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Estimating Policy Positions of Political Actors Across Countries and Time

Thomas Bräuninger, Marc Debus, Jochen Müller
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Abstract

Numerous empirical studies in comparative and international politics use estimates of policy positions of parties and political elites to analyse how preferences shape outcomes of political decision-making processes. In the past decade, data availability and methodological advances have fostered the shift from a static, cross-sectional view on positions and ideologies to a dynamic, longitudinal perspective on changing preferences and political change. A large part of the ongoing debate on what kind of data can be used for longitudinal analysis revolves around the pros and cons of using fully computerized content analysis of political texts as compared to the yardstick dataset in comparative government, the ‘Comparative Manifesto Project’ (CMP) data of hand-coded party manifestos. While a large part of this discussion is methodological, we know little how the different methods compare empirically. This is what we do in this paper. We compare estimates of parties’ policy positions from CMP with positions derived from Wordscores for 13 Western European countries in the time period between 1980 and 2010. Our analysis shows that by and large, the CMP and the Wordscores approach produce similar estimates of parties’ positions on a general left-right dimension. Yet, the degree of congruence differs considerably over countries and also varies with the type of party and party manifesto the estimate is based on. We examine outliers from the overall pattern and discuss possible reasons for them.
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Introduction

Having reliable and valid estimates of the policy preferences of political actors is imperative for answering key research questions in various fields of political science, such as comparative and international politics, or political economy. A large body of literature in these fields make theoretical arguments that are based on or, empirically, use estimates of policy positions of parties and political elites to analyse how preferences shape policy outputs and policy outcomes in decision-making processes (e.g., Adams et al. 2004; Martin/Vanberg 2004, 2005; Tsebelis 1999, 2002; Tsebelis/Chang 2004; Bräuninger 2005; Knill et al. 2010; Bäck et al. 2011; Osterloh/Debus 2012). In the past decade, data availability and methodological advances have fostered the shift from a static, cross-sectional to a dynamic, longitudinal perspective on changing preferences and political change. The work of the ‘Comparative Manifesto Project’ (CMP; see Volkens 2001, 2007; Volkens et al. 2012) resulted in a comprehensive dataset covering party saliencies for 56 policy categories in the OECD world since 1945 (see Budge et al. 2001; Klingemann et al. 2006). The theoretical baseline of the CMP methodology – saliency theory as developed by Robertson (1976) – came, however, under attack for theoretical reasons (Laver 2001). The current debate on which kind of data can be used for longitudinal analysis concentrates on the pros and cons of the ‘Comparative Manifesto Project’ dataset and methods based on fully computerized content analysis of political texts (Benoit et al. 2009a; Mikhaylov et al. 2012).

In this paper, we join this debate from a more empirical perspective. We estimate parties’ policy positions on a left-right-axis from party manifestos in 13 Western European countries in the time period between 1980 and 2010 using Wordscores (Laver et al. 2003; Lowe 2008) and compare these estimates to the ones from the CMP data. Our analysis shows that applying Wordscores results in fairly similar patterns of party positions on a general left-right dimension as compared to the CMP data but the match of these patterns clearly varies across the countries under consideration. Furthermore, the results of a multi-level regression model shows that Wordscores indeed does a better job replicating the CMP estimates when, firstly, reference texts (and scores) cover a wide range, and, secondly, the percentage of scored words is high. Finally, we examine outliers from the overall pattern and discuss possible reasons for them. The remainder of this paper begins with a brief review of methods of estimating policy preferences which focuses in particular on content analysis techniques. Afterwards, we discuss potential pros and drawbacks of each approach. In the ensuing section, we compare estimates on the parties’ left-right position derived from the CMP dataset with estimates based on the Wordscores technique and analyse their pattern resemblance using multilevel regression. The final section concludes.

Methods for estimating policy preferences from political texts

Various approaches can be found in the literature that allow for estimating preferences of political actors (Mair 2001). While a number of studies seek to make inferences on the positions of parties or individual politicians from behaviour, e.g., by analysing recorded votes in the parliament (e.g., Poole/Rosenthal 1997; Hix 2002; Clinton et al. 2004), other approaches measure programmatic positions of political parties more directly by conducting elite or mass surveys, so that the ideological position of, e.g., a party is measured by the mean placement of experts, voters, party activists or likely supporters (see, e.g., Kitschelt 1994, 1995; Norris/Lovenduvsky 1995; Adams et al. 2005). The major and most prominent alternative to both approaches focuses on the self-presentation of parties as expressed in the written programmatic statements parties’ issue before an election. In all modern democracies, nearly every (electorally relevant) party or party alliance publishes a – briefer or longer – programme for government, in which its goals for the next legislative period are outlined. A key advantage of election manifestos is that they are published at and
before each election. Moreover, because election programmes have normally to be passed by a party congress or at least by a wider group of party elites, they should reflect the preferences and priorities as well as the importance and bargaining power of different intra-party groups. Practically, the programmatic statements in these pre-election programmes can be used – and are used – as a starting point for subsequent coalition negotiations and as a point of reference for the policy assertiveness in a later formed coalition government (Kavanagh 1981; Klingemann et al. 1994: 27; Müller/Strøm 2008). In what follows, we compare advantages and caveats of hand-coded and computational techniques of political documents such as election manifestos, government declarations and coalition agreements (see for a more detailed overview Laver/Hunt 1992: 31-40; Benoit/Laver 2006: 82-101; Volkens 2007; Pappi et al. 2011; Seher/Pappi 2011).

Generally speaking, there are two principal ways of a positional analysis of policy documents. The first one involves a great deal of human interpretation of the substantial meaning of a text and uses manual coding based on a coding scheme to make inferences on positions or salience.1 Such a procedure is used by the Manifesto Research Group (MRG; since 1989 known as Comparative Manifesto Project, CMP; cf. Volkens 2001; Budge et al. 2001; Klingemann et al. 2006; Volkens et al. 2012). The second, more recent variant is based on computer-aided procedures that either combine human building of dictionaries containing a priori defined signal words with machinecoding of texts (e.g., De Vries 1999; Laver/Garry 2000; De Vries et al. 2001; Garry 2001; König et al. 2003; König/Luig 2009), or transform texts fully automatically into frequency matrices of words or phrases that are then regarded as unstructured data and analysed using some statistical method (cf. Grimmer 2010; Hopkins/King 2010; Laver et al. 2003; Slapin/Proksch 2008; Monroe/Schrodt 2008).

Manual coding of political texts

The work of the MRG and the CMP, respectively, resulted in a large and complex database of party saliencies on 56 policy issues for about 3000 election manifestos from 54 countries since 1945. The approach of this research has been criticised for both theoretical and empirical reasons. First, the MRG’s coding instructions are based on saliency theory (Robertson 1976). This theory assumes that parties express issue saliencies rather than policy positions in their election programmes. Therefore, most of the 56 MRG- and CMP-categories include only information about favourable policies (valence issues) and no negative emphasis on certain policy issues. Only twelve of the 56 categories were coded bipolar, so that one is able to distinguish between negatively and positively formulated issue saliencies in the respective election manifestos (Budge 2001; Volkens 2001: 96). In an empirical test, Budge (2001: 83) finds what he conceives as evidence for the assumptions of the saliency theory: only one negative coded category has a similar share of coded ‘quasi-sentences’2 as the respective positive category (see Volkens 2002: 3-10). Still saliency theory and thus the party positions estimated by the MRG and CMP came somewhat under attack. Laver (2001) argued that parties indeed formulate positions in their programmes and apply different saliency weights for each policy issue independently of the respective positions.

Beside these more theoretically orientated reviews, a number of methodological and empirical points of criticism also appeared. Most importantly, it is quite obvious that purely manual coding may run into problems of both validity and reliability. One major requirement for cross-national comparative studies is the

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1 To simplify matters we do not refer here to any sort of qualitative content analyses of political texts. This is not because of a presumed weakness of the approach. Qualitative content analysis indeed has many advantages compared to quantitative study designs such as the possibility of a deeper analysis of intra-party structures and their influence when writing election manifestos or negotiating coalition outcomes (see, e.g., Timmermans 2003, 2006).

2 ‘Quasi-sentences’ are the coding unit of the MRG/CMP-approach. Each ‘argument’, which could be a full or a half-sentence, is sorted into one of the 56 categories (see Volkens 2002: 3-4).
aggregation of information on both dependent and independent variables, so that comparisons between countries or over time are possible. Therefore, it is a ‘necessary evil’ to restrict the number of policy categories and to define them on a level of abstraction that allows them to travel across countries. This requirement is accompanied by a number of problems. Despite extensive and well-founded coding instructions (Volkens 2002), it seems not unlikely that coders in different countries attach different meanings to the same set of sentences resulting in different classifications of ‘quasi-sentences’ into one of the 56 categories. In an experimental study, Mikhaylov, Benoit and Laver (2012) show that even trained coders of the CMP project often allocate quasi-sentences not to the same or even ‘correct’ policy category but to various others (see also Däubler et al. 2012).

The last argument gains importance when thinking about findings on equivalence problems in comparative social science studies on the one hand and the coding and policy-issue scheme of the MRG/CMP – which is stable for the whole time period – on the other hand (King et al. 2003). Consider, for instance, the meaning of the policy categories ‘multiculturalism: positive’ and ‘multiculturalism: negative’ in the case of the Netherlands. At least until the end of the 1970s these categories include the party issue saliencies on the degree of pillarization. Since then ‘multiculturalism’ has evolved into a term that is largely associated with immigration policy. If this is correct it would mean that until the 1970s the ‘positive multiculturalism’ category would signify what we think of as a more ‘right-wing’ or ‘conservative’ statement while the ‘negative multiculturalism’ is a more ‘progressive’, anti-pillarization statement. Since the 1980s, however, the ideological stance of both categories should have completely turned around. Therefore, the content and ‘ideological direction’ of some of the 56 categories might change over time but the CMP-style coded data do not allow for a more detailed analysis of each category.

Furthermore, problems might arise when working with the general left-right party placement provided by the manifesto dataset. The simple left-right index is established by a subtraction of a priori defined ‘left’ policy categories from ‘right’ labelled issues (Budge/Klingemann 2001). Yet, the MRG and CMP coders could hardly anticipate that a policy area would switch from a ‘left’ to a more ‘right’ meaning during the time period since 1945 (see also König et al. To analyse party and coalition politics in a more sophisticated way, a number of studies tried to extract policy-area specific positions of political parties using the MRG/CMP data (see, e.g., the chapters in Budge et al. 1987; see also Gabel/Huber 2000; Cusack 1997, 2001; Linhart/Shikano 2009). One way to do so is by using multivariate statistical methods, in particular techniques of dimension reduction. But these come along with other problems. To estimate positions of parties in more than one policy dimension, it is necessary to either include the manifestos from all elections in one country or to transpose the dataset (Pappi/Shikano 2004). When applying the first procedure, problems arise when interpreting the extracted principal components. Also, very recent research stress the point that studies that are based on the CMP dataset treat the extracted positions of parties as their exact location in a given policy space ignoring errors in human coding. Therefore, Benoit, Mikhaylov and Laver (2009a) developed a statistical technique that estimates error terms for each of the 56 CMP categories. The application of this technique to prominent studies in political science shows that often, after including an error term, the relevance of ideology as measured by the CMP dataset increases.

Automated text analysis

The first challenge to manual coding of party policy documents came from dictionary-based automated content analysis of political texts (for an overview, see Garry 2001). The approach has a number of advantages compared with the MRG/CMP procedure, but there are also numerous problems. As compared to the MRG/CMP approach, the effort to make here is not ‘intelligent reading’ but the intelligent setting up of a dictionary. In the Laver and Garry (2000) approach, for instance, the first step is to ex ante identify signal words which are defined as ‘left’ or ‘liberal’ or ‘right’ and ‘conservative’, or simply as a word with
‘neutral’ meaning for a particular policy or issue dimension (Laver/Garry 2000: 622). In a second step, political texts are searched for these signal words by a computer. Thus the relevant policy dimensions have also to be determined a priori. Although by applying the ‘dictionary procedure’ policy positions rather than issue saliences can be measured and the likelihood of ‘human errors’ decreases (Mikhaylov et al. 2012), there is still the problem that human coders might classify signal words erroneously. In addition, one has to create a codebook for each language so that setting up dictionaries requires experts with knowledge of both the language and the ideological background of each key word. This decreases the prospects of cross-country comparative analysis of policy positions, e.g. the analysis of similar or deviating positions of policy-area specific positions of parties belonging to similar ideological ‘families’. Another critical point is that replications of studies based on the dictionary-procedure will only be possible if the dictionaries are made available. If these word lists are not provided in the respective publications or made available from internet sources, replication will not be possible (de Vries 1999; Laver/Garry 2000; König et al. 2003). In a more recent paper, König and Luig (2009) introduce a new dictionary-based approach on textual analysis that identifies the positions of political parties and governments using a dictionary that itself is based on an automated content analysis of legislative texts.

Fully computer-aided methods of content analysis like the ‘Wordscores’ approach developed by Laver, Benoit and Garry (2003) and the ‘wordfish’ technique by Slapin and Proksch (2008) are advancements of the semi-manual ‘dictionary approach’. The main advantage of both approaches is that the position estimation is left completely to computer algorithms. Therefore, potential problems associated with the ‘dictionary procedure’ do not arise. The basic idea of both techniques is to compare the frequency of words from different texts and to estimate the policy-area specific position of a text on the basis of the differences in the share of used words within a given set of political documents. They differ, however, in one decisive aspect. Wordscores compares the word frequencies of the texts at hand to the word frequencies of so-called ‘reference texts’ with known (or assumed) positions and assigns document scores based on the similarity to these references. Wordfish, by contrast, implements a parametric word scaling model to estimate document positions and does not require choosing reference texts. It still does, however, require the identification of some texts as ‘fix points’ that mark the extremes of a policy dimension. To clarify the differences between both techniques, we briefly describe the ‘Wordscores’ and ‘wordfish’ in the following paragraphs.

‘Wordscores’ compares the relative word frequency of a text which programmatic position is known to the word distribution of a text of the same character whose position is unknown. Laver, Benoit and Garry (2003: 314-315) refer to these two sorts of documents as ‘reference texts’ and ‘virgin texts’, respectively. In a nutshell, the position of a virgin text changes if the frequencies of ‘signal words’ go up or down. Signal words are not determined ex ante but assumed to signal a (particular reference text) position to the extent that they occur more often in one virgin text than in another. The key assumption behind Wordscores (as well as wordfish) is that political actors do not use words randomly. Instead, to include ‘ideological signals’ (Pappi/Shikano 2004) in election manifestos parties will use some words more often and others less often or even never. To show their hostile position towards raising taxes, liberal parties for instance often use the word ‘tax’ in connection with the demand to decrease the tax burden. From this perspective, this approach and the theory behind are not far away from saliency theory and the idea of the CMP approach to code quasi-sentences with ideological connotation.

To be more precise, Wordscores proceeds in the following steps. The first step is decisive for the robustness of the results. One has to search for ‘reference texts’ that are used for estimating the positions of political actors from a set of ‘virgin texts’. To obtain valid results, the selected texts should be of the same character as the one whose position is unknown. Thus, when one is interested in the – policy-area specific
position of an election manifesto, it is most reasonable to use election manifestos as ‘reference texts’ (Laver et al. 2003: 315). In general, election manifestos are quite similar in terms of their structure as well as their vocabulary. The risk of obtaining invalid results increases if, for instance, one tries to estimate the position of an election manifesto when using speeches of politicians as reference, because the usage of words in the two texts will be less homogeneous, and a speech might include too few words. Another critical issue is the allocation of (policy-area specific) positions to the selected reference documents. Assuming that, due to their wide coverage of policy issues, election manifestos are the best choice for ‘reference texts’, we still have to assume some reference scores for these party platform. Reliable sources for reference scores are surveys where experts are asked to locate the parties on the basis of the last general election (e.g. Laver/Hunt 1992; Benoit/Laver 2006). In a further step, scores for any single word in reference texts are calculated as mean values based on the references scores of all reference texts, and positions of the virgin texts are then estimated as the mean of the scores of all words in the respective virgin text. Despite discussions on how to best standardize Wordscores estimates (Martin/Vanberg 2008; Benoit/Laver 2008) and on the method itself (Budge/Pennings 2007a, 2007b; Benoit/Laver 2007), a study by Klemmensen, Hobolt and Hansen (2007) finds evidence for the robustness of the method by analysing Danish election manifestos and government speeches between 1945 and 2005. The extracted policy positions of Danish political actors show a strong correlation with estimates from expert surveys and the CMP dataset.

The more recent ‘wordfish’ approach developed by Slapin and Proksch (2008) comes very close to the wordscoring technique but has some decisive differences. First and most important, estimates are obtained from an item response model that is (also) based on word frequencies so that it is not required to make use of any sort of reference texts. To extract policy-area specific positions of political actors, researchers have to single out sentences or paragraphs in the political text that refer to that policy area – a task that poses both conceptual and practical challenges. Slapin and Proksch (2008: 712-719) show that their estimates of German party positions in the time period between 1990 and 2005 correlate considerably with other measures that are based on expert surveys, CMP data or Wordscores analyses of German election manifestos. Correlations are strong for the overall left-right dimension, the economic and foreign policy domain, but weak for the social policy dimension (see for recent applications, e.g., König et. al. 2010; Seher and Pappi 2011; Pappi et al. 2013).

While the advantage of wordfish over Wordscores is that no reference scores are required (see, e.g., Benoit et al. 2009b; Bräuninger and Debus 2012: 38-51), one challenge for both techniques is the generation of policy area-specific scores. Laver, Benoit and Garry proposed a policy-blind approach: Policy-specific positions are not generated by changing the text input (e.g. foreign policy manifesto sections for foreign policy estimates) but by changing the scores assigned to the reference texts. This means that the reference scores completely drive the policy-area specific position estimation in Wordscores. Proksch and Slapin (2006), in contrast, have argued for a substantive selection of texts. Foreign policy scores should only be based on word frequency distributions in the foreign policy sections of the manifestos. This requires a manual allocation of paragraphs or even sentences to a specific policy area. The latter requires not only the knowledge of the respective document’s language but also the development of some classification scheme for the various policy areas. Slapin and Proksch (2006) refer to the dictionary-based analysis of German party competition (König et al. 2003) and use the headings of each chapter in German election manifestos to allocate them to the economic or foreign policy dimension. The remaining parts of the manifestos reflect the social policy dimension (Slapin and Proksch 2008: 712). While this is a quite straightforward approach and may explain the missing congruence with the results of other studies on the

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3 It is needless to say that ‘reference’ and ‘virgin texts’ should be written in the same language.
4 For a robustness check with regard to the usage of different reference texts and/or reference scores when applying Wordscores, see Müller (2013: Appendix B).
positions of German parties on the social policy dimension, other studies that apply the wordfish technique to extract the policy positions of German state manifestos developed an even more detailed approach which uses any single paragraph as a coding unit (Pappi et al. 2011; Schmitt 2008; Seher/Pappi 2011). In the following sections, we analyse the congruence between the left-right positions of parties included in the CMP dataset and estimates based on one fully computational method of textual analysis, Wordscores (Laver et al. 2003).

Comparing party positions estimated by CMP and Wordscores data across countries and time

Klemmensen, Hobolt and Hansen (2007) show that the left-right positions of Danish parties measured by the CMP dataset strongly correlate with positions estimated on the basis of fully computational text analysis. They apply the Wordscores technique (Laver et al. 2003) to the almost full set of Danish political parties and estimate their position on an overall left-right scale in the time period between 1945 and 2005. Their encouraging finding – a strong and significant positive relationship between the additive left-right index of the Comparative Manifesto Project and the Wordscores estimates – is, however, limited to one country. There are only a few other studies that analyse the relationship between hand-coded approaches (i.e., the data gathered by the CMP) and Wordscores estimates. In the paper that presented Wordscores, Laver, Benoit and Garry (2003: 320-324) provide correlation analysis between their estimates and the positions of parties procured by the CMP dataset and recent expert surveys. Their results show that for the three countries under study (Germany, Ireland and the United Kingdom for two points in time, respectively), the policy-area specific positions estimated by Wordscores are strongly associated to the positions estimated by experts, 'the semi-computational' dictionary approach (e.g., Laver/Garry 2000) and the ones provided by the Comparative Manifesto Project dataset. While the correlations are nearly perfect for the Irish and British parties, the estimates for the German parties in 1990 and 1994 show a less strong relationship. It is obviously unsatisfactory to draw conclusions on the congruence of the two groups of policy position estimates by referring to a small-N country sample that covers only two points in time. Budge and Pennings (2007a, 2007b), for instance, argue that the estimated party positions by applying the Wordscores technique often differ significantly when choosing different sets of virgin texts. It is, in fact, decisive that correct and complete versions of political texts are necessary to get valid and reliable results on the preferences of political actors (Lowe 2008; Slapin/Proksch 2008; Benoit et al. 2009). The analysis of Budge and Pennings in turn is, however, only based on a comparison of the positions of British and American political parties from 1970-1997 and from 1980-1996, respectively. For the Wordscores approach, we know pretty well when and how different sets of virgin texts and different methods of standardization do matter for 'laboratory' texts (Lowe 2008). What is missing so far is a thorough comparison of 'real world data', i.e. party positions derived by different techniques. This would provide insights on which differences there are and whether they really matter.

We try to fill this gap with an analysis of the congruence of different measures of party policy positions by comparing the left-right positions of parties in 13 developed democracies over time. Our country sample includes Austria, Belgium, Denmark, Finland, Germany, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom in the time period between 1980 and 2010. Table 1 displays a more detailed overview on the covered time span per country. Most of the election manifestos were provided by the Central Archive in Cologne (ZA).5 Texts that were not available from the ZA were collected

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5 Paul Pennings and Hans Keman, Vrije Universiteit Amsterdam, Comparative Electronic Manifestos Project, in cooperation with the Social Science Reserach Centre Berlin (Andrea Volkens, Hans-Dieter Klingemann) the Zentralarchiv für empirische Sozialforschung, GESIS, Universität zu Köln, and the Manifesto Research Group (chairman: Ian Budge). Financed by the Netherlands Organization for Scientific Research (NWO project 480-42-005).
by the authors and are provided by the open access archive http://www.polidoc.net (see Benoit et al. 2009). The following subsections provide a descriptive overview and a comparison of the estimated party positions.

In the case of the CMP data, we make use of the additive left-right index ‘rile’ as developed by Budge and Klingemann (2001) and by Klingemann et al. (2006). In the case of the Wordscores analysis, we selected political documents as reference texts that were drafted by the parties in the years 2001, 2002 or 2003 (depending on when an election to the national parliament took place). We use the positions of parties on the CMP’s general right-left dimension (‘rile’) as reference scores. The reason for selecting reference at the end of the time period is that we think of this procedure as a more ‘conservative’ approach of estimating policy positions of parties over time. In every language community, the usage of words and phrases changes over time so that the word pool of party programmes should become more incongruent the larger the time span between these elections. If the analysis reveals that the correlation between the CMP ‘rile’-index and the Wordscores estimates is nevertheless strong, then there is at least evidence that both techniques for measuring the ideological positions of political parties deliver similar if not valid estimates of the latent variable.

Table 1: Countries and time periods covered in the analysis

<table>
<thead>
<tr>
<th>Country</th>
<th>Covered time period</th>
<th>Number of analysed documents</th>
</tr>
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<tr>
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<td>1983-2008</td>
<td>39</td>
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<tr>
<td>Belgium</td>
<td>1981-2003</td>
<td>68</td>
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<tr>
<td>Denmark</td>
<td>1981-2007</td>
<td>83</td>
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<td>1983-2007</td>
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<tr>
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</table>

Analysis

In this section we investigate the correlation between the party positions on a left-right scale estimated by the CMP and the corresponding Wordscores data in a broader country sample to see whether specific patterns in the congruence between country groups or party families exist. In a second step, we analyse the determinants of the deviation between the left-right position of parties according to the CMP and the Wordscores data. We begin with the analysis of the correlation between Wordscores and CMP estimates of party positions on a general left-right scale by country. Table 2 and Figure 1 below show the correlations between the positions of parties numerically and graphically. We calculate the rank correlation (Spearman’s Rho) and Pearson’s r correlation coefficient that allows for a comparison of metric data. Both measures presented in Table 2 show that a positive correlation between the ‘rile’ index and the Wordscores estimates exists in all countries under study. The overall correlation of the party scores on a left-right index estimated by the two different approaches is .547 (Spearman’s Rho) and .539 (Pearson’s r), respectively.

Yet, the correlation between ‘rile’ and the Wordscores estimates of the parties’ left-right position varies between the 13 countries to a significant degree. While for two of the four Scandinavian countries under study – Norway and Sweden – as well as for the German parties the correlation is as high as about .8 for both Spearman’s Rho (ρ) or Pearson’s r, the congruence of the estimated left-right positions is clearly lower for the British, Danish, Irish, Spanish and Swiss parties: the scores for ρ and r vary between .5 and .78, indicating a weaker but still strong positive relationship between the two left-right measures. The correlation is weaker in the case of the Austrian, Belgian, Dutch, Finnish and Portuguese parties, where the coefficients are barely positive and reach scores between .12 and .41 only. According to the graphical analysis shown in figure 1, there are nearly no outliers that would systematically bias the results suggesting that to some extent Wordscores and CMP measure different things. Only for the Netherlands the Wordscores estimate of a single party – the socialist SP in 2002 – marks as a clear outlier. The reason is that the SP election manifesto of 2002 is very similar to the one presented before the 2003 Dutch parliamentary elections. The party programs for the 2003 Dutch parliamentary elections are used as our reference texts to estimate the Dutch party positions since 1981. Yet, the score of the 2002 SP election manifesto does not substantially affect the correlation. However, the easily identifiable Dutch outlier points to a general potential pitfall in applying Wordscores which might be referred to as “early elections extremism”: if large parts of a virgin text were copied into a reference text or the other way round – which is more likely to occur in case of early elections –, the respective virgin text includes an outstanding share of words with scores corresponding to a reference score.7 The more parts of a virgin text appear in a reference text, the more its estimated position corresponds to the score assigned to the respective reference text. This becomes especially clear if it involves texts positioned at the extremes. This problem might be solved in this case by simply excluding the 2002 election manifesto of the Dutch SP from the analysis. The difficulty is, however, that the problem is a) continuous and b) not necessarily easy to detect. First, the share of identical sections might not be about 93% (as in the example above), which raises the question of when a

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7 The outlined problem is not restricted to manifestos; it might also become apparent if a very similar speech has been held earlier.
text is truly independent. Second, the share of scored words is not necessarily very high, making it hard to identify a clear threshold. Therefore, we argue for consciously looking at the texts included in the analysis.

Irrespective of the outlined difficulties with regard to individual outliers, the overall positive correlation patterns, the country-wise correlation between the two datasets is not so strong that one can exclude substantially different effects when empirically testing theoretical models that make use of the ideological orientation of political parties as a dependent or independent variable.

Table 2: Correlation between Wordscores and CMP estimates of party positions on a general left-right scale by country

<table>
<thead>
<tr>
<th>Country</th>
<th>Spearman’s Rho (ρ)</th>
<th>Pearson’s r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>.412*</td>
<td>.377*</td>
</tr>
<tr>
<td>Belgium</td>
<td>.206</td>
<td>.220</td>
</tr>
<tr>
<td>Denmark</td>
<td>.556**</td>
<td>.553**</td>
</tr>
<tr>
<td>Finland</td>
<td>.123</td>
<td>.162</td>
</tr>
<tr>
<td>Germany</td>
<td>.814**</td>
<td>.843**</td>
</tr>
<tr>
<td>Ireland</td>
<td>.688**</td>
<td>.593**</td>
</tr>
<tr>
<td>Netherlands</td>
<td>.378**</td>
<td>.311*</td>
</tr>
<tr>
<td>Norway</td>
<td>.856**</td>
<td>.792**</td>
</tr>
<tr>
<td>Portugal</td>
<td>.315*</td>
<td>.347*</td>
</tr>
<tr>
<td>Spain</td>
<td>.502*</td>
<td>.553**</td>
</tr>
<tr>
<td>Sweden</td>
<td>.829**</td>
<td>.833**</td>
</tr>
<tr>
<td>Switzerland</td>
<td>.620**</td>
<td>.584**</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>.781**</td>
<td>.697**</td>
</tr>
<tr>
<td>Total</td>
<td>.547**</td>
<td>.539**</td>
</tr>
</tbody>
</table>

** significant at 1%; * significant at 5%.
Before we get back to this, we adopt a different perspective and analyse whether there are systematic differences when differentiating by party family (see Mair/Mudde 1998; Gallagher et al. 2006: 235-260). When compared to the country-wise analysis, some patterns become observable. From Table 3 it turns out that there is an only weak positive correlation between the left-right ideal point estimations of the two datasets in case of ecological/green parties and social democratic political parties (see also Figure 2). We also find a weak positive correlation of the two different measures for parties that belong to the group of nationalist parties. There is, by contrast a statistically significant and rather strong positive relationship between the left-right positions estimated by the CMP and the corresponding Wordscores estimates for liberal, Christian democratic, conservative, agrarian and ethnic-regionalist parties. It therefore seems that there is a more of difference between both hand and fully computational approaches of content analysis when it comes to the placement of parties that belong to the left of the party spectrum.

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8 We use the CMP code to identify the party family a specific party belongs to (see Budge et al. 2001: 193). One exception marks the Social Democratic Party of Portugal, which is a Christian-democratic party and a member of the Centrist Democrat International. The CMP dataset labels the PSD still as a social democratic party (simply because of its name). Because of its ideological background, we add the PSD to the Christian Democratic party family and delete it from the social democratic party family.
Table 3: Correlation between Wordscores and CMP estimates of party positions on a general left-right scale by party family

<table>
<thead>
<tr>
<th>Party family</th>
<th>Spearman’s Rho</th>
<th>Pearson’s r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ecologicals/Greens</td>
<td>.226</td>
<td>.251</td>
</tr>
<tr>
<td>(Former) communists</td>
<td>.524**</td>
<td>.604**</td>
</tr>
<tr>
<td>Social Democrats</td>
<td>.201*</td>
<td>.153</td>
</tr>
<tr>
<td>Liberals</td>
<td>.448**</td>
<td>.481**</td>
</tr>
<tr>
<td>Christian Democrats</td>
<td>.418**</td>
<td>.334**</td>
</tr>
<tr>
<td>Conservatives</td>
<td>.413**</td>
<td>.397**</td>
</tr>
<tr>
<td>Nationalists</td>
<td>.433</td>
<td>.505</td>
</tr>
<tr>
<td>Agrarians</td>
<td>.444**</td>
<td>.420*</td>
</tr>
<tr>
<td>Ethnic, regional and special interest parties</td>
<td>.632**</td>
<td>.737**</td>
</tr>
<tr>
<td>Total</td>
<td>.547**</td>
<td>.539**</td>
</tr>
</tbody>
</table>

** significant at 1%; * significant at 5%.

Figure 2: Wordscores and CMP estimates of party positions on general left-right scale by party family

Before turning to the analysis of the results in three party systems that vary in their degree of correlation between the Wordscores and CMP left-right measures, we next use a more statistical approach to examine the fit between Wordscores and CMP estimates of party positions. In a basic model setup we can think of a linear relationship between Wordscores ($y_1$) and CMP ($y_2$) estimates that would take the form

$$y_1 = \alpha + \beta y_2$$
with $\alpha = 0$ and $\beta = 1$ if the two did match perfectly and were measured on the same scale. We might expect such a complete pooling as our Wordscores estimates are based on reference scores taken from the CMP data. Whether or not the CMP scale carries over to the Wordscore estimate via the technique of using reference scores is exactly what we would like to know. Our statistical model therefore allows for country-level variance using a multilevel linear regression model with country-varying intercept and varying slope. More precisely, as we can estimate reference-text based wordscores only within one language, we have two “country estimates” for Belgium (i.e. political texts in French and in Dutch), and one set of estimates for the other countries each. What we are interested in is the question whether, given this scale transformation (i.e. the linear relationship), some of the residual variance can be explained by factors that are specific to the Wordscore method. We are therefore setting up a regression model that includes both a mean and a variance model. The statistical model we estimate is:

$$
\begin{align*}
y_{ij} &\sim N(\alpha_j + \beta_j y_{ij}, \sigma^2) \quad \text{for } i = 1, \ldots, n \\
(\alpha_j, \beta_j) &\sim N\left(N(\alpha, \beta), \begin{pmatrix} \sigma^2_{\alpha} & \rho \sigma_{\alpha} \sigma_{\beta} \\
\rho \sigma_{\alpha} \sigma_{\beta} & \sigma^2_{\beta} \end{pmatrix}\right) \quad \text{for } j = 1, \ldots, J \\
\sigma_i &= \exp(\hat{\sigma} + Z_i \lambda) \quad \text{for } i = 1, \ldots, n
\end{align*}
$$

(1)

where $j[i]$ is the country of party $i$, and the $\alpha$ and $\beta$ parameters are estimated from the data. The vector $Z$ is composed of variables that are considered to influence the variance, $\lambda$ is a set of parameters. As a baseline model, we first run the model without any $Z$. In a second model we seek to consider the uncertainty that goes along with any measurement of party positions. The Wordscores estimates of party positions are weighted means of the ‘wordscores’ of single words providing us with a – rough – guess of the uncertainty related to the point estimate. We would expect party positions with large standard error to have, ceteris paribus, larger residuals in a regression on CMP point estimates. In Model 2, the standard error of the Wordscores position is therefore used to model the data-level variance $\sigma$. With two further models we want to study whether or not the selection of a specific set of reference texts is crucial for the estimates. We consider the standard deviation of the reference scores as a second exogenous variable in the variance equation to see whether using extreme as compared to moderate reference scores (or parties) makes a difference. In a fourth model, we include the percentage of scored words in a text.

Table 4: Bayesian estimation of Models 1 and 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1 mean</th>
<th>Model 1 5%</th>
<th>Model 1 95%</th>
<th>Model 2 mean</th>
<th>Model 2 5%</th>
<th>Model 2 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_a$</td>
<td>-2.988</td>
<td>-7.349</td>
<td>1.245</td>
<td>-3.050</td>
<td>-7.159</td>
<td>1.361</td>
</tr>
<tr>
<td>$\mu_b$</td>
<td>0.508</td>
<td>0.345</td>
<td>0.666</td>
<td>0.499</td>
<td>0.346</td>
<td>0.657</td>
</tr>
<tr>
<td>Wordscores SE</td>
<td></td>
<td></td>
<td></td>
<td>0.075</td>
<td>0.061</td>
<td>0.088</td>
</tr>
<tr>
<td>$\sigma_a$</td>
<td>8.851</td>
<td>5.894</td>
<td>12.711</td>
<td>9.250</td>
<td>6.160</td>
<td>13.231</td>
</tr>
<tr>
<td>$\sigma_b$</td>
<td>0.325</td>
<td>0.209</td>
<td>0.475</td>
<td>0.331</td>
<td>0.219</td>
<td>0.491</td>
</tr>
<tr>
<td>$\sigma_{\hat{s}}$</td>
<td>2.738</td>
<td>2.689</td>
<td>2.787</td>
<td>2.372</td>
<td>2.303</td>
<td>2.439</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.270</td>
<td>-0.246</td>
<td>0.694</td>
<td>0.231</td>
<td>-0.262</td>
<td>0.654</td>
</tr>
<tr>
<td>Deviance</td>
<td>5006.159</td>
<td>4994.000</td>
<td>5020.000</td>
<td>4891.869</td>
<td>4880.000</td>
<td>4907.000</td>
</tr>
</tbody>
</table>

a Variables are z-standardized. N= 602; groups: countries = 14.
Table 5: Bayesian estimation of Models 3 and 4

<table>
<thead>
<tr>
<th></th>
<th>Model 3</th>
<th></th>
<th></th>
<th></th>
<th>Model 4</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>5%</td>
<td>95%</td>
<td>mean</td>
<td>5%</td>
<td>95%</td>
<td>mean</td>
<td>5%</td>
</tr>
<tr>
<td>( \mu_a )</td>
<td>-2.651</td>
<td>-6.732</td>
<td>1.741</td>
<td>-2.568</td>
<td>-6.434</td>
<td>1.548</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \mu_b )</td>
<td>0.497</td>
<td>0.334</td>
<td>0.653</td>
<td>0.507</td>
<td>0.342</td>
<td>0.665</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wordscores SE</td>
<td>0.076</td>
<td>0.062</td>
<td>0.090</td>
<td>0.065</td>
<td>0.047</td>
<td>0.083</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reference Scores SD(^a)</td>
<td>-0.039</td>
<td>-0.095</td>
<td>0.013</td>
<td>-0.060</td>
<td>-0.140</td>
<td>0.019</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \sigma_a )</td>
<td>0.340</td>
<td>0.227</td>
<td>0.502</td>
<td>0.342</td>
<td>0.223</td>
<td>0.520</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \sigma_b )</td>
<td>2.370</td>
<td>2.302</td>
<td>2.440</td>
<td>2.408</td>
<td>2.328</td>
<td>2.490</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \sigma_{\text{hat}} )</td>
<td>0.243</td>
<td>-0.245</td>
<td>0.656</td>
<td>0.225</td>
<td>-0.287</td>
<td>0.671</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deviance</td>
<td>4891.529</td>
<td>4879.000</td>
<td>4906.000</td>
<td>4891.641</td>
<td>4879.000</td>
<td>4906.000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) Variables are z-standardized. N= 602; groups: countries = 14.

Table 4 and 5 show the results of a Bayesian estimation of the parameters. The \( \mu_a \) and the \( \mu_b \) are estimates of the intercept and the slope for the model, averaged over countries. \( \beta \) is positive as expected, indicating that by a large CMP and Wordscores place parties in the same order on the left-right dimension. In fact, \( \mu_b \) is positive for all countries with almost certainty, specifically, 90% of the posterior distributions of the \( \beta_i \) have a positive support (not reported). As said above, there is of course no reason to expect \( \beta \) to be one or even close to one. In fact, with a mean of about 0.5 for the \( \beta \) estimates, Wordscores positions are more packed in the middle than CMP positions. The bottom part of the table gives the estimated variation, the between-country variation for the intercept (\( \sigma_a \)) and the slope parameter (\( \sigma_b \)). What is more interesting for our question is the overall variation that we have parametrized by \( \sigma_{\text{hat}} \). In model 1, \( \sigma_{\text{hat}} \) is 2.738 so that the standard deviation of the residuals is as large as \exp(2.738)=15.4. Model 2 includes the standard errors of the Wordscores estimates. The posterior of the parameter is clearly positive, suggesting that whenever there is uncertainty in the estimation of the position of a manifesto Wordscore and CMP positions differ, i.e. apart from the linear transformation there is a larger residual error. Bluntly, with small Wordscores standard errors, the model does a better job than with large ones. As a result, the “unexplained” part of the error, \( \sigma_{\text{hat}} \), decreases to 2.372.

Is there systematic difference between Wordscores and CMP estimates that can be attributed to the choice of specific reference texts? Models 3 and 4 give an answer. In model 3, we include the standard deviation of the references scores of the reference texts as a second exogenous variable in the variance equation. The parameter estimate is clearly negative (albeit with somewhat less than 90% certainty), indicating that the larger the range of reference scores, the smaller is the residual variance. This finding suggests that using a wide range of reference scores is likely to generate “better” estimates – at least estimates that better fit the CMP data. Finally, model 4 includes the percentage of scored words in each single virgin text. In general, a large number of scored words should result in better estimates, whereas at the other extreme, with zero scored words we have no information at all to make inferences on the position of the virgin text. In fact, the percentage of scored words is negatively related to the residual variance (again, with somewhat less than 90% certainty): the more information extracted from the virgin text is used, the smaller is the residual variance. While we can have some confidence about the direction of these effects, both are not really substantial (\( \sigma_{\text{hat}} \) does not decrease substantially). To sum this up, there is of course no way to find out whether CMP or Wordscores are closer to the “true positions”. But what we can say is that Wordscores does do a better job replicating the CMP estimates when, first, reference texts (and scores) cover a wide range, and, second, the percentage of scored words is high.
Figure 3: Estimated linear relationship between CMP and Wordscores party positions (Model 1)
Three case studies: Left-right positions of Austrian, British and German since the 1980s

Generally speaking, the results of the multi-level regression model revealed that three groups of countries exist that differ with respect to the association between the two measures of parties’ left-right positions (Figure 3). While the congruence is very high in case of the German, Swedish and Norwegian parties ($\rho > .81$), we find a quite low correlation of the left-right position of parties in case of Austria, Belgium, Finland, the Netherlands and Portugal ($\rho > .12$ and $\rho < .41$). In case of the parties from the remaining countries – Denmark, Ireland, Spain, Switzerland and the United Kingdom –, we get moderate correlation coefficients ranging from $\rho > .50$ to $\rho < .78$. To discuss the implications of the different measures for the analysis of party systems and to compare them with the historical development of each political party in terms of ‘face validity’, we take a look at the programmatic positions of Austrian, British and German parties over time as examples for countries that belong to one of the three identified groups mentioned above.

We begin with comparing the left-right positions of German parties – i.e. the ones provided by the CMP dataset and by the Wordscores estimates – with the development of German party competition since the 1980s. Figure 4 shows the positions of German parties on a left-right scale. Except for one major difference – the significant movement of the Christian Democrats (CDU/CSU) to the left in 1987 and 1990 – the German parties show a similar development over time when applying either the CMP left-right index or the Wordscores estimates that are based on reference data from the CMP dataset for the German parties in 2002. The Social Democrats (SPD) moved to left of the spectrum in the beginning of the 1980s and changed direction in the 1990s towards more centrist positions. In 2009, by contrast, the SPD adopted more left-wing positions according to the CMP dataset and the Wordscores estimates. This development, which is in line with the programmatic development of the party during this time period (e.g., Niedermayer 2011), is more pronounced by the CMP left-right index rather than by the Wordscores estimates, in particular when taking the error term into account. The programmatic development of the German Green Party (since 1991: Alliance 90/Greens) did not change significantly according to both data sources; the CMP data and the Wordscores estimates indicate that the German Greens remained at a left-wing position in the time period between 1980 and 2009. The same is true for the Socialists (PDS) or the 'Linke', respectively. In case of the Free Democrats (FDP), the CMP left-right index and the Wordscores estimates and place the Liberals between CDU/CSU and SPD. This finding is in line with a number of qualitative approaches that identify the Free Democrats as the pivotal player in German politics until the beginning of the 1990s because of their ideological position between Social Democrats and Christian Democrats (see, e.g., von Beyme 1984; Broughton/Kirchner 1988; Lösche 1994: 146; Saalfeld 2000: 52; Gallagher et al. 2006: 195-196). To sum up the findings from Germany, we get very similar ideological party positions when comparing estimates of the CMP data and positions derived by the Wordscores approach, indicating high face validity for both measures of ideological party positions.
In the case of the major British parties, the correlation between the estimated left-right positions of Tories, the Labour Party, the Liberals and their successor parties is weaker to some degree when comparing the CMP left-right positions with the estimated Wordscores data (Figure 5). While the Wordscores estimates suggest that the Tories moved to the right of the ideological spectrum, the CMP data indicates that the British Conservatives became more moderate over time. Yet, both data sources clearly demonstrate that Labour moved towards more centrist positions after Tony Blair became the party chair in 1994. In case of the 1983 and 1987 elections, both datasets place the alliance between the Liberals and the Social Democrats (later on: the Liberal Democrats) to the right of Labour. This is very much in line with the development of the British party system, because in 1983 the Liberal Party formed an alliance and later merged with the Social Democratic Party, the right-wing intra-party faction of the Labour Party. Also in accordance with the literature on British party competition (see, e.g., Adams 2001: 125; Russell/Fieldhouse 2005; Gallagher et al. 2006: 190-191), the Liberal Democrats were the main left-wing party in the UK in the 1997 and 2002 elections when looking at either the CMP or the Wordscores data. Only in cases of the 1992, 2005 and 2010 elections for the lower house the CMP dataset and the Wordscores estimate disagree on the left-right ordering of British parties: while the LibDems are located between Conservatives and Labour according to the manually coded CMP data (even when controlling for the standard errors of CMP categories, provided by Benoit, Laver and Mikhaylov (2009a), in case of the 1992 election), the Wordscores estimates place the Liberal Democrats to the left of Neil Kinnock’s ‘Old’ Labour party already in 1992, although Labour started its internal programmatic and organisational reform in 1994.
While the analysis of the ideological positions British parties showed some deviations from the expected programmatic ‘behaviour’, the differences among left-right positions of Austrian parties are much more intense when comparing the ideological placement of parties according to the CMP dataset with the left-right positions estimated by Wordscores. According to the literature on Austrian party politics (see for an overview Müller 2000), Social Democrats (SPÖ) belong to the left of the ideological spectrum, while the Freedom Party (FPÖ), which changed their profile from a national-liberal to a right-wing populist party in 1986, are located to the right of an overall left-right axis (see also Debus 2005). As in almost all European states, the Green Party belongs to the left of the party spectrum also in Austria. While we find evidence for these overall patterns, there are also clear differences between the Wordscores estimates and the CMP data on the Austrian party positions on a general left-right scale (see figure 6). The party positions that are based on the Wordscores estimation provide evidence for an ideological polarisation of Austrian party competition, which is mostly induced by the far-right position of the FPÖ in the 1990s. Furthermore, SPÖ and the Austrian Greens moved to the left since 1995, while both parties did not change their ideological positions when using the left-right positions provided by the CMP dataset. The degree of polarisation has, however, ended since 2002 according to the CMP data and since 2008 according to the Wordscores estimates, so that – at least in terms of broader trends – we get similar information on the programmatic development of Austrian parties at the end of our observation period. To sum up, we would get different results when applying the CMP and Wordscores data to test hypotheses on, e.g., government formation or the impact of policy positions of parties on legislative decision-making.
Concluding remarks

Policy preferences of political actors are a key variable in theoretical models in political science. The empirical evaluation of these models requires data on the ideological orientation or – more detailed – the policy-area specific position of political parties, which are the central actors in representative democracies. This paper was aiming at analysing the degree of deviation of ideological positions of parties derived from manual and automatic text analysis. Our analyses revealed that, in the first place, a positive correlation exists between the widely used CMP right-left index ‘rile’ and positions of parties that were extracted by applying the Wordscores technique. The degree of correlation, however, varies among the parties in the 13 countries under investigation and the party families the political parties belong to. Nevertheless, the varying degree of congruence of the two different left-right measures applied here has strong implications for the analysis of party systems and party competition on the national level and for comparative studies on policy outcomes where the ideological positions of political parties are generally used as a key explanatory variable. According to the results presented here, it does not make much difference when referring either to the CMP left-right index or the Wordscores estimates in case of German, Norwegian or Swedish parties. Even when applying the different datasets to the British, Danish, Spanish or Swiss parties the interpretation of the results does not differ that much. Things are different for Austria, Belgium, Finland and the Netherlands. We recommend therefore to cross-check every data on party policy preferences before using it in any kind of analysis. Despite all advancements in computerised methods of content analysis (e.g., Laver et al. 2003; Slapin & Proksch 2008; Monroe/Schrodt 2008; Grimmer et al. 2010), it seems that correlating the respective data with qualitative historical analysis of the respective party system and patterns of party competition is a major – or even the only – possibility to get a sense whether the estimated policy positions of political actors reflect the reality or not.

In the second place, we have shown that two particularities of the Wordscores technique affect the estimated positions of parties. Wordscores indeed does a better job of replicating the CMP estimates when, firstly, reference texts (and scores) cover a wide range of an ideological dimension, and, secondly, when the percentage of scored words is high. If researchers follow this advice, we are therefore quite optimistic that comparative studies that make use of party positions derived from the CMP dataset would get the same or at least similar results when applying party preferences derived from fully computerised text analyses techniques like Wordscores in their analysis.
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