Measuring District Level Partisanship with Implications for the Analysis of U.S. Elections*

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February 24, 2007

*We thank Chris Achen, David Brady, John Jackson, Gary King, Keith Poole, Doug Rivers, Howard Rosenthal, participants at the 2003 and 2005 Political Methodology Society Meetings and the Stanford Measurement Conference (August 2003) for useful comments. We also thank E. Scott Adler, Brandice Canes-Wrone, Joshua Clinton, John Cogan, Gary Jacobson, Stephen Ansolabehere and Jim Snyder, and most of all, David Brady for generously providing us with access to their data.

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Abstract

Many empirical studies of American politics, particularly legislative politics, are vitally dependent on measures of the partisanship of a district. We develop a measurement model for this quantity, estimating how Democratic (or, conversely, Republican) districts are in the absence of a election-specific, short-term forces, such as national-level swings specific to particular elections, incumbency advantage, and home-state effects in presidential elections. We estimate the model using readily available data: electoral returns and district-level demographic characteristics. We estimate the model with five decades of data (1952-2000), and describe how the distribution of district partisanship has changed over time, in response to population movements and redistricting, particularly via the creation of majority-minority districts. We validate the measure with analysis of Congressional roll call data, and show how to enrich this measure using other available indicators of district partisanship, such as survey data.

Almost all empirical studies of Congressional elections rely on a measure of district partisanship, be they studies of incumbency advantage (e.g., Gelman and King 1990), challenger effects (e.g., Jacobson and Kernell 1983), redistricting (e.g., Cox and Katz 1999), regional differences in the electorate, or national forces in elections (e.g., Kawato 1987). These analyses share a common methodological strategy: to try to assess the effects of more or less transient factors (e.g., candidates and issues) on the vote by statistically controlling for the partisan or ideological disposition of a district. These studies stand or fall on the quality of the measure of district partisanship. Consider a regression of district level vote shares on variables of substantive interest and a control for district partisanship. If the district partisanship measure is measured with error, then not only is the coefficient on district partisanship biased, but so too is the coefficient on any variable correlated with district partisanship, either directly or indirectly. Thus, an approach that better measures the underlying concept — district partisanship — can improve estimation of all of those quantities, and enhance the validity of substantive conclusions.

District Partisanship: Theory and Measurement

The decomposition of voting behavior into long-term and short-term components has a long and distinguished lineage in political science. Most notably, Converse's (1966) notion of the "normal vote" grows directly out of the Michigan team's micro-model of voting behavior, in which party identification generates stability in voting behavior, subject to election-specific responses to candidates and issues. The aggregate-level analog of enduring micro-level political loyalties is Converse's normal vote, which rests on decomposing vote shares into two components: a long-term, stable component based on party identification (the normal vote), and a short-term rate of defection generated by the specifics of the campaign and the candidates (Converse 1966, 14).[1] Our measure of

[1]The majority of work based on the concept of a normal vote has followed Converse's initial approach and used survey data, examining rates of party voting within and across categories of partisan identifiers (e.g., Goldenberg and Traugott 1981; Petrocik 1989). This approach has been rightly subject to criticism, on the grounds that party identification is not exogenous, but responds

district partisanship is analogous to Converse's normal vote, except that Converse operationalized the concept with survey data based on questions about voting and party identification, whereas our measure relies on a mix of aggregate indicators (and where available, survey data). A useful way to think about our measurement strategy is that it provides an estimate of how Democratic a given district would be absent the short term effects of a given campaign (election-specific partisan swings, incumbency, etc.). Given this, we refer to our measure as "district partisanship" throughout the paper. We use this term rather than normal vote to avoid any confusion resulting from the fact that we are working at the macro-level, whereas Converse worked at the micro-level. We stress, however, that at least at a conceptual level, the underlying quantity of interest is essentially the same: a more-or-less enduring characteristic that drives election outcomes.

We also want to be clear about what it is we are *not* measuring. Measurement models rely on observed indicators to make inferences about unobserved latent traits. Thus, the latent trait inherits its substantive content from the indicators. In our case, since we rely heavily on district level vote shares as indicators, the substantive content of our recovered latent trait can not stray far from whatever substantive content resides in vote shares (or the determinants of vote shares). For this reason, we will resist claiming that we validly measure "district ideology". Of course, to the extent that presidential and congressional voting is driven by ideology, then our measure will have ideological content. For now, we feel we are on safer ground claiming to have measured district partisanship than district ideology. However, in section we augment our model with survey measures of ideology to demonstrate how our model might validly be used to model district preferences. Likewise, we will resist stating that our model provides estimates of the relative locations of the median/mean voter in each district: we do not posit a formal voting model that maps from voter ideal points on a policy

to the same short term forces that shape vote decisions in any given election (e.g., Achen 1979). We stress that although Converse's concept of a normal vote underlies our approach, our goal is to measure district partisanship (or the normal vote) at the level of congressional districts, and we do so with aggregate data, with a set of controls that let us decompose vote shares into short-term and long-term components.

continuum to district level vote shares. While it would no doubt be worthwhile to investigate such a model (Snyder 2005), that endeavour is beyond our current scope.

Previous work has employed roughly three types of measures for district partisanship: surveys, election returns, and demographic data. Each method has significant deficiencies.

(1) Survey-based methods. Almost all survey based methods suffer from a profound design challenge, sometimes referred to as the "Miller-Stokes" problem. Miller and Stokes (1963) were interested in the extent to which members of Congress responded to their constituencies. But the data they had for any individual congressional district was extremely sparse; their study, based on a national probability sample, had an average of only 13 respondents per congressional district (see Achen 1978; Erikson 1978). And in general, generating representative samples of useful sizes from a useful number of congressional districts is very difficult, given the data gathering technologies and research budgets typically available to political scientists. With a given budget constraint, researchers face an obvious tradeoff between surveying fewer respondents in more districts (sacrificing within-district precision for cross-district coverage) or surveying more respondents in fewer districts (buying precision at the cost of coverage); Stoker and Bowers (2002) wrestle with this design problem. In the face of limited research budgets either coverage or precision must suffer, and hence most attempts to generate measures of partisanship (or preferences) specific to congressional districts rely on aggregate data.[2]

(2) Demographic Aggregates. Examples of this measurement strategy include Kalt and Zupan's (1984) analysis of specific industries capturing members of Congress: in their analysis of Senate voting on strip mining regulation, Kalt and Zupan took state-level data on membership in pro-

[2] Ardoin and Garand (2003) propose a novel application of survey data to this problem: using the Wright, Erickson and McIver (1985) state-level measures, they use the connection between demographic variables and this ideology measure to form district level estimates of constituent ideology for the 1980s and 1990s. While the method is an excellent application of survey data, it is limited in that it can only generate results for the 1980s and 1990s due to question wording changes. The method we present below, on the other hand, covers the entire post-war period and uses easily accessible data (demographic data from the US census and electoral returns).

environmental interest groups and the size of various coal producer and consumer groups as indicative of economic interests and preferences over regulation, *inter alia*. In a more general analysis, Peltzman (1984) used six demographic variables measured at the county level to tap politically relevant, economic characteristics of senators' constituencies.

A measure of district partisanship that relied solely on demographic characteristics of the district suffers from an obvious threat to validity. Demographic attributes are generally considered antecedents of partisanship, rather than indicators of it. So, while demographic characteristics may correlate highly with one another and would appear to measure *something* about districts, there is no guarantee that demographic characteristics alone would permit us to locate congressional districts on a partisan continuum. That is, the use of demographics alone may generate a measure of district partisanship with high reliability (i.e., the indicators all correlate with one another quite strongly), but dubious concept validity.

(3) Electoral Returns. Election returns are popular and easily accessed proxies for district partisanship. For instance, Canes-Wrone, Cogan and Brady (2002), Ansolabehere, Snyder and Stewart (2001), and Erickson and Wright (1980) all use district level presidential election returns as a proxy for district partisanship in models of legislative politics. The virtue of this proxy is that it is based on constituent behavior (vote choices) and is thus linked to the partisan or ideological continuum that generally underlies electoral competition. Thus, a measure of district partisanship based on vote shares can be assumed to have high validity. Of course, there are shortcomings and tradeoffs here as well. Presidential vote shares in any given election may be products of short-term forces; for instance, different issues are more or less salient in any given election, and particular candidates are more or less popular. And over the long-run, averaging a district's presidential vote shares may well be a valid (i.e., unbiased) indicator of district partisanship over the same period (e.g., Ansolabehere, Snyder and Stewart 2000), as the short-term forces could plausibly cancel one another given enough elections. But this is rather speculative. How much bias results from using the last two or three presidential elections to estimate district partisanship? Moreover, shouldn't researchers relying on presidential vote honestly confront the fact that they are using a *proxy* for the underlying variable of interest? And even more fundamentally, researchers ought to confront the reality that district partisanship can never be known with certainty. Like so many other variables of interest to political science, district partisanship is not directly observable by researchers; instead, election results are merely indicators of a quantity we do not directly observe.

The shortcomings of the measurement approaches just surveyed suggests that we need a measurement strategy that delivers the concept validity obtained via electoral returns, but that also filters out the impact of short term factors. And as we show below, this is what our model does. Finally, we note that not all district partisanship measures fit into the categorization given above. Party registration data (Desposato and Petrocik 2003), voting on down-ballot elections (e.g., Ansolabehere and Snyder 2002) or propositions (e.g., Gerber and Lewis 2004) and other factors may be used as proxies for a district's partisanship. One of the useful features of our model is that these types of partially observed indicators can be easily added to any ensemble of indicators: more information about the quantity being measured is better.

A Statistical Model for District Level Vote Shares

Our approach—relying on an underlying measure of district partisanship, plus or minus the impact of short-term, election specific factors—has a relatively straightforward statistical operationalization with aggregate data. Election outcomes are modeled as a function of a more-or-less stable latent trait, specific to each congressional district. The latent trait is considered fixed until redistricting intervenes; typically this happens once per decade. Election outcomes are also functions of election-specific short-term forces, generating vote shares either greater or smaller than that we would expect given the district's characteristics. These short-term forces include the presence of an incumbent or an experienced challenger in congressional elections, and national-level trends running in favor of one major party or presidential candidate.

It is possible to relax the assumption that each district's latent trait remains unchanged over a decade. Generational replacement and other social-structural changes are continuous processes, and it is perhaps more realistic to consider the district-specific latent trait as evolving over time. The chief difficulty with operationalizing a dynamic model of district partisanship is a lack of data: aside from election outcomes, we lack time-varying covariates at the district level. Variation in election outcomes only holds so much information: it is extremely difficult to use a sequence of presidential and congressional vote shares to recover estimates of *both* changing district partisanship and the role of election-specific factors (incumbency, presidential candidates, etc). Absent more district level data, restrictive assumptions are another way to let district partisanship evolve over time: for instance, if we are willing to assume that there are no short-term forces (i.e., each election generates a faithful mapping from district partisanship to election outcomes) then we could obtain a new estimate of district partisanship at each election. In short, without more data at the district level (and time-varying data at that), letting district partisanship vary over time requires fixing some other part of the model. Therefore throughout our paper we treat district partisanship as a constant but unknown attribute of a district, until redistricting intervenes and/or decennial census provides a new set of demographic covariates.

The statistical model we use is a latent variable model in which the level of district partisanship is embedded as a parameter to be estimated. It is useful to think of the model as having two connected parts: one in which latent district partisanship appears as an unobserved left-hand side variable, and the other in which latent district partisanship is a determinant of vote shares. Let $i = 1, \ldots, n$ index districts, x_i be the latent partisanship of district i (i.e., an unknown location on a unidimensional partisan continuum) and $\mathbf{z}_i$ be a k-by-1 vector of demographic characteristics for district i. Both x_i and $\mathbf{z}_i$ are considered time-invariant: demographic characteristics are measured just once each "era" (in the decennial census) and (as discussed above) we also treat district partisanship as fixed over this period. Thus this part of the model is

$$x_i | \mathbf{z}_i \stackrel{\text{iid}}{\sim} N(\mathbf{z}_i' \alpha, \sigma^2) \tag{1}$$

where α is a set of parameters to be estimated, and σ^2 is an unknown variance. We impose the identifying restriction that the latent x_i have mean zero and variance one across districts; note that this restriction places an upper bound on σ^2.

For the electoral data, we exploit the fact that our data have a panel structure—we have five Congressional elections, and two or three Presidential elections per district per decade. Given this structure, we estimate the following model for Congressional elections:

$$y^*_{ij}|x_i \overset{\text{iid}}{\sim} N(\mu_{ij}, \nu_j^2) \tag{2}$$

where

$$\mu_{ij} = \gamma_{j1} + \gamma_{j2}x_i + \text{controls} \tag{3}$$

and where i indexes districts and j indexes House elections; $y^*_{ij} = \ln\left(\frac{y_{ij}}{1-y_{ij}}\right)$ and $y_{ij} \in (0, 1)$ is the proportion of the two-party vote for the Democratic House candidate in district i at election j; ν_j^2 is the disturbance variance; γ_{j1} is an unknown fixed effect for each election, tapping the extent to which national level factors (e.g., macro-economic conditions or a national scandal) drive outcomes in Congressional election j; γ_{j2} is an unknown parameter tapping the extent to which district partisanship x_i determine vote shares; and we also include indicators tapping incumbency offsets (whether a Democratic incumbent is running for re-election, and similarly for Republican incumbents) and challenger quality (whether the Democratic or Republican challenger has held elected office). We also interact the indicators for Democratic and Republican incumbents with a dummy variable for Southern districts, thus making our estimates of incumbency offsets conditional on whether the district is an a southern or non-southern state (we make no distinction between open seats in southern and non-southern states). Note that we term the quantities we estimate "incumbency offsets" rather than "incumbency advantage." We adopt this rhetorical convention to avoid interpreting these parameters as the causal effects of incumbency advantage because of the potential for post-treatment bias in our model.

The model for presidential elections is similar, but with different predictors, and has the log-odds of the Democratic share of the two-party presidential vote in district i in presidential election k as the dependent variable:

$$y^*_{ik}|x_i \overset{\text{iid}}{\sim} N(\mu_{ik}, \nu^2_k) \tag{4}$$

where

$$\mu_{ik} = \beta_{k1} + \beta_{k2}x_i + \text{controls} \tag{5}$$

and where β_{k1} is an unknown fixed effect for presidential election k; β_{k2} is defined similarly to γ_{j2}, above; the controls tap home state effects, i.e., dummy variables for whether the Democratic and Republican presidential and vice-presidential hail from the state in which district i is located.

Finally, a brief word on redistricting is also warranted. Most redistricting takes place in the wake of the decennial census, in time for the election in the "2" years (1982, 1992, etc.). But a considerable amount of redistricting occurs at other times (e.g., the Texas redistricting prior to the 2004 election). This presents a problem: districts sometimes change mid-cycle, so (for example) FL-2 in 1992 is not the same district as FL-2 in 2000. We use two sources of information to track redistricting.[3] In essence, we treat the district prior to redistricting to be one district, and the district post-redistricting to be a separate district, each with its own distinct latent trait. If the redistricting occurred prior to the (say) 1996 election, then the post-redistricting district is missing elections from 1992 and 1994, and the pre-redistricting district is missing electoral returns from 1996 forward.

The model is a structural equations model (SEM) similar to those used in psychometrics (e.g., Bollen 1989). A stylized, graphical summary of the model appears in Figure 1, using the convention that unobserved quantities appear in circles, and observed quantities appear in rectangles. The elections outcomes are akin to multiple indicators of district partisanship, x, and treated as conditionally independent of each other given x and other predictors. In particular, note that we (1) augment the models for the various presidential and congressional election outcomes (equations 2 through 5) with politically relevant covariates (e.g., indicators for incumbency, challenger quality, region, home-state effects and election-specific fixed effects) and (2) exploit the information in census

[3] We use Gary Jacobson's Congressional elections dataset and Scott Adler's district demographic dataset; we treat a district as having been redistricted when these data sources concur.

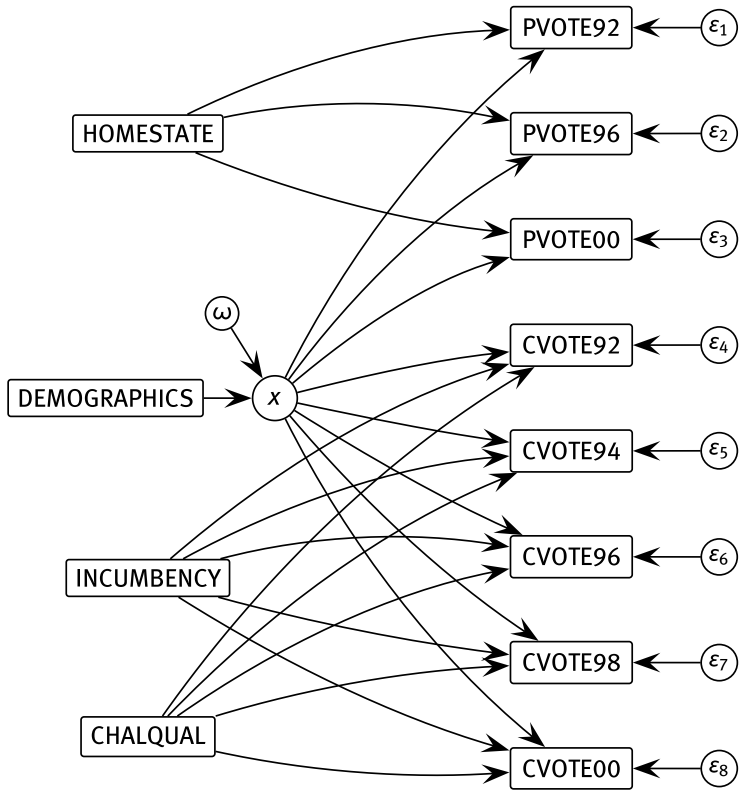

Figure 1: Stylized, Graphical Summary of Model for the 1990s. District partisanship is the latent variable denoted x in the graph.

aggregates about district partisanship via equation 1. Another interpretation of the model is as a hierarchical or multilevel model (e.g., Hox 2002; Skrondal and Rabe-Hesketh 2004); i.e., the latent district partisanship parameters, x_i, are treated here as similar to "random effects", but with a "level 2" regression model (equation 1) exploiting information about latent district partisanship in the time-invariant census aggregates, $\mathbf{z}_i$.

The Question of Dimensionality

We treat each district's partisanship as an unknown point on a single latent dimension. Our assumption of unidimensionality warrants some brief discussion. District partisanship ranges between two theoretical pure types: a purely Democratic district and a purely Republican district. Each district lies between these two pure types, and hence the latent trait in our model is unidimensional. Were we measuring district *ideology*, say, using survey data, then a multidimensional latent trait might be more appropriate, but this is not the case. The assumption of unidimensionality is consistent with a long tradition in the study of American electoral politics in which two-party competition is the norm, and the preferences of candidates, parties and voters are represented as points on a single dimension. Examples include characterizations of electoral competition and the two-party system (e.g., Downs 1957; Black 1987; Aldrich 1995) and much empirical work on congressional elections (e.g., Ansolabehere, Snyder and Stewart 2001; Canes-Wrone, Cogan and Brady 2002; Jacobson 2004) and is implicit in Converse's (1966) initial formulation of the normal vote. Indeed, in the specific context of congressional elections, the assumption of a unidimensional continuum is typically used without question.

The electoral returns we analyze strongly support the assumption of unidimensionality over the period under study. We examined the electoral data via principal components analysis (e.g., Joliffe 2002); for each decade, we computed the correlation matrix for the 5 sets of congressional vote shares and 2 or 3 sets of presidential vote shares (all on the log-odds scale), and examined how much variation was accounted for by the first principal component. In every decade, the 1st eigenvalue of the correlation matrix is quite large relative to the number of elections available for analysis (typically greater than 5), and the 2nd eigenvalue is always less than 1.0, strongly suggesting that a single dimension underlies the vote data. Similarly, the amount of variation in the electoral returns data accounted for by the first principal component is relatively large, ranging from a minimum of 69% in the 1970s data, to 84% in the 1990s data. We also examined the proportion of variation in a given decade's vote shares that is attributable to cross-district or between-district variation (equivalent to the r^2 from a regression of a decade's vote totals on district fixed effects); in each decade it is clear that bulk of the variation in the votes is cross-district variation, with the elections of the 1990s generating the least amount of within-district variation, and the 1970s elections generating the most.[4] Thus both theory and data support an assumption that levels of district partisanship can be modelled as points on a unidimensional continuum.

[4] All of this supplementary analysis is available in the on-line appendix.

The Advantages of a Bayesian Approach to Estimation and Inference

As stated earlier, our model is a SEM. While many political scientists are most familiar with estimation of these models using software that analyses the covariance matrix of the observed data (e.g., LISREL, AMOS, EQS), we adopt a Bayesian approach for estimation and inference. We do so because it offers us numerous methodological and substantive advantages over alternative approaches.

Recovering Assessments of Uncertainty for All Parameters of Interest. First, a primary goal of the analysis is *measurement*: i.e., to produce estimates of district partisanship, along with assessments of uncertainty. Most analysis of covariance structure approaches treat the latent variables x_i as nuisance parameters, and, at best, will produce point estimates of these quantities, conditional on estimates of the factor structure (typically via either regression scoring or Bartlett scoring). Producing uncertainty estimates for these quantities in an analysis of covariance structure framework is much harder. Also note that there does not exist a unique mapping from a given factor structure and raw variables into estimates of the latent trait. Given that the primaary interest centers around the estimation of these quantities, this is a sub-optimal way to proceed (for a similar point, see Aldrich and McKelvey 1977).

In contrast, our framework has the latent trait of interest (district partisanship) appearing explicitly as a parameter to estimated. Working in a Bayesian framework, we make no special distinction between latent district partisanship and other parameters in the model and we compute the joint posterior density of *all* model parameters: uncertainty in one set of parameters generates uncertainty in the other, and vice-versa, as it should; for elaboration of this point, see Dunson and Bollen (2005). Of course, the benefits of this approach come at some computational cost: with 435 x_i parameters (one for each congressional district) and numerous other parameters to estimate, the joint posterior density is high dimensional, and characterizing its properties (e.g., the location of the joint posterior mode/mean, the widths of marginal credible intervals for selected parameters) is not trivial. Happily, one of the benefits of the Bayesian approach is that we can exploit Markov chain Monte Carlo (MCMC) algorithms that will generate a computer-intensive random tour of the joint posterior density, visiting locations in the parameter space with relative frequency proportional to the posterior probability of each location. That is, let run long enough, iterations of the MCMC algorithm generates samples from the joint posterior density, which we then summarize and report; see Jackman (2000) for a review. Further details appear in the accompanying Appendix.

In addition, because the latent variable model is just that — a model for the observed indicators in which the latent traits appear as parameters (rather than a factor analytic model of the correlations across items) — we can perform inference with respect to the latent traits directly. In particular, because we recover the joint posterior density of the latent traits, we can assign probabilities to politically relevant statements such as "district i is more Republican than district j", "district j is the most Republican district in the country", "district j is the most Democratic district held by a Republican", or "district k is the median district". Again, we know of no simple way to perform statistical inference with respect to latent trait estimates ("factor scores") produced by factor analytic approaches; cf Jöreskog (2000).

Dealing with Missing Data from Uncontested Seats. But the chief advantage of the Bayesian methods we adopt here is in their flexibility and extendibility. Take the case of missing data arising from uncontested seats. In our data, this is a significant issue: in every decade we analyze, at least a quarter of the districts have at least one uncontested election (this proportion is as high as 45% in the 1980s). One solution would be to drop these particular elections from the analysis, but this could lead to significant bias (recall we would be dropping more than a quarter of the sample). This data is not missing at random, so standard imputation techniques are inappropriate here. However, the fact that an incumbent was reelected unopposed is informative about underlying district partisanship. We adopt an approach used by Katz and King (1999) in which uncontested elections are modeled as censored data; e.g., if a Democrat incumbent successfully runs unopposed then we model the unobsered vote share via the model in equation 2, subject to the constraint that $y_{ij} > .5 \iff y^*_{ij} > 0$ (i.e., the Democrat would have won a contested election) ensuring that uncontestedness is contributing some information about district partisanship. This constraint is trivial to implement with our latent variable model. Imposing this (or any other non-standard) restriction in an analysis of covariance model is extremely difficult, if not impossible. In an analysis of covariance model, to the best of our knowledge, one would have to settle for either list-wise deletion or imputation based on missing at random techniques, both of which are inappropriate here.

Prior Distributions. To complete the specification of our Bayesian model, we place prior distributions on the parameters. Recall that we impose the identifying restriction that the latent x_i have mean zero and variance one. With this restriction the other parameters in the model are identified and we impose vague priors on the other parameters, letting the data dominate inferences for these parameters: i.e., *a priori* we specify independent $N(0, 10^2)$ priors for the regression parameters γ and β and vague gamma priors for the precision parameters (τ^2). With these normal and gamma priors, and the normal distributions assumed for the hierarchical structure over the latent district partisanship (equation 1) and the observed vote shares (equations 2 and 4), the resulting posterior densities for the all model parameters are in the same family as their prior (normals and gammas), ensuring that the computation for this problem is rather simple (a case of *conjugate* Bayesian analysis); see the Appendix for further details.

Results: Measuring District Partisanship

Each congressional district's latent ideology appears in our model as a parameter to be estimated, x_i. Via our Bayesian approach and our use of a Markov chain Monte Carlo algorithm, we obtain many samples from the joint posterior density of *all* the x_i. In turn, we can induce a posterior density over the order statistics of the x_i, letting us assess the extent to which we can authoritatively distinguish districts from one another.

Figure 2 shows our estimates of each district's latent ideology (the posterior mean of each x_i) for the 1990s data; the thin gray lines are pointwise 95% credible intervals, computed as the 2.5th and 97.5th quantiles from 2,000 Gibbs samples thinned from 220,000 samples (similar graphical summaries can be constructed for earlier years; space constraints necessitate a focus on the familiar 1990s). The actual numbers attaching to the estimate are arbitrary; recall that the x_i are only defined up to scale and location (here we use the identifying restriction that the x_i have mean zero and

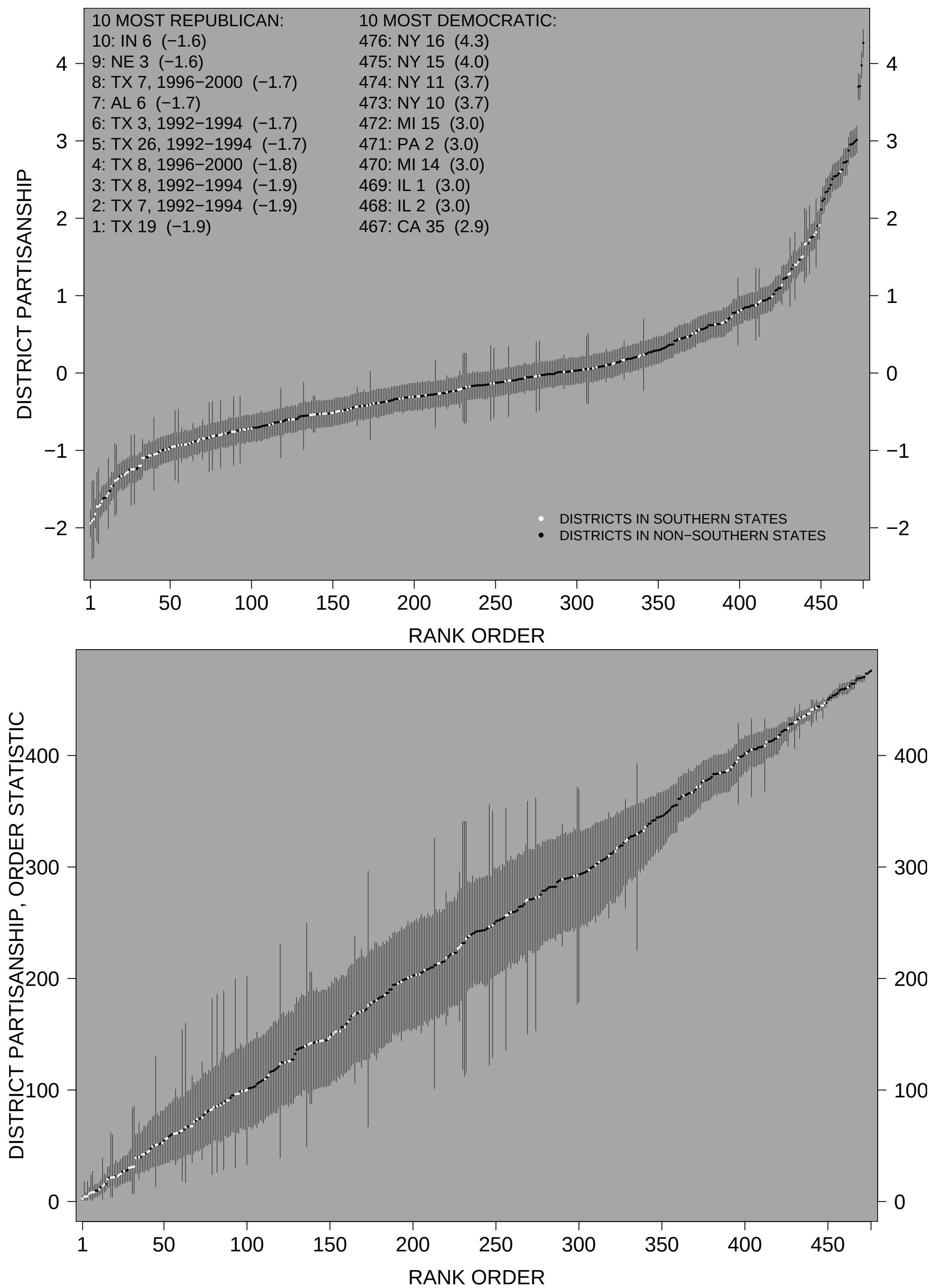

Figure 2: Latent District Partisanship, 1990s: Pointwise Means and 95% Credible Intervals (top panel), Order Statistics and 95% Credible Intervals (bottom panel).

standard deviation one). However, relative comparisons are meaningful, as is an assessment of the uncertainty attaching to each x_i relative to the between-district variation in the x_i, and the shape of the distribution of the x_i.

By construction, between-district variation in latent district variation has a standard deviation of 1.0 while the average posterior standard deviation for the 435 x_i in the 1990s data is .10; that is, as the top panel of Figure 2 suggests, differences across districts are generally large relative to the uncertainty that attaches to each district's x_i. On the other hand, the bottom panel of Figure 2 suggests the limits with which we can make fine distinctions among districts. For moderate districts, the 95% credible interval on each district's rank covers about 90 places, or about 20% of the 435 districts in the data. Some insight into the consequences of this uncertainty comes from comparing two relatively moderate districts, say, the districts at approximately the 45th and 55th percentile of the distribution of the x_i (e.g., TX 23 and OR 4), respectively. Our best guesses (posterior means) for these districts' latent partisanship are -.27 and -.09, and the probability that OR 4 is more Democratic than TX 23 is .91. Finer distinctions in the middle of the distribution of latent district partisanship are made with less certainty, and will fall short of the traditional 95% standard used in hypothesis testing. On the other hand, in the tails of the distribution, fine distinctions can be made more readily: for instance, the probability that a district at the 1st percentile (e.g., AL 6) is more Republican than a district at the 3rd percentile (e.g., KS 1) is greater than .99.

Additionally, the figure shows the effect of redistricting and uncontestedness: both increase our uncertainty of the district's partisanship. Notice that some districts in figure 2 have much longer credible intervals than others, reflecting the increased uncertainty stemming from fewer elections. Where we have fewer elections, we are less certain of the district's partisanship.

The distribution of latent district partisanship has a pronounced right-hand skew. The most Democratic districts are roughly four standard deviations away from the mean district (set to zero, by construction). On the other hand, the most Republican districts in the country are just two standard deviations away from the mean. Quite simply, the most Democratic districts in our data exhibit more consistently and more heavily Democratic voting patterns than the Republican districts exhibit

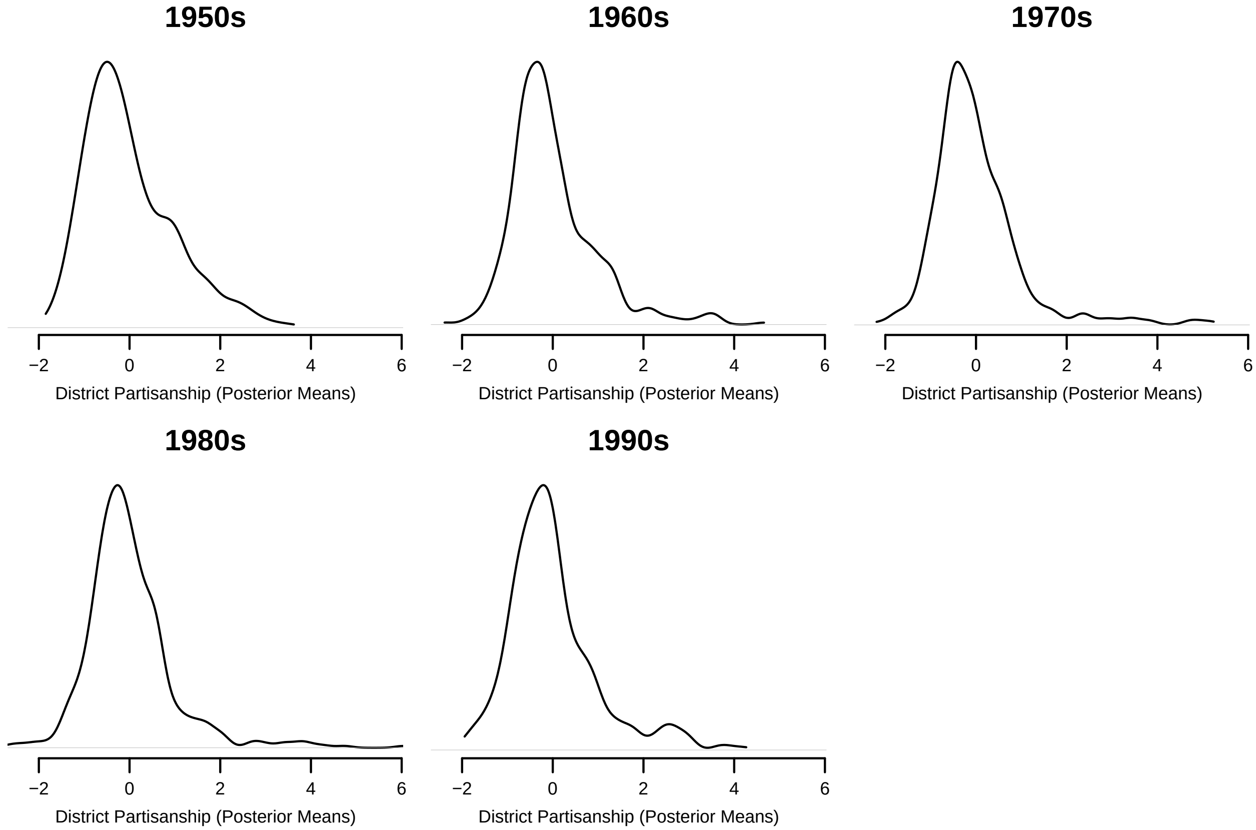

Figure 3: Density plots showing the distribution of district partisanship estimates (posterior means), by decade; higher values of district partisanship indicate more Democratic districts. Recall that for each decade, the district partisanship estimates are recovered subject to the identifying restriction that they have mean zero and unit variance.

extreme pro-Republican voting patterns. For instance, in the ten most Democratic districts, Clinton averaged 89% of the two party vote share in 1992 and 1996; in the ten most conservative districts, Clinton averaged 30%, while in the remaining 415 districts, Clinton averaged 54%.

Figure 3 shows the densities (smoothed histograms) of our district partisanship estimates in each of the five decades we study. In each decade district partisanship is normalized to have a mean of zero and unit variance across districts, so these graphs are *not* informative about any long term trends in average levels of district partisanship (e.g., say, if the country, on average, was trending in a particular partisan direction), or increases in the dispersion of district partisanship (e.g., as might arise if redistricting was a source of partisan polarization, via the creation of lop-sided districts etc). Nonetheless, the densities in Figure 3 do illustrate the way that district partisanship consistently has a skewed distribution, and ways in which that skew has changed over time, reflecting both population movements and redistricting. Specifically, in every decade we examine, there are a relatively small number of *extremely* Democratic districts, without an offsetting set of extremely Republican districts. This Democratic skew in the distribution of district partisanship is at its least pronounced in the first decade we analyze, the 1950s, and reaches its peak in the 1980s, where IL-1 (located on Chicago's south side) lies six standard deviations away from the average district.

More generally, the overwhelmingly Democratic districts in recent decades are almost all majority-minority districts; unsurprisingly, and as we elaborate below, the racial composition of a district is a powerful determinant of its partisanship (see Table 1). For instance, the most Democratic district in our analysis of the 1990s is NY 16 (centered on the South Bronx in New York City), whose population in the 1990 Census was reported as 59% Hispanic origin and 43% black (these categories are not mutually exclusive); Barone and Ujifusa (1995, 946) state that "[p]olitically ... [NY 16] ... is quite possibly the most heavily Democratic district in the country." The adjoining seat, NY 15 (centered in Harlem), is the 2nd most Democratic seat in our analysis of the 1990s; it has been held by Charlie Rangel since 1970, and was 47% black and 45% Hispanic origin in the 1990 Census. NY 10 and NY 11, both in Brooklyn, are the 3rd and 4th most Democratic seats in our analysis, with black populations of 60% and 75%, respectively. Districts in central Philadelphia (PA-2, 62% black), central Detroit (MI-15, 70% black; MI-14, 69% black), the south side of Chicago (IL-1, 70% black; IL-2, 68% black) and South Central Los Angeles (CA-35, 43% black and 42% Hispanic origin) round out the ten most Democratic districts in the 1990s. The correlation between the percentange of the district's population that is black and our measure of district partisanship is .60 in the 1990s.

Validating the District Partisanship Measure

Figure 4 shows a scatterplot of the recovered latent trait and its indicators (presidential and congressional vote shares) for the 1990s; similar plots for other decades are provided in the on-line Appendix. The relationship between the vote shares and the latent trait is fairly strong, given that our model treats vote shares as an indicator of the latent district partisanship. The non-linearities follow from using log-odds transformations of the vote shares as indicators of latent district partisanship (equations 2 and 4). Outliers are generally more prevalent in the congressional elections scatterplots, resulting from the fact that congressional elections outcomes are modeled not only as a function of latent district partisanship, but also with offsets for incumbency, challenger quality and region (south/non-south).

A more realistic assessment of both the validity and usefulness of our measure of district partisanship comes from seeing how well it predicts political outcomes *not* in our model, but still plausibly related to district partisanship. The criterion variable we use is legislative preferences (as revealed via roll call voting). Figure 5 presents a scatterplot of legislative preferences ("ideal points") against our measure of district partisanship for the 1990s. The legislative ideal points are generated with a one dimensional spatial voting model fit to all non-unanimous roll calls cast in the 107th U.S. House of Representatives (2001-2002), using the model and estimation procedures described in Clinton, Jackman and Rivers (2004). Where a district was represented by more than one legislator over the course of the 107th Congress (e.g., due to deaths and retirements), we display the ideal point of the legislator with the lengthier voting history. Both legislative ideal points and district partisanship are estimated with uncertainty, indicated with the vertical and horizontal lines covering 95% credible intervals, respectively.

In general, there is a strong relationship between district partisanship and legislative ideal points; the correlation between the two sets of point estimates is .72. The within-party correlations are also moderate to large: .43 among Republicans, and .52 among Democrats. We would not expect a perfect or even near-perfect relationship between district partisanship and a measure of legislators' preferences, since there are many plausible sources of influence on roll-call voting other than district partisanship, with party-specific whipping perhaps the most prominent. Indeed, perhaps the most noteworthy feature of Figure 5 is the separation of legislators' ideal points by party; there is almost no partisan overlap in the estimated ideal points, while there is considerable overlap in estimates of district partisanship across the two parties. No scholar of contemporary American politics would be surprised by this finding, although a lively debate continues as to the sources of polarization

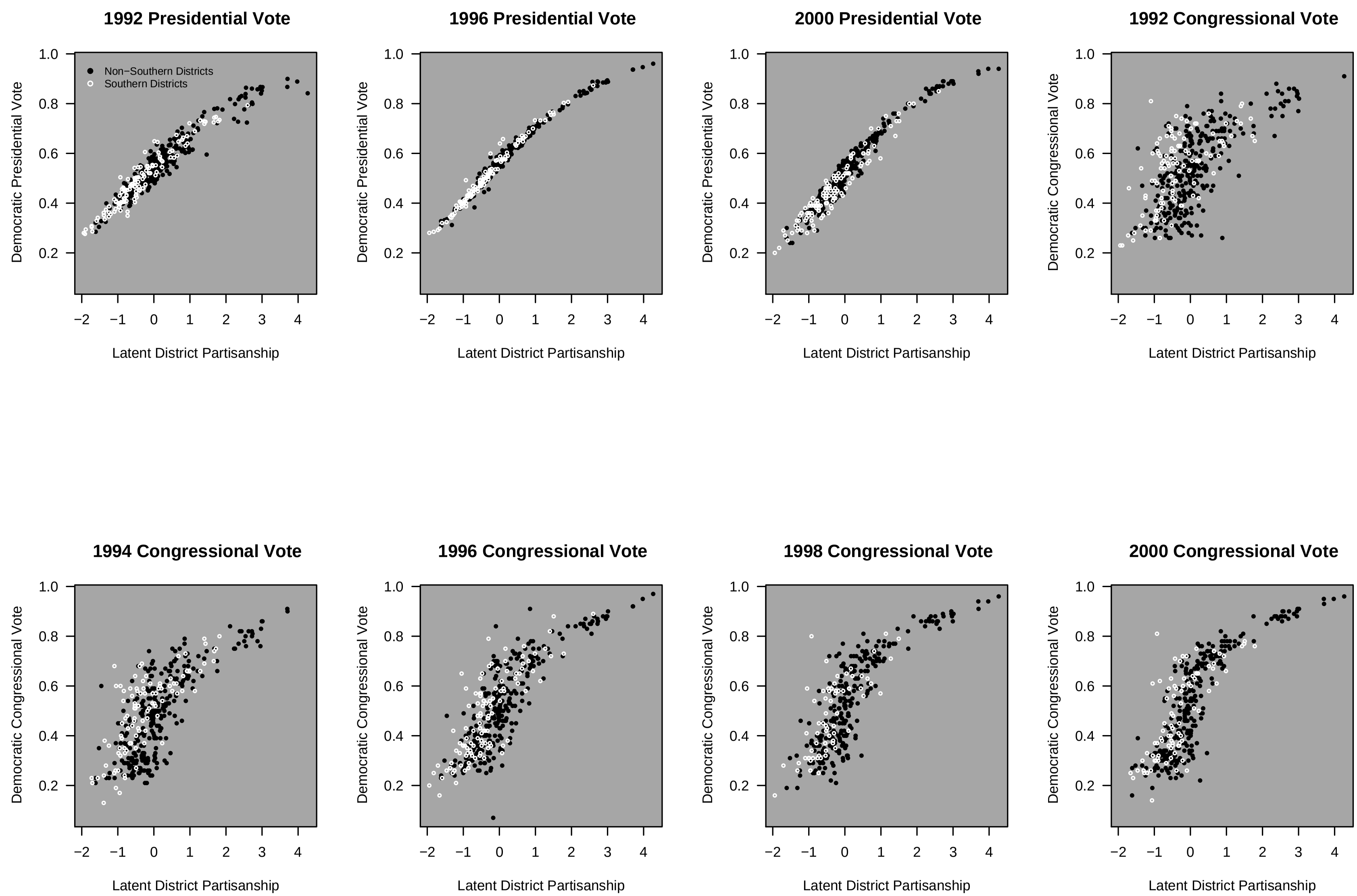

Figure 4: Vote Shares plotted against Latent District Partisanship, 1990s. Presidential election outcomes are modeled as a function of the latent trait plus intercept shifts for home-state effects. Similarly, the model for congressional election outcomes includes intercept shifts for incumbency, region and challenger quality.

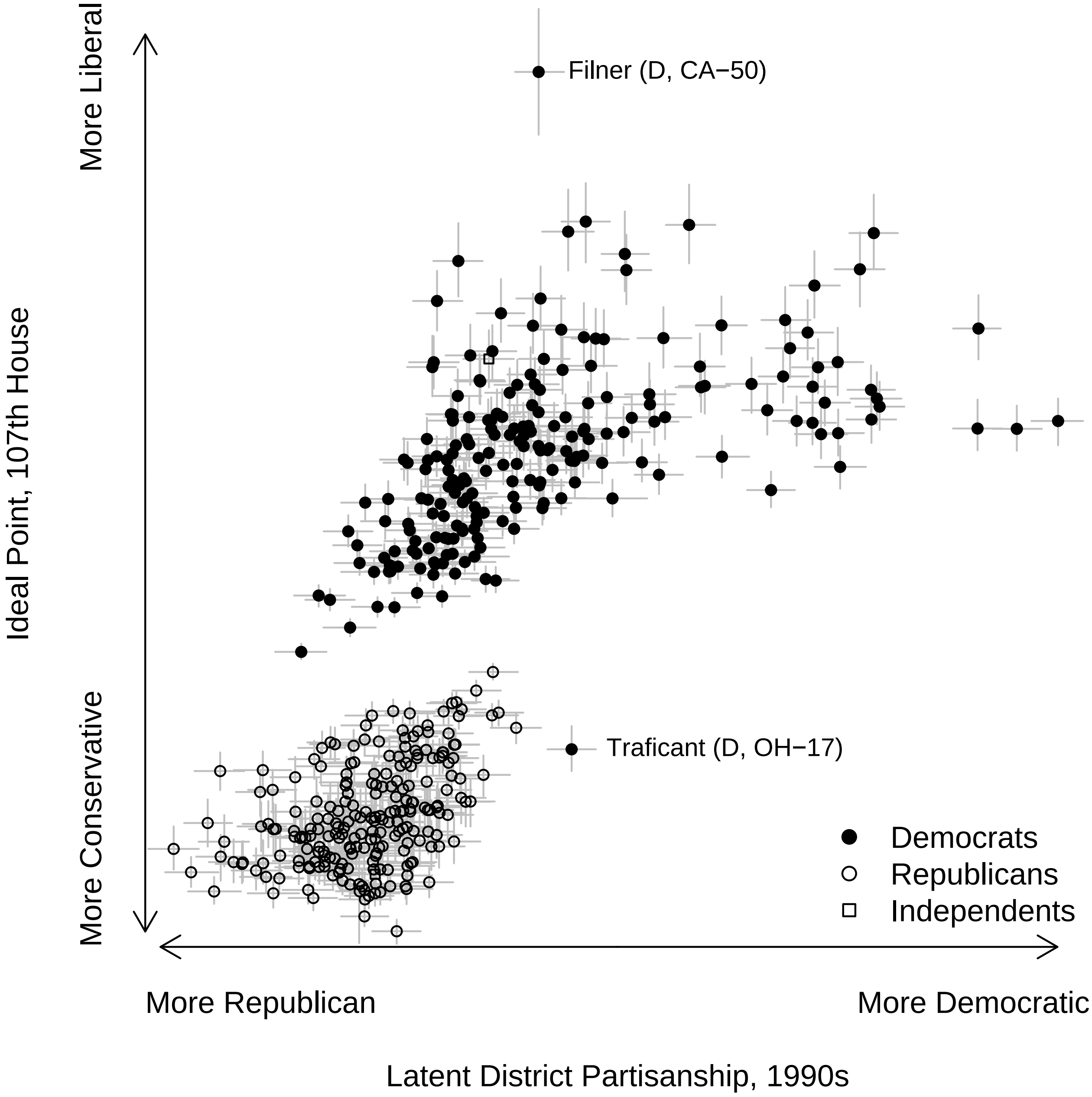

Figure 5: Legislative Preferences (legislators' ideal points) and latent district partisanship, 107th House. Vertical and horizontal lines indicate 95% credible intervals for legislative preferences and district partisanship, respectively.

within the Congress (e.g., McCarty, Poole and Rosenthal 2003). The pattern in Figure 5 is consistent with a party pressure hypothesis (e.g., Snyder and Groseclose 2000), or a more general process of polarization among political elites, showing that there is virtually no overlap between the ideal points by party, while there is considerable overlap in our estimates of district partisanship by party-of-representative.[5] Put differently, there is much more partisan polarization in the roll call voting than in the corresponding estimates of district partisanship.

Figure 6 produces similar graphs from the other four decades we examine. These graphs makes clear the way that roll call voting in the House of Representatives has become increasingly polarized along partisan lines since the 1950s. While this is a compelling and graphically vivid feature of the roll call data, our interest lies in the validating our district partisanship measure. We note that in all decades, there is moderate to very strong relationship between district partisanship and the recovered ideal point of the district's representative. An important exception to this general pattern comes in the 87th House (1961-62), which we use to validate the estimates of district partisanship for the 1950s. In this particular comparison (top left, Figure 6) Democrats representing districts in the South record voting histories that bear no relationship to the levels of partisanship we estimate in their districts, a finding that will come as no surprise to scholars of American politics. Put simply, high levels of Democratic partisanship did not translate into reliably "liberal" voting histories for Southern Democrats; conversely, the ideological and policy implications of a district being "solidly Democratic" were quite different depending on whether the district was in the Southern part of the country. Irrespective of the level of Democratic partisanship of the district, these representatives' ideal points are located on the conservative wing of the Democratic party, and are indistinguishible from the ideal points of many Republican representatives.

Since our main purpose is to measure and model district partisanship we defer a more detailed analysis of representation or polarization for another day. For now we simply note that the the relationship between our measure of district partisanship and election returns is very strong (partic-

[5]e.g., the 75th percentile of the distribution of partisanship in Republican-held districts lies at about the 21st percentile of the distribution of partisanship in Democratic-held districts.

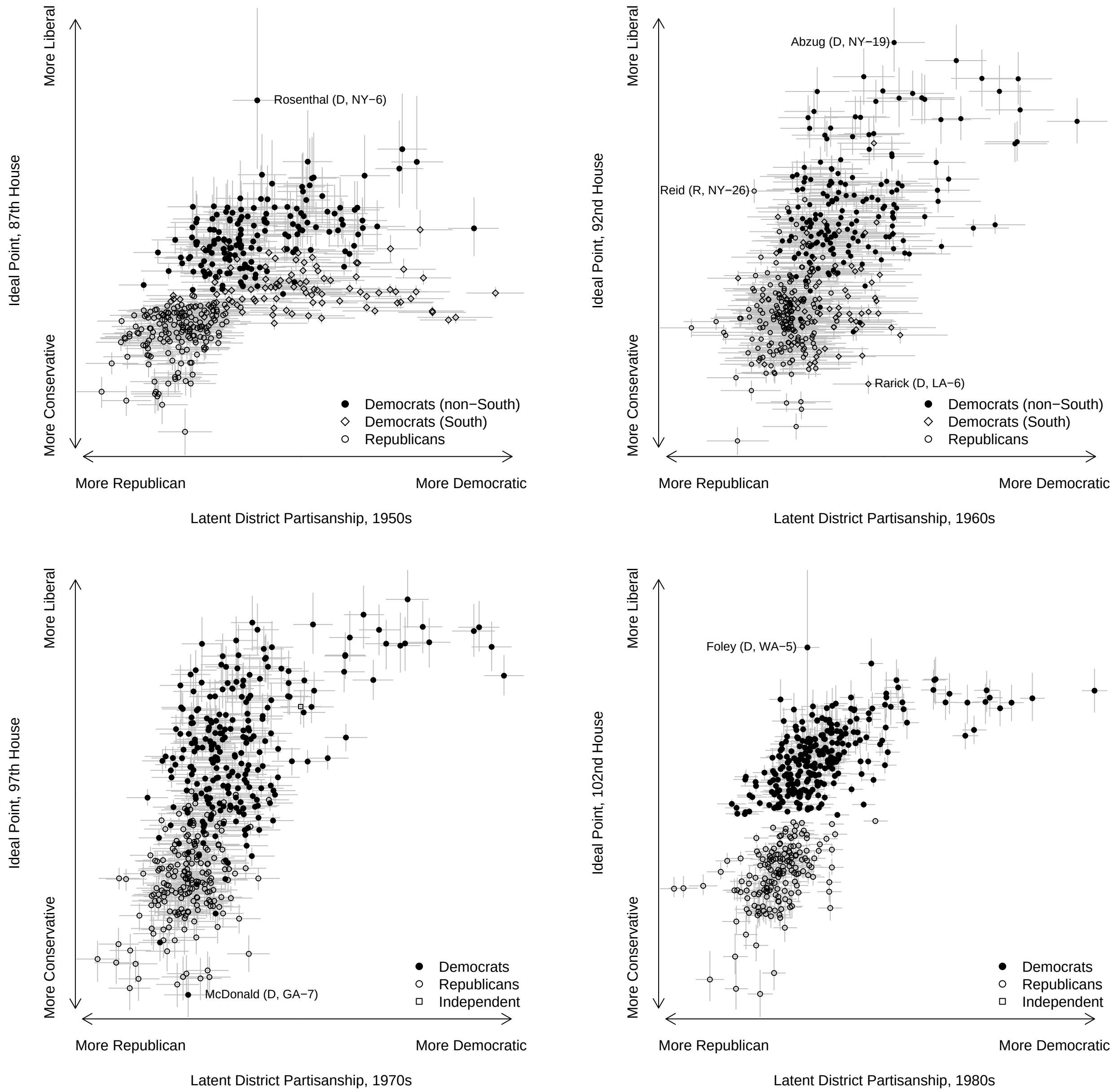

Figure 6: Legislative Preferences (legislators' ideal points) and latent district partisanship, for four decades (1950s, 1960s, 1970s and 1980s) and four Congress immediately following each respective decade: the 87th House (1961-62); the 92nd (1971-72), the 97th (1981-92) and the 102nd (1981-82). Vertical and horizontal lines indicate 95% credible intervals for legislative preferences and district partisanship, respectively.

ularly in the 1990s) and that the correlation between district partisanship and estimated legislator ideal points is consistent with our general expectations. This not only bolsters our confidence in the measure, but demonstrates its usefulness for analyzing Congressional politics.

Table 1 presents parameter estimates of the hierarchical component of the model (equation 1), where the latent district partisanship is modeled as a function of these census demographic aggregates. Of the many demographic variables aggregated to the level of congressional districts in the census, which ones are more politically relevant than others? A long line of research with its roots in political sociology suggests that indicators of social class ought to be relevant in this context: these include median income or the composition of the workforce (e.g., unemployment rates, percent blue-collar, percent unionized). In addition, studies of committee assignments have focused on the role that particular demographic characteristics play in shaping the behavior of members of Congress. These studies supply predictions about how we might expect constituent partisanship and demographic characteristics to be related; a useful summary appears in Adler and Lapinski's (1997) listing of politically-relevant district characteristics in their study of demand for policy outputs from Congress.[6]

For the most part, the relationships we find between district partisanship and demographic characteristics contain few surprises, as presented in Table 1. First, and as discussed previously, districts with high proportions of African-Americans are consistently among the most Democratic districts. Over the five decades in our analysis, the coefficient on the log of the proportion of African-Americans in the population (outside of the South) is always unambiguously positive, and averages about .10 [7]. In each decade, the distribution of African-Americans throughout congressional districts is skewed right: i.e., the median African-American proportion is consistently around .10, but attains a max-

[6] Moreover, the demographic variables we use come from E. Scott Adler's (2003) dataset on Congressional district demographics, available at http://sobek.colorado.edu/~esadler/districtdatawebsite/CongressionalDistrictDatasetwebpage.htm.

[7] To control for the fact that a large percentage of African-Americans meant something very different in Mississippi and New York in the 1950s Key (1949), we interact the percent African-American in the district with a South dummy.

	1952-1960	1962-1970	1972-1980	1982-1990	1992-2000
Intercept	8.06	27.65	21.85	0.59	14.56
	[3.97, 12.06]	[19.44, 40.90]	[15.83, 27.05]	[-1.42, 4.58]	[11.18, 18.39]
Log Proportion Aged 65+	-0.70	-0.76	-0.40	0.054	0.47
	[-1.07, -0.33]	[-1.02, -0.48]	[-0.69, -0.12]	[-0.16, 0.27]	[0.27, 0.65]
Log Proportion Blue Collar	-0.39	0.35	0.24	-0.16	-0.07
	[-0.73, -0.025]	[-0.075, 0.77]	[-0.074, 0.56]	[-0.39, 0.07]	[-0.26, 0.12]
Log Proportion Foreign Born	-0.028	0.34	0.11	0.10	0.20
	[-0.14, 0.086]	[0.23, 0.45]	[0.0077, 0.21]	[0.013, 0.18]	[0.13, 0.27]
Log Median Income	-1.23	-2.55	-2.73	-1.85	-1.06
	[-1.68, -0.76]	[-3.06, -2.02]	[-3.24, -2.21]	[-2.22, -1.48]	[-1.41, -0.69]
Log Population Density	0.14	0.17	0.27	0.18	0.22
	[0.084, 0.19]	[0.12, 0.21]	[0.21, 0.32]	[0.14, 0.23]	[0.18, 0.26]
Log Proportion Unemployed	0.32	0.58	0.47	0.61	0.85
	[0.078, 0.56]	[0.29, 0.87]	[0.21, 0.73]	[0.37, 0.85]	[0.57, 1.12]
Log Proportion Black	0.12	0.11	0.087	0.067	0.094
	[0.04, 0.19]	[0.049, 0.17]	[0.02, 0.15]	[0.011, 0.12]	[0.036, 0.15]
South (dummy)	0.59	-0.35	-0.14	-0.28	0.14
	[0.12, 1.07]	[-0.84, 0.17]	[-0.59, 0.31]	[-0.62, 0.06]	[-0.12, 0.43]
Log Proportion Black $\times$ South	0.25	0.07	0.017	0.13	0.30
	[0.066, 0.43]	[-0.14, 0.27]	[-0.16, 0.19]	[-0.0062, 0.27]	[0.19, 0.40]
Majority-Minority	-	-	-	2.05	0.92
				[1.61, 2.47]	[0.55, 1.30]
σ_x	0.74	0.71	0.69	0.57	0.50
	[0.69, 0.80]	[0.66, 0.76]	[0.64, 0.74]	[0.53, 0.60]	[0.47, 0.54]
r_x^2	0.45	0.50	0.52	0.68	0.75
	[0.36, 0.52]	[0.41, 0.57]	[0.45, 0.59]	[0.63, 0.72]	[0.71, 0.78]

Table 1: Posterior Summaries, Relationships Between Demographic Characteristics and Latent District Partisanship. Cell entries are posterior means; 95% credible intervals shown in brackets. Unless otherwise defined variables are logs of district percentages. Enroll is the percentage of the district enrolled in elementary or secondary schools; median income is median family income; population density is population per mile^2; South is defined as the 11 states of the former confederacy. See Adler (2003) for additional details.

imum of .92 in the 1980s (in IL 1), and .88 in the 1970s and 1960s, .74 in the 1990s (in NY 11), and .69 in the 1950s (in MS 3), with an average 95th percentile of .42. Thus, in the 1990s, in a non-Southern district, an increase in the proportion of the African-American population from the mean level of .13 to .57 (the 95th percentile) is associated with an increase of liberalism of about .13, or roughly 10% of a standard deviaton, net of other factors. Additionally, the coefficient for majority-minority districts is large and statistically signficant, indicating the even controlling for the fact that majority-minority districts contain a high percentage of African-Americans, such districts are even more Democratic. For example, taking a district in the 1990s from the 95th percentile of African-American to a majority minority district that is 65% African-American involves shifting latent district partisanship approximately 0.9 units, or approximately one-standard deviation, reflecting how much more sharply Democratic majority-minority districts are, even relative to other largely African-American districts.

How does being in the South affect the partisanship of a district? To assess this counter-factual, we hold the proportion of African-Americans constant at its mean in the Southern states and change the hypothetical district from North to South. In the 1950s, making such a change moves the district partisanship in a Democratic direction by 0.25 units, or roughly one-quarter of a standard deviation more Democratic. In the 1990s, by contrast, the same change moves the district 0.34 units in the *Republican* direction. In the 1950s, the average Southern district was more Democratic than its Northern counter-part. By the 1990s, the situation had reversed.

Other variables that are also consistently and strongly associated with district partisanship are median income and population density. Richer districts (as measured by the district's median per capita income) are consistently less Democratic than poorer districts. Our parameter estimates imply that net of other factors, movement from the 5th to the 95th percentile on income is associated with anywhere from a standard deviation's worth of change in district partisanship (e.g., 1950s and 1990s), to 2.1 standard deviations of change in district partisanship in the 1960s. Population density displays tremendous variation in any given decade; movement from the 5th is 95th percentile on this variable is associated with shifting latent district partisanship a standard deviation (in a Democratic direction) in the 1960s, but up to a two standard deviation shift in the 1970s.

Congressional Elections

Estimates of the Congressional elections models appear in Tables 2 and 3. The models fit reasonably well, with the r-squared values for the 25 equations ranging from a low of .72 in 1978 to a high of .90 in 2000. The parameters tapping the effects of district partisanship range from a low of .26 in 1972 to .67 in 1954. Recent House elections, say, 1994-2000, have been characterized by (a) reasonably good model fit and (b) relatively high discrimination with respect to the latent partisanship measure.

The estimates for the incumbency offset parameters are of some substantive interest. Since our dependent variable in the vote equations is the log-odds ratio of vote shares, we implicitly have a non-linear model in vote shares themselves; to simplify the assessment of the model's marginal effects, we assess all marginal effects conditional on vote shares being at 50%, corresponding to districts that are otherwise evenly split between Democrats and Republicans (note that the 50-50 vote split is also the steepest part of the logistic CDF, where marginal effects on votes take their maximum possible value). In addition, our Congressional elections model includes terms for challenger quality (i.e., a dummy variable coded 1 if the challenger has previously held elective office and zero otherwise).

Incumbency offsets are estimated separately for Northern and Southern states, and also for Democratic and Republican incumbents. The regional variation in the magnitude of the incumbency offsets is perhaps the most striking feature of this part of the results. For the 1950s, we estimate massive incumbency offsets for Democratic incumbents in the South, worth anywhere from 10 to 20 percentage points of vote share in an otherwise evenly split district. Incumbency offsets for Northern Democrats and Republicans in the 1950s are much smaller; in fact, for Northern Democrats in 1954 and 1956, and for Southern Republicans in 1952-1964 (when there are relatively few Southern Republican incumbents in the House), our estimates of incumbency offsets are indistinguishable from zero at conventional levels of statistical significance. In general, there is no systematic pattern of

Year	Intercept	District Partisanship	Democratic Incumbency	Republican Incumbency	South × Dem Incumbency	South × Repub Incumbency	Dem Challenger Quality	Rep Challenger Quality	ν_j	r^2
1952	0.047	0.49	0.093	-0.21	0.65	0.047	-	-	0.23	0.88
	[-0.019, 0.11]	[0.45, 0.53]	[0.0059, 0.18]	[-0.29, -0.13]	[0.53, 0.77]	[-0.30, 0.39]			[0.21, 0.25]	[0.85, 0.90]
1954	0.49	0.67	-0.25	-0.35	0.94	0.098	-	-	0.41	0.76
	[0.34, 0.64]	[0.59, 0.75]	[-0.43, -0.064]	[-0.53, -0.18]	[0.76, 1.13]	[-0.26, 0.45]			[0.37, 0.45]	[0.71, 0.81]
1956	0.29	0.50	-0.12	-0.35	0.44	-0.016	0.036	0.062	0.23	0.86
	[0.20, 0.38]	[0.45, 0.55]	[-0.23, -0.011]	[-0.46, -0.25]	[0.34, 0.55]	[-0.22, 0.19]	[-0.044, 0.11]	[-0.046, 0.17]	[0.20, 0.25]	[0.83, 0.89]
1958	0.32	0.44	0.31	-0.25	0.89	-0.034	0.11	-0.10	0.27	0.84
	[0.23, 0.40]	[0.38, 0.49]	[0.19, 0.42]	[-0.36, -0.15]	[0.72, 1.05]	[-0.25, 0.18]	[0.016, 0.20]	[-0.23, 0.025]	[0.25, 0.29]	[0.80, 0.86]
1960	0.18	0.42	0.23	-0.23	0.47	-0.10	0.0073	-0.096	0.25	0.84
	[0.094, 0.27]	[0.38, 0.47]	[0.13, 0.34]	[-0.33, -0.12]	[0.36, 0.57]	[-0.34, 0.12]	[-0.089, 0.10]	[-0.19, -0.0065]	[0.23, 0.27]	[0.81, 0.87]
1962	0.12	0.32	0.25	-0.40	0.48	0.19	-	-	0.29	0.79
	[0.035, 0.20]	[0.28, 0.36]	[0.15, 0.35]	[-0.49, -0.30]	[0.37, 0.61]	[-0.13, 0.49]			[0.26, 0.31]	[0.75, 0.83]
1964	0.34	0.34	0.29	-0.40	0.12	0.13	0.09	-0.12	0.29	0.78
	[0.25, 0.43]	[0.30, 0.38]	[0.18, 0.40]	[-0.51, -0.29]	[0.0068, 0.23]	[-0.088, 0.36]	[-0.016, 0.20]	[-0.24, 0.0019]	[0.27, 0.32]	[0.74, 0.81]
1966	0.062	0.36	0.28	-0.56	0.32	0.19	0.04	-0.20	0.23	0.88
	[-0.032, 0.15]	[0.33, 0.40]	[0.18, 0.40]	[-0.67, -0.45]	[0.21, 0.44]	[0.014, 0.39]	[-0.068, 0.15]	[-0.27, -0.13]	[0.21, 0.26]	[0.85, 0.90]
1968	0.22	0.41	0.14	-0.68	0.48	0.15	0.15	-0.10	0.29	0.85
	[0.12, 0.33]	[0.36, 0.45]	[0.007, 0.27]	[-0.80, -0.55]	[0.35, 0.63]	[-0.029, 0.32]	[0.049, 0.25]	[-0.20, 0.0021]	[0.27, 0.32]	[0.82, 0.88]
1970	0.10	0.37	0.53	-0.40	0.34	0.0069	0.11	-0.11	0.32	0.83
	[0.0031, 0.20]	[0.32, 0.42]	[0.40, 0.64]	[-0.52, -0.27]	[0.19, 0.50]	[-0.16, 0.17]	[-0.0085, 0.23]	[-0.24, 0.011]	[0.29, 0.34]	[0.80, 0.86]
1972	0.079	0.26	0.59	-0.61	0.021	-0.25	0.19	-0.21	0.36	0.78
	[-0.011, 0.17]	[0.21, 0.30]	[0.48, 0.71]	[-0.72, -0.49]	[-0.12, 0.16]	[-0.42, -0.079]	[0.055, 0.32]	[-0.34, -0.093]	[0.33, 0.38]	[0.75, 0.81]
1974	0.40	0.32	0.43	-0.56	0.17	-0.17	0.18	-0.10	0.36	0.76
	[0.30, 0.50]	[0.27, 0.37]	[0.31, 0.56]	[-0.68, -0.43]	[0.031, 0.31]	[-0.31, -0.027]	[0.063, 0.29]	[-0.27, 0.077]	[0.33, 0.39]	[0.73, 0.80]

Table 2: Posterior Summaries, Congressional Elections Model, 1952-1974. Cell entries are posterior means, 95% credible intervals in brackets. In all years, the dependent variable is the log-odds of the Democratic proportion of the two-party vote in contested House races. See equation 2. Challenger quality data is not available in all years.

Year	Intercept	District Partisanship	Democratic Incumbency	Republican Incumbency	South × Dem Incumbency	South × Repub Incumbency	Dem Challenger Quality	Rep Challenger Quality	ν_j	r^2
1976	0.44	0.38	0.28	-0.81	0.12	-0.065	0.087	-0.24	0.37	0.78
	[0.34, 0.55]	[0.33, 0.42]	[0.16, 0.40]	[-0.96, -0.68]	[-0.0083, 0.24]	[-0.24, 0.11]	[-0.056, 0.23]	[-0.35, -0.12]	[0.34, 0.40]	[0.75, 0.81]
1978	0.23	0.33	0.47	-0.79	0.14	-0.13	0.34	-0.34	0.44	0.72
	[0.10, 0.34]	[0.27, 0.38]	[0.33, 0.61]	[-0.96, -0.63]	[-0.016, 0.30]	[-0.37, 0.10]	[0.16, 0.52]	[-0.51, -0.19]	[0.41, 0.48]	[0.67, 0.76]
1980	0.093	0.43	0.48	-0.67	0.033	-0.27	0.11	-0.16	0.39	0.80
	[-0.032, 0.22]	[0.38, 0.48]	[0.33, 0.62]	[-0.82, -0.52]	[-0.087, 0.16]	[-0.46, -0.076]	[-0.063, 0.27]	[-0.29, -0.030]	[0.37, 0.43]	[0.77, 0.83]
1982	0.19	0.37	0.54	-0.65	0.41	0.15	0.27	-0.25	0.38	0.77
	[0.096, 0.28]	[0.32, 0.42]	[0.42, 0.67]	[-0.77, -0.53]	[0.26, 0.57]	[-0.019, 0.32]	[0.14, 0.39]	[-0.40, -0.10]	[0.35, 0.40]	[0.74, 0.80]
1984	0.023	0.38	0.49	-0.71	0.24	-0.0025	0.16	-0.24	0.37	0.82
	[-0.12, 0.17]	[0.34, 0.43]	[0.32, 0.64]	[-0.87, -0.54]	[0.11, 0.38]	[-0.18, 0.18]	[-2.3e-05, 0.31]	[-0.37, -0.10]	[0.35, 0.40]	[0.79, 0.84]
1986	0.035	0.37	0.70	-0.65	0.32	0.27	0.30	-0.22	0.35	0.85
	[-0.073, 0.14]	[0.33, 0.41]	[0.57, 0.83]	[-0.78, -0.52]	[0.19, 0.44]	[0.12, 0.42]	[0.16, 0.44]	[-0.36, -0.07]	[0.32, 0.37]	[0.83, 0.87]
1988	0.077	0.38	0.60	-0.71	0.19	0.14	0.025	0.044	0.40	0.82
	[-0.077, 0.23]	[0.33, 0.43]	[0.43, 0.78]	[-0.88, -0.54]	[0.05, 0.34]	[-0.034, 0.31]	[-0.14, 0.19]	[-0.13, 0.21]	[0.37, 0.43]	[0.79, 0.85]
1990	0.19	0.33	0.36	-0.61	0.26	0.15	0.15	-0.20	0.37	0.76
	[0.055, 0.33]	[0.28, 0.38]	[0.21, 0.52]	[-0.77, -0.46]	[0.13, 0.39]	[-0.011, 0.31]	[-0.029, 0.34]	[-0.35, -0.043]	[0.34, 0.40]	[0.72, 0.79]
1992	0.18	0.35	0.36	-0.58	0.087	0.024	0.17	-0.21	0.34	0.75
	[0.11, 0.25]	[0.31, 0.39]	[0.26, 0.45]	[-0.69, -0.47]	[-0.029, 0.20]	[-0.13, 0.17]	[0.041, 0.32]	[-0.32, -0.088]	[0.31, 0.36]	[0.71, 0.78]
1994	-0.096	0.40	0.42	-0.55	0.062	0.047	0.057	-0.20	0.28	0.85
	[-0.17, -0.019]	[0.36, 0.44]	[0.33, 0.51]	[-0.64, -0.46]	[-0.029, 0.15]	[-0.08, 0.18]	[-0.064, 0.18]	[-0.30, -0.092]	[0.26, 0.30]	[0.83, 0.87]
1996	0.089	0.52	0.39	-0.39	0.096	0.020	0.25	-0.092	0.31	0.86
	[-0.00042, 0.17]	[0.48, 0.56]	[0.27, 0.51]	[-0.50, -0.29]	[-0.025, 0.22]	[-0.076, 0.11]	[0.13, 0.38]	[-0.24, 0.06]	[0.29, 0.34]	[0.83, 0.88]
1998	0.18	0.52	0.34	-0.54	0.030	0.086	-	-	0.28	0.89
	[0.083, 0.27]	[0.48, 0.56]	[0.22, 0.45]	[-0.64, -0.43]	[-0.083, 0.15]	[-0.016, 0.19]			[0.26, 0.30]	[0.87, 0.91]
2000	0.027	0.56	0.51	-0.41	0.07	0.071	-	-	0.29	0.90
	[-0.069, 0.13]	[0.52, 0.60]	[0.39, 0.62]	[-0.53, -0.30]	[-0.042, 0.18]	[-0.031, 0.17]			[0.27, 0.31]	[0.88, 0.91]

Table 3: Posterior Summaries, Congressional Elections Model, 1976-2000. Cell entries are posterior means, 95% credible intervals in brackets. In all years, the dependent variable is the log-odds of the Democratic proportion of the two-party vote in contested House races. See equation 2. Challenger quality data is not available in all years.

incumbency offsets being larger for one party than the other. [8] There is some regional assymetry, particularly on the Democratic side, although this is concentrated primarily in the early part of our study. Although we stress we are estimating a different quantity of interest, our results closely parallel the larger literature on the incumbency advantage, which finds a substantial increase in the incumbency advantage in the 1960s and 1970s, followed by modest decline in the late 1980s and 1990s.[9]

We also estimate challenger quality offsets, following the standard operationalization of a "quality" challenger being one who has previously won an election for public office (e.g., Jacobson and Kernell 1983, 30). Our results indicate that quality challengers often – but certainly not always – improve their party's vote share. The 95% highest posterior density intervals for these offsets frequently overlap zero (11 out of 20 times for Democrats; 8 out of 20 times for Republicans). But in a typical year, the estimated offset for a quality Republican challenger on an otherwise evenly-poised race is on the order of 3 to 4 percentage points of vote share, and roughly the same for a quality Democrat. Large estimates of challenger quality are obtained for 1978, for both parties (roughly corresponding to 7 to 8 percentage points), representing the approximate peak of a not-especially-strong rise and fall in challenger quality offsets. We stress that these effects are small relative to the incumbency offsets we estimate, but, nonetheless, large enough to be decisive in an otherwise close race. We also stress that challenger quality is, no doubt, endogenous to district partisanship, with districts heavily favoring Democratic candidates less likely to attract quality Republican candidates, and vice-versa.

Presidential Elections

[8]Evidence of a partisan assymetry would be when the 95% highest posterior density interval on the sum of the Democratic incumbency offset and the (negatively-signed) Republican incumbency offset does not overlap zero.

[9]For example, see Alford and Brady (1993), Gelman and King (1990), and Ansolabehere, Snyder and Stewart (2001).

Results for our presidential elections models appear in Table 4. Two features stand out. First, the relationship between latent district partisanship and presidential elections outcomes has become considerably stronger over time; the discrimination parameter for district partisanship ranges from a low of .32 in 1964 to a maximum of .67 in 2000, with higher value appearing in the 1980s and 1990s. In addition, the implied r^2 for the presidential elections model generally increases over time, largely following the rise of the discrimination parameters, reaching levels above .90 for the 1976-2000 period. Taken together, this is evidence of the increasing partisan character of elections; in turn, this reflects the fact that at least at the district level, presidential election outcomes are more highly correlated with one another across successive elections, and with the outcomes of congressional elections.

Individual presidential elections have specific peculiarities. For instance, presidential candidates are hypothesized to receive home state effects on their vote totals back home because of personal popularity, see Lewis-Beck and Rice (1983) for the specific details.

We estimate home state offsets in all districts in the home state of a particular presidential or vice-presidential candidate (again, note that we refer to the quantity we estimate as an offset rather than an effect to make clear that we are trying to purge presidential vote of contaminants rather than trying to estimate a causal effect). When two or more of the candidates on the two major tickets are from the state, all four effects are not identified, and we drop the vice-presidential dummy variable in those years; the estimated effect in these years is an average of the two home-state effects. We evaluate the estimated home-state effects by considering a hypothetical district where the vote for the president is otherwise evenly split between the two major party candidates. While we do not have the space to engage in a long discussion of these effects, we draw the reader's attention to the fact that Carter enjoyed the largest home-state advantage (approximately 15 points), while most other candidates clearly get some boost of around 5 to 10 points. Nixon is the only candidate with a clearly negative effect.[10]

[10]The negative estimate for George H.W. Bush in 1988 masks the home-state boost for Bentsen, the Democratic vice-presidential nominee from Texas.

Year	Intercept	District Partisanship	Democrat Home State	Republican Home State	Democrat Vice-Pres Home State	Republican Vice-Pres Home State	ν_k	r^2
1952	-0.15	0.46	0.055	-0.37	0.30	-0.076	0.18	0.87
	[-0.17, -0.13]	[0.44, 0.48]	[-0.032, 0.14]	[-0.55, -0.19]	[0.15, 0.46]	[-0.15, 0.0051]	[0.16, 0.20]	[0.84, 0.90]
1956	-0.24	0.47	-0.013	-0.11	0.14	0.095	0.18	0.87
	[-0.26, -0.22]	[0.45, 0.49]	[-0.094, 0.073]	[-0.29, 0.082]	[-0.0079, 0.28]	[0.015, 0.18]	[0.17, 0.20]	[0.84, 0.89]
1960	0.052	0.38	0.47	0.019	-0.058	-	0.26	0.69
	[0.024, 0.078]	[0.36, 0.41]	[0.33, 0.62]	[-0.088, 0.12]	[-0.18, 0.062]		[0.24, 0.28]	[0.64, 0.74]
1964	0.43	0.32	0.20	-0.26	0.19	0.31	0.49	0.33
	[0.37, 0.48]	[0.27, 0.38]	[-0.017, 0.42]	[-0.83, 0.31]	[-0.16, 0.53]	[0.15, 0.47]	[0.45, 0.53]	[0.23, 0.43]
1968	-0.089	0.44	0.30	0.055	0.16	0.10	0.29	0.69
	[-0.30, 0.11]	[0.41, 0.47]	[0.069, 0.53]	[-0.054, 0.16]	[-0.27, 0.60]	[-0.085, 0.30]	[0.27, 0.32]	[0.62, 0.74]
1972	-0.54	0.38	0.62	0.31	-	-0.11	0.38	0.51
	[-0.57, -0.50]	[0.34, 0.42]	[0.083, 1.14]	[0.18, 0.43]		[-0.36, 0.14]	[0.35, 0.40]	[0.44, 0.58]
1976	0.091	0.45	0.63	-0.23	0.19	0.091	0.13	0.92
	[0.077, 0.10]	[0.43, 0.46]	[0.48, 0.78]	[-0.30, -0.15]	[0.038, 0.34]	[-0.062, 0.24]	[0.12, 0.15]	[0.90, 0.94]
1980	-0.14	0.54	0.48	-0.11	0.23	-0.07	0.17	0.91
	[-0.16, -0.12]	[0.52, 0.56]	[0.29, 0.66]	[-0.18, -0.037]	[0.037, 0.43]	[-0.16, 0.022]	[0.16, 0.19]	[0.89, 0.93]
1984	-0.38	0.55	0.11	-0.066	-0.075	0.28	0.093	0.97
	[-0.40, -0.36]	[0.53, 0.56]	[0.027, 0.21]	[-0.11, -0.024]	[-0.12, -0.028]	[0.17, 0.41]	[0.078, 0.11]	[0.96, 0.98]
1988	-0.16	0.54	0.025	0.40	-	-0.14	0.10	0.96
	[-0.18, -0.14]	[0.53, 0.56]	[-0.059, 0.10]	[0.28, 0.52]		[-0.23, -0.051]	[0.09, 0.12]	[0.95, 0.97]
1992	0.14	0.52	0.41	0.04	0.15	-0.012	0.15	0.92
	[0.13, 0.16]	[0.51, 0.54]	[0.24, 0.58]	[-0.029, 0.11]	[0.013, 0.29]	[-0.11, 0.087]	[0.14, 0.16]	[0.91, 0.94]
1996	0.24	0.62	0.33	-0.23	0.057	0.13	0.071	0.99
	[0.23, 0.24]	[0.61, 0.63]	[0.21, 0.45]	[-0.34, -0.12]	[-0.066, 0.18]	[0.092, 0.18]	[0.059, 0.084]	[0.98, 0.99]
2000	0.082	0.67	0.13	-0.17	0.14	-0.46	0.13	0.96
	[0.068, 0.096]	[0.66, 0.69]	[-0.022, 0.29]	[-0.22, -0.11]	[0.026, 0.26]	[-0.74, -0.16]	[0.12, 0.14]	[0.96, 0.97]

Table 4: Posterior Summaries, Presidential Elections Model. Cell entries are the posterior means, 95% credible intervals in brackets. Dependent variable in all years is the log-odds of the Democratic share of the two-party presidential vote; see equation 4. All four home state effects are not jointly identified where two or more of the presidential and/or vice-presidential candidates are from the same state; in these cases the vice-presidential effect is omitted.

Extension: A Model of District Preferences

So far, we have outlined a model for district partisanship based on demographic and electoral returns data. However, for some purposes, this may not be enough: scholars might want to explicitly examine district *preferences* to, say, study representation (Bartels 2002). Our model can accommodate such a request by incorporating additional indicators measuring ideology. Here, we use survey data aggregated to the district level to provide a measure of ideology. While normally the National Election Study (or other national probability samples) provide inadequate sample sizes per district for meaningful analysis (recall our discussion of the Miller-Stokes problem), in 2000, work done by Knowledge Networks and the Annenberg National Election Study provided excellent within district coverage. Clinton (2006) takes the liberal-conservative self-identification measure from each survey and merges these data and aggregates to the level of Congressional district, providing the mean liberal-conservative position, the standard deviation of those responses and the numbers of respondents per congressional district. We note here that we have coverage over 432 districts with an average sample size of 232 respondents per district, additional details about the data (including question wording) are provided in the on-line appendix. This survey-based measure correlates with 2000 Presidential vote at -0.78, suggesting a strong relationship between the average liberalism of the district measured by surveys and Presidential vote.

In order to incorporate the survey data into our model, we proceed as follows. For the 1992-2000 data, we let w_i be the mean liberal-conservative position in the district, and $\sigma^2_{w_i}$ be the sampling variance of w_i, equal to the variance of the w_i divided by the sample size in district i, n_i. The mean survey response is modeled as a function of district partisanship in 2000, i.e., $w_i \sim N(\eta - x_i, \sigma^2_{w_i})$, where η is an intercept parameter to be estimated. Note that the factor loading or discrimination on district partisanship is implicitly set to -1.0. In this way we are letting the information in the survey data contribute heavily to the substantive content of the recovered preference measures, giving our measure more construct validity as a measure of "district ideology" than relying solely on district level vote shares.[11] For that reason, we refer to this quantity of interest as "district preferences"

[11] This type of restriction is common in confirmatory factor analysis, where setting the loading of

because it more directly taps underlying ideology via the survey data. Otherwise, the model is identical to the model for district partisanship that we presented earlier.

Because the survey data is strongly correlated with vote outcomes (see above), our measure of district preferences is extremely similar to our measure of district partisanship. For example, the posterior means of the district preferences and district partisanship measures correlate at 0.997, suggesting that according to this model, aggregate district partisanship and preferences are extremely strongly related—even if the micro-level relationship is far weaker. We wish to stress, however, that the strong relationship between our two estimates does not make this additional measure a superfulous exercise. First, the survey data means that the substantive content of the measures differs. Additionally, the fact that the posterior means do not change very much largely stems from the fact that in the 1990s the survey-based ideology measure is very highly correlated with the vote-based measures. Additionally, adding another source of information boosts reliability, reducing ex-post uncertainty about each district's partisanship. The interested reader is referred to the online appendix for graphs comparing our latent trait to the survey data, they show the strong relationship one would expect given the above discussion.

Conclusion

Our pattern of results should provide reassurance to researchers who have used district level presidential vote shares as a proxy for district level partisanship. In the 1990s, presidential vote appears to be an excellent proxy for district level partisanship, as congressional election outcomes and presidential election outcomes have become more highly correlated over the period we analyze

indicator j on factor k makes indicator j a "reference item" for factor k, and, for our one dimensional latent variable model, also solves the scale indeterminacy problem (e.g., Bollen 1989, 238-247). With the restriction on the factor loading/discrimination parameter, the only identification issue is invariance to translation (i.e., intercept-shifts). To solve this problem we employ the post-processing strategy outlined in the Appendix, although in this case we only need to adjust intercept parameters throughout the model.

(1952-2000). In turn, this is consistent with the growing nationalization of elections noted by other scholars (e.g., Brady, Fiorina and D'Onofrio 2000). That is, while we find considerable variation in partisanship across districts, district level vote shares in presidential and congressional elections are more tightly tied to partisanship than in previous years. Net of the effects of incumbency and challenger quality, congressional election outcomes are increasingly driven by the same forces that determine presidential election outcomes, and vice-versa.

We again stress the flexibility of the model. So as to generate good coverage across districts and elections, we use vote shares in congressional and presidential elections as indicators of district level partisanship, with district level census aggregates providing additional information. Nothing precludes us from adding other indicators of district partisanship to the model; as mentioned above, these other indicators might include state or local level election outcomes, senate election outcomes, votes on ballot initiatives, party registration data, or survey data, aggregated to districts. Replicating our model and analysis at other levels of aggregation is another promising line of work: recovering estimates of state-level or county-level partisanship seems feasible and useful.

Finally, we concede that other researchers might have other ideas as to the nature of district partisanship and hence how to measure that concept. Our conceptualization and operationalization is based on the normal vote and so has strong, theoretical micro-foundations and a long lineage in the American politics literature. But we can imagine other researchers preferring an approach that relied more heavily on a indicators of policy preferences *per se* or ideological self-placements (say, from survey data, as we did in section), or voting on ballot initiatives or referenda. These extensions are to be encouraged, and are easily implemented with our modeling approach, a rigorous yet flexible methodology for combining disparate sources of information with which to estimate district partisanship.

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