Who Attacks, and Why? Using LLMs to Identify Negative Campaigning in 18M Tweets across 19 Countries

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Abstract

Negative campaigning is a central feature of political competition, yet empirical research has been limited by the high cost and limited scalability of existing classification methods. This study makes two key contributions. First, it introduces zero-shot Large Language Models (LLMs) as a novel approach for cross-lingual classification of negative campaigning. Using benchmark datasets in ten languages, we demonstrate that LLMs achieve performance on par with native-speaking human coders and outperform conventional supervised machine learning approaches. Second, we leverage this novel method to conduct the largest cross-national study of negative campaigning to date, analyzing 18 million tweets posted by parliamentarians in 19 European countries between 2017 and 2022. The results reveal consistent cross-national patterns: governing parties are less likely to use negative messaging, while ideologically extreme and populist parties — particularly those on the radical right — engage in significantly higher levels of negativity. These findings advance our understanding of how party-level characteristics shape strategic communication in multiparty systems. More broadly, the study demonstrates the potential of LLMs to enable scalable, transparent, and replicable research in political communication across linguistic and cultural contexts.

Keywords: negative campaigning; large language models; political communication; multiparty systems; populism; social media; text classification; European politics

Negative campaigning—commonly defined as "any criticism levelled by one candidate against another during a campaign" (Geer 2006, p. 23)—has long been a feature of democratic politics. In ancient Athens, evidence of organized efforts to exile political rivals through ostracism can be found on pottery shards used as ballots (Brenne 2020). Yet, recent scholarship has expressed growing concern that negativity in campaigning may be on the rise, particularly as political communication adapts to the affordances and logics of social media (Auter and Fine 2016; Klinger et al. 2023; Törnberg and Chueri 2025). These concerns go beyond matters of tone or style: negative campaigning can undermine democratic systems by eroding trust in political institutions (Lau, Sigelman, et al. 2007) and fueling affective polarization (Lau, Andersen, et al. 2017; Martin and Nai 2024).

Despite its normative and empirical significance, and substantial research interest in the field, the political drivers of negative campaigning remain contested. Much existing research has focused on either individual-level factors (such as candidate traits) or system-level factors (such as electoral systems), and research has primarily focused on the US context (Walter and Nai 2015). In contrast, party-level factors and the dynamics of negative campaigning in multiparty contexts have received less attention (Elmelund-Præstekær 2010; Walter and van der Brug 2013). Especially lacking are large-scale cross-national studies capable of identifying how party characteristics shape negativity across diverse institutional and cultural settings (Walter and Nai 2015).

This gap is in large part due to methodological limitations. Negative campaigning is difficult to study comparatively at scale, in part because it is a latent and contextually dependent phenomenon. Most existing studies rely on expert surveys or manual content analysis, both of which come with important limitations. Expert-based approaches raise concerns about bias, lack of transparency, and poor replicability across contexts (Lindstädt et al. 2020). Manual coding of political messages, while achieving high external validity through empirical grounding, is labor-intensive and infeasible for multilingual, cross-country datasets. While automated approaches using supervised machine learning have expanded the scale of analysis (Petkevic and Nai 2022; Licht et al. 2024), these face important limitations: they require extensive labeled training data for each language and country context, and underperform relative to human coding (van Atteveldt et al. 2021), constraining their utility for comparative research.

Recent advances in large language models (LLMs) however offer a potential novel approach. Instruction-tuned LLMs enable "zero-shot" classification, allowing researchers to specify coding instructions in natural language without the need for training data (Kojima et al. 2023). Early studies suggest that LLMs can perform classification tasks across domains and languages with high accuracy and dramatically lower costs (Gilardi et al. 2023; Törnberg 2024b). In particular, researchers have begun to consider their potential for enabling consistent annotation across languages, with potentially paradigm-shifting implications for cross-national political communication research (Rathje et al. 2024; Törnberg 2024b) – but studies on whether LLMs can produce high-quality cross-language data remain limited.

This paper carries out the first evaluation of the performance of zero-shot LLM annotation of negative campaigning across languages and country contexts. We test zero-shot LLM performance against two high-quality, manually coded datasets that are not publicly available: Petkevic and Nai's (2022) study of the 2018 U.S. Senate elections, and Klinger et al.'s (2023) multilingual coding of the 2014 and 2019 European Parliament campaigns. Results show that LLMs achieve near or above human performance across the ten included languages (English, German, Croatian, French, Hungarian, Italian, Dutch, Polish, Spanish, and Swedish), demonstrating their potential for valid, scalable comparative analysis.

Next, we apply this method to carry out the largest cross-national study of negative campaigning to date. The lack of cross-country comparative studies, and the empirical focus on the US context has meant that our understanding of negative campaigning in

multi-party systems is underdeveloped. Existing studies have focused on either system or candidate-level determinants (e.g., Maier and Nai 2023; Maier and Nai 2022; Papp and Patkós 2019), while providing limited insight into the party-level variation that is critical in multiparty systems, where parties—not individual candidates—are the central strategic actors. Existing studies have moreover primarily relied on expert surveys or self-reported behavior, which limit the granularity and validity of negativity measures (Lindstädt et al. 2020).

Our empirical analysis contributes to the literature by shifting the focus to parties as units of analysis, and using direct observations of their textual campaign output. To theorize negative campaigning in multiparty frameworks, we build on the strategic incentives framework and propose a set of hypotheses for party behavior. We test our framework by analyzing 18M political messages from elected representatives across 19 European countries. This allows us to directly examine how institutional position (governing experience), ideological extremity, and populist discourse predict the use of negative campaigning in real-world communication—thus bridging the gap between macro-level theories and micro-level expression.

In line with our theoretical expectations, our findings show that negative campaigning is most strongly associated with radical right parties, followed by the radical left. Governing experience is linked to lower levels of negativity, while ideological extremism and populist rhetoric are associated with higher levels. These results underscore that rising negative campaigning (Klinger et al. 2023; Törnberg and Chueri 2025) is not merely a byproduct of social media logics, but reflects broader dynamics of party competition and the rise of particular political movements (Törnberg and Chueri 2025).

Measuring Negative Campaigning

Negative campaigning is traditionally measured using either expert surveys or manual annotation of political messaging. Both approaches, however, come with well-documented limitations.

Expert surveys have been widely used to measure negative campaigning in comparative research due to their relatively low cost and feasibility across multiple countries (e.g., Nai and Walter 2015). However, this approach has several well-documented limitations. First, expert evaluations are inherently subjective, introducing potential biases based on the experts' political preferences, media exposure, or national context (Lindstädt et al. 2020; Walter and van der Eijk 2019). These biases can be particularly problematic in cross-national settings, where cultural and linguistic differences may influence what is perceived as "negative" campaigning (Esser and Strömbäck 2012; Esser and Pfetsch 2004). Second, expert assessments often lack transparency, as the criteria used by individual raters are rarely standardized or externally validated, raising concerns about the reliability and replicability of the data (Mikhaylov et al. 2012; Volkens 2007). Third, the aggregated nature of expert surveys tends to obscure the granularity of campaign messaging, failing to capture variation in tone across messages, platforms, or time (van Atteveldt et al. 2021). This makes it difficult to analyze how negativity evolves

in response to political events or strategic shifts. Collectively, these limitations suggest that while expert surveys offer broad coverage, they fall short in capturing the nuance and context-dependent nature of negative campaigning, particularly in multilingual and multi-platform environments.

In contrast to expert surveys, manually coding political messages provides a more direct, transparent, and empirically grounded approach to measuring negative campaigning (e.g., Geer 2006; Lau and Pomper 2004; Auter and Fine 2016; Fridkin and Kenney 2011; Elmelund-Præstekær 2010; Hansen and Pedersen 2008; Walter and van der Brug 2013). Rather than relying on second-order perceptions, manual coding evaluates the actual content of campaign messages—such as tweets, speeches, or advertisements—allowing researchers to systematically apply consistent coding rules across cases. This improves both the validity and replicability of findings, especially when coders are trained using a shared codebook and inter-coder reliability is assessed (Krippendorff 2019). Manual coding also enables a higher level of granularity, capturing variation within parties, over time, or across platforms—details that are typically obscured in aggregate expert ratings (Grimmer and Stewart 2013).

Manually coding of political messages however also comes with significant limitations. High reliability and accuracy of manual annotation are not guaranteed, even with extensive training (Weber 2018). To maximise classification accuracy, human coders typically undergo training sessions where they develop a shared, often tacit understanding of the concepts they are classifying – which often proves difficult to document explicitly and cannot be fully captured in codebooks (van Atteveldt et al. 2021). This makes replication more difficult and can leave the concept vaguely defined and variously operationalized within the field, posing serious conceptual challenges.

Manual annotation is also highly resource intensive: developing reliable codebooks, training coders, and ensuring inter-coder consistency require substantial time, labor, and funding (Krippendorff 2019; van Atteveldt et al. 2021). While crowd-sourcing offers a partial solution by leveraging the "wisdom of the crowd" to scale annotation efforts (Benoit et al. 2016; van Atteveldt et al. 2021), studies consistently find that trained coders outperform crowd-workers in both accuracy and reliability (van Atteveldt et al. 2021). Moreover, even crowd-based approaches remain too costly for large-scale or multilingual analyses. The challenges are particularly acute in cross-linguistic research, where consistency across languages and cultural frames requires aligning coders from different backgrounds around shared definitions—further increasing complexity and cost (Esser and Strömbäck 2012). As a result, most research on negative campaigning has relied on small samples or single-country studies, limiting generalizability and impeding broader comparative insights. Notable exceptions include Walter, van der Brug, and van Praag (2014), who study elections in the Netherlands, UK, and Germany; Klinger et al. (2023), who analyze European Parliament campaigns; and Nai (2020), who relies on expert surveys rather than direct content analysis.

These methodological issues have motivated efforts to automate the classification of negativity. However, while conventional dictionary-based approaches are fast and cost-efficient, they achieve limited performance on semantically subtle concepts such as

negative campaigning, and perform even worse in multilingual settings (Haselmayer and Jenny 2017). More recent studies have adopted more sophisticated supervised machine learning techniques that leverage semantic features and context. For instance, Petkevic and Nai (2022) use a multilayer perceptron to classify negativity in tweets, achieving a macro F1-score of .82. Licht et al. (2024) employ a fine-tuned transformer model to detect anti-elite sentiment, reaching an F1-score of .75. Widmann and Wich (2023) use similar models to classify emotional content, with F1-scores ranging from .60 (sadness, pride) to .84 (anger). These scores are relatively impressive given the difficulty of the task and often modest agreement among human annotators on the training data. Nevertheless, automated classifiers still lag behind well-trained human coders in both accuracy and interpretive nuance (van Atteveldt et al. 2021). More crucially, supervised machine learning still depends on large-scale manually labeled training data for each specific task and context. To build reliable models, researchers must first produce extensive hand-coded datasets, often repeating the annotation process for each new country, time period, or linguistic context (Raffel et al. 2023; Petkevic and Nai 2022; Keuchenius et al. 2021; Widmann and Wich 2023; Licht et al. 2024). As a result, supervised machine learning inherits many of the same limitations as manual annotation, limiting its applicability for fully comparative, multilingual political communication research.

The recent emergence of Large Language Models (LLMs) such as GPT has however offered hopes of overcoming these challenges, representing a paradigm-shift in natural language processing. Centrally, LLMs are capable of 'few-shot' and 'zero-shot' annotation: by using carefully formulated natural language instructions, LLMs can be used to directly annotate data without the need for manually labelled training data (Bail 2024; Brown et al. 2020; Kojima et al. 2023; Törnberg 2024b). By leveraging its understanding of language patterns gained through training on extensive data, the model can perform tasks it has not been explicitly trained on (Brown et al. 2020). Not only does this make the models orders of magnitude cheaper, more flexible and easier to use, but it may potentially have made them better annotators for many tasks: LLMs have been shown to outperform human coders, crowd-sourced coders, experts and supervised machine learning methods in many classification tasks (Törnberg 2024b; Gilardi et al. 2023).

LLMs also bring another capacity that potentially makes them particularly impactful in the context of comparative research: scholars have argued that their cross-linguistic capacities enable their use to produce comparative data across languages and country contexts (Rathje et al. 2024; Törnberg 2024b). Zero-shot prompting may enable consistent classification across languages without requiring separate models or training data for each language, while outperforming other methods in accuracy.

However, scholars have argued that the performance of models varies across languages, and the capacity to use LLMs to produce comparative data has yet to be empirically investigated. The capacities of LLM are moreover fickle: while they achieve superhuman performance on some tasks, they can seemingly inexplicably fail other (Ollion et al. 2023; Kristensen-McLachlan et al. 2025; Yu et al. 2023). Moreover, LLMs can reproduce or amplify social and cultural biases embedded in their training data,

raising important ethical and methodological concerns (Lucy and Bamman 2021). Scholars have therefore argued that rigorous validation for each use case remains essential (Törnberg 2024a).

Method: Assessing LLMs' capacity to classify negative campaigning

To evaluate the capacity of LLMs to accurately and reliably classify negative campaigning across languages and country-contexts, we compare the zero-shot LLM annotation against the manual classification data from two studies: Petkevic and Nai (2022), covering Twitter posts of candidates during the 2018 US Senate elections, and Klinger et al. (2023), covering Facebook posts of political parties during the 2014 and 2019 EP election campaigns. These datasets are not publicly shared, which means that they are not part of the training data of the LLMs. The data is moreover of high quality, and offers coding by trained native speakers across ten different languages and country-contexts (English, German, Croatian, French, Hungarian, Italian, Dutch, Polish, Spanish, and Swedish).

As is generally the case, these two studies use different definitions of negative campaigning: Klinger et al. (2023) uses a significantly stricter definition of negative campaigning than Petkevic and Nai (2022). This difference allows us to also evaluate how well LLMs function across different specific definitions (see Supplementary Material for details).

Following standard machine learning practices, we use F1-scores to evaluate the performance of the LLM. When working with imbalanced datasets, such as the Klinger et al. (2023) data, macro-averaged F1 can be misleading as it treats all classes equally regardless of their frequency. We therefore employ weighted F1, which computes the weighted average of each class's F1 score, with weights corresponding to the number of samples in each class, to assess overall performance.

We moreover use inter-rater reliability (IRR) measures to assess the degree of agreement between human coders and the LLM, treating the LLM as another rater to benchmark against human performance standards. Petkevic and Nai (2022) used Krippendorff's α_K and Klinger et al. (2023) used the Brennan-Prediger coefficient, which is less sensitive to class imbalance than Cohen's kappa. We use the same measures to enable direct comparison with these studies.

In both studies, the authors compute IRR only on a small subset of the data and in Klinger et al. (2023) only for the UK subset. We instead evaluate classification performance on the full datasets.

For the LLM annotation, we apply two OpenAI models: gpt-4o-2024-08-06 and gpt-4o-mini-2024-07-18. (The Supplementary Material includes analysis using OpenAI's recently released gpt-4.1 models, said to feature improved instruction-following and context handling. These show marginal improvements over GPT-4o. However, as the API costs outweighed these marginal performance gains, we retain GPT-4o for the main analysis.) These models show high performance and are easily scalable to large datasets. GPT-4o represented OpenAI's most advanced general-purpose model at time of writing

(excluding specialized reasoning models), while GPT-4o-mini offers a more cost-effective alternative with reduced number of parameters. Temperature is set to 0 to ensure deterministic outputs and reproducibility.

Evaluating LLM Performance for Cross-Country Annotation of Negative Campaigning

	Model	$F1_0$	$F1_1$	$F1_W$	α_K
Human coders	-	-	-	-	0.790
Machine learning	MLP	0.810	0.830	-	-
System + user context	4o	0.877	0.850	0.864	0.728
System + user context	4o-mini	0.919	0.912	0.916	0.831
System context	4o	0.904	0.891	0.900	0.795
System context	4o-mini	0.922	0.916	0.919	0.838
No context	4o	0.932	0.928	0.930	0.860
No context	4o-mini	0.929	0.926	0.927	0.855

Table 1: Classification performance comparison between human coders and machine learning methods from Petkevic and Nai (2022) and LLMs on US Senate 2018 elections. Human coders evaluated 200 randomly sampled tweets, while the machine learning baseline was tested on 20% of the data (N = 234). LLM performance was assessed against the complete dataset of singly coded tweets from combined coder efforts (N = 1186). Metrics include F1 scores for absence ($F1_0$) and presence ($F1_0$) classes, and Krippendorff's alpha for inter-rater reliability. The LLM classifiers vary in their degree of added context in the system and user prompt and the model used. The definition of negative campaigning in the prompt, as defined in the codebook of Petkevic and Nai (2022), is kept the same.

We begin with focusing on Petkevic and Nai (2022)'s data covering the 2018 U.S. Senate. These scholars employ a broad definition of negative campaigning, focusing on "the presence of an explicit attack or critique toward an opponent." Table 1 shows the result of the comparison of the LLM against this dataset, revealing exceptionally high performance of both models.

The context-free, zero-shot LLM outperformed both human coders and the machine learning method employed by Petkevic and Nai (2022). It achieved higher IRR than human coders ($\alpha_K = .860$ vs .790), and showed substantial performance improvements compared to Petkevic and Nai's (2022) machine learning method: weighted-F1 increased from .810 to .932 (+.122) for absence detection and from .830 to .928 (+.098) for presence detection.

When it comes to this task, the LLM thus not merely offers faster, cheaper, and easier-to-use method, but in fact also achieves higher performance than both human coders and task-specific supervised methods.

Turning to the Klinger et al. (2023) dataset, covering the European Parliament, we can evaluate the model's performance also across languages and country contexts.

1					
	Model	Acc	$F1_W$	α_K	κ_{BP}
Human coders	-	0.930	_	0.464	0.895
No context + codebook	4o	0.892	0.922	0.301	0.784
No context + adj. codebook	4o	0.947	0.956	0.435	0.893
No context + codebook	4o-mini	0.914	0.936	0.347	0.828
No context + adj. codebook	4o-mini	0.963	0.962	0.371	0.927

Table 2: Classification performance comparison between human coders from Klinger et al. (2023) and LLMs. Human inter-coder reliability was assessed using 13 coders who each coded the same 150 Facebook posts from the UK. LLM performance was evaluated against a single coder's annotations on 2043 posts. 65 or 3.1% was coded as negative campaigning. Metrics include percentage agreement (accuracy), weighted F1 score ($F1_W$), Krippendorff's alpha (α_K), and Brennan-Prediger coefficient (κ_{BP}). The LLM classifiers vary in whether they use the same codebook definition as the human coders or an adjusted ('few-shot') definition including more explicit instructions and labeled examples.

Country	Acc	$F1_W$	κ_{BP}	$Supp_0$	Supp ₁
AU	0.936	0.925	0.871	742	81
DE	0.969	0.968	0.937	1327	46
ES	0.956	0.944	0.912	2296	98
FR	0.976	0.973	0.952	1473	35
HR	0.964	0.960	0.929	1040	29
HU	0.886	0.867	0.771	1191	148
IE	0.990	0.992	0.980	506	2
IT	0.907	0.894	0.814	2009	267
NL	0.953	0.937	0.906	366	19
PL	0.917	0.901	0.834	1187	128
SE	0.966	0.958	0.932	988	43

Table 3: LLM classification performance (4o-mini, adjusted codebook definition) by country compared to human coders from Klinger et al. (2023). Each country was coded by a single human annotator. Metrics include percentage agreement (accuracy), weighted F1 score ($F1_W$), and Brennan-Prediger coefficient (κ_{BP}). Support columns show the number of negative (Supp₀) and positive (Supp₁) cases per country.

Klinger et al. (2023) used a stricter and more elaborate definition that distinguishes between negative tonality and negative campaigning. This resulted in highly imbalanced classes, i.e., reducing positive cases to only 3.1% in the UK subset. It also resulted in a challenging task for the human coders, who achieved only moderate agreement on this task (Krippendorff's $\alpha_K = .46$).

The LLM prompt employed was adapted to the stricter definition, also providing more labeled examples to capture the more elaborate conceptualization. Table 2 shows the resulting performance of the model. As the table reveals, the annotation task is substantially more challenging. Despite its lower performance in absolute terms, the LLM still performed comparably to human coders across all languages. (It should here furthermore be noted that the model's performance is limited by the quality of the manually coded data that is used as gold standard.)

Centrally, classification performance remains consistent across all languages without requiring language-specific adjustments (see Table 3). Compared to the data manually coded by native speakers, the model achieved a weighted F1 of at least .90 and Brennan-Prediger coefficient of at least .80 for all languages except Hungarian (weighted F1 = .89, BP = .76). The smaller model again performed comparably to the full model, consistent with the US Senate results.

These results demonstrate that, with appropriate prompting, LLMs can match or even outperform both human coders and conventional machine learning techniques. The model moreover maintained consistent performance across all languages when evaluated against native speakers, suggesting the possibility of using it to produce data for comparative research. Klinger et al.'s (2023) more elaborate and stricter definition proved more challenging for both human coders and the LLM, but the LLM still achieves high performance.

These findings carry significant implications for the study of negative campaigning and, more broadly, for comparative research in political communication. The ability of LLMs to reliably identify nuanced concepts in textual data across multiple languages opens new possibilities for large-scale, cross-national analysis that were previously out of reach due to methodological and resource constraints. Building on the demonstrated accuracy of LLM-based classification, we now turn to applying this method in a large-scale empirical study of negative campaigning on Twitter across 19 European countries.

When parties engage in negative campaigning

The lack of large-scale comparative studies means that there exists only limited comparative research on negative campaigning. Existing research moreover tends to rely on expert surveys, rather than direct empirical measurements.

Many scholars argue that political actors engage in negative campaigning based on strategic calculations, weighing anticipated gains against potential backlash (Lau and Pomper 2004). Attack messages can lower public evaluations of rivals and thereby boost one's own standing (Pinkleton 1997), but they also risk backfiring and damaging the sender's credibility (Roese and Sande 1993). The balance of these risks and rewards,

however, is not fixed: various factors shape when negativity is more or less attractive as a campaign strategy. Existing research has primarily emphasized two categories of influence—individual-level characteristics of candidates and contextual features of the electoral environment.

At the micro level, candidates' political profiles, personality traits, perceptions of campaign dynamics, social backgrounds, and resource availability influence their likelihood of going negative (Maier and Nai 2023). At the systemic level, features such as electoral disproportionality, party system fragmentation, and polarization have been found to affect campaign tone across countries (Papp and Patkós 2019). Further research links higher levels of negativity to majoritarian electoral rules, greater income inequality, ethnic divisions, and more individualistic societies (Maier and Nai 2022).

Less attention has been paid to how party-level characteristics influence the use of negative campaigning, particularly outside the U.S. context. Much of what is known stems from studies of American elections, where majoritarian rules and a two-party system encourage zero-sum competition. Within this setting, two robust predictors emerge. First, trailing candidates are more likely to go negative, while frontrunners often avoid risky strategies (Damore 2002; Lau and Pomper 2001; Walter, van der Brug, and van Praag 2014; Maier and Jansen 2017). Second, incumbents tend to emphasize achievements and avoid attacks due to higher reputational risks, while challengers—often with less visibility and governing experience—rely more on aggressive tactics (Druckman et al. 2009; Haynes and Rhine 1998; Fridkin and Kenney 2011).

These dynamics do not immediately translate to multiparty systems, where parties—rather than individual candidates—are the primary actors, and where the path to power often involves coalition-building. In proportional representation systems, electoral success does not guarantee executive authority. Campaign strategies must therefore account for post-election negotiations: overly negative campaigning, especially toward ideologically adjacent actors, may damage coalition prospects (Walter and Nai 2015). Moreover, voters in such systems have more alternatives, which increases the risk of defection in response to negativity (Walter and van der Eijk 2019; Galasso et al. 2023; Mendoza et al. 2024).

Under these conditions, familiar predictors like electoral competitiveness or incumbency offer limited explanatory power. Parties with few votes may still enter government through coalition deals, and the conventional incumbent–challenger divide becomes less relevant. A more useful distinction is coalition potential—the likelihood that a party will be included in government (Elmelund-Præstekær 2010; Walter and van der Brug 2013). This shifts the incentives: parties with governing prospects must balance criticism with the need to remain viable coalition partners, while those without such prospects can more freely adopt confrontational styles.

This divide often maps onto the distinction between mainstream and challenger parties (Vries and Hobolt 2020). The former typically have governing experience and a reputational interest in appearing competent and cooperative. The latter, being less integrated into governing coalitions, are freer to use aggressive rhetoric.

To explain variation in negativity among parties, we propose a framework grounded

in strategic incentives. Institutional position shapes both the potential costs of going negative and the need to cooperate post-election. Governing parties, or those seeking future participation in coalitions, are more likely to avoid antagonistic strategies to preserve their credibility and relationships (Walter and van der Brug 2013). In contrast, outsider or opposition parties—particularly those with limited governing experience—face fewer such constraints and can use negativity to gain attention and challenge the status quo.

H1: Parties with governing experience engage in less negative campaigning.

Strategic incentives are also shaped by parties' ideological profiles and communicative styles. Parties at the ideological margins often define themselves in opposition to the political center and use confrontational tactics to differentiate themselves. This oppositional stance is particularly pronounced when their coalition prospects are slim and reputational risks are minimal (Elmelund-Præstekær 2010; Walter and van der Brug 2013). Supporting this, Maier and Nai (2023) show that ideologically extreme candidates are more likely to attack, while Papp and Patkós (2019) link higher system polarization to a more negative tone.

H2: Parties further from the ideological center engage in more negative campaigning.

Populist parties exemplify conflict-driven communication. By framing politics as a struggle between a virtuous people and a corrupt elite (Mudde 2004), populists are incentivized to adopt an antagonistic style. Their outsider identity and anti-establishment discourse predispose them to use attacks more frequently, especially in media and digital arenas where such messages can rapidly attract attention (Engesser, Ernst, et al. 2017; Engesser, Fawzi, et al. 2017; Bracciale and Martella 2017). Negativity is thus central to how populist parties can define and perform their political identity.

H3: Populist parties engage in more negative campaigning.

Among populist actors, radical right populist parties are particularly incentivized to employ negativity. Their discourse is often driven by exclusionary nationalism, anti-immigration rhetoric, and a heightened sense of threat to the cultural or economic status quo – elements that naturally lend themselves to adversarial messaging. Moreover, their reliance on mobilizing resentment and moral outrage reinforces a style of campaigning that is intensely confrontational (Mudde 2007; Moffitt 2016).

H4: Radical right populist parties engage in more negative campaigning than other populist parties.

Data and method

We draw on van Vliet et al. (2020) which includes 18,066,672 tweets by 5,439 parliamentarians from 2017 to 2022. The data includes all tweets from all parliamentarians that had Twitter accounts in EU member states, candidate states, and EFTA countries where at least 45% of the parliamentarians used Twitter. We focus here on Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Iceland, Italy, Latvia, Netherlands, Norway, Poland, Slovenia, and Sweden. This enables measurement of negative campaigning across multiple election periods, including the COVID-19 period.

Twitter (now X) has held a special position in political communication and research (Jungherr 2016). Its affordances for brief, direct messaging that bypassed traditional media gatekeepers led to widespread adoption among journalists and politicians, extending its influence far beyond the platform itself (Enli and and Skogerbø 2013; Oschatz, Stier, et al. 2022). Unique among social media is how Twitter facilitated direct inter-politician interactions, both collaborative and adversarial (van Vliet et al. 2020; Keuchenius et al. 2021). These characteristics make Twitter a valuable data source for analysing party positions and communication strategies (Haselmayer 2019).

Based on the validation results, we employ the prompt used to replicate Petkevic and Nai (2022), as this most closely aligns with the conventionally used definition of Geer (2006). We make one minor adjustment, adding 'party' in the definition to better account for the more important role of parties in multiparty systems. The final prompt hence seeks to identify: 'the presence of explicit attack or critique toward opponent party or candidate.' (See also Supplementary Material.) Since the validation showed that the smaller model performed as well as or better than the larger model at a fraction of the cost, we employ gpt-4o-mini for the full dataset. The classification of the complete dataset cost US\$156.

A limitation of the analysis should be acknowledged. Due to the scope of the validation data, only ten of the sixteen languages used in the study were directly validated. Although the validation results indicate that classification accuracy was consistent across all tested languages, applying the model to the full Twitter dataset involves a degree of methodological uncertainty. Specifically, it requires the assumption that classification performance generalizes to the six unvalidated languages. There is, however, little reason to expect substantial degradation in performance. Existing research suggests that large language models tend to underperform primarily in less widely spoken languages (Rathje et al. 2024), which does not apply to the remaining European languages in our dataset. As an additional robustness check, we re-estimated the models excluding countries with unvalidated languages. The results remained broadly consistent, with the exception of a reduced effect of ideological extremism on negative campaigning (see Supplementary Material).

For the inferential analysis, we employed an OLS regression model to examine the predictors of negative campaigning, with the percentage of negative posts per party as the dependent variable. While modeling proportions with OLS can raise concerns—such as predictions falling outside the [0,1] range and potential non-linearity near the

boundaries—these issues are limited in our case, as observed values range from 0.03 to 0.57. Robustness checks using logit models are provided in the supplementary material. To account for party-level characteristics that may shape negative campaigning, we enriched the dataset with information from the Chapel Hill Expert Survey (Jolly et al. 2022), and cross-validated missing values using data from ParlGov (Döring and Manow 2024).

The model includes five key predictors:

- 1. Left–Right Ideology (LRGEN): This variable captures the party's overall ideological orientation on a 0–10 scale, where 0 indicates the extreme left and 10 the extreme right.
- 2. Ideological Extremism (Non-Centrist Position): Defined as the absolute distance from the ideological center, this variable is calculated as |5 LRGEN| and ranges from 0 to 5, with higher values indicating greater ideological extremism, regardless of direction.
- 3. Government Status (GOVT): A binary indicator of whether a party participates in government (1 = governing party; 0 = opposition).
- 4. Anti-Elite Salience (ANTIELITE_SALIENCE): This variable reflects the prominence of anti-elite and anti-establishment rhetoric in a party's discourse, ranging from 0 ("not important at all") to 10 ("extremely important"). It follows Mudde's (2004) minimalist definition of populism by focusing on the salience of anti-elite messaging rather than substantive policy content.
- 5. Party Family (FAMILY): Categorical classification of parties into one of 11 ideological families. The typology originates from Hix and Lord (1997) and has been refined by the CHES team.

The Twitter data were collected between 2017 and 2022, whereas the CHES data refer to 2019. This temporal mismatch introduces a degree of imprecision in the independent variables, as they do not capture within-period variation or temporal shifts. However, given that the CHES data fall near the midpoint of the Twitter collection period, and that most CHES indicators reflect relatively stable party characteristics, this limitation is considered minor.

The government status variable warrants specific attention. Because it reflects only a party's status in 2019 while the dependent variable spans 2017–2022, it is better interpreted as an indicator of "government experience" or "incumbent party type" rather than precise coalition membership at each time point. This interpretation is supported by the fact that government participation often persists across electoral cycles (Warwick 1996).

Some potentially relevant time-sensitive factors—such as electoral competitiveness or polling trends—are not included. However, prior research suggests that such campaign-specific dynamics play a more limited role in multiparty systems (Walter, van der Brug, and van Praag 2014; Elmelund-Præstekær 2010). Moreover, the focus of this study is on structural, longer-term party characteristics rather than short-term electoral fluctuations.

To account for unobserved heterogeneity at the national level, country fixed effects are included. Standard errors are clustered at the country level to address the nested structure of the data. As a robustness check, a multilevel version of the model was also estimated; results are reported in the Supplementary Material. Finally, independents and parties with fewer than 500 tweets were excluded from the analysis to reduce estimation noise due to high variance in small samples.

While our dataset consists of individual-level messages posted by parliamentarians, we aggregate these data to the party level for analysis. This decision rests on the assumption – well-grounded in research on parliamentary systems – that elected representatives typically act as strategic communicators embedded within party organizations. Their public messaging is shaped by coordinated party strategies, shared political objectives, and party discipline, particularly on highly visible platforms such as social media, where their statements are often interpreted as reflective of the party line. Aggregating to the party level allows us to identify systematic patterns in communication and relate them to party-level attributes – such as ideology, populism, and governing status – that are central to our theoretical framework. This approach also follows established research in comparative political communication, which has demonstrated that party-level characteristics are key predictors of strategic messaging behavior.

That said, several limitations of this approach merit attention. First, by aggregating tweets across the full time period, we abstract away from temporal variation and are unable to account for time-specific effects such as election campaigns, scandals, or political crises. While this allows for a structural analysis of party characteristics, future research should build on this by exploring how negativity fluctuates over time. Second, our dataset includes all tweets from parliamentarians, not just explicitly political messages. While this inclusive approach provides a comprehensive view of their communication practices, it also means that non-political content – such as greetings or personal updates – is included in the analysis. As a result, our estimates of negativity are likely to be conservative; a study focused solely on political messaging would likely reveal higher rates of negative campaigning. While such a analysis of the broader communication of politicians is valuable, care should be made when comparing the results against more narrowly defined campaign communication.

Results

To assess the level of negative campaigning across European states, Figure 1 shows the percentage of negative tweets by country, distinguishing between original tweets and retweets. As the figure shows, original tweets tend to be characterized by more negative campaigning than retweets in all countries except the Netherlands. This corroborates Licht et al.'s (2024) finding that retweets often contain non-political content such as follower spam or event links rather than political speech. While some politicians, notably Trump in the US (Brookings Institution 2020) and Wilders in the Netherlands (NOS

2024), have strategically used retweets to amplify extreme viewpoints from supporters, this pattern appears uncommon across European parliamentarians in the dataset.

Figure 1: Usage of negative campaigning on Twitter between 2017 and 2022 across European countries split out by original tweets and retweets.

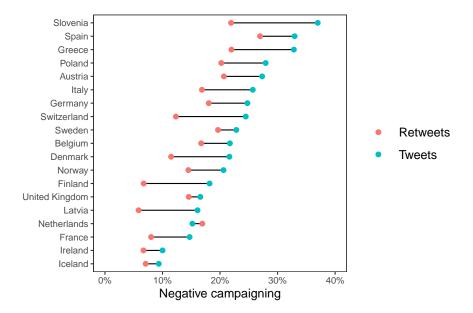


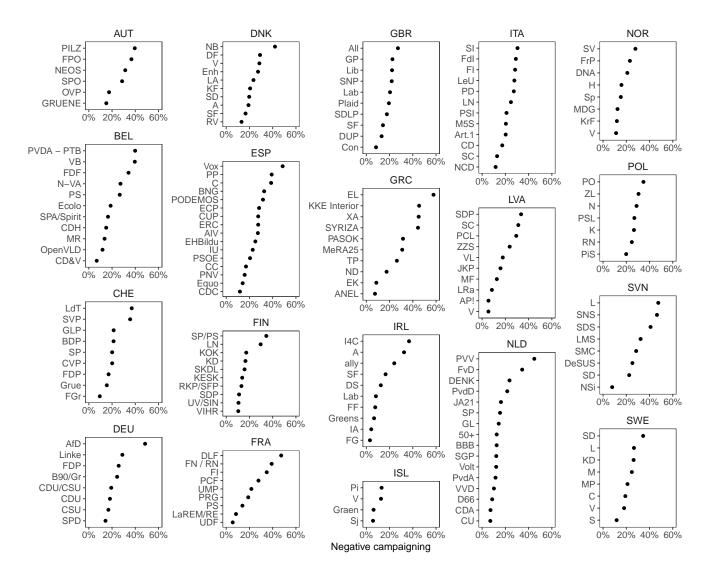
Figure 1 reveals substantial variation in the levels of negative messaging in tweets across countries, ranging from lows of 9 to 10 percent for Iceland and Ireland to highs of 32 to 37 percent for Spain and Slovenia.

These findings reflect two important factors that may lead to varying levels of negative campaigning. First, national social norms (Oschatz, Maier, et al. 2024) and political culture (Debus and Tuttnauer 2024) create different expectations for negative campaigning across countries. Depending on the national context, negative campaigning is more accepted or less likely to be punished by voters (Oschatz, Maier, et al. 2024). The structure of political coalitions also matters. In ideologically homogenous coalitions, voters may even reward attacks on coalition partners more (Debus and Tuttnauer 2024). Second, levels of political professionalisation vary considerably. Larger countries show much higher tweet volumes per party, with the UK leading at 2.4M tweets, followed by France (0.9M), Poland (0.7M), and Germany (0.6M) (see also Supplementary Material). More professionalised campaigns with dedicated social media teams may deploy negative campaigning more strategically. (Following Licht et al. (2024), we focus only on original tweets in subsequent analyses.)

To further investigate the relationship between parties and negative campaigning, Figure 2 shows average negative campaigning per party within countries.

The figure reveals several patterns. First, governing parties or those with government experience generally show lower negative campaigning levels. This is evident in the

Figure 2: Usage of negative campaigning by parties in Europe on Twitter between 2017 and 2022.



Netherlands where the four coalition parties (VVD, D66, CDA, CU) have the lowest rates, as well as in Germany (CDU, CSU, SPD), Poland (PiS), and Sweden (S). Meanwhile, challenger or opposition parties tend to have the highest levels within countries.

Second, there is no strong association between political ideology and the likelihood of engaging in negative campaigning, although right-wing parties tend to use such strategies somewhat more frequently. For instance, far-right parties exhibit the highest probabilities of negativity in Denmark (*Nye Borgerlige*) and Sweden (*Sverigedemokraterna*), while in Norway, the left-wing *Sosialistisk Venstreparti* stands out as the most negative. In Greece, the right-wing *Elliniki Lisi* (EL) leads, whereas in Belgium, the left-wing *PVDA-PTB* ranks highest, followed closely by the right-wing *Vlaams Belang*. In Germany, the far-right *Alternative für Deutschland* shows the highest level of negativity, but it is closely followed by the left-wing *Die Linke*.

Additionally, these results hint at deliberate strategic use of negative campaigning. In Switzerland, *Lega dei Ticinesi* and *Schweizerische Volkspartei*, parties with electoral alliances, show similarly high levels of negative campaigning. Similarly, Germany's *CDU* and *CSU* demonstrate coordinated low negativity.

The UK stands out for its noticeably lower levels of negative campaigning, despite being a majoritarian system that should theoretically produce higher negativity. Two factors may explain this: first, UK politicians are frequent users of Twitter (shown in the high tweet volume, with 2,021,218 messages) which may imply that many messages are constituency-focused rather than partisan, thus diluting the percentage of negative tweets. Second, challenger parties like *UKIP* and the *Brexit Party*, likely to have higher negativity rates, are missing because they were not in national parliament during data collection.

We now turn to the inferential results, presented in Table 4. Regarding party-level characteristics, there is strong evidence that government participation is associated with a lower use of negative campaigning. On average, governing parties engage in negative campaigning 7 percentage points less than opposition parties. Given that the government status variable reflects only parties' status in 2019, while the Twitter data spans 2017–2022, this likely captures a broader incumbency effect. This finding is consistent with previous research suggesting that incumbents are more risk-averse, preferring to highlight their governing record rather than attack rivals, as they face greater reputational costs from negative campaigning. In contrast, challenger parties are less constrained and thus more inclined to employ negative rhetoric against mainstream competitors. This confirms hypothesis H1.

Parties positioned further from the ideological center are likewise more prone to negativity. This confirms hypothesis H2. This association holds across both ends of the political spectrum and likely reflects lower coalition potential and a strategic emphasis on critique over cooperation. However, when ideology is measured using the left–right scale (Model 2), right-wing parties appear slightly more inclined toward negative campaigning, though the effect is modest and less robust. (See the supplementary material for standardized beta coefficients.)

Populist parties also exhibit a higher tendency to engage in negative campaigning,

	Model 1	Model 2
(Intercept)	17.77*	16.81*
_	[14.96; 20.57]	[12.80; 20.83]
Government experience	-6.57^*	-7.40^{*}
	[-9.25; -3.90]	[-10.17; -4.63]
Anti-elite salience	1.55^{*}	1.87*
	[0.63; 2.46]	[1.21; 2.52]
Ideological extreme	1.64^{*}	
	[0.15; 3.13]	
General Left-Right		0.58^{*}
		[0.12; 1.04]
R^2	0.58	0.58
Adj. R ²	0.51	0.51
Num. obs.	151	151
RMSE	7.63	7.68
N Clusters	19	19

^{*} Null hypothesis value outside the 95% confidence interval.

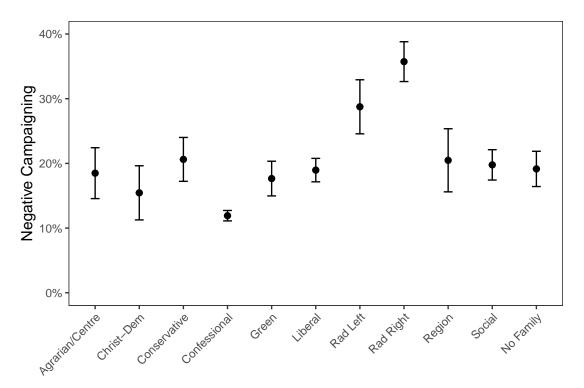
Table 4: Main Model of the Effect of Party Characteristics on Negative Campaigning in Europe. Country-fixed effects not displayed. Standard errors are clustered by country

using such strategies approximately 2 percentage points more than non-populist parties. This is in line with expectations that populist actors use divisive, anti-elite rhetoric to draw sharp distinctions between themselves and establishment parties, reinforcing their outsider appeal. This confirms hypothesis H3.

To further explore the role of ideology, we examine the effect of party family while controlling for government participation and populist orientation. The continuous ideology variables are excluded from this model to avoid multicollinearity. Figure 3 presents the average predicted levels of negative campaigning across party families, holding government status and populism constant.

The results underscore the distinct position of radical right parties, which display the highest level of negative campaigning (35.7%). They are followed by radical left parties (28.8%), with conservative (20.6%) and regional parties (20.5%) also showing somewhat elevated levels. These findings support the expectation that ideologically extreme parties—whether on the left or right—engage more frequently in negative campaigning, likely due to their limited coalition potential. At the same time, the radical right stands out for its particularly pronounced use of negative rhetoric, suggesting a uniquely adversarial communication strategy within this family. This confirms hypothesis H4.

Figure 3: Average predicted probability of negative campaigning by party family, controlling for government participation and anti-elite position. Error bars show 95% confidence intervals. The confessional party family has only 3 observations, with 2 located in the Netherlands. This geographic concentration may affect the reliability of standard error estimates for this category.



Discussion and Conclusion

While negative campaigning has become a prominent topic in political communication research, the field has long faced methodological constraints. Traditional approaches—such as manual annotation or supervised machine learning—are either prohibitively expensive or lack the accuracy and generalizability required for robust cross-national comparisons. As a result, most studies have been confined to single-country contexts, particularly the United States, limiting our understanding of how negativity operates in broader institutional and cultural settings.

This paper makes two central contributions to overcome these barriers. First, it introduces zero-shot large language models (LLMs) as a transformative tool for identifying negative campaigning. By leveraging their multilingual and contextual reasoning capabilities, we show that zero-shot LLMs enable high-accuracy annotation across languages at minimal cost—eliminating the need for language-specific training data or large annotation teams. Second, we apply this method to conduct the largest cross-country comparative study of negative campaigning to date, shedding new light on how party-level characteristics shape campaign negativity in multiparty systems.

To assess the reliability of this approach, we evaluated the performance of zero-shot LLMs against established manually coded datasets from Petkevic and Nai (2022) and Klinger et al. (2023). The results demonstrate that zero-shot LLMs perform on par with native-speaking human coders and outperform conventional supervised machine learning models across all ten languages tested. While prior studies have highlighted the high performance of LLMs for text annotation (e.g., Törnberg 2024b), this paper is among the first to demonstrate their viability for producing valid and scalable cross-country data for political communication research.

The implications extend beyond scale and accuracy, as LLMs also enhance conceptual transparency and replicability. Manual coding often relies on developing shared but largely implicit understandings among coders, which are difficult to fully capture in written codebooks (van Atteveldt 2021). This can lead to inconsistent operationalizations across studies and undermine construct validity — as illustrated by the starkly different levels of negativity reported by Klinger et al. (2023) and Baranowski (2023) for the same campaign (7% vs. 17%). LLMs, in contrast, require researchers to make their operationalizations fully explicit through the formulation of prompts, making the classification process more explicit and replicable. If implementation details are shared, results can be reproduced across studies, contexts, and languages with minimal variation. Far from triggering a "reproducibility crisis" (Ollion et al. 2023), LLMs may — when appropriately applied — in fact mark a step forward in the standardization and transparency of text-as-data.

Beyond its methodological innovation, this paper advances the substantive literature by bringing new data to the long-standing empirical question of what determines the choice to make use of negative campaigning. While existing research has often focused on either candidate-level or system-level predictors, and has focused primarily on the two-party US system, our study highlights the importance of party characteristics—such

as ideology, populism, and governing status—especially in proportional and coalition-based systems where parties, rather than individual candidates, are the main political actors.

Using a dataset of 18 million tweets from parliamentarians in 19 countries between 2017 and 2022, we test a framework grounded in strategic incentives. The results offer robust evidence for our theoretical expectations: parties further from the ideological center are more likely to employ negative campaigning, with radical left and especially radical right populist parties standing out. In contrast, parties with governing experience are significantly less likely to go negative, consistent with their need to maintain coalition potential and institutional credibility.

This study thus not only contributes new theoretical insights into the dynamics of negative campaigning in multiparty systems but also demonstrates the practical feasibility of using LLMs for large-scale, cross-country content analysis. As LLMs dramatically reduce the cost and complexity of multilingual text classification, they create new opportunities for systematic research on political communication—across time, across regions, and even across regime types.

Future research can build on these findings to explore negativity beyond democratic contexts, investigate temporal dynamics in negativity during crisis periods, or expand the analysis to include visual and multimodal political content. Most importantly, the methodological shift introduced here opens the door to a new generation of political communication research: one that is global in scope, transparent in method, and empirically grounded in rich, multilingual data. The integration of LLMs is not just a technical improvement; it represents a foundational technical development that can redefine political communication research.

Data Availability Statement

Data sharing not applicable — no new data generated. See van Vliet et al. (2020) and Klinger et al. (2023), and Petkevic and Nai (2022).

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