# Essays on the Microfoundations of Legislative Decisionmaking

by

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***For my most vital constituency, my loving wife, Joslyn.***

## Curriculum Vitae

The author was born to Youssef and Corinne Ramey in Lawrence, MA on September 13, 1983. He attended The George Washington University from 2001 to 2004, earning a B.A. in Political Science, *summa cum laude*, with honors in Political Science and a minor in Physics. He came to the University of Rochester in 2004 and began graduate studies in Political Science. He pursued his research in American Politics and Statistical Methods under the direction of Professor Lawrence Rothenberg and received the M.A. degree in Political Science in 2008.

# Acknowledgements

Man is a social animal and, in that sense, all great tasks are naturally completed with the assistance of others, many far wiser than I. My own journey to Rochester was, in large part due to the late, great Political Scientist, Lee Sigelman. As an ignorant undergraduate, I came into his office with a woefully inadequate list of graduate schools to which I planned to apply, as well as copies of my undergraduate transcript. Lee, upon seeing a large number of Math and Physics courses, asked me, "Have you considered Rochester?" To this, I replied, "Where?" From that point on, with his selfless assistance, I undertook the application process to graduate schools and, ultimately, decided to come to Rochester. Indeed, without the help of both Lee and Professor Sarah Binder, I would not be where I am today.

Upon arriving at Rochester at age 20, I was quickly welcomed by Professors Lynda Powell and Richard Niemi. Their assistance, coupled with the constant support of my graduate student colleagues, Yoji Sekiya, Daniel Gillion, Fabiana Machado, and Peter Loewen, helped make the transition easier for such a young person. Despite their greatest efforts, I decided to take a year off after my first year. During this time, I taught high school and learned a most valuable life lesson: my place was in Rochester!

Truth be told, my sweet wife (then, fiancee), Joslyn, encouraged me to go back and finish what I started. Shortly after our wedding in May of 2006, we went to Rochester together and have been there ever since. At this point, I was joined by several new colleagues who arrived in the program upon my departure. Among these, I especially want to thank Jeremy

Kedziora and Shawn Ramirez for their unfailing support, willingness to think through ideas, and, very often, entertain even the most far-fetched idea of mine.

During my absence from Rochester, Professor Lawrence Rothenberg had returned to the program. This event turned out to be monumental in my graduate career, as he warmly welcomed me as his student soon after my return. I am indebted to Larry for his constant support, wisdom, constructive criticism, and aid through every major stage of my graduate experience. Whether it was hiring me for summer work, chairing my dissertation committee, meticulously examining my job market packet, or just "checking in," Larry has proven to be an invaluable resource and I thank him for it.

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More than anyone else, I thank my wife, Joslyn. Without her, I probably would not have returned to graduate school. Her love and tenderness throughout the almost four years of marriage has helped me to bear the storms in the life of a graduate student. Joslyn has been a never-ceasing source of inspiration and I am indebted to God for the gift of her presence in my life.

Last, but not least, I thank God for granting me the graces and strength to persevere amidst adversity throughout my graduate career. Through the intercession of the great St. Thomas Aquinas, I believe that my knowledge of the world has been enriched.

## Abstract

This dissertation analyzes how preferences, parties, and constituencies jointly impact legislative policy making. It consists of three essays, each addressing this issue in different ways. In the first, I develop a new statistical model to formalize Barbara Sinclair's (2002) observation that legislators' decisions are a weighted average of multiple sources of influence. Applying this approach to the U.S. Senate since 1995 shows both its general usefulness and generates a number of important substantive results. For example, one key finding is that Republican moderates are much more sensitive to electoral and partisan pressures, reducing the weight they put on their own personal ideologies, than Republican extremists or Democrats of all ideological types. My second essay analyzes how external conditions affecting constituencies impact legislative behavior in a non-partisan environment. Specifically, I present a theory of how legislative district occupation led to observed preference change in the non-partisan Confederate Congress. I find that the crisis imparted by the occupation of legislators' districts led them to shift their behavior in favor of strengthening the Confederate government. My final essay changes gears and examines legislative behavior from the perspective of voters. Since voters are often unable to locate their legislators on an ideological scale, I present a statistical method that allows scholars to better understand the mechanisms behind voters' decisions whether to place legislators on a seven-point scale. The results suggest that informational, racial, and ethnic factors are influential in terms of saliency, but that education is a powerful predictor for decisiveness.

# Contents

# List of Tables

# List of Figures

# Chapter 1

# Introduction: The Paradox of Representation

*"[A legislator's] unbiased opinion, his mature judgment, his enlightened conscience, he ought not to sacrifice to you, to any man, or to any set of men living. These he does not derive from your pleasure; no, nor from the law and the constitution. They are a trust from Providence, for the abuse of which he is deeply answerable. Your representative owes you, not his industry only, but his judgment; and he betrays, instead of serving you, if he sacrifices it to your opinion."*

**—Edmund Burke, Speech to the Electors of Bristol**

Since at least the time of Edmund Burke's famous speech to the electors of Bristol, there has been a vocal debate between scholar and layman alike over the proper role of legislators in representative government. Burke's argument in his speech has come to be known as the view of legislators as *trustees* of the public. In this perspective, legislators are thought best serve their constituents by using their own judgments to make decisions, even if this leads to results at odds with public opinion. Opposed to this view of representation is the idea of legislators as *delegates*. From this standpoint, legislators are like chesspieces, standing in place for the large number of constituents they represent. Thus, when they make decisions, legislators are to do so based on the views of those in their electorates. While there has certainly been large swaths of normative writing on these two conflicting perspectives, we know surprisingly little about what legislators do in practice. Put alternatively, the debate has focused a lot on what *ought to be* and not nearly as much on what *is*.

Indeed, a strict commitment to either of these views yields a very poor understanding of the lawmaking environment in Congress during the first decade of the 21st Century. While all legislators come to Congress with their own views of what constitutes good public policy, they also have both partisan and constituent factors to weigh in their decision making. After all, legislators are beholden to their constituents for re-election and to their political parties for financial and logistical support. Exactly how this works and how legislators balance these countervailing forces is, until now, not well understood.

To be fair, modeling these forces in the study of Congress is no simple task. Until fairly recently, more realistic statistical models that capture the legislative environment were marred by computational infeasibility. The rapid increase in the availability of computing power, coupled with the Bayesian Markov Chain Monte Carlo (MCMC) "revolution," has made a more accurate modeling of legislative behavior more feasible than ever.

## 1.1 Purpose and Plan of the Dissertation

This dissertation seeks to improve our understanding of the linkages between voters and legislators and, in doing so, to perform three important tasks. First, it seeks to explore how the competing interests of personal preferences, party, and constituency affect the kinds of decisions that legislators make. Second, it examines how national crises can lead to shifts in legislative behavior. Third, it attempts to see how voters, in turn, evaluate their legislators' ideologies and why many cannot seem to identify the ideological views of their representatives.

The first essay (Chapter 2) provides a statistical framework for scholars to examine how preferences, party, and constituency affect legislators' choices. Specifically, I operationalize a claim by Sinclair (2002), that legislators' decisions are a weighted average of these sources of influence. From this, I derive a Bayesian statistical model and apply this model to the study of the Senate since the Republican Revolution of the mid-1990s. I find that the effects of both party and constituency are asymmetric across the ideological spectrum. More clearly, moderates feel the pull of party and constituency much more so than committed ideological extremists.

In the second essay (Chapter 3), I look back in U.S. history to the American Civil War. Therein, I analyze legislative behavior in the Confederate House of Representatives. This unique institution was almost identical in structure to its U.S. counterpart, save for its absence of a political party system. Even more interestingly, the occupation of legislative districts by Union troops over the course of the war severed the electoral connection between legislator and constituent. Given the framework in Chapter 2, it seems reasonable to believe that legislators whose districts became occupied would shift their behavior after the electoral connection was eliminated. In this chapter, I provide a Bayesian statistical model to study this hypothesis and find that, indeed, legislators from occupied districts shifted their support in favor of strengthening the central government in Richmond. In turn, this finding is at odds with Southern elites' justification for secession in the first place.

The third and final essay (Chapter 4) shifts the focus from legislators to constituents. Based on the products of legislative behavior (i.e., votes) studied in Chapters 2 and 3, voters make evaluations of their legislators' ideologies. Survey evidence reveals, however, that substantial numbers of voters cannot evaluate their legislators' ideological stances. In this chapter, I adapt a Bayesian modeling approach from the marketing literature to explicitly account for voters' inabilities to place their legislators on seven-point ideological scales. More concretely, I hypothesize that voters lack of response to such questions on surveys occurs to due to lack of *saliency* or *decisiveness*. In the case of the former, respondents are simply unable to answer the question at hand due to lack of interest or information. For the latter, indecision arises because voters cannot settle on a particular response. When applying the model to modern survey data, I find that education affects decisiveness, but a host of racial and ethnic factors affect saliency. I proceed to show that failing to model these factors explicitly can lead to inappropriate inferences post-estimation.

Chapter 5 presents a conclusion and discussion of results, as well as avenues for future work based on the findings of this dissertation.

# Chapter 2

# Weighing the Alternatives: Preferences, Parties, and Constituency in Roll Call Voting

*"When the leaders choose to make themselves bidders at an auction of popularity, their talents, in the construction of the state, will be of no service. They will become flatterers instead of legislators; the instruments, not the guides, of the people."*

**—Edmund Burke**

April 28, 2009, was a day that shook the world of American politics. The 2008 Presidential Election, just a few months earlier, witnessed the Democratic Party boost its majorities in the House and the Senate for the second election in a row. With the victory of Barack Obama, the Democrats had unified control of the U.S. Government for first time since the first two years of Clinton's first term. In the Senate, the Democrats had won 58 seats and eventually a 59th, once Norm Coleman's appeals exhausted and Al Franken was seated in the Capitol. Though this outcome was surely positive, the Democrats were one vote short of filibuster-proof control of the Senate. Indeed, it was this last pivotal actor that could stand in the way of Obama's legislative agenda being successful.

Then, on April 28, 2009, Arlen Specter, a liberal Republican Senator from Pennsylvania announced he was switching parties. Specter's decision, a surprise to both Democrats and Republicans, was accompanied by a press conference wherein Specter explained his decision further:

> As the Republican Party has moved farther and farther to the right, I have found myself increasingly at odds with the Republican philosophy and more in line with the philosophy of the Democratic Party... In the course of the last several months ... I have traveled the state and surveyed the sentiments of the Republican Party in Pennsylvania and public opinion polls, observed other public opinion polls and have found that the prospects for winning a Republican primary are bleak.

Indeed, Specter also cited that, "more than 200,000 Republicans in Pennsylvania changed their registration to become Democrats," thereby making the general election constituency more liberal and the Democratic primary constituency more conservative.[1]

What was especially puzzling about Specter's decision is that it was not

[1] To see this, assume that the distribution of Democratic primary voters was skewed to the right before the influx of 200,000 Republicans. If we assume further than these Republicans, even if they were moderates, were generally more to the right than previous Democratic primary voters, then they will shift the median of the primary distribution to the right.

part of a *quid pro quo* arrangement with the Democratic Party. He was not promised any chairmanships in advance and, indeed, his switch cost him his seniority on his existing committee assignments. Specter's decision, using this fact and his own words as a guide, seems to have been the result of balancing his own views and those of his constituents and determining that his Republican affiliation of several decades had become a liability.

To be sure, Specter was legitimately worried about his fate in the Republican primary. The departure of 200,000 (moderate) Republicans from the primary electorate meant that Specter had to worry even more about his conservative primary challenger in 2010, Pat Toomey, than he did in 2004. However, this primary story is, at best, incomplete. Specter's ideological quarrels with the Republican Party began long before his challenges from Pat Toomey. Moreover, switching parties would not necessarily mean a smooth path to the Democratic nomination. Indeed, nothing was negotiated in advance and, while the establishment ultimately decided to back him, a quality challenger (Representative Joe Sestak) emerged anyway.

This scenario, by no means unique in Congressional history, highlights the inherent tension between legislators' multiple goals and influences, something noted by many scholars (e.g. Kingdon 1989, Smith 2007, Sinclair 1995, Sinclair 2002, Fenno 1973, Smith 2007, Aldrich and Rohde 2000, Clausen and Cheney 1970). While there has been a large body of research attempting to demonstrate the presence of partisan (e.g., Cox & McCubbins 1993, 2005, Aldrich 1995, Aldrich & Rohde 1998, 2000, Krehbiel 2000, 2006) and electoral (e.g., Mayhew 1974) influences on lawmaking , this vast literature has failed to consider how the multiple goals of legislators and parties shape the legislative environment (Smith 2007). Indeed, how these factors play out has a direct relevance to researchers who proceed from these theories to the analysis of Congressional voting. That is to say, the interaction between the multiple goals of legislators and parties has a direct impact on results from the ever-burgeoning literature on ideal-point estimation (e.g. Poole and Rosenthal 1997, Clinton, Jackman and Rivers 2004).

This paper seeks to fills this gap. Herein, I present a new statistical method that builds on the insights of Levitt (1996) and, to some extent, Ansolabehere, Snyder and Stewart (2001). This method allows scholars to estimate the weights that legislators place on various competing sources of influence (e.g., their own preferences, party, and constituency). This in turn can help scholars to address a variety of key questions in the study of legislatures.

As was noted above, much of the vast literature in the so-called parties vs. preferences debate has failed to consider how multiple goals of legislators' shape legislative decision-making. This point is made clear by Smith (2007, pp. 42):

> The interdependence of parties' collective goals implies that even if party members are single-minded seekers of policy or reelection, as the single-goal theories assume, then fellow partisans share an interest in both collective goals. It appears that the assumption of multiple party goals is unavoidable, involves tradeoffs between the goals at times, and serves as a realistic basis for developing expectations about the influence of parties in floor

voting.

Sinclair (2002) expands on this observation by offering a more explicit characterization of how the multiple sources of influence affect Members of Congress' (MCs) choices. Specifically, she argues that

> members' legislatively relevant behavior is a weighted function of (1) the member's own views of what constitutes, (2) the preferences of his or her electorally relevant constituents, and (3) the preferences of other career- and influence-relevant political actors (Fenno 1973).

While few examples exist in the literature that take the multiple goals (à-la-Smith or Sinclair) into account when assessing the various influences on legislators' decisionmaking, there are at least two precursors in the literature. The first (Levitt 1996) attempts to estimate the weights that Senators place on their state-wide constituency, their re-election constituency, their party position, and their personal ideology. However, to do this, Levitt makes a number of fairly restrictive assumptions. First, Levitt assumes that these weights are constant across legislators, not allowing them to vary by party or other grouping. Second, he assumes that the weights are constant over time. Third, he assumes that Senators' ideologies are simply what is leftover after accounting for the other sources of influence. Last, he uses ADA scores of U.S. House members to proxy the measures of constituency preferences, which is problematic since ADA scores are based on roll calls and, hence, may be contaminated by majority party agenda setting (Cox and McCubbins 2005). These assumptions, while needed for the linear model Levitt runs, significantly restrict the inferences and dynamics one can explore with the estimated weights.

In Ansolabehere, Snyder and Stewart (2001), National Political Awareness Test (NPAT) responses are used to estimate legislators' ideologies. In turn, they regress roll-call-based ideal points on these scores and a party dummy to get rough estimates of the weights that legislators are employing. Their approach also requires some restrictive assumptions. First, it assumes that all legislators have a common weight. Second, given the use of a dummy for party, it also assumes that party effects are symmetric, even though features such as majority party status suggest otherwise.

In this paper, I build off of this previous work by incorporating a weighted utility framework into the standard item response model. To avoid potential biases associated with U.S. House agenda-control (Cox and McCubbins 2005), I apply the method to the study of the Senate from 1995-2009. The Senate is an ideal choice for two additional reasons. First, since the Senate is understudied and poorly understood (Smith 2007), this approach can illuminate some of mechanisms behind legislative behavior in that institution. Second, the Senate has several features (e.g., split-delegations) that allow scholars to explain diverging behavior of legislators representing the same constituency at the same time.

## 2.1 Statistical Model

### 2.1.1 Foundations

Assume there are $N$ legislators, $i = 1, 2, ..., N$, and a series of votes, $j = 1, 2, ..., J$. Each of these votes has a spatial position in a unidimensional policy space.[2] As in previous scholarship (e.g. Krehbiel 1996, Cox and McCubbins 2005, Clinton, Jackman and Rivers 2004), all players have pre-existing preferences in this space. These preferences are quadratic, centered at the actors' ideal points, $\hat{x}_i$. Besides personal policy preferences, actors in the legislative arena make decisions that also depend on electoral and partisan stimuli. I model this by using a weighted utility function.

Consider a generic legislator $i$. While he possesses his own most-preferred policy, $\hat{x}_i$, he must also balance the preferences of his district and the desires of his party. More concretely, legislator $i$ must not only consider his personal policy preferences, but also those of his constituency and his party (i.e., the party position) in decisionmaking. To capture this balancing act, let $\widehat{x}_{D(i)}$ denote the preferences of the median voter in $i$'s district and let $\widehat{x}_{P(i)}$ denote his party's preferences. For convenience, let $\Omega_i = \{\widehat{x}_i, \widehat{x}_{D(i)}, \widehat{x}_{P(i)}\}$ denote the set of these ideal points.

Now, let $\omega_i^{\widehat{x}_i}$ denote $i$'s weight on his preferences, $\omega_i^{\widehat{x}_D}$ denote the weight of $i$ on his district's preferences, and $\omega_i^{\widehat{x}_P}$ denote the weight of $i$ on his party's position. I assume the weights are exhaustive, i.e., $\sum_{k \in \Omega_i} \omega_i^k = 1$.

[2] The model can be extended to two or more dimensions easily.

Legislator $i$'s utility for policy $x_j$ is given by the following equation:

$$u_i(x_j) = -\sum_{k \in \Omega_i} \omega_i^k (x_j - \hat{x}_i^k)^2 + \varepsilon_{ij}, \tag{2.1}$$

where $\varepsilon_{ij}$ is an idiosyncratic error term for each legislator-policy combination.[3]

This equation is simply a sum of quadratic utility functions, each centered at the ideal point of the legislator's particular source of influence. The weights that premultiply the quadratic utilities attenuate how much the desirability of a policy alternative for a particular source of influence matters to the legislator. For example, his party may really like a policy that neither he nor his constituency do. So long as his weight on party is low, his overall utility for that policy will be low. However, if his weight on party is high, his overall utility for that policy will be high.

Modeling preferences in this fashion allows us to capture more complex interactions that purely policy, partisan, or electoral preference-based approaches cannot address. Indeed, my approach is a generalization that reduces to each of these as their associated weight approaches unity.

### 2.1.2 Relation to Existing Methods

In traditional ideal point models, legislators are assumed to have an ideal point $\hat{x}_i$ which is, by definition, their most-preferred policy. Ideal points are estimated using observed roll call votes by assuming various functional forms for the utility and error terms.

[3] Assumptions regarding these are discussed below.

My approach is a different enterprise. That is to say, preference measures are not objects of inference themselves. What this approach seeks to uncover is the weights that legislators are placing on the various competing influences in determining their vote choices.

To see this, consider what the ideal point in existing methodologies translates to in this model. For simplicity, assume the systematic component of the Clinton, Jackman, and Rivers (2004) utility function:

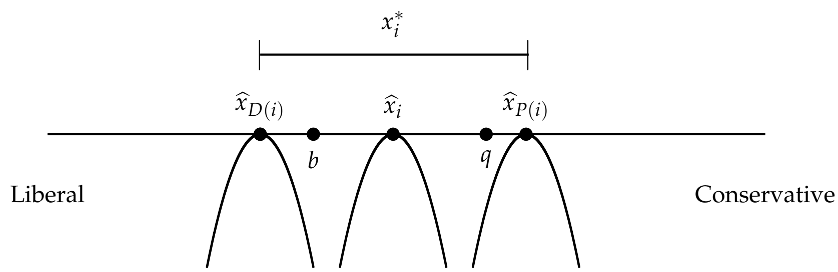
$$u_i(x|\theta_i) = -(x - \theta_i)^2,$$

where $x$ is policy and $\theta_i$ is the legislator's ideal point. Clearly, the optimal policy choice is $x_i^* = \theta_i$. In this model, differentiating the utility function in Equation 2.1 with respect to policy yields an optimal policy choice of $x_i^* = \sum_{k \in \Omega_i} \omega_i^k \widehat{x}_i^k$. In other words, legislators' net ideal points are the weighted average of the sources of influence.

Thus, my method disentangles the various influences in the $\theta_i$ that have previously been measured jointly. To see how this process plays out, consider a legislator $i$ whose preferences are seen in Figure 2.1. This setup could roughly approximate the case of Arlen Specter as a Republican. As the figure shows, the party position is further to the right and the legislator's constituency is actually slightly to the left of his personal policy position.

There is also a hypothetical bill, $b$, that is closer to his preferences and those of his constituency than is the status quo, $q$. His party, however, is closer to $q$.

Figure 2.1: Hypothetical Setup of Ideal Points




*Note:* The brackets above the line denote the set in which the net ideal point of legislator $i$, $x_i^*$, is located.

How the legislator reacts depends of how he weights his preferences, party, or constituency in the utility function. If constituency or personal preferences receive a disproportionate weight, then the net ideal point of the legislator, $x_i^* = \sum_{k \in \Omega_i} \omega_i^k \widehat{x}_i^k$, will be closer to $b$ and, hence, a "yea" vote will be observed. However, if the weights on party are higher, then the legislator is unlikely to support the bill. Thus, in order to know what the legislator will do, it is necessary to understand his weights.

### 2.1.3 Estimator

As noted above, the objects of inference in this approach are the $\omega_i^k$ that legislators place on various sources of influence, not the ideal points of legislators. I assume that preference measures of each source of influence are known and exogenous.[4] Like previous approaches, I look to the Congressional roll-call record to estimate my model. The setup of the model is as follows.

[4]See the section on the NPAT below.

For a generic roll call $j$, assume that a "yea" vote and a "nay" vote each have a spatial location in the unidimensional issue space. Specifically, let $v_j$ denote the location of "yea" and $\zeta_j$ denote the location of "nay." As in the standard spatial model, legislators vote "yea" if they get more utility from it than "nay." However, since this is a stochastic model, the utilities are perturbed by random error. To that end, rather than speak about a deterministic vote choice, I henceforth discuss voting probabilistically.

A legislator chooses the "yea" alternative with probability $Pr(y_{ij} = 1)$. This probability can be found by applying the spatial logic described above to the utility function in Equation 2.1. Specifically,

$$\begin{aligned}
Pr(y_{ij} = 1) &= Pr\left(u_i(v_j) \geq u_i(\zeta_j)\right) \\
&= Pr\left(-\sum_{k\in\Omega_i} \omega_i^k (v_j - \widehat{x}_i^k)^2 + \varepsilon_{ij} \geq -\sum_{k\in\Omega_i} \omega_i^k (\zeta_j - \widehat{x}_i^k)^2 + \varepsilon'_{ij}\right) \\
&= Pr\left(\varepsilon'_{ij} - \varepsilon_{ij} \leq -\sum_{k\in\Omega_i} \omega_i^k (v_j - \widehat{x}_i^k)^2 + \sum_{k\in\Omega_i} \omega_i^k (\zeta_j - \widehat{x}_i^k)^2\right) \\
&= Pr\left(\varepsilon'_{ij} - \varepsilon_{ij} \leq \sum_{k\in\Omega_i} \omega_i^k (\zeta_j^2 - v_j^2 - 2\widehat{x}_i^k(\zeta_j - v_j))\right). \qquad (2.2)
\end{aligned}$$

Since the quadratic terms in Equation 2.2, $\zeta_j^2$ and $v_j^2$ are free of the index of summation and, further, that the weights sum to one, we can remove the sum from these two terms. That is,

$$Pr(y_{ij} = 1) = Pr\left(\varepsilon'_{ij} - \varepsilon_{ij} \leq \zeta_j^2 - v_j^2 - 2(\zeta_j - v_j) \sum_{k\in\Omega_i} \omega_i^k \widehat{x}_i^k\right). \qquad (2.3)$$

If we assume that the error terms are jointly-Normal distributed, $E(\varepsilon_{ij}) = E(\varepsilon'_{ij}) = 0$, and $Var(\varepsilon'_{ij} - \varepsilon_{ij}) = 1/\tau_j^2$, then Equation 2.3 becomes

$$Pr(y_{ij} = 1) \quad = \quad \Phi\left(\tau_j^2(\zeta_j^2 - \upsilon_j^2 - 2(\zeta_j - \upsilon_j)\sum_{k\in\Omega_i}\omega_i^k\hat{x}_i^k\right), \qquad (2.4)$$

where $\Phi(\cdot)$ is the standard Normal distribution function. As a final simplification, let $\alpha_j = -\tau_j^2(\zeta_j^2 - \upsilon_j^2)$ and $\beta_j = 2\tau_j^2(\upsilon_j - \zeta_j)$. Plugging these into Equation 2.4 yields

$$Pr(y_{ij} = 1) \quad = \quad \Phi\left(-\alpha_j + \beta_j \sum_{k\in\Omega_i}\omega_i^k\hat{x}_i^k\right). \qquad (2.5)$$

We know that the probability associated with voting “nay” is the complement of the probability associated with voting “yea.” That is,

$$Pr(y_{ij} = 0) \quad = \quad 1 - \Phi\left(-\alpha_j + \beta_j \sum_{k\in\Omega_i}\omega_i^k\hat{x}_i^k\right). \qquad (2.6)$$

Equations 2.5 and 2.6 are, for the most part, familiar results. The probabilities of voting “yea” or “nay” are probit links applied to linear equations. The resulting equations bear much similarity to the corpus of literature on item-response theory (IRT), as well as applications in Bayesian ideal point estimation (Clinton, Jackman and Rivers 2004, Bock and Aitkin 1981). The $\alpha_j$ is the difficulty of the roll call and the $\beta_j$ is the measure of how well the roll call discriminates between legislators.

However, this result is different from past research in two important ways. First, rather than premultiplying a single ideal point, $\beta_j$ pre-multiplies the weighted-average of a legislator's three sources of influence. Second, and perhaps more important, the objects of inference are the weights on the abilities, not the abilities themselves. This turns out to ease some of the identification problems associated with ideal point estimation (see also Rivers 2003, Londregan 1999).[5]

We know the probabilities of a legislator voting "yea" or "nay" on a generic roll call and, thus, can write the Likelihood for the model easily. Since the outcome on a roll call is just a Bernoulli trial, the Likelihood is

$$\begin{aligned}\mathcal{L}(\boldsymbol{\omega}, \boldsymbol{\beta}, \boldsymbol{\alpha} | \boldsymbol{y}, \boldsymbol{x}) = \prod_{j=1}^{J}\prod_{i=1}^{N} \quad & \Phi\left(-\alpha_j + \beta_j \sum_{k\in\Omega_i} \omega_i^k \widehat{x}_i^k\right)^{y_{ij}} \\ \times \quad & \left(1 - \Phi\left(-\alpha_j + \beta_j \sum_{k\in\Omega_i} \omega_i^k \widehat{x}_i^k\right)\right)^{1-y_{ij}},\end{aligned}$$

the log of which is

$$\begin{aligned}\ln \mathcal{L} = \sum_{j=1}^{J}\sum_{i=1}^{N} \quad & y_{ij} \ln \Phi\left(-\alpha_j + \beta_j \sum_{k\in\Omega_i} \omega_i^k \widehat{x}_i^k\right) \\ + \quad & (1 - y_{ij}) \ln\left(1 - \Phi\left(-\alpha_j + \beta_j \sum_{k\in\Omega_i} \omega_i^k \widehat{x}_i^k\right)\right). \quad (2.7)\end{aligned}$$

[5]In particular, the weights have natural bounds, unlike the ideal points. That is, they must sum to one and individually cannot be less than zero or greater than one. Furthermore, since the ideal points are on a common scale, the weighted-average of the ideal points is also bounded. This point will be discussed further below. Technically, the model is exactly identified for the case where $|\Omega_i| \leq 2$. For other cases, further restrictions are needed for identification.

## 2.2 Estimation Strategy

The Likelihood above (equation 2.7), like that analyzed by Poole and Rosenthal (1997) and those within the broader IRT literature (e.g. Bock and Aitkin 1981), cannot be maximized directly using standard techniques. The literature provides a number of alternative techniques including Conditional Maximum Likelihood, Marginal Maximum Likelihood (Bock and Aitkin 1981), Bayesian MCMC (Clinton, Jackman and Rivers 2004), and the so-called "zig-zag" estimator (Heckman and MaCurdy 1980, Poole and Rosenthal 1997). For this model, I opt to use a MCMC method that involves the use of Gibbs steps for the item parameters and Metropolis-within-Gibbs for the weights.

As mentioned above, identification issues arise when the number of weights is greater than two. For the case when the number of items a legislator weighs is equal to two (e.g., the legislator only cares about his party and his preferences), the model can be run directly and unique weights for every legislator may be estimated. When the number of items that a legislator is weighing exceeds two, the model as it stands is unidentified. Specifically, the number of unknowns (e.g., weights) exceeds the amount of data that is available to estimate them. To solve this problem, I must make some stronger assumptions, chiefly that legislators within groups share a common weight.

Thus, identification and estimation involves a two-step process. The first is to partition the $N$ legislators into $L$ batches, where $|L| << N$, and assume that legislators within a common group have a common weight.

A simple approach is to group legislators by party, though one can easily extend the number of groups. Thus, rather than speak about individual weights, $\omega_i^k$, I henceforth speak of group weights, $\omega_{l(i)}^k$, where $l(i) \in L$ denotes the group $l$ that legislator $i$ belongs to. As long as the size of each group is larger than $|\Omega_i|$, identification is guaranteed.[6]

Now that the model is identified, the second step is estimation. The Bayesian MCMC setup requires, in addition to the Likelihood in Equation 2.7, priors on the item parameters and the weights. Following Clinton, Jackman and Rivers (2004), I assign Normally-distributed priors to the item parameters. That is,

$$\alpha_j \sim \mathcal{N}(0, 10)$$

and

$$\beta_j \sim \mathcal{N}(0, 10).$$

The priors on the weights are as follows:

$$\omega_l^1 \sim U[0, 1] \tag{2.8}$$

$$\omega_l^m \sim U[0, \bar{u}], \forall m > 1, \tag{2.9}$$

where $\bar{u} = \max(0, 1 - \sum_{p<m} \omega_l^p)$. This seemingly complex expression means that the first weight is drawn from the Uniform distribution on the unit interval and that all subsequent weights are drawn Uniform from 0 to the residual amount of weight left to draw from. As a practical matter, if draws

[6]The estimates of each batch of weights are from a Bayesian linear regression. To estimate the coefficients in this regression, we must have more than $|\Omega_i|$ in order to have the requisite degrees of freedom.

of the first few weights are so large that the residual weight is effectively zero, the upper bound on the prior distribution must be shifted to avoid computational problems. This means that, in practice, $\bar{u} = \max(0.000001, 1 - \sum_{p<m} \omega_l^p)$, whereby 0 has been replaced by 0.000001.[7] My model can be run in `WinBUGS`, though it is a rather simple model to code by hand. [8]

## 2.3 Data

To estimate the model, we need ideal policies on a common scale of legislators, constituencies, and parties, *a priori*. Unfortunately, while we can have good proxies for these three, it is nearly impossible to generate common-scale measures. The ideal data for this purpose would consist of candidate questionnaires whereby legislators truthfully place themselves, their party leadership, and their constituencies along a unidimensional policy space.

Here I propose an alternative using Project VoteSmart data to produce estimates of all three ideal points. Project VoteSmart has, since 1992, surveyed legislators at the congressional and state levels for all legislative, gubernatorial, and presidential races in their National Political Awareness Test (NPAT). NPAT data consists of a huge battery of questions designed to tap legislators' views on a plethora of issues raising from abortion to gun rights to the budget and so on. This data is available for scholarly

[7]Extensive Monte Carlo analysis has been performed on this model. Therein, I have found that the upper bound constraint is generally not a problem unless that actual weight is 0 in the true data generating process. Indeed, the use of 0.000001 is not even necessary, save in these razors-edge cases.

[8]Using data augmentation techniques, all steps except the weights are Gibbs; weights can be drawn using a Metropolis step and a Normal jumping distribution.

purposes.[9]

### 2.3.1 NPAT: Legislators and Parties

The first step to generate common-space ideology measures is to pool the data across years. Since the Senate has a staggered election structure, only about one-third of that body is up for election at any time and, hence, the number of possible NPAT respondents is lower than for the House. Furthermore, though the NPAT does ask a core battery of questions from year to year, many questions do change with the popular topics of the day. For example, detailed abortion questions are always asked, but questions on the balanced-budget or line-item veto were only asked during the mid-to-late 1990s.

Thus, I went through all NPAT questionnaires from 1992-2006 and identified a core of 33 questions that were the same across years (see the Appendix to this chapter). All members of the Senate serving from 1992-2006 and filling out a NPAT questionnaire at least once during that time period were included. Questions that are not asked in every survey were discarded. [10] Also, since the 33 questions I selected are prominent issues that are debated regularly in the American political arena, a scholar can

[9]Thanks to Project VoteSmart, I have obtained this data going back to 1992. I am currently working with U.S. Senate data but will be moving to the state legislatures in the future.

[10]Though one could in principle add all possible questions to the matrix and use the common questions as the linkages between the legislators across years, this turns out to produce less precise estimates. To see why, consider that a given Senator who responded to the NPAT in 1996 will have missing values for every question that was asked every other years besides 1996. This means he will have several hundred missing values. Since the Gibbs sampler in the IRT model will simply draw his latent utility differential from a diffuse Normal distribution, essentially no "good" information is added.

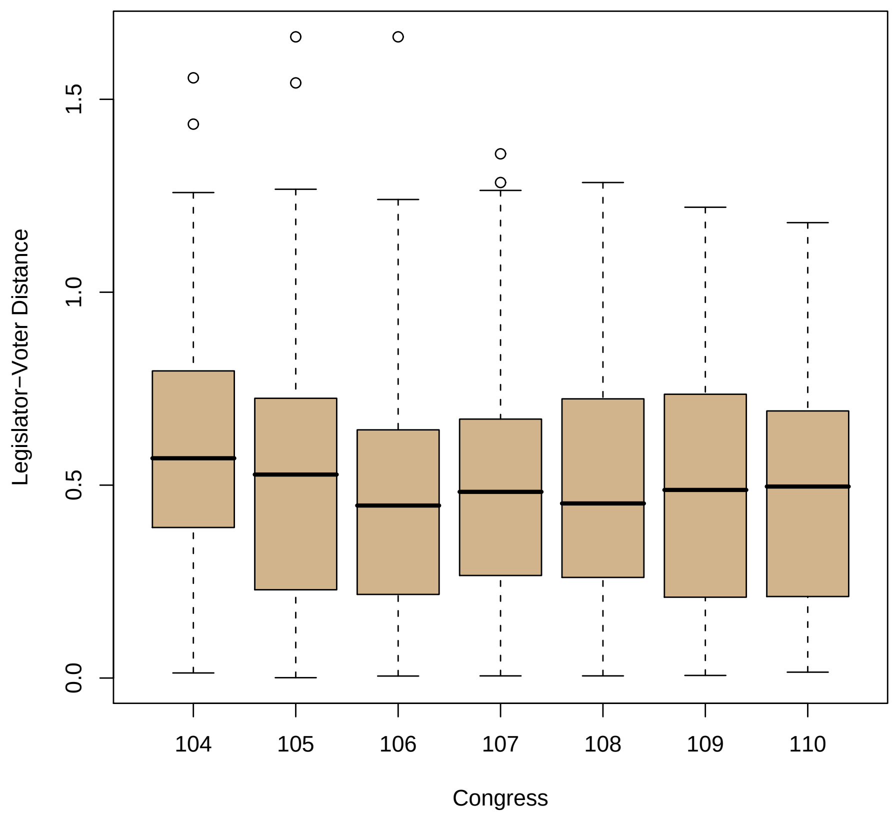
essentially fill out the NPAT for someone who did not respond. [11] For example, while John McCain has responded to the NPAT many times, Barack Obama has not. However, Obama's position on almost all of the issues investigated are public knowledge through speeches and his websites over the years. Thus, an Obama position can be assessed.

Three further issues regarding use of the NPAT require comment: the assumption of constant preferences, respondent selection effects, and the reliability of NPAT-based ideal points as a measure of respondent preferences. As for the first, since the time span I am pooling is relatively short, this assumption seems quite reasonable. Specifically, it is unlikely that Ted Kennedy or Sam Brownback are going to change their minds on abortion or gun rights over such a short span. Indeed, for legislators who respond every time they are up for re-election (e.g., McCain and Specter), their positions rarely change. Second, it is possible that NPAT respondents select themselves into the sample. This is problematic because it may induce a selection bias in the estimates of legislator weights if respondents are categorically different then non-respondents. Fortunately, it turns out that the legislators who respond come from all ideological groups, roughly evenly split between the two parties, and the characteristics of their voting behavior (e.g., NOMINATE scores, presidential support scores) are not substantially different. In an effort to be more confident in this regard, I use an imputation technique akin to Ansolabehere, Snyder and Stewart (2001) for the members not responding to the NPAT.[12] Results from the model includ-

[11] I choose to use an imputation technique instead following Ansolabehere, Snyder and Stewart (2001). Details are found below.

[12] This approach follows an observation by Synder and Groseclose (2001), that estimated

Figure 2.2: NPAT-Legislator Distances




ing imputed NPAT preferences are qualitatively unchanged.

The third issue is that NPAT may not reflect actual legislator ideology. Since the survey is completely voluntary and results are made public, responses are merely cheap talk. One way to assess this is to look at the dis-

ideal points from lopsided roll calls correlate highly with NPAT-based ideal points. Thus, if we regress the NPAT-based ideal point (which we have for many Senators) on the roll call-based ideal point from lopsided votes (which we have for all), we can then use the slope and intercept to generate imputed NPAT scores for the rest.

tances between legislator NPAT-based ideal points and voter positions (see below for method of construction). If legislators were merely telling voters what they what to hear, then legislator NPAT scores should correlate very highly with voter positions. Figure 2.2 shows the legislator-to-voter distances by Congress in the form of a box-and-whisker plot. As we see, on average, most legislators are not very close to their constituents. This either means that legislators are making lots of misjudgments about voters' positions or that NPAT is tapping something different. Given this finding, I am fairly confident that NPAT is indeed tapping the legislator's ideology and not simply capturing a mimicking of what voters desire.

The next step in getting legislator and party estimates on a common scale is to translate the responses to these questions into measures of member ideology. To do so, I mimic the methodology of Ansolabehere, Snyder and Stewart (2001). However, rather than using the Heckman and Jr. (1997) methodology, I run Bayesian IRT (Clinton, Jackman and Rivers 2004) on the matrix of responses, saving the first dimension score. I henceforth refer to legislator preference estimates generated in this way as NPoints.

We can then transform NPoints to measure party position using one of several approaches. The easiest one is to find the median of the NPoints within parties. Other alternatives would be to use the NPoints of the party majority/minority leaders, or to average the leadership team (majority/minority leader, majority/minority whip). I have done all of these and, since the results are essentially the same, I opted for the first solution. [13]

[13] One could also fill out a NPAT questionnaire with the responses as found in party platforms.

### 2.3.2 Putting Constituency in a Common Space

Finally, we need to put the electorate on a common scale with legislators and parties. Attempting this has drawn the interest of a few scholars as of late (e.g. Bafumi and Herron 2007, Shor 2009, Burden 2004). Bafumi and Herron (2007) and Shor (2009) each conducts extensive surveys, asking respondents to answer roll call and NPAT questions, respectively. This approach is highly desirable, as it can directly link the respondents with their respective legislators. Unfortunately, it is bound to 2006 and beyond. Scholars wishing to study earlier periods must resort to other techniques.

To this end, Burden (2004) introduces a technique that puts voters and legislators in a common space using the Democratic share of the two-party vote (DSTPV). As Burden (2004) notes, the DSTPV has long been regarded as a reliable measure of state-level preferences and correlates very highly with factor analytic solutions employing issue scales. Burden's technique involves rescaling the DSTPV by pinning down the Democratic and Republican presidential candidates at 0 and 1, respectively. By doing this, the DSTPV (also bound by 0 and 1) is transformed to a policy position. He then uses NOMINATE and presidential support scores to generate estimates of legislator positions and district ideologies in this space.

I take a similar approach here, but diverge from the restrictive assumption that the Democratic and Republican candidates for president are at 0 and 1, respectively. This is made possible by identifying the Democratic and Republican candidates' issue positions on the 33 common-space NPAT questions, running the Bayesian IRT model on the matrix of Senators and presidential candidates, and then using the estimated ideal points of the candidates as the glue for this space.

Formally, let $\delta$ and $\rho$ denote the ideal points of the Democratic and Republican candidates, respectively. Voters vote for the candidate closer to their ideal point. To move from the DSTPV to NPAT-space, we must make two assumptions regarding the configuration of presidential candidates and voters:

**Assumption 1.** *The Democratic presidential candidate is never to the right of the Republican candidate.*

**Assumption 2.** *No state's median voter is more liberal than the Democratic presidential candidate or more conservative than the Republican candidate.*

Assumption 1 is uncontroversial and is certainly true during the period I am studying. Assumption 2 is a bit more controversial. To be sure, I am not assuming that all voters' ideal points are bounded by the two parties' candidates, only the median. This assumption is only problematic if at least one of the major party candidates is a moderate and not from the heart of the party. Over the time period I am analyzing (mid-1990s on), this seems to be a non-issue.

This means that a state, $s$, with a 0% vote for the Democratic candidate has a median ideal point equal to the Republican candidate, i.e., $\hat{x}_s = \rho$. Similarly, a state, $s'$ with a 100% vote for the Democratic candidate has a median ideal point equal to the Democratic candidate, i.e., $\hat{x}_{s'} = \delta$. Consequently, if $d_s$ is the DSTPV of a state $s$, the ideal point of the median voter in that state is given by

$$\hat{x}_s = \rho + (\delta - \rho)d_s. \tag{2.10}$$

## 2.4 Results

I generated personal ideology measures for all Senators from the 104th to the 110th Congresses and used these to obtain estimates of party positions (i.e., the party median). I also matched known positions of presidential candidates in the 1992, 1996, 2000, and 2004 presidential elections to generate NPoints for these actors. With these in hand, I applied the transformation technique described above on the DSTPV to get a common-space measure of voter ideology. Having produced preferences of legislators, parties, and constituencies on the same scale, I can now discuss the implementation of the statistical model.

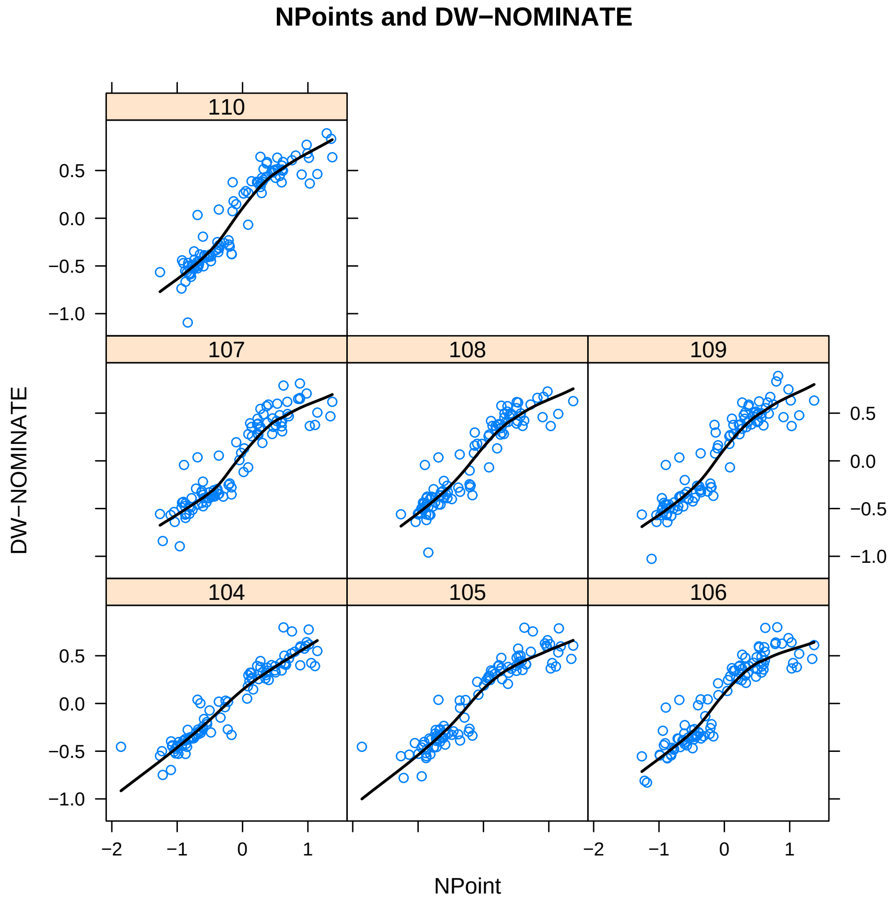
For the purpose of this paper, I grouped legislators into four bins, drawing weights from a common distribution for each bin. These bins were Republican moderates, Republican extremists, Democratic moderates, and Democratic extremists. Moderates are those Senators whose NPAT scores are to the right (left) of the party median if they are Democrats (Republicans); extremists are the rest of the chamber.

For each Congress in my sample, I ran the statistical model using WinBUGS (for code, see the Appendix to this chapter). In each Congress, I generated starting values of item parameters running a set of independent probits. Starting values of the weights were chosen arbitrarily, but the results do not change over a widely dispersed set of initial parameter values. For each Congress, the three chains of the model were instantiated and run 100,000 times. However, this was unnecessary, since the model converged very quickly (i.e., around the 2,000th iteration). Indeed, standard approaches were applied to assess convergence (e.g., the Gelman and Rubin (1992) and Geweke, Berger and Dawid (1992) diagnostics) and all of these suggested the model had converged.

With the results of the model in hand, one of the first things to assess is the relationship between the NPAT-based legislator preferences and the most common proxy for legislator preferences, DW-NOMINATE. Figure 2.3 plots the NPoint against the DW-NOMINATE score for every Senator by Congress with a smoothed Loess curve and finds the same relationship found in Groseclose and Snyder (2000). While the NPoints and DW-NOMINATE scores correlate highly, it is evident that moderates in NPAT-space appear to be pulled toward the extremists in their parties. This suggests that, especially for moderates, something other than the legislators' preferences is affecting their behavior.

Prior to looking at the weights, it is useful to see if the legislator's net ideal point, that is, the weighted average of the sources of influence, correlates with the DW-NOMINATE score. To measure the estimated net ideal point, we simply calculate: $\hat{x}_i^* = \sum_{k \in \Omega_i} \omega_i^k \hat{x}_i^k$. Figure 2.4 plots the resulting net ideal point against the DW-NOMINATE score, along with the Loess curve superimposed. As expected, the two measures match up nearly linearly, thereby providing some face validity for the model and replicating the IRT-NOMINATE relationship identified in Clinton, Jackman and Rivers

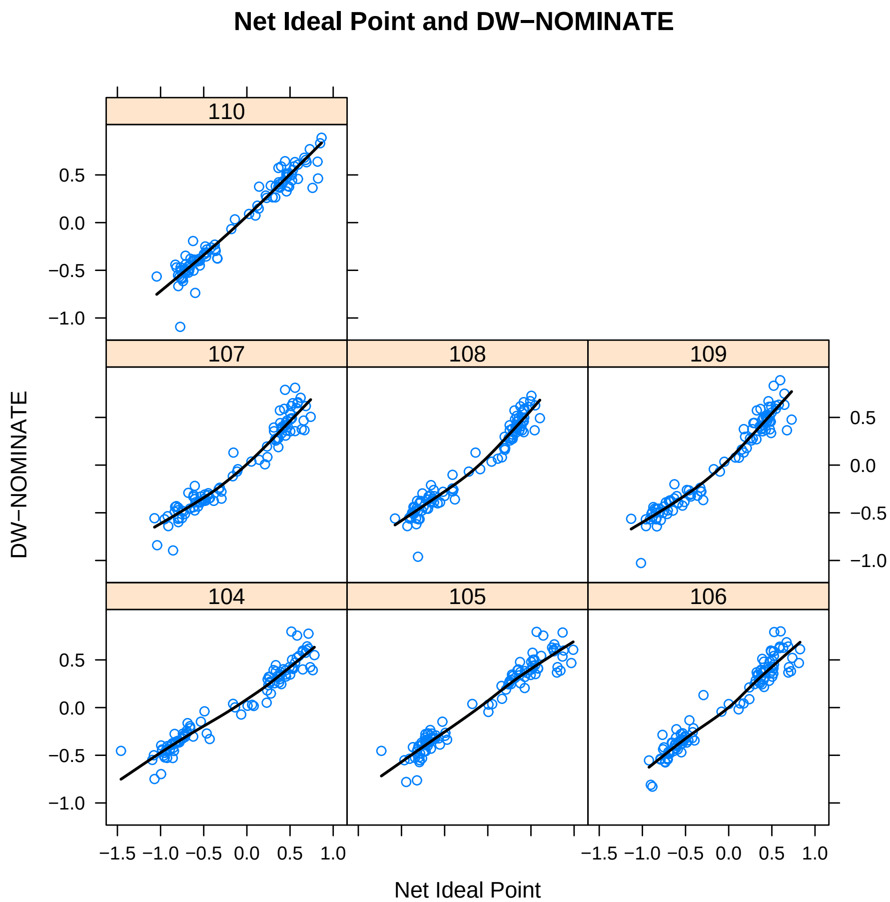
Figure 2.3: NPAT vs. DW-NOMINATE (by Congress)




(2004).

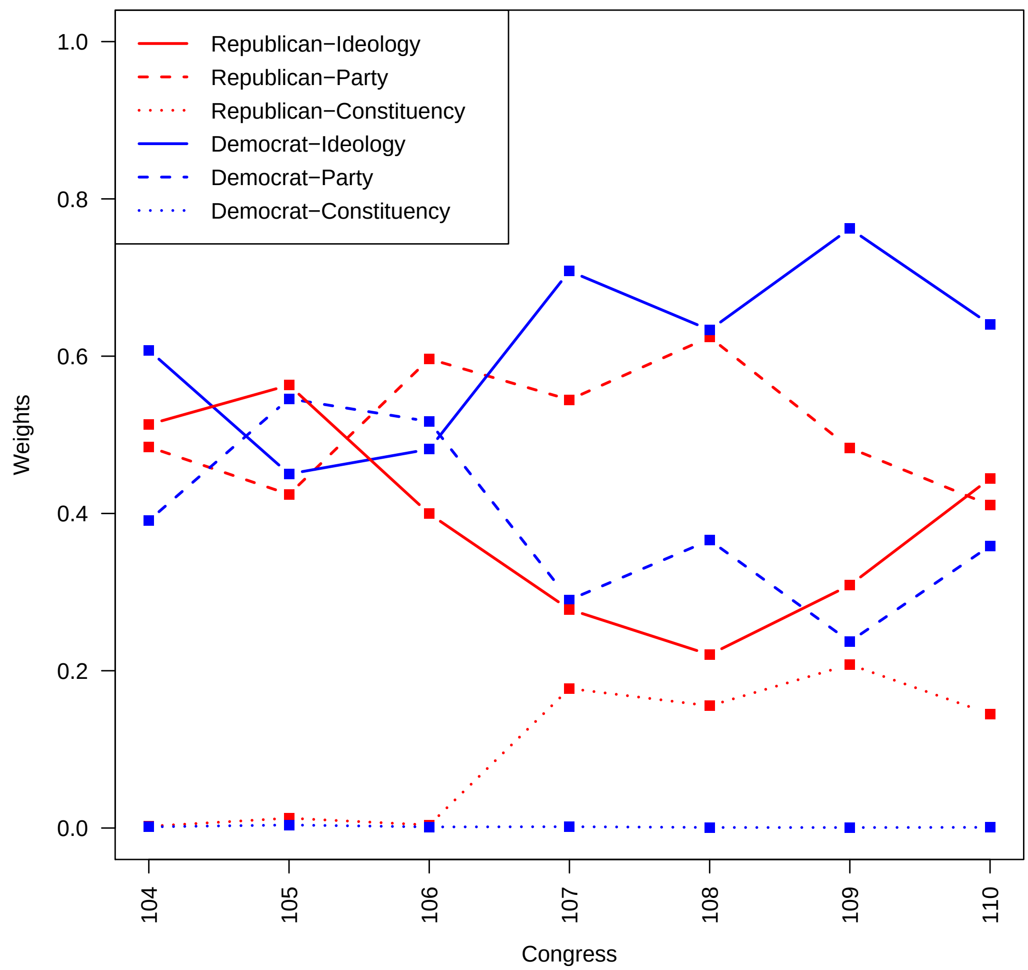
Finally, the main parameters of interest in the model, the weights, are plotted in Figure 2.5. While the pattern discovered is consistent with past research (e.g. Ansolabehere, Snyder and Stewart 2001, Levitt 1996), it also highlights patterns not previously known. The weights on legislators' constituencies are almost all very low, though Republicans are noticeably more

Figure 2.4: Net Ideal Point vs. DW-NOMINATE (by Congress)



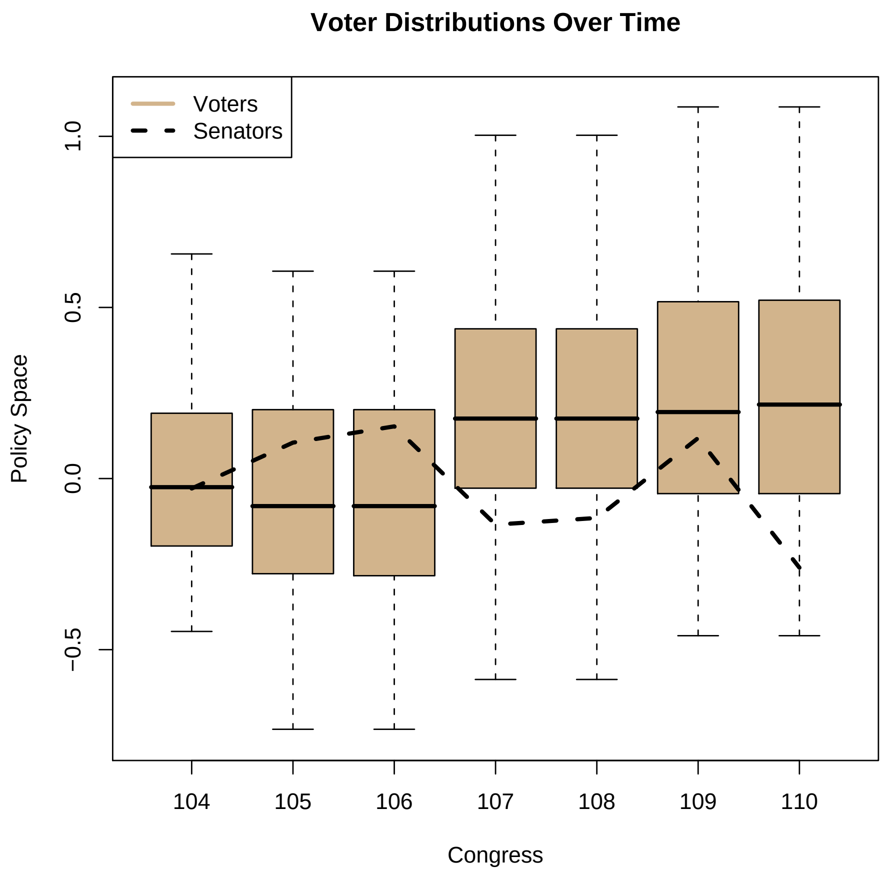

constituency-minded, especially after the 107th Congress. This has consequences for representation and is discussed below. The weights on party reflect the ideological pull of Senators' party positions. In the aftermath of the Republican Revolution, party weights were high for both parties. However, after the 105th Congress, the Republicans had a noticeably higher weight on party than the Democrats. This peaked during the Bush presi-

Figure 2.5: Weights Over Time




dency, almost invariably because Republicans were more pressured to push through their president's legislative agenda. To be sure, the Democrats' weight on party was noticeably higher during the Clinton presidency. This

Figure 2.6: Median Voters Across States and Years




suggests a presidential effect regardless of which party controls the White House.

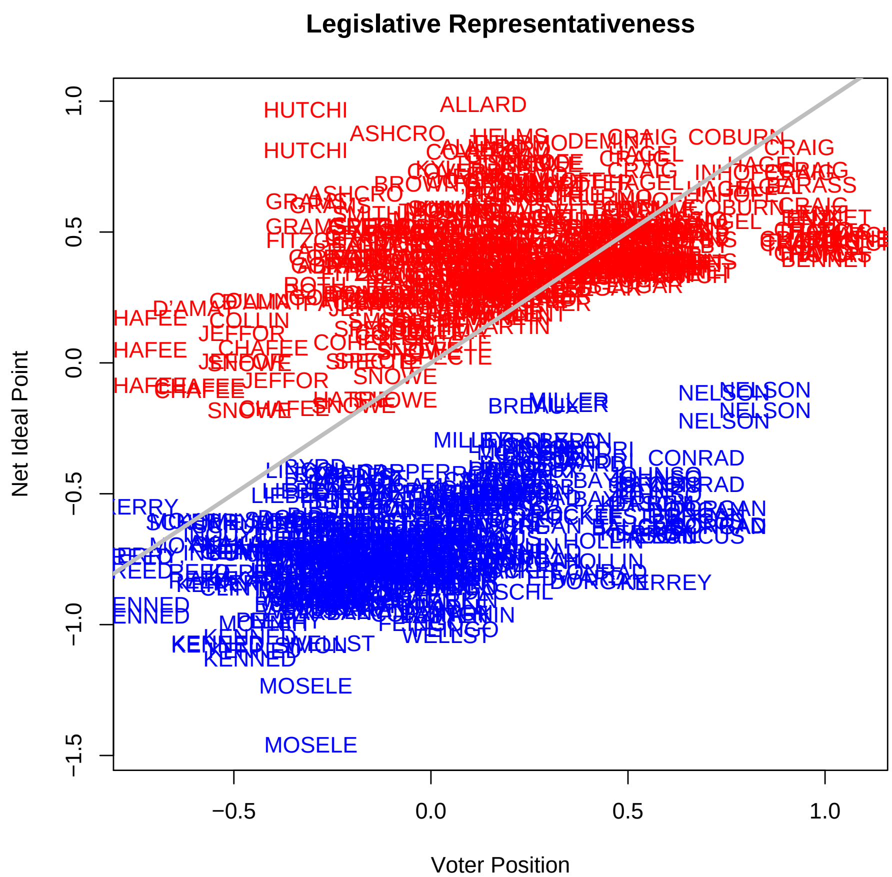
### 2.4.1 Representation

To more closely assess the inferences about representation present in the data, it is useful to consider the degree to which legislators' manifest voting records (i.e., net ideal points) correspond to voter preferences. Figure 2.6 presents this in the form of a box-and-whisker plot. The tan boxes, whiskers, and stems represent the distribution of preferences across states and years. Since presidential elections are *quadrennial*, the same DSTPV is used for each four-year block and, hence, the distributions for the 105-106th, 107-108th, and 109-110th Congresses are identical. The gray superimposed line represents the Senate median net ideal point.

From this figure, we see that the Senate appears, as a whole, to be fairly unrepresentative of public opinion. During the Clinton presidency (104-106th Congress), it was generally more conservative than the national median voter. In the Bush era, especially in the first term (107-108th Congress), the Senate was much more liberal than national opinion. This pattern exacerbates during the final two years of President Bush's presidency, where the median Senator's ideal point plummets to nearly the end of one of the stems in the last box-and-whisker plot.

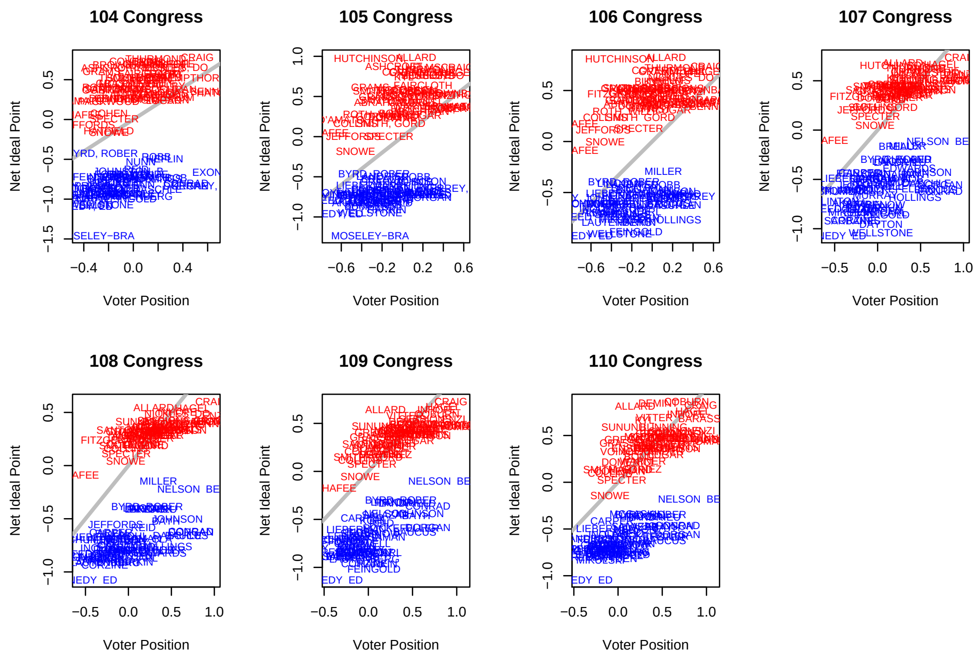
One might be tempted to suggest that this pattern may be an idiosyncratic feature of my voter ideal point rescaling technique. However, I am not the first to find such a pattern. While Jacobson (2004) discovers a general congruency between the preferences of legislators and voters, Shor (2009) has corroborated the essential finding above. Using the Cooperative Campaign Analysis Project (CCAP) survey, Shor was able to generate estimates of constituent opinion by asking respondents NPAT questions. From this, Shor finds that there is a generally liberal tilt (with respect to state opinion) of state legislatures and Congress. This finding is certainly in line with my results.

Figure 2.7: Senators' Representativeness (pooled)




Figures 2.7 and 2.8 plot the net ideal point of Senators against the median voters in their respective states. Republicans are colored red and Democrats are colored blue, where legislators' names serve as plot character labels. In Figure 2.7, all years are pooled. Legislators whose ideal points are above the gray dashed line are too conservative for their states, whereas those below the line are too liberal. We see that conservative Re-

Figure 2.8: Senators' Representativeness (disaggregated)




publicans and liberal Democrats appear to cluster close to the gray line. Moderates, however, are far from the line, with Democrat moderates especially far from state opinion. This too appears to be in line with Shor (2009).

Figure 2.8 disaggregates the pattern by Congress. While the pattern is basically the same across years, we see Republicans increasingly clustering close to the 45-degree line. Democrats appear to be doing the same, but to a much lesser extent.

The outstanding question is, what factors lead legislators to converge to, or diverge from, their state's preferences? To understand this, there are a number of possibilities that seem intuitive to investigate.[14] One is *Chamber Seniority*, which measures how long Senators have been in the chamber. It seems natural to think that Senators with less seniority would be more likely to pander to public opinion, in contrast to older statesmen like Byrd or Kennedy.

The effect of subsequent elections may also have a pressuring effect on legislators. To analyze this, I use a variable called *Status in Next Election*, a dummy variable that is equal to 1 if a legislator is re-elected in the next election and 0 if he is not. This variable captures the "forward thinking," backward inducing nature of rational legislators. If a legislator anticipates a defeat in the next election, he should be more likely to move toward the median voter (Downs 1957).

Since ideological extremism is likely to pull centrists differently than extremists, I employ a dummy variable called *Moderate*. This is equal to 1 if the Senator is to the left (right) of the party median if he is a Republican (Democrat). Moderates, typically being in tough re-election races, seem to have more need to moderate their behavior in the direction of voter prefer-

[14]Some of these variables were obtained from Stewart and Woon (2009). These include Seniority, Class of Senator, and Re-election Status

ences.

Finally, whether the state has a split delegation, where two Senators from the same state belong to different parties, may impact how legislators behave. To capture this effect, *Split Delegation* is a dummy equal to 1 if the Senator is of the opposite party of the other Senator representing his state. While it is *a priori* uncertain what effect this has on the distance between Senator behavior and voter preferences, it seems natural to think that split delegation Senators might behave differently than same-party ones.

Since the net ideal point of Senators and voter preferences are in a common space, we can calculate the Euclidean distance between them and regress this on the variables above, with appropriate Congress-specific fixed-effects. The resulting dependent variable is skewed and, thus, requires a square-root transformation in order to estimate this model via OLS. Further, since party differences could mitigate all of these effects, any regression must be run separately for each political party. In what follows, Model 1 refers to the OLS estimates for Republicans only and Model 2 refers to the OLS estimates for Democrats (and those who caucus with them). The results are found in Table 2.1.

The results are somewhat similar across the two parties (see Table 2.1). Seniority does not seem to matter for either party. Moderates in both parties are much more likely to be closer to their voters than extremists. The effect for Republicans is twice as much as that for Democrats.

Whether or not a legislator is reelected does not have an effect on Republicans, but it does in fact have a negative effect for Democrats. This difference is perhaps a majority-minority effect, but it does appear that

Table 2.1: Predicting the Distance between Senator Behavior and Voter Preferences

| | Model 1 | Model 2 |
|---|---|---|
| Intercept | 0.57 ** | 0.90 ** |
| | (0.04) | (0.04) |
| Chamber Seniority | 0.00 | -0.00 |
| | (0.00) | (0.00) |
| Status in Next Election | -0.01 | -0.06 * |
| | (0.03) | (0.03) |
| Moderate | -0.11 ** | -0.05 * |
| | (0.02) | (0.03) |
| Split Delegation | 0.10 ** | 0.06 ** |
| | (0.02) | (0.02) |
| $N$ | 354 | 329 |
| $R^2$ | 0.31 | 0.21 |
| adj. $R^2$ | 0.29 | 0.19 |

*Note*: Coefficients are estimates from an OLS model and the associated standard errors are in parentheses. The dependent variable is the square-root of the Euclidean distance between the legislator's net ideal point and the state median voter. Congress-specific fixed effects are suppressed. $* = p < 0.1, ** = p < 0.05$ (two-tailed).

Democrats are generally more sensitive to tight elections.

Perhaps most interestingly, split delegations also have a negative effect on the distance between voter preferences and legislator behavior; being in a split delegation increases the distance between voters and Senators. Thus, contrary to the logic of split-ticket voting, voters wishing to balance policy by choosing Senators of opposite parties actually create incentives

Table 2.2: Proximity of Senators to Constituency and Party

| | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|
| Intercept | -1.28 ** | -6.21 ** | -1.20 ** | -5.66 ** |
| | (0.57) | (1.81) | (0.57) | (1.63) |
| Chamber Seniority | -0.03 | 0.09 ** | -0.04 ** | 0.06 ** |
| | (0.02) | (0.03) | (0.02) | (0.03) |
| Status in Next Election | -0.79* | 0.17 | -0.82 ** | 0.33 |
| | (0.41) | (1.18) | (0.41) | (1.15) |
| Moderate | 2.33 ** | 2.11 ** | 2.42 ** | 1.73 ** |
| | (0.33) | (0.88) | (0.36) | (0.76) |
| Split Delegation | -1.02 ** | -0.29 | -0.85 ** | 0.09 |
| | (0.34) | (0.80) | (0.32) | (0.71) |
| *N* | 354 | 329 | 354 | 329 |
| AIC | 342.01 | 74.88 | 365.95 | 89.37 |
| BIC | 512.26 | 241.90 | 536.20 | 256.40 |
| log *L* | -127.01 | 6.56 | -138.98 | -0.69 |

*Note*: Coefficients are estimates from a Logit model and the associated standard errors are in parentheses. In Model 3, the dependent variable is equal to 1 if the legislator's net ideal point is closer to the state median voter than either the legislator's personal preferences or his party, Republicans only. Model 4 replicates Model 3 for Democrats and (when applicable) independents who caucus with Democrats. In Model 5, the dependent variable is equal to 1 if the legislator's net ideal point is closer to his party than either the legislator's personal preferences or the state median voter, Republicans only. Model 6 replicates Model 5 for Democrats and (when applicable) independents who caucus with Democrats. Congress-specific fixed effects are suppressed. $* = p < 0.1, ** = p < 0.05$ (two-tailed).

for legislators to diverge.

Euclidean distances are one way to look further into the results, but they can be misleading. For example, a Senator like Susan Collins has to balance a liberal constituency with her own moderate preferences and a very conservative Republican party. Even if Collins's largest weight is on her constituency, the gap between her net ideal point and her constituency's ideal point is still be large. On the other hand, Senators like John Kerry, whose own preferences are very close to their constituency, don't have to balance much and may appear closer to voters as a result. To get around this, I replace the Euclidean distance dependent variable with a binary variable that equals one if the Senator's net ideal point is closer to his constituency than either his party or his own preferences and 0 otherwise.

Table 2.2 displays the results of the Logit model using the same regressors as in the OLS model. Models 3 and 4 are for Republicans and Democrats only, respectively. The results are somewhat similar to the OLS findings, in that moderates are still more likely to be closer to their constituency and split delegations are less so.[15] However, seniority appears to have a positive effect for Democrats (and not for Republicans). As expected, more senior Senators are much less likely to weigh their constituency as most important.

In terms of electoral factors, the sign and significance for Republicans has changed in this model. This means that being re-elected in the subsequent election cycle decreases the probability that the Senator's net ideal point is closest to his voters.

[15] In this instance, the effect of split delegations is only borne out for Republicans.

### 2.4.2 What about Party?

I now use the same approach as the above Logit to see what leads legislators to have net ideal points closest to their political parties. Specifically, a dummy dependent variable is constructed that equals 1 if the Senator's net ideal point is closer to his party's position than either his personal preferences or his constituency. All other variables are the same. Results are found in Table 2.2. Model 5 is the model run on Republicans only and Model 6 is for Democrats. The results are almost always different across parties.

Seniority appears to have a reverse effect for Democrats and Republicans. Whereas senior Republicans are less likely to be closest to their party position, senior Democrats are more so. Like in the previous Logit model, Republicans are more sensitive to electoral concerns than Democrats. Specifically, Republicans who are reelected are less likely to have a net ideal point closest to their party.

Not surprisingly, moderates of both parties are more likely than extremists to be tugged toward the party position. In terms of substantive effects, this is indeed the largest. To see this clearly, consult Table 2.3. This table shows the change in the predicted probability that a Senator is closest to his party by moving him from the extremist to the moderate category. I have disaggregated this by party and by delegation type to see how these may mitigate the effect of ideology. We see that the predicted probability increases by over 50%, regardless of delegation type for Republicans. The effect is more modest for Democrats, but positive nonetheless.

Table 2.3: Predicting Party Proximity

| | Split Delegation | Same-party Delegation |
|---|---|---|
| Republican | 0.54 | 0.50 |
| Democrat | 0.03 | 0.03 |

*Note:* cell entries are the difference in the predicted probability that the Senator's net ideal point is closest to his party between moderates and extremists. These are varied by delegation type and party, fixing Seniority at 10 year (the median), the Congress at the 110th, and assuming the Senator is subsequently re-elected.

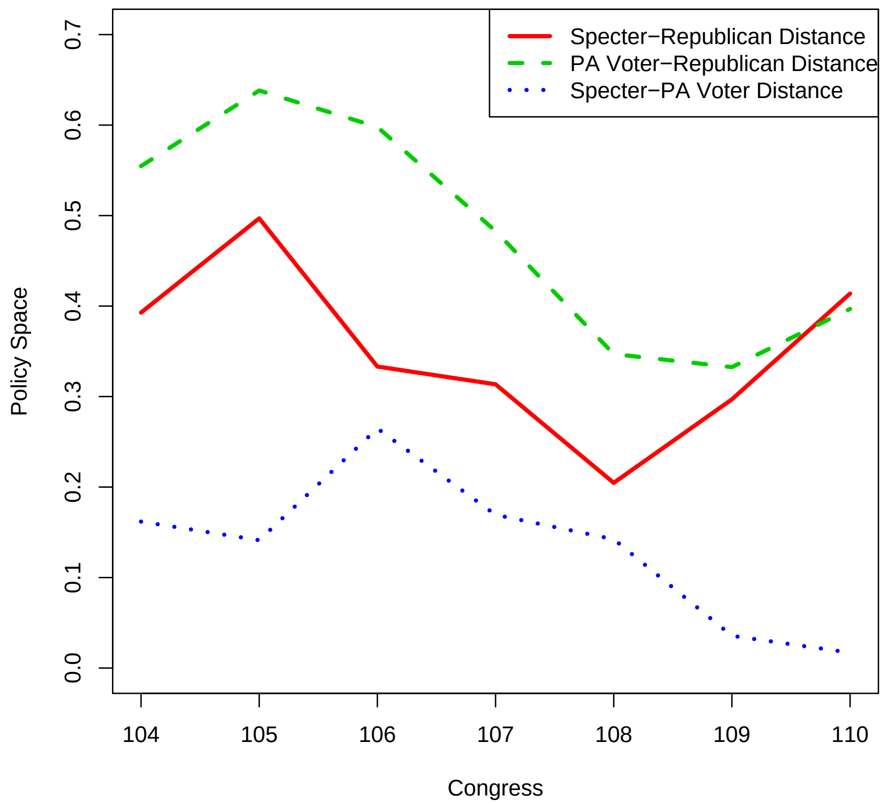
Last, split delegations lessen the probability that Senators are closest to their party for Republicans. Taking this result in stride with the similar finding in Model 3, it appears that Republican members of split delegations are simply more likely to vote according to their own personal ideologies than those of their party or constituency.

### 2.4.3 The Case of Arlen Specter

It is fitting to reconsider the case of Arlen Specter in light of the model's results. Figure 2.9 traces the distance between Specter's net ideal point and median voter in Pennsylvania over time, as well as his distance from the Republican Party and Pennsylvania's distance from the Republican Party as well. We see that, since the 108th Congress, the distance between Specter and the median Pennsylvanian continued to shrink, almost to the point of being non-existent. At the same time, his distance from the Republican Party, as well as the distance of his voters from that party, increased.

Specter, mindful of his re-election prospects, made the rational choice to switch parties. Indeed, when he spoke of distances between the Republicans and his voters, he was right on target. As a Republican moderate,

Figure 2.9: Specter Over Time




the tension between the sets of competing interests that he sought to balance became too much to handle. While he was not sweet-talked into the party switch, with gifts of prominent chairmanships, he was nonetheless rational. Specter implicitly used the weighted utility framework employed in this paper and decided that having to weigh a Republican position so far from himself and his constituency was simply not going to cut it.

## 2.5 Discussion

Until recently, it has been almost impossible to talk meaningfully about distances between legislators and other actors due to the lack of a common space. As a result, conclusions about responsiveness, in a spatial sense, have been limited at best. Though work by recent scholars (Bafumi and Herron 2007, Shor 2009) has made inroads in this respect, this line of research is designed to help scholars address issues of representation and partisan effects in the future and requires more data. As for looking to the past, rescaling techniques like the one used in this paper, are the next best alternative.

This paper has presented a new method that allows scholars to disentangle the effects of competing sources of influence on the voting behavior of legislators. The results from estimating the model on data from the last decade an a half suggest both a waning weight that legislators place on their parties and an increasing role of constituency in determining legislative behavior. Moreover, subsequent analysis revealed that ideological moderates and members of split delegations are more sensitive to partisan and constituency than ideological extremists. On the one hand, the results of this paper are not too surprising. After all, Sinclair (1995) theorized that legislators make decisions in a weighted framework. Other scholars (e.g. Smith 2007, Kingdon 1989) have also suggested that a lot of factors go into legislators' decisions. Thus, finding that neither preference nor party nor constituency alone sufficiently explains legislators' voting is not unexpected. My method delineates precisely how legislators are affected by the sources of influence.

Though these results are interesting and important in and of themselves, there is still much to do. First, refining my measures of constituency ideology can help to ensure the robustness of this paper's findings. While the rescaling technique presented is empirically sound, it is much more preferable to estimate the median voter's ideal point directly. To this end, projects like the CCAP will help to revolutionize scholars' abilities to assess the ideological congruence between legislators and voters.

Second, the analysis should be extended beyond the Senate to both the House and state legislatures, whenever possible. This will allow scholars to examine the degree to which patterns uncovered here are broad-reaching and cross-institutional. Even more interesting, this will allow scholars to see how variations in institutions and rules affect the weights legislators are placing on their various sources of influence.

Third, the set of influence that legislators weigh should be expanded. Fenno (1978) long ago observed that legislators' constituencies are much more complex than the general election electorate. The most important of these, in the context of my model, is the primary constituency. While I omitted this aspect from the applications in this paper, this was only because I lacked appropriate data. As surveys like the CCAP continue to grow, assessing preferences of the primary electorate in a common space will be possible. In turn, this will allow researchers to examine whether or not legislators' weights are higher for primary or re-election constituency.

While the tasks ahead are many, there is an important lesson that has been learned with these initial results at hand: ignoring the multiple influences on legislators is not merely a casual mistake. To the contrary, it masks a series of underlying dynamics that are reshaping American legislative institutions.

## 2.6 Appendix A to Chapter 2: NPAT Questions

*Note*: All questions below are taken verbatim from the NPAT. When an ordered question was used (e.g. lower, maintain, or raise), a dummy variable for was created. The coding of this new variable is described in parentheses, when appropriate.

1. Abortions should always be legally available.
2. Abortions should always be illegal.
3. Remove all legislative limits on campaign financing.
4. Do you support amending the United States Constitution to allow voluntary prayer and/or moment of silence in public schools?
5. Should the US have diplomatic relations with the government of Cuba?
6. Implement a universal health care program to guarantee coverage to all Americans regardless of income.
7. Decriminalize the possession and private use of marijuana.
8. Increase the minimum wage.
9. Do you support replacing the US income tax structure with a flat income tax?
10. Do you support the North American Free Trade Agreement (NAFTA)?
11. Do you support lifting the trade embargo imposed against Cuba?

12. Do you support replacing the US income tax structure with a broad-based consumption tax?
13. (Raise taxes on) Family income over $150,000.
14. The US should withdraw from the UN completely.
15. Allow law-abiding citizens to carry concealed firearms that are legally owned and registered.
16. (Raise spending on) Welfare (AFDC).
17. (Raise spending on) Education (K-12).
18. Abortions should be legal in all circumstances as long as the procedure is completed within the first trimester of pregnancy.
19. Strengthen emission controls on all gasoline or diesel powered engines, including cars and trucks.
20. Establish English as the official and recognized language of the United States.
21. Further limit the number of immigrants allowed into the country.
22. (Raise spending on) Farm subsidies.
23. (Raise spending on) Medicaid.
24. Broaden use of the death penalty for federal crimes.
25. (Raise) Estate taxes.

26. (Support) National Missile Defense Program.
27. The federal government should not provide any affirmative action programs.
28. (Raise spending on) AIDS Programs.
29. (Raise spending on) Environmental Programs.
30. (Raise spending on) Law Enforcement.
31. (Raise spending on) Military hardware.
32. (Raise spending on) Provide parents with vouchers to send their children to any participating school: public, private or religious.
33. (Raise spending on) Abortions should be legal only when the pregnancy resulted from incest or rape or when the life of the woman is endangered.

## 2.7 Appendix B to Chapter 2: WinBUGS Code

```
model{
    for (i in 1:N){
        x[i] <- (w[group[i],1]*z1[i] +
                 w[group[i],2]*z2[i] +
                 max(0.0, 1.0-w[group[i],1]-w[group[i],2])*z3[i])
        for (j in 1:J){
                y[i,j] ~ dbern(p[i,j])
```

```
                logit(p[i,j]) <- -a[j] + b[j]*x[i]
            }
        }

    for (k in 1:K){   #There are K groups
        w[k,1] ~ dunif(0.0,1.0)
        upper1[k] <- 1.0-w[k,1]
        w[k,2] ~ dunif(0.0,upper1[k])
        }

    for (j in 1:J){
        a[j] ~ dnorm(0,0.2)
        b[j] ~ dnorm(0,0.2)
        cutpoint[j] <- a[j]/b[j]
        }

}
```

# Chapter 3

# National Survival and the Confederate Congress

*"If the Confederacy fails, there should be written on its tombstone: Died of a Theory."*

**—Jefferson Davis, former U.S. Senator and Confederate President**

In *Congress: The Electoral Connection*, David Mayhew made the oft-cited observation that members of Congress are "single-minded seekers of re-election" (1974, 17). Pork-barrel spending, candidates' declarations of independence from national parties during elections, and legislators spending vast amounts of time on constituency casework all lend credence to this observation. Though there is certainly much empirical and theoretical sensibility to this argument, there do exist infrequent, but decisive, moments in American history that effectively set this understanding of legislative behavior aside. Indeed, during times of national crisis, it may very well be the case that the old adage, "desperate times call for desperate measures," is a more appropriate predictor of legislative voting than constituency interests. This of course is not a law but a proposition: can times of national crisis (especially wartime) cause legislators to alter their behavior in legislative institutions?

The American Civil War provides a rich historical case that can serve in better answering this question. It was at this unique point in the history of America where both (a) survival of the nation was on the line, and (b) members' districts were directly impacted by the war. Despite the substantive importance of the question posed, few scholars have analyzed it thoroughly. Most works on the Civil War era are either wholly concerned with the military side of the conflict or, if dealing with the political situation, are solely descriptive. Rohde, Jenkins, Carson, and Souva (2001) attempt to bridge this gap by looking at how various crisis-related variables (e.g. war deaths) affected elections in the Union. While their work provides valuable insight to the issue of how military failure can affect political outcomes, it deals only with the Union and focuses on the electoral, and not legislative, context.

On the Confederate side, an even smaller subset of literature has emerged addressing the political issues confronting the legislature. Yearns (1960) provided the first comprehensive history of the Confederate legislature from the firing upon Fort Sumter to the collapse at Appomattox Courthouse. However, Yearns' work was descriptive and did not seek to explain why Confederate legislators behaved the way they did. In *The Anatomy of the Confederate Congresses*, Alexander and Beringer (1972) comprehensively analyze the roll-call voting of Confederate legislators. Their work is impressive, documenting in great detail the various roll calls and providing scholars with a biographical directory of the legislators, complete with occupation, personal wealth, slaveholding data, and more. Yet they fail to provide a *unified model* for the voting behavior of legislators. The closest they come is providing values for the gamma measure of association between voting behavior and several demographic variables in bivariate fashion (1972,300-314). In his analysis of Confederate legislative roll calls, Bensel (1986) comes perhaps the closest to identifying causal mechanisms behind voting behavior in that body. Bensel makes the striking observation that "the consolidation of economic and social controls within the central government of the Confederacy was in fact so extensive that it **calls into question the standard interpretations of southern opposition to expand federal power in both the antebellum and post-Reconstruction periods**" (1986, 68, emphasis added). Further, Bensel provides evidence suggesting that legislators from occupied districts were more likely to support the strengthening of the federal government. Nonetheless, he too fails to provide a unified model, taking into account the cumulative effect of the various possible independent variables.

To date, only one scholar has attempted to look at all of the variables associated with the voting behavior of Confederate legislators in a unified framework (Jenkins 2000). In this analysis, Jenkins employs Poole and Rosenthal's (1997) W-NOMINATE procedure for estimating the legislators' ideal points and then uses these to run a series of regressions, treating the six sessions of the Confederate House of Representatives as panel data. Using this method, Jenkins finds no evidence to support the shock of district occupation as a significant explanatory variable. However, by employing the static W-NOMINATE and not a dynamic estimation routine, Jenkins' results are called into question. Moreover, this error highlights one of the fundamental problems in estimating legislator preferences over time.

In this paper, I seek, primarily, to fill the gap in the literature on the Confederate Congresses and, secondarily, to address the methodological problems in dynamic ideal point estimation in an applied setting. Specifically, I explain how the war-induced crisis affected the roll-call voting behavior of legislators in the First and Second Confederate House of Representatives. In Section 3.2, I describe the First and Second Congresses, providing information of their context and of legislators' individual characteristics. I also examine the previous work of Jenkins, examine extant approaches to dynamic ideal point estimation, and propose a different methodological approach that produces ideal point estimates that are comparable over time. Section 3.3 presents a theoretical model that explains the factors that affect the ideal points of legislators. I argue that the occupation of a congressional district by Union troops, given the legislature's survival crisis, led members to support a strong central government in Richmond. Section 3.4 details the estimation of the ideal points of legislators using Markov Chain Monte Carlo methods (Clinton, Jackman, and Rivers 2004). In Section 3.5, using the estimated ideal points, I employ simple linear regression to evaluate the central hypothesis of this paper. I also provide an analysis of the controversial yet instructive case of the vote to suspend the writ of *habeas corpus*. The hypothesis is again put to the test, using descriptive statistics and logit regression. Section 3.6 provides a discussion of the results and, since the results are not what one would expect from a legislature that based itself upon the Jeffersonian anti-nationalist mentality, I discuss the substantive implications of them.

## 3.1 The Confederate Congress

### 3.1.1 Historical and Organizational Basics

With the election of 1860 handing victory to Republican Abraham Lincoln, many leading White southerners felt that remaining in the Union was no longer a viable option for maintaining the Southern way of life. Seven southern states seceded soon following the election: South Carolina, Georgia, Florida, Alabama, Louisiana, Mississippi, and Texas. In April of 1861, when Confederate forces fired upon Fort Sumter, Virginia, North Carolina, Tennessee, and Arkansas followed suit. Meanwhile, delegates from these states plus Missouri and Kentucky convened in Montgomery, Alabama, on February 4, 1861 to begin the first session of the Provisional Congress of the Confederate States of America (Martis 1994, 9). A constitution was drafted and elections were scheduled. This Provisional Congress came to a close on February 17, 1862 (Martis 1994, 2). During its short existence, the Confederacy had two regular Congresses. The First Congress began February 18, 1862 and closed February 17, 1864; the Second began on May 2, 1864 and ended March 18, 1865 (Martis 1994, 2). The short tenure of the Second Congress can be attributed to the Confederacy's military surrender and the subsequent fall of the government in Richmond.

The structure of the legislature was very similar to that of the United States. Members of Congress (MCs) were elected in single-member districts. These districts were allocated proportional to the state's population. It is important to add here that, although they remained part of the Union, Southern-sympathizing citizens in Kentucky and Missouri established rival Confederate state governments and thus seated members in the Confederate Congresses (Martis 1994, 117). The MCs dealt with some of the very same issues as their Union counterparts. From 1862-1865, the legislature handled hundreds of roll-calls dealing with matters as diverse as trade and foreign affairs, central-government powers, appropriations for public works, and the pork-barrel minutiae that have become a staple in the modern U.S. Congress (Alexander and Beringer 1972). Thus, while this legislature was in a certain sense unique, it was in many ways similar to its Union counterpart and, more broadly, much like contemporary Congresses. Indeed, one of the greatest advantages in studying the Confederate Congresses or the Confederacy, more broadly, is their remarkable similarity to the United States Congress.

The Confederate Constitution was essentially identical to that of the U.S., with a few notable exceptions. First, slavery and states' rights were specifically enumerated and, hence, were "closed cases," whereas the U.S. Constitution was vague on these points (Thomas 1979, 37). Second, Section IX of the Confederate Constitution forbade export tariffs and capitation/direct taxes, matters that had been the cause of quarrels in the U.S. Congress. The important implication of these clauses was the *de facto* prohibition of a competitive, meaningful party system (Alexander and Beringer 1972; Beringer 1967; Martis 1994; Bensel 1986). When the old Democrat-Whig divisions broke apart in the aftermath of the Compromise of 1850, Southern Whigs and Democrats came together and formed a single-issue coalition around slavery or, more broadly, states' rights (Jenkins 1999). Once the South seceded, the coalition had no more meaning, as slavery and other matters of contention were taken care of in the Constitution. Thus, with the absence of political party as a factor in voting, there is a *de facto* vacuum in terms of analyzing patterns of voting behavior. Practically speaking, what this means is that one has to look to *other* possible variables affecting legislators' voting behavior.

### 3.1.2 Variables affecting voting behavior in the Confederate Congresses

Several scholars (e.g.,Martis 2004; Alexander and Berginger 1972; Yearns 1960) have suggested a number of important variables that have some sort of discernable relationship with legislative voting behavior. These variables include the legislators' personal wealth, the number of slaves he owns, his former political party, and his stance on secession. Thanks to Alexander and Beringer (1972, 354-389), the data on all of these variables has been collected and is readily available.

Table 3.1 presents the relative proportions (or means) of each of these variables for all members of the Confederate Congresses. Though political party was not a *de jure* component of the legislative process, old political rivalries and debates may have potentially resurfaced. As we see in Table 3.1, the vast majority of legislators in the Confederate Congress were former Democrats. This is not a surprise, given that party's dominance

Table 3.1: The Confederate Congresses at a Glance

| | Mean/proportion | s.d. | Median | NA |
|---|---|---|---|---|
| Former Democrat | 58.5% | — | — | 27 |
| Secessionist | 55.8% | — | — | 31 |
| Number of slaves | 36.8 | 63.4 | 13.5 | 16 |
| Estate value (1860 $) | $71,870 | $125,491.40 | $33,770 | 14 |

Table 3.2: Membership frequency by former party and secession stance

| | Secessionist | Unionist |
|---|---|---|
| Former Democrat | 55 | 13 |
| Former Whig | 8 | 42 |

in the South during the *antebellum* period. What is perhaps more surprising is the fact that only 55% of legislators could be classified as secessionist. This implies that 45% of legislators were opposed to secession and this—quite possibly—would mean that these legislators would not want to give the government even more authority than it had already wielded. To explore the relationship between partisanship and secessionist beliefs, Table 3.2 shows a crosstabulation of former party and secession stance. We readily note that most former Whigs were anti-secession and most former Democrats were pro-secession.

As for the two other variables in Table 3.1, number of slaves and personal wealth, we see that the mean legislator had a large number of slaves and was fairly wealthy. For comparative purposes, $1 in 1860 is worth approximately $21.66 in 2006 inflation-adjusted US dollars. This puts the mean estate value of Confederate legislators at $1,556,704 in 2006 dollars.

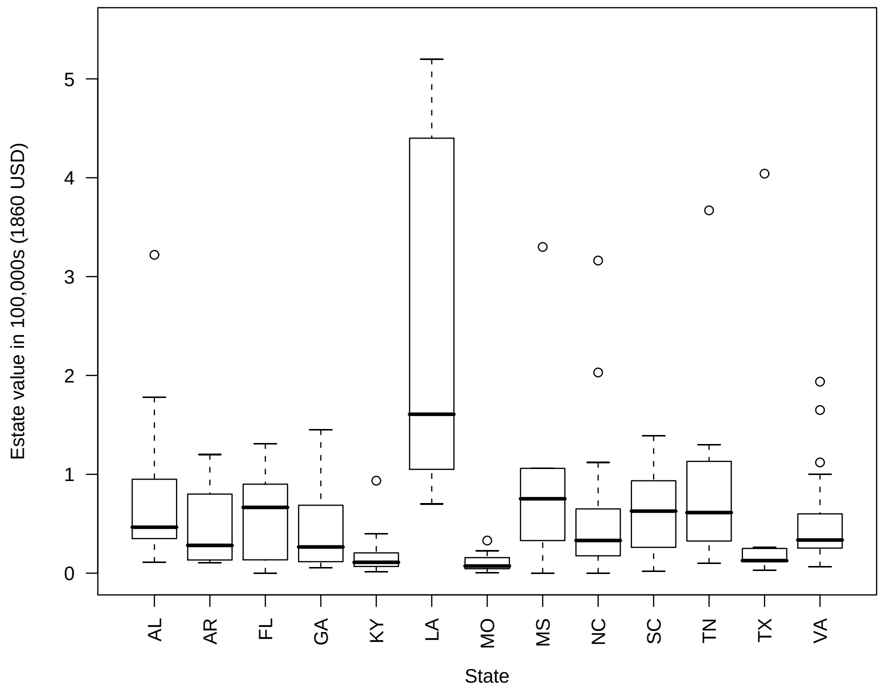
This is a bit misleading however, as the medians are significantly lower than the means. Indeed, upon closer inspection, a few legislators from the deep South (especially Louisiana) had a very large number of slaves and expensive plantations. Figures 3.1 and 3.2 demonstrate this. Note the "box and whiskers" for Louisiana stands out and that several other states (notably, Mississippi) have one significant outlier.[1] This being considered, it seems conceivable that legislators with more slaves and higher-valued estates would have more to lose by a Confederate loss and, hence, would be more willing to support a stronger central government.

The final and, as I argue in detail below, most important variable to consider is a district's occupation by Federal troops. As the war progressed, an ever-increasing number of districts were occupied by Federal troops. In fact, by the midpoint of the Second Congress, almost half of the Confederate states, mostly those along the borderlands of the Confederacy (e.g., Arkansas and Kentucky ), were occupied. The occupation forced legislators to remain in Richmond and make decisions without communication with their constituents. Intuitively, it seems reasonable that severing the electoral connection could impact the behavior of legislators.

In order to analyze the legislative behavior of members of Congress (MCs) given the lack of party organization and the above-mentioned structural circumstances, it is necessary to develop an alternative measure to categorize Confederate roll call voting. More specifically, since party is, in

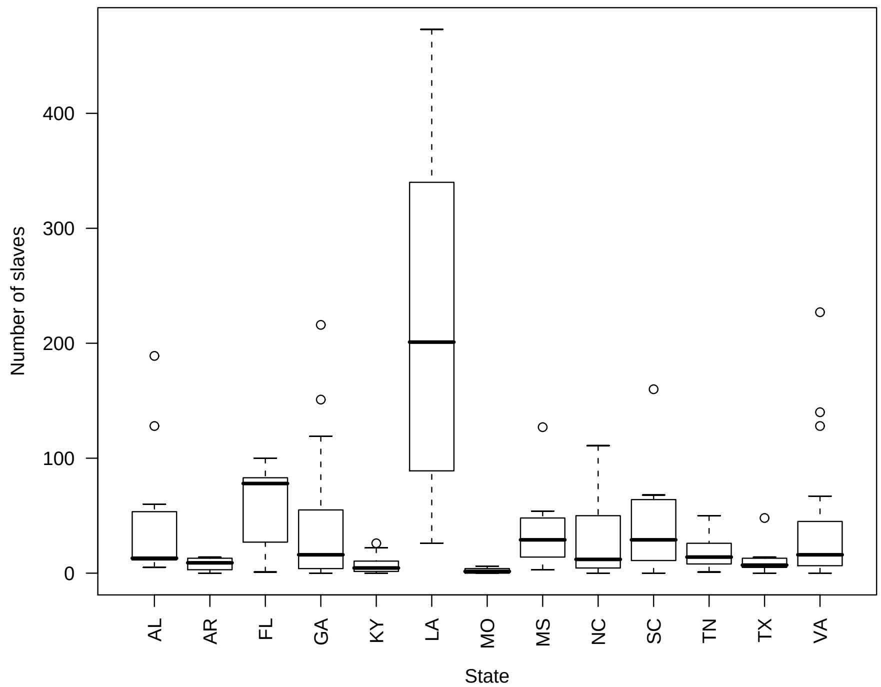
[1] Though the box and whiskers plots for both estate value and number of slaves show the presence of outliers, there was one even larger outlier from Mississippi truncated from Figure 3.1 to ensure readability. This was Representative J.W. Clapp from Mississippi's 1st; he had an estate worth about $1.76 million (1860 dollars).

Figure 3.1: 1860 Estate value by state delegation




the modern sense, the way in which legislative voting tends to divide members of legislatures, the absence of party in the Confederate Congress must imply that some other variables governed voting behavior. To examine the relationship between these variables and ideology, Alexander and Beringer develop an ideological measure and call it the Confederate support score. They derive it by performing content analyses of all roll calls in the Congresses (1972, 307-313). The score identifies how intensely a legislator supports a strong central government. The range is from zero to nine, with the former representing weak support of a powerful central government and

Figure 3.2: Number of slaves by state delegation




the latter representing strong support of a powerful central government. Though this measure is certainly useful, its ordinal nature and rather *ad hoc* construction make more fine-grained distinctions between legislators difficult to impossible. Indeed, any ordinal measure precludes researchers from getting at the more nuanced variance that is obtained by use of an interval-level measure. Fortunately, this difficulty will be overcome with roll call data by the use of ideal point estimation.

### 3.1.3 Previous attempts at Confederate ideal point estimation

Jenkins (1999; 2000) is the first scholar to actually estimate ideal points for the legislators in the Confederate Congress. Employing Poole and Rosenthal's (1997) W-NOMINATE procedure, he is able to estimate ideal points for legislators and analyze the issue space, percent correctly classified, dimensionality of voting, and host of other relevant measures (Jenkins 1999, 1152-1157). In a subsequent paper, Jenkins (2000) looks at the issues that may affect a legislator's ideal point. Specifically, he analyzes the hypothesis of whether the shock to a district caused by being occupied by Federal troops caused a statistically significant change in ideal point, controlling for other relevant demographic variables. To do this, he employs both one-way and two-way fixed effects models regressing a legislator's ideal point at session $t$ on his ideal point at $t-1$ plus some other factors (2000, 819-820). He finds no significant shock effect, but he does find that districts always or never occupied do have different ideal points in the two-way fixed effects models (2000, 820).

Unfortunately, this method relies on the assumption that the ideal points of legislators at the various points in time are directly comparable. This is key because W-NOMINATE is designed to be a *static* measure. More clearly, W-NOMINATE scores at time $t$ and $t-1$ are not directly comparable. By treating W-NOMINATE scores as dynamic, it is possible that Jenkins' coefficient estimates and, more importantly, his inferences about the effect of district occupation on ideal points are not reflective of the true underlying process.

There are a number of ways one could correct this obvious problem. First, one could employ a dynamic ideal point estimation routine, in either a frequentist (e.g., Poole and Rosenthal [1997]'s DW-NOMINATE) or Bayesian (e.g., Martin and Quinn [2002]'s Bayesian Dynamic Linear Model) framework.[2] Poole and Rosenthal's approach constrains legislators to travel in a polynomial trend over time, that is, for an ideal point $\nu_{it}$ of legislator $i$ and time $t$,

$$\nu_{it} = \sum_{\tau=0}^{T} \nu_{i\tau} t^{\tau}.$$

Instead of using time period $t$, Poole and Rosenthal use $\mathcal{T}$, a set of Legendre polynomials. This choice is out of computational convenience and is substantively the same. This approach, as noted by Snyder, Groseclose, and Levitt (1999), constrains legislators to move in the same ideological direction over time. Legislators are not allowed to move in a more conservative direction, then move to a liberal position, and then back. This constraint on legislators' behavior prevents us from using DW-NOMINATE to evaluate legislators' changing ideal points.

Martin and Quinn's (2002) method models the ideal point over time as a random walk in the parameter space that is governed by two parameters: yesterday's ideal point and the variance parameter. This is presented parametrically as follows:

$$\nu_{it} \sim \mathcal{N}(\nu_{i,t-1}, \Delta).$$

[2] As of this draft, Poole does not provide software to perform DW-NOMINATE at his website, http://www.voteview.com. Andrew Martin and Kevin Quinn do provide C++ code to run their dynamic Bayesian model, but this code is not supported. New code is expected to be released sometime in the near future.

This seems to be less restrictive than the Poole and Rosenthal approach, but a natural consequence is the exponential increase in computational time. For estimates of the Supreme Court that cover a handful of justices and a few hundred cases, the process can take weeks to implement. For the Confederate Congresses, with over 150 members and six time sessions, the method is simply impractical.

The second framework is the Snyder, Groseclose, and Levitt (1999) "scale and shift" approach. Though originally applied to ADA scores, it is equally usable for ideal points. In this framework, one would estimate six separate ideal points and then connect them by the assumption that year-to-year changes are governed by scale and shift parameters (*a* and *b*). A legislator *i*'s ideal point at time *t* is governed by the linear model

$$\nu_{it} = a_t + b_t x_i + \varepsilon_{it},$$

where the error term is normal with mean 0 and variance $\sigma^2$. $x_i$ is the legislator's "over life" ideal point, assumed to be fixed over time. Thus, year-to-year variation is only manifest as a result of the error. Moreover, this error, by virtue of the estimation process, is minimized.[3] This too causes a major problem for our purposes.

A third and more feasible approach is available if one has strong theoretical predictions about when legislators' ideal points would change.[4] As

[3]Since this is a linear model, we desire to minimize the error, i.e., the distance between the estimate and the true value.

[4]One other option would be to simply fix two legislators over the entire time period. If we believed that their ideal points truly remained fixed, then we could identify and compare cross-temporal ideal points for all legislators. Results from this approach do not vary substantially from what follows in this paper.

long as there exist some legislators who don't change, one can "pin down" the issue space and compute two sets of ideal points for the changing legislators: one before and one after. In the next section, I present a theoretical argument for when changes should occur and then, based on this argument, how to go about estimating the ideal points.

## 3.2 Theoretical Model

When a district was occupied by Federal troops, a number of things could have happened. One intuitive possibility is that a legislator "voted his conscience." That is to say, a legislator was no longer constrained by district opinion and, if he disagreed with his district on a matter, he had the ability to use his own judgment, as opposed to adopting a "single-minded seeker of reelection" mentality. This makes sense, in that the occupation of his district made a legislator acutely aware of the stakes at hand. Failure to provide the government in Richmond with the resources necessary to conduct the war, even if in opposition to district opinion, would result in the downfall of the Confederate nation and, consequently, the loss of his job.

Another possibility is that he became a trustee in the fashion of Edmund Burke, focusing his efforts on the Confederacy's best interests and setting aside the wants and desires of his district. Of course, there is the possibility that there was no change, that a legislator just stayed on the path he was on before the change in situation. Which of these best applies to the Confederate Congresses? The answer to this question lies in the nature of the circumstances. Not only were Confederate districts being occupied, but the very survival of the Confederacy was on the line.

Taking both of these into consideration, I argue that, even controlling for other relevant variables (e.g., former party, secession stance, etc.), the occupation of their districts gave legislators an exogenous shock, $s$. Not only was national survival on the line, but for these legislators, their own districts were captured. It almost certainly follows that these legislators subsequently chose to strengthen the central government, as occupation of their districts amplified the crisis of survival. Further, it is also clear that the legislators were not "voting their consciences." This was a government that argued, at least in official rhetoric, for its very independence on the issue of states' rights—of the submission of the federal government to the whims of the states. If legislators' voting behavior was moving toward their "true" ideologies, the shift in ideal point should be to the left and not to the right[5].

These claims can be formalized in a simple and straightforward fashion. Suppose there is a unidimensional policy space, $X$, such that $X \subset \Re$. Let the ideal point of legislator $i$ be denoted by $\tilde{v}_i$ and, as above, the shock to the district is $s$. For our purposes, $s^t$ will denote whether a district was shocked—i.e.,became occupied—at time $t$ or not; hence, it is a indicator variable. Let $\delta(s_i^t) \in X$ be some perturbation in the legislators' ideal point arising from a shock and let it belong to the set of possible ideal points, $X$.

[5]That is, the shift should have been towards opposition to central authority, not the promotion thereof.

Putting these together, I posit that a legislators' ideal point at time $t$ will be

$$\tilde{v}_i^{\,t} = \begin{cases} \tilde{v}_i^{\,t-1} + \delta(s_i^t), & \text{if } s^t = 1 \\ \tilde{v}_i^{\,t-1}, & \text{if } s^t = 0 \end{cases} . \tag{3.1}$$

Equation 3.1 says that districts that were either always or never occupied will not witness a change in ideal points. This does not mean that these districts remain unaffected by occupation; in fact, always occupied districts should, based on my theory, be the most supportive of a strong central government and the never occupied districts should be just the opposite. For districts that change, the direction of the shift in the ideal point should be to the right, presuming that rightward means supporting a stronger government in Richmond.

In terms of estimation of the changes in ideal points, one must begin by discriminating between legislators whose districts changed from unoccupied to occupied status and those districts that did not change. The latter category's roll call records will remain unchanged and, to our benefit, "pin down" the issue space. For legislators whose districts changed, two entries will appear in the roll call matrix: one for before and one for after. In the first entry, the legislator's roll call record will be unchanged until his district became occupied. At this point, all remaining votes will be substituted with missing values. Similarly, for his second entry, all entries up and until being occupied will have missing values. After the occupation takes place, his roll call record will be as recorded.

To make this procedure clearer, an example is in order. Suppose that

Table 3.3: Hypothetical matrix of roll call votes

| $T$ | 1 | 2 | ... | $t$ | $t+1$ | ... | $N$ |
|---|---|---|---|---|---|---|---|
| $A$ | 1 | 0 | ... | 1 | 0 | ... | 1 |
| $B$ | 0 | 1 | ... | NA | NA | ... | NA |
| $B'$ | NA | NA | ... | 0 | 1 | ... | 0 |

we have a legislature with two members, $A$ and $B$. Legislator $A$'s roll call record is chosen arbitrarily. For $B$, without loss of generality, assume that his district became occupied at time $t$ and let legislator $A$'s district remain unchanged (i.e., either always or never occupied). Now, let $B'$ denote legislator $B$'s new entry after being occupied. The matrix above presents the resulting (hypothetical) roll call matrix where the first row is $A$, the second is $B$, and the third is $B'$. Also, time $t$ occurs following the first set of ellipses. In the next section, I propose a procedure to estimate ideal points for legislators employing the theoretical argument above with the matrix structure in Table 3.3.

## 3.3 Markov Chain Monte Carlo (MCMC) Ideal Point Estimation

### 3.3.1 The Model

Though Jenkins (1999; 2000) opts to use Poole and Rosenthal's (1997) W-NOMINATE procedure for estimating legislator ideal points, I found it more expedient to apply the more recent Bayesian approach of Clinton, Jackman, and Rivers (2004). This choice is not out of a strong philosophical commitment to Bayesian inference. Rather, it comes as a result of the simplicity and computational efficiency of Bayesian Markov Chain Monte Carlo (MCMC) methods. Moreover, it has been shown (Clinton, Jackman, and Rivers 2004) that W-NOMINATE and MCMC produce essentially the same result.

The foundation of this model is the simple spatial model of voting. Following the setup of Clinton et al. (2004), I denote the roll calls $j = 1, ..., J$ and legislators $i = 1, ..., n$. Let $\psi_j$ denote the spatial position of "Yea" on roll call $j$ and $\tau_j$ denote the spatial position of "Nay." We observe a variable $y_{ij}$ that is equal to 1 if $i$ votes "Yea" and 0 if he votes "Nay." Following the well-established results of Poole and Rosenthal (1997) as well as Jenkins' (2000) previous results, I assume the policy space to be unidimensional. Furthermore, I assume that the utility functions are quadratic with normal errors.

If legislator $i$'s ideal point is given by $\tilde{v}_i$, then his utility for "Yay" is given by $u_i(\psi_j) = -||\tilde{v}_i - \psi_j||^2 + \eta_{ij}$ and his utility of "Nay" is given by $u_i(\tau_j) = -||\tilde{v}_i - \tau_j||^2 + \varepsilon_{ij}$, where $\eta_{ij}$ and $\varepsilon_{ij}$ are jointly-distributed normal errors. According to the spatial model, a legislator will choose to vote "Yea" if he gets higher utility for $\psi_j$ than for $\tau_j$. Mathematically, we may express this as follows:

$$
\begin{aligned}
Pr(y_{ij} = 1) &= Pr(u_i(\psi_j) > u_i(\tau_j)) \\
&= Pr(\varepsilon_{ij} - \eta_{ij} < ||\tilde{v}_i - \psi_j||^2 - ||\tilde{x}_i - \tau_j||) \\
&= Pr(\varepsilon_{ij} - \eta_{ij} < 2(\psi_j - \tau_j)\tilde{v}_i + \tau_j^2 - \psi_j^2) \\
&= \Phi(-\alpha_j + \beta_j \tilde{v}_i), \qquad (3.2)
\end{aligned}
$$

where $\beta_j = 2(\psi_j - \tau_j)/\sigma_j$ is the discrimination parameter, $\alpha = (\psi_j^2 - \tau_j^2)/\sigma_j$ is the difficulty parameter, $\sigma_j^2 = \text{var}(\eta_{ij} - \varepsilon_{ij})$, and $\Phi(\cdot)$ is the standard normal cdf. Our likelihood function is thus given by

$$
\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\alpha}, \boldsymbol{X}|\boldsymbol{Y}) = \prod_{i=1}^{n} \prod_{j=1}^{J} \Phi(-\alpha_j + \tilde{v}_i \beta_j)^{y_{ij}} (1 - \Phi(-\alpha_j + \tilde{v}_i \beta_j))^{1-y_{ij}}, \qquad (3.3)
$$

where $\boldsymbol{\beta} = (\beta_1, ..., \beta_J)'$, $\boldsymbol{\alpha} = (\alpha_1, ..., \alpha_J)'$, $\boldsymbol{X}$ is an $n \times 1$ matrix of ideal points, and $\boldsymbol{Y}$ is an $n \times J$ matrix of roll call votes across legislators such that $y_{ij} \in \boldsymbol{Y}$.

### 3.3.2 Identification restrictions

Identification problems are common to all models based on Item Response Theory (IRT). The likelihood in Equation 3.3 is no exception to this rule. In order to estimate the parameters of interest, one must impose an identification restriction. Rivers (2003) and Clinton, Jackman, and Rivers (2004) suggest fixing two legislators' ideal points at $+1$ and $-1$ respectively. Alternatively, one could constrain ideal points to have mean 0 and unit variance. Following the literature, I opt for the latter. In order to do the former, it is necessary for me to pin down two legislators, one on the "left" and one on the "right." This is less obvious than in modern Congresses, where scholars have a fairly clear picture of who the extremes may be. Thus, for simplicity, I choose to just let the ideal points to have a mean at 0 and variance of 1.

### 3.3.3 Priors

To employ a full Bayesian model, it is necessary to put prior distributions on the discrimination parameters, the difficulty parameters, and the ideal points. For the first two, I assume that they are drawn from a bivariate Normal distribution such that

$$\begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix} \sim \mathcal{N}_2(\zeta, \Sigma^{-1}), \tag{3.4}$$

where $\mathcal{N}_2$ is the bivariate Normal distribution, $\zeta$ is a $2 \times 1$ vector of prior means and $\Sigma^{-1}$ is a $2 \times 2$ variance-covariance matrix. For simplicity, I assume that the prior means on both of these parameters to be zero and the variance to be 4 (hence, a precision of .25), with zeroes for off-diagonal elements. As a choice for priors for the ideal points, $\tilde{\nu}_i$ I assume that they are drawn from a univariate Normal distribution such that

$$\tilde{\nu}_i \sim \mathcal{N}(\theta, \xi^{-1}), \tag{3.5}$$

where $\theta$ is a prior mean of zero, and $\xi^{-1}$ is the prior precision (and variance) of 1.

Combining these prior with the likelihood above yields the full posterior:

$$\pi(\boldsymbol{\beta}, \boldsymbol{\alpha}, \boldsymbol{X}|\boldsymbol{Y}) \propto \prod_{i=1}^{n}\prod_{j=1}^{J}\Phi(-\alpha_j + \tilde{v}_i\beta_j)^{y_{ij}}(1-\Phi(-\alpha_j + \tilde{v}_i\beta_j))^{1-y_{ij}} \times \mathcal{N}_2(\zeta, \Sigma^{-1})_j \mathcal{N}(\theta, \xi^{-1})_i. \quad (3.6)$$

Note that subscripts have been appended to priors defined above. Since the priors are assumed to be the same across all parameters, the subscripts allow us to include them in the products above.

### 3.3.4 Estimation

The advent of modern computing has made simulation from otherwise complex posteriors (e.g., Equation 3.5) much more reasonable. In particular, Political Science scholars have made use of Markov Chain Monte Carlo (MCMC) methods to estimate models of the sort presented above (see, e.g., Clinton, Jackman, Rivers 2004 or Martin and Quinn 2002). One can make use of this technology by either opting to program Gibbs sampling routines manually or resorting to existing software packages and various add-ons. Though the freely distributed `WinBUGS` software is by far the most popular method of employing MCMC, I have opted in this application to employ Martin and Quinn's library for `R`, `MCMCpack`. The choice is simply a matter of taste and computational efficiency. Since Martin and Quinn's code is written in C++, it is able to process information and retrieve estimates much faster than `WinBUGS`. Moreover, given the popularity of `R` for statistical computing, `MCMCpack` allows users to work directly in `R` and obtain `R` output, thus allowing for further analyses directly in the software of choice.

To initiate the MCMC, simple factor analysis was used to generate initial values for the $\tilde{v}_i$'s.[6] I created 3 chains of 120,000 iterations each. For each chain, I burned-in the first 20,000 observations and employed a thinning interval of 1. Thus, at completion, I had three chains of 100,000 observations each for each of the 213 legislators in my roll call matrix. To assess convergence, I employed Gelman et al. (1992)'s $\hat{R}$, given by the following equation:

$$\hat{R} = \sqrt{\frac{\widehat{var}(\psi|y)}{W}}, \tag{3.7}$$

where $\widehat{var}(\psi|y) = \frac{n-1}{n}W + \frac{1}{n}B$, $n$ is the length of each chain, $B$ is the between-chain variance, and $W$ is the across-chain variance. Values of $\hat{R}$ close to 1 indicate convergence whereas large values do not. All ideal points had values of $\hat{R}$ close to 1, thus leading us to believe that we have approached the target posterior and, hence, have the correct ideal points.

## 3.4 Results

### 3.4.1 Ideal point estimates

Table 3.4 aggregates the summary statistics of legislator ideal points by district occupation. As we see, occupation of the district *does* have a strong relationship with the legislators' ideal points. The means of legislators from districts that were either always occupied or became occupied (rows two and four) are much further to the right than those that were from districts

[6]Specifically, the initial ideal points were obtained by performing an eigenvalue-eigenvector decomposition on the matrix of agreement scores.

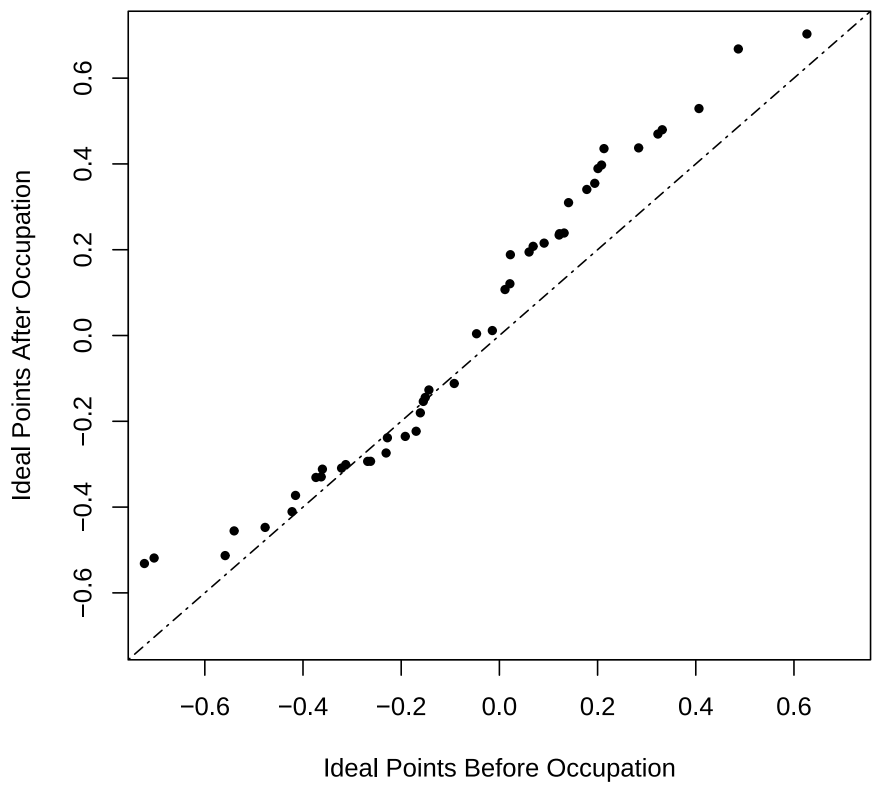
Table 3.4: Legislator ideal points disaggregated by district occupation status

| | Mean | Median | 2.5% Quantile | 97.5% Quantile |
|---|---|---|---|---|
| Never Occupied | −0.2900 | −0.3700 | − 0.5800 | + 0.2700 |
| Always Occupied | +0.1390 | +0.0650 | − 0.4500 | + 1.670 |
| Occupied—before | −0.039 | − 0.0300 | −0.7200 | + 0.7800 |
| Occupied—after | +0.0690 | + 0.0078 | − 0.5300 | + 1.2200 |

that were either never occupied or were unoccupied for a time (rows one and three). Moreover, the 95% region can be seen to shift in all four cases, thus indicating that there is unquestionably a relationship between the occupation of a district and legislators' ideology.

For those legislators who came from districts that switched from being unoccupied to occupied, one can compare their ideal points before and after occupation graphically. Figure 3.3 plots the legislator's ideal point at time $t$ (before his district was occupied) on the $x$-axis against his ideal point at $t-1$ (after occupation). Under the null hypothesis, one would expect all legislators' ideal points to lie along the line $y = x$, a 45-degree line. If a legislator's ideal point is above this line, it indicates he changed in a direction more in favor of central-state authority. Should his ideal point fall below the line, it would indicate the reverse. As we see in this figure, most legislators lie above the line, as predicted. Indeed, of the 50 legislators in my data set whose districts changed occupation status, 42 moved to the right. Furthermore, for the 8 cases falling below the line, their change is very slight and not significantly negative.

Figure 3.3: Ideal Points Before and After Occupation




### 3.4.2 OLS Results

The preliminary results established above can be explored further by employing a simple Ordinary Least Squares (OLS) regression model. While I have shown that there is obviously some relationship with district occupation and ideal point, there are a number of other factors that need to be controlled for to guarantee the robustness of the result. The variables that follow were described previously.

Former political party takes a value of 0 if the legislator was a Democrat and 1 if he was a Whig. Though there were no formal parties in the Confederacy, it is possible that old rivalries and debates could have possibly divided legislators in the Confederate Congresses. Secession stance is set to 0 if the legislator was pro-secession and 1 if he was unionist. Legislators who supported secession may simply desire to "do what it takes" to preserve the Confederacy, whereas those who were unionist would be less inclined to do so.

Personal wealth is the 1860 estate value of the legislator in U.S. dollars. This variable could potentially be significant if legislators from the wealthy cotton and tobacco districts voted differently from those representing poorer districts. The number of slaves is simply the number of slaves that the legislator owned at the time of his election. Presumably those legislators with the most number of slaves had the most to lose from a Confederate failure and would be willing to go to great lengths to achieve victory.

To consider the effect of district occupation, it is necessary to run two separate regressions. This approach is required because of the way in which legislators' ideal points were estimated. In the case where a legislator's district changed occupation status, we have two ideal points and are consequently interested in factors influencing any ideological shift that may have occurred. For the case of districts that did not change, we only have one ideal point to look at. However, in these cases, we are interested in examining the difference between the districts that were always occupied (i.e., Kentucky, Missouri, and western Virginia) and those that were never occupied (e.g., Texas and Florida).[7]

In the first regression, we consider only those districts that switched in the occupation status. To capture the effect of occupation, I consider two variables. First, to capture the effect of occupation directly, I construct a dummy variable called *Before*. This variable is equal to 1 if it is before occupation and 0 after. Second, I can examine the indirect effect of occupation using a variable called $Neighbor$. This variable ranges from 0 to 1 and measures the proportion of districts in the legislator's state that are occupied at a particular time point. This could be important if legislators are not simply reacting to their own district's occupation (and, hence, future), but rather looking at the districts of their fellow statesman. Indeed, it may be the case that occupation of neighboring districts has a "contagious effect" on a legislator's voting behavior. Moreover, since the effect of each variable is almost certainly mitigated by the other, it is necessary to interact them in the regression model that follows.

Putting these facts together with the variables above yields the following linear regression model:

$$\begin{aligned} Idealpoint &= \beta_0 + \beta_1 Before + \beta_2 Neighbor + \beta_{12} Before \times Neighbor + \beta_3 Secc \\ &+ \beta_4 Party + \beta_5 Slaves + \beta_6 Estate. \end{aligned} \quad (3.8)$$

[7] If I had estimated multiple ideal points for all legislators, the two-equation setup would not be necessary. Indeed, if one estimates ideal points using one of the alternate methods discussed in Section 3.1.3, there would be six ideal points for every legislator and subsequent analysis could be performed using a single panel data model.

The results are presented in Table 3.5. As we see first and foremost, the variable $Before$ is both negative and significant as predicted and, thus, negates Jenkins' (2000) previous finding. The related variable, *Neighbor*, is also negative and significant, implying that as the proportion of occupied neighboring districts increases, the ideal point actually shifts in the negative (anti-central authority) direction. However, since these variables are interacted, it is necessary to take partial derivatives in order to evaluate the substantive effects. For the marginal effect of occupation, we differentiate Equation (8) with respect to $Before$:

$$\frac{\partial Idealpoint}{\partial Before} = -1.11 + 1.20 Neighbor.$$

From this equation, we readily note that if none of the legislator's home-state districts are occupied, the effect of $Before$ is $-1.11$, meaning that the ideal point before occupation is 1.11 less than after occupation. To see the effect for other levels of neighboring district occupation, as well as respective confidence bounds, I provide Figure 3.4.[8] I vary the proportion of neighboring districts occupied on the $x$-axis and place the ideal points on the $y$-axis. As we see, as the proportion of neighboring districts that are occupied increases, the magnitude of the effect of occupation on the legislator's own district actually decreases. This makes sense intuitively, in that the "shock" of occupation is essentially dulled in states where the U.S. Army has already gained as substantial foothold.

[8] Standard errors for Figure 3.4 were calculated by the following equation: $s.e. = \sqrt{\sigma_1^2 + Neighbor^2\sigma_{12}^2 + 2 \times Neighbor \times \mathrm{cov}(\beta_1\beta_{12})}$. See Friedrich 1982 for more details.

Table 3.5: OLS model predicting ideal points for districts that changed control

| | Estimate | Std. Error | t value | p-value |
|---|---|---|---|---|
| Intercept | **0.82** | 0.37 | 2.24 | 0.01 |
| Before | $-$**1.11** | 0.51 | $-2.19$ | 0.02 |
| Prop. Neighbor | $-$**1.08** | 0.46 | $-2.34$ | 0.01 |
| Before $\times$ Prop. Neighbor | **1.20** | 0.62 | 1.92 | 0.03 |
| Secession | **0.42** | 0.20 | 2.07 | 0.02 |
| Former Party | $-0.23$ | 0.19 | $-1.19$ | 0.12 |
| Number of Slaves | 0.00 | 0.00 | 0.28 | 0.39 |
| Estate Value | $-0.00$ | 0.00 | $-0.06$ | 0.48 |
| Multiple-$R^2$ | 0.228 | | | |
| $N$ | 56 | | | |

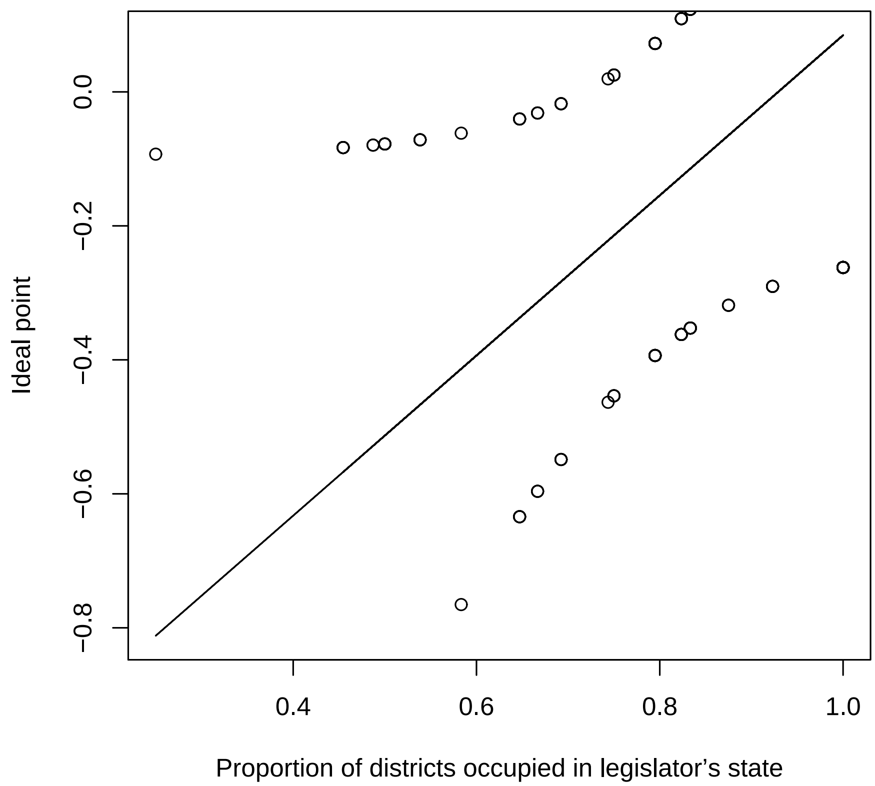
In a similar fashion, to find the effect of $Neighbor$, we differentiate with respect to $Neighbor$:

$$\frac{\partial Idealpoint}{\partial Neighbor} = -1.08 + 1.20 Before.$$

Since $Before$ is a dummy variable, there are only two possible effects for $Neighbor$. If $Before$ is equal to one, the effect is .12. If $Before$ is equal to zero, then the effect is $-1.08$. However, upon calculating the corresponding $t$-statistics, only the effect where $Before$ is equal to zero is statistically significant. Since that effect is positive and significant, this means that legislators' ideal points after occupation increase, on average, by .12 for a unit increase in the proportion of neighboring districts occupied. This effect is in line with the argument presented above and the results for the effect of $Before$ as well.

The variable $Secession$ is also significant and in the predicted direction;

Figure 3.4: Effect of occupation on voting behavior




unionists had significantly more negative ideal points than secessionists. Party, though in the predicted direction, is not statistically significant. The variable *Slaves* is in the right direction—higher values lead to, on average, more positive ideal points—but is not statistically significant. *Estate* is neither in the correct direction nor significant, though the magnitude is extremely small in any event. These results show in a clear and unambiguous fashion that, when controlling for other factors, the effect of changing district occupation is significant.

For the second model, we focus our attention on the cases that *did not* change: that is, districts that were either always or never occupied. The variables will be the same as above, except for the variable $Before$. In its place, I add a dummy indicator called *Never* that is equal to 1 if the district was never occupied or 0 if always occupied. This is important to consider, as Jenkins (2000) found that, though the "shock" of district occupation was not significant, there is a statistically significant difference for those districts that were always or never occupied. As in the case for districts that did change, I include the variable *Neighbor* and the interaction term. These could be important to consider if the difference between always and never occupied districts is related to the proportion of districts in their respective states that are occupied.

The model can be written as follows:

$$\begin{aligned} Idealpoint &= \beta_0 + \beta_1 Never + \beta_2 Neighbor + \beta_{12} Never \times Neighbor + \beta_3 Secc \\ &+ \beta_4 Party + \beta_5 Slaves + \beta_6 Estate. \end{aligned} \tag{3.9}$$

Results from estimating Equation 3.9 are presented in Table 3.6. The primary conclusion from this table is, once again, Jenkins' (2000) finding is incorrect; *Never* does not have a statistically significant impact on ideal points of legislators. Moreover, *Neighbor* and the interaction are not statistically significant. Though I suppress the marginal effects derived in the first OLS model, I find that for any value of *Never* or *Neighbor*, the respective effects are never statistically significant. Secession stance and estate

Table 3.6: OLS model predicting ideal points for districts that did not change control

| | Estimate | Std. Error | t value | p-value |
|---|---|---|---|---|
| Intercept | $-0.21$ | 0.38 | $-0.54$ | 0.30 |
| Never | 0.19 | 0.38 | 0.51 | 0.31 |
| Prop. Neighbor | $-0.26$ | 0.41 | $-0.65$ | 0.26 |
| Never $\times$ Prop. Neighbor | 0.12 | 0.48 | 0.25 | 0.40 |
| Secession | **0.43** | 0.12 | 3.45 | 0.00 |
| Former Party | 0.18 | 0.13 | 1.43 | 0.08 |
| Number of Slaves | $-$**0.01** | 0.00 | $-2.59$ | 0.01 |
| Estate Value | **0.00** | 0.00 | 2.30 | 0.01 |
| Multiple-$R^2$ | 0.445 | | | |
| $N$ | 63 | | | |

value have positive and significant effects on ideal points. However, former political party is not significant. Even more telling, the coefficient on the number of slaves is negative and significant, the opposite of what was found previously. This is not surprising and, moreover, further buttresses my argument. Legislators with a lot of slaves from districts that did not change hands did not have the "shock" caused by the invasion. This is turn did not cause them to support the desperate measures that those in the first model did.

The results from these two models indicate that the effect of *changing* district occupation and not just occupation alone is a significant and unmistakable component of legislators' voting behavior. Moreover, by controlling for the other variables and incorporating the effect of occupation of neighboring districts, the results are even more robust. Another interesting factor to consider is that former political party was not significant in either model. This suggests that the political affiliations that were forged in the

Southern legislators' pasts were not as deeply-rooted as partisanship seems to be in the modern era.

To make the inferences I have drawn here even more clear and unmistakable, I present a specific case study in the roll call history of the Confederate Congresses: the vote to suspend the writ of *habeas corpus*. This issue, where the question of central state authority is perhaps the clearest, will put the hypotheses and results derived heretofore to yet another test.

### 3.4.3 Specific case study: suspension of *habeas corpus*

The writ of *habeas corpus*, a Latin phrase meaning "ye should have the body," is considered one of the corner-stones of Anglo-Saxon law (Yearns 1960, 150; Martis 1994, 90). It expressly denies the government the right to unlawfully detain persons in captivity. As is often taught in American history courses, President Abraham Lincoln suspended the writ of habeas corpus in the North during the war in the face of desertion, draft riots, and other miscellaneous domestic problems (Yearns 1960, 150-152). Less well known is that the same measure was invoked by President Jefferson Davis in the Confederacy. It is perhaps more interesting that the Confederate government suspended the writ, in that this action is expressly opposed to the entire purpose for secession in the first place—states' and individuals' rights. A number of the South's outspoken statesmen made clear statements on these matters. One John Murray of Tennessee remarked that he did not understand "[a] political doctrine that teaches that in order to get liberty you must first lose it" (Alexander and Beringer 1972, 172-173). Another legislator, Reuben Davis, thought that the suspension of this civil liberty would lead Davis to suspend Congress (Yearns 1960, 152). Thus, the debate on the suspension of *habeas corpus* was intense and it is clear that the suspension was at odds with the Confederate nation's ideals.

Why would a legislator support such a thing? John Murray and Reuben Davis were not alone in their opposition to this apparent usurpation of individuals' rights vis-à-vis the central government. According to my hypothesis, one would expect legislators from occupied districts to be much more in favor of the suspension of the writ than their unoccupied counterparts. Although the measure was unpopular, those from occupied districts could support this "necessary" ceding of power to the executive without fears of electoral retribution. Further, legislators may have supported suspending the writ because the occupation of their districts made vivid the implications of an un-centralized government.

Upon inspection of the controversial vote to suspend the writ on December 8, 1864, we find 82% of legislators from occupied districts supported the suspension of the writ. Contrast this with a mere 22% support from legislators in unoccupied districts. This initial finding can be formalized in a simple logit model. Let $y_i$ denote legislator $i$'s vote on the bill, where $y_i = 1$ denotes "Yea" and $y_i = 0$ denotes "Nay." This observed behavior can be thought of as a realization of some latent variable $y_i^*$ where

$$y_i = \begin{cases} 1, & \text{if } y_i^* > 0 \\ 0, & \text{if } y_i^* \leq 0 \end{cases} . \tag{3.10}$$

If we let $\boldsymbol{X}$ denote the covariates in the previous OLS models (i.e., former

Table 3.7: Logit model on the vote for suspension of Habeas Corpus

| | Estimate | Std. Error | $t$-statistic | $p$-value |
|---|---|---|---|---|
| Intercept | $-1.88$ | 1.42 | $-1.32$ | 0.10 |
| Occupied | **2.78** | 1.48 | 1.88 | 0.03 |
| Secession Stance | $-0.55$ | 1.18 | $-0.47$ | 0.32 |
| Former Party | $-$**2.98** | 1.46 | $-2.04$ | 0.02 |
| Number of Slaves | **0.02** | 0.01 | 1.94 | 0.03 |
| Estate value | $-0.00$ | 0.00 | $-1.46$ | 0.07 |
| $\ln \mathcal{L}$ | -23 | | | |
| AIC | 55.56 | | | |
| $N$ | 52 | | | |

party, secession stance, estate value, number of slaves, and occupation status), the latent $y_i^*$ can be written as

$$y_i^* = \boldsymbol{X_i}\boldsymbol{\beta} + \varepsilon_i. \tag{3.11}$$

Letting $\varepsilon_i$ be distributed Type 1 Extreme Value (T1EV) yields a logit model, the estimates of which are found in Table 3.7. Though logit coefficients cannot be directly interpreted, we can assess sign and significance. As predicted, occupation of a district leads to a statistically significant increase in the probability of voting "Yea," controlling for the other variables. *Party* and *Slaves* are both significant as well, and as predicted—Democrats and legislators with more slaves have a higher predicted probability of voting in support of suspending *habeas corpus*. Neither secession stance nor estate value seem to be significant.

To go beyond the simple sign and significance found for the coefficients in Table 3.7, I produce predicted probabilities for the logit model. Using

Table 3.8: Predicted probability of voting in favor of suspending *habeas corpus*

| | Unoccupied | Occupied |
|---|---|---|
| Democrat, Secessionist | 12.0% | 68.0% |
| Democrat, Unionist | 7.20% | 56.0% |
| Whig, Secessionist | 0.68% | 9.90% |
| Whig, Unionist | 0.39% | 6.00% |

the $\hat{\beta}$'s found in the logit regression above, I hold both *Estate* and *Slaves* at their means, vary combinations of party, secession stance, and occupation status, and calculated the predicted probability of voting "Yea." The results are found in Table 3.8. As we see, members from occupied districts are always more likely to vote "Yea" than legislators from unoccupied districts. Indeed, changing from unoccupied to occupied increases probabilities exponentially. For example, a Democrat secessionist from an unoccupied district only has a 12% predicted probability of voting "Yea." Changing his district to occupied increases the predicted probability to 68%, over a five-fold increase! Though former Whigs were the least likely to vote "Yea," being from an occupied district leads to significantly higher probabilities of supporting the suspension of the writ. In short, district occupation is a clear, powerful factor in predicting voting behavior, even when controlling for other relevant factors.

## 3.5 Conclusion

In this paper, I argue that the national crisis brought about by the Civil War, exacerbated by the Federal occupation of Congressional districts in the Confederacy, led Southern legislators to alter their voting behavior. To demonstrate this, I introduce empirical evidence for the shifting of ideal points of legislators. More importantly, this shift is shown to have a close relationship with the occupation of the legislator's district. Though not a primary goal of the paper, I necessarily address two methodological issues. First, I demonstrate that treating static ideal points as cross-temporally comparable can lead to faulty inferences in subsequent analyses. Second, and related to the first, I have brought to light some of the challenges presented by estimating preferences of decision-makers over time.

All of these objectives, either primary or secondary, are certainly interrelated, at least to the degree that they influence one another. The use of statistical methodology to evaluate historical events and institutions is surely a positive development. Indeed, modern methodological tools afford scholars new and innovative ways to investigate old claims and hypotheses. At the same time, however, it is imperative that the methods employed be appropriate to the historical application. In the case of preferences, using dynamic ideal points allows scholars to evaluate historically-based claims surrounding decision-makers' preferences in a coherent and correct fashion. Nonetheless, the methods themselves are not infallible—all of them rely on a set of more-or-less restrictive assumptions. Depending on the application, some assumptions are more reasonable than others. Thus, it befalls on researchers to evaluate which approach's assumptions are appropriate to the situation at hand.

For the case of the Confederate Congress discussed at length in this paper, the methods employed have provided solid evidence that legislators' preferences shifted as a result of their Congressional district's occupation. Even when controlling for all core factors that might otherwise have affected preferences (e.g., former party, secession stance), district occupation still has a substantial impact on ideal point shifts. Though one cannot have a complete sense of the psychological factors that affected legislators' decisions to change, it seems clear that the reality of military loss and subsequent political change caused enough of a stir in legislators' minds to induce ideal point shifting. However, one must not ignore the intense normative implications of these legislators' choices. The calls for secession among Southern intellectuals were almost wholly theoretical. They based the legitimacy of a Southern Confederacy on the principles of limited, accountable government and individual liberty. To the contrary, the evidence presented in this paper has shown quite clearly that the occupation of legislators' districts caused them to vote in way contrary to these principles. Consequently, a new question begs to be answered: in the aftermath of these anti-states' rights votes, what was the new basis for an independent Southern nation? If the South did in fact win its independence, would legislators go back to their "old selves"? How would they answer to their newly un-occupied constituencies?

Future research should explore these issues further, as similar historical circumstances have reared their heads in the nearly 150 years since the Civil

War. By exploring legislators' motives, political scientists will become one step closer to explaining the relationship between historical circumstances and individual behavior. In turn, this will shed light on our understanding of legislative institutions, decision-making, and, more broadly, human behavior when under fire.

# Chapter 4

# Missing in Action

*"...whenever the people are well-informed, they can be trusted with their own government."*

**—Thomas Jefferson, 3rd President of the United States**

Political science stands in a unique position amongst the other sciences. On the one hand, our discipline lacks the ability to exercise true experimental control. Physicists and chemists are able to manipulate parameters in their models with relative ease, making ensuing statistical analyses both theoretically and practically more tractable. Political science, with its unit of analysis typically set to either individuals or nations, attempting to impose control is either impossible, immoral, or both.

On the other hand, unlike natural scientists, political scientists are able to *ask* our units of analysis about their motivations and beliefs via surveys. Indeed, the aid of surveys is indispensable when it comes to probing public opinion. Surveys are relatively inexpensive (vis-à-vis quantum mechanical experiments) and afford the researcher a tremendous opportunity to gain insight into the dynamics of politics and decision-making.

Despite their flexibility and usefulness, surveys often present more problems than they solve. Low response rates have the possibility of biasing any sort of statistical inference that is attempted, though recent scholars (e.g., Peress 2007) have proposed remedies. Perhaps more difficult to address is the presence of missing data among those who do respond to the survey. Many surveys (e.g., the American National Election Study, General Social Survey, the Eurobarometer) give individuals the opportunity to skip questions (NA) or elicit "don't know (DK)" responses. Though traditional practice usually involved deleting these observations listwise or pairwise, it seems rather clear that doing so can lead to biased inferences down the road. As such, methods are required to address this problem.

Bradlow and Zaslavsky (1999) present just such an approach—one that models the missingness by using a hierarchical, multiple latent variable approach. This method considers individuals' responses to ordinal indicators as a product of saliency, strength of opinion, and decisiveness (when opinion is weak). In this paper, I present the framework that was developed by Bradlow and Zaslavsky (1999) and demonstrate how it may be applied to the prevalent problem of NA's in American politics survey research. In Section 4.2, I discuss the existing literature on missingness in general and multiple imputation in particular. Section 4.3 presents the essential features of model as derived by Bradlow and Zaslavsky. Section 4.4 discusses the estimation strategy. The chosen technique is the data augmentation technique of Tanner and Wong (1987; see also Jackman 2000 and Albert and Chib 1993). Last, Section 4.5 applies the methodology of this paper to study respondents' perception of Congressional candidates' ideology in the 1992 general election.[1]

## 4.1 Literature

Missing data has long drawn the ire of researchers throughout the social sciences. In the case of surveys, known for their low response rates to begin with, item non-response can cause serious problems for multivariate analysis. Moreover, traditional remedies like listwise deletion or mean-insertion have been shown to cause serious bias in estimates and/or inferences (see, e.g., King et al. 2001). As a result, a large literature in both applied statistics (Rubin 1976, 1977, 1987; Gelman et al. 2004; Gelman, King, and Lin 1999) and political science/econometrics (King et al. 2001; Berinsky 1999; Brehm 1997; Heckman 1976) has emerged to model missingness in ways that minimize the inference bias that traditional remedies might induce.

This broad literature can be divided into two loosely-defined classes. The first is the class of multiple imputation models (Rubin 1976, 1977, 1987; Gelman et al. 2004; Gelman, King, and Lin 1999). This paradigm seeks to "impute" the missing values by using other observed information in the data matrix. The method has become extremely popular, as it is relatively easy to implement, as it is now commonly available in standard statistical packages like `STATA` and `R`. Some difficulty tends to arise when variables are nominal or ordinal, as is the case in surveys, but transformations can be applied to get around this. Nonetheless, imputation is about as close as

[1]For scholars interested in Monte Carlo-like analysis, the Appendix to Chapter 4 provides Monte Carlo evidence demonstrating that inferences from using an ordered probit model diverge widely from the hierarchical model presented in Section 4.3.

one can get to a one-size-fits-all missing value methodology.

While this approach has wide applicability, it certainly has limitations. Two issues in particular may limit the usage and applicability of traditional imputation methods. First, the missingness must obey the so-called *missing at random* assumption. Following the notation of King et al. (2001), let $D_{obs}$ denote observed data, $D_{mis}$ denote missing data, $D$ denote the total data, and $M$ represent missingness. We say that data are missing-at-random (MAR) if $P(M|D_{obs}, D_{mis}) = P(M|D_{obs})$. More simply, data satisfy MAR if the missingness can be modeled as a function of observed data. A canonical example of this sort of missingness is the case of high wage-earners who are reluctant to report their income in surveys. While the income may be unobserved, there are several known correlates (e.g., education) that are *not* missing. By conditioning on these observed values, we may model missingness straightforwardly using existing algorithms. However, if the missing observations do not have observed covariates that can predict them in the data, MAR is not satisfied and multiple imputation is no longer an option.

The second issue, one that is less statistical and more conceptual, is the nature of the missing values in the first place. This issue can be posited as follows: when considering NA/DK responses in surveys, particularly those on opinion-oriented questions, is it necessarily the case that missing values are simply censorings or "accidents"? Perhaps it is the case that individuals who do not choose a response or elicit "don't know" are actually making a choice, a choice in the same sense as the other categories given to them. Indeed, if this is true, King and his co-authors concede that cases "...when 'no opinion' means that the respondent really has no opinion rather than prefers not to share information with the interviewer, should be treated seriously and modeled directly..." (King et al. 2001, 59).

The other class of models for missing data are deemed by King et al. (2001) as "application specific methods" (e.g., Brehm 1997; Bartels 1998; Berinsky 1999; Heckman 1976). These methods are diverse and, as such, do not follow neatly into one category. Generally speaking, these methods require a specific modeling of the missingness mechanism, which can be difficult and will certainly vary across applications. For example, two such approaches (Berinsky 1999; Heckman 1976) consider data in terms of the so-called selection model. In particular, Berinsky (1999) models citizens' NA/DK response on racial attitude questions as a selection process, whereby those choosing NA/DK select themselves out of the sample. This approach is novel and yields to substantively interesting results, but it too presents limitations. First, this class of models require an exclusion restriction to ensure proper identification. Second, the model restricts missingness to result from only one initial selection. It is also plausible to think that missingness could be due to indifference; that is, citizens are indifferent between certain categories and this leads them to report NA/DK. The approach of Bradlow and Zaslavsky (1999) considered in this paper and presented in the next section provides scholars with an ability to model without either the deficiencies of the selection-based approach or the imputations approach.

Figure 4.1: The hierarchical model

$\psi_i$

$\psi_i < 0$ $\quad$ $\psi_i \geq 0$

$\vartheta_{ij}$

$y_i = NA/DK$ $\quad$ $\vartheta_i \in [c_L, c_H]$ $\quad$ $\vartheta_i \notin [c_L, c_H]$

$\delta_i$

$\delta_i \geq 0$ $\quad$ $\delta_i < 0$ $\quad$ $y_i = q$

$y_i = q$ $\quad$ $y_i = NA/DK$

## 4.2 The model

### 4.2.1 Latent variables

Let $i = 1, 2, ..., N$ denote the set of respondents to the survey.[2] For each individual $i$, $y_i$ is his ordinal response to the item. Typically, these sorts of items involve five- or seven-point scales. If $i$ skipped the item, it is assumed that his response is coded as either $NA$ or $DK$. In a usual analysis of this data, ordered probit or logit is the most common technique employed. The probabilities of the various $y_i$'s are modeled as a function of covariates $X$ and cutpoints $c_q$. Estimation is either achieved by maximizing a likelihood function or, with assignment of priors, a sampling from posterior distributions.

[2]The model presented herein was developed in Bradlow and Zaslavsky (1999). It was originally designed to analyze multiple ordinal indicators. However, in this paper, the decision structure has been modified so as to accommodate analysis of only one ordinal indicator. Readers interested in the analysis of multiple issues may consult the original paper.

The modeling approach employed herein can be seen as a generalization of the ordered probit. The main departure is the multiplicity of latent variables. In the ordered probit, the $y_i$'s are viewed as manifestations of an underlying $y_i^*$, where the various ordinal values are determined by cutpoints on the underlying latent scale. The hierarchical approach of this paper views an individual's response as a product of three underlying latent processes: *saliency*, *opinion*, and *decisiveness*. *Saliency*, given by $\psi_i$, is the first latent factor in the decision-maker's process. If the item is not salient, $\psi_i < 0$ and the respondent will elicit a $NA/DK$ response.

If the item is in fact salient, the next stage is the existence of a true *opinion*, $\vartheta_i$. Respondents whose latent opinion is more extreme are assumed to have "true" or definitive opinions. The extremity of opinion here is defined in terms of cutpoints, $c_q$, where $q = 1, ..., Q-1$ represents the ordinal response category, $c_0 = -\infty$ and $c_Q = \infty$. An opinion $\vartheta_i$ is considered extreme if

$$\vartheta_i < c_L \tag{4.1}$$

or

$$\vartheta_i > c_H, \tag{4.2}$$

where the cutpoints $c_L$ and $c_H$ depend on the number of possible ordinal responses given on the particular item. In particular, it is assumed that $c_L = c_{q_L-1}$ and $c_H = c_{q_H}$. $q_H$ and $q_L$ are typically chosen so that they straddle the cutpoint that corresponds to the center-most category. For example, if the observed data is from a seven-point scale, category 4 is at the center. This makes $q_L = 3$ and $q_H = 5$ ideal candidates for $c_L = c_2$ and $c_H = c_5$ respectively.[3]

Should $i$ have a $\vartheta_i$ that satisfies either (1) or (2) above, we assume that he will elicit an ordinal response and not $NA/DK$. However, if $\vartheta_i \in [c_L, c_H]$, we say that $i$ is in the *region of indifference*. This, in turn, leads to the last stage in the decision tree. We can imagine that a latent opinion in this range might lead to one of two observed behaviors. If the individual is decisive, then he would be more inclined to elicit an ordinal response than if he were indecisive. This notion is formalized in the third latent variable $\delta_i$, where $\delta_i \geq 0$ implies $i$'s decisiveness on the item and hence, an ordinal response will be given. If he is not decisive, $\delta_i < 0$ and the $NA/DK$ response is given. The entire process is depicted in Figure 4.1.

A few comments are warranted before proceeding. First, this model provides a rich description of respondents' behavior. For example, the $NA/DK$ response can be observed if the respondent is indifferent or if the item is simply not salient. These are very different kinds of $NA$'s and are necessarily modeled as such. Second, if there are no $NA$'s, this more complicated model reduces to a simple ordered probit. This model is consequently always the preferred option, as it can pick up effects that the ordered probit would miss, but still turn out the same results where $NA$'s are nonexistent.

[3] The boundaries of this zone are not by any means set in stone. Depending on the data, researchers may desire to modify the indifference region bounds accordingly.

### 4.2.2 Hierarchy I: Distribution of $y|\phi_1, \phi_2$

It is assumed that the three latent variables, $\psi_i$, $\vartheta_i$, and $\delta_i$ distributed normally with variance 1. Saliency, $\psi_i$, is assumed have a mean $\mu_i^{\psi_i}$ such that

$$\mu_i^{\psi_i} = \eta_i + X_i^{\psi} \beta^{\psi}, \tag{4.3}$$

where $\eta_i$ is a random intercept that allows individuals to vary in terms of saliency and $X_i^{\psi}$ is a vector of covariates thought to influence saliency. For the latent opinion $\vartheta_i$, the mean is given by

$$\mu_i^{\vartheta_i} = X_i^{\vartheta} \beta^{\vartheta}, \tag{4.4}$$

where $X^{\vartheta}$ is a set of covariates thought to influence the latent opinion. The final latent variable, decisiveness $\delta_i$ has a mean

$$\mu_i^{\delta_i} = X_i^{\delta} \beta^{\delta}, \tag{4.5}$$

and $X_i^{\delta}$ is a vector of covariates affecting decisiveness.

These latent draws may thus be summarized as follows:

$$\psi_i \sim \mathcal{N}(\mu_i^{\psi_i}, 1) \tag{4.6}$$

$$\vartheta_i \sim \mathcal{N}(\mu_i^{\vartheta_i}, 1) \tag{4.7}$$

$$\delta_i \sim \mathcal{N}(\mu_i^{\delta_i}, 1). \tag{4.8}$$

Figure 4.2: The hierarchical model with probabilities

$\psi_i$

$r$ $1-r$

$\vartheta_i$

$y_i = NA/DK$ $s$ $1-s$

$\delta_i$

$t$ $1-t$ $y_i = q$

$y_i = q$ $y_i = NA/DK$

The complete data likelihood is found based on the definitions of the various latencies above. In particular, the likelihood function is given by

$$\mathcal{L}(\phi_1, \phi_2 | y_{ij}, X) \propto \prod_{i=1}^{N} p_i(\phi_1, \phi_2 | y_{ij}, X), \tag{4.9}$$

where the $p_i$ are probabilities associated with the ordinal outcomes. To illustrate more simply how these are derived, Figure 4.2 presents a simplified decision tree that is broken down into three different probabilities: $r$, $s$, and $t$. To evaluate $p_i$ in these terms, we need to look at the various responses that could be provided on the ordinal items. First, we consider the case where $i$ elicits $NA/DK$. This could have resulted two ways, as is seen in Figure 4.2. Thus, the probability of observing a $NA/DK$ response is

$$\begin{aligned} Pr(y_i = NA/DK) &= r + s(1-r)(1-t) \\ &= \Phi(-\mu_i^{\psi_i}) + (\Phi(c_{q_H} - \mu_i^{\vartheta_i}) - \Phi(c_{q_L} - \mu_i^{\vartheta_i})) \\ &\times \ (1 - \Phi(-\mu_i^{\psi_i}))\Phi(-\mu_i^{\delta_i}). \end{aligned} \tag{4.10}$$

Second, we look at non-NA responses that fall outside of the indifference region. The probability of observing a response outside of this region is given by

$$\begin{aligned} Pr(y_i = q \notin [q_L, q_H]) &= (1-r)(1-s) \\ &= (1-\Phi(-\mu_i^{\psi_i}))(\Phi(c_q - \mu_i^{\vartheta_i}) \\ &- \Phi(c_{q-1} - \mu_i^{\vartheta_i})). \end{aligned} \tag{4.11}$$

Finally, there is the probability of observing a non-NA response that is within the indifference region. Examining Figure 4.2, this is given by

$$\begin{aligned} Pr(y_i = q \in [q_L, q_H]) &= (1-r)st \\ &= (1-\Phi(-\mu_i^{\psi_i}))(\Phi(c_q - \mu_i^{\vartheta_i}) - \Phi(c_{q-1} - \mu_i^{\vartheta_i})) \\ &\times (1-\Phi(-\mu_i^{\delta_i})). \end{aligned} \tag{4.12}$$

We can assemble all of these into a single statement as follows:

$$p_i(y_i) = \begin{cases} \Phi(-\mu_i^{\psi_i}) + (\Phi(c_{q_H} - \mu_i^{\vartheta_i}) - \Phi(c_{q_L} - \mu_i^{\vartheta_i}))(1-\Phi(-\mu_i^{\psi_i})) & \\ \qquad \times\Phi(-\mu_i^{\delta_i}), & \text{if } y_i = NA/DK \\ (1-\Phi(-\mu_i^{\psi_i}))(\Phi(c_q - \mu_i^{\vartheta_i}) - \Phi(c_{q-1} - \mu_i^{\vartheta_i})), & \text{if } y_i = q \notin [q_L, q_H] \\ (1-\Phi(-\mu_i^{\psi_i}))(\Phi(c_q - \mu_i^{\vartheta_i}) - \Phi(c_{q-1} - \mu_i^{\vartheta_i})) & \\ \qquad \times(1-\Phi(-\mu_i^{\delta_i})), & \text{if } y_i = q \in [q_L, q_H] \end{cases}.$$

### 4.2.3 Hierarchy II: Distribution of $\phi_1|\phi_2$

The second layer of hierarchy in this Bayesian model looks at the vector of prior parameters $\phi_1 = \eta$. Each of these parameters is normally distributed as follows:

$$\eta_i \sim \mathcal{N}(X_i^\eta \beta^\eta, \sigma_\eta^2). \tag{4.13}$$

$X^\eta$ is a matrix of covariates that is assumed to influence the saliency of individuals in the data set. In the application presented subsequently, I assume that the matrices of covariates for $\vartheta$, $\delta$, and $\eta$ are the same.

### 4.2.4 Hierarchy III: Distribution of $\phi_2$

The third and final layer of hierarchy in this model is the vector of hyper-parameters for the coefficients, variances, and cutpoints:

$$\phi_2 = (\beta^\psi, \beta^\delta, \beta^\vartheta, \beta^\eta, \sigma_\eta^2, \boldsymbol{c}).$$

Each group of regression coefficients for latent parameter $Z$ are drawn from a Multivariate Normal distribution with mean 0 and covariance $V$:

$$\beta \sim \mathcal{MVN}(0, V). \tag{4.14}$$

The choice of $V$ can be as large or as small as the researcher desires. For the variance of the random saliency intercept, I employ an uninformative conjugate prior that is defined on the positive reals. Standard results show such a distribution to be the Inverse Gamma. Thus, the prior for $\sigma_\eta^2$,

$$\sigma_\eta^2 \sim \mathcal{IG}\left(\frac{\rho}{2}, \frac{1}{2}\right), \tag{4.15}$$

and $\rho$ is chosen to be 0.5.

Last, and perhaps the trickiest, is the vector of cutpoints. All cutpoints are assumed to be drawn uniformly from the last cutpoint to the current cutpoint. More specifically,

$$c_q | c_{q-1}, c_{q+1} \sim U(c_{q-1}, c_{q+1}), q = 1, 2, ..., Q-1, \tag{4.16}$$

$c_0 = -\infty$, $c_Q = \infty$, and, for identification, some $q' \in \{1, 2, ..., Q-1\}$, $c_{q'} = 0$.

### 4.2.5 The full posterior

We can combine the expressions for the likelihood and priors above to form the complete posterior:

$$\pi(\phi_1, \phi_2 | y, X) \propto \mathcal{L}(y | \phi_1, \phi_2, X) p(\phi_1 | \phi_2, y, X) p(\phi_2). \tag{4.17}$$

As is the case with all hierarchical models, there is a very large number of parameters to estimate. Indeed, we are required to estimate a minimum of $N + Q - 1$ parameters (not including the $\beta$'s or $\sigma^2$). The choice of covariates above this number makes things even more complicated. With the number of parameter estimates far exceeding the sample size, we must consider alternate ways to sample from equation (17).

## 4.3 Estimation

### 4.3.1 Problems with Maximum Likelihood and standard Gibbs sampling

Prior to proceeding with a description of how to estimate this model using Bayesian techniques, it is important to say a word on why Maximum Likelihood Estimation (MLE) is not a feasible alternative. Some scholars who are uncomfortable with the notion of Bayesian priors (especially those chosen based on conjugacy and not on knowledge) would be more satisfied with using Frequentist analogs of Bayesian models. In the case of the complex hierarchical model presented heretofore, it would simply not be practical or even possible to estimate the model via MLE.

To understand the situation better, consider the familiar example of ideal point estimation. The two dominant approaches are Pool and Rosenthal's (1997) MLE-based DW-NOMINATE and Clinton, Jackman, and Rivers' (2004) Bayesian IRT model. If $M$ is the number of roll calls and $L$ is the number of legislators, there are at least $M + L$ parameters to estimate (two cutpoints per roll call and one ideal point per legislator). To make the estimation feasible, Poole and Rosenthal must estimate parameters in parts, fixing the $M$ cutpoints while estimating the $L$ ideal points and then vice versa, iterating until convergence. In contrast, the Bayesian approach is computationally simple and can be written and run in a few moments in `WinBUGS` or `MCMCpack` (Martin and Quinn 2007).

In the model presented in this paper, there are even *more* parameters to estimate than in the ideal point model. Indeed, the draws of the latent $\vartheta$

alone are essentially a one-dimensional ideal point model. With the addition of the other layers of hierarchy, the Bayesian approach is simply much more tractable.

This is not to say, however, that standard Gibbs sampling is without its difficulties. The Gibbs sampler requires the derivation of the conditional distributions, many of which do not exist in closed form due to the interconnectedness of various layers of the hierarchy and the complexity of the likelihood. Metropolis steps could be used in these cases, but the data augmentation strategy of Tanner and Wong (1987; see also Albert and Chib 1993 or Jackman 2000) allows straightforward Gibbs sampling.

### 4.3.2 Data-augmented Gibbs sampling and conditional posteriors

The data augmentation strategy involves sampling from latent variables $\psi$, $\vartheta$, and $\delta$. Conditional on these sampled parameters, the conditional distributions of the remaining parameters exist in closed form and, hence, a Gibbs sampling routine may be employed. Let us first present the conditional distributions for the three latent variables. All of these results follow clearly from the decision tree presented in Figure 4.1. The distribution of saliency $\psi$ can be summarized as follows

$$\psi_i|\phi_1, \phi_2, X, y \sim \begin{cases} \mathcal{TN}_{\Re_+}(\mu_i^{\psi_i}, 1), & \text{if } y_i = q \\ \mathcal{N}(\mu_i^{\psi_i}, 1), & \text{if } y_i = NA/DK, \vartheta_i \in [c_L, c_H], \delta_i < 0 \\ \mathcal{TN}_{\Re_-}(\mu_i^{\psi_i}, 1), & \text{else} \end{cases},$$

where $\mathcal{TN}$ is the truncated normal distribution and the subscript $\Re_+$ restricts the distribution to the positive reals. The first case states that non-$NA/DK$ responses are drawn with all positive values, as the item is salient. The second case allows $NA/DK$ responses from the indifference region to be either positive or negative. The final case restricts all other $NA/DK$ to be negative, as the question was definitely not salient.

The conditional distribution of the latent opinion $\vartheta_i$ follows in a similar fashion:

$$\vartheta_i|\phi_1, \phi_2, X, y \sim \begin{cases} \mathcal{TN}_{(c_{q-1}, c_q)}(\mu_i^{\vartheta_i}, 1), & \text{if } y_i = q \\ \mathcal{TN}_{(c_L, c_H)}(\mu_i^{\vartheta_i}, 1), & \text{if } \psi_i > 0, y_i = NA/DK \\ \mathcal{N}(\mu_i^{\vartheta_i}, 1), & \text{else} \end{cases},$$

where the first two conditions are drawn from Normal distributions truncated at relevant cutpoints. Non-NA/DK responses are truncated to lie between their previous and current cutpoint. Salient questions that yield NA/DK's must come from the region of indifference, $[c_L, c_H]$. All other NA/DK responses are untruncated.

The conditional distribution of decisiveness, $\delta_i$ is given by

$$\delta_i|\phi_1, \phi_2, X, y \sim \begin{cases} \mathcal{TN}_{\Re_+}(\mu_i^{\delta_i}, 1), & \text{if } y_i = q, \vartheta_i \in [c_L, c_H] \\ \mathcal{TN}_{\Re_-}(\mu_i^{\delta_i}, 1), & \text{if } y_i = NA/DK, \vartheta_i \in [c_L, c_H], \psi_i \geq 0 \\ \mathcal{N}(\mu_i^{\delta_i}, 1). & \text{else} \end{cases}.$$

In the first case, an ordinal response is given but the latent opinion is in the region of indifference, so the individual must have been decisive. The second case is also in the region of indifference, but the person elicits a NA/DK, so he was not decisive. For all other case, the normal distribution is untruncated.

Once we condition on the latent variables described above, the distributions of the others follow easily. This comes as a results of the Normal and Inverse Gamma priors chosen previously for the data generating process and the priors. To make notation simpler, let $\Omega = (\psi, \vartheta, \delta)$. We first consider the parameter at the first level of hierarchy, $\phi_1$. The conditional distribution is given by

$$\eta_i|\Omega, \phi_2, X, y \sim \mathcal{N}\left(\frac{1}{1+\frac{1}{\sigma_{\eta^2}}}\left((\psi_i - X_i^{\psi}\beta^{\psi}) + \frac{1}{\sigma_\eta^2}X_i^{\eta_i}\beta^{\eta}\right), \frac{1}{1+\frac{1}{\sigma_{\eta^2}}}\right) \quad (4.18)$$

The parameters in $\phi_2$ are even easier to derive, once again a function of conjugacy. In fact, all $\beta$'s and the $\sigma^2$ have conditional posteriors of a similar form. The $\beta$'s are each Multivariate Normally distributed, combining the prior additively with the regression-based estimate. Since they all have the same form, I will present the conditional distribution only once for a generic parameter $m$. If $Z$ is the relevant response variable, the conditional distribution of $\beta^m$ is given by[4]

$$\beta^m|\Omega, \phi_1, \phi_2 \sim \mathcal{MVN}\left(A^{-1}\frac{1}{\sigma_m^2}X_m^T Z, A^{-1}\right), \quad (4.19)$$

[4]For all parameters except $\eta$, $\sigma_m^2 = 1$ based on the definitions above.

where $A = \frac{1}{\sigma_m^2} X_m^T X_m + \frac{1}{V} I$, and the distribution for $\sigma_\eta^2$ is

$$\sigma_\eta^2 | \Omega, \phi_1, \phi_2 \sim \mathcal{IG}\left( \frac{N+\rho}{2}, \frac{(\eta - X^\eta \beta^\eta)^T (\eta - X^\eta \beta^\eta) + 1}{2} \right). \tag{4.20}$$

The final conditional distribution to consider is that of the cutpoints, $c_q$. As has been shown in Albert and Chib (1993), the conditional distribution of the cutpoints will be uniform, but there must be a correction to ensure proper and sensible estimates. In particular, for each $c_q$,

$$c_q | c_{q-1}, c_{q+1} \sim U(\max\{c_{q-1}, \max_{y_i = q} \vartheta_i\}, \min\{c_{q+1}, \min_{y_i = q+1} \vartheta_i\}). \tag{4.21}$$

If we examine (21) more closely, the max and min conditions are designed to ensure finiteness of the draws of cutpoints. For example, to draw a cutpoint $c_1$, we would need $c_0$ and $c_2$. Since $c_0 = -\infty$, we need to obtain an endpoint that is finite. Hence, we take the maximum of $-\infty$ and a value of the latent opinion, which by definition will always be the choice. A similar line of argument applies to $c_{Q-1}$. Last, for identification, I fix $c_1 = 0$.

## 4.4 Application: Perceptions of Candidate Ideology

### 4.4.1 Problem and Data

The literature on public opinion and voting behavior as far back as Converse (1964) has been concerned with citizens' ability to make ideological judgments. From this motivation, a large literature has emerged examining citizens' perception of candidates' ideology in various contexts (Feldman and Conover 1983; Conover and Feldman 1989; Delli Carpini and Keeter 1993; Rahn 1993; Sigelman et al. 1995; McDermott 1997; Althaus 1998; Koch 2000; Koch 2002). Indeed, the issue of citizens' abilities to place themselves and candidates in an ideological space is of great relevance to both scholars of voting behavior and those of formal voting theory.

To measure citizen placements, most scholars employ questions from large scale surveys like the American National Election Studies (ANES). In these surveys, respondents are given opportunities to place themselves and candidates on seven-points scales ranging from "extremely liberal" (1) to "extremely conservative" (7). Unfortunately, citizens often are unable to place themselves or candidates, evidenced by high proportions of NA/DK responses. For example, in the 1992 ANES (Miller et al. 1993), approximately 31% of respondents are unable to place themselves on the seven-point scale. Even worse is the proportion of respondents able to place Congressional candidates. In that same ANES, approximately 56% of respondents could not place their Republican House candidate. While not surprising given that scholars have found that many Americans do not even know their incumbent Congressmen, let alone a candidate (Delli Carpini and Keeter 1997), this high proportion of NA/DK responses causes problems for any possible statistical inferences.

The hierarchical model presented above can be applied to the study of this data in a straightforward manner. For comparative purposes, models employing ordered probit with listwise deletion, as well as ordered probit with multiple imputation will be considered.[5] The dependent variable in all models will be the respondent's placement of the Republican House candidate in 1992 on the seven-point liberal-conservative scale. In the listwise deletion model, all NA/DK observations will be removed. For the imputation case, five imputed datasets are obtained using the `Amelia II` package in `R` (King et al. 2007). The hierarchical model treats the NA/DK cases as products of either lack of saliency or indecisiveness, as defined in the model above.

The regressors considered in for the opinion matrix ($X^{\vartheta}$) will be the same as those considered in the listwise deletion and the multiple imputation models. All of these variables are demographics that are considered important in the literature. The first group are basic demographics. *Age* is the age of the respondent in years. *Black* is a dummy indicating whether the respondent is black. *Male* indicates whether or not the respondent was a male. *Education* is the number of years in school for the respondent.

The other set of regressors are ideological in nature. *Republican* and *Democrat* are indicators for whether the respondents are self-identified Republicans or Democrats, respectively. *Extremism* is a measure of ideological extremism of the respondent. This is measured by transforming the self-reported 7-point scale placement as follows:

$$Extremism = |4 - Self|. \tag{4.22}$$

[5]While tempting, the comparison with selection models is not considered here for a few reasons. First, varying exclusion restrictions can change the results of those models and, as a consequence, make comparability across models difficult to ascertain. Second, the dominant approaches in the literature are either listwise deletion or multiple imputation, making these two the appropriate baselines to compare the hierarchical model with.

Since 4 is the mid-point of the scale, an individual choosing this category is given an extremism score of zero. However, individuals at either 1 or 7 will get an extremism score of a 3. The motivation for rescaling ideology in this fashion is the idea that ideological extremists are probably more likely to place a Republican candidate to the right than moderates.[6]

In the hierarchical model, regressors for other levels of the model need to be specified. For simplicity, I employ the same regressors across all layers except saliency—i.e., $X^{\vartheta} = X^{\delta} = X^{\eta}$.[7] In the case of saliency, I simply consider the case of two predictors of saliency: level of political information and ideological extremism, as defined in equation (26).[8] Numerous scholars (e.g., Converse 1964; Zaller 1992) have enunciated the importance of political knowledge in citizens' abilities to make political judgments and use ideological scales. Measures of political knowledge are plentiful (Zaller 1992; Delli Carpini and Keeter 1993, 1997; Althaus 1998), and by far the most common is an additive index of correct answers to factual political questions.

To establish whether the additive index was indeed appropriate, I used the 1992 NES to obtain all components of the index used by Althaus (1998).[9]

[6] The more traditional way to do this is to put two terms into the regression: *ideology* and *ideology*$^2$. Thus, the polynomial term is able to capture the non-monotonic relationship discussed in this paragraph. This specification was attempted for this application and the results do not change. By opting for the simple linear extremism variable, interpretation of coefficients is more easily accomplished.

[7] The exception is $X^{\eta}$, which has two fewer regressors because they are included in $X^{\psi}$.

[8] I have also run the model allowing more regressors. Results do not change substantially. The choice of two regressors here is for simplicity of exposition.

[9] See Althaus (1998) for details. Components include ability to identify major political figures (e.g., the Vice President, Speaker of the House), functions associated with particular branches, ideological bent of major political parties, control of Senate and House by party, and the like.

Rather than proceed immediately, I performed a simple Principle Components Analysis on the data matrix, examining the factor loadings. All components of the index load in the same direction on the first Principal Component, which itself dominates all subsequent components in terms of variance explained. These results indicate that one the data can be largely explained by the first component. As such, I retain the factor scores for each individual on this first dimension and then correlate the factor scores with the simple additive index. The two correlate at an extremely high 0.98. Since this is the case, I opt for the simpler additive index as a measure of knowledge, as increments in these counts are more easily interpretable than increments in factor scores.

To examine the role of political knowledge in terms of decisiveness and opinion, the variable $Info$ is included in these levels as well.

### 4.4.2 Estimation and Results

The hierarchical was estimated with the regressors as defined above over three chains with overdispersed starting values. Each chain was allowed to run for 100,000 iterations, discarding the first-half as burn-in and saving every 20th iteration due to storage limitations. To examine convergence, the Gelman and Rubin (1992) and Geweke (1992) diagnostics were employed. The chains were determined to have converged.

Table 4.1: Placement of Republican House Candidates in the Hierarchical Model (Opinion/Decisiveness)

| | Posterior mean | Standard deviation |
|---|---|---|
| *Opinion equation* | | |
| Intercept | 0.6106 | 0.3602 |
| Age | 0.0065 | 0.0035 |
| Black | 0.3949 | 0.2275 |
| Male | −0.1113 | 0.1084 |
| Education | −0.0088 | 0.0243 |
| Democrat | **0.3010** | 0.1377 |
| Republican | **0.2795** | 0.1347 |
| Extremism | **0.2863** | 0.0626 |
| Info | **0.1047** | 0.0200 |
| *Decisiveness equation* | | |
| Intercept | 0.2044 | 1.7298 |
| Age | 0.0890 | 0.1031 |
| Black | −0.0213 | 1.8396 |
| Male | −0.1128 | 1.7891 |
| Education | **0.9379** | 0.4944 |
| Democrat | 0.0973 | 1.6982 |
| Republican | −0.5199 | 1.5783 |
| Extremism | 0.1520 | 1.5411 |
| Info | −0.4896 | 0.6368 |

For the listwise deletion and multiple imputation cases, the `MCMCoprobit` function of Martin and Quinn's (2007) `MCMCpack` were employed for estimation. As described above, the imputed datasets were estimated using King et al.'s `Amelia` library for `R`.

Results from all three models are found in Tables 4.1-4.4. In each case, the posterior means and standard deviations are provided. When the 95% region of highest posterior density (HPD) lies on the same side of zero, coefficients are placed in bold. For the hierarchical model, results are further

Table 4.2: Placement of Republican House Candidates in the Hierarchical Model (Saliency)

| | Posterior mean | Standard deviation |
|---|---|---|
| *Saliency intercept equation* | | |
| Intercept | $-$**1.0390** | 0.4223 |
| Age | **0.0066** | 0.0043 |
| Black | $-0.2216$ | 0.2429 |
| Male | 0.1834 | 0.1415 |
| Education | 0.0144 | 0.0290 |
| Democrat | $-0.1802$ | 0.1626 |
| Republican | 0.0371 | 0.1886 |
| *Saliency equation* | | |
| Info | **0.0352** | 0.0225 |
| Extremism | **0.1449** | 0.0752 |

divided by level of hierarchy in Table 4.1. In the first equation, we see that both forms of party identification are positive predictors of latent opinion. This is not surprising, as self-identified partisans are more likely to pay attention to the campaign in the first place. Similarly, ideological extremism and level of political information also push the latent distribution to the right. All other regressors have HPD's that cross zero, giving scholars less confidence that the effects are different from zero.

The other equations also provide valuable information. In the decisiveness equation, we see that education has a strong effect on latent decisiveness, demonstrating that increased education leads individuals in the region of indifference to have an increased probability of choosing an ordinal response. The saliency intercept ($\eta$) equation reveals that individuals' saliency intercepts are significantly influenced by respondent age. Last, the saliency equation reveals that increasing levels of information and ideological extremism have strong effects on the saliency of the placement question.

Given the information acquired from the hierarchical model in Tables 4.1-4.2, we may now compare the results from the listwise-deleted and multiply imputed cases and examine how inferences change. For listwise deletion in Table 4.3, the changes are noticeable. First, the standard deviations for all regressors are larger than those in the hierarchical model. Second, and more importantly, *Age* and *Black* are found to have HPD's on the same side of zero in the listwise deletion model, indicating a "significant" impact on latent opinion. Further, while being a Republican has an effect on latent opinion, the effect of being a Democrat has an HPD that crosses zero. All three of these results contradict the results in Tables 4.1-4.2. Age and race were not significant predictors, yet Democratic identification was. Thus, scholars employing listwise deletion would have come to incorrect conclusions regarding the effects of these three key demographics on individuals' opinions.

The results from multiple imputation in Table 4.4 are not much better from an inferential stand. *Age* and *Black* are revealed to be "significant" predictors of latent opinion, though the magnitude of effect for *Black* is much smaller. As was the case in the hierarchical model, *Democrat* is found to be a "significant" predictor, unlike the result in the listwise deletion case. Last, and still important, the coefficient on $Info$, though still a significant predictor, is greatly reduced in magnitude. In turn, this would lead scholars to imply a less substantial role for levels of information in candidate placement.

Table 4.3: Placement of Rep. House Candidates—Ordered Probit Model with Listwise Deletion

| | Posterior mean | Standard deviation |
|---|---|---|
| Intercept | **0.9022** | 0.3656 |
| Age | **0.0075** | 0.0038 |
| Black | **0.4738** | 0.2497 |
| Male | −0.1167 | 0.1257 |
| Education | −0.0071 | 0.0279 |
| Democrat | 0.2781 | 0.1540 |
| Republican | **0.3139** | 0.1551 |
| Extremism | **0.3038** | 0.0703 |
| Info | **0.1133** | 0.0217 |

Table 4.4: Placement of Rep. House Candidates—Ordered Probit Model with MI

| | Posterior mean | Standard deviation |
|---|---|---|
| Intercept | **1.3430** | 0.2689 |
| Age | **0.0077** | 0.0024 |
| Black | **0.3090** | 0.1365 |
| Male | −0.0414 | 0.0772 |
| Education | 0.0330 | 0.0173 |
| Democrat | **0.2160** | 0.0921 |
| Republican | **0.3449** | 0.0971 |
| Extremism | **0.2921** | 0.0436 |
| Info | **0.0457** | 0.0131 |

In sum, the results from this application are clear. Employing listwise deletion or multiple imputation, due to the nature of the missing data, can lead to false positive inferences (i.e., *Age* and *Black*) and, in the case of listwise deletion, false negatives (i.e., no effect for *Democrat*). Moreover, the hierarchical model is able to go a step further and look at the factors that influence the saliency and decisiveness factors across individuals. In turn, this helps scholars to develop a better understanding of the processes that lead to the NA/DK response in public opinion data.

## 4.5 Conclusion

This paper introduces the multiple latent variable approach to dealing with NA/DK responses in surveys pioneered by Bradlow and Zaslavsky (1999). The model was developed in detail and was shown to produce more accurate inferences than the ordered probit model. Though the method is computationally intensive and more difficult to implement than standard ordered probit or IRT models, the leverage gained is considerably worth the extra effort. By modeling the process that leads to NA/DK responses, we do not discard the observations and actually estimate parameters for them. Moreover, we do not simply impute the responses as if the NA/DK are missing at random. Indeed, this would have caused bias if the NA/DK responses are not random but instead deliberate.

The method can be extended to even more settings than the simple example presented herein. Scholars can use surveys with several ordinal indicators of the same sort (i.e., all 5- or 7-point scales) and examine cross-item effects as well as individual effects. The method works especially well when the covariates are chosen based on strong theory. The hierarchical approach allows scholars to more realistically model the data-generating process and, hence, generate more reliable estimates of the effects. Further effort is needed to improve computational efficiency of this approach.

Nonetheless, this approach is invaluable for survey researchers who seek to understand public opinion but have, until now, been restrained by an overabundance of NA/DK responses.

## 4.6 Appendix: Data Experiment—When Ordered Probit Goes Wrong

To explore the features of this estimator, I construct a simple Monte Carlo experiment. In this experiment, some data will be generated according to the data-generating process described in the model and the $\hat{\beta}$'s will be estimated. The results from this estimation will be compared with an ordered probit that omits the missing values in a listwise fashion.[10]

Before proceeding, a few cautionary words are in order. First and foremost, the mere idea of a Monte Carlo experiment is a bit of an oddity in the Bayesian statistical framework. Monte Carlo analyses are typically used to analyze large-sample properties of estimators. In the Bayesian framework, large-sample properties are not usually of interest. Second, the way in which a Monte Carlo proceeds is in itself a violation of Bayesian philosophical principles. Monte Carlos usually begin with declaring knowledge of "true parameters," generating data thereafter with this knowledge. If the estimator at hand is unbiased, for a very large number of repetitions, the Monte Carlo should return a distribution whose mean is the "true" parameters set in the first place.

For a Frequentist, this setup is perfectly legitimate. The "true" parameter $\theta$ is assumed *a priori* to be some fixed value. One generates estimates $\hat{\theta}$ which vary due to randomness. For a Bayesian, $\theta$ does not exist as a single

[10]This experiment was also run for the case in which multiple imputation was employed in the ordered probit model. The distributions of coefficients, as well as predicted probabilities, very nearly match the results from the ordered probit model. As such, the plots are not distinguishable and are not presented. Results from this approach are available upon request.

point that is out there in the world. Rather, $\theta$ (and not $\hat{\theta}$) is a distribution. This of course presents a philosophical conundrum for the Bayesian.

I approach these matters with a pragmatic mindset. On the one hand, I accept the philosophical barrier that Monte Carlo analysis presents to the Bayesian framework. On the other hand, however, it is extremely useful to demonstrate the estimator's ability to recover the "true" parameters (or posterior mode, if you prefer) and, in turn, to compare this vis-á-vis extant estimation techniques. With this in mind, I construct a simple Monte Carlo experiment to examine the properties of this estimator.

The sample size for this analysis will be set to $1,000$.[11] For simplicity, I assume the covariates for the latent opinion, decisiveness, and the random intercept are the same. Specifically, for the latent opinion, $\vartheta_i$,

$$\vartheta_i = \beta_0^{\vartheta} + \beta_1^{\vartheta} x_1^{\vartheta} + \varepsilon_i, \tag{4.23}$$

where $\varepsilon_i \sim \mathcal{N}(0,1)$. The first term is simply a constant intercept. The variable $x_1^{\vartheta}$ is simply a collection of $1,000$ draws from the Standard Normal Distribution. This variable will be the same for the decisiveness and individual-saliency effects, so I abbreviate it henceforth as $x_1$.

[11]The choice of $1,000$ is in a certain sense arbitrary, as it can modified without noticeable differences in results. My choice to use this level hinges on two points. First, smaller samples tend to lead the ordered probit model to artificially "fall apart," as the NA values become a greater percentage of the data. Second, very large samples (e.g., 5,000 or 10,000) tend to mute the effects of missing values, except when the missingness is heavily systematic. Since my goal is for this method to be employed by those who analyze survey data, the choice of $1,000$ fits squarely within the range of usual sample sizes, making this Monte Carlo analysis more sensible.

The decisiveness equation is derived similarly:

$$\delta_i = \beta_0^\delta + \beta_1^\delta x_1 + \varepsilon_i. \tag{4.24}$$

Saliency is a bit trickier due to the hierarchy. At the highest level, it is Normal with mean equal to $\eta_i + X_i^\psi \beta^\psi$ and variance 1. The individual saliency intercepts, $\eta_i$, are in turn Normal with mean $X_i \beta^\eta$ and variance $\sigma_\eta^2$. The full draw for saliency can be written as

$$\begin{aligned} \psi_i &= X_i^\eta \beta^\eta + X_i^\psi \beta^\psi + \varepsilon_i + \varepsilon_i' \\ &= \beta_0^\eta + \beta_1^\eta x_1 + \beta_1^\psi x_1 + \beta_2^\psi x_2 + \varepsilon_i + \varepsilon_i' \end{aligned} \tag{4.25}$$

where $\varepsilon_i'$ is Normal with mean 0 and variance $\sigma_\eta^2$. $x_1$ is the same as in the previous models, but now I introduce $x_2$, which is just a uniform random variable on the range $-2$ to 4.

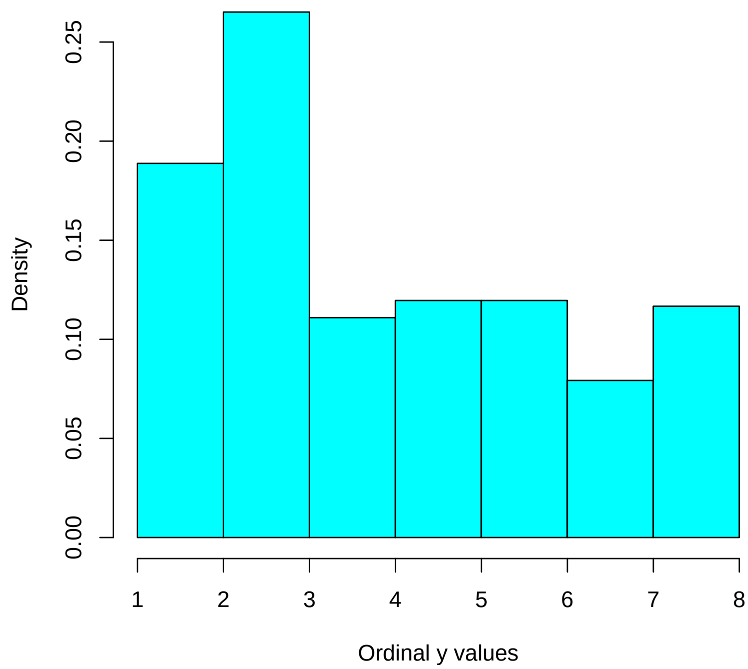
All parameters, $\beta$'s and $\sigma^2$'s, are set to 1 and the cutpoints are set to

$$c = (-\infty, 0, 1.0, 1.5, 2.0, 2.5, 3.0, \infty).$$

These cutpoints are then used to define the observed ordinal $y$'s. Finally, individuals whose saliency draws were less than zero *or* whose decisiveness draws within the region of indifference were less than zero had their ordinal $y$ replaced with an missing value.

A histogram of the non-NA $y$'s is presented in Figure 4.3. This figure shows a high clustering at the low end of the scale, with a fair degree of uniformity to the right of the first two categories. A *prima facie* analysis

Figure 4.3: Ordinal $y$-values for the Monte Carlo experiment



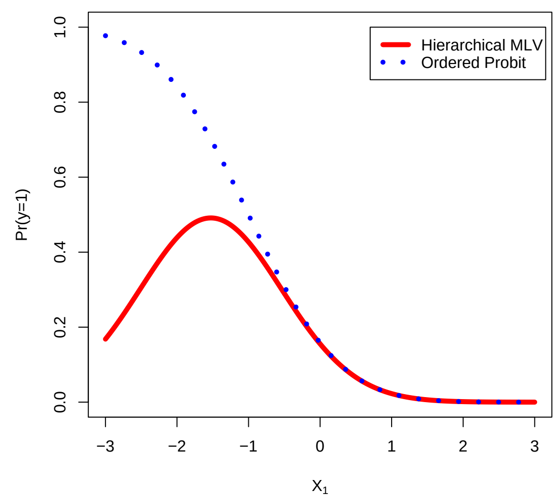

of this data would suggest that respondents tend to be on the liberal end of the scale, provided we interpret $y$ as an ideological scale. At this point, one would usually use ordered probit to analyze the predicted probabilities of falling into one of these bins. The major challenge to any subsequent analysis is the presence of missing values. Based on the parameters chosen, the number of NA's found was 306 out of the total sample of $1,000$ observations. These include cases due to lack of saliency and lack of decisiveness when in the region of indifference. Note however that the *latent* opinion is unaffected by missingness. This important feature allows the results from the hierarchical model to be compared directly to the ordered probit model. The ordered probit is derived in precisely the same manner as the latent $\vartheta_i$'s. Since that model cannot accommodate the NA's, however, they must be deleted from the analysis. The deletion of these cases *should* bias the estimates of the latent opinion slopes, $\beta^\theta$.

To examine this further, I use Martin and Quinn's `MCMCpack` (Martin and Quinn 2007) package in `R` to estimate the Bayesian ordered probit model, as well as my own C++ code, employing the Scythe Statistical Library (Martin and Quinn 2001) to estimate the hierarchical model described above.[12] In both cases, priors were identical for the $\beta$'s and cutpoints (see Section 4.2). Starting values were Standard Normal random draws for all parameters except the cutpoints and $\sigma^2_\eta$ (for the hierarchical model). The cutpoints were evenly spaced over the interval 0 to 5 and the variance was drawn from an Inverse Gamma Distribution with shape and scale of 1. For each case, 100,000 iterations were used in the analysis. The first half were discarded as burn-in. Due to storage limitations with the hierarchical model, every $20^{th}$ iteration was saved. Three chains were examined for each and standard convergence diagnostics were employed to check convergence (i.e., Gelman and Rubin's [1992] $\hat{R}$ and Geweke's [1992] diagnostic). Both models were found to have converged.

While the coefficient estimates are not that different for the two models, the divergence in substantive effects (i.e., predicted probabilities) is quite

[12]For the C++ code, I am indebted to Martin and Quinn, as their Scythe Statistical Library (2001) greatly assisted in the writing and running of code.

Figure 4.4: When Ordered Probit Goes Bad



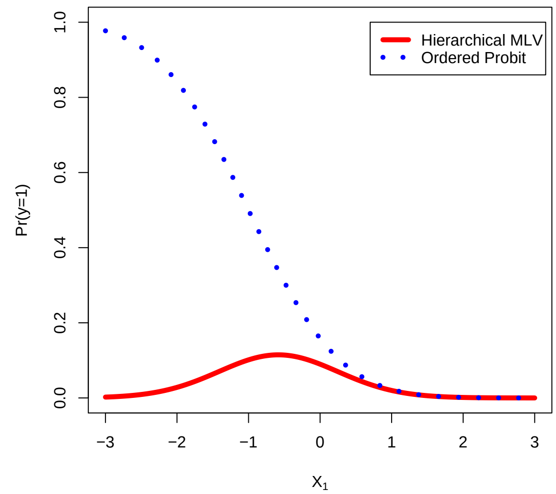

significant.[13] In the hierarchical model, for a given specification of the regressors, predicted probabilities are given by equations (10), (11), and (12). For the ordered probit, predicted probabilities are given by

$$Pr(y_i = q) = \Phi(c_q - \mu_i^{\vartheta_i}) - \Phi(c_{q-1} - \mu_i^{\vartheta_i}). \tag{4.26}$$

Note that for non-NA categories, the degree of divergence between the ordered probit and the hierarchical model depends on saliency and decisiveness. If there is a variable that affects both saliency and latent opinion, it in natural to think that our inferences in terms of predicted probabilities will differ. To see this analytically, consider a response that is a non-NA,

[13] As the posteriors are not too different, presenting the relevant plots is not very useful. Nonetheless, they are available from the author upon request.

Figure 4.5: When Ordered Probit Gets Worse




non-indifference region value. The divergence between predictions is given by dividing equation (11) by equation (25), which yields $1 - \Phi(-\mu_i^{\psi})$. If the mean is very large (and positive), the Normal cdf approaches zero and the two models should be approximately equal. However, as the mean gets very small (and negative), the cdf approaches one and the models are maximally divergent.

As a concrete example of this divergence, set $x_2$ and the random intercept, $\eta$, at its mean value and allow $x_1$ to vary along its domain. This allows calculations of the predicted probabilities for both models. A plot of the predicted probability of the respondent choosing category 1 in each of the models is found in Figure 4.4. As $x_1$ increases, the ordered probit suggests the probability of being in this category should decrease monotonically from 1 to 0. The hierarchical model suggests a different story, however. At low values of $x_1$, the predicted probability is 0. The probability then increases until about $-1$, where it begins to decrease and match the ordered probit results. This non-monotonic result leads to starkly different inferences than the ordered probit model.

To make this contrast even clearer, suppose that $y$ represents a seven-point ideology scale and $x_1$ is the income of the respondent. The ordered probit predictions suggest that very poor respondents are very likely to pick the extremely liberal category. As income increases, this probability goes to zero. The hierarchical model presents a different picture, whereby the very rich and very poor have a low predicted probability of choosing the extremely liberal category. The lower-middle class individuals are the ones with the highest probability of choosing this category.

The divergence in inference is exacerbated when one considers that the saliency intercept, $\eta$, was held at its mean in deriving the hierarchical probabilities. If this value is allowed to take on its minimum value, the gap in predictions is even wider. Figure 4.5 shows that the predicted probabilities are essentially zero for choosing $y = 1$ for all values of $x_1$. Thus, the two models give vastly different predictions for $x_1 \in [-3, 1)$.

# Chapter 5

# Discussion and Conclusion

*"Hominem unius libri timeo [Beware the man of one book]."*

**—St. Thomas Aquinas, Philosopher and Theologian.**

As the above quote by Aquinas suggests, one book is less than sufficient to develop a complete understanding of a particular phenomenon. That said, one book can help us to shed preconceived notions and to develop new avenues for further exploration. This dissertation has sought to achieve these two goals, namely, to refocus scholars in the study of legislative behavior and to open up new paths for deeper understanding of the trends found herein.

In regards to the first of these goals, it is my hope that the reader has been convinced of a few important points. First, legislators are not preprogrammed automatons who blindly follow one source of influence. More concretely, they are neither single-minded seekers of re-election, nor are they pure partisans, always bending to the whims of their respective political parties. Rather, legislators are decision-makers like any average citizen.

They face constraints, challenges, and shifting environments in which they interact and, most importantly, they respond to these conditions rationally.

Chapters 2 and 3 in this dissertation demonstrated that particular sorts of legislators shift their behavior in responding to changing conditions. Chapter 2 found that legislators who are successful at re-election were found to have adapted to the ideology of their electorate. In a similar vain, moderates and those with seniority also adapt their views to those of their respective constituencies. Chapter 3 showed how severing the electoral connection in times of national crisis could lead legislators to support policies at odds to their own personal preferences. Though this chapter focused on the mid-19th Century, the implications are more far-reaching. Take, for instance, the rush to pass the USA PATRIOT Act and the near-universal support it received after September 11, 2001. This more modern example seems to fit well with the results found in Chapter 3.

Chapter 4 moved away from legislators and looked at how voters are able to understand and interpret the behavior of their representatives. Not surprisingly, large portions of the electorate are unable to identify where their legislators stand. This chapter presented a technique to account for the underlying mechanism behind the voter's inability to place their representative on an ideological scale. The results confirmed that race, ethnicity, information, and education all play a large role in whether and when voters are able to successfully answer the question at hand.

## 5.1 Avenues for Further Work

As I said above, the second goal of the dissertation was to open new paths to further understand the results found herein. The first two essays in the dissertation show us that statistical modeling of legislative behavior must take advantage of new technologies and innovations. In particular, scholars must be careful to explicitly model the motivations and underlying mechanisms behind legislator decisions. While the approaches used in this dissertation have not been perfect, they are a launching point for more sophisticated modifications and adaptations.

As I noted in Chapter 2, a large part of future work needs to focus on gathering better data. In order to match legislators with their constituencies, it is vital to develop new instruments that allow for comparisons in a common space. The recent Cooperative Campaign Election Study (CCES) is one great example of how scholars can survey constituents by asking common questions to both respondents and legislators. More work like this is necessary to more precisely pin down the links between voters and legislators identified in Chapter 2.

This much-needed data also has tremendous implications for the results of Chapter 4. If scholars are able to study the attitudes of legislators and voters in a common framework, then the results of these studies could help voters to make more informed decisions. Since a large proportion of the electorate is unable to figure out where their legislators stand, public availability of such data would help to close the information gap.

As the quote by Thomas Jefferson at the beginning of Chapter 4 states, information is the essential component of democratic accountability. If voters are informed, then they can make clearer decisions and hold their legislators more accountable. Similarly, if legislators know their constituents are informed, they will respond in rational and responsible way. Though it is almost surely the case that problems would persist in our imperfect republic, one thing is certain: information is the key to responsive and responsible government.

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