

Game of Tones

A longitudinal analysis of media tone
towards political parties in Flemish
newspapers (2004-2024)

Janne Verschraegen

s0213531

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Supervisor

Prof. dr. Stefaan Walgrave

Co-evaluator

Priscilla Hau

1 Abstract

Hoe politieke partijen in de media worden voorgesteld, beïnvloedt hoe burgers hen waarnemen, beoordelen en uiteindelijk ook stemmen. Evaluatieve toon functioneert daarbij als een belangrijke interpretatieve shortcut. Deze studie onderzoekt hoe de toon van nieuwsberichtgeving over Vlaamse politieke partijen geëvolueerd is tussen 2004 en 2024, en in welke mate er structurele verschillen bestaan tussen partijen en tussen kranten. Met behulp van een RoBERTa-taalmodel wordt op zinsniveau het sentiment gemeten in meer dan 275.000 artikels uit zeven Vlaamse kranten. De analyse toont dat negatieve berichtgeving structureel overheerst, maar dat deze geleidelijk is afgenomen over de tijd. Tegelijkertijd worden systematische verschillen vastgesteld tussen partijen en tussen kranten. Vlaams Belang en N-VA worden over de hele periode het meest negatief voorgesteld, terwijl Groen vaker voorkomt in positieve contexten. Kwaliteitskranten zoals De Morgen, De Standaard en De Tijd zijn in het algemeen kritischer dan populaire kranten zoals Het Laatste Nieuws, Het Nieuwsblad, Gazet van Antwerpen en Het Belang van Limburg. Opvallend is dat die kwaliteitskranten relatief minder negatief zijn over Vlaams Belang dan de populaire kranten. Hoewel alle partijen een lichte afname in negativiteit vertonen, daalt het negatieve sentiment tegenover Vlaams Belang het sterkst, wat mogelijk wijst op een proces van normalisering. PVDA vormt hierop een uitzondering: de partij is de enige waarvoor het negatieve sentiment (licht) toeneemt over de tijd. Beperkingen van het onderzoek liggen in het feit dat het model niet gefinetuned werd op de Vlaamse politieke context, en dat de analyse geen objectieve maatstaf hanteert voor bias, maar enkel patronen van toon in kaart brengt. Toekomstig onderzoek kan nagaan welke factoren bijdragen aan verschillen in toon, bijvoorbeeld door te controleren voor electorale macht, partijcommunicatie en issue coverage.

Trefwoorden: media bias; sentiment analysis; tone; political news; newspapers; Belgium; computational text analysis

2 Preface

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4 Introduction

“[...] that Bart Brinckman of this newspaper [*De Standaard*] has been granted free rein to pursue a personal vendetta against me.”

— Bart De Wever, former leader of the New Flemish Alliance (N-VA) (Belga, 2017)

“But hey, according to the traditional media, we are the ‘populists’, simply because we persist in digging deeper...”

— Peter Mertens, leader of the Workers’ Party of Belgium (PVDA/PTB) (Mertens, 2020)

“Tell me that journalism in Flanders is really ‘*regimepers*’ (regime press) without saying it is ‘*regimepers*’ 🗨️🗨️ @HLN_BE @Nieuwsblad_be @tijd @demorgen @destandaard @hbtv”

— Tom Van Grieken, leader of Vlaams Belang (Van Grieken, 2023)

Criticism of the media is far from new. In Belgium as elsewhere, politicians from across the ideological spectrum have questioned the performance and neutrality of journalism. Such criticism concerns a wide range of issues, including the selection of topics, accuracy of reporting, sensationalist headlines, or editorial framing. In democratic societies where press freedom is a cornerstone, questioning journalism helps holding it accountable (Wyatt, 2019). However, over the past decades claims of media bias have become more frequent and more central in political rhetoric (Domke et al., 1999).

Not only in the United States, but increasingly in Belgium as well, politicians suggest that certain news outlets systematically favor or attack particular parties. For example Bart De Wever, current Prime Minister of Belgium, once claimed that the newspaper *De Standaard* “publishes just about anything, as long as it’s against N-VA” (Cochez, 2015). Such statements are part of a broader trend across Western democracies, where journalists are more often accused of partisanship, even without clear evidence (De Mulder & Paulussen, 2021; Groeling, 2013; Soontjens, Beckers, & Van Remoortere, 2023).

Public criticism of the media by political leaders can have far-reaching consequences. When politicians repeatedly challenge journalistic neutrality, they risk undermining public trust in news institutions and weakening the media’s role as a democratic watchdog (Smith, 2010). This raises a fundamental question: are these criticisms simply a matter of perception, or is there empirical evidence that some parties are systematically favored or disfavored by the media? Given that many citizens depend on the media to form political judgments, even subtle forms of bias can shape attitudes, engagement, and voting behavior (Druckman, 2005; Druckman & Parkin, 2005; McCombs, 2005; Shultziner & Stukalin, 2021). Understanding how journalists frame political actors is therefore essential to evaluating the press’s democratic function and its influence (Eberl, Boomgaarden, et al., 2017).

In the Flemish context, recent research by Soontjens, Beckers and Van Remoortere (2023) shows that right-leaning politicians, in particular, perceive the media as structurally biased against them and their positions. To challenge such perceptions, empirical evidence is needed to demonstrate that this is not the case. Their study indeed found little support for overt partisan bias in media content, but the authors also caution that

bias may operate through more subtle mechanisms, such as tone or framing, which their research did not capture. This highlights the need to move beyond general claims and to examine bias in a more precise and structured way.

When scholars and politicians speak of media bias, they usually refer to two distinct aspects. The first concerns *how much* coverage parties receive, often referred to as visibility bias or selection bias. This form of bias has been the subject of considerable research in Belgium. Annual monitoring reports by Van Aelst et al. (2024), among other studies, indicate that certain parties, particularly Vlaams Belang and to a lesser extent PVDA, have historically received less media attention than their electoral weight would justify. Although this visibility gap has narrowed in recent years, it remains a point of concern, especially among parties that feel excluded from mainstream coverage. The importance of visibility is well established: numerous studies have demonstrated that media exposure significantly influences voter attitudes and can directly impact how well a political party performs at elections (Geiß & Schäfer, 2017; Hopmann et al., 2010; Oegema & Kleinnijenhuis, 2000; Van Aelst et al., 2008).

The second type of bias concerns *how* parties are portrayed, often referred to as tonality or statement bias. This form of bias is more difficult to measure and has received less systematic attention in Belgian media research. It relates to how the media frame a political actor and whether they systematically present some parties in a more favorable setting compared to others. The tone of coverage matters greatly because it lays out the foundations for the audience to interpret the news in. Positive coverage of political actors increases electoral support, while negative coverage tends to decrease it (Aaldering et al., 2018). News tone shapes political attitudes, influences voting behavior, and affects how satisfied citizens are with political leaders (Bos et al., 2011; De Vreese et al., 2011).

Despite growing insight into the effects of tonality bias, the empirical evidence on it remains mixed. Some studies suggest that mainstream or governing parties are treated more favorably, while others show the opposite pattern or no clear differences at all. Across countries, there is evidence of systematic variation in tone depending on media outlet, party ideology, or audience profile, as shown in contexts such as Austria (Lengauer & Johann, 2013), Germany (Falck et al., 2020) and Turkey (Çarkoğlu et al., 2014). These diverging findings suggest that the presence and direction of tonality bias may be highly context-dependent.

In the Flemish case, the picture is equally inconclusive. The recent study by Soontjens, Beckers and Van Remoortere (2023), based on a manual coding of more than 4,000 headlines, found no systematic differences in tone between parties, newspapers, or time periods. However, their analysis focused exclusively on headlines and lacked sufficient observations for some parties, such as PVDA, to allow meaningful comparison. As such, it offers limited insight into the broader tone and framing of political actors across full news texts.

By contrast, earlier research by Junqué de Fortuny et al. (2012), using large-scale text mining techniques, did identify substantial tone differences during the political crisis of 2011, with particularly negative sentiment towards Vlaams Belang and, to a lesser extent, N-VA. Similarly, Schafraad et al. (2012; 2013) found that Vlaams Belang was systematically framed in negative or stigmatizing terms over a longer time span (1987–2004), with a consistent treatment as ‘controversial outsider’.

These contrasting findings between earlier and more recent research highlights the need for broader empirical analysis. Yet most existing studies, both in Flanders and internationally, remain limited in scope: they focus on short time frames, often limited to a single campaign, or look at one specific issue over multiple years (Enevoldsen & Hansen, 2017; Entman, 2010). There is a lack of longitudinal research employing large datasets to examine how tone evolves over time, across parties, and across different types of newspapers. To my knowledge, only a handful of studies have done this (Dallmann et al., 2015; Falck et al., 2020; Purohit et al., 2025), with Junqué de Fortuny et al. (2012) being the only one attempting this in the Flemish context, though it only covers one year.

Together, these studies provide a fragmented and at times contradictory picture of how political parties are portrayed in Flemish media. Differences in methodology, time periods, and empirical focus, make it difficult to draw firm conclusions about the presence, direction, or consistency of tonality bias. In a media landscape often described as politically balanced and professionally restrained (Soontjens & Van Erkel, 2022), it remains unclear how parties are framed in everyday reporting. This uncertainty calls for a more comprehensive, longitudinal, and data-driven analysis.

Building on these gaps, this thesis asks whether Flemish newspapers have portrayed political parties in a more positive or negative tone over the past two decades. To do so, it applies large-scale sentiment analysis to a corpus of over one million sentences from full-text newspaper articles published between 2004 and 2024. Unlike previous research, often limited to headlines, short periods, or manual coding, this study adopts a computational approach covering multiple parties, newspapers and time periods. Using natural language processing techniques with a pre-trained RoBERTa model, it investigates how the tone of political reporting has evolved for all seven major Flemish parties, in both online and print articles. In recent years, sentiment analysis of political news has become an increasingly valid method to uncover media bias (Enevoldsen & Hansen, 2017; Falck et al., 2020; Rawat & Vadivu, 2022).

5 Theoretical framework

5.1 Media bias

Media bias is one of the most widely discussed and researched concepts in political communication studies. Given the sheer volume of work on this topic, especially in recent years, it is impossible to do full justice to the field within the scope of this thesis. Therefore, this chapter will briefly introduce the most essential concepts and foundational research needed to understand the framework for this study. For more detailed overviews of media bias and their different types, see D'Alessio and Allen (2000), Hopmann et al. (2012), Groeling (2013), Eberl (2017), Castro (2021) and more.

Media bias generally refers to systematic patterns in news reporting that advantage or disadvantage particular political actors, ideologies, or issue positions (Entman, 2007). In liberal democracies, journalism is normatively expected to function as a neutral and independent intermediary between politics and the public. However, scholars have long argued that this ideal of objectivity is difficult to achieve in practice (Schudson & Anderson, 2009). Journalists inevitably make editorial decisions about what stories to report, how to frame them, and which voices to include. These decisions are shaped not only by professional norms and ethical standards, but also by newsroom routines, economic pressures, and broader institutional structures (Carlson & Lewis, 2015; Shoemaker & Reese, 1996).

Importantly, media bias can be understood in both normative and empirical terms. Normatively, it touches on questions of fairness, pluralism, and the democratic function of journalism (Hackett, 1984). Empirically, it concerns observable patterns in content that systematically favor or disadvantage certain actors or ideas. The distinction between *objective bias* and *perceived bias* is central in this context. While objective bias refers to measurable imbalances in coverage, perceived bias relates to how audiences or political elites interpret that coverage. These two dimensions do not always align. Decades of research, including the well-known “hostile media effect,” have shown that individuals frequently perceive media coverage as biased against their own views, even when it is objectively balanced (Vallone et al., 1985). This suggests that perceptions of bias are shaped not only by media content itself, but also by the audience’s political orientation, prior beliefs, and trust in journalism (Elejalde et al., 2018).

These conceptual distinctions are not only relevant for scholarly debate, they also have direct implications for how media influence democratic life. In modern democracies, most people rely on the news to help them understand politics, judge political leaders, and decide how to vote. This is especially true in political systems with many parties like Belgium and Flanders, where it can be difficult for citizens to keep track of all the political actors and issues (Shehata & Strömbäck, 2014; Strömbäck, 2005). Because of this, the way the media cover politics, how often they report on parties, and in what tone, can shape public opinion in uneven ways, influencing vote choice, trust in institutions, and perceptions of legitimacy (Brosius et al., 2019; Hopmann et al., 2010; van Spanje & de Vreese, 2014).

The nature and intensity of media bias vary significantly across countries, depending on how media systems are structured. In the United States, where journalism is highly commercialized and ideologically segmented, partisan bias is often more explicit and prevalent (Entman, 2010; Newman & Fletcher, 2017; Niven, 2003). In

European contexts, bias tends to be more constrained by professional norms, though it is by no means absent. Hallin and Mancini (2004) distinguish between *democratic-corporatist* systems, as found in Belgium, the Netherlands, and Scandinavia, and *polarized pluralist* systems, such as those in France or Italy. The former are characterized by strong public broadcasting, institutionalized press freedom, and high levels of journalistic professionalization, while the latter exhibit greater political parallelism and less separation between media and political elites.

However, even in highly professionalized media systems, subtle forms of bias can persist. Research has shown that, even in the absence of explicit partisanship, media outlets may still exhibit systematic differences in how much attention they devote to particular actors and how they portray them (Enevoldsen & Hansen, 2017; Lengauer & Johann, 2013). Because these forms of bias are often harder to detect, especially in media that appear balanced on the surface, systematic analysis of evaluative tone remains essential (Eberl, 2017).

Belgium is often considered an unlikely case for partisan media bias (Soontjens & Van Erkel, 2022). Its media system aligns with the democratic-corporatist model, combining a strong public broadcaster with a historical tradition of press-party ties and a high degree of journalistic professionalization in recent decades (De Bens & Raeymaeckers, 2007). In Flanders, overt political alignment has largely disappeared from the mainstream press, and media organizations emphasize formal norms of balance and objectivity (De Swert, 2011).

Nonetheless, recent research shows that concerns about bias still dominate, among citizens, politicians, and even journalists themselves. Right-wing elites in particular frequently accuse the press of ideological hostility (De Mulder & Paulussen, 2021; Soontjens, Van Remoortere, & Walgrave, 2021), while survey studies show that many journalists perceive structural imbalances in how parties are covered, with mainstream parties receiving more favorable treatment and radical or non-traditional actors being disadvantaged (Soontjens, Beckers, Walgrave, et al., 2023).

These findings highlight the need to distinguish between perceived and actual bias. While perceptions influence political trust, media credibility, and elite-media relations, they do not necessarily point to actual inequality in coverage (Soontjens, Van Remoortere, & Walgrave, 2021). Even when bias is present, it often operates through subtle cues such as tone, word choice, or framing, which are difficult to detect systematically (Lazaridou & Krestel, 2016). In recent years, this has led to the development of increasingly fine-grained typologies of bias, each referring to a distinct stage of the news production process (Castro, 2021; Groeling, 2013).

Among the various forms of media bias, two have become especially central in empirical research: visibility bias and tonality bias. The first concerns how much coverage a political actor receives, the second refers to the evaluative tone of that coverage. Whereas visibility reflects the quantity of exposure, tonality introduces a qualitative dimension by assessing how actors are portrayed. Although these forms often overlap in practice, they are analytically distinct and relatively easier to measure through large-scale content analysis.

Other types of bias, such as agenda bias, framing bias, or gatekeeping bias, have also been identified in the literature (Eberl, Boomgaarden, et al., 2017; Entman, 2007; Hopmann et al., 2012). These refer to decisions about which issues are prioritized, how events are interpreted, or which voices are included or excluded. While important, they are more difficult to measure systematically, and fall outside the scope of this study.

This thesis focuses specifically on tonality bias, which remains underexplored in the Flemish context. Concerns about visibility bias have already been empirically substantiated. Annual monitoring reports of the public broadcaster (Van Aelst et al., 2024), as well as large scale analyses of the written press (Soontjens, Beckers, & Van Remoortere, 2023), have shown that the media attention for political actors largely reflects political reality, with governing parties receiving more coverage. For tone, however, no comparable large-scale, systematic analysis exists to date. The next section elaborates on the concept of tonality bias and explains why it is central to this study.

5.2 Tonality bias

Tonality bias, also referred to as statement bias, plays a significant role in shaping public perceptions of political actors and parties. It is defined as systematic differences in the evaluative tone of media coverage of political figures, parties, or events (Eberl, Wagner, et al., 2017). Unlike visibility bias, which concerns how much attention an actor receives, tonality bias affects how positively, neutrally, or negatively those actors are portrayed in the media. While it does not necessarily distort factual accuracy, it can subtly affect audience perceptions by consistently casting some actors in a more favorable or unfavorable light.

Tonality bias can be explicit, through direct positive or negative assessments, or more implicit, embedded in framing choices, word selection, and image portrayal (Entman, 2010; Hehman et al., 2012). Most studies operationalize it by analyzing tone in either individual sentences or full news articles, using either manual or automated content analysis (de Veen & Thomas, 2022; Van Remoortere & Vliegthart, 2024; van Spanje & de Graaf, 2018). When the tone systematically favors or disfavors particular parties or ideologies, it can be considered a form of partisan media bias.

This form of bias is particularly relevant because tone functions as a powerful interpretive shortcut for news consumers. For most people, the media is their primary or only source of political information. As Hopmann et al. (2010) note, citizens rarely encounter party representatives directly and therefore rely heavily on how the media depicts them. In this context, tone becomes a key framework for evaluating whether a party is competent, trustworthy, or aligned with the voter's interests (De Vreese et al., 2011; Zaller, 1992).

Empirical studies confirm that repeated exposure to positive or negative portrayals can shape both short-term and long-term voter attitudes. One of the earliest and most influential contributions by Norris et al. (1999) found that positive media tone towards a political party leads to more favorable evaluations among voters. Similarly, Kleinnijenhuis et al. (2007), examining the Dutch 2003 elections, concluded that news about parties' successes and failures, more than issue coverage, has the greatest influence on electoral evaluations.

In the longer term, Brettschneider (2002) found that in Germany the tone of media evaluations correlated closely with public satisfaction or dissatisfaction with party leaders over time. Even minor evaluative terms can influence public opinion, particularly among voters with lower political knowledge or weaker party attachments (Eberl, 2017). Studies investigating both visibility bias and tonality bias find that tone often has a greater impact on voting behavior than exposure alone, and that these biases are not necessarily consistent in their effects (Eberl, Boomgaarden, et al., 2017).

Tonality bias has been documented across a wide range of countries and political contexts. In the United States and the United Kingdom, partisan divides in media tone are well established, particularly in outlets such as Fox News and The Daily Mail (Groeling, 2013; Newman & Fletcher, 2017). In Denmark, Green-Pedersen et al. (2017b) found that while government actors often appeared in negatively toned news stories, their presence was associated with slightly more positive coverage compared to similar stories without them.

However, media coverage in Austria displayed a reversed pattern. Lengauer et al. (2012) found that opposition parties received more positive treatment, while governing parties, especially the conservative ÖVP, were systematically portrayed more negatively. Tone also varied considerably between Austrian newspapers, pointing to outlet-level differentiation. A similar dynamic was found in Turkey, where Çarkoğlu et al. (2014) demonstrated that evaluative tone closely reflected the vote intentions of each outlet's readership. Together, these studies suggest that tonality bias is shaped by both institutional media structures and party-specific characteristics.

In Flanders, tone has also received some empirical attention, but research remains limited and inconclusive. Some studies point to systematic negativity towards radical-right parties (Junqué de Fortuny et al., 2012; Schafraad et al., 2012), while more recent work found no clear patterns across parties or newspapers (Soontjens, Beckers, & Van Remoortere, 2023). However, these studies focus on headlines or short periods, and lack the scale to detect structural trends. This study addresses that gap through sentence-level sentiment analysis of over one million newspaper sentences for the past two decades (2004–2024), using a NLP model to examine how tone varies across parties, newspapers, and time.

Although situated within the broader field of media bias research, this study does not measure bias in the normative sense of unfair or intentionally skewed coverage. Instead, it focuses on the evaluative tone in political news reporting: how political actors are portrayed as positive, neutral, or negative. Such tone differences may suggest imbalance but are not necessarily signs of partisanship. As Junqué de Fortuny et al. (2012) point out, negative tone does not always indicate bias as some political actors naturally attract it due to their actions or statements. For instance, an article criticizing a political party's corruption scandal may appear strongly negative, but if the reporting is factual, it does not necessarily constitute tonality bias or partisanship.

This study does not assess journalistic intent or subjectivity, nor does it make normative claims about the presence of bias in the Flemish press. The measurement of tone should be understood as an associative measure (i.e. a party is associated with a negative image when most of its coverage contains negative content). No conclusions can be made about whether that image is built by the media or by the party's own actions, only that it *exists*. Nonetheless, recent research by Falck et al. (2020) in Germany strengthens the argument that sentiment analysis is a valid method for detecting structural patterns that may indicate political bias.

The following sections examine how tone is influenced by factors such as negativity dominance, temporal dynamics, party characteristics, and newspaper profiles. Whether these patterns reflect underlying media bias or are driven by external factors, such as party behavior or issue salience, falls outside the scope of this study. Further research is needed to establish causal explanations.

5.3 Factors influencing tone

5.3.1 Negativity dominance

The tone of political coverage is shaped by a variety of internal and external factors. One of the most consistent findings in political communication research is the tendency towards negativity dominance, which refers to the prevalence of negative tone over positive tone in political news. This reflects a broader negativity bias in journalism, whereby conflict, failure, and controversy are more likely to be reported on than consensus, achievement, or routine governance (Lengauer et al., 2012; Soroka, 2014; Vliegenthart et al., 2011). Negative events are considered more newsworthy, while political stability or effectiveness is often seen as less urgent or engaging to cover.

This pattern has important implications. Studies show that negative information carries more weight than positive information in shaping public opinion (Eberl, 2017; Van Remoortere & Vliegenthart, 2024). At the same time, most journalists, particularly in Belgium, strongly emphasize their duty to inform citizens in a reliable and objective manner (Van Leuven et al., 2019). As a result, most tone analyses find that neutral coverage is the most frequent overall sentiment, but that negative tone is significantly more common than positive tone (Çarkoğlu et al., 2014; de Vries, 2022; Soontjens, Beckers, & Van Remoortere, 2023).

Hypothesis 1: The tone of political news coverage is more negative than positive.

5.3.2 Party characteristics

In addition to general negativity, the tone of political coverage is also shaped by characteristics of the parties themselves. Not all parties are covered in the same way: their status, ideology, and position within the political system can influence how they are portrayed. While media visibility tends to favor governing parties, a phenomenon often referred to as the incumbency bonus, there is no clear consensus on whether this also holds true for tone (Green-Pedersen et al., 2017a).

Some studies find that government parties are framed in a somewhat more positive light (Green-Pedersen et al., 2017b), while others report the opposite, with incumbents, especially conservatives, receiving more critical treatment (Lengauer & Johann, 2013). These divergent findings suggest that tone is not determined by government status alone, but may also depend on other party characteristics, such as ideological orientation or association with particular issues.

Perceptions of ideological bias further complicate the picture. In many Western democracies, citizens, particularly those on the political right, believe that mainstream media favor left-leaning parties (Eberl, 2019; Lee, 2005). This perception is partly supported by evidence and is correlated with the fact that journalists tend to hold more left-liberal views than the general population (De Clercq & Paulussen, 2007; Kirkegaard et al., 2021).

Similar patterns are observed in Belgium. Right-wing politicians and voters often perceive the Flemish press as biased against their views (Soontjens, Beckers, & Van Remoortere, 2023). While journalists in Belgium do indeed lean left on average, many report actively trying to counterbalance their personal views to avoid accusations of partisanship (Soontjens, Beckers, Walgrave, et al., 2023). Interestingly, journalists themselves believe that their outlets are most favorable towards the right-wing party N-VA, while the most extreme parties Vlaams Belang, and to a somewhat lesser extent PVDA, are viewed as structurally disadvantaged.

These perceptions reflect broader ideas about how political outsiders are treated in the media. In Flanders, Vlaams Belang (VB) has long been the clearest example. Positioned at the radical-right edge of the spectrum and excluded from coalition politics through the cordon sanitaire, the party has often been framed in stigmatizing ways. Schafraad et al. (2012) showed that between 1987 and 2004, Flemish newspapers portrayed Vlaams Belang (then Vlaams Blok) as a ‘controversial outsider’ with associations of being anti-democratic and xenophobic. A similar tendency has been observed in Germany, where recent research confirms a negative media bias towards the populist radical-right AfD in terms of tone and coverage (Falck et al., 2020).

However, this dynamic may not be exclusive to the radical right. The same German study also identified predominantly negative sentiment towards Die Linke, a left-wing party that can be seen as populist (Siefken, 2025). This suggests that parties perceived as ideologically extreme or anti-establishment tend to receive harsher media treatment in terms of tone. In the Flemish context, the radical-left PVDA represents a comparable case. While the party has existed for decades, it only began to gain substantial electoral momentum around 2012 under the leadership of Peter Mertens. Since then, it has positioned itself as a sharp critic of the political mainstream (Delwit, 2022). Although PVDA has received less academic attention than VB, its outsider status and confrontational rhetoric may likewise attract more critical coverage.

Hypothesis 2a: The tone towards the radical-right party Vlaams Belang is more negative than towards mainstream parties.

Hypothesis 2b: The tone towards the radical-left party PVDA is more negative than towards mainstream parties.

However, this pattern may be changing. Following its rebranding in 2004, after the conviction of Vlaams Blok for racism, media coverage of the party began to evolve. Where earlier studies and news articles showed systematic exclusion or highly negative framing (Schafraad et al., 2012; Vandermeersch, 2003), more recent analyses suggest that coverage has intensified and become more nuanced (de Jonge, 2018).

Several factors likely contributed to this shift. Most notably, Vlaams Belang’s sustained electoral growth made it increasingly difficult to ignore in a competitive media environment. Commercial pressures, combined with changes in journalistic routines, encouraged more comprehensive reporting (de Jonge, 2019). As a result, overtly negative portrayals may have declined over time, reflecting a broader process of normalization.

By contrast, no similar trend is expected for the radical-left PVDA. Although the party has existed for decades, it only gained significant electoral visibility from 2012 onwards. Unlike Vlaams Belang, whose normalization process began more than a decade earlier, PVDA most likely remains in an earlier phase of political mainstreaming.

Hypothesis 2c: The tone towards the radical-right party Vlaams Belang becomes less negative over time, more so than any other party.

5.3.3 Newspaper profiles

Different types of newspapers operate according to distinct journalistic routines, which may influence how they report on politics. A widely used distinction in media research is that between quality newspapers and popular newspapers (or tabloids). These outlet types differ in their treatment of political news: popular newspapers are more likely to employ personalization or anti-elite framing, while quality newspapers tend to give more attention to politics and economics, focusing on presenting information in a complex but understandable manner (Akkerman, 2011; Schäfer & Schemer, 2023). It is important to note, however, that this distinction functions more as a continuum than as a strict binary.

This is particularly true in the Belgian context, where the quality–popular divide is less pronounced. Belgium does not have tabloids in the Anglo-American sense. Popular newspapers in Flanders, such as *Het Laatste Nieuws* and *Het Nieuwsblad*, still dedicate substantial attention to political reporting and operate within professional journalistic norms (Soontjens, Van Remoortere, & Beckers, 2021).

Since the early 2000s, the gap between popular and quality outlets has narrowed, with both adopting certain tabloid elements. Nonetheless, notable differences in content, tone, and style remain. Traditional broadsheets such as *De Morgen*, *De Standaard*, and *De Tijd* position themselves as quality outlets, while *Het Laatste Nieuws*, *Het Nieuwsblad*, *Gazet van Antwerpen*, and *Het Belang van Limburg* are generally categorized as popular newspapers (De Bens & Raeymaeckers, 2007). Human-interest stories and “feel good” content are more prevalent in popular newspapers, while quality outlets maintain a stronger focus on policy issues and critical analysis.

These structural differences may also translate into variation in tone. Given their emphasis on hard news and political accountability, quality newspapers are expected to adopt a more critical tone than popular outlets, which may present politics in a more accessible or neutral manner.

Hypothesis 3a: The tone in quality newspapers is more negative than in popular newspapers.

In this study, the conventional distinction between quality and popular newspapers is adopted for analytical purposes. *De Morgen*, *De Standaard*, and *De Tijd* are categorized as quality newspapers, while *Het Laatste Nieuws*, *Het Nieuwsblad*, *Gazet van Antwerpen*, and *Het Belang van Limburg* are considered popular newspapers. This classification follows countless other Flemish studies that have done this as well (Beckers et al., 2019; De Smaele, 2007; Hendrickx et al., 2021; Raeymaeckers & Heinderyckx, 2017). Although this binary is a simplification, and the distinction has become less pronounced over time, it offers a useful framework for comparing differences in content and tone.

A second reason to expect variation in tone between newspapers lies in Belgium's pillarized media history (De Bens & Raeymaeckers, 2007). Like many Western European countries, Belgium historically exhibited strong political parallelism, with media outlets structurally aligned to political parties and their broader ideological communities (Hallin & Mancini, 2004). Readers tended to select newspapers that matched their political identity, and editorial content often favored affiliated parties while criticising their opponents. *De Morgen*, for instance, has a socialist background, while *Het Laatste Nieuws* traditionally served a liberal readership. *De Tijd* is the only newspaper included in this analysis that is not historically tied to any political movement. The other newspapers *De Standaard*, *Het Nieuwsblad*, *Gazet van Antwerpen*, and *Het Belang van Limburg* used to be part of the Catholic movement.

Since the late 20th century, however, this pillarized model has largely eroded due to processes of depoliticization and commercialization. Formal party ties disappeared, newsrooms diversified, and journalism increasingly embraced norms of objectivity and independence (Soontjens, Van Remoortere, & Beckers, 2021). Today, explicit alignments are less visible, but traces of ideological heritage may still shape editorial tone in more subtle ways (de Vries & Thesen, 2023).

Hypothesis 3b: The tone in newspapers is less negative towards parties that align with their historical ideological orientation.

Previous research has shown that the political tone of news coverage often correlates with the ideological preferences of newspaper audiences. A study by Çarkoğlu et al. (2014) demonstrated that in Turkey, newspapers could be grouped based on their readers' vote intentions, with each group systematically favoring particular parties. While explicit partisanship has largely disappeared in Western European media systems, many outlets can still be positioned along a left-right axis (Hallin & Mancini, 2004, pp. 180-182).

In the Flemish context, similar patterns are observable, not only among readers, but also in how journalists perceive the ideological orientation of different outlets. Audience surveys indicate that *De Morgen* has the most (and only) left-leaning readership, while *De Standaard* attracts a more centrist public. The remaining newspapers, *Het Laatste Nieuws*, *Gazet van Antwerpen*, and *Het Nieuwsblad*, also lean modestly to the right, although all remain relatively close to the center.

According to Flemish journalists, however, these last three outlets were perceived to have a more right-leaning audience, especially when compared to the more centrist *De Standaard* (Soontjens, Beckers, & Van Remoortere, 2023). *De Tijd* and *Het Belang Van Limburg* were not included in that study, but *De Tijd* is generally understood to cater to an economically liberal readership, while *Het Belang van Limburg* shares characteristics with other regional newspaper *Gazet van Antwerpen*.

Based on these patterns, it is expected that quality newspapers lean slightly more to the left than popular newspapers, which may influence their tone towards different parties.

Hypothesis 3c: The tone in quality newspapers is relatively more negative towards right-leaning parties than in popular newspapers.

Hypothesis 3d: The tone in quality newspapers is relatively less negative towards left-leaning parties than in popular newspapers.

Table 1 provides an overview of the editorial profiles of all seven outlets included in this study. Each of these titles is a daily newspaper.

Table 1. Profiles of the seven Flemish newspapers used in the analysis

Newspaper	Former pillarization	Total readership ¹	Commercial orientation	Socio-demographic audience ²	Geographical area ³
De Morgen	Socialist	483,510	Quality newspaper	Popular among young urbans	National
De Standaard	Catholic	624,000	Quality newspaper	Higher educated	National
De Tijd	'Neutral'	333,390	Financial, business quality newspaper	Entrepreneurs, managers, and investors	National
Het Laatste Nieuws	Liberal	2,145,400	Popular newspaper	Wide audience	National
Het Nieuwsblad	Catholic	1,520,890	Popular newspaper	Wide audience, middle-class	National
Gazet van Antwerpen	Catholic	678,040	Regional newspaper	Wide audience, popular among Catholic middle class	Regional (Antwerp)
Het Belang van Limburg	Catholic	515,850	Regional newspaper	All social classes	Regional (Limburg)

¹ Readership figures are based on data from the press readership study by the Centre for Information on the Media (CIM), which measured media consumption in Belgium between 1 September 2023 and 31 May 2024 (www.cim.be/nl/pers).

² Based on van der Burg, M. (2017). *Consolidation of ownership in media industries: survival strategies of newspaper publishers and regulation in the digital era* [Docotral thesis, University of Antwerp]. Antwerp.

³ In the Belgian context, the distinction between 'national' and 'regional' newspapers is somewhat relative. So-called national newspapers target only the Dutch-speaking region (Flanders), while 'regional' newspapers are in fact provincial in scope (De Smaele, 2017).

5.3.4 Temporal dynamics

Beyond structural differences between parties and newspapers, media tone can also fluctuate over time due to political context, seasonal cycles, or broader changes in journalistic practice. Major events such as wars, pandemics, or institutional crises may temporarily shift the tone of coverage. One well-documented phenomenon is the “rally around the flag” effect, in which national crises lead to increased institutional trust and more favorable media coverage of political leaders (Mueller, 1970). During such periods, negative sentiment may temporarily decline as the press adopts a more unifying tone.

Election periods are also often assumed to moderate media coverage. In Belgium, pre-election reporting is typically marked by heightened efforts to ensure balance and fairness. Journalists become more consciously aware of their democratic responsibilities and actively attempt to give all parties equal visibility (Van Aelst, 2007; Van Aelst & De Swert, 2009). This emphasis on balance in visibility may also extend to tone, resulting in more neutral or less explicitly negative coverage during electoral campaigns.

At other times, media tone can become increasingly critical as dissatisfaction with the political system rises. In Belgium, this is likely to occur during moments of political deadlock, such as prolonged government formation processes and periods of caretaker governments, both of which have characterized Belgian politics in recent decades (Dandoy & Terrière, 2021).

In the existing literature, long-term changes in tone have been difficult to observe, as most studies focus on short campaign periods or isolated news events. Consequently, little is known about how evaluative tone changes across decades of political and journalistic transformation. In the Belgian context, Soontjens (2019) suggests that conflict framing has become more prominent in recent years, driven by a shift towards more interpretative journalistic styles. A similar trend is observed in the United States, where Rozado et al. (2022) report a steady increase in negative sentiment in news headlines over the past two decades.

In addition to journalistic change, political communication itself appears to have become more emotionally and negatively charged, according to both academics and journalists (Pipal et al., 2024; Rhodes & Vayo, 2019). This evolution may in turn affect how political actors are portrayed in the media. Based on all these developments and findings, it is expected that tone will fluctuate over time, but with a gradual overall increase in negativity.

Hypothesis 4: The tone of political news coverage fluctuates over time, but becomes more negative overall.

Finally, this study also explores interactions between party, newspaper, and time. However, due to the complexity of three-way dynamics, no formal hypothesis is proposed. Instead, exploratory analyses will investigate whether tone has become more positive or negative for specific party–newspaper combinations over the past two decades. Only the most consistent and remarkable observations will be discussed.

Table 2 below summarizes the hypotheses formulated in the previous section and will later be used to provide a clear overview of the results regarding each hypothesis.

Table 2. Overview of hypotheses tested in this study

Hypotheses	
Hypothesis 1	The tone of political news coverage is more negative than positive.
Hypothesis 2a	The tone towards the radical-right party Vlaams Belang is more negative than towards mainstream parties.
Hypothesis 2b	The tone towards the radical-left party PVDA is more negative than towards mainstream parties.
Hypothesis 2c	The tone towards radical-right party Vlaams Belang becomes less negative over time, more so than for any other party.
Hypothesis 3a	The tone in quality newspapers is more negative than in popular newspapers.
Hypothesis 3b	The tone in newspapers is less negative towards parties that align with their historical ideological orientation.
Hypothesis 3c	The tone in quality newspapers is relatively more negative towards right-leaning parties than in popular newspapers.
Hypothesis 3d	The tone in quality newspapers is relatively less negative towards left-leaning parties than in popular newspapers.
Hypothesis 4	The tone of political news coverage fluctuates over time, but becomes more negative overall.

6 Data and method

6.1 Operationalization

This study defines tonality bias as systematic differences in the evaluative tone of media coverage towards political actors. Measuring this type of bias requires identifying the underlying sentiment, also called valence, of a sentence or passage. While the concept is relatively clear, capturing tone in the political context is complex. Political news reporting often depends on contextual understanding and frequently draws on statements by politicians. These statements may involve rhetorical strategies or ambiguous phrasing, which complicate the interpretation of sentiment. Moreover, tone is shaped not just by word choice, but by broader framing choices and the relationships between speaker, subject and source within a sentence (Lazaridou & Krestel, 2016).

Earlier studies relied almost entirely on manual content analysis, where trained coders assessed whether a sentence or paragraph portrayed a political party positively, negatively, or neutrally. Some approaches used more detailed five-point or seven-point scales to capture nuance (Entman, 2010; Hehman et al., 2012; Hopmann et al., 2012; Hopmann et al., 2010; van Spanje & de Vreese, 2014). These methods allowed for careful interpretation, but also came with important limitations: they were slow, costly, and hard to apply consistently across large datasets or longer time periods. In addition, human coders inevitably bring in their own biases, and results depend heavily on intercoder reliability.

To address the limitations of manual coding, many researchers have turned to sentiment dictionaries, containing predefined lists of words with positive or negative connotations. Software then estimates tone by counting the frequency of sentiment-laden words or by assessing their presence within a set proximity window, often around the name of a political party (Enevoldsen & Hansen, 2017; Taboada et al., 2011; Van Remoortere & Vliegenthart, 2024). While these methods allow for scale and replicability, they lack contextual understanding. A negative word may still convey a positive judgment depending on how it is used. For instance, “Vooruit fights against injustice” contains conflict-related terms but frames the party in a supportive light. Dictionary-based approaches also struggle with negation, irony, and indirect evaluation, features that are common in political language.

Recent developments in natural language processing (NLP) offer more context-aware alternatives. NLP applies computational techniques to analyze human language, with transformer-based models playing a groundbreaking role in recent sentiment analysis research (Acheampong et al., 2021). Models such as BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), and GPT (Radford et al., 2018) are pre-trained on massive text corpora and learn to detect meaning based on syntax, semantics, and context. These models can capture sentiment at the sentence level, including the effects of word order and emphasis. RobBERT, a Dutch-language adaptation of RoBERTa, has shown strong performance in sentiment classification and outperforms lexicon-based approaches (Van Hee et al., 2021).

However, this cutting-edge technology is still mainly developed and tested within computer science. Most studies focus on model performance, comparing accuracy for different datasets or improving fine-tune techniques (Boukes et al., 2020; Kaya et al., 2012; Souma et al., 2019). Only a few recent and often small studies actually implement these methods for large-scale analysis on political news (Purohit et al., 2025; Ring et al., 2024; Rozado et al., 2022). In Dutch-language contexts, such applications remain rare. Most notably, Boon et al. (2024) fine-tuned a Dutch BERT model (RePublic) to classify sentiment in public service communication and media texts. However, the use of these models for studying political bias in newspapers remains limited, especially in long-term and cross-party settings.

This study applies and compares four pre-trained BERT-based models, selecting the best-performing one to analyze sentiment in a large corpus of Flemish political news. However, before evaluating model performance, it is important to clarify what these models actually measure. While transformer models can detect tone with impressive accuracy, they still struggle with a core challenge in political language: determining who is evaluating whom. Political communication often contains indirect praise and criticism together with complex speaker-target relationships. For instance, a sentence like “I am disappointed that Groen lost the election” carries a negative tone, but the underlying evaluation of Groen is actually positive (de Vries, 2022).

Capturing this type of nuance requires identifying the source, the target, and the evaluative predicate, an approach referred to as *stance detection* (Aldayel & Magdy, 2021). Although recent developments in semantic role labeling aim to extract these structures, current models are not yet able to do this reliably in large-scale, multilingual political corpora. As a result, most sentiment models, including those used here, estimate only the *valence* of a sentence: the general emotional tone based on positive or negative language. This is not the same as measuring whether a news article supports or criticizes a particular party.

The operationalization of tone varies across studies. Some measure sentiment at the article level (Jacobs, 2020), while others focus on the sentence level (van Spanje & de Vreese, 2014) or paragraph level (Niven, 2003). Article-level coding offers a broad impression of sentiment but lacks detail, as a single article may contain both positive and negative elements. Sentence- or paragraph-level analysis provides more precision, but typically requires greater coding effort. This study applies sentence-level analysis using an automated model. This approach makes it possible to isolate how parties are framed in individual statements. However, it also comes with limitations: the model cannot attribute sentiment to specific actors within a sentence, nor can it capture meaning that unfolds across multiple sentences or paragraphs.

In addition, this study incorporates a longitudinal design to track changes in tone over time. While earlier research has often examined short-term periods or single election campaigns (e.g., Bos et al., 2011; Castro, 2021; D’Heer et al., 2022; Entman, 2010; Hopmann et al., 2010; Junqué de Fortuny et al., 2012), this study investigates whether media tone towards political actors remains stable or fluctuates across political events and electoral cycles over a 21-year period. This long-term perspective adds depth to the analysis of tone patterns and allows for the detection of broader trends and shifts.

6.2 Automatic content analysis

This study applies a state-of-the-art RoBERTa model, based on supervised machine learning (SML) and natural language processing (NLP) to analyze sentiment towards Flemish political parties in news articles. The dataset covers the period from 2004 to 2024 and includes all seven Flemish-language daily newspapers: De Morgen, De Standaard, De Tijd, Het Laatste Nieuws, Het Nieuwsblad, Gazet van Antwerpen and Het Belang van Limburg. The free newspaper Metro was excluded, as it ceased publication in 2023 and was therefore not consistently available in the archive (Belga, 2023).

All articles were manually scraped from the Belgapress archive (Belga, 2025), which includes both print and online content. According to the archive's classifications, approximately two-thirds of the dataset originates from print newspapers and one-third from their websites. The analysis includes the seven largest Flemish parties: PVDA, Groen, Vooruit, CD&V, Open VLD, N-VA, and Vlaams Belang. To ensure consistency over time, historical party names were kept. For example, both "SP.A" and "Vooruit" were used as search terms to maintain continuity.

Articles were selected based on whether the introduction explicitly mentioned one of the political parties, ensuring that the party was central to the article. However, during data collection, it became clear that some periods returned no results at all. Not because no relevant articles existed, but due to a technical issue in the archive system. For certain time periods and newspapers, layout errors caused the system to treat all articles as if they lacked an introduction. To avoid leaving large gaps in the dataset, an adjustment was made: for these affected periods⁴ only, all articles were included if they contained a political party, regardless of their introduction. This adjustment accounted for a little more than 10% of the total dataset. While this approach may introduce a small degree of noise, it ensures that coverage remains as complete as possible and avoids excluding entire months of political reporting.

Each article was split into sentences, and sentiment was calculated at the sentence level. Every sentence that mentioned a political party was extracted and treated as a separate unit of analysis. If a party appeared in multiple sentences, each was included individually. When multiple parties were mentioned in the same sentence, that sentence was duplicated so that each party could be analyzed separately. In those cases, the sentence appears multiple times in the dataset, once for each party it refers to. This structure allows the analysis to capture how each political actor is framed, even when mentioned alongside others.

This process resulted in a dataset of approximately 275,000 articles and 1.15 million sentences. While the data aims to approximate a full population of articles, it is likely that older years (2004–2007) suffer from partial digitalization, which may result in lower absolute coverage.

⁴ The affected periods, identified based on gaps in the dataset and taken with considerable margin of error, include: De Morgen (19/12/2007–14/11/2011, approx. 7,000 articles), De Tijd (11/03/2009–19/11/2011, approx. 1,500 articles), Het Laatste Nieuws (07/09/2007–12/11/2011, approx. 10,000 articles), Gazet van Antwerpen (01/01/2009–20/08/2015, approx. 7,500 articles), and Het Belang van Limburg (01/01/2012–24/06/2015, approx. 3,500 articles). After these additional articles were extracted, the full dataset was re-processed to remove any duplicate sentences. This procedure resulted in approximately 125,000 additional party-sentence combinations.

Before sentiment analysis, the dataset was cleaned to remove duplicates and scraping errors. Sentences with incorrect party references were either corrected or removed, including mentions of non-political uses of terms like “Vooruit” or “Groen,” and mentions of the Dutch PVDA. After cleaning, the final dataset contains 849,515 unique, well-formed political sentences. Duplicating each sentence for every party mentioned resulted in 1,019,683 party-sentence combinations.

Roughly one fourth of the original sentences was removed, mainly due to duplicate sentences. Many of these came from identical content published across sister newspapers, often on the same day or shortly thereafter. For example, local outlets such as *Gazet van Antwerpen* and *Het Belang van Limburg*, and occasionally *De Standaard*, frequently reused articles from their parent paper *Het Nieuwsblad*. In such cases, only one version of each sentence was retained. Other duplicates resulted from updated versions of earlier articles within the same newspaper.

The sentiment analysis in this study builds on recent advances in contextual language models, which enable more nuanced interpretation of textual data. To identify the most suitable model for this task, four pre-trained sentiment classifiers were tested. The first is RobBERTje, based on the Dutch RobBERT (v2) model, fine-tuned on book reviews (Delobelle et al., 2020). The second is XLM-RoBERTa, a multilingual transformer trained on tweets in various languages, including Dutch (Barbieri et al., 2022). The third model, RePublic, is designed for Dutch-language news and public service communication and is based on BERTje (Boon et al., 2024). The fourth is a fine-tuned DistilBERT model built for multilingual sentiment analysis (Tabularisai et al., 2025).

To evaluate the performance of these models, a benchmark dataset of around 5,000 political sentences was manually coded. Sentences were sampled from folders grouped by party mentions in the article introductions. This method aimed to achieve a more balanced distribution across parties, but did not fully equalize representation. Within each folder, sentences were selected at random, meaning that parties mentioned more frequently in the overall dataset may still be slightly overrepresented. Each sentence was labelled as positive, neutral, or negative, depending on whether it conveyed praise, factual reporting, or criticism of a political party.

Typically, after manual annotation, the next step would involve fine-tuning a model on the labeled data (Anastasopoulos & Whitford, 2018). This helps the model learn how sentiment is expressed in the specific context of Flemish political reporting. Fine-tuning can significantly improve performance, especially when dealing with highly context-based words. However, due to time and resource constraints, this step could not be implemented in the current study.

Instead of fine-tuning, this study selects the best-performing pre-trained model out of the four candidates, based on their accuracy on the benchmark dataset. This validation step ensures that the chosen model generalizes well to the task of sentiment detection in political news, even if it was not originally trained on this specific domain. While this approach is more practical for large-scale analysis, future research could improve performance further by fine-tuning a model on Dutch political texts.

The original coding scheme used for the benchmark set was actor-centred: coders were instructed to assess sentiment from the perspective of the political party mentioned. As discussed in the operationalization, this actor-focused reading does not align with how transformer models process sentiment. These models classify sentences based on their overall linguistic tone, regardless of speaker or target. For example, the sentence “Vlaams Belang calls the government’s policy disastrous” was originally coded as neutral, since it reflects Vlaams Belang’s opinion rather than criticism of the party. Yet the model, observing the strongly negative phrasing, classified the sentence as negative. This misalignment led to systematic classification errors and prompted a revision of the coding guidelines.

In the updated scheme, each sentence was coded based on the general tone of the text, regardless of who is speaking. Sentiment is interpreted as an approximation of affective tone, not as a direct indicator of media bias. Coders were instructed to consider how an external reader would perceive the tone, moving from an actor-specific to a text-based approach consistent with how language models function. The full set of 5,000 sentences was then manually recoded according to the new guidelines. Each sentence was labelled as one of three categories:

- “positive” if the overall framing emphasized strength, success, popularity, or favorable positioning. This includes references to political momentum, public support, achievements, or constructive evaluations of performance, whether self-attributed or described by others. For example, “Vooruit decisively won the election and reaffirmed its leadership role” is coded as positive due to the framing of stability and political strength, regardless of the source of the statement.
- “neutral” if the overall framing conveyed information without affective language, or if evaluative content was balanced, ambiguous, or insufficient to determine a clear tone. For instance, “Groen and N-VA talk about the upcoming pension reform” is coded as neutral, as it reports an event without implying praise or critique. Sentences in which sentiment terms were either absent or equally balanced across parties were also classified as neutral.
- “negative” if the overall framing emphasized struggle, conflict, controversy, reputational risk, or loss of support. This includes references to internal divisions, scandals, electoral decline, or critiques by opponents. For example, “Open VLD continues to suffer from internal disputes” is coded as negative due to the framing of instability and political vulnerability, regardless of the source of the statement.

One of the most important limitations of this approach is that the model cannot determine *who* the sentiment is directed at. It treats each sentence as a single unit and assigns one overall sentiment label. This becomes problematic when multiple parties appear in different roles within the same sentence. For example, in “The criticism from N-VA was harsh, but Vooruit’s proposal remained popular,” both negative and positive sentiment are present, but the model cannot attribute each part to the correct party. This is a known limitation of transformer models when applied to attribution or stance detection. As a result, when parties express support for themselves or critique others, the model evaluates only the overall tone of the sentence, regardless of the speaker. These constraints make sentence-level sentiment less precise than full actor-specific annotation.

To ensure that this method does not introduce systematic bias, two robustness checks were conducted, as discussed in the next section. The first test compares the model’s output with the original actor-centred coding, to check whether sentiment is consistently over- or underestimated for specific parties. The second test focuses on quoted speech, where sentiment may reflect the speaker rather than the subject, and assesses whether this disproportionately affects certain parties. Together, these checks help validate the model as a reliable tool for sentence-level sentiment analysis in Flemish political reporting.

To assess the reliability of the manual coding, intercoder agreement was calculated using two complementary measures. Ten percent of the recoded dataset (500 sentences) was independently labeled by a second coder. The level of agreement between the two coders was very high, with a Cronbach’s alpha of 0.92 and a Krippendorff’s alpha of 0.85. These values indicate strong internal consistency and coding reliability. Cronbach’s alpha reflects the overall correlation between coder scores, while Krippendorff’s alpha accounts for chance agreement and is more conservative in its estimation (De Swert, 2012). Together, both measures confirm that the recoded dataset is stable and suitable for validating model performance.

Based on this revised dataset, all four models were re-evaluated. The best-performing model was the multilingual RoBERTa variant trained on tweets, known as *Cardiffnlp/twitter-xlm-roberta-base-sentiment* (Barbieri et al., 2022). Different performance metrics were used to evaluate the accuracy of the model. Table 3 provides an overview of these metrics for the chosen model, when applied to the second manually annotated dataset of 5,011 political sentences.

Table 3. Performance metrics of the Cardiff RoBERTa sentiment model (N = 5,011)

	Precision	Recall	F1-score
Negative sentiment	77.9%	70.6%	74.1%
Neutral sentiment	83.6%	90.8%	87.1%
Positive sentiment	76.7%	58.5%	66.3%
Macro averaged	79.4%	73.3%	75.8%
Weighted average	81.3%	81.6%	81.2%

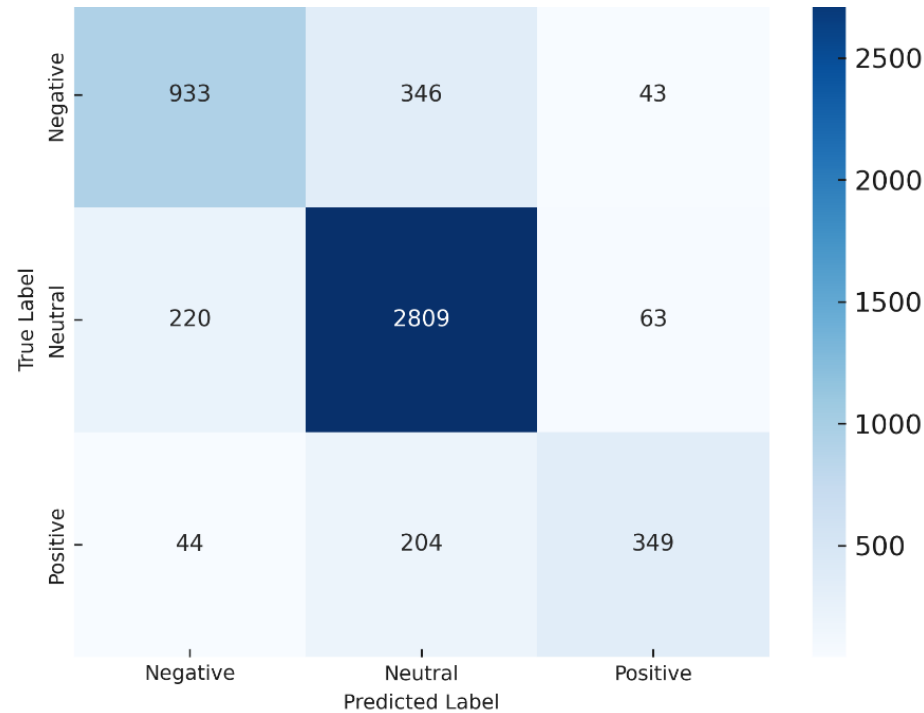
The table reports three key evaluation metrics, precision, recall, and F1-score for each of the three sentiment classes: negative, neutral, and positive. These metrics are standard in natural language processing to assess how well a model classifies different categories (Anastasopoulos & Whitford, 2018). For example, the row “Negative sentiment” shows a precision of 0.78 and a recall of 0.71. This means that when the model predicts a sentence as negative, it is correct 78% of the time (precision), and it correctly identifies 71% of all truly negative sentences (recall). The F1-score, which combines these two measures into a single value, is 74.1% for the negative class.

The macro-averaged and weighted-average rows summarize model performance across all three classes. The macro-average treats each class equally, while the weighted average adjusts for class size. Both metrics exceed the commonly accepted threshold of around 65-70% (Boon et al., 2024). Importantly, the overall accuracy of the model is 81.6%, meaning it predicted the same sentiment as the human annotators in more than eight out of ten cases. This represents a substantial improvement compared to the original accuracy of

65% achieved under the previous actor-centered coding framework. The increase in performance can be attributed directly to the alignment between the revised coding scheme and the model’s analytical logic.

These metrics were calculated based on the confusion matrix in Figure 1, which is a common tool for visualizing where the model’s predictions go right or wrong. Each row represents the true label assigned by human coders and each column shows the model’s predicted label. Diagonal cells therefore show correct predictions, off-diagonal cells show errors. In this case, the matrix confirms that the model is especially accurate at detecting neutral sentences, because most of the “neutral” rows fall on the diagonal. However, it has more difficulty with positive sentiment, which is often misclassified as neutral.

Figure 1. Confusion matrix: manual coding versus computer coding (N = 5,011)



These misclassifications of positive sentiment are likely due to the nuanced and often implicit nature of positive political framing. Praise is often embedded in formal language or strategic phrasing that lacks overtly positive terms. Expressions of support or legitimacy may be implied rather than explicitly stated, making them harder for sentiment models to detect. For example, the sentence “At PVDA, not profit, but people and nature come first” contains no strongly affective words, yet it conveys a positive moral positioning. The model classified this as neutral, likely because it did not detect clear sentiment indicators, even though a human reader might interpret the sentence as positively framed.

Similarly, the sentence “SP.A is the only party that can block a right-wing government” was also classified as neutral. On the surface, this sentence appears factual. But it implicitly frames SP.A as a competent and powerful political actor, capable of influencing government formation. Such ambiguous cases remain challenging for the model. So despite the overall improvement of the model, there are still a number of structural flaws.

These issues are not limited to positive sentiment alone, but affect the classification logic across the entire dataset. The inability to detect sentiment in actor-specific contexts or in sentences that contrast multiple evaluations was already mentioned earlier. However, due to the lack of training or fine-tuning on Flemish political texts, the model also struggles with Dutch idiomatic expressions and context-dependent language, often misclassifying sentences that contain figurative or culturally specific terms.

For example, “Ik heb een zwak voor Vlaams Belang” (meaning “I have a soft spot for Vlaams Belang”) was incorrectly labeled as negative, probably because the word “zwak” (weak) has a negative literal meaning, whereas the intended sentiment was positive. Similarly, phrases like “in een nauw schoentje zitten” (to be in a tight spot) or “zich laten rollen” (to be tricked) were misunderstood. Connotative Flemish terms and newer terms such as “flexi-job” also led to errors. These examples, again, highlight the need for sentiment models to be trained on Dutch-language political data in order to capture tone more accurately.

While the Cardiff model achieved the best overall results, three alternative models were also tested. None of these alternatives surpassed 70% accuracy. Most performed around 60–65%, which is comparable to the Cardiff model's performance when evaluated on the original actor-centred dataset. Without fine-tuning on political texts, pre-trained models remain limited in their ability to capture the rhetorical subtleties and ideological nuances of this domain. Although fine-tuning was beyond the scope of this thesis, the findings show both the potential and current limitations of automated sentiment analysis in Dutch political media.

6.3 Robustness checks

As outlined in the previous section, two robustness checks were conducted to assess whether the sentiment model introduces systematic bias. Each test addresses a distinct potential source of distortion in the measurement process.

The first test examines whether the shift from actor-centred to sentence-based coding, combined with the use of an automated model, leads to systematic differences in sentiment detection. As noted earlier, the model correctly classified 81.6% of the recoded sentence-level annotations, but only 65.8% of the original actor-based labels. This gap suggests that the model performs better under the revised coding scheme, but it also raises the question of whether this change affects how sentiment is distributed across parties, especially in sentences with multiple actors or complex constructions. The second test looks at how well the model handles quoted speech, since quoted criticism from a party can easily be misread as criticism directed to that party. Both tests aim to determine whether such misclassifications could distort the overall results.

In both tests, the differences turned out to be small, usually only a few percentage points, and relatively balanced across parties. While the model sometimes misses or misattributes negative sentiment, especially in ambiguous or quoted sentences, these errors are not large enough to distort the overall patterns. Given the size of the dataset, over one million sentences, such fluctuations are unlikely to affect the validity of the main findings. The results reported in the following chapters can therefore be considered valid and robust.

Below, each test and its results are explained in more detail.

The first test compares the original actor-based coding with the model-based, sentence-level coding used in the main analysis. This comparison uses the same sample of 5,011 sentences described in the previous section. These sentences were manually coded based on how they would be interpreted from the perspective of the mentioned party. The model, by contrast, assigned sentiment based on the overall tone of the sentence. For each party, two error types were calculated: *false negatives*, cases where the computer model (sentence-based) flagged a sentence as negative while my original coding (actor-based) did not, and the opposite *missed negatives*, where the manual coding marked the sentence as negative while the model did not.

Table 4 shows the number and percentage of both error types per party. The final column shows the difference between them, labelled as “excess negativity.” This represents whether the sentence-based model coding tends to assign *too much* or *too little* negativity to a party compared to the actor-based manual coding. For example, if the false negative rate exceeds the missed negative rate, the computer model is assigning more negative sentiment than necessary. If the opposite is true, it is underestimating negativity.

Table 4. Differences between actor-based manual coding and sentence-based computer coding (N = 5,011)

	Total Appearances	False negatives	False negatives (%)	Missed negatives	Missed negatives (%)	Excess negativity
PVDA	601	98	16.3%	38	6.3%	+10.0%
Groen	783	74	9.5%	67	8.6%	+0.9%
Vooruit	824	102	12.4%	88	10.7%	+1.7%
CD&V	1141	154	13.5%	132	11.6%	+1.9%
Open VLD	912	122	13.4%	111	12.2%	+1.2%
N-VA	1252	164	13.1%	176	14.1%	-1.0%
Vlaams Belang	738	105	14.2%	104	14.1%	+0.1%

These findings confirm that the model-based sentence-level coding generally assigns slightly more negativity than the actor-based method. For most parties, this excess negativity ranges between -1% and +2%, suggesting only minor differences. However, PVDA stands out with an excess of +10%. This indicates that the model labeled PVDA as negative significantly more often than the actor-based coding did. At first glance, this suggests a substantial overestimation of negativity towards the party.

However, this pattern is likely a result of the sampling method. To balance the dataset, additional PVDA sentences were drawn from articles where PVDA appeared prominently in the introduction. As a result, PVDA’s sample contains relatively few sentences where it is mentioned alongside other parties. These solo mentions often involve PVDA making strong critical statements, which the model may misinterpret as negativity directed at the party itself. This would explain the high number of false negatives and the relatively low number of missed negatives.

In other words, the inflated excess negativity for PVDA is in all probability a product of sampling rather than a structural flaw in the model. The full dataset used in the analysis is not stratified but includes all relevant sentences from the archive, with a natural distribution of party mentions and contexts. Therefore, it is unlikely that the distortion observed for PVDA in the test sample carries over into the full dataset.

For all other six parties, the differences between the two coding approaches remain minimal. This indicates that, although the model does not explicitly distinguish between actor roles, it still captures the general direction and distribution of sentiment effectively. The low and balanced excess negativity rates suggest that the model's predictions align closely with the more detailed hand-coded baseline. As such, this first robustness test provides reassuring evidence that the shift from actor-based to model-based coding does not introduce systematic bias.

The second robustness test builds on earlier findings that the sentiment model struggles with stance detection, specifically when a party expresses strong criticism. In such cases, the model sometimes interprets the negative tone as being directed *at* the party, rather than *originating from* it. This risk of misattribution is especially relevant for opposition parties like Vlaams Belang and PVDA, which frequently issue critical statements in public discourse.

To assess whether this results in systematic bias, I examined model performance on quoted versus non-quoted speech in the manually annotated sample of 5,011 sentences. Each sentence was classified as containing a quotation or not, based on the presence of quotation marks and verbs indicating reported speech (e.g., “says,” “claims,” “argues”). Although this method does not detect all quotes, especially fragmented or paraphrased quotations, it identifies the majority of the subset. Of the total sample, 818 sentences contained quoted speech, amounting to 16.3% of the dataset.

The model performed slightly worse on quoted speech. As shown in Table 5, accuracy for non-quoted sentences was 65.4%, compared to 63.5% for quoted ones. False negatives (when the model wrongly assigns negative sentiment) were notably more frequent in quoted speech (20.2% vs. 13.0%), while missed negatives (when the model fails to detect negativity) were slightly less frequent (8.4% vs. 11.3%). These patterns confirm that quoted statements, with their richer context and layered meaning, pose greater challenges for automated sentiment detection.

Table 5. Sentiment model accuracy for quoted vs. non-quoted sentences

	Total Appearances	Overall Accuracy	False negatives	False negatives (%)	Missed negatives	Missed negatives (%)	Excess negativity
Full sample	5,011	65.1%	712	14.2%	542	10.8%	+3.4%
Only quoted speech	818	63.5%	165	20.2%	69	8.4%	+11.7%
Only non-quoted speech	4193	65.4%	547	13.0%	473	11.3%	+1.8%

To determine whether this difference affects the main findings, the same quotation filter was applied to the full dataset of 1,019,683 sentences. Of these, 156,000 (18.1%) contained quoted speech. I then compared the proportion of negative sentiment across parties, once on the full dataset including quoted sentences and once on the dataset excluding quoted sentences.

As Table 6 shows, the overall differences are minimal. Across the full dataset, removing quoted sentences leads to a drop of just 0.2 percentage points in overall negativity. For individual parties, the largest changes are for PVDA (-0.8) and Vlaams Belang (-0.5), which aligns with expectations. However, even these effects are too small to meaningfully affect trend interpretations or party rankings. Open VLD is the only party to show a slight increase (+0.3%), which is also negligible.

Table 6. Negative sentiment per political party: full dataset versus dataset without quotes

	Number of sentences in full dataset	Negative sentences in full dataset (%)	Number of sentences without quotes	Negative sentences without quotes (%)	Differences in negativity (%)
PVDA	21,561	24.8%	18,568	24.0%	-0.8%
Groen	116,902	23.9%	96,949	23.6%	-0.3%
Vooruit	151,622	24.9%	128,284	24.7%	-0.2%
CD&V	219,001	24.8%	186,582	24.7%	-0.1%
Open VLD	184,791	23.2%	153,068	23.5%	+0.3%
N-VA	245,056	28.3%	209,665	27.9%	-0.4%
Vlaams Belang	80,750	30.1%	70,563	29.6%	-0.5%
Total	1,019,683	25.7%	863,679	25.5%	-0.2%

In short, while the model is slightly less accurate on quoted speech, this does not lead to structural bias in the final results. Party-level differences remain stable, and the distribution of sentiment across the dataset is nearly identical. Given that excluding quoted speech would remove nearly one in five sentences, without improving the overall balance, there is no methodological reason to do so. The model remains sufficiently reliable, and the results can be considered valid and robust.

7 Results

7.1 Overall sentiment distribution

After cleaning and validating the dataset, sentences mentioning more than one party were duplicated to ensure that each sentence could be assigned to a single party, as previously described. This process resulted in a total of 1,016,683 sentence-party combinations. These combinations form the basis of this study and were imported into SPSS to begin the statistical analysis.

Given that the dataset approaches population-level coverage of all articles with political parties in their lead paragraphs, the findings provide an exceptionally robust insight into media sentiment towards political actors over a 21-year period (2004–2024). Therefore it is not necessary to specifically look at significance level, because the dataset is nearing population. The sentiment of each sentence was classified as negative (-1), neutral (0), or positive (+1), resulting in the distribution shown in Table 7.

Table 7. Sentiment distribution across all sentences

	Number of sentences	Percent
Negative sentiment	261,817	25.7%
Neutral sentiment	671,092	65.8%
Positive sentiment	86,774	8.5%
Total	1,019,683	
Mean	-0.1717	

The first row shows that 261,817 of the total 1,019,683 sentences were classified as negative, which corresponds to 25.7% of the dataset. The large majority of sentences are neutral (65.8%), likely due to the descriptive nature of journalistic reporting and the frequent use of factual language. However, the volume of negative sentiment substantially outweighs positive sentiment (8.5%). The overall mean sentiment score is therefore slightly below zero, indicating a mild but systematic tilt towards negativity across the dataset.

These results confirm **Hypothesis 1**, which predicted that overall sentiment would be more negative than positive due to negativity dominance. The high share of neutral sentences aligns with expectations, but does not undermine the structural tendency towards negativity. This pattern confirms that even in a largely informational context, evaluative language tilts towards the negative.

7.2 Sentiment trends per political party

The dataset includes coverage of seven major Flemish political parties: PVDA, Groen, Vooruit, Open VLD, CD&V, N-VA and Vlaams Belang. Throughout this chapter, they are presented in order from most left- to right-leaning. These parties are not equally represented in terms of frequency, nor do they receive the same tone of coverage. Table 8 shows how often each party is mentioned in the corpus, as well as how those sentences are distributed across negative, neutral and positive sentiment. For instance, PVDA is mentioned in 21,561 sentences, which represents 2.1% of all party-sentence combinations. Of those, 24.8% are negative, 66.5% are neutral, and 8.7% are positive.

Table 8. Sentiment distribution across all political parties

	Number of sentences	Share (%)	Negative sentences (%)	Neutral sentences (%)	Positive sentences (%)
PVDA	21,561	2.1%	24.8%	66.5%	8.7%
Groen	116,902	11.5%	23.9%	64.9%	11.3%
Vooruit	151,622	14.9%	24.9%	66.7%	8.4%
CD&V	219,001	21.5%	24.8%	66.7%	8.5%
Open VLD	184,791	18.1%	23.2%	69.0%	7.8%
N-VA	245,056	24.0%	28.3%	63.7%	8.0%
Vlaams Belang	80,750	7.9%	30.1%	61.9%	8.0%

Not surprisingly, N-VA accounts for the largest share of mentions (24.0%), reflecting its dominant role in Flemish politics throughout the period. CD&V and Open VLD also receive substantial coverage, in line with their recurring presence in government coalitions. Vooruit, Groen, and Vlaams Belang follow at some distance, while PVDA is the least frequently mentioned. With only 2.1% of all sentences, PVDA remains underrepresented, especially before 2012. This low share should be kept in mind when interpreting the results for PVDA, although the party is still represented by over 20,000 sentences.

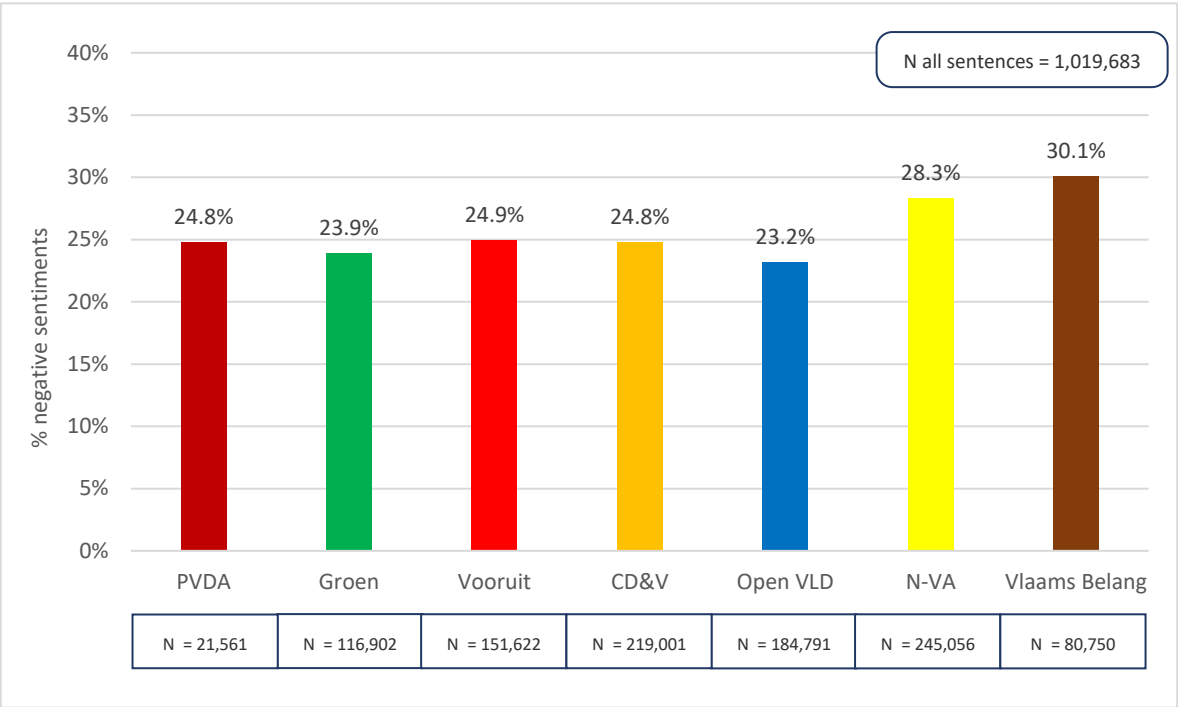
Table 8 also shows how each party is portrayed in terms of sentiment. The distribution across negative, neutral, and positive categories provides an initial indication of potential bias in tone. On the negative end of the spectrum, Vlaams Belang and N-VA receive the most critical coverage. Nearly one in three Vlaams Belang sentences is classified as negative, the highest of all parties. N-VA also scores well above average (28.3%), despite its status as a mainstream party. This is surprising. This shows initial support for the first hypothesis concerning political parties, not only for radical right party Vlaams Belang as expected but also for N-VA.

Vooruit, CD&V, and PVDA all hover just below 25% negative sentiment, placing them in the middle range compared to other parties. PVDA, despite being less frequently mentioned, shows sentiment levels that align closely with those of mainstream parties, and even slightly exceeds them in positive sentiment (8.7%). This is noteworthy in light of the second hypothesis for political parties, which expected radical-left party PVDA to receive more negative coverage than other parties.

Groen stands out with by far the highest share of positive sentiment (11.3%), remarkable given the overall low baseline of positivity in the dataset. This may reflect the party’s association with future-oriented issues such as climate, which possibly attracts more positive framing. It could also be related to a more hopeful communication style by Groen itself, or potentially point to a subtle positivity bias in some media outlets. While the cause cannot be confirmed based on sentiment alone, the pattern is notable.

Open VLD stands out with the highest share of neutral sentences (69.0%). At the same time, it receives the lowest share of both negative sentiment (23.2%) and positive sentiment (7.8%), suggesting that the party is often presented in a less emotive tone. These results are further illustrated in Figure 2, which provides a clear visual comparison of negative sentiment across all parties.

Figure 2. Distribution of negative sentences per political party



While Figure 2 shows clear variation in negative sentiment across parties, it is important to test whether these differences hold when controlling for statistical variance. To do so, a binary logistic regression was performed. The model predicts whether a sentence is negative (coded as 1) or not (coded as 0), based on which political party is mentioned. CD&V was chosen as the reference category in this model, as it is a long-standing centrist party with a consistent presence in government across the full twenty-one-year period and shows average levels of negativity in the descriptive analysis. This makes it a suitable baseline against which more ideologically distinct parties can be meaningfully compared.

Table 9 presents the regression results. Vlaams Belang shows the strongest effect, with a coefficient of $\beta = 0.268$ and an odds ratio of 1.308. This means sentences mentioning Vlaams Belang are about 30.8% more likely to be negative than those mentioning CD&V. The standard error reflects the uncertainty of the estimate: lower values imply more precise results. The Wald statistic tests whether the coefficient significantly differs from zero; the high value of 864.441 for Vlaams Belang suggests the effect is highly unlikely due to chance. The associated p-value confirms this statistical significance. While p-values are reported throughout the results, they are not the main focus, as the analysis is based on a near-complete population.

Table 9. Logistic regression predicting negative sentiment by party, CD&V as reference category (N = 1,019,683)

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
PVDA	.003	.017	.025	.874	1.003
Groen	-.049	.008	33.451	<.001	.952
Vooruit	.008	.008	1.171	.279	1.008
Open VLD	-.085	.007	131.176	<.001	.919
N-VA	.182	.007	745.901	<.001	1.200
Vlaams Belang	.268	.009	864.441	<.001	1.308
Constant	-1.111	.005	50400.761	<.001	.329

Nagelkerke $R^2 = 0.004$

N-VA also shows a significant increase in negativity, with a 20% higher chance of a negative tone than CD&V. These findings confirm the descriptive trend: both right-wing parties are associated with a more negative tone. In contrast, Open VLD and Groen show a modest decrease in negativity, suggesting they are more often covered in a neutral or slightly more positive tone. Vooruit and PVDA show no meaningful difference from CD&V, indicating that their sentiment profiles align with the centrist average.

Although the model's explanatory power is limited (Nagelkerke $R^2 = 0.004$), this is expected in large and complex datasets. With over one million observations, even small coefficients can indicate meaningful patterns. For that reason, this study focuses less on statistical significance and more on whether differences are consistent and substantial across methods.

These results provide strong support for **Hypothesis 2a**, which predicted that Vlaams Belang would be portrayed more negatively than mainstream parties. N-VA also receives significantly harsher coverage. This is very surprising, given the fact that political journalists in Flanders believed that their outlet favored N-VA the most out of all parties (Soontjens, Beckers, & Van Remoortere, 2023).

By contrast, **Hypothesis 2b** is not confirmed: PVDA receives only average levels of negativity and slightly more positive sentiment than most other parties. While the negativity faced by N-VA and Vlaams Belang could indicate a broader ideological bias against right-wing actors, alternative explanations, such as their issue focus, communication style, or political behavior, must also be taken into account.

7.3 Sentiment trends per newspaper

One important structural factor behind differences in tone is the role of different newspapers. Table 10 presents the distribution of sentiment across the seven newspapers included in the dataset, as well as the frequencies of sentences from these outlets. For example, De Morgen accounts for 10.8% of the dataset, representing 110,603 sentences from the total 1,019,683 sentences. Of these, 33.2% are classified as negative, while only 7.6% are positive.

Table 10. Sentiment distribution across all newspapers

	Number of sentences	Share (%)	Negative sentences (%)	Neutral sentences (%)	Positive sentences (%)
De Morgen	110,603	10.8%	33.2%	59.1%	7.6%
De Standaard	129,244	12.7%	30.7%	61.0%	8.3%
De Tijd	84,439	8.3%	30.8%	63.3%	5.8%
Het Laatste Nieuws	265,626	26.0%	24.0%	66.8%	9.2%
Het Nieuwsblad	243,339	23.9%	22.4%	68.5%	9.1%
Gazet van Antwerpen	106,431	10.4%	21.0%	69.7%	9.3%
Het Belang van Limburg	80,001	7.8%	23.5%	68.5%	8.0%

Het Laatste Nieuws and Het Nieuwsblad are by far the most represented newspapers, together accounting for nearly half of all sentences (49.9%). This reflects their wide readership and the large number of regional political stories they publish, especially during election periods. By contrast, regional outlets like Gazet van Antwerpen and Het Belang van Limburg contribute fewer sentences, as they only cover specific provinces.

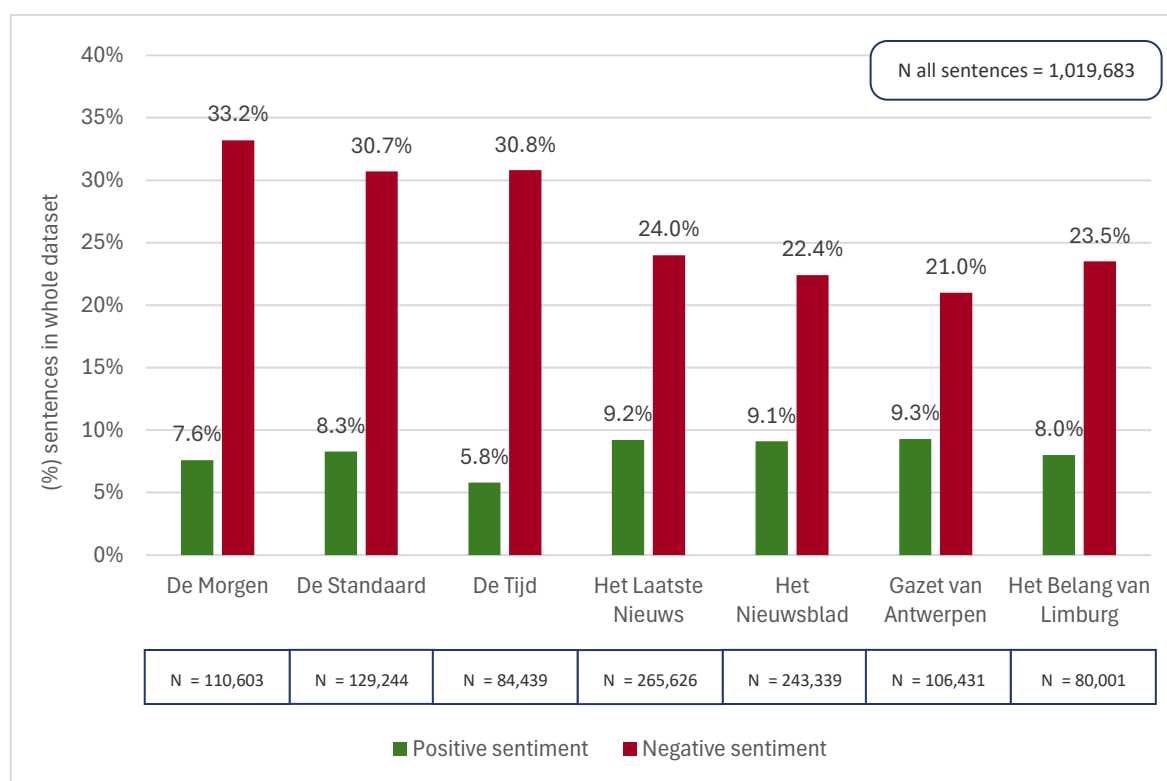
The three quality newspapers, De Morgen, De Standaard, and De Tijd, make up about 31.8% of the dataset. These outlets focus more on national and analytical content, often with fewer short or local news articles. The remaining 68.2% comes from the four popular newspapers. It is also worth noting that six of the seven outlets belong to just two publishing groups: Mediahuis (which owns De Standaard, Het Nieuwsblad, Gazet van Antwerpen, and Het Belang van Limburg) accounts for 54.8% of all sentences, while DPG Media (De Morgen and Het Laatste Nieuws) accounts for another large share. Despite editorial diversity, ownership concentration should be kept in mind when comparing across titles.

When examining sentiment distribution by newspaper, Table 10 shows clear differences across outlets. De Morgen shows the highest share of negative sentiment (33.2%), followed by De Tijd (30.8%) and De Standaard (30.7%). All three quality newspapers also score relatively low in positive sentiment, particularly De Tijd (5.8%). These results suggest a more critical and analytical tone, with less reliance on neutral reporting.

By contrast, the popular press adopts a softer tone. Het Nieuwsblad (22.4%) and Gazet van Antwerpen (21.0%) show the lowest levels of negative sentiment and the highest shares of neutral and positive coverage. Het Laatste Nieuws and Het Belang van Limburg fall in between, with approximately 24% negativity. The slightly higher positivity in these outlets – except for Het Belang van Limburg – supports the idea that popular newspapers may use a more accessible and less confrontational tone.

This becomes even more visible in Figure 3, which compares the shares of negative and positive sentiment across the seven titles. A clear divide emerges between quality and popular newspapers, even among outlets owned by the same parent company. For example, both De Standaard and Het Nieuwsblad belong to Mediahuis, yet display notably different tone profiles. This suggests that shared media ownership does not necessarily result in uniform editorial tone, and that individual newspaper identity continues to shape how political actors are portrayed.

Figure 3. Distribution of negative and positive sentences per newspaper



These descriptive findings are further substantiated by a binary logistic regression model in Table 11, that tests whether the observed differences in negative sentiment between newspapers are statistically robust. Het Laatste Nieuws serves as the reference category, because it is the largest outlet in the dataset and occupies a central position in terms of sentiment balance. The model follows the same logic as the party-based regression in the previous section.

Table 11. Logistic regression predicting negative sentiment by newspaper, Het Laatste Nieuws as reference category (N = 1,019,683)

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
De Morgen	.456	.008	3388.596	<.001	1.578
De Standaard	.340	.008	2031.144	<.001	1.405
De Tijd	.346	.009	1571.839	<.001	1.413
Het Nieuwsblad	-.089	.007	179.944	<.001	.915
Gazet van Antwerpen	-.173	.009	387.268	<.001	.841
Het Belang van Limburg	-.026	.009	7.370	.007	.975
Constant	-1.154	.005	64453.810	<.001	.315

Nagelkerke $R^2 = 0.013$

The results confirm that De Morgen is the most negative outlet, with an odds ratio of 1.578. Political sentences in De Morgen are thus 58% more likely to be negative than those in Het Laatste Nieuws. De Standaard (OR = 1.410) and De Tijd (OR = 1.405) also show significantly higher negativity. In contrast, Gazet van Antwerpen is 16% less likely to publish negative political sentences, while Het Nieuwsblad shows a smaller but still significant reduction with 8.5% less chance. Het Belang van Limburg differs only slightly from Het Laatste Nieuws (–2.5%).

Overall, the analysis offers strong support for **Hypothesis 3a**, which predicted that quality newspapers would display a more negative tone than popular outlets. Several factors may underlie this pattern, including editorial stance, audience expectations, or journalistic style. Quality outlets are probably more likely to engage in analytical and watchdog-style reporting, which tends to result in a more critical tone. Popular newspapers, by contrast, often prioritize accessibility and regional context, which may contribute to their more neutral or human-interest framing.

7.4 Sentiment trends over time

The dataset covers a full 21-year period, from January 2004 to December 2024, divided into 252 months. This allows for a unique and detailed look at how media sentiment has changed over time. Table 12 shows the yearly distribution of political sentences.

Table 12. Distribution of sentences in the dataset for every year

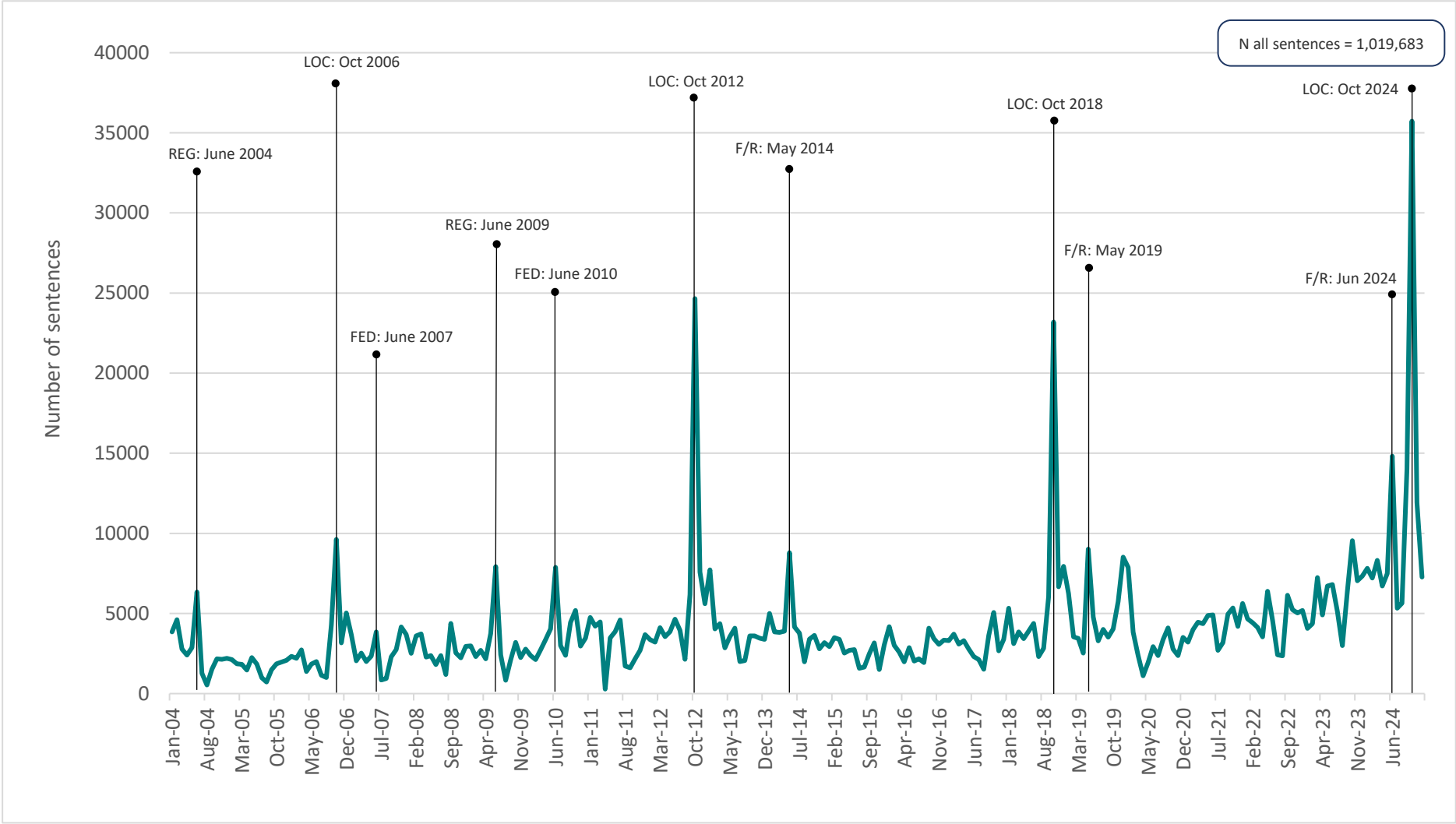
Year	Number of sentences	Percent	Year	Number of sentences	Percent
2004	32,708	3.2	2015	31,245	3.1
2005	20,493	2.0	2016	34,703	3.4
2006	36,759	3.6	2017	36,881	3.6
2007	31,142	3.1	2018	73,021	7.2
2008	31,950	3.1	2019	58,713	5.8
2009	35,412	3.5	2020	38,558	3.8
2010	43,959	4.3	2021	51,807	5.1
2011	37,520	3.7	2022	54,077	5.3
2012	72,859	7.1	2023	72,539	7.1
2013	44,732	4.4	2024	132,309	13.0
2014	48,296	4.7	Total	1,019,683	100

Most years contribute between 3% and 5% of the total dataset, but several peaks stand out. Sentence volume is especially low in 2005 (2.0%), while from 2018 onward a structural rise is visible. The sharpest increase appears in 2024, which alone accounts for 13.0% of the total data, adding up to more than 130,000 sentences. This rise in recent years is likely linked to improvements in digital availability of articles and more automated content production.

Several noticeable increases in the number of political sentences can be observed in the years 2012 (7.1%), 2018 (7.2%) and 2019 (5.8%). These coincide with election years, suggesting that media attention intensifies during electoral cycles. The temporary drop in 2020 (3.8%) breaks the upward trend and likely reflects the impact of COVID-19 on political journalism. This is followed by a recovery between 2021 and 2023, each contributing 5% to 7% of the total.

To better visualize these dynamics, Figure 4 presents a more detailed monthly breakdown of sentence volume. It confirms both the steady increase in political content since 2018 and the recurring spikes during electoral cycles.

Figure 4. Distribution of sentences in the dataset for every month



The monthly trends in Figure 4 show pronounced peaks during election periods, especially in months when local elections took place. October 2006, 2012, 2018, and particularly October 2024 stand out, October 2024 alone contains nearly 36,000 political sentences, more than twice the number recorded during the federal elections in June that same year. A likely explanation is that municipal elections generate separate articles for each locality, which multiplies the number of articles and, by extension, the number of sentences.

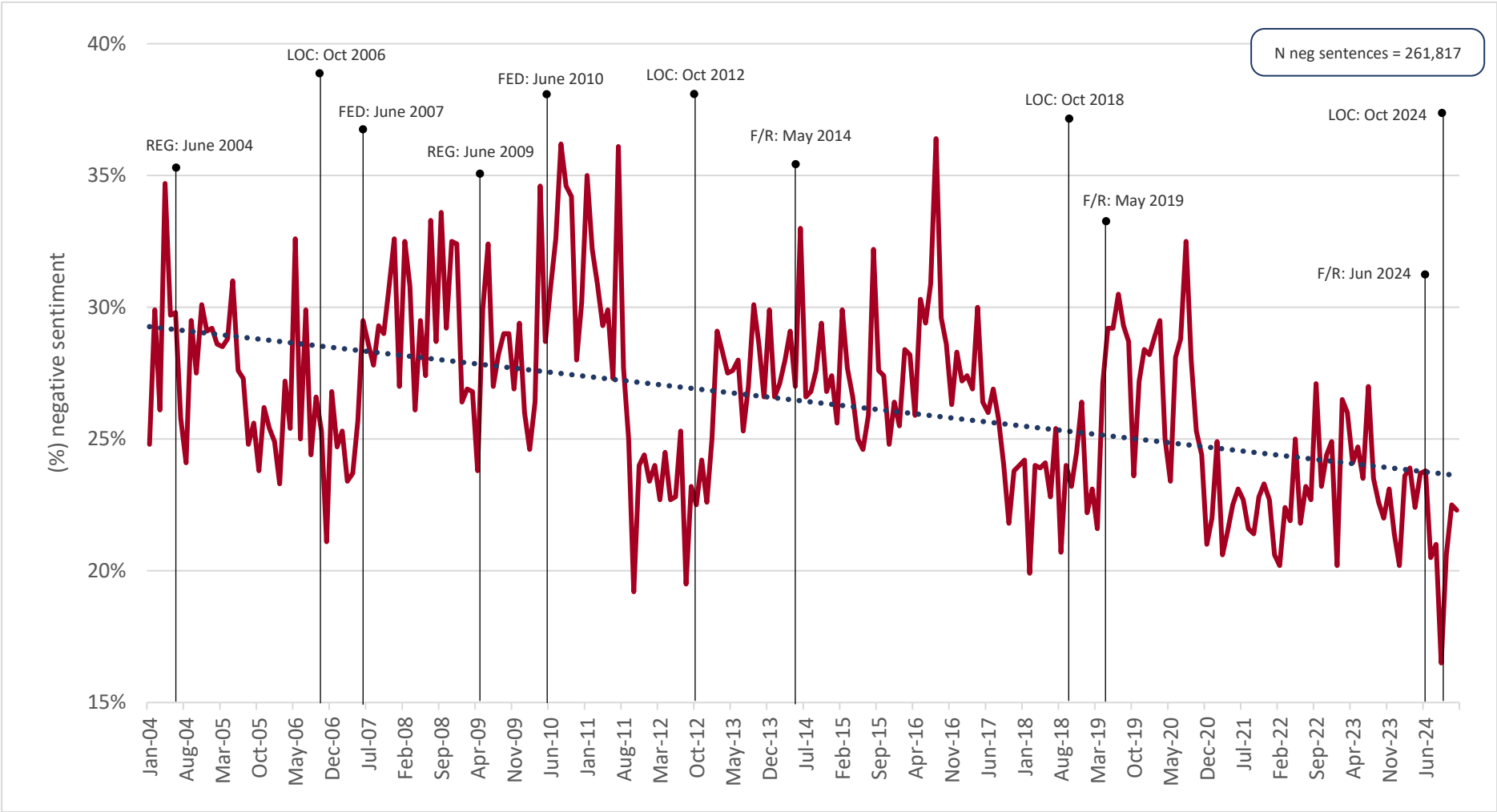
In contrast, federal and regional elections, held in June 2004, 2007, 2009, 2010, May 2014, May 2019, and June 2024, also produce notable peaks, though typically less pronounced than their local counterparts. These campaigns tend to be more centralized, with fewer articles but broader national focus.

As noted earlier, 2020 marks a temporary break in the upward trend. Sentence volume drops sharply after January and hits its lowest point in April, coinciding with the first COVID-19 lockdown in Belgium (Boogaerts et al., 2022). It is also worth noting that the months of August, and in some years July, consistently show a dip in the number of political sentences. This seasonal decline is likely due to the summer holiday period, when political activity slows down and newsrooms typically produce less political coverage.

While the overall number of political sentences increases steadily over the 21-year period, the share of negative sentiment shows a clear downward trend. This pattern is shown in Figure 5, which plots monthly negativity rates alongside a dotted trendline. Although the trend is not strictly linear, the overall decline is clear.

It is important to note that this figure is intentionally zoomed in to better highlight month-to-month differences. While earlier graphs used a consistent y-axis ranging from 0 to 40%, Figure 5 and subsequent figures use a narrower scale (15% to 40%) to make patterns more visible. As a result, the visual differences may appear larger than they actually are. Readers should keep this adjustment in mind when interpreting the figures.

Figure 5. Distribution of negative sentences for every month



FED = Federal elections – REG = Regional elections – LOC = Local elections – F/R = Federal and regional elections

The sentiment distribution of negativity is shaped by a sequence of peaks and dips that reflect the political dynamics of specific periods. Several noticeable declines in negativity occur in 2006, the second half of 2011, 2012, 2018, and 2024. With the exception of 2011, these years coincide with municipal elections in Flanders. This suggests that local campaigns may generate a less negative tone in media coverage. While it is difficult to isolate causality, a plausible explanation is that local campaigns center around community-focused issues and proposals for the future, which are often framed in hopeful or solution-oriented language.

The dip in late 2011 deviates from this pattern, but corresponds with a different moment of political resolution: the end of the long-standing Brussels-Halle-Vilvoorde conflict. In September of that year, caretaker Prime Minister Yves Leterme announced he would leave office by the end of the year (Rettman, 2011), marking a turning point after a long institutional stalemate.

The year 2024 stands out not only for its volume, but also for its exceptionally low negativity. In September 2024, the monthly proportion of negative sentiment drops to 16.5%, the lowest recorded in the dataset. Across the entire year, negativity falls to 21.4%, while positive sentiment rises to 11.3%, the highest yearly value. This shift may result from multiple factors: the positive framing of upcoming local elections, an unusually constructive tone in the political discourse, or even editorial decisions to focus more on neutral and positive coverage. Later in this chapter, an additional analysis will take a closer look at party-level sentiment in 2024 to assess whether this softening of tone is driven by changes in coverage of specific parties and if this could skew the overall findings.

By contrast, the data also reveal several sharp spikes in negativity. One extended period of heightened negativity runs from late 2007 to mid-2011, corresponding with a major political crisis in Belgium. The most pronounced spikes occur between mid-2010 and mid-2011, following the collapse of the Leterme II government. During this time, Belgium experienced a record-breaking 541-day government formation, and news coverage likely focused on institutional deadlock, political conflict, and governance failure (Dandoy & Terrière, 2021).

Another phase of instability appears after the May 2019 elections, lasting until the summer of 2020. This period partly overlaps with the COVID-19 pandemic and is characterized by sharp month-to-month fluctuations in sentiment. The volatility likely reflects a rapidly shifting news agenda, driven by coalition negotiations in the early months and later by evolving public health developments. As new policy decisions, lockdowns, and political debates unfolded, media tone probably adapted in real time to an uncertain and dynamic context.

Beyond these prolonged crises, an isolated peak in negativity appears in August 2016, when negative sentiment reaches 36.4%, one of the highest monthly values in the dataset. This abnormality can likely be explained by two factors: low article volume typical for the summer holiday period, and a spike in conflict-oriented coverage. That month, fewer than 2,000 political sentences were recorded, and coverage focused heavily on divisive debates around racism and migration (Paelinck, 2016). When political reporting is scarce, as in August, even a handful of highly negative articles can strongly influence monthly averages. This case underscores a broader pattern: during low-volume periods, sentiment is more easily skewed by the nature of the limited content that appears.

Interestingly, local elections consistently coincide with dips in negativity, seen in October 2006, 2012, 2018, and 2024. In contrast, federal and regional elections tend to be followed by higher levels of negativity, as observed in July 2010, June 2014, and July 2019. However this pattern is not always consistent. In earlier cycles and in the most recent 2024 elections, post-election negativity is far less pronounced. In some cases, pre-election months show a softer tone, while the aftermath varies depending on the success of coalition talks or political turbulence. Overall, the data suggest that while local elections often align with reduced negativity, federal election periods are more volatile and sensitive to the broader political context.

Despite these fluctuations, the overall trend is one of gradual decline. As shown in Figure 5, negative sentiment in Flemish political reporting has decreased steadily over the past two decades. To test the statistical validity of this trend, a binary logistic regression was performed with the number of years since 2004 as the predictor, as shown in Table 13.

Table 13. Logistic regression predicting negative sentiment over time (N = 1,019,983)

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
Year (since 2004)	-.018	.000	2378.040	<.001	.982
Constant	-.834	.005	26129.654	<.001	.434

Nagelkerke $R^2 = 0.003$

The model confirms a small but significant yearly decrease in negativity. The odds ratio of 0.982 indicates that with each passing year, the likelihood of a sentence being negative drops by approximately 1.8%. While modest on a yearly basis, the effect becomes substantial across the full 21-year period. In total, this corresponds to a 31.5% lower chance of negativity in 2024 compared to the beginning of the dataset.

To complement this, a linear regression analysis was conducted using monthly data (see Appendix B.1). That model confirmed the same trend and produced an R^2 of 0.173, indicating that 17.3% of monthly variation in negativity can be explained by the passage of time alone. In the context of a large and varied dataset, this represents a substantial share.

Taken together, the data show a gradual and consistent decline in negative sentiment, with particularly low negativity in 2024 and during local election periods. These results directly contradict **Hypothesis 4**, which expected a rise in negativity over time. Contrary to widespread assumptions about the increasing harshness of political journalism, both the logistic and linear models provide quantitative evidence for a long-term softening in tone in Flemish political news coverage.

7.5 Sentiment trends per political party per newspaper

The previous sections showed that sentiment varies both across political parties and across newspapers. This section now explores how those two dimensions interact: how are different parties framed depending on the newspaper in which they appear? To answer this, Figure 6 presents a heatmap of negative sentiment across all party–newspaper combinations. Each cell shows the percentage of negative sentences for a given party in a specific newspaper. Row and column weighted averages are added to facilitate comparisons.

Figure 6. Heatmap of negative sentiment per political party per newspaper

De Morgen	30.2	29.6	32.1	32.9	30.2	36.5	37.8	33.2
De Standaard	29.5	28.5	29.3	29.5	28.8	33.4	35.0	30.7
De Tijd	32.9	29.8	28.7	30.4	26.0	34.3	35.6	30.8
Het Laatste Nieuws	23.1	22.7	23.4	23.4	21.4	26.3	28.3	24.0
Het Nieuwsblad	22.2	21.5	22.3	21.0	21.1	24.1	26.4	22.4
Gazet van Antwerpen	23.6	20.1	20.4	19.4	18.6	22.6	25.5	21.0
Het Belang van Limburg	21.9	22.8	22.2	22.1	21.4	26.4	28.2	23.5
Average per political party	24.8	23.9	24.9	24.8	23.2	28.3	30.1	25.7
	PVDA	Groen	Vooruit	CD&V	Open VLD	N-VA	Vlaams Belang	Average per newspaper

Negative sentiment (%)

Among the quality newspapers, De Morgen and De Standaard follow strikingly similar patterns, with De Morgen being slightly more negative overall (33.2% vs. 30.7%). In both outlets, Vlaams Belang and N-VA receive the harshest coverage, with Vlaams Belang peaking at 37.8% in De Morgen, the single highest value in the dataset. N-VA follows closely in both papers, while CD&V and Vooruit place somewhere in the middle.

Interestingly, Open VLD and Groen consistently receive the least negative sentiment in both outlets, particularly Groen, which even drops below Open VLD with the lowest negativity. PVDA falls in the mid-range for both, with De Morgen being a little less negative ranking it together with Open VLD.

De Tijd, while also a quality outlet, shows a slightly different pattern. It is more negative towards PVDA (32.9%) and Groen (29.8%) than any other quality paper and less negative towards Vooruit (28.7%) and Open VLD (26.0%). This diverges from the broader trend and may reflect De Tijd's business-focused editorial line. Vlaams Belang and N-VA still top the list.

The popular newspapers show a more moderate tone overall. Negativity levels are generally lower, especially for CD&V and Open VLD, who are consistently among the least negatively portrayed parties in these papers. In *Gazet van Antwerpen*, for instance, only 19.4% of CD&V and 18.6% of Open VLD sentences are negative, the lowest values in the entire matrix.

Most party rankings are stable across the popular press, with Vlaams Belang and N-VA at the top, CD&V and Open VLD at the bottom, and Groen, Vooruit, and PVDA in the middle. However, there are a few notable exceptions. In *Gazet van Antwerpen*, PVDA receives the second-highest level of negativity (23.6%), even more than N-VA (22.6%). By contrast, in *Het Belang van Limburg*, PVDA receives only 21.9% negativity, even lower than Groen, suggesting that local political dynamics and regional stories may influence tone.

Across all newspapers, Open VLD consistently receives the least negative sentiment, except in *De Morgen* and *De Standaard*, where Groen scores slightly better. This pattern suggests that centrist parties benefit from more neutral framing in the popular press, while left-leaning parties like Groen and Vooruit enjoy a somewhat more favorable tone in quality newspapers. This provides early support for Hypothesis 3d, which expected less negative sentiment towards left-wing parties in quality outlets. Statistical models later in this chapter will test whether these patterns hold.

As for Hypothesis 3b, which expected newspapers with a historical background to be less negative about their legacy party, the results remain inconclusive. *De Morgen*, *De Tijd*, and *Het Laatste Nieuws*, the only outlets without a Catholic-pillar legacy, seem to be relatively more negative towards CD&V, but the difference is not large enough to support or reject the hypothesis confidently. The same holds true for historically liberal *Het Laatste Nieuws* that does appear somewhat less negative about Open VLD, the trend is not very outspoken. Previous socialist newspaper *De Morgen* does not seem more favorable towards Vooruit in comparison to Groen or PVDA.

For Hypothesis 3c, it is not clear if quality newspapers are relatively more negative about right-wing parties Vlaams Belang or N-VA since they receive the most negative coverage, regardless of outlet. This will need to be confirmed or denied in the logistic regression later in this section, which is able to compare party-newspaper combinations in relative terms to the reference category and each other.

Figure 7 below presents the second heatmap, showing the percentage of positive sentiment for each party across newspapers. As expected from earlier findings, positivity levels are significantly lower than negativity across the board. Still, distinct patterns emerge that further clarify how political actors are framed in Flemish press coverage.

Figure 7. Heatmap of positive sentiment per political party per newspaper

De Morgen	9.4	10.9	7.5	7.5	7.0	6.9	7.4	7.6
De Standaard	7.2	12.1	8.1	8.1	7.5	7.4	8.3	8.3
De Tijd	7.4	8.7	5.7	5.7	5.3	5.3	6.3	5.8
Het Laatste Nieuws	8.5	11.0	9.2	9.4	8.7	8.9	7.9	9.2
Het Nieuwsblad	9.3	11.7	8.8	9.2	7.9	8.7	8.4	9.1
Gazet van Antwerpen	9.0	12.0	9.0	8.9	8.2	9.3	8.7	9.3
Het Belang van Limburg	9.5	10.2	7.9	8.1	7.7	7.3	8.4	8.0
Average per political party	8.7	11.3	8.4	8.5	7.8	8.0	8.0	8.5
	PVDA	Groen	Vooruit	CD&V	Open VLD	N-VA	Vlaams Belang	Average per newspaper

Positive sentiment (%)

The most striking result is the consistently high positivity towards Groen, which tops the rankings in nearly every outlet. Groen achieves the highest average across all parties at 11.3%, peaking in De Standaard (12.1%) and Gazet van Antwerpen (12.0%), and performing strongly in Het Nieuwsblad and Het Laatste Nieuws as well. Even De Tijd, which shows the lowest overall positivity (5.8%), still ranks Groen highest among all parties. This widespread positivity suggests that Groen is framed differently than other parties, possibly due to the party's focus on less divisive, forward-looking themes like climate or maybe because of a different political communication rhetoric.

Surprisingly, PVDA ranks as the second most positively covered party, with 8.9% positivity on average. This is notable because PVDA also received relatively high negativity in certain outlets (especially De Tijd and Gazet van Antwerpen). This dual framing, high on both positive and negative sentiment, suggests that PVDA attracts polarized coverage, perhaps reflecting its increasingly visible position in political debates. The party scores particularly high in Het Belang van Limburg (9.5%) and De Morgen (9.4%), both of which gave PVDA less negative coverage in the previous heatmap as well.

By contrast, Open VLD consistently scores the lowest in positive sentiment, with an average of just 7.8% across all newspapers. It ranks lowest or second-lowest in nearly every outlet, except for De Standaard. This confirms its earlier profile as the most neutrally framed party, one that is seldom portrayed in strongly positive or negative terms. CD&V and Vooruit cluster around the middle, with average scores near the overall party mean of 8.5%.

Vlaams Belang, despite being the most negatively framed party overall, does not rank lowest in positivity. While it gets the lowest score in Het Laatste Nieuws (6.3%), other outlets like De Tijd (8.3%) and Het Belang van Limburg (8.5%) assign Vlaams Belang above-average positivity, suggesting that this party also occasionally receives favorable framing. N-VA shows a similarly mixed pattern, with a modest average of 8.0% but stronger scores in Gazet van Antwerpen (9.3%) and Het Laatste Nieuws (8.9%).

Overall, the heatmap for positive sentiment shows less pronounced and consistent differences between quality and popular newspapers than the negative sentiment heatmap. This suggests that positive sentiment is less strongly shaped by newspaper type. However, since this study does not examine the underlying causes of tone, no firm conclusions can be drawn. Differences in positive coverage could result from many factors, such as issue selection, party rhetoric, or the way certain actors present themselves in the news. Further research would be needed to understand what drives these patterns in positive tone (and as for negative tone) across parties and newspapers.

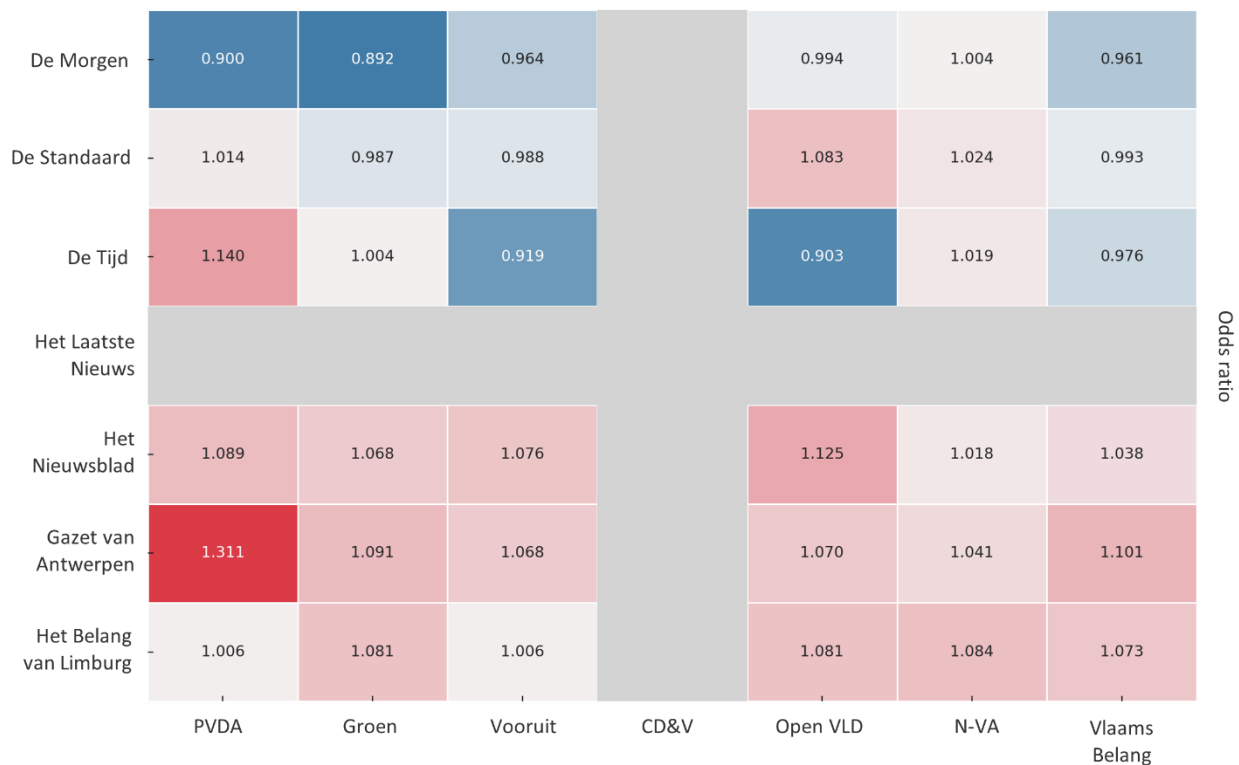
To further examine whether the patterns observed in the heatmaps hold up under statistical control, a binary logistic regression model was estimated. This model includes both main effects for political parties and newspapers, as well as two-way interaction terms (party $\times$ newspaper). This approach makes it possible to isolate whether certain party-newspaper combinations are systematically more or less negative than expected, after controlling for each party's general treatment and each outlet's overall tone.

For this model, CD&V and Het Laatste Nieuws were selected as reference categories. These choices are methodologically sound: both show relatively average sentiment scores and large observation counts, which ensures stability in the model. CD&V is a centrist, long-standing party frequently present in coverage, and HLN is the largest newspaper in the dataset with a relatively balanced tone.

The results of this model are visualized in Figure 8, which presents the odds ratios for each party-newspaper combination. These ratios indicate the relative likelihood of negative sentiment compared to the baseline expectation, given the party's average treatment and the newspaper's overall tone. Odds ratio above 1 indicate that the combination is more negative than expected. Conversely, an odds ratio below 1 means that the combination is less negative than expected.

It is important to note that these results are relative to the expected tone given both the party and the outlet's general characteristics. They do not reflect absolute negativity, but rather deviations from a baseline, after correcting for overall trends. The full regression table, including coefficients, standard errors, and significance levels, can be found in Appendix B.2.

Figure 8. Heatmap of odds ratio for party x newspaper interaction effects predicting negativity



The findings reveal important differences. PVDA, for instance, is framed much more negatively in De Tijd and Gazet van Antwerpen, with odds ratios of 1.14 and 1.31 respectively. This means that even when controlling for the fact that, for example, De Tijd is generally more critical and PVDA is moderately negatively covered, the tone in this party-outlet combination is still more negative than anticipated with a 31% higher chance of a negative sentence than for CD&V in Het Laatste Nieuws. In contrast, De Morgen treats PVDA significantly less negatively than expected, with an odds ratio of 0.90. This shows that the same party can be framed very differently across newspapers.

Groen follows a similar trend, receiving the most favorable treatment in De Morgen and slightly more critical coverage in popular outlets. Vooruit also enjoys relatively softer tone in the three quality papers, especially in De Tijd. Open VLD is also treated less negative in De Tijd, which aligns with expectations based on the party's economic-liberal profile. However, it receives relatively more negative treatment in Het Nieuwsblad and Gazet van Antwerpen, possibly indicating local criticism.

The results for N-VA are particularly interesting. In every newspaper, the odds ratios are just above 1, indicating that N-VA consistently receives slightly more negative coverage than expected, even after accounting for the party's overall tone and the general tone of each newspaper. Although these differences are very small, their consistency across outlets suggests that N-VA is subject to a subtle but more all-round negative coverage. The most notable result is found in Het Belang van Limburg, where the odds of negative coverage are more clearly elevated.

The most unexpected finding concerns Vlaams Belang. While this party is the most negatively covered overall, the interaction model shows that this negativity is relatively lower in the quality newspapers: De Morgen, De Standaard, and De Tijd all have odds ratios just below 1. This means that in these outlets, the party is slightly less negative than expected, considering both the party's average treatment and the critical nature of these newspapers. In contrast, Het Nieuwsblad, Gazet van Antwerpen, and Het Belang van Limburg display higher-than-expected negativity towards Vlaams Belang.

Taken together, the findings provide limited support for **Hypothesis 3b**, which posited that newspapers would be less negative towards parties aligned with their historical ideological orientation. While a few subtle patterns emerge, such as Het Laatste Nieuws relatively softer tone towards Open VLD, these effects are neither consistent nor strong enough to confirm the hypothesis. For most outlets, there is no clear evidence of sustained favoritism towards their legacy-aligned parties. For instance, De Morgen, despite its socialist roots, does not frame Vooruit more favorably than Groen or PVDA.

Importantly, because CD&V served as the reference category in the interaction models, it was not possible to assess whether newspapers with a Catholic legacy (e.g., De Standaard, Het Nieuwsblad, Gazet van Antwerpen, Het Belang van Limburg) treat CD&V more favorably relative to other parties. But when looking at the same model with reference category Open VLD in Het Nieuwsblad (see Appendix B.3), there was also no clear historical ideological alignment systematically affecting tone.

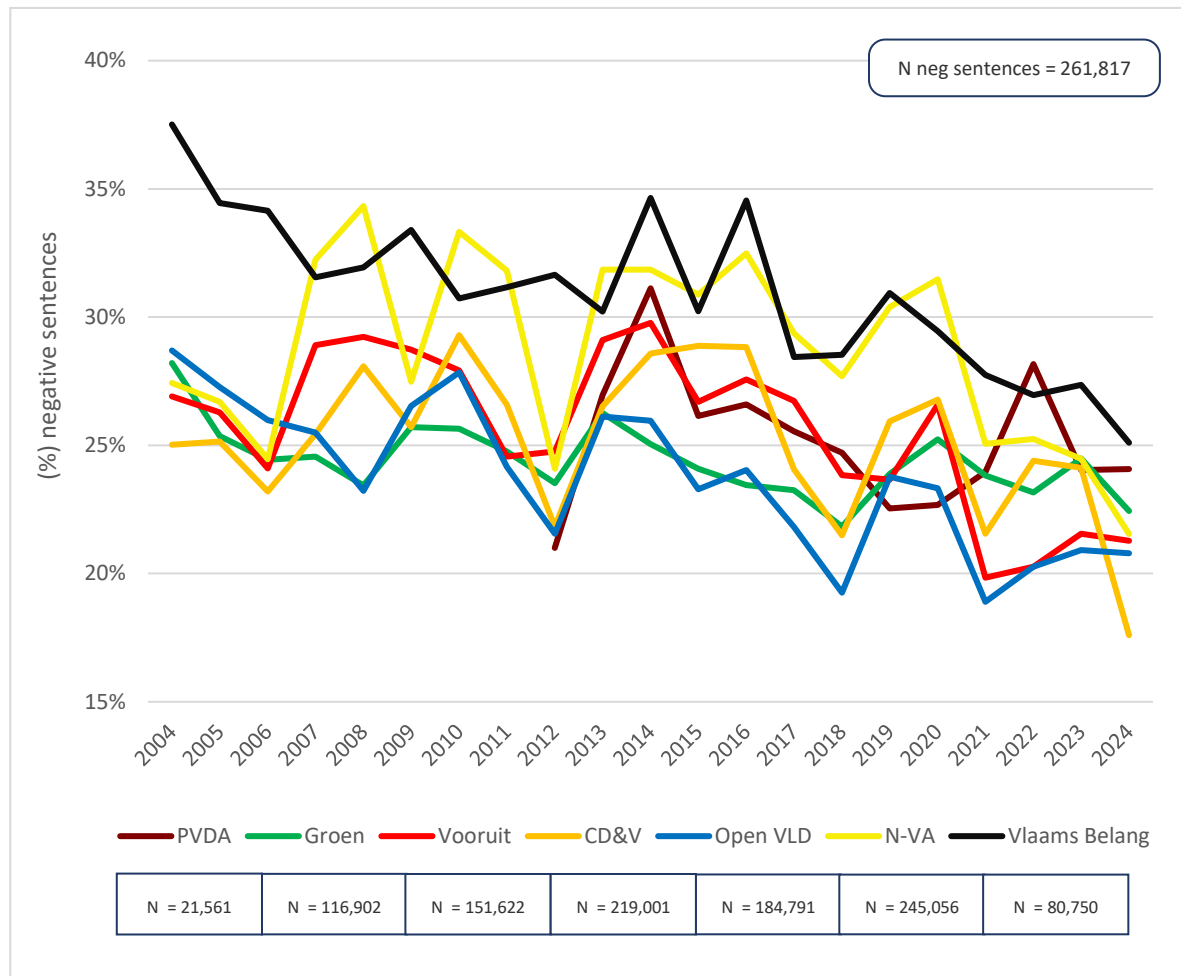
Hypothesis 3c, which expected that quality newspapers would be more negative towards right-leaning parties, is contradicted. For Vlaams Belang, the opposite appears to be true: quality newspapers are relatively less negative, while popular newspapers apply more critical framing. De Morgen, De Standaard, and De Tijd all report below-expected negativity, while Het Nieuwsblad, Gazet van Antwerpen, and Het Belang van Limburg show heightened negativity. For N-VA, negativity is slightly elevated in all outlets, but the differences are marginal and do not follow a clear quality–popular divide. These findings challenge the common assumption that ideologically left-leaning outlets adopt a structurally harsher tone towards right-wing actors.

The results also offer partial support for **Hypothesis 3d**, which expected quality newspapers to be less negative towards left-wing parties. This is mostly true for Groen and Vooruit, both of which receive relatively softer coverage in quality outlets. For PVDA, however, the picture is mixed: it is only treated more positively in De Morgen, while receiving the harshest relative treatment in De Tijd and Gazet van Antwerpen. These patterns indicate that moderate left parties do receive somewhat more favorable treatment in the quality press, but that this does not extend uniformly to more radical actors like PVDA.

7.6 Sentiment trends per political party over time

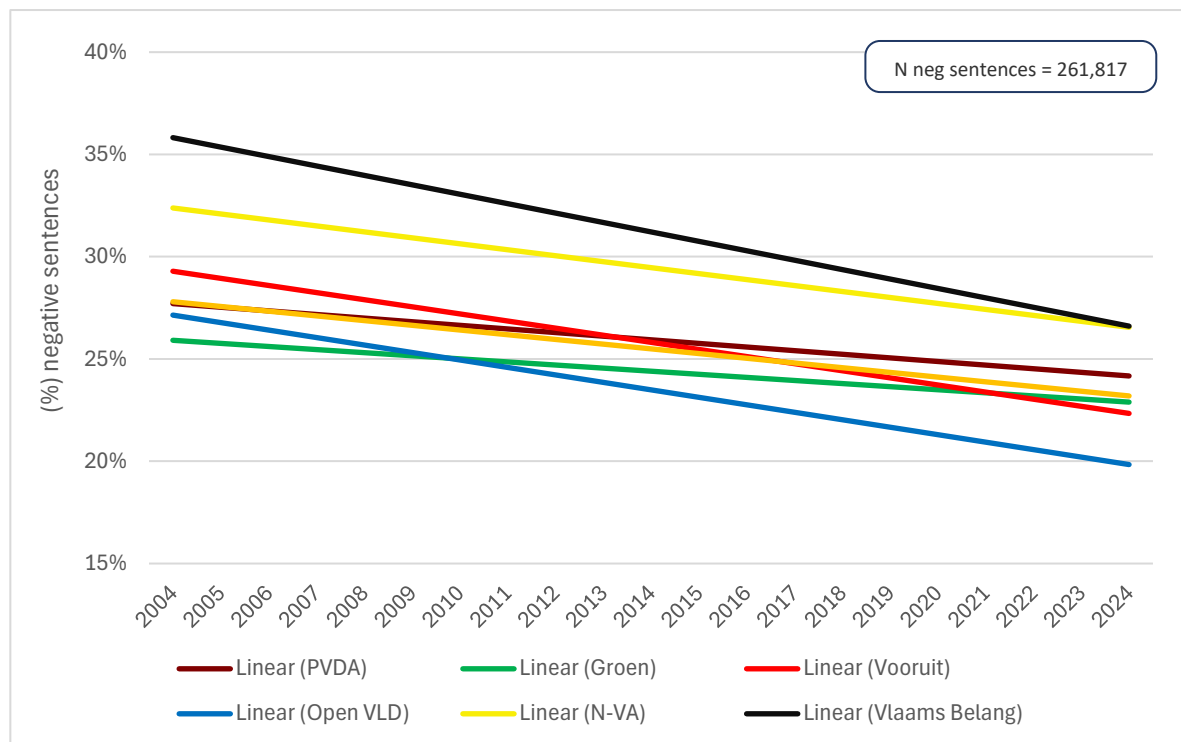
To analyze whether sentiment evolved differently across parties, this section examines how the share of negative sentences has changed between 2004 and 2024. Figure 9 visualizes these trends year by year, allowing for comparison of both the direction and magnitude of change across parties. For more detailed insight, individual trend graphs and stacked area graphs per party are included in Appendix A.

Figure 9. Overview of negativity share per political party from 2004-2024



Additionally, Figure 10 shows the corresponding trend lines for each party, plotted separately to make underlying patterns more visible. It should be kept in mind that in both figures the y-axes do not start at 0%, in order to make the differences more clear. However, this also makes the fluctuations seem bigger than they are in reality.

Figure 10. Overview of negativity trendlines per political party from 2004-2024



A few trends stand out immediately. Vlaams Belang (black line) begins the period in 2004 as the most negatively covered party, with over 37% of its sentences labeled as negative. Over the next two decades, this share declines steadily, albeit with some fluctuations, reaching approximately 25% by 2024. This represents the most substantial and consistent reduction in negativity across all parties. Figure 10 confirms this trajectory, with Vlaams Belang displaying the steepest downward trend line.

The second most notable trend is that of N-VA (yellow line). Initially, the party is treated comparably to others, but from 2007 onward, it begins to attract increasing levels of negative coverage. Between 2010 and 2020, N-VA consistently ranks among the most negatively portrayed parties, even briefly overtaking Vlaams Belang in 2020. After 2021, however, negativity decreases sharply, and by 2024, the party occupies a more middle position relative to other parties. The trajectory of N-VA's sentiment is thus more cyclical and irregular, but clearly not consistently marginalized as with Vlaams Belang.

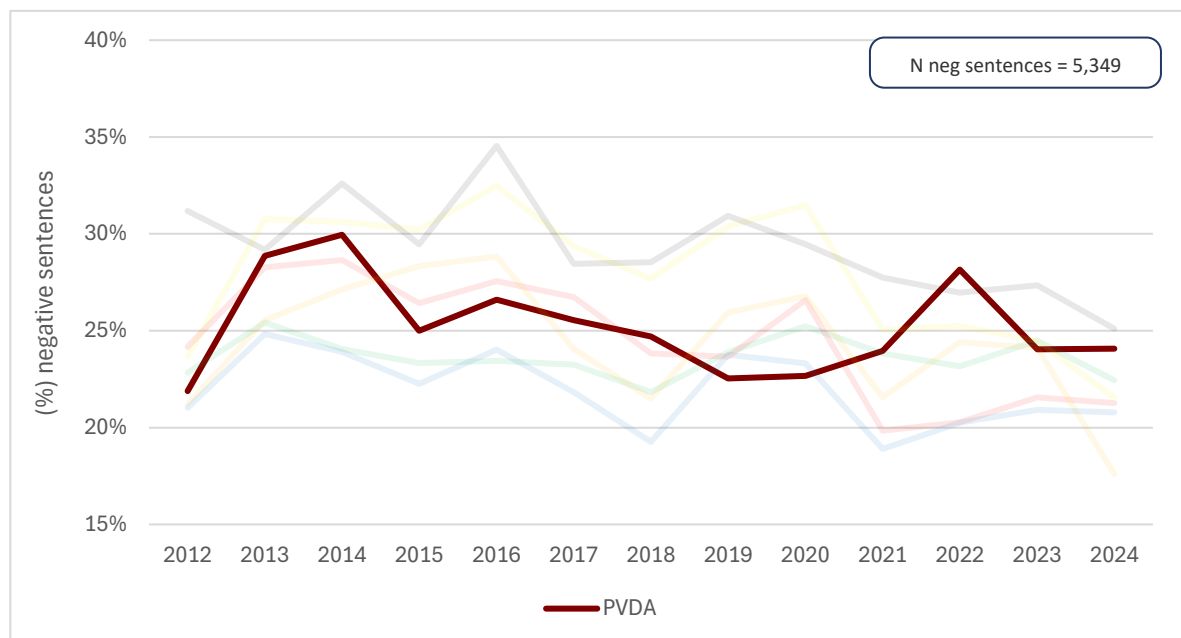
Open VLD (blue line) shows a clear and steady decline in negative coverage as well, dropping from roughly 28% of negative sentences in 2004 to around 21% by 2024. Its trend line is among the steepest, resembling that of N-VA, albeit with less volatility. In contrast, Vooruit and CD&V follow somewhat more irregular trajectories. Both parties experience periods of heightened negativity, interspersed with dips, but their overall downward movement is modest and lacks the consistency observed for the right-leaning parties.

Groen stands out for its stability. The party maintains relatively low levels of negative coverage throughout the entire period, with minimal fluctuation. Unlike other parties, Groen does not display pronounced peaks or drops. Although it starts as one of the least negatively portrayed parties, this distinction becomes less prominent after 2018, when negativity begins to drop more broadly across the board.

Finally, PVDA requires special attention. Although the party appears in the dataset before 2012, its presence is too limited to produce a reliable trend. From 2012 onwards, however, PVDA is consistently covered, allowing for a more meaningful analysis of its tone over time. As shown more closely in Figure 11, the sentiment line for PVDA initially mirrors that of most other parties (except for N-VA and Vlaams Belang), with a rise in negativity followed by a gradual decline.

However, after 2020, this pattern diverges. While the share of negative coverage decreases for nearly all other parties, PVDA experiences a renewed increase, peaking in 2022. In that year, the party even surpasses Vlaams Belang in negative tone, which is surprising given the consistent high negativity for the radical-right party. This may reflect the PVDA's relatively recent entry into mainstream politics, with the accompanying challenge of establishing its role and visibility in both the public debate and the media.

Figure 11. Overview of negativity share for PVDA from 2012-2024 (N = 20,741)



To statistically verify the visual trends observed in the previous figures, a series of binary logistic regression models were performed. These models included interaction terms between each political party and time (measured in years since 2004). The purpose of these interaction terms is to assess whether the likelihood of negative sentiment has increased or decreased over time for each party.

Because interaction effects are interpreted relative to a reference category, multiple regressions were run with different parties set as the reference. This approach ensures that each party's trend can be compared fairly to the others. The coefficient and odds ratio for a party's interaction with time indicate whether that party's tone has become more or less negative over time compared to the reference party. A value below 1 means a stronger decline, and a value above 1 means a weaker decline (or even an increase) relative to the reference.

For example, in the model using CD&V as the reference category (see Table 14), Vlaams Belang has an odds ratio of 0.996. This indicates that the likelihood of negative sentiment for VB decreased by about 0.9% more per year than for CD&V. N-VA shows a similar pattern with an odds ratio of 0.997. Open VLD and Vooruit also display modest declines in negativity compared to CD&V, with odds ratios of 0.993 and 0.995 respectively.

In contrast, Groen and PVDA have odds ratios above 1, indicating that their decline in negativity was less steep than that of CD&V. It does not necessarily mean that negativity increased for these parties in absolute terms. It simply means their sentiment trend over time was relatively more stable or flatter than CD&V's. The full set of regression outputs, each using a different party as reference, are provided in Appendix B.4.

Table 14. Logistic regression predicting negative sentiment with party x year interaction effects, CD&V as reference category (N = 1,019,983)

Variables	β	Standard Error	Wald's χ^2	<i>p</i>	Odds ratio (e^β)
PVDA_year	.005	.004	1.457	.227	1.005
Groen_year	.006	.001	13.991	<.001	1.006
Vooruit_year	-.005	.001	16.663	<.001	.995
Open VLD_year	-.007	.001	30.714	<.001	.993
N-VA_year	-.008	.001	38.171	<.001	.992
VB_year	-.009	.001	41.379	<.001	.991

Nagelkerke $R^2 = 0.007$

Across all models, the results are consistent: Vlaams Belang shows the steepest and most robust decline in negative sentiment between 2004 and 2024. Regardless of which party is used as the reference, the odds ratio for Vlaams Belang is consistently the lowest among all parties. This confirms the earlier visual finding that VB experienced the most significant and consistent softening in tone over the 21-year period.

N-VA ranks second, consistently showing a strong decline in negativity, followed closely by Open VLD. Other parties show either very modest downward trends like Vooruit or CD&V or, in the case of PVDA, a slight increase in negativity over time. When using Groen as the reference party, all other parties show odds ratios below 1. This means that their tone became less negative more rapidly than Groen's, suggesting that Groen maintained the most stable sentiment trend over time. Although CD&V also shows a relatively flat slope, Groen's trajectory is more consistent and less volatile.

Overall, the analysis provides strong and consistent evidence in support of **Hypothesis 2c**, which predicted that Vlaams Belang would experience the most pronounced decline in negative media tone. The findings suggest that VB has gradually come to be portrayed less critically and more similarly to mainstream parties. This may reflect a process of media normalization of radical-right actors, but it could also be the result of strategic communication changes within the party itself. PVDA, on the other hand, is the only party with a (modest) increase in negative sentiment over time. This divergence lends further support to the idea that while certain previously marginalized actors (like Vlaams Belang) are becoming more integrated into routine political coverage, newer challengers (such as PVDA) may still be met with a more skeptical or critical tone.

7.7 Additional analyses

To validate and contextualize the main findings, this section presents two additional analyses. The first addresses the potential influence of 2024 on the overall results, given that this single year accounts for approximately 13% of all sentences in the dataset. It is important to assess whether this disproportionately large contribution may distort broader sentiment patterns.

The second analysis delves further into how sentiment evolves over time for specific combinations of political parties and newspapers, using a more complex three-way interaction model. Because this model is complicated to interpret correctly, only the main patterns are summarized here.

The first analysis compares the sentiment distribution in 2024, as shown in Table 15, with the overall averages for the full 2004–2024 period, as discussed earlier. Before turning to tone, two noticeable differences emerge regarding the number of sentences for each party and newspaper. First, Open VLD, which on average represents 18.1% of all sentences and typically ranks among the three most-covered parties, experiences a sharp drop in visibility in 2024. It is surpassed by Vooruit, Groen, and even Vlaams Belang in terms of number of sentences.

This shift, while substantial, is not unexpected. It reflects the well-documented link between electoral performance and media coverage. Open VLD, having supplied the Prime Minister from 2019 to 2024, suffered a significant electoral decline, dropping from 24.4% of the vote in 2003 to 13.1% in 2019 and just 8.7% in the latest elections of 2024 (Michiels, 2025). This loss of electoral weight likely contributed to reduced media attention and should be considered when interpreting sentiment patterns for the party, particularly in the final year of the dataset.

The second evident change concerns Het Nieuwsblad, which records an unusually large share of all sentences in 2024. While the paper accounts for 23.9% of coverage on average, its share jumps to 34.3% in 2024, making it the most represented outlet that year. The exact reason for this increase is unclear, but it likely reflects intensified regional reporting in the context of the local elections.

It is notable that Het Nieuwsblad becomes significantly more dominant than Het Laatste Nieuws, which had previously been the largest contributor. This shift may affect average sentiment scores for 2024, as Het Nieuwsblad is by far the least negative outlet that year, likely due to the tone and content of local election coverage. As such, that newspaper data may somewhat lower the overall negativity levels in the final year, and should be interpreted with this caution in mind.

Table 15. Sentiment distribution by political party and newspaper for 2024 (N = 132,309)

	Number of sentences	Share (%)	Negative sentences (%)	Neutral sentences (%)	Positive sentences (%)
PVDA	6,332	4.8%	24.1%	65.0%	10.9%
Groen	17,597	13.3%	22.4%	64.9%	12.6%
Vooruit	22,475	17.0%	21.3%	66.8%	12.0%
CD&V	22,662	17.1%	17.6%	70.4%	12.0%
Open VLD	12,849	9.7%	20.8%	70.2%	9.0%
N-VA	34,355	26.0%	21.5%	67.5%	10.9%
Vlaams Belang	16,039	12.1%	25.1%	64.0%	10.9%
De Morgen	6,699	5.1%	30.9%	59.8%	9.4%
De Standaard	13,621	10.3%	27.3%	63.1%	9.7%
De Tijd	10,350	7.8%	31.4%	61.5%	7.1%
Het Laatste Nieuws	27,500	20.8%	22.0%	66.0%	12.0%
Het Nieuwsblad	45,334	34.3%	16.8%	70.9%	12.2%
Gazet van Antwerpen	20,413	15.4%	18.9%	68.5%	12.6%
Het Belang van Limburg	8,392	6.3%	21.1%	68.4%	10.5%
Total	132,309	100%	21.4%	67.3%	11.3%

The results reveal a clear overall softening of tone. On average, the share of negative sentiment in 2024 is 21.4%, noticeably lower than the 25.7% across the entire period. At the same time, positive sentiment increases from 8.5% to 11.3%. Although the size of the shift varies by actor, the direction is consistent: coverage becomes less negative and slightly more positive.

Vlaams Belang, although still the most negatively portrayed party, sees its share of negative coverage decline from 30.1% to 25.1%. Similar downward shifts are observed for N-VA (from 28.3% to 21.5%) and Open VLD (from 23.2% to 20.8%). While these changes confirm the broader trend towards softer coverage, they also alter the relative positioning of parties. Vlaams Belang remains at the top in terms of negativity, but PVDA has now overtaken N-VA as the second most negatively covered party.

Notably, N-VA's negativity drops below that of Groen and aligns more closely with parties like Vooruit, placing it near the middle of the spectrum in 2024. CD&V stands out with the lowest negativity score of all parties, just 17.6%, while Open VLD continues to be among the less negatively covered, yet receives limited positive sentiment. This reinforces its profile as one of the most neutrally framed actors in the media.

The ranking among newspapers remains largely consistent, though with some important shifts. De Morgen, De Standaard, and De Tijd continue to apply the most critical tone overall. However, De Tijd deviates from the general trend. It is the only outlet for which negativity increases, from 30.8% across the full period to 31.4% in 2024, making it the most negative newspaper that year, overtaking De Morgen. At the other end of the spectrum, Het Nieuwsblad becomes the least negative outlet, surpassing Gazet van Antwerpen with a notable drop in negativity, likely linked to its extensive coverage of local politics.

These developments suggest a subtle repositioning of political actors in the media landscape. Populist parties, notably Vlaams Belang and PVDA, now form the two most negatively framed outliers. In contrast, N-VA, currently leading the federal government, appears increasingly framed as a mainstream governing party. This shift may be reinforced by current Prime Minister Bart De Wever's public efforts to distance N-VA from Vlaams Belang (Michiels & Arnoudt, 2024). Whether this signals a lasting transformation in how parties are framed remains an open question for future research.

To further examine how sentiment varies across parties, newspapers, and time, a binary logistic regression with three-way interaction effects (party $\times$ newspaper $\times$ year) was conducted. The full model results are presented in Appendix C.1. However, the complexity of this model and its sensitivity to the choice of reference categories made direct interpretation difficult. To aid understanding, the regression was complemented by a series of visualizations showing the evolution of negative sentiment for each party in each newspaper between 2004 and 2024.

While many party–newspaper combinations show no substantial shifts over time, a few clear trends stand out. Most strikingly, PVDA is the only party to experience a consistent increase in negative sentiment across nearly all outlets. Since 2016, newspapers such as De Morgen, Het Nieuwsblad, and Het Laatste Nieuws have shown a steady rise in critical tone, with an estimated increase of 3–5% in the odds of negative coverage per year. This trend reinforces the earlier observation that PVDA remains more critically framed over time, in contrast to the broader softening of tone across the board.

By contrast, Vlaams Belang and N-VA exhibit a general decline in negativity. This trend is especially pronounced for Vlaams Belang in Het Belang van Limburg, where the tone has become considerably more neutral over time. N-VA shows a similar, albeit more moderate, softening trend in several outlets. These findings further substantiate the earlier conclusion that these right-wing parties have undergone the biggest decline in negative media framing.

For most other parties, tone remains relatively stable with a minor decline throughout the 21-year period. One minor exception is Open VLD, which shows a slightly lesser decline in negative tone than expected, particularly in popular outlets. However, these patterns should be interpreted cautiously, as results vary depending on the choice of reference categories and are influenced by year-to-year fluctuations in newspaper content.

Across newspapers, a general downward trend in negative sentiment is observable, particularly in De Morgen, Het Nieuwsblad, and Het Laatste Nieuws, all of which display the strongest declines over time. In contrast, De Tijd and, to a lesser extent, Gazet van Antwerpen, show a gradual increase in negativity. While Gazet van Antwerpen displays a more erratic pattern with considerable year-to-year fluctuations, De Tijd reveals a more consistent and structural rise in negative coverage. Het Belang Van Limburg remains remarkably stable, showing little variation in its share of negative sentiment throughout the period. These outlet-specific trends are visualized in Appendix C.2, which presents the full distribution of newspaper tone over time.

8 Discussion

This study examined how tone towards Flemish political parties varies across newspapers and over time, using large-scale sentiment analysis. Rather than confirming a single ideological pattern, the results show that tone is shaped by a mix of party identity, media profile, political situation, and broader changes in journalism. Some findings align with expectations, while others challenge common assumptions about how the press treats radical or mainstream actors. A summary of all hypotheses and their outcomes can be found below in Table 16.

While negativity dominates over positivity, as expected in **Hypothesis 1**, the tone has softened over time, challenging the widespread narrative of an increasingly hostile media environment. This contradicts **Hypothesis 4** and suggests that Flemish political journalism may be undergoing a form of depolarization, at least in tone, possibly due to evolving journalistic norms, with more automated content, increased reliance on press releases and curated messaging, or less opinion pieces. This long-term trend stands in contrast to international patterns, especially in the U.S., where negativity in news has been steadily rising (Rozado et al., 2022).

The softening of tone in 2024, the most recent and heavily represented year in the dataset, points to an electoral context in which the journalistic tone has become more neutral or positive. While this could be attributed to a heightened sense of responsibility during elections, it may also reflect a shift towards human-interest framing in local campaigns, or even a softening of tone in political rhetoric. Whatever the cause, it marks a noteworthy development in the tone of Flemish political reporting.

Perhaps the most consistent pattern is the evolving media portrayal of Vlaams Belang. Once the most stigmatized party, it has seen the steepest drop in negative coverage over two decades. This confirms **Hypothesis 2c** and aligns with theories of normalization: as the party gains electoral strength and becomes more central in the political arena, media actors may be less inclined, or less able, to sustain earlier forms of exclusion or stigmatization (De Jonge, 2021). That said, Vlaams Belang remains the most negatively portrayed party overall (**Hypothesis 2a** confirmed), so it is likely that this evolution is still in progress. This raises important normative questions about whether press tone adjusts to electoral reality or reflects changing ideological perceptions.

This pattern of structural negativity does not apply to the radical-left party PVDA. However, it is noteworthy that in 2024, the party is also evaluated more negatively than most others. This shift is relatively recent: prior to 2022, PVDA's sentiment scores were largely in line with those of other mid-range parties, and even after 2022, the degree of negative coverage remains well below that of Vlaams Belang. As such, **Hypothesis 2b** is not confirmed overall. PVDA is the only party for which negative sentiment has slightly increased in recent years, particularly in 2022 and 2024, but this trend remains modest compared to the persistent and pronounced negativity directed at Vlaams Belang.

This divergence between the radical left and right could indicate that the media system is more receptive to the mainstreaming of right-wing populism than left-wing alternatives. It may also relate to PVDA's more recent breakthrough into the mainstream political arena compared to Vlaams Belang. Alternatively, topic-based dynamics may play a role: PVDA might be more frequently associated with negatively charged issues. Finally, differences in communication style among party leaders and representatives could also contribute to this pattern.

In contrast, the negative sentiment towards radical-left party PVDA has remained relatively stable and even increased slightly in recent years, which contradicts **Hypothesis 2b**. This divergence between the radical left and right could indicate that the media system is more receptive to the mainstreaming of right-wing populism than left-wing alternatives. It can also be because of PVDA's more recent rise in the mainstream political arena compared to Vlaams Belang. Alternatively, it may reflect topic-based dynamics: PVDA may be associated more frequently with negative-laden issues. Or it could be a difference in the party communication style of their party leaders and members.

When it comes to differences between newspapers, the quality press is, as predicted (**Hypothesis 3a**), more negative overall. This could reflect journalistic norms of analytical distance, greater use of interpretative reporting, or a stronger watchdog orientation. However, contrary to **Hypotheses 3b and 3c**, this more negative tone is not consistently directed at ideological opponents. In fact, popular newspapers were relatively harsher towards Vlaams Belang than quality outlets, an unexpected yet clear finding. This calls into question the assumption that ideological legacy or audience alignment directly predicts tone. Instead, tone may be more dependent on individual journalists or the kinds of stories different outlets prioritize.

There is, however, partial support for **Hypothesis 3d**. Moderate left-wing parties like Vooruit and Groen receive relatively less negative coverage in quality newspapers. This may reflect their progressive affinity, but again it is possibly that it correlates with issue coverage or some other factor as long as this is not researched. Interestingly, this pattern does not extend to PVDA, reinforcing the idea that radicalism, rather than ideology per se, may be a more important predictor of tone. That is at least the case for De Standaard and De Tijd, because De Morgen did relatively favor the two most left-leaning parties PVDA and Groen.

Another important insight is that N-VA, although a mainstream right-wing party, has consistently received above-average levels of negativity, second only to Vlaams Belang. This could suggest a form of ideological asymmetry in tone, but it may also be a byproduct of the party's prominent role in Belgian politics, especially during polarizing debates and institutional crises. Notably, the tone towards N-VA softened significantly after 2021, perhaps reflecting its changing image from oppositional force to governing actor.

Taken together, these findings complicate the notion of straightforward ideological media bias. While some tone patterns may align with editorial orientation such as De Tijd's favorability towards Open VLD, it can certainly not be defined by party ideology alone. The data suggest that tone is shaped by a combination of various factors. Vlaams Belang's gradual tone moderation coincides with its steady presence in public discourse and electoral success. PVDA's increasing negativity may stem from growing media scrutiny as its visibility rises. These dynamics reflect broader trends in how political actors are integrated into the media landscape, and how journalistic routines adapt to shifting political realities.

Table 16. Overview of hypotheses tested in this study (confirmed/rejected)

Hypotheses		
Hypothesis 1	The tone of political news coverage is more negative than positive.	+
Hypothesis 2a	The tone towards the radical-right party Vlaams Belang is more negative than towards mainstream parties.	+
Hypothesis 2b	The tone towards the radical-left party PVDA is more negative than towards mainstream parties.	-
Hypothesis 2c	The tone towards radical-right party Vlaams Belang becomes less negative over time, more so than for any other party.	+
Hypothesis 3a	The tone in quality newspapers is more negative than in popular newspapers.	+
Hypothesis 3b	The tone in newspapers is less negative towards parties that align with their historical ideological orientation.	-
Hypothesis 3c	The tone in quality newspapers is relatively more negative towards right-leaning parties than in popular newspapers.	-
Hypothesis 3d	The tone in quality newspapers is relatively less negative towards left-leaning parties than in popular newspapers.	+/-
Hypothesis 4	The tone of political news coverage fluctuates over time, but becomes more negative overall.	-

8.1 Limitations

This study, while extensive in scope, faces several important limitations that should be taken into account when interpreting the results. The most significant methodological challenge lies in attributing sentiment to the correct political actor. This attribution problem, discussed in detail earlier, may result in overestimating negativity for opposition parties that frequently use critical language. However, two robustness checks were conducted to assess the impact of this limitation, comparing the manual coding to the computer assessment and specifically controlling for quoted speech. These checks showed that while attribution errors exist, they do not fundamentally alter the ranking of parties or the key trends over time.

A second major limitation is that the model is not fine-tuned on political texts from Flanders, meaning it misses some language cues and interpretations specific to the context in which the analysis is conducted. The model reached a very good accuracy of 81.6%, but this will most likely only improve when fine-tuning the current model on a manual coded set of relevant news articles.

Related to this, working at the sentence level limits contextual understanding. Important framing elements, such as irony, buildup, or contrast, often require paragraph-level context to be properly interpreted. Splitting articles into individual sentences may remove cues that help disambiguate sentiment, leading to false positives or false negatives. While sentence-based analysis allows for scalable and consistent measurement, it may flatten more complex rhetorical structures and underrepresent indirect forms of evaluation. A study using paragraph-based analysis or item-based analysis could validate these results, but still remain challenging and mostly impossible for a RoBERTa model.

Another limitation is the absence of politicians as actors. This study measures sentiment towards parties as a whole and does not distinguish between individual politicians or factions within a party. This is particularly relevant for Flemish politics, where party leaders like Bart De Wever, Conner Rousseau, or Tom Van Grieken often dominate media narratives. Sentences about such individuals may reflect personal reputation, style, or controversy, but are not included here as an observation of itself. Future research could include the most important political actors to get an even broader understanding of political discourse.

There are also data-related limitations. While the dataset is large and comprehensive, older years most likely suffer from partial digitalization, potentially leading to underrepresentation of some newspapers or periods. Small inconsistencies in the data are also inevitable, like the technical problems surrounding the introduction will account for some minimal changes. Moreover, the dataset does not distinguish between article types (e.g., opinion vs. news) or journalists, which limits analysis of journalistic voice and article format effects. Certainly because journalists increasingly write from their personal perspective rather than adhering to their outlet's ideological line, as happened in the past (Soontjens, Van Remoortere, & Beckers, 2021).

And lastly, as stated in the theoretical framework, the results show differences in tone, but the study does not link these differences to news topics or party communication. As a result, it is not possible to explain *why* certain parties are covered more negatively. A negative tone may be justified by real-world events (e.g., scandals or conflicts) or it could be related to issue coverage (for example, if Groen emphasizes biodiversity, which is probably framed positively), but this is not tested. The study only measures *how* parties are described, not whether that tone is fair or proportionate.

8.2 Future Research

Several directions for future research emerge from the limitations above. A first step would be to improve actor-specific sentiment attribution and context-specific language. This could involve fine-tuning a transformer-based model on a manually labeled dataset. However, to this day sentiment models struggle with attribution or stance detection to identify who is speaking and who is being evaluated (Aldayel & Magdy, 2021). Even a relatively small but high-quality corpus could significantly improve the precision of sentiment classification in complex political texts. Such improvements would reduce misattribution errors and allow for more accurate comparisons between parties or actors. This could also improve the model's performance in Dutch, and its ability to handle expressions, idioms or context-based words.

In addition, future work could aim to incorporate different additional factors into the sentiment analysis. A first step would be to connect sentiment scores to political outcomes, such as election results, polling data, or party popularity trends. This would allow researchers to test whether the tone of media coverage reflects broader political shifts or diverges from public opinion. Such analyses could help identify whether certain parties systematically receive more critical or favorable media treatment than their electoral relevance would suggest.

In the same vein, future research could compare media tone with party-controlled communication, such as press releases, party programs, or social media content. This would reveal whether the media amplifies, filters, or counterbalances the tone used by parties themselves. For instance, a party that consistently frames itself in positive or solution-oriented terms may still receive neutral or negative press coverage, suggesting editorial reinterpretation or selectivity. Exploring these discrepancies could improve understanding of how media shape or reshape party narratives.

Another valuable extension would be the inclusion of issue-level tagging. Currently, the study aggregates all party mentions across topics, but sentiment likely varies by domain. For example, discussions of environmental policy possibly carry more constructive or optimistic framing, potentially benefiting parties like the Green party. Conversely, topics like migration or security are more likely to involve somber or critical tone, which may affect how certain parties are portrayed. Tagging sentences by policy area, whether through keyword filtering or supervised classifiers, could clarify how tone interacts with issue salience and party ownership.

There is also scope to explore cross-platform comparisons. This study focused exclusively on newspaper coverage, but political news consumption increasingly includes online-only media, TV, radio, and social media platforms. Including additional sources, such as public broadcaster VRT NWS articles or TV news transcripts, could reveal whether tone dynamics vary across platforms, especially in relation to audience segmentation and media format.

Finally, the methods used here can also be applied in other countries or regions. Comparing tone dynamics in different media systems could show how institutional, cultural, or economic factors shape media tone. Within Belgium, future research could also compare Flemish and Francophone newspapers or study public broadcasters separately from commercial outlets.

There is a wide range of possibilities for future research building on this approach. Large-scale sentiment analysis allows for systematic comparisons over time, parties, and media outlets, but it also opens the door to exploring broader concepts in relation to tonality bias. It would be especially valuable to study how tone interacts with other forms of media bias, such as visibility bias, or what effects evaluative tone may have. For example, future research could examine whether changes in tone are associated with shifts in party support, media trust, or citizen perceptions of political legitimacy.

9 Conclusion

In democratic systems, news coverage plays a central role in shaping how citizens perceive political actors, especially for voters who rely heavily on the media to form opinions. Evaluative tone, while subtle, can influence whether a party is seen as capable, reliable or legitimate. Studying how that tone is distributed across parties, newspapers and time allows public debates about media bias to move beyond perception and be grounded in evidence.

This study applied applying sentence-level sentiment analysis to over one million newspaper sentences from seven Flemish outlets between 2004 and 2024. It provides one of the most comprehensive long-term analyses to date of how political tone evolves in a multi-party context. By spanning two decades, it uncovers a series of subtle but significant shifts in how Flemish political parties are portrayed. The results show that while negative sentiment structurally outweighs positive tone, this tendency has gradually softened, contradicting widespread assumptions about the increasing harshness of political journalism.

Importantly, not all parties are treated equally. Right-wing parties Vlaams Belang and N-VA structurally receive more negative coverage than others, though this tone has softened, particularly for radical-right party Vlaams Belang. By contrast, the radical-left party PVDA is the only party for which negative coverage has increased slightly, possibly reflecting its growing electoral relevance and more recent entry into the mainstream political arena.

These patterns are relevant, as earlier research has shown that sentiment analysis can be used to detect indicators of media bias (Falck et al., 2020). However, this study does not assess journalistic intent, nor does it control for factors like public opinion, party communication or issue salience. As such, the presence of bias cannot be confirmed or ruled out based on tone alone. Further research is needed to explain *why* certain parties are framed more negatively than others.

The findings also challenge simplified assumptions about ideological media bias. While progressive newspaper De Morgen is relatively less negative towards left-wing parties, all quality newspapers are also less negative towards the radical-right Vlaams Belang than the popular press, contrary to expectations. This suggests that tone is not strictly driven by ideology, but shaped by a broader set of factors, including readership expectations, journalistic style and more.

In the Flemish context, often described as a highly professionalized, non-partisan media system (Soontjens, Van Remoortere, & Walgrave, 2021), these findings offer a nuanced perspective on how tone in the news can reflect processes of normalization, evolving journalistic practices and changing patterns of political relevance. While tone differences alone do not prove structural bias, they offer a useful lens for understanding how political actors are presented in the press. These results may contribute to further research into tone and its relationship with media bias, and could serve as a starting point for greater tone awareness and reflection within journalism on how political balance is shaped in practice.

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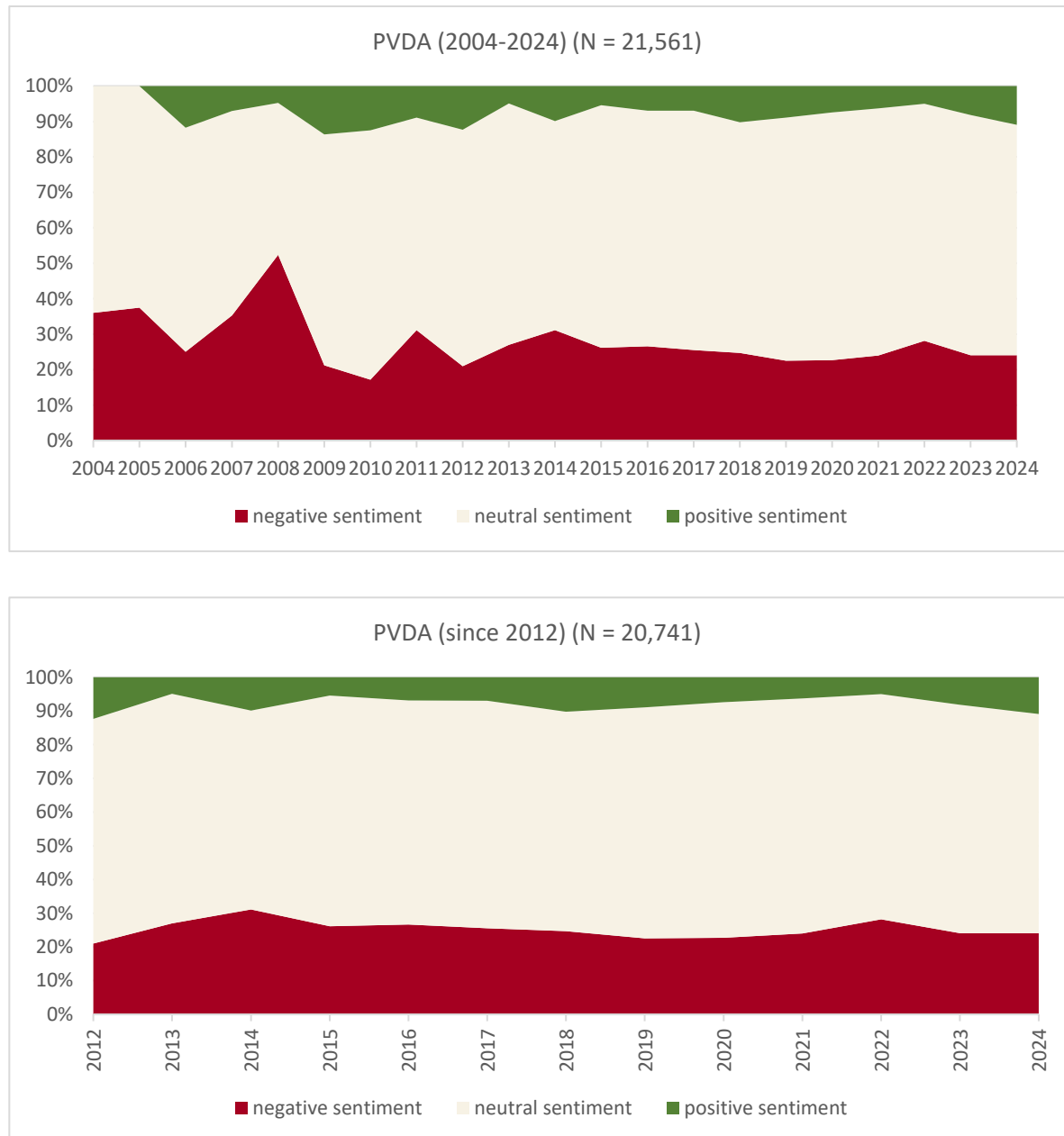
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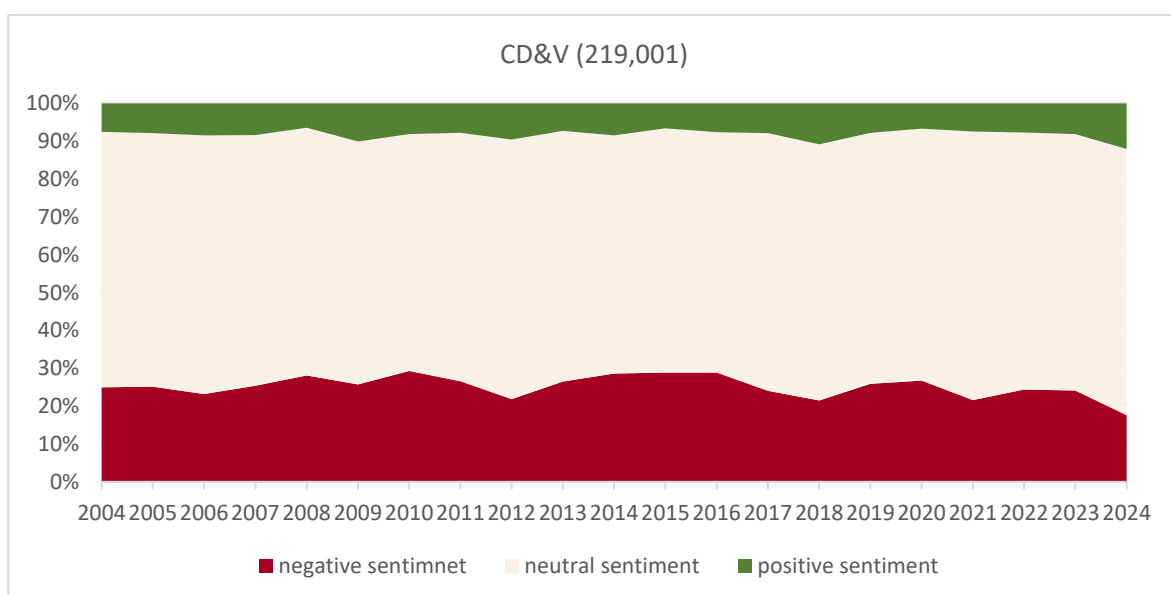
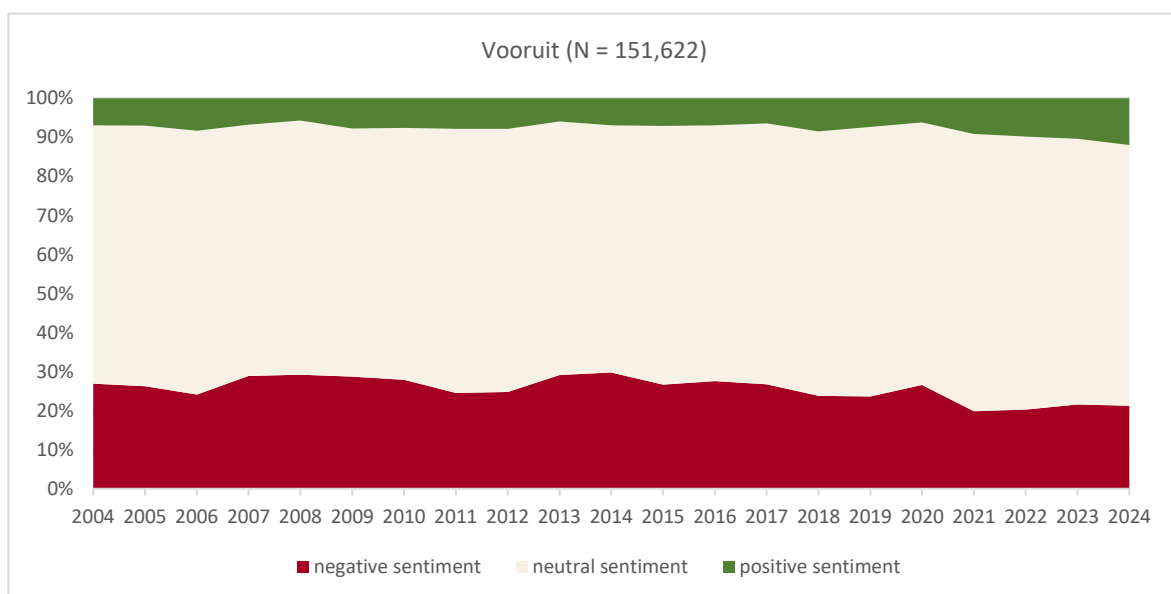
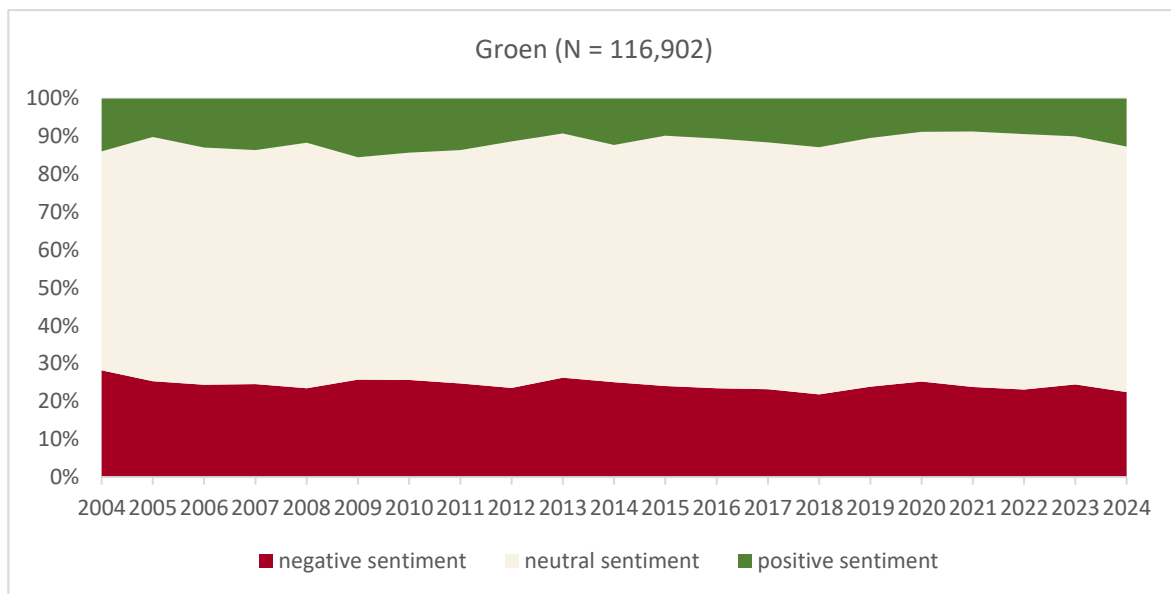
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11 Appendix

11.1 Appendix A – Supplementary figures for political parties

Figure A.1 Full party-specific trendlines (stacked area charts)





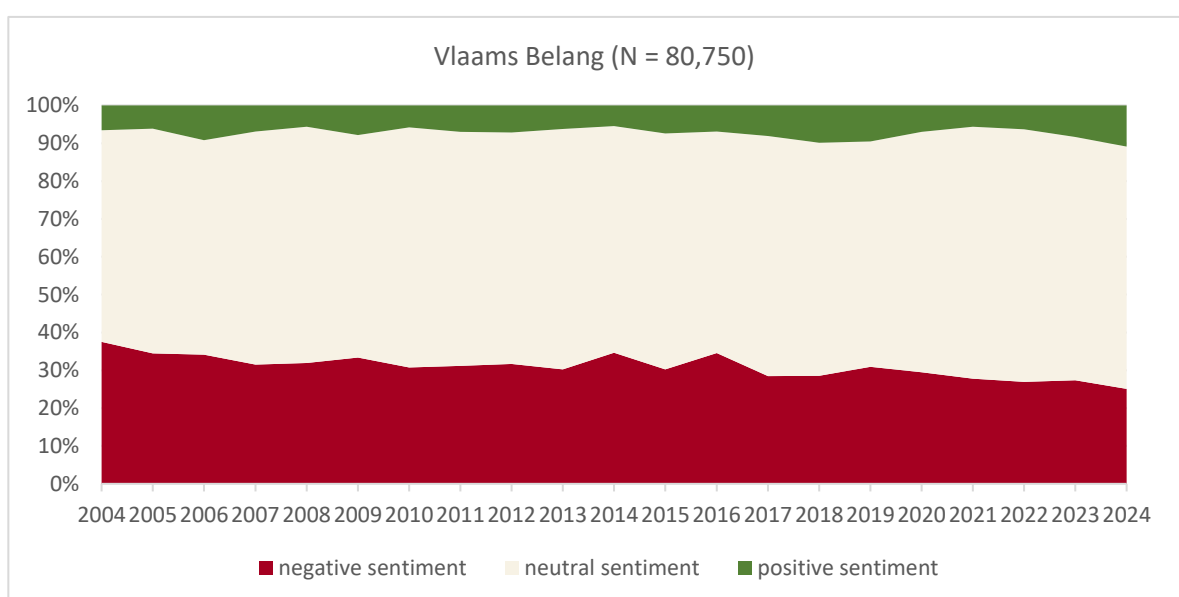
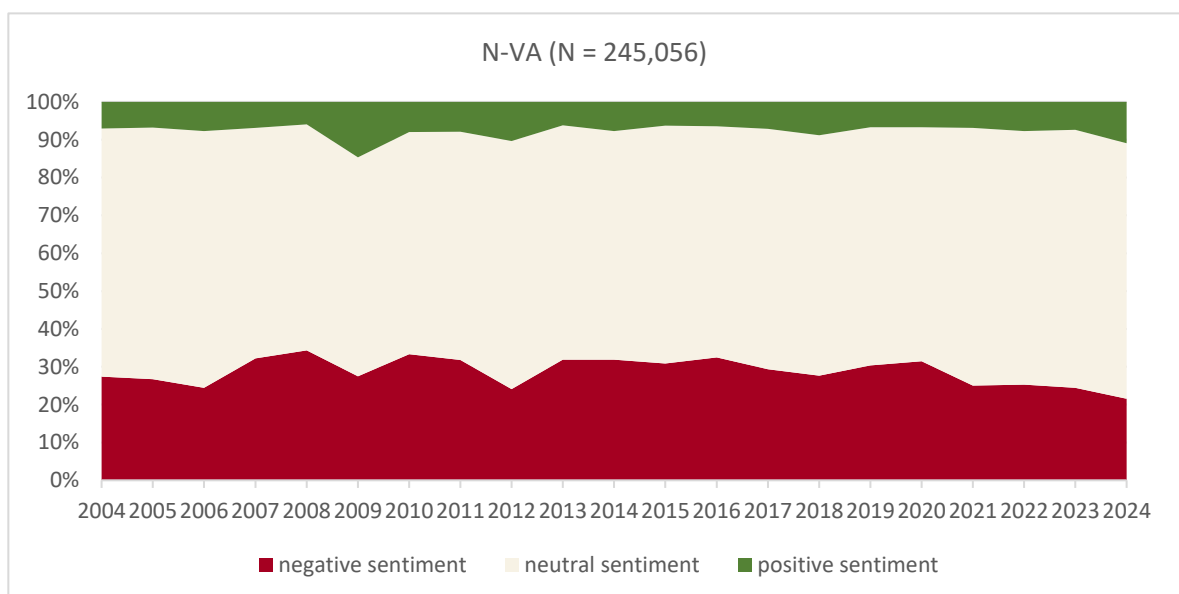
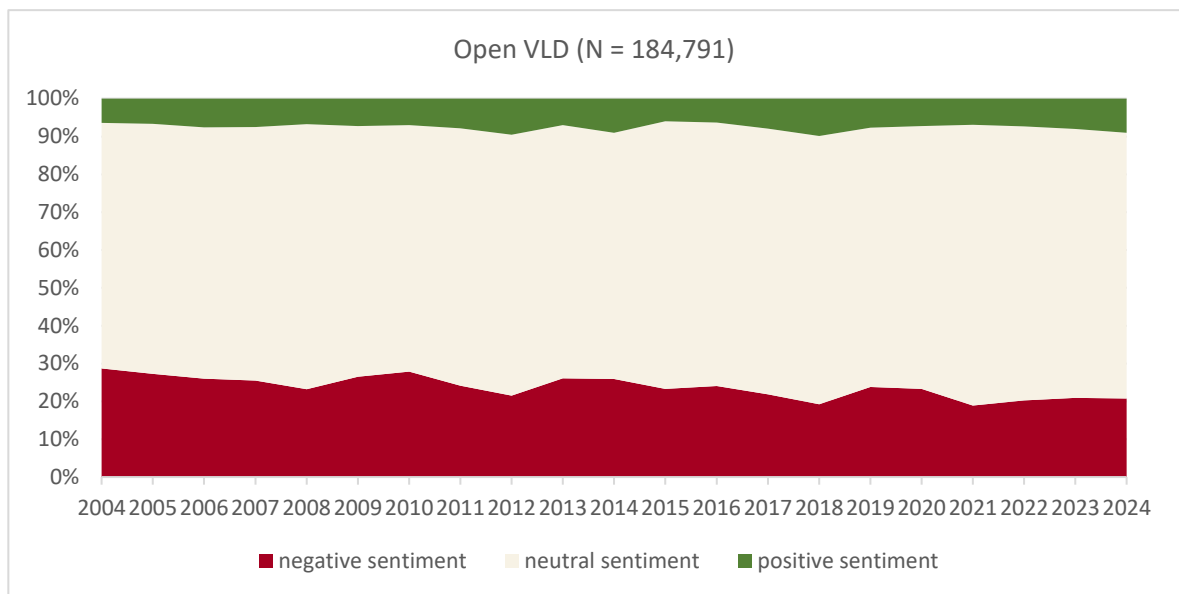
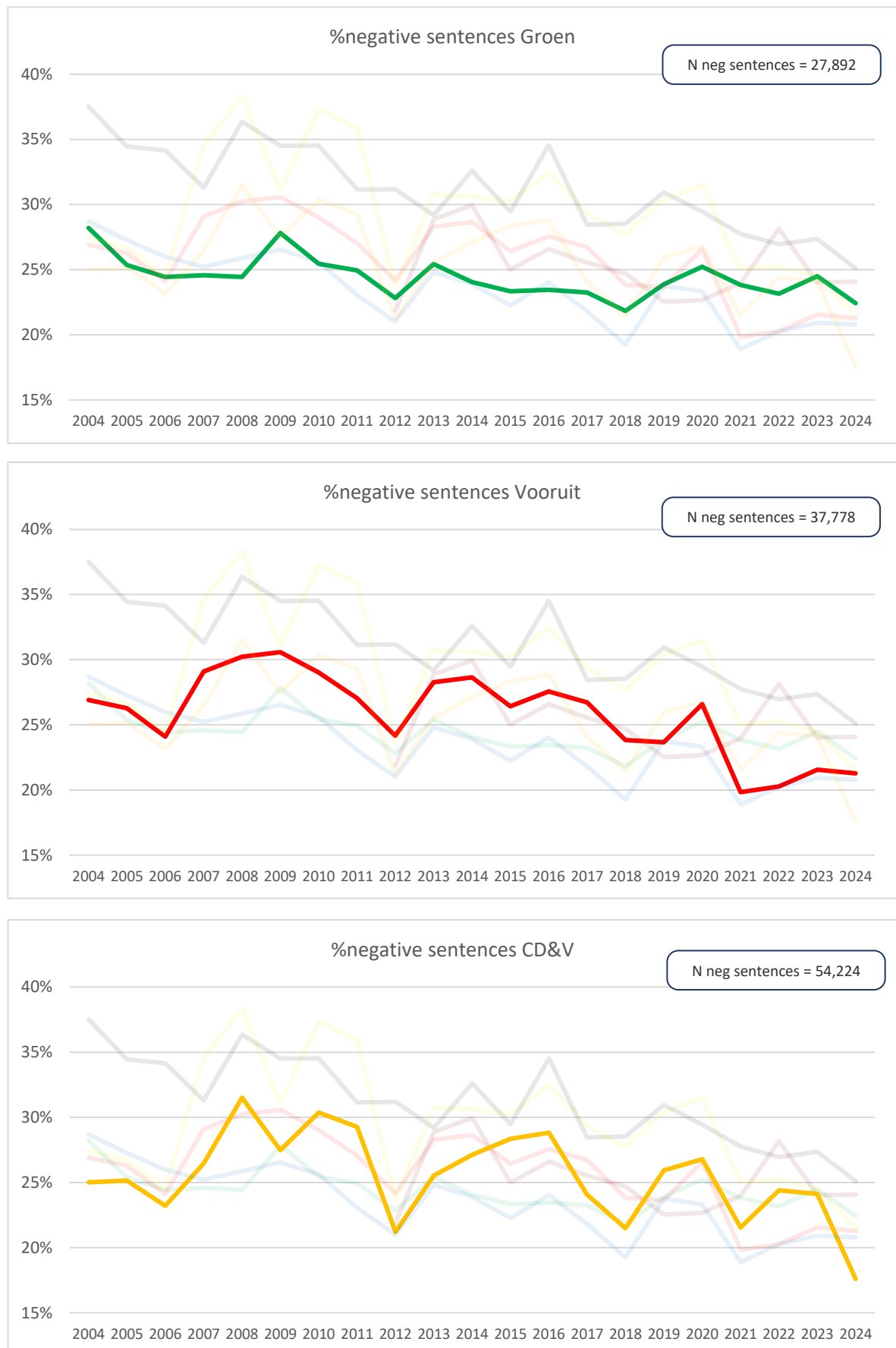
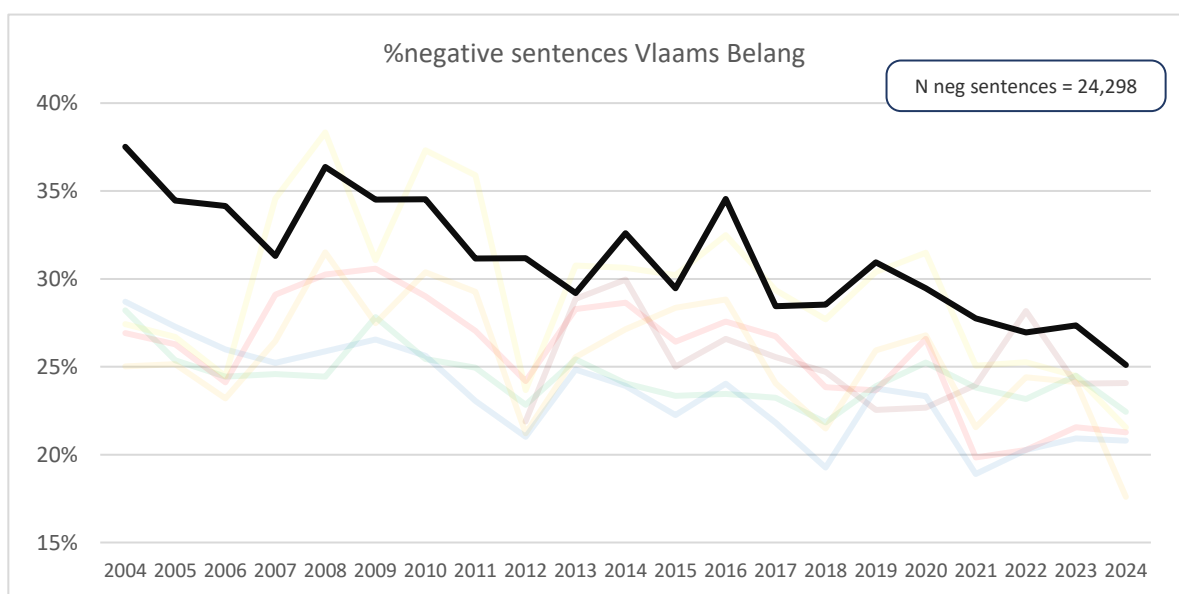
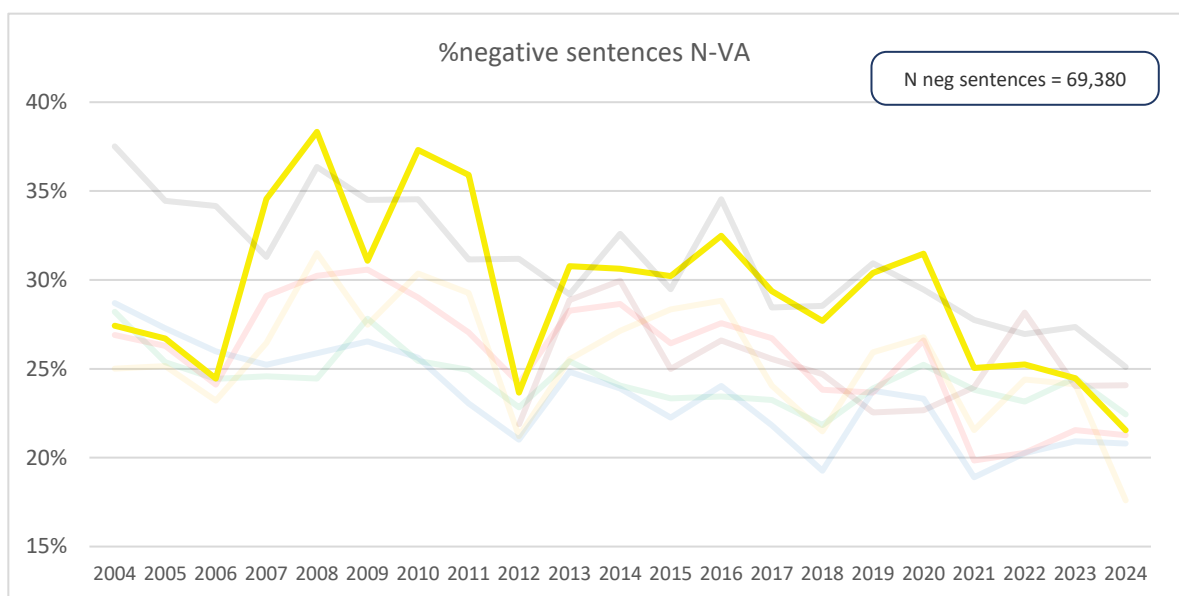
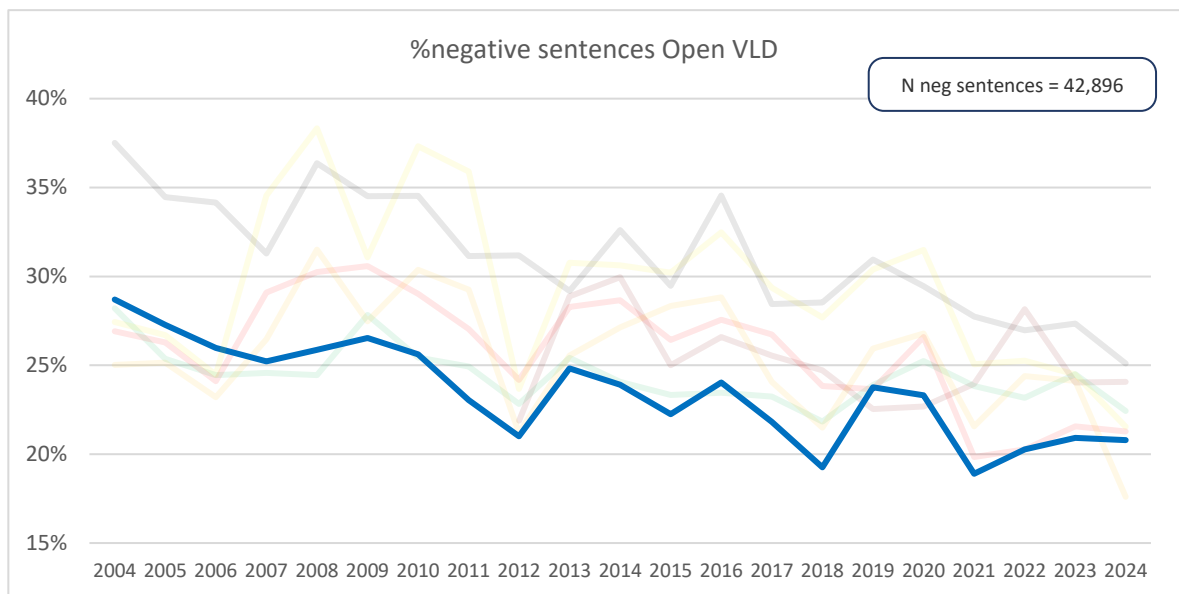


Figure A.2 Overview of negativity share for each political party individually from 2004-2024 (without PVDA)





11.2 Appendix B - Full regression models

Table B.1 Linear regression for predicting negative sentiment over time using monthly data (N = 1,019,683)

Variables	Estimate	Standard Error	β	t	p
Month (since Jan 2004)	-0.019	0.003	-0.416	-7.239	< .001
Constant	28.799	0.392	—	73.506	< .001
R ²	0.173				
Std. Error of Estimate	3.10				
F	52.405				
Sig. (ANOVA)	<.001				

Table B.2 Binary logistic regression for predicting negative sentiment with interactions of newspaper and political party, CD&V in Het Laatste Nieuws as reference category (N = 1,019,683)

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
PVDA	-.018	.031	.313	.576	.983
Groen	-.038	.017	5.105	.024	.963
Vooruit	.002	.016	.011	.916	1.002
Open VLD	-.117	.015	62.020	<.001	.890
N-VA	.155	.013	133.796	<.001	1.168
Vlaams Belang	.257	.019	184.639	<.001	1.293
De Morgen	.472	.017	781.914	<.001	1.604
De Standaard	.317	.017	358.608	<.001	1.373
De Tijd	.360	.019	376.580	<.001	1.434
Het Nieuwsblad	-.136	.015	86.504	<.001	.873
Gazet van Antwerpen	-.241	.020	139.648	<.001	.786
Het Belang van Limburg	-.074	.020	13.594	<.001	.929
PVDA_demorgen	-.106	.059	3.212	.073	.900
PVDA_destandaard	.014	.056	.067	.796	1.014
PVDA_detijd	.131	.074	3.117	.077	1.140
PVDA_nieuwsblad	.085	.048	3.104	.078	1.089
PVDA_gva	.270	.053	25.712	<.001	1.311
PVDA_hbvl	.006	.076	.007	.933	1.006
Groen_demorgen	-.114	.030	14.401	<.001	.892
Groen_destandaard	-.013	.028	.199	.656	.987
Groen_detijd	.004	.034	.016	.898	1.004
Groen_nieuwsblad	.066	.024	7.615	.006	1.068
Groen_gva	.087	.032	7.286	.007	1.091
Groen_hbvl	.078	.039	4.069	.044	1.081
Vooruit_demorgen	-.037	.026	1.942	.163	.964
Vooruit_destandaard	-.012	.026	.233	.629	.988
Vooruit_detijd	-.084	.030	7.830	.005	.919
Vooruit_nieuwsblad	.073	.023	10.356	.001	1.076
Vooruit_gva	.066	.031	4.485	.034	1.068
Vooruit_hbvl	.006	.032	.038	.845	1.006
Open VLD_demorgen	-.006	.026	.061	.805	.994
Open VLD_destandaard	.080	.025	10.211	.001	1.083
Open VLD_detijd	-.102	.028	12.908	<.001	.903
Open VLD_nieuwsblad	.118	.022	29.707	<.001	1.125
Open VLD_gva	.068	.030	5.114	.024	1.070
Open VLD_hbvl	.078	.030	6.722	.010	1.081
N-VA_demorgen	.004	.023	.026	.872	1.004
N-VA_destandaard	.024	.022	1.120	.290	1.024
N-VA_detijd	.019	.025	.565	.452	1.019
N-VA_nieuwsblad	.018	.020	.790	.374	1.018

N-VA_gva	.041	.027	2.274	.132	1.041
N-VA_hbvl	.081	.027	8.611	.003	1.084
VB_demorgen	-.040	.033	1.460	.227	.961
VB_destandaard	-.007	.030	.056	.813	.993
VB_detijd	-.024	.035	.472	.492	.976
VB_nieuwsblad	.038	.027	1.900	.168	1.038
VB_gva	.096	.035	7.682	.006	1.101
VB_hbvl	.070	.039	3.307	.069	1.073
Constant	-1.186	.010	14169.500	<.001	.305

Nagelkerke $R^2 = 0.017$

Table B.3 Binary logistic regression for predicting negative sentiment with interactions of newspaper and political party, Open VLD in Het Nieuwsblad as reference category (N = 1,019,683)

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
PVDA	.067	.037	3.266	.071	1.069
Groen	.028	.018	2.443	.118	1.028
Vooruit	.074	.017	18.653	<.001	1.077
CD&V	-.001	.016	.002	.962	.999
N-VA	.172	.015	126.891	<.001	1.188
Vlaams Belang	.294	.020	209.194	<.001	1.341
De Morgen	.484	.020	612.063	<.001	1.623
De Standaard	.414	.019	489.624	<.001	1.513
De Tijd	.276	.022	162.203	<.001	1.318
Het Laatste Nieuws	.018	.016	1.270	.260	1.018
Gazet van Antwerpen	-.155	.022	48.270	<.001	.857
Het Belang van Limburg	.022	.023	.957	.328	1.022
PVDA_demorgen	-.067	.063	1.134	.287	.935
PVDA_destandaard	-.032	.059	.299	.584	.968
PVDA_detijd	.265	.077	11.834	<.001	1.304
PVDA_hln	.033	.049	.452	.502	1.033
PVDA_gva	-.039	.079	.241	.624	.962
PVDA_hbvl	.235	.057	16.930	<.001	1.265
Groen_demorgen	-.056	.032	3.113	.078	.946
Groen_destandaard	-.040	.030	1.851	.174	.960
Groen_detijd	.158	.036	19.060	<.001	1.171
Groen_hln	.052	.025	4.356	.037	1.053
Groen_gva	.071	.033	4.454	.035	1.073
Groen_hbvl	.052	.040	1.667	.197	1.053
Vooruit_demorgen	.014	.028	.254	.614	1.014
Vooruit_destandaard	-.047	.027	2.949	.086	.954
Vooruit_detijd	.062	.032	3.705	.054	1.064
Vooruit_hln	.045	.024	3.600	.058	1.046
Vooruit_gva	.043	.033	1.709	.191	1.044
Vooruit_hbvl	-.027	.034	.644	.422	.973
CD&V_demorgen	.124	.026	22.583	<.001	1.132
CD&V_destandaard	.038	.025	2.276	.131	1.039
CD&V_detijd	.220	.029	58.181	<.001	1.246
CD&V_hln	.118	.022	29.707	<.001	1.125
CD&V_gva	.050	.030	2.702	.100	1.051
CD&V_hbvl	.040	.030	1.725	.189	1.041
N-VA_demorgen	.110	.025	19.220	<.001	1.116
N-VA_destandaard	.044	.024	3.311	.069	1.045
N-VA_detijd	.221	.028	63.430	<.001	1.247
N-VA_hln	.100	.021	22.941	<.001	1.105
N-VA_gva	.073	.029	6.433	.011	1.076
N-VA_hbvl	.103	.030	11.910	<.001	1.108
VB_demorgen	.047	.035	1.791	.181	1.048
VB_destandaard	-.007	.031	.043	.835	.993
VB_detijd	.158	.037	18.462	<.001	1.171
VB_hln	.080	.028	8.092	.004	1.083

VB_gva	.108	.036	8.982	.003	1.114
VB_hbvl	.072	.040	3.223	.073	1.075
Constant	-1.321	.012	13179.379	<.001	.267

Nagelkerke $R^2 = 0.017$

Table B.4 Binary regressions results (full models) (N = 1,019,683)

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
Groen	-.078	.076	1.037	.309	.925
Vooruit	.087	.075	1.337	.248	1.091
CD&V	-.002	.075	.001	.980	.998
Open VLD	.017	.075	.054	.816	1.018
N-VA	.314	.075	17.486	<.001	1.369
Vlaams Belang	.414	.076	29.897	<.001	1.513
Year (since 2004)	-.008	.004	3.997	.046	.992
Groen_year	.000	.004	.013	.910	1.000
Vooruit_year	-.010	.004	6.063	.014	.990
CD&V_year	-.005	.004	1.457	.227	.995
Open VLD_year	-.012	.004	8.135	.004	.988
N-VA_year	-.013	.004	9.403	.002	.987
VB_year	-.014	.004	11.006	<.001	.986
Constant	-.973	.074	173.802	<.001	.378

Nagelkerke $R^2 = 0.007$; **PVDA** is the reference party

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
PVDA	.078	.076	1.037	.309	1.081
Vooruit	.164	.024	48.132	<.001	1.179
CD&V	.076	.023	11.238	<.001	1.079
Open VLD	.095	.023	17.712	<.001	1.100
N-VA	.392	.024	273.093	<.001	1.480
Vlaams Belang	.491	.025	376.734	<.001	1.635
Year (since 2004)	-.008	.001	41.048	<.001	.992
PVDA_year	.000	.004	.013	.910	1.000
Vooruit_year	-.011	.002	49.134	<.001	.989
CD&V_year	-.006	.001	13.991	<.001	.994
Open VLD_year	-.013	.002	68.674	<.001	.988
N-VA_year	-.013	.002	77.437	<.001	.987
VB_year	-.015	.002	79.428	<.001	.985
Constant	-1.050	.019	3082.352	<.001	.350

Nagelkerke $R^2 = 0.007$; **Groen** is the reference party

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
PVDA	-.087	.075	1.337	.248	.917
Groen	-.164	.024	48.132	<.001	.848
CD&V	-.089	.019	22.189	<.001	.915
Open VLD	-.069	.019	13.587	<.001	.933
N-VA	.227	.020	126.648	<.001	1.255
Vlaams Belang	.327	.022	219.487	<.001	1.387
Year (since 2004)	-.019	.001	362.318	<.001	.981
PVDA_year	.010	.004	6.063	.014	1.011
Groen_year	.011	.002	49.134	<.001	1.011
CD&V_year	.005	.001	16.663	<.001	1.005
Open VLD_year	-.002	.001	1.444	.230	.998
N-VA_year	-.003	.001	3.483	.062	.997
VB_year	-.004	.001	6.327	.012	.996
Constant	-.886	.014	3847.790	<.001	.412

Nagelkerke $R^2 = 0.007$; **Vooruit** is the reference party

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^{β})
PVDA	.002	.075	.001	.980	1.002
Groen	-.076	.023	11.238	<.001	.927
Vooruit	.089	.019	22.189	<.001	1.093
Open VLD	.019	.017	1.233	.267	1.020
N-VA	.316	.019	281.061	<.001	1.372
Vlaams Belang	.416	.021	397.871	<.001	1.515
Year (since 2004)	-.013	.001	235.399	<.001	.987
PVDA_year	.005	.004	1.457	.227	1.005
Groen_year	.006	.001	13.991	<.001	1.006
Vooruit_year	-.005	.001	16.663	<.001	.995
Open VLD_year	-.007	.001	30.714	<.001	.993
N-VA_year	-.008	.001	38.171	<.001	.992
VB_year	-.009	.001	41.379	<.001	.991
Constant	-.975	.012	6.275.291	<.001	.377

Nagelkerke $R^2 = 0.007$; **CD&V** is the reference party

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^{β})
PVDA	-.017	.075	.054	.816	.983
Groen	-.095	.023	17.712	<.001	.909
CD&V	.069	.019	13.587	<.001	1.072
Vooruit	-.019	.017	1.233	.267	.981
N-VA	.297	.019	247.804	<.001	1.346
Vlaams Belang	.396	.021	361.797	<.001	1.486
Year (since 2004)	-.020	.001	501.795	<.001	.980
PVDA_year	.012	.004	8.135	.004	1.012
Groen_year	.013	.002	68.674	<.001	1.013
CD&V_year	.002	.001	1.444	.230	1.002
Vooruit_year	.007	.001	30.714	<.001	1.007
N-VA_year	-.001	.001	.504	.478	.999
Vlaams Belang_year	-.002	.001	2.200	.138	.998
Constant	-.658	.014	2122.096	<.001	.518

Nagelkerke $R^2 = 0.007$; **Open VLD** is the reference party

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^{β})
PVDA	-.314	.075	17.486	<.001	.730
Groen	-.392	.024	273.093	<.001	.676
CD&V	-.227	.020	126.648	<.001	.797
Vooruit	-.316	.019	281.061	<.001	.729
Open VLD	-.297	.019	247.804	<.001	.743
Vlaams Belang	.100	.022	20.324	<.001	1.105
Year (since 2004)	-.021	.001	516.387	<.001	.979
PVDA_year	.013	.004	9.403	.002	1.013
Groen_year	.013	.002	77.437	<.001	1.014
CD&V_year	.003	.001	3.483	.062	1.003
Vooruit_year	.008	.001	38.171	<.001	1.008
Open VLD_year	.001	.001	.504	.478	1.001
Vlaams Belang_year	-.001	.001	.688	.407	.999
Constant	-.658	.014	2122.096	<.001	.518

Nagelkerke $R^2 = 0.007$; **N-VA** is the reference party

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
PVDA	-.414	.076	29.897	<.001	.661
Groen	-.491	.025	376.734	<.001	.612
CD&V	-.327	.022	219.487	<.001	.721
Vooruit	-.416	.021	397.871	<.001	.660
Open VLD	-.396	.021	361.797	<.001	.673
N-VA	-.100	.022	20.324	<.001	.905
Year (since 2004)	-.022	.001	405.456	<.001	.978
PVDA_year	.014	.004	11.006	<.001	1.014
Groen_year	.015	.002	79.428	<.001	1.015
CD&V_year	.004	.001	6.327	.012	1.004
Vooruit_year	.009	.001	41.379	<.001	1.009
Open VLD_year	.002	.001	2.200	.138	1.002
N-VA_year	.001	.001	.688	.407	1.001
Constant	-.559	.017	1104.206	<.001	.572

Nagelkerke $R^2 = 0.007$; **Vlaams Belang** is the reference party

Appendix C – Additional analyses

Table C.1 Binary logistic regression results for predicting negative sentiment with three-way interaction effects, with Groen in De Standaard as reference category (N = 1,019,683)

Variables	β	Standard Error	Wald's χ^2	p	Odds ratio (e^β)
Years (since 2004)	.004	.002	4.187	.041	1.004
PVDA	.424	.177	5.709	.017	1.528
Vooruit	.193	.041	22.221	<.001	1.213
CD&V	.214	.039	30.073	<.001	1.238
Open VLD	.143	.028	25.207	<.001	1.154
N-VA	.413	.041	99.871	<.001	1.512
Vlaams Belang	.477	.045	112.889	<.001	1.612
De Morgen	.202	.043	21.838	<.001	1.223
De Tijd	-.184	.046	16.074	<.001	.832
Het Laatste Nieuws	-.052	.039	1.816	.178	.949
Het Nieuwsblad	-.070	.036	3.734	.053	.932
Gazet van Antwerpen	-.682	.049	191.135	<.001	.506
Het Belang van Limburg	-.379	.053	51.521	<.001	.684
pvda_dmorg	-.452	.232	3.807	.051	.636
pvda_dtijd	-.134	.343	.153	.695	.874
pvda_hln	-.530	.224	5.629	.018	.588
pvda_nieuwsblad	-.423	.233	3.277	.070	.655
pvda_gva	.322	.267	1.456	.228	1.380
pvda_hbvl	-.459	.316	2.107	.147	.632
vooruit_dmorg	.044	.061	.510	.475	1.045
vooruit_dtijd	-.080	.066	1.477	.224	.923
vooruit_hln	-.006	.058	.010	.920	.994
vooruit_nieuwsblad	-.001	.054	.000	.989	.999
vooruit_gva	.106	.075	1.999	.157	1.111
vooruit_hbvl	-.090	.076	1.388	.239	.914
vld_dmorg	-.079	.059	1.816	.178	.924
vld_dtijd	-.208	.061	11.599	<.001	.812
vld_hln	-.215	.054	16.065	<.001	.806
vld_nieuwsblad	-.161	.050	10.297	.001	.851
vld_gva	-.236	.069	11.591	<.001	.789
vld_hbvl	.027	.071	.146	.702	1.027
cdv_dmorg	.072	.035	4.330	.037	1.075
cdv_dtijd	.017	.038	.200	.655	1.017
cdv_hln	-.013	.029	.201	.654	.987
cdv_nieuwsblad	-.093	.029	10.151	.001	.911

cdv_gva	-.046	.037	1.607	.205	.955
cdv_hbvl	-.070	.042	2.743	.098	.932
nva_dmorg	.108	.060	3.270	.071	1.115
nva_dtijd	.022	.065	.112	.738	1.022
nva_hln	.044	.056	.604	.437	1.044
nva_nieuwsblad	-.040	.055	.545	.460	.960
nva_gva	.021	.076	.080	.777	1.022
nva_hbvl	-.105	.076	1.936	.164	.900
vb_dmorg	.098	.072	1.830	.176	1.102
vb_dtijd	.057	.069	.693	.405	1.059
vb_hln	-.047	.067	.505	.477	.954
vb_nieuwsblad	.028	.061	.220	.639	1.029
vb_gva	.126	.081	2.412	.120	1.134
vb_hbvl	.222	.082	7.252	.007	1.249
dmorg_year	-.012	.003	20.155	<.001	.988
dtijd_year	.019	.003	54.154	<.001	1.020
hln_year	-.018	.002	59.040	<.001	.982
nieuwsblad_year	-.022	.002	100.567	<.001	.978
gva_year	.014	.003	24.490	<.001	1.014
hbvl_year	.006	.003	3.594	.058	1.006
pvda_year	-.023	.010	5.238	.022	.977
vooruit_year	-.014	.003	22.944	<.001	.986
vld_year	-.021	.003	48.983	<.001	.980
cdv_year	-.008	.001	34.421	<.001	.992
nva_year	-.015	.003	27.505	<.001	.985
vb_year	-.016	.003	24.364	<.001	.984
pvda_dmorg_year	.029	.014	4.243	.039	1.029
pvda_dtijd_year	.008	.019	.191	.662	1.008
pvda_nieuwsblad_year	.029	.013	4.758	.029	1.029
pvda_hln_year	.032	.013	6.402	.011	1.033
pvda_gva_year	-.010	.015	.428	.513	.990
pvda_hbvl_year	.020	.018	1.225	.268	1.021
vooruit_dmorg_year	.001	.005	.048	.827	1.001
vooruit_dtijd_year	.003	.005	.408	.523	1.003
vooruit_hln_year	.003	.004	.547	.459	1.003
vooruit_nieuwsblad_year	.002	.004	.185	.667	1.002
vooruit_gva_year	-.004	.005	.734	.392	.996
vooruit_hbvl_year	.004	.005	.629	.428	1.004
vld_dmorg_year	.008	.004	2.973	.085	1.008
vld_dtijd_year	.008	.004	3.112	.078	1.008
vld_hln_year	.012	.004	10.630	.001	1.012
vld_nieuwsblad_year	.010	.004	8.252	.004	1.010
vld_gva_year	.019	.005	15.693	<.001	1.019
vld_hbvl_year	-.006	.005	1.652	.199	.994
nva_dmorg_year	-.004	.004	.754	.385	.996
nva_dtijd_year	-.003	.004	.654	.419	.997
nva_hln_year	-.004	.004	1.010	.315	.996
nva_nieuwsblad_year	.000	.004	.009	.924	1.000
nva_gva_year	-.004	.005	.733	.392	.996
nva_hbvl_year	.007	.005	1.759	.185	1.007
vb_dmorg_year	-.003	.005	.316	.574	.997
vb_dtijd_year	-.005	.005	1.279	.258	.995
vb_hln_year	.006	.004	1.914	.166	1.006
vb_nieuwsblad_year	-.003	.004	.567	.451	.997
vb_gva_year	-.004	.005	.698	.404	.996
vb_hbvl_year	-.019	.006	11.147	<.001	.981
Constant	-.967	.030	1048.862	<.001	.380

Nagelkerke $R^2 = 0.021$

Figure C.2 Overview of negativity per newspaper from 2004-2024

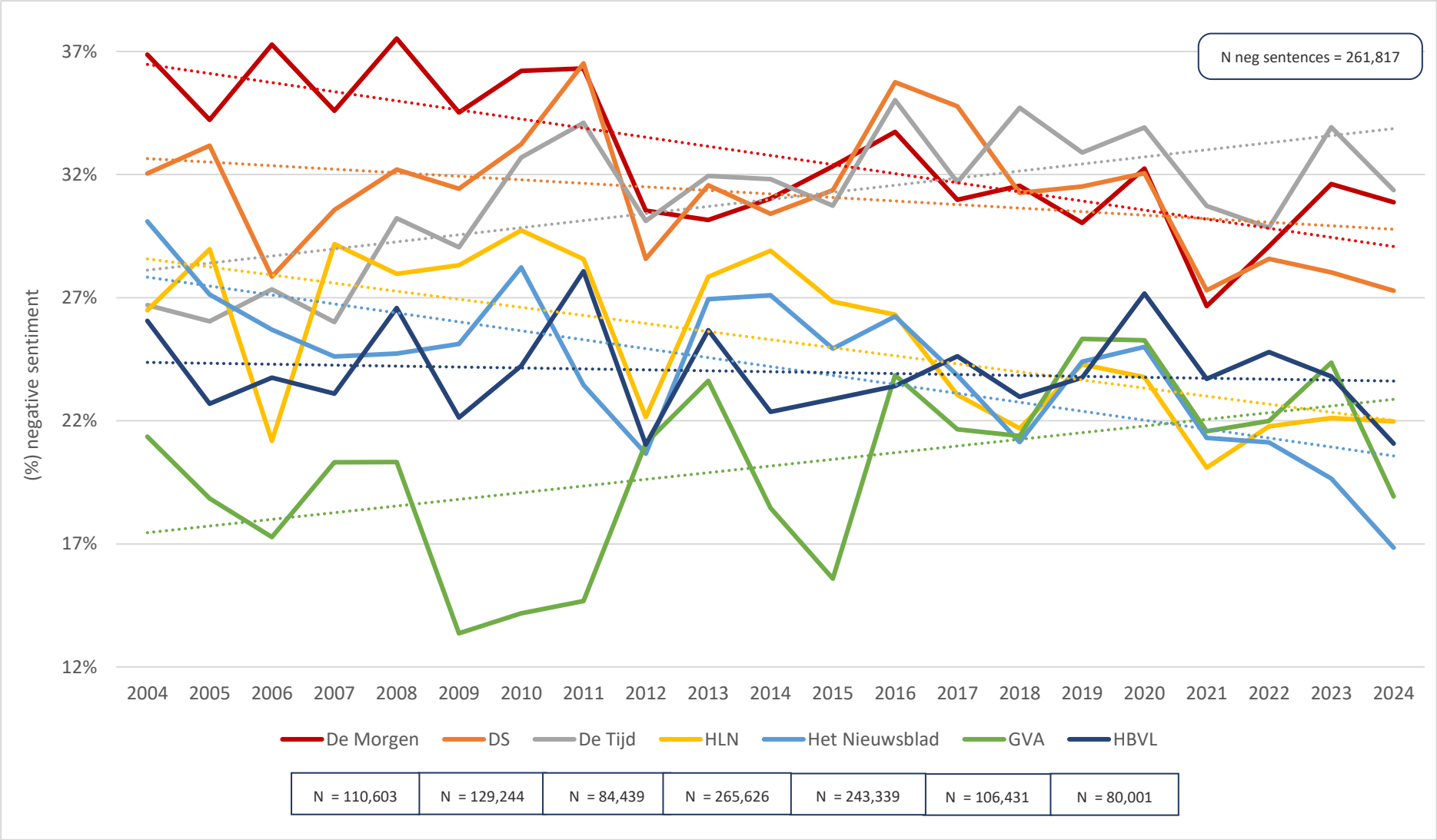


Table C.2 Overview of trendlines and explained variance from Figure C.2

	Equation of trendline	R ² value for trendline
De Morgen	$y = -0.0037x + 0.3685$	0.5949
De Standaard	$y = -0.0014x + 0.3279$	0.1141
De Tijd	$y = 0.0029x + 0.2783$	0.4154
Het Laatste Nieuws	$y = -0.0033x + 0.289$	0.397
Het Nieuwsblad	$y = -0.0036x + 0.282$	0.5085
Gazet van Antwerpen	$y = 0.0027x + 0.1718$	0.2215
Het Belang van Limburg	$y = -0.0004x + 0.2441$	0.0158