Assessing the Measurement of Policy Positions in Expert Surveys

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Abstract

Expert surveys provide a common means for assessing parties' policy positions on latent dimensions. These surveys often cover a wide variety of parties and issues, and it is unlikely that experts are able to assess all parties equally well across all issues. While the existing literature using expert surveys acknowledges this fact, insufficient attention has been paid to the variance in the quality of measurement across issues and parties. In this paper, we first discuss the nature of the measurement problem with respect to expert surveys and then propose methods borrowed from the organizational psychology and medical fields to assess the ability of experts to assess where parties stand on particular dimensions. While we apply our technique to one particular study, the Chapel Hill Expert Survey, the method can be applied to any expert survey. Finally, we propose a simple non-parametric bootstrapping procedure that allows researchers to assess the effects of expert survey measurement error in analyses that use them.

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1 Introduction

Expert surveys provide a common means of assessing the positions of political actors, most notably parties, on a wide array of latent policy dimensions. Rather than estimate positions directly from the actions that parties and their members take — e.g., votes or speeches — researchers ask experts to synthesize their knowledge of a party system and assign positions to parties on specific dimensions of interest. Depending upon the specificity of the dimensions under investigation in the survey, researchers may require a great deal of detailed knowledge from their experts. It is unlikely that experts are able to assess all parties equally well across all dimensions, meaning that almost certainly some parties and some issues are better measured than others. The existing expert survey literature in political science has explored covariates to explain the variation in expert placement within parties, but we argue that this approach is insufficient to understand the nature of the measurement problem in these data.

In this paper, we use techniques commonly found in the psychometric and medical fields — intraclass correlation and within-group agreement — to assess levels of agreement and reliability among experts when they place parties on scales in expert surveys. These techniques allow us to examine agreement at the party-dimension level and account for the fact that experts may use the scale in a different manner. To date political scientists conducting and using expert surveys have given insufficient attention to the distinction between inter-rater agreement and reliability and do not sufficiently examine the variability in quality of responses of experts across parties and dimensions.

The paper proceeds by first discussing the nature of the measurement problem and statistical inference with respect to expert surveys. We then discuss the differences between agreement and reliability, and introduce measures to capture each concept. To demonstrate the extent of the measurement problem in expert surveys, we apply the measures to one particular survey, the Chapel Hill Expert Survey (CHES). Lastly, we propose a simple non-parametric bootstrapping procedure that allows researchers to assess the effects of expert survey measurement error in analyses that use them. Through a replication of a recent study

using the CHES data, we demonstrate that measurement error in expert surveys may have consequences for our analyses.

2 Expert Surveys and Statistical Inference

As others have noted before (see Benoit and Laver, 2006, ch. 4), the statistical inference problem in expert surveys differs quite substantially from that in public opinion surveys. In public opinion surveys, researchers wish to measure a quantity of interest regarding a population by randomly sampling observations from that population. For example, we draw a random sample of voters from the population of all voters to assess the public's support for the US President. Opinion surveys ask n respondents to report their *own* opinions, x_i, to estimate a sample mean, $\bar{x}$, in an effort to make inferences about a population parameter, μ, namely the true public support for the President. We consider each individual response, x_i, as a random draw from the true population distribution of support for the President. By itself, each individual x_i offers no useful information about μ. But according to the central limit theorem, our estimate of μ, the true mean opinion of the President in the population, improves as n increases.

Now compare this with the measurement problem when evaluating expert surveys. The primary objective of expert surveys is to aggregate knowledge about states or political parties or some other object of interest. Experts are not chosen at random from a population because researchers are usually not interested in inferring the value of a parameter from a population of experts. Rather, they are interested in gleaning information from them about a topic on which they have expertise — in other words, the latent concept they wish to measure. In this case, one highly knowledgeable expert may, in fact, be better than several lesser informed ones. The problem, though, is that the researchers conducting the survey do not necessarily know how knowledgeable their experts are. Assume that a party has a true, latent position γ on some continuous scale, which researchers ask n experts to assess. If all n experts are

perfectly informed, they will all respond in an identical manner — that the party has a position γ. Having one expert is as good as having 20. However, if the experts are not all equally informed, or they are uniformly poorly informed, they may not all answer in the same manner. Instead, each expert i may state that the party's position is $\gamma + \epsilon_i$, where ϵ_i is drawn from some distribution D with mean, μ, and standard deviation σ. We might say that γ is well-measured when D follows a symmetric distribution, $\mu = \gamma$ and σ is small. In other words, all experts assign the party similar scores, which are tightly clustered around the true score. As D becomes skewed, μ deviates from γ, and σ grows large, the experts are less able to capture the position of the party or the nature of the dimension.

Interestingly, increasing the number of experts does nothing to improve the measurement of γ. Benoit and Laver (2006, ch. 4) claim otherwise, saying that increasing the number of experts increases the certainty around the estimate of the party position. They calculate standard errors for party positions based on the standard deviation of expert placements as well as the number of expert placements. However, this approach has almost unanimously been rejected by the literature on interrater agreement (e.g., Kozlowski and Hattrup, 1992; LeBreton and Senter, 2008). If experts were drawn at random from the population of all experts, increasing respondents would shrink the standard deviation of the sampling distribution of the mean expert perception of a party's position. But being increasingly confident about the *mean* expert perception does not imply that experts are actually good at assessing the latent party position. The sample distribution of expert placements could be uniformly distributed across the entire range of the scale, yet with a sufficient number of experts, the standard error of the mean would be quite small. Again, we are not interested in inference about a population of experts, but rather we wish to learn about a latent characteristic of the parties the experts are rating. Thus, the sampling distribution of the average expert opinion is not of primary interest to us. Unlike with traditional statistical inference as applied to opinion polls, when assessing the effectiveness of experts at capturing a latent position, it is the *shape* of the distribution D that most interests us. Increasing the number of expert

responses does not provide us with a better measure of γ, but does allow us to get a better sense of the shape of the distribution D.

However, to date none of the robustness and validity checks that political scientists apply to expert survey responses adequately assess the shape of the distribution of expert placements. Most analyses focus on the mean expert placement or, at best, the standard deviation of placements (Hooghe et al., 2010).[1] But in actuality, we are most interested in the *consistency* and *agreement* of expert responses.[2] In the remainder of the paper, we first demonstrate why the dominant approach in political science for assessing expert surveys is problematic, and then propose a set of solutions and good practices.

3 Distribution of Expert Placements

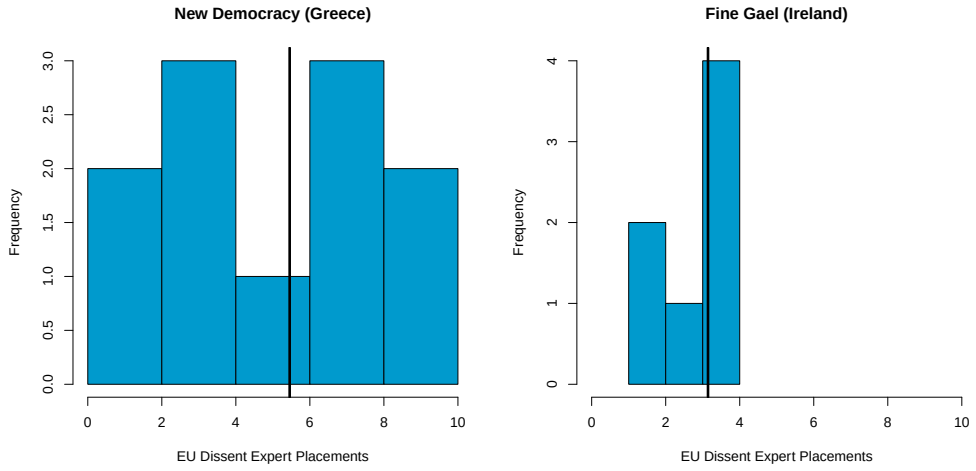
We begin by demonstrating that the shape of expert placement distributions can vary quite drastically. We examine policy dimensions from the commonly used Chapel Hill Expert Survey (Bakker et al., forthcoming). The most recent iteration of the Chapel Hill survey, conducted in 2010, queried 343 experts to estimate positions for 237 parties across 24 EU member states on numerous dimensions. On average, slightly more than 13 experts responded per party-dimension. Expert surveys typically report the average expert placement on each policy dimension in the published data (Benoit and Laver, 2006; Bakker et al., forthcoming). In practice, this can mean that political parties have an estimated mean party position based on very different distribution of expert placements. We focus here on five prominent dimensions from the Chapel Hill expert survey: three dimensions related to the European Union (intra-party dissent on EU, the party position on the EU, and the salience of the EU) and two dimensions related to the traditional left-right partisan con-

[1] Or in the case of Benoit and Laver (2006) the standard error.

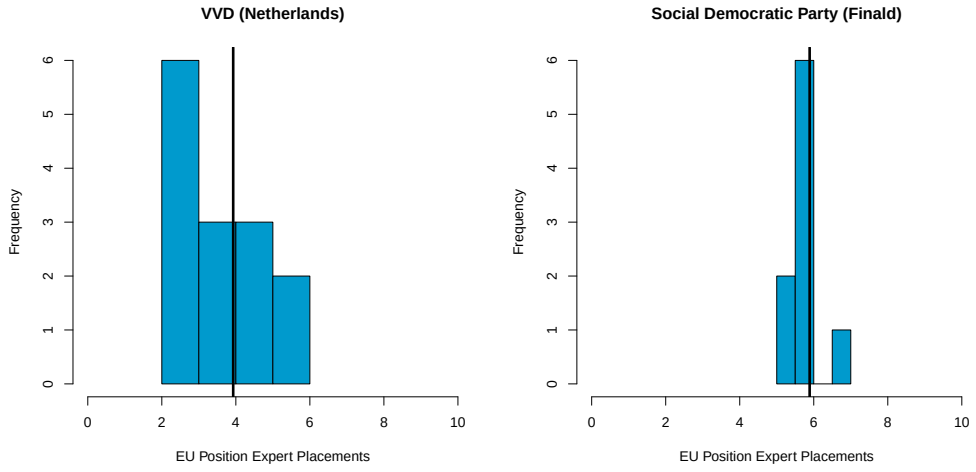
[2] van der Eijk (2001) makes a similar point, but he focuses solely on agreement and fails to consider consistency.

flict (left-right position on economic policy and general left-right position). Figure 1 shows distributions of expert responses for six parties across the three EU dimensions. For each dimension, we selected two parties with similar mean positions but different distributions of expert responses. For instance, on the dimension measuring intra-party dissent, the mean expert placement suggests that the Irish Fine Gael and the Greek New Democracy party have moderate levels of intra-party dissent, denoted by the black vertical line. However, whereas experts in Greece strongly disagree about the levels of intra-party dissent, leading to a nearly bimodal distribution spanning the entire scale, experts in Ireland agree that Fine Gael only has moderate levels of dissent. Figure 1 includes similar graphs for the Dutch VVD and Finnish SDP on the EU dimension and for the Hungarian JOBBIK and French Greens on the EU salience dimension. In each case, experts cannot agree on the placement of one party. And in two of the three instances, the party was a mainstream and not a fringe party.

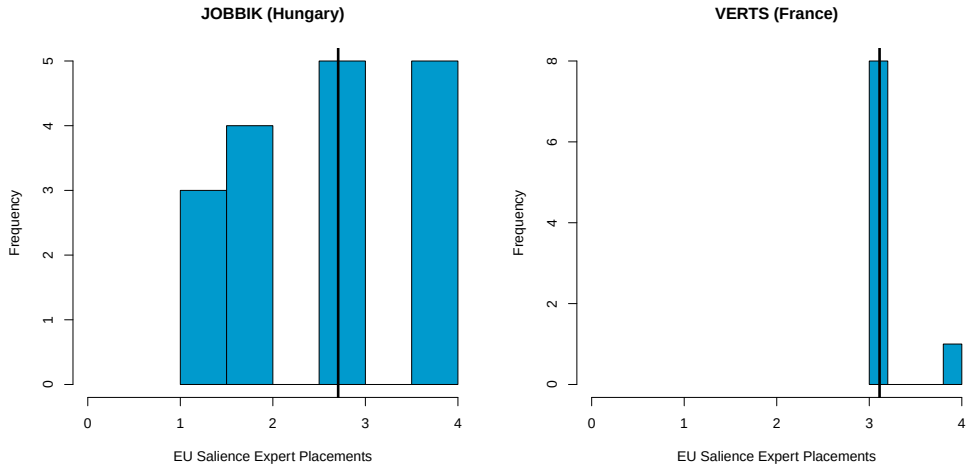
Similarly, the left-right dimension, which typically shows smaller variation in expert placements, is subject to the same problems. Figure 2 presents expert placements for left-right economic policy for the French Front National and the Polish Civic Platform. For the Front National, we observe a distribution of expert placements that is bimodal. On average, the Front National is estimated to be a centre-right party, but the contrast to the Civic Platform in Poland — a party with a similar average position — is obvious. Experts use almost the entire scale to place the French party, whereas there is agreement among experts that the Polish party is centre-right. This contrast occurs even on the (supposedly best) measured dimension, the general left-right dimension. Here, experts have trouble locating the DeSUS from Slovenia, whereas they agree strongly on the Portuguese PS. In the aggregate, however, both parties are estimated to hold identical left-right positions. These illustrations underscore that distributions of expert placements can vary drastically.



(a) EU Dissent

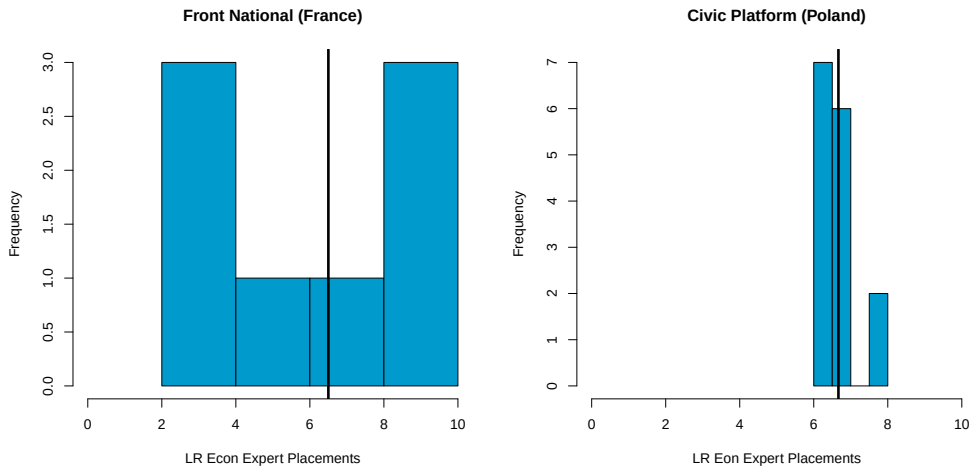


(b) EU Position

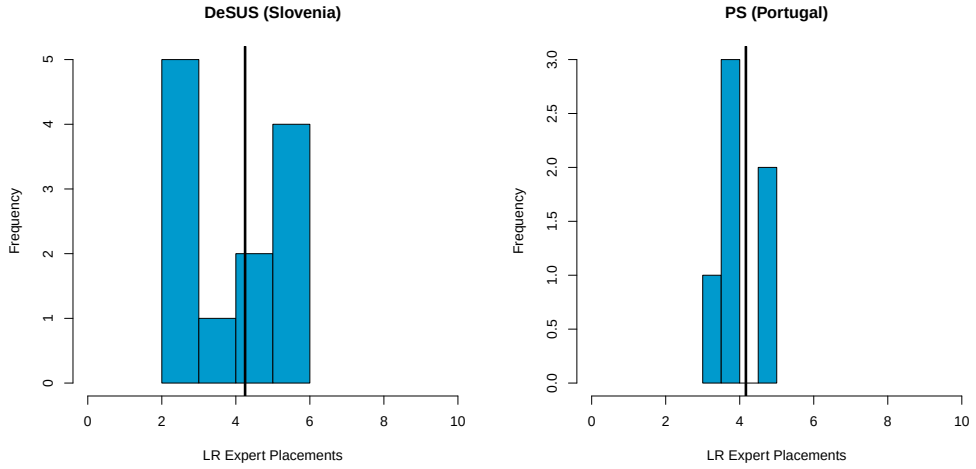


(c) EU Salience

Figure 1: *Distribution of expert responses on select EU-related dimensions.*



(a) Left/Right Economic Policy



(b) Left/Right General

Figure 2: *Distribution of expert responses on select left-right dimensions.*

4 Measures of Agreement and Reliability

The political science literature has largely confined itself to looking at expert placement means, standard deviations, and standard errors.[3] Beyond political science, though, a large literature in (organizational) psychology and medicine seeks to understand how to best assess agreement and reliability in responses to particular (survey) items. The same issues that crop up in political science expert surveys arise in any analysis in which K raters score N targets on J items. In medicine, multiple doctors may rate patients on several scales to arrive at a diagnosis. In organizational psychology, researchers often ask employees at a firm about their perceptions of various items, such as the firm's adequacy in handling consumer complaints, on a Likert scale. In these examples, the doctors and employees are equivalent to our experts, the patients and firm equivalent to our parties, and the various scales, to our dimensions.

The literature makes a significant distinction between reliability and agreement. Kozlowski and Hattrup (1992, pp. 162–63) describe reliability "as an index of consistency; it references proportional consistency of variance among raters [...] and is correlational in nature [...]. In contrast, agreement references the interchangeability among raters; it addresses the extent to which raters make essentially the same ratings." In other words, reliability is concerned with the equivalence of *relative* ratings of experts across items, whereas agreement refers to the absolute consensus among raters on one or more items (LeBreton and Senter, 2008, p. 816). Thus, there could be relatively high reliability among raters, but low agreement. For example, all raters may rate party A higher than party B than party C, but they may use the scale differently. On an eleven point 0–10 left-right scale, perhaps Rater 1 assigns a 10, 8, and 6 to parties A, B and C respectively; Rater 2 assigns them scores of 8, 6, and 4; and Rater 3 rates them 4, 2, and 0. There would be perfect reliability among these scores, but little agreement. It is worth noting that reliability can only be assessed when the

[3]One exception is van der Eijk (2001), who constructs an agreement index, which we will discuss below.

same raters rate multiple targets (e.g., parties), and thus can only be assessed at the item level. Agreement, in contrast, can be assessed at the target-item level.

We discussed above that the literature on interrater agreement has deemed the standard error to be an inappropriate measure of agreement, but it also suggests that the standard deviation is not much better. The standard deviation is a measure of dispersion, rather than agreement. There are two primary drawbacks to the standard deviation as a measure of agreement (Kozlowski and Hattrup, 1992). First, the standard deviation is scale-dependent — items assessed on a Likert scale ranging from 0–10 will likely have a smaller standard deviation than those assessed on a 0–100 scale — such that we can only compare standard deviations of items that are measured on the same scale. Second, it does not account for within-group agreement that could occur due to chance. The most common measure of agreement, the r_{wg} (Finn, 1970; James, Demaree and Wolf, 1984), does both by examining the dispersion of responses with reference to a null distribution. It is calculated as

$$r_{wg} = 1 - \frac{S_x^2}{\sigma_E^2}, \tag{1}$$

where S_x^2 is the observed variance of expert response on the item x, and σ_E^2 is the expected variance when there is a complete lack of agreement among experts.[4] The measure ranges from 0 (no agreement) to 1 (perfect agreement) and can be interpreted as the proportional reduction in error variance.[5] Of course, r_{wg} requires researchers to choose an appropriate null distribution. In practice, researchers typically use a rectangular or uniform distribution, estimated as $\frac{A^2-1}{12}$, where A is the number of response options. But any number of distri-

[4]One could also calculate agreement across multiple items, using the $r_{wg}(j)$ measure, if the items were essentially parallel, meaning that they measure the same construct. Given that most items in political science surveys tap into different dimensions, this measure is less appropriate for our purposes.

[5]In rare instances, it could be negative, meaning there is more observed variance than we would expect according to the assumption of the null distribution. In these instances, it is usually truncated at zero.

butions could be used, and ideally one's results would be robust to the choice of the null distribution (Meyer et al., 2014). At the moment, we use the rectangular distribution as the null distribution.

The r_{wg} measure captures agreement, but does not take into account differences in how raters may use the scale. For that, we need a measure of reliability, which examines how judges place multiple targets. Here we use a measure of intraclass correlation. In particular, we employ a two-way mixed-effects intraclass correlation coefficient. This measure is appropriate when a fixed set of K judges assesses multiple targets on multiple items. It is calculated as follows

$$ICC = \frac{MS_R - MS_E}{MS_R + (K-1)MS_E + \frac{K}{N}(MS_C - MS_E)}, \tag{2}$$

where MS_R is the mean square of the targets, MS_C is the mean square for the judges, and MS_E is the mean square error (LeBreton and Senter, 2008). This measure captures both the consensus among as well as the consistency across judges. In effect, if we knew that judges used the scales in the same manner, we could arrive at the same answer by simply aggregating the r_{wg} scores over the targets on each item.

5 Application to the Chapel Hill Expert Survey

We now apply these measures of agreement and reliability to the 2010 CHES expert survey discussed above. We first calculate the r_{wg} measure, which captures agreement only. The advantage of the r_{wg} coefficient is that, since we are only concerned with agreement and not reliability, it can be applied to the party-dimension level. The disadvantage, of course, is that it cannot account for differences in how experts use the scale (i.e., reliability). We use box plots to display the distribution of r_{wg} coefficients by dimension across parties and by party across dimensions. These plots are displayed in Figures 3 and 4. There are no hard and fast rules as to what constitutes an acceptable level of agreement, but the extant literature often

considers scores in excess of 0.7 to be indicative of strong agreement and scores below 0.5 of weak agreement. In Figures 3 and 4, these two cut-off values are demarcated with vertical dashed lines.

The first plot, Figure 3a, displays a box plot for each party in the CHES data. Due to the large number of parties, it is difficult to assess how any particular party is measured. Thus, we suppress the party names on the y-axis and do not plot outlying points in this figure. The purpose of the plot is not to see where individual parties lie, but rather to show the overall distribution of the levels of agreement across all parties. The plot does show that there are many parties for which the median r_{wg} over the dimensions is quite a bit better than the 0.7 cut-off for strong agreement. It is also worth noting that even for the parties on which experts agree quite often, there are many dimensions with agreement scores in the moderate or even poor range. There are also many party-dimensions for which there is only moderate or poor agreement. Figure 3b presents box plots by dimension. Again, we see that there is particularly low agreement on the salience items. Figure 4 plots the best performing parties (i.e., those with a median dimension $r_{wg} > 0.75$) and the worst performing parties (i.e., those with a median $r_{wg} < 0.55$).

Most of the parties with the highest levels of agreement are found in northern and western Europe. However, some parties in post-communist countries also show high levels of agreement, namely some Latvian, Czech, and Slovenian parties. The parties with the lowest levels of agreement among experts are found in southern and eastern Europe. There is virtually no agreement on the positions of the Turkish parties on many dimensions. But even here, there is strong agreement on certain items for certain parties. For example, on the CHES *galtan* dimension (Green/Alternative/Libertarian to Traditional/Authoritarian/Nationalist), the ruling AK party, the MHP, the DYP and the Greens all display high agreement, while the CHP and BDP display virtually no agreement at all. Thus, while there appears to be agreement with respect to the center-right Islamist parties AKP and DYP, the ultranationalist MHP, and the Greens, there is little agreement on the secular CHP, which ruled Turkey

for much of the post-war era, or the Kurdish BDP. Interestingly, while in most countries the left-right general and left-right economics dimensions display more agreement than the *galtan* dimension, in Turkey, with the exception of the AKP, experts display higher levels of agreement on the *galtan* dimension than on either of the left-right dimensions.

We next calculate the intraclass correlation coefficient (ICC), which accounts for both agreement and reliability (i.e., scale shifts across experts). As discussed above, we use a two-way mixed-effects ICC. Because we assess expert placements across parties, the coefficients are measured at the level of country-dimension. We again plot the results in two different ways. Using box plots, we first examine the distribution of ICC coefficients within country and across dimensions (Figure 5a) and then within dimension across countries (Figure 5b).

The distributions of ICC coefficients reveal interesting trends, similar to those found using the agreement scores. ICC is higher in virtually every EU15 state compared with new members from Eastern Europe, with particularly low ICCs in Romania. With respect to dimension, *Left-Right General* is the best-measured dimension based on ICC. Other dimensions, including *immigration policy*, *taxes vs. spending*, *religious principles*, *left-right economics*, *galtan*, and *EU position*, perform also quite well. There is less agreement among and reliability across experts when considering salience items and items, such as intra-party dissent on EU integration. It should be noted, though, that parties with missing data on any dimension are not included in the analysis. On average, 3.66 fewer parties per country-dimension are included in our analysis than are scored in the original data. In future work, we will examine various methods to handle missing data. If anything, dropping these parties biases our results towards finding more agreement and reliability than actually exists, since parties about which experts have less information are more likely to have missing values.

6 Including Uncertainty in Secondary Analysis via the Bootstrap

The R_{wg} and ICC coefficients provide a useful means to assess the extent of measurement error in expert surveys across different parties and policy dimensions. Once we know that a lack of agreement among experts exists, we would ideally take this information into account when building empirical models. However, researchers do not incorporate the information contained in these coefficients into analyses in a straightforward manner. Existing approaches to handling measurement error require finding an appropriate instrument for the poorly measured variable (Hausman, 2001), or using an estimate of the measurement error in a simulation-extrapolation (SIMEX) model (Cook and Stefanski, 1994). In the case of expert positions, we often have neither of these. Matters are complicated if the quantity of interest in the secondary analysis relies on a transformation of party positions, such as party system polarization or shifts in party positions between elections. Because not all parties are equally well measured, we do not know *a priori* how variation across expert placements affects such derived measures.

To account for uncertainty around expert placements of parties, we propose a simple solution: bootstrapping observed expert responses by sampling with replacement from the observed expert responses. Through a non-parametric bootstrap we can generate n expert datasets and calculate any quantity of interest within them (e.g. mean expert placements, party system polarization, etc.). Any regression analysis using expert placements, or a derivation thereof, as an independent variable can then be conducted n times using the simulated values of the expert placements. The coefficients and their associated uncertainty estimates across these n models can then be averaged just as one would do with multiply imputed datasets when faced missing data. Indeed, missing data can be thought of as a special case of measurement error (Blackwell, Honaker and King, 2014). This approach is also similar to the Monte Carlo approach taken by Treier and Jackman (2008) to account for

the measurement error associated with a variable measured using a Bayesian measurement model.

Party System Polarization

Measuring party system polarization has a long tradition in the comparative literature on party politics (e.g. Taylor and Herman, 1971; Gross and Sigelman, 1984; Alvarez and Nagler, 2004; Sartori, 2005; Dalton, 2008; Rehm and Reilly, 2010). In their study on the effects of elite communication over European integration on public opinion, Gabel and Scheve (2007) rely on expert surveys to calculate polarization measures for several European countries. Following Warwick (1994), they calculate the weighted standard deviation of party positions in each country k as follows:

$$\text{Polarization}_k = \sqrt{\sum_{j=1}^{N} v_j (x_{jk} - \bar{x}_k)^2},$$

where v_j is the j-th party's share of the vote in country k with N parties (excluding parties who do not receive any votes), x_{jk} is the placement of the j-th party on European integration by the experts, and $\bar{x}_k$ is the weighed mean of parties on European integration, where each party is weighted by its vote share.[6] Gabel and Scheve calculate these measures using data from the Chapel Hill expert survey (Steenbergen and Marks, 2007).

We replicate the polarization measures for the 1999 Chapel Hill survey and generate confidence intervals for them using 100 bootstrapped expert datasets. The average bootstrapped polarization measure correlates with their original measure at 0.97. Figure 6 shows the bootstrapped mean estimates and the confidence intervals, which correspond to the 2.5-th and 97.5-th percentile of the bootstrapped polarization measure. When we take into account the uncertainty in expert placements, there are a number of countries for which we

[6]The equation in footnote 4 in their paper erroneously mentions the mean instead of the weighted mean.

cannot safely conclude that their polarization measures are different from each other. For instance, Belgium is estimated to have a mean polarization measure that is forty percent *greater* than Spain's. However, on the basis of the variability of expert placements for some of the parties, we actually cannot reject the null hypothesis that the two measures are identical. Not all countries are equally affected by measurement error. For instance, elite polarization on European integration is well measured in Denmark, Germany, and Greece, but poorly measured in countries such as Finland, Spain, and United Kingdom. In sum, these results demonstrate that a simple incorporation of the measurement uncertainty can translate into sizable measurement error in a derived variable such as party system polarization.

Party Position Shifts

The Chapel Hill surveys have also recently been used to answer questions about mass-elite linkages. Here, we look at one particular study from this literature by Adams, Ezrow and Somer-Topcu (2014), who propose an innovative research design to improve our understanding of how citizens update their views on parties' policy positions. Specifically, their argument states that citizens, rather than relying on party manifestos to update their information on party policy positions — a view that has had a long tradition in the extant literature —, draw on a variety of information sources when updating their beliefs.

Clearly, testing this proposition using standard mass survey instruments would be quite difficult (though, probably not impossible), which is why Adams, Ezrow and Somer-Topcu use expert opinions from the Chapel Hill surveys as a proxy for broad information gathering and contrast it with the more narrow approach of relying on party manifestos. In particular, they hypothesize that if mass public opinion on party policy shifts more closely tracks expert opinions on these shifts than policy shifts derived from party manifestos, then this suggests that citizens rely on multiple information sources. Their empirical analysis confirms the hypothesis, and the finding is an important contribution to the ongoing debate about political sophistication of citizens.

Table 1: *Analyses of Citizens' Perceptions of Parties' Policy Shifts on European Integration (Adams, Ezrow and Somer-Topcu, 2014).*

	W/O Clustered SE	**Clustered SE**	**Bootstrapped**
Party j's perceived shift	0.263	0.263	0.211
– experts (t)	(0.092)	(0.082)	(0.092)
Party j's shift	−0.192	−0.192	−0.183
– Euromanifestos (t)	(0.170)	(0.137)	(0.175)
Intercept	0.138	0.138	0.136
	(0.069)	(0.062)	(0.071)
Adjusted R^2	0.0848	0.0848	
N	78	78	78

Of course, the concern is that measurement error resulting from aggregating potentially divergent expert opinions on party policy shifts drives these results. To address this question, we applied the same bootstrap method described above to Adams, Ezrow and Somer-Topcu analysis. We present the results of our empirical analysis in Table 1.

Specifically, we estimate three different models. The first model in Table 1 replicates the *Multivariate Model (3)* in Adams, Ezrow and Somer-Topcu, but without clustering. The second model in Table 1 uses clustered standard errors and therefore is an exact replication of their *Multivariate Model (3)*. Comparing the results from these two regressions clearly shows that the clustering has very little effect on the standard errors, and the substantive results do not change across these two regressions (i.e., no changes in statistical significance). As such, we proceed to estimate the third model in Table 1, which summarizes the coefficients and standard errors from 100 bootstrap regressions, without clustering.

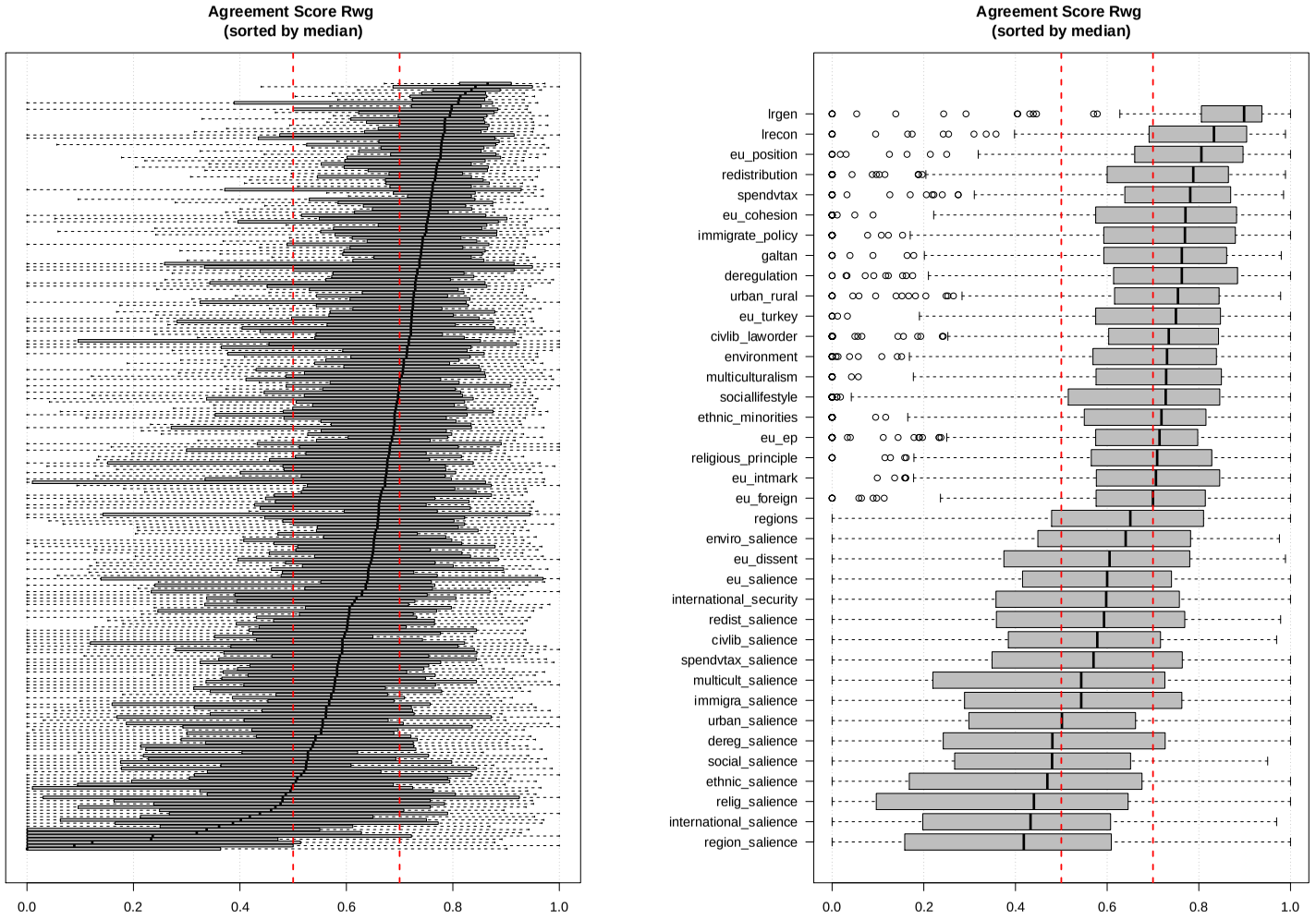
The first thing to notice in Table 1 is that the results are remarkably robust, giving additional credence to the findings by Adams, Ezrow and Somer-Topcu. Yet, taking a closer look at the bootstrapped results also shows that the coefficient is smaller and standard error estimates are larger than in the original regression. Stated differently, on average, our model would predict a weaker effect of the expert variable with more uncertainty. While the

substantive results do not change with this application, the increase in uncertainty around the estimates should give us pause for using aggregate expert opinions in our regressions without considering the level of disagreement among experts.

7 Conclusion

Political scientists make frequent use of expert surveys, but have not properly examined agreement and reliability within these surveys. A vast literature in organizational psychology and medicine provides us with the tools to assess the degree to which experts can capture the latent dimensions of party politics that are of interest to political scientists. In this paper, we have applied these techniques to one particularly prominent expert survey. The methods, though, are very general and can be applied in any number of settings. The analysis has clearly uncovered that the positions of some parties and on some dimensions are clearly easier to assess than others. General items, such as left-right general, left-right economic policy, and position with respect to EU integration, are clearly easier to capture than more specific items. In addition, positions are clearly easier to gauge than saliency. Lastly, experts in advanced industrialized countries are better able to capture parties in their countries compared with experts from newer, post-communist democracies. Because experts only rank parties in one country — the country where they have the greatest expertise — we cannot say whether this is a function of the experts, the parties they are asked to rate, or both.

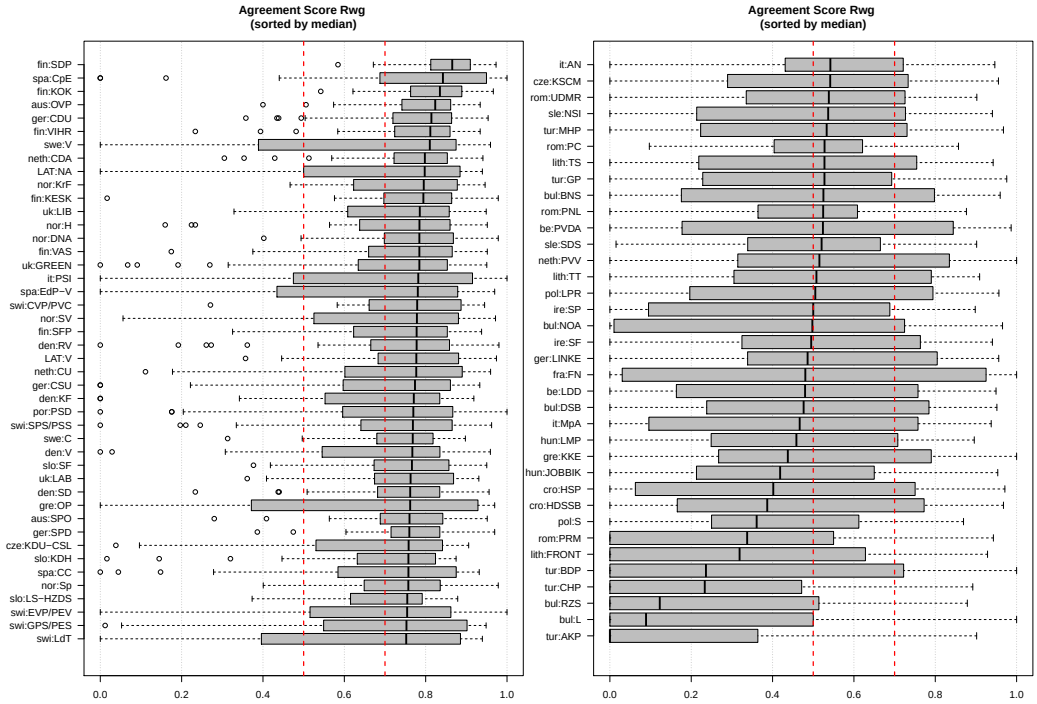
In future iterations, we plan to examine the effect of relaxing the assumption about the null distribution. Lastly, we will account for missing data in the bootstrap procedure. In doing so, we will be able to make recommendations to researchers looking to conduct expert surveys with regard to how many experts they should ask and what type of items are most accurately assessed.



(a) R_{wg} by Party

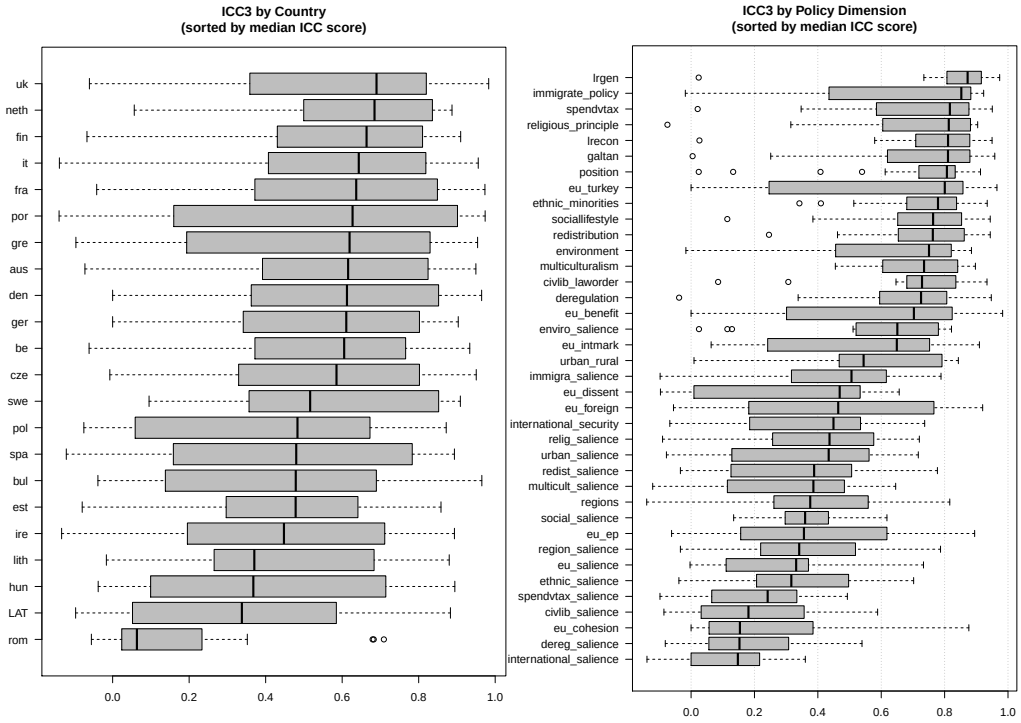
(b) R_{wg} by Dimension

Figure 3: *R_{wg} by party and dimension.*



(a) Median $R_{wg} > 0.75$ (b) Median $R_{wg} < 0.55$

Figure 4: *R_{wg} by party — best and worst.*



(a) ICC by Country (b) ICC by Dimension

Figure 5: *Intraclass correlation coefficients (ICCs) by country and dimension.*

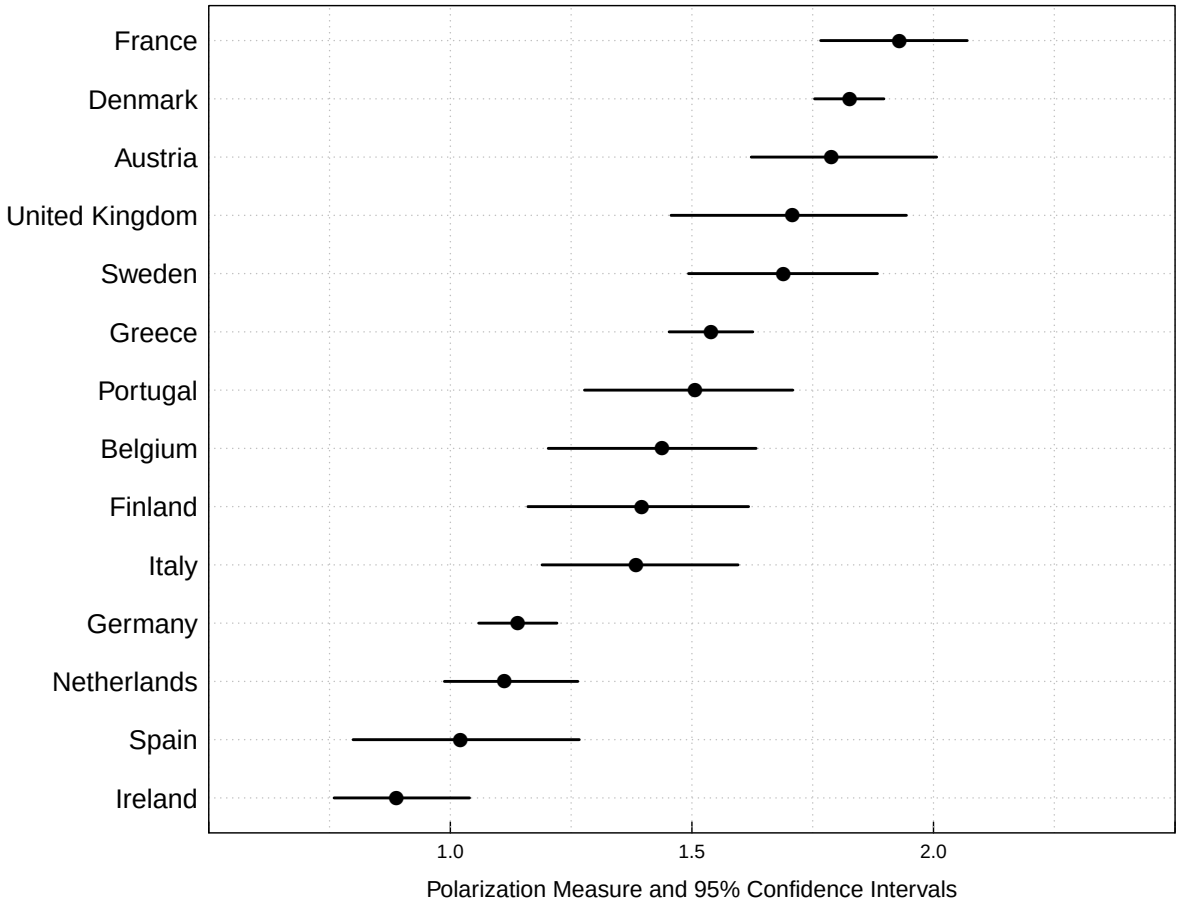


Figure 6: Party System Polarization with Boostrapped Confidence Intervals

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