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

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Studies of American politics, particularly legislative politics, rely heavily on measures of the partisanship of a district. We develop a measurement model for this concept, estimating partisanship in the absence of election-specific, short-term factors, such as national-level swings specific to particular elections, incumbency advantage, and home-state effects in presidential elections. We estimate the measurement model using electoral returns and district-level demographic characteristics spanning five decades (1952–2000), letting us assess 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 partisanship measure with an analysis of congressional roll-call data. The model is easily extended to incorporate other 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: estimating 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. In this paper we provide such a measure.

District Partisanship: Theory and Measurement

Our approach rests upon decomposing voting behavior into long-term and short-term components, an approach with a long and distinguished lineage in political science, dating at least to Converse's (1966) concept of the "normal vote." The normal vote grows directly out of the Michigan team's micromodel of voting behavior, in which party identification generates stability in voting behavior, subject to election-specific responses to candidates and issues. The normal vote is the aggregate-level analog of enduring micro-level political loyalties and rests on decomposing vote shares into two components: a long-term, stable component driven by party identification (the normal vote), and a short-term rate of defection generated by the specifics of the campaign and the candidates

*We thank Chris Achen, Daniel Bergan, David Brady, Jay Goodliffe, 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.

The Journal of Politics, Vol. 70, No. 3, July 2008, Pp. 736–753 doi:10.1017/S0022381608080729
 ISSN 0022-3816

(Converse 1966, 14).[1] Our measure of district partisanship is analogous to Converse's normal vote, except that Converse operationalized the concept with survey data on voting and party identification, whereas our measure relies on a mix of aggregate indicators (and in the extensions discussed in the online appendix at www.journalofpolitics.org, survey data). Like Converse, we seek to identify the more-or-less stable partisan force driving election outcomes. As such, our measure of district partisanship provides an estimate of how Democratic a given district would be absent the impact of a given campaign (election-specific partisan swings, incumbency, etc.). That is, without any short-term forces, how Democratic or Republican would a given district be?

We also want to be clear about what it is we are *not* measuring. Measurement models use observed variables to make inferences about latent variables. Consequently, the latent variable inherits its substantive content from the indicators available for analysis and our modeling assumptions. 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). Given that we have data on vote shares, but not, say, survey data, 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, using only vote shares (as opposed to, say, survey data on individual preferences), we take a conservative approach and interpret our measure as district partisanship rather than district ideology. However, in the online appendix, we augment our model with survey measures of ideology to demonstrate one approach to validly estimating district ideology. Likewise, we will resist stating that our model provides valid estimates of district preferences, such as the relative locations of each district's median/mean voter. Our measurement model does not operationalize a structural voting model that maps from voter ideal points on a policy continuum to district-level vote shares. While it would no doubt be worthwhile to investigate such a model (e.g., 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 limitations.

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 district opinion. But the data they had for any individual congressional district was extremely sparse; their study used a national probability sample that 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.[2] 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); see Stoker and Bowers (2002) for an elaboration. 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.[3]

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-environmental interest groups and the size of various coal producer

[1]The majority of work using 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 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.

[2]Clinton (2006) is a rare exception, exploiting the unusual confluence of two large studies of the American electorate in 2000 (the Annenberg National Election Survey and a large panel of online respondents from Knowledge Networks) to yield estimates of district ideology with an average of 232 respondents per district.

[3]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 U.S. census and electoral returns).

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, but dubious concept validity.

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 utilizing vote shares can be assumed to have high validity. But there are shortcomings and trade-offs 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 confront the reality that they are using a *proxy* for the underlying variable of interest? And even more fundamentally, researchers ought to deal with the fact 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. Cast in this light, we view election results as merely indicators of an unobserved variable of substantive interest.

The shortcomings of the approaches just surveyed suggests that we need a measurement strategy for district partisanship that delivers the concept validity provided by election returns, but that also filters out the impact of short-term factors. And as we show below, this is precisely what our model does. We also 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 Synder 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, consistent with the notion that more information about the quantity being measured is better.

A Statistical Model for Latent District Partisanship

We model district-level election outcomes as a function of a more-or-less stable latent trait, specific to each congressional district. The latent trait is considered constant until redistricting intervenes; typically this happens once per decade. Election outcomes are also partially determined by election-specific short-term forces, generating vote shares either greater or smaller than that we would expect given the district's partisanship. 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 many time-varying covariates at the district level. Variation in election outcomes only supplies 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 time-varying, 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, but these assumptions seem too strong. Therefore 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.

Our statistical model has 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 $i = 1, \dots, n$ index districts, $x_i \in \mathbb{R}$ be the latent partisanship of district i 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

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

where $\alpha \in \mathbb{R}^k$ 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.[4] The assumptions of normality and conditional independence and homoskedasticity for x_i given demographic characteristics $\mathbf{z}_i$ are standard, if tacit, in measurement models.[5]

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., macroeconomic 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 reelection, 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 nonsouthern state (we make no distinction between open seats in southern and nonsouthern 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.[6]

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:

$$y_{ik}^*|x_i \overset{\text{iid}}{\sim} N(\mu_{ik}, \nu_k^2) \tag{4}$$

where

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

[4]Our assumption that x_i is unidimensional is supported by both theory and the data. From a theoretical perspective, district partisanship (like normal vote) runs from a purely Republican district to a purely Democratic one, with each district in between these two types. Empirically, principal components analysis of the data overwhelmingly supports a unidimensional construct, see the appendix for further details.

[5]Moreover, since x_i is unobserved, it is not straightforward to check these assumptions. The conditional independence assumption could be replaced with some kind of spatial dependence structure, although we are reasonably confident that the set of demographic predictors $\mathbf{z}_i$ assembled for analysis does generate conditional independence among the x_i; we would be less confident in this assertion if $\mathbf{z}_i$ was a less exhaustive set of indicators.

[6]Because district partisanship is fixed over a decade, the (say) 1996 vote returns influence the estimate of district partisanship, which in turn might influence the 1992 incumbency offset parameter, so what we provide is *not* an estimate of incumbency advantage as conventionally understood. Rather, we are trying to remove the short-term effect of incumbency so we can estimate the underlying latent partisanship more accurately.

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 offsets, i.e., dummy variables for whether the Democratic and Republican presidential and vice-presidential candidates hail from the state in which district i is located.

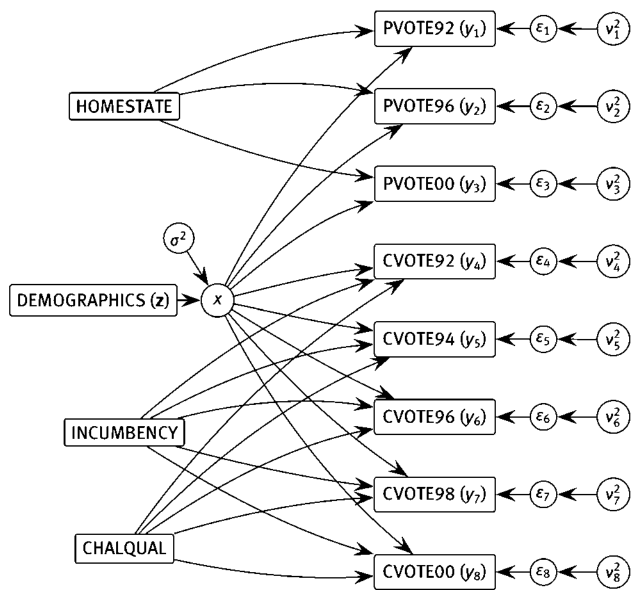
Finally, a brief word on redistricting is also warranted. Most redistricting takes place in the wake of the decennial census, in time for the election in the "2" years (1982, 1992, etc.). But a considerable amount of redistricting occurs at other times (e.g., the Texas redistricting prior to the 2004 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. To resolve this problem, we treat the district prior to redistricting as one district, and the district post-redistricting as a separate district, each with its own distinct latent trait.[7] 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.

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. Election outcomes are akin to multiple indicators of district partisanship, x_i, and are treated as conditionally independent of each other given x_i 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 aggregates about district partisanship via equation (1). As Figure 1 demonstrates, demographic characteristics give rise to district partisanship, and then that district partisanship is used to model the election outcomes.[8]

[7]To determine whether or not a district has been redistricted, 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.

[8]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, $\mathbf{z}_i$.

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



Bayesian Estimation and Inference

Our model is a structural equations model (SEM), as they are known in psychometrics. While many political scientists are most familiar with estimation of these models using covariance structure methods—via software such as LISREL, AMOS, EQS—we adopt a Bayesian approach for estimation and inference.

Advantages of a Bayesian Approach

First, a primary goal of our analysis is *measurement*: i.e., to produce estimates of district partisanship, along with rigorous assessments of uncertainty (e.g., standard deviations, confidence intervals), since absent uncertainty assessments, the point estimates of district partisanship can not be meaningfully compared. We also require uncertainty assessments when we use our measure in subsequent analysis. Uncertainty over levels of district partisanship ought to propagate into assessments of the effects of district partisanship when it appears as a predictor of political outcomes (e.g., in models of election outcomes, legislative behavior, and the like).

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; the resulting latent trait estimates are known as "factor scores" in the factor analysis literature (e.g., Mardia, Kent, and Bibby 1979). Producing uncertainty estimates for factor scores in an analysis of covariance structure framework poses both statistical and computational challenges and is seldom done (cf. Jöreskog 2000). In our analysis, levels of district-level partisanship are of primary interest, and relegating them to the status of nuisance parameters is problematic (for a similar point, see Aldrich and McKelvey 1977).

However, working in a Bayesian framework, latent district partisanship is treated no differently from any other model parameter. We compute the joint posterior density of *all* model parameters, recognizing the fact that in measurement models it is almost always the case that uncertainty in measurement parameters generates uncertainty in the latent traits, and vice-versa; for a recent elaboration of this point, see Dunson, Palomo, and Bollen (2007). Of course, working with the joint posterior density of all parameters comes at some computational cost: with one latent district partisanship parameter for each congressional district and numerous other parameters to estimate, there are many parameters in our model, and the resulting posterior density is high dimensional. Happily, one of the benefits of the Bayesian approach is that we can exploit Markov chain Monte Carlo (MCMC) algorithms that visit locations in the parameter space with relative frequency proportional to the posterior probability of each location. That is, let run long enough, each iteration of the MCMC algorithm produces a sample from the joint posterior density. We summarize these samples so as to make inferences about the parameters. See Jackman (2000) for a review; further details appear in the appendix.

Once we possess arbitrarily many samples from the posterior density, inference for the latent traits is straightforward. For example, we can assign probabilities to politically relevant statements such as "district i is more Republican than district j," "district i is the most Republican district in the country," "district i is the most Democratic district held by a Republican," or "district i is the median district," simply by noting the proportion of MCMC iterates in which a particular assertion about the latent traits is true. This is a remarkably simple way to perform inference for the latent traits, relative to the work one would have to do to obtain such inferences with the output of factor analytic/covariance-structure approaches.

Perhaps the chief advantages of the Bayesian approach lie in its flexibility and extensibility. Take the case of missing data arising from uncontested seats. This is a significant issue in our data. In every decade we analyze, at least a quarter of the districts have at least one uncontested election, and in the 1980s the corresponding figure is 45%. 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. Indeed, the fact that an incumbent was reelected unopposed is informative about underlying district partisanship. We model uncontested elections as censored data, an approach used by Katz and King (1999) in their analysis of British House of Commons election returns. That is, if a Democratic incumbent successfully runs unopposed then we model the unobsered vote share via equation (2), subject to the constraint that the two-party Democratic vote share is greater than 50% (i.e., that $y_{ij} > .5 \Leftrightarrow y^{\star}_{ij} > 0$) 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 nonstandard) 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.[9]

Priors Densities over Parameters

In any Bayesian analysis it is incumbent on the researcher to report what prior densities are employed. Recall that we impose the identifying restriction that the latent x_i have mean zero and variance one. With this restriction the model parameters are identified and we use vague priors, 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 inverse-Gamma priors for the variance parameters. With these normal and inverse-Gamma priors, and the normal distributions assumed for the hierarchical structure over the latent district partisanship

[9]As an additional robustness check, we have also reestimated our model using both an unconstrained imputation technique (e.g., imputations without the constraint) and treating election outcomes in uncontested seats as missing at random. The substantive results generally remain similar.

(equation 1) and the observed vote shares (equations 2 and 4), the resulting posterior densities for all model parameters are in the same family as their prior (normals and inverse-Gammas), ensuring that the computation for this problem is rather simple (a case of *conjugate* Bayesian analysis); see the appendix for further details.

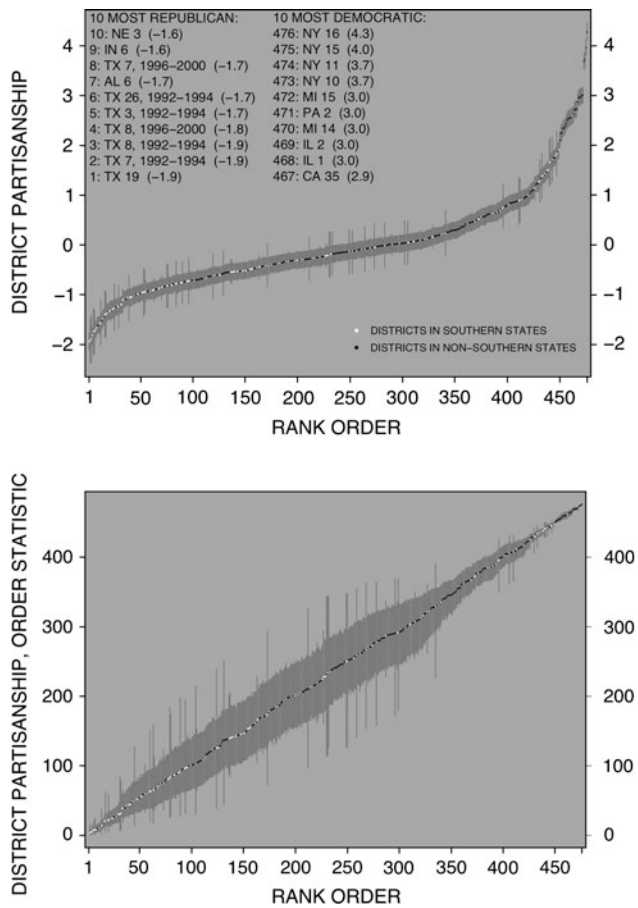
Results: Measuring District Partisanship

Each congressional district's latent partisanship 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 induce a posterior density over the order statistics of the x_i, letting us assess the extent to which we can a distinguish districts from one another. Graphical summaries appear in Figure 2.

The top panel of Figure 2 displays point estimates of each district's latent partisanship (the mean of the marginal posterior density for 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 1,000 Gibbs samples thinned from 250,000 samples. Similar graphical summaries can be constructed for earlier years; space constraints restrict this detailed examination to the most recent decade in our analysis, the 1990s. The actual numbers in the top panel attaching to the estimate are arbitrary; recall that the x_i are only defined up to scale and location, and the identifying restriction we employ is that the x_i have mean zero and 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 partisanship has a standard deviation of 1.0 while the average posterior standard deviation for the district partisanship estimates 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 districts in the data. Some insight into the consequences of

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



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., MI-7 and PA-4), respectively. Our best guesses (posterior means) for these districts' latent partisanship are -.26 and -.09, and the probability that PA-4 is more Democratic than MI-7 is .91. Finer distinctions in the middle of the distribution of latent district partisanship are made with less certainty, and will fall short of traditional standards 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, Figure 2 shows the effect of redistricting and uncontestedness: both increase our uncertainty of the district's partisanship. Notice that some districts have much wider credible intervals than others, reflecting the increased uncertainty stemming from having fewer elections contributing data for those districts.

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 consistent and more heavily Democratic voting patterns than the Republican districts exhibit extreme pro-Republican voting patterns. For instance, in the 10 most Democratic districts, Clinton averaged 89% of the two-party vote share in 1992 and 1996; in the 10 most Republican districts, Clinton averaged 30%, while in the remaining 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 second most Democratic seat in our analysis of

FIGURE 3 Density plots of district partisanship estimates (means of marginal posterior densities), 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 across districts.

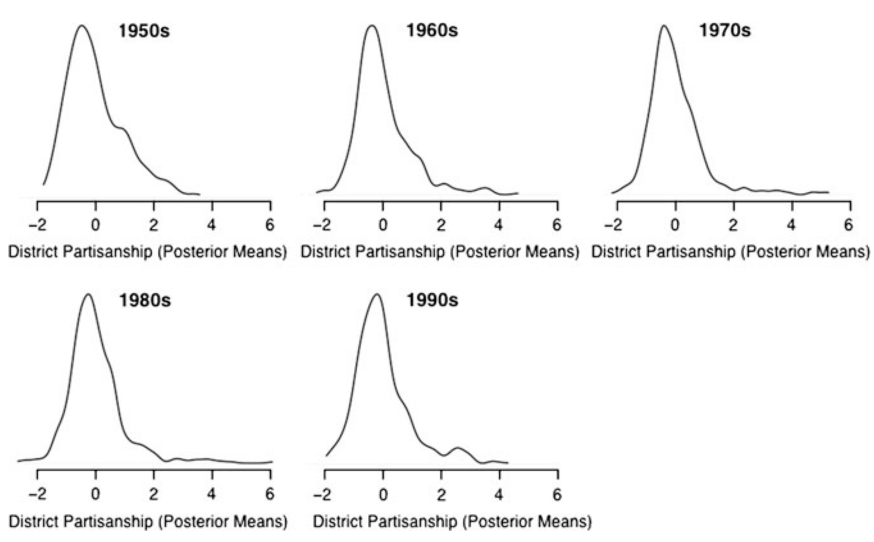


Table 1 Posterior Summaries, Relationships Between Demographic Characteristics and Latent District Partisanship. Cell entries are posterior means; 95% credible intervals shown in brackets. Median income is median family income; population density is population per mile^2; South is defined as the 11 states of the former confederacy. See Adler (2003) for additional details.

	1952-1960	1962-1970	1972-1980	1982-1990	1992-2000
Intercept	7.94 [3.96, 11.87]	27.13 [20.17, 35.58]	31.16 [21.67, 41.94]	22.88 [17.90, 29.88]	16.94 [13.17, 21.22]
Log Proportion Aged 65+	−0.71 [−1.07, −0.34]	−0.79 [−1.06,−0.53]	−0.40 [−0.67, −0.14]	0.038 [−0.18, 0.26]	0.47 [0.28, 0.65]
Log Proportion Blue Collar	−0.24 [−0.58, 0.11]	0.33 [−0.088, 0.74]	0.24 [−0.085, 0.57]	−0.16 [−0.39, 0.077]	−0.071 [−0.26, 0.12]
Log Proportion Foreign Born	−0.05 [−0.16, 0.05]	0.33 [0.22, 0.44]	0.11 [0.0069, 0.21]	0.08 [−0.0075, 0.17]	0.20 [0.13, 0.28]
Log Median Income	−1.18 [−1.60, −0.72]	−2.62 [−3.14, −2.11]	−2.70 [−3.27, −2.12]	−1.88 [−2.23, −1.52]	−1.05 [−1.40, −0.68]
Log Population Density	0.14 [0.087, 0.20]	0.17 [0.13, 0.21]	0.27 [0.22, 0.32]	0.19 [0.14, 0.23]	0.22 [0.18, 0.26]
Log Proportion Unemployed	0.34 [0.10, 0.58]	0.57 [0.28, 0.86]	0.48 [0.19, 0.75]	0.60 [0.37, 0.85]	0.85 [0.59, 1.14]
Log Proportion Black	0.12 [0.045, 0.20]	0.12 [0.058, 0.18]	0.089 [0.022, 0.16]	0.066 [0.0088, 0.12]	0.094 [0.035, 0.15]
South (dummy)	0.49 [0.0095, 0.98]	−0.36 [−0.87, 0.11]	−0.14 [−0.61, 0.28]	−0.27 [−0.62, 0.074]	0.14 [−0.15, 0.43]
Log Proportion Black x South	0.23 [0.043, 0.42]	0.12 [−0.074, 0.32]	0.0088 [−0.17, 0.18]	0.14 [0.0083, 0.27]	0.30 [0.19, 0.40]
Majority-Minority	–	–	–	2.05 [1.61, 2.47]	0.93 [0.56, 1.31]
σ_x	0.75 [0.69, 0.80]	0.70 [0.65, 0.75]	0.69 [0.64, 0.73]	0.56 [0.53, 0.61]	0.50 [0.47, 0.54]
r_x^2	0.44 [0.36, 0.52]	0.51 [0.43, 0.58]	0.53 [0.46, 0.59]	0.68 [0.63, 0.72]	0.75 [0.71, 0.78]

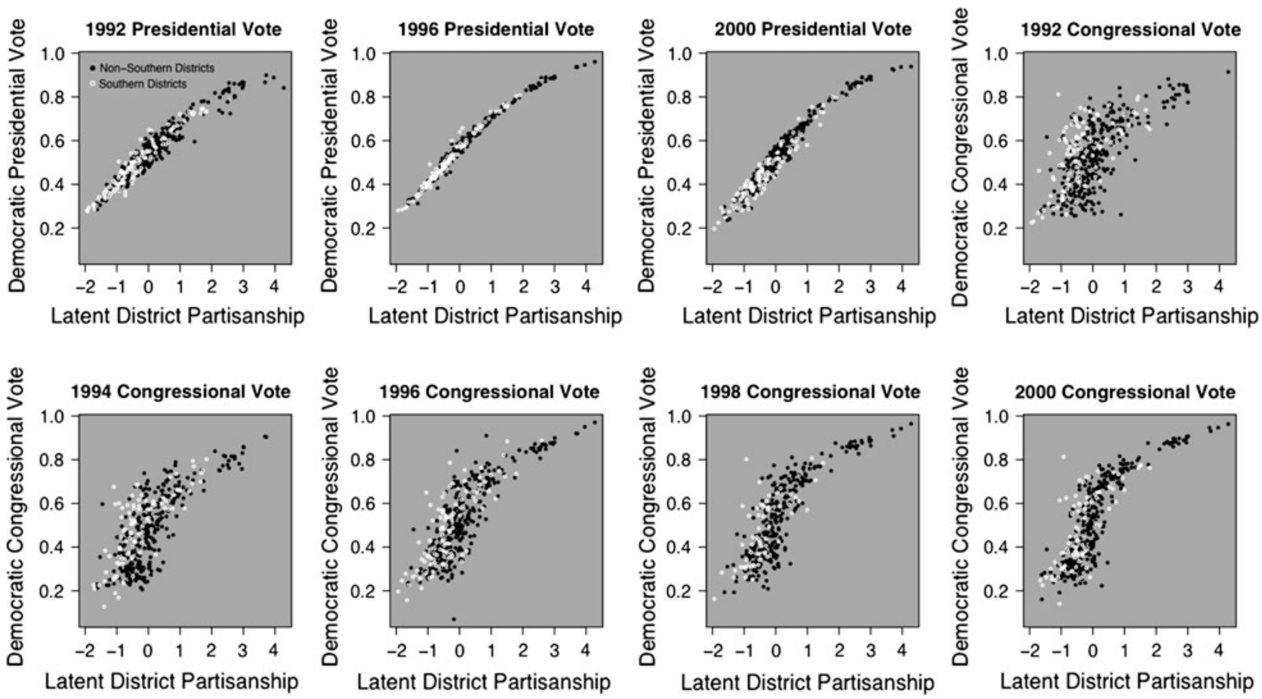
the 1990s; it has been held by Charlie Rangel since 1970 and was 47% black and 45% Hispanic origin in the 1990 Census. NY-10 and NY-11, both in Brooklyn, are the third and fourth most Democratic seats in our analysis, with black populations of 60% and 75%, respectively. Districts in central Philadelphia (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 10 most Democratic districts in the 1990s. The correlation between the percentage of the district's population that is African American 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 online 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 nonlinearities 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/nonsouth).

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 (again, see the appendix for similar displays from other decades). The legislative ideal points are generated with a one-dimensional spatial voting model fit to all nonunanimous 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

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.

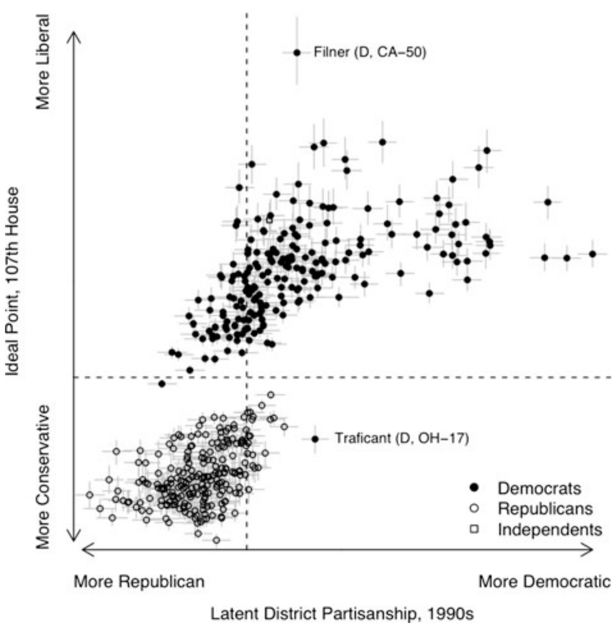


deaths and retirements), we display the ideal point of the legislator with the lengthier voting history. Both legislative ideal points and district partisanship are estimated with uncertainty, indicated with the vertical and horizontal lines covering 95% credible intervals, respectively.

In general, there is a strong relationship between district partisanship and legislative ideal points; the correlation between the two sets of point estimates is 0.73. The within-party correlations are also moderate to large: 0.47 among Republicans, and 0.52 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 within the Congress (e.g., McCarty, Poole, and Rosenthal 2003). The pattern in Figure 5 is consistent with a party-pressure hypothesis (e.g., Synder 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. Put differently, there is much more partisan polarization in the roll-call voting than in the corresponding estimates of district partisanship.

Further, suppose we break the distribution of district partisanship at its mean value of zero, labeling districts to the left of this point ''Republican'' districts and districts to the right as ''Democratic.'' Figure 5 reveals that there are 28 Democrats and six Republicans (13% and 3% of their respective caucuses) who represent districts that, by this criterion, should be represented by the other party. What can we say about these districts? First, all but two of these districts were represented by incumbents in the 107th Congress, many of them long-time incumbents. While most are still serving in Congress, nine of these 31 incumbents had been defeated by 2007, and nearly all of these defeated members had their loss attributed to their fit with the district by sources like

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. The dotted vertical and horizontal lines show the mean of the respective measures.**



the *Almanac of American Politics* (Barone Cohen 2006; henceforth, *AAP*). And of the members still serving, when they retire, the seat is likely to change partisan hands. Take the case of Gene Taylor (D-MS): the *AAP* argues that if he were to retire, "Republicans would have an excellent chance to capture this seat" (*AAP*, 957). Indeed, of the members who have retired (a number of them were strategic retirements prompted by redistricting), in all but one case party control of the seat flipped (the exception is Ted Strickland who retired to become governor of Ohio in 2006 and was replaced by Democrat Charles Wilson; undoubtedly the corruption scandal in the Ohio Republican Party played a role). Furthermore, nearly all of these members are described as being political moderates and mavericks out of step with their national parties and more in line with their districts. In fact, 80% of the members with mismatched seats are described by the *AAP* as "moderate," "centrist," "conservative Democrat," "straddles both parties," and so forth. Indeed, Ralph Hall, one of the Democrats representing a Republican district, switched parties in 2004. Of the handful of members described as more typical partisans, nearly all of them are described by the *AAP* as focusing on the "grassroots" or other issues important to their district, suggesting that they win by promoting service to the district. Taken as a whole, this analysis suggests even more validity for our measure of district partisanship.

Since our main purpose is to measure and model district partisanship, we defer a more detailed analysis of representation or polarization for another day; a complete list of "mismatched" members of Congress and their districts appears in the online appendix. For now we simply note that the the relationship between our measure of district partisanship and election returns is very strong (particularly 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.

Social-Structural Correlates of District Partisanship

Table 1 presents parameter estimates of the demographic component of the model (equation 1), where latent district partisanship is modeled as a function of these census 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.[10]

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

[10]Moreover, the demographic variables we use come from Adler's (2003) dataset on Congressional district demographics.

the proportion of African Americans in the population (outside of the South) is always unambiguously positive, and averages about .10. In each decade, the distribution of African Americans throughout congressional districts is skewed to the right: i.e., the median African American proportion is consistently around .10, but attains a maximum 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 district partisanship of approximately 15% of a standard deviaton, net of other factors. Additionally, the coefficient for majority-minority districts is large and statistically significant, indicating the even controlling for the fact that majority-minority districts contain a high percentage of African Americans, such districts are even more Democratic.

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 to the 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. Overall, the main result we stress from this section is the strong and sensible relationship between the demographics and our district partisanship measure.

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 .65 in 1954 to a high of .90 in 2000. The parameters tapping the effects of district partisanship range from a low of .26 in 1972 to .62 in 1956. 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 nonlinear 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 elected office and 0 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 all Republicans in the 1950s are much smaller; in fact, for Southern Republicans prior to the 1970s (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 incumbency offsets being larger for one party than the other.[11] There is some regional asymmetry, 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.[12]

[11]Evidence of a partisan asymmetry 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.

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

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 x Dem Incumbency
1952	0.053 [-0.031, 0.14]	0.50 [0.45, 0.55]	0.077 [-0.043, 0.19]	−0.22 [−0.32, −0.11]	0.95 [0.80, 1 09]
1954	0.65 [0.47, 0.83]	0.58 [0.50, 0.67]	−0.37 [−0.59, −0.15]	−0.58 [−0.78, −0.37]	0.99 [0.76, 1.19]
1956	0.31 [0.11, 0.53]	0.62 [0.54, 0.71]	−0.22 [−0.48, 0.029]	−0.29 [−0.51, −0.052]	1.17 [0.95, 1.40]
1958	0.27 [0.18, 0.36]	0.37 [0.31, 0.42]	0.38 [0.26, 0.51]	−0.28 [−0.39, −0.17]	0.87 [0.70, 1.04]
1960	0.20 [0.053, 0.33]	0.46 [0.39, 0.52]	0.19 [0.036, 0.37]	−0.23 [−0.40, −0.066]	0.73 [0.58, 0.89]
1962	0.11 [0.038, 0.19]	0.32 [0.28, 0.36]	0.25 [0.15, 0.34]	−0.40 [−0.49, −0.30]	0.48 [0.36, 0.60]
1964	0.34 [0.25, 0.43]	0.33 [0.29, 0.38]	0.30 [0.19, 0.40]	−0.40 [−0.51, −0.29]	0.10 [−0.012, 0.21]
1966	0.061 [−0.028, 0.15]	0.36 [0.33, 0.40]	0.28 [0.17, 0.39]	−0.57 [−0.67, −0.45]	0.32 [0.21, 0.43]
1968	0.22 [0.12, 0.32]	0.40 [0.36, 0.45]	0.15 [0.017, 0.28]	−0.67 [−0.78, −0.55]	0.46 [0.33, 0.59]
1970	0.10 [0.0016, 0.20]	0.37 [0.32, 0.42]	0.51 [0.39, 0.64]	−0.40 [−0.51, −0.27]	0.38 [0.24, 0.53]
1972	0.08 [−0.0039, 0.17]	0.26 [0.22, 0.30]	0.59 [0.47, 0.70]	−0.61 [−0.73, −0.49]	0.015 [−0.13, 0.15]
1974	0.40 [0.29, 0.51]	0.32 [0.27, 0.37]	0.43 [0.31, 0.57]	−0.55 [−0.69, −0.41]	0.12 [−0.023, 0.26]

Year	South x Repub Incumbency	Dem Challenger Quality	Rep Challenger Quality	ν_j	r^2
1952	0.023 [−0.46, 0.47]	-	-	0.32 [0.29, 0.35]	0.81 [0.77, 0.84]
1954	0.06 [−0.36, 0.50]	-	-	0.52 [0.48, 0.57]	0.65 [0.59, 0.70]
1956	−0.022 [−0.47, 0.41]	0.023 [−0.16, 0.20]	0.12 [−0.11, 0.39]	0.55 [0.50, 0.59]	0.65 [0.59, 0.71]
1958	−0.021 [−0.26, 0.22]	0.13 [0.032, 0.23]	−0.13 [−0.26, 0.0068]	0.29 [0.27, 0.32]	0.80 [0.77, 0.84]
1960	−0.12 [−0.48, 0.23]	0.031 [−0.13, 0.18]	−0.075 [−0.21, 0.07]	0.40 [0.37, 0.43]	0.73 [0.68, 0.76]
1962	0.15 [−0.14, 0.40]	–	–	0.29 [0.26, 0.32]	0.79 [0.75, 0.83]
1964	0.076 [−0.13, 0.28]	0.091 [−0.0087, 0.19]	−0.13 [−0.25, −0.010]	0.30 [0.27, 0.32]	0.78 [0.74, 0.81]
1966	0.15 [−0.027, 0.31]	0.044 [−0.062, 0.15]	−0.19 [−0.28, −0.11]	0.23 [0.21, 0.26]	0.88 [0.85, 0.90]
1968	0.082 [−0.083, 0.24]	0.15 [0.047, 0.26]	−0.10 [−0.21, 0.012]	0.30 [0.27, 0.33]	0.85 [0.82, 0.87]
1970	0.014 [−0.14, 0.18]	0.10 [−0.017, 0.22]	−0.11 [−0.23, 0.012]	0.31 [0.29, 0.34]	0.83 [0.80, 0.86]
1972	−0.26 [−0.43, −0.099]	0.20 [0.059, 0.33]	−0.21 [−0.33, −0.091]	0.35 [0.33, 0.38]	0.78 [0.75, 0.81]
1974	−0.18 [−0.32, −0.037]	0.18 [0.06, 0.29]	−0.09 [−0.27, 0.098]	0.37 [0.34, 0.40]	0.76 [0.72, 0.79]

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.**

Year	Intercept	District Partisanship	Democratic Incumbency	Republican Incumbency	South x Dem Incumbency
1976	0.44 [0.34, 0.54]	0.37 [0.33, 0.42]	0.29 [0.17, 0.40]	−0.82 [−0.96, −0.68]	0.094 [−0.028, 0.22]
1978	0.22 [0.098, 0.34]	0.33 [0.27, 0.38]	0.47 [0.33, 0.61]	−0.79 [−0.96, −0.63]	0.13 [−0.020, 0.29]
1980	0.09 [−0.03, 0.21]	0.43 [0.38, 0.48]	0.48 [0.34, 0.63]	−0.66 [−0.81, −0.51]	0.028 [−0.095, 0.15]
1982	0.19 [0.093, 0.28]	0.36 [0.31, 0.42]	0.54 [0.42, 0.66]	−0.65 [−0.78, −0.53]	0.38 [0.24, 0.53]
1984	0.021 [−0.14, 0.18]	0.38 [0.33, 0.43]	0.49 [0.32, 0.67]	−0.71 [−0.89, −0.55]	0.24 [0.10, 0.36]
1986	0.033 [−0.077, 0.14]	0.37 [0.32, 0.41]	0.70 [0.57, 0.83]	−0.65 [-0.78, −0.52]	0.29 [0.15, 0.42]
1988	0.078 [−0.085, 0.24]	0.38 [0.33, 0.43]	0.61 [0.42, 0.79]	−0.70 [−0.90, −0.51]	0.20 [0.06, 0.34]
1990	0.19 [0.056, 0.32]	0.33 [0.28, 0.37]	0.36 [0.21, 0.51]	−0.62 [−0.77, −0.46]	0.24 [0.11, 0.35]
1992	0.18 [0.11, 0.25]	0.35 [0.31, 0.39]	0.35 [0.26, 0.45]	−0.58 [−0.69, −0.48]	0.094 [−0.016, 0.20]
1994	−0.098 [−0.18, −0.024]	0.40 [0.37, 0.44]	0.42 [0.32, 0.52]	−0.54 [−0.64, −0.45]	0.063 [−0.025, 0.15]
1996	0.088 [0.0044, 0.17]	0.52 [0.48, 0.56]	0.39 [0.28, 0.50]	−0.39 [−0.49, −0.29]	0.096 [−0.031, 0.22]
1998	0.18 [0.082, 0.27]	0.52 [0.48, 0.56]	0.33 [0.23, 0.45]	−0.54 [−0.65, −0.43]	0.028 [−0.088, 0.15]
2000	0.025 [−0.078, 0.12]	0.55 [0.51, 0.59]	0.51 [0.39, 0.63]	−0.41 [−0.52, −0.30]	0.067 [−0.041, 0.17]

Year	South x Repub Incumbency	Dem Challenger Quality	Rep Challenger Quality	ν_j	r^2
1976	−0.069 [−0.25, 0.11]	0.094 [−0.039, 0.24]	−0.24 [−0.35, −0.13]	0.37 [0.35, 0.40]	0.78 [0.74, 0.81]
1978	−0.14 [−0.37, 0.10]	0.33 [0.15, 0.53]	−0.33 [−0.49, −0.16]	0.44 [0.41, 0.47]	0.72 [0.68, 0.76]
1980	−0.28 [−0.48, −0.087]	0.12 [−0.052, 0.28]	−0.16 [−0.30, −0.036]	0.39 [0.36, 0.42]	0.80 [0.77, 0.83]
1982	0.13 [−0.041, 0.30]	0.27 [0.14, 0.39]	−0.24 [−0.39, −0.094]	0.38 [0.35, 0.41]	0.77 [0.73, 0.80]
1984	−0.015 [−0.19, 0.16]	0.15 [−0.0019, 0.32]	−0.24 [−0.38, -0.11]	0.38 [0.36, 0.41]	0.81 [0.78, 0.83]
1986	0.24 [0.10, 0.39]	0.31 [0.17, 0.45]	−0.21 [−0.36, -0.069]	0.35 [0.32, 0.38]	0.85 [0.82, 0.87]
1988	0.087 [−0.088, 0.26]	0.036 [−0.13, 0.21]	0.042 [−0.13, 0.20]	0.41 [0.38, 0.44]	0.82 [0.79, 0.84]
1990	0.15 [−0.0074, 0.29]	0.14 [−0.035, 0.33]	−0.19 [−0.35, −0.032]	0.37 [0.34, 0.40]	0.76 [0.72, 0.79]
1992	0.028 [−0.12, 0.18]	0.18 [0.033, 0.32]	−0.21 [−0.31, -0.10]	0.34 [0.32, 0.36]	0.75 [0.71, 0.78]
1994	0.047 [−0.088, 0.19]	0.049 [−0.078, 0.17]	−0.19 [−0.29, −0.096]	0.28 [0.26, 0.30]	0.85 [0.83, 0.87]
1996	0.023 [−0.077, 0.13]	0.25 [0.13, 0.37]	−0.092 [−0.24, 0.063]	0.32 [0.29, 0.34]	0.86 [0.83, 0.87]
1998	0.087 [−0.026, 0.19]	-	-	0.28 [0.26, 0.30]	0.89 [0.87, 0.91]
2000	0.069 [−0.043, 0.17]	-	-	0.29 [0.27, 0.31]	0.90 [0.88, 0.91]

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; eight out of 20 times for Republicans). But in a typical year, the estimated offset for a quality Republican challenger in an otherwise evenly poised race is on the order of three to four 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 seven to eight 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

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.[13] In addition, the 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 their own unique aspects. For instance, presidential candidates are hypothesized to receive a boost in their home states because of personal popularity, see Lewis-Beck and Rice (1983) for details. We estimate home-state offsets in all districts in the home state of a particular presidential or vice-presidential candidate. When two or more of the candidates on the two major tickets are from the same 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. Space constraints do not permit a lengthy discussion of these estimates, but we draw 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.[14]

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 (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 have become more tightly tied to partisanship over the period we study. 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

[13]The term "discrimination" parameter comes from the educational testing literature, where a test item helps us discriminate among test-subjects of higher and lower abilities; analogously, elections differ in the extent to which they convey information about varying levels of partisanship. The identifying restriction that district partisanship has a mean of zero and a standard deviation of one across districts within any given decade allows us to make these over-time comparisons about the discrimination parameters.

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

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.**

Year	Intercept	District Partisanship	Democrat Home State	Republican Home State
1952	−0.15 [−0.17, −0.13]	0.47 [0.46, 0.49]	0.023 [−0.055, 0.10]	−0.32 [−0.49, −0.15]
1956	−0.24 [−0.26, −0.22]	0.47 [0.45, 0.49]	−0.051 [−0.14, 0.042]	−0.055 [−0.25, 0.13]
1960	0.048 [0.023, 0.074]	0.39 [0.37, 0.41]	0.49 [0.36, 0.63]	0.023 [−0.087, 0.13]
1964	0.43 [0.38, 0.48]	0.32 [0.27, 0.37]	0.20 [−0.010, 0.42]	−0.24 [−0.80, 0.35]
1968	−0.084 [−0.28, 0.10]	0.45 [0.42, 0.48]	0.31 [0.074, 0.53]	0.056 [−0.049, 0.17]
1972	−0.54 [−0.57, −0.50]	0.38 [0.34, 0.41]	0.63 [0.12, 1.13]	0.30 [0.19, 0.42]
1976	0.092 [0.078, 0.11]	0.44 [0.43, 0.46]	0.62 [0.47, 0.76]	−0.23 [−0.31, −0.15]
1980	−0.14 [−0.16, −0.12]	0.54 [0.53, 0.56]	0.47 [0.29, 0.66]	−0.11 [−0.17, −0.034]
1984	−0.38 [−0.40, −0.36]	0.55 [0.53, 0.56]	0.11 [0.012, 0.20]	−0.066 [−0.11, −0.024]
1988	−0.16 [−0.18, −0.14]	0.54 [0.53, 0.56]	0.030 [−0.051, 0.12]	0.38 [0.27, 0.50]
1992	0.14 [0.13, 0.16]	0.52 [0.51, 0.54]	0.41 [0.23, 0.57]	0.042 [−0.028, 0.12]
1996	0.24 [0.23, 0.25]	0.62 [0.62, 0.63]	0.33 [0.20, 0.45]	−0.23 [−0.33, −0.12]
2000	0.081 [0.067, 0.095]	0.67 [0.66, 0.69]	0.13 [−0.017, 0.28]	−0.17 [−0.23, −0.11]

Year	Democrat Vice-Pres Home State	Republican Vice-Pres Home State	ν_k	r^2
1952	0.30 [0.15, 0.42]	−0.072 [−0.15, 0.013]	0.13 [0.11, 0.15]	0.93 [0.91, 0.95]
1956	0.17 [0.037, 0.30]	0.096 [−0.0016, 0.19]	0.18 [0.16, 0.20]	0.87 [0.85, 0.90]
1960	−0.027 [−0.13, 0.081]	-	0.24 [0.22, 0.26]	0.73 [0.69, 0.77]
1964	0.20 [−0.16, 0.53]	0.31 [0.15, 0.47]	0.49 [0.45, 0.53]	0.33 [0.22, 0.43]
1968	0.16 [−0.30, 0.62]	0.097 [−0.08, 0.28]	0.29 [0.26, 0.32]	0.70 [0.64, 0.76]
1972	-	−0.10 [−0.36, 0.16]	0.37 [0.35, 0.40]	0.52 [0.44, 0.58]
1976	0.19 [0.033, 0.34]	0.092 [−0.057, 0.25]	0.13 [0.12, 0.15]	0.92 [0.90, 0.94]
1980	0.24 [0.05, 0.43]	−0.081 [−0.17, 0.0037]	0.17 [0.15, 0.19]	0.91 [0.89, 0.93]
1984	−0.075 [−0.12, −0.026]	0.27 [0.16, 0.39]	0.096 [0.081, 0.11]	0.97 [0.96, 0.98]
1988	-	−0.14 [−0.22, −0.06]	0.10 [0.084, 0.11]	0.97 [0.96, 0.98]
1992	0.15 [0.012, 0.28]	−0.015 [−0.12, 0.086]	0.15 [0.14, 0.16]	0.92 [0.91, 0.94]
1996	0.061 [−0.066, 0.18]	0.13 [0.09, 0.18]	0.07 [0.058, 0.083]	0.99 [0.98, 0.99]
2000	0.14 [0.012, 0.25]	−0.45 [−0.74, −0.17]	0.13 [0.12, 0.14]	0.96 [0.96, 0.97]

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 microfoundations and a long lineage in the American politics literature. But we can imagine other researchers preferring an approach that relied more heavily on indicators of policy preferences per se or ideological self-placements (say, from survey data, as we do in the appendix), 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.

Manuscript submitted 28 February 2007
Manuscript accepted for publication 10 November 2007

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