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Re-Measuring Left-Right: A Better Model for Extracting Left-Right Political Party Policy Preference Scores.

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A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctorate of Philosophy in the Department of Political Science.

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ABSTRACT

Ryan Bakker: Re-Measuring Left-Right: A Better Model for Extracting Left-Right Political Party Policy Preference Scores.
(Under the direction of Gary Marks)

The left-right dimension of political party competition is one of the most fundamental concepts used in political science. Several measures of this concept are available for use by scholars in the field. In this dissertation, I examine the strengths and weaknesses of two of the most prominently used sources of these placements: party manifestos and expert survey data. I then develop a more sophisticated technique for extracting such a dimension from these data and demonstrate its superior reliability and validity.

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Chapter 1: Introduction

One of the most fundamental concepts used in the study of political parties is the left-right dimension of party competition. This dimension is, “vital is evaluating hypotheses on structures of democratic competition and conflict, on the interplay between electorates and political parties, or on how public policy is shaped by political parties with different agendas” (Marks 2006). The left-right dimension gives us the ability to compare parties within a common space and across time (see Duverger 1951, Downs 1957, Converse 1964, Dahl 1966, Satori 1976, Rabinowitz and MacDonald 1989, Van der Eijk 1999 to name a few) and has been referred to as the “core currency of political exchange in Western Democracies “ (MacDonald et at 2005). Given the centrality of this concept to such a vast array of empirical analyses, it is necessary to develop a valid and reliable measure of the left-right positions of political parties.

The use of the terms left and right to describe political affiliation dates back to Revolutionary France. Feuillant, a monarchist and a reactionary, sat on the far right of the Legislative Assembly of 1791, while the radical Mantagnard positioned himself to the far left of the chamber in order to distance himself from Feuillant (Blattbert 2001). The concept of left-right politics originally was used to distinguish attitudes toward the ancient regime and only later came to be associated with economic issues such as redistribution of wealth and the equality versus liberty debate, for example.

As is often the case in the social sciences, there is no direct measure of this dimension. Unfortunately, we cannot simply count off the number of steps between

Feuillant and Montagnard in the Legislative Assembly and observe this dimension directly. We must, instead, develop a measurement technique that allows us to place political parties on an abstract dimension which we call left-right. To do this, we estimate the distance between parties by evaluating observable imperfect measures that, combined, compose the concept of interest. This process introduces a degree of uncertainty that is often ignored by researchers. That is, it is commonplace for researchers to estimate a latent dimension and then treat this estimate as observed data.

Hubert Blalock once wrote that "…the most serious and important problems that require our immediate and concerted attention are those of conceptualization and measurement, which have too long been neglected" (1979). Although some recent advances in methodological sophistication, such as item response theory, have helped in this regard, our attempts to measure abstract concepts are often based on subjective assessments based on the perceptions of scholars or survey respondents, for example. This process introduces two issues that must be addressed when measuring abstract concepts.

First, we must decide which assessments of which indicators should be used. That is, we are forced to choose, often arbitrarily, which observable indicators, and how many of them, are necessary to construct a valid measure of the abstract concept of interest. Second, we must decide upon the proper aggregation or data reduction technique. These techniques vary in complexity and appropriateness—from simple linear additive scales to more complicated data reduction methods (see Trier and Jackman 2003 and Bollen and Paxton for a detailed discussion). Added to these issues is the fact that most researchers employing such techniques ignore the problem of measurement error that is inherent in these processes. Given that the latent dimension we extract form the data is an estimate, regardless of the technique used to extract it, we should report the uncertainty involved in this estimation process.

The following series of articles addresses the measurement of left-right policy preferences for political parties in Western Europe keeping in mind the issues described above. In order to develop a more reliable and valid measure of left-right, I argue that we should combine the available sources of information rather than rely on any single instrument. This should allow us to build off the strengths while minimizing the weaknesses of the different measures of left-right that are currently available.

Before combining sources, however, we must identify the available sources of left-right placement and the relationships between them. The first article in this dissertation examines the Comparative Manifesto Project (CMP) data. These data are particularly desirable in that they provide estimates of policy preferences from the end of World War II to the present for OECD countries. No other source spans such a long time frame nor contains such a large number of cases, which is why the CMP data are the most widely used source of left-right placements. This is also why the measurement techniques used to create scales from CMP data deserve such close scrutiny and attention.

This article outlines some of the major problems with the treatment of CMP data in their present form. Most of these issues are methodological rather than substantive, but substantive criticisms of the CMP scale are certainly possible. These data suffer from problematic coding decisions, large amounts of missingness, and untenable assumptions regarding the creation of a summated rating scale. In this article I identify these problems and demonstrate their effects in terms of comparability of left-right scores (or the lack thereof) across time and space and offer a simple solution, albeit suboptimal, to ‘cleaning up’ the data.

The second article builds of the findings of the first by using the CMP data in a more sophisticated manner in order to extract a left-right dimension. In this piece, I argue for the use of a Bayesian item response model. I demonstrate that the data generation process behind the CMP measure yields the common methods of data reduction inappropriate. Most notably, the items used to create the CMP data should not be treated as normally distributed. The Bayesian framework grants nearly unlimited flexibility in terms of specifying distributional characteristics of the data as well as allowing us to incorporate prior information in the model. In this model, the left-right placement at a previous time point serves as the prior for the present time point, creating a smoother path across time than the original CMP measure. More importantly, this addition makes intuitive sense—that is, political parties rarely completely reinvent themselves from election to election.

Having developed a better model for extracting left-right placement from CMP data, the third article explores different techniques for combining these data with other sources, most notable of which are surveys of party experts. I begin by presenting two structural equation models (SEMs). The results of the first model show that the CMP data stand out as the least reliable indicator in the model. One possible explanation is that there is a bias toward some parties in these data. In order to account for this, the second SEM includes a method factor for the CMP indicators. Another possible explanation for the poor fit of the CMP indicators is that the common factor model is inappropriate given the structure of the CMP data. I argue, then, that a Bayesian model using expert surveys as priors for CMP data yields the best results as this measure possesses desirable statistical properties while combining two very different measures of left-right. Finally, I argue that given the design of this model the placements are cross-nationally comparable, a characteristic that other sources do not possess.

The combined result of these three articles will hopefully help not only researchers interested in left-right placements of political parties, but anyone interested in combining data sources to develop better measures of abstract concepts. Although requiring some statistical sophistication, the techniques used in these articles vastly improve the quality of measurement. Given this sophistication, however, it is likely the case that many substantive scholars would not employ such techniques. As my research continues, then, I am working with others to develop software routines in R and Stata that will facilitate the use of the methods I suggest. Presently, I am working on a project that will allow users to estimate left-right placements from CMP data and incorporate these estimates in predictive models, while taking account for the uncertainty in the placement. The next step is to generalize this routine for use with other data sources. Once completed, I am hopeful that the arguments made in this dissertation combined with user-friendly software for implementing these arguments, will improve the quality of our measurement and of our substantive interpretations of models using estimated variables.

Chapter 2. Fickle Parties or Changing Dimensions?

1. Introduction

Since Duverger (1951), scholars of political parties have moved beyond simple typologies of parties as socialist or Christian-democratic by analytically combining key political issues into a single Left/Right dimension of political conflict. The Left/Right dimension constitutes the core aspect of political exchange in Western Industrial democracies and allows us to compare party systems, locate political parties in a common ideological space or comparatively study the determinants of party choice (e. g. Downs, 1957; Dahl, 1966; Blondel, 1968; Satori, 1976; Van der Eijk and Niemöller, 1983; Oppenhuis, 1995; Van der Eijk, et al., 1999). Several sources of data have been used to order parties along a Left/Right continuum, including surveys of country experts or dimensional analysis of mass survey data (Castles and Mair, 1984; Laver and Hunt, 1992; Huber and Inglehart, 1995; Inglehart and Klingemann, 1976; Sani and Satori, 1983). One of the most prominent data sources on left-right positioning of political parties is the Comparative Manifesto Project (CMP) data (Budge, et al., 2001. This data source measures ”[…] the policy preferences publicly endorsed by political parties in their election programmes” (Budge and Bara, 2001: 1). The CMP data are the only source of its kind that maps political party preferences consistently across time and space. Hence, the uniqueness of the data source results from the fact that it allows researchers to track policy preferences of political parties over time and across countries (Budge and Klingemann, 2001).

However, despite this abundance of Manifesto data and its repeated use in time-series investigations, rigorous analyses of the substantive makeup of the left-right dimension across time and space are rare. This lack of interest in the cross-temporal and cross-national dynamics of left/right ideological continuum using CMP data is especially worrisome, since questions if the abundance of work on Left/Right party positioning thus far is actually comparing like with like. This paper attempts add to the literature Left/Right party positioning by examining the prevalent assumption that the CMP data can be used as a valid time-series to track dynamics of party positioning on the Left/Right dimension. This paper empirically tests two major concerns with this assumption. First, that the dimensionality of Left/Right remains constant across time and second, that the construction of the Left/Right scale meets the standards of statistical reliability assumed by the CMP research group.

The paper is structured as follows. First, we elaborate the specific structure of the CMP data and eludicate the theoretical assumptions underlying this data source. Second, we present an overview of types of Left/Right scales that have developed on the basis of the CMP data. In the third section, we elaborate our own operationalization of the Left/Right dimension using CMP data. Fourth, we present the main findings of the empirical analysis. Finally, we conclude by discussing the implications of our findings for the longitudinal use of the CMP data.

2. Comparative Manifesto Project Data: Structure and Assumptions

This section presents an overview of the specific structure und theoretical underpinnings of the CMP data. We first shortly introduce the coding and structure of the data. Secondly, elaborate the two major theoretical assumptions underlying the

CMP project: Firstly, policy preferences of political parties are best measured using manifestos and secondly, that party competition should be understood in terms of valence issues and salience.

The Manifesto Research Group (MRG) has collected and coded party manifestos since 1979. The data comprises of party manifestos from the main political parties in 24 OECD countries plus Israel from 1945 to 1998. Within the CMP framework, policy preferences are characterized by the quantitative examination of party stances on policy on the basis of the content analysis of election programmes or manifestos (Budge, et al., 2001). The election programmes of the respective parties are coded on the basis of a so-called 'quasi-sentence'. "A quasi-sentence is defined as an argument which is the verbal expression of one political idea or issue." (Volkens, 2001b: 34) Hence, one sentence in a manifesto may contain several quasi-sentences. In turn, these quasi-sentences are connected to categories in a classification scheme by individual coders. Presently, the classification scheme is made up out of 56 standard categories, measuring parties' views on a large array of issues ranging from market regulation to multiculturalism or European integration. quality control and reliability of the CMP expert coders. The quality and reliability of the CMP expert coders is monitored since 1989 by intra- and inter-coder reliability tests, which thus far demonstrate high levels of correspondence among coders and a low degree of variation across coders (see Volkens 2001a, 2001b).

In eyes of the MRG the study of manifestos yields three major advantages. First, the estimation of party preferences regarding policy fields is based on authoritative documents issued by the parties or governments themselves. Secondly, manifestos are typically prepared prior to every election, which enables the study of ideological party positioning across time. Finally, the coding on the basis of common classification scheme allows researchers to track changes in policy positioning within and across political parties, as well as across countries and time (Budge, Robertson, and Hearl, 1987; Budge and Bara, 2001; Budge and Klingemann, 2001; Volkens, 2001a, 2001b).

The CMP data underlie two main assumptions: First, policy preferences of political parties are best measured using manifestos and, secondly, that party competition should be understood in terms of valence issues and salience. The coding of the party programmes is based on the idea that parties argue with each other "[…] by emphasizing different policy priorities rather than directly confronting each other on the same issues" (Budge and Bara, 2001: 6-7). This idea is the central theoretical assumption underlying the CMP data: *valence and salience theory* (Budge and Farlie, 1983; Budge, et al., 2001). Budge and Farlie (1983) argue that party competition cannot be characterized as a direct confrontation between parties on the basis of opposing views on the same issues (position issues). Rather, parties differ in terms of the issues important to them. They focus on a limited number of valence issues and ignore the issues important to other parties.

In this context, the distinction between 'position' and 'valence' issues is relevant (Stokes, 1963: 373). While position issues involve issues that imply different options of political action (i.e. opposing or supporting euthanasia or abortion), valence issues concern the strength of the link between a party and a certain positively or negatively evaluated condition (e.g. the unemployment issue). Thus, the main tenet of the salience theory of party competition is that parties compete on the basis of valence issues by consciously and strategically highlighting or de- emphasizing selected issues. In this view, certain parties come to 'own' a particular issue, e.g. welfare for social-democratic parties or law and order in the case of conservative parties. Voters will come to associate certain parties with specific issues and, as a result, other parties will de-emphasize issues that are connected to rival parties. According to this view, confrontational models attempting to explain vote choice and party competition on basis direct conflict among parties simply miss the point, as they are based on position issues (Rosema, 2004: 37). Or put in the words of Budge (2001: 85):

> The picture that emerges [from the saliency perspective] is more subtle and differentiated than that provided by a mechanistic counterposing of 'pro' and 'con' positions on each issue. Parties do not square up to each other, landing heavy blows on each others' strong points, like a pair of inexperienced pugilists. Instead they duck and weave, avoiding direct hits from their opponents, while seeking an opening for their own blow to a weak spot.

It is important to point out that the two main assumptions of CMP data - policy preferences of political parties are best measured using manifestos and, secondly, that party competition should be understood in terms of valence issues – are contested. With regard to the data used to describe party preferences, one could argue that expert judgements are more useful than the content analysis of manifesto data, as these expert data take into account both the policy pledges made by parties and the extent to which they are translated into actual behaviour either in government or in opposition. Election programmes are not about actual behaviour. Manifestos present the program with which a party intends to distinguish itself from other parties in order to win elections and office. Yet, issues may come up during election campaigns or during a government period that were hardly dealt with in the manifesto.

Expert surveys, on the other hand, are based on the judgement of national party experts. One can argue that expert judgements combine what parties say and what parties do. If an expert is asked about the policy preference of a party on a particular issue, she will tap from various sources of information. It is likely that the expert will have a more detailed and accurate knowledge of party programmes than the average voter. In addition, the expert will have a good view on the conduct of parties. Yet, expert surveys also have clear disadvantages when compared to content analysis based coding of political texts. First, they are less valid than text-based techniques in terms of tracking party positions across time, as most expert surveys are cross-sectional (Mair, 2001). Second, "[…] a given text can typically be located at a precise time point so that a time line of cause and effect can be more confidently established" (Laver and Garry, 2000: 622). On the whole however, the debate with regard to the 'true' measurement of the 'factual' position of a party is endless and fruitless, "[…] since the 'real' policy position of a political actor is a fundamentally elusive, even metaphysical, notion" (Laver and Garry, 2000: 620).

The second assumption underlying the CMP data, stating that party competition should be understood in terms of salience, is in our view much more important and problematic. The saliency theory of party competition is criticized as it equates party positions with issue salience (cf. Irwin and Holsteyn, 1989; Rabinowitz and McDonald, 1989; Kitschelt, 1994; Laver and Garry, 2000; Laver, 2001a; Pellikaan, et al. 2003). Of course, there may well be a sets of issues, such as unemployment or environmental protection, in which direction equals salience. In the case of unemployment for instance, parties will most likely agree on the ideal policies, i.e. less unemployment, but differ in the relative importance given to them. Hence, in this case, party positioning may be inferred from the variation in salience levels. However, in many other issues areas, such as social redistribution, abortion or euthanasia, parties do not share a common understanding of the ideal policy (Laver, 2001a). When dealing with these kind of issues it is impossible to deduce a party's position from the emphasis attached to these issues in manifestos. Hence, advocates of the confrontational approach argue that contrary to the assumption underlying the saliency theory of party competition parties may take opposing stands on the same issue. They contend that to understand party competition, we need to distinguish between position and emphasis (i.e. salience). The different assumptions about the nature of party competition –salience or confrontation – is ultimately an empirical question (Gabel and Huber, 2000: 96; Laver and Garry, 2000: 620).

3. Analysing the Left-Right Dimension using Comparative Manifesto Project Data: The Story So Far

In this section, we review the five common approaches to calculating party Left/Right positions using manifestos data. The first, used by Budge, Robertson, and Hearl (1987) in their original analysis of the manifestos data, employs a two-stage factor analysis to obtain estimates of party positions on a first factor. This factor then becomes the left-right dimension. Briefly, the first stage in this technique involves dividing the fifty-four sentence categories into seven policy domains and extracting from each of the seven domains one or two factors. In the second stage, the two leading factors are extracted from the factor-based variables obtained in the first step of the procedure. The first of the second-stage factors supplies the left-right positions.

The second approach, employed by Laver and Budge in *Party, Policy, and Government Coalitions* (1992), is a more explicit attempt to estimate left-right positions. Using exploratory principal component analyses, the authors begin by collapsing the fifty-four sentence categories into twenty policy dimensions, thirteen of which are one category codings from the original data and seven of which are the sum of at least two categories. They then utilize these twenty policy dimensions to run additional country specific factor analyses. Based on the results of their country specific examination, the authors divide the twenty variables into three groups: variables that load consistently at one end of the scale, variables that consistently load on the other end of the scale, and variables that fail to load consistently. Laver and Budge discard this final group and calculate the left-right position as the difference between the sums of the references of the right cluster the left cluster.

Laver and Garry (2000) and Kim and Fording (1998) offer a third approach that slightly modifies the technique introduced by Laver and Budge (1992). Rather than the subtractive scores employed by Laver and Budge, these authors use ratio measures, i.e. they subtract left references from right references and then they divide the difference by the total percent of left and right references. Although the subtractive method is in line with salience theory, the ratio scoring system presumes that Left/Right positions should be understood in respect to how much concern a party has for items of the left and right.

The fourth approach to calculating left-right position using manifestos data was developed by Klingemann (1995). Confining his investigation to domestic policy categories, Klingemann makes a substantive assumption concerning which categories should and should not be incorporated in a left-right schema. He then utilizes country-specific principal factors analysis to extract the primary underlying dimension. Finally, using the factor loadings of the policy categories, he creates a ten-point scale of party factor scores. This provides his left-right dimension.

The final approach is Gabel and Huber's (2000) so-called "vanilla" method for inferring left-right party positions from manifestos data. As the name implies, this technique is entirely inductive, making no assumptions on the substantive policy content of the left-right dimension. According to Gabel and Huber, the left-right dimension is defined as "the 'super issue' that most constrains parties' positions across a broad range of policies" (2000: 96). Their vanilla method seeks to uncover this "super issue" and to determine party positions on it. The technique uses principal factor analysis to identify the underlying dimension that best accounts for the observed covariation among the fifty-four policy categories. Based on the results of this analysis, the authors position the parties on this dominant dimension using regression scoring. Finally, they place the parties on the left-right dimension using the parties' factor scores after normalizing the scores to an eleven-point scale.

4. Empirical Analysis

Much recent work regarding the CMP data has focused on cross-validating various Left/Right measures with the manifesto-based measures (Laver and Garry 2000; Gabel and Huber 2000; McDonald and Mendes 2001a, 2001b among others). Little to no work, however, has systematically analyzed the reliability of the dimensionality of the manifesto Left/Right scales. Further, no one has yet to compare the dimensionality across time and space in order to assess the validity of the Left/Right scale over different time periods. That is, can one validly compare (or track) policy preferences over time using these data? As discussed above, it is a highly contentious assertion that the manifesto data accurately predict policy preference. Russel Dalton perhaps says it best:

> One problem is that the Comparative Party Manifestos Project does not measure positions along a policy continuum, but simply counts the salience given to each policy in the party programme (that is, the percentage of the party programme that discusses the issue, regardless of the context of the discussion). In addition, the [CMP] devotes little attention to how separate issues are combined to measure the left/right dimension. The project assumes that a constant set of items tap a broad left/right dimension, but factor analyses do not yield such a clear empirical structure among these items. Moreover, a single, constant measure does not accommodate the changing meaning of left/right over time. For example, while economic and welfare state issues

> may have divided political parties in the mid-twentieth century, by the end of the century a new set of cultural and quality of life issues had joined the political agenda. In sum, the [CMP] data might not be sufficient to determine systematically how party positions have changed over time (Dalton 2004: 133).

Even if we assume, then, that CMP data can be used to help understand a party's policy preference, it is far from clear that these positions can be validly traced over time using the measures developed by the MRG. One of the most problematic aspects of the CMP placement measures is what the MRG group refers to as 'leapfrogging'. This occurs when one party moves to the left or to the right of another party in the system. For example, the British Liberal Party in 1955, according to the CMP placement score, is the most 'right' party in the system. In 1966, however, the Liberals actually cross-over Labour and are the most 'left' party in the system until the early 1970s. This preference volatility is illustrated in Figure 2.1.

Another troubling characteristic of these data is the seemingly absurd placement of some parties given an intuitive understanding of European party systems. For example in 1946 the French Communist party is actually coded as a right-wing party and it is not until after the 1956 election that they cross-over to the 'left' side of the scale and not until 1958 that they 'leapfrog' to the left of the Socialists. Figure 2.2 shows this movement.

Such leapfrogging is, unfortunately, the norm in many countries included in the CMP data set. It is unlikely the case that this policy preference volatility represents true changes in parties' placement; rather, problems with both the measurement and interpretation of the CMP Left/Right scales are more likely the cause of these changes.

In order to assess the reliability and sources of volatility of the Left/Right measures, we systematically un-bundle the scales employed by the MRG group. That is, we conduct country specific factor analyses for the Left/Right scales in order to see which items load consistently across time on the dimension and to get a country specific measure of scale reliability.

As described above, the MRG constructed additive scales of both left and right by combining 26 items (13 for the left, 13 for the right) from the original 54 coding categories. Table 2.1 presents an overview of the items used in the construction of these scales.No measure of reliability, however, is included in the results presented in Budge et al. (2001). Hence, we calculated reliability statistics for the respective items used for the construction of the MRG Left/Right scale. Tables 2.2 and 2.3 below present the Cronbach's Alpha for left and right items respectively across the EU-15.

For the left scale, only France surpasses the conventional standard 0.6, while only Great Britain, Spain and Sweden meet this level for the right scale. These results seriously question the scalability of these items, particularly when constructing simple additive scales. These results are somewhat counter-intuitive, however, in that the categories that are combined to create the scales (arguably) should align together along one or perhaps two dimensions. Country specific factor analyses, however, confirm that these items do not consistently load together across time and/or space. Table 2.4 illustrates how different items load at different levels and in varying combinations across countries pooling over all manifestos included in the CMP data set. What is most striking about these results is that no single item loads consistently across all countries for either the left or the right scales.

Similar results are obtained when we perform factor analysis controlling for both country and time. For example, if we divide the time period for which the CMP collected data in half and perform factor analysis on the items for either the left or the right scales, we see that the items that load highly on the first factor change (drastically in some instances) and that different items load on different factors within country over time. The following tables illustrate this effect in the UK for the 13 items that comprise the Left scale.

Here we see that not only do the items load in different patterns and levels, but that no fewer than 5 components are extracted from the 13 items (principal axis factoring using varimax rotation). The above results are repeated regardless of country or length of time period and are indicative of Dalton's criticism regarding the changing meaning of left/right across time.

The question still remains, though, as to why these items do not neatly align given their substantive similarities and our understanding of what issues comprise a Left and a Right issue agenda. Laver and Garry (2000) suggest that it may be the mutually exclusive coding of the MRG that cause some of these issues. For example, some statements should perhaps be coded into two categories, such as Peace and Military Negative. They go on to argue that neutral categories combined with balanced items (Pro/Anti issue) would also increase the reliability of these measures.

A related issue is the fact that many of the items used to construct these scales are primarily filled with zeros. That is, out of 1,261 cases, over half of the 26 items have over 75% zeros as entries in the data set. These zeros greatly reduce the correlations among items and this, in turn, can help to explain the limited reliability of the scales. Figures 2.3 and 2.4 are histograms of two of the items and illustrate the 'zero' problem present in much of these data.

One possibility, then, is to eliminate items that are mostly zero in the data set and to only use items that load significantly, both substantively and significantly, within county. With these items, then, we can construct country specific Left/Right scales that should be more reliable and more stable across time.

Following the above procedure, we constructed new Left/Right scores for the 15 EU countries. Tables 2.7 and 2.8 list the reliability measures for the new, country specific left and right scales using only items that load above 0.3 and for which the number of zeros was attempted to be kept to a minimum.

With few exceptions (notably Finland on the Right), these new scales represent drastic improvements over the original ones used by the MRG. Following the same procedure as the MRG and taking the difference of these two scales, we constructed a new measure of Left/Right and plotted these across time. Figures 2.5 and 2.6 show the change over time of these new scores for the UK and for France.

Although there is still some volatility and some leapfrogging, both of these are less pronounced than with the original measures. More importantly, the French Communist party is coded as left wing and crosses to the left of the Socialists much earlier than with the previous MRG measure of Left/Right. Similar improvements occur across all countries and parties using our method of constructing the left and the right scales.

5. Concluding Remarks

Although far from the optimal solution, our method of addressing the lack of reliability in the CMP left and right scales demonstrates a serious deficiency with the data in their present form. Even if we assume that issue saliency is equivalent to policy preference, our results show that the validity of the dimensionality of the MRG Left/Right measure is dubious at best. This is the case both across time and space and brings into question the comparability of these measures and, therefore, the ability to accurately trace preference changes over time.

The ‘too many zeros’ issue does desperately need to be addressed with these data. Simply discarding items with mostly zeros, however, is certainly not the best solution, given the loss of information that occurs. An alternative method, then, would be to condition estimates of the Left/Right dimension of information that we do have and to treat the zeros as missing data. Conventional methods of factor analysis, however, do not allow for inclusion of such unbalanced items and imputing missing data given the preponderance of zeros for many items would be incorrect at best. Presently, techniques for addressing this issue are being explored and will be used to analyse the dimensionality of these data in the near future.

Another possible method for analysing these data would be to allow some items to cross load on both the left and the right scales, treating the scales as latent variables in a confirmatory factor analysis. In fact, modification indexes show that such cross loadings would, in fact, improve the fit of the model in this setting. Identification issues, once again stemming from the zeros problem, need to be overcome before such alternatives will be feasible, however.

We have shown that the scales used to construct the Left/Right measure in the CMP data are far from reliable and have attempted to offer an explanation for this problem. We have also demonstrated that the dimensionality of Left/Right changes over time and space. Researchers employing these data should be aware of these issues when drawing inferences from this measure. Future research and technological advances will serve to better the use of this data set, which certainly is a rich source of data for scholars of party systems in the advanced industrialized world.

Chapter 3: Take That, You Lousy Dimension

1. Introduction

One of the most fundamental concepts used in the study of political parties is the leftright dimension of party competition. This dimension is, ”vital in evaluating hypotheses on structures of democratic competition and conflict, on the interplay between electorates and political parties, or on how public policy is shaped by political parties with different agendas” (Marks et al. 2006). The left-right dimension gives us the ability to compare parties within a common space and across time (See Duverger 1951; Downs 1957; Converse 1964; Dahl 1966; Satori 1976; Rabinowitz and McDonald 1989; Van der Eijk, Cees, Mark Franklin and Wouter van der Burg 1999). Given the centrality of this concept to such a vast array of empirical analyses, it is necessary to develop a reliable measure of the left-right positions of political parties.

As is often the case in the social sciences, there is no direct measure of this dimension. Rather, we estimate the measure by evaluating observable imperfect measures that, combined, compose the concept of interest. This process introduces a degree of uncertainty that is often ignored by researchers. That is, it is commonplace for researchers to estimate a latent dimension and then treat this estimate as observed data.

There are several available measures of parties’ left-right position placements which can be grouped into two categories. First are expert surveys, which elicit the opinions of party experts as to the position of parties on a variety of different issue areas. These issue-level placements are then used to construct measures of left-right through a variety of methods, ranging from simple additive scales to factor analytic techniques (See Castles and Mair 1984; Laver and Hunt 1992; Ray 1999; Benoit and Laver 2006).

The second category of left-right placements are derived from content analyses of parties' electoral manifestos. The Manifesto Research Group (see Budge et. al) has developed the most widely used measure of left-right party placements using this technique. They have compiled data for twenty-four OECD countries plus Israel from 1945-1998. Over one hundred published books and articles have used the MRG data in various forms, yet only recently have researchers begun to analyze the reliability and validity of these data (See Laver and Garry 2000; Harmel, Janda and Tan 1995; Gabel and Huber 2000; Bakker, Edwards and Netjes 2006; Marks et al. 2006).

The MRG data set is particularly desirable in that it is the only source that includes such a large number of countries for such a long period of time. This gives researchers the added advantage of being able to track changes in party positions over time, as opposed to using expert data which restricts the researcher to a single time point or, at best, a small set of time points. Because of this, the MRG data have been widely used in comparative party research and are the single most important source of data available to this sub-field (see Schofield 1993; Budge, Roberson and Hearl 1987; Baron 1991; Laver and Budge 1992; Budge 1994; Adams 1998; Warwick 1994, N.d.).

Although there exists a reasonably strong correlation between the survey-based and the manifesto-based data (Gabel and Huber 2000),neither of these sources includes a measure of uncertainty with their estimates of party position. Within the manifesto-based research there has been a rich discussion as to how best use the data to construct a left-right dimension, but no discussion of assessing the uncertainty inherent in the process of estimating party positions. This limits the ability to discern whether or not different placements are statistically significantly different from one another. Given the importance of manifesto-based placements this could be an extremely important omission. That is, if one could estimate the uncertainty of these party placements, the significance of changes within party over time and differences between parties in a party system could be accurately assessed.

The aim of this article is to improve the use of manifesto-based data in constructing a leftright dimension. Ideally, the resulting measure would be based on a model appropriate to the data, take account of the dynamic nature of the data, and provide a measure of uncertainty in order to make meaningful comparisons across time and space. The structure of this article is as follows. First, we will provide a detailed description of the MRG data. Next, we will discuss the different techniques that have been employed in order to extract a left-right dimension out of these data. Then, we will present our model for estimating a left-right measure with the above mentioned properties. We will conclude with a discussion of the implications that our research has for the use of manifesto-based data and, more generally, for estimating latent variables across time.

2. MRG Data and the Left-Right Dimension

The MRG began collecting and coding party manifestos in 1979. They identified fifty-four policy areas into which each quasi-sentence of a party's manifesto were placed. A quasi-sentence is the "verbal expression of one political idea or issue" (Volkens 2001).That data set contains the percentage of a party's manifesto that fell into each coding category. The resulting left-right scale is constructed by summing across certain groups of issues that represent opposing sides of the dimension. The difference of these two sums is then interpreted as the party's left-right policy preference placement.

There is a considerable degree of dissent regarding the seemingly innocuous process described above. Two of the most problematic issues are the manner in which the issues that represent left and right are selected and the way in which the left and right group scores are combined. The remainder of this section will describe the various techniques that have been employed by researchers interested in developing reliable measures from the MRG data.

The original measure, used by Budge, Roberson and Hearl (1987), resulted from a two-stage factor analysis. In the first stage, the fifty-four coding categories were collapsed into seven issue areas. These seven issue areas were then factor analyzed and one or two factors were extracted for each area. The second stage involved factor analyzing the issue-area factors obtained in the first stage. The first factor from the second stage was interpreted as the left-right dimension.

Laver and Budge (1992)employ a second technique for extracting a left-right dimension from these data. Through exploratory principal components analysis, they identify twenty policy dimensions composed of combinations of the fifty-four coding categories. These twenty policy dimensions were then used in country-specific factor analyses from which three groups of coding categories were identified. The first two groups, each composed of thirteen categories, loaded on opposite ends of the scale and the third group, which was discarded, contained items which did not consistently load on either end. The resulting left-right placement was created by summing across the percentages of manifestos that fell into the two opposing groups and taking the difference of these two sums.

A third approach was developed by Laver and Garry (2000) and Kim and Fording (1998).These authors felt the Laver/Budge method was flawed in that it did not take into account the percentage of a party’s manifesto that fell into left and right groups. That is, the Laver/Budge method is biased by a function of how much of a manifesto’s space was dedicated to the categories used to construct their scale. To correct for this, the new method used a difference of ratios rather than a difference of sums. The two sums from the Laver/Budge method were divided by the total number of left and right statements in a party’s manifesto and the resulting difference was the left-right placement.

Klingemann (1995)developed a fourth method for extracting a left-right dimension from these data. As a point of departure from the previously described methods, Klingemann started with a deductively driven choice of categories to construct his scale. He then performed country-specific factor analyses and used the loadings from these analyses to develop a left-right placement score for each party.

Gabel and Huber (2000)use yet another method to create a left-right measure from these data. Their ’vanilla method’ is designed to extract the ”underlying dimension that best accounts for the covariation among the fifty-four policy categories”. They argue that there is no a priori set of issues that defines left-right ideology over time and space. Rather, they seek to uncover the ’super issue’ that ”most constrains parties’ positions across a broad range of policies” (Gabel and Huber 2000).Using regression scoring to develop a factor scale, the authors create an 11 point scale on which parties are placed.

These results of these five techniques all correlate quite highly (from 0.75 to 0.88) demonstrating that there is some common structure to these data which is argued to represent a left-right policy preference dimension. Strikingly, however, none of the measures address the issue of uncertainty involved with estimating a latent dimension. Rather, the resulting scales are treated as observed data. There are additional issues regarding the estimation techniques discussed above. The following section will discuss some of the data-driven problems before moving on to a formal treatment of the uncertainty issue and the presentation of our model for dealing with this.

3. Problems with the MRG Data

The manner in which the MRG data were collected and analyzed poses several problems which are not addressed by any of the techniques described above. Much of the research in the measurement-oriented literature on the MRG data has focused on cross-validating the different measures developed from manifesto data and comparing these results to placements derived from expert surveys. Little attention, however, has been paid to the statistical reliability of these scales and the assumptions underlying the different models used to extract substantive dimensions from these data. In this way, a majority of the work in this area has been dedicated to ’rearranging the deck chairs’ rather than improving the quality of measurement.

Perhaps the most difficult problem to overcome with the MRG data is the prevalence of zeros in the data. If a party makes no mentions of one of the fifty-four coding categories in its manifesto, the resulting cell entry in the data set is zero. These zeros are the result of at least three different data generating processes, but have only one substantive interpretation: the party is neutral on that issue. First is the mutually exclusive nature of the content analysis coding procedures. That is, a statement from a party’s manifesto can only be coded into one category, forcing the coders to make subjective decisions when faced with statements that crosscut coding categories Laver and Garry (2000).Second is that a party may be truly be neutral or have no position on an issue or set of issues and therefore makes no references to it (them) in their manifesto. If this is the case, then the zero poses no substantive problem in the estimation of the latent dimension.

Finally, zeros may be the result of a missing data problem. That is, a party may have a position on an issue, but may choose not to reference it in its manifesto for several reasons. It may be that the party is split over an issue and therefore cannot present a coherent view. It is also likely the case that some parties do not feel the need to publish their position on some issues in that their stance is obvious (i.e. communist parties and favoring a controlled economy). Related to this explanation is the fact that space is limited in manifestos and parties must make strategic decisions as to which issues to address. Therefore the saliency of certain issues during certain elections could lead parties to omit references to issues on which they have a position in favor of issues that carry more weight given the electoral context at the time.

Regardless of the data generating process, the zeros are problematic in the estimation of a latent dimension, since all of the strategies used to extract a left-right measure from the data are based on correlational structures. Treating the zeros as missing data rather than as neutral policy stances has the advantage of improving both the quality of the estimation and the substantive interpretation of the resulting scale(s).

Another problematic issue with the treatment of the MRG data thus far involves the correlation of a party's left-right placements across time. That is, the best guess for a party's placement at time t is that party's placement at time t- 1. The placements derived from the techniques described above, however, make no use of this information. The manner in which each party's placements are estimated assumes that a party's current left-right placement is independent of its previous placement, when this is clearly not the case. The result of this assumption is that parties 'leapfrog' each others positions on the left-right dimension. Given our understanding of political parties, this is unlikely to accurately reflect reality; it is difficult to imagine the British Conservatives as being 'left' of Labour in any context.

Finally, without a measure of uncertainty, we cannot know if movements within a party's placement across time or different placements between parties in the same time period are statistically significant. This seriously detracts from the expressed purpose of the MRG project, that is, tracking changes in policy preference over time and space. The techniques described above simply assume that differences in placements are meaningful while providing no evidence that this is the case (more on this below).

4. A Better Model?

A more appropriate model for these data would address these issues directly. That is, a better measure of manifesto-based left-right scores would treat zeros as missing data rather than neutral stances, incorporate previous information in the estimation of current positions, and estimate the variance of these placements. Given these desired characteristics, conventional data reduction techniques are inappropriate for these data.

A Bayesian approach to estimating this latent dimension offers solutions to the above mentioned problems. In the following section, we present a model that possesses the desired properties and results in a substantively intuitive measure of left-right placements. We also give a detailed description of our choice of items that represent differences in the policy preferences of political parties. For comparability with previous results, including expert surveys, we apply our model to the EU-15 countries for the time period 1945-1998.

5. Data

The data provided by the Comparative Manifestos Project are an attempt to measure the important characteristics of party manifestos with the idea that given these data, parties will be able to be placed on comparable dimensions. At base, each manifesto variable is a count of sentences in the party manifesto that corresponds to a particular characteristic. Of these items, a number of them are “balanced” items or those that comprise two variables -one coding the number of positive statements about the characteristic and another coding the number of negative statements. Often, these positive and negative statements correspond clearly to left or right positions. We use these and a set of economic items that are not necessarily balanced, but are still identifiable as either left or right in orientation. Table 3.1 shows the set of variables used in this study.

In previous studies, these variables have been used in their percentage form -that is each variable corresponds to the percentage of manifesto quasi-sentences that correspond to that characteristic. However, we found that using either these variables or the logit of these variables (to put them on the entire real number line) produce suboptimal results. Instead, we choose to use these a bit differently. We use the total number of quasi-sentences to obtain the total number of conservative statements according to each of the above-mentioned variables. We then estimate this as a binomial with *n* equal to the total number of left plus right statements corresponding to the specific characteristic.

Here, we treat zeroes differently as well. When a party makes absolutely no statements about a specific subject, for example centralization, we code the number of conservative sentences about that subject as missing and the number of total sentences about that subject as 25. Thus, we actually will get a sense of how many statements out of 25 would a party most likely have made had they chosen to talk about this issue. So, rather than treating no statement as completely neutral, we are treating it as missing and filling it in with “reasonable values” from the posterior distribution of the observed variable given the latent variable and coefficient.

For each country, we do not use all of these variables. Realizing that we wish to distinguish between the different parties, we use the 5 variables (in percentage form) from the above list that have the most variance. This selection mechanism implies yet another major difference between this study and several of the previous studies, namely that it is not appropriate here to compare parties across countries, though within-country comparisons are permitted and even encouraged. The original Manifesto work suggested, at least implicitly, that the parties would be comparable across countries.

6.1 The Usual Suspects

All of the Manifesto dimension reduction has been in the form of a summated rating scale. The theoretical model suggests that every observed variable is an imperfect manifestation of some underlying variable, in this case the left-right placement. In the limit, the idiosyncratic errors in these observed variables cancel out when they are summed or averaged. The underlying model is a linear one:

$$X_{i,j} = T_i + \varepsilon_{i,j}$$

where i indexes observation and j indexes observed variable. Notice two things - first, there is no coefficient on T and second, there is no j subscript on T , the true underlying dimension is the same across all observed variables for the same observation. The model does make a few assumptions:

1. $\varepsilon \sim iid.$
2. $\text{cov}(T_i, \varepsilon_l) = 0$
3. $E(\varepsilon_i) = 0.$
4. Monotone Homogeneity: This simply states that each observed variable is monotonically related to the underlying true dimension.

The first three are different aspects of conditional independence. The fourth is self-explanatory.

The manifesto data (and all TSCS data) present a problem for this theoretical model. It is exceedingly unlikely that parties start from the ground up every election to remake their manifestoes. In fact, the most likely situation is one where parties start with largely the same document and tweak as necessary. This suggests that if the left-right score is off at time t, it will probably be off in the same direction at time $t + 1$. Thus, the second assumption is almost certainly violated.

The so-called “structural zeros problem” remains problematic here. When zeroes exist, the errors cannot be *iid* as predictions below zero are nonsensical. This is problematic not only for the original manifesto data, but also for the measures that use ratios and differences of ratios. Variables that have deterministic bounds cannot be *iid*. In sum, the assumptions underlying the summated rating model are not likely to hold given the unique characteristics of the MRG data.

Another problem with the summated rating model is that there is no method inherent to the model for generating uncertainty estimates. The outcome of the modeling process is an estimate of the latent dimension (not the latent dimension itself). As with any estimate, we would like to know how precise it is -we would rather not treat our estimates as fixed-known parameters. Without any knowledge of

precision, there is no other option than to assume observed differences are statistically significant (or on the other hand to assume that no differences are statistically significant).
We propose a model that does not make these restrictive assumptions. Further, our model does produce estimates of uncertainty for each latent variable point and the Bayesian framework allows these to be easily incorporated into predictive statistical models. It is this model we investigate below.

6.2 The New Model

Political Science has recently begun to move to the next level of latent variable modeling by using Bayesian models to estimate latent dimensions. These models have two basic advantages over their frequentist counterparts:

1. Observations can be modeled directly rather than relying on unreasonable assumptions such as multivariate normality.

2. The model provides a straightforward method for obtaining standard error estimates for the latent variable and incorporating those into a predictive statistical model.

Beyond these advantages, Bayesian models allow the user to estimate latent variable models that have no clear frequentist analog. Given the lack of fit (both empirical and theoretical) between the manifesto data and the set of "usual suspect" dimension-reducing models (Summated Rating and Factor models), we chose to specify a Bayesian model that would take account of the unique nature of the Manifesto data and generate latent variable estimates that include standard errors. Specifically, we are estimating the following model (explanation to follow):

$$Y \sim \text{Binomial}\,(p_{pie,}\, n_{pie)}$$

$$\log\,(p_{pie}\,/1\text{-}\ p_{pie}\,) = \beta iXpe$$

where *p* indexes party, *i* indexes manifesto issue, *e* indexes election and:

$$\beta_i \sim N(0,1)$$

$$Xp1 \sim N(\mu p,1)$$

$$Xpt \sim \ (Xpt\text{-}1,1)\ t = 2 : T$$

$$\mu p = \xi \eta p$$

$$\xi \sim N(0,\tau\xi\ )$$

This model simply estimates the observed manifesto counts as arising from a binomial distribution with a party-issue-election specific probability that is a function of a party-election specific latent variable (*Xpe*) and an issue specific coefficient (β). Since the variables are all right-wing issues, the coefficients are truncated to be positive. As right-wing statements increase so should "rightness" (not to be confused with "correctness"). It is also often necessary to set at least the sign of one coefficient to prevent label switching. The variance of the latent variable scores is 1 for identifiability.

This model has several interesting features. First, it incorporates a random effect in the prior for each party's first election latent variable score. Given that Gelman (2005) suggests priors on the variances of such random effects are often more informative than we are led to believe, especially IG(x, x), we take his suggestion and the model above uses a half-cauchy with a scale parameter of 10 for the variance of the random effect. The model also uses a random-walk prior for each party's latent variable scores for elections 2:T, where the prior distribution is normal with a variance of 1 and is centered at the party's latent variable score for the previous election. This directly operationalizes the idea that our best guess of a party's position (before looking at its manifesto) is its position in the previous period. If the manifesto suggests something different, we want it to be able to speak loudly enough to override this prior belief. The best way to include this, then, is in the prior rather than the likelihood function.

7. Results

The result of this model is a latent dimension and a coefficient relating that dimension to the observed variable. The higher this coefficient, the more closely the observed number of manifesto sentences follow a function of the latent left-right dimension. As was stated above, the latent variable model in general suggests that one underlying dimension (in this case, the general left-right dimension) is a good predictor of some observed characteristics (that are imperfect manifestations of this underlying dimension). However, very rarely do we actually look at the nature of these predictions. Table 3.2 shows the coefficients for the models for the UK, France and Germany.

The result in which we are most interested is the latent variable estimate. Not only do we get an estimate of the underlying dimension, but we also get an estimate of the variance of each point estimate. From this, we can make statements about the probability that any two point estimates are statistically different from each other. This is a particularly useful innovation. In previous studies, differences between parties were taken to be deterministic. That is to say party differences were taken to be fixed at the difference between their latent variable scores. However, given that our estimates of latent variable positions are just that, *estimates*, we should take this uncertainty into account. For any two parties, if the t-statistic of the difference is greater than the chosen critical value, we are sufficiently certain that the two estimated party placements are different for some reason other than chance, presumably because their true, but unknown party positions are distinct.

All of this is pretty straightforward, but it doesn't mean anything to practical researchers unless the resulting party placements make sense from a substantive point of view. This is not a statistical criterion, so there is no t-test for practicality, but we are confident that practical researchers will know it when they see it. We feel that our results make substantive sense. They capture the more prominent trends shown in the original manifesto data while smoothing out many of the places where parties cross over each other (which is largely a function of noise).

It is difficult to present visually all of the results from these models. Figure 3.1 attempts to do this for the UK. This is a dotplot which is increasing from bottom to top in "rightness" (i.e, the rightmost party is at the top-right corner and the left-most party is at the bottom right corner. The light gray lines represent +/-2 standard deviations. From this, it is easy to see a general pattern -Labour on the left and Conservative on the right with SDP and LDP in the middle. Furthermore, the error bars show us which party-elections are significantly different from which others. For instance, we can see that the Thatcher conservatives are significantly more conservative than most other party-elections.

In essence, any hypothesis about party differences could be tested with these graphs and a straight-edge. If two party-election confidence bounds are overlapping, there is no significant difference. If they do not overlap, there is a statistically significant difference between the party-elections. It would be even easier with a table of numeric placements and their confidence intervals or standard errors. These are available from the authors upon request.

It is also instructive to look at our placements versus those of the MRG. While we wouldn't expect them to be identical, we would expect them to be similar at least in broad trends. If our model is picking up something drastically different from that of the MRG, it would be cause to revisit our results, but certainly not to throw them out. Figure 3.2 presents the MRG results along side our placements. In the interest of clarity, we do not present standard error bars here, but they do exist and could be plotted if desired.

It is clear that the general trends are about the same for each country. The series are considerably smoother, though the correlations are relatively high between the Manifesto points and our points. Probably the biggest difference is that for France where the early Communists are right-wing. In our placements, the early French Communists start out on the far-left and generally stay there.

8. Conclusion

Few topics in Western-European Politics have been more contentious than the left-right placement of political parties. Form surveys of experts and voters to the numerous analyses of party manifestoes -scholars have tried to "nail down" as precisely as possible the placement of parties on a left-right dimension. We specifically engage manifesto based research and attempt to move it in a new direction. We argue that previous studies, while varied in their use of particular variables, have all employed a theoretical model that is inappropriate for the reduction of manifesto dimensionality. Although the summated rating model has been a workhorse in Political Science (and rightly so), it is inappropriate for these data (and TSCS data in general) because of its underlying assumptions.

At least as problematic on practical grounds is the lack of a measure for uncertainty for the manifesto-based measure. If differences in party placements are observed, one is left with only two reasonable options: 1) assume all observed differences are meaningful or 2) assume no observed differences are meaningful, neither of which is particularly appealing. We feel that due to this lack of uncertainty, researchers have been prompted to look at the wrong things. Are the early French Communists right-wing? We don't think so, but most researchers have chosen to look at all observed differences as meaningful, so the fact that the French Communists are toward the right-wing side, this is a major finding. We feel that many of these anomalous findings are a function of noise in the data and ought not be looked at as meaningful.

We introduce a Bayesian factor model that has a few interesting characteristics:

1. It models observed counts of conservative statements about specific subjects as binomial using the total number of statements about that subject as *n*. In the case of zero, the count is coded as missing and is imputed by the model.

2. We use a party-specific random-effect prior for each party's first election and a random walk prior for elections 2:T to operationalize our thoughts about party differences and the carryover of party manifestoes from election to election.

3. From this model, we can easily obtain standard errors for each point estimate.

These can then either be used to see whether observed differences are significant or they can be incorporated into predictive statistical models.

On substantive grounds, we are proposing a new measure of left-right party placements using manifesto data. This new measure is considerably smoother than previous measures and comes complete with standard error estimates for each point. On methodological grounds, rather than really proposing an innovation, we are echoing the suggestions of Treier and Jackman (2005); Martin and Quinn (2002) and others proposing Bayesian latent variable models. These allow the user to estimate the correct model for the observed variables rather than assuming *iid* errors or multivariate normality. While this article may be a debut for this particular model, its sentiment can be found in numerous preceding works.

Chapter 4. Combining Data through SEM and Bayesian Approaches

1.Introduction

When dealing with probabilistic events, people seek information. Not fully trusting a single source, we often turn to others in order to get as much information as possible before making a decision. We do this when we do something as trivial as deciding where to go for dinner or as serious as questioning the diagnosis of a highly skilled physician. Of course we have our impulsive moments, but generally we know that the 2^{nd}, 3^{rd} and 4^{th} opinions will help us make the ‘right’ choice.

Unfortunately, this standard operating procedure is *not* the standard in much social science research. That is, when dealing with probabilistic events many researchers base their conclusions on models that include estimates of concepts they wish to measure. This is because many of the concepts we wish to include in our models are not directly measurable (i.e . democracy), but must instead be estimated using observable traits (ie free press, open elections) of the concept. In our efforts to locate ‘good’ indicators of our concept or latent variable, we often find that we our choices are limited at best. In these situations, we must sometimes rely on a single source of information with no option for a second opinion.

As technology and time progress, however, the body of empirical evidence and quantified data continues to grow. This means that we are more likely to have more choices of observable traits of our latent variables. Even in light of this development, vast amounts of research across the sub-fields of political science continue to base estimates of latent variables on single sources of data. We often form attachments to individual sources for a variety of reasons ranging from their performance in our models to the politics of academia, but it is also the case that properly combining sources of data requires a level of statistical sophistication that make some feel uncomfortable. With nicely behaved data this is not usually the case, but more complicated data generating processes often require more complicated estimation procedures.

Regardless of the cost, it is always better to have more data. More sources of information allow us to triangulate our estimates and increase their reliability and validity. "…But more data are better. Triangulation then, is another word for referring to the practice of increasing the amount of information to bear on a theory or hypothesis" (King et al 1995).

In this article, I will compare the results of different techniques for combining sources of data to estimate a latent dimension. Specifically, I will combine data from the Comparative Manifesto Project (CMP) and surveys of party experts, MPs and MEPs, and voters in order to estimate a left-right dimension of political parties in Western Europe. The article will proceed by first introducing the sources of data and briefly discussing their strengths and weaknesses. Next, I estimate a structural equation model (SEM) with two latent variables, economic left-right and GAL/TAN or new politics. I then present a second SEM, this time including a latent variable to control for potential bias in the CMP data. Next, I estimate a Bayesian model using expert survey data as the prior information and combining this with the CMP data to extract a single left-right dimension. The paper concludes with a discussion of the strengths and weaknesses of the different modeling strategies.

2. Sources of Data

There are several sources of political parties' left-right positions that fit into two broadly-defined categories. These are survey-based and content analysis-based. Surveys-based measures elicit opinions from party experts, political elites and voters as to the positions of parties on a variety of different issue areas. These individual placements are then combined to construct left-right scores or placements through a variety of methods ranging from simple additive scales to more advanced factor analytic techniqes (Castles and Mair 1985, Laver and Hunt 1992, Ray 1999, Marks et al 2001, Benoit and Laver 2004—just to name a few).

The content analysis-based measures use data collected by quantifying the content of parties' electoral manifestos. The Comparative Manifesto Project (Budge et al) has developed the most widely used measure of left-right party placements using this technique. The CMP data covers the entire post-War era and includes the OECD countries plus Israel. Recently, the CMP data have expanded to include the countries of Central and Eastern Europe. The relatively large sample size and long time period make the CMP data highly desirable to those interested in tracking parties' movements across time. Because of these features, the CMP data are arguably the most important source of data on left-right party positions and have been used in over 100 published books and articles (see Schofield 1985, Budge et al 1987, Baron 1991, Laver and Budge 1992, Budge 1994, Adams 1998 and 2007, Warwick 1994 and 2000, MacDonald et al 2005 and 2007—for just a few examples).

Even though these data have been so widely used for over 20 years, only recently have scholars begun to scrutinize their reliability and validity (Laver and Garry 1999, Harmel et al 1995, Gabel and Huber 2000, Bakker, Edwards and De Vries 2007, Benoit, Laver and Mikhaylov 2007). My own previous research details the results of this scrutiny. Perhaps the most important finding thus far is that the data generating process behind the CMP data is not appropriately modeled using standard data reduction techniques (Armstrong and Bakker 2006). The effects of this inappropriate modeling are difficult to predict and can range from over-confidence in one's results to nonsensical substantive interpretations.

As previous research has demonstrated, the CMP data are quite volatile and parties seem to move all over the political spectrum from election to election. Experts, on the other hand, tend to provide much more stable, flat estimates over time with parties moving much less obviously. Believers in the CMP data argue that this difference in predicting change in the strength of their data and the weakness of the expert surveys (Budge and MacDonald 2006) while defenders of expert surveys say the opposite (Marks et al 2007). By combining these sources, we should be able to borrow from the relative strengths while limiting the effects of the weaknesses in order to triangulate on a more valid measure of left-right. Given some data-based restraints (short time series vs. long time series) and some difficulties in estimation, I will present cross-sectional results of different techniques for combining these sources below. Having said that, work is presently underway on developing models that take account of the temporal nature of these data and allow us to combine sources that are available at irregular intervals or missing for certain time points.

3. The Structural Equation Modeling Approach

"Structural equation modeling can perhaps best be defined as a class of methodologies that seeks to represent hypotheses about the means, variances, and covariances of observed data in terms of a smaller number of "structural" parameters defined by an underlying model" (Kaplan 1955). Factor analysis and other similar latent variable and data reduction models are widely used in the social sciences (see Jacoby 1991 and Bollen 1989). These techniques are very useful for discovering underlying structure to data and for confirming hypotheses about relationships between latent concepts and observable indicators. Given these characteristics, this seems an appropriate technique for combining different sources of left-right placements in order to recover a more valid measure.

The first model below is a confirmatory factor analysis that estimates a two-latent variable solution. The latent concepts in this model are economic left-right, representing the classic left-right continuum of European party politics (Lipset and Rokkan 1967) and GAL/TAN (Green, Alternative, Libertarian/Traditional, Authoritarian, Nationalistic) or new politics (Marks, Hooghe, and Wilson 2003). I use three sources of data in order to estimate this model: the CMP data, surveys of party experts (Marks and Steenbergen 1999) and surveys of MP/MEPs (Katz et al 1999). Do to the timing of the surveys, this analysis is restricted to a cross-section of 85 parties using data for 1999.
For indicators of the economic left-right latent variable I used the general left-right measure from the experts, scaled from 0 to 10 with low numbers representing left-wing positions. I additively combined three variables from the MP survey (all Likert scales) to

construct an economic left-right variable and I selected issues from the CMP data that clearly aligned with left and right-wing policy preferences to construct the manifesto economic indicator. Figure 4.1 presents the path diagram and Table 4.1 presents the results of this model.

The results of this model show that this model fits the data very well. The non-significant X^2 tells us that the difference between the implied and the empirical covariance matrices is not statistically significant. This somewhat rare result may be due to a relatively small sample size (Bollen 1989), but is most likely illustrative of a good-fitting model. These results tell us that the latent constructs of economic left-right and GAL/TAN account for over 70% of the variance in the observed indicators from the survey-based measures, but only 60% of the CMP economic variable and only 40% of the CMP GAL/TAN.

The above model also allows the two latent variables to be correlated rather than imposing orthoganality. This makes good substantive sense and yields a much better fitting model. The estimated correlation between the two factors is 0.77, showing a strong relationship between general left-right and GAL/TAN in this sample.

Although a very good fitting model, the CMP measures stand out as the least valid observable indicators of these two latent variables. One possibility is that the CMP data suffer from some sort of systematic error or bias. The multi-trait multi method model (MTMM) developed by Campell and Fiske (1959) was designed for exactly this purpose—to uncover systematic error. More recently, Bollen and Paxton (1998) have shown that the MTMM model can be used to predict, thus control for, systematic error.

The MTMM model is quite simple, although some of the data requirements are somewhat demanding. In order to run the MTMM model, you must have at least two latent concepts and three indicators of each concept (as in model 1). This model adds an additional latent variable, called a method factor, which is used to explain the residual variance for a particular set of indicators. That is, this factor is meant to uncover the *instrument specific shared bias* not the substantively shared variance. You can estimate as many method factors as there are sources of data in the model in theory, however identification issues do come into play.

In order to test whether or not there is systematic error in the CMP indicators, I specified exactly the same model as above but added an additional latent variable—Manifesto Method Factor. If the factor loadings and the variance of the latent variable are significant, then there is evidence of bias in the CMP indicators. Also, we would expect to see an overall improved model fit if this were the case. The results of this model are presented in Table 4.2 and Figure 4.2 shows the path diagram.

Two things stand out when looking at these results. First the factor loadings from the method factor are non-significant. Also, the overall fit of the model actually gets marginally worse when including this method factor. The explained variance of the manifesto-based indicators does increase, but this is not evidence to support a method factor. Finally, the variance of the method factor is not significant leading me to reject the inclusion of this factor and to favor the first model based on parsimony and ease of interpretation.

There are several possible reasons why the MTMM model shows no evidence of systematic error in the CMP indicators. The first is that there may be no systematic error in the CMP indicators. Although a nice, clean solution, it does not follow that there is bias in these indicators simply because they are the least valid indicators in the model. A second possibility is that the common factor model with its assumptions of multivariate normality is not the appropriate model for CMP data. As shown in my previous research, attempting to model these data as normal can be highly problematic. The variables used in the CMP data are not *iid*, in fact values of all indicators are highly dependent on the values of the other indicators given the mutually exclusive coding categories in the original data collection procedures. Also, the high prevalence of zeros in the data creates additional noise in these indicators that almost certainly looks random *not* systematic.

Regardless of the specific issues with the CMP data in this analysis, these types of factor models are often misused by researchers in the social sciences. It is very common for researchers to run models similar to those above and then to extract factor scores, values of the latent variable for each case, and then to treat this estimate as an observed variable with no measure of uncertainty. This technique obviously leads to over-confident results as the uncertainty inherent in the estimated variable is ignored when using this latent variable in a predictive model.

SEMs, however, were designed to simultaneously estimate predictive and measurement models—seemingly overcoming the problem described above. This is not exactly the case, though. That is, when estimating full structural models, those with measurement and predictive components, the joint likelihood of both parts of the model is estimated at the same time. In other words, the values of the latent variable are not first estimated allowing uncertainty to propagate through to the predictive part of the model. Rather, SEM attempts to fit the model that has been specified through a comparison of means and covariances. Presently, research is underway comparing the results of SEMs to other techniques (Armstrong, Dutch, Bakker 2007). The initial results show that SEMs often lead to inflated coefficients with overconfident results compared to other techniques, such as Bayesian models, which first estimate values of the latent variable along with measures of uncertainty and then incorporate this uncertainty in the predictive model.

4. The Bayesian Approach

Although SEMs provide a user-friendly procedure for combining sources of data to estimate latent variables, problems still exist when using the estimates on either side of the equation in predictive models. We must choose to either ignore the uncertainty and treat our latent variable as observed or model the measurement and predictive models simultaneously without recovering estimates of our latent variable—which is often of substantive interest.

Bayesian models, on the other hand, allow the research considerably more flexibility than traditional SEMs and yield the quantities we are interested in while possessing desirable statistical properties. For example, the Bayesian framework allows us to more directly and appropriately model the data generating process rather than relying on assumptions of normality. We can also get estimates of our latent variables along with measures of uncertainty and directly model this uncertainty into predictive models. Most importantly, Bayesian models allow researchers to incorporate prior subjective information into our models, which is particularly valuable when using social science data. Rather than ignoring previous research, we can directly model our expectations based on this previous research (see Gill 2002 for a detailed discussion of these benefits).

As a means of combining sources of information, this modeling technique makes intuitive sense. In terms of estimating left-right party placements, a Bayesian model gives the opportunity to specify priors as a sort of ‘best guess’ as to the parties left-right score while letting the data diverge from this prior when it speaks loudly enough. The resulting posterior distribution is then a weighted compromise between prior information and the data used to predict party placements, with the data carrying more weight as sample size increases.

A recent development in Bayesian work is the use of elicited priors. That is, priors that are elicited from subject-area specialists in such a way as to develop “probability structures that reflect their specific qualitative knowledge and perhaps experiential intuition about the studied effects” (Gill and Walker 2005). An example of this is when researchers query doctors as to the probability of survival of patients with varying symptoms and characteristics. After collecting or eliciting such information, the researcher can then specify a probability distribution for survival, in this example, given a set of covariates.

Following this logic, the combination of expert surveys and CMP data seems quite amenable to this modeling strategy. The nature of the party expert survey, with parties being placed by several experts, allows us to develop probability structures around the parties’ placements. That is, we can take a mean and standard deviation of placement scores for each party, based on *n* experts and specify a probability distribution for each party in the sample. Assuming normality somewhat simplifies this process, but this is not a difficult assumption to defend given the empirical distribution of the raw expert placements.

With this expert prior in hand, the rest of the model is rather straightforward to estimate. Following the previous chapter's advice, I specify a binomial distribution for the CMP data estimating the probability a party makes a right-wing statement given their value on the latent variable. There are two major differences between this model and the Bayesian model from the previous chapter. First, the present model is only a cross-section rather than time series cross sectional data. In this model, I use the 2002 Chapel Hill Party Expert Survey to form the prior distributions and the most recent version of the CMP data. The resulting data set has 72 parties from Western Europe.

A more important difference, however, is the inclusion of a country- issue specific intercept in the model. This allows different party systems to be more left or right than others and facilitates cross-national comparisons of party placements. The only assumption this requires is that the effect of the latent variable on each of the observed variables is constant across countries. The model is as follows:

$$Y_{ij} \sim Binomial(p_{ij}, n_{ij})$$

$$Logit\ (p_{ij}) = a_{ij} + b_j X_i$$

Where Y_{ij} is the number of statements party *i* makes about issue *j*, p_{ij} is the probability that party *i* makes a right-wing statement about issue *j*, and n_{ij} is the total number of left and right-wing statements party *i* makes about issue *j*. The a_{ij} term is the country-issue intercept, X_i is the value of the latent variable for party *i*, and b_j is the effect of the latent variable on the probability that a party makes a right-wing statement about issue *j*.

The elicited prior specification described above is modeled in the following way:

$$X_i \sim Normal(\mu_{i,} \tau_i)$$

Where μ_i is the mean of the expert placements for party *i* and τ_i is the precision (the inverse of the variance) of the expert placement for party *i*. The priors for the b_j and a_{ij} parameters are all given diffuse normal priors. The model was estimated using WinBUGS and showed strong evidence of convergence after 5000 iterations. The first 1000 iterations were discarded and the model results are based on the remaining 4000 chain values.

There are two sets of quantities of interest from the model results. First are the factor loadings (the b_j estimates) and next are the X_i values (the left-right placements). The model was also run using so-called 'non-informative' or naïve priors to demonstrate that the expert prior is not driving the results that we see. The factor loadings are presented in Table 4.3. These loadings are posterior means and standard deviations.

With the exception of Internationalism, the latent variable has the expected effect on the observed indicators. That is, the more right-wing a party is, the more likely they are to make right-wing statements about these issues. Given that the model specified a logit link function; these parameters indicate the effect of the latent variable on the probability that a party will make right-wing statements about these issues, conditional on the number of sentences dedicated to both right and left-wing positions on that issue. The coefficient for the effect of the latent variable on Internationalism is troubling at best. This result is interpreted as meaning the more right-wing a party is, the less likely it is to make right-wing statements about this issue.

These results can also be displayed graphically by plotting p_{ij} against the latent variable score. Figure 4.3 shows this relationship for the CMP category Military.

Here we can see the value of the country-issue specific intercept in allowing cross-national comparison as well as the validity of this indicator and its ability to discriminate between parties on the left-right dimension. For this indicator Figure 3 shows that in France a party need only move a bit to the right to drastically increase the probability that it makes a pro-military statement in its manifesto whereas in Ireland a party must be very far to the right in order to do so. Therefore we can assess the impact of the left-right score on the probability of making right-wing states both between and within countries. The steepness of the curve also tells us that this is an issue that discriminates between parties on the left-right dimension and corresponds to a relatively large factor loading. Flatter curves indicate issues on which the difference between left and right parties is less clear. The graphs for the remaining nine items are included in the appendix to this paper.

The similarity between the model results is striking given the very different nature of the priors used in the two models and the relatively small sample size. This is a nice robustness test and demonstrates that the prior is not driving these results. The expert prior model is slightly more efficient on average, but the substantive results of the two models are practically identical.

The other main quantity of interest from this model is latent variable itself. As mentioned earlier, the posterior distribution is a compromise between the expert judgments and the CMP data. Comparing the ordering of the parties from left to right across the original CMP data, the original expert data and the posterior distribution of this model yields some very interesting results. The best way to view this comparison is to look at the individual orderings together and to note the differences. Tables 4.4 and 4.5

present this comparison. For ease of viewing, I have split the data between the two tables.

The middle column of Tables 4.4 and 4.5 is the ordering of the parties from left to right using the posterior distribution of the latent variable with expert priors. What is most striking about this result is how different the posterior ordering is from the CMP ordering or the expert ordering. Here you can see the Bayesian machine at work—that is, you can see the compromise between the two sources of data.

A final feature of this model is that it yields both estimates of the left-right placements and their standard deviations. Given this information, we can test whether or not the difference between two parties is statistically significant. With further advances to this model, time could also be included and we could then also test whether or not movements over time were significant or not.

5. Discussion

This paper has attempted to address the question of how best to combine different sources of left-right party placements in order to develop a more reliable and valid measure of this concept. The two main strategies are structural equation modeling and Bayesian modeling. Adjudicating between these two choices is neither straightforward nor is it based solely on statistical criteria. The SEM framework allows the researcher to estimate such dimensions with relative ease, but imposes some unrealistic assumptions. The Bayesian model is free from many of the assumptions necessary in the SEM world and provides a much more flexible tool for extracting latent dimensions, but comes at the cost of relatively high technological sophistication. The answer to which is better ultimately comes down to a question of philosophical belief. I argue that the Bayesian model is superior in that it directly estimates the latent variable and incorporates the uncertainty present in these estimates into the predictive model. The Bayesian framework also gives us the opportunity to utilize prior information when estimating or quantities of interest, rather than forcing us to pretend that we know nothing *a priori* about the world we are researching.

In terms of how each of the above modeling techniques perform in light of a predictive model, the results (not presented here) are somewhat mixed. Presently, we are exploring the differences between modeling strategies in terms of their predictive ability. Initial results show that the traditional SEM models tend to over-inflate coefficients while under-estimating uncertainty (Armstrong, Dutch, Bakker 2007). This result leads to the conclusion that the most efficient estimator is not necessarily the best estimator. Although somewhat counter-intuitive, this fact is widely recognized in the social sciences (robust standard errors for example).

Finally, the Bayesian model allows us to use expert judgments in a creative, appealing fashion. This paper demonstrates that even if priors were not explicitly elicited from experts, we can use these types of surveys to design intelligent and informative priors. In the case of party experts and CMP data, we see that the experts provide a 'second opinion' that is often quite different from the CMP placements. The resulting scale incorporate features of both data sources, has desirable statistical properties and is easily amenable to predictive models.

Appendix A:
Tables from Chapters 2-4.

Table 2.1: Left/Right Items used in the MRG:

Left Items	Right Items
Anti-Imperialism	Military Positive
Military Negative	Freedom-Human Rights
Peace	Constitutionalism Positive
Internationalism Positive	Political Authority
Democracy	Free Enterprise
Market Regulation	Incentives
Economic Planning	Protectionism Negative
Protectionism Positive	Economic Orthodoxy
Controlled Economy	Welfare State Limitation
Nationalization	National Way of Life Positive
Welfare State Expansion	Traditional Morality Positive
Education Expansion	Law and Order
Labour Groups Positive	Social Harmony

Table 2.2: MRG Left Scale Reliability Statistics:

Country	Cronbach's Alpha	N of Items
Sweden	.305	13
Denmark	.539	13
Finland	-.207	13
Belgium	.367	13
Netherlands	.536	13
Luxembourg	-.547	13
France	.669	13
Italy	.349	13
Spain	-.107	13
Greece	.151	13
Portugal	.051	13
Germany	-.023	13
Austria	.308	13
Great Britain	.456	13
Ireland	.168	13

Table 2.3:MRG Right Scale Reliability Statistics:

Country	Cronbach's Alpha	N of Items
Sweden	.594	13
Denmark	.424	13
Finland	-.303	13
Belgium	.353	13
Netherlands	.383	13
Luxembourg	.268	13
France	.367	13
Italy	.334	13
Spain	.590	13
Greece	.401	13
Portugal	-.435	13
Germany	.256	13
Austria	.376	13
Great Britain	.635	13
Ireland	.150	13

Table 2.4: Left and Right Items with Loadings above 0.3, by country

Country	Left Items	Right Items
Sweden	Nationalization, Controlled Economy, Market Regulation	National Way Life Positive, Free Enterprise, Military Positive, Freedom-Hum Rights
Denmark	Labour Groups Positive, Education Expansion, Welfare State Expansion, Democracy	Law and Order, Political Authority, Incentives
Finland	Military Negative, Peace, Nationalization	Economic Orthodoxy, Welfare State Limitation, Free Enterprise
Belgium	Nationalization, Controlled Economy, Economic Planning, Military Negative	
Netherlands	Economic Planning, Controlled Economy, Democracy, Peace, Nationalization,	Economic Orthodoxy, Military Positive, Incentives, Free Enterprise
Luxembourg	Military Negative, Market Regulation, Labour Groups Pos, Peace	Protectionism Negative, Law and Order, Welfare Limitation, Incentives.
France	Labour Groups Poitive, Nationalization, Military Negative, Peace, Controlled Econ	Traditional Morality, Law and Order, National Way Life, Military Positive
	Table 4 cont'd	
Italy	Military Negative, Peace, Protectionism, Labour Groups Positive	Protectionism, Free Enterprise, Economic Orthodoxy.
Spain	Anti-Imperialism, Military Negative, Education Expansion	Economic Orthodoxy, Traditional Morality, Law and Order, Incentives, Free Enterprise
Greece	Internationalism Positive, Welfare State Expansion, Education Expansion	Military Positive, Traditional Morality, Law and Order
Portugal	Anti-Imperialism, Democracy, Labour Groups Positive, Internationalism Positive	Law and Order, Incentives, Military Positive, Welfare Limitation.
Germany	Peace, Internationalism Positive, Military Negative	Economic Orthodoxy, Military Positive, Social Harmony, Free Enterprise
Austria	Democracy, Internationalism Positive, Peace	Incentives, Free Enterprise, Economic Orthodoxy, Constitutionalism Positive
United Kingdom	Labour Groups Positive, Nationalization, Market Regulation, Controlled Econ.	Military Positive, Free Enterprise, Economic Orthodoxy, Constitutionalism Positive, National Way Life.
Ireland	Military Negative, Peace, Internationalism Positive, Economic Planning.	Traditional Morality, National Way Life, Constitutionalism Positive

Table 2.5: Results of the Factor Analysis of the Left Items for United Kingdom, 1945-1970:

	Component				
	1	**2**	**3**	**4**	**5**
Military: Negative	.862	-.093	.004	-.145	.242
Anti-Imperialism	.860	.076	-.275	.036	-.257
Peace	.244	.756	-.003	-.039	.099
Welfare State Expansion	-.375	.734	-.011	.047	.007
Market Regulation	.050	.615	.531	-.099	.010
Education Expansion	-.504	.549	-.475	.272	.015
Labour Groups: Positive	-.212	-.050	.861	.065	.029
Controlled Economy	-.039	.120	.778	.393	-.338
Economic Planning	-.094	.182	.077	.857	-.010
Protectionism: Positive	-.040	-.208	.100	.833	-.053
Democracy	-.104	-.234	.118	-.240	.816
Internationalism: Positive	-.057	.341	-.207	.239	.755
Nationalization	-.380	-.177	.156	.054	-.562

Table 2.6: Results of the Factor Analysis of the Left Items for United Kingdom, 1970-1998:

	Component					
	1	2	3	4	5	6
Labour Groups: Positive	.909	-.021	-.058	.043	-.065	.001
Nationalization	.743	-.104	.062	.183	.094	.187
Market Regulation	.501	.351	.116	-.115	.195	-.235
Education Expansion	-.101	.851	.049	-.192	-.028	.201
Welfare State Expansion	.040	.811	.142	.289	-.005	-.223
Internationalism: Positive	.125	.118	.797	-.126	-.187	.020
Peace	-.090	.063	.785	.062	.212	-.113
Controlled Economy	.377	-.150	-.083	.753	.029	-.175
Military: Negative	.343	-.124	.166	-.630	.064	-.177
Economic Planning	.301	.097	.428	.591	-.003	.211
Democracy	-.142	-.148	.160	-.072	-.834	-.127
Anti-Imperialism	-.070	-.294	.386	-.158	.680	-.057
Protectionism: Positive	.062	-.007	-.051	.054	.081	.912

Table 2.7: New Left Reliability Statistics:

Country	Cronbach's Alpha	N of Items
Sweden	.687	6
Denmark	.489	5
Finland	.642	3
Belgium	.548	5
Netherlands	.605	6
Luxembourg	.658	4
France	.826	6
Italy	.566	4
Spain	.547	4
Greece	.510	5
Portugal	.468	5
Germany	.566	3
Austria	.566	3
Great Britain	.630	6
Ireland	.723	4

Table 2.8: New Right Reliability Statistics

Country	Cronbach's Alpha	N of Items
Sweden	.540	5
Denmark	.544	4
Finland	.249	4
Belgium	.440	3
Netherlands	.590	5
Luxembourg	.638	5
France	.767	4
Italy	.516	3
Spain	.841	5
Greece	.441	4
Portugal	.523	4
Germany	.684	5
Austria	.643	4
Great Britain	.678	5
Ireland	.510	3

Table 3.1. Balanced Manifesto Items

	Right-Wing	Left-Wing
Military	+	-
Internationalism	-	+
Constitutionalism	+	-
Centralization	-	+
Protectionism	-	+
Welfare State	-	+
Educational Expansion	-	+
National Way of Life	+	-
Multiculturalism	-	+
Labour Groups	-	+

Table 4.1 Confirmatory Factor Anaysis of Economic Left-Right and GAL/TAN

	Factor Loading	Residual Variance	R^2
Expert_Econ	0.91	0.17	0.83
Man_Econ	0.77	0.40	0.60
MP_Econ	0.85	0.27	0.73
Expert_G/T	0.84	0.30	0.70
Man_G/T	-0.63	0.60	0.40
MP_G/T	0.99	0.01	0.99

X^2 = 6.88 df = 6. CFI = 0.99. 90% CI RMSEA = [0.00 ,0.115] n = 85.
Factor loadings are fully standardized. All factor loadings are significant at the p<.05 level.

Table 4.2. MTMM model of Economic Left-Right and GAL/TAN

	Factor Loading	Residual Variance	R^2
Expert_Econ	0.91	0.17	0.83
Man_Econ	0.77	**0.38**	**0.62**
MP_Econ	0.86	0.27	0.73
Expert_G/T	0.84	0.30	0.70
Man_G/T	0.99	**0.48**	**0.52**
MP_G/T	0.63	0.01	0.99
Man_Econ Method Factor	0.16*		
Man_G/T Method Factor	0.34*		

Chi^2 = 6.13 df = 6. CFI = 0.98. 90% CI RMSEA = [0.00 ,0.14] n = 85.
Factor loadings are fully standardized. All loadings are significant at the p<.05 level except *.

Table 4.3. Factor loadings from Bayesian measurement model with expert and naïve priors

	Expert mean	Expert SD	Naïve mean	Naïve SD
Military	1.33	0.02	3.13	0.15
Internationalism	-0.41	0.01	-0.97	0.05
Constitutionalism	0.06	0.01	0.15	0.02
Protectionism	0.69	0.02	1.65	0.09
Welfare State	0.77	0.01	1.82	0.09
Education	0.61	0.03	1.61	0.10
Natl Way of Life	1.68	0.05	4.01	0.22
Multinationalism	1.98	0.04	5.01	0.26
Labour Groups	1.28	0.03	3.17	0.17
Economic Policy	0.63	0.01	1.48	0.07

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Table 4.4. Order of parties' left-right placements for the left half of the data

man.order	man.expert.order	expert.order
AUT: GA Gr	SWE: Vp Co	GRE: KKE C
SPA: PCE-I	SPA: PCE-I	POR: CDU D
SWE: Vp Co	AUT: GA Gr	FRA: PCF C
IRE: Green	GRE: KKE C	GER: PDS P
ITA: RC Ne	SPA: PSOE	SWE: Vp Co
GER: PDS P	FIN: VL Le	ITA: RC Ne
IRE: LP La	SWE: Green	IRE: Green
DEN: SF So	GRE: SAP C	DEN: SF So
POR: CDU D	AUT: SPO S	FIN: VL Le
BEL: Agale	FIN: VL Gr	SPA: PCE-I
GER: Allia	UK: LDP Li	NET: GL Gr
GRE: SAP C	SPA: CiU C	BEL: Ecolo
SPA: PSOE	SWE: KdS C	BEL: Agale
BEL: Ecolo	SPA: PNV E	FRA: Green
SWE: Green	BEL: Agale	AUT: GA Gr
BEL: PS Fr	IRE: Green	GRE: SAP C
BEL: CVP F	FRA: PS So	ITA: PCI-P
POR: PSP S	BEL: Ecolo	IRE: LP La
FRA: Green	SWE: FP Li	SWE: Green
FIN: VL Le	AUT: FPO F	BEL: PS Fr
NET: GL Gr	FRA: Green	GER: Allia
FRA: PS So	FIN: SKL C	BEL: SP Fl
SPA: PNV E	ITA: RC Ne	SWE: SdaP
AUT: SPO S	DEN: SF So	FIN: SSDP
UK: LDP Li	BEL: CVP F	FIN: VL Gr
FIN: VL Gr	SWE: SdaP	AUT: SPO S
NET: D 66	FIN: SK Fi	UK: LDP Li
BEL: PSC F	BEL: PS Fr	FRA: PS So
BEL: VB Fl	POR: CDU D	GRE: PASOK
IRE: PD Pr	BEL: VB Fl	DEN: SD So
BEL: SP Fl	GER: PDS P	GER: SPD S
IRE: Fiann	IRE: LP La	SPA: PSOE
ITA: PCI-P	DEN: RV Ra	NET: PvdA
GRE: PASOK	UK: Labour	POR: PSP S

Table 4.5. Order of parties' left-right placements for the right half of the data

man.order	man.expert.order	expert.order
DEN: RV Ra	UK: Conser	NET: D 66
IRE: Fine	FIN: SSDP	DEN: RV Ra
SPA: CiU C	FRA: PCF C	UK: Labour
FIN: RKP S	SPA: AP,PP	SWE: CP Ce
NET: PvdA	NET: GL Gr	IRE: Fiann
GRE: ND Ne	GER: Allia	BEL: PSC F
FIN: SSDP	BEL: PSC F	SPA: PNV E
GER: SPD S	AUT: OVP C	FRA: UDF
SWE: SdaP	SWE: CP Ce	IRE: Fine
SWE: KdS C	NET: D 66	GER: CDU-C
FIN: SK Fi	BEL: PVV F	BEL: CVP F
UK: Labour	GRE: ND Ne	GER: FDP F
AUT: FPO F	GRE: PASOK	FIN: SK Fi
POR: PP Po	NET: PvdA	NET: CDA C
NET: CDA C	BEL: SP Fl	SPA: CiU C
FIN: SKL C	POR: PSP S	SWE: FP Li
SWE: FP Li	DEN: SD So	GRE: ND Ne
POR: PSD S	FRA: UDF	BEL: PVV F
DEN: SD So	FRA: FN Na	POR: PSD S
FRA: UDF	NET: CDA C	FIN: RKP S
SPA: AP,PP	DEN: V Lib	FIN: SKL C
BEL: PVV F	FIN: KK Na	SPA: AP,PP
GER: FDP F	GER: SPD S	ITA: FI Fo
NET: VVD L	ITA: PCI-P	DEN: KF Co
UK: Conser	NET: VVD L	AUT: OVP C
DEN: V Lib	IRE: Fiann	FIN: KK Na
SWE: CP Ce	FIN: RKP S	SWE: KdS C
FRA: PCF C	IRE: PD Pr	DEN: V Lib
DEN: KF Co	SWE: MSP C	NET: VVD L
AUT: OVP C	GER: FDP F	ITA: LN No
GER: CDU-C	IRE: Fine	UK: Conser
FIN: KK Na	GER: CDU-C	IRE: PD Pr
GRE: KKE C	DEN: KF Co	SWE: MSP C
ITA: LN No	POR: PSD S	ITA: AN Na
ITA: FI Fo	POR: PP Po	POR: PP Po
ITA: AN Na	ITA: FI Fo	AUT: FPO F
SWE: MSP C	ITA: AN Na	BEL: VB Fl
FRA: FN Na	ITA: LN No	FRA: FN Na

Appendix B:
Figures from Chapters 2-4

Figure 2.1: Tracking Party Positions across Time on MRG Left/Right Dimension, United Kingdom

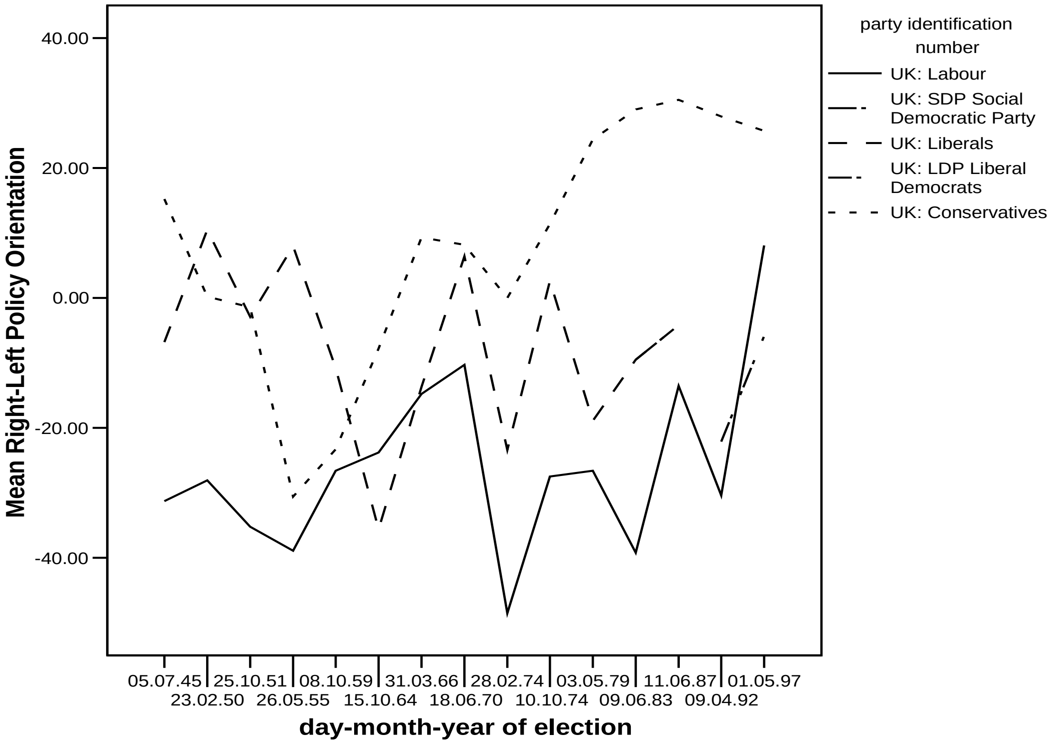


Figure 2.2: Tracking Party Positions across Time on MRG Left/Right Dimension, France

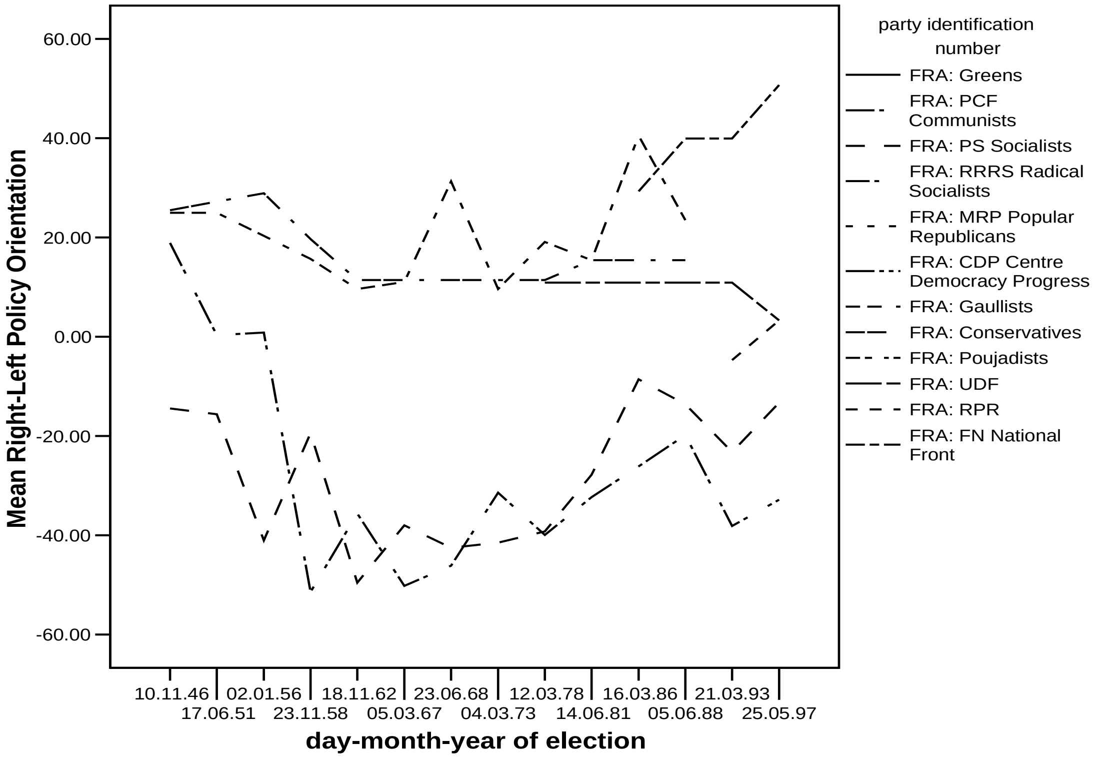


Figure 2.3: Frequency of Zeros: Ant-Imperialism

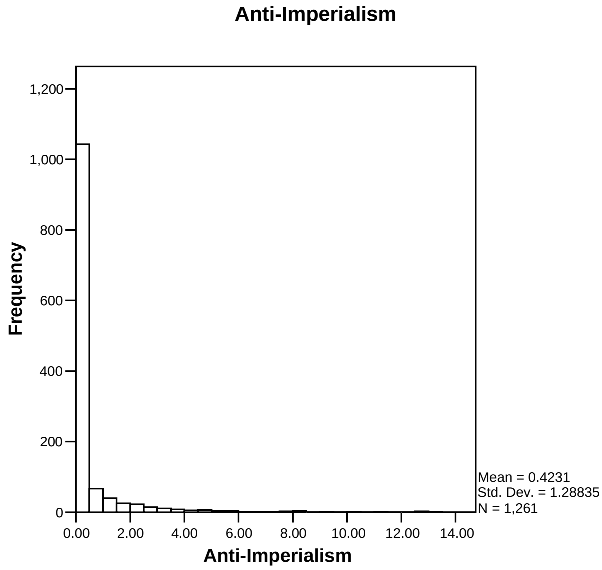


Figure 2.4: Frequency of Zeros: Nationalization

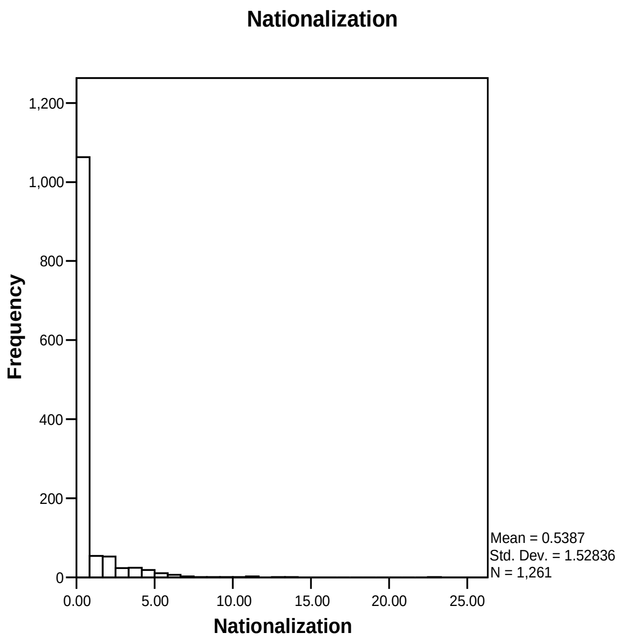


Figure 2.5: Tracking Party Positions across Time on New Left/Right Dimension, United Kingdom:

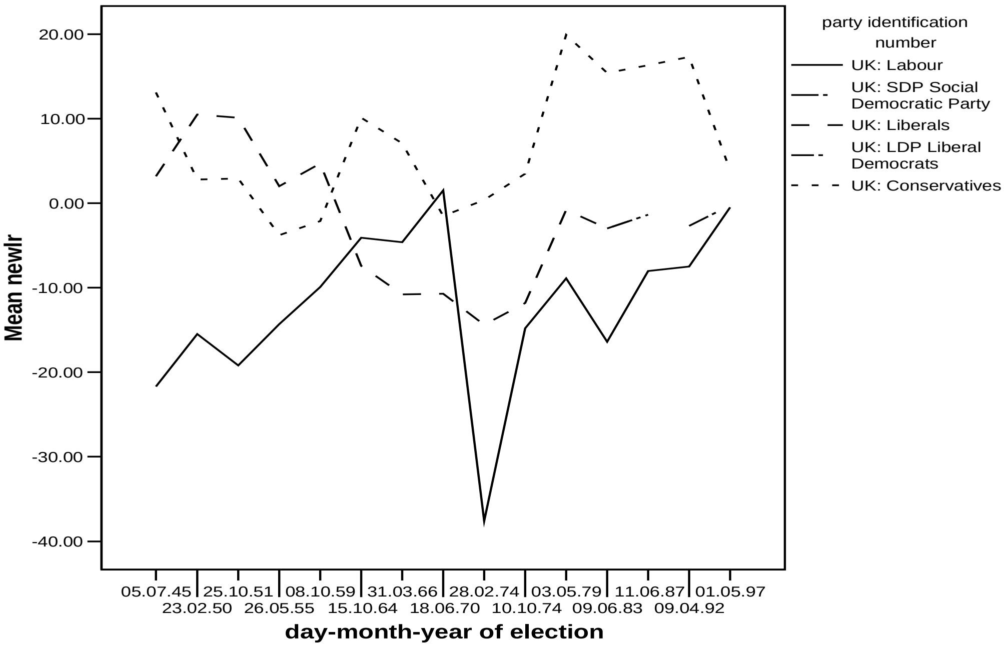


Figure 2.6: Tracking Party Positions across Time on New Left/Right Dimension, France

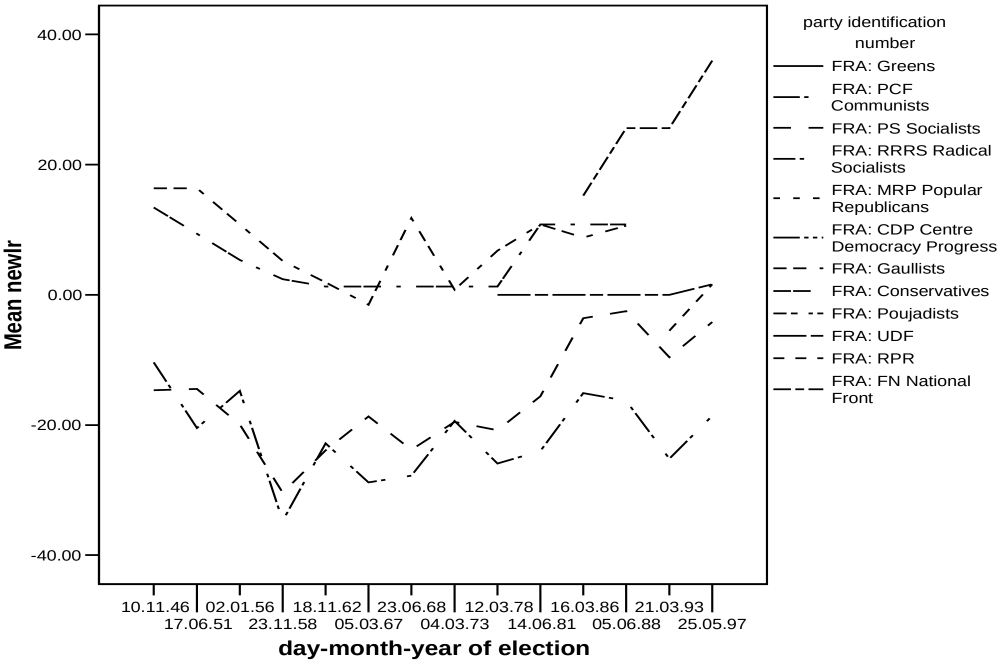


Figure 3.1. UK Party Placements from Bayesian Factor Model

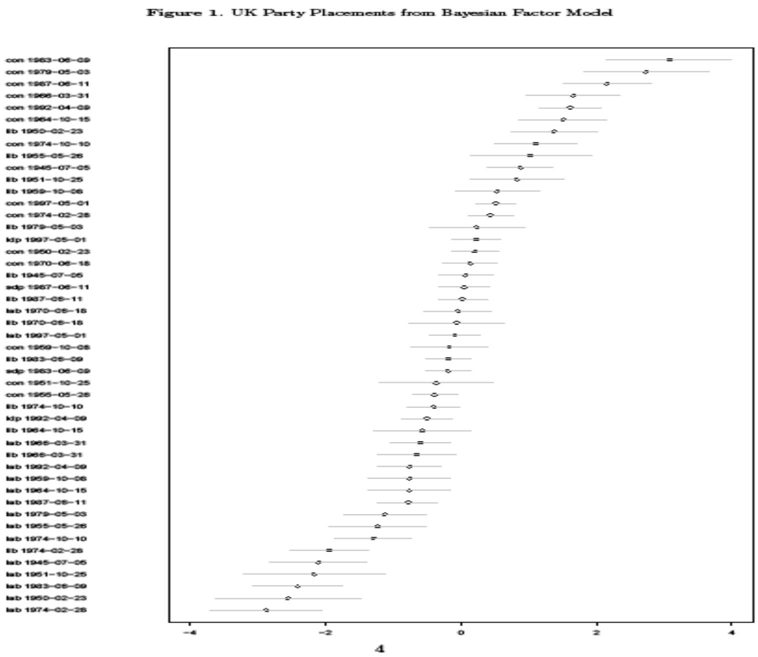
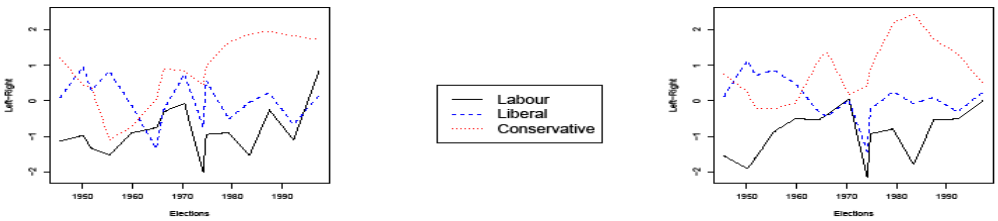


Figure 3.2 Comparison of CMP and Armstrong-Bakker Left-Right Placements for UK

Figure 4. Manifesto and Armstrong-Bakker Placements for the UK



(a) Manifesto

(b) Armstrong-Bakker

7

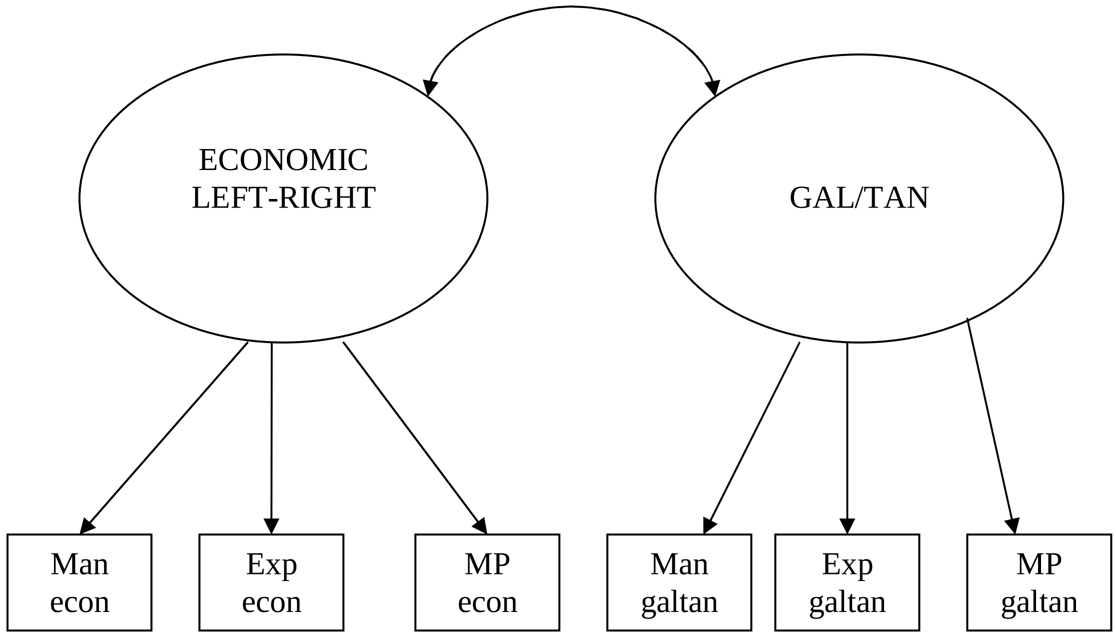


Figure 4.1. Two-latent variable measurement model.

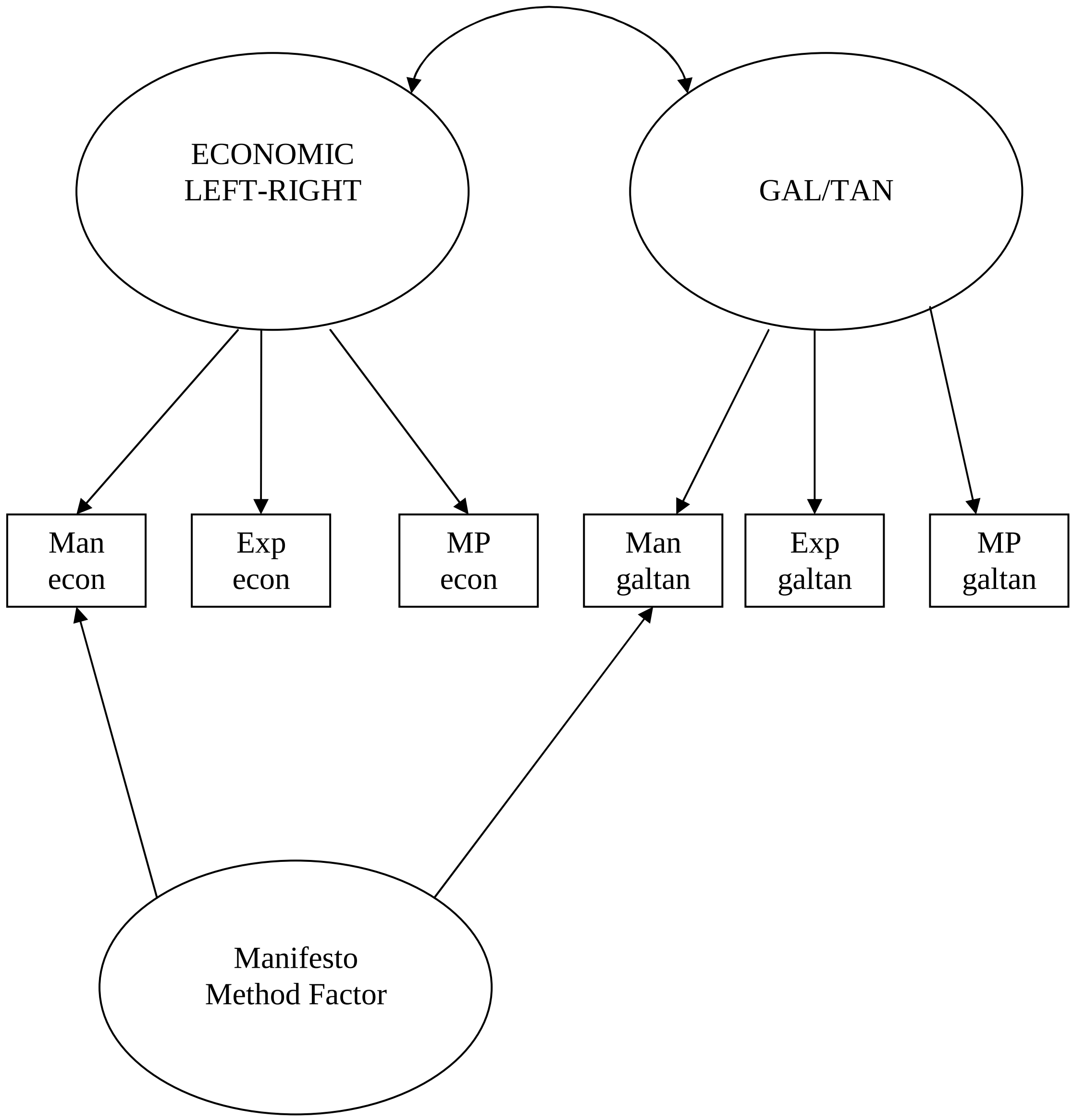


Figure 4.2. Two-latent variable model with method factor.

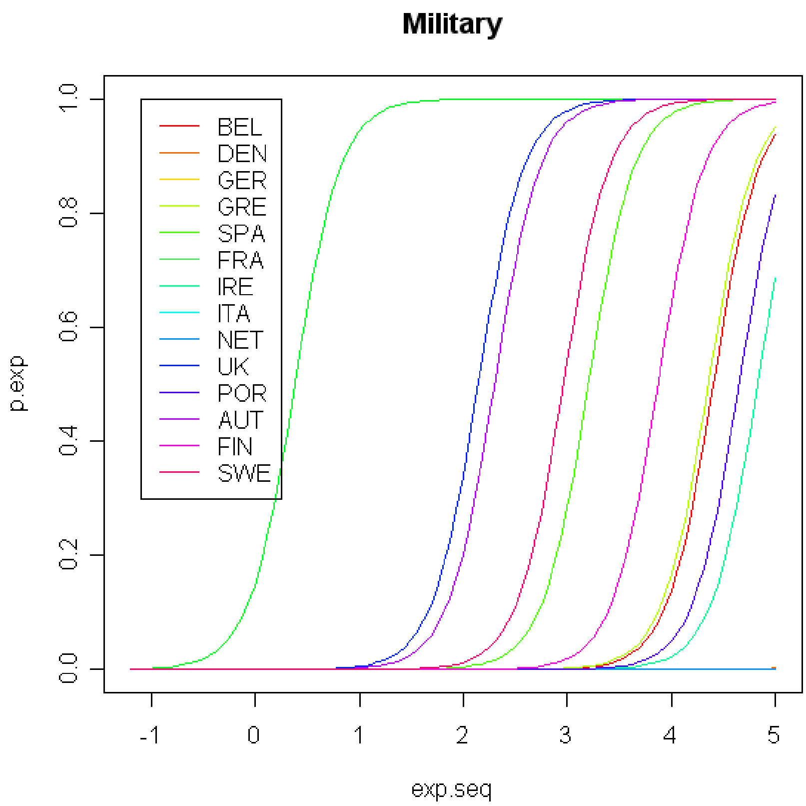


Figure 4.3. Probability of making pro-Military statements given left-right score.

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