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Re-measuring left–right: A comparison of SEM and Bayesian measurement models for extracting left–right party placements

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A B S T R A C T

This paper demonstrates the relative strengths and weaknesses of SEM and Bayesian approaches to combining different sources of data when estimating latent variables. Data on party left–right positioning collected from party manifestos and surveys of party experts, MPs and voters are used to illustrate the two techniques. Although widely used and accepted, the SEM approach is less useful than the Bayesian approach, particularly when using the latent variable in subsequent predictive estimations.

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 2nd, 3rd and 4th 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 imperfectly measured observable traits (i.e. free press, open elections) of the concept. In our efforts to locate 'good' indicators of our concept or latent variable, we often find that 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. It is also the case that properly combining sources of data across time and space often requires a reasonably advanced level of statistical sophistication. 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

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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 set of SEMs, which test cross-temporal reliability of the indicators and stability of the latent concepts using the Wiley–Wiley model (Wiley and Wiley, 1970). Finally, I estimate a Bayesian model using expert survey data as 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 techniques (Castles and Mair, 1984; Laver and Hunt, 1992; Ray, 1999; Marks et al., 2006; Benoit and Laver 2006,—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., 2001) has developed the most widely used measure of left–right party placements using this technique. The CMP data cover 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, 1993; Budge et al., 1987; Baron, 1991; Klingemann, 1995; Laver and Budge, 1992; Budge, 1994; Adams, 1998, Van de Eijk et al., 1999; Warwick, 1994, 2000; Budge and McDonald, 2006—for just a few examples).

Even though these data have been widely used for over 20 years, only recently have scholars begun to scrutinize their reliability and validity (Kim and Fording, 1998; Laver and Garry, 2000; Marks et al., 2006; Harmel et al., 1995; Gabel and Huber, 2000; Volkens, 2001; Bakker et al., 2007; Benoit and Laver, 2006). 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, forthcoming). 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 is the strength of their data and the weakness of the expert surveys (Budge and McDonald, 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, this paper focuses on 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; 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 et al., 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). Due 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 (Fig. 1). 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. Table 1 presents the results of this model:

The results 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

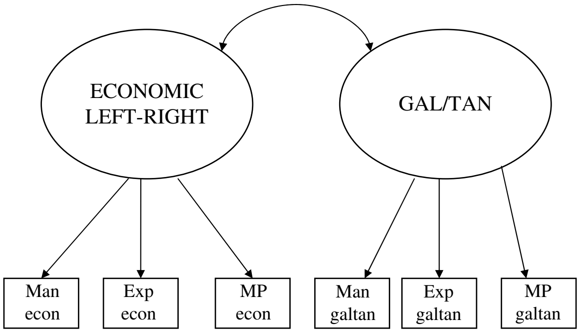


Fig. 1. Two-latent variable measurement model.

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 orthogonality. 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 multitrait multi method model (MTMM) developed by Campbell 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.

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 2.

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.

Table 1
Confirmatory Factor Analysis 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	0.99	0.60	0.40
MP_G/T	0.63	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 $p < 0.05$ level.

Table 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 $p < 0.05$ level except *.

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 previous research, attempting to model these data as normal can be highly problematic (Bakker et al., forthcoming). 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. Although there are SEM approaches that allow one to model more complicated data generating processes, these require specialized software. 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.

Full 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 et al., 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 are often of substantive interest.

Bayesian models, on the other hand, allow the researcher 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 in our predictive models. Most importantly, Bayesian models allow researchers to incorporate prior 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 in the social sciences 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. 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. 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.

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 right-wing 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 a 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 3.

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. Fig. 2 shows this relationship for the CMP category Military.

Table 3
Factor loadings from Bayesian measurement model with expert and naïve priors.

	Expert mean	Expert SD	Naïve mean	Naïve SD
Military	1.33	0.22	3.13	0.15
Internationalism	−0.42	0.01	−0.10	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	0.62	0.03	1.61	0.10
Natl Way of Life	1.69	0.04	4.01	0.22
Multinationalism	1.99	0.04	5.00	0.26
Labour Groups	1.28	0.03	3.17	0.17
Economic Policy	0.63	0.01	1.48	0.07

These loadings are posterior means and standard deviations.

Here we can see the validity of this indicator and its ability to discriminate between parties on the left–right dimension. For this indicator Fig. 2 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 (Fig. 3). 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 as the latent variable scores from the two models correlate at 0.96.

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 and 5 present this comparison. For ease of viewing, I have split the data between the two tables:

The middle column of Tables 4 and 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 errors. 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

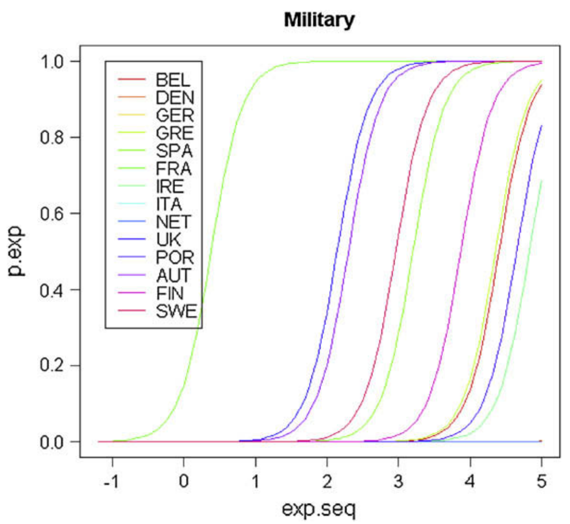


Fig. 2. Probability of making pro-military statements given left–right score.

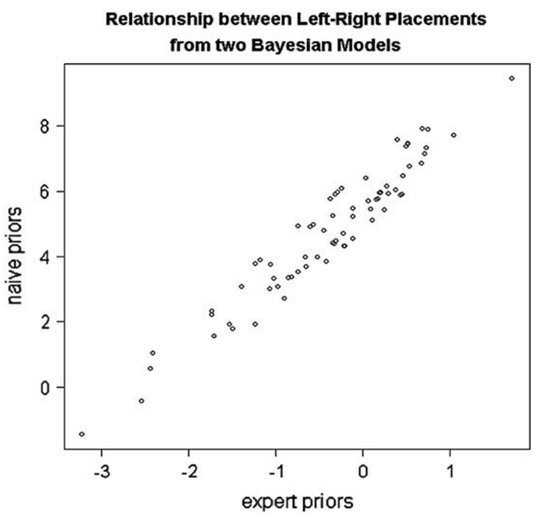


Fig. 3. . Relationship between Left–Right Placements from two Bayesian Models.

Table 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 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 Nab
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

extracting latent dimensions, but comes at the cost of relatively high technological sophistication. Table 6 briefly presents some of the strengths and weaknesses of the two approaches. The answer to which is better ultimately comes down to a question of philosophical belief. Having said 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 our 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 et al., 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).

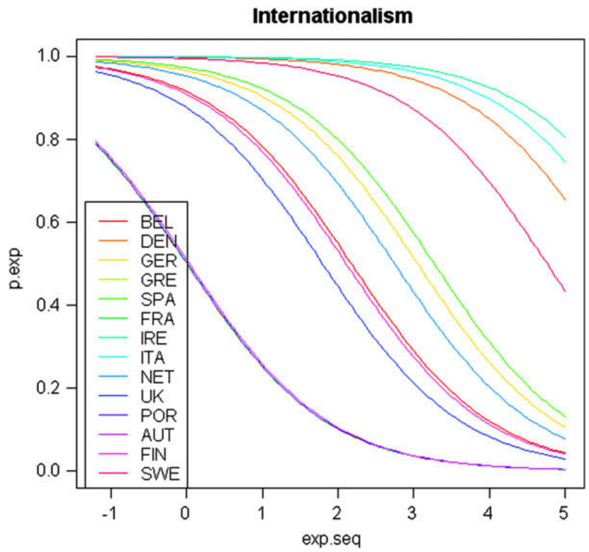
Table 6
Trade-offs between SEM and Bayesian Approaches.

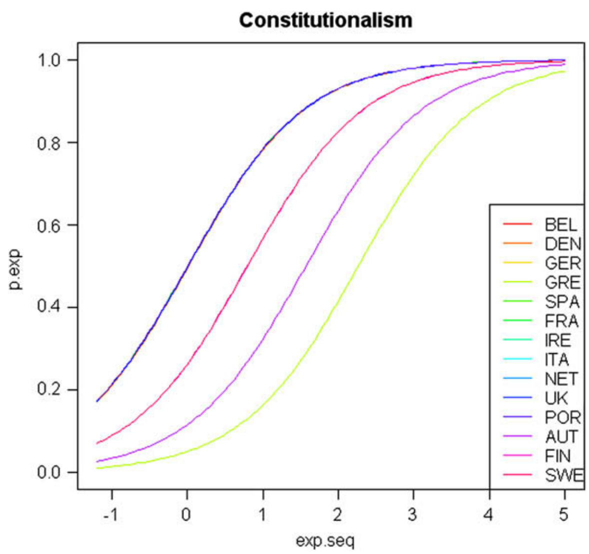
	Pros	Cons
SEM	-simple to estimate in most stats packages. -can estimate measurement and predictive models simultaneously -straightforward model fit assessment.	-often imposes assumptions of normality. -full SEMs do not directly provide estimates of the latent variable and their uncertainties. -does not propagate uncertainty through the predictive model. -hidden assumptions
Bayesian	-provides estimates of latent variable with their associated uncertainties. -flexible with regard to data generating process. -can incorporate prior information in meaningful ways. -simple to adjudicate between significant and non-significant differences in latent variable scores. -explicit assumptions	-requires reasonably advanced level of statistical training. -can be problematic to estimate with very large N. -prior information can 'influence' results. -model fit statistics are underdeveloped.

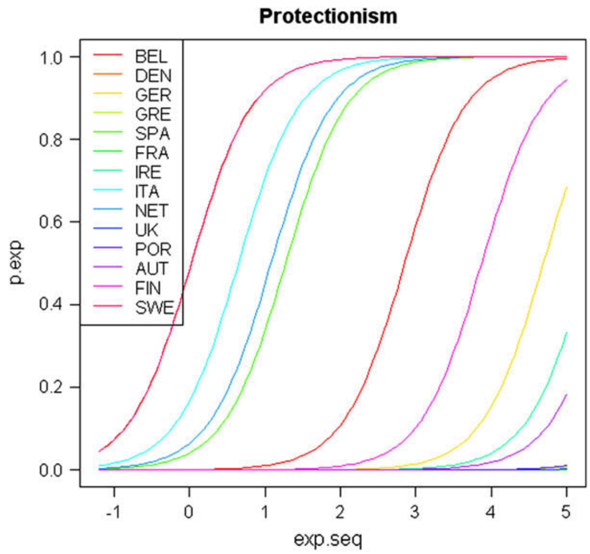
Finally, the Bayesian model allows us to use expert judgments in a creative, appealing fashion. This paper demonstrates that even if priors were not explicitly elicited from experts, we can use these types of surveys to design intelligent and informative priors. In the case of party experts and CMP data, 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.

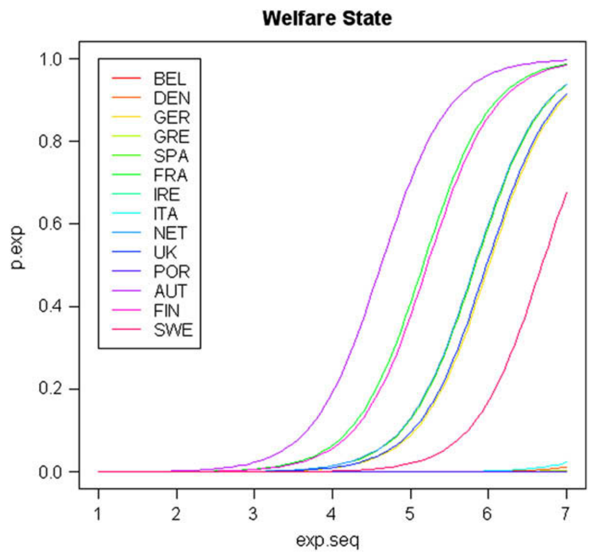
Appendix

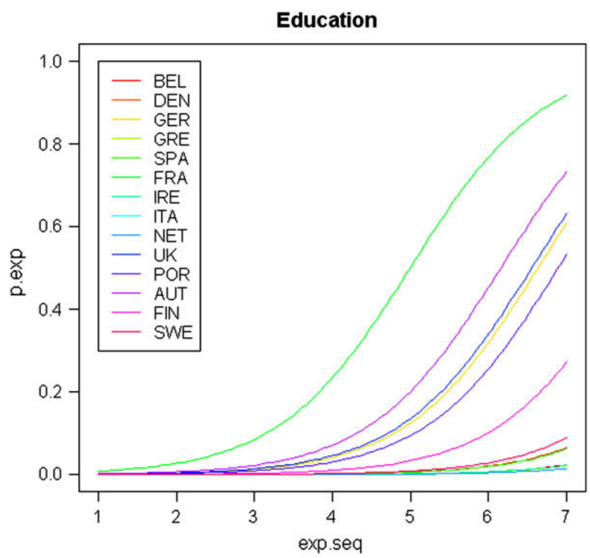
Graphs of left–right scores against the probability of making right-wing statements

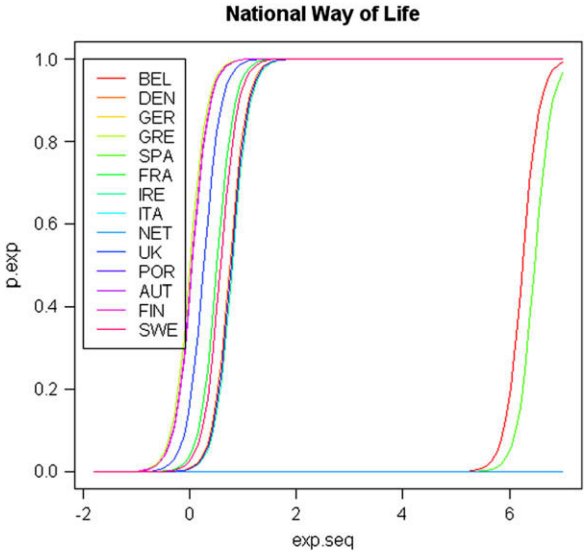


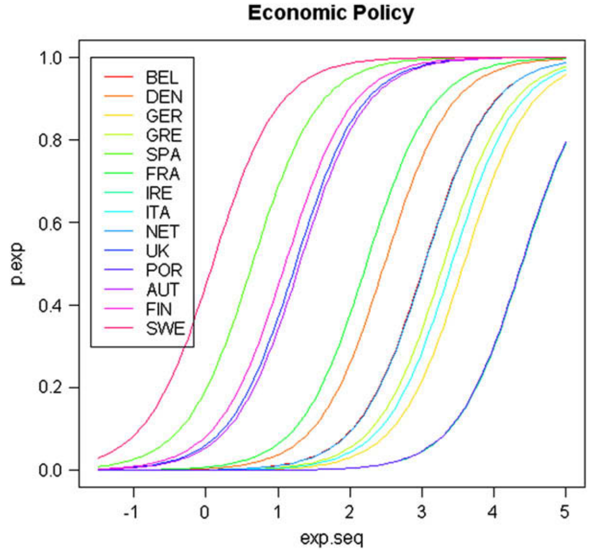


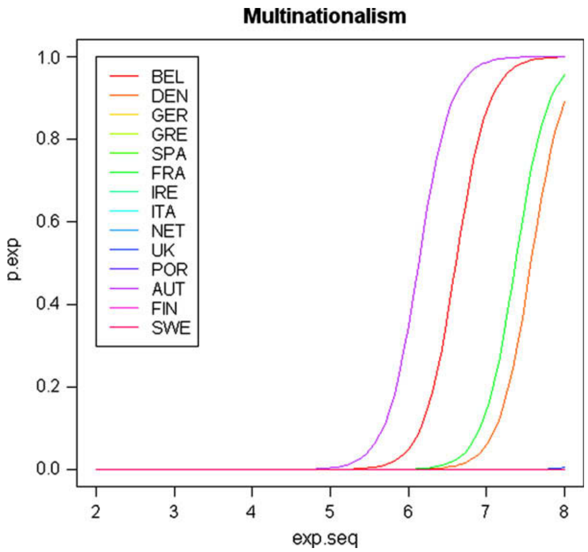


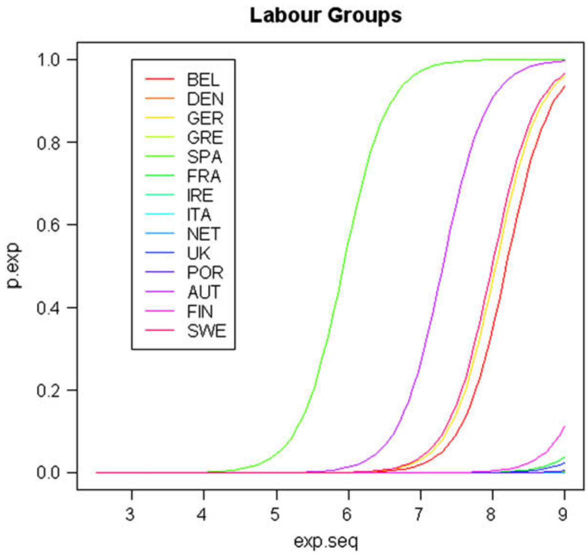












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