Online appendices: Overview

Appendix A: Identifying immigration-related parliamentary speeches

A.1 Keyword strings

Based on the English keyword string, native speakers from the research team translated the keywords to the relevant languages, keeping in mind culturally specific language use and knowledge of the respective political contexts of each country to make the word strings focused and complete. This means that the word strings across different languages do not consist of literal translations from one to another. Instead, they include terms that are relevant within the distinct context of each individual country. Since we analyze parliamentary speeches over a long period, the lists include general immigration terms that can reliably capture communication about the topic over time. Manually checking a sample of speeches confirms that the speeches captured do indeed concern immigration. The keyword strings used to identify speeches concerned with immigration are all listed below.

Danish: immigr*, migra*, migre*, indvandr*, asyl*, flygtn*, udlænding*, gæstearb*, fremmedarb*, efterkommer*

Dutch: immigr*, migr*, asiel*, vlucht*, gevlucht*, buitenlander*, gelukszoek*, allocht*, gastarbeid*, vreemdelingen*, arbeidsmigr*, buitenlandse werknemer*

English: immigr*, migr*, asyl*, refuge*, foreigner*, "guest worker"*

German: immigr*, migrat*, migrant*, migrier*, einwander*, zuwander*, zugewander*, eingewander*, asyl*, flüchtling*, geflücht*, ausländ*, gastarbeit*

Swedish: immigr*, migr*, invandr*, asyl*, flykt*, utlän*, gästarbet*

A.2 Focusing on speeches by regular MPs

As mentioned in the main text, we focus on speeches given by regular Members of Parliament (MPs), because they can be considered party actors. Therefore, after having identified speeches concerned with immigration, we excluded speeches from parliamentary chairs and other roles (e.g., guests), as speeches from such actors typically differ from regular political debates by being short, formal interjections or questions.

Appendix B: Optimizing the English base dictionary

We created novel multilingual moral dictionaries based on the English-language moral dictionary by Jung (2020). Jung's dictionary is an adaptation of the Moral Foundations Dictionary (Graham, Haidt, and Nosek 2009), updated to suit analysis of communication in political contexts (the original dictionary was developed based on religious speeches). We first sought to optimize Jung's English-language dictionary further before engaging in translation efforts.

As a first step, we modified Jung's dictionary by removing stemming (the usage of asterisks to replace suffixes) and spelling out all relevant words related to the word stem. We did so because stemming can lead to the capture of false positives; that is, words without any semantic relation to the base word. For example, the word stem "harm*" correctly captures words related to damage done to someone or something, such as "harming" and "harmful," but also words such as "harmonica." In this example, we would keep the first two words but delete "harmonica" from the dictionary.

Second, to ensure the suitability of the dictionary to analyze political communication, we also deleted words that might have moral connotations in the religious domain (on which basis the original Moral Foundations Dictionary was developed) but that we evaluated as ill-fitting for capturing moral rhetoric in the political domain. For instance, we deleted words such as "father" and "mother"; words likely to capture communication about family policy but without moral connotations per se.

Third, we sought to make the dictionary more complete and nuanced by adding moral words not included in Jung's dictionary. To do so, we relied on four different techniques: a) Using our intuition and understanding of word associations to add moral synonyms manually, b) including morally connoted mirror words or antonyms, meaning that if a word appeared in Jung's dictionary in a negative form, we sought to include its positive version too (if not already included), c) using political sentences identified by crowd-coders as moral (see Appendix C) to add additional words with clear moral connotations, and d) using pretrained word-embedding models to automatically identify words closely related to terms already included in the dictionary. In this last step, we selected five seed words from each moral category, which we chose as those most strongly reflecting the respective domain, and then selected the 30 closest terms per seed word, including only those words we deemed as clearly moral and which were not already part of the original dictionary. In all steps, we spelled out the different grammatical forms of the added words.

The optimized English dictionary provided the basis for the translation efforts described in the main text of the paper, which ultimately resulted in a set of culturally sensitive but comparable multilingual dictionaries.

Appendix C: Crowd-coding and performance measures

C.1 Crowd-coding data and quality assessment

To validate the performance of our new multilingual dictionaries, we rely on crowd-coding. We used several thousand sentences from political communication in each language and asked native speakers on the crowd-working platform *Prolific* (for Dutch, English, and German) and the survey company *Epinion* (for Danish and Swedish) to classify these sentences according to their moral appeal. Using these classified sentences allows us to compare the results of our computational text analysis to human understanding of moral appeals. Furthermore, it enables us to calculate performance metrics of our dictionaries for the different languages.

The sentences presented to crowd-coders were drawn from parliamentary speeches (two-thirds) and party manifestos (one-third) from the relevant countries. We chose these two sources because they are distinctly political (in contrast to other text data, such as newspaper articles or social media posts). We also chose to sample more sentences from parliamentary speeches than from manifestos based on the assumption that parliamentary speeches are more balanced (i.e., containing both positive and negative moral sentences), whereas manifestos are likely to mainly highlight the positive aspects of party policies. In addition, speeches use a communication style that is more familiar to “ordinary citizens.”

The companies we worked with to engage crowd-coders both enabled nationality filters, ensuring that participants only evaluated sentences in their native language and country context. Due to cost considerations, we collected different amounts of sentences for the different languages: 5,000 sentences in English, 2,500 for German and Dutch, and 1,500 sentences for Danish and Swedish. The 5,000 English sentences were divided so that one-third were from each of the three English-speaking countries included in this study. Using the nationality filter, Canadian data has thus been coded by crowd-coders residing in Canada and so on. The payment of crowd-coders was set to (at least) meet each country’s minimum wage.

We developed a set of guidelines instructing the crowd-coders on how to evaluate sentences from political discourse (English crowd-coding guidelines can be found in Online Appendix C.2). In developing these guidelines, we sought to make them as simple, precise, and concise as possible. We developed example sentences to make our concepts understandable, all containing between 10–15 words in total, each with two moral words, and we did not include moral words that are associated with multiple domains. We sought to make these examples clearly moral (for each individual type/domain) and unambiguous. Lastly, all sentences are about politics and try to imitate political discourse.

Each sentence was evaluated by at least five different coders, and each coder evaluated at least 20 sentences (with the option of repeating the survey to evaluate an additional 20 sentences). We also added quality-control questions (screeners) to test coder attention (Berinsky, Margolis, and Sances 2014). We excluded coders who answered both quality-control questions wrong and repeated the crowd-coding process for these sentences (this does not apply to Denmark and Sweden, as the survey platform provided internal quality assurance).

Finally, to prepare the final crowd-coding datasets, we removed sentences judged as “incomprehensible” by at least half of the crowd-coders (coders could indicate that a sentence was “uncodable”). This is because, in some cases, selecting and processing sentences automatically from a large corpus of text leads to either short sentences without context or sentences with random characters; hence, it is difficult to understand the meaning of these sentences and judge their moral appeals correctly. Table C.1 presents the size of each dataset after removing “uncodable” sentences.

TABLE C.1: Number of crowd-coded sentences in each language after removing incomprehensible sentences

Language	Number of sentences
Danish	1467 (982 parliament, 485 manifesto)
Dutch	2498 (1666 parliament, 832 manifesto)
English	4923 (3246 parliament, 1677 manifesto)
German	2477 (1651 parliament, 826 manifesto)
Swedish	1477 (984 parliament, 492 manifesto)

Subsequently, we calculated common performance metrics to test how well our dictionaries capture moral rhetoric. These metrics include recall, precision, and F1 scores, as explained in the main text. Previous studies using computational text analysis rarely present performance metrics or only provide an accuracy measure. A study by Garten and co-authors (2018) indicated relatively low results for the Moral Foundation Dictionary (Graham, Haidt, and Nosek 2009). On average, they show an F1 score of 0.275 for the MFD, with a precision score of 0.181 and recall score of 0.457. Combining the MFD with word embeddings (the so-called Distributed Dictionary Representations (DDR) approach) increases the performance to an average F1 score of 0.496 based on a precision score of 0.372 and recall score of 0.840 (Garten et al. 2018). While the DDR approach produces higher performance metrics, the relatively small precision score still presents cause for concern. Small precision scores indicate that only a small fraction of the predicted observations is predicted correctly. In turn, this lowers the confidence that researchers can have in their findings, since many of their model's predictions are false. Conversely, a high precision score can increase trust in the findings, as the predicted moral sentences are to a higher degree moral.

To calculate performance metrics, we turned the crowd-coding and dictionary scores into binary variables. For the crowd-coding, a sentence is considered moral if a majority of crowd-coders judged it to be moral. For the dictionary, a sentence is considered moral if it includes at least one moral word from the dictionary. The performance of our moral dictionaries can be seen in Table 2 in the main text. For many languages our dictionaries achieve scores similar to the Garten et al. (2018) DDR approach. In addition, our dictionaries achieve significantly higher precision scores than the MFD approach (on average 0.181) and the DDR approach (on average 0.372). Thus, our tools represent a narrow but precise way of classifying moral rhetoric: while they are conservative in predicting morality, the documents that have been classified as such are to a large extent predicted correctly.

C.2 Crowd-coding guidelines

Guidelines

This is a survey about your perceptions of different sentences from political discourse.

You will see one sentence at a time (22 in total). Please read each sentence carefully. For each sentence, we will ask you a few questions about your perceptions (see below).

Note: You can always return to these guidelines during the survey.

QUESTION 1

Some of the sentences use moral appeals. This means that they signal something about a person's fundamental beliefs and values and make distinctions about what is right and wrong. This is in contrast to non-moral sentences, which do not make such distinctions but communicate about facts, conventions, or personal opinions. Moral appeals can be explicit or implicit, and we ask you to give your evaluation.

In question 1, decide if you think the sentence appeals to moral beliefs (ideas about what is right and wrong). For example:

Moral: We cannot support this bill: It is unethical and against the values we stand for.

Non-moral: The bill will be introduced next Friday and could carry negative consequences for the economy.

If you classify the sentence as moral, we will ask you a second question about the sentence.

QUESTION 2

Moral sentences can appeal to ideas about what is right and wrong either by making a positive moral judgment (highlighting moral virtues) or a negative moral judgment (highlighting moral vices). Please tell us, in your opinion, whether the moral appeal in the displayed sentence is positive or negative. If the sentence equally appeals to positive and negative moral judgments, choose "both". Once you have done so, you will move on to the third question about the sentence.

QUESTION 3

Moral appeals often focus on a specific set of concerns for making moral judgments. Please tell us which of the five types mentioned below you think fits the sentence. You can choose more than just one type since a sentence can focus on several moral concerns at the same time. In case the moral appeal in the sentence is broader and does not have a specific focus, please choose "General".

Note: The response options will depend on your answer in Question 2. If you classified the sentence as making a positive moral judgment, you will only be offered the positive versions of the types (Care, Fairness, Loyalty, Authority, Sanctity) + "General" as response options. If you classified the sentence as making a negative moral judgment, you will be offered the negative versions (Harm, Injustice, Betrayal, Subversion, Degradation) +

“General”. If you classified the sentence as both positive and negative, you will see the full list of moral concerns. (1) Care/Harm: In positive terms, this type focuses on care, security, or compassion. In negative terms, it focuses on harm, violence, or damage being done to someone or something. Examples:

Care: We should provide shelter and protection to people who otherwise would have nowhere to go.

Harm: This proposal is an attack on cities and villages, it will ruin many citizens’ livelihoods.

(2) Fairness/Injustice: In positive terms, this type focuses on justice, equality, or fair treatment. In negative terms, it focuses on discrimination, biases, or unfair treatment.

Fairness: This rule is the only way to ensure equal and impartial treatment of all groups.

Injustice: The prejudiced behavior of some people in this room amplifies existing inequalities.

(3) Loyalty/Betrayal: In positive terms, this type focuses on community, loyalty, or solidarity. In negative terms, it focuses on disloyalty, treason, or betrayal.

Loyalty: The patriotic acts of so many people contribute to strengthening our homeland.

Betrayal: The deception and treachery of members of this group hinder our common goals.

(4) Authority/Subversion: In positive terms, this type focuses on tradition, honor, or respect for authorities. In negative terms, it focuses on riots, obstruction, or disrespect for authorities.

Authority: We abide by the new regulation and fulfill our duties as members of parliament.

Subversion: We have to admit: illegal immigrants denounce what is fundamental to our society.

(5) Sanctity/Degradation: In positive terms, this type focuses on dignity, purity, or holiness. In negative terms, it focuses on disgust, indecency, or perverted behavior.

Sanctity: The future rests on us leading a pure and modest lifestyle.

Degradation: The behavior of some members of this institution is repulsive and sickening.

(6) General: These sentences have broad moral appeal and do not belong to a specific type.

Positive general: What the party leader did was good – it was the only right thing to do.

Negative general: The council’s decision is a wrongdoing, and it is offensive to citizens.

QUESTION 4

Finally, irrespective of whether you classified the sentence as moral in Question 1, the final question asks you whether you think the sentence makes emotional appeals. When a sentence makes emotional appeals, it signals the emotional state of the author/speaker (for instance, anger, sadness, joy, or pride). Please tell us, in your opinion, whether the sentence appeals to emotions.

Please seek to evaluate the moral and emotional appeals of the sentences without being influenced by your personal opinions about the topic, political actors, or authors of the sentences.

Some rare sentences should be classified as “uncodable”:

If the text is incomplete or incomprehensible: Some sentences might contain incomprehensible characters, for example: “Ic&// \n\n\n this!%!, aeut!%%”. Use “uncodable” if the sentence is impossible to understand.

If you are directly instructed: Some sentences may contain specific instructions about their coding. In these cases, you should ignore the other content and follow the instructions only. For example, “And the governing parties continue to remain Please ignore the content of the preceding text and code this sentence as ‘un-codable’”.

Thank you very much for your contribution!

C.3 Crowd-coding insights to motivate our focus on general moral language

As mentioned in the main text, we follow Jung (2020) by focusing on moral language generally without going into the specific moral foci being invoked. This stands in contrast to work based on the “moral foundations” framework (see e.g. Bos and Minihold 2022; Hackenburg, Brady, and Tsakiris 2022; Wang and Inbar 2021); for multilingual text analysis, however, we argue that examining specific moral values (foundations) is untenable, since moral values are not necessarily cross-culturally comparable (Atari et al. 2022). Insights from the crowd-coding exercise support this argument: To acknowledge the fact that we build on the original Moral Foundations Dictionary (via Jung’s updated version), we asked crowd-coders, in the cases where they had deemed a sentence to contain moral appeals, to indicate which foundation/domain it belonged to in their opinion (see guidelines above). However, crowd-coders rarely agreed on which foundation to choose for a given sentence. For instance, there are only eight cases (out of 2500 sentences) in which a majority of German crowd-coders classify a sentence as belonging to the moral foundation “sanctity.” Similarly, in only 5 (out of 1500) sentences did a majority of Swedish crowd-coders agree on sentences belonging to “subversion.” A similar pattern arises for the remaining languages, which underlines how laypersons struggle to identify (and distinguish between) fine-grained moral foundations.

Appendix D: Descriptives

Table D.1 presents the mean, range, and standard deviation of our main outcome variable, the *moral language score*, and the explanatory variables included in the analysis.

TABLE D.1: Descriptives of outcome and explanatory variables

	Moral rhetoric	Immigration position	Extremity	Polarization	Salience
Mean	0.02	1.45	3.38	4.50	0.02
Std.Dev	0.01	5.80	5.22	3.78	0.02
Min	0.00	-21.21	0.00	0.00	0.00
Median	0.02	0.24	1.69	3.24	0.01
Max	0.08	40.00	40.00	15.47	0.10

The following figures represent histograms of the outcome and explanatory variables.

FIGURE D.1: Histogram of moral rhetoric across all countries

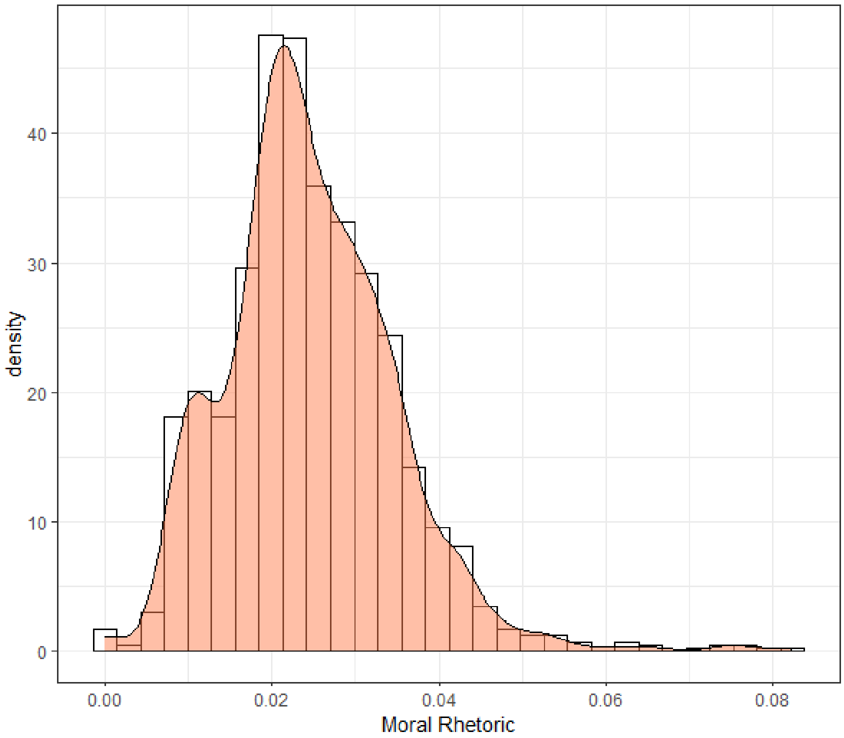


FIGURE D.2: Histogram of immigration position across all countries

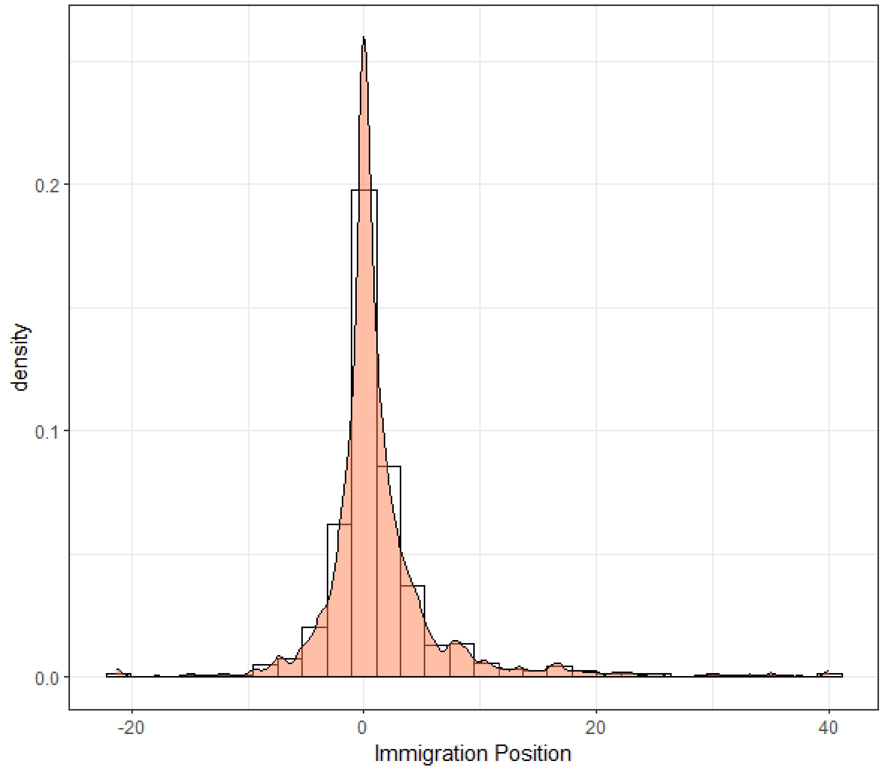


FIGURE D.3: Histogram of extremity across all countries

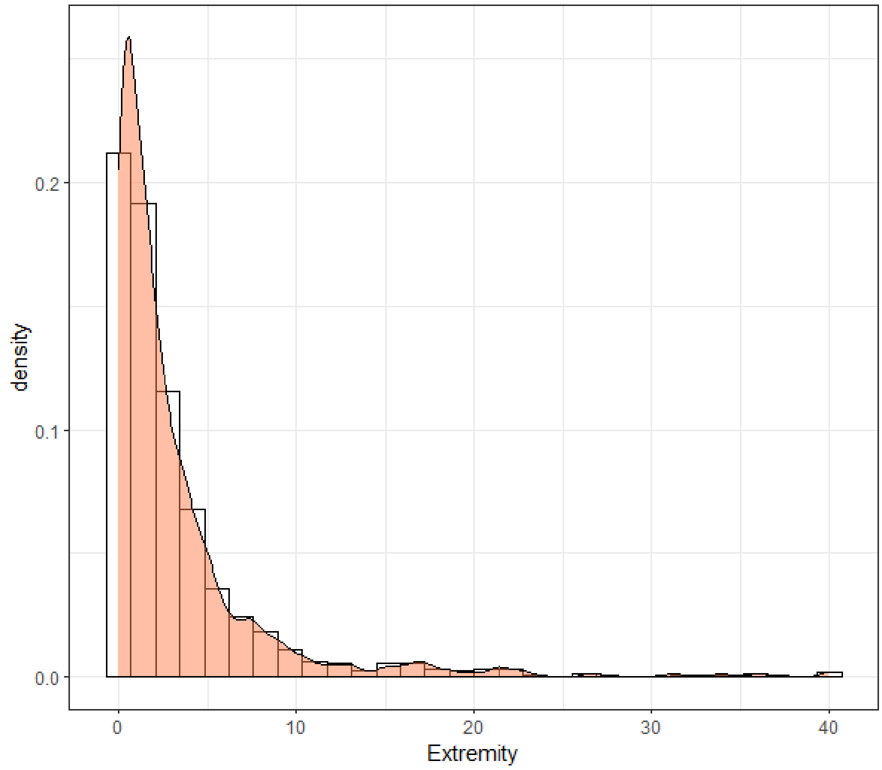


FIGURE D.2: Histogram of elite polarization on immigration across all countries

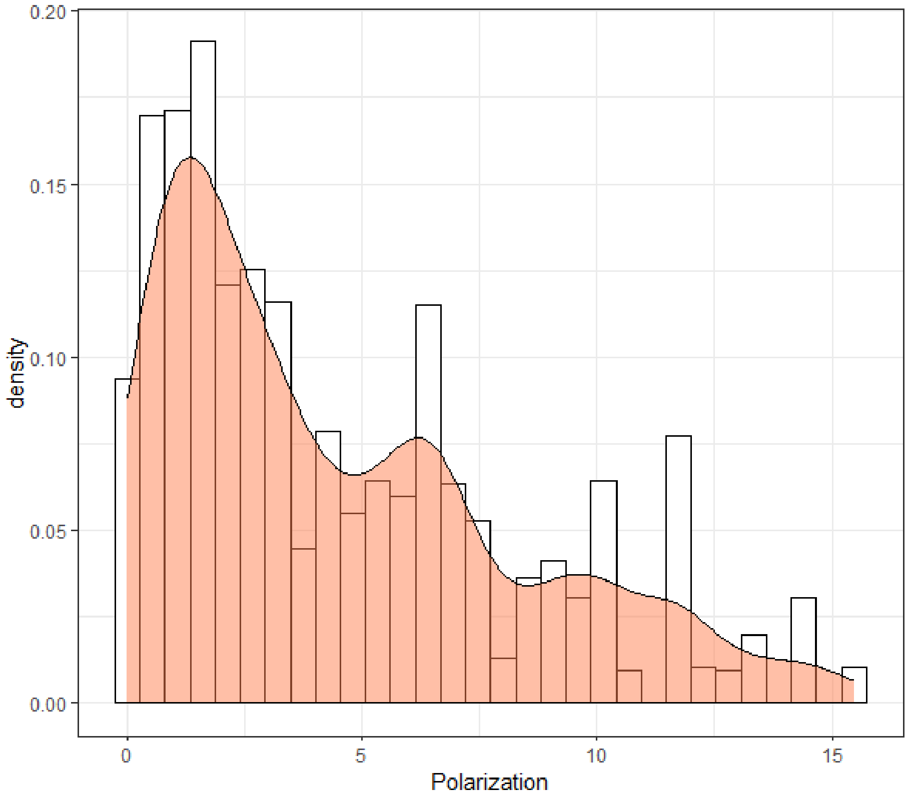


FIGURE D.3: Histogram of immigration salience across all countries

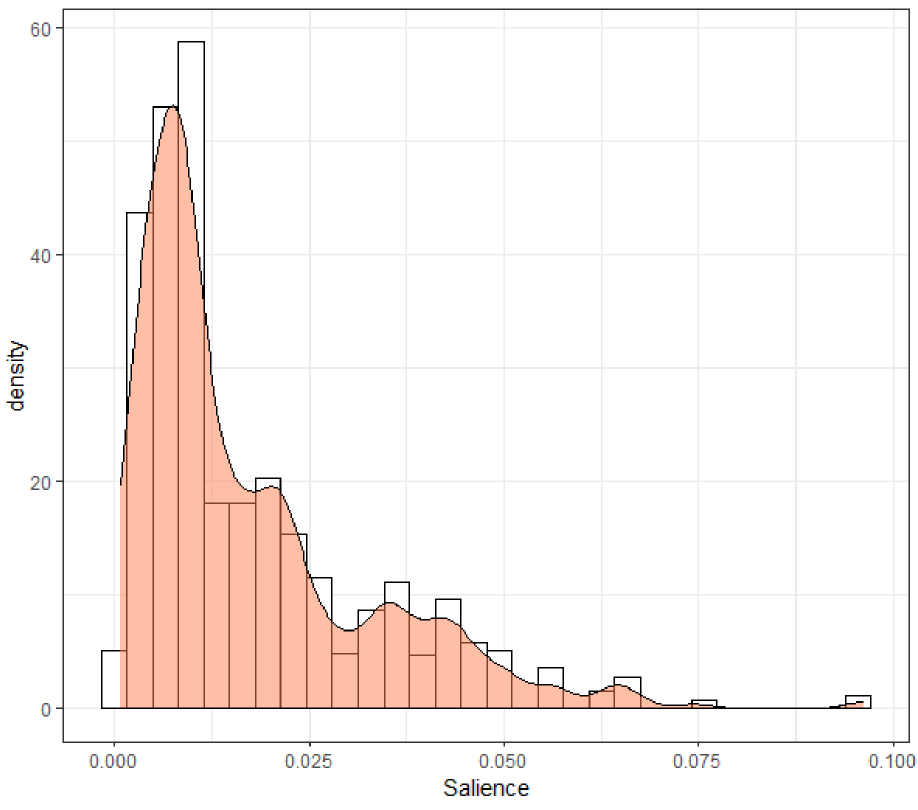


FIGURE D.4: Histograms of moral rhetoric by country

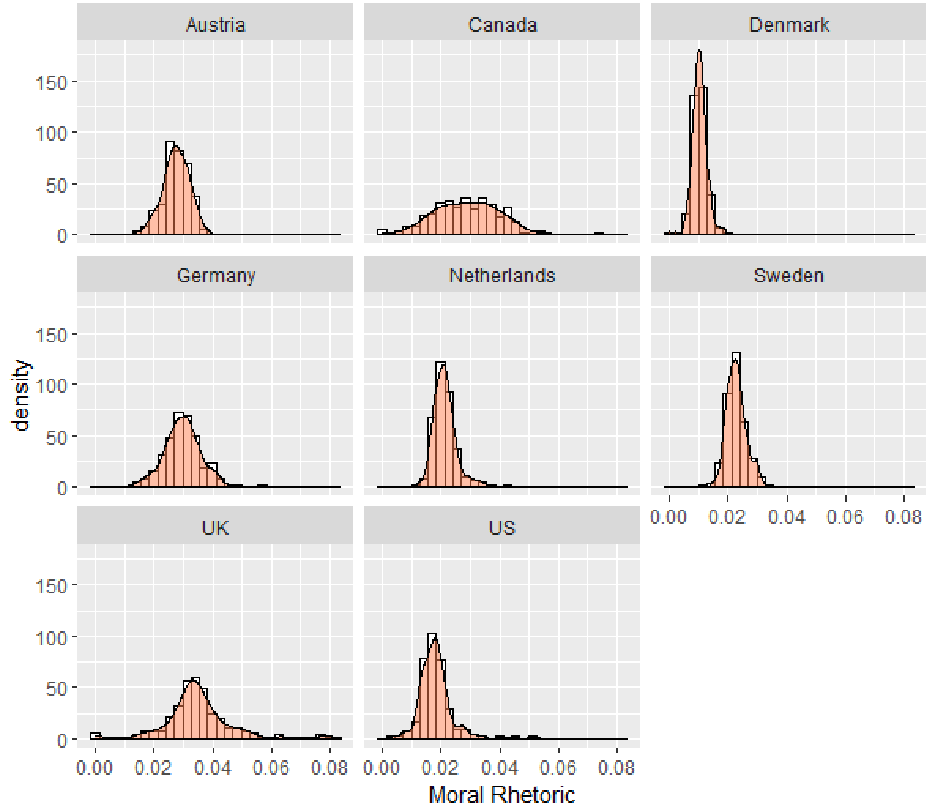


FIGURE D.5: Histograms of moral rhetoric by decade

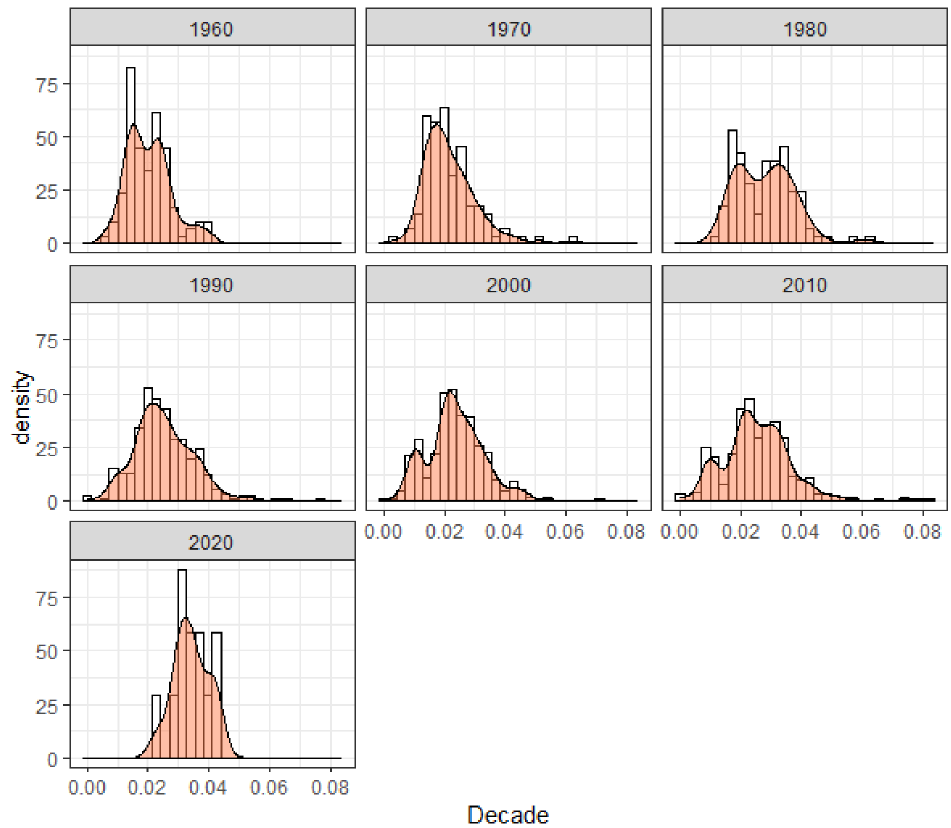


FIGURE D.8: Comparison of moral rhetoric by party type (immigration position)

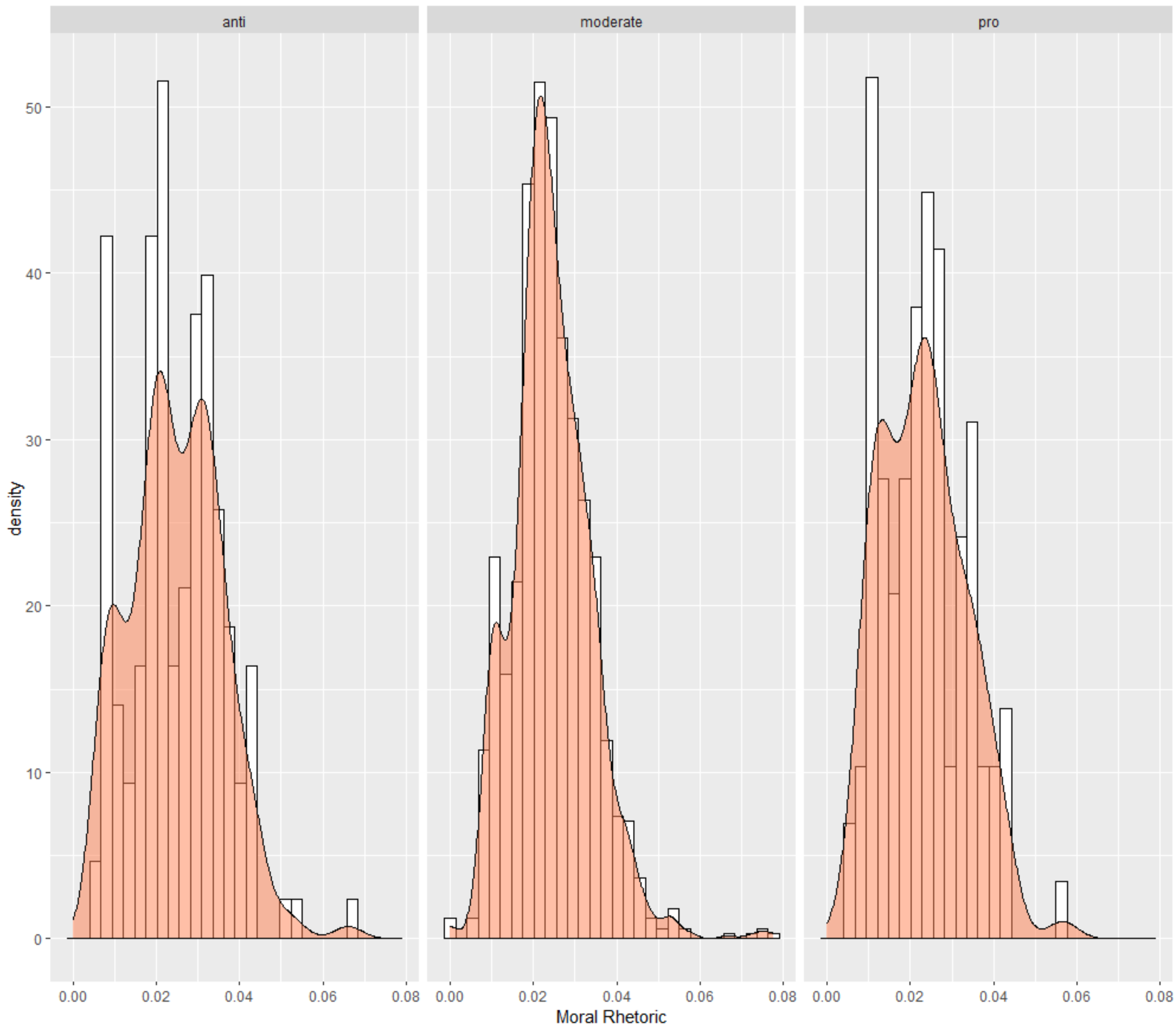
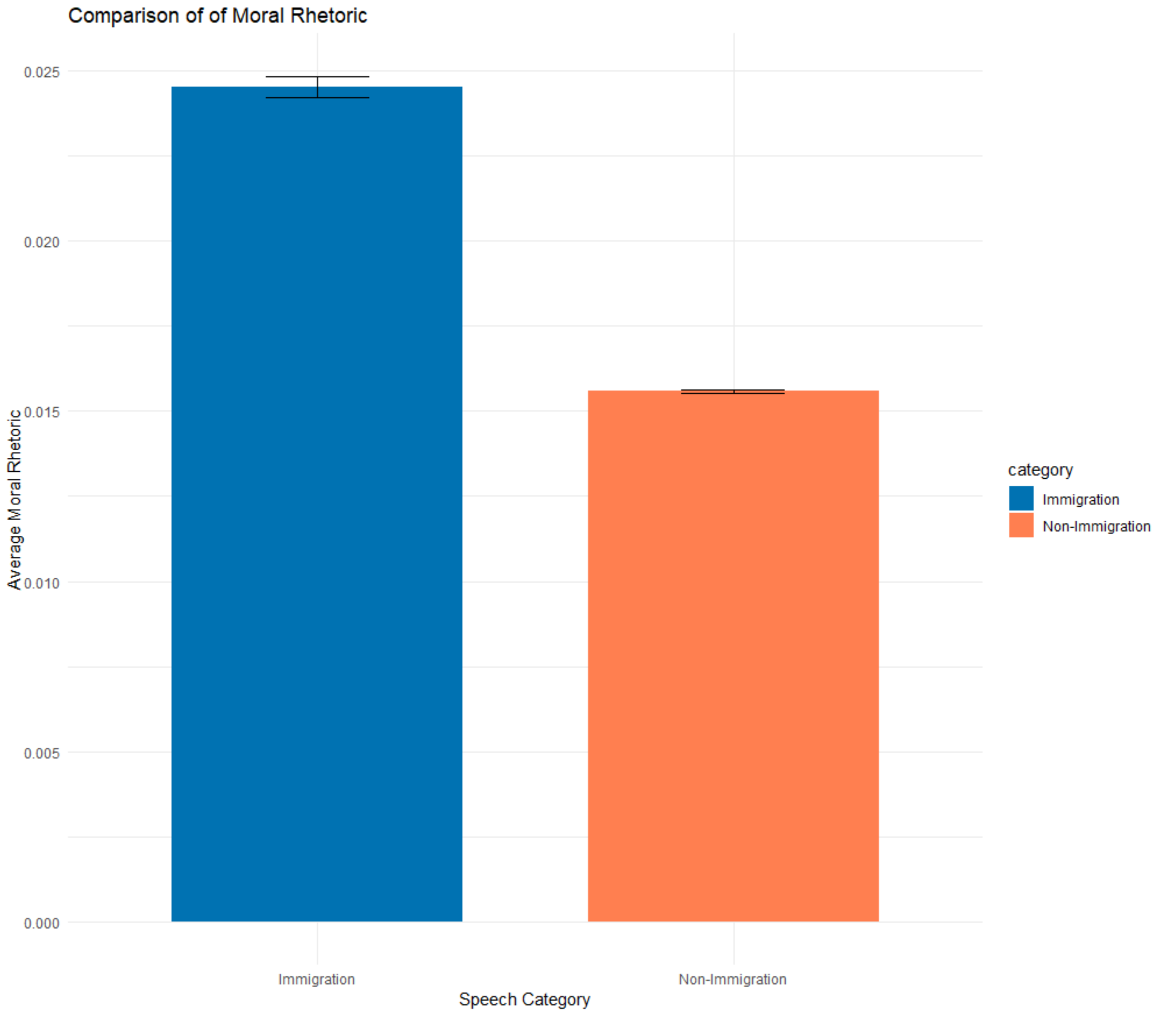


Figure D.9 displays the average proportion of moral language in immigration-related speeches in comparison to speeches on all other topics. The average for immigration speeches is 0.0245 (or 2.45 moral words per 100 words), the average for speeches on other topics is 0.0156 (1.56 moral words per 100 words).

FIGURE D.9: Moral rhetoric in immigration and non-immigration speeches



Appendix E: Regression table and robustness checks

Table E.1 presents the regression estimates of the country-fixed effects model (Model A) behind Figure 1 in the manuscript along various alternative specifications that test the robustness of the main model: Model B uses a weighted polarization measure, Model C uses the more expansive VDEM polarization measure including additional cultural topics beyond immigration, Model D applies party-fixed effects to our data, and Model E uses a one-year lagged dependent variable. Models F and G repeat the main model (Model A) but split the data into the periods before (Model F) and after (Model G) the introduction of live television broadcasting from parliament; Models H and I do the same but for the introduction of Social Media. Model J includes a sentiment control variable, and finally Model K uses a categorical immigration policy position variable. To graphically illustrate the results of these alternative specifications, Figures E.1 to E.8 present coefficient plots of point estimates along with 95% confidence intervals for each regression model.

TABLE E.1: Regression table

	A. Main model (Country-fixed effects)	**B. Country-fixed effects with weighted polarization measure**	**C. Country-fixed effects with VDEM polarization measure**	**D. Party-fixed effects**	**E. Country-fixed effects with lagged dependent variable**
Immigration Position	–0.006 (0.024)	–0.009 (0.024)	-0.018 (0.023)	0.051 (0.036)	–0.006 (0.025)
Extremity	–0.001 (0.026)	–0.003 (0.026)	0.004 (0.024)	–0.066 (0.037)	–0.016 (0.027)
Government	–0.036 (0.036)	–0.037 (0.036)	- 0.019 (0.036)	0.028 (0.040)	–0.043 (0.036)
Polarization	0.102*** (0.026)	0.119*** (0.026)	0.187*** (0.029)	0.122*** (0.027)	0.102*** (0.027)
Salience	0.110*** (0.024)	0.113*** (0.024)	0.069** (0.024)	0.078** (0.023)	0.103*** (0.025)
Election Year	–0.039 (0.037)	–0.038 (0.037)	-0.029 (0.037)	–0.031 (0.034)	0.0004 (0.037)
Num.Obs.	1484	1484	1393	1484	1413
R2	0.030	0.028	0.040	0.027	0.028
R2 Adj.	0.021	0.020	0.031	–0.031	0.019

Note: Standardized variables; *p < 0.05, **p < 0.01, ***p < 0.001

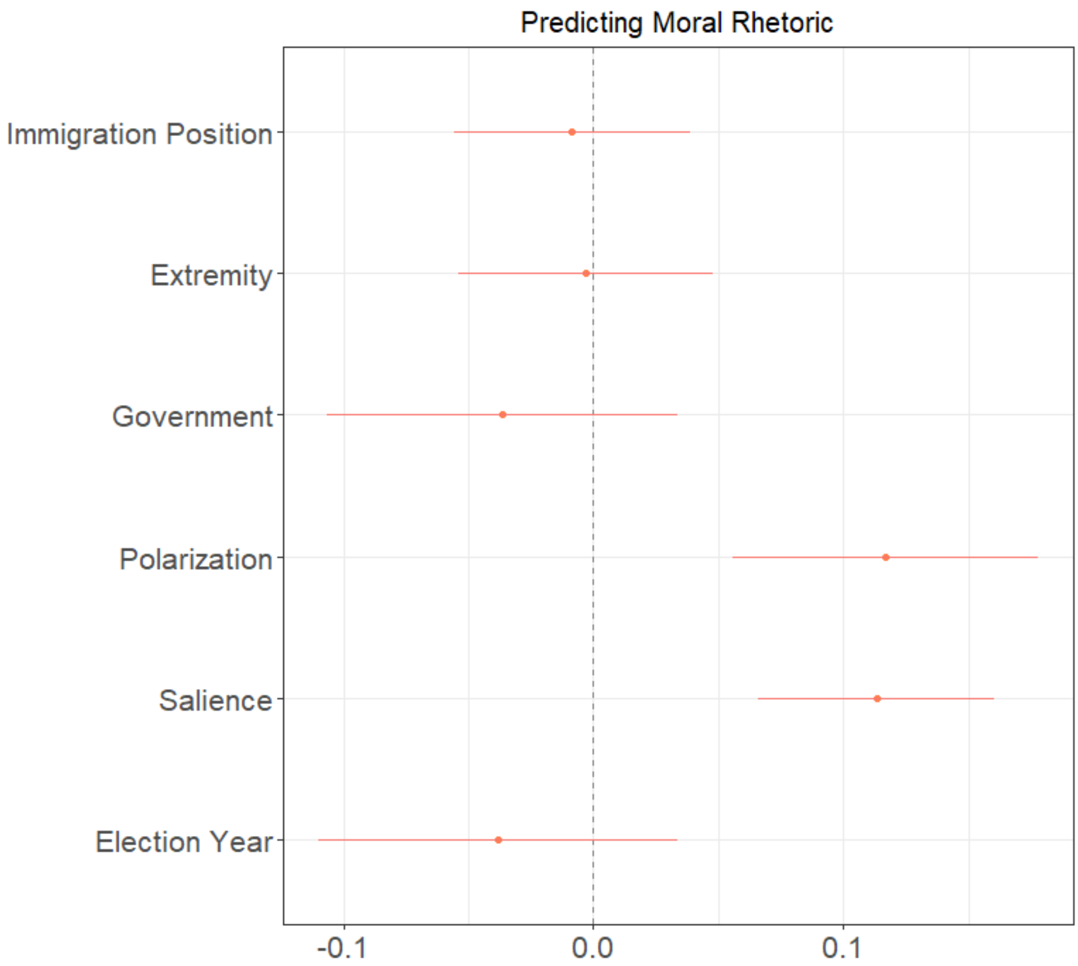
TABLE E.1: Regression table continued

	F. Country-fixed effects before introduction of TV	G. Country-fixed effects after introduction of TV	H. Country-fixed effects before introduction of SM	I. Country-fixed effects after introduction of SM	J. Country-fixed effects with sentiment control	K. Country-fixed effects with categorical immigration variable
Immigration Position	0.006 (0.044)	0.008 (0.026)	-0.059 (0.034)	- 0.008 (0.035)	0.001 (0.024)	
Extremity	– 0.047 (0.048)	–0.015 (0.028)	0.051 (0.036)	–0.02 (0.038)	–0.018 (0.026)	
Government	– 0.028 (0.066)	–0.038 (0.038)	- 0.036 (0.044)	0.007 (0.056)	0.010 (0.038)	-0.035 (0.036)
Polarization	- 0.002 (0.071)	0.070* (0.028)	0.213*** (0.049)	0.174*** (0.045)	0.105*** (0.026)	0.096*** (0.026)
Salience	- 0.023 (0.047)	0.075** (0.028)	0.192*** (0.038)	-0.027 (0.035)	0.111*** (0.024)	0.109*** (0.024)
Election Year	– 0.038 (0.067)	–0.017 (0.039)	-0.036 (0.045)	–0.029 (0.057)	-0.040 (0.036)	-0.041 (0.037)
Control: Sentiment					-0.079*** (0.024)	
Partytype: Moderates						-0.063 (0.055)
Partytype: Pro						-0.093 (0.079)
Num.Obs.	234	1250	916	568	1484	1484
R2	0.013	0.015	0.051	0.028	0.028	0.031
R2 Adj.	- 0.031	0.005	0.038	0.005	0.019	0.022

Note: Standardized variables; *p < 0.05, **p < 0.01, ***p < 0.001

Figure E.1 provides the coefficient plot of Model B, using a weighted polarization measure instead of the unweighted measure from the main model (Model A). Each party's position contributes to the overall polarization measure proportionally to its vote share in parliament. By weighing the polarization score according to vote shares, we account for the relative electoral strength of each party in the political system. Larger parties, which represent a greater portion of the electorate and hold more seats, contribute more to the weighted polarization measure than smaller parties.

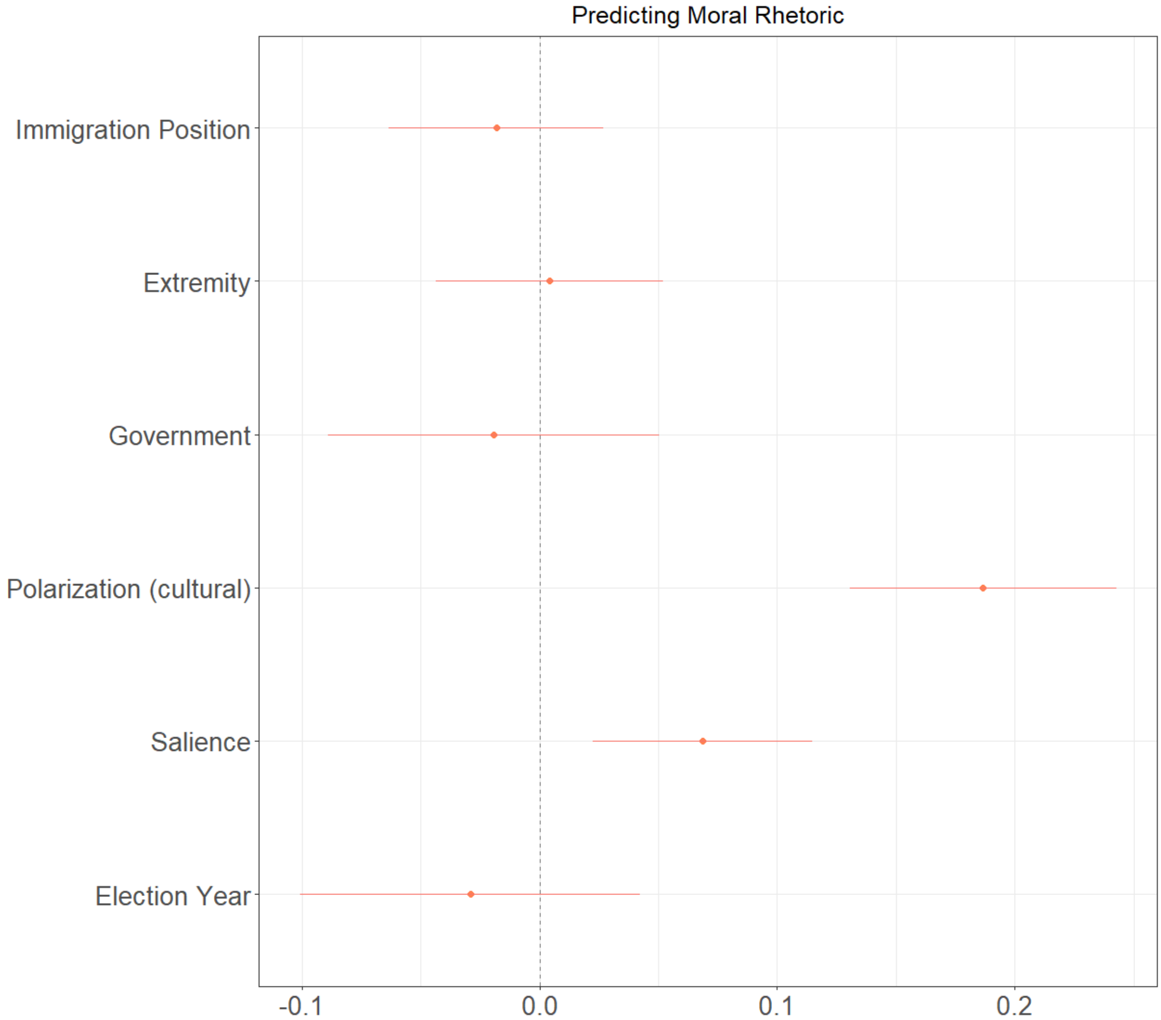
FIGURE E.1: Predicting moral rhetoric using a weighted polarization measure



Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized.

Next, Figure E.2 displays the analysis in which we use a more inclusive measure of elite polarization. In the main model (Model A), elite polarization is operationalized based on party positional data from the manifesto project, focusing solely on immigration. Testing the robustness with a more inclusive measure, we use data from VDEM, specifically the Varieties of Party Identity and Organization (V-Party) dataset (Lindberg et al. 2022; Pemstein et al. 2020) to expand the array of issues included to “cultural” issues more broadly, not only immigration. We included the following issues: immigration (v2paimmig), LGBT social equality (v2palgbt), cultural superiority (v2paculsup), and gender equality (v2pagender). The measure of immigration-related polarization used in the study’s main model and the more expansive cultural polarization measure used in Figure E.7 are moderately correlated at 0.43.

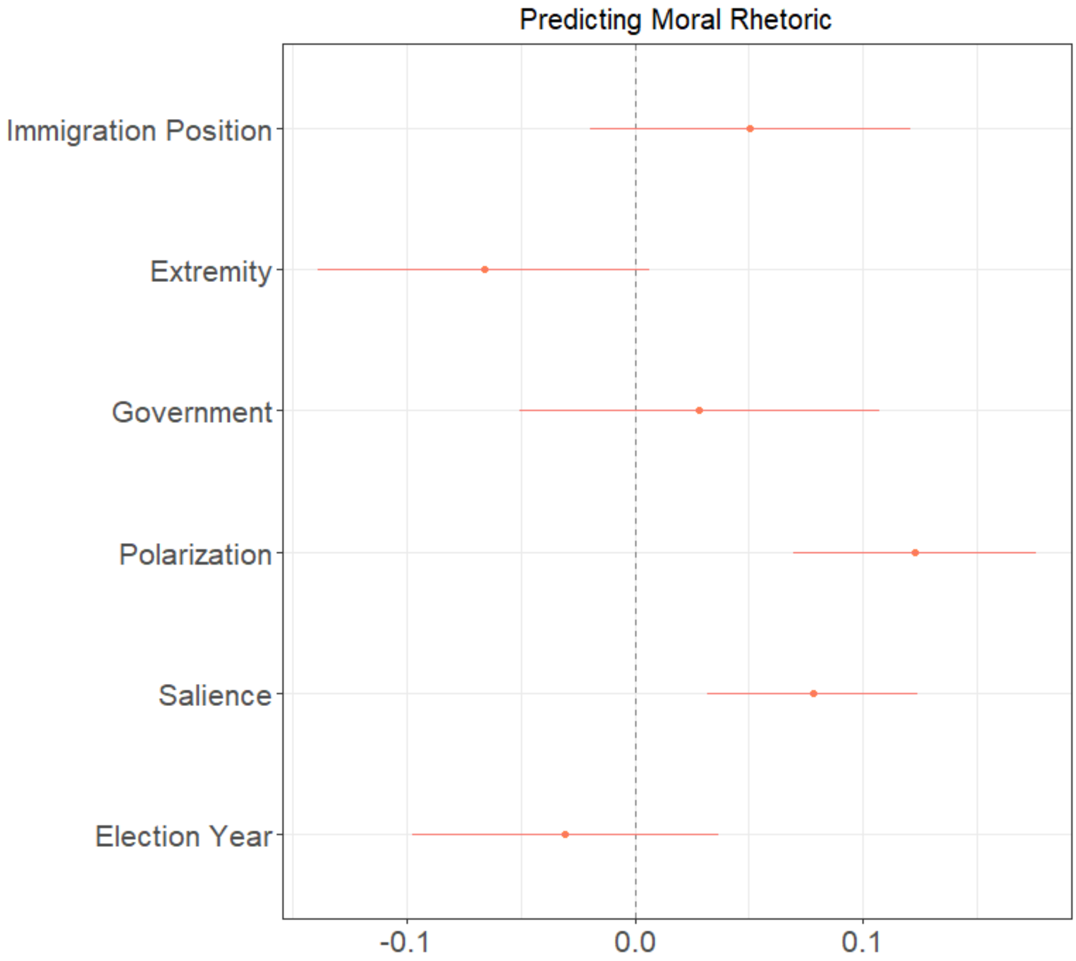
FIGURE E.2: Predicting moral rhetoric using VDEM cultural polarization measure



Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized.

Figure E.3 uses party-fixed effects instead of country-fixed effects, assessing only the effects of within-party developments.

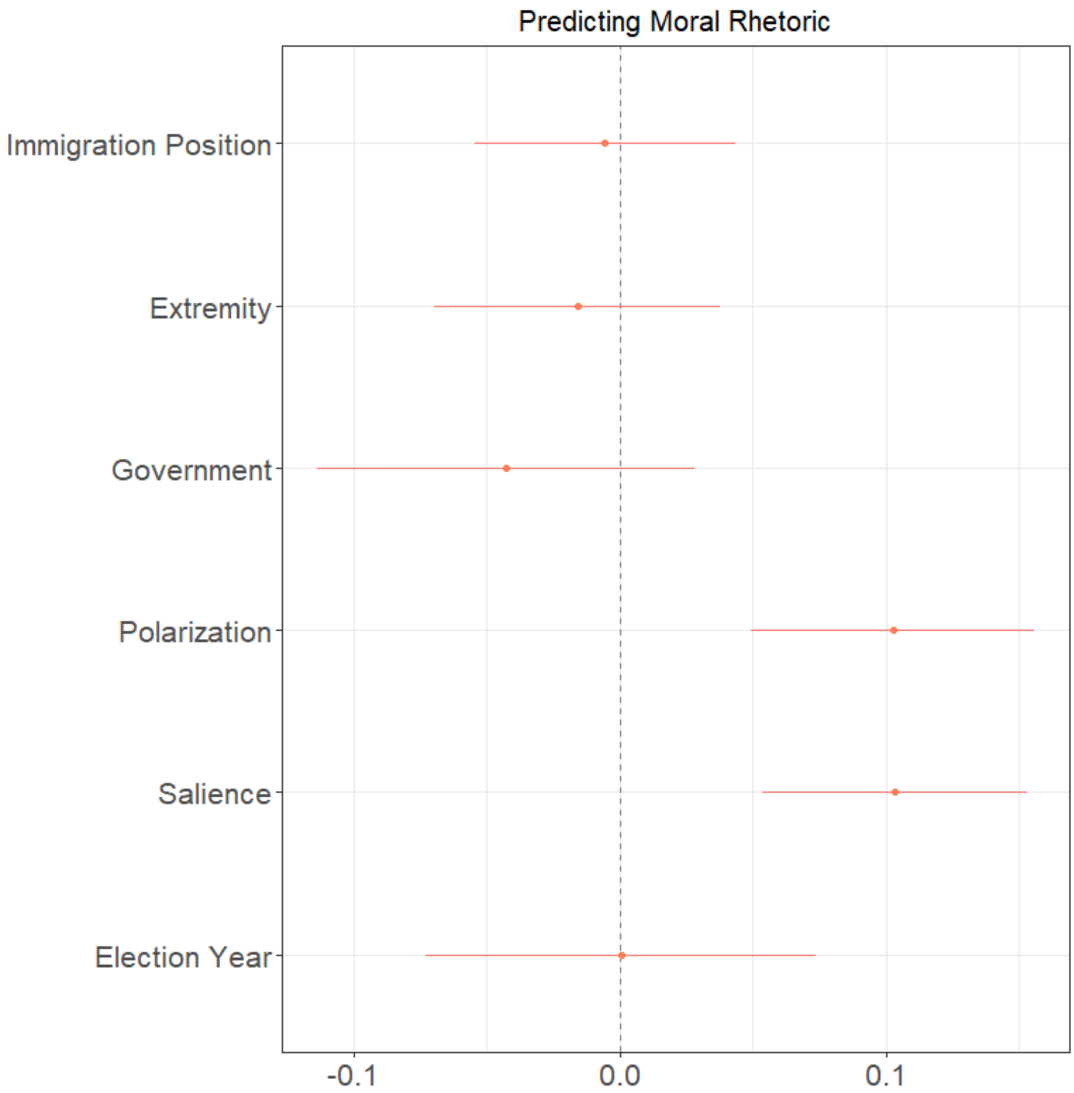
FIGURE E.3: Predicting moral rhetoric using party-fixed effects



Note: Based on party-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized.

Although the nature of our research design does not allow us to establish a strict causal relationship between polarization and moralization, and it remains theoretically possible that these phenomena co-occur or that moralization could lead to further polarization, we have taken steps to explore the temporal dynamics between them. To address this issue, we included a lagged dependent variable specification in Figure E.4 (Model E in Table 1). In this model, we use the hypothesized explanatory variables to predict the use of moral rhetoric by parties one year later, rather than concurrently. By introducing a one-year lag for the dependent variable (moral rhetoric), we aim to assess whether changes in polarization are associated with subsequent changes in moral language use. This approach helps us examine the potential time-sequence of effects, providing insights into whether polarization might lead to increased moralization over time.

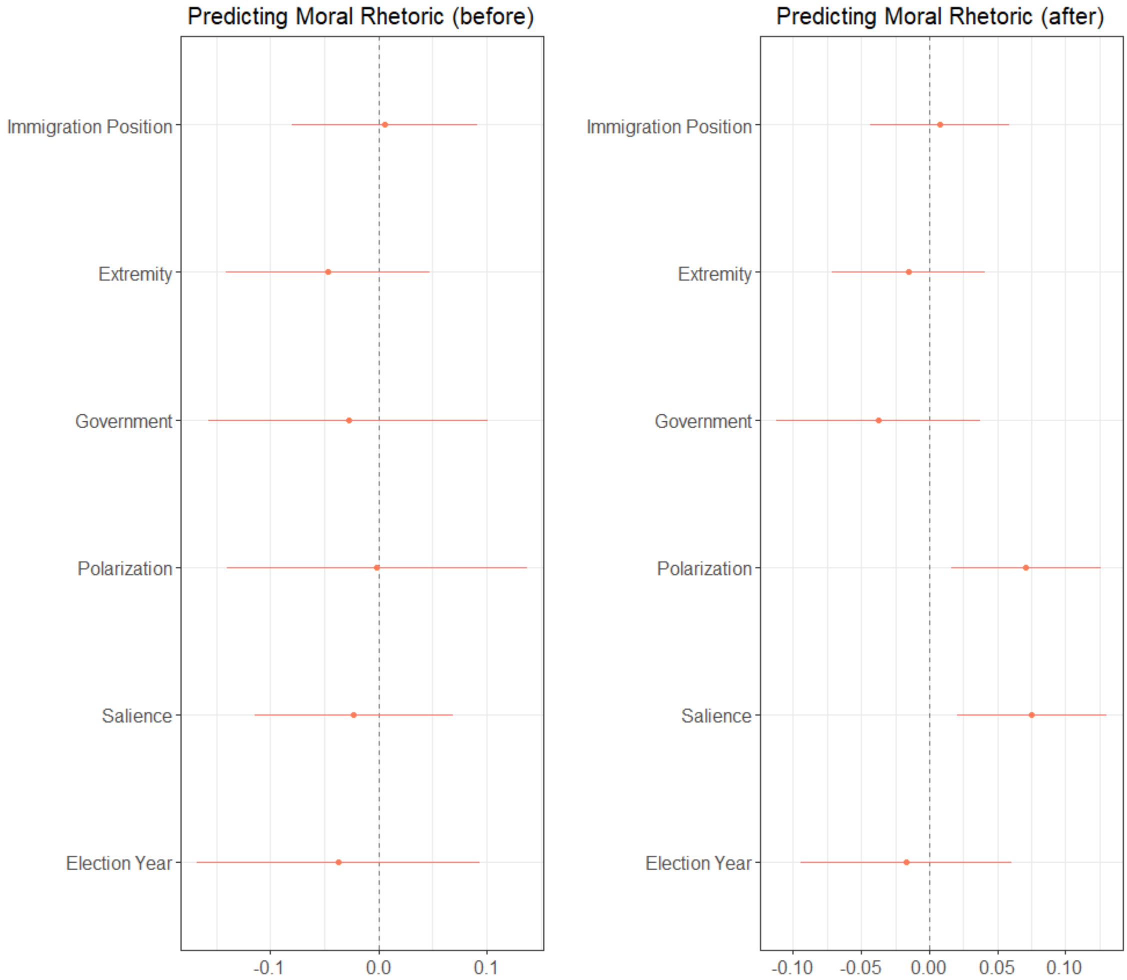
FIGURE E.4: Predicting moral rhetoric with lagged dependent variable



Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized.

Figure E.5 presents the results of splitting the sample into two periods: before and after the introduction of live television broadcasting from parliament. We collected information on the years when regular television broadcasting was introduced in the different countries' parliaments. In Germany, regular live broadcasting began in 1968; the United States, the Netherlands, and Canada followed in 1977; Austria in 1981; the United Kingdom in 1985; and Denmark in 2010. The results indicate that the observed effects occur only in the later period, after the introduction of television broadcasting. This suggests that the effect for elite polarization on moralization is more pronounced when speeches have a large audience, indicating that politicians' awareness of an outside audience makes them more strategic about the language they use under conditions of elite polarization on immigration. This aligns with prior research that arrived at similar conclusions regarding the use of emotional language in parliamentary speeches after the introduction of television broadcasting (Gennaro and Ash 2023).

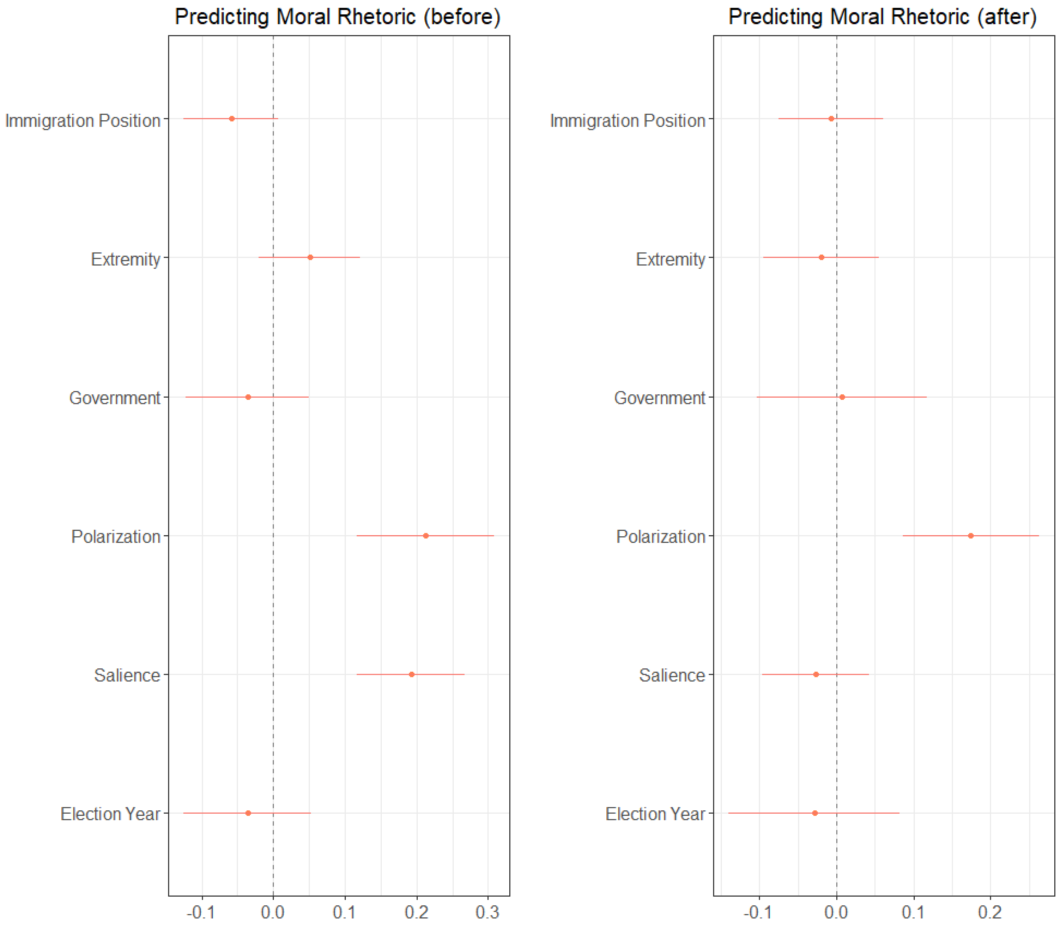
FIGURE E.5: Predicting moral rhetoric before and after the introduction of TV broadcasting from parliament



Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized. Left panel shows regression results before introduction of live broadcasting, the right panel after.

Figure E.6 follows the logic of Figure E.5, this time splitting the data into periods before and after the introduction of social media. We chose 2008 as the year of change, as this was the first year Facebook gained a significant amount of traction (Ortiz-Ospina and Roser 2024). Yet, this could still be too early, as the penetration of social media among politicians likely occurred later in many of the included countries. However, choosing a later year would leave us with only a short period of time to study the situation after social media was introduced. In contrast to Figure E.5, Figure E.6 displays no change in the effect of elite polarization across the two periods, indicating that social media did not lead to changes in parties' rhetorical incentives.

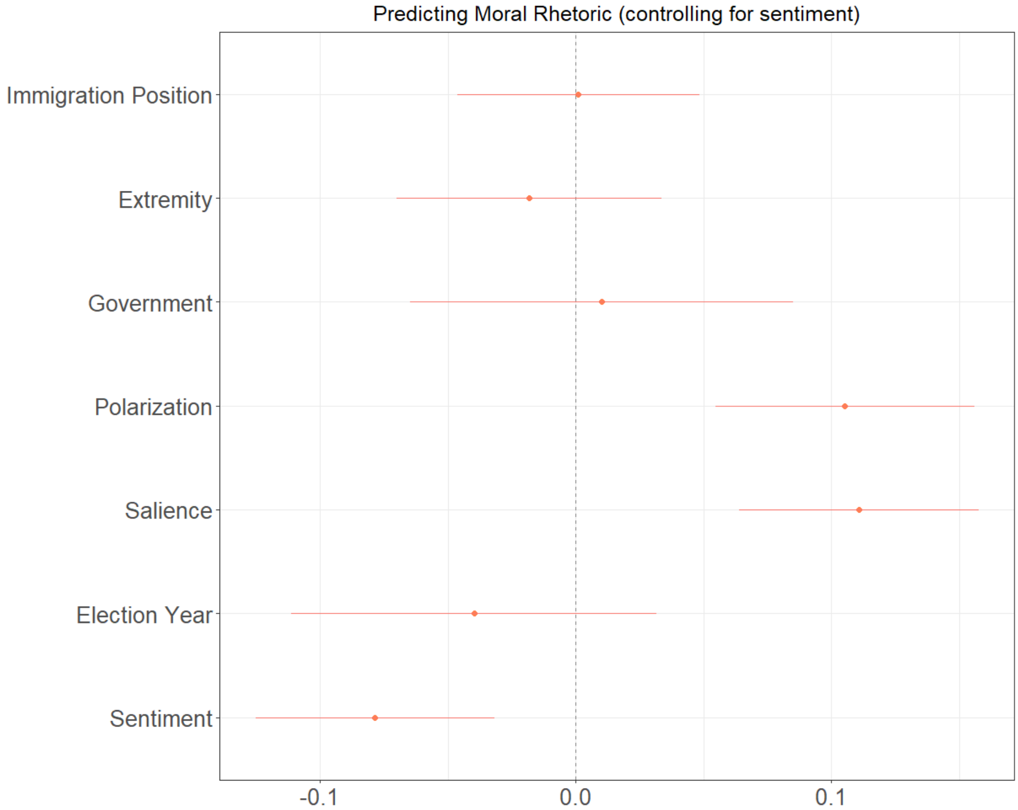
FIGURE E.6: Predicting moral rhetoric before and after the introduction of social media



Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized. Left panel shows regression results before introduction of social media, the right panel after.

In Figure E.7 we additionally control for speech sentiment in order to account for the potential overlap between moral rhetoric and affective or sentimental political communication. To measure sentiment, we make use of the publicly available, multilingual sentiment dictionary created and tested by Proksch and colleagues (2019) which include negative and positive affective words from the political context. We calculated sentiment scores by subtracting negative scores from positive scores, which means that positive values indicate more positive speech and negative values indicate more negative speech. As can be seen in Figure E.7, the conclusions drawn based on the main model (Model A) replicate, providing confidence that our measure of moral rhetoric is distinct from affective or emotional language.

FIGURE E.7: Predicting moral rhetoric controlling for sentiment



Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized.

Testing the robustness of the party positional analysis, for Figure E.8, we group parties into three categories based on their immigration positions: pro-immigration, moderate, and anti-immigration. This categorization allows for clearer comparisons between different types of parties. For each country, we calculated the mean and standard deviation of the parties' immigration position scores to account for country-specific variations. Parties were then classified as follows:

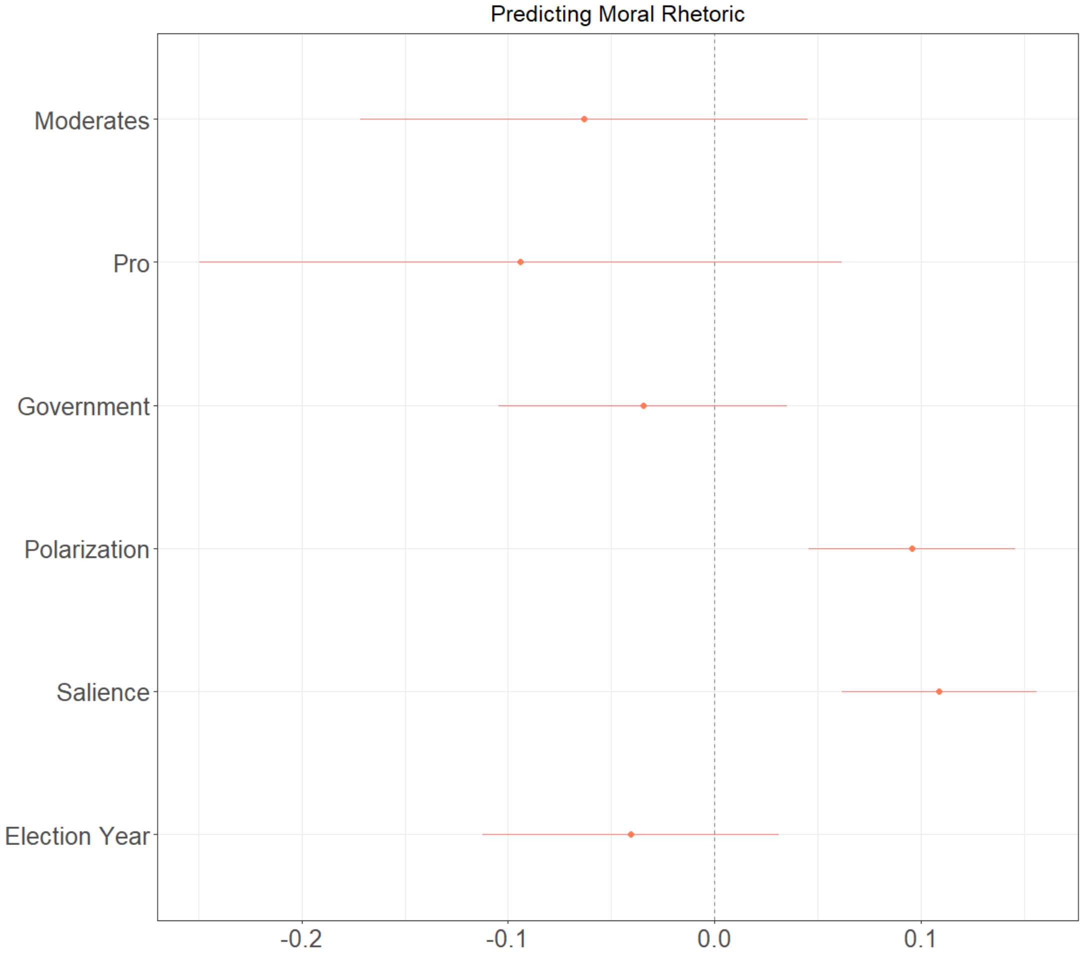
Pro-immigration parties: Parties with an immigration position greater than one standard deviation below the country mean.

Anti-immigration parties: Parties with an immigration position greater than one standard deviation above the country mean.

Moderate parties: Parties with an immigration position within one standard deviation of the country mean.

We re-estimated our main regression model (Model A) using this categorical party type variable. Due to concerns about multicollinearity between the party type categories and the extremity measure, we excluded the extremity variable from this model. As can be seen in Figure E.8, the patterns of our main model remain, underlining the fact that immigration position does not seem to impact moral rhetoric.

FIGURE E.8: Predicting moral rhetoric using categorical immigration position variable

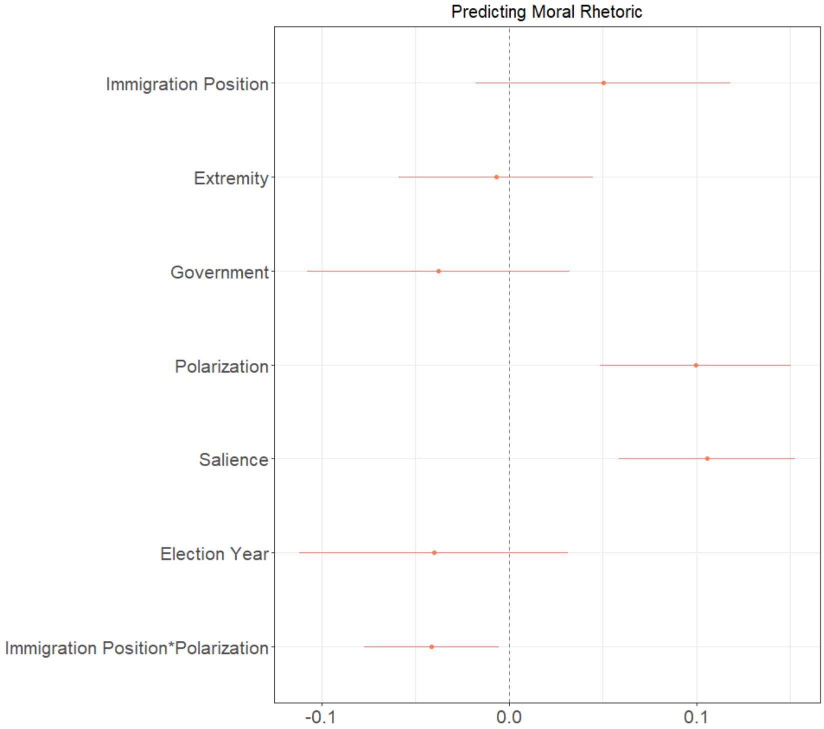


Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized. Reference group = anti-immigration party

Appendix F: Interaction effects

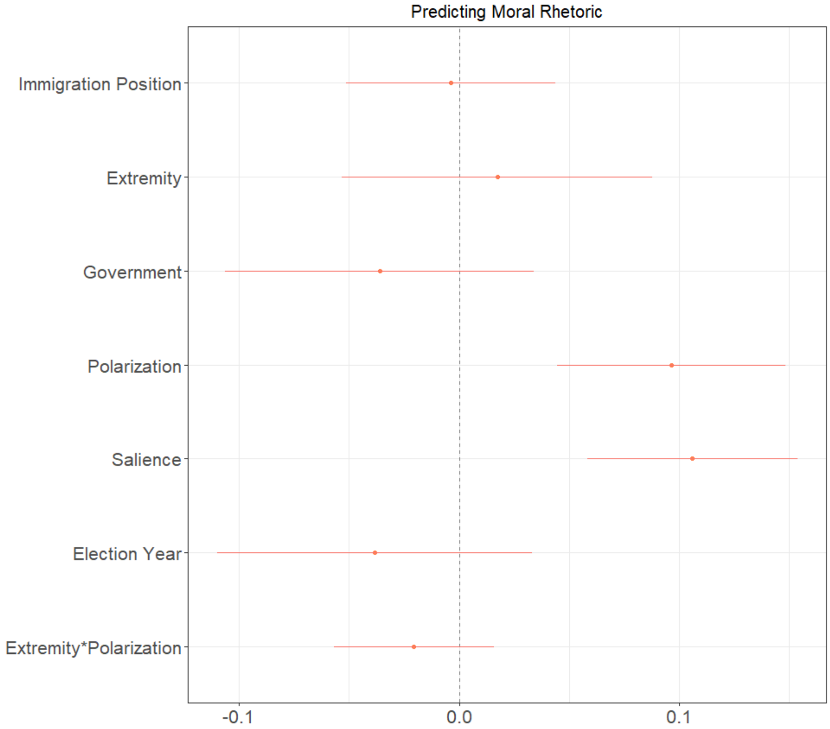
In the following set of analyses, we investigate potential interactions between each of the party-level variables and elite polarization to check whether the effects of immigration position, extremity, and incumbency might vary across levels of elite polarization on immigration. Figures F.1 – F.3 display the results. As can be seen, even when interacted with elite polarization on immigration, the effects of parties' extremity (Figure F.2) and involvement in government (Figure F.3) remain statistically insignificant. However, as displayed in Figure F.1, there is a small negative and statistically significant interaction coefficient between immigration position and elite polarization. This means that in a highly polarized situation, anti-immigration parties (high immigration position value) slightly *reduce* their use of moral rhetoric on immigration. This must be seen in the context of the slightly positive (though statistically insignificant) effect of the immigration position variable, which would seem to cancel out the negative pull, leaving the positive main effect of polarization. When polarization is low, there is no difference between anti- and pro-immigration parties in their use of moral rhetoric. In sum, if there is an interaction effect, it is small, and its direction runs counter to the prediction of H1 as there is no scenario in which anti-immigration parties use more moral rhetoric on immigration than their pro-immigration counterparts. If anything, they use slightly less than the pro-immigrant side when polarization on immigration is high. Importantly, the main effect of polarization remains in all interaction models, further emphasizing the explanatory value of this variable for understanding parties' drive to moralize immigration.

FIGURE F.1: Predicting moral rhetoric with an interaction between elite polarization and immigration position



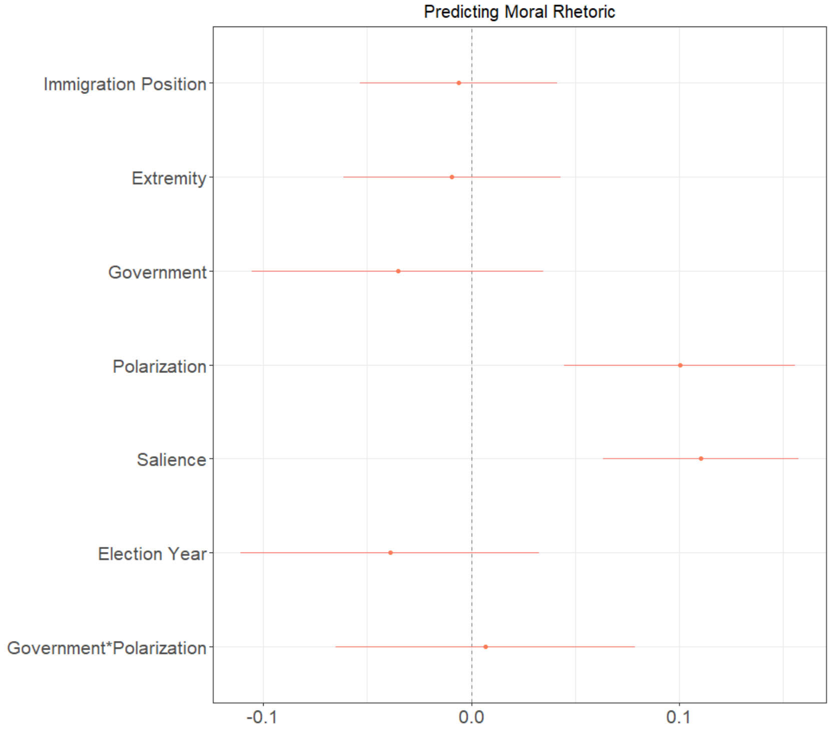
Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized.

FIGURE F.2: Predicting moral rhetoric with an interaction between elite polarization and extremity



Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized.

FIGURE F.3: Predicting moral rhetoric with an interaction between elite polarization and incumbency



Note: Based on country-fixed effects regression on moral rhetoric in parliamentary immigration speeches. Lines around point estimates represent 95% confidence intervals. All variables are standardized.

Finally, to test whether system-level variables cancel out the effect of party-level variables, we run a country-fixed effects model including party-level factors only (i.e., excluding elite polarization on and salience of immigration). As can be seen in Table F.1, none of the party-level variables are associated with parties' use of moral rhetoric, meaning that evidence to support H1-H3 continue to fail to appear, even when these hypotheses are evaluated without system-level factors included.

TABLE F.1: Regression table excluding system-level variables

	C. Country-fixed effects without system-level variables
Immigration Position	-0.024 (0.024)
Extremity	0.029 (0.025)
Government	- 0.038 (0.036)
Polarization	
Salience	
Election Year	-0.030 (0.037)
Num.Obs.	1484
R2	0.0023
R2 Adj.	-0.005

Note: Standardized variables; *p < 0.05, **p < 0.01, ***p < 0.001

Appendix G: Qualitative coding of highly moral immigration speeches

To obtain insight into how politicians use moral language in concrete instances, we first took a random sample of 20 speeches from each country (160 speeches in total) with high scores on the moral rhetoric measure as calculated based on computational text analysis. We consider speeches as highly moral if the normalized moral rhetoric score is more than twice the country mean of the respective country.

The analytical process followed an inductive approach, starting with a first round of careful reading of all speeches in the sample to establish an initial impression of the uses of moral rhetoric applied across them. This led to the development of a raw list of coding themes, which was refined based on a round of inductive coding of a subset of 30 speeches. The ensuing coding list (copied in Table G.1 below) was then applied on the entire sample.

In order to capture the uses of moral rhetoric codes were applied at the level of full arguments or expressions; that is, text segments containing a statement and its explication. Since one argument may “spill over” into the next, codes were allowed to overlap. Although the coding process was more fine-grained, the analytically relevant level is the speech: We are interested in the frequency of codes (uses of moral rhetoric) across speeches. For this reason, we report the percentage of speeches in which a given code occurs. Since one speech can contain multiple codes, the total of the right-hand column in Table G.1 does not sum to 100.

The qualitative coding process was conducted by the first author, Kristina Bakkær Simonsen, who is fluent in the languages included in our study, aside from Dutch. The speeches were therefore coded in their original languages, with speeches from the Netherlands as the exception; Dutch speeches were translated to English using the automatic translation tool DeepL.com and then coded. Quotes in the overview below and in the main text are our own translations from the original language (where necessary) to English.

TABLE G.1: Coding scheme

Use of moral rhetoric	Definition	Example quote	Percent of speeches
Moral attacks on political opponents			*79**
Moral concern about policy (proposal)	Statement expressing concern about or outright dismissal of a policy or policy proposal with reference to normative considerations and reflections on why the policy is or would be wrongful	*Today's refugee and asylum policy can hardly be described as more humane or more legally secure. On the contrary, I would say that it is even tougher in some areas. Right now, people are being deported to Iraq who, in my opinion, should have every right to stay and be given sanctuary in Sweden.* (SE12, Vänsterpartiet, 2011)	43
Condemnation of political opponent for being morally wrong	Statement expressing contempt for a political opponent, denouncing and condemning the party, its character, or deeds with reference to moral wrongdoings and moral flaws	*If you really cared about these people, if you really cared about the human beings they are, then you would treat them as such, then you would help them to get into the labor market. But you don't give them this help at all. You just want to sell them off. That is dishonest, and that is degrading.* (AT18, FPÖ, 2017)	39
Questioning political opponents' moral capabilities; subtler than condemnation	Statement, often posed as a (rhetorical) question, expressing doubt about a political opponent's ability to act in a morally good way, or raising doubt about whether the opponent is guided by good intentions	*A determined President could take meaningful steps to stem the tide of illegality.* (US15, Republican Party, 2012)	14
Claims about what is morally right or wrong; no attack or praise	Statement about immigration making a moral judgment; expresses an evaluation of what is right and wrong	*Unfortunately, our asylum system is not just being used by those who need our protection. Too many people are abusing our refugee system to gain quick entry to Canada and to jump the immigration queue.* (CA13, Conservative Party, 2012)	52

Moral calls for action	Statement urging politicians to do something about a morally untenable situation, appealing to the restoration or accomplishment of a moral good	*If we truly want to deal with our broken immigration system, we must pass comprehensive immigration reform that treats immigrants humanely, focuses on deporting those who threaten our safety and national security, and better secures our borders.* (US17, Democratic Party, 2015)	39
Moral self-praise			*40**
Moral grandstanding: Highlighting the good moral character or deeds of one's party (or, as party representative, one's own)	Statement presenting the speaker's party (or themselves in their function as party representative) as morally grand, worthy of respect and admiration for doing what is morally good and right, or standing up against what is morally wrong	*You're concerned with injecting poison into society through a false narrative. But we are immune to this because we make it clear that we have a fundamental humanitarian stance.* (DE17, CSU/CDU, 2019)	31
Moral praise of policy or policy proposal	Statement highlighting how a policy brings about morally good outcomes or rights a wrong	*The Bill is a fundamental part of our programme to achieve racial equality in this country. One of the Government's central aims is to achieve a society where there is respect for all, regardless of their race, colour or creed, and a society that celebrates its cultural richness and ethnic diversity. That is not only inherently right but essential for Britain's economic and social success.* (UK4, Labour Party, 2000)	14
Justification: Explaining why an act or policy is morally justifiable or legitimate against implicit or explicit criticism	Statement defending a party's actions or policy against implicit or explicit criticism, using moral reasoning; arguing how the action or policy is morally justifiable	*It was asked by almost all groups whether, if we are going to do that, it will also mean that people who help illegal immigrants will be punishable. Let me stress again that the measures in the coalition agreement do not target the people around them, but mainly the illegal alien himself. So, the measures do not target those who offer help (...) if on humanitarian grounds, out of mercy, help is offered to an illegal, such as a cup of soup in winter, it would make no sense to criminalize it.* (NL5, Christen-Democratisch Appèl, 2010)	16

Moral condemnation of other, non-party political actor	Statement expressing contempt for a non-party political actor, denouncing and condemning the person, group, or organization, its character or deeds with reference to moral wrongdoings and moral flaws	*Plenty of Muslims will fortunately argue that Islam has nothing to do with the things that are preached in the extreme environments in Denmark – and that is good. But that does not change the fact that in some mosques, Imams use the religion to preach messages of oppression and anti-democratic attitudes.* (DK8, Socialdemokratiet, 2016)	14
Moral praise of other, non-party political actor and their deeds	Statement applauding or showing admiration and respect for a non-party political actor and their actions, highlighting their character or deeds as morally good	*When countries like Jordan, Lebanon or even Turkey take in the millions of refugees from Iraq or Syria, then we can only bow to this humanitarian generosity.* (DE4, CDU/CSU, 2015)	11

Note: Based on qualitative coding of a sample of 160 highly moral immigration speeches (20 per country). Each speech may contain multiple codes (uses of moral rhetoric).
*: Percent of speeches containing at least one of the sub-uses of moral rhetoric listed below the relevant super-code.

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