
WORKING PAPER

Joana Ferreira Cima

Marco Catussi Paschoalotto

Hélder Costa

Bruno Fernandes

“From Words to Votes: Decoding Sentiment in Brazilian Presidential Candidates' Tweets”

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Joana Ferreira Cima ^{a*}, Marco Catussi Paschoalotto ^b, Hélder Costa ^a and Bruno Fernandes ^a

^aCentre for Research in Economics and Management (NIPE), School of Economics, Management and Political Science, University of Minho, Braga, Portugal; ^bResearch Centre in Political Science (CICP), School of Economics, Management and Political Science, University of Minho, Braga, Portugal

*Corresponding author. Address: Universidade do Minho, Escola de Economia, Gestão e Ciência Política, Campus de Gualtar, 4710 - 057 Braga – Portugal (joana.cima@eeg.uminho.pt)

ORCID

Joana Ferreira Cima <https://orcid.org/0000-0002-2780-7467>

Marco Catussi Paschoalotto <https://orcid.org/0000-0003-2276-8531>

Hélder Costa <https://orcid.org/0000-0002-3265-1153>

Bruno Fernandes <https://orcid.org/0000-0002-5942-0566>

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From Words to Votes: Decoding Sentiment in Brazilian Presidential Candidates' Tweets

This study investigates the sentiment analysis of tweets from the four most influential presidential candidates in the 2022 Brazilian elections. Tweets from July 1 to October 30 were gathered using a custom Python script, and the sentiments expressed in these tweets were analyzed with the VADER sentiment analysis library. Two econometric models were estimated to study temporal shifts in sentiment and the effect of opponents' sentiment. Results showed strategic shifts in sentiment during different campaign phases. Lula da Silva, the election winner, showed significant increases in negative tweets during the second-round campaign and seemed to adjust his sentiment based on opponents' sentiments, suggesting the potential effectiveness of adaptable communication strategies. This study contributes to understanding political communication dynamics on social media and their potential impact on electoral outcomes.

Keywords: Elections; Sentiment Analysis; Twitter; Electoral Studies; Political Econometrics; Polarization

Introduction

In recent years, platforms like Twitter have been at the forefront of political activities. Research highlights Twitter's utility in understanding societal behaviours, particularly in politics (Tumasjan et al., 2011; Burnap et al., 2016; Lacatus, 2019; Gorodnichenko et al., 2021; Antypas et al., 2023).

While many studies have utilized sentiment analysis to forecast election outcomes based on voter sentiment (V-PC logic) (Gorodnichenko et al., 2021; Budiharto & Meiliana, 2018; Burnap et al., 2016; Hagemann & Abramova, 2023; Rita et al., 2023), the sentiment analysis starts to look to the candidates' tweets, to describe and analyse the variation of negative tweets in the electoral campaign (Yaquib et al., 2017) and there remains a clear void in understanding its political candidates to political candidates (PC-PC) capabilities and their potential influence on election outcomes.

Moreover, the thematic in electoral studies often revolves around specific contexts of sentiment analysis. These include exploring political polarization during elections (Giavazzi et al., 2023; Park et al., 2023), comparing sentiments between presidential

candidates (Budiharto & Meiliana, 2018), and notably, juxtaposing entirely opposing political figures (Proksch et al., 2019). However, to the best of our knowledge, no study has holistically combined these contexts to assess how sentiment in opposing candidates' tweets might influence another's propensity for negativity.

Given candidates' growing reliance on Twitter, understanding their interactive dynamics is crucial (Jungherr, 2016). It's essential to discern how a candidate's messaging might be influenced by another's, and how these exchanges influence public sentiment and, subsequently, election results.

Our research explores sentiment trends in tweets of presidential candidates and how opposition sentiment might sway a candidate's messaging. Using the 2022 Brazilian presidential election as a backdrop, marked by two polarized electoral sides and centrist factions, we seek patterns and triggers in candidate communication.

Analysing tweets' evolving tone during campaigns gives us insights into communication strategies, potentially revealing patterns like increased negativity closer to election days or periodic positivity waves. This can significantly shape the course of political rhetoric and future campaign strategies.

Moreover, in exploring how candidates' tweets respond to rivals' sentiment trends, we examine whether they echo negativity or counter with contrasting sentiments. This dissection of interactions not only highlights strategy details but also underscores the importance of flexible campaign strategies over rigid ones, as frequent adjustments in messaging in response to opponents are crucial.

In conclusion, our study aims to enhance electoral studies by emphasizing social media and sentiment analysis in politics, focusing on digital dynamics and factors influencing candidates' communication tone.

Materials and Methods

- **Case Study – Brazil**

Brazil is a presidential federal republic and democratic country, composed by 26 states plus one federal district and 5570 municipalities (IBGE. Brazilian Institute of Geography and Statistics, 2022), which the national president plays the political and executive power (Federal Constitution of Brazil, 1988). The presidential elections occur every four years

by direct votes and there is the possibility of two rounds, going to the second round the two most voted just in case of none of the candidates had achieved 50% plus one vote in the first round (TSE. Supreme Electoral Court., 2022).

It's important to notice that Brazil lived an extremism political moment in the 2022 presidential election, with Lula and Bolsonaro representing the extremes of the left and right political wings (Massuda et al., 2023).

Therefore, the 2022 Brazilian presidential election is an interesting case study, such USA and UK were in the past studies (Burnap et al., 2016; Yaqub et al., 2017).

- **Data collection**

The research team collected tweets from the four most voted presidential candidates in the 1st election round: Lula @lulaoficial (PT party – left side - winner); Bolsonaro @jairbolsonaro (PL party – far-right side – lost in the second round); Simone Tebet @simonetebetbr (MBD party – centre side – lost in the first round); and Ciro Gomes @cirogomes (PSB party – centre left side – lost in the first round). Sentiment analysis of tweets from Simone and Ciro was also considered in the second round due to the significance of the ‘losers’ support in the Brazilian runoff.

Tweets were collected using a custom Python script from July 1st to October 30th, 2022, with time periods divided in: a) July 1st to August 15th – previous the official first round campaign; b) August 16th to October 2nd – official first round campaign; and c) October 03rd to October 30th – official second round campaign. The first and second round's election dates were scheduled on October 2nd and on October 30th, respectively. The dataset includes the tweet's text, the date it was posted, and the tweet's author (candidate).

- **Sentiment analysis**

Each tweet's sentiment was analysed using VADER, a lexicon and rule-based tool designed for social media sentiments (Hutto and Gilbert, 2014). Given VADER's design for English, tweets in Portuguese were translated via Googletrans package for analysis. VADER assigns tweets a sentiment score from -1 (extremely negative) to +1 (extremely

positive), with scores at or below -0.5 considered negative, following the suggestion of VADER's creators.¹

- **Econometric specification**

- i. **Model I**

The first econometric model is a logit regression that aims to explain the temporal variation in the sentiment of the tweets, as it follows:

$$P(Y = 1|X) = \lambda(\theta) = \frac{\exp(\theta)}{1 + \exp(\theta)} \quad (1)$$

where $P(Y = 1|X)$ represents the conditional probability of a tweet being negative given a set of covariates X . $\lambda(\theta)$ represents the logistic transformation, and the term θ denotes the linear predictor, which is derived from:

$$\theta = X\beta \quad (2)$$

In this context, X is our design matrix encompassing the independent variables, which include candidate dummy variables, election phases, and interactions between the candidate and election dummy periods. The vector β captures the associated coefficients or effects of these independent variables. Election phases are defined as: 1 July until 15 August; 16 August until 2 October, and 3 October until 30 October. However, election day tweets were treated as missing data to ensure they did not influence the results.

Including the interaction term is crucial as it allows us to uncover an additional layer of complexity in the relationship between a candidate's identity, the campaign phase, and the likelihood of a negative tweet. This enables us to capture any strategic shift in a candidate's communication over time, offering a more subtle understanding of how campaign tactics can adapt to the dynamic political landscape.

- ii. **Model II**

The second model maintains the logistic regression structure of Model I but pursues a distinct objective: to explore if the average sentiment score of an opponent's tweets over

¹ See VADER Sentiment Analysis. VADER (Valence Aware Dictionary and Sentiment Reasoner) – <https://github.com/cjhutto/vaderSentiment>.

the previous week² affects a candidate's inclination to post negative tweets. While the dependent variable continues to measure the polarity of a tweet (1 for negative, 0 for non-negative), the independent variables in this model introduce a spillover factor from the opposition's tweets in the past seven days, campaign period dummy variables, and an interaction term capturing the relationship between the spillover effect and campaign periods.

The spillover variable was computed through a two-step process. Firstly, we calculated the daily median of the sentiment analysis compound for the opposing candidates. This daily compound sentiment measure assesses the overall sentiment of the opposing candidates' tweets for each day. The choice of the median, over the mean, was driven by the nature of the data. Sentiment expressed in tweets can range widely and include extreme values. In such circumstances, the median, a robust measure of central tendency resistant to outliers, provides a more accurate representation of the 'typical sentiment.' This offers significant advantages over the mean, which is heavily influenced by extreme values and can misrepresent the general sentiment when outliers are present. Secondly, we computed a 7-day lagged average of these daily measures, spanning from day -7 to day -1.³ This approach provides a time-averaged measure of the spillover sentiment from the opposing candidates leading up to the day in question.

Individual estimation by a candidate in this model allows for a more focused analysis that is less prone to potential econometric problems. Since the spillover variable is constructed based on the sentiments of the opponents' tweets, these sentiments can be correlated among candidates. If we estimated the model using all candidates at once, the spillover variable could be affected by multicollinearity, undermining the precision of our estimates. We believe we avoid this issue by estimating the model separately for each candidate. Both models are estimated using the statistical software Stata 17.

² The decision to analyse tweets from the last 7 days up to the day before is based on the idea that social media environment is highly dynamic, and the sentiment expressed in tweets can change rapidly. Therefore, very old tweets may no longer be relevant to the current situation. However, we will employ robustness checks using different periods.

³ During the runoff period, observations from October 2nd to October 9th, inclusive, were treated as missing data to ensure the spillover variable did not draw information from the first-round period.

Results

- **Results from Model 1: Temporal Shifts in Sentiment**

Table 1 presents the marginal effects derived from the estimation of the logit model, model 1. These results offer compelling insights into the temporal variation in the sentiment of tweets, shedding light on the shifts in the candidates' political communication strategies throughout different stages of the election campaign.

[TABLE 1 GOES HERE]

Our baseline period includes the official first-round campaign from August 16th to October 1st. This period serves as a crucial reference point for understanding the strategic shifts in communication among candidates as they sought to differentiate themselves and establish the foundations of their campaign narratives.

According to the logit model estimations, Lula da Silva's propensity for posting negative tweets decreased by 5.7 percentage points comparing to the previous period. Conversely, Simone Tebet's likelihood of expressing negativity in her tweets increased by 17.6 percentage points. No significant changes were observed for the other two candidates during this time frame.

The logit model estimated noteworthy strategic shifts as we transitioned to the second-round official campaign period from October 3rd to October 29th. Both Bolsonaro and Lula showed statistically significant increases in the probability of negative tweeting, with boosts of 9.3 percentage points ($p < 0.05$) and 4.08 percentage points ($p < 0.05$), respectively. This could suggest an escalating rivalry, with both candidates potentially adopting a more aggressive communication style in response to the rising pressures of the second-round campaign.

Simone Tebet, who did not continue to the second-round campaign, demonstrated a significant shift in her communication strategy. The logit model estimated that her tweets notably increased negativity by 17.6 percentage points during the first-round campaign period, from August 16th to October 2nd. However, after her exit from the race (October 3rd to October 29th), her tweets substantially decreased in negativity by 16.2 percentage points ($p < 0.01$). This marked shift towards fewer negative tweets could signify a strategic realignment, reflecting a return to a less combative discourse after the direct electoral competition ended.

These findings underscore the strategic malleability in political communication, showing how candidates may adjust their approach to suit different campaign periods. The significance of these temporal shifts provides key insights for future political campaigns, furthering our understanding of the dynamics of strategic communication in the political arena.

- **Results from Model 2: Spillover effects**

The marginal effects detailed in Table 2 are derived from the logit model, Model 2. This model was designed to scrutinize potential reciprocal effects—specifically, how the sentiment of one candidate's tweets is influenced by or reacts to the sentiment expressed in the tweets of their fellow contenders.

[TABLE 2 GOES HERE]

Initially, from July 1st to August 15th, the model does not identify substantial spillover effects for any of the candidates. This suggests that during the earliest campaign period, a candidate's sentiment in tweets was not notably affected by their competitors', or vice versa.

Transitioning into the primary campaign period—August 16th to October 1st—a shift in sentiment for some candidates becomes apparent. However, these variations lack statistical significance. Thus, it appears that during this vital campaign stage, a candidate's tweet sentiment remained independent of their opponents' sentiment.

Interestingly, a significant alteration in this trend emerges in the final campaign phase, from October 3rd to October 29th. Lula da Silva presents a notable deviation, as the probability of him posting negative tweets increases in line with a rise in the negativity of his opponents' tweets. This effect bears statistical significance at the 10% level, pointing towards a potential spillover effect. Conversely, other candidates do not demonstrate any significant spillover effects during this timeframe.

As a robustness check, we explored different time periods (5-day and 3-day windows) for the spillover variable to assess its impact on the results. Generally, the results proved robust, with a negative and significant coefficient observed in the case of candidate Lula.

In summation, Lula da Silva appears to be the exception, exhibiting a sentiment strategy in his tweets that seemingly responded to his opponents. This finding provides an

intriguing insight into the dynamics of political communication strategies on social media during election campaigns. However, these conclusions are preliminary, and further research is necessary to comprehensively understand these potential reciprocal effects.

Significantly, Lula da Silva, the candidate displaying this reactive sentiment strategy, was the election winner. This conclusion prompts fascinating considerations about the efficacy of an adaptable communication strategy. It posits that candidates who responsively adjust their messaging in reaction to their competitors might gain an advantage in the electoral arena. Nevertheless, these interpretations should be approached with caution. A successful political campaign is a complex orchestra of numerous factors, with tweet sentiment being only one instrument. To fully understand and evaluate the potential of such a communication strategy, in-depth investigations across broader elections and various political contexts would be invaluable.

Discussion and Conclusion

Elections are central political events in democratic nations, with politicians striving to collect the majority of votes. To achieve this, they leverage every democratic tool at their disposal. The emergence of social media has granted politicians an additional platform, enabling them to disseminate their ideologies and challenge those of their rivals (Gainous & Wagner, 2013; Enli, 2017).

Building on this trend and using sentiment analysis on Twitter data, our study explored Twitter dynamics of the 2022 Brazilian Presidential election. The incumbent, President Jair Bolsonaro, sought a second term, and his main competition came from former Brazilian President Lula da Silva. A considerable level of polarization characterized this particular election. Both contenders represented extreme positions of the political spectrum, and throughout the campaign, they attracted moderate voters from both the centre-right and centre-left of the spectrum (Brum et al., 2022). Meanwhile, candidates like Simone Tebet and Ciro Gomes, the third and fourth most-voted candidates in the first round, were victims of this polarization and saw their supporters moving to the strongest candidates (Rennó, 2022).

Given the heated political climate, Twitter became a key battleground for these candidates. Consequently, we evaluated these candidates' tweet sentiment and their evolution across the three periods.

Our results show that to appeal to others' supporters, Bolsonaro and Lula increased tweet negativity during the runoff. Such an uptick in negativity is consistent with Antypas et al. (2023), who posited that negative tweets propagate more rapidly within political communication on Twitter. This reflects 'negativity bias', where negative events and emotions impact the psyche more than neutral or positive ones (Baumeister et al., 2001)

This implies that negative messages could resonate more deeply with voters, influencing their perceptions and actions. Additionally, amplifying negative rhetoric can serve as a deliberate tactic within markedly polarised political landscapes. Politicians might use this approach to galvanize their base, reinforce partisan identities, and delineate themselves distinctly from their opponents, a sentiment echoed in studies by Huddy et al. (2015) and Iyengar et al. (2019).

Our analysis also explored how the sentiments expressed in opponents' tweets might influence a candidate's tweet sentiment. Drawing from the idea of competitive framing, where one party's messaging can shape their competitors' narratives, we used the concept of spillover effects. We found that the sentiment expressed in Lula's tweets was mainly influenced by the sentiments found in his opponents' tweets. Consequently, the observed increase in negative tweets during the runoff was, in part, a reaction to the negative sentiments of his competitors.

To interpret our results accurately, one must consider the political context at that time in Brazil. The country was very polarized, divided between supporters of the President and the former President (Massuda et al., 2023). Interestingly, many supporters were less driven by their favoured candidate's ideologies and more motivated by their disdain for the opposing candidate. The first round yielded unexpected results: neither did Lula secure over 50% of the votes, nor was Bolsonaro significantly behind Lula in the count. These outcomes reinforce the notion that both candidates perceived the runoff's outcome as uncertain. To consolidate votes from supporters of eliminated candidates and secure a majority, they escalated the negative sentiment in their tweets. Recognizing the volatile nature of the electoral outcome, Lula, in particular, adopted an aggressive strategy, leveraging the negative sentiment embedded in his opponents' tweets.

While our study has evaluated the sentiment dynamics within the tweets of the 2022 Brazilian Presidential election candidates, we acknowledge two primary limitations. First, our research focuses exclusively on Twitter, a platform that captures a subset of the

Brazilian electorate. Thus, the sentiments analyzed might not capture the full range of candidates' messages and the tweets of people associated with each one's message, but rather a specific subset tailored to certain voters on Twitter.

Second, though advanced, sentiment analysis may occasionally overlook linguistic undertones, like irony, leading to potential sentiment misclassifications. However, it is crucial to highlight that our study used state-of-the-art sentiment classification algorithms tailored for political discourse, thereby minimizing potential errors. Additionally, despite the focus on Twitter, the platform's significant influence on political communication ensures that our findings are relevant to the broader political conversation. While these limitations offer avenues for future research, we believe they do not undermine the integrity or significance of our current conclusions.

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Tables

Table 1: Model 1 estimation: Marginal effects

	Ciro	Bolsonaro	Lula	Simone
1jul-15aug	0.00932 (0.0283)	0.0359 (0.0343)	0.0569*** (0.0202)	-0.176*** (0.0409)
3oct-29oct	0.0518 (0.217)	0.0930** (0.0420)	0.0408** (0.0165)	-0.162*** (0.0582)
N	3389	3389	3389	3389

Robust Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Model 2 estimation

Spillover model – marginal effects				
	Ciro	Bolsonaro	Lula	Simone
1jul-15aug	-0.0780 (0.270)	0.288 (0.302)	0.112 (0.225)	-0.00752 (0.172)
16aug-1oct	0.291 (0.185)	-0.292 (0.234)	0.0679 (0.151)	0.0708 (0.307)
3oct-29oct		-0.814 (0.578)	-0.411* (0.241)	-0.400 (0.467)
<i>N</i>	870	473	1386	439

Robust Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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