548	0.599	0.445
HI	0.126	0.183	0.254	NA	NA	NA	0.628	NA
IA	0.115	0.321	0.292	0.876	1.952	0.537	0.534	0.412
ID	0.117	0.267	0.271	0.926	1.567	0.520	0.547	0.417
IL	0.129	0.244	0.275	0.996	1.596	0.523	0.628	0.475
IN	0.126	0.241	0.279	0.661	1.503	0.474	0.553	0.415
KS	0.110	0.206	0.263	0.886	1.430	0.580	0.567	0.481
KY	0.134	0.233	0.273	0.954	0.995	0.565	0.532	0.593
LA	0.128	0.234	0.278	1.031	1.764	0.540	0.598	0.468
MA	0.125	0.292	0.271	0.984	1.820	0.544	0.600	0.483
MD	0.124	0.236	0.275	0.861	1.877	0.567	0.612	0.410
ME	0.153	0.277	0.287	0.921	1.733	0.581	0.486	0.546
MI	0.123	0.249	0.275	0.877	1.979	0.583	0.580	0.481
MN	0.136	0.345	0.299	1.152	2.240	0.475	0.558	0.518
MO	0.124	0.259	0.281	1.041	2.144	0.610	0.562	0.516
MS	0.115	0.208	0.270	0.719	1.420	0.595	0.551	0.315
MT	0.140	0.333	0.289	0.740	1.472	0.577	0.525	0.472
NC	0.127	0.248	0.278	0.958	1.310	0.485	0.563	0.471
ND	0.113	0.234	0.261	0.691	0.231	0.592	0.532	0.480
NE	0.127	0.206	0.277	0.869	1.736	0.431	0.563	0.351
NH	0.163	0.377	0.316	1.025	1.948	0.673	0.518	0.475
NJ	0.122	0.267	0.279	0.938	2.354	0.465	0.610	0.416
NM	0.140	0.308	0.292	1.074	1.890	0.690	0.623	0.499
NV	0.130	0.276	0.287	1.148	1.701	0.543	0.629	0.515
NY	0.138	0.258	0.275	1.057	1.674	0.557	0.657	0.479
OH	0.135	0.260	0.286	0.705	1.502	0.498	0.566	0.486
OK	0.121	0.222	0.275	1.212	1.992	0.562	0.568	0.460
OR	0.172	0.342	0.302	1.076	1.896	0.589	0.568	0.584
PA	0.133	0.234	0.283	1.132	1.349	0.542	0.573	0.467
RI	0.128	0.234	0.264	1.485	1.070	0.615	0.601	0.429
SC	0.123	0.279	0.285	1.148	1.742	0.574	0.567	0.413
SD	0.110	0.160	0.253	1.263	1.839	0.623	0.535	NA
TN	0.126	0.256	0.282	1.086	1.948	0.514	0.556	0.537
TX	0.134	0.296	0.292	1.010	1.745	0.574	0.644	0.521
UT	0.113	0.221	0.263	0.781	1.701	0.541	0.553	0.333
VA	0.135	0.268	0.283	1.223	2.328	0.558	0.591	0.493
VT	0.112	0.157	0.242	1.196	1.216	0.610	0.487	NA
WA	0.152	0.360	0.299	1.367	2.507	0.607	0.582	0.512
WI	0.125	0.274	0.287	0.720	1.968	0.501	0.562	0.470
WV	0.100	0.182	0.252	1.215	0.703	0.506	0.484	0.542
WY	0.145	0.282	0.281	1.401	0.575	0.307	0.548	NA

Note: CCES: Cooperative Congressional Election Study. NAES: National Annenberg Election Study. "NEP Variance, Libcon" refers to the self-identification item from the 2006 National Exit Poll (where available).

NOTES

We thank the anonymous referees, Kevin Arceaux, David Canon, Morris Fiorina, Jay Goodliffe, Jeffrey Grynaviski, Stephen Jessee, Chris Karpowitz, Frances Lee, Seth Masket, Lynn Vavreck, Stephen Voss, Chris Wlezien, and seminar participants at Brigham Young University, the University of California Los Angeles, the 2007 American Political Science Association meeting, the 2008 Midwest Political Science Association meeting, and the 2008 State Politics and Policy conference for helpful comments. Any remaining errors are our own.

1. Bishin and Dennis (2002) extended Bailey and Brady's model and demonstrated that the relevance of a heterogeneous constituency varies across votes.

2. Our interpretation is also consistent with Fenno's 1978 discussion of multiple constituencies that depend not only on geography but also on commitment to candidates and parties.

3. There is a long tradition of measuring the average liberalism or conservatism of a given state (e.g., Erikson, Wright, and McIver 1994), but that tradition does not focus on measuring opinion heterogeneity, so we omit discussion of it here. Lax and Phillips (2009) recently provided an overview of this literature and the associated methods.

4. We included partisan leaners with Independents (Miller 1991). We also classified members who did not identify with a party (less than 2% of the sample) as Independents.

5. For more information on the CCES, see http://web.mit.edu/polisci/portl/cces/index.html.

6. Although we refer to our measure as "ideology" throughout the article, we would note, to be consistent with extant work and our data, that what we really have is an *indicator* of ideology.

7. This form of operational ideology is closely related (albeit at a different level of aggregation) to measures of policy mood. For more details, see Erikson, MacKuen, and Stimson 2002, and Stimson 2004.

8. Erikson, Wright, and McIver (1994) used this method to generate their estimates of state ideology.

9. Unless otherwise indicated, all textual references are to the estimates we generated using the CCES data.

10. For a delineation of the similarities and differences between the NAES and CCES estimates, see the online Appendix (http://www.uiowa.edu/~lsq/Levendusky_Pope_Appendix.pdf).

11. For instance, Jackson and Kingdon (1992) pointed out the statistical inconsistencies that can arise from interest group scores, and Londregan (1999) argued that spatial models for legislator ideal points and legislative proposals require careful identification strategies. But neither of these objections overrides the main point that roll-call based methods are generally useful.

12. The primary reason that earlier generations of scholars used demographic proxies was because the researchers lacked any other suitable measures. Now that other types of data are available, however, other more appropriate techniques should be considered when feasible.

REFERENCES

Achen, Christopher. 1975. "Mass Political Attitudes and the Survey Response." *American Political Science Review* 69: 1218–31.

Aistrup, Joseph. 2004. "Constituency Diversity and Party Competition: A County and State Level Analysis." *Political Research Quarterly* 57: 276–81.

Alvarez, R. Michael, and John Brehm. 2002. *Hard Choices, Easy Answers*. Princeton, NJ: Princeton University Press.

Ansolabehere, Stephen. 2006. "Cooperative Congressional Election Study—Common Content Module." http://web.mit.edu/polisci/portl/cces/commoncontent.html

Ansolabehere, Stephen, and Nathaniel Persily. 2008. "Vote Fraud in the Eye of the Beholder: The Role of Public Opinion in the Challenge to Voter Identification Requirements." *Harvard Law Review* 121: 1737–74.

Aranson, Peter, and Peter Ordeshook. 1972. "Spatial Strategies for Sequential Elections." In *Probability Models of Collective Decision Making*, ed. Richard Niemi and Herbert Weisberg. Columbus, OH: Merrill.

Bailey, Michael, and David Brady. 1998. "Heterogeneity and Representation: The Senate and Free Trade." *American Journal of Political Science* 42: 524–44.

Berry, William, Evan Ringquist, Richard Fording, and Russell Hanson. 2007. "The Measurement and Stability of Citizen Ideology." *State Politics and Policy Quarterly* 7: 111–32.

Bishin, Benjamin. 2009. *Tyranny of the Minority: The Subconstituency Politics Theory of Representation*. Philadelphia, PA: Temple University Press.

Bishin, Benjamin, and Christopher Dennis. 2002. "Heterogeneity and Representation Reconsidered: A Replication and Extension." *Political Analysis* 10: 210.

Bishin, Benjamin, Jay Dow, and James Adams. 2006. "Does Democracy 'Suffer' from Diversity? Issue Representation and Diversity in Senate Elections." *Public Choice* 129: 201–15.

Bond, John. 1983. "The Influence of Constituency Diversity on Electoral Competition in Voting for Congress, 1974–1978." *Legislative Studies Quarterly* 8: 201–17.

Bond, Jon, Cary Covington, and Richard Fleisher. 1985. "Explaining Challenger Quality in Congressional Elections." *Journal of Politics* 47: 510–29.

Bullock, Charles, and David Brady. 1983. "Party, Constituency, and Roll-call Voting in the U.S. Senate." *Legislative Studies Quarterly* 8: 29–43.

Clinton, Joshua, Simon Jackman, and Douglas Rivers. 2004a. "The Most Liberal Senator? Analyzing and Interpreting Congressional Roll Calls." *PS: Political Science and Politics* 37: 805–11.

Clinton, Joshua, Simon Jackman, and Douglas Rivers. 2004b. "The Statistical Analysis of Roll-call Data: A Unified Approach." *American Political Science Review* 98: 355–70.

Cohen, Richard E. 2004. "How They Measured Up." *National Journal* 39: 613–19.

Coleman, James S. 1971. "Internal Processes Governing Party Positions in Elections." *Public Choice* 11: 35–60.

Cooperative Congressional Election Study [CCES]. 2006. http://web.mit.edu/polisci/portl/cces/index.html.

Erikson, Robert, Michael MacKuen, and James Stimson. 2002. *The Macro Polity*. New York: Cambridge University Press.

Erikson, Robert, Gerald Wright, and John McIver. 1994. *Statehouse Democracy: Public Opinion and Policy in the American States*. New York: Cambridge University Press.
Fenno, Richard. 1978. *Home Style: House Members in Their Districts*. Boston: Little, Brown.
Fiorina, Morris. 1974. *Representatitives, Roll Calls, and Constituencies*. Lexington, MA: D.C. Heath.
Gerber, Elisabeth R., and Rebecca B. Morton. 1998. "Primary Election Systems and Representation." *Journal of Law, Economics, and Organization* 14: 304–24.
Gray, Virginia, and David Lowery. 1993. "The Diversity of State Interest Group Systems." *Political Research Quarterly* 46: 81–97.
Grofman, Bernard, and Guillermo Owen. 2006. "Two-stage Electoral Competition in Two-party Contests: Persistent Divergence of Party Positions." *Social Choice and Welfare* 26: 547–69.
Gronke, Paul. 2000. *The Electorate, the Campaign, and the Office*. Ann Arbor: University of Michigan Press.
Harden, Jeffrey, and Thomas Carsey. 2008. "State Ideology, Senate Roll Calls, and Heterogeneity in Representation." Presented at the annual meeting of the Midwest Political Science Association, Chicago.
Hill, Seth, James Ho, Lynn Vavreck, and John Zaller. 2007. "The Opt-in Internet Panel: Survey Mode, Sampling Methodology, and the Implications for Political Research." Presented at the annual meeting of the Midwest Political Science Association, Chicago.
Jackman, Simon. 2004. "What Do We Learn from Graduate Admissions Committees? A Multiple Rater, Latent Variable Model, with Incomplete Discrete and Continuous Indicators." *Political Analysis* 12: 400–24.
Jackson, John E., and John Kingdon. 1992. "Ideology, Interest Group Scores, and Legislative Votes." *American Journal of Political Science* 36: 805–23.
Jacobson, Gary. 2007. "The War, the President, and the 2006 Midterm Congressional Elections." Presented at the annual meeting of the Midwest Political Science Association, Chicago.
Jessee, Stephen. 2005. "Estimating Ideology from Issue Beliefs: A Hierarchical Model of State Voter Distributions." Presented at the annual meeting of the American Political Science Association, Washington, DC.
Johnson, Valen E., and James H. Albert. 1999. *Ordinal Data Modeling*. New York: Springer Verlag Press.
Jones, David. 2003. "Position Taking and Position Avoidance in the U.S. Senate." *Journal of Politics* 65: 851–63.
Krasno, Jonathan. 1994. *Challengers, Competition, and Reelection*. New Haven, CT: Yale University Press.
Kuklinski, James. 1977. "Constituency Opinion: A Test of the Surrogate Model." *Public Opinion Quarterly* 41: 34–40.
Lax, Jeffrey, and Justin Phillips. 2009. "How Should We Estimate Public Opinion in the States?" *American Journal of Political Science* 53: 107–21.
Levendusky, Matthew, and Jeremy C. Pope. 2008. "Red States vs. Blue States: Going beyond the Mean." Manuscript. University of Pennsylvania, Philadelphia.
Lewis, Jeffrey. 2001. "Estimating Voter Preference Distributions from Individual-level Voting Data." *Political Analysis* 9: 275–97.

Lewis, Jeffrey, and Elisabeth Gerber. 2004. "Beyond the Median: Voter Preferences, District Heterogeneity, and Representation." *Journal of Political Economy* 112: 1364–83.

Londregan, John B. 1999. "Estimating Legislators' Preferred Points." *Political Analysis* 8: 35–56.

Malhotra, Neil, and Jon Krosnick. 2007. "The Effect of Survey Mode and Sampling on Inferences about Political Attitudes and Behavior: Comparing the 2000 and 2004 ANES to Internet Surveys with Nonprobability Samples." *Political Analysis* 15: 286–323.

Miller, Warren. 1991. "Party Identification, Realignment, and Party Voting: Back to the Basics." *American Political Science Review* 85: 557–68.

Patterson, Samuel, and Gregory Caldeira. 1984. "The Etiology of Partisan Competition." *American Political Science Review* 78: 691–707.

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

Rivers, Douglas. 2006. "Sample Matching: Representative Sampling from Internet Panels." http://www.polimetrix.com/documents/Polimetrix_Whitepaper_Sample_Matching.pdf

Romer, Daniel, Kate Kenski, Paul Waldman, Christopher Adasiewicz, and Kathleen Hall Jamieson. 2004. *Capturing Campaign Dynamics: The National Annenberg Election Study*. New York: Oxford University Press.

Shafer, Byron, and William Claggett. 1995. *The Two Majorities: The Issue Context of Modern American Politics*. Baltimore, MD: Johns Hopkins University Press.

Shapiro, Catherine, David Brady, Richard Brody, and John Ferejohn. 1990. "Linking Constituency Opinion and Senate Voting Scores: A Hybrid Explanation." *Legislative Studies Quarterly* 15: 599–621.

Stimson, James. 2004. *Tides of Consent*. New York: Cambridge University Press.

Sullivan, John. 1973. "Political Correlates of Social, Economic, and Religious Diversity in the American States." *Journal of Politics* 35: 70–84.

Treier, Shawn, and Sunshine Hillygus. 2006. "The Contours of Policy Attitudes in the Mass Public." Presented at the annual meeting of the Midwest Political Science Association, Chicago.

Treier, Shawn, and Simon Jackman. 2002. "Beyond Factor Analysis: Modern Tools for Social Measurement." Presented at the annual meeting of the Midwest Political Science Association, Chicago.

Treier, Shawn, and Simon Jackman. 2008. "Democracy as a Latent Variable." *American Journal of Political Science* 52: 201–17.

Vavreck, Lynn, and Douglas Rivers. 2008. "The 2006 Cooperative Congressional Election Study." *Journal of Elections, Public Opinion, and Parties* 18: 355–66.