# Party and Constituency:
## How constituents influence conditional party government and roll call voting

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## Introduction

This paper's title, "*Party and Constituency*," is a reference to Julius Turner's classic account, which marked the beginning of the behavioral revolution in, in his case, the study of Congress (1970 [1952]). It stands alongside the equally classic *The Congressional Party* by David Truman (1959). Both Turner and Truman achieved a great deal in studying the role of the political party in congressional politics, but they were both limited to the study of the congressional party in one arena: the (congressional) party-in-the-electorate and the (congressional) party-in-government, respectively (Key 1964).

Their concentration on one aspect of the party at a time is by far the most common way to study the political party. It can, however, be misleading, generating concepts and ideas that are unique to the particular circumstances of the single arena in which the work is transpiring. The risk is that the detailed specification of, say, the party-in-the-electorate loses its ability to integrate with the party-as-an-organization or the party-in-government. And, in any event, testing hypotheses with data drawn from a single component of the theory is certain to risk misspecification and thus lead to incorrect inferences. The project we report here is an attempt to remedy this weakness in the study of parties, at least with respect to the specific theory of political parties we engage.

In this paper, we test notions drawn from the theory of Conditional Party Government (CPG; see, e.g., Rohde, 1991; Aldrich, 1995; Aldrich and Rohde, 2000). Most of the empirical tests of this theory have been concentrated in observing patterns within the legislature, and thus studying the empirical effects of conditional party government on the party-in-the-government. This is natural in that the theory's most important derivations are about the concentration or dispersal of powers within the legislature and about the nature of policy that emerges from it. The theory of CPG, however, roots the development of the "condition" in conditional party government in the electorate (Aldrich and Rohde, 2001). We therefore continue our project studying the effects of constituency on CPG in this paper. In particular, we are interested in understanding the role of constituency preferences on the partisan affiliation of members of Congress, on the patterns of choices legislators make in casting roll call votes on the floor, and on the inter-party heterogeneity and intra-party homogeneity that results in the legislature. That is, we seek to establish how constituency opinion shapes CPG.

To do so, we explore the constituency/party and constituency/legislative behavior relationships with a series of simple models. Using party and DW-NOMINATE scores as dependent variables, we assess the performance of different combinations of demographic and issue-based survey responses as predictors over time. We then explore the relationship between the fit of our simple party model and the level of CPG in Congress. Showing this link between party/constituency fit and observed patterns of conditional party government is, we think, a first step toward tying together the party-in-the-electorate and party-in-government.

## Theory

In this paper, we will seek to explain partisan affiliations, roll call voting records, and CPG scores from the U.S. Senate using simple models consisting of state-level independent variables aggregated from two surveys, the 1988-92 Senate Election Study conducted by the American National Election Study (NES) and the Annenberg surveys of 2000 and 2004 (NAES). We then compare our results to similar models estimated using state-level aggregate characteristics derived primarily from the U.S. Census. The latter type of data is, of course, easily available for a very long time period and can be used to study other types of legislative districts.[1] Indeed, we have written such papers on the Senate (from the 1930s on) and on the House in the 1980s and 1990s (Aldrich et al 2006a, Aldrich et al 2006b). In those papers, our assumption has been that Census data serve as proxies for the political preferences and beliefs of the voters in the constituency. In this paper, we test the plausibility of that assumption.[2]

The theory is fairly straightforward. The first step in our process is that constituents i vote for either the Democratic or the Republican candidate j in an election in constituency k at time t. If we let $C_{i,j,k,t}$ denote the preferences of the constituents, and V their vote, then, the simple assumption is that preferences are translated directly into votes (plus a stochastic term, suppressed here for convenience):

$$V_{j,k,t} = f(C_{i,j,k,t}) \quad (1)$$

One assumption we seek to test is whether these typically unobserved preferences can be modeled as a function of measurable characteristics, such as those available from the Census, etc. Let $X_{i,k,t}$ denote such measures. Our assumption, then, is:

$$C_{i,k,t} = g(X_{i,j,k,t}) \quad (2)$$

While this equation cannot generally be estimated, the NES and NAES data is one of the few cases in which it possible to do so. If this estimation is satisfactory, then we can simply substitute (2) into (1). We can do so because the X's are assumable to be exogenous (at least with respect to time period t). These two equations are therefore strictly recursive, which means that the substitution is simply generating the reduced form for the model of preferences and the vote:

$$V_{j,k,t} = f(C_{i,j,k,t}) = f(g(X_{i,j,k,t})) = f'(X_{i,j,k,t}) \quad (3)$$

[1] Although we hasten to note that using Census data for US congressional or state legislative districts requires a considerably greater amount of work.

[2] While we tend to describe broadly available statewide variables as "demographic" measures, such as those from the Census, we should note that there are some narrowly political and aggregated attitudinal measures that are available quite often at least at the state level. One example is the percentage Democratic presidential vote in the state (or district for the House). We will mix these measures as appropriate. Of course, care in assuring the plausibility of such assumptions as recursivity, which we assume below, is important.

As we turn to a dataset that contains variables about both the "inside" and the "outside" of Congress, we can begin to explain representation – that is, the connection between state-level outcomes and behavior within the Senate. In principle, we could map equations such as (1) or (3) directly into individual roll call votes to assess the effect of constituent preferences on senators' voting behavior. However, it is very often the case that there is too little information in House or Senate votes to estimate such effects for a large set of independent variables, (that is, the roll call vote is over-determined, especially when voting starts off close to party-line; see Aldrich et. al., 2006a). In principle, we could instead use this framework to assess the electoral connection with some interesting compilation of votes. Here we do so for two such compilations, the "score" received by each senator on the first and second dimensions of DW-NOMINATE.

We can interpret this in the following way. These scores represent the two most important (orthogonal) summary indices of all roll call votes the senator cast in the congressional session, relative to that of all other senators, and we assume that constituent preferences are prior to (and unaffected by rational anticipation of) the voting of the senator in the congress after the election. (The senator, of course, may well be anticipating the effect of his roll call votes on constituent preferences and choice in the next election.) Suppressing the subscripts and stochastic terms, we can then write this as (where DWx denotes DW1 and DW2 respectively):

$$DWx = h(V) = h'(f(C)) = h''(f(g(X)) \qquad (4)$$

This general expression leaves open a great deal of specification. Perhaps most importantly, we have treated constituents as equal (or at least not specified any differences among them). Given the presence of survey data, we will be able to test whether, for example, the preferences of partisans of the winning candidate are more important than those of the state constituency as a whole – and we will examine this particular example specifically in this paper.

The final step in our process is to investigate the relationship between the constituency and the distribution of senatorial preferences in the way we define the condition in conditional party government. Here, instead of having an observation for each senator, we have one for each congress. To estimate CPG, we use the two-dimensional procedure developed in Aldrich, Rohde, and Tofias on DW-NOMINATE data (forthcoming). The explanatory variable will be the fit of the constituency preferences to party affiliation (eq. 3) – the better the prediction, the higher the levels of satisfaction of the condition for CPG.

## Data

### *Description*

The data required for this analysis needs to capture individual policy preferences and opinions, party identification, presidential approval, demographics, and state of residence.

Most importantly, the surveys need to (1) ask very similar questions in order to make comparisons across congresses possible and (2) have sufficient numbers of respondents in each state to make inferences about state-level constituency responsiveness possible.

We collected individual-level constituency data from two sources. First, we used data from the National Election Study Senate Pooled Data Study (NES), which ran in 1988, 1990, and 1992. This study consisted of three separate cross sections with identical questions; each wave included approximately 2500-3000 respondents. Because of our particular interest in studying the second dimension of DW-NOMINATE, we dropped the 1990 cross-section, which omitted a question about opinion on trade that was present in the 1988 and 1992 versions. Second, we used data from the 2000 and 2004 National Annenberg Election Study (NAES), which surveyed 75,000 and 85,000 respondents, respectively. The Annenberg studies comprise a large set of individual surveys conducted over the duration of the two presidential election campaigns, including surveys of specific states with primary elections, small panel studies, national cross-sections, and national panels.[3]

We identified a set of shared questions across all four studies that covered respondent demographics, party identification, opinion of the president, and issue preferences. (See Appendix A for a list of all variables.) We then computed mean values of individual-level data by state and Congress, giving us state-level data for the 101st, 103rd, 107th and 109th Congresses.

It is important to note that the sample size of the responses used to construct our independent variables varied by state, survey, and variable. Smaller states tended to have fewer respondents; the NES surveys had fewer respondents than the NAES ones; and the number of respondents asked a particular NAES question often varied dramatically. For the NES 1988-1992 data, each wave's sample size ranged from approximately 2600 to 3000 respondents. Almost every question in the 1988 and 1992 waves had at least 40 respondents per state (with an overall state mean of approximately 65 respondents per question). The issue question on trade policy generated as few as 17 respondents in the smallest case, but this question had significantly fewer respondents than any of the others. The NAES data for 2000 and 2004 produced at least 100 respondents per demographic question for each state. The minimum number of respondents for the issue questions was 41; other questions ranged between 62 and 146 minimum respondents per state. Finally, because the NAES surveys omitted Alaska and Hawaii, we dropped respondents from those states in the NES survey. Respondents from the District of Columbia were also dropped. (See Appendix A for further details.)

*Empirical approach*

To evaluate our hypotheses, we compare the performance of simple logit and OLS models for three dependent variables – party and the two dimensions of DW-NOMINATE (Poole and Rosenthal 1997). These comparisons are made both across different specifications and over time.

[3] For panel respondents, we used their first survey response.

Specifically, the independent variables for these models were state demographic and issue preference data from the NES and NAES surveys plus standard political variables (Democratic presidential vote, partisan affiliation, etc.). Two sets of state-level values were computed from the survey data: one for all respondents and one for party identifiers. In this way, we hope to test to what extent politicians respond to within-party constituencies rather than the population as a whole. We then compare our survey-based results with those obtained using interpolated Census data to predict the same three dependent variables (Aldrich et al, 2006b). Appendix B tabulates the independent variables that were used in the previous paper and those used in this one.

This strategy is intended to address a threat to inference that comes from our use of aggregated survey data based on relatively small numbers of respondents. This limitation of current data will increase measurement error in our independent variables. In particular, our estimates of demographic characteristics will almost surely be less precise than those obtained from the Census. On the other hand, they have the virtue of having been measured in the appropriate period rather than having been interpolated across a ten-year period.

Finally, we must consider whether model performance will vary by survey since the NAES surveys had much larger sample sizes than the NES study. In addition, there may be variations in the methodology of the surveys (question wording, ordering, sampling, etc.) that could impact our results.

For all of these reasons, it is important to show that our results are consistent across both groups of surveys and the Census. When this happens, our confidence in the results increases greatly.

To evaluate model performance, we rely on two summary statistics. For party, we report the area under the receiver operating characteristic (ROC) curve, which provides a more comprehensive measure of predictive accuracy for binary dependent variables than the commonly used threshold of .5 (Swets 1988). ROC curves vary the relevant threshold of predicted probability that counts as a positive prediction (ie a Republican) from 0 to 1. We then calculate how the rates of "true positives" (y-axis) and the "false positives" (x-axis) vary over that range. By connecting those dots, we create a curve that goes from (0,0) – where we have no true or false positives predicted – to (1,1), where all predictions are either true positives or false positives. The area under this curve typically ranges from .5 (the rate possible from random chance) to 1 (the model perfectly differentiates all positive and negative cases). For DW-NOMINATE scores, we use adjusted $R^2$ – a well-known indicator of OLS model fit that includes a penalty term for the use of additional explanatory variables.

Due to the large number of models estimated in this paper and our interest in model fit rather than estimates of individual coefficients, we do not report regression results in tabular format. Instead, we summarize model fit by Congress in a series of figures. All estimation results are available upon request. Appendix C presents results from a sample regression for illustrative purposes.

## Results

*Party*

As we have shown, models predicting the partisan affiliation of a member of Congress are improved by including demographic characteristics of her constituency (Aldrich et al 2006a, 2006b). Previous analyses have been limited, however, to demographic predictors available through the Census plus previous presidential vote share. No other *political* variables were considered. In particular, we could not consider whether demographic variables were a reasonable proxy for constituent issue opinion.

In this study, we seek to answer that question using the demographic and issue variables collected from the 1988-1992 NES Senate study and the 2000 and 2004 NAES aggregated to the state level.[4] Specifically, we estimated the following model predicting the party of each Republican as a function of demographics, district partisanship, and presidential favorability/approval, a model we will call "demographics-plus":[5]

$$\begin{aligned}\Pr(\text{GOP}) = \text{logit}^{-1}[&\beta_0 + \beta_1(\%\text{ seniors}) + \beta_2(\%\text{ black}) + \beta_3(\text{median income}) + \beta_4(\%\text{ union members}) + \\ &\beta_5(\%\text{ Latino}) + \beta_6(\text{party ID}) + \beta_7(\text{median presidential favorability/approval})]\end{aligned} \tag{5}$$

Figure 1 compares ROC area for the four congresses available with the performance of our previous model, which used Census demographics and presidential vote share. Happily, the pattern is consistent across data sources – predictive performance is comparable and seems to improve over the time span.

[Figure 1]

Given that the survey and census measures track well together, we compare constituent demographics and issue opinion as predictors of party choice. To do so, we computed the average position of respondents by state on six issue questions that were comparable across all four surveys and estimated the following model predicting party, which we will call "issues-plus":

[4] Technically, the data is multilevel in nature with individual characteristics predicting vote choice within states. By aggregating individual demographics and issue opinions we are bypassing the multilevel structure and treating every variable as a state-level characteristic. In addition, we cluster standard errors by state to correct for the fact that both senators from the state share the same values on the independent variables. We hope to explore the multilevel structure of the data more fully in future work.

[5] It is worth noting that the logit model for each regression includes all sitting senators rather than just those up for election. This is necessary to obtain more precise ROC estimates by Congress (n=100 rather than n=33 or 34). As such, we are not modeling the partisan choice of the state in each election, but the fit of each senator's party to the state by Congress. Put differently, we are attempting to model what party the state would choose if it could. Another way to interpret this model is to say that senators can and sometimes do switch parties between elections if they feel that their party is a poor fit for their state.

$$\begin{aligned}\Pr(\text{GOP}) = \text{logit}^{-1}[&\beta_0 + \beta_1(\text{anti - abortion}) + \beta_2(\text{pro - defense}) + \beta_3(\text{more education spending}) + \\ &\beta_4(\text{more health care spending}) + \beta_5(\text{pro - lower taxes}) + \beta_6(\text{anti - trade}) + \\ &\beta_7(\text{party ID}) + \beta_8(\text{presidential favorability/approval})]\end{aligned} \quad (2)$$

We then compare the demographics-plus model to the issue-plus model and a combined model that includes all of the variables listed above. Our expectation is that both issues and demographics have independent predictive power.

Figure 2 depicts the ROC results for the demographics-plus, issues-plus, and combined model of party and contrasts those results with the equivalent demographics-plus model previously estimated on Census data (again, see Appendix B for details on the Census models):

[Figure 2]

We observe that all three models trend together over time with the issues-plus and demographics-plus models performing similarly. This suggests that the demographic values used in previous work (Aldrich et al 2006a, 2006b) are valid proxies for issue opinion in predicting party choice.

However, the combined model shows an increase in predictive power **[test]**, including three congresses with ROC values greater than 0.8. With the exception of the 109th Congress, where performance is similar, this improvement suggests that the predictive power of demographics on party is not completely captured by issue opinion.

*DW-NOMINATE 1*

Having considered party membership, we now turn to the halls of Congress and evaluate model performance in constituency variables' ability to predict senatorial roll-call voting on the floor, i.e., the DW-NOMINATE scores for US senators using our aggregated survey data. We start by predicting senators' first-dimension scores for the 101st, 103rd, 107th, and 109th Congress using their party, median presidential favorability/approval in their state, median party ID in their state, and the same set of state demographic estimates presented above.[6] This OLS model is analogous to equation 5.

In Figure 3, we compare model fit for demographics-plus, issues-plus, and combined models of first dimension scores to results from the Census data. Here we find little difference in performance between the NES/NAES models. Figure 3 also illustrates how closely NES/NAES model performance matches previous results using Census data for the 101st-108th Congress (Aldrich et al 2006a), which show a similar increase in model performance over this time period and comparable levels of fit. Measured in terms of adjusted $R^2$, the Census model increases from approximately .85 to .9 over the eight terms.

[6] Party identification is, of course, excluded in the party model.

[Figure 3]

To compare responsiveness to the party constituency with responsiveness to the overall state constituency, we calculate the independent variables above separately for identifiers with the senator's party and run a party identifier version of the demographics-plus model above.[7] Model fit (omitted for clarity) is essentially identical to the demographics-plus model in Figure 4.

However, we also want to isolate and measure the predictive power of demographic variables alone. As such, we remove the party dummy variable, the presidential favorability/approval term, and party ID (from the all respondent model) from the demographics-plus model, creating what we will call the demographics-only model.

Results for the demographics-only model reveal differences between the party model and the general constituency model that are more drastic. Figure 4 presents model fits by Congress for both the total set of respondents and only those respondents who identified as members of the senator's party in the state. In the figure, we can see that party demographics dominate state demographics as a predictor of DW-NOMINATE first dimension scores, with an adjusted $R^2$ of approximately .4 increasing to approximately .8 between the $101^{st}$ and $109^{th}$. (Both models also show the familiar trend toward increased model fit over time.)

[Figure 4]

Finally, we create an issues-only model with party and approval/favorability variables and a stripped down combined model that omits the same variables. When we compare the demographics-only model to these two specifications in Figure 5, we see that the combined model outperforms the demographics-only or issues-only models alone.

[Figure 5]

As in our previous work based on Census data (Aldrich et al 2006a, 2006b), we find that demographic variables improve our ability to predict the first dimension of DW-NOMINATE. The issue variables available in our survey data are slightly more predictive of first dimension scores than demographics, but a combined model offers a performance improvement for three of the four congresses we consider. In addition, when we remove all political variables from the model, we find that the demographics of constituents from a senator's party are a better predictor of first dimension scores than the demographics of constituents as a whole, suggesting that senators are more responsive to the characteristics of party members.

[7] We also ran models of DW-NOMINATE using independent variables calculated only for those respondents who reported voting or an intention to vote; the results were largely indistinguishable from those for all respondents and are therefore omitted (but available upon request).

*DW-NOMINATE 2*

As with the first dimension, we seek to assess our ability to predict second dimension DW-NOMINATE scores using different constituencies and characteristics of those constituencies. Figure 6 compares models using survey measures of demographic characteristics, issue opinion, and the combination of the two sets of variables with the Census demographics model. As we previously observed for party and the first dimension of DW-NOMINATE, the demographics-plus and issues-plus models perform similarly, while a combined model improves model fit somewhat. The downward trend in model performance in the survey data is mirrored in the Census data.

[Figure 6]

Next, we predict second dimension scores using constituency demographics for both all respondents and party identifiers. We estimate both a demographics-plus model (which includes presidential favorability/approval, party ID, and senator party) and a demographics-only model for each group. Figure 7 plots model fit over time for all four specifications. Once again, we see a dramatic decline in model fit when we remove the political variables from the model – the adjusted $R^2$ of the demographics-only models never exceeds 0.3. More importantly, we observe a striking divergence over time. The predictive power of party and overall constituent demographics are comparable in the 101$^{st}$ and 103$^{rd}$ Congress. But the predictive power of both overall constituent models fall in the 107$^{th}$ and 109$^{th}$ Congress, while the party models are relatively stable.

[Figure 7]

*Comparing the first and second dimension*

Given these results, what can we say about responsiveness to constituency demographics across the two dimensions of DW-NOMINATE? To answer this question, we compare model fit by dimension using only demographic variables for all respondents in the NES/NAES data and the Census data. Figure 8 presents a plot of adjusted $R^2$ values by Congress for both dimensions and both datasets. For the survey data, we see that the model fit for the first dimension improves dramatically across the four congresses, with an adjusted $R^2$ over .4 for the 109th Congress, while the adjusted $R^2$ for the second dimension approaches zero by the 109$^{th}$. In addition, the divergence we observe is consistent with results from the Census data, which also show increased predictive power for the first dimension and reduced predictive power for the second dimension in recent congresses.

[Figure 8]

Figure 10 then plots the results from the NES/NAES data for all respondents against the results for party identifiers only in the NES/NAES data. In this figure, we see that party demographics outperforms constituent demographics in the 107$^{th}$ and 109$^{th}$ Congress. The difference is particularly dramatic for the first dimension, where demographic variables alone achieve an adjusted $R^2$ of approximately .7. It appears that the first dimension of the Senate has become more closely linked with constituent demographics in recent years. In particular, the first dimension is increasingly well explained by the demographics of identifiers with the senator's party in their state.

[Figure 9]

*CPG*

Finally, we consider the hypothesis that increased fit between constituency and party lead to greater levels of conditional party government. Previous work found evidence of this relationship in the House of Representatives for the period of 1982-2000 (Aldrich et al 2006b). To see whether it holds for the Senate as well, we calculated measures of conditional party government (CPG) for the Senate through the 109$^{th}$ Congress based on the first two dimensions of DW-NOMINATE (Poole and Rosenthal 1997). The two-dimensional CPG measure is a factor score constructed from four components representing inter-party heterogeneity, intra-party homogeneity, majority cohesion, and party fitness (Aldrich, Rohde, and Tofias forthcoming).

Figure 10 presents the estimated relationships between the ROC area and CPG for the demographics-only model for each Congress in our survey and Census data (Aldrich et al 2006a). As expected, conditional party government in the Senate appears related to the fit between constituencies and the party of their elected representatives in both datasets. The pattern for the Census data is quite similar to the survey-based results (though the Census data has somewhat higher ROC values). In both cases, it appears that constituency/party fit is positively related to CPG. The slope of the fitted line in the NES/NAES panel is 1.38 (se=0.38), while the slope of the fitted line using Census data (which allows for more Congresses and a wider range of ROC/CPG values to be included) is 2.94 (se=0.94).

[Figure 10]

Taken as a whole, the above figures are largely supportive of our hypothesis that demographics are an important predictor of the party affiliation of a constituency's elected representatives. Aggregate issue positions are also predictive of party affiliation, but neither issues nor demographics prove more valuable than the other in terms of predicative power. In fact, the combination of both sets of independent variables significantly improves model fit. Lastly, as the fit between constituency and party increases, CPG appears to increase.

## Conclusion

This paper has been a part of an ongoing effort to more closely examine the links between the demographic characteristics of electoral constituencies, election outcomes, the behavior of members of Congress, and levels of conditional party government.

Unlike our previous work, which focused almost entirely on Census data, this analysis considers the relationship of survey data to the dependent variables of interest as well as to the previously used measures of independent variables. We do so because each type of data presents different potential threats to inference. The degree of confidence we can have in our results increases if the evidence from these two very different types of data points in the same direction. The results presented here offer encouragement on that score. With respect to each major section of our analysis—the relation of demographics to election outcomes, the factors that explain variation in DW-NOMINATE scores, and the linkage between party-demographics fit and CPG—the two types of data support similar conclusions.

A second reason for bringing survey data to bear on our analysis was that it permitted direct measurement of voters' issue preferences rather than simply assuming that constituency characteristics were a valid surrogate for those preferences. The results we have presented show that survey data on issue preferences generally point in the same direction as the data on demographics but that each makes an independent contribution. This validates our larger research agenda's focus on the importance of demographics in explaining phenomena of interest. It also suggests the finite numbers of questions possible to include in a survey may fail to include all considerations with systematic effects on election outcomes and subsequent member behavior in Congress.

In addition to these general conclusions, our analysis also offers insight on some more focused substantive matters. First, explanatory power of our simple models increases over time for party and first-dimension DW-NOMINATE. We see these results as consistent with contemporary research that emphasizes increased partisanship and polarization in American politics, at least at the elite level. In one case, however, our explanatory power decreased over time: variation in the second dimension of DW-NOMINATE. When coupled with the increased explanatory power of demographics for the first dimension, this finding is consistent with the idea that the preferences reflected in demographic data are getting folded into the main dimension of two-party conflict nationally. Finally, the survey data permitted us to distinguish between the views of the general public and party identifiers. We find that the views and demographics of partisans are an increasingly superior predictor of party and legislative behavior. This, of course, presents a challenge: how can we provide dependable surrogates for partisan preferences in analyses where such data are unavailable? We will address this challenge in future stages of our project.

**Figure 1**

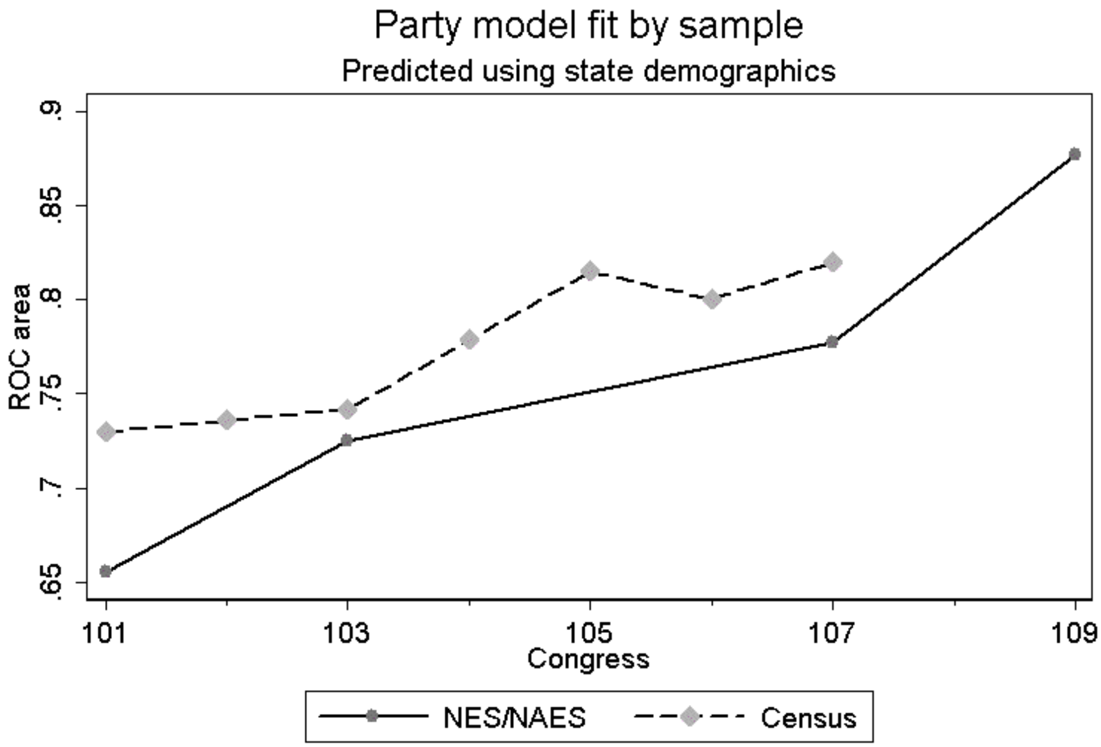
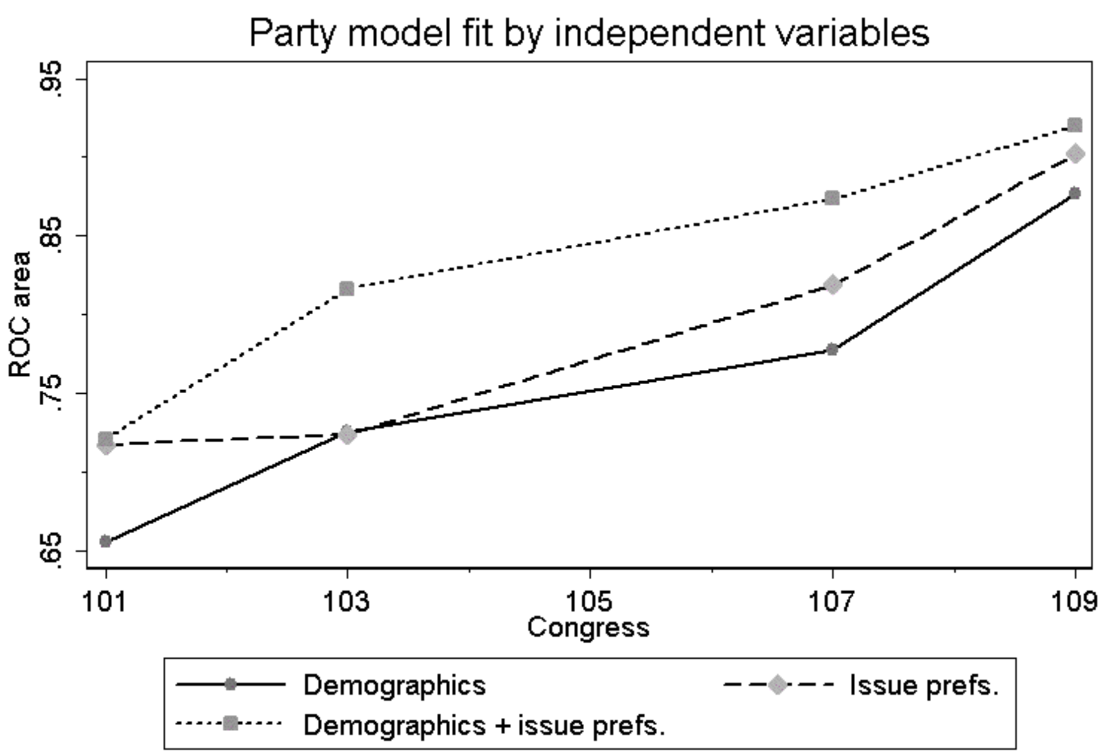



**Figure 2**



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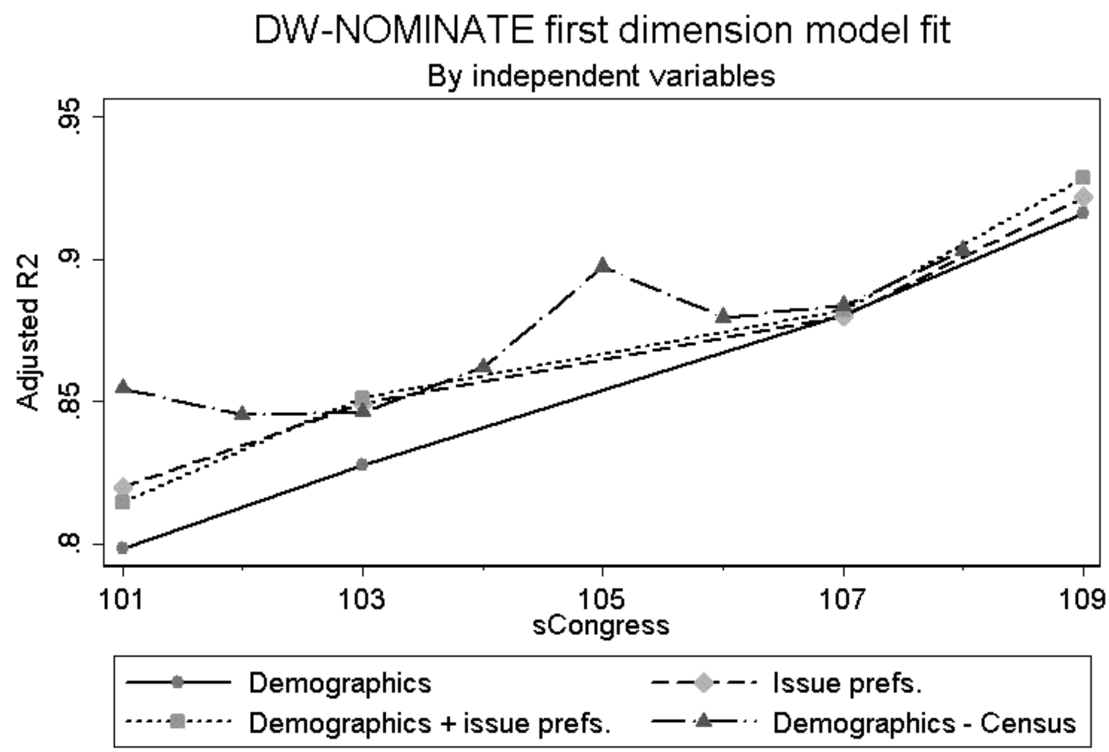
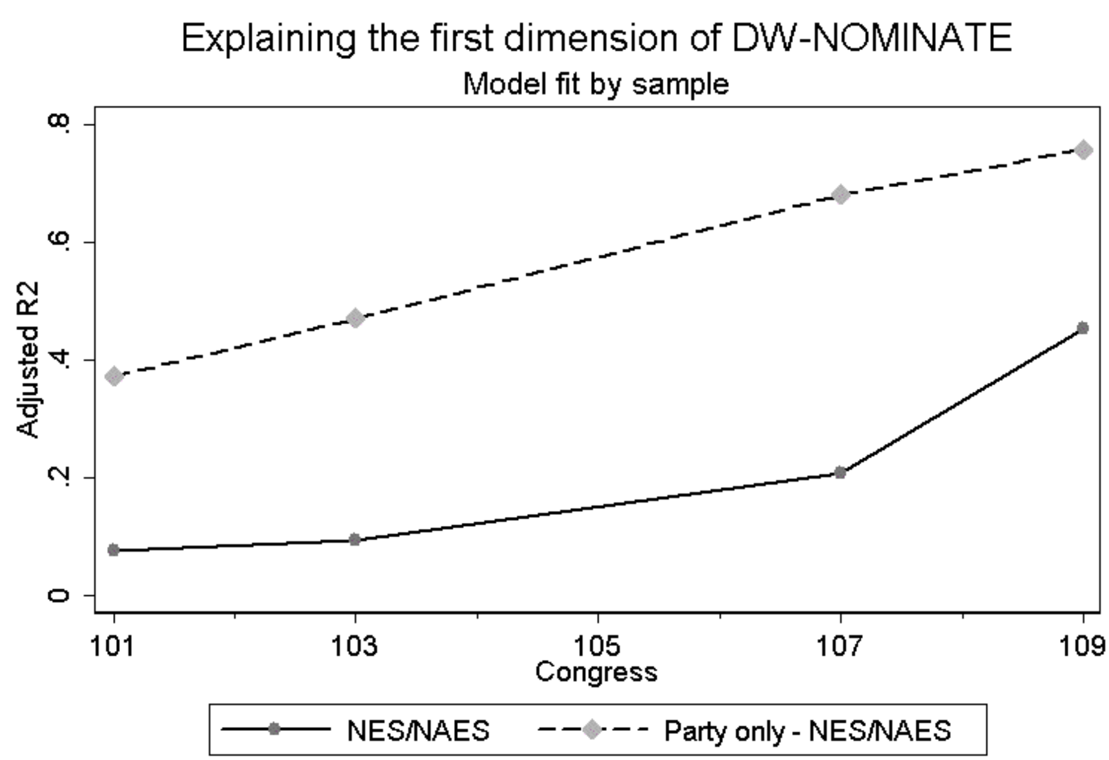



**Figure 4**



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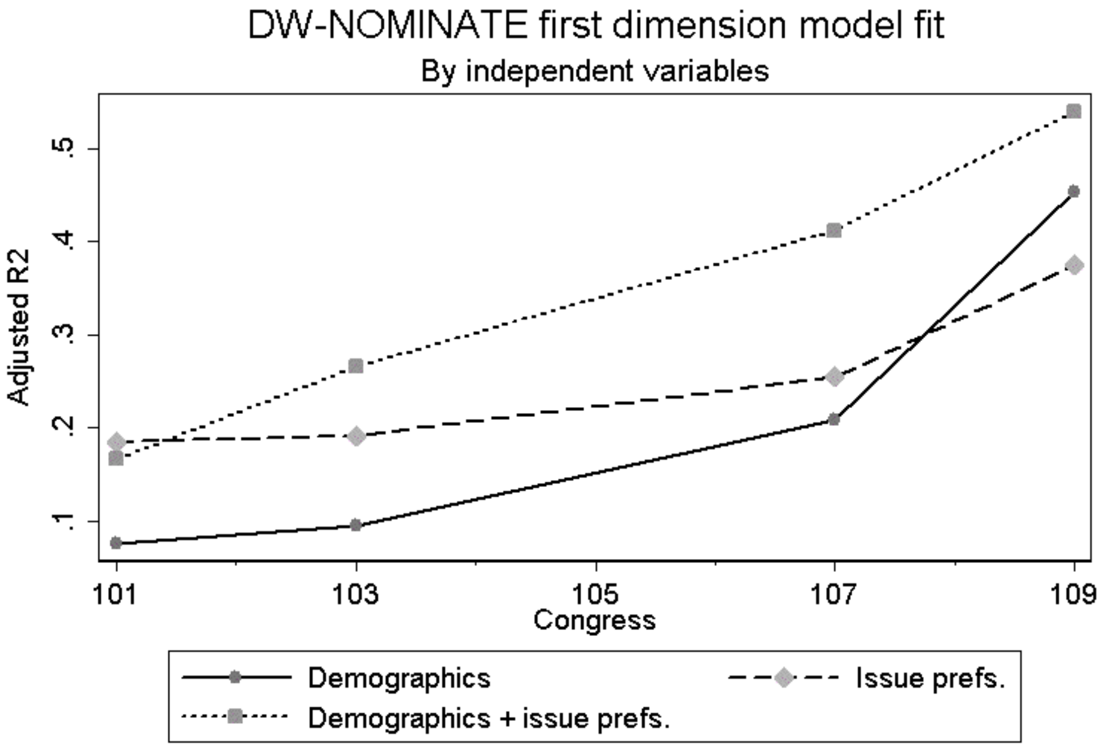


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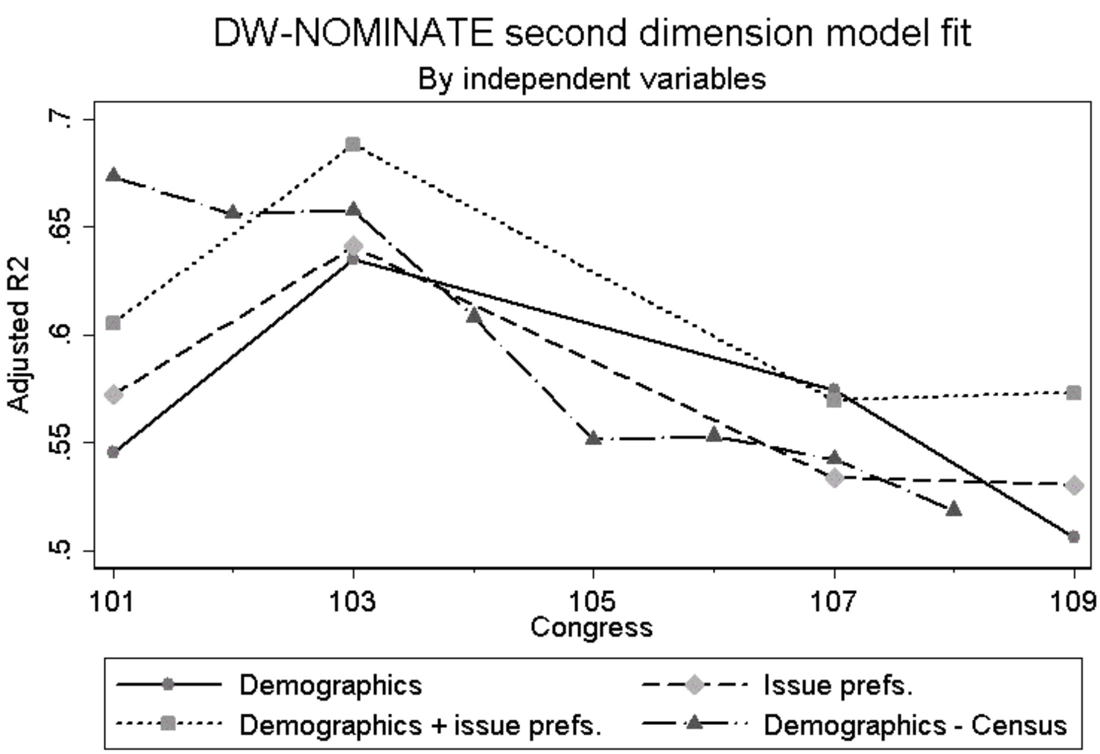

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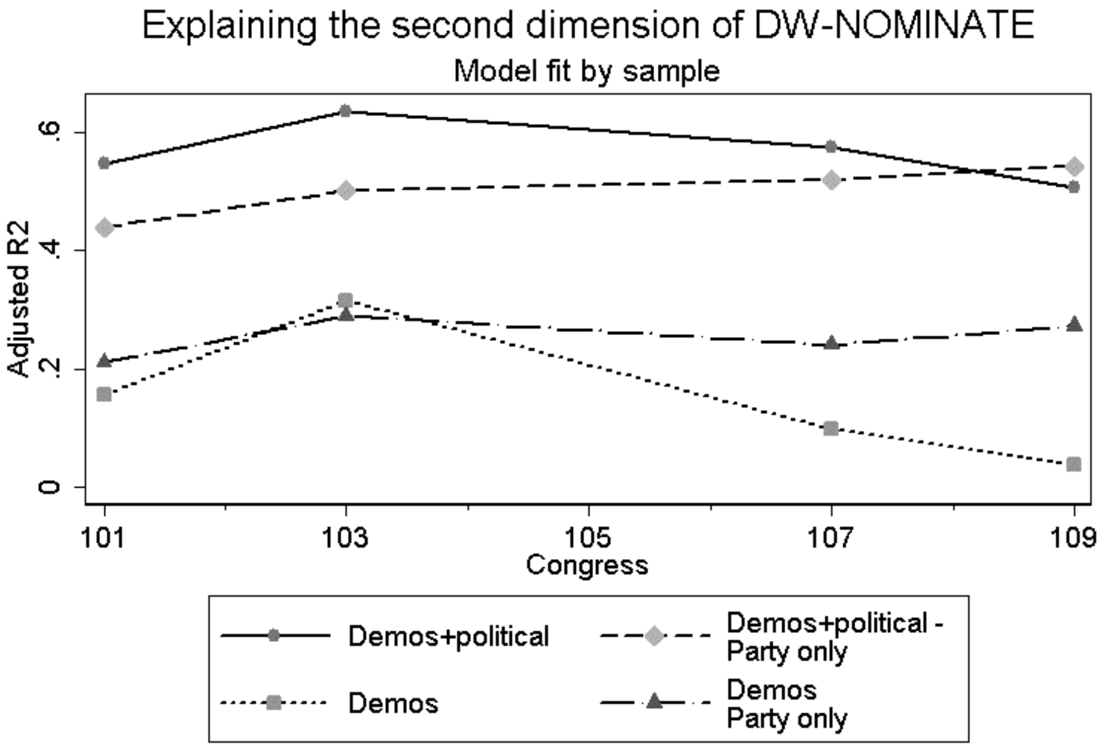


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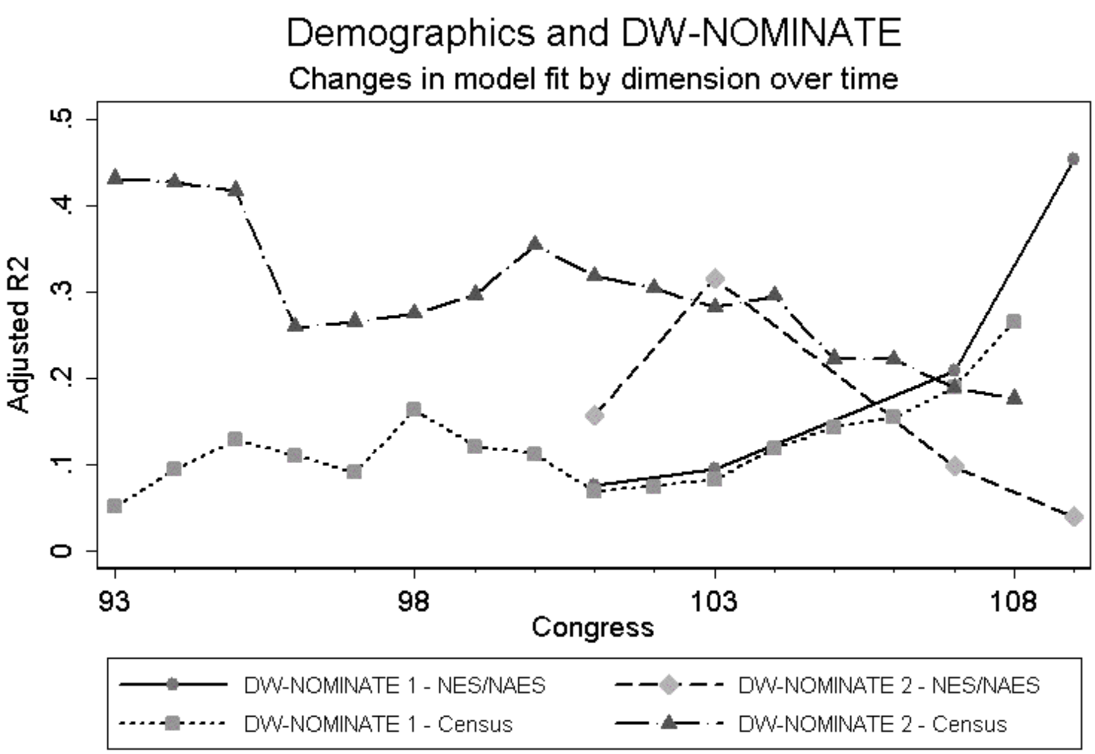


**Figure 9**

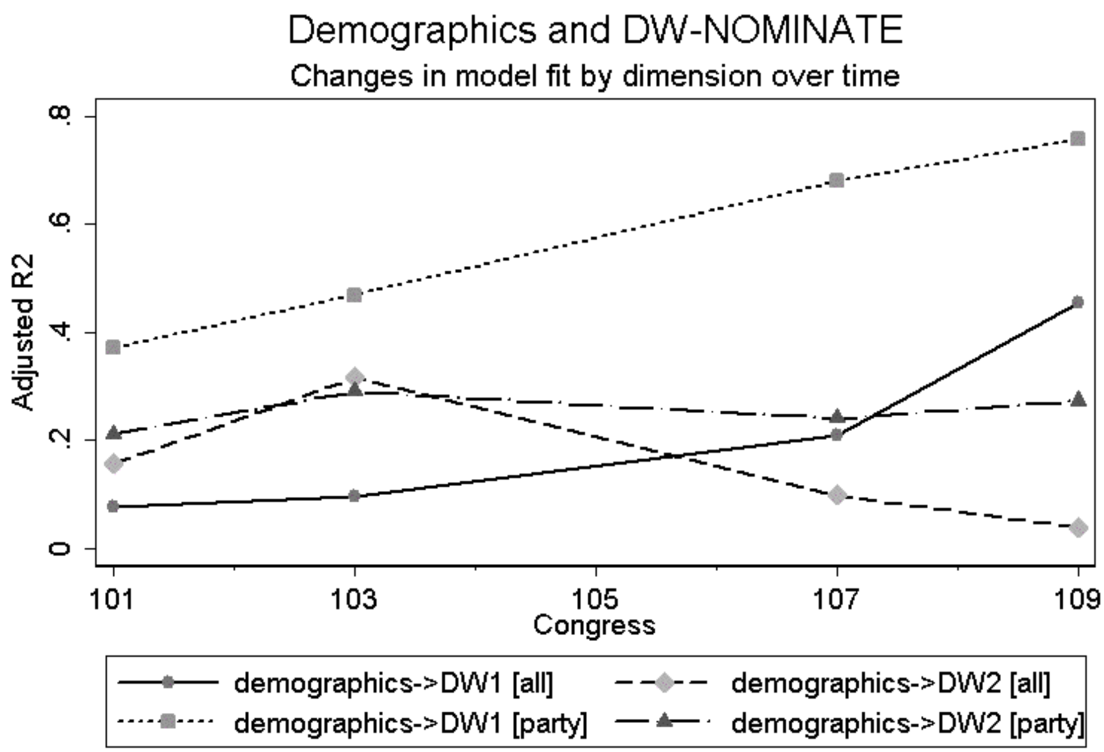
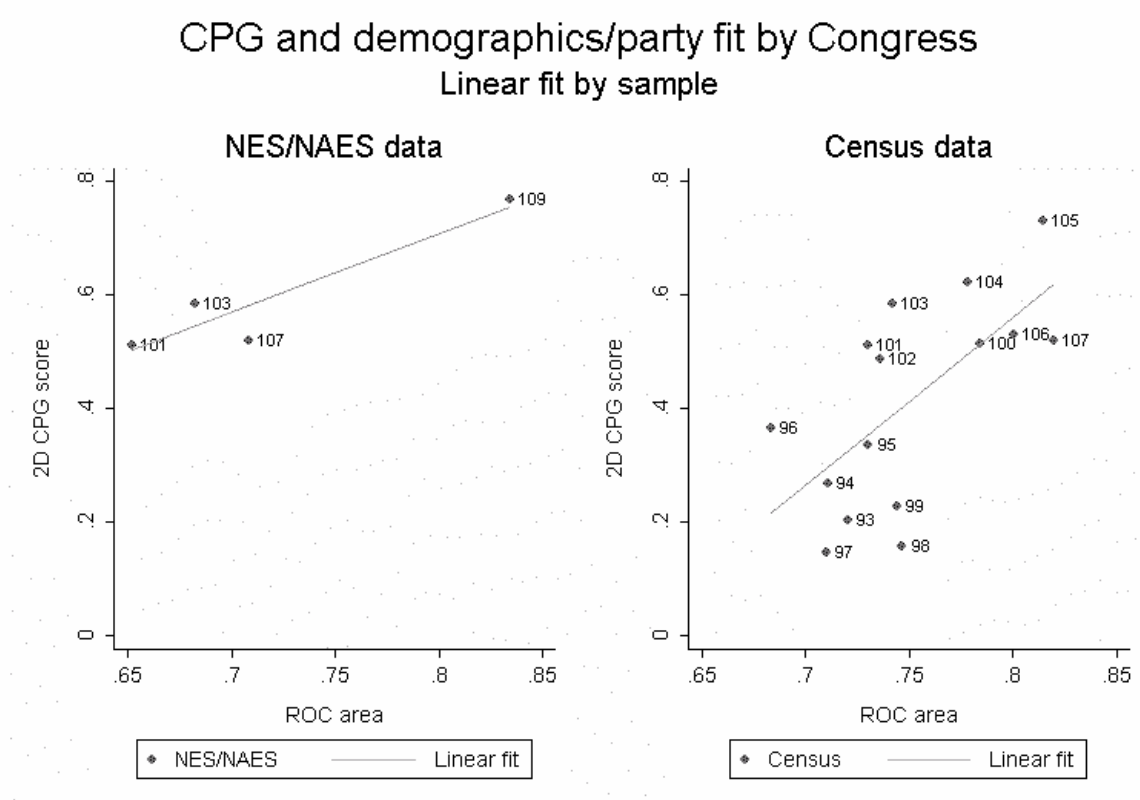



**Figure 10**



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## Appendix A

| | | NES: Responses by state | | | NAES : Responses by state[8] | | |
|---|---|---|---|---|---|---|---|
| | Type | Mean | Min | Max | Mean | Min | Max |
| Age 65+ | Binary | 60.0 | 42 | 87 | 3117 | 145 | 7774 |
| Black | Binary | 59.8 | 40 | 88 | 3155 | 146 | 7883 |
| Hispanic | Binary | 60.3 | 43 | 89 | 3155 | 146 | 7883 |
| Income | Continuous[9] | 60.3 | 43 | 89 | 3155 | 146 | 7883 |
| Unemployed | Binary | 60.1 | 43 | 89 | 3155 | 146 | 7883 |
| Union member | Binary | 59.8 | 43 | 89 | 3155 | 146 | 7883 |
| Party ID | Categorical (7) | 58.5 | 41 | 88 | 3155 | 146 | 7883 |
| Pres. fav./approval[10] | Continuous (10,100)[11] | 56.7 | 38 | 83 | 3115 | 142 | 7822 |
| Anti-abortion | Binary/categorical (3,5)[12] | 57.4 | 42 | 86 | 2896 | 139 | 7186 |
| Pro-defense spending | Categorical (3,4)[13] | 58.5 | 42 | 85 | 2090 | 72 | 7229 |
| Pro-school spending | Categorical (3,4)[14] | 58.8 | 43 | 85 | 1221 | 62 | 3079 |
| Pro-health spending | Categorical (3,4)[15] | 58.1 | 38 | 86 | 1040 | 41 | 3010 |
| Pro-lower taxes | Categorical (3,4,5)[16] | 58.0 | 38 | 86 | 2300 | 85 | 7245 |
| Opposition to trade | Binary/categorical (4,5)[17] | 38.6 | 17 | 60 | 1703 | 60 | 5424 |

[8] As noted in the text, the widely varying number of responses for NAES variables is not an indication of high levels of non-response. Most issue questions were simply asked much less frequently than the standard demographic questions.

[9] Income measures were constructed from the median income level by state and transformed to the midpoint of the range of that category. For instance, a median response of \$30,000-\$40,000 was coded as \$35,000. Income values were not adjusted for inflation because we did not estimate a pooled model comparing states across time.

[10] Presidential approval was not available for the 1988 NES survey, so favorability was substituted.

[11] 101st: 100 point; 103rd: 100 point; 107th: 100 point; 109th: 100 point.

[12] 101st: 3 point; 103rd: 3 point; 107th: binary; 109th: 5 point.

[13] 101st: 3 point; 103rd: 3 point; 107th: 4 point; 109th: 4 point.

[14] 101st: 3 point; 103rd: 3 point; 107th: 4 point; 109th: 4 point.

[15] 101st: 3 point; 103rd: 3 point; 107th: 4 point; 109th: 4 point.

[16] 101st: 3 point; 103rd: 3 point; 107th: 4 point; 109th: 5 point.

[17] 101st: Binary; 103rd: Binary; 107th: 4 point; 109th: 5 point.

**Appendix B: Variables in NES/NAES and Census models**

Figures 1, 4, 6, 8 and 10 present comparisons to previously estimated models predicting senator's party and the two dimensions of DW-NOMINATE (Aldrich 2006b). The following table describes the variables used in the two analyses.

| | Both models | NES/NAES | Census |
|---|---|---|---|
| *Demographic*[18] | | | |
| Age 65 and over | X | | |
| Black residents | X | | |
| Farmers and farm workers | | | X |
| Finance workers | | | X |
| Foreign born | | | X |
| Government workers | | | X |
| Hispanic | | X | |
| Income[19] | X | | |
| Manufacturing workers | | | X |
| Population density | | | X |
| Total population (log) | | | X |
| Unemployed | | X | |
| Union members | | X | |
| Urban population | | | X |
| | | | |
| *Political* | | | |
| Democratic presidential vote | X | | |
| Senator's party[20] | X | | |
| Presidential favorability/approval | | X | |
| Aggregate party identification | | X | |

[18] All demographic variables representing subpopulations (number of African Americans, farmers, etc.) were recorded as proportions of total state population.
[19] In the Census data, income is recorded as the log of per capita income. The NES/NAES data used the raw value of median income by state.
[20] Used as an independent variable when predicting DW-NOMINATE scores only.

## Appendix C: Sample estimations

**Predicting Party and DW-NOMINATE (107th Congress)**

| COEFFICIENT | GOP (SE) | 1st Dimension DW-NOM (SE) | 2nd Dimension DW-NOM (SE) |
|---|---|---|---|
| % seniors | -45.6** | -0.78 | -1.29 |
| | (23.0) | (1.1) | (2.1) |
| % black | -33.5** | 0.24 | 1.76 |
| | (13.0) | (0.6) | (1.1) |
| State median income | -0.000012 | -0.0000047 | -0.000010 |
| | (0.00006) | (0.000004) | (0.000007) |
| % unemployed | -153.0** | -1.23 | 3.73 |
| | (64.0) | (3.1) | (5.9) |
| % union members | 0.44 | -0.49 | -1.12 |
| | (7.7) | (0.4) | (0.8) |
| % Latino | -4.32 | 0.14 | -0.021 |
| | (5.6) | (0.4) | (0.7) |
| Anti-abortion | -13.0* | -0.57* | 0.85 |
| | (7.3) | (0.3) | (0.6) |
| Pro-defense | 23.8*** | 0.98** | 0.13 |
| | (8.4) | (0.4) | (0.7) |
| Pro-school spending | 3.80 | 0.031 | 0.58 |
| | (6.0) | (0.3) | (0.6) |
| Pro-medical spending | 4.55 | 0.12 | 0.41 |
| | (6.1) | (0.4) | (0.7) |
| Pro-lower taxes | 6.91 | 0.12 | -0.35 |
| | (5.6) | (0.3) | (0.5) |
| Anti-trade | 6.29 | -0.18 | -0.14 |
| | (4.8) | (0.3) | (0.5) |
| Party ID | -6.50*** | 0.16 | 0.28 |
| | (2.4) | (0.1) | (0.3) |
| Pres. favorability/approval | 0.30 | -0.020** | -0.052*** |
| | (0.2) | (0.010) | (0.02) |
| Senator's party (GOP) | -- | 0.71*** | -0.61*** |
| | | (0.04) | (0.08) |
| Constant | -117.0*** | -3.15 | -0.73 |
| | (43.0) | (2.0) | (3.7) |
| Observations | 97 | 97 | 97 |
| Pseudo R-squared | 0.35 | | |
| Adjusted R-squared | | 0.88 | 0.57 |

*** $p<0.01$, ** $p<0.05$, * $p<0.10$