Moderating Criticism of the EU While in Government? The Party Politics of European Integration in Czech Parliamentary Debates

Štěpán Jabůrek

Institute of Political Studies, Faculty of Social Sciences, Charles University

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Abstract

This paper expands the text-as-data literature on parliamentary debates about the EU by examining how government status shapes the discursive strategies of parties. While existing research has identified an "opposition deficit" in EU salience, where governing parties discuss the EU more frequently than opposition parties, little is known about the qualitative differences in the contents of the speeches. Utilizing the unique case of Czechia I use computational stance detection to analyze the government-opposition differences and dynamics in how parties talk about the EU - do they express support or opposition? Using panel data from speeches from the Czech Chamber of Deputies (1993–2023), I find that governing parties systematically express more supportive stances toward the EU than opposition parties. This pattern holds even when analyzing only within-party variation, with the most euroskeptic parties (who enter government at some point), ODS and ANO, showing the largest shifts towards more supporting stances while in government. The results suggest that government membership plays a crucial role in partisan discourse. While the paper empirically contributes to the literature on EU accountability, legislative behavior, and the rhetorical costs of governing, the possible mechanisms at play (socialization, strategic adaptation, or top-down party discipline) remain under-theorized.

Keywords: European Union, parliamentary debates, opposition deficit, natural language processing, stance detection

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1 Introduction

The European Union is an increasingly contested point of debate in the political arena. But how exactly is the EU communicated and debated by the political elites in parliamentary debates? With growing opportunities to study large textual data, this question has been gaining traction among political scientists in the past few years and has garnered some early research (Rauh, 2014; Rauh and De Wilde, 2018; Lehmann, 2022). The existing research has covered many member states (at least to some degree) and has produced significant insights into the salience of the EU in parliamentary debates.

In this paper I mainly focus on how government membership can structure discursive strategies used by members of parliament (MPs) using methods of natural language processing (NLP). I employ a computational approach of stance detection (sometimes called opinion mining), which aims to uncover whether a speaker (here an MP) presents a supporting or opposing stance towards the EU. The

The main research puzzle is concerned with the government-opposition dynamics in partisan discourse about the EU. Existing empirical results suggests that governing parties talk quantitatively more often about the EU than opposition parties Rauh (2014); Rauh and De Wilde (2018). However, the is a lack of research systematically analyzing the content of these speeches on a large scale. My main research question is thus twofold. 1. *How does government status structure partisan discursive strategies about the EU?* 2. *Can parties change their discourse upon entering the government?*

To accomplish this, I use a novel dataset of plenary speeches in the Czech Chamber of Deputies from 1993 to 2023 (Rauh and Schwalbach, 2020; Jaburek, 2024). The dataset covers the entire population of Czech parliamentary debates with almost 500,000 speeches and more than 60 million words. I employ various NLP methods, but mostly rely on natural language inference (NLI) to answer these questions.

The paper is organized as follows. First, I provide a review of the relevant literature. Second, I present my conceptual and theoretical framework and case selection. I then proceed to operationalize the measurement. I then state my main assumptions and define my hypotheses. Third, I present the dataset and describe the relevant variables. Fourth, I present the NLP methods I employ, including the choice of large language models, machine translation, and human validation of the results. Fifth, I present the results. Finally, I offer a conclusion and state limitations of the study.

2 Literature

2.1 Motivating Literature

Why is it important and interesting to study the EU in the context of national parliaments and specifically their plenary debates?

Generally, parliamentary debates are one of the most time-consuming and visible activities that politicians and parties have (Proksch and Slapin, 2012). As such, they serve various functions. First, they serve a procedural function in the legislative process (Proksch and Slapin, 2012). Second, they serve as a channel where politicians can display issue ownership, communicate their legislative results, political positions, or explain their roll call voting behavior to the public (Michal, 2024). Finally, they also have a crucial function of deliberation and communication regarding accountability and legitimacy of international organizations (Auel, 2007; Rauh, 2014; Lehmann, 2022).

National parliaments also play important formal and informal roles in EU affairs. The question of how much control they can exercise has garnered research attention for a long time. Over time, national parliaments gained more powers, which presented a shift from the role that parliaments previously played in the European Communities and the early EU. Sprungk (2013) argues that national parliaments accumulated new roles of gate-keeping, networking, and scrutinizing, and began to have formal power to shape policy. With the introduction of the Early Warning System, national parliaments gained even further formal powers to affect EU policy directly through reasoned opinions about possible noncompliance with the subsidiarity principle (Gattermann and Hefftler, 2015).

Parliaments, however, don't have just formal powers to exert control over national positions on foreign policy topics, but also have more informal processes to hold the government accountable to the voters. As mentioned before, public deliberation is a key factor that can have a strong informal influence (Auel, 2007). In a review, Raunio (2009) argues that further research should perhaps focus less on formal procedures and more on actual behavior of the relevant actors and analyze strategies of parties and MPs.

2.2 Existing Quantitative Studies of the EU in Political Texts

There is already existing quantitative research on the EU using political text analysis. The largest body of work has been done in regard to the salience of the EU in national parliamentary debates; that is, how often MPs talk about the EU. This research agenda was sparked by Rauh (2014), who analyzed the salience of the EU in the German Bundestag between 1991 and 2013. Rauh (2014) provides a general framework for studying the topic and uses full plenary texts combined with quantitative text analysis to find references to the EU based on a German dictionary for mentions of the EU. Furthermore, Rauh (2014) establishes an approach of using exploratory regression models to move past simple descriptive patterns of textual data. Overall, he finds a rising salience of the EU over time and that authority transfers to the supranational EU level, public EU visibility, and contested public opinion about the EU drive higher salience of the EU (Rauh, 2014).

In a follow-up paper, Rauh and De Wilde (2018) replicate the finding that EU authority transfers and exercises of these powers drive EU salience. However, they also show that the salience of the EU has an opposition deficit. They empirically show that the governing parties systematically talk about the EU more than the opposition in all 4 studied countries (Germany, Netherlands, the UK, and Spain). Other research using quantitative text analysis explored how the EU communicates directly through the European Commission (Rauh, 2023) or how the EU is portrayed in the media (Rauh and Parizek, 2024).

Despite these studies, there seems to be a lack of quantitative research studying how political actors talk about the EU in more nuanced aspects than just the sheer number of mentions. This is where my research aims to contribute to the existing literature by building on qualitative approaches to text analysis but utilizing large-scale quantitative and computational methods.

2.3 Case Selection

Czechia constitutes an extremely interesting case from several theoretical points of view. First, Czechia is continuously one of the most euroskeptic countries in the EU and currently is *the most euroskeptic country* (Statista, 2025). Second, Czechia is highly trade dependent and economically benefits from the access to the common market (which the political elites understand). And third, Czechia is currently still a member of the Eurozone and faces significant public opposition towards adopting the Euro (Čábelková et al., 2015).

These qualities make Czechia a country where EU policies have large impact (trade) and voters are more euroskeptic. This makes Czechia perhaps the least-likely case to see an effect of joining the government on stances towards the EU. Since Czech voters are comparatively more skeptical of the EU, moving a party position on the EU more positively could lead to electoral losses stronger than in other EU countries.

The Czech political system was long dominated by 2 main parties. The main right-wing and conservative party, the Civic Democrats (ODS), which produced several Prime Ministers and a President. And the main left-wing party, the Social Democrats (ČSSD), which also produced several Prime Ministers and a President.

Until 2017, every Prime Minister was either from ODS or ČSSD. Only two other parties were prominent from the very beginning of the democratic regime in 1993 until the 2020s.- the Christian Democratic party (KDU-ČSL) and the unreformed Communist Party (KSČM), which ruled Czechoslovakia until 1989.

Only in the 2010s, several new parties managed to become staples in the parliament and even participate in governments. The liberal and strongly pro EU party TOP 09 in 2010. The party ANO (soon to be dominant party of the billionaire Andrej Babiš) in 2013. The most Euroskeptic and radical right party SPD in 2017. The moderate pro EU party STAN in 2017. And the progressive and strongly pro EU Pirate party in 2017.

These 9 parties are the only parties with at least 500 mentions of the EU during the studied period. Thus in the main partisan analyses and statistical models, I only work with them for statistical power and interpretability.

3 Theoretical Framework

But why should it be the case, that parties change their discursive strategies about the EU once they join the government? The two main possible mechanisms are socialization and strategic adaptation (which might not be independent, but could also be mutually reinforcing). Probably add some theory about electoral incentives for opposition parties???

3.1 Socialization

First, a socialization mechanism might be at work. MPs whose party joins the government get into more contact with EU legislature, procedures, bureaucrats, and possibly peers from other member states. This might be even more relevant for MPs who also become members of the cabinet who further start working and get into contact with fellow government officials from other EU countries (e.g. during Council meetings). These effects could be exacerbated by a mechanism of cognitive dissonance (Dinas and Riera, 2018; Schulte-Cloos, 2019; Acharya et al., 2018). Through behavior within the EU structures, MPs might get socialized into the EU nature and adopt more favorable stances.

This might also work (or not work) through a top-down effect, wherein only party leaders and cabinet members get socialized. They can then successfully pass this to the back-benchers who also adopt more supporting stances (or less opposing) stances in their speeches. Or it might only work for the cabinet members who get embedded into the EU workings. While they get socialized, the back-benchers might still retain their original stances. This mechanism is dependent on party rules and the level of party centralization around the leadership? maybe?

3.2 Strategic Adaptation

Second, the effect might be a strategic choice, instead of a genuine change in preferences and beliefs. Here, the parties might strategically adapt more supporting stances, for example to increase bargaining chances with potential partners in the EU. Again, this might also possibly be a top-down process wherein party elites instruct back-benchers to moderate their speeches.

3.3 Differentiating or Bridging the Gap?

These two effects could in theory be differentiated based on the time dynamics. If it were the case that the MPs get socialized (either directly or through their party leaders and cabinet members) the effect should be long term and persist even after an exit out of government. However, if the effect were to be driven mainly by strategic considerations, the stances could (and possibly should) revert to previous levels after an exit from government.

However, due to nature of my data and real world limitations I can only examine the manifestations of some of these mechanisms. Most importantly, I am not able to distinguish effects between MPs who ale become members of the cabinet or those who do not due to a lack of power (only very few MPs become ministers/members of cabinet). Thus I only focus on the overall party effect, but I can say little about whether the mechanism was manifested individually across the MPs or pushed through by party leaders and/or cabinet members.

And second, due to the limited amount of data, I cannot strictly differentiate whether or not the governing effect lasts after a party's exit from government (which might signal more evidence for either the socialization or strategic adaptation mechanism).

However, they might also work in combination. IR theory would suggest that these two mechanisms are a lower order manifestation of the logic of consequences (strategic adaptation) and the logic of appropriateness (socialization). However, there need not be a stark difference. It could easily be the case that behaving appropriately (socializing into more supporting stances) is also beneficial for the country's ability to pursue its preferences.

4 Conceptualization and Operationalization of Stance Towards the EU

Next, I move to a conceptualizing and operationalizing stance.

4.1 Conceptualization

Stance in computational political research has been a topic of intense debate. However, recently there seems to be some consensus on how it should be conceptualized. Building on ALDayel and Magdy (2021); Bestvater and Monroe (2023), Burnham (2024, p. 612) defines stance as: *"How an individual would answer a proposition"* and that *"[stance] may be directed toward individuals, groups, policy, etc"*.

In the case of the EU, I work stance with stance as statements directed towards the EU. This stance can be expressed either about the EU as an organization in general (in terms of leaving or strengthening integration) or on specific issues (opposing a specific EU decision). I work with stance on both of these macro and micro dimensions. Of course, many texts will not have supporting or opposing stance and are just referring to the EU descriptively or in procedural matters. These mentions fall in the neutral category.

4.2 Operationalization

Each party p has a continuous latent parameter γ representing its true policy position towards the EU:

$$\gamma_p \in [-1, 1] \quad \text{(Latent position towards the EU)}$$

where -1 is complete opposition an 1 is complete support.

An empirical approximation of γ for individual parties can be taken from external sources such as the Chapel Hill Expert Survey (Jolly et al., 2022). While I do not attempt to directly estimate this parameter in this paper, the Stance Score defined next could serve as a on part of such an approximation.

Each MP j can express his or her stance towards the EU in each mention i of the EU expressed as a categorical variable that is measurable using NLP [1]:

$$\lambda_{ji} \in \{\text{Oppose, Neutral, Support}\} \quad \text{(Stance towards the EU)}$$

While MPs can express varying stances in individual mentions, they are constrained in the long term by their party's latent position γ_p. For example, an MP from a party with $\gamma_p = -1$ (complete opposition) cannot consistently express supportive stances (λ_{ji} = Support) without facing internal party sanctions or being prevented from speaking by the party leadership. However, MPs may still strategically deviate from the party line in specific contexts, though their average stance over time is expected to remain close to the party's position.

[1] Again, I discuss this in further detail in Section 6 on Methodology.

Party leadership can again strategically instruct MPs to deviate from the party's typical position in certain periods t; for example, while in government, during election campaigns, or in response to shifts in public opinion (see next section for hypotheses based on this expectation).

Stance can be further aggregated in a party-level stance score. I build on a sentiment aggregation method used in political text analysis adapted to stances (Young et al., 2012; Warode, 2025). Let P be the set of MPs belonging to party p. The stance score for party p at time t is defined as:

$$\text{Stance Score}_{pt} = \frac{\sum_{\substack{j \in P \\ i \in t}} [\lambda_{ji} = \text{Support}] \; - \; \sum_{\substack{j \in P \\ i \in t}} [\lambda_{ji} = \text{Oppose}]}{N_{pt}}$$

where N_{pt} is the total number of mentions of the EU by MPs of party p during time t.

To summarize this informally, the Stance Score is a measure of which stance was more prevalent in a time period a by how much. If supporting stances dominated, the number is positive; if opposing stances dominated, the number is negative. The measure is normalized by the total number of mentions in the time period, so if a lot of mentions are neutral, the score will converge to zero.

5 Assumptions and Hypotheses

Building on the literature review and my conceptual framework, I proceed to stating my key assumptions and defining my hypotheses. First, based on existing research I assume that:

- MPs use plenary debates as a key communication channel to explain their preferences and behavior to the voters (Proksch and Slapin, 2009; Michal, 2024)
- MPs use plenary debates as a way to claim issue ownership (Michal, 2024)
- MPs use plenary debates as a deliberative space about the legitimacy of

international organizations (Auel, 2007; Rauh, 2014).

- MPs use plenary debates as a space to publicly hold the government accountable in terms of EU policy (Auel, 2007; Sprungk, 2013).
- Governing parties are affected by a ”curse of governing” that also affects their discursive strategies and leads to more rhetorically complex language (Hjorth, 2025)

Moreover, I assume that:

- MPs and parties are trying to get reelected and either maintain or gain more power.
- MPs have limited physical resources for the length of their speeches.
- MPs are constrained by their parties internal rules and leadership positions, by parliamentary procedural rules, and by exogenous events (e.g. domestic or world crises that dictate the topics of a session).

From this I can formulate a set of observable expectations and hypotheses. First, based on the literature about government effects on partisan discourse, I hypothesize that governing parties will be more discursively constrained by their international commitments, socialization in EU structures, and by exogenous events. This might materialize in several forms. First, it might lead governing parties to be more supporting of the EU to signal a commitment to their partners in Europe and towards people in the Council or European Council they have to deal with (whether the end goal is to behave appropriately and observe norms or to create a stronger foundation for cooperation built on expected consequences).

Main hypotheses:

- **H1: Governing parties are more likely to express supporting stances towards the EU than opposition parties.**
- **H2: When a party enters government, it becomes more likely to**

express supporting stances of the EU, than while it was in opposition.

6 Data

I use a dataset of all plenary speeches in the Czech Chamber of Deputies between 1993-2023 containing 470,007 plenary speeches. This dataset was built on top of a dataset by Rauh and Schwalbach (2020) for data between 1993 and 2016. I then scraped the website of the Czech Chamber of Deputies to retrieve the data for the remaining years until 2023. I built my scraping code in large part on top of an existing streamline by Kokeš (2024). The current version of my dataset is freely available on the Harvard Dataverse (Jaburek, 2024).

In the basic form the dataset consists of individual speeches as written in the stenary protocols complemented with the name of the politician delivering the speech, his or her party affiliation, the date of the speech, a binary variable indicating whether he or she is the speaker of the Chamber.

I further enrich the dataset with various other variables of interest. First, I added a binary indicator whether the MPs party is a member of the government coalition. Next, I added two binary variables designating the electoral cycle of the national elections and the European elections (the ones that concerned Czechia). I opt for a simpler measurement than Rauh (2014); Rauh and De Wilde (2018), only designating the 6 months prior to the election as 1. Following Rauh (2014); Rauh and De Wilde (2018) I also included a binary variable for EU summits (takes 1 in the month where an EU summit takes place).

I also included a continuous measure of monthly inflation from the European Central Bank (ECB, 2025) and a yearly measure of how many citizens trust or don't trust the EU. The key variable is the difference between the % of people who declare trust minus the % of people who declare distrust (Czech Academy of Sciences, 2025). Finally, each speech has a range of variables indicating the number of references to: the EU in general, only directly the EU, and each of the 6 main EU institutions - the European Parliament, European Commission, Council of the EU, European Council, European Court of Justice, European Central Bank.

In the analysis I only focus on substantive speeches and drop speeches of the Chamber Speaker who introduces the topics and delegates speeking floor to MPs.

7 Methodology

This paper draws from several quantitative methods to try to best capture the entire complexity of the issue and the size of data analyzed.

7.1 Keyword Extraction

First of all I needed to find the relevant mentions of the EU in the original Czech texts for calculating the salience. For this, I used regular expressions (regex) in R using the stringr (Wickham et al., 2023) and quanteda (Benoit et al., 2018) packages. I built two different dictionaries to capture these mentions in natural text. You can see the full regex formulas in Appendix 1.

First, I built a minimalist dictionary consisting of only direct mentions of the EU - in the various full forms of European Union or the acronym EU. This serves as a baseline measure with (hopefully) no false positives. This pattern yields 41,908 unique mentions.

Second, I followed Rauh and Parizek (2024) and built a complex dictionary that includes the main treaties, Bruxelles, Euro, economic and security cooperation, European Parliament, Commission, Council, European Council, European Court of Justice, European Central Bank [2]. This dictionary significantly expands the vocabulary but dilutes the research question, as these individual term might

[2] I opted not to include the European Communities in the dictionary as the data came after the creation of the EU. Though it only represented a small number of mentions, the direct interpretation along the other terms would be even further diluted with possible mentions about the past ”version” of the organization.

Institution / Salience	Raw mentions	% of speeches
European Union	41 908	7.57
European Commission	6 593	1.58
European Parliament	2 927	0.87
Council of the EU	728	0.24
European Council	1 339	0.31
European Court of Justice	413	0.13
European Central Bank	228	0.06
EU - total	54 136	8.66

Table 1: Salience Results

have their own variation. All these patterns together yield an additional 19 000 mentions.

However, after qualitative insights, I ended up dropping them for the main inferential analyses due to the noise they entail. This means that while I lose some data, the data is relatively noisy, and the interpretation could not have been as straightforward and confident. Also, I still have more than 41,000 mentions of the EU (down from ≈ 54,000), which is a massive sample size for my analyses.

In Table 1 we can see the raw counts of mentions of the EU and salience. Here I differentiate between direct EU mentions (only EU and variations of European Union), the 6 main EU institutions and finally an aggregated measure combining both. However, in the following analytical sections, I only work with the direct EU mentions as discussed before.

The EU directly has more than 40 000 mentions and was mentioned in more than 7.5% of the speeches between 1993-2023. The European Commission is a distant second with less than 7 000 mentions in 1.6% of the speeches, while the remaining key EU institutions were mentioned in less than 1% of the speeches. Overall, the EU was mentioned in 8.66% of the speeches, making it a very salient topic.

I then extract the mentions of the EU in a keywords-in-context (KWIC) approach. Each mention is extracted with a context of 100 words around (50 to the left, 50 to the right) [3] and the relevant metadata. Moving forward, this becomes

[3] I tested windows of 60, 80, 100, and 150 tokens, before settling on 100 tokens (100 words, 50 to the right, 50 to the left) as the ideal size limiting noise from while keeping as much important context as possible.

my key unit of analysis - a mention of the EU with a 100-word context. I use this in the machine translation, stance detection, and even in the statistical analyses. My working dataset thus consists of 41,908 mentions of the EU each with 100 words around.

7.2 Model Choice and Machine Translation

Instead of relying on Generative AI, I opt for a completely open source a reproducible path. Specifically I use the Political DEBATE model (Burnham et al., 2024). This model is in its base form a DeBERTa model (Laurer et al., 2024) which is itself a newer model based on the original BERT model (Devlin et al., 2019). The advantage of the Political DEBATE model is that it has been trained on more than 200 000 labeled political texts to tackle political science research questions specifically. At the time of its release, the authors claimed it to be the best model for political science research while being much faster and cheaper than proprietary Generative AI models and fully open source (Burnham et al., 2024). I access the model through the transformers library (Wolf et al., 2020) in Google Colab. However, this model was trained and fine-tuned for English. Thus my route is predicated on machine translating the texts first.

Machine translating political texts into English and then analyzing them is a relatively common approach in computational political text analysis; e.g. (Parizek, 2024; Parizek and Stauber, 2024; Tesař and Parizek, 2025). I use one of the best open source models to machine translate the texts with the NLLB-200 model (Meta Team et al., 2022). I further used the Opus-MT model (Tiedemann et al., 2024) on a subset of the data as a robustness check. This confirmed that both translations give almost identical results when being the foundation for further textual analysis, so I continued to only use the NLLB-200 model for the final analysis.

7.3 Natural Language Inference Approach to Stance Detection

After machine translating the keyword-in-context windows, I move to the main part of the text analysis. To analyze the stance I use an approach called *natural language inference* (NLI). NLI works by pairing a text (called a *premise*) with a *hypothesis* (defined by the researcher). The model then determines whether the *hypothesis* is supported by the *premise* or not (Laurer et al., 2024; Burnham et al., 2024). The output is typically a score from 0 to 1 that shows how confident the model is with evaluating the hypothesis based on the given text. The researcher can specify one or more hypotheses for each text to be evaluated independently.

For stance detection, the approach is very straightforward. Stance detection is a key method in political text analysis and the Political DEBATE model was in large part pretrained specifically for this task. I tried various complex hypotheses, but the best performance was achieved with one of the simplest forms. I defined the base hypothesis as follows:

- "The author of this text {} the European Union".

I then provide three labels/classes - "supports", "opposes", and "is neutral towards". This means, that each text (premise) was evaluated independently against these three different hypotheses:

1. "The author of this text supports the European Union"
2. "The author of this text opposes the European Union"
3. "The author of this text is neutral towards the European Union"

To human validate the performance I took a random sample of 300 texts (mentions of the EU with 100 words of context around them) and coded them according to my research questions in terms of stance taking either support, oppose, or neutral stances. Afterwards a ran the Political DEBATE model on the English translated texts of these 300 mentions and compared the models predictions with my human coded labels. For the stance detection I achieve great results. Using a weighted F1 score [4] the model scores at 0.89, showing extremely good performance.

7.4 Empirical Strategy and Statistical Methods

Moving from descriptive analyses in the NLP phase, I next turn to statistical models to quantify the results in a systematic manner. In order to utilize as much variation as possible, I use the individual mentions of the EU as the unit of observation. I thus take the same approach as Hunter and Walter (2025) in a similar study. Again, I work with the 41,908 mentions of the EU as my unit of analysis. Each of the mentions now has a label for stance from the NLP analysis (oppose, neutral, support) as the dependent variable (DV). And I am trying to model which independent variables (IV) affect the probability of mentions having a given label.

However, using individual mentions means that I face some additional problems in my regression models. This type of data violates the assumption of independence between observations. At the lowest level, I cannot assume that two mentions of the EU by the same MP are independent. And second, I cannot assume that mentions from different MPs within the same party are independent. Thus, I encounter hierarchical clustering in data, and I should account for both sources of clustering - within MPs and within parties. Finally, I also have time dependence as the data are in a Time-Series Cross-Section format.

In my first empirical strategy, I want to look at the overall partisan patterns in the data. I thus turn to multilevel/hierarchical models as suggested by the literature on political methodology (Gelman and Hill, 2006; Gelman, 2006; Bafumi and Gelman, 2007; Shor et al., 2007; Stegmueller, 2013; Bell and Jones, 2015) and also used by Hunter and Walter (2025).

Recent literature on panel data has shown, the traditional two-way fixed effects

[4] Weighted F1 score is the harmonic mean of precision and recall, where the contribution of each class to the overall F1 score is weighted by its prevalence in the dataset. This metric is useful calculating model performance on imbalanced datasets (like mine), as it accounts for the unequal distribution of classes.

(2FE) approach has severe limitations and cannot adjust for confounders on both unit and time dimensions (Kropko and Kubinec, 2020; Imai and Kim, 2021). As a results, the resulting estimates cannot be interpreted as true effects controlled for unobserved variation (Kropko and Kubinec, 2020). I thus try to measure as much relevant time varying factors (related to both the EU and domestic politics) to model the time dimension instead of relying on time fixed effects. The variables included are defined within each model in the following sections. Full descriptions of the variables are provided in section 4 Data.

When modeling the stances I come back to the already measured variable λ_{ji} designating stance (oppose, neutral, support) and I am trying to model it using a set of independent variables. I mainly model stance as a binary variable, but I also fit ordered logit models for robustness (see Appendix for the specification and results which support the findings from the binary logit models).

For each *mention* i of MP j in party p, I model the stance as a binary outcome variable defined as:

$$y_{ijp} = \begin{cases} 1 & \text{if the mention is } \textbf{supporting} \text{ the EU} \\ 0 & \text{if the mention is } \textbf{opposing} \text{ the EU} \end{cases}$$

I first use a multilevel logit model with random intercepts:

$$\text{logit}(P(y_{ijp} = 1)) = \alpha_0 + \alpha_{j[i]} + \alpha_{p[i]} + \mathbf{X}_i\boldsymbol{\beta} \tag{1}$$

where:

- α_0 is the global intercept,
- $\alpha_{j[i]} \sim \mathcal{N}(0, \sigma^2_{MP})$ is the random intercept for MP j,
- $\alpha_{p[i]} \sim \mathcal{N}(0, \sigma^2_{party})$ is the random intercept for party p,
- $\mathbf{X}_i\boldsymbol{\beta}$ is the linear predictor for the fixed effects:

$$
\begin{aligned}
\mathbf{X}_i\boldsymbol{\beta} = \beta_2\text{National Election Period}_i + \beta_3\text{European Election Period}_i \\
+\beta_4\text{EU Summit}_i + \beta_5\text{Lagged Quarterly Inflation}_i \\
+\beta_6\text{Public Trust in EU}_p + \beta_7\text{Government}_p
\end{aligned}
$$

Second, I fit a multilevel logit model with random intercepts and a random slope for government for each party:

$$
\text{logit}(P(y_{ijp} = 1)) = \alpha_0 + \alpha_{j[i]} + \alpha_{p[i]} + \mathbf{X}_i\boldsymbol{\beta} + \beta_{7p}\text{Government}_p \tag{2}
$$

where:

- α_0 is the global intercept,
- $\alpha_{j[i]} \sim \mathcal{N}(0, \sigma^2_{MP})$ is the random intercept for MP j,
- $\alpha_{p[i]} \sim \mathcal{N}(0, \sigma^2_{party})$ is the random intercept for party p,
- $\beta_{7p} \sim \mathcal{N}(\beta_7, \sigma^2_{\text{Gov:Party}})$ is the random slope for `Government` varying by party p,
- $\mathbf{X}_i\boldsymbol{\beta}$ is the linear predictor for the fixed effects:

$$
\begin{aligned}
\mathbf{X}_i\boldsymbol{\beta} = \beta_2\text{National Election Period}_i + \beta_3\text{European Election Period}_i \\
+\beta_4\text{EU Summit}_i + \beta_5\text{Lagged Quarterly Inflation}_i \\
+\beta_6\text{Public Trust in EU}_p
\end{aligned}
$$

I always fit two different sets of models. The main models are suing on mentions from 2004 when Czechia was already an EU member. The second models also include periods prior to the Czech EU accession and go back until 1993.

7.4.1 Getting closer to causal estimation: event study models

THIS SECTION PROBABLY GOES AWAY? *This part was motivated by a paper by Frederik Hjorth from Copenhagen (Hjorth, 2025), who did Event Study models and Diff-in-Diff (I think?) on parliamentary data to study difference between govenrment and opposition in language complexity. But I don't think it makes too much sense in my setup, because his data was much richer*

In an attempt to get closer to a causal estimation of the effect of joining government the data structure suggests one main method. Given the staggered nature of the treatment (and its non-random assignment) I could focus only on ever-treated units and fit an event study model with staggered treatment adoptions (sometimes called staggered difference-in-differences) to distill the effect of first joining the government (Miller, 2023). For this, I would specify periods before treatment, during treatment, and periods after treatment and two-way fixed effects (year and MP-level fixed effects) to control for unobserved heterogeneity. This setup should in theory isolate the effect of joining the government by comparing the treated period (first chamber in which the MPs party was a member of the government coalition) and the post-treatment period (the following chamber) with the pretreatment period (the chamber before) [5]

However, this approach is riddled with potential pitfalls that could lead to biased estimates. Lately, event study models with staggered treatments and two-way fixed effects have been shown to have many problems (Baker et al., 2022; Sun and Abraham, 2021). Sun and Abraham (2021) show that in event study models the effects of pre- and post-treatment periods can get contaminated by the other periods. Specifically for models with only treated units, Baker et al. (2022) show that they can lead to biased estimates if the treatment effects are heterogeneous, because the model implicitly compares units treated earlier with units treated

[5] The (final) pre-treatment period as is ommited form the model to serve as the reference period. The coefficients of δ_c therefore represent the estimated effect of the treatment at their respective periods relative to the period before treatment. This design crucially assumes that the trend is flat between the pre-treatment period and the treatment period.

later. Both offer some best practices or more reliable estimators (e.g. Sun and Abraham (2021) or Callaway and Sant'Anna (2021)). However, almost all of the literature is focused on OLS models and the most developed methods for remedy are not applicable to Maximum Likelihood Estimation (MLE) in binary or ordered outcomes.

Additionally, my sample size decreases significantly when trying to fit a staggered model, because MPs typically don't spend too much time in parliament and spend even less time in opposition before their parties enter government. Here, while 343 MPs mentioned the EU while their party was in power (after Czechia had joined the EU in 2004), only 134 had no variation on the DV [6]. Thus, only 209 MPs could even enter the final model with enough variation on the DV and the total mentions sample size dropping to 6,000 observations (mentions of the EU).

Furthermore, most MPs do not spend enough time in parliament to appear in all 3 periods (pre-treatment, treatment, and post-treatment). In fact, only 15 MPS appear in all three. 53 MPs appear in pre-treatment and treatment and 144 MPs appear in treatment and post-treatment. This means, that the sample size for estimating the treatment effect (entering government) is 68 MPs and the sample size for estimating the post-treatment effect (leaving government) is 159 MPs. However, there are stil thousands of observations in total entering the model, because each MP has many mentions of the EU over the course of time. While these are not tiny sample sizes, combined with the previous drawbacks, the reader might be right to be skeptical of the results from such an event study model. I fit a fixed effect logit model defined as:

$$\text{logit}(P(y_{ijp} = 1)) = \alpha_0 + \alpha_j + \delta_c D_{c,jt} + \mathbf{X}_i \boldsymbol{\beta} \tag{3}$$

where:

[6] This means they only had supporting or opposing mentions of the EU - mostly because of their short stints in parliament or back-bench positions with little floor time

- α_0 is the intercept
- α_j is the MP fixed effect
- $D_{c,jt}$ is a dummy variable indicating the distance c from the treatment for MP j.
- $\mathbf{X}_i\boldsymbol{\beta}$ is the linear predictor for the fixed effects:

$$\begin{aligned}\mathbf{X}_i\boldsymbol{\beta} = \beta_2\text{National Election Period}_i + \beta_3\text{European Election Period}_i \\ +\beta_4\text{EU Summit}_i + \beta_5\text{Lagged Quarterly Inflation}_i \\ +\beta_6\text{Government}_p + \beta_7\text{Public Trust in EU}_p\end{aligned}$$

I use robust clustered standard errors by MPs. I always use two-way fixed effects for year and MP first and then omit the year fixed effects in the following model. The latter one-way fixed effect models rely on the time varying variables (election cycles, eu cycle, inflation, and public opinion) to control for key time confounders.

8 Results

8.1 Descriptive Text Analysis Results

Looking at the aggregated descriptive results of stance in Figure 1, we observe an interesting trend. During the 1990s there is a gradual increase of the Stance Score, suggesting a rising share of supporting mentions compared to opposing mentions. This increase peaks around 2007 and then starts to gradually decrease.

We can see a significant drop towards opposing stances where the Stance Score reached a local minimum, which seemingly again corresponds to the Migration crisis where the Stance Score reached a local minimum. A temporary shift towards more opposing stances of the EU might make theoretical sense given the strong Czech opposition to quotas, which where used as a strong talking point against the EU. Afterwards, the Stance Score relatively quickly returns to a roughly neutral average from 2018 to 2021.

However, in 2022 and 2023, corresponding to the Ukraine invasion, we again observe a strong change of patterns as we saw with salience and framing. This time, the Stance Score declines sharply towards a global minimum of the entire studied period. Again, any stronger inferences about the true effect of the Ukraine invasion would require qualitative insights or cross-national studies.

However, looking at Figure 3, the trend seems to be driven by a strong negative shift towards opposing stances by the leading opposition party ANO, which had more than a third of all MPs in the Chamber of Deputies at the time. The remaining parties seem to shift towards more supporting stances of the EU.

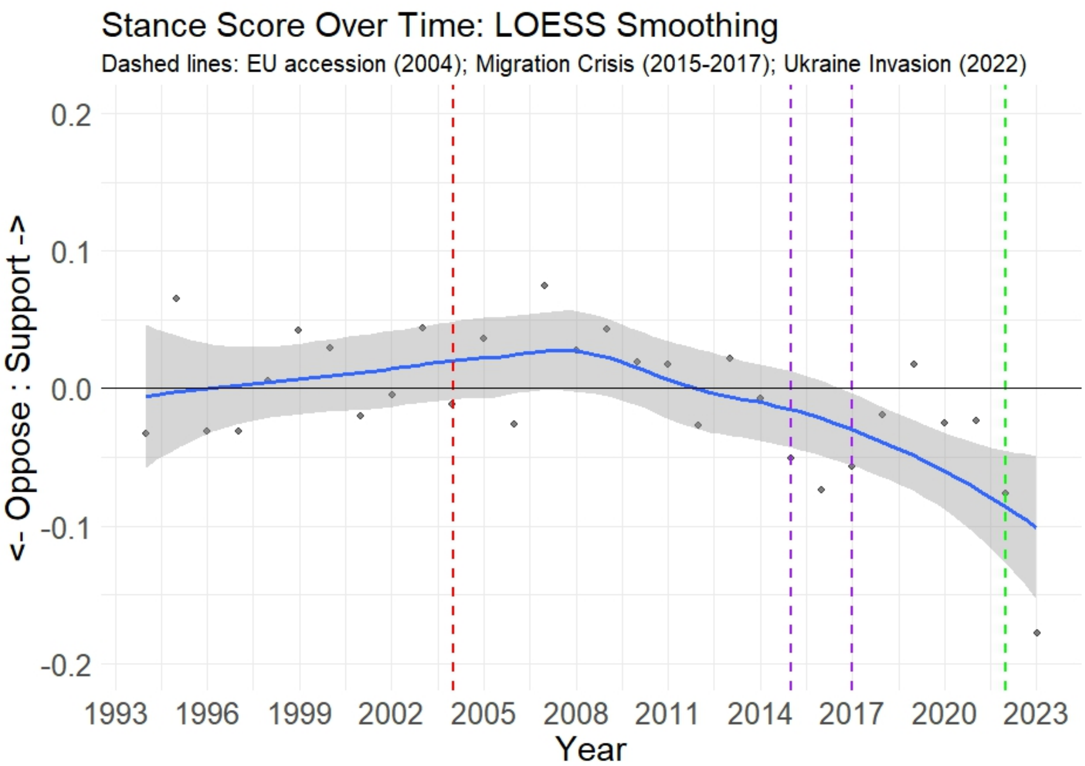

Figure 1: Stance Score Over Time

Analyzing stance by parties in Figure 2 yields few surprises. Most parties hover more or less around the neutral point, and SPD being the outlier with by far the lowest average Stance Score of almost -0.5. KSČM and ODS are the only other parties with an opposing stance towards the EU on average. On the other hand, the new liberal parties - STAN, TOP 09, and the Pirates all have a clear supporting average Stance Score. The remaining traditional parties, KDU-ČSL and ČSSD, also have a positive Stance Score.

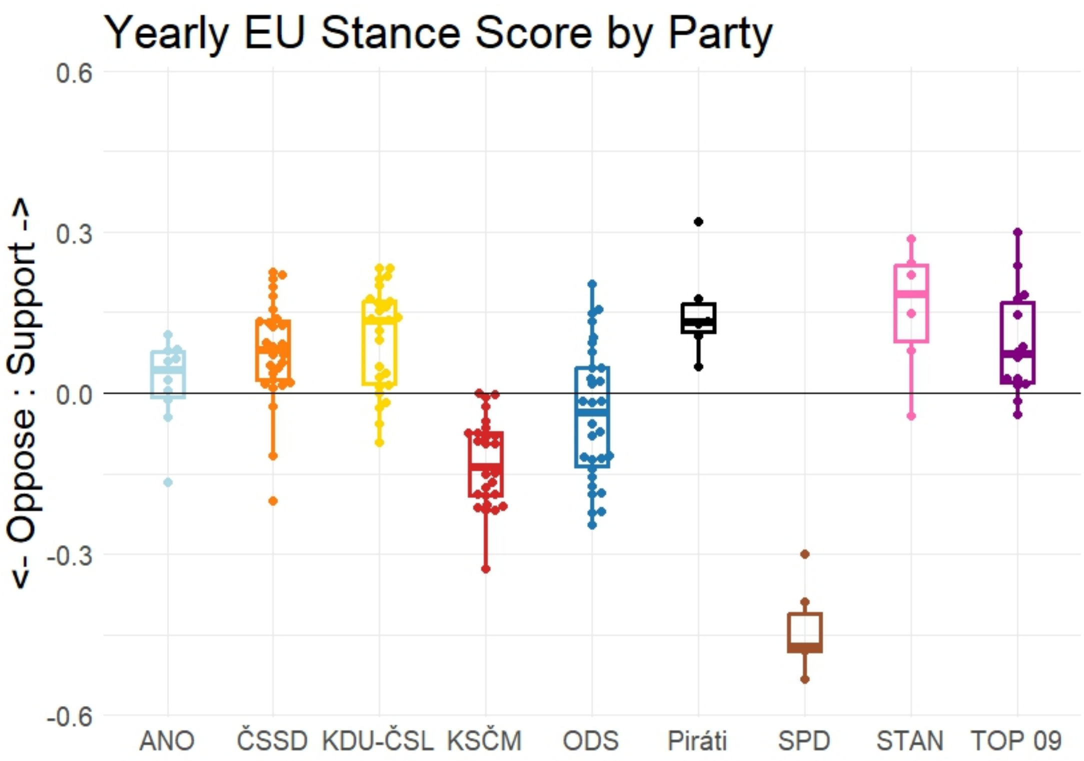

Figure 2: Partisan EU Stance Score

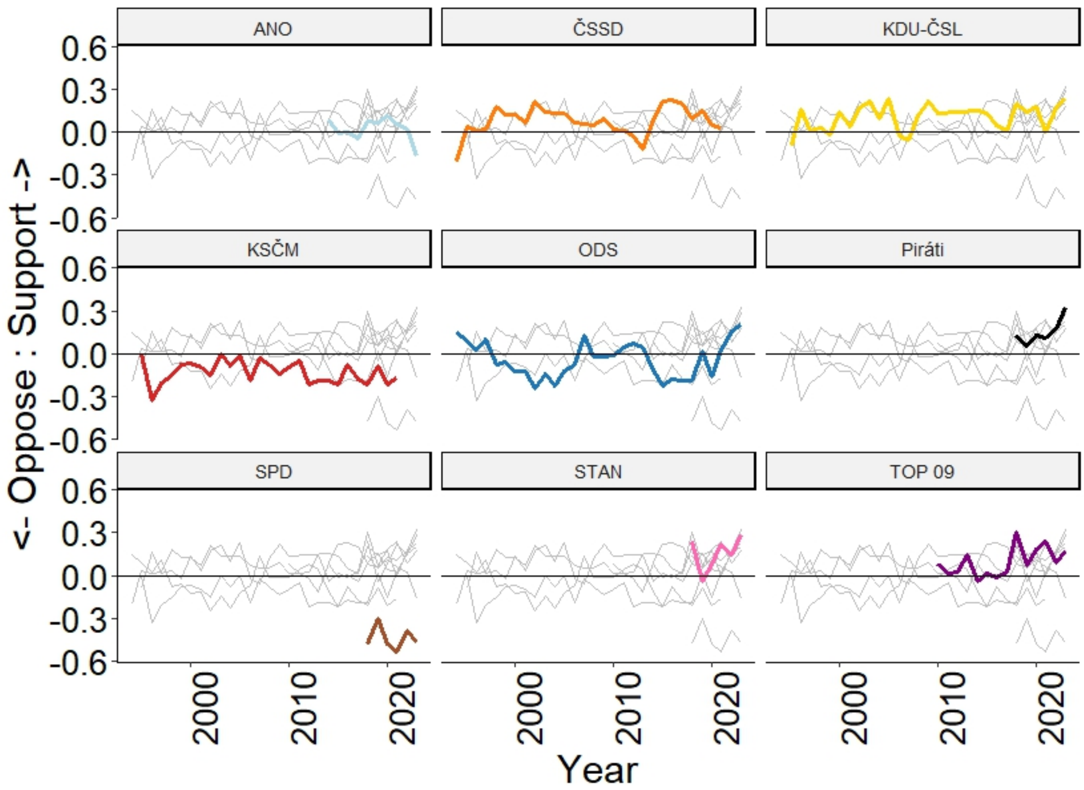

Figure 3: Partisan EU Stance Score - Evolution

8.2 Statistical Results

Moving to the statistical results in Table 2 I find that governing parties are more likely to express supporting stances towards the EU. The effect size in the random intercept model (M1) is large, with an average marginal effect of being in government is associated with a 200 % increase in odds of a supporting stance (an odds ratio of 3). Public Trust in the EU has a significant but substantively small positive effect. Additionally, both national and EU electoral cycles seem to have a negative effect, suggesting that parties take more opposing stances during election campaigns.

I next look at results from the random slopes model (M2) in Table 3, where parties with no government experience, KSČM and SPD, were omitted. Interestingly, parties with the lowest baseline of supporting stances towards the EU have the largest positive effects of being in government (slopes model). Specifically

Table 2: Supporting (=1) vs Opposing (=0) Stance Towards the EU: Multilevel Logit Models

	M1: (>=2004)	M2: (>=2004)	M3: (>=1993)	M4: (>=1993)
Government	1.10***		1.09***	
	(0.06)		(0.05)	
Quarterly Inflation (Lag)	0.01	0.02*	0.01**	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Election Period	−0.36***	−0.35**	−0.29**	−0.26*
	(0.10)	(0.11)	(0.09)	(0.10)
EU Election Period	−0.19*	−0.16+	−0.12	−0.11
	(0.08)	(0.08)	(0.07)	(0.08)
EU Summit	−0.04	−0.09	−0.06	−0.09+
	(0.05)	(0.05)	(0.04)	(0.05)
Public Trust EU	0.01***	0.01***		
	(0.00)	(0.00)		
Num.Obs.	9192	6886	11 969	9272
Random Intercepts: Party	Yes	Yes	Yes	Yes
Random Slopes: Government::Party	No	Yes	No	Yes
AIC	10 721.3	8647.5	13 980.2	11 413.5
BIC	10 778.3	8709.0	14 031.9	11 470.6
ICC	0.2	0.3	0.2	0.4
RMSE	0.44	0.47	0.45	0.46

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001
Effects are reported as log odds

ODS and ANO have only about a 30% probability of supporting mention while in opposition, but more than 60% while in government (and difference of more than 30 percentage points). On the other hand, parties with the highest baseline of supporting stances show the lowest positive effects - Piráti, TOP 09, and STAN. These results suggest, that Euroskeptic parties can significantly change their rhetoric towards the EU to more supporting stances once in government. And that pro-European parties take an even more positive stance as well.

Table 3: Predicted Probabilities of Supporting Stances by Party

Model	**M1: Random Intercept**	**M2: Random Intercept + Slopes**		
Party/Probability	**Gov = 0**	**Gov = 0**	**Gov = 1**	**Change**
ANO	34%	32%	62%	+ 30 pp
ČSSD	54%	56%	76%	+ 20 pp
KDU-ČSL	53%	63%	75%	+ 12 pp
KSČM	31%	-	-	-
ODS	31%	29%	62%	+ 32 pp
Piráti	66%	67%	79%	+ 12 pp
SPD	9%	-	-	-
STAN	59%	61%	77%	+ 15 pp
TOP 09	57%	58%	74%	+ 15 pp

Note. Baseline probabilities are calculated from the random-intercept model as

$$p_i = logit^{-1}(logodds) = \frac{\exp(\text{logodds})}{1+\exp(\text{logodds})} = \frac{\exp(\beta_0 + u_{0i})}{1+\exp(\beta_0 + u_{0i})}$$

For the random-slope model (government effect), probabilities are calculated as

$$p_{i,\text{gov}=0} = \text{logit}^{-1}(\beta_0 + u_{0i}), \quad p_{i,\text{gov}=1} = \text{logit}^{-1}(\beta_0 + \beta_{\text{gov}} + u_{0i} + u_{1i}),$$

where u_{0i} and u_{1i} are the party-specific random intercept and slope for the government effect. Dashes indicate parties not included in the government-slope model.

Again these results will probably be omitted? Turning to the results of the event study models in Table 4, I find a substantive effect of the treatment (first term in parliament during which the party of MP j is in government). The effect is large stable across all model specifications with a roughly 266 % increase in odds of a supporting stance (an odds ratio of 3.66). Interestingly, the effect disappears in the chamber following the treatment and reverts back to pre-treatment levels in the 2FE models (Model 5 and Model 6), but remains substantive and significant in the one-way specification (Model 7). This might signal, that MPs adopt a strategic discourse rather than being completely socialized into more supportive stances.

However, it is important to remind of the limitations of event study models coupled with 2FE as discussed in section 6. The reader should at least be skeptical about the size of the treatment effect.

The event study treatment effects can be seen in Figures 5 and 6.

Table 4: Event Study Model Logit: Supporting vs Opposing Stance Towards the EU (>2004)

	M5 (2FE)	M6 (2FE)	M7 (1FE)
Treatment (1st Chamber in Government)	1.32***	1.28***	1.37***
	(0.37)	(0.37)	(0.34)
Post-Treatment (Chambers after)	0.57	0.50	0.93*
	(0.55)	(0.55)	(0.40)
Quarterly Inflation (Lag)		0.01	−0.03
		(0.02)	(0.02)
Election Period		−0.28	−0.15
		(0.23)	(0.18)
EU Election Period		−0.02	−0.14
		(0.22)	(0.22)
EU Summit		−0.02	−0.07
		(0.09)	(0.09)
Public Trust EU			0.01
			(0.00)
Num.Obs.	5916	5916	5916
Std.Errors Clustered	by: MP	by: MP	by: MP
Fixed Effects: MP	Yes	Yes	Yes
Fixed Effects: year	Yes	Yes	No
AIC	6948.7	6954.1	6997.6
BIC	8432.9	8465.0	8388.2
RMSE	0.43	0.43	0.43

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001
Note: Coefficients are reported as log odds.

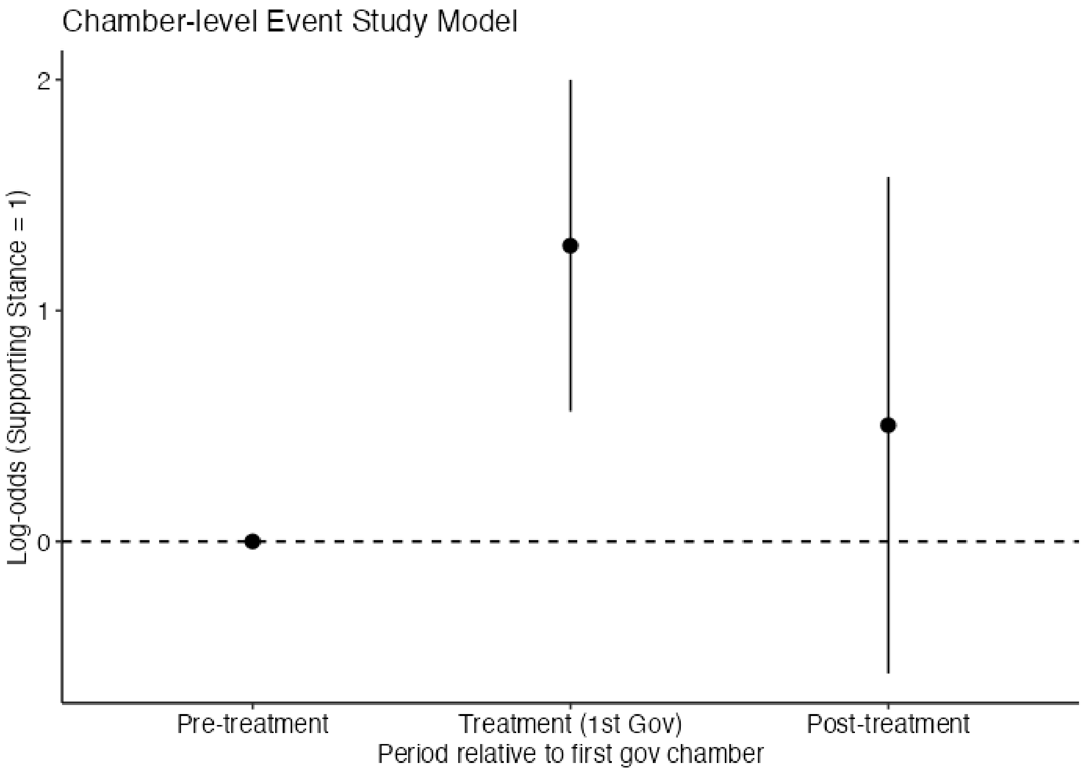

Figure 4: Model 6 - Two-Way Fixed Effects + Covariates

9 Discussion and Conclusion

In this paper, I set out to expand the current literature on national parliamentary debates about the EU. Using a large novel dataset of almost 500,000 plenary speeches from the Czech Chamber of Deputies (1993-2023), I added a focus on stance in a large quantitative and computational setting.

Focusing on the case of Czechia, I used a complex NLP approach, where I combined keywords-in-context, machine translation, and natural language inference to analyze how Czech MPs talk about the EU in terms of stance.

My results suggest that governing parties are systematically more likely to express supporting stances towards the EU than opposition parties. This finding is robust to alternative specifications and even holds when accounting only for within party variation. These results suggest that even parties which are very Euroskeptic in opposition (ODS, ANO) radically change their discourse when entering government and significantly moderate their stances to more supporting.

Generally, my results speak to previous results suggesting an opposition deficit in EU accountability where governing parties talk about the EU significantly more often (Rauh, 2014; Rauh and De Wilde, 2018). However, it could also be of interest to an emerging literature on the (rhetorical) cost of government, which suggests that governing parties adopt more rhetorical complexity, which can lead to losing touch with their voters who can no longer easily understand their message (Hjorth, 2025). My findings that governing parties adopt more supporting stances towards the EU might be an interesting starting point for future research about the control of EU affairs or other international organizations.

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Appendix

10 Appendix 0: Descriptive Statistics

Table 5: Descriptive statitics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
year	2,014.662	6.050	2,004	2,010	2,015	2,020	2,023
government	0.387	0.487	0	0	0	1	1
quarterly_inflation	4.061	4.807	−0.133	1.167	2.333	3.700	18.000
eu_election_period	0.121	0.326	0	0	0	0	1
eu_summit	0.589	0.492	0	0	1	1	1
trust	50.984	5.973	37.700	49.500	51.700	55.500	58.200
not_trust	43.136	6.782	33.900	37.100	44.200	45.600	57.000
avg_trust	7.849	12.647	−19.300	3.900	8.000	19.500	24.300

Appendix 1 - Regex formulas

Target	Regex fromula
European Union	eu | evropskw* uniw*
European Parliament	evropskw* parlamentw*
European Commission	evropskw* komisw*
Council of the EU	radw* (eu | evropskw* uniw*)
European Council	evropskw* radw*
European Court of Justice	evropskw* soudnw* dvůr | evropskw* soudnw* dvow*
European Central Bank	evropskw* centrálnw* banw* | ecb
Euro	eurozónw* | eur[oa]
Economic cooperation	hospodářskw* a měnovw* uniw* | sgp | paktw* stability a růstu
Treaties	(římskw* | maastrichtskw* | amsterdamskw* | lisabonskw*) smlouvw* | smlouvw* o fungování evropskw* uniw*
Bruxelles	bruselw*

Table 6: Regex Formulas

Appendix 2 - Robustness checks for stance models

Multilevel ordered logit

And second, I fit a multilevel ordered logit. Here, I model all 3 options of stance including neutral.

For each *mention* i of MP j in party p, I model the stance as towards the EU as an ordinal outcome variable defined as:

$$y_{ijp} = \begin{cases} 0 & \text{if the mention is } \textbf{opposing} \text{ the EU} \\ 1 & \text{if the mention is } \textbf{neutral towards} \text{ the EU} \\ 2 & \text{if the mention is } \textbf{supporting} \text{ the EU} \end{cases}$$

I use an ordered logit multilevel model. The model works by predicting the cumulative probabilities of being in a category or lower. For an outcome with K categories, there are $K - 1$ cutpoints. Thus I have two cutpoints, τ_1 and τ_2.

The cumulative probability of $y_{ijp} \leq k$ is modeled as:

$$\text{logit}(P(y_{ijp} \leq k)) = \tau_k - (\alpha_0 + \alpha_{j[i]} + \alpha_{p[i]} + \mathbf{X}_i\boldsymbol{\beta}) \tag{4}$$

where:

- τ_k are the ordered cutpoints (thresholds), such that $\tau_1 < \tau_2$.
- α_0 is the global intercept
- $\alpha_{j[i]} \sim \mathcal{N}(0, \sigma^2_{MP})$ is the random intercept for MP j.
- $\alpha_{p[i]} \sim \mathcal{N}(0, \sigma^2_{party})$ is the random intercept for party p.
- $\mathbf{X}_i\boldsymbol{\beta}$ is the linear predictor for the fixed effects:

  The probabilities for each individual category are derived from the cumulative probabilities:

$$\begin{aligned} P(y_{ijp} = 0) &= P(y_{ijp} \leq 0) \\ P(y_{ijp} = 1) &= P(y_{ijp} \leq 1) - P(y_{ijp} \leq 0) \\ P(y_{ijp} = 2) &= P(y_{ijp} \leq 2) - P(y_{ijp} \leq 1) = 1 - P(y_{ijp} \leq 1) \end{aligned}$$

  For each *mention* i of MP j in party p, I model the stance as towards the EU as an ordinal outcome variable defined as: