ARTICLE TYPE

Measuring Illiberalism: Mapping Illiberalism in Seven Countries, 2000-2022

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Abstract

This paper presents a text-based method for measuring illiberalism. Our approach distinguishes between political actors within the same country and is sensitive to different subtypes of illiberalism—such as anti-pluralism, nationalism, religious fundamentalism, and the villainization of political opponents. The model combines word embeddings, trained on actor- and time-specific text, with dictionaries of liberal and illiberal terms. We apply our measures to 67 political parties across seven European legislatures (1996-2022) and two issues: gender politics and immigration. Our results identify differences in the degrees and varieties of illiberalism across countries, systematically demonstrating illiberalism's political relevance.

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1. Introduction

Illiberalism threatens democracy (Laruelle 2022). Illiberal ideas about representation, which emphasize anti-pluralism, majoritarianism, and leaders-over-institutions, have independent causal effects on democratic erosion (Kellam and Benasaglio Berlucchi 2023). Existing studies show that robust democratic institutions help contain illiberal leaders, as in the cases of Donald Trump in the US and Jair Bolsonaro in Brazil (Levitsky and Ziblatt 2018; Weyland 2020). However, illiberal actors can harm formal liberal institutions, such as constitutions, as in the case of Fidesz in Hungary, and informal institutions, such as fundamental rights, as in the case of Law and Justice (PiS) in Poland (Halmai 2021). What is less evident is whether such actors broadcast their illiberal positions in a measurable way. Identifying illiberal actors systematically through their speech would allow us to detect the emergence of illiberal leaders, identify their degrees of illiberality, and recognize varieties of illiberalism. In this paper, we address this gap by using text-as-data methods to measure illiberalism across seven countries and two policy areas.

However, studying illiberalism systematically is not a straightforward task. On the one hand, existing studies of illiberalism are primarily conceptual and qualitative, without clear conclusions on how to quantify illiberal ideologies (Waller 2024; Surowiec and Štětka 2020; Enyedi 2016). While a few studies use text-as-data methods to measure illiberal speech across political leaders around the globe (Maerz and Schneider 2020; Maerz 2019), they do not analyze what kinds of policy issues are associated with illiberalism, leaving the political consequences of illiberalism unexplored. Furthermore, establishing illiberalism as a global phenomenon is a resource-intensive task. Such an approach requires a research design sensitive to country- and context-specific differences, such as semantic variations across languages and political institutions (Kircher and Kutlu 2023), and allows for variation in the intensity and types of illiberalism (Guasti and Bustikova 2023).

In this paper, we overcome these hurdles by proposing a word-embeddings-based measure of illiberalism. We build on existing legislative speech datasets that combine 3,584,120 legislative speeches across seven European countries, covering 67 political parties across a period from 1996 to 2022 and 67. We identify degrees and varieties of illiberalism by measuring the semantic association of illiberal speeches with two policy topics: gender and immigration. To measure illiberalism across policy areas, we utilize four sets of novel dictionaries that are applicable cross-nationally.

Our results suggest that illiberal discourses vary systematically across actors and correlate with well-known dimensions of party politics. Our approach can distinguish between political actors both within and across countries on the illiberal-liberal dimension. Furthermore, our approach distinguishes between varieties of illiberalism; we show that some parties, such as the Conservatives in the UK, are illiberal on the immigration dimension while being moderately liberal on gender issues. Finally, our approach is sensitive to time trends and can distinguish a party's level of illiberalism in one year compared to other years, indicating that illiberalism is a dynamic ideology that is sensitive to the salience of issues. Our validation exercises, using Chapel Hill Expert Survey data (Jolly et al. 2022) and alternative word embedding methods, show that our approach replicates and extends existing measures.

Our study makes several contributions to the comparative study of illiberal ideologies. Firstly, we demonstrate that word embeddings are an effective technique for studying illiberalism across countries and policy areas. To the authors' best knowledge, our study is the first to develop a quantifiable measure of illiberalism systematically. Future studies could use our approach to understand the relevance of illiberalism in contexts they are interested in, whether historical cases, political campaigns, or newspaper articles. Secondly, we show that the degrees and types of illiberal rhetoric vary across actors and policy areas. This supports existing qualitative arguments and suggests that, like populism and nationalism, illiberalism comes in a variety of forms (Gidron and Bonikowski 2013; Devinney and Hartwell 2020). Finally, we show that illiberalism as an ideology is sensitive to dimensions of party competition. Therefore, illiberalism is likely not just cheap talk but at the core of the appeals of political actors to voters.

The paper is organized as follows. The next section discusses illiberalism, providing conceptual grounding for our operationalization of the term. We also review previous text-based approaches for measuring concepts such as ideology, nationalism, and populism. The data section details our sources for parliamentary speeches and provides some descriptive statistics. The methods section elaborates on our process for validating the liberal-illiberal dictionary and training word embedding models. The results section provides evidence of the face validity of our model by applying it to immigration policy as well as rhetoric surrounding gender. Finally, we discuss the contributions of the model and suggest avenues for future research.

2. "Illiberalism as Ideology"

2.1 Conceptualizing Illiberalism

Illiberalism has received increased attention in the recent years. However, its features are still debated. Guasti and Bustikova (2023, 2) argue that illiberalism refers to "a set of principles opposed to pluralism, minority accommodation, and ideological heterogeneity". It thus consists of multiple elements related to the backlash to liberal progress and is in line with (radical) right-wing ideas. One of the most comprehensive definitions has been offered by Laruelle (2022), who besides the liberal backlash also emphasizes the prevalence of solutions that are majoritarian, nation-centric, or sovereigntist, favoring traditional hierarchies and cultural homogeneity, the concept's shift from politics to culture, and its rootedness in an age of globalization. Accordingly, expressions of illiberalism can take several forms.

Illiberalism is defined by a few stable, coherent features (Laruelle 2022), on which we build our measurement. At the same time, illiberalism can be innovative, doctrinally fluid, and context-based (Enyedi 2020). Therefore, we account for the varieties of illiberalism detectable in speech by adopting a definition that combines primary and secondary qualities. A set of primary qualities constitutes the core of the concept.

The primary qualities of illiberalism contradict the basic liberal principles of pluralism, consensus politics, rational debate, and institutional checks on majority dominance. In speech, we focus on three primary qualities of illiberalism. *Anti-minority* language refers to the curtailment of individual rights, the prioritization of the dominant group, and the violation of the principle of non-discrimination. *Moral other* is a similar category to the above, but refers specifically to placing the cultural and moral standards of the in-group over universalist principles. Finally, the category *uncivil, non-rational* refers to a Manichean discourse that villainizes the opposition and precludes compromise or negotiation.

Table 1. Primary Qualities of Illiberalism

Primary Qualities	
Contradicting liberal principles such as pluralism, consensus politics, rational debate, and institutional checks on majority dominance	
Anti-Minority:	Against pluralism, individual rights, and institutional checks on majority dominance
Moral Other:	Placing cultural and moral standards of the in-group over universalist principles
Uncivil, Non-Rational:	Manichean discourse that villainizes the opposition and precludes compromise or negotiation

We do not claim that these categories exhaust the possible qualities of illiberalism. Rather, these categories best distinguish the liberal-illiberal axes in a study focused on the speech of European politicians. We describe the logic of the dictionaries that measure these dimensions, and the validation measures we took, in Section 4.

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2.2 Measuring Illiberalism

Ideology represents a notoriously difficult concept to measure. Traditionally, therefore, researchers have relied on hand coding of text. A notable project following this approach is the *Manifesto Project*, which employs research assistants to code party election manifestos to measure parties' positions on a range of issues from anti-imperialism, pro-democratic sentiment, and market regulation (Volkens et al. 2013). Their project is the gold standard but requires a team of over 200 people. Computational methods, on the other hand, are less labor intensive, can be quickly scaled up, and are closing the accuracy-gap with handcoding methods. Another well-established measure working with congressional roll call vote in the US relies on DW-NOMINATE (**D**ynamic **W**eighted **NOMINA**l **T**hree-step **E**stimation), a scaling approach that represents legislators on a spatial map using their voting behavior (Poole and Rosenthal 2001). However, while roll call votes can approximate basic left-right positioning, they are not able to capture positions on more narrowly defined policy areas, such as immigration, education, and gender. We therefore turn to a discussion of several different approaches to measuring ideology.

Statistical-scaling methods for measuring ideology rely on text features to place them on a one-dimensional scale (generally requiring no or minimal human coding). One of these first computer-based analyses of ideology leverages reference texts that represent extreme examples of the concept of interest. *Wordscores* uses expert scores of these reference texts—such as ideological scores given to party manifestos—to estimate a one-dimensional left-right space derived from the relative frequency of words found in these texts (Benoit and Laver 2003). Party manifestos that researchers have not seen can then be placed on this left-right dimension depending on their similarity to the reference texts. Building on a similar scaling method, Slapin and Proksch (2008) develop one of the first unsupervised approaches for measuring ideology using text data. They estimate the position of documents on a latent left-right dimension based on word frequency. They assume that the words in each document are drawn independently from a Poisson distribution and include word fixed-effects to account for the fact that some words are used much more often. Word weights capture which words are most important for differentiating between party positions. More recently, Glavaš, Nanni, and Ponzetto (2017) move beyond word frequencies. They propose a method that leverages word embeddings to produce semantic representations of text. They then use pairwise similarity between texts—anchored by two texts that represent the extremes—to place them on a left-right dimension.

A drawback of unsupervised methods for left-right scaling of texts is that this approach requires us to assume that ideology is the primary feature that distinguishes the language of political actors. When texts are more clearly distinguished by other qualities, such as style, tone, or even topical focus, unsupervised scaling methods will fail to capture ideological differences. Unsupervised methods are particularly ill-suited to measuring more subtle qualities, such as sentiment, antidemocratic preferences, or nationalist attitudes.

Supervised machine learning, on the other hand, is better equipped to measure subtle or abstract concepts. A machine learning approach requires human coding to develop a training data set that the computer program "learns" from, detecting word patterns that identify the human-assigned categories (Benoit et al. 2020). The resulting model can then be applied to texts that the researchers have not seen to classify them according to their categories of interest. A disadvantage of such an approach is that developing a training set is a labor-intensive process, especially when trying to measure multiple concepts, because each concept requires its own training dataset. Our goal is to develop an approach for identifying several country-specific variations of illiberalism that can be applied to multiple actors in multiple countries and periods. For this reason, we turn to an approach that is comparably less resource-intensive.

Word embeddings offer an unsupervised approach to modeling language grounded in Wittgenstein's (1973) theory of meaning. This method leverages the distributional hypothesis of language, which proposes that we can know the meaning of a word by "the company it keeps" (Firth 1957)—that is, a word's meaning is correlated with its linguistic context. Word embedding models learn the meaning of words from the words that appear frequently in a small window around that word (Mikolov et al. 2013). Going beyond bag-of-words approaches, embeddings have been shown to capture semantic properties in language. Word embeddings are often combined with other models such as topic modeling to achieve higher context-sensitive results. They have been shown to successfully capture ideology in parliamentary corpora (Rheault and Cochrane 2020). And, crucially, they are sensitive to changes in word usage over time (Rodman 2020). For example, while the word "immigration" will likely always refer to the same topic, it might be embedded in language of a dramatically different ideological valence, depending on the speaker and the time.

Word embeddings combined with dictionaries offer an efficient but context-sensitive method for measuring subtle concepts. *Dictionaries* use keywords that are common in specific discourses and when discussing certain concepts. Keywords should clearly distinguish texts according to target categories, and, typically, the frequency of those keywords then measures the extent to which a document belongs to a particular category. Dictionaries can be tailored to classify texts in separate categories (such as policy areas) or to measure tone or sentiment (Laver and Garry 2000). The terms in a dictionary can be developed on the basis of a researcher's domain expertise or can be adapted from validated lists. The advantage of a dictionary approach is that the researcher's task is streamlined—they must identify relevant keywords, and these can then be applied to a large number of documents. We explain further in our methods section how we combined word embeddings with dictionaries to develop a liberal-illiberal dimension for measuring speech.

Overall, our survey of the existing work on measuring ideology with text suggests three tentative conclusions. Firstly, while human-coded and supervised learning methods can be considered effective ways of scaling the ideology of texts, they are labor-intensive tasks that require abundant resources. Secondly, while unsupervised methods are cost-efficient and have been successful for specific tasks of measuring ideology, they are prone to random errors that derive from qualities of the texts that have nothing to do with ideology. Thirdly, word embedding methods, combined with dictionaries, are cost-efficient and internally valid alternatives to other unsupervised methods, as they focus on the context of words and require minimum input—i.e., a set of keywords—from the researcher.

3. Data

To compile the dataset we brought together several datasets of parliamentary speech. Table 2 shows an overview of the data included. We combined data from the *Comparative Agenda Project* (CAP) dataset (Boda and Sebők 2021)—which lists metadata on parliamentary speeches from 1990 to 2022, depending on the country—with speech data from *ParlaMint* (Kuzman et al. 2023) and *ParlSpeech V2* dataset (Rauh and Schwalbach 2020) for several countries. In total, the dataset contains 3,584,120 speeches (documents) from 67 parties across 7 country legislatures.

In the following paragraphs we detail the pipeline for our embeddings models in combination with dictionaries. This process is also visualized in Figure 1.

4. Methods

Dictionaries. We develop dictionaries for each of our policy areas (immigration and gender) and for liberal and illiberal discourse. We started with a master list of liberal and illiberal terms validated by Maerz and Schneider (2020) and Schafer (2023). Terms indicative of discourse referring to illiberal, anti-minority language, for example, are words such as*invasion*, *threat*, *abuse*, or *illegal*. In essence, these are terms that, for example, refer to the construction of immigrant groups as deviant, inferior, and/or undeserving *Others*, while prioritizing the dominant in-group (Van Dijk 1993). These terms have been selected based on our conceptualization of illiberalism in combination with previous literature measuring (il)liberalism. This allowed us to capture the semantic context of speeches, while at the same time remaining close to the initial concept of illiberalism.

Table 2. Overview of Data

Country	Time Period	Number of Documents	Parties Included	Source
Austria	1996 - 2022	102,862	BZÖ, FPÖ, Grüne, JETZT, LIF, NEOS, ÖVP, SPÖ, STRONACH	ParlEE
Hungary	2010 - 2022	52,498	Fidesz, KDNP, JOBBIK, MSZP, LMP, Párbeszéd, DK, Mi Hazánk, Momentum	CAP
Poland	2015- 2022	122,443	PiS, Konfederacja, UPR, KO, Teraz, KP-PSL, Lewica, Kukiz15	CAP
Italy	2013 - 2022	931,62	AP (NCD-UDC), Aut, FdI, FI, GAL, IV-PSI, L-SP, M5S, Misto, NCD, PD, PdL, SCpl	
United Kingdom	2000 - 2022	1,666,813	CON, GP, LAB, LD, SNP	CAP
Czechia	2013 - 2023	86,078	ANO, ČSSD, KDU-CSL, KSCM, ODS, Pirati, SPD, STAN, TOP09, Úsvit	ParlSpeech V2
France	2017-2022	621,806	FN, LR, LAREM, FI, UDI, SOC, UDI-A-I, GDR, UDI-I, NG, MODEM, AGIR-E, UDI-AGIR, DEM, LC, LT	ParlEE

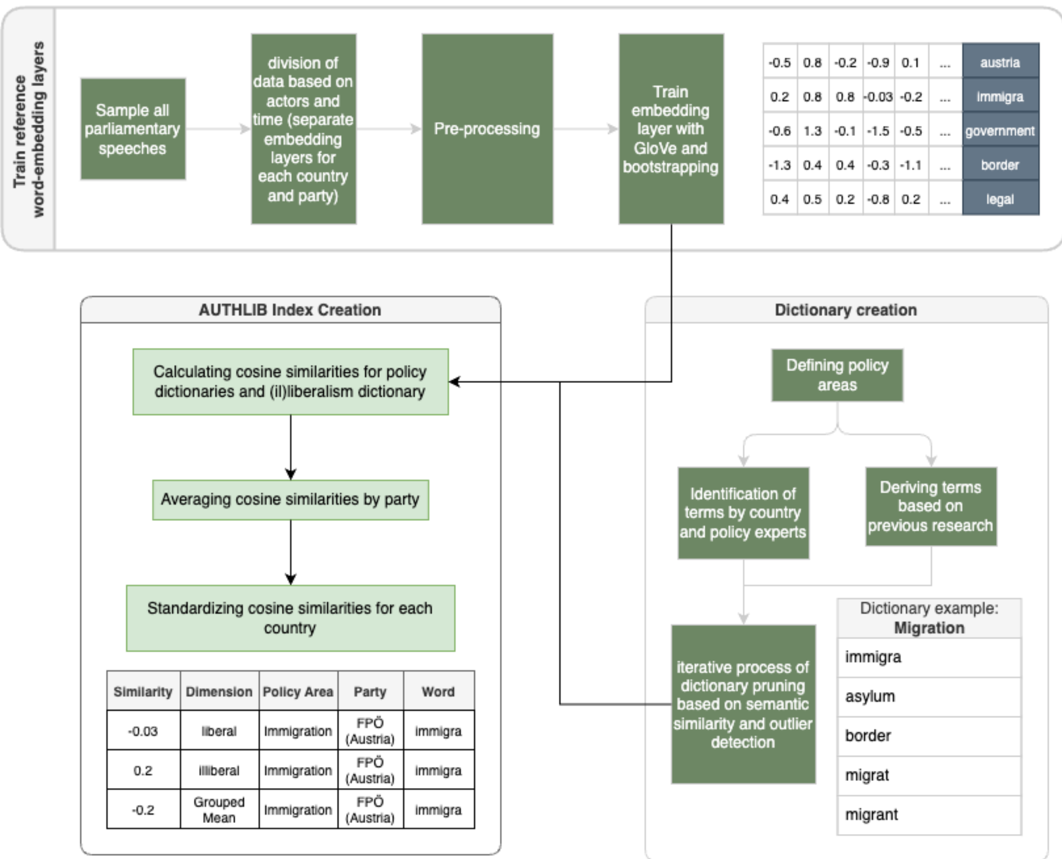

Figure 1. Embedding Pipeline.

Liberal and illiberal vocabulary varies depending on the topic. We tailored liberal and illiberal terms to the specific policy words. For example, illiberal terms for "migrant" include "illegal" and

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“threat”, whereas illiberal terms for “border” include “close” and “invade”. We also avoided terms from Maerz and Schneider (2020) that were coded as liberal and pro-women and pro-minorities— such as “girl”, “gay”, “woman”, “transgender”—but which can be used by actors such as the Hungarian government under Viktor Orbán in an illiberal, derogatory context, and so do not help define a liberal-illiberal distinction. The illiberal use of these words by certain actors becomes clear when looking at their context. Their dissimilarity with core liberal terms such as “tolerance” and “acceptance” is also very apparent mathematically when calculating how close they are in the word embedding space with other liberal and illiberal terms. The full list of dictionary terms can be found in the supplementary material (see Table 3).

Regarding the policy dictionaries, we consulted national policy experts for each country and policy area. We decided on short policy dictionary (see cursive terms in Table 4) that focused on narrowly defined policy areas (or issue areas in the case of Gender) as this method reduces noise and results in more precise results. For instance, while many terms can be used to define immigration policy broadly—such as human rights, citizenship, naturalization, or inclusion—we chose to focus solely on terms indicating immigration specifically. This reduction is both conceptual and based upon a cosine similarity analysis that measured the distance of each policy term in the context of the illiberal and liberal dictionaries. Outliers or terms that had no consistent direction were removed from the policy dictionary. A full list of dictionary terms can be found in Table 4 in the supplementary material.

Word Embeddings. We used word embeddings to model the language of party elites. Word embeddings encode the similarity between words based on the frequency of their co-occurrence in usage. Because we are interested in the speech of liberal and illiberal political elites, training sets for the word embedding models were divided by country and year. This way, the word embedding model captures the usage and meaning of words for each actor and allows us to measure shifts in parties’ ideological positions as well as differences between actors within the same country.

We used the *text2vec* GloVe algorithm (Selivanov, Bickel, and Wang 2022) to train the word embedding models. After trialing different word windows, dictionaries, and bootstrap values, we concluded upon a model with a 10-word window and 100 bootstraps. The corpora normally used to train word embeddings are extremely large, containing billions of words. Our corpora are relatively smaller. We, therefore, use a bootstrapping method shown by Rodman (2020) to stabilize model outputs and make analysis less vulnerable to bias produced by single documents.

Cosine Similarity. Word embeddings represent words in low-dimensional space, and we can measure the similarity between words in this space by calculating their cosine distance. Specifically, we look at the cosine similarity between the set of words in our dictionaries. The cosine similarity between the liberal and illiberal dictionaries and each policy dictionary represents the degree to which each policy area is defined by a liberal or illiberal discourse. For example, when immigration terms used by the Hungarian government show a stronger similarity with the illiberal dictionary, this indicates that Fidesz and KDNP are more likely to mobilize an illiberal discourse when discussing immigration. We took the difference between the cosine similarity of the liberal and illiberal dictionaries to produce a single score for each policy area on a one dimensional liberal-illiberal scale.

5. Evaluating the Model

A model is useful if it reflects meaningful differences in the world. This paper aims to measure concepts such as illiberalism. Our model, therefore, is useful insofar as it can capture differences in how words that define these concepts are used. We leverage two already established methods to validate our approach: the Chapel Hill Expert Survey (CHES) (Jolly et al. 2022) and the embedding regression model (conText) by Rodriguez, Spirling, and Stewart (2023). While CHES provides us

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with an evaluation method to ensure the validity of our final scores of illiberalism across country and policy area, conText provides an additional assessment of the method: word embeddings as a technique for capturing sentiment such as illiberalism.

5.1 Comparing with CHES

First, we compare our text-based measures and CHES on two dimensions: immigration and gender. Our text-based measure for immigration is designed to capture the extent to which party actors frame immigration as an issue of keeping out unwanted others and managing an out-of-control border. Gender focuses on whether parties emphasize the need for women to play traditional roles as mothers, for example, and the villainization of LGBTQ identities (see APPENDIX for dictionaries used). In our approach, -2 indicates highly illiberal rhetoric, while 2 represents more liberal rhetoric. For CHES variables, we use immigration policy, and social lifestyle for comparison with gender. We inverted the CHES values, where 0 corresponds to highly illiberal positions (restrictive immigration policy or illiberal on social lifestyle) and 10 to a strongly liberal position.

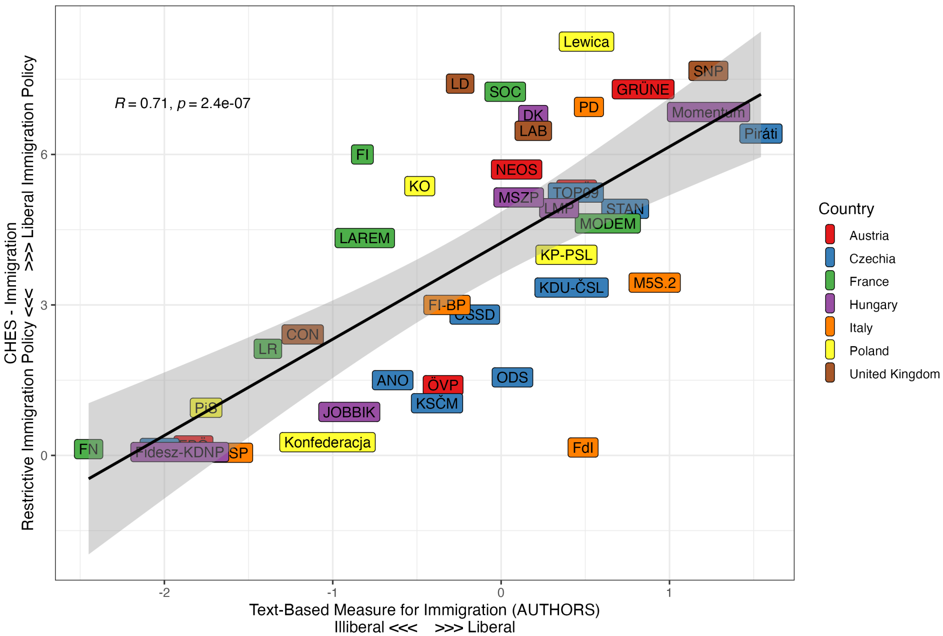

Figure 2. Comparing CHES and Text-Based Measures for Positions on Immigration.

Figure 2 presents the values for immigration policy. Our measure shows a strong positive correlation with the CHES measure. There are some outliers such as Fratelli d'Italia (FdI), which our model assesses as more liberal than we might expect, and, for instance, France Insoumise (FI), which appears to be too illiberal. Still, our approach aligns closely with CHES scores in assessing positions on immigration. Parties' policy positions are reflected in their rhetoric. It is possible to use text analysis of parliamentary speeches to approximate the survey results of a large group of country experts.

In Figure 3 we can see that CHES's "social lifestyle" variable and our gender dimension are comparing two related but different concepts. We can also see how text-based approaches can be less biased. The correlation of the two variables is reasonably high (0.44) and significant. Whereas both axes in Figure 2 above measure the exact same thing—immigration—social lifestyle is broader and

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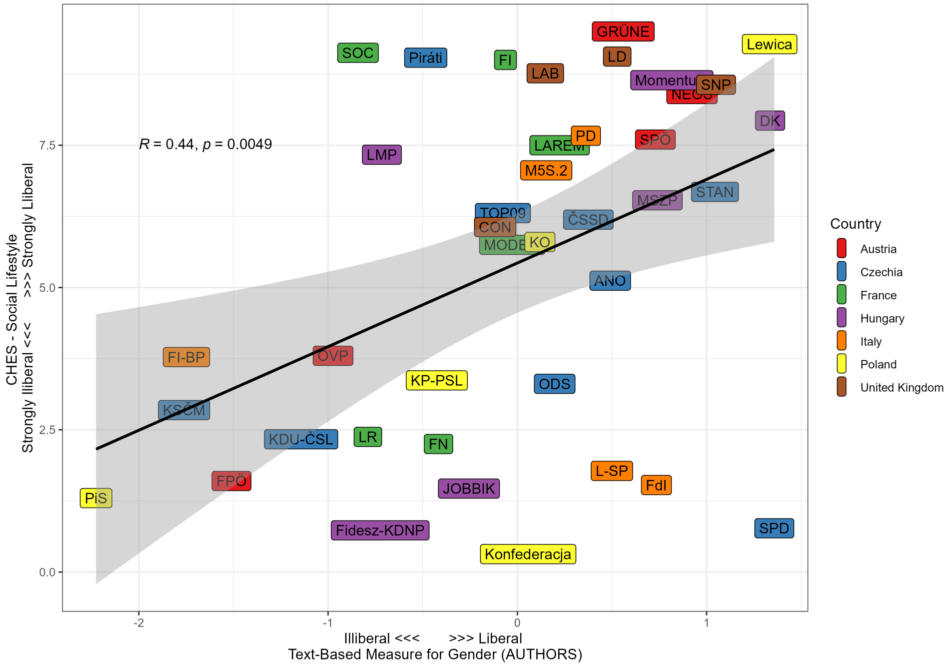

Figure 3. Comparing CHES and Text-Based Measures for Positions on Gender.

more ambiguous than gender. We can also see that expert coders for CHES tend to cluster parties into two clear types: either liberal or liberal. Most parties receive scores close to the extremes, with a gap in the middle of the range around 5. Our two measures disagree the most about parties on the far right, which are nationalist or even neo-fascist (such as the SPD in Czechia, or Lega Nord and Fratelli d'Italia), rather than religious conservative (such as PiS). Our text-based measure reflects the fact that otherwise illiberal parties like Meloni's can sound very contemporary on specific issues like gender.

Granted, there are limitations to our approach. The discrepancies we see when comparing these scores may stem from biases inherent in speech data. While CHES relies on experts to assess parties' true positions, those same parties' rhetoric may attempt to disguise those positions. This incongruence can be attributed to issue avoidance or vague statements on specific issues (as discussed by Rovny and Polk (2020)). At the same time, text-based approaches can serve as a corrective for subjective scores, which can be influenced by tendencies in political science to see authoritarianism everywhere (Little and Meng 2023) Thus, our approach extends the analysis of parties' positions, offering discourse as an additional data point to better understand illiberalism.

5.2 Comparing with ConText

The conText package Rodriguez, Spirling, and Stewart (2023) provides an à la carte approach for measuring the meanings of words as used by different actors. Rather than training new word embeddings—which is a computationally expensive process—conText makes it possible to use pretrained word embeddings together with word windows around key words of interest. A handful of utterances of words like "immigration", "border", "mother", or "lgbtq" by party actors is usually sufficient to then measure the connotation with which actors use these words.

The second validation step, using conText word embeddings, is illustrated in Figure 4. We employ the à la carte embeddings model (Khodak et al. 2018) for this validation, maintaining the

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same word window as in the main model. This model leverages a pre-trained embedding trained on the complete corpus of 67 parties across 7 countries, with party affiliation used as a covariate to generate embeddings for each party individually[1].

The results depicted in Figure 4 indicate that the (il)liberality of parties is consistent between the conText word embedding model and our model. The cosine similarity between the conText word embedding model and our model is 0.63, which is statistically significant at the 99% confidence level. Moreover, the order of parties within each country along the liberal–illiberal dimension is consistent across both models.

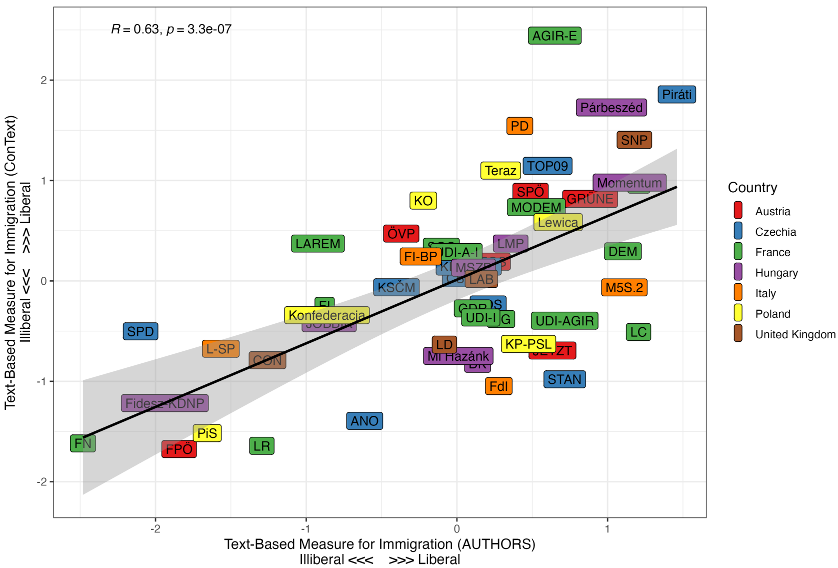

Figure 4. Comparing conText and Text-Based Measures for Positions on Immigration.

Our model shows only a moderate correlation with conText word embeddings on the gender dimension. Figure ?? indicates that the correlation between our gender measure and the conText word embedding-based gender measure is 0.24, which is not statistically significant. We attribute this discrepancy to the sparsity of data on the gender dimension. While immigration is a highly salient issue in European legislative discourse and central to party competition (Dekeyser and Freedman 2023), gender politics is secondary, with some parties emphasizing it more than others. In the conText approach, which utilizes the entire corpus across seven countries, this data sparsity likely introduces bias and noise, possibly random. In contrast, our method involves training models locally by party. As a result, even if a party uses a term like "homosexual" only once, the vector for "homosexual" is derived solely from that party's speeches. On the other hand, in conText-based embeddings, the results are skewed towards parties that use gender-related terms more frequently, as they dominate the pre-training data.

Overall, both validation approaches support our method of combining embeddings and a minimal dictionary. The correlation with CHES provides an external validity test and shows can text- and expert survey-based measures can be complementary. On the other hand, the modest correlation with conText on the gender dimension suggests we should be cautious when applying off-the-shelf methods, especially for cross-country comparisons. Most importantly, however, we show that it

1. While the conText package offers the possibility to include countries as an additional covariate, we do not include country information in our models as this leads to perfect collinearity

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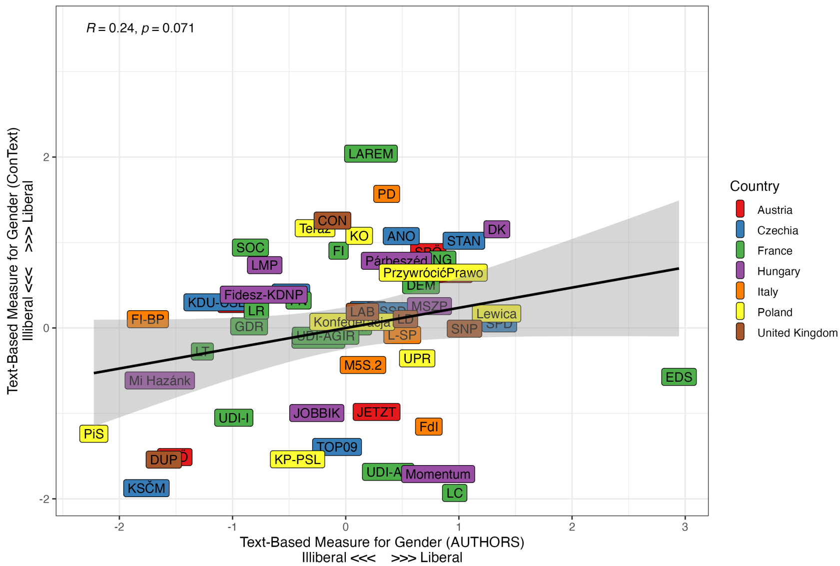

Figure 5. Comparing conText and Text-Based Measures for Positions on Gender.

is possible to measure illiberalism in speech while while also making within- and across-country comparisons.

6. Results: Applying the Model

We now turn to an empirical example of how our method can be used substantively. Specifically, we want to descriptively analyze discourse on immigration before and after the migrant crisis in 2015. For that we are focusing on the countries detailed in Table 2, namely Austria, Hungary, Poland, Italy, the UK, Czechia, and France from 2013 - 2022.

The migrant crisis of 2015 is a direct crisis specifically about immigration. It has led to immigration becoming a highly politicized issue in Europe, dominating both parliamentary discussions and public opinion. Moreover, it affected party competition with new anti-immigration parties emerging, and center (right) parties competing with far right parties on immigration issues by emphasizing more anti-immigrant positions (Abou-Chadi and Krause 2020). Although immigration has been a salient topic since the 1990s, the 2015 crisis increased the salience and politicization of the issue, potentially forming a new political cleavage (Hooghe and Marks 2018; Grande, Schwarzbözl, and Fatke 2019).

The resulting anti-immigration debates contained several illiberal qualities at its core. They have turned deeply anti-minority, constructing immigration and thus, immigrants as a threat to national values and culture. Immigrants are constructed as deviant and undeserving *Others*, which highlights the *Moral Other* quality of illiberalism. Lastly, following the *uncivil, non-rational* quality, migrants are villanized as opposition to the in-group (Mudde 2019). Considering these core illiberal qualities of anti-immigration discourse, we are also expecting to see a similar pattern of increasing illiberalism with our measurement.

The 2015 migrant crisis has affected countries to different degrees. Similarly, while immigration has always been a highly polarizing issue, immigration discourse was affected by the crisis to a different extent as well. Comparing pre-crisis and after 2015 politicization of immigration during election campaigns in different European countries, Hutter and Kriesi (2022) shows that while the UK or France showed no differences in their levels, other countries such as Austria or Italy display a clear increase in politicization of immigration after 2015.

Consequently, we are also expecting a similar development using our approach. In the case of countries with a higher difference in politicization levels (Austria, Italy, Poland or Hungary), we are anticipating a similar trend towards more illiberal discourse, especially for (center) right parties. Respectively, countries that have only low levels of variation according to Hutter and Kriesi (2022) (France or the UK) are expected to show equally little variation with our method as well.

Figure 6. Immigration positions of Austrian parties as measured by authors' approach.

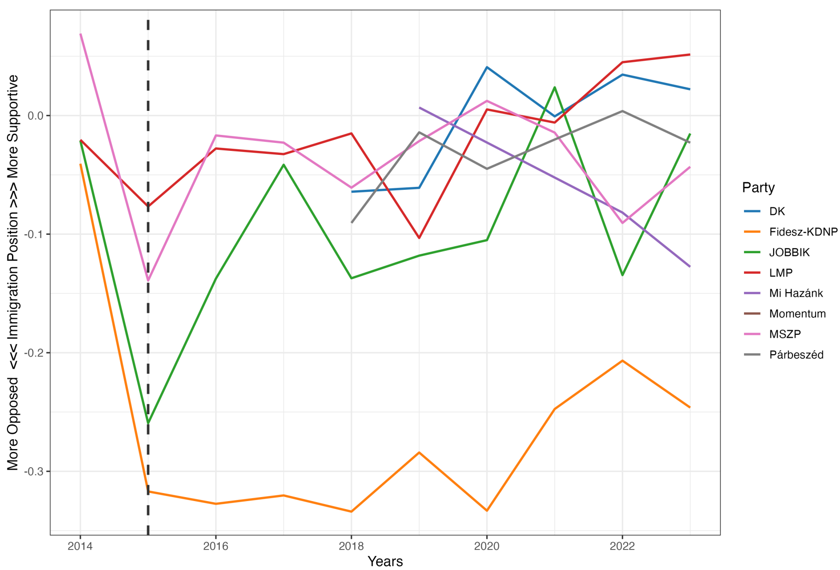

Figure 7. Immigration positions of Hungarian parties as measured by authors' approach.

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Figure 6 presents the immigration discourse of Austrian parties in the parliament as measured by our approach. The graph shows a clear shift with 2015, especially in the case of the far right FPÖ, which significantly became more illiberal in its discourse. While other parties have also adopted a more illiberal rhetoric, the shift is not as extreme. Conversely, Figure 7 shows a very different pattern in the Hungarian case, which shows a much more polarized parliamentary discourse on immigration with Fidesz, the governing party of Viktor Orbán since 2010, having a very strong illiberal rhetoric.

To analyze whether our approach shows similar developments in increased politicization as Hutter and Kriesi's 2022 findings, we have calculated the standard deviations of immigration values to measure how dispersed or similar immigration discourse is across parties within each country in a given year as shown in Figure 8. Interestingly, our results do not fully overlap with their findings. While Hungary is equally high in politicization, other countries seem to rather cluster on a similar level. One reason for this could be the strong polarization in the Hungarian case. While Fidezs, as shown in Figure 7, has become highly illiberal in its immigration discourse, the other parties do not show the same tendency. Additionally, after 2015 parties have started to compete on the issue of immigration with several mainstream and conservative parties turning to more illiberal rhetoric in order to capitalize on far right parties' success (Abou-Chadi and Krause 2020). This development decreases the variation between parties and results in more conformity within countries.

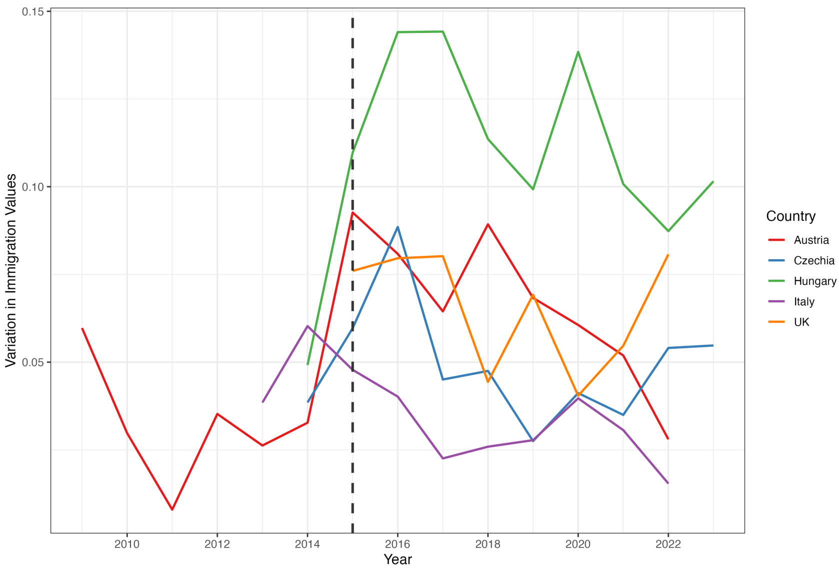

Figure 8. Variation in immigration values over time by country. Based on standard deviations of parties' immigration values within a country.

6.1 Limitations

One limitation of our method is that it is not fully automated. Unlike text-specific tools such as conText (Rodriguez, Spirling, and Stewart 2023), which offer a simple and fast approach that is accessible to those with less coding experience, our method requires both coding skills and more time to define and fine-tune the dictionaries. However, we believe this trade-off allows us to keep the human in the loop, leading to more accurate and reliable results. While simpler models are effective for generating initial insights, our approach provides a more nuanced and refined measurement.

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7. Conclusion

Our findings make a novel contribution to existing debates on measuring illiberalism. We propose a flexible approach that allows us to study differences in semantics between countries, parties, and policy areas, and time. This method has advantages over previous approaches that only facilitated scaling text on simple left-right political dimensions. We show how word embedding models, combined with dictionaries, may reveal context-specific variations of illiberalism in three ways.

Firstly, we show that word embeddings can help us differentiate illiberals in power from other political actors. We show that by quantifying how parties talk about specific policy issues, we can identify variations in parties' stances that correspond to their actual policy positions. This more nuanced approach for measuring parties' positions works with data sources such as parliamentary speeches, but can also be extended to social media communication or press releases. Context-specific embeddings in combination with dictionaries should be able to uncover the variation of illiberal rhetoric across a variety of text mediums.

Secondly, we show that our approach can differentiate between actors' degrees of illiberalism across policy areas. Hence, word embeddings might help us detect (in)consistent use of (il)liberal discourse between political actors. The goal is to identify different types of illiberal actors. For example, the National Rally in France tends to be vehemently anti-immigrant, but is comparatively more liberal on gender issues; whereas Law and Justice in Poland is illiberal on both topics. Such findings suggest that word embeddings can help scholars detect issue-specific illiberalism. This way, we may avoid labeling illiberal actors as centrist or liberal just because they use liberal rhetoric in some policy issues.

Thirdly, by tracking terms across time, we show that their discourse shifts according to political developments and discrete events. An important application of this method could be in the context of party competition. Measuring when and how parties shift their discourse can provide us with a better understanding of both policy space and how actors relate to each another.

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Notes

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Appendix 1. Supplementary Material

Appendix 1.1 Dictionary Terms

Liberalism Dictionary		Illiberalism Dictionary	
acceptance	respect	against_our_country	separatist
authoritarian	rights	against_the_nation	soldier
autocra	suppression	against_the_homeland	stabil
choice	transparen	allah	subversive
cooperation	violat	almighty	territory
corrupt	voluntary	anarch	terror
cruel	dialect	betrayal	traitor
demilitarization	ethni	chaos	treachery
detention	gay	christ	treason
dictator	gender	christianity	uniqueness
disarmament	genocide	christians	unity
discriminat	girls	church	unlawful
diverse	handicapped	danger	ancestors
diversity	harmon	destabili	brothers
equal	indigenous	disease	discipline
fair	injustice	evil	family
fascism	intolerance	father	forefather
free	justice	god	glories
freedom	lesbian	hero	glorious
harassment	lgbt	homeland	heritage
holistic	marginaliz	illegal	honor
human_rights	minorities	invincible	honour
humanity	multiethnic	islam	inherit
inclusion	queer	jesus	jubilee
inclusiv	racist	militar	loyalty
innocent	sister	minaret	majesty
interfaith	solidarity	motherland	monarch
interreligious	transgender	muslim	moral
liberal	unfair	negative	obscen
mediat	voice	patriot	pervert
multicult	woman	police	pornograph
negotiat	women	pride	principle
oppression		proud	recapture
pluralis		religi	reliab
repress		riot	shameful

Table 3. Final dictionary terms for liberalism and illiberalism.

Gender	Immigration and Citizenship	Law and Order
lgbt	immigra	
homosexual	asylum	
transgender	border	
woman	migrat	
gay	migrant	

Table 4. Dictionary terms for all policy areas.

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