SUPPLY AND DEMAND OF MEDIA BIAS IN THE U.S. ELECTIONS

SHEN JINLIANG

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The Hong Kong Polytechnic University

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Department of Applied Social Sciences

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Shen Jinliang

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CERTIFICATE OF ORIGINALITY

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Shen Jinliang (Name of student)

Abstract

The media has a powerful impact on public opinion and public actions. In political elections, on the supply side, media bias matters because it shapes how political realities are presented to the public, influencing what information voters receive, and affecting voters' preferences, thereby playing a critical role in the functioning of democracy. On the demand side, media bias is important because it not only reveals how citizens engage with political news but also affects the financial performance of media companies. This thesis seeks to provide insights into understanding both the supply and demand sides of media bias in the U.S. elections.

In Study 1, I use entity sentiment toward presidential candidates in news coverage to construct a daily media bias index for 237 newspapers during the U.S. presidential elections from 1980 to 2020. This study contributes to the literature by introducing election closeness, measured by narrowing pre-election polling margins, as an important factor affecting newspapers' strategies of media bias on the supply side. I find that the election news coverage was predominantly against Republican presidential candidates, regardless of whether the newspapers were left-leaning or right-leaning. This bias in both newspaper groups consistently decreases when pre-election polls become closer. These findings suggest a general liberal bias and the different strategic responses between left- and right-leaning newspapers.

In Study 2, I construct a series of emotion and information variables for political news tweets from four prominent left-leaning and four right-leaning media outlets during the 2022 U.S. midterm elections, aiming to find out which variables are associated with higher retweet counts. This study contributes to the literature by applying an automated NLP-based method to measure the informational value of news articles, whereas previous research has relied on human coders. I also first apply facial emotion analysis to news emotion measurement, using SOTA techniques from the computer vision field.

However, neither the descriptive visualizations nor the regression analyses reveal strong and consistent patterns; only overall emotion intensity and anger show relatively consistent positive effects across most outlets.

In Study 3, I am the first to introduce the divergence between journalists and audiences in evaluating the informational value of news into research on political communication. This divergence distorts the understanding of audiences' demand for informational value and increases financial pressures on media companies. By addressing the same research question as in Study 2 but adopting a survey experiment design, Study 3 overcomes the limitations inherent in Study 2's observational data approach. The results show that respondents significantly prefer news they perceive as informational, while disfavoring news classified as informational based on journalistic criteria. This supports my argument that it is the audience's perceived informational value—rather than objective informational value—that shapes media preferences.

Overall, this thesis uses data science methods to measure media bias in the U.S. elections, highlights differences in bias strategies between left- and right-leaning outlets, and provides empirical evidence of audiences' preferences for emotional and informational news based on Twitter observations and a survey experiment.

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Thesis Introduction

The media is important for democracy. It structures the public sphere by informing citizens, scrutinizing those in power, and providing an arena in which diverse social groups can voice their interests and contest political decisions (Curran, 2011). In political elections, news media tells citizens who is running, what is at stake, how candidates perform, and how others are reacting—thereby shaping what people know, what they care about, and how they evaluate the candidates and parties (Hansen & Pedersen, 2014; Weaver, 1996). A substantial body of research shows that campaign news coverage can affect voters' candidate evaluations and vote choices (Druckman & Parkin, 2005; Nadeau et al., 2008). Media bias in elections refers to systematic and non-random skew in which campaign events are selected, how much they are covered, or how favorably they are described, in ways that consistently favor one party or candidate over the other (D'Alessio & Allen, 2000). As news from television, newspapers, news websites, and social media are dominant sources of campaign information for citizens, far ahead of direct contact with parties or candidates (Shehata & Strömbäck, 2014), biased media can distort voters' information environment and undermine the fairness and perceived legitimacy of elections. Thus, understanding how the media outlets supply media bias is important.

Apart from the supply side, in a commercial and high-choice media environment on the internet, the demand side of media bias is becoming more important than in the past. From X (Twitter) and Facebook to Instagram and TikTok, social media has become an important way the public accesses news (Christopher & Jacob, 2024). Furthermore, users on these platforms increasingly rely on algorithmic feeds, instead of actively searching for the news (Elisa et al., 2024; Weeks & Lane, 2020). As news companies have shifted their revenue increasingly toward digital advertising and digital subscription (Bekh, 2020), they treat social media as a vital channel to build influence and to redirect traffic back to their websites to get digital revenues (Sismeiro & Mahmood, 2018). Journalists and official outlet accounts post large volumes of news with URLs on social media, and they need to compete with other media outlets and news influencers for audience attention (Flamino et al., 2023). Especially during large political events like elections, when the public has a higher demand consuming political news, media outlets consider it as a great strategic window to attract the audience on social media (Boulianne & Theocharis, 2020). Thus, understanding what the public prefers for political news during elections is important for the media companies.

In this thesis, media bias is defined in relation to the journalistic ideal of objectivity. In journalism, the idea of "unbiased" media does not refer to a perfectly neutral or perspective-free press. Rather, objectivity is better understood as historically developed professional norms, such as factuality, verification, sincerity, and the separation of fact from opinion (Schudson, 1978, 2001; Tuchman, 1972). The meaning and practice of objectivity also vary across countries and over time (Esser & Umbricht, 2014; Hanitzsch et al., 2011). Relative to this ideal, media bias in the political context can take at least two forms. The first is partisan or ideological bias, in which coverage systematically favors one party or candidate through story selection, amount of coverage, or tone (D'Alessio & Allen, 2000; Druckman & Parkin, 2005). The second is structural bias, which refers to patterns in how news is gathered, framed, and presented, that arise from the inherent structures of the news industry, including professional norms, reporting conventions, commercial pressures, platform incentives, and organizational routines, rather than from journalists' ideological beliefs (Graber, 2006; Groeling, 2013; Hofstetter, 1976; Strömbäck & Shehata, 2007; van Dalen, 2012). While partisan bias may appear in a journalist's use of language that favors one candidate over another, structural bias may lead the same journalist to emphasize dramatic events, scandals, or horse-race developments surrounding a candidate rather than policy positions or issue proposals (Cappella & Jamieson, 1997; Strömbäck & Shehata, 2007). This thesis examines ideological bias in Study 1 and structural bias in Studies 2 and 3.

Study 1 focuses on the ideological (left and right) bias in U.S. news and aims to identify how mass media outlets supply this bias during electoral campaigns. I collected 146,723 news articles from 237 newspapers during the U.S. presidential elections from 1980 to 2020. I captured entity sentiment toward the final two presidential candidates in news coverage and calculated the bias score in an article by subtracting the Democratic candidate sentiment score from the Republican candidate sentiment score (e.g., net Trump minus Biden sentiment). The final high-frequency media bias index is constructed by averaging each outlet's daily bias score across all news articles published on that day.

The descriptive results of Study 1 show a generally left bias against Republican nominees since 1992 (Groseclose, 2011), which may be driven by the left-turning public opinion. Furthermore, when an election gets closer, there are more election campaigns (Cox & Munger, 1989), more public participation (Dawson & Zinser, 1976; Larcinese, 2007), polarized voters (Howell & Justwan, 2013), and stronger emotions (Howell & Justwan, 2013; Kostadinova, 2003). This amplifies the amount of bias in response to the public demand and can reveal outlets' preferred ideological positioning under intense competition. This study contributes to the literature by innovatively introducing election closeness as an important factor revealing newspapers' strategy of supplying bias in response to public opinion. The results suggest that when an election gets closer, newspapers endorsing a Republican nominee tend to publish articles with stronger supportive sentiment, whereas newspapers endorsing a Democratic nominee—or endorsing no one—report in a more neutral manner. The different strategies may be driven by the diverse demands of newspapers' target readers.

Study 2 focuses on two features of structural bias in political news posts during the U.S. elections—emotional support and informational value—to find out (1) how news outlets present these features and (2) which types of political news are more likely to be shared on social media during elections. Audience demand for news that is emotionally supportive of "their side" and perceived as informationally valuable directly shapes which kinds of biased content are rewarded in the marketplace. The two factors are widely studied in communication research and are considered important to news dissemination (Berger & Milkman, 2012; Boczkowski & Mitchelstein, 2013; Brown et al., 2020; Hasell & Weeks, 2016; Rudat et al., 2014). I collected 9263 news tweets from four conservative and four liberal outlets during the 2022 U.S. midterm election. I constructed 7-class emotion variables for news tweets, attached images, and full articles, as well as three informational variables (article length, entity density ratio, and hyperlink density ratio) for the full articles. For the first research question, I found that conservative outlets provided stronger emotions, especially anger and fear, while liberal outlets provided longer articles with lower information density. For the second research question, through both descriptive visualizations and regression analysis, I found that news with higher overall emotional intensity and more anger is more likely to be shared, which is consistent with the literature (Berger & Milkman, 2012; Brown et al., 2020). However, the positive effect of informational value on sharing, which is supported by the literature (Rudat et al., 2014), was not supported by my findings. I offer three explanations: the limitation of external shocks in real-world observational data; the gap between how professionals and the public assess informational value (Bobkowski, 2015); and many users not clicking the attached URL before sharing (Sundar et al., 2025). The limitations are overcome in Study 3 through a survey experiment. Study 2 contributes to the literature by: (1) translating the common photojournalism practices into a programming model for classifying facial emotions with multiple faces and introducing facial emotion analysis to political communication; (2) first applying an automated NLP-based method to measure the informational value of news.

Motivated by the methodological limitations of Study 2's observational data method and its informational value results that conflict with existing literature, Study 3 uses a survey experiment to investigate the same research question (RQ2) of Study 2 and highlights the importance of distinguishing between a news item's objective informational value and the audience's perceived informational value when analyzing public preferences. U.S. citizens recruited through Prolific.com were shown representative news items from Study 2 that aligned with their political ideology and were asked to evaluate the informational value of the news and indicate their preferences. I find that respondents significantly prefer news they perceive as informational, while showing a significant dislike for news classified as informational based on linguistic or journalistic criteria. These results support my argument that it is the audience's perceived informational value—rather than objective informational value—that shapes media preferences. Study 3 contributes to the literature by being the first to introduce the divergence in evaluating informational value between journalists and the audience, which distorts the understanding of audiences' demand for informational value, to the political communication field.

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Study 1: Media Bias in U.S. Presidential Elections: Evidence from Sentiment Analysis

Abstract

Media bias can manifest itself in multiple forms. In addition to citation sources and stories covered, the bias may arise from the semantic characterization of an event or an individual. To measure the potential media bias, we conduct an automated sentiment analysis of presidential election news published in 237 major newspapers between 1980 and 2020. We find that election news was predominantly against Republican presidential candidates, regardless of whether the newspapers were left-leaning or right-leaning. This sentimental bias, however, decreases in the closeness of pre-election polls. We validate our news-sentiment measures with human coders.

Keywords: Media bias, US Presidential Election, Sentiment Analysis, Election Closeness

1.1 Introduction

The media have a powerful impact on public opinions and public actions (McCombs & Shaw, 1972; Schattschneider, 1975). In presidential elections, as a dominant source of campaign information (Shehata & Strömbäck, 2014), news media inform citizens about who the candidates are, what issues are on the agenda, how politicians are performing thereby structuring what people know, what they consider important, and how they judge parties and candidates (Hansen & Pedersen, 2014; Weaver, 1996). Scholars have documented that campaign news exposure can influence voters' assessments of candidates and their voting decisions (Druckman & Parkin, 2005; Nadeau et al., 2008). Thus, unbiased media is essential for democracy (Dahl, 2005). Even in the era of social media, traditional newspapers still have the power to lead the political issue agendas through online news articles and posts on social media (Barberá et al., 2019; King et al., 2017). The public requires unbiased media with more objectivity and less ideological bias, so it's vital to find out how the media is biased. Media bias in elections refers to systematic and non-random skew in which campaign events are selected, how much they are covered, or how favorably they are described, in ways that consistently favor one party or candidate over the other (D'Alessio & Allen, 2000). Presidential election provides a good opportunity to monitor the media bias. On the one hand, during presidential elections, news about the elections occupies a high percentage of daily issues (Stovall & Solomon, 1984); this enables us to monitor newspapers' bias with high frequency. On the other hand, many polls are conducted to capture the public preferences (Enns et al., 2017; Gelman & King, 1993), which helps us estimate the media bias's position relative to the public opinion.

We contribute to the literature by introducing election closeness as an important factor affecting newspapers' strategy of media bias. A fierce competition is often associated with more election campaigns (Cox & Munger, 1989), more public participation (Dawson & Zinser, 1976; Larcinese, 2007), polarized voters' feelings between winners and losers (Howell & Justwan, 2013), and stronger emotions like anxiety (Howell &

Justwan, 2013) and enthusiasm (Kostadinova, 2003). The election closeness could amplify the amount of bias in response to the public demand and reveal newspapers' preferred ideological positioning under intense competition, thus helping us better find out how the media is biased on the supply side.

The literature agrees that the direction of media bias is largely driven by the average public ideology for profit-maximizing (Gentzkow & Shapiro, 2007)[1], and it is even located exactly at the median position among voters (Puglisi & Snyder, 2015). That is, in elections where the Republicans (Democrats) take a big lead, newspapers are very likely to choose a right- (left-) leaning position publishing articles about the elections to maximize their profit or circulation.[2] However, in closer elections, the theories (Gentzkow & Shapiro, 2007; Puglisi & Snyder, 2015) predict a more neutral position of bias for newspapers, as vote shares—reflecting public ideology—approach an even 50–50 split. This implication runs somewhat against the intuition that neck-and-neck races stir up more passion and stronger emotions. Thus, the research question of Study 1 is: when the election is close, will the newspapers publish election articles in a neutral position with less bias to attract or amuse more readers? Or will they select one side, either left or right, and publish articles with a stronger slant to amuse more emotional readers on that side?

In this research, we measure the media bias by conducting an automated sentiment analysis that quantifies the tone of newspaper coverage of the two nominees from 1980

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[1] The article on NBER (working paper 12707), instead of the one published in 2010, discussed more clearly the average profit-maximizing position of media slant on p27, p28, and p31. They constructed and estimated a linear function between the profit-maximizing slant (very close to the actual slant) for newspapers and the presidential vote in the newspapers' market, where the significant constant and coefficient for Republican's vote share are relatively 0.41 and 0.10.

[2] Gentzkow and Shapiro (2007) found that the Republican vote share in the 2004 election is a less noisy proxy for market ideology.

to 2020 during the three months before each election. While most literature focuses on one or several elections (Hayes, 2008), this article is the first to use a large dataset of news articles covering 11 US presidential election campaigns. This allows us to examine long-term trends and test existing theories on the relationship between media bias and public preferences. The descriptive results show a generally left-leaning bias against Republican nominees since 1992. Next, we estimate the media bias by the public preference from polls and find a positive correlation, which supports the literature (Gentzkow & Shapiro, 2010; Wlezien & Soroka, 2019). But after controlling for the public preference, we do not see the bias shifting to the left, compared with the bias in the 1980s. This result suggests that it is the left-turning public opinion that drives the newspapers to turn left.

Furthermore, we hypothesize that newspapers with different ideologies will behave differently under dynamic election closeness. We estimate the media bias with election closeness from polls during presidential elections, and find that when an election gets closer, newspapers endorsing a Republican nominee tend to publish articles with stronger supportive sentiment, whereas newspapers endorsing a Democratic nominee—or endorsing no one—report in a more neutral manner. Their different strategies of publication consistently present a pro-Republican bias. The different strategies but consistent bias results may be driven by newspapers' distinct target readerships and by differences in demand among liberal and conservative audiences.

1.2 Literature review

1.2.1 Drivers of media bias

The literature has found that factors from both the demand and supply sides drive media bias (Gentzkow & Shapiro, 2010). On the demand side, the literature generally accepts that the newspapers would choose a median position among the public opinion/preferences for profit-maximizing (Anderson et al., 2016; Garz et al., 2020;

Gentzkow & Shapiro, 2010; Ho & Quinn, 2008; Puglisi & Snyder, 2015). On the supply side, the newspapers usually have some ideological bias either from the ownership (Dunaway, 2013; Gentzkow & Shapiro, 2010) or from newsroom journalists (Hassell et al., 2021). The newspapers would also present persuasive incentives from their endorsement during the elections (Dunaway, 2013; Kahn & Kenney, 2002).

1.2.2 A debate about the existence of liberal bias

On the ideological bias of newspapers, after Groseclose (2011) provided quantitative evidence for a liberal bias, there has been a debate for years on the existence of liberal bias (Faris et al., 2017; Gasper, 2011; Hassell et al., 2020; Hout, 2021; McCarty, 2012; Nyhan et al., 2012). However, apart from finding the absolute position of the media bias, it's also essential to discover the relative position of the media to the overall US people. Presidential elections give us an excellent chance to monitor the relative position of media bias because many polls are conducted during the election to capture the dynamic public opinion. In addition, newspapers publish far more articles with potential ideological bias during the election period. We will use the polls and the large media content with a potential bias to find out how the media was biased in the US Presidential Elections over the four decades.

1.3 Theory and hypothesis

In presidential elections, newspapers are well informed about public preferences through past polls and can anticipate potential shocks from breaking news when preparing their reports. They need to decide on the tone covering the candidates as a response to the expected readers' demand for benefit maximization. Two diversified demands arise with the election closeness. Firstly, voters are eager to let their supported candidate win if the election is getting closer; this desire increases their demand for more information that supports their favored candidate. A portion of republican readers were found to consume more extremely slanted news content than the majority of readers (Guess, 2021). Secondly, as a closer election attracts more voters to participate in the election (Bursztyn et al., 2017) or just want to know more about how the election is going, the demand for media increases. The extra voters include those with priorly diverged ideologies and those with a median ideology. While partisan voters tend to consume like-minded content, the new voters with a median ideology need more information from the media, including more valuable and less biased information, to help them judge whom to vote for (Larcinese, 2007). As the most prominent mainstream newspapers are left-leaning or slightly left-leaning (Bakshy et al., 2015), we consider that more Democratic-endorsing newspapers will respond to this demand when the election gets closer.

Differences in the demand for media bias across ideological groups may also stem from their different average psychological orientations and personality traits. Research in political psychology suggests that liberals tend to score higher on openness to experience, curiosity, fairness, and tolerance for ambiguity, whereas conservatives tend to place greater value on order, certainty, cognitive closure, loyalty, and purity (Carney et al., 2008; Graham et al., 2009; Jost et al., 2003; Stewart & Morris, 2021). When an election becomes closer, Democratic-endorsing newspapers may have stronger incentives to reduce the emotional intensity of anti-Republican coverage, because their core left-leaning audiences, who are on average higher in openness, may be relatively more receptive to neutral-sentiment reporting on the two candidates. By contrast, because right-leaning audiences may have a stronger demand for ideologically aligned campaign news to reduce the anxiety associated with uncertainty in the electoral process, Republican-endorsing newspapers may have stronger incentives to publish clearly supportive coverage of Republican candidates.

In addition to the different demands, the target readers are not consistent among newspapers with different ideologies. For years, many researchers highlighted the diverged self-exposure in media use (Iyengar & Hahn, 2009; Mullainathan & Shleifer, 2005; Nelson & Webster, 2017). However, after methods involving digital traces of media use were developed, researchers found the asymmetric media diets from both social media following (Eady et al., 2019; Shin, 2020) and news website visits (Guess, 2021). Their findings suggest that conservatives or Republicans are more likely to consume left-leaning content. For example, Guess (2021) found that in October 2016, over half of Republicans also visited left-slanted political news sites, while most Democrats only visited left-slanted sites. The large overlap of political media diet is from portals[3], and mainstream news websites like NYTimes.com, whose ideological slant (Bakshy et al., 2015) is left-leaning (-0.55); in contrast, actively browsing hard news on politics is a rare activity which only accounts for 7% to 9% of total web visits. These findings support the argument by Graber (1988) that the public reads the newspapers just by convenient physical reach (now by clicking a mainstream website or a URL shared on a social network). Thus, with a large percentage of readers from the opposite ideology, left-leaning newspapers have the incentive to tune the content ideology a bit right instead of honestly insisting on their left-turning ideological stance so that they won't annoy their Republican readers. Furthermore, the right-leaning (or less left-leaning) content published by Democratic-endorsing newspapers could help build and maintain a reputation of high-quality journalism (Gentzkow & Shapiro, 2006). Considering both the different target readers and the readers' different demands, we hence hypothesize that:

Hypothesis: When the election gets closer, Republican-endorsing newspapers will publish articles with more bias supporting Republican nominees; and Democratic-endorsing newspapers will reduce the emotional intensity against Republican nominees.

[3] www.aol.com, www.msn.com, www.google.com, www.yahoo.com (Guess, 2021)

1.4 Methodology

1.4.1 Data

Our source of news is ProQuest U.S. Newsstream (*proquest*.com), which contains comprehensive coverage of political news in the United States. We exhausted what we found on ProQuest by searching all news articles within the last three months of every US Presidential Election campaign that took place between 1980 and 2020 inclusive. As we measure media bias by analyzing the tone of news coverage of presidential nominees, we retained articles with at least one mention of any of the two nominees who represented the Republican Party and the Democratic Party. Our dataset contains 146,723 news articles from 237 newspapers over the last 11 US Presidential Election campaigns. Table 1 in the appendix shows the number of newspapers and articles each year. Figure 1 in the appendix is a heatmap of endorsement for 67 newspapers with the least missing values, it suggests the diverged ideology of newspapers in our dataset.

1.4.2 Measuring media bias

Measurement of media bias in empirical studies can be put into four classifications: Firstly, citation bias is measured by the relative frequency a newspaper cites phrases or arguments from congressmen and think-tanks with different party affiliations (Gentzkow & Shapiro, 2010; Groseclose & Milyo, 2005). Secondly, agenda coverage bias counts from articles the frequency of specific policies or topics that are favored by different parties (Haselmayer et al., 2017; Hayes, 2008; McCombs & Shaw, 1972). Thirdly, visibility bias is measured by the relative amount of coverage devoted to each candidate (Eberl et al., 2017). Fourthly, tonality bias is measured by the sentiment a news article describes different candidates (Druckman & Parkin, 2005; Hayes, 2008; Kahn & Kenney, 2002; Wlezien & Soroka, 2019). Citation bias has a limitation on the amount of bias in each article, thus it cannot be measured frequently (McCarty, 2012). Eberl et al. (2017) compared the other three types of media bias and found that both agenda coverage bias and tonality bias can effectively capture the newspapers' party preference. Furthermore, tonality bias has an advantage on its larger variation, which makes it clearer to compare the bias across outlets and years. Therefore, we choose tonality bias as our measurement of media bias.

We measure the media bias of a newspaper from its tone of articles covering the two final candidates in a presidential election. Similar measurements were conducted by Bélanger & Soroka (2012) and Wlezien & Soroka (2019). First, we respectively summed up the sentiment scores of both candidates for every article in a day mentioning their names from the newspaper. Second, we calculated the media bias score in an article by subtracting the Democratic candidate sentiment score from the Republican candidate sentiment score (e.g., net Trump minus Biden sentiment). A positive value implies that this article's tone is more positive toward the Republican candidate vis-à-vis the Democratic one. Thirdly, we averaged the article scores for each newspaper in a day, as the daily media bias score. This measure has several advantages. First, tonality directly shows whether news coverage is more favorable or unfavorable toward a candidate, and prior research suggests that tone can have a strong impact on audiences (de Vreese et al., 2011; Eberl et al., 2017). Second, every sentence that mentions a candidate can generate a sentiment score, allowing us to observe media bias more frequently. Third, this "R minus D" measure uses one simple variable to capture the relative bias between the two candidates (Wlezien & Soroka, 2019). A sentence with a negative net Republican minus Democratic sentiment score is shown as follows:

"I'm deeply grateful for Obama's confidence in me, and I am humbled by the task ahead."

To get the sentiment score for a candidate in an article, Bélanger & Soroka (2012) and Wlezien & Soroka (2019) count the positive and negative words in sentences mentioning the candidates. However, the accuracy of this lexicon-based approach is not high, mainly due to the mismatch between the candidate name and the probably irrelevant sentimental words in one sentence (Liu, 2015). Instead, we use the 'Entity Sentiment' function from Google Cloud Natural Language API (*Analyzing Entity*

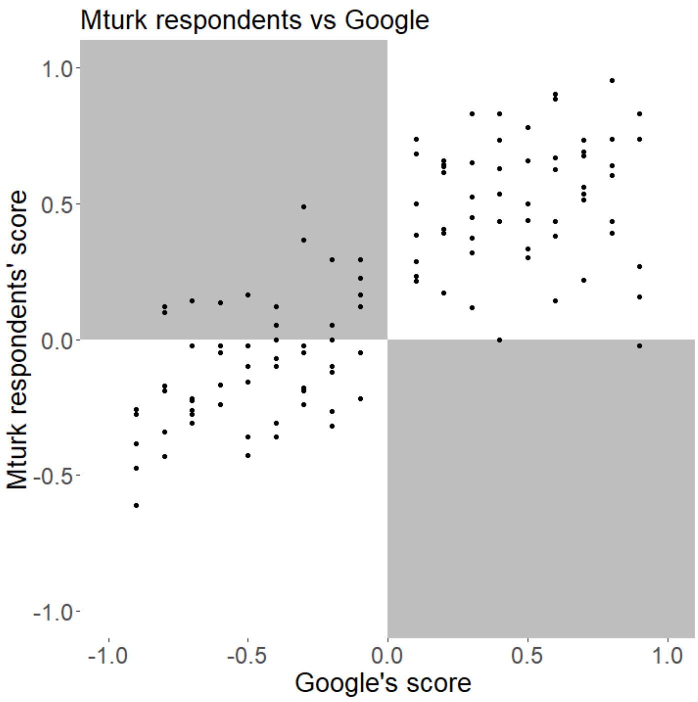
Sentiment | Cloud Natural Language API). This API involves Google's machine learning models, and it is trained on large open-source datasets for NLP tasks. It combines both entity analysis and sentiment analysis, and it can determine the sentiment score describing each entity in sentences. The entity's score in each sentence ranges from -0.9, most negative, to +0.9, most positive. The score of an article sums up the scores from all sentences in the article that contain the candidate's name. This API automatically recognizes the same candidate entity with different appellations.

With all the good staff with the Google Natural Language API, people may still find it a black box. To validate whether Google's API could return reliable sentiment results, we conducted a survey on Amazon Mechanical Turk (*Amazon Mechanical Turk*, n.d.) as a comparison. We used M-Turk because of its reliability. Lind et al. (2017) show that crowdsourcing workers can provide valid results like that from expert coders, furthermore, because the audience of the newspapers are the broad public in the U.S., not trained experts, the judgement from crowdsourcing workers should be attached more importance.

Our survey contains 120 sentences with candidate names from the news articles in our dataset. We recruited 492 American M-Turk workers to judge whether the sentence's description of the candidate is positive, negative, or neither. To reduce the bias from respondents' personal preferences on the candidates, we let the candidate's name in each sentence be randomized from the candidate pool when the survey page is loaded. We also included a reminder before the survey questions: "NOTE: We are NOT asking your personal opinion about the candidate." Every sentence is tagged by, on average, 41 respondents, and the tag selected by the most respondents is considered ground truth to validate Google's results. When two tags are equally chosen by the respondents, we considered this sentence as neutral describing the candidate, thus if Google's score is -0.1 or 0.1, we considered Google's score as correct.

Figure 1 shows the consistency between M-Turk respondents' score and Google's score for the 120 sentences (120 points). The overall accuracy is around 84%. We processed the M-Turk respondents' score to transform the categorized results to linear scores, by denoting a positive tag as 1, while a negative tag as -1, and calculating the average score from the respondents who tagged the sentence, so that the two different scores can be better compared. A small issue exists here that Google's API is likely to tag positive sentences as negative. As the strong correlation between Google's score and M-Turk respondents' score is significant and this kind of error rate is low, we still consider Google's score as reliable.

Figure 1. M-Turk respondents' scores VS Google's scores for 120 sentences

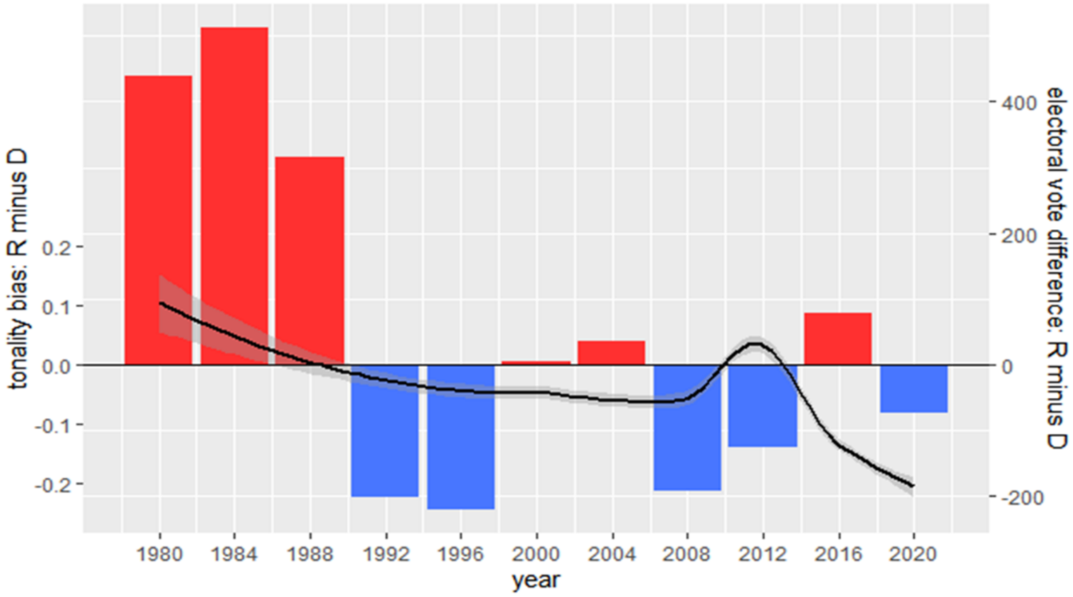


1.5 Descriptive findings

As news articles' bias is strongly driven by the public opinion, in Figure 2, we compared the average media bias for all 237 newspapers across 11 presidential election years and the final electoral vote difference, representing the public opinion each year. The shift of ideological bias, whether to the left or not, has been in debated for years (Groseclose & Milyo, 2005; Gasper, 2011; Groseclose, 2011; McCarty, 2012; Hassell et al., 2020).

Figure 2 shows a strong trend of shifting liberally relative to the public opinion over time except 2012. In the 1980s, when Republican candidates (Ronald Reagan and George H. W. Bush) won the elections by a large margin, the average tone of news articles mentioning the candidates in all the newspapers from my dataset was pro-Republican, but the relative tone started going down. Since 1992, the average tone has been pro-Democratic in every campaign except 2012, even in years (2004, 2008, and 2016) that Republican candidates won the elections.

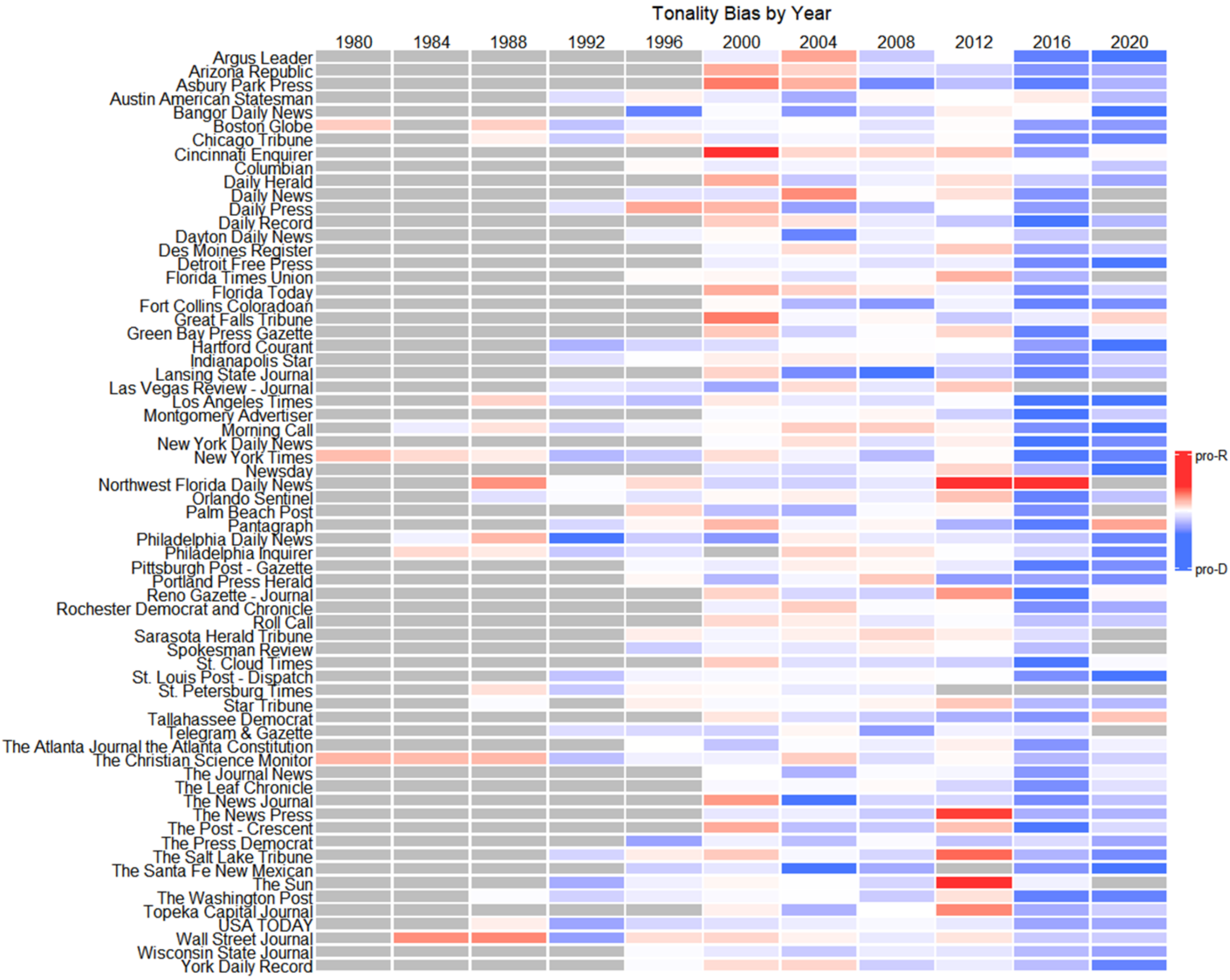
Figure 2. Average media bias and the final electoral vote difference



Note: The line with a 95% confidence interval: average tonality bias for each year (from 1 September to the election date in November) of all 237 newspapers. The bar graph: electoral vote difference between the two candidates. Both the media bias and the vote difference are "Republican minus Democratic".

As the aggregate trend shows some divergence, we dive into individual newspapers in Figure 3. It shows the yearly bias for respectively 67 newspapers with the least missing values from 1980 to 2020. Although the missing value problem is so serious that a lot of newspaper-year observations before 1992 are removed in grey from this graph, most newspapers across the 11 years, except the year 2012, share a common trend of gradually turning left. We next provide an estimation of media bias across the 11 campaigns.

Figure 3. Average media bias across 11 years respectively from 67 newspapers in alphabetical order with the least missing values.



Note: A red block means the newspaper's average tone of all the sentences covering the two candidates from 1 September to the election date in November is biased towards the Republican candidate, and the deeper the color of red is, the more the average tone is biased. Similarly, blue blocks represent the bias toward a Democratic candidate. A grey block means that there are not enough articles in this newspaper this year from ProQuest U.S. Newsstream (proquest.com), so we remove the observations in this graph.

1.6 Modeling media bias

1.6.1 Polls: the public preference

Gentzkow and Shapiro (2010) build a theory of demand-supply for the media bias. On that basis, Wlezien and Soroka (2019) build a time-series model involving media bias and commercial polls within a year, our empirical framework is modified from that. We first model the newspapers' daily media bias in Equation 1 using polling preference[4] (net Republican minus Democratic) as the demand factor and newspapers' endorsement[5] as the supply factor:

$$Media\ Bias_{it} = \alpha + \beta_1 * Polling_t + \beta_2 * Endorsement_{it} + \beta_3 * Polling_t * Endorsement_{it} + v + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

where $Polling_t$ represents the daily measurement of public preference. We select $Endorsement_{it}$ to be the supply factor of newspaper ideology because it is time-varying, so that we can model the bias across multiple years. An interaction term of polling and endorsement is put into the model to test whether the marginal effect of polling on media bias could be affected by newspapers' ideology from endorsement. v is a vector of other control variables, including whether one of the nominees is the incumbent president from the Republic/Democratic party, and the number of days to

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[4] For the polling data, we use the national polling average dataset provided by *Fivethirtyeight/Data* (2022) which includes a large set of polls, averages the polling from their reliability, and adjusts the house effects.

[5] For the endorsement data, we combined two open-source datasets from Gentzkow & Shapiro (2010) and Veltman (2020) to retain more newspapers with endorsements. Those newspaper-year endorsement values that conflict between two datasets were manually checked from the raw news article source. We found that the endorsement information from Veltman (2020) was always the correct one. Both the endorsement data and polling data covers the last 11 Presidential Elections in this research. Figure 1 in the appendix shows the endorsement each year for a sample of 53 newspapers.

the election date. We control the number of days to the election date so that the potential time trend could be fixed within a year. μ_i and η_t are respectively the newspaper fixed effect and year fixed effect. Pooled and random effect models will also be estimated.

By estimating this model, on the one hand, we try to test whether our measurement of media bias for 237 newspapers across 11 elections can provide consistent results with the theory by Gentzkow and Shapiro (2010) as well as with other similar empirical findings (Hassell et al., 2021) derived from that. On the other hand, the year fixed effects could capture how the overall newspapers' ideologies were shifted across the 11 elections, after controlling for polls, newspapers' endorsement, and incumbent president.

1.6.2 Election closeness

We next try to estimate the media bias by replacing polling preference with polling closeness ($Closeness_t$). The model is shown in Equation 2 as follows:

$$Media\ Bias_{it} = \alpha + \beta_1 * Closeness_t + \beta_2 * Endorsement_{it} + \beta_3 * Closeness_t * Endorsement_{it} + v + \mu_i + \eta_t + \varepsilon_{it} \quad (2)$$

Here, the measurement of $Closeness_t$ is modified from that by Matsusaka and Palda (1993). We subtracted their measurement value from 1, so that a higher value represents the closer election. Equation 3 shows the calculation:

$$Closeness_t = 1 - \left|\frac{votes\ 1_t - votes\ 2_t}{votes\ 1_t + \ votes\ 2_t}\right| \quad (3)$$

where $votes\ 1_t$ and $votes\ 2_t$ are the percentage of support for either of the nominees from polls. We use the same dataset to calculate $Polling_t$ and $Closeness_t$.

1.7 Regression results

Table 1 presents the regression results of Equation (1), which estimates the net Republican minus Democratic candidates' sentiment by standardized polling gap, newspaper endorsement, and yearly fixed intercepts. We removed the upper 0.5% and the lower 0.5% extreme observations. The significantly positive coefficients for national polling (both newspapers that endorsed a Republican candidate and those that did not) support the literature that newspapers consistently follow the public preferences in the same direction. Regarding the supply side, the coefficient of endorsing a Democratic candidate is significantly negative; this implies that newspapers endorsing a Democratic candidate are more biased towards the Democratic candidate than other newspapers. As the absolute value of the standardized polling (R minus D) being less than 2 represents 97.8% of the whole observations in Figure 4, this figure shows that most of the time, the bias is against the Republican candidate, regardless of whether the average newspapers were left-leaning or right-leaning (with most observations below zero). The three lines, all having positive slopes, imply that all three groups of newspapers tend to positively respond to the overall public ideology position. And, if the public favors the Republican candidate, the newspapers with a Democratic endorsement respond a bit more strongly to the public preference, with the slope in blue being more positive.

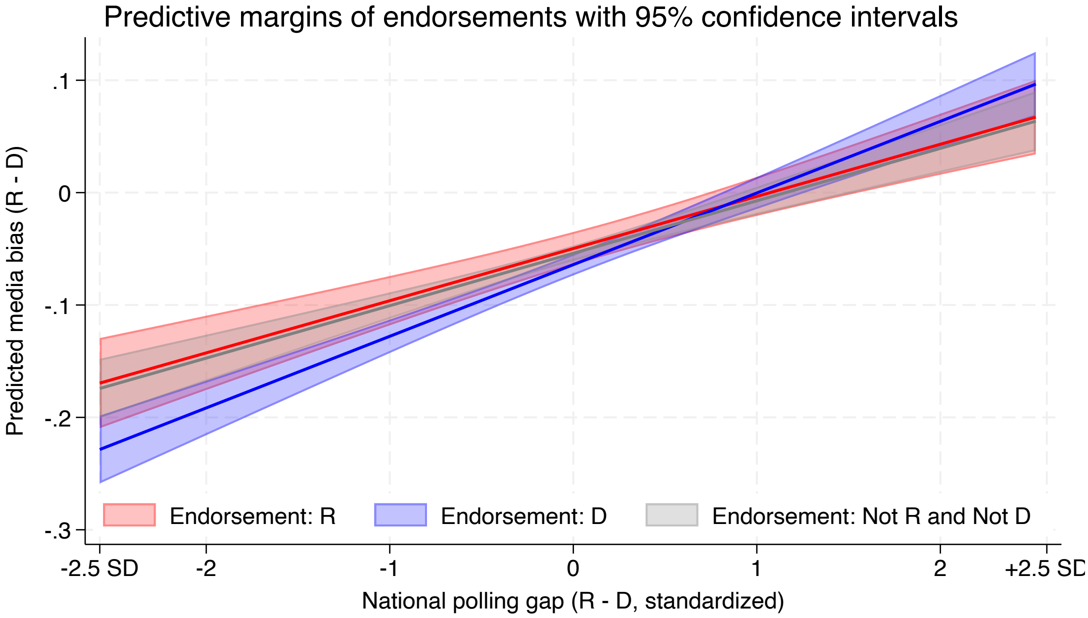
Table 1. Regression results for Equation (1)

Media bias ~ national polling

	Dependent variable:		
	Media Bias: Mean candidate score (R − D)		
	Pooling	FE	RE
National polling gap (R − D, standardized)	0.047***	0.046***	0.047***
	(0.007)	(0.007)	(0.007)
Endorsement: D	−0.027***	−0.014*	−0.021***
	(0.006)	(0.009)	(0.008)
Endorsement: not R and not D	−0.005	−0.004	−0.004
	(0.006)	(0.009)	(0.008)
Polling gap × Endorsement: D	0.014**	0.017***	0.015***
	(0.005)	(0.006)	(0.006)
Polling gap × Endorsement: not R and not D	0.001	0.0002	−0.0001
	(0.006)	(0.006)	(0.006)
Days to election	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)
Republican incumbent	−0.119***	−0.120***	−0.120***
	(0.026)	(0.027)	(0.026)
Democratic incumbent	0.069**	0.072**	0.069**
	(0.029)	(0.030)	(0.030)
Election year: 1992	0.153***	0.155***	0.155***
	(0.034)	(0.035)	(0.034)
Election year: 1996	0.066**	0.063*	0.066**
	(0.031)	(0.032)	(0.032)
Election year: 2000	0.011	0.011	0.011
	(0.014)	(0.015)	(0.014)
Election year: 2004	0.084***	0.083***	0.084***
	(0.025)	(0.026)	(0.026)
Election year: 2008	0.028*	0.026	0.027*
	(0.016)	(0.016)	(0.016)
Election year: 2012	−0.025	−0.029	−0.026
	(0.027)	(0.028)	(0.028)
Election year: 2016	−0.083***	−0.084***	−0.084***
	(0.016)	(0.016)	(0.016)
Election year: 2020	0.111***	0.109***	0.110***
	(0.032)	(0.033)	(0.032)
Constant	−0.056***		−0.057***
	(0.015)		(0.016)
Observations	37,972	37,972	37,972
R^2	0.034	0.031	0.033
Adjusted R^2	0.033	0.024	0.032
F Statistic	82.553*** (df = 16; 37955)	74.275*** (df = 16; 37719)	1,260.190***
Note:			*p<0.1; **p<0.05; ***p<0.01

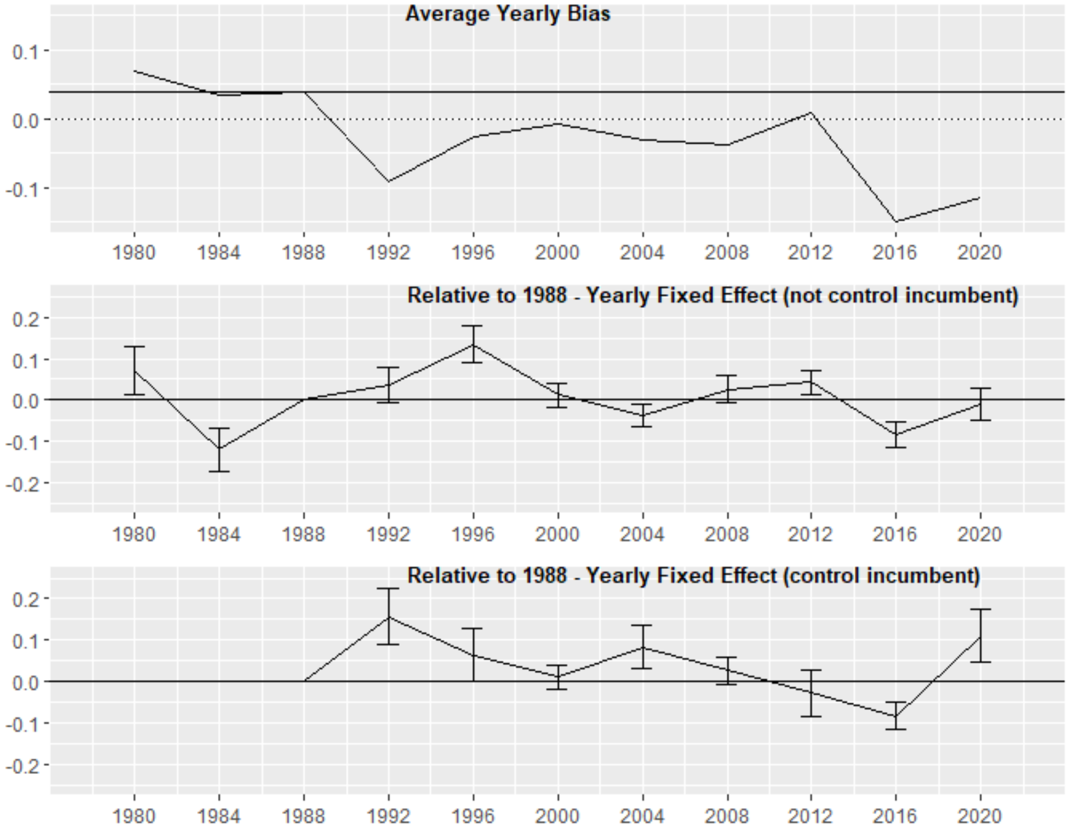
Note: The table does not report the coefficient for “Endorsement: R” and its interaction term because most newspapers endorsed either Republicans or Democrats, and including these two values will lead to multicollinearity.

Figure 4. Marginal effect of polling on newspapers' tonality bias with different endorsements



The coefficients of yearly fixed effects could show us the trend of media bias after controlling for polls (the public preference), endorsement, and the incumbent president's party. Figure 5 presents three graphs, from top to bottom they are respectively: 1. the average yearly tonality bias; 2. the bias after controlling for polls, endorsement, and their interaction terms; 3. The bias after further controlling the party of the incumbent president. We select 1988 as the baseline for convenience because neither of the two nominees is the incumbent president this year. Comparing the second and third graphs with the first graph, we discover that although the newspapers' bias is becoming more against the Republican nominee after 1988, this bias is reduced after controlling for the polls. The bias is even relatively more pro-Republican except in 2016 after controlling for the incumbent president). This finding indicates that the left-turned public preference is the driver of the left-biased newspapers during the presidential elections in the past four decades.

Figure 5. Average yearly bias and yearly fixed effects



Note: Three graphs from top to bottom: 1. Average yearly tonality bias from 99% of newspapers in my dataset (the upper 0.5% and the lower 0.5% extreme observations are removed before regression, so this graph is different from Figure 2); 2. Yearly fixed effects without controlling for incumbent, 1988 is the baseline; 3. Yearly fixed effects after controlling for incumbent, 1988 is the baseline. The binary intercepts for 1980 and 1984 are captured by "Democratic incumbent" and "Republican incumbent", so 1980 and 1984 are the baselines as well, after controlling for incumbents. The confidence interval is 95%.

With the help of election closeness, we dive deeper into presidential elections to see how newspapers adjust their strategies of media bias with the dynamic election process. We modeled the same media bias variable using polling closeness (has no direction) in Equation (2). Table 2 presents the results. While the endorsement's coefficients are similar to those of Table 1, which is within the expectation, the coefficients of polling closeness for newspapers from all endorsement groups should be significantly positive without group differences. This implies that when the election gets closer, observed from the polling, the newspapers, whether they endorsed a Republican candidate, a Democratic candidate or not, will be consistently more biased against the Democratic candidate (or less biased against the Republican candidate). Figure 6 plots the media bias (R minus D) against the polling closeness for three endorsement groups. Most of the time, the bias is against the Republican candidate (similar to Figure 5, with most observations below zero). When the election gets closer, the bias consistently shifts towards the Republican candidate, regardless of whether the newspapers are left-leaning or right-leaning. As shown in the heatmap in Figure 3, many newspapers have substantial missing values. Larger newspapers such as the New York Times contribute far more observations and therefore disproportionately influence the regression estimates. Thus, the grouped regression results should be interpreted as reflecting the general tendencies of mainstream left- and right-leaning newspapers, while recognizing that some outlets may exhibit different patterns of supplying bias.

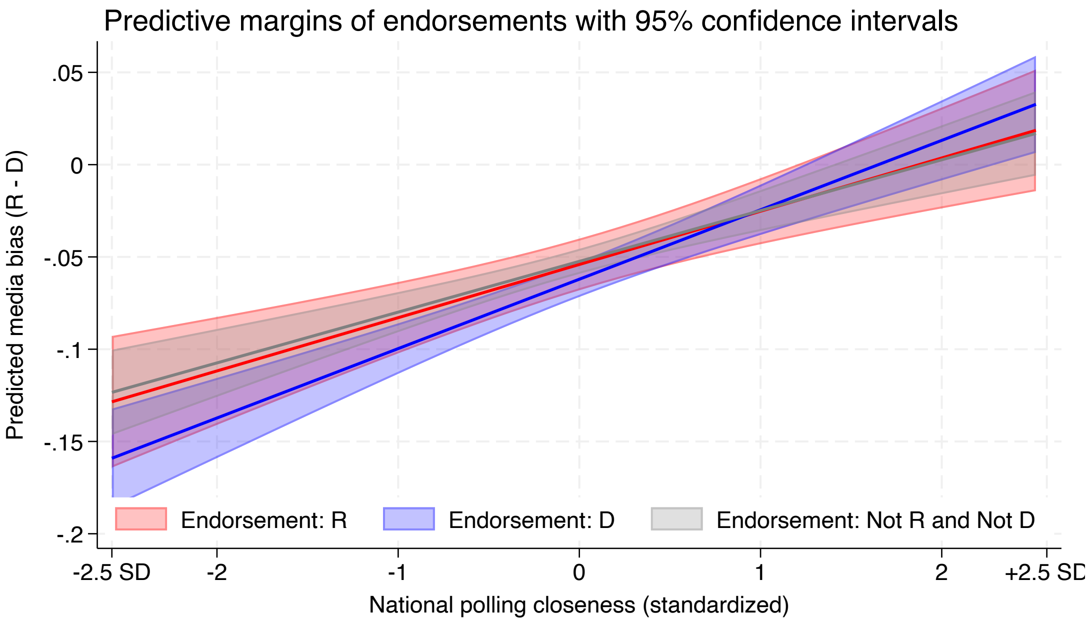
Table 2. Regression results for Equation (2)

Media bias ~ national polling closeness

	Dependent variable:		
	Media Bias: Mean candidate score (R — D)		
	Pooling	FE	RE
National polling closeness (standardized)	0.031^{***}	0.029^{***}	0.030^{***}
	(0.006)	(0.006)	(0.006)
Endorsement: D	-0.023^{***}	-0.008	-0.016^{**}
	(0.006)	(0.008)	(0.007)
Endorsement: not R and not D	-0.001	0.002	0.001
	(0.006)	(0.009)	(0.007)
Polling closeness × Endorsement: D	0.006	0.009	0.007
	(0.006)	(0.006)	(0.006)
Polling closeness × Endorsement: not R and not D	-0.003	-0.001	-0.002
	(0.005)	(0.006)	(0.006)
Days to election	0.0004^{***}	0.0005^{***}	0.0004^{***}
	(0.0001)	(0.0001)	(0.0001)
Republican incumbent	0.095^{***}	0.098^{***}	0.096^{***}
	(0.026)	(0.027)	(0.027)
Democratic incumbent	0.005	0.007	0.005
	(0.029)	(0.030)	(0.030)
Election year: 1992	-0.189^{***}	-0.192^{***}	-0.190^{***}
	(0.024)	(0.025)	(0.024)
Election year: 1996	-0.005	-0.010	-0.007
	(0.030)	(0.031)	(0.031)
Election year: 2000	-0.083^{***}	-0.083^{***}	-0.083^{***}
	(0.014)	(0.015)	(0.014)
Election year: 2004	-0.190^{***}	-0.194^{***}	-0.191^{***}
	(0.026)	(0.027)	(0.027)
Election year: 2008	-0.098^{***}	-0.103^{***}	-0.101^{***}
	(0.012)	(0.013)	(0.013)
Election year: 2012	-0.081^{***}	-0.085^{***}	-0.082^{***}
	(0.027)	(0.028)	(0.028)
Election year: 2016	-0.210^{***}	-0.213^{***}	-0.211^{***}
	(0.012)	(0.013)	(0.013)
Election year: 2020	-0.240^{***}	-0.247^{***}	-0.244^{***}
	(0.024)	(0.025)	(0.025)
Constant	0.049^{***}		0.048^{***}
	(0.013)		(0.014)
Observations	37,972	37,972	37,972
R^2	0.032	0.029	0.031
Adjusted R^2	0.032	0.022	0.030
F Statistic	78.343^{***} (df = 16; 37955)	69.681^{***} (df = 16; 37719)	$1,189.354^{***}$
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: The table does not report the coefficient for “Endorsement: R” and its interaction term because most newspapers endorsed either Republicans or Democrats, and including these two values will lead to multicollinearity.

Figure 6. The marginal effect of polling closeness on newspapers' media bias with different endorsements



It's surprising that the newspapers that endorsed a Democratic candidate turn right when the election gets closer. Ji and Zhao (2021) discovered a similar trend in 2016, that the New York Times displayed a neutral coverage of news targeting Trump when the election campaign was going on during the last several months. Our previous findings for the general Democratic-endorsing newspapers coincide with their results for the NYT. In addition, as negativity and neutrality are among the key indicators of media content value (Haselmayer et al., 2017), which can be measured by our sentiment analysis, we are glad to use the current dataset to estimate media content value by the magnitude of sentiment. Here, we further tested in Equation (4) a more general argument that the Democratic-endorsing newspapers attract the readers with more informational and neutral content when reporting the election campaigns:

$$Sentiment\ Magnitude_{it} =$$
$$\alpha + \beta_1 * Closeness_t + \beta_2 * Endorsement_{it} + \beta_3 * Closeness_t * Endorsement_{it}$$
$$+ v + \mu_i + \eta_t + \varepsilon_{it} \tag{4}$$

From our limited measurement of media content value, we here simply measure the $Sentiment\ Magnitude_{it}$ by the average sentiment magnitude of the whole news articles, not limited to the sentences mentioning the candidates. Table 3 reports our estimation results. The coefficients for sentiment magnitude suggest that when the election gets closer, Republican-endorsing newspapers will publish articles with a stronger emotion. In contrast, Democratic-endorsing newspapers will present less emotion. These naïve but clear results could shed some light on how newspapers adjust their tone of articles when facing different election trends.

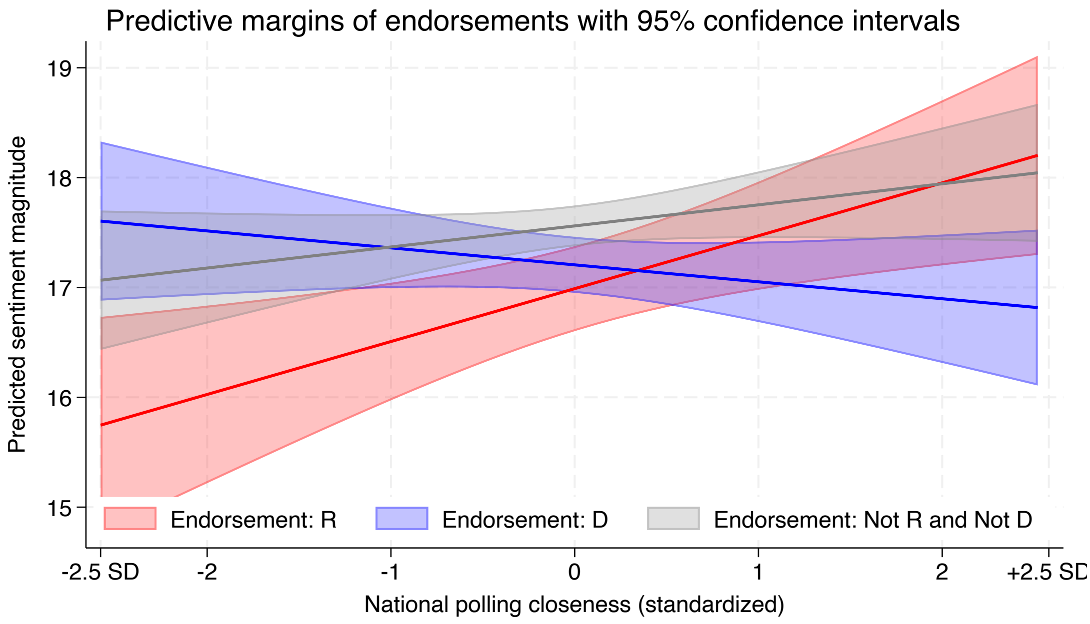
Table 3. Sentiment Magnitude ~ polling closeness

Emotion strength ~ national polling closeness

	Dependent variable:		
	Emotion strength : sentiment magnitude		
	Pooling	FE	RE
National polling closeness (standardized)	0.706***	0.482***	0.491***
	(0.173)	(0.173)	(0.172)
Endorsement: D	1.588***	0.217	0.285
	(0.174)	(0.224)	(0.220)
Endorsement: not R and not D	1.446***	0.571**	0.578**
	(0.177)	(0.245)	(0.237)
Polling closeness × Endorsement: D	−0.958***	−0.636***	−0.646***
	(0.156)	(0.161)	(0.161)
Polling closeness × Endorsement: not R and not D	−0.406***	−0.290*	−0.294*
	(0.153)	(0.159)	(0.158)
Days to election	−0.023***	−0.024***	−0.024***
	(0.003)	(0.003)	(0.003)
Republican incumbent	−1.356*	−1.010	−1.008
	(0.725)	(0.710)	(0.710)
Democratic incumbent	−2.406***	−1.975***	−1.966**
	(0.769)	(0.763)	(0.763)
Election year: 1992	0.443	0.801	0.779
	(0.654)	(0.646)	(0.646)
Election year: 1996	1.892**	2.776***	2.717***
	(0.797)	(0.794)	(0.794)
Election year: 2000	−1.246***	0.009	−0.036
	(0.382)	(0.387)	(0.385)
Election year: 2004	1.165	2.240***	2.172***
	(0.729)	(0.722)	(0.722)
Election year: 2008	−1.809***	−0.316	−0.383
	(0.342)	(0.354)	(0.352)
Election year: 2012	0.759	1.694**	1.675**
	(0.711)	(0.718)	(0.717)
Election year: 2016	−1.623***	−0.146	−0.177
	(0.339)	(0.351)	(0.349)
Election year: 2020	3.049***	4.406***	4.359***
	(0.664)	(0.661)	(0.660)
Constant	17.722***		17.124***
	(0.360)		(0.427)
Observations	32,837	32,837	32,837
R^2	0.018	0.018	0.049
Adjusted R^2	0.018	0.010	0.049
F Statistic	37.697*** (df = 16; 32820)	37.451*** (df = 16; 32584)	600.448***
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: The table does not report the coefficient for "Endorsement: R" and its interaction term because most newspapers endorsed either Republicans or Democrats, and including these two values will lead to multicollinearity.

Figure 7. The marginal effect of polling closeness on newspapers' emotion strength with different endorsements



1.8 Conclusion and discussion

Presidential elections give us a good chance to monitor media bias because 1) During the elections, the bias can be measured in one dimension, newspapers support more the nominee from the Republican (Democratic) party than the one from the Democratic (Democratic) party; and 2) While the literature agrees that the media would choose a median position among the public preferences (Anderson et al., 2016; Garz et al., 2020; Gentzkow & Shapiro, 2010; Ho & Quinn, 2008; Puglisi & Snyder, 2015), many polls are conducted during the elections to estimate the dynamic public opinion, regardless of their accuracy (Enns et al., 2017; Gelman & King, 1993), they could somehow help us further monitor how the media is biased relative to the public opinion or change with the dynamic election process. This article contributes to the literature by conducting the first high-frequency measurement of media bias from a large dataset of news articles covering 11 US presidential elections (from 1980 to 2020) and providing a new estimation of media bias involving election closeness.

We measured the tonality bias for news articles describing the two nominees and found that election news was predominantly against Republican presidential candidates, regardless of whether the newspapers were left-leaning or right-leaning. Our multilevel model across four decades suggests that this kind of left bias is due to the left-turning public preference (polls). After controlling for the public preference, we did not see the bias shifting to the left, compared with the bias in the 1980s.

In addition to the public preference, we provided a new estimator for the media bias, election closeness, which represents the dynamic election process. We found that newspapers that endorsed a Republican nominee or not responded differently to the election closeness. When the election gets closer, Republican-endorsing newspapers publish articles with stronger sentiment supporting the Republican nominee, while the newspapers that endorsed a Democratic nominee or neither tend to report more neutrally, covering the nominees. We argue that the different strategies adopted by left-leaning and right-leaning newspapers are due to differences in their target readerships and in the demands of liberal and conservative audiences. When the election gets closer, newspapers with both ideologies need to respond to the demand for media bias from extra voters attracted by the election closeness. Right-leaning newspapers tend to publish news articles with more bias toward Republican nominees to meet their Republican readers' preferences. While left-leaning newspapers need to reduce the emotional intensity against Republican nominees because their readers include around half of the Republican readers that consume media from portals, mainstream media sites, and social network followings that are left-leaning (Eady et al., 2019; Guess, 2021; Shin, 2020; Wittenberg et al., 2021). The relatively neutral content could also help build and maintain their reputation for high-quality journalism.

This study provided observational evidence on how media outlets strategically adjust ideological bias in response to public opinion. However, it did not directly examine the decision-making processes from newsrooms that generated such bias. Future research could use interviews, surveys, and document tracing to better identify the causal processes.

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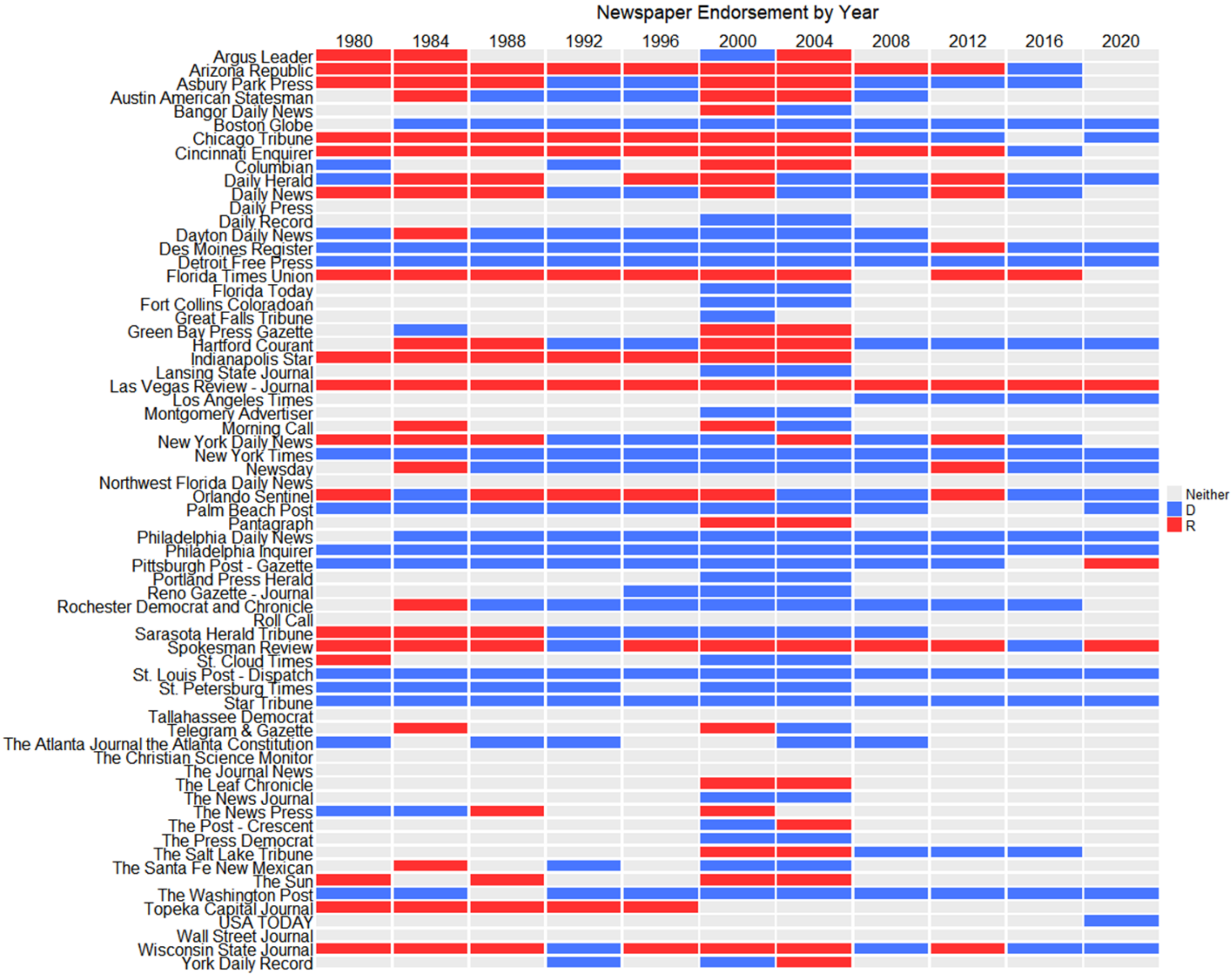
Appendix

Table 1. List of newspapers (first 12 by alphabet) every year

year	newspapers(first 10 by alphabet)	No. newspapers	No. articles
1980	Boston Globe, New York Times, The Christian Science Monitor	3	1825
1984	Morning Call, New York Times, Philadelphia Daily News, Philadelphia Inquirer, The Christian Science Monitor, Wall Street Journal	6	2439
1988	Boston Globe, Chicago Tribune, Colorado Springs Gazette - Telegraph, Los Angeles Times, Morning Call, New York Times, Northwest Florida Daily News, Orlando Sentinel, Philadelphia Daily News, Philadelphia Inquirer, St. Petersburg Times, Star Tribune, Sun Sentinel, The Christian Science Monitor, The Washington Post, USA TODAY, Wall Street Journal, ...	17	7771
1992	Austin American Statesman, Boston Globe, Chicago Tribune, Colorado Springs Gazette - Telegraph, Daily Press, Hartford Courant, Indianapolis Star, Journal Record, Las Vegas Review - Journal, Los Angeles Times, Morning Call, New York Times, Northwest Florida Daily News, Orlando Sentinel, Pantagraph, Philadelphia Daily News, Philadelphia Inquirer, St. Louis Post - Dispatch, St. Petersburg Times, Sun Sentinel, ...	27	11482
1996	Albuquerque Journal, Austin American Statesman, Bangor Daily News, Boston Globe, Chicago Tribune, Colorado Springs Gazette - Telegraph, Columbian, Daily News, Daily Press, Dayton Daily News, Florida Times Union, Hartford Courant, Indianapolis Star, Intelligencer Journal Lancaster New Era, Lancaster New Era, Las Vegas Review - Journal, Lincoln Journal Star, Los Angeles Times, Milwaukee Journal Sentinel, Morning Call, ...	47	11176
2000	Albuquerque Journal, Argus Leader, Arizona Republic, Austin American Statesman, Bangor Daily News, Boston Globe, Charleston Daily Mail, Chicago Defender, Chicago Tribune, Cincinnati Enquirer, Columbian, Courier - News, Daily Breeze, Daily Herald, Daily News, Daily Press, Daily Record, Dayton Daily News, Des Moines Register, Detroit Free Press, ...	80	27286
2004	Albuquerque Journal, Arizona Republic, Asbury Park Press, Asheville Citizen - Times, Austin American Statesman, Bangor Daily News, Battle Creek Enquirer, Bismarck Tribune, Boston Globe, Capital, Charleston Daily Mail, Chicago Defender, Chicago Tribune, Cincinnati Enquirer, Columbian, Courier - Journal, Courier - News, Courier Post, Daily Breeze, Daily Herald, ...	131	29251
2008	AM New York, Albuquerque Journal, Argus Leader, Arizona Republic, Asbury Park Press, Asheville Citizen - Times, Austin American Statesman, Bangor Daily News, Battle Creek Enquirer, Bennington Banner, Bismarck Tribune, Boston Globe, Bucks County Courier Times, Burlington County Times, Capital, Charleston Daily Mail, Chicago Tribune, Chillicothe Gazette, Cincinnati Enquirer, Citizens' Voice, ...	176	35829
2012	AM New York, Argus Leader, Arizona Republic, Asbury Park Press, Asheville Citizen - Times, Austin American Statesman, Bangor Daily News, Bennington Banner, Bismarck Tribune, Boston Globe, Bozeman Daily Chronicle, Charleston Daily Mail, Chicago Tribune, Cincinnati Enquirer, Citizens' Voice, Columbian, Concord Monitor, Contra Costa Times, Courier - Journal, Creators Syndicate, ...	143	29623
2016	AM New York, Argus Leader, Arizona Republic, Asbury Park Press, Asheville Citizen - Times, Austin American Statesman, Bangor Daily News, Battle Creek Enquirer, Baxter Bulletin, Bennington Banner, Bismarck Tribune, Boston Globe, Capital, Carlsbad Current - Argus, Charleston Gazette - Mail, Chicago Tribune, Chillicothe Gazette, Cincinnati Enquirer, Citizens' Voice, Columbian, ...	161	53366
2020	Arizona Republic, Asbury Park Press, Asheville Citizen - Times, Austin American Statesman, Bangor Daily News, Battle Creek Enquirer, Bismarck Tribune, Boston Globe, Capital, Carroll County Times, Chicago Tribune, Chillicothe Gazette, Cincinnati Enquirer, Columbian, Coshocton Tribune, Courier - Journal, Courier - News, Creators Syndicate, Daily Herald, Daily Record, ...	105	28062

Figure 1. Endorsement across 11 years respectively from 67 newspapers in alphabetical order with the least missing values



Study 2: Media Preference in the 2022 U.S. Midterm Election: Informational Value or Emotional Support?

Abstract

During U.S. elections, online traffic surges and social media becomes a primary source of political news for citizens. Understanding the content characteristics that people prefer to share is crucial for media outlets to compete for online attention. Informational value and emotional support are two main characteristics of news content; however, previous research relies on human annotators and lacks analysis of facial emotions. This research is the first to apply an automated NLP-based method to measure the informational value of news articles and to incorporate facial emotion analysis in political communication research. I construct a series of emotion and information variables for political news tweets from four prominent left-leaning and four right-leaning media outlets during the 2022 U.S. midterm elections, aiming to find out which variables are associated with higher retweet counts. However, neither the descriptive visualizations nor the regression analyses reveal strong and consistent patterns; only overall emotion intensity and anger show relatively consistent positive effects across most outlets. I interpret this divergence from prior literature as stemming from external shocks in real-world observational data, a gap between how professionals and the public assess the informational value of news, and users' tendency to engage with posts without clicking the attached article URL.

Keywords: U.S. elections, media preference, emotional support, informational value, automated measurement, facial emotion

2.1 Introduction

From X (formerly Twitter), Facebook and Instagram to YouTube and TikTok, social media has become a major channel through which the public accesses news, with fewer than 28% of U.S. adults reporting that they never got news from social media in 2024 (Christopher & Jacob, 2024). Users often encounter news unintentionally via shares from other people they follow or through algorithm-driven feeds (Elisa et al., 2024; A. M. Guess et al., 2023; Weeks & Lane, 2020). As a result, news organizations have increasingly shifted their revenue toward digital advertising and digital subscriptions (Bekh, 2020). For example, The New York Times Company reported that approximately 70% of its advertising and subscription revenue in 2024 came from digital sources (The New York Times Company, 2025). News companies treat social media as a vital channel to build influence and to redirect traffic back to their websites to generate digital revenues (Sismeiro & Mahmood, 2018). To seize these opportunities, journalists and official outlet accounts now post large volumes of news with URLs on social media, competing for audience attention with both news influencers and other media organizations (Flamino et al., 2023).

Furthermore, during large political events like elections, the public has a higher demand consuming horse-race news or public affairs news to track campaign dynamics (Iyengar et al., 2004). This creates a strategic window for media outlets to expand their audience base and maximize revenue on social media, especially in attracting younger adults (Boulianne & Theocharis, 2020). Therefore, understanding what people like for political news in elections and what drives social media sharing of news is important to the media companies. This study aims to find out what content characteristics make political news more likely to be shared on social media during elections.

From the literature, Uses and Gratifications Theory is widely used to explain the public's preference for news and sharing behaviors (E. Katz et al., 1973). Among the content characteristics of news, emotions are frequently examined with various empirical results (e.g., Berger & Milkman, 2012; Hasell & Weeks, 2016). Anger and the overall emotional strength are found to have relatively consistent positive effects on news dissemination, compared to other specific emotion classes (e.g., Berger & Milkman, 2012; Brown et al., 2020; Hasell & Weeks, 2016; Stieglitz & Dang-Xuan, 2013). Another content characteristic is informational value of news, which is a cross-disciplinary concept. In election research, it refers to news that helps citizens learn about candidates, issue priorities, policy positions, and developments in the race (Hansen & Pedersen, 2014; Weaver, 1996). Producing high-quality, information-rich news requires greater effort from journalists, including significant time devoted to information gathering and source verification in an environment where social media accelerates the spread of rumors (J. E. Katz & Mays, 2019; Shapiro et al., 2013). For media organizations, the efforts journalists invest in ensuring news quality are reflected in higher labor costs and efficiency trade-offs (Klinenberg, 2005). Thus, informational value of news is an important content characteristic in understanding readers' demand. It has been found in the literature to have a consistently positive effect (e.g., Boczkowski & Mitchelstein, 2013; Brown et al., 2020; Fahmy, 2012; Rudat et al., 2014).

However, I found two methodology gaps in measuring emotional support and informational value of news. Firstly, in the field of political communication, current research only focuses on text emotion (e.g., Hasell & Weeks, 2016), but emotion does not only lie in text. Mehrabian (2008) argues that over half of human emotion is expressed through faces and X. Wang et al. (2023) suggest the effectiveness of emotional emoji in marketing. Although CNN and Vision-Transformer models can recognize facial emotions with high accuracy (Dosovitskiy et al., 2021; LeCun & Bengio, 1998), existing models struggle to determine which face is most important when multiple faces appear in an image, thereby limiting accurate assessment of the image's overall emotional expression.[6] Secondly, in measuring the informational value

[6] Multimodal large language models are developing very fast. The gap may not exist in December 2025.

of news, current research relies on human annotation (e.g., Zhu & Hu, 2023); however, the high labor costs and long research cycles make it limited in fast-paced communication research for media companies. There is a lack of automated approaches for measuring the informational value of news.

For the two gaps, this study contributes to the literature by 1. translating the common practice in photojournalism to a programing model that calculates the importance weights for multiple faces in an image as well as introducing facial emotion analysis to political communication field; and 2. introducing *Hyperlink Density Ratio* and *Entity Density Ratio*, together with article length as automated proxy indicators for assessing the informational value of news. The method of *Entity Density Ratio* is validated by the only open-source dataset from (Zaczynska et al., 2025). In applying the two methods, this study tries to answer two research questions:

RQ1: How do the U.S. outlets differ in their presentation of news regarding emotional support and informational value?

RQ2: Emotional support vs. Informational value, what kind of news are more preferred by the readers?

To answer the two questions, I collected 9,263 news tweets—along with the news full articles and images—from eight major news outlets' verified accounts, with both conservative and liberal ideological orientations, on Twitter during the 2022 U.S. midterm election from Sep 1 to Nov 8. The number of retweets is used as a proxy for readers' share preferences. After providing automatic measurements of emotional support and informational value, both descriptive visualizations and regression analysis are conducted. For RQ1, my visualization results showed clear divergence in presenting emotions and information among the eight outlets. Conservative outlets like @nypost, @FoxNews, and @theblaze showed stronger emotions, especially anger and fear, while liberal outlets provided longer articles with lower density ratios.

For RQ2, the only findings that are relatively consistent across both descriptive visualizations and regression analyses are: during elections, news with higher overall emotional intensity and more anger emotion is more likely to be shared, consistent with prior literature. However, the positive effect of informational value on sharing preference, which is consistently suggested by the literature (e.g., Rudat et al., 2014), is not supported by my results. None of the three proxy variables for informational value—article length, entity density, and hyperlink density—nor the LPA-clustered binary variable of informational, show consistent results across the eight news outlets. In the discussion part, I provide three explanations for the inconsistency between my findings and those reported in the existing literature: external shock in real-world observational data; a gap between how professionals and the public assess the informational value of news (Bobkowski, 2015); and the possibility that users engage with posts without clicking the attached URL or reading the full article (Sundar et al., 2025). Finally, an overview of Study 3 with a survey experiment method is introduced to overcome the limitations of Study 2.

2.2 Literature review

I adopt the following steps to conduct the literature review. Firstly, I introduce the background of public news consumption via social media and news organizations' increasing reliance on these platforms, especially in large political events like elections, as a strategic window to address the importance of my research topic: media preference in the 2022 U.S. midterm election. Secondly, I review the empirical literature in communication and political communication on the content characteristics that increase the likelihood of news being shared on social media, with a focus on emotional support and informational value. Thirdly, I review the measurement of emotional support and informational value in the literature, as well as introducing the gaps and my contributions.

2.2.1 Social media is important to the media industry, especially in the elections

Social media has transformed the way the public accesses information. People usually access news in three ways in the digital era: by visiting news outlets' websites (homepages, internal pages, or saved bookmarks); by searching with engines and news aggregators, such as Google or Google News; or through social media platforms (Möller et al., 2020). The convenience and timeliness of social media have led more people to adopt it as a key channel for accessing news (Christopher & Jacob, 2024; Newman et al., 2021). Among major platforms, roughly half of Facebook and X (formerly Twitter) users regularly obtain news through these sites, whereas the proportion of users relying on video-based platforms such as TikTok and YouTube for news has increased rapidly since 2020 (Aridor et al., 2025; Christopher & Jacob, 2024; Hendrickx, 2024). Within these social media platforms, users often come across news unintentionally via reshares or retweets from people they follow, which they tend to trust more (Bond et al., 2017), and, in recent years, through algorithm-driven feeds, instead of actively searching for it (Elisa et al., 2024; A. M. Guess et al., 2023; Weeks & Lane, 2020).

For media companies, the internet and social media have transformed revenue models, forcing them to compete for online traffic and audience attention. In the early social media era, the internet had already caused the closure of many print outlets—particularly local newspapers—before 2010 (Cho et al., 2016). Yet research also shows that the internet simultaneously increased online readership while reducing print readership (Bhuller et al., 2024). As a result, news organizations have shifted their revenue streams increasingly toward digital advertising and subscription models (Angelucci & Cagé, 2019; Bekh, 2020; Penttilä, 2024; The New York Times Company, 2025).

While social media has drawn users away from direct consumption of news on outlet websites, particularly from homepage visits and through search engines (Möller et al., 2020), social media has also become a vital channel to build influence on social platforms and to redirect traffic back to their websites (Vermeer et al., 2020). Posts containing news links can increase click-throughs to news sites (Aral & Hanselmann, 2013; Sismeiro & Mahmood, 2018), and concerns about the reliability of information on social media often motivate users to turn to news websites for higher quality and more comprehensive coverage of certain topics such as weather (Aral & Zhao, 2019) or stock markets (Ren et al., 2024). In this sense, the circulation of news on social media often encourages users not only to share it but also to click through to the original websites for further information, thereby increasing page views (Welbers & Opgenhaffen, 2018). To capture these opportunities, journalists and official outlet accounts now post large volumes of news stories and links on social media, competing directly with news influencers (Flamino et al., 2023; Singer, 2013) and other media organizations for online news attention (Hermida, 2013; Molyneux & Nelson, 2024), and in doing so they have to pay closer attention to audience preferences and performance metrics (Belair-Gagnon et al., 2020; Hendrickx & Opgenhaffen, 2024; Penttilä, 2024; Peterson-Salahuddin, 2024).

Large political events like elections trigger sharp increases in news demand, with audiences consuming horse-race news, like polls and candidate updates, to track campaign dynamics and to understand why their preferred candidate is leading or trailing (Iyengar et al., 2004). The novelty and currency of social media make it appealing for the public, especially for young adults, who use it both to obtain election news and to participate in political discussions (Boulianne & Theocharis, 2020; Elisa et al., 2024). At the same time, heightened concerns about misinformation increase the demand for fact-checking, promoting users to turn to original news websites for verification (Chopra et al., 2022; Graham & Porter, 2025). Furthermore, evidence from a large field experiment on Facebook shows that when individuals are incidentally exposed to political news posts from an outlet, even when the outlet's ideology does not align with their own, the individuals' total visits to the outlet's website still increase by 79 percent, compare with those not exposed (Levy, 2021). Similar gains were observed in sharing and subscription behaviors across both conservative and liberal participants (Levy, 2021). Therefore, major political events like elections provide a strategic window for media outlets to expand their audience base and maximize revenue, underscoring the importance of understanding what drives social media sharing of news during the events.

2.2.2 What kinds of news are more shared on social media? Empirical evidence

Scholars have identified a range of news content characteristics that make the news more likely to be shared on social media. The frequently examined factors are the emotion support and informational value.

Emotion has been widely studied in communication research, with various empirical results. For 2-class emotions, or sentiment tones, Berger & Milkman (2012) and McIntyre & Gibson (2016) find that positively toned articles that make people feel good are more likely to go viral, whereas more recent research highlights a growing preference for negative content (Antypas et al., 2023; de León & Trilling, 2021; Jiménez-Zafra et al., 2021; Tsugawa & Ohsaki, 2017). Both strands of the literature agree that news with higher emotional intensity is more likely to be shared than neutral news. More specifically, when sharing political content, Weismueller et al. (2022) find that ideologically moderate news with positive tones is more likely to be shared, while ideologically extreme content gains greater diffusion when framed with negative emotions. Among specific emotion categories, anger has been widely studied. Angry news can evoke high-arousal emotions that make readers more likely to engage in action-related behaviors such as sharing (Berger, 2011; Berger & Milkman, 2012). This positive effect is consistently supported (Brown et al., 2020; M.-J. Wang et al., 2021). In the context of elections, Hasell and Weeks (2016) further find that anger can motivate people to participate in politics (Valentino et al., 2011), thereby increasing the sharing of political news online. Anger has also been shown to have negative effects: angry news leads some audiences to perceive the writing as lacking cognitive effort and to judge the news as less believable (B. Deng & Chau, 2023). Other emotional categories show more contested effects. Berger and Milkman (2012) argue that sadness, as a low-arousal emotion, suppresses sharing behavior, whereas more recent studies suggest that this negative effect is overstated(Brown et al., 2020; B. Deng & Chau, 2023; M.-J. Wang et al., 2021). Similar inconsistencies appear for anxiety and joy, with prior research suggesting both positive and negative effects on sharing.

For informational value of news, the definition is a cross-disciplinary concept rather than a single fixed definition. In election research, informational news is news that helps citizens learn about candidates, issue priorities, policy positions, and developments in the race (Hansen & Pedersen, 2014; Weaver, 1996). In communication research, definitions include being meaningful for a large audience and likely to impact people's minds (Rudat et al., 2014); having topics that are worthy to the public (Boczkowski & Mitchelstein, 2013); and conveying a message to the audience with high magnitude, likelihood, and immediacy (Carpentier, 2008). In linguistics and NLP, the related concepts include measurable textual cues such as text length, lexical richness or diversity, lexical density, and named entities (Kyle, 2019; Yaqian & Lei, 2020). They suggest how much specific information a text carries and how densely that information is packaged. Furthermore, Bobkowski (2015) distinguishes between actual and perceived informational value: the former refers to the level of informational richness intentionally built into a news item by producers such as journalists, whereas the latter reflects readers' subjective judgments of how useful or relevant the content is to them personally. To produce high-quality and information-rich news, journalists need to make a greater effort, and media companies must balance higher labor costs against production efficiency (Klinenberg, 2005). Therefore, it is important to determine whether informational value could bring more readership and shares, which is closely tied to media outlets' revenue.

The informational value of news has been identified as an important factor across general news, political news, and public health communication. Rudat et al. (2014) find that when respondents perceive news as having high informational value, they are more willing to share it because they believe it is valuable to their followers. Scholars also find that during crises, people have a greater need for informational value from news, such as during health crises like COVID-19 (Hwang et al., 2021; Zhu & Hu, 2023) and political crises like the Arab Spring in 2011 (Fahmy, 2012; Papacharissi & de Fatima Oliveira, 2012). For political news, Boczkowski and Mitchelstein (2013) identify a gap between the journalists' preference for informational news—measured by the proportion of public affairs topics—and the public's weaker preference for that, with audiences instead tending to prefer more entertainment-oriented news. This gap narrows during periods of heightened political activity. The authors also find that Fox News viewers show the weakest preference for informational news. Other factors that promote news sharing on social media include source credibility (Bandari et al., 2012), the geographic localization of the news story (Brown et al., 2020; Trilling et al., 2017), and topical relevance of the news during a specific political event (Boczkowski & Mitchelstein, 2013).

2.2.3 Gap and contribution in methodology: measurement of emotional support and informational value

Early research measured the emotional support of news using human annotation (Aman & Szpakowicz, 2007) based on Ekman's six classifications (Ekman, 1992a). Later studies adopted lexicon-based methods that count emotional words in the text (S. Mohammad, 2023), where the emotional words are from dictionaries like WordNet Affect (Strapparava & Valitutti, 2004), LIWC (Tausczik & Pennebaker, 2010), and NRC (S. M. Mohammad et al., 2013). With the development of deep learning models such as CNN, LSTM, and Transformer (Hochreiter & Schmidhuber, 1997; LeCun & Bengio, 1998; Vaswani et al., 2017), researchers began to adopt commercial APIs and open-source models based on them. Despite advances in emotion classification methods, scholars in neuroscience have found the difference between the emotion supplied and the emotion responses by individuals, suggesting the use of neurophysiological measures on the demand side (Schreiner & Riedl, 2019).

Emotion not only lies in text. Wang et al. (2023) find that emotional emojis could effectively affect consumer engagement on social media in the field of Marketing. In addition, Mehrabian (2008) argues that over half of human emotions are expressed through faces. There is a gap in the literature: visual emotion has not been studied in the field of political communication. To measure visual emotion, models based on CNN (LeCun & Bengio, 1998) and Vision-Transformer (Dosovitskiy et al., 2021), and recent multimodal large language models (Sanderson, 2023) have achieved high accuracy in recognizing facial emotions in images. However, when there are multiple faces in one image, the emotion recognition is not accurate.[7] In common photojournalism practice, facial importance is inferred from cues such as face size, sharpness, compositional salience, and relative position (Kobre, 1990). However, the literature in facial emotion methodology lacks the weight assignments for individual faces to better recognize the overall emotion in the image. I fill the gaps by transferring the common practice in photojournalism to a computer vision program that calculates the importance weights for faces in an image, and introducing the facial emotion measurement to the field of political communication.

To measure the informational value of news, human annotation (Htoo et al., 2023; Tellis et al., 2019) and simple proxies like article length and writing complexity (Berger & Milkman, 2012) are used in the literature. Zhu and Hu (2023) construct a small manually annotated sample to train a machine learning model and apply it to the full dataset. Bobkowski (2015) used experimentally manipulated news content—rather than real-world news—to classify articles into high and low informational utility categories. However, current methods in the literature require human participation; although they achieve high accuracy, their high labor cost and long research cycles limit their

[7] Data cleaning and variables construction are completed in November 2023. Multimodal large language models are developing very fast. The gap may not exist.

applicability in fast-paced media communication research for media companies. I fill this gap by introducing *Hyperlink Density Ratio* and *Entity Density Ratio*, together with article length, as an automatic composite proxy for measuring the informational value of news.

2.3 Theory and hypothesis

This research aims to find out what kind of news tweets in political elections are more shared on social media, and it focuses on two content characteristics of news tweets: emotional support and informational value. I draw on Uses and Gratifications Theory, Affective Intelligence Theory, and other related theoretical frameworks to how (1) overall emotion strength (or, equivalently, neutrality), (2) anger emotion, and (3) informational value affect the audience's preference to share political news on social media during elections.

Uses and Gratifications Theory sees audiences as active users to choose content that satisfies specific psychological and social needs (E. Katz et al., 1973), and this theory has been widely applied to predict or explain media use and communication behavior (Thompson et al., 2020; Whiting & Williams, 2013). During election campaigns, citizens typically experience a mix of emotions, including enthusiasm/joy, anger, anxiety/fear, and, to a lesser extent, sadness or disgust (Brader, 2006). When citizens encounter horse-racing news indicating that their preferred candidate is leading, they tend to experience pride, hope, and enthusiasm; conversely, when the candidate is falling behind, they are more likely to feel worry, anxiety, fear, and anger (Nadeem, 2024; Stolwijk et al., 2017). Moreover, when people are exposed to scandals or moral violations, feelings of shame and disgust are evoked; and even more intensely, when voters perceive norm violations or unfairness, high-arousal negative emotions such as anger and outrage are elicited (Coleman & Wu, 2024; Walter & Redlawsk, 2023). News with these emotions could satisfy common emotional gratifications during election periods, and thereby trigger reactions on social media, including shares, comments (online debates), and likes (Blassnig et al., 2021; Wollebæk et al., 2019). Conversely, news with weaker emotions or being more neutral doesn't satisfy the user gratifications and therefore has a lower probability of dissemination on social media. Thus, I hypothesize that:

Hypothesis 1: During elections, news with lower emotional intensity is less likely to be shared on social media.

Among discrete emotions, anger is one of the few for which the literature shows relatively consistent evidence of a positive effect on the diffusion of news on social media (e.g., Berger, 2011; Berger & Milkman, 2012; Brown et al., 2020; Hasell & Weeks, 2016; M.-J. Wang et al., 2021). In particular, Affective Intelligence Theory argues that anger, as a high-arousal emotion characterized by heightened activation, tends to stimulate action-oriented behaviors such as content sharing and campaign involvement, and later research shows that anger likewise motivates participation in online debates (Berger & Milkman, 2012; Marcus, 2013; Wollebæk et al., 2019). Hasell and Weeks (2016) suggest that because anger stems from perceptions of injustice toward an opposed political candidate, it would drive people to take short-term political involvement including sharing political information online seeking to punish the disliked candidate, as a convenient and low-cost way of expressing anger. Furthermore, research shows that U.S. politics is now characterized by high levels of polarization, with anger appearing more frequently in public attitudes, election campaigns, political advertising, and media (Webster, 2018; Webster et al., 2022). Thus, I hypothesize that:

Hypothesis 2: During elections, news with stronger anger intensity is more likely to be shared on social media.

Apart from emotional gratifications, sharing political news on social media could also be driven by information-seeking gratifications and status-seeking needs. Firstly, information-seeking gratification refers to individuals' need to improve knowledge of their surrounding environments through sharing information for self-education (Whiting & Williams, 2013). Sharing information on social media stores the content on a user's personal profile, making it easy to retrieve later and thereby satisfying future information needs. Thus, when users encounter a high-quality, informational-rich news article, sharing it on social media satisfies their information-seeking gratification (Lee & Ma, 2012; Ma et al., 2011). Secondly, by sharing and exchanging information online, users enjoy stronger social connections with others (LaRose & Eastin, 2004). This could satisfy users' socializing gratification (Lee & Ma, 2012). Thirdly, users also seek psychological status gratification through sharing content on social media. Lee and Ma (2012) find that when people share information on social media, they experience greater recognition and enhanced popularity among peers, which provides status gratification and increases their willingness to share in the future. In addition to Uses and Gratifications Theory, Affective Intelligence Theory argues that anxiety, triggered by novelty and uncertainty, activates the surveillance system and leads citizens to pay closer attention and seek more information (Marcus & MacKuen, 1993). As anxiety is common in elections (Niederdeppe et al., 2021), this mechanism is particularly relevant. Taken together, news perceived as having higher informational value or originating from more reputable media organizations is more likely to provide users with information-seeking and socializing gratifications, as well as a heightened sense of social status through sharing. Thus, I hypothesize that:

Hypothesis 3: During elections, news with higher informational value is more likely to be shared on social media

2.4 Methodology

2.4.1 Data

I collected news tweets from eight news outlets' verified accounts on Twitter during the

2022 midterm election from September 1 to November 8. The news outlets include four left-leaning outlets: @nytimes, @washingtonpost, @latimes, @PhillyInquirer, and four right-leaning outlets: @nypost, @FoxNews, @theblaze, @BreitbartNews. I chose these outlets because: 1. they are among the major source of media across the liberal and conservative Americans ("American News Pathways," 2020; Gentzkow & Shapiro, 2010; Matsa, 2014); 2. they include both outlets with the highest audience among the public that has some interactions between the liberals and the conservatives and outlets that have a relatively homogeneous audience group that are consistently left and consistently right ("American News Pathways," 2020); 3. the left- and right-leaning outlets are respectively trusted by their audience (Mitchell, 2014). I filtered the tweets to be about politics using the annotations option in the Twitter API V2. Tweet metrics, the image attached to tweets, the news full article, and HTML sources from outlets' websites were scraped. The tweet metrics were collected in April 2023, which was five months after the midterm election, and the metrics figures were stable. In total, 9263 tweets, along with the full article, images, metrics, and the audience user IDs from the metrics (for detecting bots), were collected. One limitation is that Twitter was acquired by Elon Musk on 27 October, about 1.5 weeks before the end of the dataset period. Although most observations were recorded before the acquisition, post-acquisition changes to the platform may still have introduced some noise into the final engagement counts collected in April 2023.

2.4.2 Measuring informational value

In the literature, mainly in the field of public health and public communication, researchers use a binary variable to express whether an article is informational or not through human annotation (Chung et al., 2020; Rudat & Buder, 2015; Thongmak, 2024; Zhu & Hu, 2023). This study aims to provide an automated measure, so I focus on definitions drawn from linguistics and NLP, which allows informational value to be approximated with scalable indicators. I here provide more precise measurements of informational value involving both simple statistics and NLP techniques. As media and

Tweets are common sources of training dataset for Transformer-based NLP models (Vaswani et al., 2017), the top performing models I used can be directly applied to my dataset through Transfer Learning, without further training or finetuning (Weiss et al., 2016).

2.4.2.1 Entity density ratio

The *Entity Density Ratio*, calculated as the count of Named Entities (NEs) in an article divided by the total number of words, offers a quantitative measure of the concentration of named entities within the text. NEs, in the field of NLP, refer to specific entities within text that are classified into predefined categories, such as person names, locations, organizations, and numerical values (Nadeau & Sekine, 2007). It originated from the need to extract information from unstructured text, such as journalistic articles (Grishman & Sundheim, 1996). As a fundamental task of information extraction, Named Entity Recognition can answer "when, who, where, what" (Kwok et al., 2001), and it is widely used to support further NLP tasks such as text summarization and question answering (Alshibly et al., 2023; Li et al., 2022). Thus, by quantifying the presence of named entities in an article, the *Entity Density Ratio* can represent the richness and specificity of the information presented in a news article.

I recognize the NEs with one of the top-performing models by Flair (*Flair/Ner-English-Ontonotes-Large · Hugging Face*; Schweter & Akbik, 2021). The model is finetuned on the Ontonotesv5 dataset for the 18-class NER task with a F1-score of 90.93. Table 1 reports the 18-category entities of the Ontonotesv5 dataset (Pradhan et al., 2013).

Table 1. 18-class named entities from Ontonotesv5

Tag	**Meaning**	**Examples**
CARDINAL	*Numerals*	*one, 23*
DATE	*Calendar date*	*January 1, 2024, 2023-05-12*

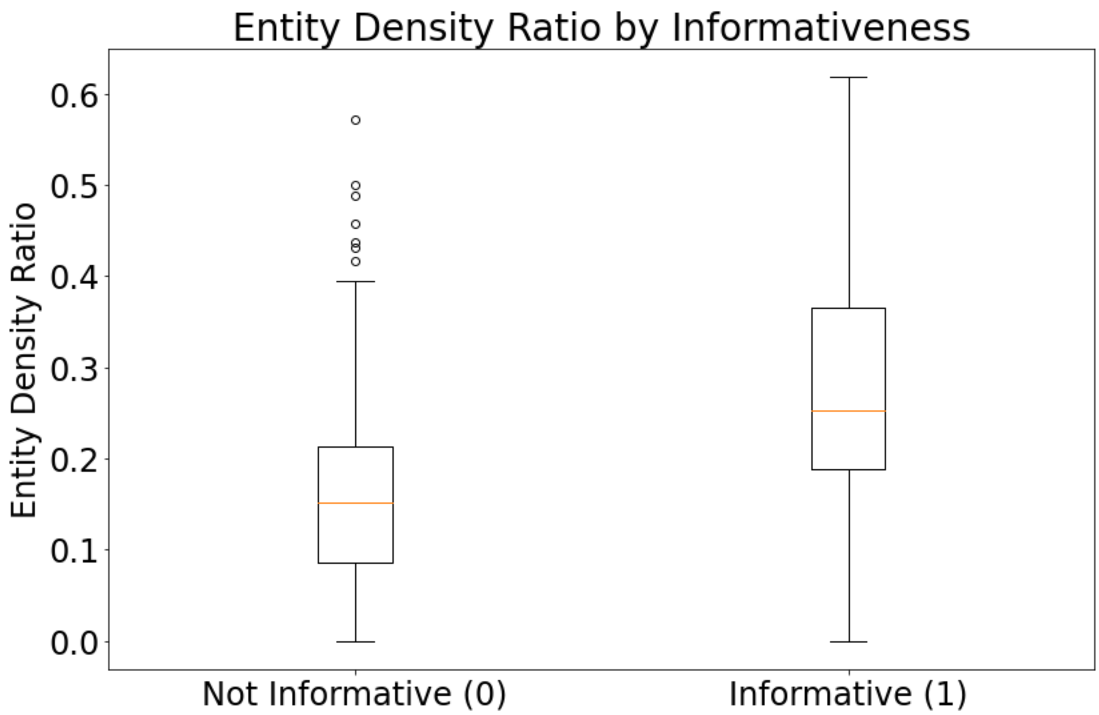
EVENT	*Event name*	*Olympic Games, TED Conference*
FAC	*Building or facility name*	*Hospital, Airport*
GPE	*Geopolitical entity*	*United States, Brazil*
LANGUAGE	*Language name*	*English, Spanish*
LAW	*Law name*	*Constitution, Copyright Act*
LOC	*Geographical place*	*Tokyo, Mount Everest*
MONEY	*Monetary value*	*$100, €50*
NORP	*Nationalities, religious, political groups*	*Japanese, Buddhists*
ORDINAL	*ordinal value*	*first, third*
ORG	*organization name*	*Google, Harvard University*
PERCENT	*Percentage values*	*50%, 75.5%*
PERSON	*person name*	*John, Mary*
PRODUCT	*product name*	*iPhone, Toyota Prius*
QUANTITY	*quantity value*	*5 kilograms, ten people*
TIME	*time value*	*3:30 PM, 10:00 AM*
WORK_OF_ART	*Artistic work name*	*Mona Lisa, Hamlet*

To validate my use of *Entity Density Ratio* as a proxy for informational value, I draw on the German COVID-19 Twitter dataset (Zaczynska et al., 2025), which consists of 463 annotated tweets related to COVID-19. It contains a binary "informative" variable that is annotated by linguistics undergraduate students. Though the tweets in the dataset are not news articles and are in the language of German, the dataset is the only open-source dataset related to "informational value" of text[8]. I computed the *Entity Density Ratio* using the same method as that in my dataset, and compared it between the informative group and the non-informative group. Figure 1 shows the comparison

[8] On 24 November 2025, the dataset is available on: https://github.com/elenanereiss/Twitter_COVID19

results. The *Entity Density Ratio* from the group of informative tweets is significantly higher than that from the other group, with a t-statistic of about 11.95 (p-value is around 0.000). Thus, despite the German language and the COVID-19 topic, the results could somehow be interpreted as evidence of validation for my *Entity Density Ratio*.

Figure 1. Entity density ratio between the informative group and not informative group



Note: Between the two groups, t-statistic: 11.95, and two-tailed p-value: 3.148e-29.

2.4.2.2 Hyperlink density ratio

The *Hyperlink Density Ratio*, calculated as the count of references with a hyperlink in an online news article divided by the total number of words, serves as an indicator of the extent to which external sources are integrated into the article. Figure 2 displays several paragraphs of a news webpage that contain five hyperlinks. A reference usually has an underline or a hyperlink (Dimitrova et al., 2003), like "created by former Education Secretary Betsy DeVos" in Figure 2. When a reader clicks this hyperlink, the webpage jumps to a new page, another news article from May 2020 titled 'New campus sexual assault rules bolster rights of accused'. The new page allows readers to get a deeper understanding of the issue associated with the preceding keywords of reference (Debatin, 2002). The hyperlinks also improve the efficiency of readers getting information by providing both a more readable presentation from a short page and a detailed context from the hyperlinks (Tremayne, 2004).

Figure 2. An example news article from the outlet's official website

The Philadelphia Inquirer SIGN IN / SIGN UP

The rights of LGBTQ+ students will be protected by federal law and victims of campus sexual assault will gain new safeguards under rules finalized Friday by the Biden administration.

The new provisions are part of a revised Title IX regulation issued by the Education Department, fulfilling a campaign pledge by President Joe Biden. He had promised to dismantle rules created by former Education Secretary Betsy DeVos, who added new protections for students accused of sexual misconduct.

Notably absent from Biden's policy, however, is any mention of transgender athletes.

» READ MORE: Title IX's legacy in Philadelphia, in the words of those it impacted most

The administration originally planned to include a new policy forbidding schools from enacting outright bans on transgender athletes, but that provision was put on hold. The delay is widely seen as a political maneuver during an election year in which Republicans have rallied around bans on transgender athletes in girls' sports.

Instead, Biden is officially undoing sexual assault rules put in place by his predecessor and current election-year opponent, former President Donald Trump. The final policy drew praise from victims' advocates, while Republicans said it erodes the rights of accused students.

Note: Part of the news: "Biden's new Title IX rules protect LGBTQ+ students, but transgender sports rule still on hold." The paragraphs here contain 5 hyperlinks in blue font. The screenshot is taken on 20240421, from: https://www.inquirer.com/politics/nation/president-joe-biden-title-ix-rules-transgender-students-rights-sports-20240419.html

Having more hyperlinked references doesn't guarantee a higher informational value. De Maeyer (2014) investigated the use of hyperlinks in news stories and found that the link page content and sources do not always match. Researchers also found that most of the hyperlinks are from the media websites' internal sites, which are not the raw sources (Mayerhöffer & Heft, 2022; Steensen, 2011; Tremayne, 2005). However, both the information provided by journalists and how the information is received and interpreted by the audience are important in the field of communication (Herman & Chomsky, 2002). In online news consumption, the readers' perception of news is found to be more deterministic (Bobkowski, 2015). Researchers have found that hyperlinks in news articles can increase readers' perceptions of news credibility (Borah, 2014; Eysenbach & Köhler, 2002; Hargittai et al., 2010); and make readers more willing to seek further information (Borah, 2014). Thus, regardless of inappropriate use of hyperlinks by journalists, the *Hyperlink Density Ratio* could provide insights into the informational value of the news article perceived by the audience.

2.4.3 Measuring emotion support

Emotion analysis is widely used in empirical communication studies (Anspach et al., 2019; Bruter & Harrison, 2017; Sivek, 2018; M.-J. Wang et al., 2021; Wollebæk et al., 2019; Zhu & Hu, 2023). While the literature focuses on text emotion, I here extend the emotion analysis to facial emotion in this field. Researchers found that over half of human emotions are expressed through faces, while less than 10% are expressed through words (Mehrabian, 2008). Facial or visual emotions should be important as well in the field of communication. The latest techniques in Computer Vision make facial emotion analysis available. I use Ekman's 6-class emotion for both the text (tweet and full article) emotion and facial emotion (Ekman, 1992b). The six basic classes include *anger, disgust, sadness, fear, surprise,* and *joy*. Each emotion variable, a floating-point number, ranges from 0 to 1, as the probability of content expressing a type of emotion. The steps and models for emotion analysis are introduced in the following paragraphs.

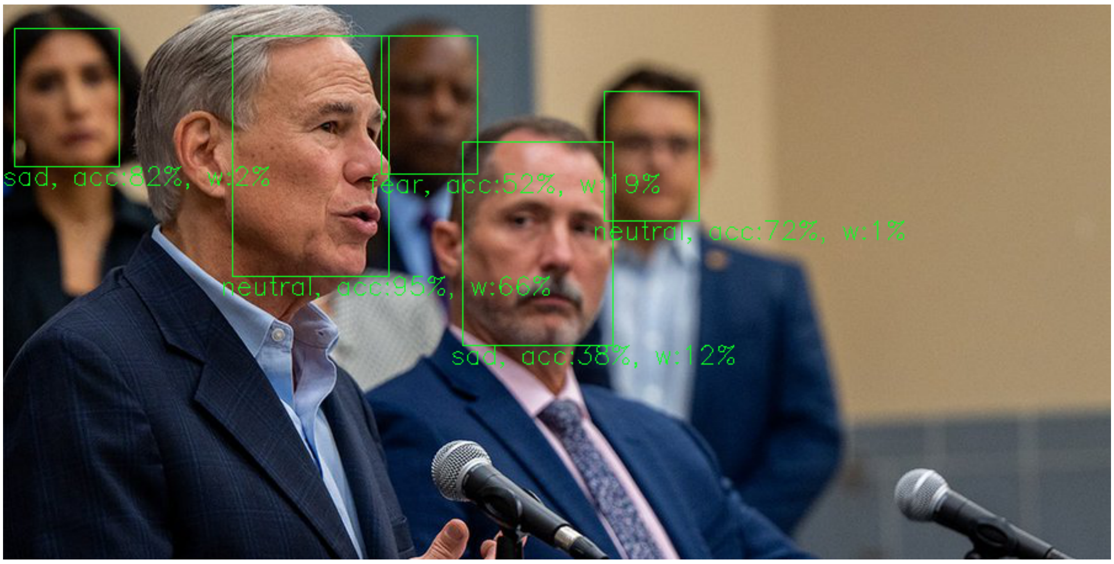
2.4.3.1 Tweet and full article emotion classification

For the 6-class emotion classification of tweets and full articles, I use the DistilBERT model developed by Sanh et al. (2020) and finetuned by Hartmann and Jochen (2022), with an evaluation accuracy of 66%. For the full article, I also provide a sentiment analysis to measure the overall strength of emotion (Hartmann et al., 2021), with an accuracy of 86.1%. Both models are imported from Hugging Face.

2.4.3.2 Face detection, weighting, and emotion classification

I first detect all the faces in this image, using Deepface (S. I. Serengil, 2020/2024), an open-source facial recognition and analysis tool that integrates multiple SOTA models (S. I. Serengil & Ozpinar, 2020, 2021; S. Serengil & Özpınar, 2024). I chose RetinaFace, even small and blurred faces could be detected with both high precision and recall (J. Deng et al., 2019). I then attribute the six emotion classes' probabilities to every face, using the VGG-Face model with an accuracy of 57.42% (S. I. Serengil & Ozpinar, 2021). Among all the faces in one image, some faces are important, some are not. This depends on journalists' judgment of the importance of different faces in the picture. There aren't open-source algorithms to assign a weight of importance to each face in the image. So I referred to the common practices in the photojournalism (Kobre, 1990), using face size, sharpness, special composition (e.g., bilateral/trilateral symmetry), and relative position (e.g., distance to the 1/3 up-left point or the central point) to assign a weight of importance to all faces in an image. Figure 3 shows a sample image with multiple faces. Dominant emotion, the probability of the face expressing the dominant emotion, and the weight of importance are shown under each face in this figure. After assigning weights to all faces, the overall probability of this image expressing an emotion (e.g., angry) is the weighted probability of an emotion class (e.g., angry) for all faces. One drawback of my method using facial emotion to represent the image emotion is that, if there is no face in the image, the emotion expressed by some kind of Art cannot be detected in this study. Art style, not only the human faces, can be a strong source of emotion (Gutierrez et al., 2025; Matravers, 1998). However, as most election news on social media has faces, this drawback is somewhat minor.

Figure 3. An example of tagged faces, with dominant emotion for each face



Note: "acc": the probability of the face expressing the dominant emotion; "w": the weight of importance of this face.

2.4.4 Measuring reader preference

I use the number of *retweets*, which is mostly used in the literature (Doroshenko & Tu, 2023; M.-J. Wang et al., 2021; Weismueller et al., 2022), to measure the readers' preference. Retweeting, as a simple copying and publicly rebroadcasting act, shows agreement with the source tweet (Boyd et al., 2010). In contrast, quoting allows users to add a short comment when retweeting, which can include disagreement or neutral sentiment in a political context (Garimella et al., 2016); and liking, as a more passive act, is considered a weaker measure of users' preference compared to retweeting (Lahuerta-Otero et al., 2018; Sekimoto et al., 2020).

As the presence of bots will distort the discovery of user preference in Twitter (Caldarelli et al., 2020; Yang, Hui, et al., 2022), I calibrated the number of retweets for bots. I use Botometer 101 to detect the bots for all user IDs that retweet the news tweets (Yang, Ferrara, et al., 2022). Botometer 101 provides a Bayesian probability of a user ID being a bot; thus, my calibration summed up the probability values for all user IDs, rather than arbitrarily setting a threshold, to determine whether each user ID is a bot or not. This calibration can yield more accurate metrics (Yang, Ferrara, et al., 2022).

2.5 Data analysis

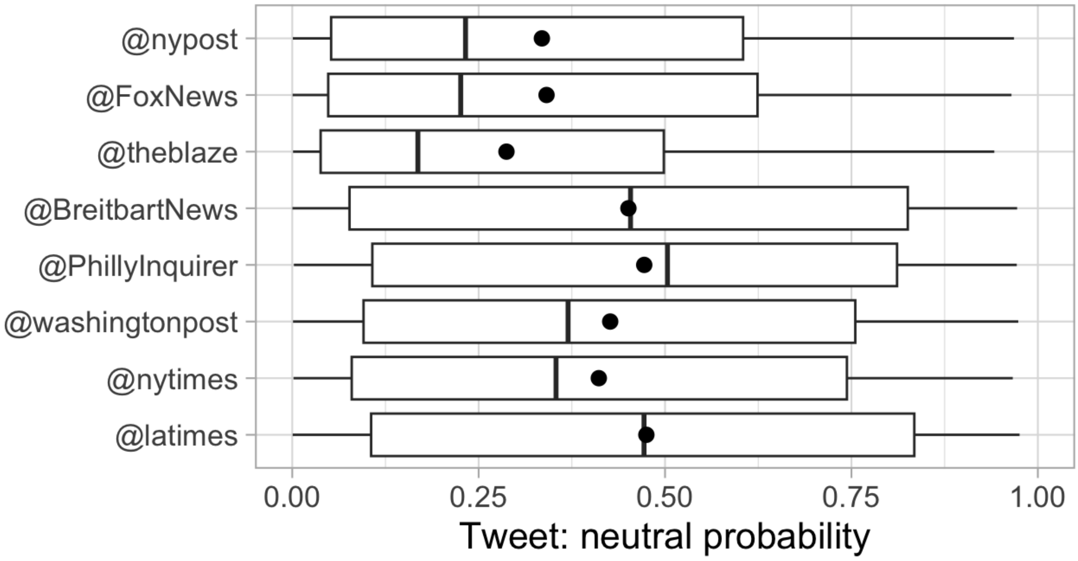
2.5.1RQ1: How do the U.S. outlets differ in their presentation of news regarding emotional support and informational value?

2.5.1.1RQ1a: emotional support

The question of whether a news outlet is more emotional includes two sub-questions: the overall emotional intensity and the specific strength of various types of emotions. First is the overall emotional intensity. Apart from the 6-class primary emotions, the machine learning models of emotion classification also yield the probability of the seventh class, neutral. The neutral probability serves as an index for the likelihood that the content (text/face) does not fall into the six emotion classes, thereby providing a quantitative measure of how "neutral", or equivalently how "not emotional", the news is. The box plots from figures 4, 5, and 6 summarize the distribution of the probability that news content is neutral across three sources: tweets, faces, and full articles by four ideologically right-leaning and four left-leaning news outlets. Images without faces are excluded here.

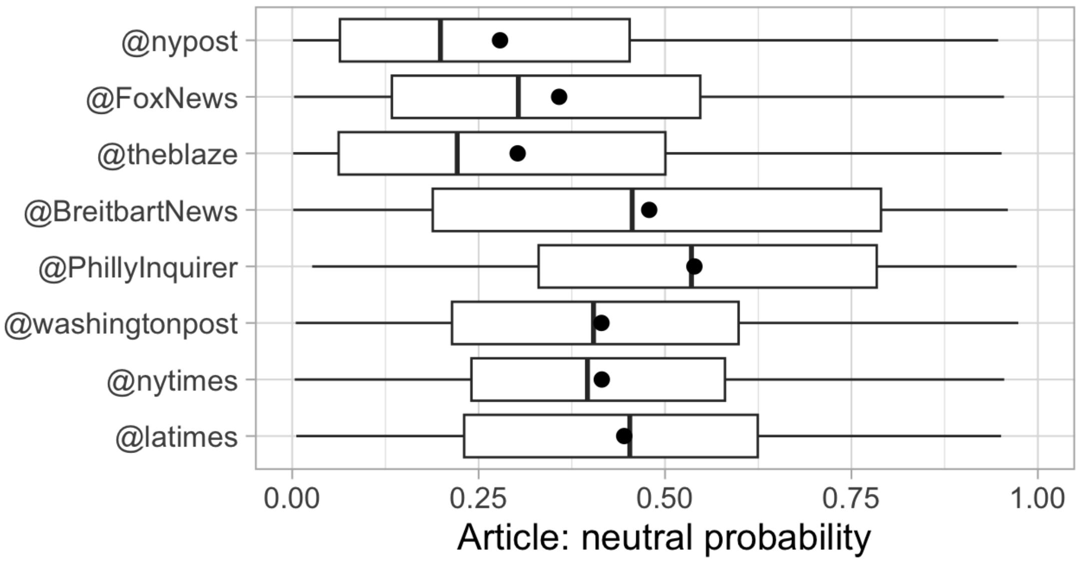
The trends observed in the tweet data (Figure 4) and the full articles (Figure 5) are notably similar, with @nypost, @FoxNews, and @theblaze exhibiting lower mean (in black dots) and median neutral probabilities compared to the other five media outlets. Regarding facial emotions (Figure 6), the left panel presents the probability that facial images display neutral emotion, and the right panel reports the percentage of images that have faces for each outlet. Among the eight outlets, the upper two conservative outlets (@nypost, @FoxNews) and the bottom two liberal outlets (@nytimes, @latimes) tend to use more neutral faces, while the remaining four outlets use more emotional faces. Additionally, @nypost tends to prominently present faces in images, while @latimes appears more likely to post images without faces.

Figure 4. Boxplot of neutral probability for tweets



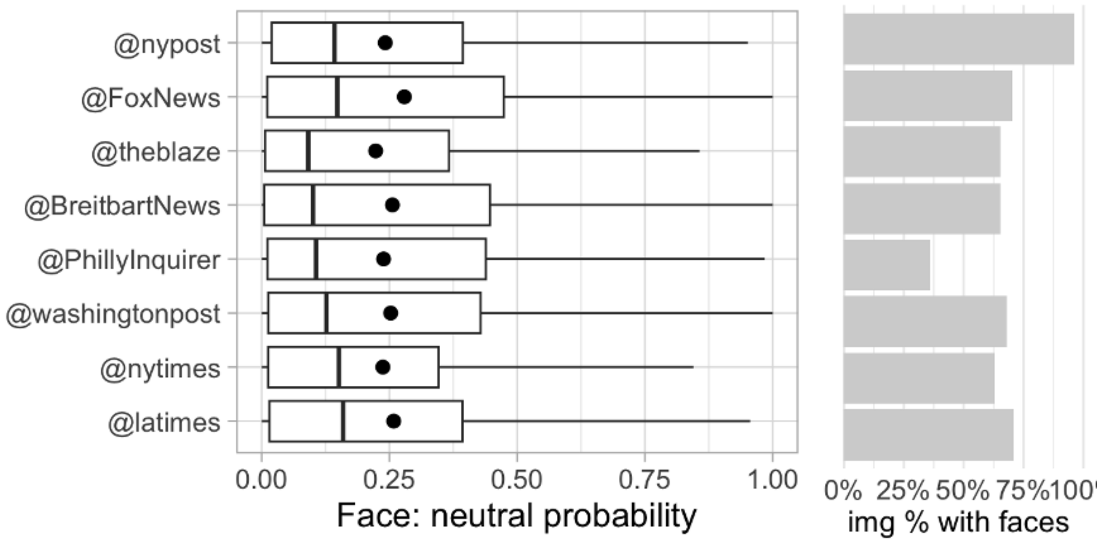
Note: Boxes indicate the interquartile range (25th–75th percentiles), horizontal lines show medians, and dots represent means.

Figure 5. Boxplot of neutral probability for article full text



Note: Boxes indicate the interquartile range (25th–75th percentiles), horizontal lines show medians, and dots represent means.

Figure 6. Boxplot of neutral probability for images with faces

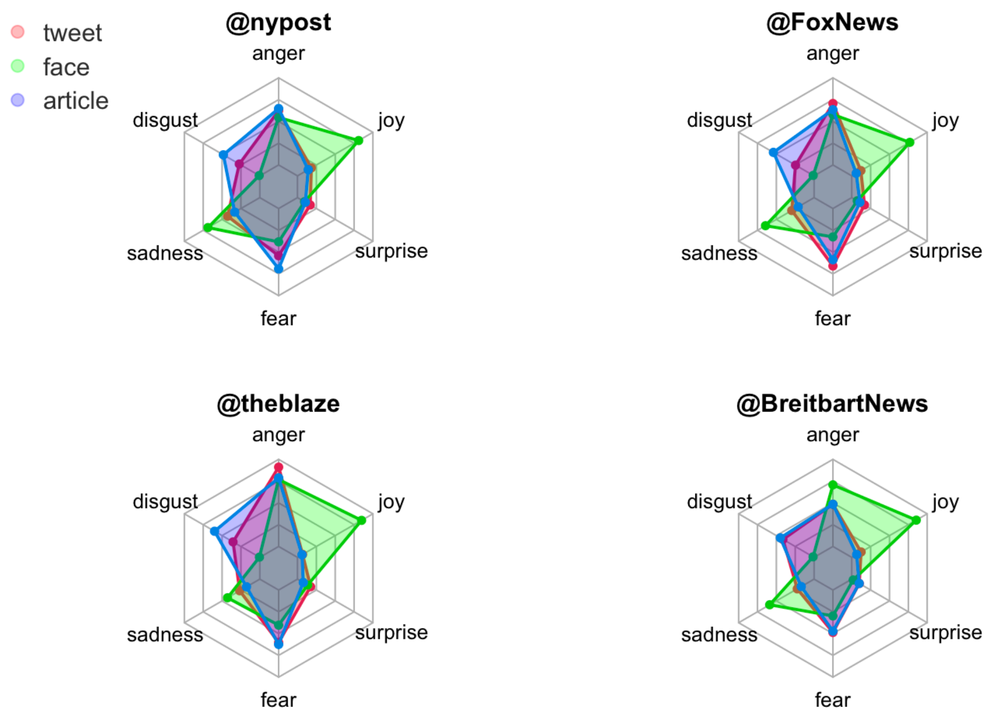


Note: Boxes indicate the interquartile range (25th–75th percentiles), horizontal lines show medians, and dots represent means.

Apart from the overall strength of emotion derived from the previous neutral probability, I used radar plots in Figures 7 and 8, to sequentially display the average intensity of each 6-class emotion for four right-leaning newspapers and four left-leaning newspapers. The three colors represent three sources (tweet in red, face in green, and article in blue), and the range of each axis on the radar chart is 0 to 0.3, representing the average probability of the 6-class emotion in political news from these outlets during the election. Although the category order has an impact, the size of the shaded area can, to some extent, represent the overall strength of the emotion.

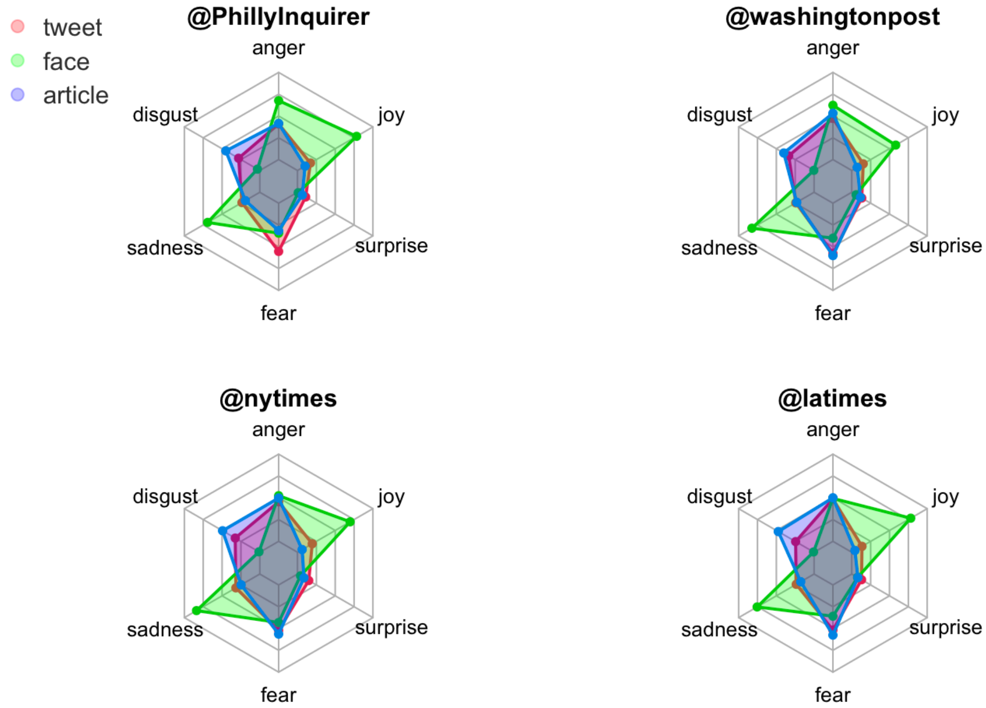
Firstly, overall, tweet emotions (in red) and article emotions (in blue) have relatively similar shapes and sizes. The red and blue areas for the three outlets, @nypost, @FoxNews, and @theblaze, are larger compared to the other five outlets. This finding about the overall strength of emotions aligns with the neutral probability boxplots in Figures 4 and 5 from the previous paragraphs. Secondly, focusing on tweet emotions (in red), anger and fear are the emotions most frequently expressed by the outlets. @theblase has the highest average intensity of anger, while @FoxNews exhibits the highest average intensity of fear. Thirdly, focusing on articles (in blue), the shape of the plots is similar to that of tweets. The key difference is that for every outlet except @BreitbartNews, articles contain more disgust emotion compared to tweets, and @PhillyInquirer's articles contain less fear. Fourthly, focusing on facial images (in green), their shapes differ significantly from those of tweets and articles. Anger, joy, and sadness are the emotions most used across the eight outlets. Among these, @theblaze displays relatively more anger over sadness, while the three liberal outlets, @nytimes, @washingtonpost, and @latimes, display more sadness in their images.

Figure 7. Average six-class emotion scores for four right-leaning outlets



Note: Emotions are derived from tweet text (red), tweet images containing faces (green), and full articles (blue). Each radar axis ranges from 0 to 0.3 and represents the average emotion probability.

Figure 8. Average six-class emotion scores for four left-leaning outlets



Note: Emotions are derived from tweet text (red), tweet images containing faces (green), and full articles (blue). Each radar axis ranges from 0 to 0.3 and represents the average emotion probability.

2.5.1.2 RQ1b: informational value

I provide two precise measurements of informational value: entity density ratio and hyperlink density ratio. The two density ratios are calculated by the count of named entities and the count of hyperlinks, respectively, divided by the total word count. Here, I used scatterplots with transparency to visualize these two variables. The x-axis represents the word count of the whole article, the y-axis represents the count of named entities or the count of hyperlinks, and the transparency indicates the density ratio. On one hand, among articles of the same length, some points positioned higher indicate that these articles have more named entities or hyperlinks; therefore, the color of these points is darker, representing a higher density ratio. On the other hand, articles with similar length and number of entities (or hyperlinks) should have similar transparency levels; however, the concentration of the articles is shown in the plots as overlapped points, making the area appear darker. Some individual points appear darker compared to nearby points due to this type of overlap. I included transparency as an additional dimension in these scatterplots to facilitate comparison across outlets. Below each scatterplot, I summarize the distribution of the density ratio for each media outlet using a boxplot.

In terms of named entity distributions, left-leaning outlets generally have longer articles than right-leaning outlets, but their named entity ratios tend to be lower. Figures 9 to 16 respectively show the named entity counts, entity density ratios, and word counts for each of the eight outlets. Focusing on the article length represented by word count, the four right-leaning outlets mostly have articles under 1000 words, whereas the left-leaning outlets have many articles over 1000 words. As the count of named entities is strongly correlated with article word count, points for the four right-leaning outlets are more concentrated in the lower-left corner. Comparing the boxplots of entity density ratios under each scatterplot, three right-leaning outlets, @nypost, @FoxNews, and particularly @BreitbartNews, have higher median entity density ratios.

Figure 9. Named entity count, entity density ratio, and word count for @nypost

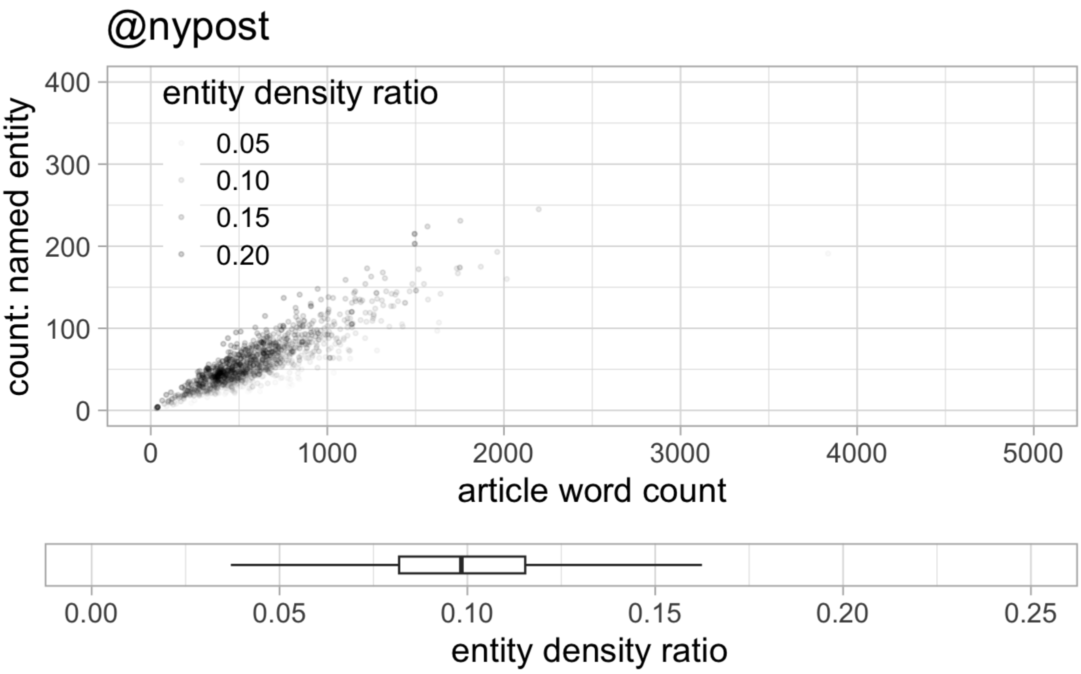


Figure 10. Named entity count, entity density ratio, and word count for @FoxNews.

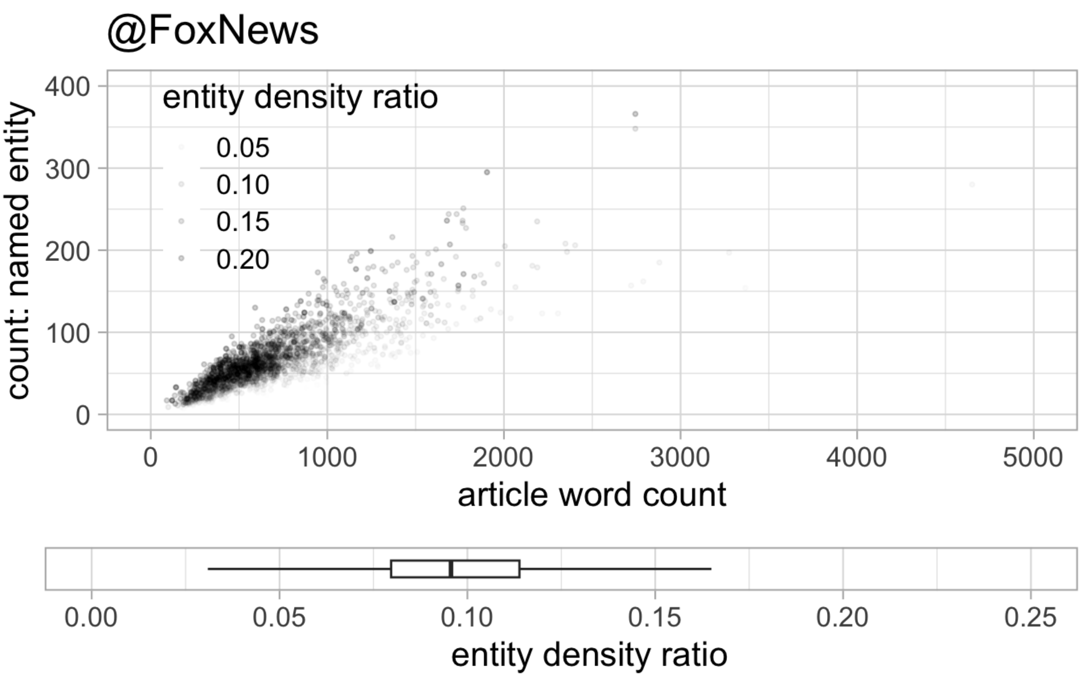


Figure 11. Named entity count, entity density ratio, and word count for @theblaze

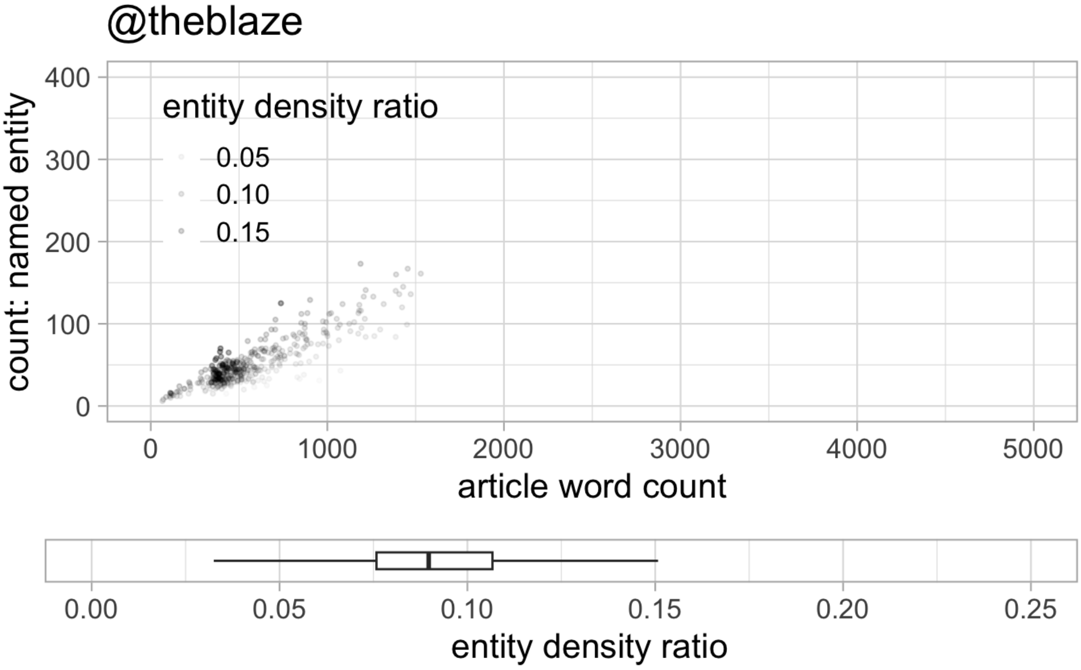


Figure 12. Named entity count, entity density ratio, and word count for @BreitbartNews

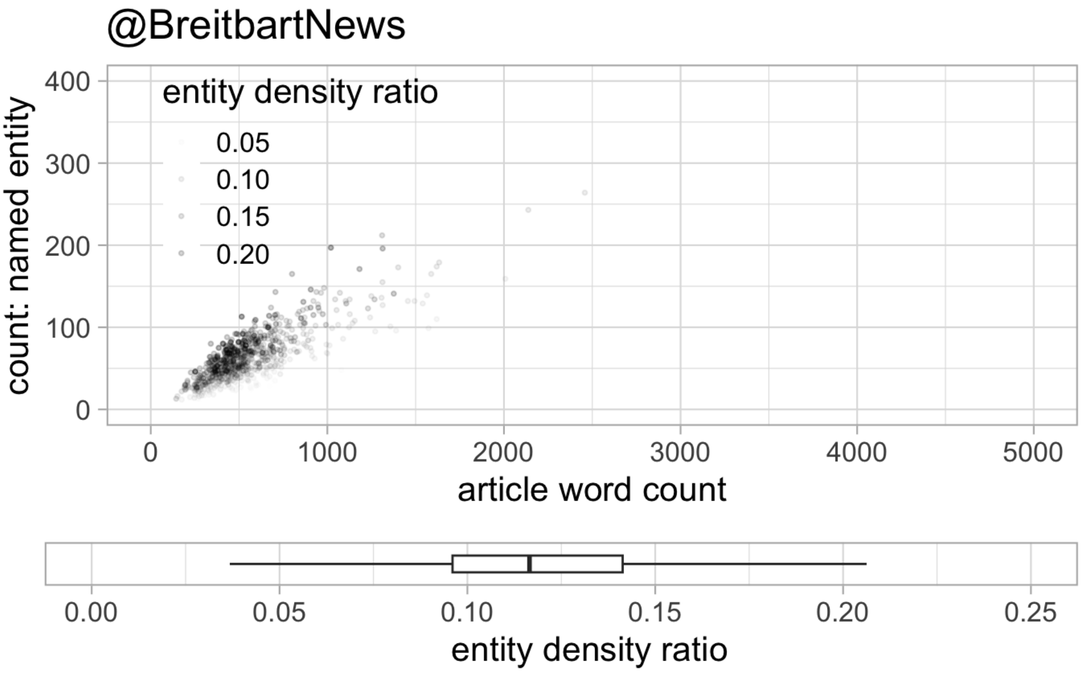


Figure 13. Named entity count, entity density ratio, and word count for @PhillyInquirer

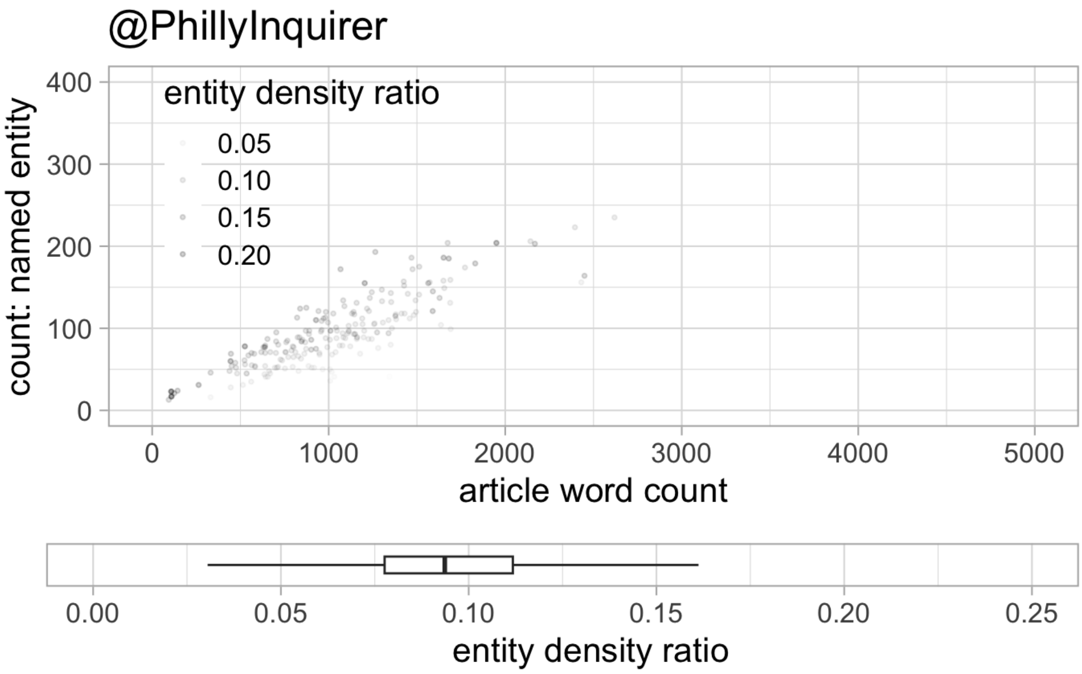


Figure 14. Named entity count, entity density ratio, and word count for @washingtonpost

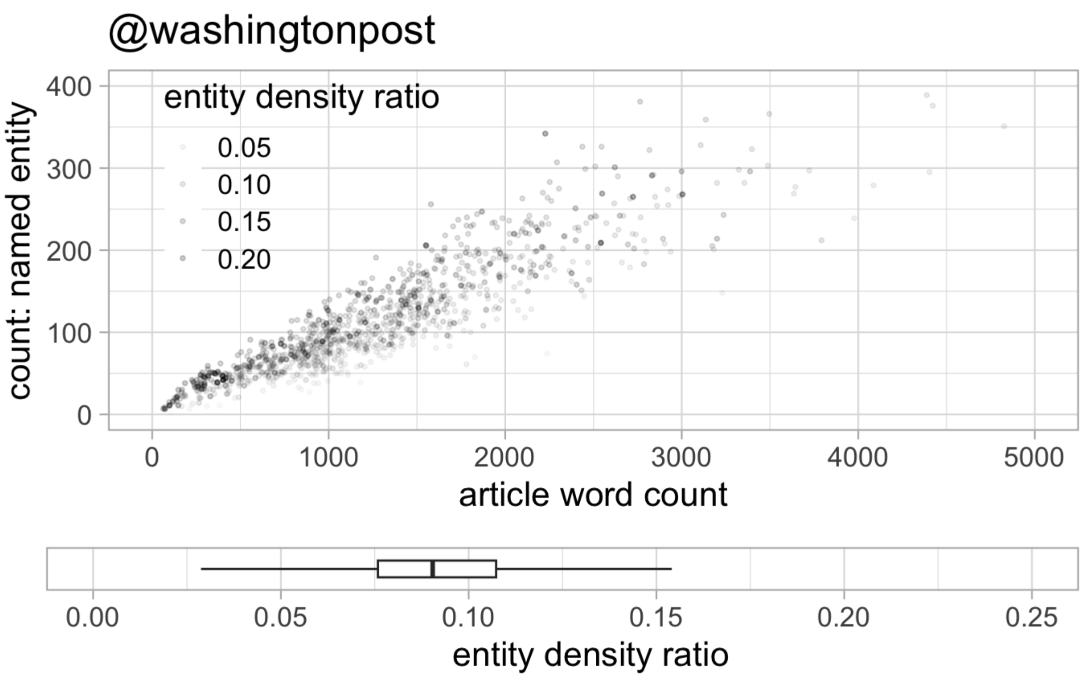


Figure 15. Named entity count, entity density ratio, and word count for @nytimes

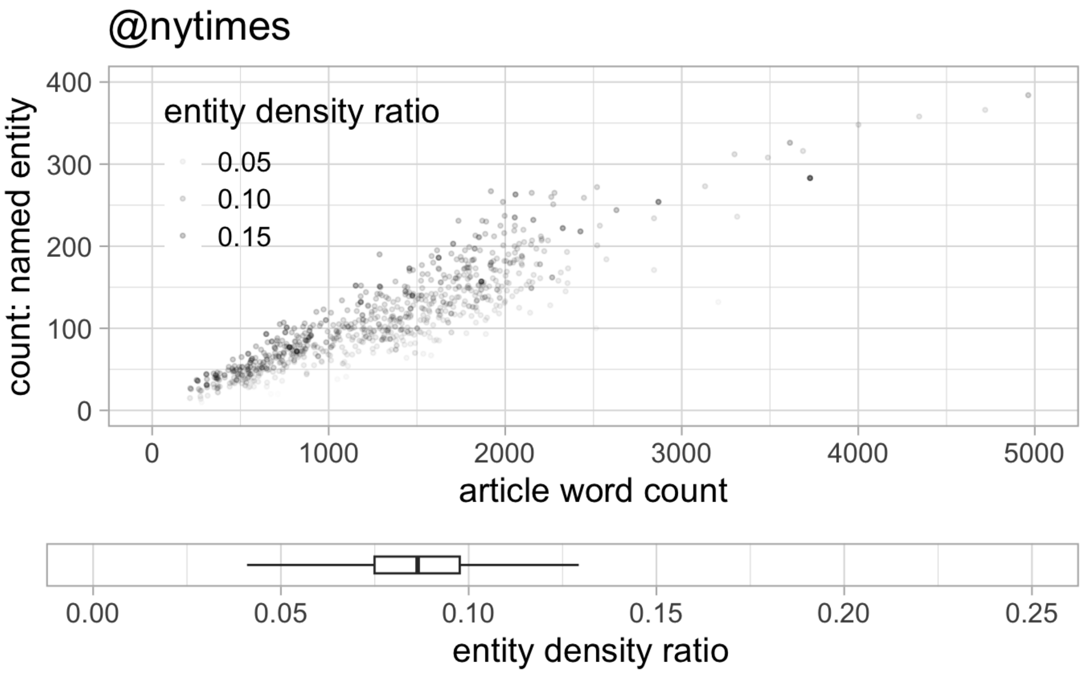
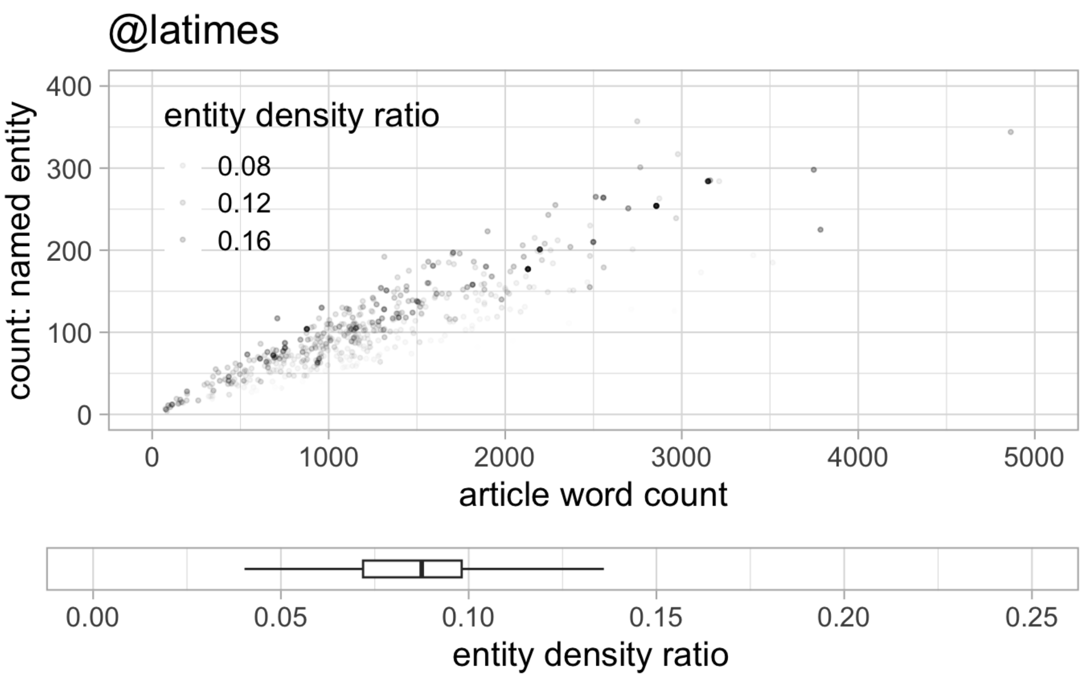


Figure 16. Named entity count, entity density ratio, and word count for @latimes



Similarly, in terms of hyperlink distributions, the left-leaning outlets generally have longer articles than the right-leaning outlets, but with a lower density ratio. Figures 17 to 24 respectively show the hyperlink counts, hyperlink density ratios, and word counts for each of the eight outlets.

Figure 17. Hyperlink count, hyperlink density ratio, and word count for @nypost

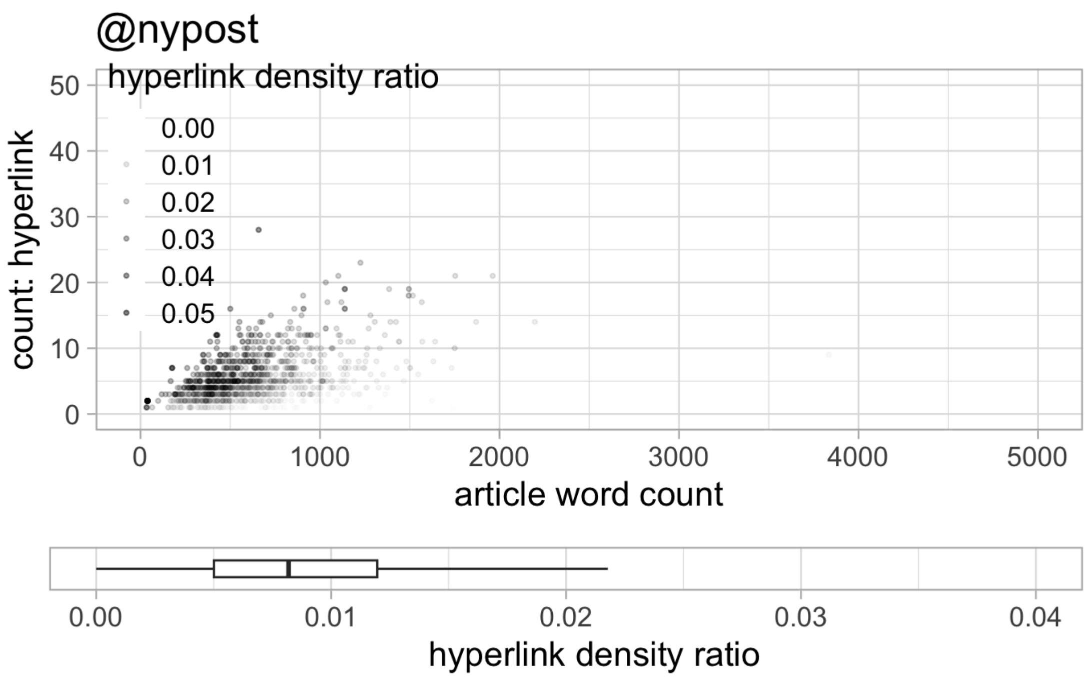


Figure 18. Hyperlink count, hyperlink density ratio, and word count for @FoxNews

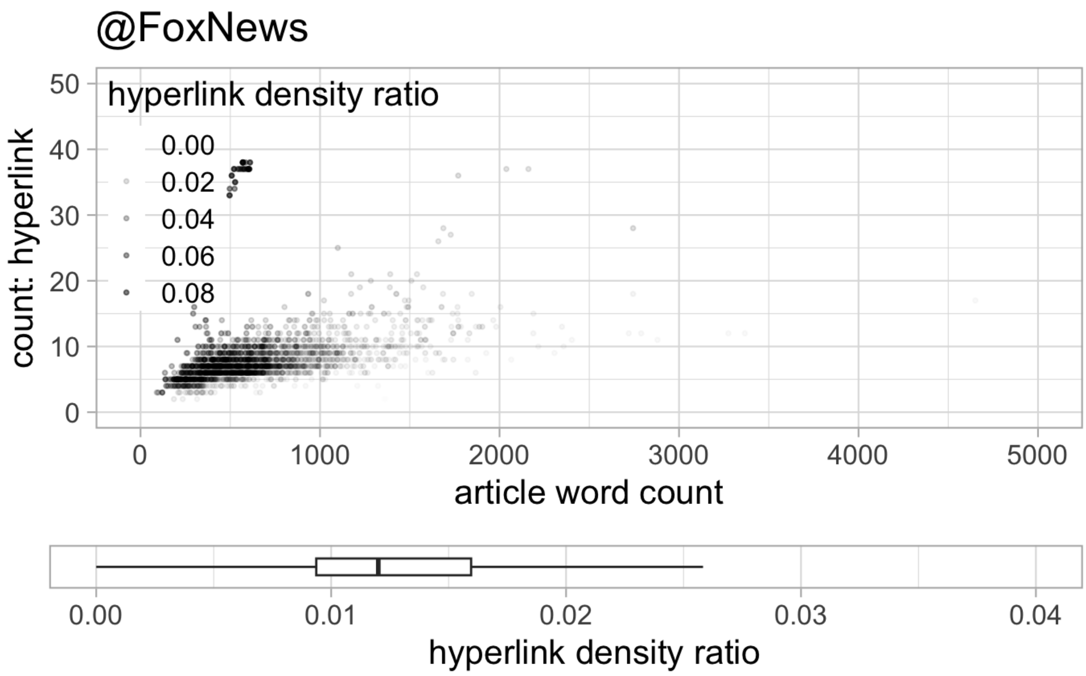


Figure 19. Hyperlink count, hyperlink density ratio, and word count for @theblaze

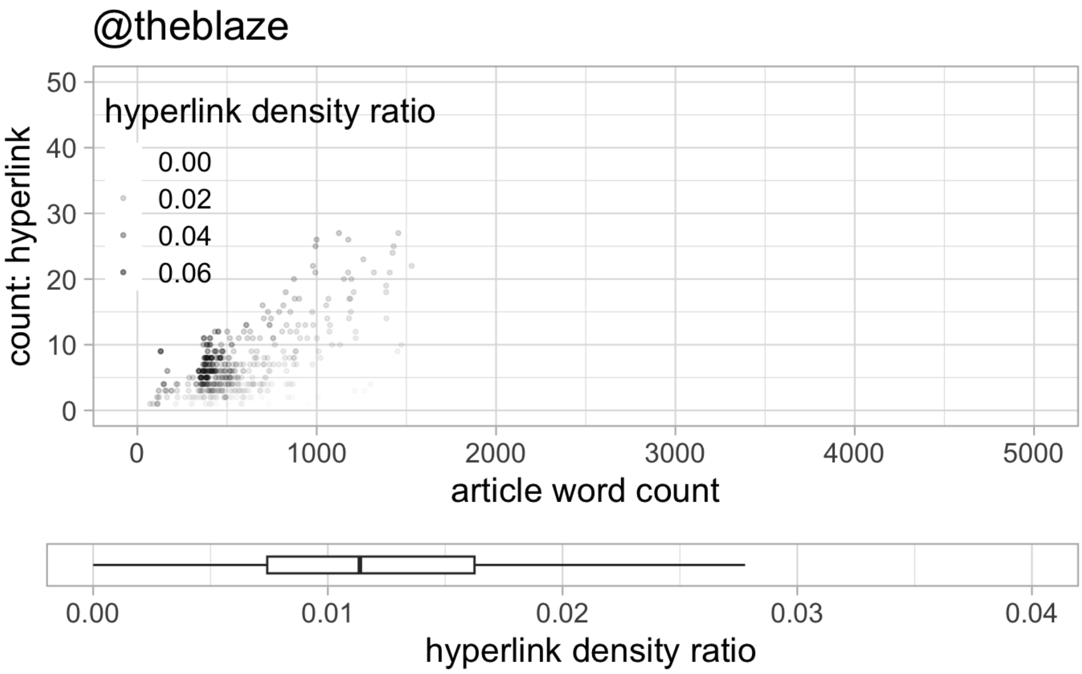


Figure 20. Hyperlink count, hyperlink density ratio, and word count for @BreitbartNews

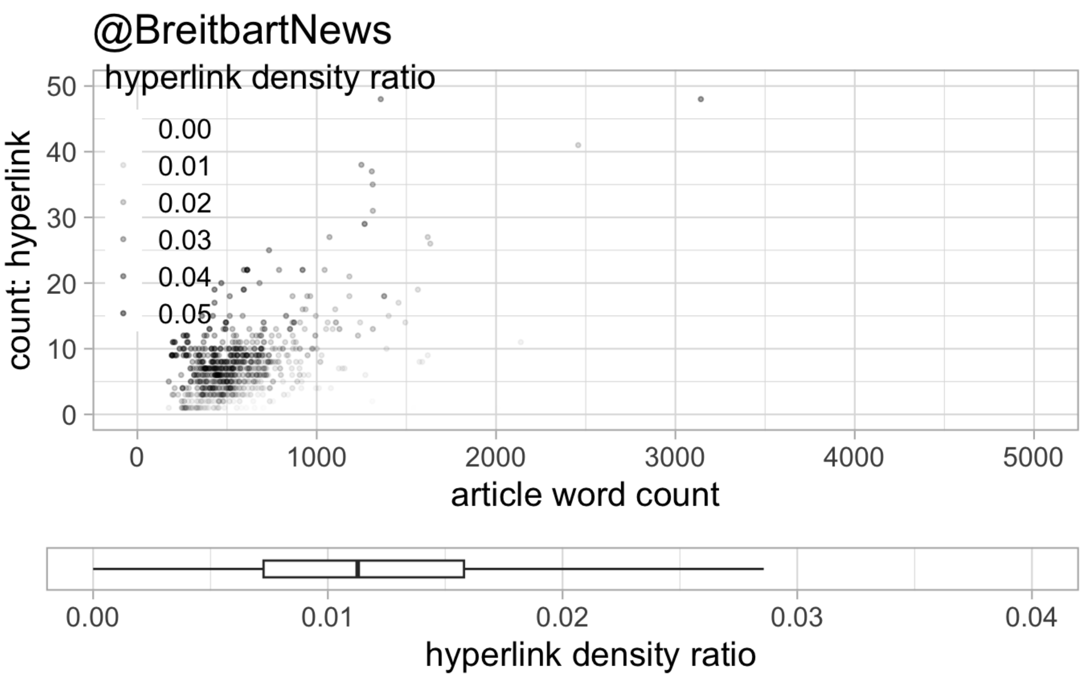


Figure 21. Hyperlink count, hyperlink density ratio, and word count for @PhillyInquirer

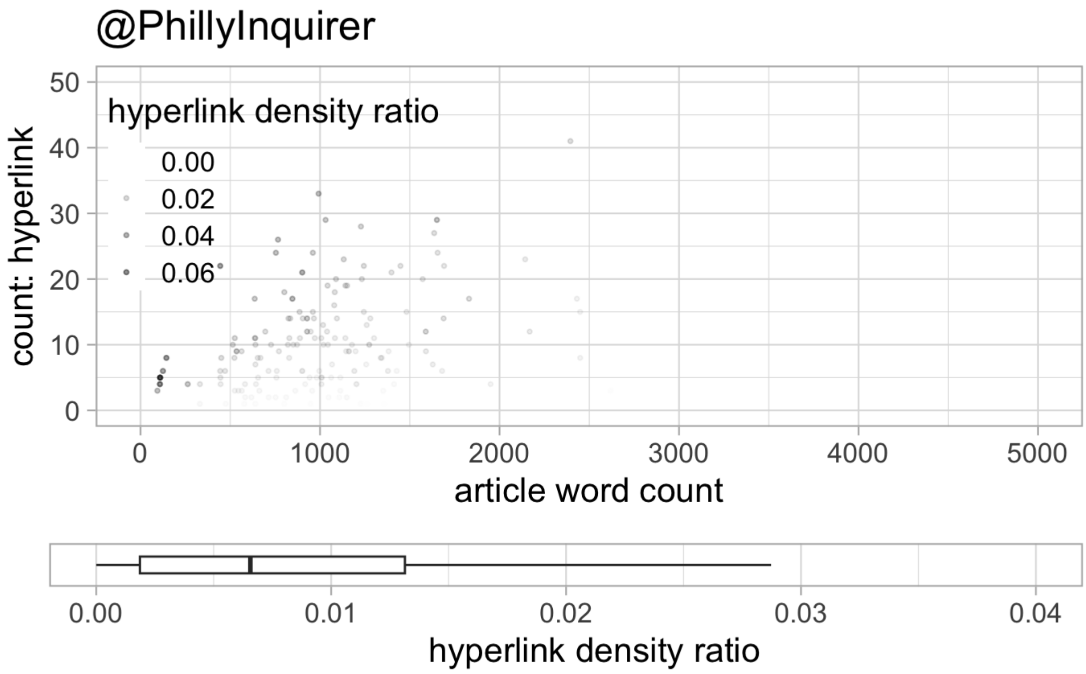


Figure 22. Hyperlink count, hyperlink density ratio, and word count for @washingtonpost

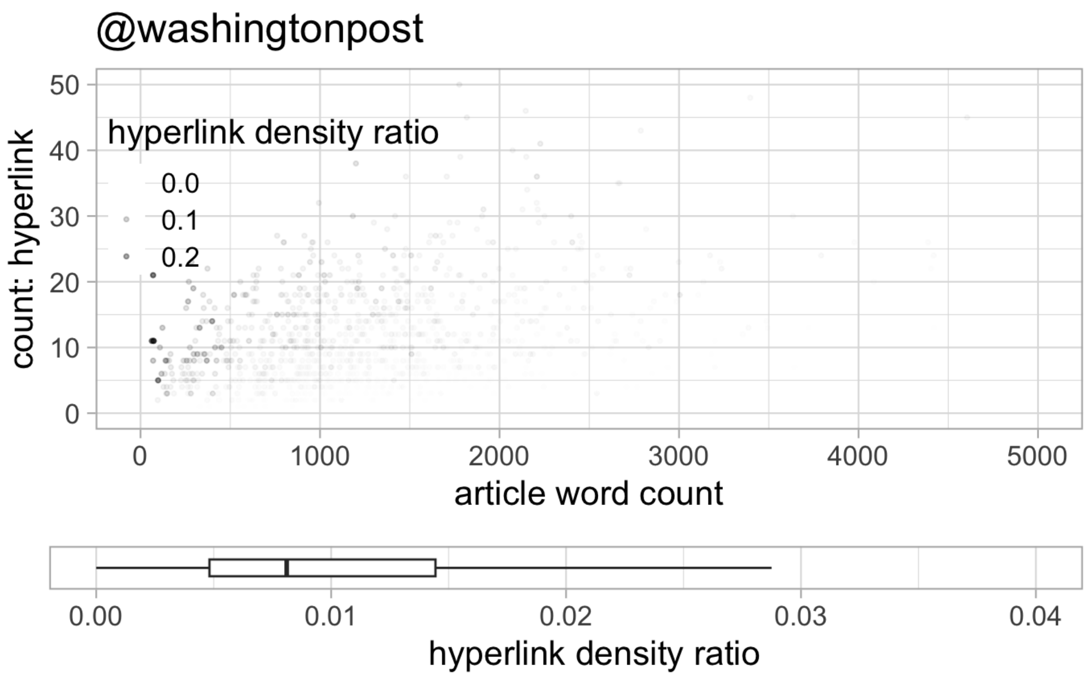


Figure 23. Hyperlink count, hyperlink density ratio, and word count for @nytimes

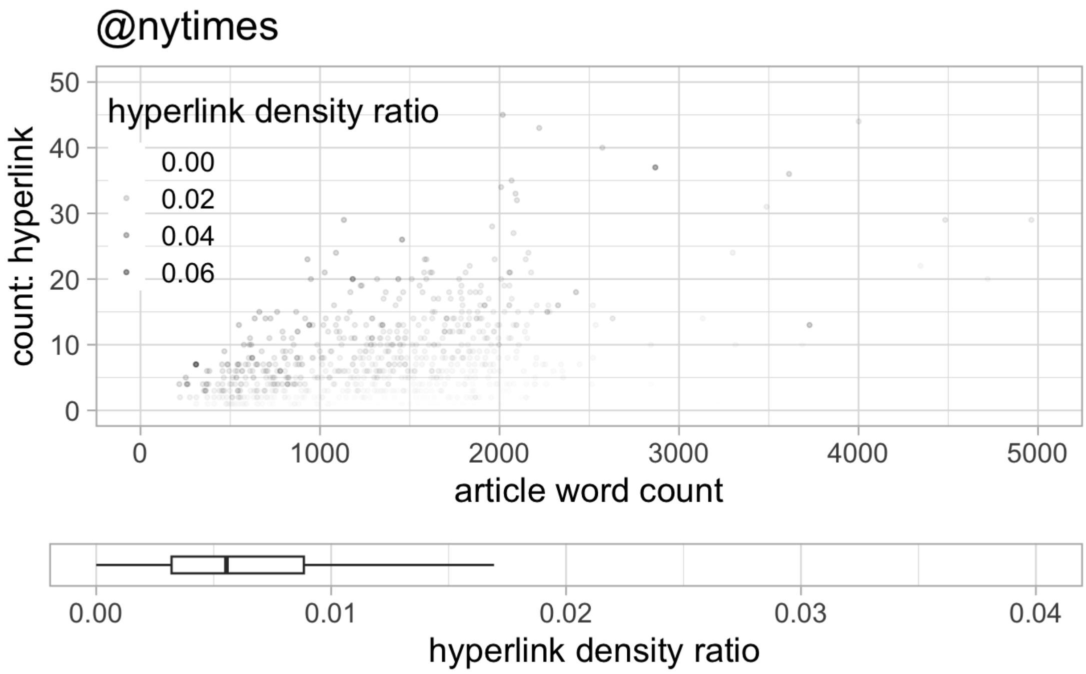
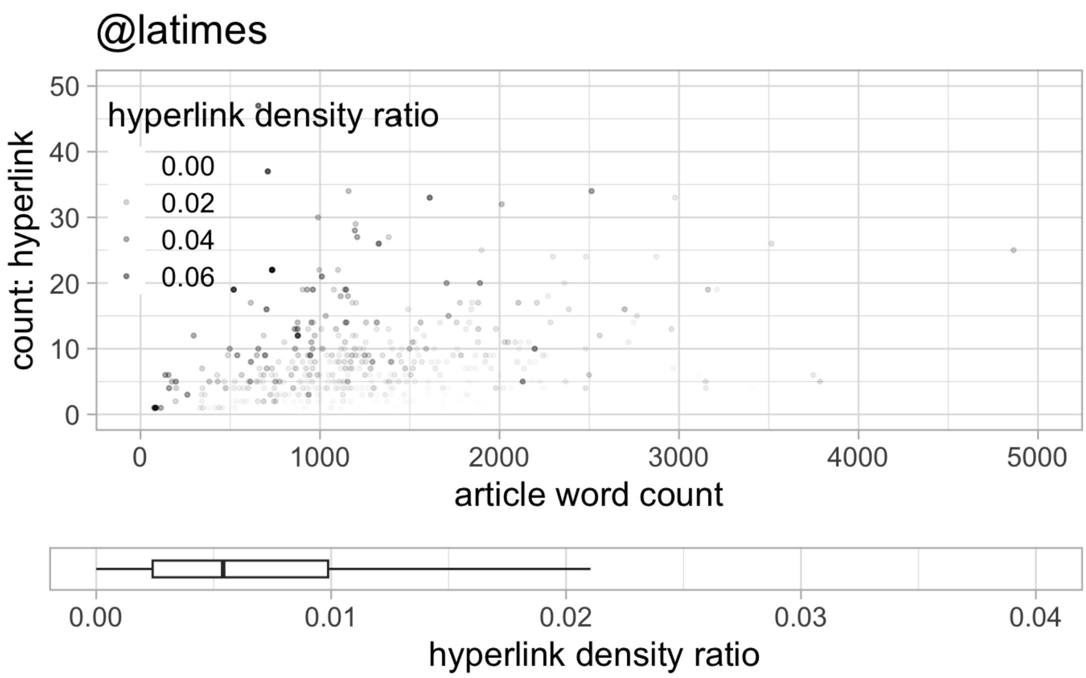


Figure 24. Hyperlink count, hyperlink density ratio, and word count for @latimes



2.5.1.3 Summary for RQ1

In summary, during the 2022 mid-term election, the eight U.S. media outlets showed clear differences in how they presented emotions and information. Regarding emotional presentation, conservative outlets like @nypost, @FoxNews, and @theblaze often showed stronger emotions, especially anger and fear, in both tweets and articles. In tweets' visual presentation, anger, joy, and sadness were the most common emotions across all eight outlets, with conservative outlets displaying more anger than sadness, while liberal outlets showed the opposite pattern. Regarding informational presentation, conservative outlets tended to publish shorter articles with higher densities of named entities and hyperlinks, while liberal outlets provided longer content with a lower density ratio, suggesting their divergence in delivering information.

2.5.2 RQ2: Emotional support vs. Informational value, what kind of news are more preferred by the readers?

As introduced previously, I use the bot-calibrated number of *retweets* to measure reader preference for each news tweet. To capture the emotional characteristics of the news, I use 6-class emotions and one neutral probability from news tweets, images, and full articles. I use entity density, hyperlink density, and article length to measure the news article's informational value. My goal is to find out what kind of news content, across these emotional and informational dimensions, are preferred by readers. Tables 2 and 3 report summary statistics of all the variables across the eight outlets.

Table 2. Summary statistics of four right-leaning outlets

Summary statistics: Right-leaning outlets

	BreitbartNews		FoxNews		nypost		theblaze	
	mean	sd	mean	sd	mean	sd	mean	sd
"retweets"	89.089	69.285	96.378	143.139	68.634	118.403	39.084	30.614
"retweets_bot calibrated"	67.199	52.384	72.287	106.576	49.750	86.046	28.274	22.217
"article: word count"	569.062	318.588	685.544	431.291	604.160	311.447	545.515	258.888
"article: named entity count"	66.835	46.441	65.666	39.847	59.435	32.662	49.393	27.034
"article: hyperlink count"	7.051	6.518	8.013	4.632	5.074	3.568	6.450	4.705
"article: entity density ratio"	0.119	0.033	0.098	0.027	0.100	0.026	0.092	0.025
"article: hyperlink density ratio"	0.013	0.008	0.014	0.008	0.009	0.007	0.012	0.007
"article: sentiment neutrality"	0.617	0.396	0.520	0.394	0.554	0.390	0.414	0.400
"tweet: neutral"	0.451	0.348	0.341	0.314	0.335	0.299	0.287	0.289
"tweet: anger"	0.146	0.220	0.212	0.273	0.187	0.262	0.273	0.289
"tweet: disgust"	0.124	0.199	0.074	0.135	0.081	0.154	0.106	0.154
"tweet: sadness"	0.067	0.145	0.089	0.168	0.128	0.221	0.080	0.151
"tweet: fear"	0.146	0.261	0.198	0.289	0.163	0.262	0.181	0.269
"tweet: surprise"	0.030	0.066	0.051	0.107	0.051	0.097	0.052	0.130
"tweet: joy"	0.037	0.099	0.036	0.113	0.055	0.145	0.020	0.073
"face: neutral"	0.427	0.344	0.419	0.336	0.262	0.276	0.406	0.334
"face: anger"	0.139	0.264	0.122	0.233	0.157	0.225	0.151	0.271
"face: disgust"	0.003	0.031	0.002	0.036	0.002	0.021	0.001	0.007
"face: sadness"	0.115	0.212	0.136	0.229	0.198	0.244	0.084	0.167
"face: fear"	0.058	0.152	0.069	0.164	0.110	0.179	0.079	0.171
"face: surprise"	0.004	0.023	0.015	0.086	0.027	0.105	0.027	0.135
"face: joy"	0.168	0.319	0.162	0.307	0.234	0.322	0.167	0.313
"article: neutral"	0.479	0.311	0.358	0.262	0.279	0.252	0.302	0.268
"article: anger"	0.145	0.185	0.190	0.183	0.194	0.213	0.236	0.240
"article: disgust"	0.134	0.175	0.162	0.162	0.145	0.166	0.180	0.189
"article: sadness"	0.051	0.113	0.063	0.131	0.100	0.180	0.053	0.120
"article: fear"	0.142	0.209	0.176	0.212	0.208	0.245	0.187	0.240
"article: surprise"	0.030	0.079	0.032	0.079	0.032	0.089	0.023	0.067
"article: joy"	0.020	0.068	0.018	0.064	0.043	0.131	0.018	0.059

Note: a note at the bottom of the table.

Table 3. Summary statistics of four left-leaning outlets

Summary statistics: Left-leaning outlets

	latimes		nytimes		PhillyInquirer		washingtonpost	
	mean	sd	mean	sd	mean	sd	mean	sd
"retweets"	13.211	28.206	174.385	324.777	5.630	11.849	87.880	137.026
"retweets_bot calibrated"	8.391	19.373	125.787	234.193	3.264	8.378	63.122	93.684
"article: word count"	1653.806	1287.002	2158.205	1956.042	1083.928	525.624	1372.653	953.771
"article: named entity count"	147.751	140.885	187.890	177.377	99.809	54.620	124.040	94.022
"article: hyperlink count"	11.556	15.885	15.925	25.555	9.383	12.448	12.015	8.976
"article: entity density ratio"	0.087	0.022	0.087	0.019	0.096	0.028	0.093	0.025
"article: hyperlink density ratio"	0.007	0.008	0.007	0.006	0.010	0.011	0.013	0.017
"article: sentiment neutrality"	0.664	0.327	0.709	0.276	0.668	0.337	0.671	0.306
"tweet: neutral"	0.475	0.348	0.411	0.331	0.472	0.342	0.426	0.330
"tweet: anger"	0.146	0.231	0.136	0.216	0.123	0.203	0.142	0.218
"tweet: disgust"	0.073	0.146	0.098	0.156	0.084	0.159	0.101	0.168
"tweet: sadness"	0.071	0.152	0.095	0.192	0.071	0.165	0.073	0.153
"tweet: fear"	0.155	0.264	0.156	0.258	0.166	0.257	0.173	0.273
"tweet: surprise"	0.039	0.079	0.045	0.112	0.032	0.052	0.040	0.095
"tweet: joy"	0.041	0.112	0.059	0.146	0.052	0.132	0.046	0.127
"face: neutral"	0.401	0.331	0.427	0.325	0.567	0.296	0.413	0.337
"face: anger"	0.105	0.193	0.099	0.201	0.073	0.188	0.127	0.238
"face: disgust"	0.001	0.014	0.002	0.020	0.003	0.029	0.001	0.006
"face: sadness"	0.161	0.249	0.158	0.244	0.074	0.179	0.168	0.256
"face: fear"	0.076	0.154	0.081	0.172	0.037	0.128	0.082	0.177
"face: surprise"	0.016	0.073	0.008	0.042	0.001	0.005	0.012	0.074
"face: joy"	0.166	0.288	0.132	0.266	0.084	0.224	0.118	0.256
"article: neutral"	0.445	0.247	0.415	0.228	0.539	0.270	0.415	0.243
"article: anger"	0.150	0.143	0.149	0.141	0.124	0.143	0.159	0.150
"article: disgust"	0.142	0.120	0.148	0.128	0.135	0.144	0.120	0.119
"article: sadness"	0.053	0.084	0.074	0.125	0.057	0.109	0.069	0.128
"article: fear"	0.173	0.177	0.169	0.176	0.094	0.134	0.180	0.203
"article: surprise"	0.024	0.051	0.026	0.047	0.019	0.024	0.035	0.069
"article: joy"	0.012	0.036	0.019	0.047	0.030	0.095	0.022	0.066

Note: a note at the bottom of the table.

2.5.2.1 Descriptive visualizations for RQ2

Before running the regression models, I first conduct descriptive visualizations to explore the relationships between emotion/information variables and reader preferences, providing initial insights for RQ2. As there are too many variables: 3*7 emotions and three informational variables, I adopted the Latent Profile Analysis (LPA) separately for each outlet to reduce the dimension of variables to seven emotion binary variables (overall more emotional, overall more anger, and the other five emotions) and two informational binary variables (overall more entities and overall more hyperlinks) (Rosenberg et al., 2019). For example, to get the "overall more anger" variable for @nytimes, I let LPA automatically classify the observations into two groups, one with generally higher values across all three anger variables (tweet anger, image anger, and article anger) and one with generally lower values. Similarly, the "overall more entities" class is based on two variables: the named entity count in articles and the entity density ratio of articles. Compared with other dimension-reduction methods, LPA can interpretably identify distinct groups and does not need a manual threshold like PCA (Pastor et al., 2007).

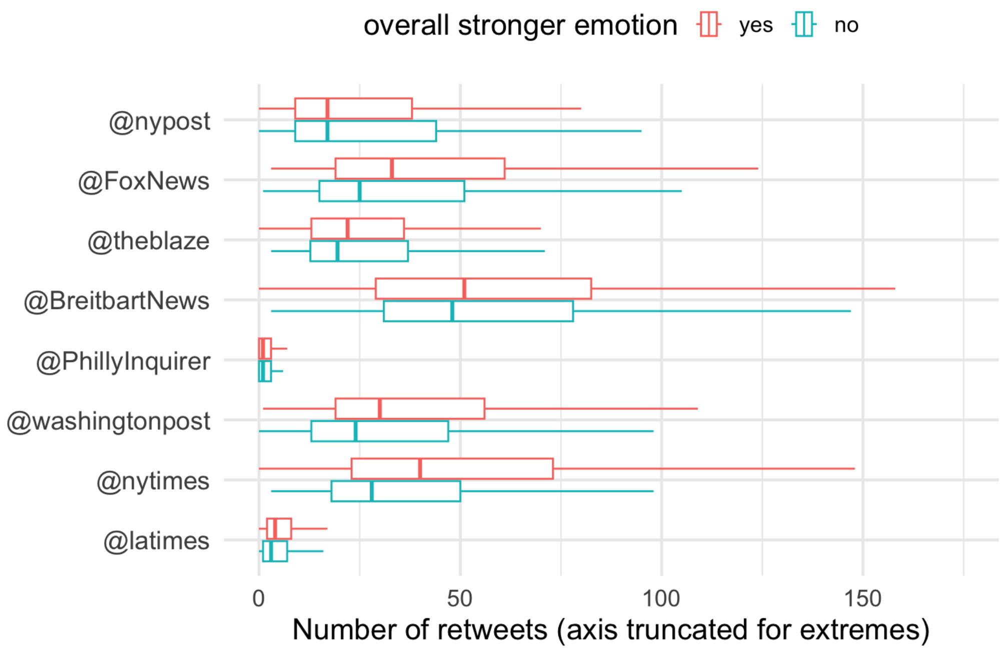
In the following analyses, I retained all observations whose images did not contain faces (around 29%). I have manually set the neutral probability at a relatively high level of 0.75, a midpoint between 0.5 and 1. And other emotion classes remained 0. This adjustment accounts for the fact that emotions can be conveyed in images through context, composition, and artistic expression, in the absence of faces (Matravers, 1998). Figure 25 is an example from @FoxNews, depicting lines of migrants crossing into Eagle Pass on Sept. 16, 2022, in an artistic style. However, the emotional content in most images without faces is considerably weaker than in those with faces. Therefore, the 0.75 I set is higher than a neutral position, 0.5, but is not as high as 1, a totally neutral position.

Figure. 25 An example image without faces that is likely to convey emotional cues

Note: "Lines of migrants cross into Eagle Pass on Sept. 16, 2022." The image is from: https://twitter.com/FoxNews/status/1581057316816027651 The tweet is "Rep. Biggs' bill would allow states to pass immigration enforcement laws, in response to 'historic invasion'" by @FoxNews.

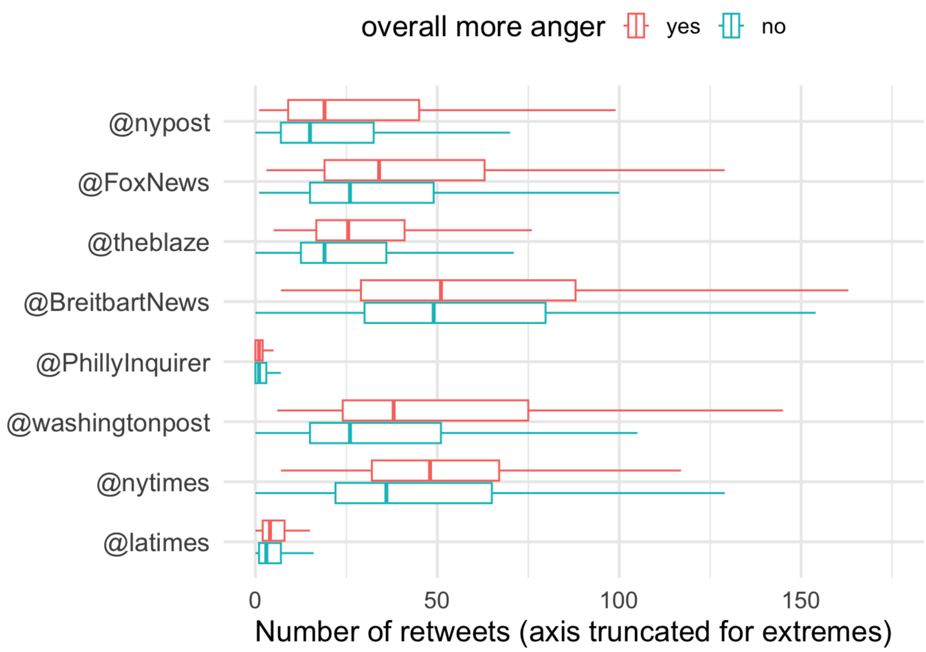
After using LPA to group news articles by their emotional and informational characteristics for each outlet, I visualized the number of bot-calibrated retweets for these groups using boxplots for RQ2. Figures 26 to 34 show the visualization results. Overall, stronger emotional content generally receives more retweets, but the difference is not substantial. Specifically, anger and disgust tend to slightly increase retweets more consistently, compared with other types of emotions, although these differences are also minor. Results for other emotions and informational variables are mixed. Specifically, news from @nytimes that is classified as surprising tends to receive more retweets. News from @nypost and @theblaze that contain more named entities and hyperlinks tend to receive more retweets compared to those with fewer, although the differences are again not large.

Figure 26. Boxplot comparing bot-calibrated *retweets* between two classes: overall strong emotion or not



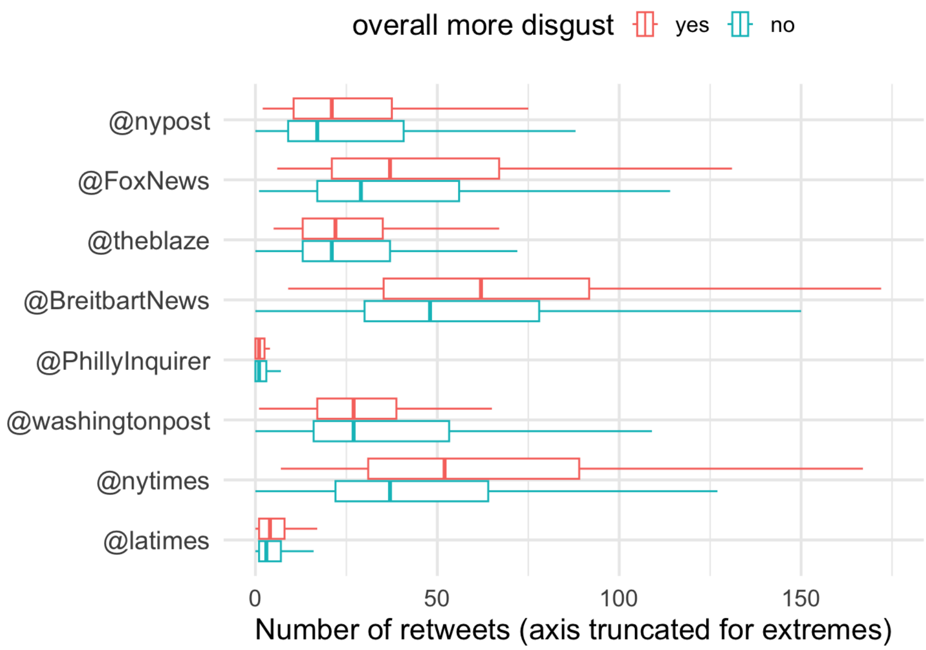
Note: The x axis is truncated for extremes of top outlets.

Figure 27. Boxplot comparing bot-calibrated *retweets* between two classes: overall more anger or not



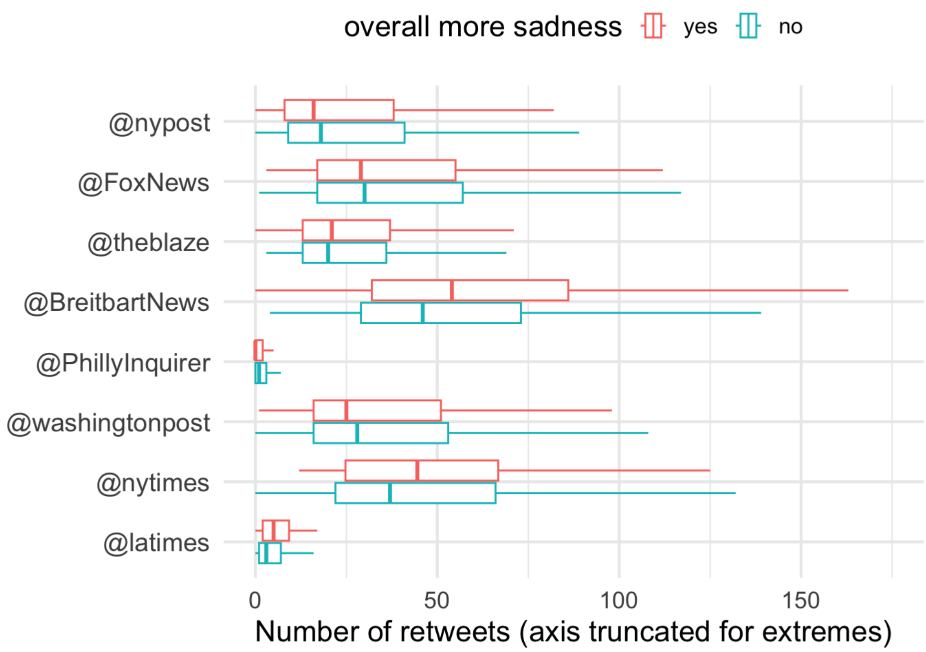
Note: The x axis is truncated for extremes of top outlets.

Figure 28. Boxplot comparing bot-calibrated *retweets* between two classes: overall more disgust or not



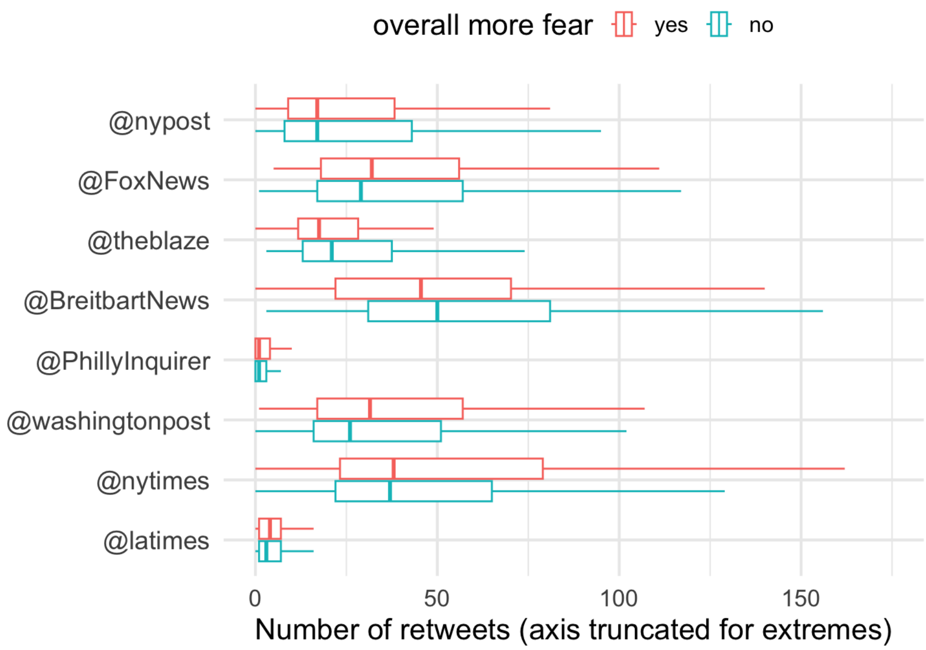
Note: The x axis is truncated for extremes of top outlets.

Figure 29. Boxplot comparing bot-calibrated *retweets* between two classes: overall more sadness or not



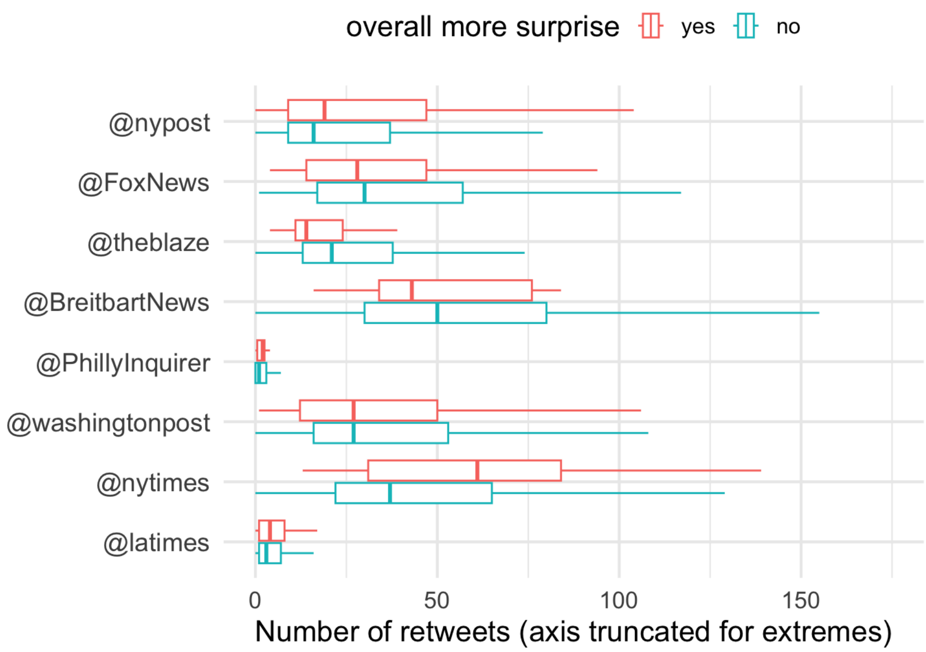
Note: The x axis is truncated for extremes of top outlets.

Figure 30. Boxplot comparing bot-calibrated *retweets* between two classes: overall more fear or not



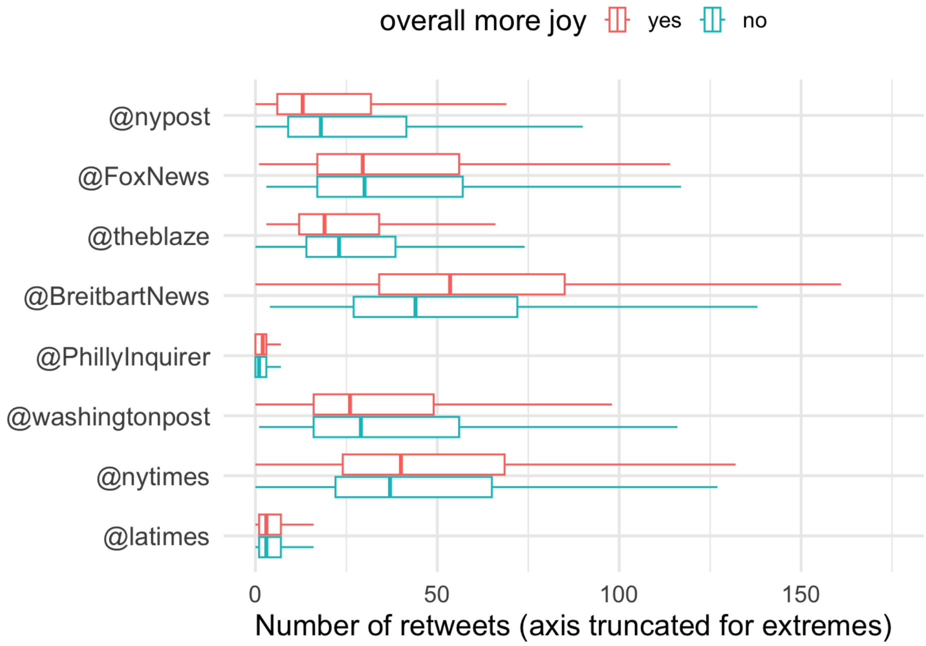
Note: The x axis is truncated for extremes of top outlets.

Figure 31. Boxplot comparing bot-calibrated *retweets* between two classes: overall more surprise or not



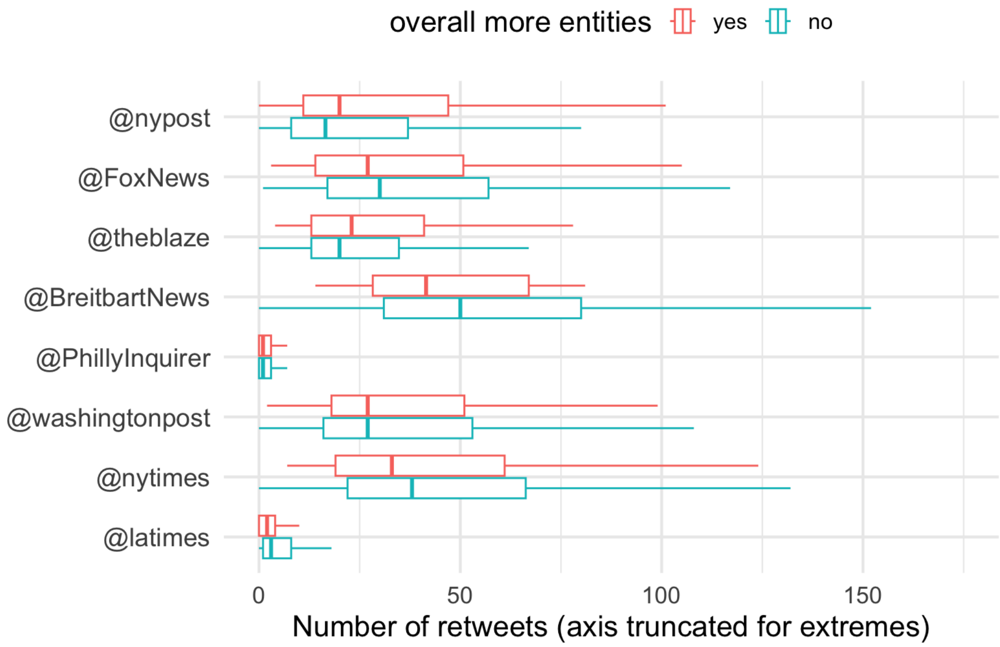
Note: The x axis is truncated for extremes of top outlets.

Figure 32. Boxplot comparing bot-calibrated *retweets* between two classes: overall more joy or not



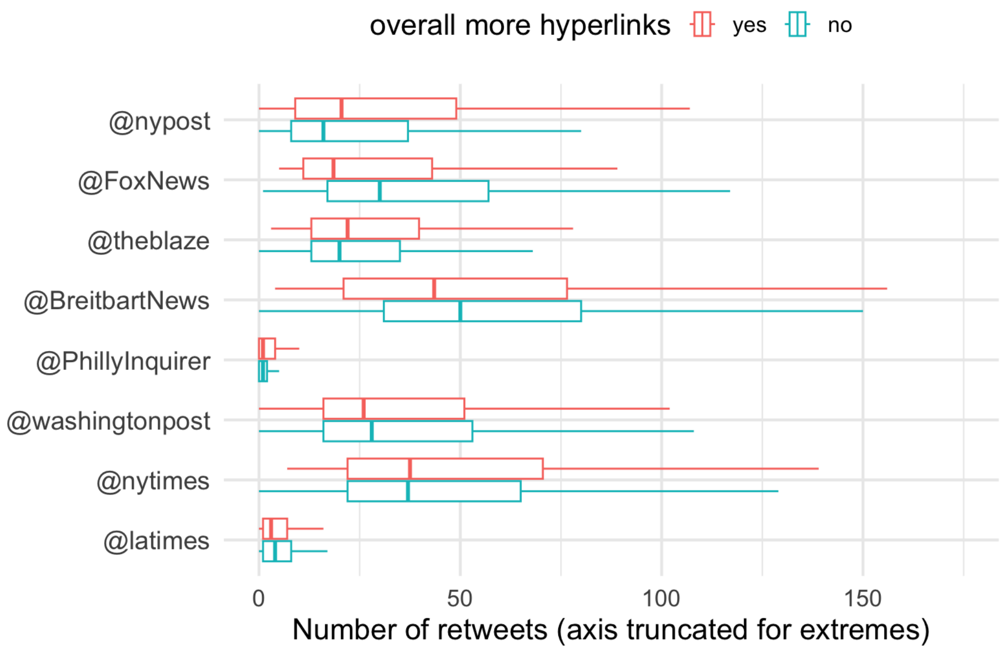
Note: The x axis is truncated for extremes of top outlets.

Figure 33. Boxplot comparing bot-calibrated *retweets* between two classes: overall more entities or not



Note: The x axis is truncated for extremes of top outlets.

Figure 34. Boxplot comparing bot-calibrated *retweets* between two classes: overall more hyperlinks or not



Note: The x axis is truncated for extremes of top outlets.

2.5.2.2 Regression analysis

The count of retweets was tested to be overdispersed, with variance greater than the mean, so I applied negative binomial regression models to estimate the bot-calibrated retweet counts for each news outlet (Hilbe, 2011). In Equation (1), I used the raw emotion probability variables (3*6 emotions and one sentiment neutrality) and three standardized informational variables (two density ratios and word count) as independent variables. I removed three neutrality classes because of multi-collinearity, and I replaced them with one sentiment neutrality from article text. In Equation (2), I used the LPA clustered binary variables, seven emotional ones and two informational ones, as independent variables to get some tidy regression results.

$$\log(retweet) \sim \begin{matrix} article\ emotions \\ \text{and} \\ tweet\ emotions \\ \text{and} \\ facial\ emotions \end{matrix} + \begin{matrix} std\ entity\ density\ ratio \\ \text{and} \\ std\ hyperlink\ density\ ratio \\ \text{and} \\ \text{std}\ word\ count \end{matrix} + \text{controls}$$

Equation (1)

$$\log(retweet) \sim Overall\text{: }7\ emotions + \begin{matrix} Overall\text{: }more\ entities \\ \text{and} \\ Overall\text{: }more\ hyperlinks \\ \text{and} \\ \text{std}\ word\ count \end{matrix} + \text{controls}$$

Equation (2)

The news topics are clustered respectively for left- and right-leaning outlets, and the topics are controlled as binary variables. I use BERTopic, instead of LDA, to conduct the clustering (Grootendorst, 2022). It employs word-embedding from current cutting-edge Transformer Models, as well as dimensionality reduction (UMAP) and clustering algorithm (HDBSCAN), it performs better in topic modeling (Grootendorst, 2022). Days-to-election is also controlled because, as the final election data approaches, people pay more attention to election news, which in turn leads to higher retweet volumes.

Observations with the highest 1% retweets are removed in regression, because the figure size differs too much, so that the estimation of negative binomial regression models for small outlets cannot converge. Another reason to remove the extreme 1% observations is that even small outlets on Twitter have several popular tweets being retweeted thousands of times more than the usual daily volume. Extreme observations may distort the regression results, even after log transformation in the negative binomial model. To address this issue, standard errors are obtained via 1,000 bootstrap replications

2.5.2.3 Regression results

Table 4 and table 5 report the regression results of eight outlets respectively for Equation (1) and Equation (2). Overall, the findings do not reveal a clear or consistent pattern across all outlets; instead, the results vary case by case, especially when compared to the earlier descriptive visualizations. I analyze both tables together to try to identify any relatively consistent patterns in reader preferences across outlets.

Table 4. Regression results for Equation (1).

	@nypost	@FoxNews	@theblaze	@BreitbartNews	@PhillyInquirer	@washingtonpost	@nytimes	@latimes
Intercept	4.070***	4.026***	3.198***	3.918***	1.387+	3.815***	4.566***	1.581***
	(0.264)	(0.141)	(0.204)	(0.110)	(0.737)	(0.241)	(0.325)	(0.412)
article: std word count	0.059	−0.040	0.107**	0.070*	0.104	0.017	−0.004	−0.195***
	(0.043)	(0.039)	(0.036)	(0.027)	(0.160)	(0.048)	(0.051)	(0.052)
article: std entity density ratio	0.027	0.031	0.006	0.018	0.073	0.121**	0.084	−0.032
	(0.052)	(0.029)	(0.039)	(0.031)	(0.157)	(0.043)	(0.054)	(0.061)
article: std hyperlink density ratio	0.100*	−0.097***	−0.015	−0.025	0.163	−0.003	0.020	−0.034
	(0.048)	(0.028)	(0.038)	(0.028)	(0.137)	(0.051)	(0.061)	(0.057)
article: sentiment neutrality	−0.491***	−0.384***	−0.156	−0.032	−0.652	−0.171	−1.025***	−0.522+
	(0.148)	(0.092)	(0.122)	(0.090)	(0.520)	(0.171)	(0.245)	(0.297)
days to election	0.001	0.005**	0.002	0.003*	−0.012	0.000	0.002	0.011***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.009)	(0.002)	(0.003)	(0.003)
tweet: anger	−0.170	0.112	0.157	−0.035	−0.411	0.658**	0.480+	0.527*
	(0.204)	(0.123)	(0.170)	(0.147)	(0.686)	(0.205)	(0.275)	(0.263)
tweet: disgust	−0.286	0.140	0.448	0.099	−0.767	0.487+	1.346***	1.573***
	(0.319)	(0.197)	(0.289)	(0.141)	(0.861)	(0.259)	(0.347)	(0.442)
tweet: sadness	−0.083	0.241	0.523+	−0.126	−1.149	0.433	0.452	1.277**
	(0.231)	(0.205)	(0.281)	(0.211)	(1.065)	(0.352)	(0.322)	(0.464)
tweet: fear	−0.243	0.116	−0.088	−0.242*	0.161	0.485**	0.135	0.387+
	(0.210)	(0.115)	(0.174)	(0.119)	(0.716)	(0.168)	(0.212)	(0.215)
tweet: surprise	0.222	0.391	−0.169	0.251	−1.867	−0.054	2.098***	1.055+
	(0.499)	(0.273)	(0.337)	(0.315)	(2.577)	(0.365)	(0.618)	(0.629)
tweet: joy	−1.037***	−0.056	−0.061	−0.371	1.319	0.577+	0.435	1.085*
	(0.311)	(0.293)	(0.490)	(0.283)	(1.276)	(0.322)	(0.389)	(0.543)
face: anger	−0.026	0.233+	0.035	0.057	−0.603	−0.001	−0.240	0.524*
	(0.205)	(0.128)	(0.117)	(0.088)	(0.828)	(0.165)	(0.205)	(0.258)
face: disgust	−1.594	−1.415*	−2.344	−1.415	−4.444	6.461	0.646	−3.288
	(1.958)	(0.590)	(5.054)	(2.017)	(821.044)	(6.109)	(1.798)	(3.375)
face: sadness	0.355	0.192+	0.104	0.108	0.424	−0.004	0.036	−0.480*
	(0.217)	(0.116)	(0.243)	(0.110)	(0.675)	(0.143)	(0.195)	(0.244)
face: fear	−0.168	0.488**	0.187	0.174	−0.189	−0.194	0.000	0.381
	(0.244)	(0.152)	(0.211)	(0.154)	(1.413)	(0.177)	(0.247)	(0.399)
face: surprise	−0.088	−0.308	−0.420*	0.780	20.173	−0.024	−0.271	0.387
	(0.343)	(0.280)	(0.207)	(1.479)	(25.294)	(0.321)	(0.823)	(1.044)
face: joy	0.401*	0.138	−0.013	0.290***	0.248	−0.203	0.177	0.058
	(0.183)	(0.093)	(0.118)	(0.076)	(0.705)	(0.134)	(0.194)	(0.176)
article: anger	0.009	0.362+	0.014	0.491**	−0.483	0.756*	0.765	−0.271
	(0.310)	(0.190)	(0.194)	(0.177)	(1.040)	(0.315)	(0.478)	(0.610)
article: disgust	0.084	0.088	−0.046	0.009	0.265	−0.390	−0.265	−0.534
	(0.348)	(0.211)	(0.250)	(0.190)	(1.175)	(0.381)	(0.582)	(0.764)
article: sadness	−0.307	0.064	−0.390	0.974***	3.347**	0.666+	1.093*	−1.199
	(0.335)	(0.240)	(0.340)	(0.269)	(1.298)	(0.343)	(0.534)	(0.747)
article: fear	0.033	−0.052	0.217	0.212	−1.182	−0.116	0.047	−0.353
	(0.245)	(0.146)	(0.189)	(0.145)	(1.197)	(0.241)	(0.303)	(0.385)
article: surprise	−0.287	−0.450	0.068	−0.060	−5.185	−0.725	−0.917	0.530
	(0.523)	(0.320)	(0.567)	(0.244)	(4.756)	(0.580)	(1.059)	(1.908)
article: joy	0.084	0.837	−0.553	0.235	−0.072	0.219	0.742	2.043
	(0.368)	(0.683)	(0.806)	(0.484)	(2.679)	(0.635)	(0.954)	(2.683)
Num.Obs.	1282	2719	511	963	235	1376	1025	1056
AIC	12308.1	28453.7	4315.9	9733.2	1010.5	14027.1	11705.7	6380.6
BIC	12550.5	28731.4	4515.0	9962.1	1131.5	14225.7	11898.0	6574.1
Log.Lik.	−6107.057	−14179.840	−2110.968	−4819.599	−470.229	−6975.554	−5813.828	−3151.299
RMSE	81.56	103.28	20.48	48.44	6.60	90.37	224.06	19.02
Std.Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Regression results for Equation (2) with LPA clustered variables

	@nypost	@FoxNews	@theblaze	@BreitbartNews	@PhillyInquirer	@washingtonpost	@nytimes	@latimes
Intercept	3.887***	4.115***	3.366***	4.022***	0.082	4.140***	4.138***	1.557***
	(0.188)	(0.091)	(0.120)	(0.089)	(0.448)	(0.148)	(0.168)	(0.204)
article: std word count	0.090+	0.060+	0.101*	0.088*	−0.039	−0.003	−0.215	−0.322**
	(0.052)	(0.036)	(0.042)	(0.035)	(0.148)	(0.046)	(0.137)	(0.100)
overall: more entity	−0.119	−0.209*	0.065	−0.054	0.207	0.039	0.606	0.434
	(0.121)	(0.082)	(0.078)	(0.208)	(0.280)	(0.118)	(0.387)	(0.416)
overall: more hyperlink	0.126	−0.268*	−0.037	−0.122	0.906***	0.038	0.006	−0.014
	(0.107)	(0.136)	(0.078)	(0.080)	(0.229)	(0.100)	(0.154)	(0.126)
days to election	0.000	0.005**	0.002	0.004**	−0.013	0.000	0.003	0.012***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.009)	(0.002)	(0.004)	(0.003)
overall: anger	0.088	0.155**	−0.002	0.072	0.447	0.266*	0.450*	0.155
	(0.099)	(0.057)	(0.085)	(0.097)	(0.396)	(0.123)	(0.204)	(0.221)
overall: disgust	−0.067	0.136+	−0.014	0.079	−0.225	0.013	0.462**	0.204
	(0.174)	(0.078)	(0.100)	(0.083)	(0.503)	(0.148)	(0.164)	(0.161)
overall: sadness	−0.039	−0.043	0.032	0.139**	0.526	0.016	0.241	0.315
	(0.099)	(0.055)	(0.071)	(0.050)	(0.487)	(0.084)	(0.229)	(0.332)
overall: fear	−0.124	−0.082	−0.151	−0.194*	0.301	0.068	−0.035	−0.141
	(0.099)	(0.074)	(0.105)	(0.092)	(0.345)	(0.127)	(0.165)	(0.190)
overall: surprise	0.069	−0.278*	−0.341**	−0.191	0.196	−0.292+	0.876*	0.376
	(0.096)	(0.118)	(0.129)	(0.144)	(0.522)	(0.152)	(0.407)	(0.298)
overall: joy	−0.286*	0.071	−0.073	0.106*	0.302	−0.072	0.069	−0.102
	(0.121)	(0.055)	(0.072)	(0.050)	(0.378)	(0.081)	(0.154)	(0.127)
overall: neutrality	0.077	−0.124+	−0.140	−0.052	0.047	−0.229*	−0.199	−0.237
	(0.103)	(0.068)	(0.091)	(0.072)	(0.283)	(0.097)	(0.154)	(0.161)
Num.Obs.	1282	2719	511	963	235	1376	1025	1056
AIC	12338.9	28513.1	4308.3	9735.3	1001.9	14076.5	11797.6	6404.3
BIC	12519.4	28719.9	4456.6	9905.7	1081.5	14212.4	11930.7	6538.3
Log.Lik.	−6134.466	−14221.548	−2119.175	−4832.631	−477.950	−7012.247	−5871.777	−3175.139
RMSE	82.43	103.88	20.78	48.85	7.79	91.12	225.68	18.91
Std.Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

For the informational variables: (1) Readers of conservative outlets, especially @theblaze and @BreitbartNews, show a slight preference for longer articles, with one standard deviation increase in article length (approximately 250 to 300 words) bringing around 7.25% ($e^{0.07}$) to 10.5% ($e^{0.1}$) expected more real retweets. While @latimes shows a relatively strong negative effect for article length, with consistent results across both regression tables. (2) Readers of @washingtonpost tend to prefer news tweets with a higher entity density ratio in the full articles. (3) For @FoxNews, the readers appear to be less likely to retweet news with high hyperlink density. Furthermore, based on the LPA-clustered variables that combine both density and count, @FoxNews readers exhibit a general negative preference toward both named entities and hyperlinks. (4)

@PhillyInquirer readers show a slight positive preference for articles with overall more hyperlinks.

For the emotional variables: (1) Sentiment neutrality of articles is generally negatively associated with retweet counts. Four of the eight outlets (@nypost, @FoxNews, @nytimes, and @laitmes) in table 4 present negative and significant coefficients, and the rest of the outlets present similarly negative but non-significant coefficients. When considering overall neutrality of news tweets through the LPA clustered "overall: neutrality" variable in Table 5, which takes both text and image into account, readers of @FoxNews and @washingtonpost similarly show some preference against neutral news.

Among the six specific emotions: (2) Anger across the three sources of news (tweets, images, and articles) can generally bring more expected retweets. Readers of @FoxNews, @washingtonpost, and @nytimes are more likely to share news tweets with high levels of anger, approximately 17%, 30%, and 57% more retweets, from the coefficient of LPA clustered variable, "overall: anger", in Table 5. (3) The disgust emotion expressed through tweet text brings more expected retweets than that through the other two sources. This effect is significant in three liberal outlets: @washingtonpost, @nytimes, and @latimes. For example, in table 4, 50% higher probability being disgust in a news tweet from @nytimes is associated with around 96% ($e^{1.346*50\%}$) more expected retweets. But this effect is observed only in the tweet text; in other sources, image and article full text, the correlation is negative, though not statistically significant. (4) In terms of sadness, readers of @BreitbartNews generally show a higher likelihood of retweeting sad content. However, for other outlets, preferences are more diverse depending on the content source. For example, @latimes readers tend to retweet tweets with sad text, but are less likely to retweet sad images. (5) For the emotion of fear, I did not find any consistent pattern of preference or avoidance across all eight outlets. (6) Regarding the surprise emotion, readers of two liberal outlets, @nytimes and @latimes, show some preference for surprising tweet text.

In contrast, readers of @FoxNews and @theblaze are less likely to retweet news that is overall surprising from the LPA clustered variable. (7) For joy, similar to fear, I did not find clear and consistent trend of preference or rejection across eight outlets. Especially in the case of @nypost, joy expressed in tweet text and joy expressed in images are associated with opposite effects on retweets.

2.5.2.4 Summary for RQ2

To answer the RQ2 "*Emotional support vs. Informational value, what kind of news are more preferred by the readers?*" in the politics context, I collected news tweets from eight news outlets' verified accounts on Twitter during the 2022 midterm election from Sep 1 to Nov 8. Reader preference was measured using bot-calibrated retweet counts, while the emotional and informational value of each news item was assessed using NLP and computer vision techniques. Overall, neither the descriptive visualizations nor the regression results revealed strong and consistent patterns. The observed differences are generally small and vary across outlets, including between liberal and conservative outlets, on a case-by-case basis. In the regression models, where multiple emotional and informational variables, as well as topics, are controlled, some of the minor patterns seen in the visualizations disappear.

The relatively robust findings include the following: stronger emotional content is generally associated with more effective retweets, especially the anger emotion, which shows a relatively consistent positive effect across the three sources (tweet text, image, and full article) and across most outlets. And disgust, when present only in tweet text, let the readers of liberal outlets more likely to retweet. Other emotional categories do not exhibit consistent effects. In terms of informational variables, readers of conservative outlets slightly prefer to retweet longer articles, while @FoxNews readers consistently show a negative preference toward articles with more entities and hyperlinks.

2.6 Discussion

The empirical results support Hypothesis 1 and Hypothesis 2: during elections, news with lower emotional intensity is less likely to be shared on social media, whereas news with stronger anger intensity is more likely to be shared. Despite some noise in the regression estimates, the results remain relatively robust. However, Hypothesis 3—which argues that news with higher informational value is more likely to be shared on social media—is not supported by my results. None of the three proxy variables for informational value—article length, entity density, and hyperlink density —shows consistent results across the eight news outlets. Neither the regression models with appropriate methods and robust standard errors, nor the descriptive results, with clustered visualizations, can suggest any positive correlation between the informational value of news tweets and the metrics of the tweets. The results are different from the positive effects from previous similar research (Fahmy, 2012; Papacharissi & de Fatima Oliveira, 2012; Rudat et al., 2014; Trilling et al., 2017).

One explanation for the lack of support for Hypothesis 3 stems from a limitation of real-world observational data: external shocks. In the last several months of an election, the occurrence of a major real-world event could dominate public attention and thereby generate large volumes of news sharing on social media. External shocks constitute an important causal determinant of whether news content achieves widespread diffusion. Even though I generated topics with the latest BERTopic model and I controlled them in the regressions, as well as applying the negative-binomial models, the external shock noise cannot be fully eliminated. The shock, the variance, and the sample size in each topic could influence the regression results.

Another explanation for the inability to support Hypothesis 3 may arise from a gap between how professionals and the public assess the informational value of news. From journalists' perspective, good and informational news should be timely, autonomous, accurate, objective, and could help audiences make sense of the world (Beam et al., 2009; Croteau & Hoynes, 2006; Weaver et al., 2009). Their journalism education and professional norms shape these evaluative judgments (Benson, 2006; Gravengaard & Rimestad, 2014; Parks, 2019). However, from the audience's perspective, researchers have shown that political ideology shapes how individuals judge misinformation (A. Guess et al., 2020; Michael & Breaux, 2021; Pereira et al., 2023). Additionally, information overload from too many posts, notifications, and unlimited information streams on social media or short-video platforms has been found not only to reduce individuals' social media information literacy (SMIL) (Heiss et al., 2023), but also to raise their threshold for recognizing information, prompting greater attention to dramatically framed headlines (Pelau et al., 2023). These influences of political ideology and information overload could widen the gap between how audiences and journalists assess the informational value of news, thereby potentially skewing the news-sharing preferences in my dataset.

The last explanation for the inability to support Hypothesis 3 is that some users may engage with posts—liking, commenting, or sharing—without thoroughly reading the news text, or even without opening the attached article link at all. In such cases, the informational value of the news in the article text has little relevance to users' behavior on Twitter. This explanation aligns with evidence from Sundar et al. (2025), analyzing 35 million Facebook posts between 2017 and 2020, and the authors found that around 75% of shares occurred without clicking the news URLs. Furthermore, this proportion is higher for political news posts than for non-political ones. Sundar et al. (2025) suggest that most users simply skim a post's text or images and share it without deeply processing the underlying news content. Thus, the informational value of news that requires more effort from professional journalists appears to have a limited effect on large-scale social media spread, contrary to what much of the literature suggests.

2.7 Conclusion

As social media has become the primary channel through which people access news (Christopher & Jacob, 2024), news companies increasingly treat it as a critical platform for building influence and redirecting traffic to their websites to boost digital revenues (Sismeiro & Mahmood, 2018). Especially in large political elections, the public shows strong demand for news to track campaign dynamics (Iyengar et al., 2004). This gives media outlets a great strategic window to expand their audience base and maximize revenue. Thus, understanding what increases the dissemination of political news posts on social media is important to media companies.

This study focuses on two main content characteristics of political news posts in the U.S. elections: emotional support and informational value, to find out: (1) how news outlets present these content characteristics; and (2) what kind of political news is more likely to be shared on social media during elections. I collected 9263 news tweets from four conservative outlets and four liberal outlets during the 2022 U.S. midterm election, together with tweet metrics, images, and full articles. Using natural language processing and computer vision techniques, I constructed 7-class emotion variables for news tweets, attached tweet images, and full articles, as well as three informational variables (article length, entity density ratio, and hyperlink density ratio) for full articles.

For the first research question, I found that conservative outlets provided stronger emotions, especially anger and fear, while liberal outlets provided longer articles with lower information density. For the second research question, through further descriptive visualizations and regression analysis, I found that news with higher overall emotional intensity and more anger emotion is more likely to be shared. In contrast, the positive effect of informational value, which the literature consistently supports (e.g., Rudat et al., 2014), cannot be supported by my results. I provided three explanations for the results not being consistent with the literature: the limitation of external shock in real-world observational data; a gap between how professionals and the public assess the informational value of news (Bobkowski, 2015); and users not clicking the attached URL and not reading the news full article before sharing the post (Sundar et al., 2025).

This study makes two key contributions. First, it develops a computational model that addresses the challenge of identifying the overall emotional expression in images containing multiple faces, based on practical photojournalistic conventions used in portrait news photography. It is also among the first studies to apply facial emotion analysis to political communication research on social media. Second, it introduces the *Hyperlink Density Ratio* and *Entity Density Ratio*, together with article length, as automated proxy measures of the informational value of news, substantially reducing reliance on labor-intensive and costly human annotation.

2.8 Limitations of Study 2 and overview of Study 3

This study has two groups of limitations. The first is the facial emotion method I developed. On one hand, if there are no faces in an image, the image can still express emotions through artistic style, as illustrated in Figure 25. On the other hand, my methodological innovation—translating a common photojournalistic practice into a Python program that assigns importance weights to multiple faces—may become less meaningful in the era of multimodal large language models such as GPT-5.1. However, the computing cost of my method is far less than that of the multimodal large language models.

The second group of limitations is from the shortcomings in real-world observational data: (1) external shocks, which are the vital causal factors determining whether news is widely shared; and (2) the fact that many users may engage with posts—liking, commenting, or sharing—without thoroughly reading the news text, or even without opening the attached article link at all (Sundar et al., 2025). The second shortcoming makes the informational value of news in the article's full text much less meaningful in analyzing the effects from the real-world data research.

Finally, Study 3, aiming to answer the same research question as that in Study 2, "media preference on social media during elections, emotional support or informational value?" but involves a survey experiment method. The two purposes of Study 3 are: (1) to complement the second group of limitations from real-world observational data in Study 2. Although neither approach alone is sufficient, together they provide a more comprehensive perspective in answering the research question. And (2) to examine how the gap between professionals and the public in assessing the informational value of news (Bobkowski, 2015) could affect people's preference for the news in political elections.

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Study 3: It Is the Audience's Perceived Informational Value—Rather Than Objective Informational Value—That Shapes Media Preferences

Abstract

Media outlets produce news of high quality and higher informational value to attract audiences, but readers may disagree on the news's informational value. The gap has widened due to polarization and information overload on various social media platforms. It is important to distinguish the objective informational value of news from the audience's perceived informational value when analyzing public preferences. This study contributes to the literature by introducing this divergence into research on political communication. By addressing the same research question as in Study 2 but using a survey experiment design, Study 3 overcomes the limitations inherent in Study 2's observational data approach. The results show that respondents significantly prefer news they perceive as informational, while disfavoring news classified as informational based on linguistic or journalistic criteria. This supports my argument that it is the audience's perceived informational value—rather than objective informational value—that shapes media preferences.

Keywords: Media preference, perceived informational value, actual informational value, emotional support

3.1 Introduction

Media companies increasingly rely on social media dissemination and digital revenues (Bekh, 2020; The New York Times Company, 2025). They treat social media as a vital channel to build influence on social platforms and to redirect traffic back to their websites to get digital revenues (Sismeiro & Mahmood, 2018). Understanding public preferences for media is important, especially in large political events, such as elections, when public attention is highly concentrated and online traffic is high (Boulianne & Theocharis, 2020). Media companies and journalists strive to produce high-quality news to meet journalistic standards and attract audiences for generating revenue. However, there is a gap in assessing news value between professional journalists and the public (A. M. Lee & Chyi, 2014), with informational value being a key dimension of this divergence.

From the producers' perspective, journalism education and professional norms shape their views of high-quality and informational news (Benson, 2006; Gravengaard & Rimestad, 2014; Parks, 2019), emphasizing watchdog roles that deliver timely, autonomous, accurate, and objective information (Beam et al., 2009; Weaver et al., 2009). However, producing information-rich news is resource-intensive, particularly due to fact-checking demands amid rapidly spreading rumors on social media (J. E. Katz & Mays, 2019; Klinenberg, 2005; Shapiro et al., 2013). Thus, understanding whether the public prefers news with more informational value is crucial to the media industry.

From the public's perspective, evaluations of the informational value of political news may be shaped by personal factors such as political ideology, particularly when consuming ideologically divergent news (Guess et al., 2020) and increasingly by information overload due to over exposure to unlimited information streams and short videos (Chung et al., 2023; Zhang et al., 2022). Information overload has been shown to reduce individuals' social media information literacy (Eppler & Mengis, 2004; Heiss et al., 2023) and to lead the public to perceive news with dramatic headlines as highly informative (Pelau et al., 2023). Thus, when examining audience preferences for the informational value and emotional support of news, it is important to distinguish between objective informational value from a professional journalistic view and the audience's perceived informational value. If journalists invest greater effort, guided by professional values, to provide highly informative news that is not recognized by general audiences, this mismatch can affect media companies' financial outcomes.

This study contributes to the literature by introducing the divergence in evaluating informational value between journalists and the audience, which distorts the understanding of audiences' demand for informational value, together with emotional support, to the political communication field. It answers the same research question as that in Study 2, "Emotional support vs. Informational value, what kind of news are more preferred by the readers?" This study also makes use of the survey experiment approach to overcome some limitations from the real-world observational data method in Study 2, including: (1) external shocks in the reality, which are the vital causal factors determining whether news is widely shared; (2) the fact that many users engaging with posts on social media without reading the article full text and even not clicking the news URL (Sundar et al., 2025); and (3) by selecting news items that express emotion or information in a simpler and more consistent way, reader preferences for these features can be identified more clearly.

Using news tweets with images and full articles, along with the variables constructed in Study 2, I manually selected representative examples of emotional versus non-emotional (seven classes) and objectively informational versus non-informational news content. U.S. citizens recruited through Prolific.com were shown different versions of news aligned with their political ideology and were asked to evaluate their perceived informational value of the given news and how they prefer the news. For the informational variables, I found that the respondents significantly prefer news they perceive as informational, while significantly disfavoring news that is informational according to linguistic or journalistic criteria. The results support my argument that, as both the processing of news information and preference formation are fundamentally reader-centered, it is the audience's perceived informational value—rather than objective informational value—that shapes media preferences.

For the emotional variables, I found that the respondents neither preferred angry news nor expressed any discernible positive or negative preference for neutral news, but they did consistently favor joyful news. I suggest that this result differs from both Study 2 and the literature because of the social desirability and "positivity norm" in answering survey questions, as well as the gap between survey-reported preference and actual liking or sharing behaviors on social media. Both the observational data method in Study 2 and the survey experiment method in Study 3 have strengths and weaknesses. They together provide a comprehensive perspective to investigate the public's preferences for content characteristics of political news during elections.

3.2 Literature review

3.2.1 Informational value, how it differs between professional journalists and the public

Generally, informational value of news refers to being meaningful and worthy to the public and could satisfy readers' gratifications (Boczkowski & Mitchelstein, 2013; Rudat et al., 2014; Ruggiero, 2000). However, researchers have found that producers such as newsrooms and journalists often differ from audiences in how they evaluate the informational value of news. From the producers' perspective, news that helps audiences make sense of the world (Croteau & Hoynes, 2006), provides autonomous, accurate, and objective information (Beam et al., 2009), fulfills a watchdog function for the pubic by delivering timely and relevant updates (Weaver et al., 2009), and, in the political contexts, offers information that enables citizens to better understand political events like elections and participate in democratic processes (Zaller, 2003), is widely regarded by newsrooms and journalists as high-quality, informational news. These values that shape judgments of what constitutes "good news" are formed through journalism education, professional socialization within the newsroom, and incentive structures such as organizational expectations and audience reputation (Benson, 2006; Gravengaard & Rimestad, 2014; Parks, 2019). Professional values require journalists to devote more time to ensuring news quality, which increases labor costs for media companies, particularly for verifying facts and sources in an era of rapidly spreading social media rumors (J. E. Katz & Mays, 2019; Shapiro et al., 2013).

From the audience perspective, beyond shared expectations of journalists' roles as informers and observers (Riedl & Eberl, 2022), evaluations of news informational value may also be influenced by personal factors such as political ideology and information overload by short-form media content. For political news, scholars find that both left- and right-leaning groups perceive news from ideologically opposing outlets as less reliable (Michael & Breaux, 2021; Pereira et al., 2023). Moreover, during the 2016 U.S. presidential election, Trump supporters consumed more misinformation from low-credibility conservative websites (Guess et al., 2020). In recent years, scholars in media studies have increasingly focused on information overload, which refers to the notion of people receiving too much information that exceeds their processing capacity (Eppler & Mengis, 2004; Heiss et al., 2023). The overwhelming volume of news items, posts, notifications, and unlimited information streams on social media and short-video platforms exacerbates information overload (Chung et al., 2023; Zhang et al., 2022). Such overload has been shown to reduce individuals' social media information literacy (SMIL), thereby widening the gap between audiences' and journalists' assessments of news informational value (Heiss et al., 2023). Furthermore, when people are overloaded with information, the constant stimulation raises their threshold for what counts as informative or important; only highly emotional content or dramatically framed headlines tend to be perceived as having informational value (Pelau et al., 2023).

3.2.2 Gap and contribution

Differences in how professional journalists and the public assess informational value could bias the estimated effect of informational value on news dissemination. Bobkowski (2015) is the only research that distinguishes between perceived and actual informational utility in explaining news sharing intention. However, the topic is not about political news, and emotion is not included in the research. My study contributes to the literature by introducing the divergence on informational value in the political communication field. I conduct a survey experiment that presents respondents with emotionally categorized and informationally diverse news items and asks them how they evaluate the informational value of news and their preferences. In addition, respondents are sampled by political ideology and exposed only to news outlets that match their ideological orientation, thereby reducing potential bias in judgments of informational value.

3.3 Theory and hypothesis

This study aims to find out a similar research question as in Study 2: what kind of news tweets in political elections are more preferred by the public. Hypotheses 1, 2, and 3 are adopted directly from Study 2, and their theoretical explanations are not repeated. An additional Hypothesis 3b is introduced to shift the focus from objective informational value to the readers' perceived informational value.

Hypothesis 1: During elections, news with lower emotional intensity is less likely to be preferred by the public.

Hypothesis 2: During elections, news with stronger anger intensity is more likely to be preferred by the public.

Hypothesis 3: During elections, news with higher informational value is more likely to be preferred by the public.

Hypothesis 3b: During elections, news that readers perceive as having higher informational value is more likely to be preferred by the public.

For Hypothesis 3b, the Uses and Gratifications Theory sees audiences as active users to choose content that satisfies specific psychological and social needs (E. Katz et al., 1973). These psychological and social satisfaction processes are personal and subjective to the users (Ruggiero, 2000). People have their own topic preferences and personal judgments on whether a news item is useful for understanding their surrounding environment. And their judgement on whether the information they tend to share carries high status—closely related to the concept of social media information literacy (SMIL) (Heiss et al., 2023), and could bring them status seeking gratifications in sharing (C. S. Lee & Ma, 2012)—also depends on personal factors such as age, education, socioeconomic status, and social networks (Eveland Jr & Hively, 2009; Hargittai & Hinnant, 2008; Heiss et al., 2023; Mani et al., 2013), but not common factors from the view of linguistic or journalism. Therefore, as both the processing of news information and the formation of preferences are fundamentally reader-centered, I argue that it is the audience's perceived informational value—rather than objective informational value—that shapes media preferences.

3.4 Methodology

3.4.1 Selecting news

The news used in this study comes from the same source as in Study 2: news tweets posted by eight major news outlets' verified accounts on Twitter during the 2022 midterm election. Based on the emotional and informational variables constructed in Study 2, I selected 14 scenarios representing a 2 (informational vs. non-informational) * 7 (7-emotion categories) design. Emotion classification considers all three sources: tweet text, image, and full article. Informational or not is based on a combination of measurements from Study 2: article length, entity density ratio, and hyperlink density ratio. For the seven emotion classes, the news items were manually selected to be as singular as possible, that is, each item was chosen to express primarily only one type of emotion, such as anger. For each scenario, five news tweets were selected from liberal outlets and five from conservative outlets. Totally 140 news tweets are selected. Table 1 reports the distribution of the selected news across the 14 scenarios.

Table 1. 14 scenarios of selected news

scenario	informational	emotional	No. of news from conservative media	No. of news from liberal media
1	0	neutrality (weak emotion)	5	5
2	0	anger	5	5
3	0	disgust	5	5
4	0	sadness	5	5
5	0	fear	5	5
6	0	surprise	5	5
7	0	joy	5	5
8	1	neutrality (weak emotion)	5	5
9	1	anger	5	5
10	1	disgust	5	5
11	1	sadness	5	5
12	1	fear	5	5
13	1	surprise	5	5
14	1	joy	5	5

3.4.2 Survey design

In the survey experiment, each respondent is asked to read 10 news articles after answering a set of demographic questions. For each news item, respondents are shown the tweet text, the image attached to the tweet, and the full article. Since hyperlink density in the full article is one of the indicators used to evaluate whether a news item is informational, hyperlinks are displayed with blue underlining, and participants can click on them to access the original sources.

Next, on the same page below the news content, respondents are asked to answer two groups of questions. The first group directly measures their preference by asking how much they like the news and how likely they are to share it with others. The second group asks respondents to self-assess the emotional content of the news by rating the strength of each of the seven emotion classes, as well as how informative they perceive the news to be. Figure 1 shows a screenshot of how a news item is presented in the survey and how these questions are displayed in the survey.

Figure 1. Screenshot of a sample news article and survey questions shown to respondents

Democrat defector Tulsi Gabbard has endorsed Republican Tudor Dixon in her race to unseat Democrat Michigan Governor Gretchen Whitmer.

Tulsi Gabbard Endorses Republican Tudor Dixon for Michigan Governor

Democrat defector Tulsi Gabbard has endorsed Republican Tudor Dixon in her race to unseat Democrat Michigan Governor Gretchen Whitmer.

In a tweet on Thursday, Tudor Dixon gleefully accepted Tulsi Gabbard's endorsement, announcing that she will be campaigning with her in Michigan next week.

"[Tulsi] has been a voice of reason across party lines. She is courageously speaking her mind and showing us all what it means to be a leading independent thinker. I am honored to have her support and cannot wait to welcome her to Michigan next week!" announced Dixon.

A recent White Law Firm/Michigan Association of Broadcasters poll showed that Gretchen Whitmer holds a four-point lead — 48 percent to 44 percent — over Tudor Dixon. Just a little over a week ago, before the debate, Whitmer led Dixon by six points; a Detroit News poll in early September showed Whitmer leading Dixon by 13 points.

Tulsi's endorsement of Tudor Dixon comes after she campaigned for Republicans Blake Masters and Kari Lake in Arizona and after she pledged to campaign for Republican U.S. Senate candidate Don Bolduc in New Hampshire.

Though Tulsi Gabbard has long been a favorite among Trump supporters for her unwillingness to toe the Democrat Party line, she upgraded her status to legendary this month when she formally defected from the party she previously called home.

"I can no longer remain in today's Democratic Party that is now under the complete control of an elitist cabal of warmongers driven by cowardly wokeness, who divide us by racializing every issue & stoke anti-white racism," Gabbard said on an episode of The Tulsi Gabbard Show.

"Who actively work to undermine our God-given freedoms that are enshrined in our constitution. Who are hostile to people of faith and spirituality. Who demonize the police, but protect criminals at the expense of law-abiding Americans. Who believes in open borders," she added.

How much do you **like** this news?

Strongly dislike										Strongly like
0	1	2	3	4	5	6	7	8	9	10

How likely are you to **share** this news with others?

Not likely at all										Very likely
0	1	2	3	4	5	6	7	8	9	10

How would you rate the **overall emotional strength** in this news?

Not strong at all										Extremely strong
0	1	2	3	4	5	6	7	8	9	10

How would you rate the **anger** in this news?

Not strong at all										Extremely strong
0	1	2	3	4	5	6	7	8	9	10

How would you rate the **disgust** in this news?

Not strong at all										Extremely strong
0	1	2	3	4	5	6	7	8	9	10

How would you rate the **sadness** in this news?

Not strong at all										Extremely strong
0	1	2	3	4	5	6	7	8	9	10

How would you rate the **fear** in this news?

Not strong at all										Extremely strong
0	1	2	3	4	5	6	7	8	9	10

How would you rate the **surprise** in this news?

Not strong at all										Extremely strong
0	1	2	3	4	5	6	7	8	9	10

How would you rate the **joy** in this news?

Not strong at all										Extremely strong
0	1	2	3	4	5	6	7	8	9	10

How **informative** do you consider this news to be?

Not informative										Very informative
0	1	2	3	4	5	6	7	8	9	10

3.4.3 Respondents recruited from Prolific

Among commonly used platforms for recruiting survey participants, respondents from Prolific were found to provide higher data quality (higher pass rate of attention checks, better adherence to instructions, and more meaningful answers) (Douglas et al., 2023), and they could be sampled by multiple background characteristics. Given that the ideological orientation of news content may influence how American readers judge and prefer certain news, I chose Prolific for respondent recruitment. I recruited 140 U.S. participants from each political leaning (left and right). And the party affiliation by Prolific aligned with their responses to demographic questions in my survey. Each participant was only shown news from media outlets that matched their political ideology, and the eight outlets in Study 2, where I selected news, are widely recognized and trusted within their respective ideological groups (Mitchell, 2014). This design tries to ensure that participants' evaluations focus on the content of the news rather than being confounded by partisan perceptions of the media source. Each respondent read 10 news items, and each news item was evaluated by approximately 20 participants. After filtering out respondents who completed the survey too quickly and provided the same answers for most of the provided news, observations from 127 left-leaning and 124 right-leaning respondents were retained for analysis. Table 2 reports the demographic characteristics of the left- and right-leaning respondent groups.

Table 2. Demographic characteristics of the left- and right-leaning respondent groups

Variable	Category	Left in %	Right in %
age_group	21–29	40.9	37.1
	30–44	37	36.3
	45–59	15.7	23.4
	60+	6.3	3.2
gender	Female	49.6	41.9
	Male	48.8	58.1
	Non-binary	0.8	0
	Other. Please specify:	0.8	0
racial_identity	American Indian or Alaska Native	2.4	0
	Asian	7.1	0.8
	Black or African American	32.3	35.5
	Hispanic or Latino	3.1	1.6
	Other. Please specify:	1.6	0.8
	White	53.5	61.3
partisan_identification	Democrat	95.3	0.8
	Independent	0.8	1.6
	No preference	1.6	0
	Republican	2.4	97.6
employment_status	Full-time employment	59.1	65.3
	Homemaker	0.8	2.4
	Part-time employment	18.1	16.9
	Retired	0.8	1.6
	Self-employed	10.2	5.6
	Student	4.7	2.4
	Unemployed	6.3	5.6
marital_status	Divorced	3.1	4.8
	Never married	44.9	37.1
	Now married	50.4	53.2
	Separated	0.8	2.4
	Widowed	0.8	2.4
education	Advanced degree (Master's, Professional, or Doctorate degree)	29.9	34.7
	Associate degree	7.1	3.2
	Bachelor's degree	45.7	38.7
	High school diploma or equivalent degree	7.1	8.9
	Less than a high school diploma	0.8	0.8
	Some college, no degree	9.4	11.3
	Trade/technical/vocational training	0	2.4

3.5 Data analysis

To answer the same research question as of Study 2, "*Emotional support vs. Informational value, what kind of news are more preferred by the readers?*" I conducted a linear regression analysis using participants' self-reported media preferences and the eight binary variables representing emotional (seven classes) and informational (one class) characteristics of each scenario in the survey experiment. In the survey, respondents are asked both how much they "like" a news item and how willing they are to "share" it. I use "like" as the primary measurement of preference in the following regression analysis. This is because "like" is a more intuitive and direct measurement of preference, while self-reported "share" intention in a survey does not always align with real-world sharing behavior, with a 0.44 correlation measured by Mosleh et al. (2020). Additionally, in my data, the centered values (at the respondent level) of "like" and "share" have a strong correlation of 0.61, and "like" has a higher variance. Table 1 in the appendix reports the regression results when like is replaced with share. The results are highly consistent across the two models, except that joyful content is significantly preferred in the like model but not in the share model.

The regression model is presented in Equation (1) with informational variables and emotion variables, where i means scenario, and j means respondent. The "like" variable is centered at the respondent level to reduce between-respondent bias in their preference judgment. Both objective informational value and the respondents' perceived informational value are included in the equation. $Objective\text{:}\,Informational$ is a binary informational variable based on a combination of measurements from Study 2: article length, entity density ratio, and hyperlink density ratio. $Respondents\text{:}\,Informational$ is the evaluation of the news' informational value by each respondent within a 0-10 scale and is centered at the respondent level to reduce between-respondent bias in their judgment. Since the seven emotion variables are mutually exclusive in my scenario design, the "*Surprise*" variable, which shows the weakest effect, is automatically excluded in the R program to prevent multicollinearity.

Respondent-level fixed effects are applied for a robustness check. Standard errors are estimated using 1,000 bootstrap replications. Respondents with left- and right-leaning political ideologies, who are shown different sets of news, are analyzed separately to reduce bias from political ideology (Michael & Breaux, 2021; Pereira et al., 2023).

$$\begin{aligned} Like_{ij} - \overline{Like_i} = {} & \beta_0 + \beta_1 Objective{:}\, Informational_i \\ & + \beta_2 Respondents{:}\, Informational_{ij} + \beta_3 Neutral_i + \beta_4 Anger_i \\ & + \beta_5 Disgust_i + \beta_6 Sadness_i + \beta_7 Fear_i + \beta_8 Joy_i + \beta_9 Surprise_i \\ & + \varepsilon_{ij} \end{aligned}$$

Equation (1)

3.6 Results

Table 3 reports the regression results of Equation (1). Figure 2 visualizes the right three columns with fixed effects. Overall, the findings from here using a survey experiment are more consistent than those of Study 2, but the results are different. For the two informational variables, news that respondents perceive as more informative is significantly more preferred: a one-point increase in a respondent's informational rating of political news is associated with an average 0.46-point increase in preference on the 0–10 scale. In contrast, news evaluated as informational from journalistic and linguistic perspectives—characterized by longer articles, higher entity density, and more hyperlinks—is significantly less preferred by respondents, with average preference ratings approximately 0.31 points lower. The two results are consistent among respondents in both ideological groups. For the six emotional variables, results of the anger emotion, together with sadness and fear, suggest a bit negative, but the effects are not consistently significant across the two groups of respondents. Respondents with left-leaning ideologies show lower preferences for overall angry and sad news, while those with right-leaning ideologies exhibit lower preferences for fear-related news. In contrast, both groups show a larger and consistently significant preference for joyful news, with left-leaning respondents exhibiting a relatively stronger preference. Finally, neutral news has no significant effect overall.

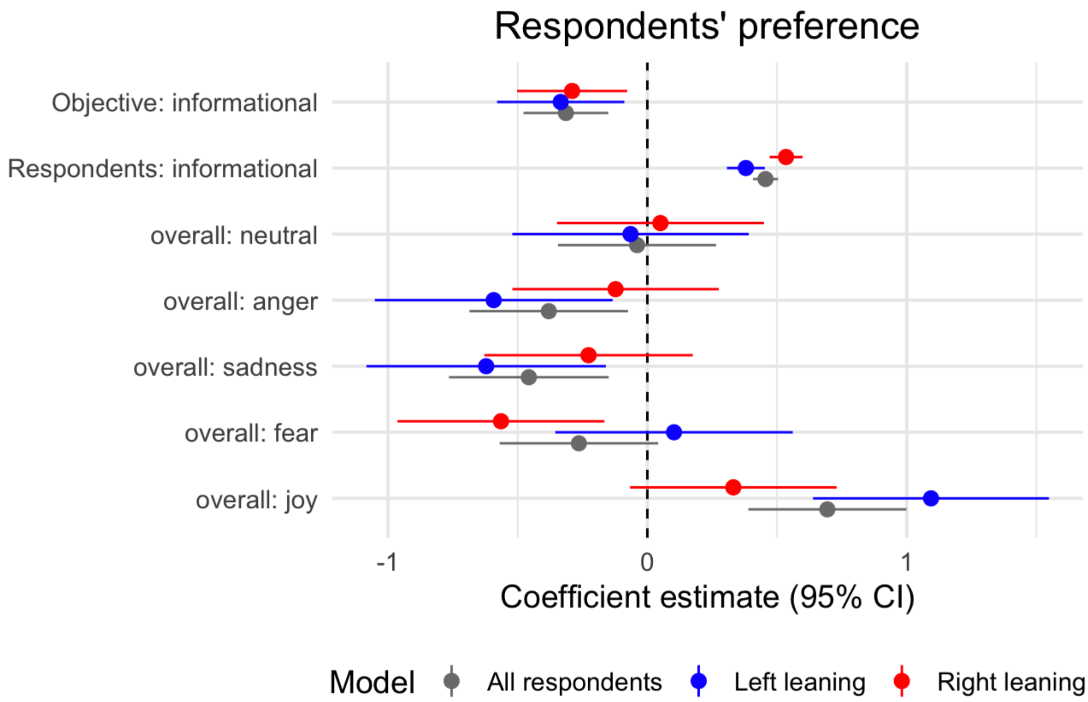
Table 3. Regression results for Equation (1)

	all respondents	left-leaning	right-leaning	all respondents	left-leaning	right-leaning
Intercept	0.055	0.045	0.102	−0.601***	−0.116	−0.714**
	(0.117)	(0.178)	(0.162)	(0.173)	(0.311)	(0.237)
Objective: informational	−0.300***	−0.312*	−0.287**	−0.314***	−0.334**	−0.290**
	(0.081)	(0.122)	(0.108)	(0.085)	(0.126)	(0.112)
Respondents: informational	0.227***	0.199***	0.259***	0.456***	0.380***	0.535***
	(0.019)	(0.027)	(0.025)	(0.028)	(0.043)	(0.038)
overall: neutral	0.141	0.049	0.217	0.130	0.057	0.159
	(0.148)	(0.222)	(0.204)	(0.158)	(0.241)	(0.214)
overall: anger	−0.174	−0.480*	0.104	−0.210	−0.471+	−0.014
	(0.159)	(0.244)	(0.208)	(0.166)	(0.261)	(0.218)
overall: disgust	0.179	0.005	0.328	0.170	0.122	0.109
	(0.153)	(0.230)	(0.210)	(0.166)	(0.245)	(0.213)
overall: sadness	−0.217	−0.481*	0.039	−0.287+	−0.500*	−0.118
	(0.155)	(0.238)	(0.204)	(0.161)	(0.251)	(0.214)
overall: fear	−0.127	0.152	−0.422*	−0.094	0.225	−0.456*
	(0.149)	(0.223)	(0.209)	(0.159)	(0.235)	(0.216)
overall: joy	0.853***	1.140***	0.536*	0.863***	1.215***	0.440*
	(0.153)	(0.228)	(0.212)	(0.161)	(0.235)	(0.211)
Num.Obs.	2510	1270	1240	2510	1270	1240
R2	0.092	0.093	0.122	0.157	0.132	0.222
R2 Adj.	0.089	0.087	0.116	0.060	0.030	0.130
AIC	10673.2	5528.1	5110.2	10988.7	5724.4	5206.7
BIC	10731.5	5579.5	5161.4	12504.0	6424.4	5888.1
Log.Lik.	−5326.615	−2754.031	−2545.092	−5234.361	−2726.201	−2470.356
Fixed Effect	N	N	N	Y	Y	Y
RMSE	2.02	2.12	1.88	1.95	2.07	1.77
Std.Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: "$Surprise$" is excluded to prevent multicollinearity. "$Objective: Informational$" is a binary variable. "$Respondents: Informational$" is a 0-10 scale and is centered at respondent level. The left three columns present results without fixed effects, and the right three include respondent-level fixed effects. The two sets of results are quite similar.

Figure 2. Visualization of regression results for Equation (1) with fixed effects



Note: The results are the column 4 to column 6 in table 3.

3.7 Discussion

Using a survey experiment selecting representative news examples in the 2022 U.S. mid-term election and recruiting U.S. citizens to answer, this study aims to find out the same research question as in Study 2: what kind of news tweets in political elections are more preferred by the public, emotional support or informational value? The empirical results fail to support Hypothesis 1 and Hypothesis 2: the recruited U.S. participants neither preferred angry news nor expressed any positive or negative preference for neutral news, but they did consistently favor joyful news. These outcomes diverge from the patterns observed in the Twitter-based data of Study 2, where angry and overall emotional news tweets are more shared. Two potential explanations may account for this divergence. First, respondents' self-reported preferences and sharing intentions in surveys may differ from their actual sharing behavior, as individuals often lack full awareness of the psychological motives underlying their sharing decisions (Nisbett & Wilson, 1977). Nevertheless, recent empirical studies report moderate correlations between survey responses and real-world behavior, ranging from 0.32 to 0.47 (Guess et al., 2019; Mosleh et al., 2020). Second, social desirability and positivity norms in survey responses may bias respondents toward positive choices (Caputo, 2017; Krumpal, 2013), such as preferring joyful news while avoiding selecting negative news like anger, fear, and sadness, as observed in my regression results.

For Hypotheses 3 and 3b, although biases from self-reported preferences and social desirability may persist, the results provide strong support for the positive effect of informational value on public preference during elections, consistent with the existing literature (Fahmy, 2012; Papacharissi & de Fatima Oliveira, 2012; Rudat et al., 2014; Trilling et al., 2017). However, after distinguishing between perceived informational value and actual informational value in this study, I find that respondents prefer news they perceive as informational, while disfavoring news that is classified as informational based on linguistic and journalistic criteria. The finding supports my argument that it is the audience's perceived informational value—rather than objective informational value—that shapes media preferences. Furthermore, because informational value can exert both positive and negative effects, the non-significant results observed in Study 2 are reasonable, particularly given the biases associated with the limitations of the observational data approach.

Taken together, Study 2 and Study 3 employ complementary methods with trade-offs. Study 2 uses observational Twitter data that captures audience preferences in real-world settings while being sensitive to external shocks. The results could also be biased because social media users may share news without reading it (Sundar et al., 2025). Study 3 adopts a survey experiment, which reduces such shocks by presenting respondents with typical emotional and informational news that aligns with their political ideologies. But self-reported responses may be subject to social desirability bias. Combining both approaches therefore allows this thesis to draw more reliable inferences than either method alone (Reveilhac et al., 2022).

Among the results of both studies, the findings on informational value in Study 3 not only replicate the positive effects reported in prior literature but also reveal an unexpected dislike of news that is more informative according to linguistic and journalistic criteria. From a professional perspective, news with informational value should provide autonomous, accurate, and objective information (Beam et al., 2009), and in elections, enables citizens to better understand the political affairs (Zaller, 2003). Although some news is valued by both journalists and audiences, highly informative articles tend to be longer on average, which may impede readers' willingness or ability to grasp the message, especially under conditions of information overload (Heiss et al., 2023). This concern may also apply to the survey experiment, as some articles exceed 1,000 words, although I selected shorter articles whenever possible[9]. Moreover, because journalists often express emotions cautiously (Tuchman, 1972), news they consider highly informational may be perceived as relatively bland by audiences. In contrast, social media users are more likely to notice and engage with sensational 'big news' and prominent headlines in crowded timelines (Milli et al., 2025), interpreting such stories as more important and informative while overlooking less dramatic posts. These factors can explain why respondents in the survey experiment dislike news with higher objective informational value.

However, this study does not directly examine what factors shape audiences' judgments of news informational value. As shown in Figure 3, respondents struggle to distinguish informational from non-informational news when informational value is based on linguistic and journalistic criteria. Table 4 further indicates that, among the three proxies used in Study 2, only article length serves as a potential cue for respondents' evaluations.

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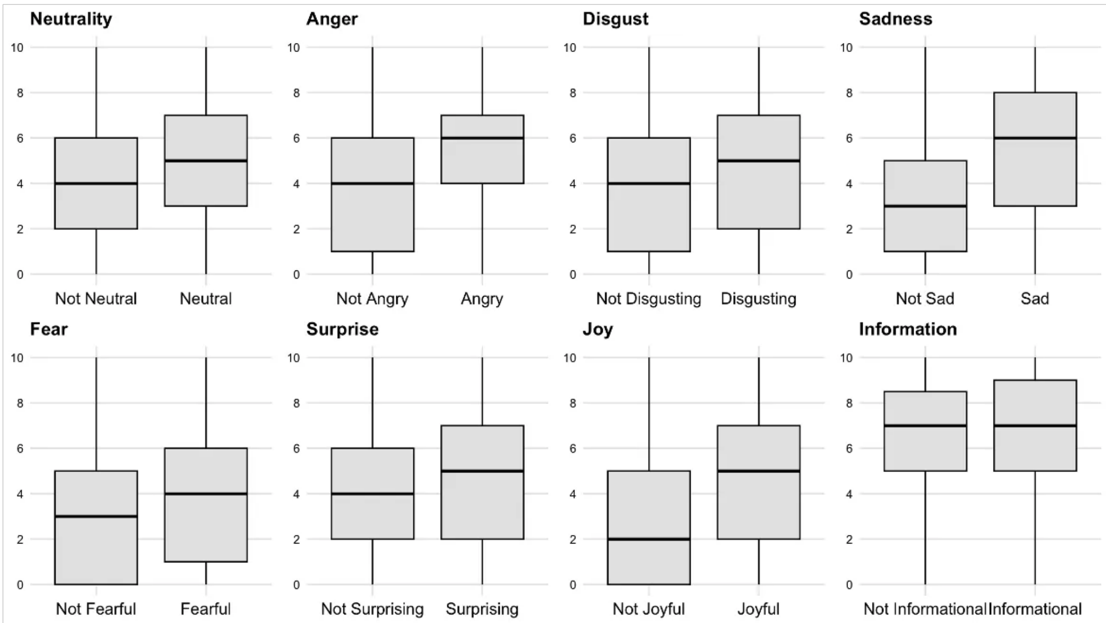
[9] See figures 9-24 in Study 2 for the distribution of news article length.

These findings partially support a gap between journalists' and the public's assessments of informational value (Bobkowski, 2015).

Figure 3. Distribution of respondents' ratings grouped by manual classification



Note: Respondents rate the perceived emotional or informational expression of each news item on a 0–10 scale. The groupings on the x-axis were predefined in the survey scenarios based on a combination of measures from Study 2. Each panel shows a boxplot for one emotion or information category. Respondents can hardly tell the difference between informational and non-informational news from a linguistic or journalistic view.

Table 4. Relationship between respondents' perceived informational value and objective proxy variables

	Mean(Respondents: informational)	Objective: informational
Article: words count * 100	0.145***	0.128***
	(0.031)	(0.013)
Article: entity density ratio	−3.539	10.131***
	(2.318)	(1.001)
Article: hyperlink density ratio	7.530	8.783*
	(7.884)	(4.362)
Intercept	6.299***	−1.275***
	(0.356)	(0.106)
Num.Obs.	140	140
R2	0.166	0.563
R2 Adj.	0.148	0.553
AIC	305.6	97.4
BIC	320.3	112.1
Log.Lik.	−147.802	−43.709
RMSE	0.70	0.33
Model	Linear	Linear
Std.Errors	Bootstrap	Bootstrap

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Linear regression results examining the correlation between three article-level variables—used in Study 2 as automated measures of informational value—and respondents' perceived and objective informational value defined in Equation (1) and Table 3. The dependent variable in the left column is the mean of respondents' ratings (0–10) of perceived informational value for each news item. The dependent variable in the right column is a binary indicator based on the manual classification of informational versus non-informational news used in the experiment.

3.8 Conclusion

Producing news content with good quality and higher informational value requires more labor cost for media companies (Klinenberg, 2005). But readers' perceptions of informational value do not fully align with professional journalistic standards (Bobkowski, 2015). This gap has widened in recent years due to polarization (Guess et al., 2020) and information overload from unlimited information streams on social media (Chung et al., 2023), which reduces individuals' information literacy (Heiss et al., 2023). Without a better understanding of audience demand, media organizations face increasing pressure in both production costs and digital revenue generation. Thus, it is crucial to distinguish between actual or objective informational value from professional journalistic views and the audience's perceived informational value in communication research.

This study tries to answer the same research question (RQ2) as that in Study 2: "Emotional support vs. Informational value, what kind of news are more preferred by the readers?" But it uses a survey experiment method. U.S. citizens recruited through Prolific.com were shown representative news items from Study 2 that aligned with their political ideology and were asked to evaluate the informational value of the news and indicate their preferences. I found that the respondents significantly prefer news they perceive as informational, while significantly disfavoring news defined as informational based on linguistic and journalistic criteria. The results support my argument that it is the audience's perceived informational value—rather than objective informational value—that shapes media preferences.

This study contributes to the literature by introducing the divergence in evaluating informational value between journalists and the audience, which distorts the understanding of audiences' demand for informational value, to the political communication field. It also overcomes the methodological limitations in Study 2 from the real-world observational data method: external shocks in real-world observational data; the gap between how professionals and the public assess informational value (Bobkowski, 2015); and many users not clicking the attached URL before sharing (Sundar et al., 2025).

3.9 Limitations and future study

The first limitation concerns the survey experiment's limited ability to represent respondents' real-world social media behavior. Social desirability bias may account for the non-significant effects of overall emotional intensity and anger, with the latter showing a negative effect. Both the observational data method and the survey experiment method have strengths and weaknesses. Study 2 and Study 3 together provide a more comprehensive perspective on the public's preference for content characteristics of political news during elections.

The second limitation of this study is that, although it distinguishes the effects of readers' perceived informational value from objective informational value defined by journalistic and linguistic standards, it does not examine what leads audiences to perceive certain news as more informational. Future research could address this question, which is of practical importance to media producers facing pressure to build influence and generate revenue on social media.

The third limitation is the problem of reverse causality between audiences' perceived informational value and their preference. In the survey experiment, both preference and perceived informational value were reported by the same respondent in the same questionnaire. While this design makes it possible to observe both evaluations simultaneously, it also leaves the possibility that respondents may judge a news item as more informational because they already liked it. This concern is consistent with research on information credibility, which suggests that perceived online credibility is often shaped by heuristics, including whether the information matches prior expectations, rather than by purely objective assessment (Metzger et al., 2010). Accordingly, the findings of Study 3 should be interpreted more cautiously as indicating that audience preference is more closely aligned with perceived than with objectively defined informational value, rather than as definitive evidence of a one-way causal effect from perceived informational value to preference. Future research could better address this issue by separating informativeness judgments from preference measures in the survey experiment.

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Appendix

Table 1. Regression results for Equation (1), using share instead of like

	all respondents	left-leaning	right-leaning	all respondents	left-leaning	right-leaning
Intercept	0.169	0.301+	0.007	−0.706**	−0.053	−0.827***
	(0.107)	(0.161)	(0.142)	(0.219)	(0.391)	(0.235)
Objective: informational	−0.322***	−0.299**	−0.348***	−0.339***	−0.326**	−0.353***
	(0.077)	(0.115)	(0.104)	(0.078)	(0.117)	(0.106)
Respondents: informational	0.288***	0.309***	0.268***	0.583***	0.602***	0.556***
	(0.017)	(0.026)	(0.023)	(0.027)	(0.038)	(0.036)
overall: neutral	−0.154	−0.361	0.074	−0.179	−0.346	0.005
	(0.140)	(0.222)	(0.181)	(0.147)	(0.234)	(0.186)
overall: anger	0.078	−0.296	0.473*	0.039	−0.259	0.362+
	(0.143)	(0.221)	(0.196)	(0.156)	(0.232)	(0.199)
overall: disgust	0.020	−0.395+	0.484**	−0.003	−0.219	0.257
	(0.144)	(0.221)	(0.182)	(0.154)	(0.240)	(0.190)
overall: sadness	0.075	−0.127	0.294	−0.002	−0.127	0.143
	(0.143)	(0.215)	(0.191)	(0.146)	(0.220)	(0.202)
overall: fear	−0.151	−0.328	0.044	−0.108	−0.222	0.024
	(0.139)	(0.218)	(0.181)	(0.163)	(0.227)	(0.186)
overall: joy	0.084	−0.135	0.327+	0.063	−0.069	0.219
	(0.138)	(0.196)	(0.192)	(0.150)	(0.218)	(0.195)
Num.Obs.	2510	1270	1240	2510	1270	1240
R2	0.116	0.116	0.130	0.227	0.216	0.245
R2 Adj.	0.113	0.111	0.125	0.138	0.124	0.156
AIC	10514.8	5471.9	5025.3	10680.2	5571.6	5095.7
BIC	10573.1	5523.3	5076.6	12195.5	6271.5	5777.1
Log.Lik.	−5247.410	−2725.933	−2502.673	−5080.120	−2649.780	−2414.872
Fixed Effect	N	N	N	Y	Y	Y
RMSE	1.96	2.07	1.82	1.83	1.95	1.70
Std.Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

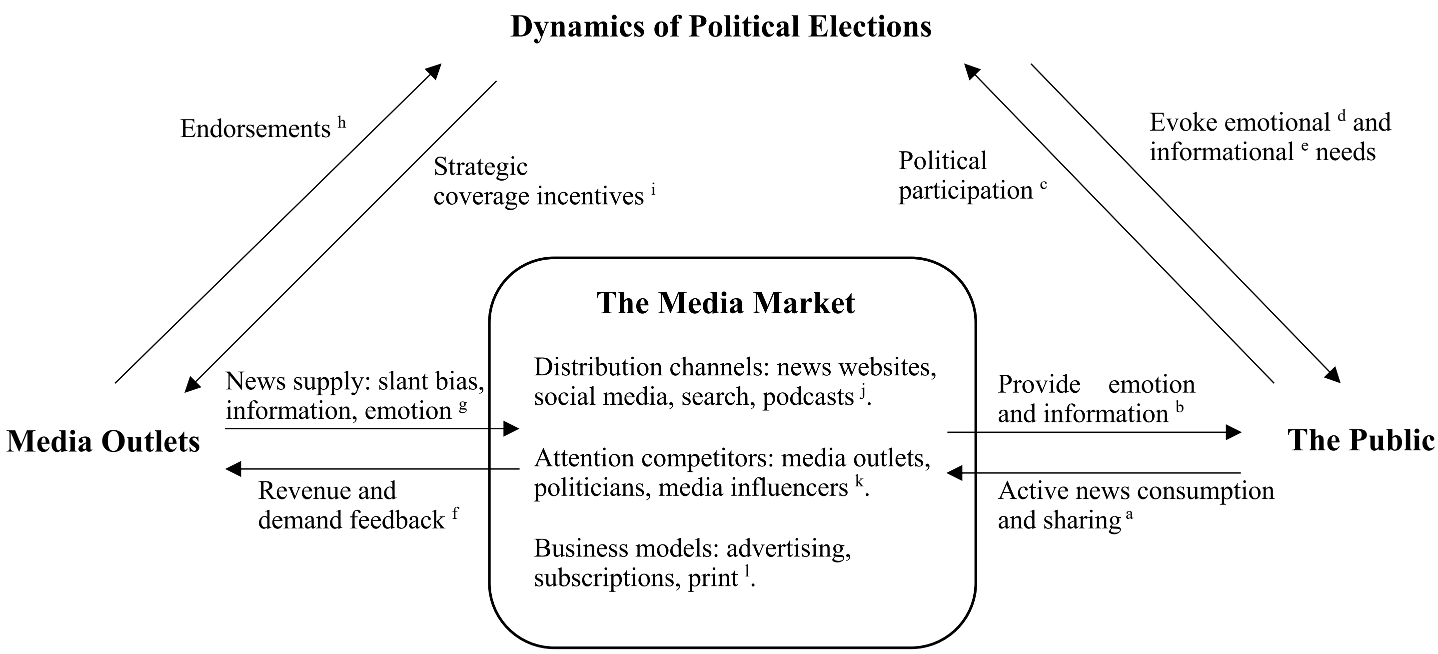
Note: The results are consistent with those in Table 3, except that joyful content is no longer significantly preferred by respondents. This pattern is reasonable, as respondents may be more likely to express a preference for joyful content when evaluating whether they like a news item, but less likely to show the same preference when evaluating whether they would share it.

Thesis Conclusion

The overarching research question

Media is important for democracy, and media bias in U.S. elections is shaped by both what media outlets supply and what the audiences demand. The media is citizens' primary source of campaign information (Shehata & Strömbäck, 2014), and biased coverage can influence how voters judge candidates and decide their vote (Druckman & Parkin, 2005; Nadeau et al., 2008), thus, understanding how the media is biased is important. During elections, as the public has a heightened interest in consuming political news, news outlets capture this strategic window by producing large volumes of news articles attracting the audience, giving researchers a good chance to study bias. The thesis aimed to shed light on how media outlets supply media bias (slant bias, informational value, and emotional support) and what the public prefers for such bias (informational value and emotional support) in U.S. political elections. Figure 1 visualizes the theoretical framework of this thesis.

Figure 1. Theoretical framework of the thesis



Note: [a] Uses and Gratifications Theory (Katz et al., 1973). [b] Media's role for the public in elections (Hansen & Pedersen, 2014; Weaver, 1996). [c] The public's evaluation of candidates and political participation (Druckman & Parkin, 2005; Hasell & Weeks, 2016; Nadeau et al., 2008). [d] The public experiences a mix of emotions in elections (Brader, 2006; Coleman & Wu, 2024; Nadeem, 2024; Stolwijk et al., 2017; Walter & Redlawsk, 2023). [e] The public needs to improve knowledge of election dynamics (Lee & Ma, 2012; Whiting & Williams, 2013). [f] Media outlets' revenue components (Bekh, 2020; Penttilä, 2024; The New York Times Company, 2025) and their competition for attention in response to audience demands (Flamino et al., 2023; Hermida, 2013; Molyneux & Nelson, 2024; Welbers & Opgenhaffen, 2018). [g] Media outlets' supply of slant bias (Gentzkow & Shapiro, 2010), emotion (e.g., Brady et al., 2017; Wollebæk et al., 2019), and information (Beam et al., 2009; Zaller, 2003). [h] Endorsements of media outlets in U.S. political elections (Ansolabehere et al., 2006). [i] Political dynamics and the strategic positioning of media bias (Barberá et al., 2019; Gentzkow & Shapiro, 2010). [j] Sources that U.S. citizens get news (Christopher & Jacob, 2025). [k] Sources that Americans get news on social media (Elisa et al., 2024). [l] Media outlets' revenue components (The New York Times Company, 2025).

Synthesis of key findings

In understanding how the media outlets supply media bias, I focused on two types of bias: ideological bias (left- and right-leaning) and content characteristic bias (emotional support and informational value) of news. For ideological bias, I constructed a high-frequency daily media bias index in Study 1 from the average tone of news covering the two candidates for 237 newspapers during the U.S. presidential elections from 1980 to 2020. I found a generally left-biased trend against Republican candidates since 1992 (Groseclose, 2011), and the trend may be driven by the left-turning public opinion. Furthermore, when the elections got closer, my results suggested that newspapers endorsing a Republican nominee tend to publish articles with stronger supportive sentiment, whereas newspapers endorsing a Democratic nominee—or endorsing no one—report in a more neutral manner. The different strategies may be driven by differences in newspapers' target readerships and by differences in demand between liberal and conservative audiences. For content characteristic bias, I constructed automated emotional and informational measurements of news tweets, images, and full articles in Study 2 for 9263 news tweets from four conservative and four liberal outlets during the 2022 U.S. midterm election. I found that, on average, conservative outlets used stronger emotional tone, particularly anger and fear, while liberal outlets tend to publish longer articles with more neutrality and lower information density.

In understanding what content characteristics—emotional support and informational value—the public prefers during elections, I applied two approaches: an observational data approach in Study 2 that used retweet counts on X (formerly Twitter) as an indicator of audience preference, and an online survey experiment in Study 3 in which U.S. citizens read representative news items and stated their preferences. Despite trade-offs of pros and cons inherent in the two approaches, two relatively robust findings emerge: emotionally intense news, especially anger-driven content, is more likely to be shared on social media, and audience preferences are driven by perceived rather than linguistically or journalistically defined informational value.

From the earlier presidential elections in Study 1 to the more recent presidential elections and the 2022 midterm election in Studies 2 and 3, political communication moved from a legacy newspaper environment to a hybrid media system that includes both traditional news organizations and personal or platform-native accounts on social media. Traditional media outlets have faced growing pressure to respond to audience demand to compete for online attention. In addition, since the 2016 presidential election, American society appears to have become more conservative, and the 2020 sample in Study 1 suggests that newspapers showed a slightly more conservative tendency relative to audience preferences, rather than a liberal bias.

Overall contributions

Methodologically, the thesis contributed to the literature by providing automated measurements of media bias. First, I developed a high-frequency daily measure of ideological bias during U.S. presidential elections from 1980 to 2020, based on the entity sentiment toward the final two candidates in news coverage. Second, to address the limitation of existing models in distinguishing the relative importance of multiple faces within an image, I translated common photojournalistic practices into a programming model that assigns weights to individual faces, thereby being the first to introduce facial emotion analysis into the study of political news dissemination. Third, whereas prior research relies on labor-intensive human annotation to measure the informational value of news, I introduced entity density and hyperlink density, together with article length, as automated proxy measures, with entity density validated using a recent open-source dataset (Zaczynska et al., 2025).

Empirically, the thesis made two contributions to the literature in understanding the supply and demand of media bias. First, Study 1 innovatively leveraged periods of close elections, characterized by median-centered public opinion alongside more voter polarization and stronger emotions (Howell & Justwan, 2013), to uncover how media outlets strategically adjust ideological bias in response to public opinion. Second, Study 3 addressed the divergence between professional journalists' and the public's evaluations of news informational value and was the first to introduce this divergence into the field of political communication.

Practical implications

For the public and any other audiences seeking to monitor high-frequency ideological bias of media outlets during elections, compared with existing methods, such as survey-based measures (Matsa, 2025), citing sources from party affiliations (Gentzkow &

Shapiro, 2010; Groseclose & Milyo, 2005), and topic-based indicators linked to partisan preferences (Haselmayer et al., 2017), my daily measurement in Study 1 from entity sentiment of candidates in news coverage could provide more timely insights.

For media outlets and journalists seeking greater dissemination of their news on social media, my findings suggested a need to align professional judgments of informational value more closely with audience perceptions. What is considered informative from a journalistic view is not always recognized or preferred by audiences. Although this divergence conflicts with traditional professional norms, it becomes unavoidable for outlets competing for public attention in an increasingly competitive media market. This thesis did not provide detailed insights into what leads audiences to perceive news as informational. However, it offered automated proxy measures of informational value that were faster than human annotation and less computationally intensive than large language models. Combined with emotion variables and other content characteristics from the literature, these proxies could help news producers objectively evaluate the characteristics of media posts and news articles for further research.

Limitations and future research directions

The first limitation is methodological. My contributions of high-frequency ideological bias, automated proxies for informational value, and facial emotion measurement with multiple faces are accurate and cost-efficient. However, rapid progress in multimodal large language models (LLMs) has already outperformed most traditional natural language processing (NLP) and computer vision (CV) methods. Furthermore, advances in small LLMs, alongside increasing GPU capacity, could diminish the computational efficiency advantages of the approaches in this thesis. The methodological contributions of this thesis may soon become less meaningful.

The second limitation concerns identifying the mechanisms linking election closeness to ideological bias. Although Study 1 provided observational evidence, it could not directly observe the newsroom decision-making processes that generated such bias. Future research could therefore complement the findings with evidence from newsrooms, such as interviews, surveys, and document tracing, to better examine the decision strategies.

The third limitation relates to the divergence between journalists' and the public's evaluations of news informational value. Although I argued that the audience's perceived informational value—rather than objective informational value—shaped media preferences, I did not identify the factors that lead audiences to judge a news item as more informational. Furthermore, there is a problem of reverse causality between respondents' perceived informational value and their preference. Addressing this question is an important direction for future research and has clear practical relevance for media producers.

Concluding remarks

Overall, this thesis develops automated measures of multiple forms of media bias in electoral news and advances understanding of both how outlets strategically produce these biases and which content characteristics the public prefers. The results document a leftward shift in newspaper coverage during U.S. presidential election and reveal ideological differences in how outlets respond to public opinion, with left-leaning outlets adopting a more neutral tone. This thesis also argues that audiences favor news they perceive as informational over news classified as informational by professional criteria, highlighting the importance for news producers to align more closely with public demand, especially under intense competition for online attention.

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