A New Bayesian Scaling Approach to Party Position and Issue Salience

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Abstract

In this paper we develop a new Bayesian scaling method for estimating party policy preferences (position and salience) from the popular Comparative Manifestos Project (CMP) data. Our method uses a Bayesian hierarchical modelling approach that integrates theory-driven model specification with data-driven parameter estimation, to achieve meaningful and flexible measure construction from the entire CMP dataset. In particular, it (1) takes more appropriate distributional assumptions about observed data, (2) incorporates multiple levels of information (party, election, and country) into the model, and (3) estimates the full set of parameters at the same time, that improves upon the quality, generalisability, and efficiency of the resulting measures. Our method also allows for scale decomposition at different levels of analysis as well as uncertainty quantification through built-in procedure. Compared to existing measures using the CMP data, our new scales are shown to have superior performances in capturing parties' latent strategic preferences across countries and electoral contests. Beyond the CMP data, our method can also be readily applied to other types of pre-processed text data for latent feature recovery and measure construction.

Keywords: measurement, Bayesian modelling, party politics, Comparative Manifestos Project

1 Introduction

Information about political parties' strategic preferences is key to many topical areas of empirical political research. These areas include, to name but a few, party system evolution, cabinet formation and survival, mass electoral behaviour, party-voter correspondence, and many others (e.g. Adams & Somer-Topcu, 2009; Budge, 2015; Dennison & Kriesi, 2023; Ezrow, 2008; Golder, 2006; Hutter & Kriesi, 2019; Lindvall, Rueda, & Zhai, 2023; Martin & Stevenson, 2001). Among existing efforts to systematically quantify such information, the Comparative Manifesto Project/Manifesto Project Database (CMP/MARPOR; henceforth simply CMP) (Volkens et al., 2018) has been one of the best known and most widely used data sources. The extensive geographical, temporal, partisan, and policy (issue) coverage of its data, combined with its text-analytic instead of survey-based measurement strategy, allows for comprehensive insights into the complex electoral landscape across many countries and time periods in a relatively more objective and less bias-prone way.

In principle, the CMP is based on the saliency theory of party politics, which posits that strategic parties field positions on and allocate attention (salience) to different policy issues in such a way as to maximise their chances of winning the election; this they typically achieve by emphasising those issues on which their own positions may give them an electoral advantage while downplaying or ignoring areas that may benefit their competitors (McDonald & Mendes, 2003). Accordingly, the CMP meticulously classifies each party's manifesto statements into 56 issue categories by manual coding, each of which is associated with a certain number of quasi-sentence counts normalised as percentage shares. Each party's strategic preferences about position and salience are not observed but need to be inferred from the manifest data represented in this way. This brings a number of challenges to the analyst: first, the marginal distribution of the quasi-sentence percentage measure is unlikely to be normal but rather following some categorical-proportional logic; second, the full sample covers multiple levels of data generation when pooled over countries, elections, parties, and issues; and third, the conceptual and empirical relationship(s) between position and salience need to be carefully defined and distinguished to be identifiable from the same data. Existing methods for scaling the CMP data have typically failed to address these problems adequately. In particular, they usually take the observed quasi-sentence shares as input variables and seek to compute preference measures as their functions, (Budge et al., 2001; Kim & Fording, 2002; König, Marbach, & Osnabrügge, 2013; Lowe, Benoit, & Laver, 2011), which not only reverses the actual causal order underlying the data generative process (that the observed text allocation is the outcome of latent party strategies) but more problematically, risks conflating the supply (party strategy) and demand (voter preference) sides of the electoral process as well. Moreover, they often also exhibit such symptoms as poor distributional assumptions, negligence of context specificities, or insufficient distinction between different parameters of interest. Pioneering as they were at their respective time of inception, existing methods are unlikely adequate for rigorous work today.

In this paper we attempt to improve upon existing methods by proposing a new Bayesian method for scaling party position and salience parameters from the CMP data. Using a Bayesian hierarchical model with Dirichlet likelihood and multiplicative specification with multilevel priors, we seek to develop a statistical method that better accounts for the three just-mentioned issues confronting CMP users: non-normal density of the response, multidimensional structure of the data, and functional form of the position-salience relationship. Our key point of departure from existing methods lies in the generative logic of modelling, in which the observed quasi-sentence shares are explicitly modelled as the manifest outcomes of a latent data generating process (DGP) controlled by the target parameters characterising party preference. In addition, we also allow for multilevel dynamics in the two parameters by including party-, election-, and country-specific random effects and issue-specific baselines, which simultaneously incorporates sample variation at multiple levels of measurement and facilitates effect decomposition and comparison along corresponding lines. In essence therefore, our Bayesian approach proactively utilises available information from the pre-coded party document data to effectively and meaningfully learn about the shape and configuration of the latent space of electoral competition and generate useful low-dimensional measures for its empirical characterisation.

Our new method offers several distinct benefits. Substantively, our model setup is aligned with canonical models of party competition with spatial and salient components, so that the resulting measures are well-positioned to serve theory testing purposes. Methodologically, the model also adopts a generative approach which better separates the supply side from the demand side in electoral interaction, which allows for more nuanced and less conflated understanding of party strategic manoeuvres and their effects on voters' perceptions about partisan offers. Statistically, our method also offers greater flexibility and honesty in estimating the strategic parameters. For the flexible part, the method's categorisation imposes little to no 0² 9j§0 constraints about the dimensionality of the issue space, whether defined among all issues or specifically between so-called "paired" issues where two issues supposedly constitute two opposing sides of the same spectrum. This is a particularly useful relaxation when dealing with complex policy spaces that cannot be easily reduced to a single or two dimension(s). For the honest part, the method's Bayesian approach directly incorporates uncertainty into the estimation process, and generates both point and interval estimates from the same posterior draws. This allows for a more robust and sincere interpretation of the constructed measures, that acknowledges and raises awareness about the inherent aleatoric and epistemic uncertainties in the real-world and modelling processes, respectively (Gill, 2014; Jackman, 2009).

Importantly, we also note that our method is not limited to scaling the CMP data only, and can be readily adapted to other types and sources of pre-processed text data with minimal efforts. For instance, one may take topically allocated text data obtained from previous application of some topic or large language models to raw document-word data, where the original document has been classified into a finite set of topics and appropriated scaled to proportional terms, and apply our model to further extract latent traits of sentiments and dispositions in the data, especially in terms of their nature and intensity. Our method is by design agnostic about the specific upstream techniques used for initial upstream processing, focusing instead solely on the extraction and interpretation of latent traits from the resulting pre-processed data. This versatility may further enhance its utility for broader political science research using text data, particularly for but not restricted to empirical electoral studies using party documents and speeches.

Our initial results also show the promise and utility of the new method. In concrete terms, the new measures (1) reveal substantial variation in party strategic preferences in cross-country and over-time comparisons, (2) show strong agreement with major existing measures using expert judgements with more narrow issue coverage, and (3) easily lends themselves to derivation of second-order indicators capturing more intermediary aspects of party strategising, such as the empirical correlation between position and salience on the same issue or the joint preference on naturally paired issues. We are therefore reasonably confident of the validity, reliability, and utility of the new scale estimates.

The subsequent sections proceed as follows. First, we provide a brief overview of existing approaches to estimating party policy parameters from the CMP data especially in relation to the latter's peculiar features. Then we introduce our new model designed to improve upon these methods and better account for the aforementioned issues in the data. Next, we outline the model's application and present early results obtained therefrom. Finally, we conclude with a discussion of our method's contribution, limitations, and major empirical and methodological implications.

2 Existing Approaches

Existing approaches to scaling party preference measures from the CMP data can be roughly classified into one of two schools. The first school directly utilizes raw texts in the original manifesto corpus and treats individual words as the units of analysis. The second school relies on pre-coded data produced by the data team and treats each pre-defined issue category as the unit of analysis. Within the first school, two particular branches stand out. The Wordscore method (Laver, Benoit, & Garry, 2003) which identifies party issue positions by a two-step procedure. First two reference text are identified for which parties' policy positions are known. Next the reference texts are used to calculate "word scores" that are essentially the relative frequencies of each word in the two texts. At last the word scores are used to calculate the "text score" for a new text, which becomes the estimated policy position of the associated party. By contrast, the Wordfish method (Slapin & Proksch, 2008) models the word frequencies of party manifestos assuming an underlying Poisson process, and then uses the estimated text parameters to compute the policy positions of the associated parties.

Before introducing methods in the second school, it is worth briefly elaborating on the coding process and resulting structure of the CMP data on which such methods heavily rely. The CMP follows a coder-based content-analytic approach where each manifesto is manually cut into 56 items of categories, some of which could be paired up with others to form two diverging sides of the same issue dimension and others meant to be standalone by themselves. Each issue itself consists of several (if any) "quasi-sentences" that represents the smallest linguistic unit conveying a message. A party's political message on a given issue is measured as the percentage share of quasi-sentences dedicated to this issue out of all quasi-sentences in the same document.

Within the second school, existing methods can be further divided into two sub-schools, depending on where they place the observed data in their scaling recipes. On one hand are the input-based group of methods that use the data as inputs in some usually very simple mathematical formulas. In general, these methods take observed shares as given and place them on the right-hand side (RHS) of the scaling formula and directly compute the left-hand side (LHS) measures based on them. Three methods stand out in this sub-school: the earliest and most widely used saliency method (Budge et al., 2001) using simple addition and differencing, the later proposed relative proportional difference method (Kim & Fording, 2002), and the most recently developed log odds-ratio method Lowe et al. (2011). Table 1 summarises the three approaches in terms of their particular recipes for point and uncertainty estimation of the parameters of interest. The former two follow classical theories of party politics and assumes a party's position and salience on a given issue to be approximated by the difference and sum between positive and negative mentions about the issue, respectively. The key difference between the two is in positional estimates only, for which the former (saliency) normalises differences by total manifesto length and the latter (relative proportion) by total mentions of the analysed issue only. The two methods share the same recipe for scaling salience measures. By comparison, the logit scale is more rooted in linguistic theory and assumes the party's position and salience on an issue to be better approximated by the log-transformed difference and sum of the party's manifesto mentions of this issue in opposing directions. Therefore, the former two assume more-or-less constant marginal effects on the party's stance on an issue from additional quasi-sentence shares assigned to it, whilst the latter emphasises diminishing effects from additional quasi-sentence shares following a logarithmic curve. With respect to uncertainty quantification, the former two approaches offer no (official) interval estimates, while the logit scale does offer a parametric measure of uncertainty using Bayesian approximation.

Table 1: Summary of main existing CMP-as-input approaches to scaling coded CMP data.

Method[9]	Position	Salience	Uncertainty
Saliency	$P^L \quad P^R$	$P^L + P^R$	None
Relative proportional difference	$(P^L \quad P^R)$=$(P^L + P^R)$	$P^L + P^R$	None
Log odds-ratios	$\ln[(P^L + :5{=}N){=}(P^R + :5{=}N)]^{@}$	$\ln[P^L + P^R + 1]$	Bayesian approximate

i n§0I

a Methods inclusion following Lowe et al. (2011).

b N = total document length (in quasi-sentence count terms).

c P = the share of quasi-sentences on a specific issue dimension.

On the other hand, the output-based methods take the observed data as outputs on the LHS and seek to infer party parameters through statistical procedures. Featured methods include, for instance, the "vanilla method" of Gabel and Huber (2000), the Bayesian measurement model of Bakker (2009), the latent variable model of König et al. (2013), and the dynamic state-space model of Elff (2013). Notably, however, these models either impose restrictive assumptions about the dimensionality of the data (as in the vanilla method's case), or are tailored after a different type of data source (expert surveys, as in the following two models' cases).

Cumulatively and aggregately, these existing methods have fostered both vibrant methodological discussions and frontier-pushing empirical works (e.g. Dinas & Gemenis, 2010; Gemenis, 2013). Their relative simplicity, operationalisability, and interpretability and the overall contribution to the field are not to be denied. Nevertheless, there remains several major drawbacks to these methods, which we now critically engage with in order to put our new effort in context.

- First, existing methods typically take overly simplistic if unrealistic distributional assumptions about the CMP data. By construction, the CMP's quasi-sentence share measure is a continuous proportion which ranges between 0-1 for each issue category and sums up to 100% across all issues, for any given manifesto. Such ratio-categorical nature of the data signals the technical need for special care when fitting statistical models; in particular, changes in one issue's quasi-sentence share necessarily affects all other issues' shares given the convex constraint, normal-style distributional assumptions are unlikely to lead to well-fitting likelihood functions that yield good parameter estimates.

- Second, they also generally under-appreciate the multidimensional structure of the data and the underlying generative processes. Because a party's strategic preferences at each given election is often influenced by factors at multiple levels of the electoral process, including the issue, party, election, and country levels, effect heterogeneity across these levels should be explicitly taken account of in the measurement model, the omission of which could not only lead to inaccurate estimates but also limit cross-context comparability of the scales at the corresponding levels.

- Last but not least, at both the conceptual and especially the empirical level, the methods also rarely distinguish position and salience parameters in a clear enough way. Given the different meanings and associated causal mechanisms of the two parameters, an ideal scaling method should minimise design similarities in their respective estimation formulas, to avoid inducing mechanical correlations that convey little meaningful empirical information. Highly similar functional forms containing overlapping elements as in the three reviewed methods' cases (Table 1) risks conflating theoretically distinct constructs and obstruct clear and tractable empirical inference.

3 Our Approach

3.1 Theoretical Framework

To build a new model that better addresses these diagnosed symptoms, we first construct a more solid theoretical foundation by reference to well-known theories about party politics in a multidimensional issue space. Specifically, we integrate the spatial and salience models of issue competition to better conceptualise the relationship between the corresponding parameters under later inference. Importantly, we will discuss how this relationship is be more likely to be multiplicative than additive in real-world processes. The electoral context we consider is a classically dynamic one, in which parties strategically adjust two key parameters to increase their chances of winning the election: the 9e_0jH0 they assign to various issues and the qn _§_nj they take on these issues simultaneously, which occur at both the individual party and the entire party system level and can be influenced by a combination of contextual and agent-strategic factors (Grossman & Guinaudeau, 2021).

Our key assumptions (presented in more intuitive terms) link our model to core tenets of spatial and saliency competition and set the perimeter of our modelling exercise. The three assumptions can be summarised as follows:

1. Parties compete by taking issue-specific positions. On the spatial side, we assume parties position themselves close to voters' (inferred) positions on different issues to win votes by preference congruence. Such positioning is necessarily constrained by multiple factors including the party's own ideological origin, government readiness, issue ownership, mass preference distribution, and more, specific to the issues under contest (see e.g., Abou-Chadi, 2016; Abou-Chadi & Orlowski, 2016; Downs, 1957; Grofman, 2004; Meguid, 2005; Spoon, 2009). For each contested issue dimension, we assume a left-right gradient representing a party's predispositions on this issue, with larger values indicating stronger support and smaller values weaker support for policy efforts favouring the issue. When properly centred at a meaningful origin (e.g., 0 on the real line), the sign of each position conveys straightforwardly the pro or anti stance taken by the party on the issue.

2. Parties also compete by emphasising certain issues more than others. On the saliency side, we assume parties to give unequal levels of attention to different issues to win votes as well. Such selective emphasis often serve the purpose of highlighting a party's genuine positional proximity to a voter on some issues and concealing their distances on others. Typical strategic motivations include valence perception and issue ownership (Brazeal & Benoit, 2008; Budge, Farlie, & Laver, 1983; Petrocik, 1996; Walgrave, Tresch, & Lefevere, 2015). For each contested issue dimension, we assume a high-low multiplier representing a party's preferred attention given to this issue, with larger values indicating greater preference for and smaller values less interest in talking about the issue. When compared against a neutral benchmark (e.g., 1 on the ratio scale), the magnitude of each salience indicates proportionally the party's interest in emphasising each issue.

3. Parties have incomplete control over either position or salience; they are also subject to the influence of other parties and the strategic context they are in. For both sides, we also assume multilevel constraints on parties' abilities in strategic manoeuvres, as a result of diverse factors like internal pressures, competitors' actions, public focus, media cues, or long-term trends and geopolitical contexts (Gilardi, Gessler, Kubli, & Müller, 2022; Klüver & Sagarzazu, 2016; McAllister & bin Oslan, 2021; Stimson, 2004). As such, parties position themselves on contested issues with various salience levels by reference to multiple agental and structural factors. We therefore further assume both parameters to include party, election (time), and country level variation at a minimum, and can be decomposed in this way following some simple functional forms (e.g., linear additive) accordingly.

Our theoretical model for the position-salience nexus directly follows from these basic assumptions, which can be framed as solutions to an optimisation problem of party-voter convergence as

$$ {}^{j}_{k};\ {}^{j}_{k}\ {}^{K}_{k=1} := \arg\min_{;} \sum_{k=1}^{K}\ {}^{j}_{k}\ {}^{j}_{k}\ {}_{k} \qquad (1)$$

for party j competing on K issues in a hypothetical election. $^{j}_{k}$ and $^{j}_{k}$ represent the party's position and salience associated with each issue k, and $_{k}$ is a summary indicator of voter preference (we keep its precise measurement agnostic for genericity here). The difference term between party and voter positions inside the innermost bracket encodes our assumption about spatial competition (1), and the multiplicative term between effective position and salience inside the norm operator encodes our assumption about selective emphasis (2). The multilevel constraints are partly taken up by the voter term but can be more expressively given by expanding the two parameters too, encoding our last assumption about limited agency (3). The summation over all K issues accounts for the multidimensional nature of the issue space. Together, Model 1 conveys our key idea that position and salience work side-by-side in increasing a party's chances of winning votes: by moving closer to the voter and by emphasising those issues on which it has an advantage, over all possible issues under competition. Issue positions and salience are not only codependent within but also between these issues, the exact nature and extent varying across contexts and partisan actors. In such a framework, a party's strategic parameters over these issues are the best solutions to the constrained optimisation problem, where it tries to minimise preference gaps with the electorate by a combination of positional and attentive manoeuvres traded off over multiple issues.

3.2 Model Setup

Our measurement model builds directly on the theoretical model of 1. Specifically, we maintain the multiplicative relationship between salience ( ) and position ( ) and their respective inclusion of multilevel factors of influence (the latter of which we make more explicit here), and use them as latent parameters that stochastically determine the manifest text data. In essence, we share the same rationale with the previously mentioned output-based methods on other types of party data to preference scaling (Bakker, 2009; Elff, 2013; König et al., 2013), and apply the generative logic to recover preference parameters from the CMP data. The particular modelling approach we adopt is Bayesian which allows us to combine prior knowledge with observed information and effect both point and uncertainty estimation in an efficient built-in manner.

To keep our model theoretically meaningful and statistically valid, we take a few basic assumptions about distributional situations and functional forms:

- First, we assume the observed response to follow a Dirichlet distribution ($\boldsymbol{x}$ Dir( )). This is to respect the non-negative and unit-sum properties of the variable, where each issue category has quasi-sentence share within the unit interval and together add up to 100%. Such a distributional assumption should better approximate the statistical behaviour of the CMP measure and yield more accurate parameter estimates.

- Second, we assume the position parameter to take on full support (2 R) and the salience parameter to be non-negative (2 R^{+}).[o] This is to implement our previous introduced notions of a signed gradient and a non-signed multiplier for the two parameters, respectively: put concisely, position carries with it both directional and locational aspects of information, while salience serves as but a signal processor that amplifies or dampens the perceived distance between party platform and voter preference. For salience specifically, we also constraint it to have unit sum so as to enforce the notion of limited issue attention in real-world elections. Their product is the joint strategic preference of the party on the associated issue, which we will use as the issue-specific parameter determining the multi-issue distribution.[©]

- Third, we assume both parameters can be decomposed into a linear hierarchical form. This corresponds with a linear additive specification with a grand mean (issue average) and three random effects (party, election, and country) for each issue category. We keep the number of the random effect relatively small so as to focus on major sources of variation only and reduce model complexity. The hierarchical

[o]Technically we allow for the salience term to take on any positive values in a small neighbourhood of zero but not exactly zero, to represent corner-solution style cases where a party chooses not to mention an issue at all. The preemptive imposition of strict positivity is for mathematical and computational convenience in later steps.

[©]Note also that we have conspicuously refrained from imposing any correlation/orthogonality conditions on the position-salience relationship. We prefer to allow the data to "speak loud" on this issue and accordingly examine the estimated relationship between the two terms in terms of their posterior correlation (;).

specification directly incorporate multilevel dynamics into our model. Given their supports and empirical analogues, we use a linear form for position ($= \; + \sum_c \; {}_c$) and a log-linear form for salience ($\ln \; = \ln \; + \sum_c \ln \; {}_c$), respectively.

We may now present our Bayesian model setup.[¨] Let $j; t; m$ index for party, election, and country, respectively, with $J; T; M$ units in each case. Let k index for policy issues for which a total of K issues exist in all cases. Each party's coded manifesto is then uniquely identified by the three earlier indices and partitioned by the last index. Denote the quasi-sentence shares for the K issues in each such manifesto as $f x^k_{jtm} g^K_{k=1} = [x^1_{jtm}; :::; x^K_{jtm}]^T$. We model them with a Dirichlet likelihood where the concentration parameters are determined by the latent party parameters:

$$x^1_{jtm}; :::; x^K_{jtm} \quad ^T \qquad \text{Dir} \qquad {}^1_{jtm}; :::; \quad {}^K_{jtm} \quad ^T \quad ; \tag{2a}$$

$${}^k_{jtm} = \tilde{}^k_{jtm} \quad \tilde{}^k_{jtm}; \tag{2b}$$

where the two multiplicative terms on the RHS of Equation 2b are adjusted party parameters with position $\tilde{}^k_{jtm} := j \; {}^k_{jtm} j$ and salience $\tilde{}^k_{jtm} := \; {}^k_{jtm} = \sum^K_{k=1} \; {}^k_{jtm}$, respectively. Briefly, the first adjustment ensures correctly non-negative values for the Dirichlet distribution's parameters and the second ensures the budget constraint on issue attention is respected. Next, we decompose these parameters of interest and place priors on them:

$${}^k_{jtm} \qquad N \qquad {}^k + \; {}^k_j + \; {}^k_t + \; {}^k_m; \quad {}^2{}_k \quad ; \tag{3a}$$

$$\ln \; {}^k_{jtm} \qquad N \quad \ln \; {}^k + \ln \; {}^k_j + \ln \; {}^k_t + \ln \; {}^k_m; \quad {}^2{}_k \quad ; \tag{3b}$$

following the linear hierarchical decomposition assumption we haven taken earlier. The full-support position parameter (${}^k_{jtm}$) is give a normal prior and the non-negative salience parameter (${}^k_{jtm}$) is given a log-normal prior.[V]. For appropriate yet not over-

[¨]A complete presentation of the full model and associated technical details can be found in Appendix B.

[V]As an aside, the salience model (3b) can be seen as a log-transformed version of a Cobb-Douglas style multiplicative model where the total signal is a joint product of individual signals linked together. Formally, ${}^k_{jtm} = \; {}^k \; {}^k_j \; {}^k_t \; {}^k_m \; e^{\; k} \; ! \; \ln \; {}^k_{jtm} = \ln \; {}^k + \ln \; {}^k_j + \ln \; {}^k_t +$

complicated partial pooling within the data, we use multivariate normal hyperpriors on the grand mean, group-level normal hyperpriors with group-specific means and variances for the random effects, and inverse Gamma hyperpriors for the variances.[U]

Further technical details about the model are left to Appendix B to save space here. In terms of model fitting, we estimate our model with Markov Chain Monte Carlo (MCMC) method, specifically by Gibbs sampling, with four chains and 10,000 iterations with 5,000 burn-ins per chain. In terms of convergence diagnostics, we assess MCMC performance with Geweke and Gelman-Rubin statistics (Gelman & Rubin, 1992) among other diagnostic tools.

3.3 Identification

We impose further restrictions on the parameter space to allow for unique identification. Similar to issues afflicting by item response theory (IRT) models, under the present formulation (2) the two parameters suffer from scale and rotational invariance problems (see Bafumi, Gelman, Park, & Kaplan, 2005). The product formulation of the joint strategic parameter (2b) means that the two multiplying terms are only identified up to a positive scaling factor, and the absolute transformation of the position term means that each estimate may have an oppositely signed complement that renders it non-distinct.

To address such aliasing problems we use proven tricks in Bayesian IRT models to fix the posterior distributions invariant (Bafumi et al., 2005; Gelman & Hill, 2006). For multiplicative aliasing we scale both parameter estimates by one of their standard deviations to fix posterior dispersion to common scale. We use the standard deviation of position estimate and effect a likelihood-preserving paired scaling on both parameters' estimates:

$$^{adjust} := \quad ^{1}; \quad ^{adjust} := \quad ; \tag{4}$$

$\ln {}^{k}_{m} + {}_{k}$. Incidentally but non-accidentally, this further demonstrates the signal processor interpretation of salience we have mentioned earlier.

[U] More specifically, for the grand means ^{k} and ^{k} we use K-dimensional multivariate normal (MVN) and log-normal hyperpriors with means and variances drawn from standard MVN and inverse-Wishart$(I_K; K + 1)$ distributions, respectively; for the three random effects, we use group-level normal and log-normal hyperpriors for each of them, which in turn have been given standard normal hyperpriors for mean and inverse-Gamma(1,1) hyperpriors for variance terms separately. All other variances have independent inverse-Gamma(1,1) priors.

and plug these into the concentration model (2) at each stage of updating. Other potential sources of aliasing in the random effects parameters are more easily accounted for by the standard Gaussian prior choices built into the model (Binding, Koedam, & Steenbergen, 2023).

For rotational invariance, we fix the rank order of the position estimate by imposing a regression constraint on one of the better-studied issues, environmental protection (CMP code q0}U·V, the 37§\ issue). We assume that on this issue the green parties have a distinctly positive position that on average exceeds that of the other party families. Therefore we run the following auxiliary regression to force the 37§\ issue (and by interdependence, all other issues) to have a specific directional layout:

$$ {}^{37}_{jtm} \quad N \quad {}^{37}_{jtm} + \quad \mathbb{1}\{ParFam = Greens\}_j ; e^2_{jtm} \quad (\quad > 0); \tag{5} $$

in which a party's estimated position on the environment issue is constrained to be higher if it belongs to the green family and lower otherwise. This forced asymmetry in one issue's positional alignment effectively anchors the posterior space in a simple and theoretically meaningful way. For the discrimination parameter ( ) we ensure its strict positivity by assigning to it a half-normal prior.

3.4 Paired and single items

Finally, we also provide conversion formulas to construct overall party measures on the earlier mentioned "paired" issues where two issue categories are 0² 9j§0 considered as opposing ends of the same spectrum. We remain agnostic about the utility of such pairing[£] but provide guidance on computing associated measures both for completeness and to facilitate bridging and comparison with the existing literature.

For paired items $k^{pro}; k^{anti}$, we recommend the following formula for their issue-wise aggregation along position and salience lines, respectively:

[£] See e.g., Lowe et al. (2011) for discussion about issues in using matched pairs and standalone policy items in the CMP data.

$$ {}^{paired} := \quad k^{pro} \qquad k^{anti}; \tag{6a} $$

$$ {}^{paired} := \quad p\overline{\quad k^{pro} \qquad k^{anti}}; \tag{6b} $$

where the first formula takes into consideration the signed and left-right nature of the position measure and the second accounts for the non-negative and ratio-style nature of the salience measure. The two formulas can be seen as analogous ways to compute averages of the corresponding base measures.

4 Empirical Application (*TRIAL RUN with limited sample*)

We demonstrate the new method's utility with empirical application to three country cases, Germany, Sweden, and the United Kingdom in the post-Fordist period (1980 onward). These cases are helpful as their party politics are among the best known and studied by researchers and represent three typical cases of different welfare regimes. Whenever in-depth examination is warranted we focus on the German case only. Substantively, we focus on two key policy dimensions in the period under coverage: welfare state and the environment. The former has two paired items: "Welfare State Expansion" (`qO}U·V`) and "Welfare State Limitation" (`qO}U·U`), and the latter a single item: "Environmental Protection" (`qO}U·o`). We compare both the estimated measure's face validity and its comparative performance against other scaling approaches, chiefly the saliency and logit approaches discussed earlier.[¢]

4.1 Cross-sectional estimates

Let us start with an inspection of cross-sectional estimates for the 2017 German federal election. Figures 1 and 2 present estimated issue position and salience parameters on

[¢]For brevity, all decomposed parameter estimates are not shown here but are available upon request. Same goes for uncertainty/interval estimates.

the two issue dimensions, welfare state (1) and the environment (2) for the five recorded parties in this election. For each party, the location of each point corresponds with the estimated position, and the size of it corresponds with the estimated salience. For the paired issue (welfare state), we also 0^{2} qn § calculate the "overall" position and salience for the unified dimension, using the simple difference formula introduced before. For the unpaired issue (environment) we present one-sided estimates.

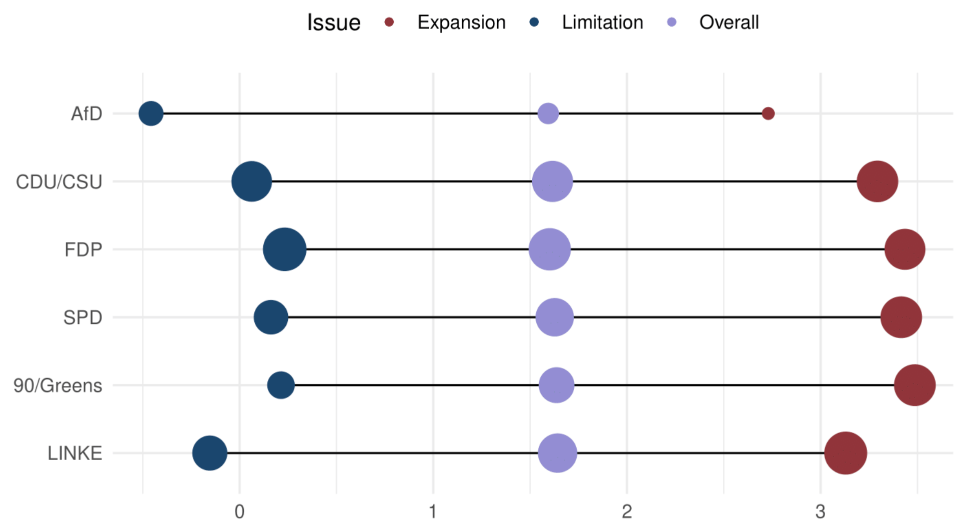

Figure 1: Estimated party policy parameters for welfare state issues in the 2017 German federal election. The location of the points corresponds with the estimated positions, and the size of the points corresponds with the estimated salience.

At a glance, the estimated party preferences appear to have quite good face validity. For the welfare dimension, on balance all parties appeared to have taken supportive stances on these issues, as indicated by their overall positive positions in the middle (coloured in lilac); interestingly this seems to be the result of an endogenous balancing mechanism where parties that took stronger pro-expansion (in red) positions also took somehow stronger pro-limitation (in blue) positions at the same time. Such that, the resulting differences between the two positions are more or less similar across the parties, which likely speaks to the substantively constrained issue space on this dimension — one cannot openly oppose the existence of the welfare state as such but may propose to modify, add to and/or limit certain aspects of it instead. In terms of salience, parties on the left appeared to have attributed slightly more weights to the pro side and parties on the right did weakly the opposite, although such differences seemed to be limited in scale

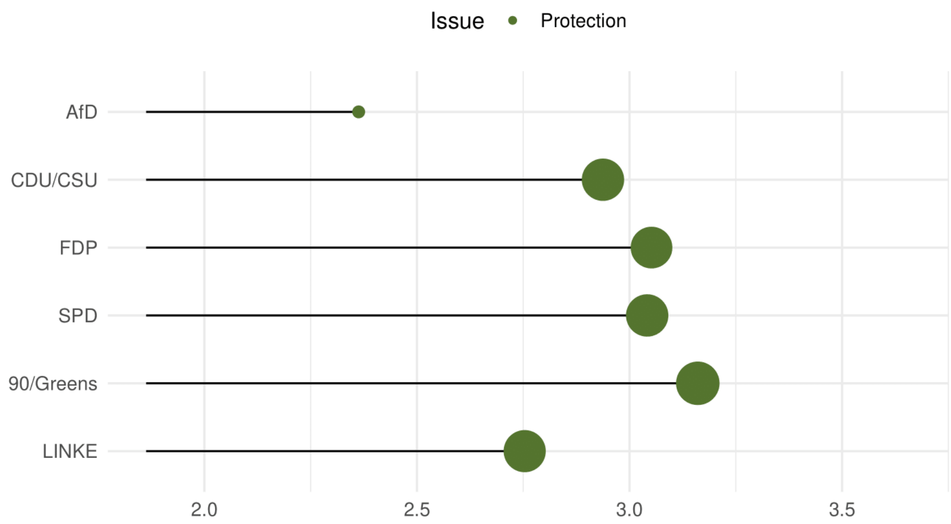

Figure 2: Estimated party policy parameters for environment issues in the 2017 German federal election. The location of the points corresponds with the estimated positions, and the size of the points corresponds with the estimated salience.

except in the case of the far-right AfD which left the least attention to this dimension.

Of particular interest is the curiously convergent pattern in issue positioning between the far left and the far right: notice that both parties, the LINKE and the AfD respectively, have taken especially strong positions 9X9_j § the limitation of the welfare state. This very likely speaks to their self-claimed roles as champions of the "underclass", though with difference class and ethnic emphasis, in relation to the mainstream parties on welfare issues. What distinguishes the two far ends however is the difference in the level of salience: the far right predictably emphasised welfare state issues much less than the far left.

A more familiar story emerges from the environment side, where most parties took supportive stances and similar emphases on this "valence" issue, with the Greens taking a stronger-than-average position — though notably without too much more emphasis — and the AfD putting the least effort into either supporting or highlighting the issue. For space reasons we refrain from further interpretation of the results here. Suffice to say the current approach seems to yield satisfactory estimates for key party preference measures at the cross-sectional level and, particularly for paired issues, more refined insights into the subtleties of party strategic manoeuvring along seemingly singular issue dimensions, as the earlier noted case of the far left and right's one-sided convergence on opposing welfare state limitation demonstrates.

4.2 Longitudinal estimates

Next let us extend our attention to the longitudinal dimension and inspect our approach's performance over time. For tractability I focus on the seven latest elections in the country and again assess scaling results on the two key issue dimensions. Figure 3 shows results for the welfare state dimension and figure 4 shows results for the environment dimension. In both cases the height of the bars represent the position estimates and the opacity of their colours the salience estimates. The taller the bar, the stronger the position; and the more intense the colour, the higher the salience. To avoid visual clutter no summary position for the entire welfare dimension is added in the corresponding figure (fig. 3).

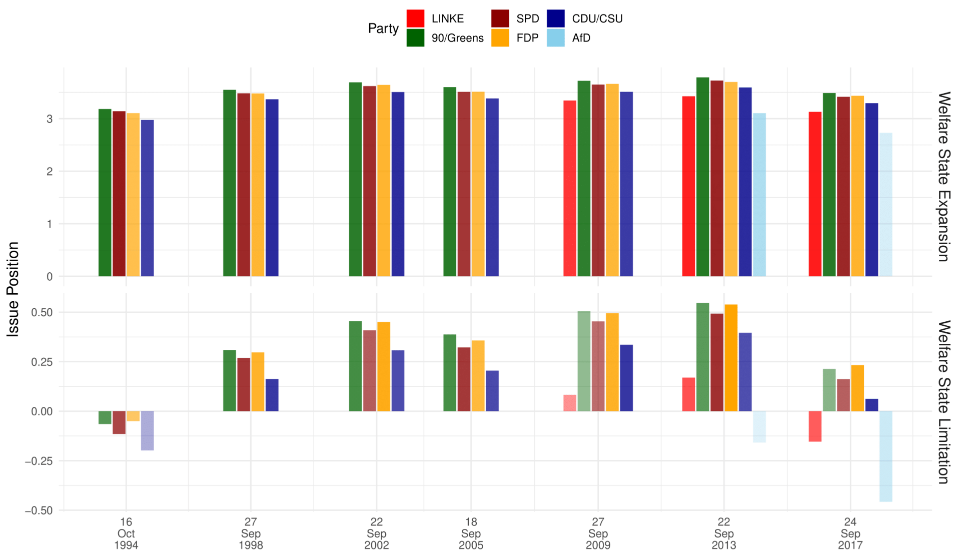

Figure 3: Estimated party policy parameters for welfare state issues in German federal elections 1994-2017. The height of the bars corresponds with the estimated positions, and the opacity of the colours corresponds with the estimated salience.

Upon first look the results again appear to support the face validity of the estimated parameters. We see in general all parties' professed support for welfare state expansion versus their more varied stances on its limitation; the valence-style support for environmental protection with even slight increase in its intensity over time; and the more distinct behaviour of the far left and right parties especially on welfare state issues compared to their mainstream rivals.

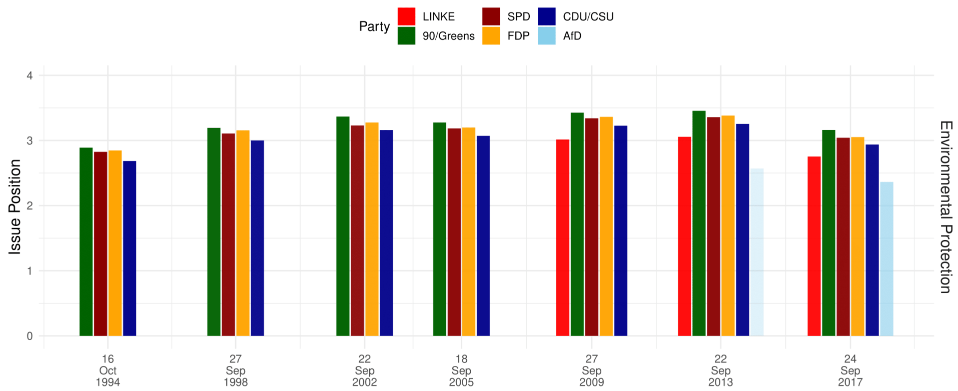

Figure 4: Estimated party policy parameters for environment issues in German federal elections 1994-2017. The height of the bars corresponds with the estimated positions, and the opacity of the colours corresponds with the estimated salience.

Interestingly, here we see both shared and party-specific changes in preferences over welfare limitation over time: at first all parties (whichever present at the time) were against limiting welfare benefits around the mid-1990s; then between the late 1990s and the mid-2010s they started to move towards supporting some limits on the latter, with the AfD notably being the sole opponent against such measures; and finally in the late 2010s the mainstream parties moderated their positions towards less overt support for welfare limitation, whilst the two far-end parties both strengthened their opposition against it. The AfD in particular has seemingly intensified its opposition against restricting welfare services, though this is accompanied by lower issue salience too, possibly due to its greater attention to its more invested sociocultural issues. The current approach may therefore aptly capture over-time variation in party preferences as well.

4.3 Scale comparison

Finally, let us compare estimates from our approach to those from the two major existing alternatives, the saliency and logit scales. To save space we only engage with the more recent logit scale in this section. Figures 5 and 6 display comparative results for the welfare state (overall) and the environment dimension respectively, with both scales standardised for both dimensions to facilitate comparison. The top panels display results for position estimates, and the bottom panels display results for salience estimates. Each dot in a panel represents a party's estimated issue preference in a particular election, and the dashed line represents the linear best fit between the two scales for the given country. The stronger the agreement between the scales the closer this line should be to the 45-degree diagonal line in the background (grey solid line).

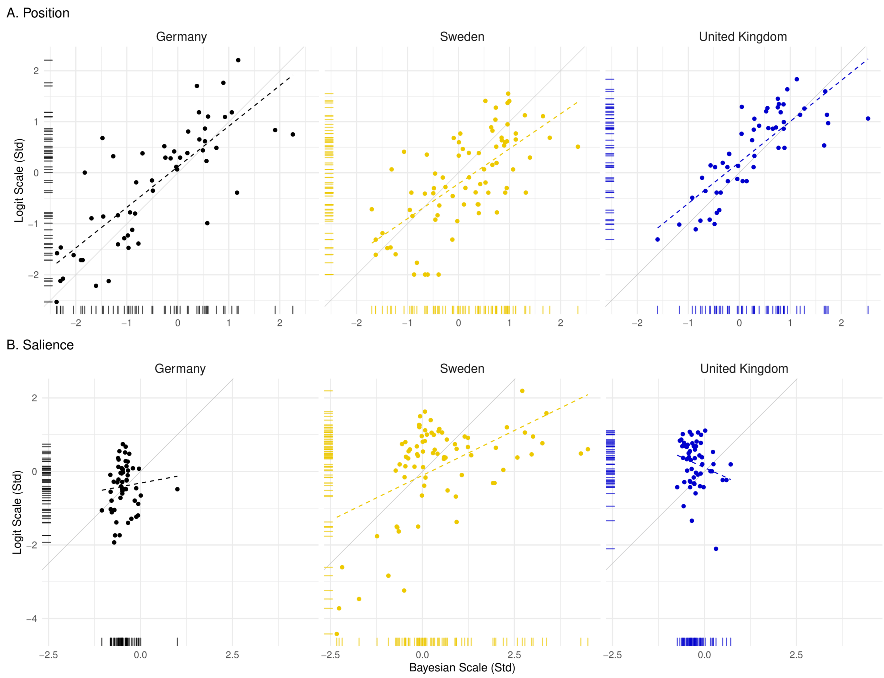

Figure 5: Comparison of party policy parameters estimated by logit (y-axis) and Bayesian (x axis) methods for welfare state issues, using all three country cases in the post-1980s period. The top panel shows results for positions, and the bottom panel shows results for salience. Both measures have been standardised to facilitate comparison.

Looking through the two figures one notes two main patterns. The first is that scale agreement seems to be stronger on position than salience estimates for a given issue dimension. The second is that scale agreement also seems to be stronger on paired (welfare state) than unpaired (environment) issue dimensions. More specifically, whilst the two scales broadly agree on the underlying distribution of party positions on welfare state issues, they disagree substantially on both the distribution of such positions over environment issues as well as the one of salience over both issue dimensions. It appears that the logit scale consistently yields higher variation, as well as stronger correlation between, position and salience estimates than the Bayesian scale.

This is particularly the case for the environment dimension, where the logit estimates seem to suggest a striking scene of intense competition over diverse positions and varying attentions on this dimension, and the Bayesian estimates seem to suggest a more subdued

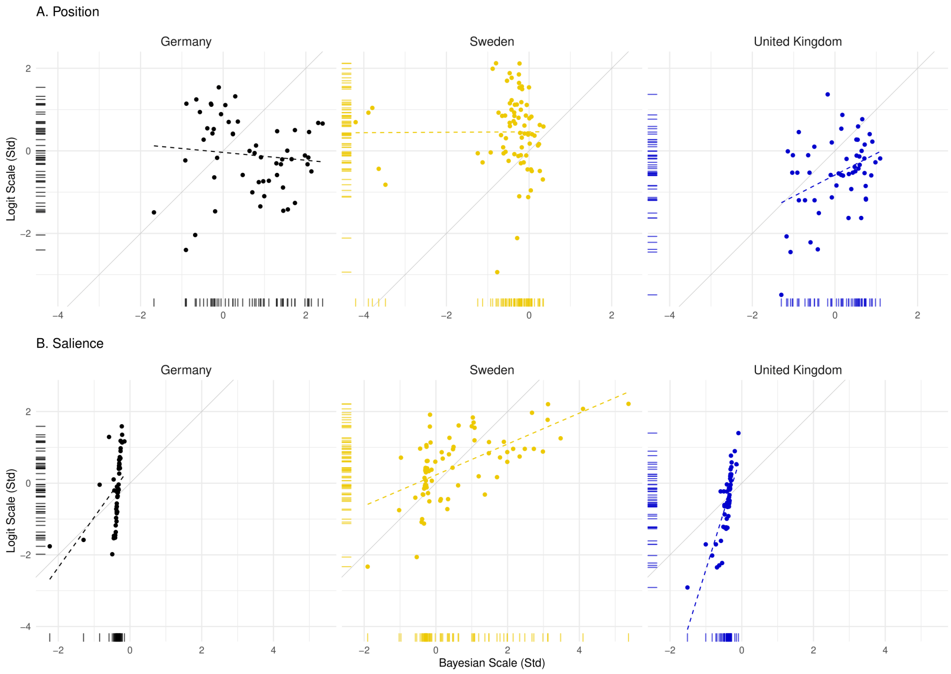

Figure 6: Comparison of party policy parameters estimated by logit (y-axis) and Bayesian (x axis) methods for environment issues, using all three country cases in the post-1980s period. The top panel shows results for positions, and the bottom panel shows results for salience. Both measures have been standardised to facilitate comparison.

picture where, in addition to still visible though weaker disagreements over preferred positions, the level of attention dedicated to these issues do not seem to differ much either by election or by party. The notable — and by real-life experience, probably also accurate — exception is the Swedish case, where some parties assigned much higher salience to this dimension, leading to a uniquely spread-out marginal distribution over this dimension compared to the other two cases. This seems to be consistent with the general impression of the country being a leader in both politicisation and policy-making with respect to environmental issues.

More generally, one may conjecture that the observed differences in parameter estimates reflects a deeper difference in scaling philosophy between the two approaches. As touched upon earlier, the logit scale is centred around the notion of issue-based comparison, where the position and salience of each party on an issue dimension are simply derived by aggregating information over the quasi-sentence shares limited to *§\9§ ®0}´ L_h0j _njJ §\9§ ®0}´ h9j_T0 §n 9jL §\9§ ®0}´ 0eOH§_nj* only. A by-product of this approach is that preference estimates are not only hard to compare across countries or over time in a macro-structural way, but also questionable between even two parties in the same election, as measurements are taken principally within each party's manifesto only. Meanwhile, the Bayesian scale is set up such that latent variations at all these levels are accounted for and combined into the final estimate in a conjoint manner. So in this respect comparability across different levels and units is higher by construction in the latter than the former case.

This might also partly explain the fact that the Bayesian estimates over party salience are so much more different between Sweden and the other two countries over environment issues, as this is partly a genuine reflection of cross-national heterogeneity in party politics over this dimension. As a reminder, purely statistical considerations aside greater variation is not always a desirable property, especially if it misrepresents the empirical realities of interest. As another side note, the stronger correlation between position and salience estimates by the logit scale might also have been in part a by-product of the way it calculates the two measures, especially for single-item issues like the environment as noted earlier. These results suggest that the new approach bodes greater potentials for comparative research involving contextual heterogeneity and cross-context comparability.

5 Conclusion

In this paper we have presented a new Bayesian scaling method for making empirical measures of party strategic preferences from pre-categorised document data. Our approach builds on recent advances in text and measurement modelling and seeks to improve upon existing methods by better utilising information about the multidimensional structure of the data and of the underlying generative processes. A major part of our contribution lies in the development of a theoretically motivated yet also data-driven measurement model that explicitly accounts for both agental and contextual effects, which are often ignored or underappreciated in extant methods and their measure estimates.

To briefly recap, our model adopts a generative approach and models the observed text share of each policy issue as the manifest response of a latent generative process controlled by the strategic parameters of interest, position and salience alike. Novel aspects of our model include the Dirichlet-distributed response assumption and the multiplicative relationship between the ancestral parameters. Our design allows for more clear separation of supply-side measures from demand-side factors which can better serve theory-testing purposes and further understanding of key aspects of the party-voter interactive dynamics. Our (preliminary) results also suggest that existing measures are likely to be affected by actor- and context-specific biases that may affect the quality and reliability of statistical inference using such measures.

Our study has therefore implications for both present and future research on party and electoral politics. For one thing, researchers should be more cautious about interpreting test results using existing measures that may well conceal systematic errors from measurement biases. For another, our first-attempt model can be used as a building block for methodological works that seek to reach even more valid and reliable measures of party strategic preference. More broadly, our model with its versatile and largely agnostic attitude to source data naturally lends to application in analysing pre-processed text data of other sociopolitical processes, which may help advance other sub-fields of empirical research as well.

Future research could extend the insights from this study in several ways. for example, the statistical impact of different distributional assumptions can be explored. We mentioned that normal-style distributional assumptions may not lead to well-fitting likelihood functions that yield good parameter estimates. Future research could explore different distributional assumptions and their impact on the model's performance. Likewise, different model specifications could be explored by iteratively in/excluding different sources of structural information — issue, party, country, and election inclusive — one at a time to explore which source contributes the most to improving model performance in explaining observed variation in the data. Another promising direction relates to the incorporation of the auto-regressive aspect of party preferences. Drawing from the dynamic state-space model literature (Elff, 2013), such an addition would acknowledge that party preferences are not static but rather correlated over time, influenced by past positions and salience. This could provide a yet more nuanced understanding of party competition, capturing the dynamic nature of parties' electoral strategies as they adjust their positions and salience in response to changing political landscapes and past strategies. Moreover, the auto-regressive component could very plausibly enhance model fitting too, potentially providing more accurate and efficient estimates of party preferences.

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Appendix

A The CMP project database

Electoral manifestos describe and outline the official policy preferences and proposals that political parties present to their electorate during an electoral campaign. Written in a competitive setting, party manifestos are helpful not only for assessing party positions on specific issues but also for evaluating the relative importance they attribute to the diverse political issues. Party manifestos tend to be long and, thus, provide substantial and detailed information on diverse political issues and dimensions. Additionally, these documents can be analysed retrospectively as, unlike expert surveys, they are independent of someone's memory.

Amongst the examples of manual coding of party manifestos, the Comparative Manifesto Project (CMP) dataset consists of one the most used sources to measure party preferences. It is a seminal initiative that systematically analyses the manifestos of political parties across diverse countries. Initiated in the late 1960s, the project aims to generate a comprehensive understanding of parties' political positions by quantifying the content of their manifestos. The unique feature of the CMP dataset is its utilisation of 'quasi-sentences' as a unit of analysis. A quasi-sentence is identified as the smallest textual unit that expresses a singular political idea or argument. Each quasi-sentence is categorised under an array of predefined codes, encompassing a wide spectrum of political, social, and economic issues.

The resultant dataset presents a detailed account of a party's political stance, enabling a comparative study of the position and evolution of political parties over time. It offers a profound insight into the ideological shifts within parties and contrasts between parties across nations. Similar to the Chapel Hill Expert Survey (CHES) dataset, the CMP provides good-quality data that are cost-efficient, publicly available and cover salience and positions on diverse political issues.

The current coded CMP dataset includes over 50 categories, each represented by a unique code. Broadly, the categories are divided into seven domains:

- External Relations: This includes categories related to international affairs, European integration, and internationalism.
- Freedom and Democracy: This encompasses categories concerning human rights, democracy, and constitutionalism.
- Political System: This covers issues such as decentralisation, centralisation, and the political authority.
- Economy: This domain includes categories related to the economic system, such as economic planning, market regulation, and economic orthodoxy.
- Welfare and Quality of Life: This covers categories such as social justice, welfare state expansion, and the environment.
- Fabric of Society: This domain includes issues related to social harmony, multiculturalism, and national way of life.

- Social Groups: This domain includes categories related to the representation of different social groups, like farmers, middle class, underprivileged minority groups, etc.

Each of these domains includes several specific categories. For example, the "Economy" domain includes categories such as "Labour Groups: Positive" or "Control over Globalisation: Positive". Each quasi-sentence in a party's manifesto is coded based on its content, and the frequency of each code is used to analyse the party's political stance on various issues. Figure A1 presents the domains, categories and corresponding item code in the CMP dataset.

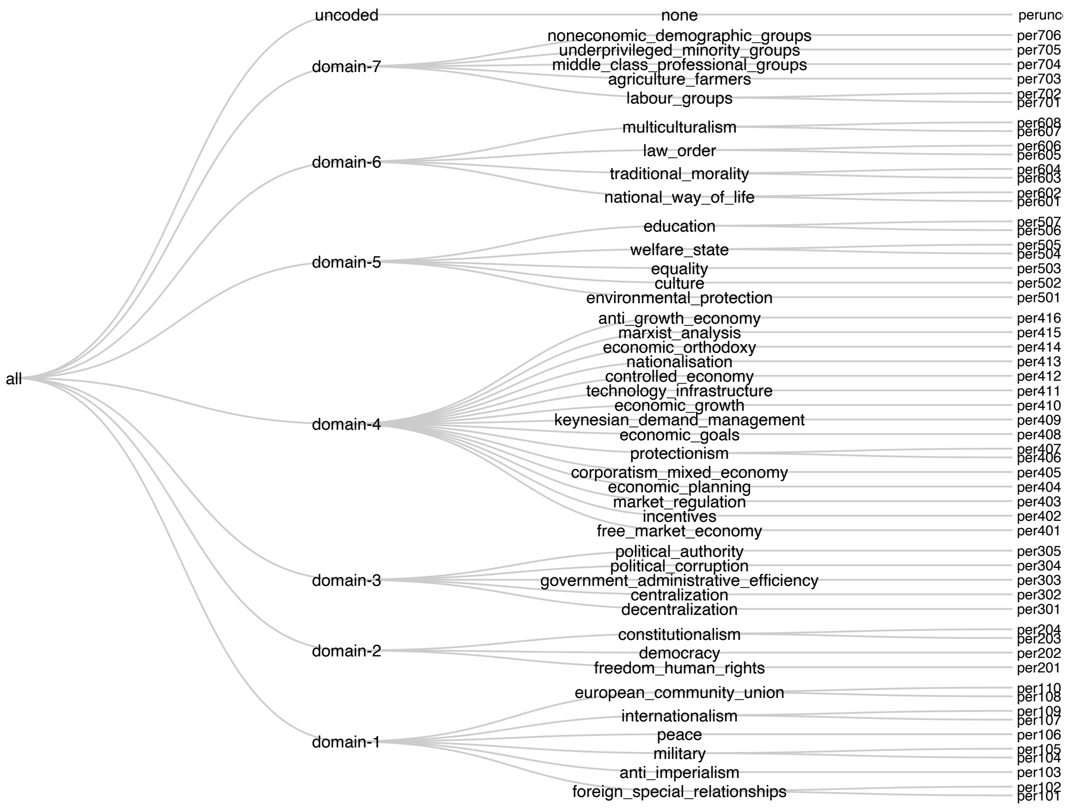

Figure A1: Overview of the Comparative Manifesto Project Dataset

B The Full Bayesian Model

Suppose we observe data $\{(\mathbf{x}_i; J_i; T_i; M_i; 1_i^{ECO})\}_{i=1}^N$, where $\mathbf{x}_i = (x_i^1; \ldots; x_i^K)^T$ is a non-negative vector of length K with $x^k \in [0;1]\ \forall\ k$ and $\sum_{k=1}^K x_i^k = 1$, $J_i \in \{1; \ldots; J\}$, $T_i \in \{1; \ldots; T\}$, and $M_i \in \{1; \ldots; M\}$. $1_i^{ECO} \in \{0; 1\}$ is an indicator function.

We model the latent generative process for $\{\mathbf{x}_i\}_{i=1}^N$ as:

$$\mathbf{x}_i \quad Dir(\ _i); \tag{7}$$

$$_i = \tilde{\ }_i \quad \sim_i; \tag{8}$$

where $_i; \tilde{\ }_i; \sim_i$ are each a length-K vector. We model the two last parameters as, respectively:

$$\sim^{k[i]} = j \bullet^{k[i]} j; \tag{9}$$

$$\bullet^{k[i]} = \frac{k[i]}{}; \tag{10}$$

$$^{k[i]} \quad N \quad ^k + \ ^k_{j[i]} + \ ^k_{t[i]} + \ ^k_{m[i]}; \ ^2 \ ; \tag{11}$$

$$N_K(\ _0; \quad) \ (\ ^k \text{ is the } k\text{th element in the } K\text{-vector } \ ); \tag{12}$$

$$_0 \quad N_K(0_K; I_K); \quad ^1 \quad W_K(I_K; K+1); \tag{13}$$

$$^k_{j[i]} \quad N \quad ^k_j; \ ^2_{^k_j} \ ; \quad ^k_j \quad N(0;1); \quad ^2_{^k_j} \quad Gamma \ 1; 10 \ ^3 \ ; \tag{14}$$

$$^k_{t[i]} \quad N \quad ^k_t; \ ^2_{^k_t} \ ; \quad ^k_t \quad N(0;1); \quad ^2_{^k_t} \quad Gamma \ 1; 10 \ ^3 \ ; \tag{15}$$

$$^k_{m[i]} \quad N \quad ^k_m; \ ^2_{^k_m} \ ; \quad ^k_m \quad N(0;1); \quad ^2_{^k_m} \quad Gamma \ 1; 10 \ ^3 \ ; \tag{16}$$

$$^2 \quad Gamma \ 1; 10 \ ^3 \ ; \tag{17}$$

and

$$\sim^{k[i]} = \bullet^{k[i]} \quad ; \tag{18}$$

$$\bullet^{k[i]} = \frac{k[i]}{\sum_{k=1}^K \ ^{k[i]}}; \tag{19}$$

$$\log \ ^{k[i]} \quad N \ \log \ ^k + \log \ ^k_{j[i]} + \log \ ^k_{t[i]} + \log \ ^k_{m[i]}; \ ^2 \ ; \tag{20}$$

$$\log \quad N_K \ \log \ _0; \quad (\log \ ^k \text{ is the } k\text{th element in the } K\text{-vector } \log \ ); \tag{21}$$

$$\log \ _0 \quad N_K(0_K; I_K); \quad ^1 \quad W_K(I_K; K+1); \tag{22}$$

$$\log \ ^k_{j[i]} \quad N \ \log \ ^k_j; \ ^2_{^k_j} \ ; \quad \log \ ^k_j \quad N(0;1); \quad ^2_{^k_j} \quad Gamma \ 1; 10 \ ^3 \ ; \tag{23}$$

$$\log \ ^k_{t[i]} \quad N \ \log \ ^k_t; \ ^2_{^k_t} \ ; \quad \log \ ^k_t \quad N(0;1); \quad ^2_{^k_t} \quad Gamma \ 1; 10 \ ^3 \ ; \tag{24}$$

$$\log \ ^k_{m[i]} \quad N \ \log \ ^k_m; \ ^2_{^k_m} \ ; \quad \log \ ^k_m \quad N(0;1); \quad ^2_{^k_m} \quad Gamma \ 1; 10 \ ^3 \ ; \tag{25}$$

$$^2 \quad Gamma \ 1; 10 \ ^3 \ : \tag{26}$$

Onto which we impose the following constraints:

$$\beta^{k'[i]} \sim N\left(\beta_0^{k'[i]} + \beta_1 \mathbb{1}_i^{ECO}; \sigma^2_{k'}\right); \tag{27}$$

$$\beta_0^{k'[i]} \sim N(0;1); \quad \beta \sim HN(0;1); \quad \sigma^2_{k'} \sim Gamma\left(1; 10^{-3}\right) \tag{28}$$

where k' corresponds with a particular issue, environment protection in this case.

C Further Results

Figure A2 and Figure A3 display comparative results for the current Bayesian scale against the saliency scale. The patterns are broadly similar to those discussed in the main text.

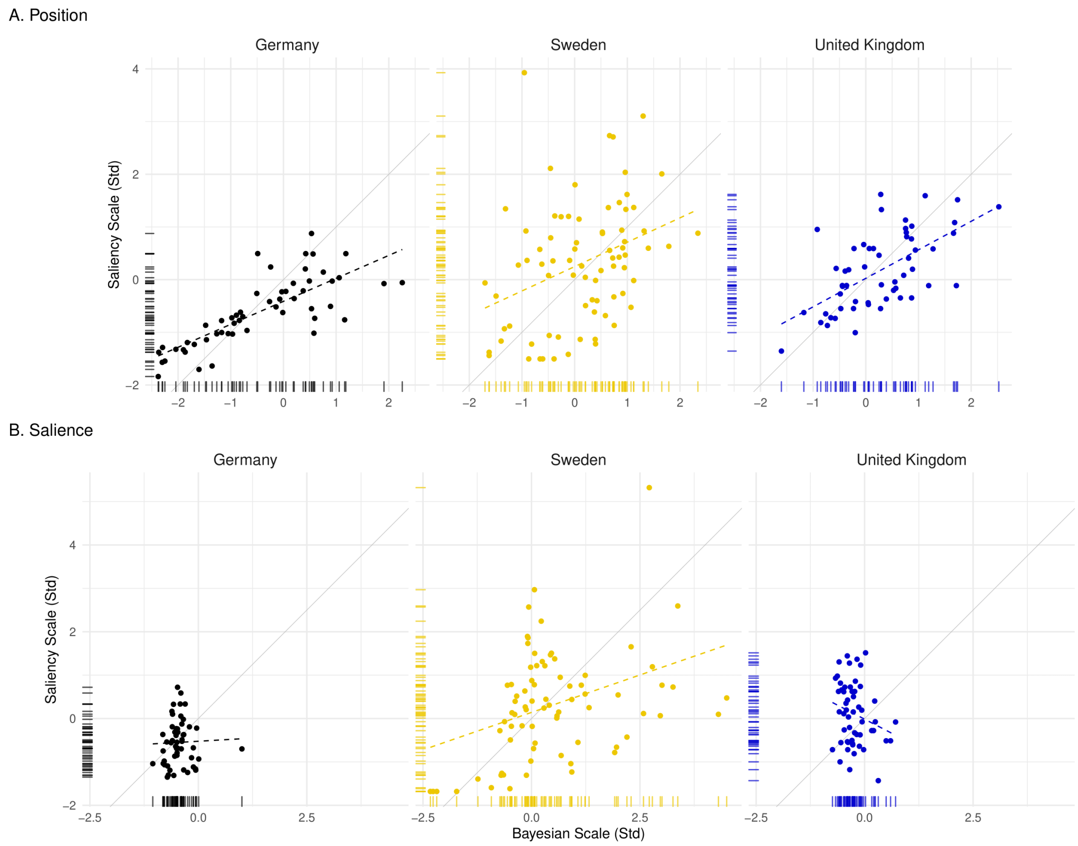

Figure A2: Comparison of party policy parameters estimated by logit (y-axis) and Bayesian (x axis) methods for welfare state issues, using all three country cases in the post-1980s period. The top panel shows results for positions, and the bottom panel shows results for salience. Both measures have been standardised to facilitate comparison.