Mapping Positioning Dynamics in Political Communication

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Abstract:

We introduce a novel approach to analyze the positioning strategies of political actors based on their public communication. Leveraging recent advancements in natural language processing and market structure analysis, we create dynamic maps that capture the evolving positioning of political actors. By utilizing textual data from public records, embedding models, and dynamic mapping methods, our approach reveals how political actors position themselves in their communication and how their positioning changes over time. We illustrate our approach using data from Germany, including all public speeches in the German parliament between 2009 and 2022. Our application yields two major insights. First, our proposed approach provides an intuitive representation of the German political landscape and recovers pronounced shifts in the positioning of several German parties. Thereby, our estimates of party positioning exhibit high validity, aligning well with external measures of party ideology or parties' actual voting behavior. Second, our proposed approach can help explain substantial variation in parties' performance. Using our estimates, we quantify various aspects of German parties' positioning, such as the degree of differentiation or stability over time. Panel regressions show that party positioning, as captured by these metrics, explains a substantial portion of within-party variation in regular election polls (+28%).

Keywords: Positioning, Political Marketing, Natural Language Processing, Dynamic Mapping

4.1 Introduction

Positioning is a crucial element of marketing strategy. A clear and consistent positioning strategy can establish strong brand associations, develop a compelling brand image, and differentiate market offerings from competitors (Kotler & Keller, 2013). Positioning helps to maintain a competitive edge in the market and secure firm performance in the long term (Porter, 1996). Thus, developing an effective positioning strategy is crucial for market actors and forms the basis for a range of marketing activities, including communication to consumers via advertising, public relations, websites, or social media.

The importance of an effective positioning strategy extends beyond markets. In the realm of politics, political actors, including political parties, individual candidates, or political action committees (PACs), strive to secure the support of their voters. Just as firms position their product brands to appeal to consumers, political actors position their human brands to resonate with voters (Thomson, 2006). As for firms, the positioning strategies of political actors guide most of their public communication, including speeches, interviews, or statements, and can wield a profound impact on their performance.

Despite the significant impact of positioning strategies in the political sphere, marketing research has paid limited attention to studying them. This gap contrasts an extensive body of literature that explores the positioning of market actors' offerings, such as firms, their brands and products, typically through market structure analysis (Lilien & Rangaswamy, 2003). Notably, political actors are significant beneficiaries of marketing knowledge, evident in the millions of dollars spent annually by political parties on marketing themselves and their candidates (Fossen et al., 2022; Lovett, 2019). Thus, there is an opportunity to explore how the toolbox of market structure analysis can help understand the effectiveness of political actors' positioning strategies.

A crucial challenge for studying the positioning of political actors lies in the dynamic nature of the political sphere. Political competition involves continuous adaptation, as political actors adjust their positioning in response to competitors' moves and evolving voter preferences (Laver, 2005). Political actors often react to shifts in public sentiment and adjust their positioning in response (Adams et al., 2004, 2006; Somer-Topcu, 2009). Moreover, personal change (Desposato, 2006), shifts in public sentiment (Williams, 2015), and external events such as a global pandemic (Louwerse et al., 2021) can also prompt political actors to adapt their positioning. Thus, to study the positioning strategies of political actors and assess their effectiveness, an approach capable of capturing these dynamics is needed.

This paper aims to develop, validate, and illustrate an approach to analyze the positioning dynamics of political actors based on their public communication. Our proposed approach capitalizes on two recent developments. (I) The increased availability of records documenting public speeches, advertising content, or social media discourse, which reveal how political actors communicate with the public. (II) Methodological advances in dynamic market structure analysis, offering a framework to uncover the evolving positions that underlie such communication (Matthe et al., 2023). By combining these elements, our approach seeks to uncover how political actors position themselves and how they adapt their positioning over time. The resultant estimates can serve as the basis for downstream tasks, such as modeling voter support, and thus help understand these strategies' effectiveness or lack thereof.

The basic idea of our approach is to derive time-evolving spatial representations, "dynamic maps", that reflect the positioning of political actors in their public communication. These dynamic maps serve as graphical representations that depict variations in how political actors position themselves throughout the course of time. By analyzing these maps, we can identify differences in positioning strategies, observe the timing and nature of positional changes, and quantify their positioning along different dimensions. These dimensions may include the level of differentiation, or the stability over time, among others.

To generate the dynamic maps, our approach involves two major steps. First, we employ pre-trained embedding models to compute pairwise (dis-)similarities between the statements found in the public communications of political actors. This process forms a dynamic network that captures the evolving relationships between political actors' statements over time. Second, we utilize the dynamic mapping method EvoMap, as proposed by Matthe et al. (2023). EvoMap allows us to project the dynamic network into a low-dimensional latent space. The resultant dynamic maps condense the manifold differences in how political actors communicate into simplified positions within a low-dimensional latent space. These maps provide a parsimonious summary of the speakers' positioning strategies, making them easy to comprehend and validate. Once validated, we can use these maps to quantify the underlying positioning strategies using various metrics.

We illustrate the validity and effectiveness of our approach using data from Germany, specifically records of all speeches delivered by all members of parliament between 2009 and 2022. Our analysis covers four legislative periods, which encompass significant events such as the entrance and exit of entire parties, shifts in government and coalitions, and party membership changes at the individual level. Using our approach, we generate monthly estimates for each political party in the German parliament. Our subsequent analysis provides three major results:

First, our approach produces maps with high validity. Our high-frequency measures of party positioning converge with existing, low-frequency measures of party ideology (e.g., based on party manifestos). Further, our estimated maps are strong indicators of actual party behavior: Parties with similar positioning, as indicated by our maps, tend to vote similarly on legislative bills.

Second, our approach uncovers important shifts in the political landscape. For instance, we recover key features of Germany's political landscape, with parties positioned along the left-right spectrum and exhibiting varying degrees of differentiation. The entrance of the right-wing Alternative for Germany (AfD) expands the ideological range and brings other parties closer together. The estimated temporal evolution paths demonstrate shifts in party positioning, including the Christian Democrats' (CDU/CSU's) transition towards the center, or the Green party's move from fringe to mainstream.

Third, we find that the generated maps help explain substantial amount of additional within-party performance in regular election polls. Panel regressions suggest a strong association between different aspects of party positioning, such as its temporal consistency or its niche-/fringeness, and the success of parties in election polling. For instance, changes in party positioning, measured as the length of movements on the map, indicate worse subsequent election poll results, in particular for parties that take more mainstream, central positions. While, as we discuss later, our ability to establish causal interpretations is limited, our findings provide at least correlational support for the idea that voters penalize parties that change their positioning over time, favoring consistency over adaptability. Without considering further external factors, our estimates of party positioning alone can help explain a substantial degree of within-party variation in performance (+28% R2). Thus, besides supporting substantive research on party positioning, our approach also yields practical insights for campaign managers, by helping them understand and monitor voter preferences and anticipating future shifts in voter support.

Our paper contributes to two streams of literature. First, our work extends existing marketing research on market structure analysis. Prior studies have developed approaches to derive market structure maps using various types of data, such as surveys, text, or search logs, in diverse contexts, such as social media, user-generated content, or price comparison websites (e.g., Kim et al., 2011; Tirunillai & Tellis, 2014; Ringel & Skiera 2016; Liu et al., 2020; Ringel 2023). We extend this line of work towards a new context: political communication. Methodologically, our approach expands on recent work on dynamic mapping (Matthe et al., 2023) by demonstrating how to construct dynamic maps using extensive archives of textual data through the integration of embedding techniques. Furthermore, while previous applications of dynamic maps have primarily focused on exploration and description, we showcase that the estimated map positions can also be linked to performance metrics and help explain shifts therein.

Substantively, our work adds to the literature studying marketing concepts in the political context. While the application of brand management ideas in the political sphere has gained attention (Reeves et al., 2006), empirical work has primarily focused on the effectiveness of political advertising (Lovett, 2019). These studies mostly examine individual advertising dimensions, such as tone, source, volume, or slant, to understand their impact on voter behavior (Fossen et al., 2022; Lovett & Shachar, 2011; Wang et al., 2018; Zhang & Chung, 2020). In contrast, our approach goes beyond isolating individual predefined dimensions of difference. Instead, we utilize the embedding step to identify (dis-)similarities in politicians' communication, allowing us to capture their overall positioning in dynamic maps. This enables us to quantify differences in communication in a novel manner, going beyond established measures of tone or slant. Importantly, our approach is applicable to various forms of political communication beyond advertising. Thereby, our paper demonstrates how leveraging the toolbox of market structure analysis can aid substantive discovery in political marketing.

The paper proceeds as follows. In the next section, we review the methodological background of market structure analysis. Section 4.3 introduces our proposed approach, while section 4.4 illustrates its application to data from the German parliament. Section 4.5 presents the descriptive findings of our application, while section 4.6 assesses our findings' validity. Section 4.7 showcases a use case on how our approach can aid empirical research. Finally, section 4.8 closes with a discussion of limitations and avenues for further research.

4.2 Methodological Background

Our approach is centered around mapping, a set of methods aiming to derive low-dimensional spatial representations of competing actors. This section provides a concise overview of the underlying ideas and situates our approach within the body of existing work. Table 4-1 provides a summary of the most important points of similarity and difference.

In market structure analysis, spatial representations, often referred to as "maps", are an established tool to analyze the positioning of market actors. These maps capture the differences among market actors, such as firms, brands, or products, through their proximity in a low (often two)-dimensional latent attribute space. By doing so, these maps offer a concise summary of the key differences among the competing actors in a market (Lilien & Rangaswamy, 2003). To further understand the drivers of these differences, researchers can link the maps to observable attributes, typically via property-fitting techniques. Maps have a long history in marketing research (Day et al., 1979; Green, 1975; Hauser & Koppelman, 1979; Shocker & Srinivasan, 1979) and continue to find applications in new domains or benefit from ongoing methodological developments.

The positioning of competing actors is typically unobservable, requiring market researchers to infer it from available data. One of the primary techniques used for this purpose is Multidimensional Scaling (MDS) and its various variants and successors. These methods create maps of market actors based on pairwise (dis-)similarity measures that quantify the degree of difference between any pair of actors under analysis. The analyst can choose to study different actors, such as firms, their brands, or products, and adopt various perspectives, such as examining firms' positioning strategies or evaluating the resulting positions in consumers' perceptions. Moreover, researchers can take measurements from various sources, such as surveys or user-generated content, and apply different methods (e.g., t-SNE vs MDS).

Recent marketing research has explored various sources for obtaining the required measures of (dis-)similarity among market actors. These sources include text (Matthe et al., 2023; Netzer et al., 2012), consumer search (Kim et al., 2011; Ringel, 2023; Ringel & Skiera, 2016), social networks

(Yang et al., 2022), shopping baskets (Gabel et al, 2019), or large language models (Li et al., 2023). To project the resultant measures of (dis-)similarity into a low-dimensional space, researchers use MDS (Netzer et al., 2012), MDS variants (Kim et al., 2011), or more recent alternatives such as DRMABS (Ringel & Skiera, 2016) or t-SNE (Gabel et al., 2019; Matthe et al., 2023; Ringel, 2023; Yang et al., 2022). While most of these approaches utilize static methods, studying the positions at a specific point in time, recent research has introduced dynamic variants of the most popular techniques (Matthe et al., 2023).

Our suggested approach follows a similar principle. We derive pairwise (dis-)similarity measures and subsequently project these measurements into a latent space via MDS-like techniques. However, we extend the existing line of research along two dimensions. Firstly, we examine a novel context: the positioning of competing political actors, as opposed to firms, brands, and products. Unlike firms and brands, political actors position themselves on a multitude of dimensions (such as immigration, societal questions, or economic policies), that can be in constant flux. These dimensions of differentiation are constantly impacted by current affairs and events (e.g., a specific crisis emerging), while in the standard marketing context the dimensions of differentiation are much more static (e.g., product attributes).

Secondly, we demonstrate the integration of the novel dynamic mapping framework EvoMap (Matthe et al., 2023) with modern embedding techniques. Previous applications of EvoMap focus on highly standardized texts, such as 10-K reports, using simple measurements of textual similarities like word co-occurrences. However, these simplistic measures yield inaccurate results when dealing with less standardized data or when there are significant changes in language over time, both of which are common in the realm of political communication. While embeddings have been used in static analyses, such as studying search patterns or shopping baskets, we showcase their particular utility in dynamic analyses of market structure. Thereby, our study also presents a blueprint for future dynamic mapping applications in diverse contexts.

Table 4-1: Related Mapping Research in Marketing

Paper	Unit of Analysis	Context	Empirical Aim	Data Type	Data Source	Similarity Measurement	Mapping via	Static / Dynamic Positions
Kim et al. (2011)	Products	Digital camcorders	Visualize browsing behavior in search maps	Search	Online retailer	Co-occurrence	Asymmetric MDS	Static
Netzer et al. (2012)	Brands	Sedan cars, diabetes drugs	Derive market structure from consumer-generated content	Text	Consumer forum discussions	Co-occurrence	MDS	Static
Ringel & Skiera (2016)	Products	LED-TVs	Visualize asymmetric competition in large markets	Search	Price comparison website	Co-occurrence	DRMABS	Static
Gabel et al. (2019)	Products	Groceries	Derive market structure of a full retailer assortment	Shopping baskets	Retailer	Product embedding	t-SNE	Static
Yang et al. (2022)	Brands	U.S. brands on Facebook	Identify brand positions across product categories	Brand-user network	Social media	Node embedding	t-SNE	Static
Li et al. (2022)	Brands	Cars and apparel	Identify brand positions via generative language models	Mention frequency	LLM answers	Co-mentions	MDS	Static
Ringel (2023)	Products	DSLR cameras	Visualize how products compete in multiple submarkets	Search	Price comparison website	Product embedding	UMAP + t-SNE	Static
Matthe et al. (2023)	Firms	Publicly listed US firms	Create dynamic maps of firm positioning	Text	10K product descriptions	Word co-occurrence	EvoMap (t-SNE)	Dynamic (20 periods)
This paper	Political parties	Members of the German parliament	Measure dynamics of party positioning	Text	Parliamentary speeches	Pre-trained sentence embeddings	EvoMap (MDS)	Dynamic (129 periods)

Notes: MDS, Multidimensional Scaling; t-SNE, t-distributed Stochastic Neighbor Embedding; UMAP, Uniform Manifold Approximation and Projection, DRMABS, Decomposition and Re-assembly of Markets by Segmentation, LLM: Large Language Model

4.3 Our Proposed Approach

Next, we introduce our proposed approach, outline data requirements, and then detail each step of the underlying methodology.

4.3.1 Data Requirements

We intend to analyze data in the form of time-stamped documents, such as records of public statements, press releases, social media posts, or parliamentary speeches. We choose textual data for two primary reasons.

First, language is the primary tool used by political actors to position themselves and plays a crucial role in their communication. The words politicians use convey their identity, values, priorities, and the ideas they want to associate with themselves in the minds of the public. Public relations strategists, campaign managers, or consultants often carefully craft public statements to align with the desired positioning of the speaker. Therefore, analyzing the language in public communication can provide valuable insights into the underlying positioning strategies that informed its creation. As Berger et al. (2020) stated, language not only influences the recipient but also reveals information about the sender.

Second, textual data is abundantly available in various forms. Political parties regularly publish transcripts of candidate speeches, newspapers report on public statements, and parliamentary speeches are often transcribed and made publicly available in many countries. Most of these data are archived and easily accessible, providing researchers with a persistent record of political communication (Monroe & Schrodt, 2008). In contrast, alternative data sources, such as surveys, require extensive planning, ongoing efforts and funding to produce reliable estimates at regular intervals (Slapin & Proksch, 2008). Moreover, the costs associated with surveys increase at least linearly with the desired frequency, making them considerably more expensive compared to leveraging publicly available textual data.

4.3.2 Methodology

The basic idea of our approach is to estimate latent positions in a low-dimensional space for each political actor, capturing the degree of (dis-)similarity in how they position themselves in their communication. To achieve this, we leverage pre-trained embedding models to measure the dissimilarity between statements made by different political actors. These models allow us to capture differences in various aspects of their communication, such as the issues addressed, the framing employed, or the emphasis placed on specific topics. Similar models have been successfully applied in tasks such as analyzing customer feedback (Timoshenko & Hauser, 2019) or studying story-telling (Toubia et al. 2021).

In each period, we apply pre-trained embedding models to all corresponding documents and quantify all actors' pairwise (dis-)similarities. Subsequently, we utilize dynamic mapping to project the entire temporal network into a joint lower-dimensional space, generating a time-series of spatial positions for each actor. Our approach can be summarized in four main steps, as illustrated in Figure 4-1: 1) Corpus creation, 2) Embedding, 3) Dissimilarity measurement, 4) Dynamic mapping. We now provide a detailed explanation of each step.

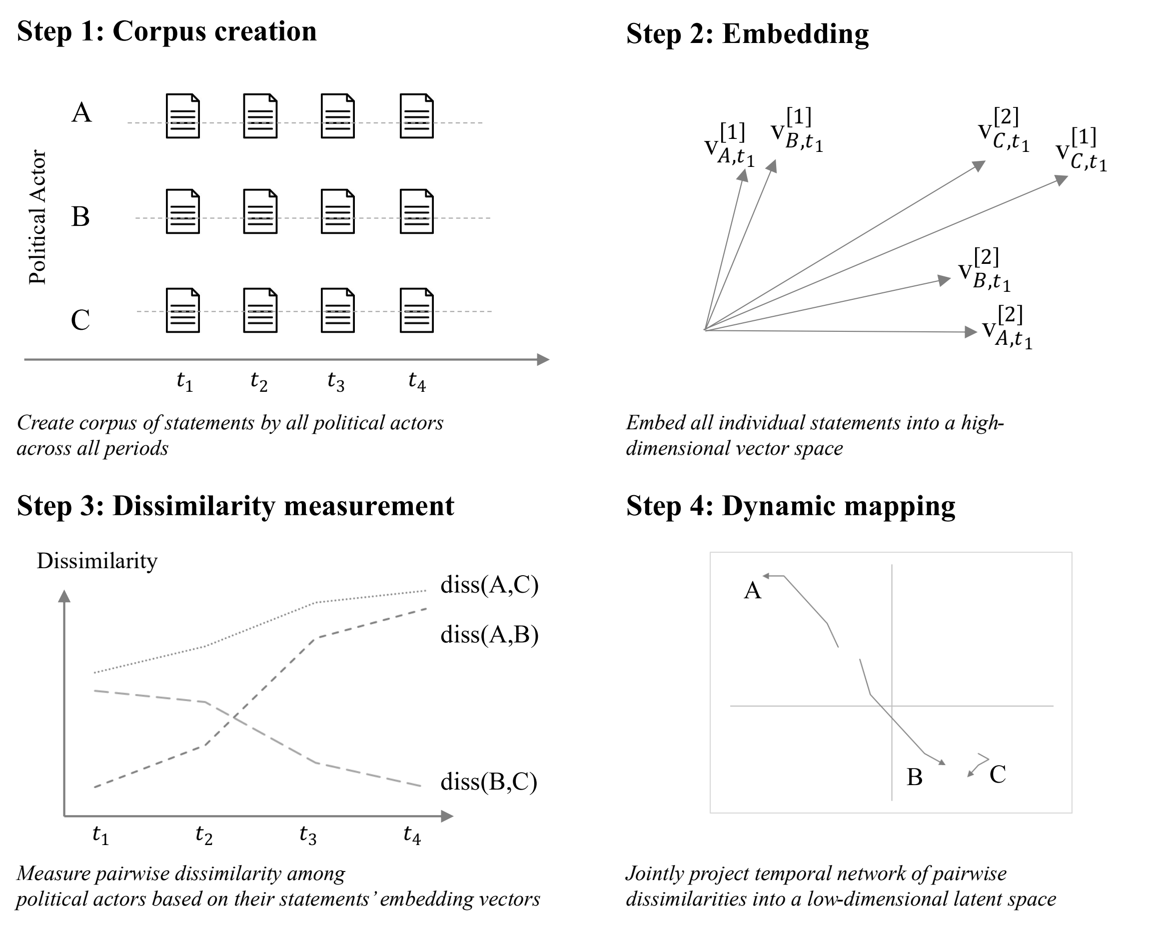

Figure 4-1: Illustration of our Proposed Approach

Step 1: Corpus creation

First, we create a corpus consisting of statements from each political actor throughout the observation period. Here, a statement represents a distinct unit of speech that conveys a message. A statement can take the form of a sentence, phrase, tweet, or longer stretch of discourse. These statements can originate from public communication channels such as social media, interviews, or public speeches, ensuring they are reliably attributable to a specific political actor.

To create the corpus, we partition the timeline into equally spaced intervals, such as weeks or months, and assign a time index to each statement. Within each period, denoted as $t = 1, \ldots, T$, each political actor, denoted as $i = 1, \ldots, k$, is associated with a set of $n_{i,t}$ statements, denoted as $D_{i,t} = \left\{D_{i,t}^{[1]}, \ldots, D_{i,t}^{[n_{i,t}]}\right\}$, forming a corpus $\left(D_{i,t}\right)_{i=1,\ldots k, t=1,\ldots,T}$.

Step 2: Embedding

Next, we transform each statement into a vector representation leveraging pre-trained embedding models. Many open-source repositories, such as Hugging Face, provide pre-trained models for different languages and fine-tuned for specific tasks. As a result of this step, each political actor $i = 1, \ldots, k$ at each period $t = 1, \ldots, T$ is associated with a set of $n_{i,t}$ high-dimensional embedding vectors $v_{i,t} = \left\{v_{i,t}^{[1]}, \ldots, v_{i,t}^{[n_{i,t}]}\right\}$ that allow us to quantify the dissimilarity between them.

Step 3: Dissimilarity measurement

Third, we measure the dissimilarity between pairs of political actors within each period using the embedding vectors of their statements. For a period *t*, where n_t represents the number of actors for which statements are present in the corpus at that time, we obtain $\frac{n_t\,(n_t-1)}{2}$ unique dissimilarities. Importantly, each actor is typically associated with multiple statements, resulting in multiple embedding vectors. Therefore, we utilize distance functions that can accommodate multiple vectors per actor, such as the earth mover's distance (Rubner et al., 1998). We provide more detailed information on these functions when applying our approach empirically. The outcome of this step is a temporal network $(Dis_t)_{t=1,\ldots,T}$ where each element Dis_t is a square matrix containing pairwise, non-negative dissimilarities between n_t political actors.

Step 4: Dynamic mapping

In the final step, we project the entire temporal network $(Dis_t)_{t=1,\ldots,T}$ into a low-dimensional latent space using the dynamic mapping framework EvoMap (Matthe et al., 2023). This framework allows us to estimate a sequence of spatial positions from a sequence of dissimilarity matrices by jointly fitting static mapping methods, such as MDS, while incorporating certain constraints. EvoMap addresses common challenges encountered in dynamic mapping, including the lack of alignment among different solutions and the sensitivity to noise, by incorporating a regularization component. This regularization helps in preventing overfitting to individual periods and ensures smoother transitions over time. As a result, EvoMap is particularly well-suited for analyzing high-frequency unstructured data.

Upon completion of this step, we obtain a time-series of positions on *d* latent dimensions $(Y_t)_{t=1,\ldots,T}$, where $Y_t \in \mathbb{R}^{n_t \times d}$. These positions aim to capture the underlying differences in the positioning of these speakers. The analyst can choose the number of dimensions *d* as required. While one or two are often sufficient, the framework can accommodate more dimensions if necessitated by the data's complexity.

We next outline how we implement our approach in an empirical application to parliamentary speeches within the German Bundestag.

4.4 Application to German Parties, 2009 - 2022

Our empirical application serves three main objectives: (1) to demonstrate the practical implementation of our approach in a specific context, (2) to validate the dynamic maps generated, (3) to showcase its potential value for empirical research. We begin by outlining the specific steps required to implement our approach using data from the German parliament.

4.4.1 Setting

We use Germany as the setting for our empirical application due to the inherent richness and dynamics of its parliamentary system. The German Bundestag is characterized by the presence of multiple parties, the formation of varying coalitions, and entrance as well as exits of parties (such as the recent entry of the "Alternative for Germany", AfD). This context provides the ideal testing environment with a dynamic and diverse set of actors who exhibit different positioning and potentially engage in substantial repositioning. To gather data for our analysis, we collected digitized records of all parliamentary sessions across 14 years from 2009 to 2022. These records are publicly available from the German Bundestag[9].

We focus our analysis on public communication through speeches delivered in parliamentary speeches. Parliamentary speeches are structured discussions within a legislative body, such as a parliament or congress. These speeches are accessible to the public and are often broadcasted or referenced on television, radio, or other media platforms. They also receive substantial coverage in newspapers. During parliamentary speeches, members of the legislative body engage in discussions, arguments, and the exchange of views pertaining to proposed legislation, policies, and matters of public interest.

Compared to other forms of public communication, speeches in parliamentary speeches offer several advantages for analyzing the underlying positioning strategies of political actors. Parliamentary speeches provide detailed and substantive content, offering a nuanced understanding of speakers' positions compared to other forms of communication. They are a public record, ensuring a higher level of accountability. These speeches address current issues and offer a continuous stream of information on different actors' positions. Statements made within speeches receive media coverage, are discussed on social media, and shape public perception. Politicians often reuse speech statements in other contexts, highlighting their importance in expressing positions and influencing public discourse. Together, these features (comprehensiveness, accountability, currency, and media attention) make parliamentary speeches a well-suited source of information to capture political actors' positioning.

[9] https://www.bundestag.de/services/opendata

4.4.2 Implementation of Main Steps

Step 1: Corpus Creation

We collect the transcripts of all parliamentary sessions within the German parliament from October 2009 up until May 2022 in XML format. We extract all speeches and augment them with metadata, including the session date, respective speaker, and the speaker's party affiliation. We clean the texts by removing annotations, such as speaker titles, interjections, noise, and applause.

We conduct our analysis on the party-month level, tagging each speech with a time index based on the session year and month (e.g., "2009-10"), and combining statements of all speakers with the same party affiliation within the same month. We exclude months without ordinary parliamentary sessions, such as summer breaks or the first session in each legislative period.

Table 4-2 provides a descriptive summary of the resultant corpus, covering six parties: The Left (DIE LINKE), The Greens (B90/Die Grünen), The Social Democrats (SPD), The Liberal Democrats (FDP), The Christian Democrats (CDU/CSU), and The Alternative for Germany (AfD). While we observe most parties for the entire 129-month period, the AfD's data start with their entry in October 2017, and the FDP's data exclude their period of absence between October 2013 and September 2017.

Table 4-2: Corpus Overview

	Total Statements		Monthly # of Statements				Months Observed	
Party	#	%	Min	Mean	Median	Max	#	%
The Left	260,695	12	120	2,021	1,965	5,878	129	100
The Greens	290,141	14	158	2,249	2,100	9,487	129	100
SPD	512,654	24	248	3,974	3,689	16,266	129	100
CDU/CSU	746,755	35	739	5,789	5,286	19,251	129	100
FDP	202,296	9	183	2,299	2,278	8,077	88	68
AfD	119,372	6	552	2,540	2,574	6,624	47	36

Notes: Numbers are based on the sentences identified within the entire corpus of parliamentary speeches in the German parliament during October 2009 – May 2022. We exclude occasional guest speakers affiliated with parties that are not members in the parliament, or who do not have a party affiliation at all.

Step 2: Embedding

We proceed to compute embedding vectors for each statement in our corpus using a pre-trained cross-lingual RoBERTa model. This model, available from the "Hugging Face" repository, is specifically designed to generate embeddings for short segments of English or German texts. We opt for this model due to its pre-training on a sizeable German corpus and its fine-tuning for measuring semantic similarity of short linguistic elements like sentences or phrases (Reimers & Gurevych 2019). We implement the model using the "sentence-transformers" library in Python, resulting in 768-dimensional vectors for each of the 2,131,913 statements in our corpus.

Step 3: Dissimilarity measurement

Before measuring dissimilarities, we draw samples from the entire corpus. As seen in Table 4-2, parties strongly differ in their share-of-voice within the parliament, which poses potential challenges, as all dissimilarity measurements (and subsequent position estimates) derived from such data will be associated with different levels of uncertainty. To make the resulting measures more comparable, we create monthly subsamples of 500 statements for each party for each month.

To measure the dissimilarities between parties within each period, we employ the "sentence mover's distance" (SMD), a variant of the earth mover's distance (EMD). The SMD measures the dissimilarity between two documents by calculating the minimum total distance that the embedded sentences in one document need to "travel" to match the embedded sentences of the other document. In our context, for every sentence spoken by a member of one party, the SMD identifies the most similar sentence spoken by a member of the other party and measures their distance within the embedding space. This pairwise matching is performed for all sentences, and the dissimilarity between the two parties is obtained as the total distance across all sentence pairs.

The key advantage of the SMD is its ability to measure the dissimilarity between two sets of sentences rather than just between a pair of two sentences. Unlike other methods, it does not require prior aggregation, such as averaging the embedding vectors, which helps to preserve more embedded information (Kusner et al., 2015).

As a result, we obtain a sequence of dissimilarity matrices $(Dis_t)_{t=1,\dots,T}$, $Dis_t \in \mathbb{R}_0^{+nxn}$ $\forall t \in \{1, \dots, T\}$ across $T = 129$ periods and $n = 6$ parties. In cases where parties are not present in a particular period, we set their dissimilarities to others to zero[10] and exclude them in the subsequent mapping stage by setting their respective indicator variables to zero.

Step 4: Dynamic mapping

Finally, we use the dynamic mapping framework EvoMap to estimate spatial positions $(Y_t)_{t=1,\dots,T}$, $Y_t \in \mathbb{R}^{nxd}$ from the sequence of matrices $(Dis_t)_{t=1,\dots,T}$. To derive these positions, we use EvoMap paired with interval-based Multidimensional Scaling, a MDS variant that allows for linear transformations of the input dissimilarities. Allowing for these transformations help accommodating non-Euclidean input dissimilarities, as the ones we derive via the SMD function (Borg & Groenen, 2005).

To determine an appropriate value for the misalignment penalty α, we first identify a target misalignment of approximately 10% by visual inspection of different results. We then run a grid search across a broad hyperparameter space to identify the minimum required misalignment penalties and smoothing values to achieve the desired outcome. The right part of Figure 4-2 displays the resultant Misalignment values for varying values of α, and highlights the selected value. We set

[10] Any arbitrary number would do, as they are ignored by the mapping algorithm in the next step.

the number of dimensions to two, as increasing the dimensionality further provides only marginal gains in goodness-of-fit between the estimated map positions and input dissimilarities (see left part of Figure 4-2). To speed up optimization, we initialize all estimated positions using the classical MDS solution (Torgerson, 1952).

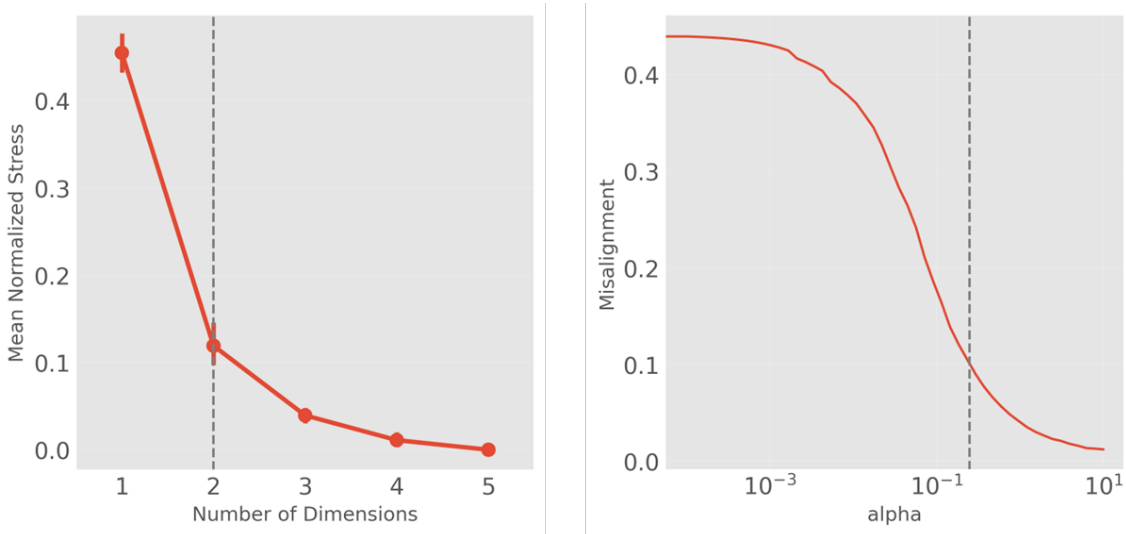

Figure 4-2: Choice of Dimensionality and Hyperparameters. Quality of Mapping Solutions vs. Number of Dimensions (Left) and Misalignment Penalty (Right). To Generate the Left Figure, We Vary the Number of Dimensions, Run MDS Independently for All Periods, and Average the Normalized Stress. Each Point Represents the Mean Across 10 Runs With Different Random Initializations. To Generate the Right Figure, We Run EvoMap (Implemented for MDS), Fixing the Number of Dimensions to Two, for Varying Levels of the Hyperparameter α. For Each Value of α, We Report the Misalignment Metric.

As a result, we obtain a total of 651 party-month observations, where each observation corresponds to the position of one party in one period on two latent variables.

4.5 Descriptive Findings

Figure 4-3 illustrates the resultant position estimates in four static snapshots, while Figure 4-4 displays their temporal evolution.

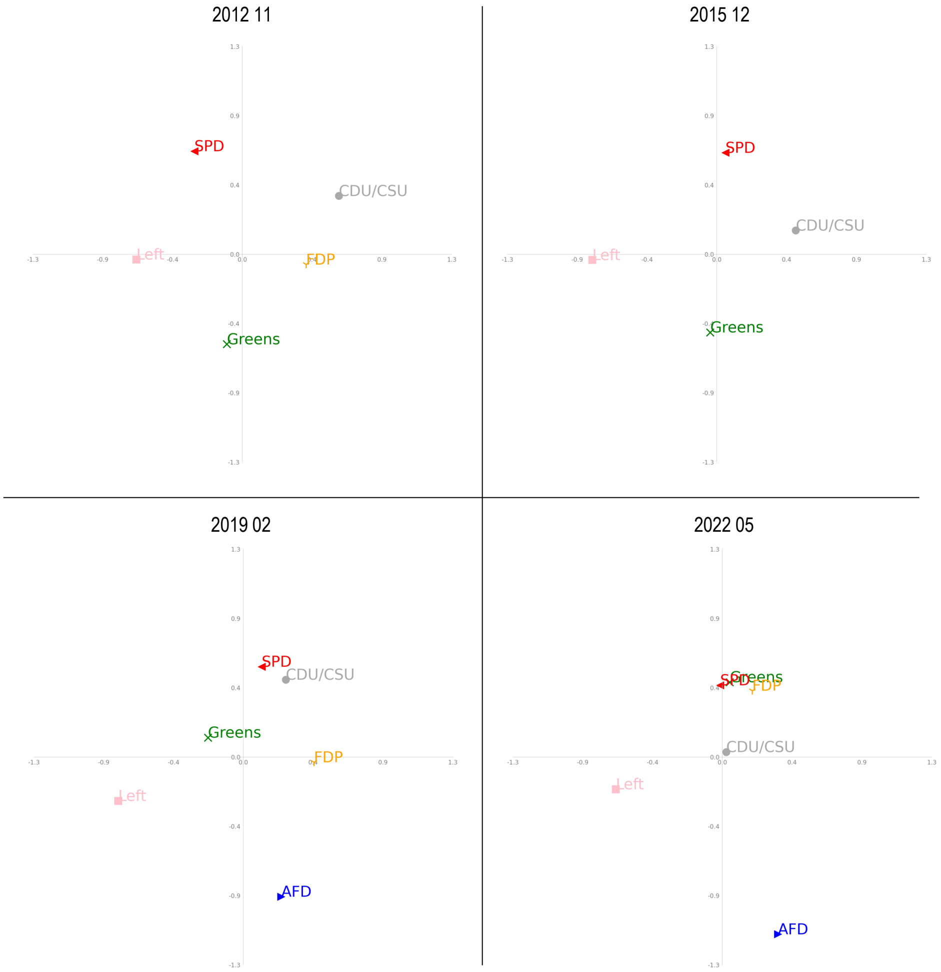

Figure 4-3: Static Snapshots of Estimated Party Positions. Static Snapshots of the Estimated Party Positions, Taken at Four Points in Time During Our Observation Period. The Positions are Estimated via EvoMap, Implemented for Interval-based MDS. As MDS Solutions are Invariant to Linear Transformations, We Rotate All Solutions Using a Common Rotation Matrix such that “The Left” Tends to be Located in the Left Part of the Map.

The static snapshots in Figure 4-3 confirm that our approach accurately recovers various features of Germany's political landscape. Parties with more similar agendas, such as the socially oriented "Left," "SPD," or "Greens", tend to be located closer together, while parties with differing agendas, such as the more conservative "CDU/CSU", tend to be located more distant from them. The maps effectively capture different intuitive points of differentiation between the parties. For instance, drawing an imaginary line between “The Left” and the more conservative parties such as “CDU/CSU”, or more recently, the ”AfD”, yields a typical left-to-right scale. Niche parties, such as the "AfD", tend to be most secluded at the outskirts of the map, while more mainstream parties tend to gravitate closer to the center. Furthermore, in all legislative periods, parties forming governing coalitions consistently exhibit the shortest distances on the map, as observed with CDU/CSU & FDP and 2x CDU/CSU & SPD.

Next, consider the temporal evolution paths in Figure 4-4. These paths reveal that the estimated positions, to some degree, are in constant flux. For instance, we observe a gradual convergence between the CDU/CSU and the SPD, with the CDU/CSU transitioning towards the center. This finding aligns well with the CDU/CSU's campaign strategy, which often emphasized being "The Center" ("Die Mitte"). It is also consistent with their legislative decisions, where the party shifted away from some of its more conservative stances and embraced more centrist positions, such as the nuclear phase-out or the introduction of women's quotas and minimum wages. Additionally, this convergence reflects the perception of the SPD's loss of distinctiveness and differentiation, which is often associated with its participation in the grand coalition government (together with the CDU/CSU).

Furthermore, Figure 4-4 reveals the impact of the right-wing party Alternative for Germany (AfD) on the overall political spectrum. The AfD's tendency to adopt extreme positions expands the ideological range and, as a result, brings the positions of other parties closer together. Further shifts are evident in the case of the Greens, who initially shift towards the center and then converge with formerly more distinct parties like the SPD or FDP. This strategic repositioning aligns with the Greens' pursuit of forming a government and their transition from a fringe party to a more mainstream player. It is worth noting that parties differ in the extent of their dynamics within a term. Parties with more extreme positions, such as the Left or the AfD, tend to exhibit less change in their positioning compared to more centrist parties.

In summary, our approach provides estimates of party positions that effectively capture changes in parties’ positioning across various dimensions, such as shifts from the fringe to the center or vice versa, losses or gains in differentiation, and the stability or dynamism of positions over time. We further examine these aspects in a more formal manner when examining their link to voter support. However, before proceeding with their analysis, we first validate the reliability of our estimated positions beyond their initial face validity.

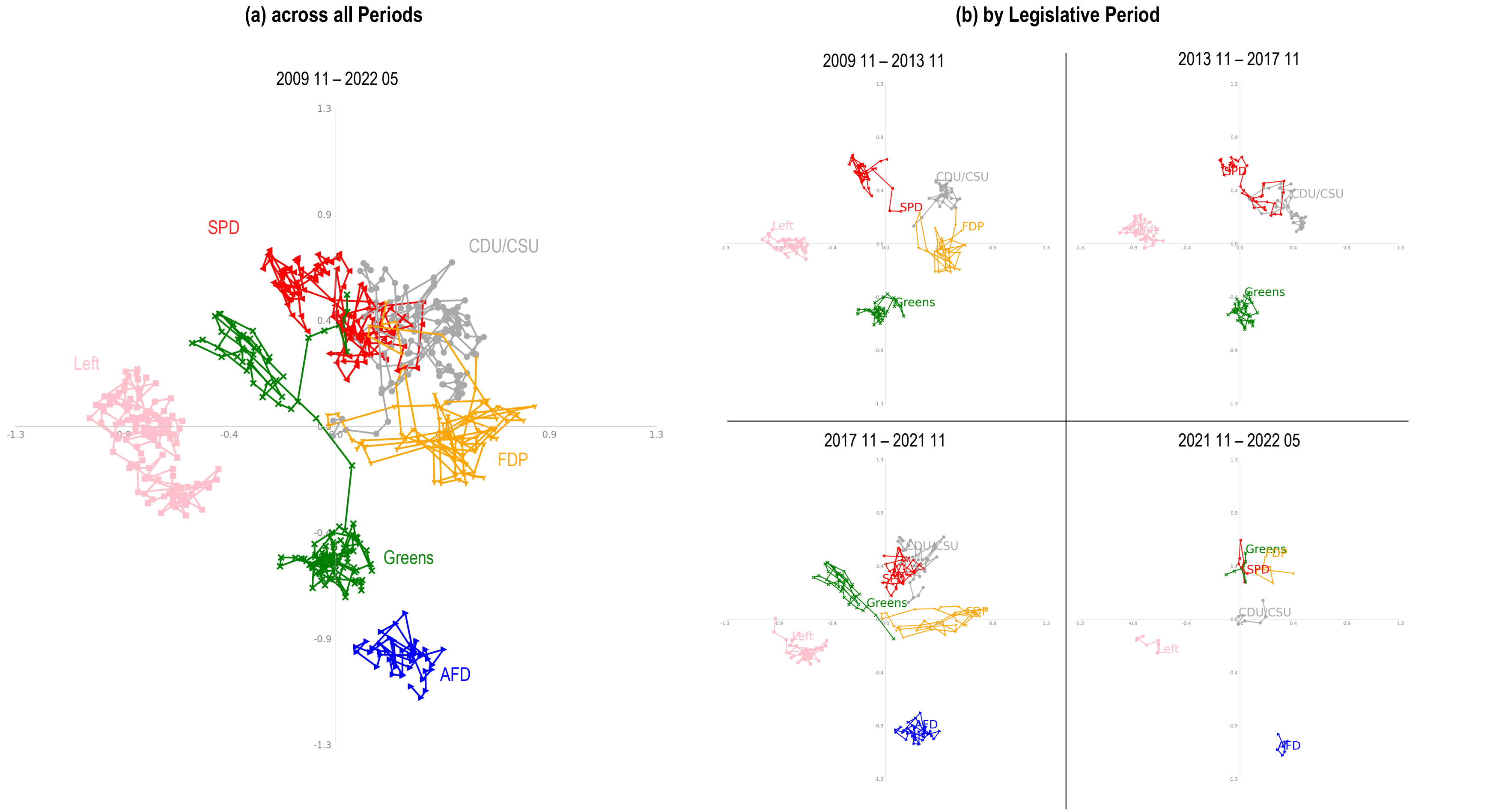

Figure 4-4: Monthly Estimated Party Positions, 2009 – 2022. The Time-series of All Estimated Positions Across the Entire Observation Period of 14 Years (Left), Generated by Applying EvoMap (Paired With Interval-based MDS) to the Full Sequences of 129 Dissimilarity Matrices.

4.6 Validation Assessments

Next, we test the validity of our estimates more rigorously through two validation assessments. The first assessment examines whether our estimated positions can predict parties' tendencies to behave similarly or dissimilarly, specifically regarding their decision making on legislative bills. The second assessment examines whether our positioning estimates can recover benchmarks of party ideology established in political science research.

4.6.1 Party Positioning and Legislative Agreement

In the first assessment, we examine the relationship between the estimated party positioning displayed in Figure 4-4 and their actual legislative decision-making. We specifically investigate the connection between the distance of their map positions and their agreement on legislative bills, measured through yes/no votes. Our hypothesis is that as their distance on the map increases, they have less cohesion, and their agreement on legislative bills should decrease (and vice versa).

To conduct this analysis, we collect all roll call votes for the observation period, which the German Bundestag publishes[11]. For each bill, we calculate the yes share that each party casts[12]. To measure disagreement between parties i and j, we then calculate the absolute difference in their yes shares on the respective bill. Finally, we average their disagreement across all bills within any given month

$$disagree_{i,j} = \left| \frac{YES_{i,k}}{YES_{i,k} + NO_{i,k}} - \frac{YES_{j,k}}{YES_{j,k} + NO_{j,k}} \right| \tag{4-1}$$

where $YES_{i,k}$ denotes the number of yes votes cast by party i on bill k, and $NO_{i,k}$ denotes the respective no votes. The resultant measure ranges from 0 to 1, where a value of 0 indicates perfect agreement with equal yes shares, while a value of 1 indicates total disagreement in the votes cast. We measure disagreement for a total of 549 bills and 89 months.

To examine its relationship to the estimated map positions, we first average disagreement across all bills in a given month. We then measure the average Euclidean distance among all parties' map positions and calculate the correlation to their disagreement. Figure 4-5 displays both measures, averaged across parties, for all months in which roll-cast votes are available.

[11] https://www.bundestag.de/abstimmung

[12] Not all bills are passed through the roll call system, therefore we only observe roll call votes for a subset of all bills that the German Bundestag adopts.

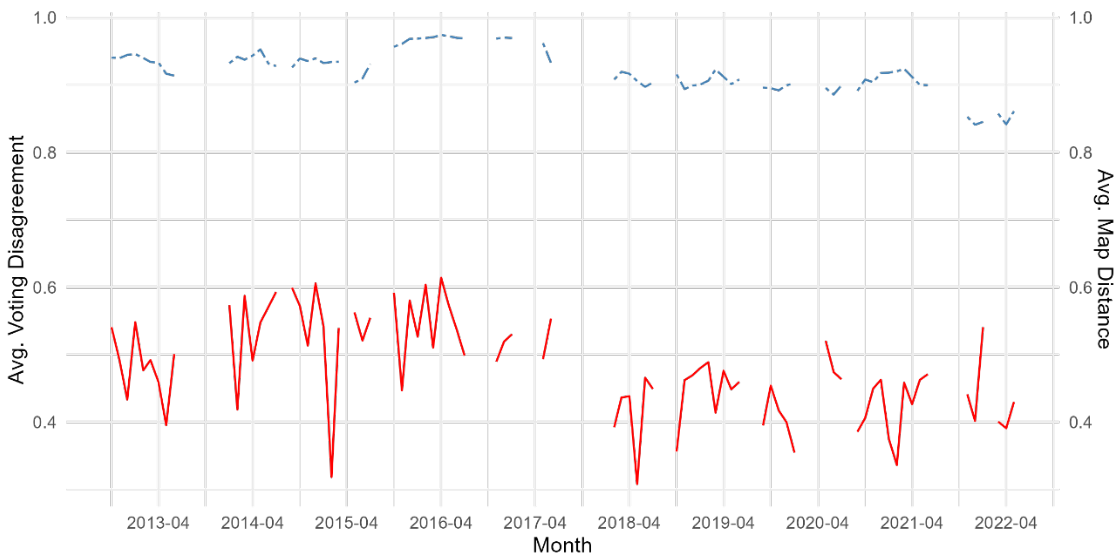

Figure 4-5: Average Voting Agreement vs. Position Dispersion. The Red Solid Line Displays the Average Level of Disagreement Across All Party Pairs in Each Month. The Blue Dashed Line Displays the Average Map Distance Between All Party Pairs in Each Month. Gaps in the Time-series Correspond to Months in Which No Record of Roll Call Votes are Available.

Consistent with our hypothesis, we find a significant positive correlation coefficient of 0.49 ($p < 0.01\%$) between the distance of parties' map positions and their level of disagreement in votes. This indicates that the more the estimated map positions diverge, the agreement in their voting patterns decreases. These results support the validity of our estimated maps by demonstrating their association to actual legislative decision making.

4.6.2 Party Positioning and Party Ideology

In the second assessment, we compare our estimates against established benchmarks of parties' ideological placement. Political science research offers various approaches to place parties on an ideological scale, often interpreted as a left-to-right spectrum. While a single left-to-right scale may not capture all nuances of how parties position themselves in their communication, our estimates should still reflect ideological differences to some extent. Therefore, we examine how accurately we can recover established ideological scales from our estimated maps. These established ideological scales are typically available once per legislative period (i.e., every four years). Although our maps are available at much higher frequency (monthly), we can still assess if they tend to converge with the ideological scales by aggregating map positions over time.

To conduct this analysis, we proceed as follows. First, we aggregate our estimates within each legislative period by calculating the average map position for each party. This provides us with an estimate of average party positioning during each legislative period.

Second, we try to extract an ideological left-to-right scale from these estimates. To achieve this, we left-align our map by rotating it such that the clearly left-leaning party "The Left" is located left to the origin on the x-axis. We then project all party positions onto the x-axis, obtaining a one-dimensional left-to-right scale. We provide visual illustrations of the resultant scales in the Appendix.

We then compare the resultant scale, derived from our map, to two kinds of benchmarks: expert coding of party manifestos and textual analysis of party manifesto texts. For the expert coding benchmarks, we refer to the Comparative Manifestos Project (CMP, Budge et al., 1987). The CMP evaluates party manifestos on various policy questions using a predefined and normalized coding scheme. From these evaluations, we employ established methods to derive a one-dimensional scale. Rile scaling, which utilizes an additive index (Budge et al., 2001), and Vanilla scaling, which utilizes factor analysis (Gabel & Huber, 2000). Both scaling methods are frequently used in political science research. Additionally, we employ WordFish, a Poisson scaling model, to derive a similar scale from the actual manifesto texts (Slapin & Proksch, 2008).

For each comparison, we calculate the Pearson and Spearman correlation coefficients between the respective benchmark scale and the scale derived from our map. Further, we report the pairwise accuracy (i.e., the percentage of party pairs ordered consistently between our scale and the benchmark scale). Table 4-3 reports all results. Next to our approach, Table 4-3 also reports results for a potential alternative to estimate party positioning from our data that does not utilize dynamic mapping, but directly estimates party positionings via the embedding step. Specifically, we report results from training a doc2vec model with party- and legislative-period indicators, from which we extract party positions as the first principle component of the (party, period) vectors (for more details, see Rheault & Cochrane (2020) who apply a similar approach to the US congress). Similar to our approach, we left-align the resultant scale.

The results in Table 4-3 show strong convergence between our high-frequency estimates of party positioning to established, low-frequency benchmarks of party ideology. The correlation coefficients range from .86 (vs. the Rile scale) and .92 (vs. the WordFish scale), while the Pairwise Accuracy and Rank Correlation are comparably high. Compared to the doc2vec approach, our estimates are substantially more in line with these benchmarks.

Table 4-3: Comparison to Ideological Placement Scales

Ideological Placement Scale	Data Source	Metric	Our Approach	Party Embeddings
Rile	Manifesto Evaluations (CMP)	Correlation	**0.86**	0.55
		Pairwise Accuracy	**0.92**	0.72
		Rank Correlation	**0.93**	0.52
Vanilla	Manifesto Evaluations (CMP)	Correlation	**0.90**	0.64
		Pairwise Accuracy	**0.92**	0.75
		Rank Correlation	**0.92**	0.62
Logit	Manifesto Evaluations (CMP)	Correlation	**0.91**	0.69
		Pairwise Accuracy	**0.90**	0.78
		Rank Correlation	**0.90**	0.62
WordFish	Manifesto Texts	Correlation	**0.92**	0.68
		Pairwise Accuracy	**0.92**	0.79
		Rank Correlation	**0.91**	0.66

Notes: All benchmarks correspond to placements of all parties on a one-dimensional left-to-right scale. Correlation measured as Pearson correlation coefficient, Pairwise Accuracy measured as percentage of consistent orderings for all party pairs, Rank correlation measured as Spearman correlation coefficient. All benchmarks are available once per legislative period, estimates from our approach are averages of each party's positions within each legislative period. Party embeddings derived as the first Principal Component of the (party, period) vectors obtained by training a doc2vec model on the full corpus. Bold face indicates better results. N = 21 (4 legislative periods x 6 parties – 3 periods without AfD and/or FDP).

In summary, our approach provides accurate estimates of party positioning that converge with established measures of ideological differences. Importantly, however, our estimates are available at a much higher frequency, and allow to quantify positioning beyond a single scale. We leverage this advantage to investigate the relationship between party (re-)positioning and voter support in the next section.

4.7 Use Case: Linking Party Positioning to Voter Support

To showcase how our approach can support empirical research, we use it to explore the link between party positioning and voter support. Specifically, we aim to investigate two questions: First, to what extent can differences in party positioning explain differences in party success? Second, are changes in party positioning over time associated with subsequent shifts in voter support? Understanding this link between party positioning and voter support has practical relevance for campaign managers, as it can help understand voters' preferences, anticipate shifts in voter support, or – if support for a causal link can be established - allows to anticipate the costs or benefits of changing their positioning.

Considering the (static) positions depicted in Figure 4-4, its straightforward to assume a link to voter support exists. The strength of that link, however, determines if these maps can be used beyond merely descriptive purposes. If the positions depicted therein are linked to voter support, they can not only be used to understand party's positions relative to their competitors', but also to align positioning with the preference of voters.

With regard to the (dynamic) evolution of party's positions, however, it is not directly clear if a link to voter support exists and which direction that link would have. Adopting a more or less dynamic position presents parties with a dilemma between consistency and adaptability.

On the one hand, brand management theories emphasize the value of consistency in brand communication (Kotler & Keller, 2013). A less dynamic (i.e., more stable) positioning can expose voters to consistent ideas, contribute to building a stronger brand image, and provide clarity about what voters can expect. In line with this reasoning, Fossen et al. (2022) find higher effectiveness of television ads that promote consistent messages throughout an electoral campaign. Moreover, a more dynamic positioning may increase uncertainty among voters about the future stances a party might take, or signal divergence of a party's core values (Adams, 2012). Supporting this idea, empirical research of party manifesto texts finds an electoral cost associated with large ideological shifts from one legislative period to another (Adams et al., 2006; Adams & Somer-Topcu, 2009).

On the other hand, political parties operate in dynamic environments that require a certain degree of adaptability. External events can prompt shifts in economic and societal regimes, as seen with a recent pandemic. The ability to adapt to such changes can signal a higher capability to act, that can appeal to voters. Adaptability can also indicate that parties are responsive to the changing needs of their constituents, similar to brands that quickly react on customer feedback (Jayachandran et al. 2004).

To investigate which perspective finds empirical support, we link our position estimates to data from public election polls, which capture voters' support to different parties on a regular basis. Using panel regressions, we examine whether different aspects of party positioning are associated with higher or lower levels of voter support, and explore how this association differs across parties.

4.7.1 Variable Definition and Model Specification

We employ panel regressions to investigate the link between party positions and voter support empirically. Our dependent variable is *Voter Support* measured through weekly election poll surveys. We collect these surveys from the Forsa institute, the leading opinion polling company in Germany[13]. The surveys track the estimated share of votes measured in percentage points that each party would receive if a general election were to take place the following week, commonly known as "Sonntagsfrage" (Sunday question). The entire time-series of survey results is publicly available through the German NGO wahlrecht.de[14]. We average all weekly polls to generate monthly averages and make them comparable with our monthly position estimates. Figure 4-6 displays the monthly time-series of voter support for the six major parties in the German parliament across the observation period.

[13] Forsa conducts a weekly election poll surveys (approx. 1,000-2,500 respondents) (Zicht & Cantow, 2021).

[14] https://www.wahlrecht.de/umfragen/forsa.htm

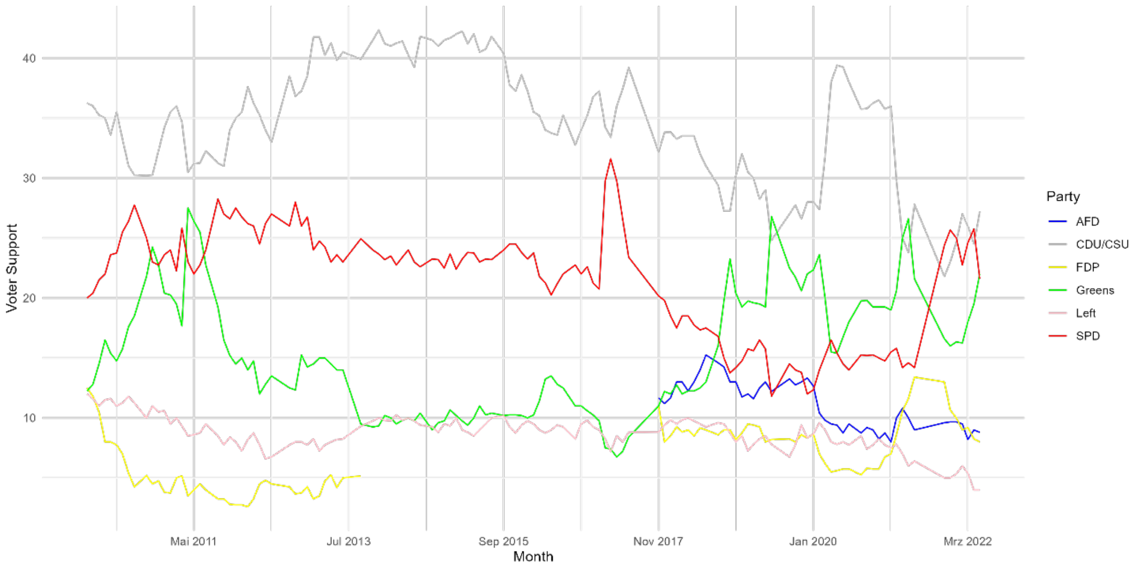

Figure 4-6: Monthly Voter Support. The Figure Displays the Independent Variable of Our Panel Regressions, Voter Support. Gaps in the Time-series of Individual Parties Reflect Periods of Absence From the Parliament (FDP) or Periods Prior to Initial Entry (AFD).

Our independent variables consist of different aspects of party positioning, measured using the estimated positions depicted in Figure 4-4. Specifically, we derive the following monthly features to quantify how each party positions itself in its speeches: *X, Y, Fringeness*, *Differentiation*, *Dynamism, and Moved to Center.* X and Y denote a party's current position on the two latent map dimensions, capturing their absolute positioning on the map. *Fringeness* and *Differentiation* are measured as the maximum and minimum distance to other party's positions, quantifying their relative positioning to others. *Dynamism* captures the total distance traveled on the map in the preceding six months and *Moved to Center* indicates if the respective move brought the party closer to or further from the center. Our intuition is as follows.

Including the absolute *X* and *Y* positions allow us to estimate the general preference vector of the average voter. The relative positioning features *Fringeness* and *Differentiation* allow to differentiate between niche vs. mainstream parties, for which research in both marketing and politics often reports asymmetric gains and costs (Adams et al., 2006; Hydock et al., 2020). Finally, *Dynamism* and *Moved to Center* allow us to examine if changes in a party's positioning over time are associated with changes in voter support. Table 4-4 shows the respective variable definitions and measurement objectives for all variables, and Table 4-5 displays summary statistics. We measure each variable at the party-month level.

Table 4-4: Description of Regression Variables

Variable	Type	Definition	Intuition
Voter Support	Dependent variable	Polling result for a given party, averaged across all weekly election polls in month *t* over the course of four weeks	Current degree of voter support
X, Y	Independent variable	The x and y coordinate of the party on the map at month *t*	Current positioning of a party within the political spectrum
Fringeness	Independent variable	Maximum Euclidean distance on the map to other parties in month *t*	Extent to which party is positioned at the periphery of all parties' positions, suggesting a more unconventional positioning
Differentiation	Independent variable	Minimum Euclidean distance on the map to other parties in month *t*	Degree of closeness to vs. differentiation against other parties' positioning
Dynamism	Independent variable	Length of the movement path of party's position on the map over the last 6 months	Degree of dynamism of a party's positioning during the last 6 months
Moved to Center	Independent variable	1, if the current position is closer to the center of the map, defined as the average position across all parties, else 0.	Indicates if the party recently moved closer to or further away from the center

All estimated panel regressions include party fixed effects to account for unobservable time invariant differences across individual parties that are likely correlated with our independent variables. We further include time fixed effects for each month to account for differences in the composition of the parliament and associated differences in parties' average polling results.

Table 4-5: Descriptive Overview of Regression Variables

Variable	Obs	Min	Max	Mean	SD
Voter Support	651	2.6	42.333	17.565	10.544
X	651	-0.999	0.806	-0.021	0.437
Y	651	-1.108	0.722	0.040	0.445
Differentiation	651	0.007	1.184	0.593	0.269
Fringeness	651	0.780	1.683	1.278	0.157
Dynamism	609	0.139	1.349	0.502	0.194
Moved to Center	609	0	1	0.535	0.499

Notes: *Dynamism* and *Moved to Center* are calculated based on the estimated positions in the six preceding periods, therefore 42 less observations are available: 6 lags * 6 parties + 6 additional lags when FDP re-entered the sample in 2017.

4.7.2 Panel Regression Results

Table 4-6 reports estimation results for four panel regressions using the same dependent variable, *Voter Support*, and different sets of independent variables. Model (1) only estimates the preference vector of the average voter using the absolute *X* and *Y* positions, model (2) accounts for parties' relative positioning by incorporating *Fringeness* and *Differentiation*, model (3) adds the temporal evolution using *Dynamism* and *Moved to Center*, and model (4) includes further interaction terms. We standardize all continuous independent variables to ease interpretation of the estimated coefficients.

First, we find substantial associations between party positioning and voter support: The proposed features of party positioning help to explain ~28% of additional within-party variation in voter support (i.e., variation after accounting for time-invariant party differences via fixed effects), see model (4). While a single preference vector for the average voter, estimated via *X* and *Y,* explains roughly 18% of variation, adding the additional aspects increases the within R2 by further 10 percentage points.

Further, the estimated coefficients are in line with a negative link between dynamism and voter support. According to our estimates, a one standard deviation increase in *Dynamism* is associated with a 1ppt decrease in voter support. Likewise, moving closer to the center is associated with a 1.5ppt decrease in voter support (both coefficients are significant at the 1% level). We find weak statistical support for heterogeneity in this link across parties: Based on model (4), more niche positioning, indicated through higher *Differentiation* and *Fringeness*, lowers the negative association between *Dynamism* and *Voter Support* (the coefficients of their interaction terms with *Dynamism* are positive and significant at the 10% and 5% level).

Table 4-6: Panel Regression Main Results

Dependent Variable	Voter Support			
Model	(1)	(2)	(3)	(4)
X	-1.213** (0.523)	-0.825 (0.574)	-1.450** (0.593)	-1.408** (0.609)
Y	2.848*** (0.354)	3.325*** (0.413)	3.589*** (0.427)	3.625*** (0.427)
Differentiation		-0.474 (0.297)	-1.002*** (0.323)	-1.079*** (0.322)
Fringeness		-0.743*** (0.221)	-1.297*** (0.244)	-1.247*** (0.261)
Dynamism			-1.092*** (0.303)	-1.002*** (0.308)
Moved to Center			-1.624*** (0.373)	-1.518*** (0.371)
Differentiation * Fringeness				0.637*** (0.219)
Dynamism * Differentiation				0.529* (0.273)
Dynamism * Fringeness				0.448** (0.183)
Party Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	651	651	609	609
Within R2	0.179	0.204	0.255	0.283
F Statistic	56.332*** (df = 2; 515)	32.813*** (df = 4; 513)	27.120*** (df = 6; 475)	20.706*** (df = 9; 472)

Note: *** $p < 0.01$, standard errors in parentheses. See Table 4-4 for a detailed description of all independent variables. *Dynamism* and *Moved to Center* are calculated based on the estimated positions in the six preceding periods, therefore model (3) and (4) lose 42 observations (6 lags * 6 parties + 6 additional lags when FDP re-entered the sample in 2017). All continuous independent variables are standardized (i.e., all variables except the binary variable *Moved to Center*). For these variables, the estimated coefficients indicate the percentage point in-/decrease in voter support associated with a one standard deviation increase of the corresponding variable.

Further estimation results, reported in the Appendix, show that the estimated relationship is robust across various modifications: Using different functional forms, such as log-log regressions, using a different measure of *Dynamism*, excluding individual parties, or measuring *Dynamism* along different time lags, all yield a consistent negative association between *Dynamism* and *Voter Support*.

It is important to note that our ability to establish a causal link is limited within this setting, as variation in parties' positioning may not be exogenous. Nevertheless, our results provide at least correlational support for the idea that voters value consistency over adaptability, in particular for mainstream parties that are closely positioned to each other. Niche parties, that are more differentiated, however, appear to experience more flexibility in how they can adapt their positioning without hurting their voters' support. The remaining estimated coefficients are in line with expectations, which builds confidence in our estimation: the average voter leans towards the top area of the map, where more conventional parties are located, and leans slightly to the left. In contrast, more niche parties with higher degrees of *Differentiation* and *Fringeness* are less appealing to the average voter. Further, our findings are in line with brand management theories, as well as empirical findings in other settings, such as studies of message consistency in political advertising (Fossen et al., 2022).

In summary, our estimation results provide two key findings. First, the estimates of party positioning provided by our proposed approach can be linked to measures of party success. Therefore, our approach can practically support campaign managers or market researchers seeking to understand voter preferences and monitor them in high frequency. Second, our findings support the hypothesis that substantial changes to a party's positioning are negatively associated with voter support, illustrating how our approach can also support substantive empirical research.

4.8 Discussion and Conclusion

This paper introduces a novel approach to analyze the positioning dynamics of political actors based on their public communication. With records of political communication—from public speeches to advertising content and social media discourse—becoming increasingly available, our methodology provides a versatile tool.

Specifically, we envision our approach to be particular useful in two main applications. First, it can be used descriptively to reveal political actors' positioning and monitor their evolution over time. Such insights are practical for tracking competitors and guiding campaign strategies. Secondly, our methodology can be used as input for downstream analyses, like modeling voter preferences. As demonstrated by our analysis of German parties, our approach can provide the necessary input to further investigate how voters may respond to parties' positioning and shifts therein.

Exploring this link to voter support opens many avenues for future applications. Naturally, our approach could be applied to different units of analysis, such as individual politicians, instead of focusing on entire parties. This could unveil additional insights, particularly regarding alignment or dissent in the positioning among party members. Likewise, our approach can easily be applied to different settings, including different kinds of communication or different countries. Given that our approach is agnostic regarding the specific language model used to measure the (dis-)similarities of political statements, one can easily exchange the model we used in favor of suitable pre-trained embedding models tailored to a desired language and context. It would be intriguing to investigate whether the relationships we've established in our panel regressions are consistent across other contexts, countries, or units of analysis.

Finally, our approach offers ample opportunities for methodological extensions, in particular when using it as an input to model voter preferences. While we used a simple modeling framework including only a measure of preference for an average voter, it would be natural to jointly estimate the preferences of various voter segments. A large methodological toolbox is available in the context of product positioning that combines MDS solutions with preference estimation (e.g., Andrews & Manrai 1999; DeSarbo & Rao 1986; Desarbo et al., 2008; DeSarbo & Kim 2012). Combined with our high-frequency position estimates, such models could offer more nuanced insights into the preferences of different voter segments, and their evolution over time. We hope that our approach can thus open new avenues for substantive and methodological research at the intersection of positioning and politics.

4.9 Appendix

4.9.1 Overview of all Ideological Placement Scales

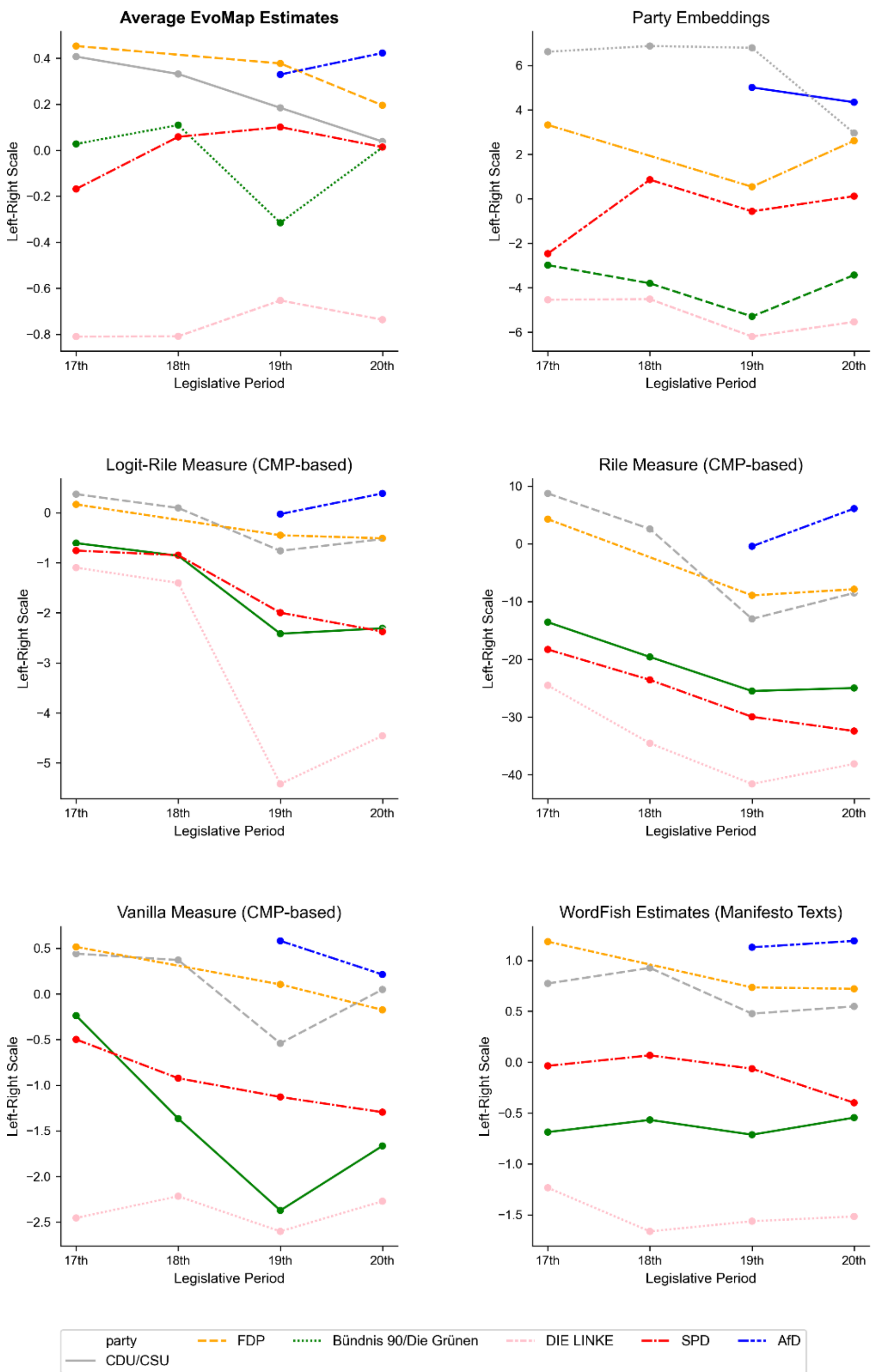

Figure 4-7: Ideological Placement Scales for all Compared Models. Each Plot Shows the Ideological Placement on a Left-to-Right Scale Derived for Each Model Displayed in Table 4-3.

4.9.2 Additional Panel Regression Results

Table 4-7: Pairwise Correlation Coefficients for Regression Variables

Variable	Voter Suppor t	X	Y	Fringe-ness	Differen -tiation	Dynamism	Moved to Center
Voter Support	1	0.365	0.544	-0.051	-0.418	-0.254	-0.048
X	0.365	1	0.032	0.012	-0.408	0.219	-0.047
Y	0.544	0.032	1	-0.081	-0.589	0.054	-0.001
Fringeness	-0.051	0.012	-0.081	1	0.042	0.017	-0.293
Differen-tiation	-0.418	-0.408	-0.589	0.042	1	-0.346	-0.155
Dynamism	-0.254	0.219	0.054	0.017	-0.346	1	0.029
Moved to Center	-0.048	-0.047	-0.001	-0.293	-0.155	0.029	1

Notes: Pearson correlation coefficient for all pairs of variables used in the panel regression reported in section 4.7.

Table 4-8: Panel Regression Results for Non-Linear Functional Form

Dependent Variable	log(Voter Support)			
Model	(1)	(2)	(3)	(4)
X	-0.213***	-0.091	-0.183**	-0.157*
	(0.080)	(0.087)	(0.088)	(0.089)
Y	0.409***	0.517***	0.558***	0.566***
	(0.053)	(0.060)	(0.061)	(0.062)
log(Differentiation)		0.013	-0.014	-0.155*
		(0.026)	(0.027)	(0.083)
log(Fringeness)		-0.431***	-0.712***	-0.347
		(0.116)	(0.125)	(0.264)
log(Dynamism)			-0.226***	-0.332***
			(0.054)	(0.093)
Moved to Center			-0.075***	-0.075***
			(0.024)	(0.024)
log(Differentiation) * log(Fringeness)				0.325*
				(0.194)
log(Dynamism) * log(Differentiation)				-0.084
				(0.078)
log(Dynamism) * log(Fringeness)				0.179
				(0.268)
Party Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	651	651	609	609
R2	0.177	0.199	0.258	0.264
F Statistic	55.412*** (df = 2; 515)	31.883*** (df = 4; 513)	27.582*** (df = 6; 475)	18.831*** (df = 9; 472)

Note: *** $p < 0.01$, standard errors in parentheses. Replication of estimation results for models (1) to (4) reported in Table 4-6, using a non-linear functional form. See Table 4-4 for a detailed description of all independent variables. *Dynamism* and *Moved to Center* are calculated based on the estimated positions in the six preceding periods, therefore model (3) and (4) lose 42 observations (6 lags * 6 parties + 6 additional lags when FDP re-entered the sample in 2017). All variables, except for the position estimates X and Y, and the binary dummy variable Moved to Center, are log transformed. For these variables, the estimated coefficients indicate the percentage in-/decrease in voter support associated with a one-percentage increase of the corresponding variable.

Table 4-9: Panel Regression Results for Different Measurement of Dynamism

Dependent Variable	log(Voter Support)			
Model	(1)	(2)	(3)	(4)
X	-1.450**	-1.339**	-1.408**	-1.050*
	(0.593)	(0.599)	(0.609)	(0.616)
Y	3.589***	3.450***	3.625***	3.565***
	(0.427)	(0.430)	(0.427)	(0.437)
Differentiation	-1.002***	-0.852***	-1.079***	-0.838***
	(0.323)	(0.324)	(0.322)	(0.324)
Fringeness	-1.297***	-1.269***	-1.247***	-1.116***
	(0.244)	(0.249)	(0.261)	(0.267)
Dynamism (Distance Traveled)	-1.092***		-1.002***	
	(0.303)		(0.308)	
Dynamism (Distance Start - End)		-0.385*		-0.482**
		(0.227)		(0.244)
Moved to Center	-1.624***	-1.574***	-1.518***	-1.435***
	(0.373)	(0.378)	(0.371)	(0.379)
Differentiation * Fringeness			0.637***	0.653***
			(0.219)	(0.227)
Dynamism (Distance Traveled) * Differentiation			0.529*	
			(0.273)	
Dynamism (Distance Traveled) * Fringeness			0.448**	
			(0.183)	
Dynamism (Distance Start - End) * Differentiation				-0.133
				(0.246)
Dynamism (Distance Start - End) * Fringeness				0.189
				(0.165)
Party Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	609	609	609	609
R2	0.255	0.239	0.283	0.253
F Statistic	27.120*** (df = 6; 475)	24.910*** (df = 6; 475)	20.706*** (df = 9; 472)	17.790*** (df = 9; 472)

Note: *** $p < 0.01$, standard errors in parentheses. Replication of estimation results for models (3) and (4) reported in Table 4-6, using a different measure of Dynamism. Our main results use a measure of Dynamism computed as the total distance traveled within the preceding six periods (i.e., the total length of the party's movement path). Here, we use the Euclidean distance between the start and end point within the preceding six periods. All continuous independent variables are standardized (i.e., all variables except the binary variable *Moved to Center*). For these variables, the estimated coefficients indicate the percentage point in-/decrease in voter support associated with a one standard deviation increase of the corresponding variable.

Table 4-10: Panel Regression Results Excluding Parties

Dependent Variable	Voter Support					
Model	(1) No SPD	(2) No Left	(3) No Greens	(4) No FDP	(5) No CDU/CSU	(6) No AfD
X	-0.179	-1.782**	-1.264*	-2.803***	-1.291*	-1.642***
	(0.668)	(0.726)	(0.645)	(0.699)	(0.675)	(0.628)
Y	3.118***	4.843***	1.980***	2.947***	3.565***	3.550***
	(0.479)	(0.525)	(0.661)	(0.450)	(0.448)	(0.446)
Differentiation	-1.596***	-0.934**	-0.105	-2.186***	-0.249	-0.996***
	(0.393)	(0.400)	(0.347)	(0.374)	(0.336)	(0.340)
Fringeness	-1.211***	-1.574***	-0.829***	-1.158***	-1.274***	-1.287***
	(0.294)	(0.300)	(0.279)	(0.285)	(0.238)	(0.257)
Dynamism	-0.850**	-1.362***	-1.127***	-0.753**	-1.011***	-1.202***
	(0.346)	(0.377)	(0.309)	(0.372)	(0.306)	(0.319)
Moved to Center	-1.977***	-2.050***	-0.907**	-1.641***	-1.436***	-1.517***
	(0.446)	(0.491)	(0.391)	(0.402)	(0.376)	(0.398)
Party Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	486	486	486	533	486	568
R2	0.219	0.344	0.118	0.296	0.323	0.261
F Statistic	16.482*** (df = 6; 353)	30.809*** (df = 6; 353)	7.845*** (df = 6; 353)	28.091*** (df = 6; 400)	28.103*** (df = 6; 353)	25.664*** (df = 6; 435)

Note: *** p < 0.01, standard errors in parentheses. Replication of estimation results for model (3) reported in Table 4-6, dropping individual parties from our sample prior to estimation. All continuous independent variables are standardized (i.e., all variables except the binary variable *Moved to Center*). For these variables, the estimated coefficients indicate the percentage point in-/decrease in voter support associated with a one standard deviation increase of the corresponding variable.

Table 4-11: Panel Regression Results for Different Rolling Windows

Dependent Variable	Voter Support			
Model	(1)	(2)	(3)	(4)
X	-0.718 (0.577)	-0.995* (0.580)	-1.450** (0.593)	-1.024* (0.610)
Y	3.471*** (0.419)	3.481*** (0.421)	3.589*** (0.427)	3.699*** (0.444)
Differentiation	-0.490 (0.300)	-0.689** (0.311)	-1.002*** (0.323)	-0.834** (0.334)
Fringeness	-0.873*** (0.229)	-1.067*** (0.237)	-1.297*** (0.244)	-1.171*** (0.260)
Dynamism (1 Month)	-0.486** (0.213)			
Moved to Center (1 Month)	-0.392 (0.326)			
Dynamism (3 Months)		-0.778*** (0.247)		
Moved to Center (3 Months)		-0.854** (0.356)		
Dynamism (6 Months)			-1.092*** (0.303)	
Moved to Center (6 Months)			-1.624*** (0.373)	
Dynamism (9 Months)				-1.008*** (0.345)
Moved to Center (9 Months)				-1.322*** (0.392)
Party Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	644	630	609	588
R2	0.213	0.227	0.255	0.241
F Statistic	22.726*** (df = 6; 505)	24.191*** (df = 6; 493)	27.120*** (df = 6; 475)	24.142*** (df = 6; 457)

Note: *** p < 0.01, standard errors in parentheses. Replication of estimation results for model (3) reported in Table 4-6, using different rolling windows to calculate the dynamic positioning features *Dynamism* and *Moved to Center*. All continuous independent variables are standardized (i.e., all variables except the binary variable *Moved to Center*). For these variables, the estimated coefficients indicate the percentage point in-/decrease in voter support associated with a one standard deviation increase of the corresponding variable.

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