A Global Scale of Economic Left-Right Party Positions

Cross-National and Cross-Expert Perceptions of Party Placements

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Abstract: We examine the cross-national comparability of expert placements of political parties on the economic left-right dimension using a novel dataset combining data from Europe, Latin America, Australia, Israel, Canada, and the United States. Using anchoring vignettes and Bayesian Aldrich-McKelvey Scaling (BAM), we assess evidence of geographic and expert-level differential item functioning (DIF) in how experts interpret the left-right scale. We find statistically significant but substantively small variations in how experts perceive party positions cross-nationally, particularly in terms of directional bias and the spread of their ideological placements. While the correlation between "raw" survey scores and DIF-corrected estimates is high (0.992), we observe meaningful deviations for individual parties, with larger discrepancies between rather than within regions. These results indicate that the economic left-right dimension exhibits broad consistency in expert understanding across countries, yet researchers should still exercise caution when making cross-national comparisons, particularly across regions where expert perceptions show greater variation.

Keywords: Expert Surveys; Ideology; Left-Right; Bayesian Aldrich–McKelvey scaling.

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Can we accurately compare the positions of political parties across different contexts? Is it feasible to place political parties from different countries on a single economic ideological dimension? How can we reliably assess whether the British Conservative Party is to the right of the American Republican Party or if the Chilean Communist Party is further left than Podemos in Spain?

Expert surveys provide a valuable tool for answering these questions by applying a consistent set of questions across different countries (Benoit and Laver 2007; Düpont et al. 2022; McElroy and Benoit 2010). However, it is unclear to what extent party placements are truly comparable across different contexts, since experts' perceptions of political parties can be influenced by contextual and individual-level differences (Hare et al. 2015; Martínez I Coma and Van Ham 2015; Zechmeister 2006). This concern has grown with the global expansion of expert surveys like CHES, V-Party, and GPS (Düpont et al. 2022; Martínez-Gallardo et al. 2023; Norris 2020). While prior research on CHES data in Europe suggests high levels of cross-national comparability (Bakker et al. 2014; Bakker, Jolly, and Polk 2022), indicating robustness to contextual effects (Albright and Mair 2011), systematic assessment of economic left-right placements beyond Europe remains limited.

Differences in how stimuli are perceived can be conceptualized as differential item functioning (DIF), occurring when experts perceive scales differently due to geographic or personal characteristics (Bølstad 2024; Marquardt and Pemstein 2018). Assessing DIF in expert surveys is challenging since respondents typically evaluate country-specific parties, resulting in data sets lacking common reference points. The CHES survey addresses this by incorporating "anchoring vignettes," hypothetical political parties presented identically to all experts. These vignettes allow researchers to isolate systematic perception differences arising from geography or individual characteristics.

Using CHES vignettes, we assess the comparability of party placements on the economic left-right continuum. We employ Bayesian Aldrich-McKelvey (BAM) models to achieve two goals: (1) placing parties on a globally comparable ideological scale and (2) examining sources of expert bias. We anticipate that the economic left-right dimension will translate well across borders due to its relative simplicity, though systematic regional and individual-level differences may persist. For instance, U.S. experts may exhibit a right-wing bias, positioning parties further left than experts elsewhere, while Latin American experts may exhibit the opposite trend (Lührmann et al. 2020; Martínez-Gallardo et al. 2023; Norris 2020).

Our findings contribute to three key areas. First, we show that raw and BAM-corrected scores are highly correlated (ρ=0.992), suggesting broad consistency in expert placements but revealing systematic DIF across regions and parties. These findings indicate that while cross-national comparisons are feasible, they still require careful implementation, particularly when comparing parties across different regions, where expert perceptions show the greatest variation. Second, by analyzing expert-level distortion parameters (stretch and shift) from the BAM model, we demonstrate the utility of this approach in studying perceptual biases. This methodology can extend beyond party competition to study ideological biases in mass opinion surveys. Finally, and significantly for users of the Chapel Hill Expert Survey, we provide fully comparable BAM-corrected estimates of left-right economic party positions across a wide geographical range, from Australia to Israel to Europe to the Americas. While these corrected scores offer optimal cross-regional comparability by accounting for systematic perceptual differences, our findings suggest that raw left-right placements can also be meaningfully interpreted, particularly within geographic regions where expert perceptions show greater consistency

Why Examine the Cross-National Comparability of Party Positions?

Political scientists regularly make assertions about the relative ideological positions of parties across national borders. In comparative research, we might examine whether global economic downturns shift parties to the left (Haupt 2010). In public commentary, we might want to compare domestic policy positions to international norms. When we use data derived from expert surveys to make these kinds of assessments, we make two key assumptions about comparability: first, that there exist agreed-upon understandings of concepts such as left and right that transcend national and regional boundaries; second, that political experts are free from systematic ideological predispositions that might bias their responses.

Regarding the first assumption, Budge (2000) warns that "it may be that the same criteria underlie the locations of parties when experts are asked to place them from Left to Right. But they may not. We do not know." As for the second, evidence to date has shown that, for example, almost 16 percent of experts who participated in the Benoit and Laver (2007) classic comparative study of party positions demonstrated ideological biases affecting their responses (Curini 2010). In light of these concerns, this paper examines both potential sources of bias in the Chapel Hill Expert Survey dataset, with a view to both identifying and correcting any systematic error.

This exercise has significant implications for social scientists interested in comparative political party competition and policy output. Although these phenomena are usually nationally circumscribed, we identify at least three important reasons to be concerned with the comparability of national-level estimates of party positions: first, the emergence of transnational party competition, second, the increasingly prominent evidence that party policy diffuses across national borders, i.e., that political parties learn from and adopt what are seen as successful policy positions from parties outside their country, and third, the importance of international coalitions in solving transnational problems. We briefly discuss each in turn.

One of the most prominent examples of transnational party competition is the European Parliament (EP). While EP elections are still conducted domestically, with electoral lists created by the political parties of each Member State, the elected Members of European Parliament (MEPs) are organized according to transnational political groups, defined by shared ideology (McElroy and Benoit 2010). Furthermore, the EP itself is structured by the left-right dimension (Mair and Thomassen 2010). In the more intergovernmental Council of the European Union, the relevance of the ideological orientations of national governments for legislative cooperation is more debated, but even here recent evidence indicates that party ideology affects the formation of cooperative ties between countries (Huhe et al. 2022). Thus, for the countries within the European Union, the relevance of cross-nationally comparable estimates of party positions for understanding transnational political competition is clear.

Another dynamic area of recent party politics scholarship focuses on the ability of parties to learn from and emulate successful foreign incumbent parties, referred to as party policy diffusion (Böhmelt et al. 2016). From the analyst's perspective, if we are to understand and explain this process of party diffusion across national boundaries, we must have confidence in the underlying comparability of our estimates of party ideology. Although much of the party policy diffusion research is based on EU members,[1] there are solid grounds for expecting it to be a wider phenomenon. Social democratic parties, for example,

[1] For instance, Senninger and co-authors (2022) show that being in the same EP political group enhances learning and emulation between national political parties.

are particularly poised to pick up on cross-national policy diffusion from within their party family because the center-left has faced sustained and major competitive challenges and because social democrats possess strong transnational organizations (Schleiter et al. 2021). This suggests that social democratic or affiliated parties outside of Europe could also participate in this cross-national diffusion.

The cross-national collaboration of far-right parties also highlights the relevance of party policy diffusion beyond Europe. For example, Donald Trump's loss in the 2020 USA presidential election had a sizeable negative effect on voting intentions for Spain's new far-right party, VOX (Turnbull-Dugarte and Rama 2022). Scholars of the phenomenon in Central and Eastern Europe draw attention to the centrality of similar underpinning ideologies and regional affinities that facilitate cross-border learning from backsliders (Kelemen, 2017; Vachudova, 2021). Empirical analyses indicate that far-right transnational diffusion is facilitated by geographic and cultural proximity (Roumanias, Rori, and Georgiadou 2022), but this suggests that the extensive colonial legacies of European countries throughout the globe could be an important alternative source of cultural proximity.

Finally, the nature and scope of the most pressing challenges of our era point toward the importance of transnational politics. Climate change, asylum policy, and international commerce cannot be contained within or managed by a single country. These policy areas require deep, coordinated cooperation between political actors, and the construction of new, multinational coalitions. To fully understand the makeup and success of these new coalitions, we require comparability in our estimates of party ideologies.

The Search for Differential Item Functioning (DIF)

The most recent waves of the CHES data, conducted in Australia (2021), Canada

(2023), Europe (2019), Israel (2022), Latin America (2021), and the United States (2020), incorporated anchoring vignettes for three hypothetical parties' economic left-right positions. These vignettes consist of concise statements describing key characteristics of each political party. They are designed to be easily placed along a continuum from left to right, with the correct ordering being A-C-B.

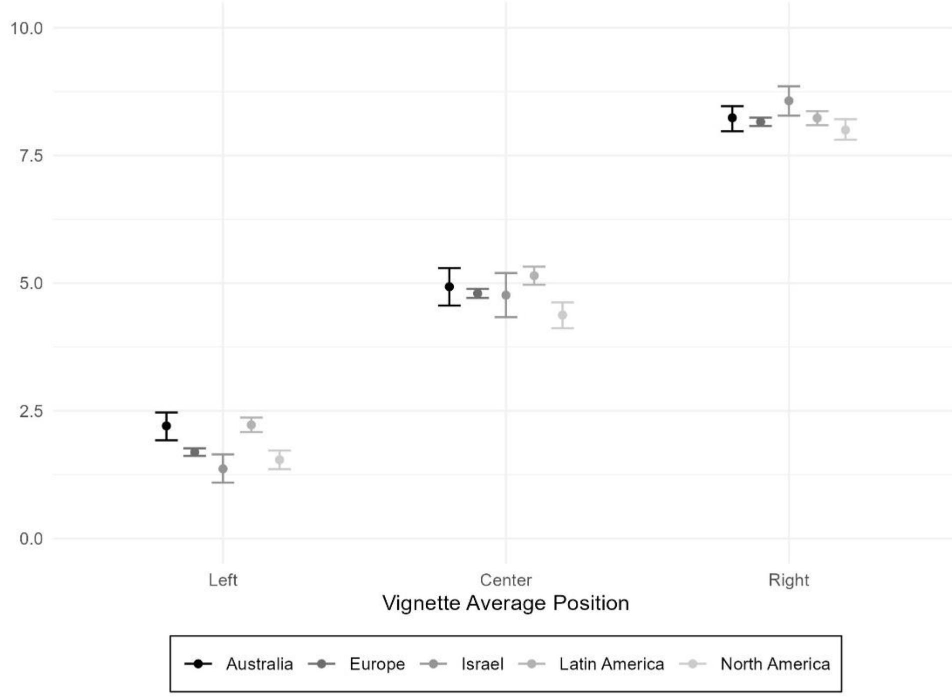
Table 1: Hypothetical Parties Vignettes

Party A supports a strong role for government in redistributing wealth, protecting jobs, and regulating business. It favors steeply progressive taxes to fund social programs.
Party B believes in small government. It favors minimal regulation of business, supports the privatization of many government operations, and opposes high taxes.
Party C advocates welfare policies within a market economy. This party supports social investment in education and health to spread individual opportunity.

Experts were instructed to place these hypothetical parties on a scale ranging from 0 (extreme left) to 10 (extreme right), matching the scale used in their respective countries. The text of the three vignettes is presented in Table *1*.

Combining the survey data from the above-mentioned regions yields a comprehensive dataset encompassing 434 parties from 48 countries. Using just the vignette placements, we can preliminarily assess whether our initial expectations about geographical DIF are supported by the data. That is, we can aggregate the vignette placements to the region/country level and lookfor any systematic differences.

Figure 1: Average Vignette Party Position by Region



Note: 95% confidence intervals estimated using non-parametric bootstrap.

The first step in analyzing vignette placements is to verify whether respondents correctly perceived the ordering of the vignette parties. Experts who mis-ordered the vignette parties were excluded from the analysis due to a presumed misunderstanding of the scale and related methodological concerns (discussed later). Out of the initial 735 experts, 53 did not respond to any vignette questions, 8 mis-ordered the vignettes, and 8 responded to fewer than 3 stimuli. Consequently, our final dataset comprises placements from 666 experts.

The next step is to compare the placements of the three vignette parties across regions and countries.[2] In Figure 1, we present the mean and 95% confidence interval of the vignette party placements across regions.[3] The consistent ordering of the vignette parties is evident across regions, but there are notable differences in the specific placements of each

[2] We treat single country cases (Australia and Israel) as both a country and a region in subsequent analyses.
[3] Mexico was categorized as a Latin American country.

hypothetical party. Most striking is the placement of the Center party by the North American experts. North American experts view this party as considerably more left-wing than their counterparts from Australia, Europe, Israel, and Latin America, supporting the hypothesis that North American experts, or as Figure A2 shows, US experts in particular, are more prone to place parties further to the left. The vignette with the most variation in terms of expert placements is the Left party. Compared to European experts, Australian and Latin American experts tend to see this hypothetical party as slightly more moderate, whereas experts from North America and Israel see this party as being slightly more extreme. Finally, by comparing levels of uncertainty around the estimates in Figure 1, it is also clear that European experts tend to be in closer agreement with one another than experts from other regions. Even though this is, in part, a function of the fact that there are more European experts than in the other regions, sample size alone does not explain this difference.

Figure A2, available in the supplemental material, displays the same information at the country, rather than the regional level. There are several interesting results to notice from Figure A2. For example, Danish experts place the right-wing vignette party further right than experts from other countries, likely reflecting their vantage point of living in a state with a more generous set of welfare programs. The opposite is true for US experts and the center and left parties. As expected, we also find that Latin American experts tend to place parties further to the right. The relevant observed differences across regions and countries regarding the placement of the three hypothetical parties bring into question the cross-national comparability of experts' placements on the left-right economic dimension. In the next section we directly address this question.

Methods: Bayesian Aldrich-McKelvey Scaling

In this section, we move beyond descriptive analysis to rigorously assess potential sources of DIF in experts' placements. While we acknowledge the merits of other methods such as nonparametric techniques (King and Wand 2007), black-box scaling (Bakker et al. 2014), or Item Response Theory (IRT) models (Marquardt and Pemstein 2018), our analysis employs the Bayesian implementation of the Aldrich-McKelvey (A-M) scaling routine. This method was initially introduced by Hare et al. (2015), previously used on CHES' European data (Bakker, Jolly, and Polk 2022), and further extended into a hierarchical framework by Bølstad (2024). A key advantage of this approach lies in its capacity to assess the sources of DIF through its two main distortion parameters—shift and stretch (discussed below)—which can be subsequently modeled. Accordingly, this approach not only enables us to identify and quantify DIF, but also provides a useful empirical framework for understanding its underlying causes.

Aldrich and McKelvey (1977) introduced a scaling routine designed to place respondents and stimuli on a common scale while controlling for DIF. Their application used US public opinion data, where respondents placed themselves and political candidates on an ideological scale. The primary concern regarding DIF was that people of differing ideological positions may perceive the underlying scale differently; specifically, those on the far-left placing stimuli further to the right, while those on the far right placing it further to the left.

The A-M model operates under the assumption that respondents' placements of the stimuli are imperfect perceptions of the true stimuli positions. To correct for these biases, the model features respondent-level parameters that map individual perceptions of stimuli positions to the true stimuli positions. The basic model is[4]:

$$Y_{ij} = \alpha_i + \beta_i X_j + \varepsilon_{ij}$$

Where Y_{ij} is expert i's placement of party j, α_i and β_i are individual distortion parameters (shift and spread, respectively), X_j is a true stimulus position, and e_{ij} is the error associated with the placements.[5] The true stimulus position is thus defined as the mean placement of political parties absent of any expert-level perceptual distortions. The use of anchoring vignettes allows us to estimate these two expert-level distortion parameters because they constitute common reference points. In turn, we can use these two parameters to derive the true position of all political parties on a single, common, comparable scale.

Estimating this model presents significant challenges, as all variables on the right-hand side of the equation are unobserved. However, the Bayesian implementation offers a relatively straightforward solution with two key advantages over the classic A-M solution. First, while the classic A-M method cannot handle missing data, defaulting to listwise deletion, the Bayesian implementation can accommodate incomplete datasets. This is of particular relevance for the CHES data since it contains substantial amounts of missingness, making the frequentist A-M approach unsuitable for our analysis. Second, unlike the classic A-M method, the Bayesian implementation provides measures of uncertainty. Using BAM we can quantify the political parties' stimuli positions and measures of uncertainty around these estimates.

We estimated three different versions of the Bayesian Aldrich-Mckelvey model to

[4] In their original formulation, the A-M model was expressed using this slightly different equation and notation: $\alpha_i + \beta_i Z_{ji} = Z_j + u_{ij}$.

[5] The terms "spread" and "shift" are further explained in the section titled "Examining Perceptual Biases Among Experts."

estimate party positions from expert placements. Our baseline specification employs uniform prior distributions for the distortion parameters (shift and stretch). This model closely resembles previous implementations by Hare et al. (2015) in the United States and Bakker et al.(2022) in Europe. Following these studies, we employed uninformative priors on α and β [U(-100, 100)] and set the polarity of the scale by constraining the left- and right-wing anchoring vignette stimuli to lie between [-1.3 and -1.2] and [1.2 and 1.3] respectively. We derived these constrained intervals from the average standardized placements of the left and right stimuli [-1.26 and 1.22 respectively]. The priors on these parameters are formally specified in the supplemental material.

We employed a hierarchical error structure where we decomposed observation-specific variance (σ_{ij}) into expert (σ_i) and party (σ_j) specific components. These components were parametrized using non-centered parametrization to aid with computational efficiency and sampling behavior. The components were parameterized as $\sigma_i = \sigma \cdot \exp(\tau_i \cdot \sigma_{i\_raw})$ and $\sigma_j = \sigma \cdot \exp(\tau_j \cdot \sigma_{j\_raw})$ where σ represents a global average and the $(\tau_i \cdot \sigma_{i\_raw})$ and $(\tau_j \cdot \sigma_{j\_raw})$ represent the expert and party-specific deviations from the global σ[6]. This structure reflects two key insights about measurement error in expert placements: some experts may provide more precise estimates than others, and some parties may be more difficult to place than others on the ideological spectrum.

We specified a $\sigma \sim N(0,2)$ for the global error reflecting our expectation that most expert placements fall within two standard deviations on the standardized scale. Given the high degree of within-party agreement amongst experts on the raw data, this prior is both

[6] The non-centered parameterization is mathematically equivalent to the centered parameterization. However, it significantly improves the efficiency of Markov Chain Monte Carlo (MCMC) sampling by enhancing mixing, reducing autocorrelation, and accelerating convergence.

reasonable and well-justified. Additionally, we informed our prior specifications using results from a preliminary model with only global error with prior $\sigma \sim N(0,3)$, which estimated a posterior global error of 0.429 [0.421-0.437 95% Credible Intervals]. For σ_{i_raw}, σ_{j_raw}, τ_i, and τ_j which represent relative differences or random effects between units (coders or parties), we used standard normal distributions. The formal specification for the error term priors is available in the supplemental material.

Before estimating the model, we standardized the observed party positions, removed experts with less than 3 total and 2 unique placements to aid with identification, and then implemented the model using **Stan** in **R** for 4,000 iterations discarding the first 2,000 as warmup.[7] All parameters showed strong evidence of convergence according to the R-hat value, effective sample size, and graphical inspection of posterior density plots.[8]

Following Bølstad's (2024) recommendations, we additionally estimated two hierarchical versions of the BAM model. As previously discussed, in the original specification of the BAM model, each expert's parameters are drawn from uniform independent distributions. In contrast, in the hierarchical versions of the model, all expert parameters are drawn from a common distribution, thus allowing for pooling across cases. We estimated two versions of the Hierarchical Bayesian Aldrich-McKelvey model (HBAM). In the first specification expert-level parameters are drawn from a distribution common to all respondents. The second version models differences between groups, in this case, countries, since the expert-level parameters are set to be drawn from country-specific

[7] We addressed missingness by preprocessing the data and omitting missing values from the dataset used as an input in the Stan model. This approach is similar to full information maximum likelihood in the sense that all the available information is used to estimate the model.
[8] For more details regarding this model, see supplemental material..

distributions. Both models were estimated using the HBAM R package.[9]

The results presented below are based on the unregularized version of the model, which closely resembles the modelling strategy implemented by Hare et al. (2015). While we agree with Bølstad that a hierarchical version of the BAM model introduces several advantages, particularly regarding model fit and regularization of the estimated parameters, we believe that the Hare et al.'s version is better suited for our goals. The HBAM model minimizes the risk of overfitting, making the estimates less sensitive to error. However, like all hierarchical models, it also has the potential for shrinkage toward the prior mean, thus limiting the amount of DIF that we might otherwise detect. If the interest is in extracting a DIF-free version of the latent variable, the Bølstad hierarchical specification would almost certainly be superior to the original BAM model. In our current setting, however, we aim to identify potential sources of DIF and, as such, we use estimates from the unregularized model to maximize the potential for DIF in the data. Given that one of our main goals is to evaluate whether experts' placements are comparable across regions, we believe that this version of the model is more likely to yield results that challenge the comparability of the placements, thus providing a more conservative approach. Nevertheless, as the results in the supplemental material clearly show, the results across models are largely consistent.[10]

In addition to Bølstad's hierarchical approach to BAM, Marquardt and Pemstein (2018) propose using Item Response Theory (IRT) models to aggregate expert-coded data. While the family of models proposed by the authors provides an intuitive way of aggregating

[9] For more details regarding these models, see supplemental material.
[10] For details regarding different approaches to model specification, see supplemental material, section Bayesian Aldrich–McKelvey Model Different Specifications.

expert-coded data, we believe their approach is less suited to the needs of this study for several reasons. First, as the authors note, the ordinal IRT model contains more parameters than BAM. With sparse data, such as the CHES data set, such model complexity can often result in difficulties in estimation. Second, although this family of IRT models can handle DIF, the models assume that experts perceive the latent values with error, without disaggregating this term in two of the main parameters of interest of our study, shift and stretch (see page 437, equation 1). As such, while we could obtain DIF-free estimations of party positions using Marquardt and Pemstein's approach, we would be unable to study systematic differences in perceptual biases across coders and regions. Finally, while these models are certainly superior to simple averages across experts' scores, they do not outperform BAM (p. 453).

In the following section, we focus on the expert-level individual parameters from the Bayesian Aldrich-McKelvey (BAM) model: the shift (α) and stretch (β) parameters. Our goal is to evaluate individual and geographical sources of perceptual biases. As previously noted, these parameters can be utilized to examine differential item functioning (DIF) at both the individual level and, through aggregation, at various geographical levels.

Examining Perceptual Biases among Experts

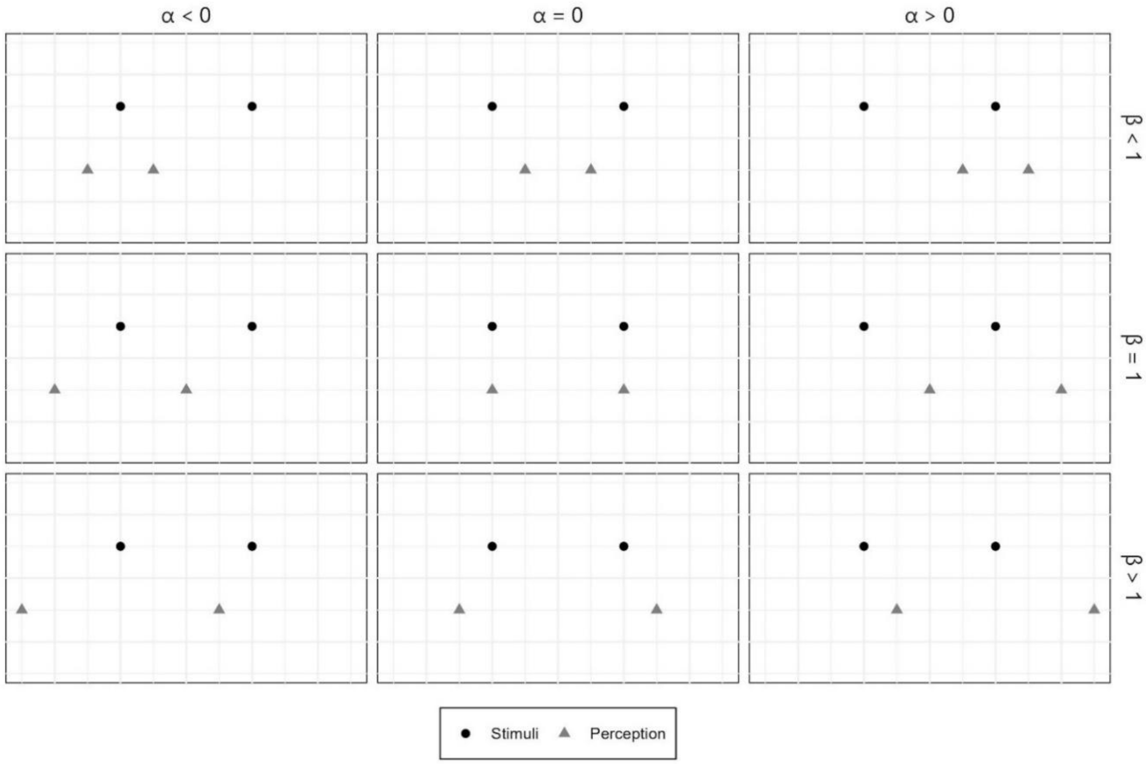
To examine perceptual biases among experts, we focus our attention on the shift (α) and stretch (β) terms from the BAM model. These expert-specific distortion parameters allow us to understand the extent, direction, and spread of experts' biases. Prior work using BAM and HBAM models has focused primarily on the stimuli position X_j, giving little attention to these parameters. Given the limited attention these parameters have received, in this section, we provide a brief overview of their interpretation and show how they can be leveraged to understand perceptual biases.

Under the BAM framework, experts' perceptions of political parties are conceptualized as the result of the true stimuli position (X_j) and two distortion parameters, commonly referred to as shift (α) and stretch (β). The shift parameter is the individual-level intercept of the model, which captures the degree to which experts' perceptions are biased to the right or left, reflected by the sign of the coefficient. A positive α indicates that the expert is systematically placing parties to the right of the true stimuli position. Conversely, a negative α suggests that the expert places parties further to the left. If α equals 0, that means that the expert does not place parties systematically to the right or left of the stimuli.

The second distortion parameter, the stretch term (β), captures the degree to which expertsperceive differences across parties. When β equals one, the expert's perception of the distance between parties equals the actual distance between the true stimuli (X_j). If β is larger than one, then the expert's perception of the distance between parties is bigger than the distance between the stimuli. In contrast, β smaller than one means that the expert perceives parties closer to each other than they actually are. In summary, β allows us to evaluate the extent to which experts widen or narrow the distance between political parties.[11]

[11] Negative values of β indicate that a respondent had reversed the order of the scale. We deleted any observations in which this is the case during data processing stage, and then constrained β to be equal to or higher than 0 for model identification purposes.

Figure 2: Hypothetical αs and βs



The alpha and beta parameters serve distinct analytical functions in understanding party placements. The alpha parameter captures systematic bias in perceived party positions having substantive consequences for inferences studies on spatial voting, democratic representation, and related phenomena. The beta parameter provides insights into the distinguishability of parties' ideological positions, informing measures of party system polarization and variance-based metrics. As such, the goals of a specific project would determine which of these parameters would be more interesting for researchers using this approach.

Figure 2 illustrates how perceptual biases in expert placements can be decomposed into shift (α) and stretch (β) parameters and their consequences for the perceived or observed party positions. The circles represent the true position of the stimuli, in this case, the true position of political parties. We understand the "true position" of a political party as its location on an underlying latent scale after removing expert biases (captured by the alpha and beta parameters).[12] The triangles depict an expert's hypothetical placement of these stimuli. The center pane represents a case in which the expert's perception of the stimuli equals the stimuli position ($\alpha = 0$ and $\beta = 1$), free of distortion or perceptual biases. The left-hand column ($\alpha < 0$) shows cases in which experts place parties to the left of the stimuli position (left-wing placement bias) and the right-hand column ($\alpha > 0$) depicts cases in which experts place parties to the right of the stimuli (right-wing bias). The rows describe variation in terms of β, the second distortion parameter. The first row shows a case in which β is smaller than one, indicating that the expert perceives the distance between stimuli as narrower than it actually is. In contrast, the bottom row shows a case in which a given expert perceives parties further away than they are. Figure A1, available in the supplemental material, presents examples of experts with extreme values of shift and stretch.

Geographical and Expert Level DIF Patterns

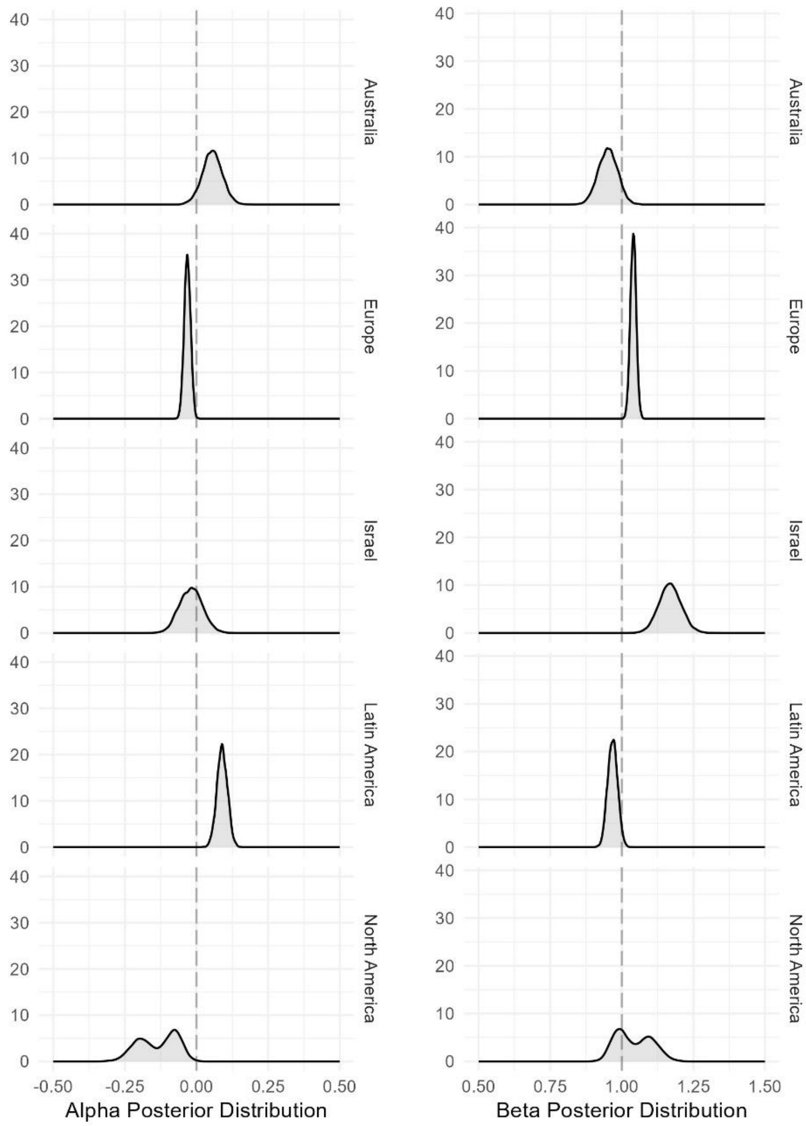
We hypothesize that DIF can arise from both geographical and expert-level characteristics. Regional differences, socialization experiences with the specific political legacies and institutions of each country, and individual characteristics could all potentially shape how experts perceive the political parties' positions. To test these hypotheses, we employed a two-step approach. First, we obtained the posterior distributions of the shift (α) and stretch (β) parameters at the regional and country levels. This was done by averaging the shift and stretch parameters in each country/region across each iteration of the Markov chain Monte Carlo (MCMC) chain. We then used Bayesian regression models to formally test for systematic differences at the expert, country, and regional levels.

[12] While the scale itself is technically defined as normally distributed with mean 0 and standard deviation 1 (see section: "Methods: Bayesian Aldrich-McKelvey Scaling"), each position on this scale represents the point that best reconciles different expert placements while accounting for expert individual patterns and measurement error.

Figure 3 shows the regional posterior distributions shift (α) and stretch (β) parameters. The left panel presents the shift (α) parameter's posterior distribution, with a reference dashed line positioned at zero denoting no ideological bias. Although the posterior distributions of the distortion parameter α generally center at zero across regions, we observe meaningful regional variation. Latin America's posterior distribution exhibits a noticeable right-wing bias (average $\alpha = 0.09$), whereas North America's (the United States and Canada) distribution shows a left-wing bias (average $\alpha = -0.14$). To contextualize these differences, the stimuli distribution ranges from -1.87 to 1.87 and has a standard deviation of 0.81. The mean shift (α) deviation in Latin America represents approximately 11% of the stimuli positions' standard deviation, while North America, exhibits the largest regional (α) shift, representing approximately 17% of this standard deviation. This suggests that while Latin American experts are inclined to position parties rightward of the stimuli, North American experts tend to place them further to the left.

The right panel of Figure 3 displays the regional posterior distributions of the stretch (β) distortion parameter. The stretch parameter captures the extent to which there is bias in the spread of the placements. When β exceeds one, it indicates that experts perceive greater ideological differences among parties than the ones present in the stimuli, implying a heightened perception of ideological polarization. In contrast, β values below one signal that experts perceive smaller differences across political parties.

Figure 3: Shift (α) and Stretch (β) Parameters Posterior Distributions by Region



Note: Posterior distributions of shift (α) and stretch (β) *parameters* by region. Vertical dashed line centered at α's and β'sDIF free values, zero and one respectively.

Figure 3 shows modest regional variations in the stretch parameter (β), with all posterior distributions centered close to one. Israel exhibits the largest deviation (β = 1.17), indicating Israeli experts systematically overstate ideological polarization among parties. For illustration, an Israeli expert's placement of 1.0 on the standardized scale, adjusts to 0.85 after accounting for DIF. Conversely, Australian experts show the greatest tendency to understate party differences ($\beta = 0.95$), such that a placement of 1 corresponds to an actual stimuli position of 1.05. Though systematic, these levels of perceptual distortion remain modest relative to the full range of stimuli positions (-1.87 to 1.87).

Figure A3, available in the supplemental material, presents country-level posterior distributions of the shift and stretch parameters, offering a more granular view of the data. To enhance interpretability, instead of plotting the posterior distributions for each country, we present the average value of each parameter along with a 95% credible interval, defined by the 2.5 and 97.5 percentile of the distribution. Consistent with the regional patterns observed in Figure 3, countries with higher α values are predominately from Latin America. Indeed, eight of the ten countries with larger α values belong to this region. Conversely, both Canada and the United States exhibit low α values, positioning them at the lower end of the distribution. This suggests that differences in experts' perceptions are more pronounced across than within regions.

We find significant regional patterns in how experts perceive ideological differences between parties, as captured by the stretch (β) parameter. European experts tend to perceive wider ideological gaps between parties, with eight of the ten highest β values appearing in European countries. In contrast, Latin American experts generally show lower β values, suggesting they may underestimate ideological polarization in their party systems relative to the true stimuli positions.

To formally test whether differences in experts' perceptions are larger between than within regions, we estimate the between- and within-region mean squared error (MSE) for each Markov chain Monte Carlo (MCMC) draw and derive a distribution of these quantities with corresponding 95% credible intervals. The results, presented in the supplemental material (Figure A4 and Figure A5), provide strong quantitative evidence that perceptual differences in both shift (α) and stretch (β) parameters are substantially larger across regions than within them. For the shift parameter, the between-region MSE (0.689) exceeds the within-region MSE (0.052) by more than an order of magnitude, with a similar pattern observed for the stretch parameter (0.332 versus 0.069).

Expert-Level DIF as a Function of Individual and Contextual Characteristics

In this section, we evaluate whether expert-level variation in the distortion parameters α and β can be attributed to individual and contextual characteristics, such as ideology, gender, age, country, and region. As α and β are individual-level terms derived from the BAM model, we can extract their posterior distributions and treat them as dependent variables in Bayesian Linear Models. To estimate these models, we computed the posterior mean of the α and β coefficients at the expert level, and then used them as dependent variables. This approach enables us to determine the extent to which individual and contextual expert characteristics can shape differential item functioning (DIF).

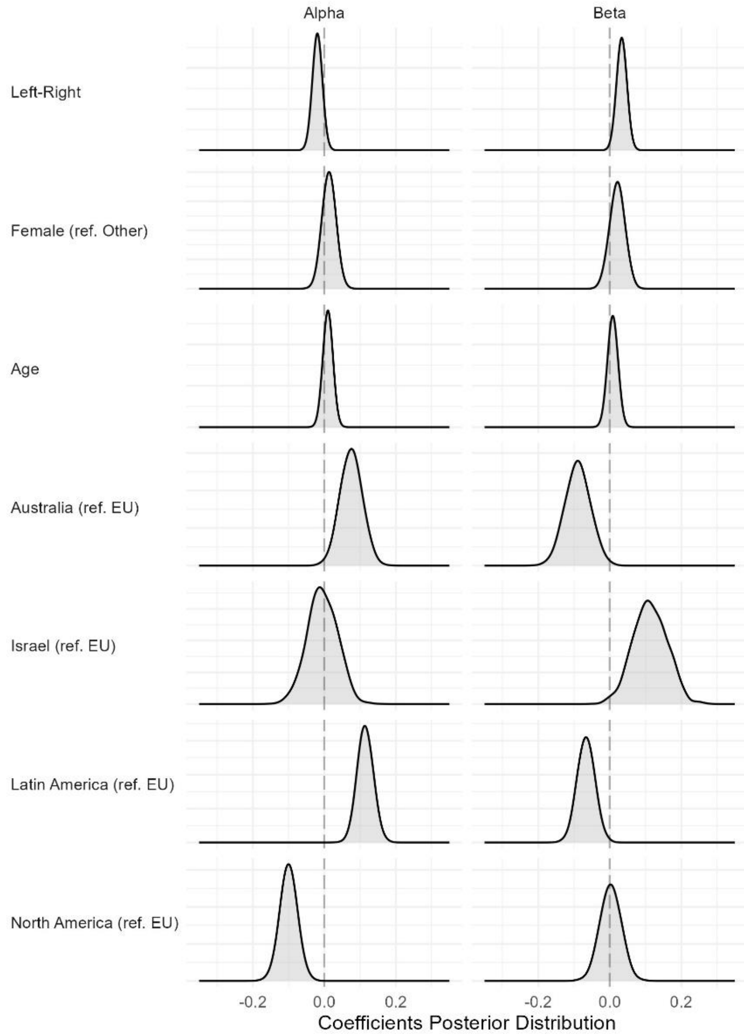
Figure 4 provides a visual representation of the posterior distributions of the coefficients for each model. The left-side panel presents results for the shift (α) parameter, while the right panel shows those for the stretch (β) parameter. Each row in the figure corresponds to a specific predictor variable, illustrating its posterior distribution in relation to α and β.Both models share a similar specification, with one key difference: the model predicting the shift term (α) incorporates the experts' left-right ideological position, whereas the model for the stretch term (β) includes the experts' left-right distance from the center of the distribution. This distinction in model specification was determined based on optimal model fit. The coefficients of the Bayesian Linear Models were drawn from wide prior distributions for the intercept, slopes, and error term [n ~ (0, 10)].[13] All continues variables were standardized (left-right position, left-right distance from the center, and age).

Results from the left panel indicate a negative association between experts' left-right positions and α. Specifically, the model predicts that experts holding more right-wing positions tend to have lower α levels. While this effect aligns with our theoretical expectations—experts' ideological position influences their perceptions of political parties—the magnitude of the effects is relatively small. The posterior distribution mean for the effect of experts' left-right positions is -0.03, indicating that a one standard deviation increase on the expert left-right standardized scale corresponds to a 0.03 decrease in α. To contextualize this finding, considering that the left-right standardized scale spans approximately 5-points, the predicted differences in α between an expert on the opposing ends of the ideological spectrum is 0.15, which is less than 9% of the full empirical range of the posterior means [-0.891- 0.797].

Our analysis of the α parameter model reveals no significant effects of gender or age on experts' perceptions of political party positions. Even though the posterior distribution of the female coefficient is slightly shifted to the right, the effect is too small to warrant meaningful interpretation. Overall, this model shows that there are small systematic differences across experts at the individual level, with the biggest ones at the ideological level.

[13] For more details regarding these models, see supplemental material.

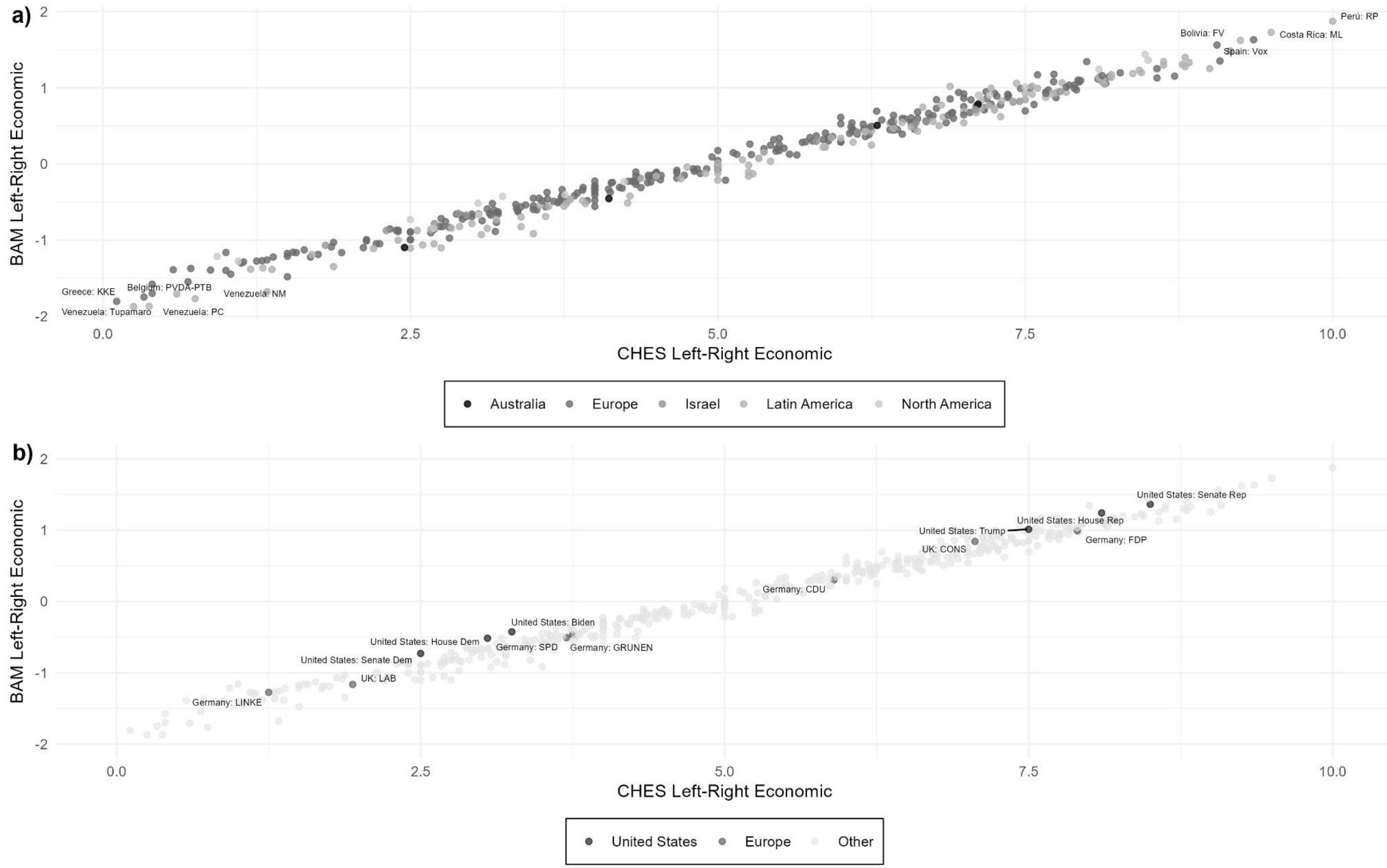
Figure 4: Posterior Distributions of Coefficients Predicting α and β



Note: Coefficients distributions based on Bayesian linear regression models with region fixed effects. Right-panel Left-Right variable is distance from center.

However, we do find some interesting regional differences in line with what was demonstrated in the previous sections. Latin American experts exhibit a significant right-wing bias, on average placing parties 0.11 points further to the right of the stimuli position. This is 7% of the empirical range of alpha's posterior mean. In contrast, North American experts exhibit a left-wing bias, positioning parties 0.10 points left of the stimuli position. Meaning that differences between Latin American and North American experts' placements are substantial (0.22 points) and worth considering, particularly for research that compares these two regions.

Figure 5:Left-Right Economic "Raw" Scores vs BAM Scores



Note: Panel a) Most Extreme Parties. Panel b) US, UK, and Germany

Figure *4*'s right panel summarizes the results of the models predicting the stretch (β) parameter. Consistent with the results observed for the shift term (α), we see statistically significant differences in stretch associated with ideological differences across experts. Experts with ideological positions that are closer to the edges of the left-right scale tend to perceive bigger differences across political parties. This effect is comparable to the one of the alpha coefficient (0.03). We observe no discernible effect of expert gender or age on scale stretching. We find notable geographical differences in scale usage among experts. Compared to their European counterparts, Israeli experts tend to expand the scale while Australian experts compress it. The magnitude of this regional difference is substantial: the average difference between Israel and Australia is 0.20 points, representing 8% of the empirical range of the beta coefficient. These systematic regional differences, while not dominant effects, suggest the need for careful methodological consideration when analyzing expert data from these regions.

In summary, our analysis reveals subtle, yet systematic differences in experts' perceptions of political parties. At the individual level, characteristics such as gender and age have negligible effects, while experts' ideology plays only a minor role in shaping their perceptions. However, at the geographical level, regional factors exert a more substantial, albeit still circumscribed, influence on expert judgments. Latin American experts, for instance, tend to exhibit a slight right-wing bias, while North American experts show a marginal left-wing bias. Additionally, experts from different regions vary in how they perceive ideological distances between parties, with Israeli experts tending to expand the ideological scale and Australian experts underestimating these distances. In light of these patterns, the next section explores whether systematic differences in experts' perceptions of political parties substantially influence the placement of party positions in the Chapel

Hill Expert Survey, thereby assessing the robustness of expert-based measures of party positioning across diverse geographical contexts.

Comparing Raw CHES and BAM Party Positions

Having identified and explained the stretch and shift parameters, we now turn our attention to assessing the overall cross-national comparability of experts' placements of political parties in the Chapel Hill Expert Survey. In this section, we employ the BAM model to generate a latent scale (X) of political parties' positions on the economic left-right dimension and compare it to the "raw" data (the unscaled party means). Given that the resulting party positions are theoretically free from DIF, we can use it as a benchmark to evaluate the comparability of the raw scores. The primary objective of this analysis is to evaluate whether the raw CHES scores are sufficiently free from DIF for scholars to use with confidence for cross-national comparisons.

Figure 5 presents a comparison between the BAM corrected scale and the raw scale from CHES, with data points gray-scaled by region. Remarkably, the analysis reveals limited amounts of DIF in the data. The two scales exhibit a strong positive relationship, with a correlation of 0.992, illustrating that the BAM scale has small differences relative to the "raw" CHES data. Despite the small differences across the two scales, there are some systematic patterns. For instance, the BAM estimates consistently push United States parties to the right, which is evidence of leftward bias among US experts. The opposite is true for Latin America, where, compared to the left-right economic position, the BAM estimates are further to the left.

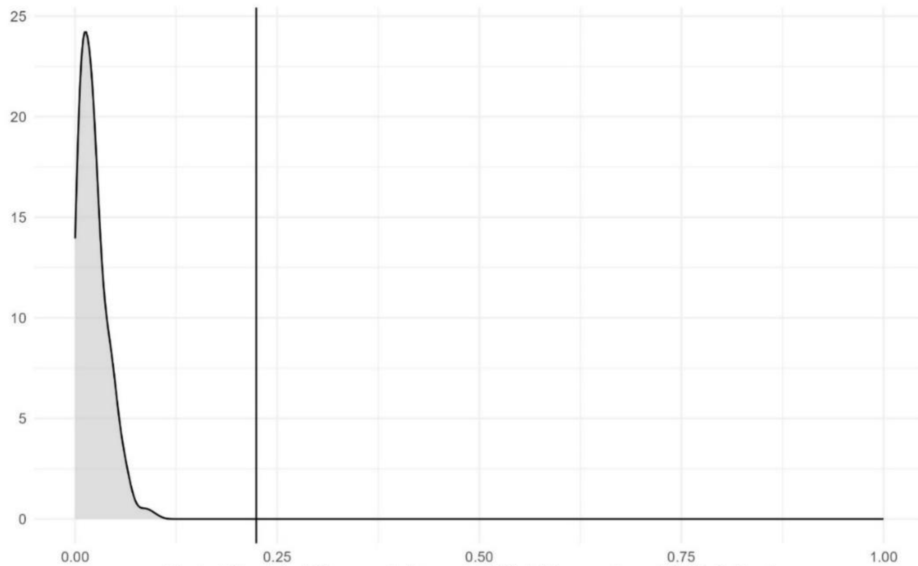
A key advantage of the BAM model is that we can use its estimates to identify the most extreme left and right-wing parties on the economic dimension, while accounting for experts' bias. Figure 5, panel a), illustrates the placements of all the parties in CHES, highlighting those that are more extreme according to the BAM estimates. Of all the parties available in CHES, the Peruvian party Renovación Popular stands out as the most right-wing, while the Venezuelan parties, Tupamaro and Communist, occupy the most far left of the spectrum. Notably, only European and Latin American parties appear at both extremes, suggesting potential regional patterns in party ideology.

Given that the experts in the United States exhibit, on average, the highest level of DIF in terms of the α parameter, we now focus our attention on US parties. Figure 5, panel b), highlights the positions of US political parties and two political leaders on the raw and BAM-corrected scales. As points of reference, we also include several German and UK parties. In this plot, parties falling exactly on the 45-degree line would indicate no presence of systematic DIF in the experts' perceptions of the party placements. The US parties, particularly the Democratic Party and Democratic leaders, are all above the 45-degree line, indicating that the raw expert placements are further to the left than the BAM-corrected placements. This is particularly true for Biden and the House and Senate Democrats, the left-wing stimuli in the US. While the Republican Party and leaders are also adjusted further to the right, these changes are less pronounced than for the more left-wing stimuli.

Left-Right Economic and BAM Differences

In this section, we evaluate the extent to which DIF leads to differences between mean "raw" placements and BAM estimates. To do so, we rescaled raw and BAM scores on a 0 to 1 scale, allowing us to directly compare estimates and assess the extent to which DIF leads to substantive differences across party positions. After rescaling both variables we estimated the absolute difference between both scores. These scores theoretically range from 0, when there are no observed differences between a party's "raw" and BAM rescaled score, and 1 when a party's "raw" score is at the opposite end of the empirical distribution of the BAM score.

Figure 6: Left-Right Economic and BAM Scaled Absolute Differences



Note: Absolute differences between Left-Right Economic Score and BAM Estimates. We rescaled both variables from 0 to 1 and then calculated the absolute difference. Vertical line drawn at one standard deviation of the Left-Right economic scaled scores.

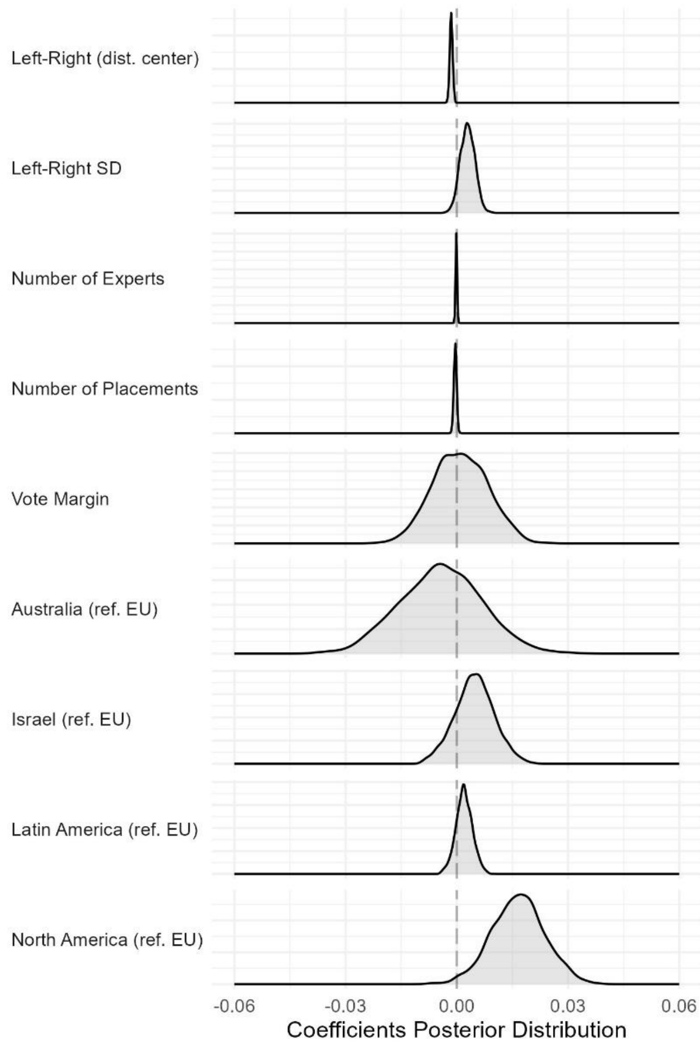
Figure 6 shows the distribution of the absolute difference of the left-right and BAM scores. For reference, the x-axis shows the full possible range of the absolute difference scores and the vertical line shows one standard deviation of the left-right "raw" scores (.22). The distribution is right-skewed, with a mean and median of .022 and .019 respectively. The highest observed score in the dataset is .099 and the 95th percentile is .057. To put these differences in context, the 95th percentile absolute difference of 0.057 is approximately one-quarter of the standard deviation of the "raw" rescaled left-right economic scores (0.22). This means that even for the parties with comparatively large observed discrepancies between their raw and BAM-adjusted scores, the impact of DIF is only shifting their relative placements by a modest amount.

We further investigate potential sources of these differences by fitting a Bayesian linear regression model with party-level characteristics as predictors, the results are provided in Figure 7. The model incorporates several covariates that could be theoretically linked to differences between raw and BAM-adjusted scores such as distance from the center, the standard deviation of the placements of the left-right economic variable, the number of experts placing the political parties, the number of parties placed by the experts, the vote margin, and the region.

The results indicate that political parties further from the center in the left-right economic dimension tend to have smaller differences between raw and BAM-adjusted scores. This finding suggests that experts may have more difficulty accurately placing parties in the middle of the economic left-right scale. Additionally, political parties for which experts have lower levels of agreement (i.e., higher standard deviation) tend to have bigger differences between raw and BAM-adjusted scores, implying that parties with more ambiguous or contested positions are more susceptible to perceptual biases among experts. Consistent with the previous analyses, North American parties also exhibit higher differences compared to parties in other regions, possibly due to regional differences in the understanding or interpretation of the economic left-right scale. In contrast, there are no significant effects associated with the number of experts that placed the party, the number of placements done by the experts, or the vote margin of the political party.

Overall, although there are some systematic differences between political parties with larger or smaller discrepancies between raw and BAM-adjusted scores, these differences are substantively very small. For example, an increase from 0 to 5 in left-right distance from the center, which is the full theoretical range, only predicts a decrease in .008 of the differences between the raw and BAM-adjusted scores. This is only 0.8% of the theoretical range of the variable and less than 4% of the standard deviation of the left-right scaled mean placements, indicating that even the most influential predictors have only a modest impact on the discrepancies between raw and BAM-adjusted party placements.

Figure 7: Posterior Distributions of Coefficients Predicting Scaled Differences between Left-Right and BAM



Note: Coefficients distributions based on Bayesian linear regression models with region fixed effects.

Conclusion

This article examines whether political parties' scores on the economic left-right dimension obtained through expert surveys are comparable across countries and regions. Using Bayesian Aldrich-McKelvey scaling (BAM), we assess Differential Item Functioning (DIF) by analyzing two expert-level distortion parameters—shift (alpha) and stretch (beta).

Our DIF-corrected estimates allow for cross-country comparisons of party positions on the economic left-right scale. While "raw" survey scores and BAM estimates are highly correlated (ρ=0.992), our analysis reveals meaningful geographical patterns in how experts perceive party positions, with systematic variations across regions.

These findings have significant implications for comparative political research. The strong correlation between raw and BAM-corrected scores suggests broad expert agreement on the economic left-right scale. However, regional biases affect some individual party placements. U.S. experts tend to place parties further left, while Latin American experts shift parties rightward. Australian experts perceive wider ideological differences, whereas Israeli experts underestimate polarization. These patterns suggest caution in cross-regional comparisons but support the validity of within-region analyses.[14]

Researchers should prioritize DIF-free measures for cross-national studies but can still use raw scores for within-region analyses. While expert surveys are not perfectly comparable across regions, they reflect a shared ideological understanding, making them useful even when DIF-free corrections are unavailable. Nevertheless, researchers must account for how regional perceptual biases might influence findings.

Beyond expert surveys, our study informs broader research on perceptual biases. By directly analyzing BAM shift (α) and stretch (β) parameters, we provide a framework for studying systematic distortions in expert and public opinion data. This method can enhance research on ideological biases, polarization, and public perceptions.

Our findings also contribute to studies using party ideology as an independent or dependent variable. Cross-national analyses rely on comparable party positions,

[14] See supplemental material (Figure A4 and Figure A5) for a formal test of between and within region variability.

impacting research on trade policy (Milner and Judkins 2004), COVID-19 responses (De La Cerda, Hartlyn, and Martinez-Gallardo 2024; Rovny et al. 2022), public spending (Blais, Blake, and Dion 1993; Kang and Powell 2010), and affective polarization (Algara and Zur 2023; Gidron and Hall 2020). Our results bolster confidence in such studies, particularly within single regions where comparability is highest.

Future research should expand DIF assessments beyond the economic left-right scale. While this dimension offers a relatively straightforward comparison, other ideological dimensions—such as general left-right ideology or democracy—require targeted vignettes for systematic evaluation. Additionally, further research should establish acceptable DIF thresholds for different research applications, helping scholars determine when raw scores suffice and when DIF corrections are necessary. Addressing these issues will improve cross-national political analysis and enhance the reliability of expert survey data.

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A Global Scale of Economic Left-Right Party Positions: Cross-National and Cross-Expert Perceptions of Party Placements

Supplemental Material

BAM Model Priors

$$\alpha_i \sim U(-100, 100)$$

$$\beta_i \sim U(-100, 100)$$

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

$$\sigma \sim N(0, 2)$$

$$\sigma_{i\_raw} \sim N(0, 1)$$

$$\sigma_{j\_raw} \sim N(0, 1)$$

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

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

Stan Code

BAM

```
data {
int<lower=0> J; // Number of coders
int<lower=0> N; // Number of parties
int<lower=0> nobs; // Number of observations in long data
int<lower=0> ctry[nobs]; // country ID number
int<lower=0> pty[nobs]; // Party ID number
int<lower=0> id[nobs]; // Coder ID
real place[nobs]; // Party placements
}
parameters {
real<lower=-1.3, upper=-1.2> Z_1; // First stimuli (anchored negative)
real<lower= 1.2, upper= 1.3> Z_2; // Second stimuli (anchored positive)
real Z_rest[N-2]; // Remaining stimuli
real alpha[J]; // Shift parameters
real beta[J]; // Stretch parameters
real<lower=0> sigma_global;
vector[J] sigma_j_raw;
vector[N] sigma_n_raw;
real<lower=0> tau_j; // Scale for coder variance
real<lower=0> tau_n; // Scale for party variance
}
transformed parameters {
real Z[N];
// Combine stimuli into a single vector
Z[1] = Z_1;
Z[2] = Z_2;
Z[3:N] = Z_rest;
// Error term
vector<lower=0>[J] sigma_j;
vector<lower=0>[N] sigma_n;
vector<lower=0>[nobs] sigma;
// Non-centered parameterization
sigma_j = sigma_global * exp(tau_j * sigma_j_raw);
sigma_n = sigma_global * exp(tau_n * sigma_n_raw);
for(k in 1:nobs){
	sigma[k] = sqrt(square(sigma_j[id[k]]) + square(sigma_n[pty[k]]));
```

```
}}
```

```
model {
// Estimuli priors
Z_1 ~ normal(-1.25, 0.1); // Centered near -1.25
Z_2 ~ normal(1.25, 0.1); // Centered near 1.22
Z_rest ~ normal(0, 1);
// Stretch and Shift Parameters Priors
alpha ~ uniform(-100, 100); // Noninformative uniform prior Equation (5)
beta ~ uniform(-100, 100); // Noninformative uniform prior Equation (5)
// Priors for variance components
sigma_global ~ normal(0, 2);
tau_j ~ normal(0, 1);
tau_n ~ normal(0, 1);
sigma_j_raw ~ normal(0, 1);
sigma_n_raw ~ normal(0, 1);
//Model
for(k in 1:nobs){
        place[k] ~ normal(alpha[id[k]] + beta[id[k]] * Z[pty[k]], sigma[k]);
        }
}
```

HBAM

To estimate both HBAM models we used the hbamr package(Bølstad 2024). We estimated two Hierarchical Bayesian Aldrich–McKelvey models: HBAM_NF and HBAM_MULTI_NF.

HBAM_NF: HBAM model that does not allow for scale flipping.

HBAM_MULTI_NF: HBAM model that models differences between groups, in this case, countries. It does not allow scale flipping.

For details regarding the Stan code, see Bølstad (2024).

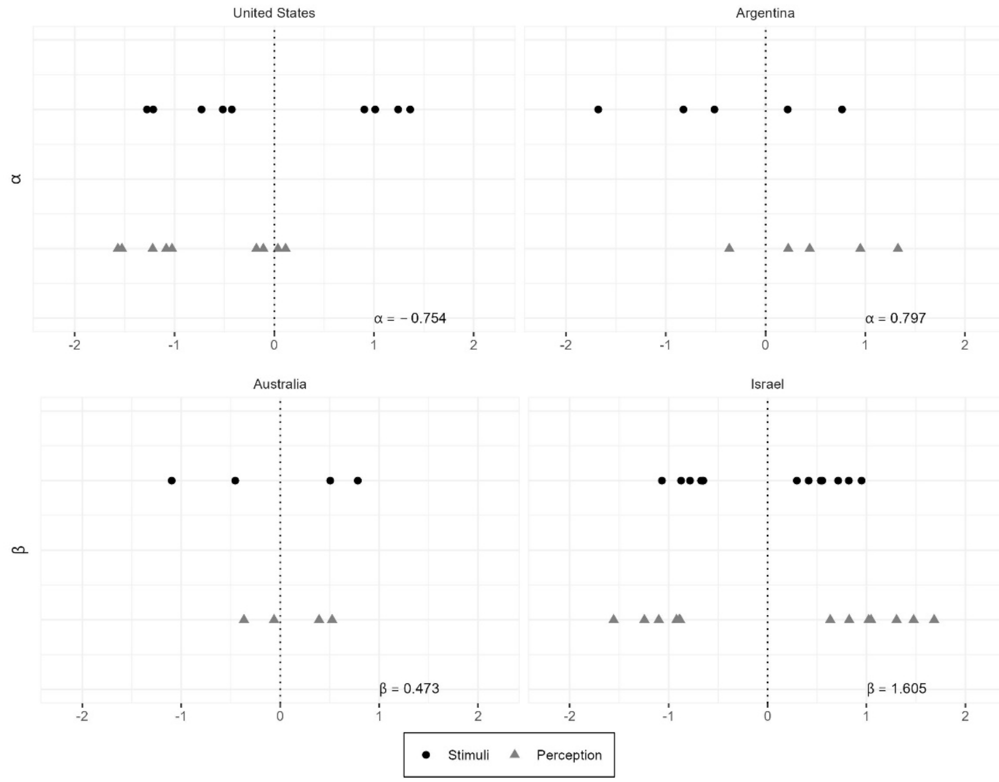
Bayesian Linear Regression Models

```
data {
	int<lower=0> N; // number of rows
	int<lower=0> K; // number of predictors
	matrix[N, K] x; // predictor matrix
	vector[N] y; // outcome vector
	}
parameters {
	real alpha; // Intercept
	vector[K] beta; // Coefficients
	real<lower=0> sigma; // Error Scale
	}
model {
	// Priors
	alpha ~ normal(0, 10);
	beta ~ normal(0, 10);
	sigma ~ normal(0, 10);
	// Model
	y ~ normal(alpha + x * beta, sigma);
	}
```

Experts with Extreme Shift and Stretch

Figure A1 displays four examples of the extreme values of the shift and spread parameters in our dataset. The circles represent the "true" position of the parties, as estimated by the model, while the triangles illustrate individual expert placements of the parties. The top left cell shows the placements of one of the United States experts which displays a left-wing bias (negative α), consistently placing parties to the left of the stimuli. In contrast, the top-right pane shows an Argentinian expert displaying a right-wing bias, consistently positioning parties to the right of the stimuli. The bottom row provides examples of high and low levels of stretch. Compared to the stimuli positions, while the Australian expert (bottom left) places parties much closer to each other, the Israeli expert (bottom right) perceives greater distance between the parties.

Figure A1: Experts with Extreme Shift (α) and Stretch (β)



Note: Vertical lines represent the center of the scale.

Bayesian Aldrich–McKelvey Model Different Specifications

Table A1: Bayesian Aldrich-McKelvey Models Stimuli (Z) Correlation

	CHES	BAM	HBAM	HBAM MULTI
CHES	1.000	**0.992**	0.996	0.992
BAM	**0.992**	1.000	0.996	0.998
HBAM	0.996	0.996	1.000	0.998
HBAM MULTI	0.992	0.998	0.998	1.000

Table A2: Bayesian Aldrich-McKelvey Models Alpha Correlation

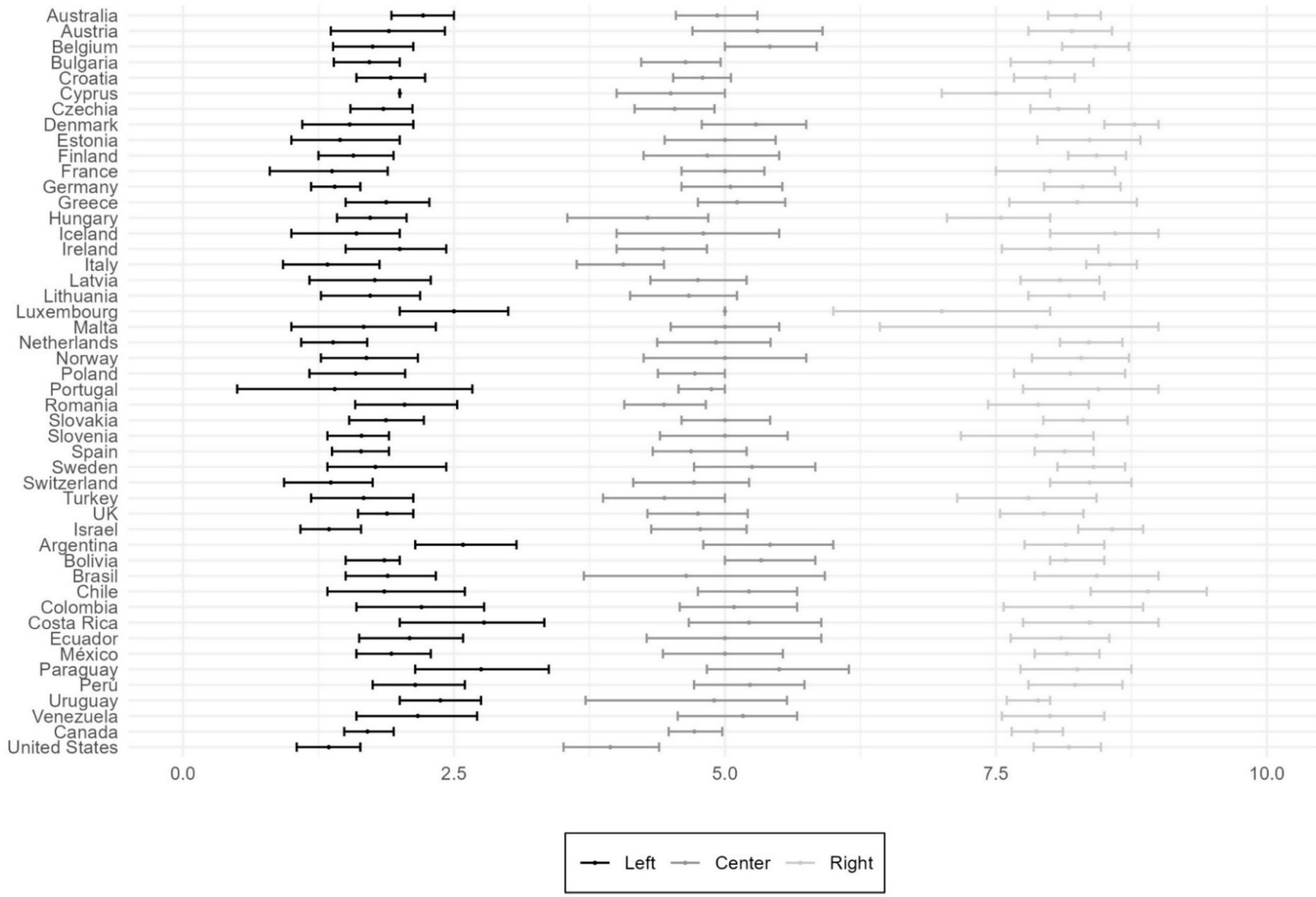
	BAM	HBAM	HBAM MULTI
BAM	1.000	0.906	0.802
HBAM	0.906	1.000	0.819
HBAM MULTI	0.802	0.819	1.000

Table A3: Bayesian Aldrich-McKelvey Models Beta Correlation

	BAM	HBAM	HBAM MULTI
BAM	1.000	0.880	0.868
HBAM	0.880	1.000	0.970
HBAM MULTI	0.869	0.970	1.000

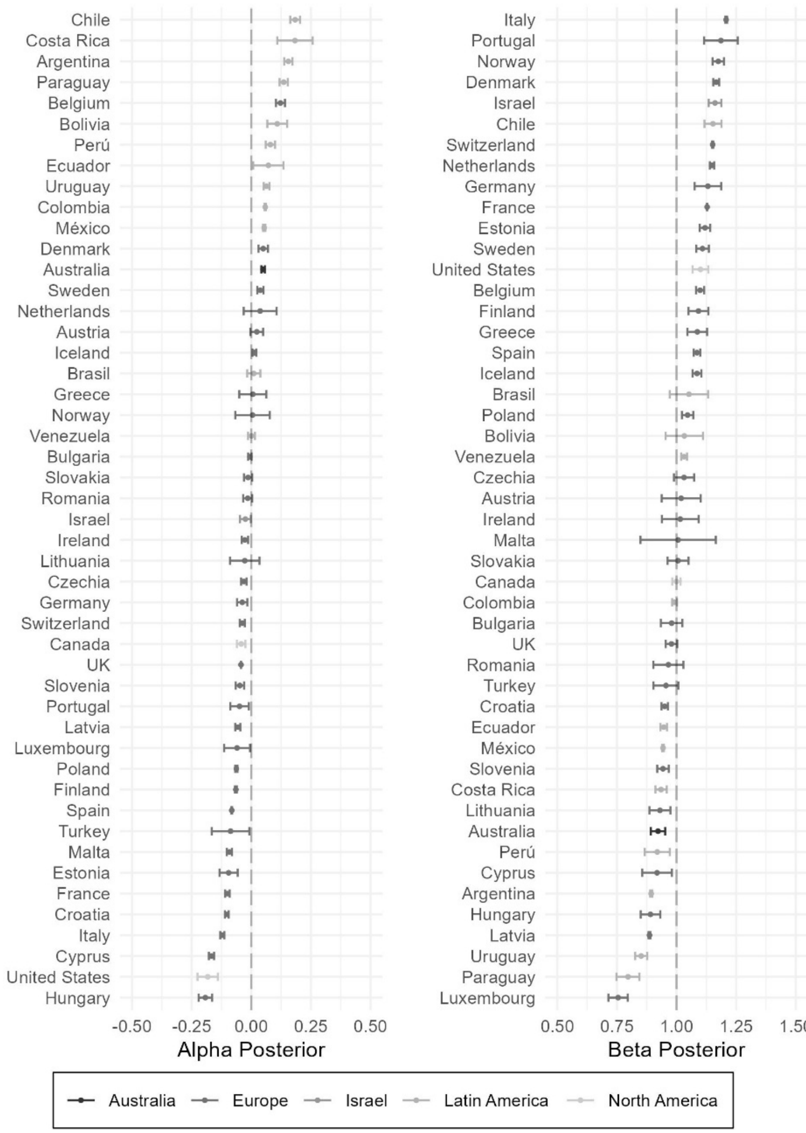
Country-Level Estimates

Figure A2: Average Vignette Party Position by Country



Note: 95% confidence intervals estimated using non-parametric bootstrap.

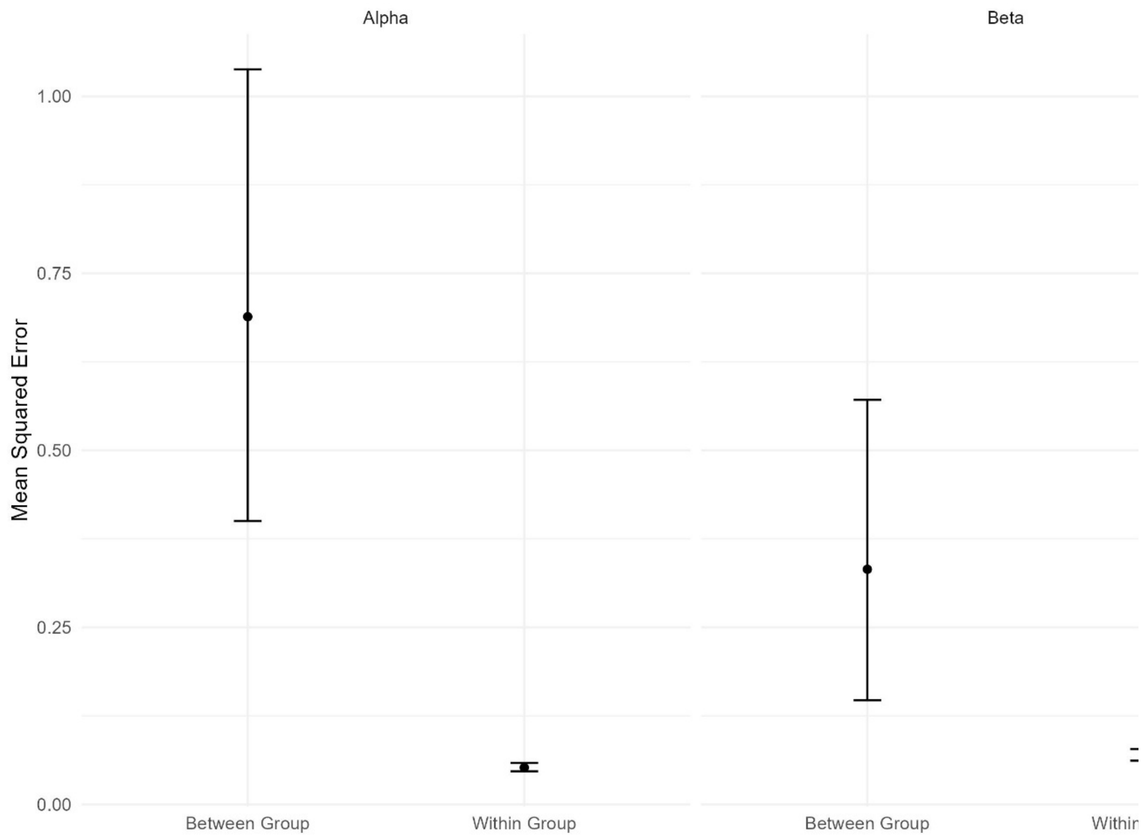
Figure A3: Shift (α) and Stretch (β) Parameters Posterior Distribution Average and Credible Intervals by Country



Between and Within Group Differences in Experts' Perceptions

Figure A4 examines regional variation in expert perceptions (alpha and beta) using a formal comparison of between- and within-group differences. To quantify these differences, we computed the mean between-group square error (MSB), which captures variation across regional means, and the within-groups square error (MSW), which identifies the residual variation among experts within the same region. By comparing these two quantities, we can determine whether perceptual differences among experts are more pronounced across regions than within them. For each parameter of interest (alpha and beta), we estimated the MSB and MSW values for each posterior draw to recover the full distribution for these quantities. We then computed the mean along with the 0.025 and 0.975 distribution percentiles.

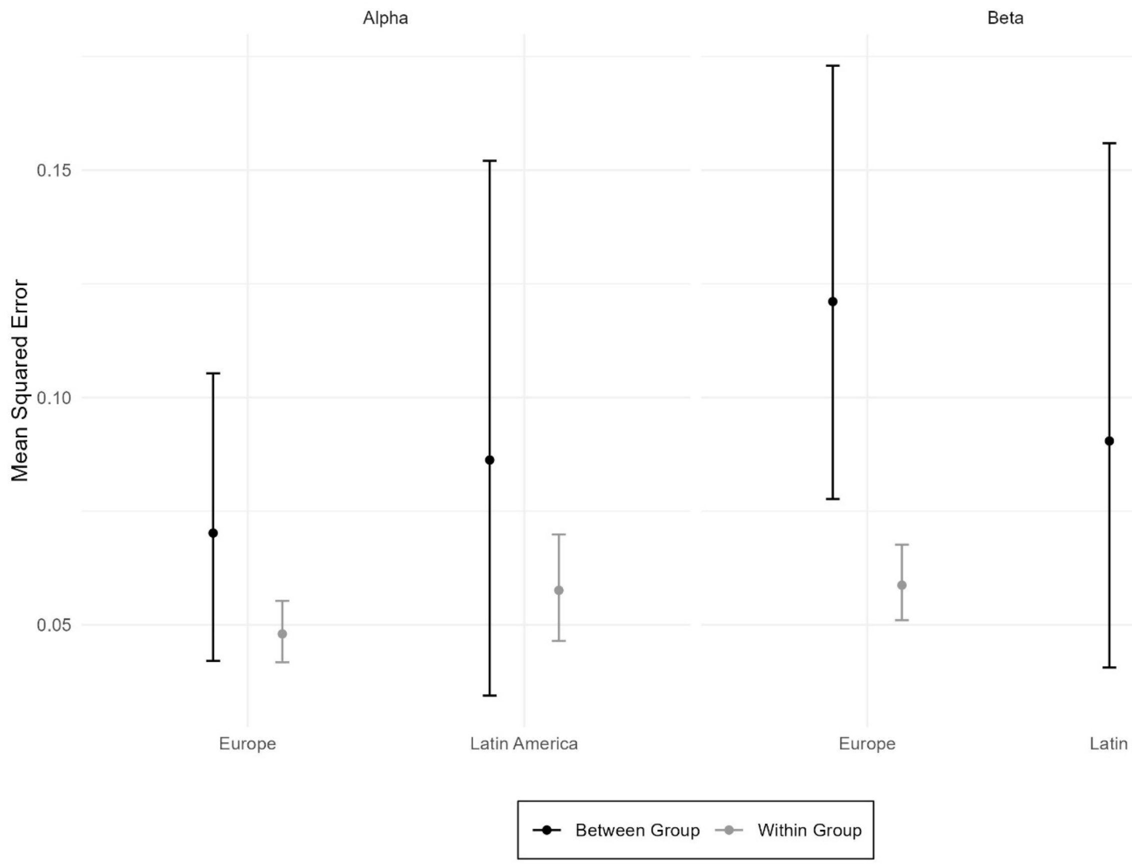
Figure A4: Alpha and Beta Regional Between and Within Mean Squared Error



Note: This figure displays the between-group (MSB) and within-group (MSW) mean square errors for alpha and beta parameters at the regional level. For each parameter, we computed MSB and MSW values from every MCMC draw, then derived the mean and 95% credible intervals from the resulting distributions.

The results provide strong evidence that cross-regional differences substantially outweigh within-region variation. For alpha, the average of the posterior distribution of the MSB is 0.689, while the MSB is only 0.052. Between and within regional differences for the beta coefficient present a similar pattern: MSB of 0.332 and MSW of 0.069. These differences are statistically significant at any conventional statistical level, suggesting that differences in perceptions across experts are much more accentuated across than within regions.

Figure A5: Alpha and Beta Country-Level Between and Within Mean Squared Error



Note: This figure displays the between-group (MSB) and within-group (MSW) mean square errors for alpha and beta parameters at the country level. For each parameter, we computed MSB and MSW values from every MCMC draw, then derived the mean and 95% credible intervals from the resulting distributions.

As an additional test, we estimated the between and within country-level mean squared error. Given that our sample contains only one Middle Eastern and one Oceanic country (Israel and Australia, respectively) and two North American ones[1], we present these results exclusively for Europe and Latin America. The patterns shown in Figure A5 diverge considerably from those observed at the regional level. While between- and within-region differences differ by an order of magnitude, the corresponding differences at the country level are substantially smaller. For the alpha coefficients, between- and within-country differences are not statistically distinguishable. For the beta coefficients, these differences reach statistical significance only in Europe, although the magnitude of this difference is much smaller than at the regional level. Collectively, these findings provide strong evidence that expert perceptions vary far more substantially across regions than across countries within the same region.

[1] We considered Mexico as a Latin American country throughout all analyses.