Hate in the Tropics: Bolsonaro's Triumph and the Surge of Online Hate Speech in Brazil*

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Abstract

How does the advent of new information shape social norms and individual behavior? We delve into the aftermath of Bolsonaro's triumph in the 2018 Brazilian presidential election, examining its impact on the prevalence of online hate speech. Leveraging Twitter data spanning 2017 to 2019, we employ Natural Language Processing techniques to detect hate speech in tweets. To precisely identify the impact of Bolsonaro's election on online expressions of hate, we adopt a difference-in-differences methodology, utilizing the election outcome as an information shock. We document a significant surge in hate speech via Twitter after the elections, particularly in municipalities where Bolsonaro's support was comparatively low. We observe similar results in the individual-level analysis, indicating that intensive and extensive margins of hate speech contributed to the overall increase. We interpret these findings through the lens of a belief updating mechanism, emphasizing the process of revising social norms that dictate what is deemed acceptable to express (or not) in public. This interpretation is reinforced by the differential impact of the election based on the targets of hate speech. We find no differential effect on political hate and insults, but we observe a significant effect on homophobia, racism, and sexism – speeches that Bolsonaro is widely known to hold.

Keywords: Hate speech; Social Media; Social Norms

JEL Codes: D72, D83, J15, Z13

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1 Introduction

Social norms are unwritten rules and beliefs governing attitudes and behaviors considered acceptable (or not) in a particular social group or culture. Social norms give us an expected idea of how to behave and function to provide order and predictability in society. Notwithstanding, social norms are not inherently good - examples of harmful social norms are revenge or genital mutilation. Many scholars have shown that social norms tend to be stable over time - Fernandez (2007), Giuliano (2007), Alesina et al. (2013). However, a growing number of studies show how certain events can trigger quick changes in the prevailing social norms (Bursztyn et al., 2020). These events can be very different in nature, ranging from famines to the arrival of new information, e.g., electoral outcomes.

Social norms establish standards on different aspects of life, ranging from contractual relationships to conceptions of right and wrong, reciprocity, and fairness. A relevant type of social norm regards the acceptability of certain speeches, including hate speech. The latter relates to offensive discourse targeting a group or an individual based on inherent characteristics. Naturally, these speeches destroy social cohesion and generate conflict, with consequent repercussions on citizens' lives and well-being.

In this paper, we study the effect of the Brazilian presidential election of Jair Bolsonaro on the prevalence of online hate speech. Bolsonaro, sometimes called "the Trump of the Tropics," is widely recognized for his contentious viewpoints, encompassing homophobia, racism, and sexism.[1] Therefore, following the Bursztyn et al. (2020)'s argument, we posit that Bolsonaro's victory in the 2018 election may trigger a quick update of the prevailing social norm governing what types of speech are socially acceptable.

Identifying a *causal effect* of the election of Bolsonaro on hate speech is not straightforward. Observing a change in the latter could be a cause of the election results, or other elements might affect both events. Our identification strategy relies on considering the 2018 election outcome as an *information shock* - new and potentially unexpected political information. Following Ajzenman et al. (2023) and Albornoz et al. (2022), we assume this shock varies by municipality, allowing us to identify its marginal effect. Bolsonaro's victory surprised

[1] To illustrate this point, consider a sample of Bolsonaro's statements: "*I would be incapable of loving a homosexual son*," "*The scum of the earth is showing up in Brazil as if we did not have enough problems of our own to sort out*," and (speaking to a Brazil Congresswoman) "*I would not rape you because you do not deserve it*." Sources: CNBC web portal, https://www.cnbc.com/2018/10/29/brazil-election-jair-bolsonaros-most-controversial-quotes.html; Reuters, https://www.reuters.com/article/us-brazil-politics-bolsonaro-factbox-idUSKCN1II2T3; AP News, https://apnews.com/article/1f9b79df9b1d4f14aeb1694f0dc13276; USA Today, https://eu.usatoday.com/story/news/world/2018/10/29/jair-bolsonaro-brazils-new-president-has-said-many-offensive-things/1804519002/. Access date: June 2023.

the Brazilian community, which suggests that considering the election outcome as an information shock is a realistic assumption. Precisely, Bolsonaro got 46% of the votes in the 1º round of the election and 55% in the 2º round. The opinion polls conducted by diverse companies in the days before the election estimated that Bolsonaro's vote share would be approximately 35% for the 1º round, and only one polling company estimated a vote share above 40%.[2]

To conduct the empirical analysis, we propose two difference-in-differences design models. First, we split municipalities into control and treatment groups according to the vote share received by Bolsonaro in the 1º round of the election. Specifically, any municipality in which Bolsonaro's vote share is lower (higher) than the national outcome, i.e., 46% of the votes, falls into the treatment (control) group. Second, as in Albornoz et al. (2022), we propose a difference-in-differences design with a continuous treatment variable - see Callaway et al. (2021) for a theoretical reference. In this case, the treatment variable is Bolsonaro's vote share in each Brazilian municipality, which measures the local incidence of the information shock, that is, the 1º round election outcome.

Studying hate speech, as opposed to hate crimes, presents some advantages. Since hate speech is directly observable, it is not subject to underreporting. Furthermore, it differs from hate crimes in cost and timing, as the perpetrator immediately pays the cost of expressing hate. Similarly, social media content has been shown to affect real-life events, such as the propagation of anti-refugee and immigrant incidents (Müller and Schwarz, 2021; Cao et al., 2023) and social distancing during the pandemic (Ajzenman et al., 2023). In practice, we rely on data from the widely used social media platform Twitter in the period spanning between July 2017 and December 2019.[3]

We measure hate speech using two text analysis techniques - see Gentzkow et al. (2019) and Ash and Hansen (2023). Firstly, we fine-tune a pre-trained *Bidirectional Encoder Representations from Transformers* (BERT) model, which allows us to classify tweets as with or without hate content. Our classification model was trained using the Portuguese BERT model introduced by Souza et al. (2020) and the hate speech dataset presented by Fortuna et al. (2019). Secondly, we rely on a dictionary-based method to introduce a multi-level classification of hate speech. Our goal is to classify hate speech based on its targets, so we consider these five categories: political hate, homophobia, racism, sexism, and insult.

We document an increase in online hate speech at the national level following the 2018 presidential election. This increase is mainly driven by municipalities where Bolsonaro *lost*.

[2]Source: Wikipedia, https://en.wikipedia.org/wiki/Opinion_polling_for_the_2018_Brazilian_general_election, access date: June 2023.

[3]This time frame covers approximately one year leading up to the electoral rally and another year following the assumption of office by the 38th Brazilian president.

Furthermore, our findings suggest that the magnitude of the information shock, i.e., the election results, is crucial to explaining the extent of the rise in hate expressions. The largest increase in hate speech is observed in municipalities where Bolsonaro was particularly unpopular. We interpret these findings through the lens of a belief update mechanism.

The information shock, induced by the election outcome, allowed individuals living in a relatively anti-Bolsonaro municipality to reassess their beliefs regarding socially acceptable speeches. Once the social norm is updated, these individuals may feel justified in expressing controversial and hateful viewpoints through social media platforms, even if they reside in a municipality where the prevalence of such behavior was relatively low before the elections.

This interpretation of the results is reinforced when analyzing the differential impact of Bolsonaro's victory on each type of hate speech – namely, homophobia, racism, political hate, insult, and sexism. We do not find such a differential impact for political hate and insults, but we find it for homophobia, sexism, and racism. While finding an effect on political hate might be interpreted as a sign of growing polarization, the effects on homophobia, sexism, and racism underline a social norms channel. That is, having a harmful speech that targets specific groups, such as the LGBT community, women, and different races, highly depends on the social acceptability of such behavior.

Since our rich dataset allows us to follow Twitter accounts over time, we further explore *who* is driving the results. We find that both the intensive and extensive margins of hate speech contributed to explaining this phenomenon. In other words, users posting tweets with hate content before the elections increased the frequency of these tweets after the elections (i.e., intensive margin). Similarly, we also observe some Twitter users who post hate speech tweets only after the elections (i.e., extensive margin), especially in the municipalities where Bolsonaro lost.

Related Literature. We contribute to the economic literature that studies the impact of political information on social norms, particularly the literature documenting that political changes can lead to fast changes in social norms and behavior. Bursztyn et al. (2020) show that Trump's victory increased individuals' willingness to express xenophobic opinions. Similarly, Albornoz et al. (2022) argue that the Brexit referendum caused a shift in the social acceptability of xenophobic expressions, such as hate crimes. Compared to the previous studies, our setting presents several differences and advantages. First, our results are representative of one of the largest developing countries, while Bursztyn et al. (2020) focus on one metropolitan area in the US and Albornoz et al. (2022) study a very extreme type of hate expression (i.e., hate crimes). Second, the stakes for expressing hate differ in their and our contexts.

Twitter users who post hate speech are immediately available for social scrutiny, especially friends, whereas, in Bursztyn et al. (2020), the information is said to be posted at a later date in a likely unknown website and, in Albornoz et al. (2022), perpetrators only pay a cost if they get caught. Third, since we have an (unbalanced) panel of individuals, we can observe the evolution over time at the individual level and explore intensive vs. extensive margins.

In broader terms, our paper speaks to the economic literature on social norms and conformity. We analyze the effects of a social norm update, departing from the literature that studies its persistence (see Bisin and Verdier (2011) for a survey). In addition, our paper contributes to the literature that examines the interplay between norms and political institutions (Acemoglu and Jackson (2017)) or behaviors (e.g., Gerber et al. (2008), DellaVigna et al. (2016), and Perez-Truglia and Cruces (2017)). Finally, our paper connects with the literature on social norms by studying their geographical variation within a country and analyzing high-frequency individual-level data.

This paper speaks to the literature linking social media and expressions of hate, particularly against minority groups.[4] Müller and Schwarz (2023) find a positive relationship between Twitter usage and ethnic hate crimes since the presidential election of Donald Trump in the US, pointing out that social media may enable people with extreme viewpoints to find a source of legitimacy. Bursztyn et al. (2019) show that social media increased ethnic hate crimes in Russian cities with high pre-existing anti-immigrant sentiments. Müller and Schwarz (2021) find evidence that social media affects the propagation of anti-refugee incidents in Germany. Focusing on sex crime, Bhuller et al. (2013) document an increase in this type of crime associated with the roll-out of broadband internet in Norway. This piece of literature covers social media platforms like Twitter and Facebook but focuses mainly on xenophobia and ethnic hate crimes. This paper considers a wider definition of expressions of hate, encompassing its different targets. In contrast to the existing literature, this paper focuses on hate speech rather than hate crime and online rather offline expressions of hate.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents the identification strategy, and section 4, the results at the municipality and individual levels. Section 5 concludes.

[4] In addition to this literature, other research has linked diverse types of traditional media to violence, for example, Dahl and DellaVigna (2009), Card and Dahl (2011), Yanagizawa-Drott (2014), DellaVigna et al. (2014), and Ivandic et al. (2019), among others.

2 Data

In this paper, we aim to understand how the 2018 presidential election of Bolsonaro affected online hate speech in Brazil. An advantage of this setting is that online hate speech, as opposed to hate crime, can be directly observed and quantified and, thus, is not subject to changes in reporting. Online hate speech also differs from hate crime regarding its cost and timing. In the former, the perpetrator immediately pays the cost of expressing hateful content. On the other hand, a hate crime must be reported and processed by justice before the perpetrator pays its cost.

Our primary data source is the social media platform formerly known as Twitter, from which we measure online hate speech at the municipality level and in the period under study. We combine the data we retrieve from Twitter with three types of administrative data. First, we use the 2018 election results at the municipality level, whose data source is the Superior Tribunal Court (in Portuguese, *Tribunal Superior Eleitoral* - TSE), the highest structure within the Brazilian Electoral Justice system. In addition, we rely on geospatial data from the Brazilian Institute of Geography and Statistics (in Portuguese, *Instituto Brasileiro de Geografia e Estatística* - IBGE) to geo-locate tweets and election results. Lastly, we use the 2010 Population Census in Brazil microdata from IBGE to construct demographic variables aggregated at the municipality level.

2.1 Twitter data

Twitter, currently re-branded as X, was an online platform allowing users to publish short messages of a maximum of 140 characters on their profiles. With one of the largest Twitter user bases in the world, Brazil is an appealing case of study for online activity - in this case, related to Twitter users' speech. In January 2022, Brazil ranked fourth worldwide regarding the number of Twitter users, with an estimated 19 million active accounts (after the United States, Japan, and India).[5] Given our purposes, it is important to note that most of the Brazilians who were online in 2022 used social media for news (64%) and political discussion (78%).[6]

In the empirical analysis, our main variable of interest is the proportion of tweets classified

[5] Source: Statista web portal, https://www.statista.com/statistics/242606/number-of-active-twitter-users-in-selected-countries/, access date: June 2023.

[6] Sources: Digital News Report, 2022, Reuters Institute & University of Oxford, https://reutersinstitute.politics.ox.ac.uk/digital-news-report/2022/brazil; Statista web portal, https://www.statista.com/statistics/1326518/brazil-social-media-users-political-discussion/, access date: June 2023.

as hate speech per municipality (or individual) and date. To construct this variable, we rely on Natural Language Processing (NLP) techniques. Precisely, we train a pre-trained *Bidirectional Encoder Representations from Transformers* (BERT) model, and we construct a multi-level classification of hate based on a dictionary method. By integrating these two NLP techniques, we produce two independent measures of predicted hate speech – which we use to check the robustness of the main results of this paper. Moreover, the dictionary classification enables us to analyze the differential effect of Bolsonaro's victory on each type of hate speech – obtaining enriching evidence on the mechanism behind the main results. The next paragraphs describe how we collected and processed Twitter data to construct the corresponding variables.

Data collection. We use the Twitter Application Programming Interface v2 (Twitter API v2) to collect our data. Specifically, we rely on the *v2 full-archive search endpoint*, which gives access to the entire history of publicly available (and yet undeleted) tweets. We retrieve all the tweets, net of retweets, which satisfy three conditions specified in the Twitter query. First, tweets must be written in Portuguese. Second, tweets must provide geo-location information and be located in Brazil. Lastly, tweets must belong to the period between July 2017 and December 2019, both included. As the daily amount of data retrieved by this query is around 300.000 tweets, we further restrict the Twitter query to retrieve only tweets posted on any Monday belonging to the mentioned period. This query imposes two main assumptions on our tweets' sample. We assume that (i) tweets posted on any Monday and (ii) geo-located tweets are representative samples of the tweets' universe. Appendix A.1 provides supportive evidence for these assumptions and complementary information to this section.

Data processing. We extract relevant content from the tweets' text, which will serve as input for the hate speech detection task. We anonymize user mentions and URL links but keep hashtags in their native Twitter format, as they may contain relevant information. We drop all tweets containing only links and (or) user mentions and those posted by accounts created after 2018. The reason for the latter is to exclude accounts potentially created in the context of the electoral rally from the analysis. Before classifying tweets with our BERT model, we perform an additional step in the data processing. Precisely, we exclude punctuation marks, stop-words, and multimedia items. We do not remove negative stop-words that may change the statement's meaning: "*mas*" (but), "*nem*" (neither), "*não*" (no), "*sem*" (without), and "*fora*" (out).

Hate speech detection. We rely on NLP techniques to detect hate speech in our tweets' database.[7] We implement two classification techniques. Firstly, we train a pre-trained BERT model (Devlin et al., 2018) on a dataset specific to the hate speech detection task. This process is known as *fine-tuning* a pre-trained model. Once fine-tuned, our BERT model is able to classify tweets as having or not hate speech, i.e., it leads to a binary classification of tweets. Secondly, we construct a dictionary that enables us to obtain a multi-level classification of hate speech. Precisely, we classify tweets into five categories, which are associated with specific hate targets. In the next paragraphs, we discuss each method. Appendix A.2 provides further details on the hate speech detection task and the resources utilized.

BERT model fine-tuning. We use *BERTimbau*, a BERT model for Brazilian Portuguese by Souza et al. (2020), and train it on a dataset of tweets in Portuguese, by Fortuna et al. (2019). Souza et al. (2020) present *BERTimbau*, a BERT model for Brazilian Portuguese, in two sizes, Base and Large. In this paper, we fine-tune BERTimbau-Base for the hate speech detection task. The authors trained their model on the *brWaC corpus* by Wagner Filho et al. (2018) and two NLP tasks, Masked Language Modeling (MLM) and Sentence Prediction (NSP).

In their paper, Fortuna et al. (2019) collected 5668 tweets in Portuguese through Twitter API from January to March 2017. The authors provide two annotation schemes for the dataset, a binary and a hierarchical multiple classification. This paper uses the binary classification dataset to fine-tune the mentioned BERT model, in which 31.5% of the tweets were annotated as "hate speech." To construct it, three (Portuguese native) annotators labeled every tweet as "hate speech" or "not hate speech," and the authors applied the majority vote to determine the final annotation of each tweet.

Before fine-tuning, we divide the dataset between 80% for training, 10% for validation, and 10% for testing. In NLP applications, the performance of a model in a given task is directly influenced by the characteristics of the training sample. In the case of Fortuna et al. (2019)'s dataset, as in other datasets on hate speech detection, a class imbalance exists. Tweets annotated as "hate speech" constitute the minority class. As class imbalance may affect a model's performance in a text classification task, we use a Random Oversampling technique to equalize the number of tweets per class in the training sample (Mohammed et al., 2020).[8] Our model attains an overall accuracy of 77% in both the validation and test samples.

[7] See Ayo et al. (2020) for a review on hate speech detection via machine learning techniques.

[8] Random oversampling involves transforming the existing data to adjust the class distribution. It consists of randomly selecting examples from the minority class and adding them to the original dataset.

Dictionary method. We introduce a dictionary-based method for the detection of hate speech in tweets. We create this dictionary with the specific aim of classifying hate speech according to its targets. Precisely, we consider five distinct categories of hate speech: "political hate," "homophobia," "racism," "sexism," and "insult". The class "political hate" is less common in the existing literature but highly relevant to the context of our study.

For the dictionary construction, we draw upon top-frequency words associated with each type of hate speech from three different papers. First, we use the hierarchical classification of hate speech presented by Fortuna et al. (2019). Second, we employ the multi-level classification of toxicity in tweets provided by Leite et al. (2020). Lastly, we enrich the class "homophobia" by using information in Pereira (2018). In addition, we consider a tweet to contain "hate speech" if it includes at least one of the hate categories listed in the dictionary.

Data classification. After training the BERT model and constructing the dictionary, we use them to detect hate speech in the tweets we collected. As a result of the BERT classification, we construct a binary variable 0/1, named "predicted hate speech." As a result of the dictionary classification, we construct six binary variables 0/1, named "predicted hate speech," "predicted political hate," "predicted homophobia," "predicted sexism," "predicted racism," and "predicted insult." Then, we use the tweet-specific geo-location information to map each tweet to the Brazilian municipalities based on latitude and longitude through IBGE's geospatial shape files. Finally, we compute the proportion of tweets containing different types of hate speech by municipalities (or individuals) over time, which are the main outcome variables of this paper.

2.2 Administrative data

The election result we use as an information shock is the vote share obtained by Bolsonaro in the 1º round of the 2018 Brazilian presidential election. The Superior Tribunal Court (TSE) has provided official data at the municipality level on all election results in Brazil since 1994. Given that TSE's records do not contain the geo-coordinates of the electoral districts, we rely on geospatial data from the Brazilian Institute of Geography and Statistics (IBGE) to determine their location. IBGE provides Brazilian geospatial data at country, state, and municipality levels. Lastly, we use microdata from the 2010 Population Census in Brazil, the last available for the pre-Bolsonaro period. Consistently with our analysis unit, we aggregate the census microdata at the municipality level.

2.3 Descriptive statistics

We study how the 2018 Brazilian presidential election influenced online hate speech. To accomplish this, we create two longitudinal datasets of geo-located tweets spanning from July 2017 to December 2019.

In the first dataset, the time unit is a day t - for any Monday included in the tweets' sample - and the cross-sectional unit is a Brazilian municipality m. The main variable is the proportion of tweets classified as hate speech for a given date t and municipality m. Brazil is divided into twenty-six states and one federal district. Each sub-national entity is further divided into municipalities, and Brazil currently has 5570 municipalities. For the empirical analysis, we include any municipality for which we observe (i) at least 10 tweets daily and (ii) at least 10 times during 2017-2019. This leaves us with approximately 1500 municipalities. The longitudinal dataset at the municipality level is unbalanced, with some municipalities present over the entire period and others for which Twitter data is relatively more scarce. On average, we observe each municipality on approximately 100 Mondays (with a standard deviation of 37 days).

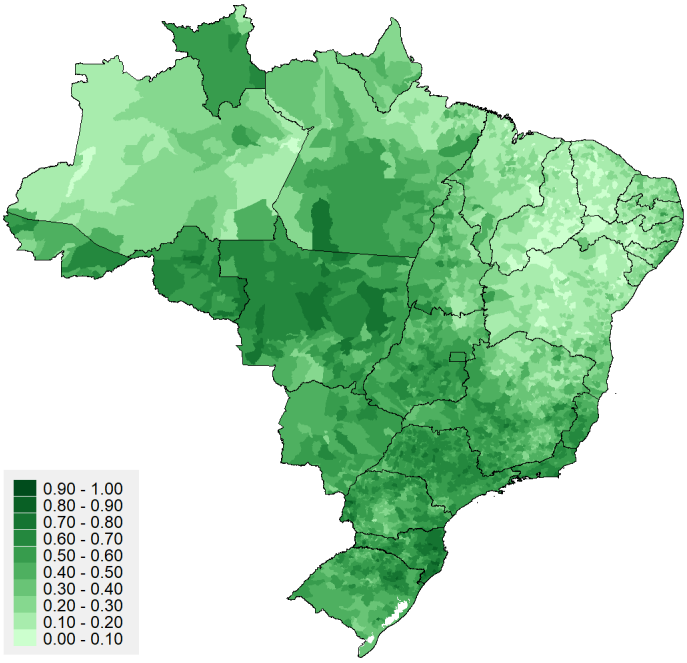
In the second longitudinal dataset, the time unit is a month t, and the cross-sectional unit is a Twitter user i. We include any Twitter user whose tweets are geo-located in no more than two different municipalities. When an individual appears in two locations, we implicitly assume she is engaged in an activity (such as working or studying) in a municipality different from where she lives. The longitudinal dataset at the individual level is also unbalanced, as Twitter activity significantly varies for various individuals. In the regression analysis, we further restrict our attention to the sub-sample of users (i) who posted tweets in the pre and post-election periods and (ii) such that we observe at least 5 tweets per user per month. On average, we observe 190 tweets for each Twitter user distributed over approximately 12 months (6 months before and 6 months after elections).

This paper builds upon two fundamental observations. Firstly, the presidential election, which we consider an information shock, did not uniformly affect all Brazilian citizens. Instead, we observe a geographical variation in Bolsonaro's vote share, which helps us to identify the effect of interest. Secondly, the evolution of online hate speech was not consistently constant throughout the period. Regarding the first observation, Figure 1 shows that Bolsonaro's popularity varied across states and municipalities. Specifically, Bolsonaro's vote share was between 3% and 79% in the 1º round of the 2018 presidential election, which is the result we use in our empirical strategy to measure the information shock. As can be seen, the corresponding map for the 2º round results shows a similar geographical pattern. In Appendix

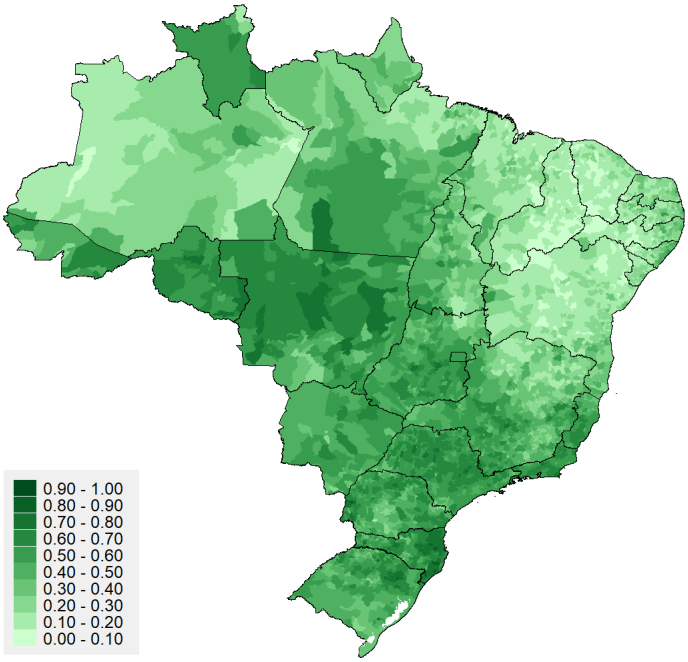
A.3, we present the (bimodal) distributions of these vote shares at the municipality level.

Figure 1: Bolsonaro's vote share at the municipality level.

a. 1º Round, October 7th.

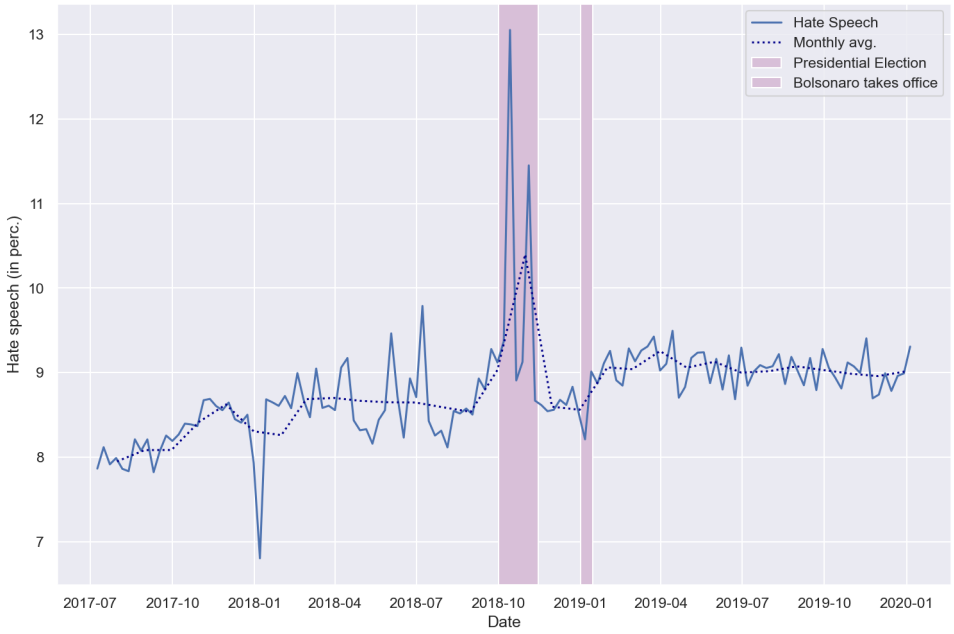


b. 2º Round, October 28.



As for the second observation, Figure 2 shows the proportion of Brazilian tweets classified as hate speech in the period under study. The solid line corresponds to the raw data, consisting of the daily proportion of hate speech tweets, whereas the dotted line corresponds to the monthly average of hate speech. The shadow areas in the graph delimit the periods in which (i) the Presidential Election took place and (ii) Bolsonaro took office.[9] As can be seen, there was a sharp increase in hate speech during this period. The hate speech peaks on the data correspond to the closest (but later on time) date in our sample to the 1º and 2º rounds of the election.[10]

Figure 2: Evolution of hate speech in Brazilian tweets, 2017-2019.



Note: The variable Hate speech is, for each date, the percentage of tweets classified as hate speech by the BERT model .

Importantly, Figure 2 reveals that hate speech through Twitter increased post-election. The average proportion of hate speech from July 2017 to July 2018 was 8%, whereas it was

[9] Specifically, the 1º and 2º rounds of the presidential election took place on October 7th and 28th, respectively. Bolsonaro took office as Brazil's 38th president on January 1, 2019.

[10] There exist two other (although smaller) peaks in the data, during June and July 2018, corresponding to dates when Brazil's football team played a match in the 2018 World Cup. Figure 6 in the Appendix shows that these peaks also correspond to a sharp increase in Twitter activity. Specifically, the daily amount of tweets is around 50% higher during the period relative to the average. It is also worth noticing that the period with lower levels of hate speech corresponds to dates around the 2018 New Year break. Remarkably, this sharp decrease in hate speech was not observed around the 2019 New Year break, as the date coincides with when Bolsonaro took office.

9% from January to December 2019. This is approximately equivalent to an increase of 3000 tweets containing hate speech on an average day. Note that the above figure is constructed by aggregating hate speech at the national level, so it does not explore the sub-national evolution of hate speech over the period. The rest of this paper aims to answer whether this evolution was uniform (or not) across municipalities and why.

3 Empirical strategy

We aim to estimate the effect of Bolsonaro's election - and the electoral rally - on hate speech. In the previous section (see Figure 2), we showed that hate speech on Twitter increased after Bolsonaro's election in comparison to the pre-election period at the national level. However, this is not sufficient to conclude that his election is to blame. It is possible that the election result responded to the rise in hate speech or that some other social phenomena are causing both the increase in hate speech and the political movement to the right.

The fact that these are national elections leaves us with no clear control group where Bolsonaro is not elected for president. However, his popularity varies across states and municipalities (see Figure 1). We can then follow Albornoz et al. (2022) and exploit this differential informational shock to study whether hate speech increased relatively more in some places than others. First, we separate the municipalities based on the results of the 1º round of the elections: those where Bolsonaro got *at least* or *at most* the percentage of votes he got at the national level, 46%. For the sake of simplicity, we say that Bolsonaro "lost" the 1º round of elections (or simply, lost) in a municipality if his vote share was lower than 46%. Otherwise, we say that Bolsonaro "won" the election in that municipality. Thus, we perform a difference-in-differences analysis. Formally, we regress,

$$Hate_{mt} = \alpha_0 + \alpha_1 * Post_t * Lost_m + \delta_t + \pi_m + \epsilon_{mt} \tag{1}$$

where $Hate_{mt}$ is the share of tweets that contain hate speech in municipality m and date t, $Post_t$ is a dummy variable that takes the value one after the elections, $Lost_m$ is a dummy variable that takes the value one for the municipalities where Bolsonaro lost the elections (that is, his vote share was lower than 46%), δ_t and π_m are time and municipality fixed effects, and ϵ_{mt} is a municipality-time specific error term. In this case, the identifying assumption is the traditional parallel trends assumption. That is, in the absence of the information shock, the difference in hate speech between municipalities where Bolsonaro won and lost the elections

is constant over time.

Since our rich dataset allows us to follow Twitter accounts over time, we can further analyze hate speech at the individual level. Indeed, the availability of data at the individual level is an advantage of this paper, compared to Albornoz et al. (2022) and Carr et al. (2020), who studied hate crime at a more aggregate level. The purpose of the individual-level regressions is twofold. Firstly, it allows us to rule out the possibility that the rise in hate speech is driven by a change in the composition of the users before and after the elections. Secondly, individual data allows us to explore the intensive and extensive margins of hate speech. In other words, is the increase in hate speech driven by people already tweeting hate content before the elections, i.e., intensive margin, or is it caused by people who had not tweeted hate content before, i.e., extensive margin? Formally, we regress,

$$Hate_{imt} = \tilde{\alpha_0} + \tilde{\alpha_1} * Post_t * Lost_{im} + \delta_t + \gamma_i + \epsilon_{imt} \tag{2}$$

where $Hate_{imt}$ is the share of tweets that contain hate speech of account i in municipality m at month t, $Post_t$ is a dummy variable that takes the value one after the elections, $Lost_{im}$ is a dummy variable that takes the value one for the accounts located in municipalities where Bolsonaro lost the elections, δ_t and γ_i are time and user fixed effects, and ϵ_{imt} is an account-municipality-time specific error term. Our coefficients of interest are $(\alpha_1, \tilde{\alpha_1})$, which, given parallel trends, capture the *average treatment effect* (ATE).

Finally, we also exploit the continuous variation in Bolsonaro's vote share across municipalities. To do this, we replace $Lost_m$ in equation (1) and $Lost_{im}$ in equation (2) with the actual vote share Bolsonaro received in each municipality, $VoteShare_m$ and $VoteShare_{im}$. Formally,

$$Hate_{mt} = \beta_0 + \beta_1 * Post_t * VoteShare_m + \delta_t + \pi_m + \epsilon_{mt} \tag{3}$$

and,

$$Hate_{imt} = \tilde{\beta_0} + \tilde{\beta_1} * Post_t * VoteShare_{im} + \delta_t + \gamma_i + \epsilon_{imt} \tag{4}$$

where $Hate_{mt}$ ($Hate_{imt}$) is the share of tweets that contain hate speech in municipality m and date t (for user i in month t), $Post_t$ is a dummy variable that takes the value one after the elections, $VoteShare_m$ ($VoteShare_{im}$) is the share of votes obtained by Bolsonaro

in municipality m (where individual i is located), δ_t, π_m and γ_i are time, municipality and individual fixed effects, respectively, ϵ_{mt} is a municipality-time specific error term, and ϵ_{imt} is an account-municipality-time specific error term.

In both cases, our coefficients of interest are $(\beta_1, \tilde{\beta}_1)$, which capture the *average causal response* (ACR) on the treated to an incremental change in the dose, where the dose is the share of votes obtained by Bolsonaro in the municipality. The main identification assumption, in this case, is the strong parallel trends. It requires that, for all doses, the average change in hate speech over time across all municipalities that received a given dose is the same as the average change in hate speech that would have occurred over time for all municipalities that experienced a different dose - see Callaway et al. (2021).[11] Notice that, by definition, $(\alpha_1, \tilde{\alpha_1})$ in equations (1) and (2) and $(\beta_1, \tilde{\beta}_1)$ in equations (3) and (4) have opposite signs: while the former capture the effect of $Lost_m = 1$, which depend negatively on Bolsonaro's vote share, the latter are proportional to it.

4 Results

In this section, we present the main results of this paper. First, we document that hate speech increased after the 2018 presidential elections, especially in the municipalities where Bolsonaro lost. Then, we present the results at the individual level, indicating that both the intensive and extensive margins of hate speech contributed to this phenomenon.

4.1 Municipality level

Before presenting the regression results, let us describe the municipalities that are in the treatment and control groups according to equations (1) and (2). Figure 3 below is an analogous figure to Figure 2, but now splitting the hate speech trends between treatment and control groups.[12]

The green lines correspond to the daily and monthly proportion of Brazilian tweets classified as hate speech by the BERT model for the municipalities in which Bolsonaro got at least 46% of the votes in the 1º round of the 2018 presidential election, i.e., where $Lost_m = 0$. On the contrary, the red lines correspond to the municipalities where Bolsonaro's vote share was

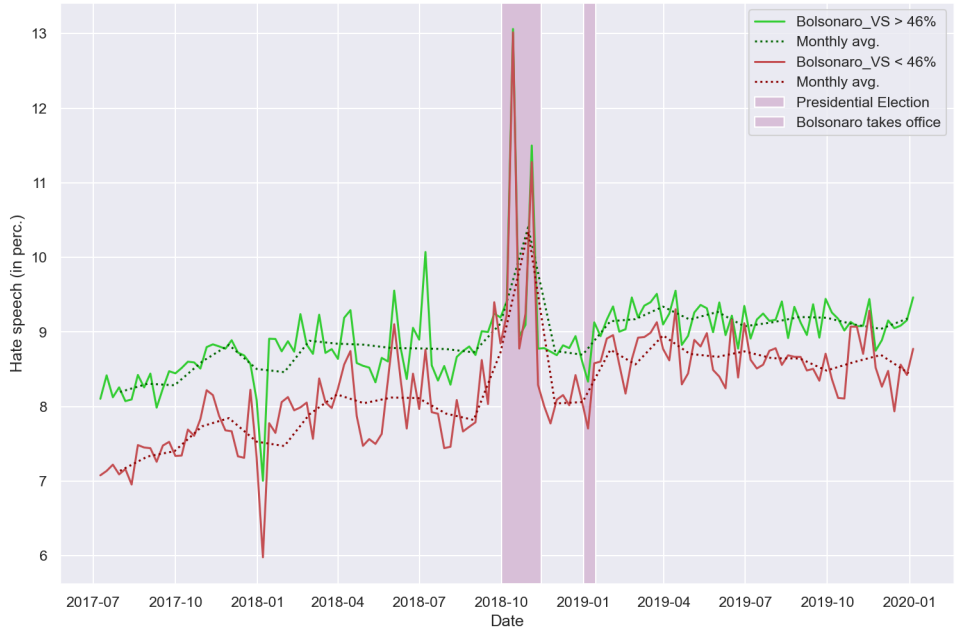
[11] Formally, let d be the dose and Y_t be the potential outcome in time t. Then, the strong parallel trends assumption implies that for all d in D: $E[Y_t(d) - Y_{t-1}(0)] = E[Y_t(d) - Y_{t-1}(0)|D = d]$.

[12] In Appendix A.3, we present analogous graphs to Figures 2 and 3 but with hate speech aggregated at the monthly level. That is, only plotting the dotted lines in Figures 2 and 3.

at most 46%, that is, where $Lost_m = 1$. Again, the shadow areas in the graph delimit the periods in which the presidential election took place and Bolsonaro took office.

Importantly for our identification strategy, the gap between hate speech pre-trends for treatment and control groups seems constant over time, i.e., pre-trends are parallel. Furthermore, the prevalence of hate speech in municipalities where Bolsonaro won and lost seem to respond similarly to shocks; for example, both decreased around the 2018 New Year's Eve and increased during the 2018 World Cup (in July). After the elections and taking up of office by Bolsonaro, the previously constant gap was reduced significantly, with the municipalities where Bolsonaro was least popular increasing the most.

Figure 3: Evolution of hate speech in Brazilian tweets, 2017-2019. Municipalities, by the 2018 election result.



Note: Percentage of tweets classified as hate speech by the BERT model split by Bolsonaro's vote share in the 1º round of election.

Let us turn to the regression results. Table 1 answers the main question of this paper, *how the 2018 presidential election of Bolsonaro affected online hate speech*. The first column in the table corresponds to the classic difference-in-differences estimation, presented in equation (1). The second column corresponds to the difference-in-differences model with a continuous treatment variable, i.e., equation (3). In the two models, we define $Post_t$ as a dummy

variable, taking a value of zero between July 2017 and July 2018 (both included) and one between January and December 2019 (both included). In the main specification, we drop the period between the start of the election rally and the day when Bolsonaro took office to avoid contamination from politically related hate. Appendix A.3 confirms that our results are robust to changes in the definition of $Post_t$.

Column (1) shows the increase in hate speech after the elections that we observe in Figures 2 and 3 was more pronounced in municipalities where Bolsonaro lost (0.062 standard deviations higher than the municipalities where Bolsonaro won). Consistent with this evidence, column (2) shows that the proportion of hate speech decreases as the share of votes for Bolsonaro increases. As the estimate in column (2) comes from a difference-in-differences model with a continuous treatment variable, provided the strong parallel trends assumption, the coefficient is a positively weighted average of the average causal response $ACR(d)$ parameters across doses. Thus, on average, across doses, an increase of 1 standard deviation in $VoteShare_m$ decreases hate speech in that municipality by 0.025 standard deviations.

Table 1: Municipality level regressions.

	(1)	(2)
Variables	$Hate_{mt}$	$Hate_{mt}$
$Post_t$ X $Lost_m$	0.062***	
	(0.016)	
$Post_t$ X $VoteShare_m$		-0.025***
		(0.008)
Constant	-0.019***	-0.010***
	(0.004)	(0.003)
Municipality FE	Yes	Yes
Date FE	Yes	Yes
Municipalities	1,482	1,482
Observations	89,865	89,865
R-squared	0.074	0.073

Note: Standardized variables. Robust standard errors are in parentheses. $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to July 2018 and a value of 1 from January to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

We interpret our results from columns (1) and (2) as evidence of an update in the beliefs held by the citizens regarding the acceptability of hate speech. The difference in the election results at the municipality and national levels may serve as a proxy for the extent of the

information shock, which triggered an update in beliefs about the prevailing social norms. In other words, individuals residing in municipalities where Bolsonaro lost (thus, predominantly surrounded by individuals who do not support Bolsonaro) are more likely to have the highest level of misperception regarding the actual number of people who share Bolsonaro's viewpoints. Hence, these are the municipalities where hate speech increases the most.

If our interpretation of the results is accurate, we should expect that the types of hate speech experiencing a surge are related to topics influenced by social norms. That is, the expressions of hate should be targeted to specific groups, such as women, the LGBT community, and different races. To study this, we rely on our dictionary-based method to classify tweets into five different categories: homophobia, racism, sexism, political hate, and insults. Table 2 presents the regressions using each of these as outcomes. Confirming our hypotheses, we find significant effects for sexism, homophobia, and racism. Importantly, we find no effects of Bolsonaro's election on political hate and insults, which reassures that an increase in polarization does not drive the results.

Table 2: Municipality level regressions. Results by hate targets.

	(1)	(2)	(3)	(4)	(5)
Variables	$Political_{mt}$	$Homophobia_{mt}$	$Racism_{mt}$	$Sexism_{mt}$	$Insult_{mt}$
Panel A: Binary Treatment					
$Post_t$ X $Lost_m$	-0.016	0.036**	0.038**	0.040**	0.018
	(0.016)	(0.019)	(0.017)	(0.017)	(0.017)
Constant	-0.022***	-0.005	-0.024***	-0.009**	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	89,865	89,865	89,865	89,865	89,865
R-squared	0.094	0.036	0.131	0.038	0.075
Panel B: Continuous Treatment					
$Post_t$ X $VoteShare_m$	0.003	-0.021**	-0.021**	-0.018**	-0.007
	(0.009)	(0.010)	(0.009)	(0.009)	(0.008)
Constant	-0.024***	0.001	-0.018***	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	89,865	89,865	89,865	89,865	89,865
R-squared	0.094	0.036	0.131	0.038	0.075

Note: Standardized variables. Robust standard errors are in parentheses. $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to July 2018 and a value of 1 from January to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

4.2 Individual level

In the previous section, we have shown that the proportion of online hate speech increased after the 2018 presidential election. At the municipality level, this increase is mainly driven by regions where Bolsonaro *lost* the election. As our Twitter data is at the individual level, we can further extend our main analysis and explore *who* is driving this result. In particular, this increase may be driven by (i) users already posting tweets with hate content before the elections, i.e., intensive margin, (ii) users who start posting hate speech tweets after the elections, i.e., extensive margin, or (iii) both.

In this section, we focus on a sub-sample of Twitter users whose tweets are located in *no more than two* different municipalities. For the regression analysis, we restrict our attention to the sub-sample of Twitter users (i) who appear at least one month before and one month after the election and (ii) such that we observe at least 5 tweets per user per month. When a user's tweets are located in multiple municipalities, we assume the information shock she received is a *weighted average* of Bolsonaro's vote share in the corresponding locations.

Figure 4 shows that the rise in hate speech results from both the intensive and extensive margins. This figure is constructed using all the Twitter accounts in our sample (after restricting it to the upper bound on the number of locations). Panel a shows how the share of Twitter accounts posting zero hate content becomes smaller after the elections. Specifically, 55% of the Twitter users in our sample had never published hate speech content before the 2018 elections, and this number reduced to 53% after Bolsonaro was elected president. This reduction is stronger for the sub-sample of Twitter users who post tweets from a municipality where $Lost_m = 1$ - the corresponding percentages are 51.4% in the pre-election period and 50.1% in the post-election period.

Panel b focuses on the intensive margin by zooming in on those Twitter accounts that have posted messages with hate speech at least once. We can see that the distribution of individual hate speech has shifted to the right after the elections. On average, the intensity of hate speech increased by 0.9 standard deviations in the post-election period (from 15.9% to 16.7% in the sub-sample of users who posted hate speech content).

This observation is further confirmed by the estimates in Table 3, corresponding to the difference-in-differences models at the individual level, equations (3) and (4). We focus on the intensive margin of hate speech, dropping the user accounts that did not publish hateful content during the period under study. Specifically, we delete all Twitter users for whom the proportion of tweets classified as containing hate speech over the period is lower than 5%. Although we lost power in estimating the election's impact on individual hate speech,

especially for the continuous treatment differences-in-differences model, the estimates are comparable in sign and magnitude to those previously presented in Table 1. In Appendix A.3, we present supplementary regressions, redefining the intensive margin of hate speech and restricting the sub-sample of users according to their online activity.

Table 3: Individual level regressions. Intensive margin of hate speech.

	(1)	(2)
Variables	$Hate_{imt}$	$Hate_{imt}$
$Post_t$ X $Lost_{im}$	0.009*	
	(0.005)	
$Post_t$ X $VoteShare_{im}$		-0.003
		(0.002)
Constant	0.052***	0.053***
	(0.001)	(0.001)
Individual FE	Yes	Yes
Month FE	Yes	Yes
Individuals	85,494	85,494
Observations	418,616	418,616
R-squared	0.257	0.257

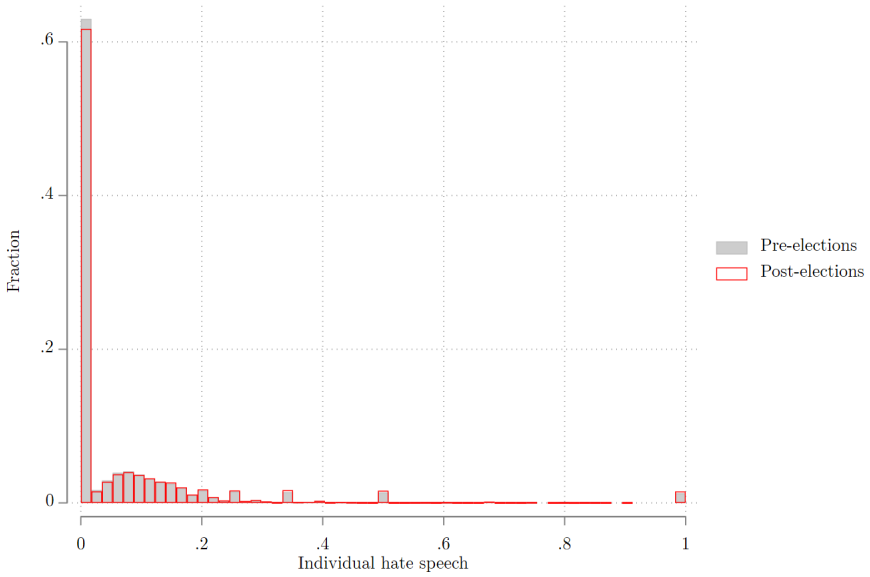
Note: Standardized variables. Robust standard errors are in parentheses. Only Twitter users for whom the proportion of tweets classified as containing hate speech over the period is greater than 5%. $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to July 2018 and a value of 1 from January to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

4.3 Robustness checks

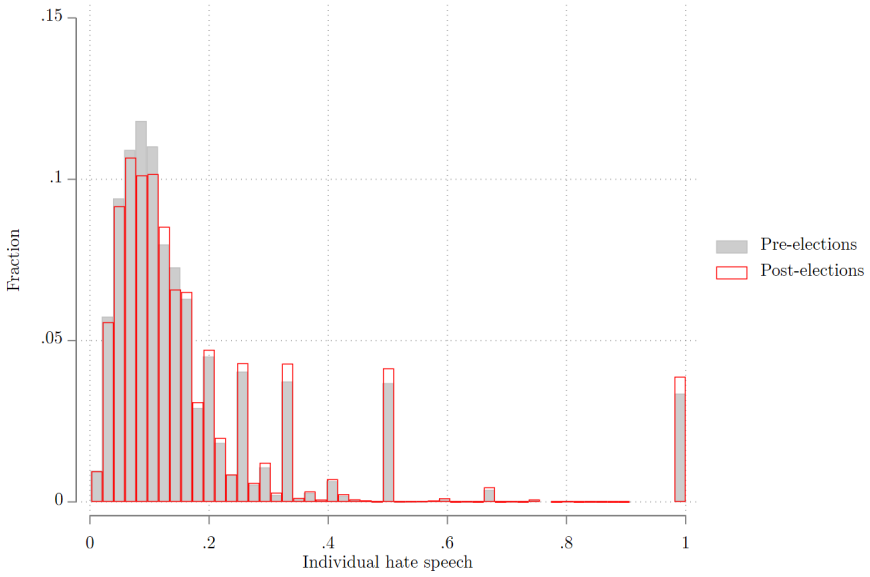
In this section, we check the robustness of the results by relaxing the assumptions we made throughout the paper. For the regressions at the municipality level, we change the variables' definitions and the period under study, among others. For the individual-level regressions, we present results for all Twitter users in the sample, redefine the intensive margin of hate speech, and restrict the sub-sample of users according to their online activity. Appendix A.3 presents the corresponding results, showing that the main results of this paper remain qualitatively unchanged.

Figure 4: Individual hate speech, pre- and post-elections.

a. Extensive margin



b. Intensive margin



Note: Histograms at the individual level. The pre-election period is between July 2017 and July 2018, whereas the post-election period goes from January to December 2019. Panel a: all the Twitter accounts in the sample. Panel b: only Twitter accounts who posted hate speech content at least once. The vertical lines indicate the average hate speech of the accounts before and after the elections.

5 Conclusion

As social media platforms have proliferated, a new public sphere where individuals share ideas has emerged. Among them are the ones related to hate speech, offensive language, and discrimination. Understanding what factors impact the online spread of these harmful speeches is crucial for modern societies, especially regarding social media content moderation. In this line, we provide novel evidence on how political outcomes impact online expressions of hate.

We document that the 2018 election of Bolsonaro in Brazil, a far-right candidate, increased online hate speech. Interestingly, this impact is more pronounced in regions where Bolsonaro was relatively less popular - according to the regression results at the municipality and individual levels. Then, we propose an update on beliefs regarding the social acceptability of hate speech as an underlying mechanism.

There are at least two natural extensions of this project, which are left for future research. Firstly, an extension of this paper will look at the persistence of information shocks that potentially trigger both a social norms update and the spread of harmful expressions. In our study case, we did not extend the period under analysis as it would require going over the COVID-19 pandemic, which is a completely different type of shock. Lastly, comparing online and offline expressions of hate, especially analyzing their interdependency, is a policy-relevant question closely related to this paper.

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A Appendix

A.1 Twitter data

Twitter was (X is) an online platform allowing users to publish short messages of a maximum of 140 characters on their profiles. In January 2021, Twitter launched an Academic Research product track, which enabled researchers to access all v2 endpoints. Notably, the *Twitter Search API v2* gave access to the entire history of public conversations and not only recent tweets. To collect the Twitter data used in this paper, we relied on the *v2 full-archive search endpoint*. We collected tweets using the command line tool and Python library, twarc2, https://twarc-project.readthedocs.io/en/latest/twarc2_en_us/ from June 2022 to May 2023.

The Twitter query we create to download tweets restricts our search to all publicly available (yet undeleted) tweets written in Portuguese, geo-located in Brazil, that are not retweets, and belong to any Monday between July 2017 and December 2019, both included. This query imposes two main assumptions on our tweets' sample. We assume the sample of (i) tweets posted on any Monday and (ii) geo-located tweets are representative samples of the tweets' universe. The figures below present supportive evidence for these assumptions.

Figure 5 presents the average number of tweets per day of the week for the period under study. The figure shows that the amount of tweets is quite stable over the weekdays and slightly decreases on weekends. The daily average of tweets is around 305.000. Figure 6 shows the daily amount of tweets retrieved by the Twitter query used in this paper but without the restriction of being posted on a Monday. The red dashed line corresponds to the monthly average of tweets.[13] It can be seen that the monthly trend in Figure 6 exhibits higher variation than the average number of tweets per weekday in Figure 5. Altogether, it suggests that (i) long-run variation on tweets is larger than short-run variation and (ii) data for one day per week for the whole period correctly captures how data behaves.

Lastly, Figures 7 and 8 compare the trends of geo-located tweets and the universe of tweets that contain a specific word. In all the sub-graphs of the two figures, the red line corresponds to the amount of geo-located tweets, and the blue line is the amount of all tweets multiplied by a *scalability factor*. This factor is the ratio of geo-located tweets over total tweets in the sample for each word, which is between 4% and 8%.

[13] Peaks during June/July 2018 corresponds to dates when Brazil's football team played a match in the 2018 World Cup.

Figure 5: Average number of tweets per day in the tweets' sample.

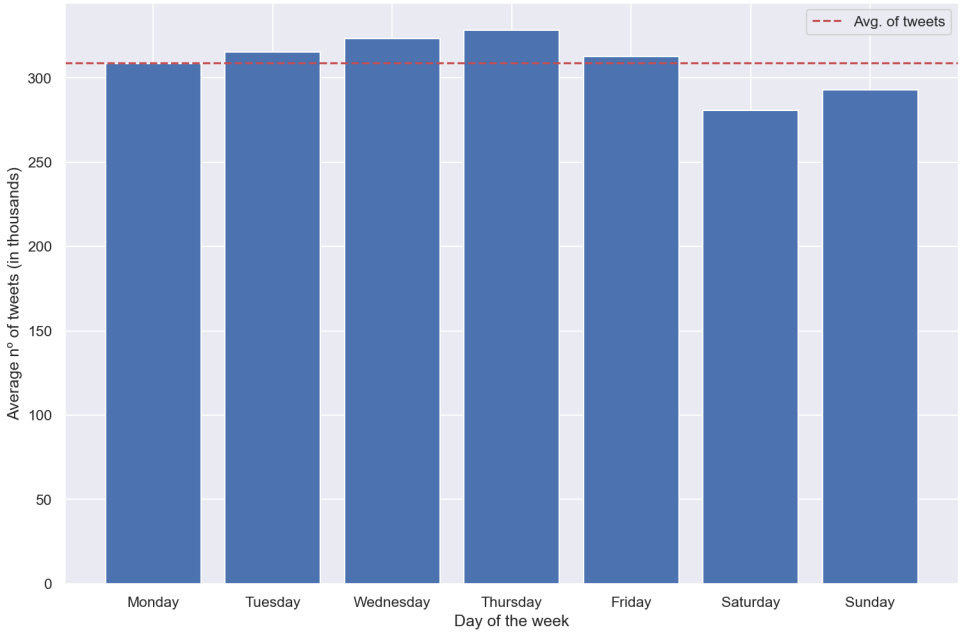
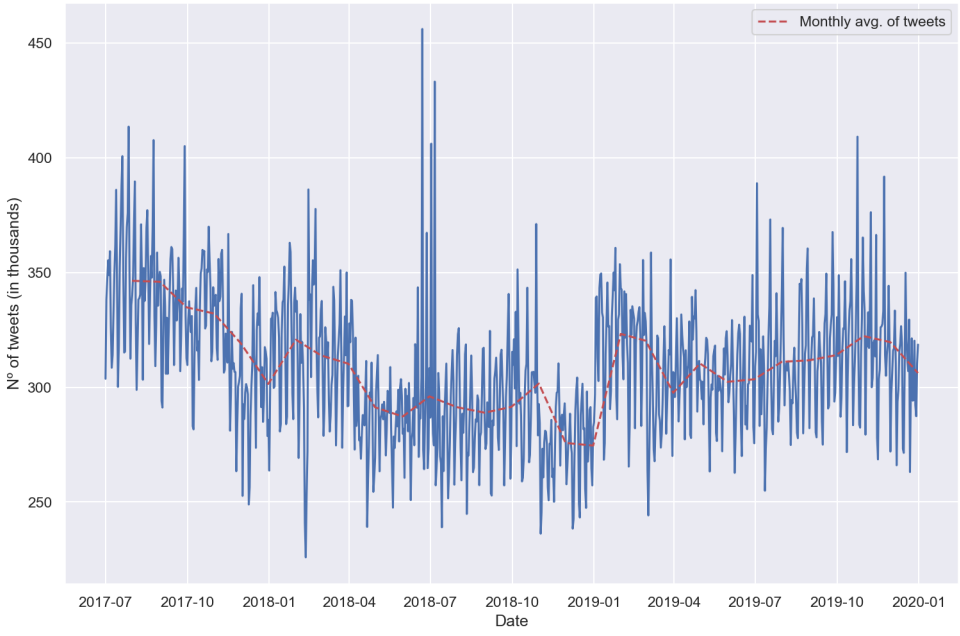


Figure 6: Trend of geo-located and total tweets.



In Figure 7, the words used are: "*Bolsonaro,*" "*braço*" (arm), "*bom*" (good), "*cão*" (dog), "*cerveja*" (beer), and "*hoje*" (today). In Figure 8, we use sensitive words - that may reflect hate

speech. Specifically, these words are: "*mariquinha*" (offensive word for a gay man) "*sapatão*" (offensive word for a lesbian), "*nego*" (black), "*preto*" (black), and "*piranha*" and "*putinha*" (offensive words for a woman). As can be seen, both trends behave similarly for each word, suggesting that the sub-sample of geo-located tweets correctly captures how the universe of tweets behaves. This is especially true for the tweets containing "Bolsonaro."

Figure 7: Daily count of tweets retrieved by the Twitter query.

Figure 8: Daily count of tweets retrieved by the Twitter query.

A.2 Hate speech detection

In this paper, we implement two NLP techniques to detect hate speech in tweets. Firstly, we fine-tune a BERT model on a dataset specific to the hate speech detection task. To do so, we use a BERT model in Portuguese, by Souza et al. (2020), and a dataset of tweets in Portuguese, by Fortuna et al. (2019). Secondly, we construct a dictionary that enables us to classify tweets by capturing specific hate targets. The reason to propose two NLP techniques is twofold. First, by applying two different techniques, we obtain two independent predictions of hate speech, which we compare through this paper. Secondly, we construct a dictionary which provides a

multi-level classification of hate speech. It allows us to differentiate hate speech by its targets and to study separately the dynamics of each class. In the next paragraphs, we describe the resources employed and the procedures followed for each classification.

A.2.1 BERT model

Model. In this paper, we take *BERTimbau*, a BERT model for Brazilian Portuguese by Souza et al. (2020), as a base model and fine-tune it for the hate speech detection task - where fine-tuning refers to the technique of training a pre-trained model on a suitable dataset for a new task. Souza et al. (2020) present the model in two sizes: Base (12 layers, 768 hidden dimensions, 12 attention heads, and 110M parameters) and Large (24 layers, 1024 hidden dimensions, 16 attention heads, and 330M parameters). The authors train the models in two tasks: Masked Language Modeling (MLM) and Sentence Prediction (NSP). The model training is based on the *brWaC corpus* by Wagner Filho et al. (2018), the largest open Portuguese corpus. After training, they evaluate the model in other traditional NLP tasks, namely, Sentence Textual Similarity (STS), Recognizing Textual Entailment (RTE), and Named Entity Recognition (NER). The model improves the state-of-the-art on these tasks, outperforming Multilingual BERT models. The authors made their models publicly available at these Hugging Face links: Base, https://huggingface.co/neuralmind/bert-base-portuguese-cased, and Large, https://huggingface.co/neuralmind/bert-large-portuguese-cased.

Dataset. We relied on the dataset presented by Fortuna et al. (2019) to fine-tune the BERT model for the hate speech detection task. It is a dataset of tweets in Portuguese collected through Twitter's API, and it comprises 5668 tweets in the period from January to March 2017. The authors provide two annotation schemes for the dataset, binary and hierarchical multiple classifications. For the first classification, three annotators classified every tweet. Each of them had to label the tweet as "hate speech" or "not hate speech," and the authors applied the majority vote to determine the final annotation of each tweet. As a result, 31.5% of the tweets were annotated as "hate speech" on the binary classification dataset. For the hierarchical classification, the authors followed a Rooted Directed Acyclic Graph (DAG) in which "hate speech" is the graph's root. As a result, 22% of the tweets were annotated as "hate speech" on the multi-labeled dataset. The authors made their datasets publicly available at this GitHub repository, https://github.com/paulafortuna/Portuguese-Hate-Speech-Dataset.

Text pre-processing. During text pre-processing, we follow Fortuna et al. (2019) and remove stop-words and punctuation marks using the *NLTK* and *re* Python libraries, respectively. Unlike the authors, we do not remove negative stop-words that may change the statement's meaning. Explicitly, we keep the words: "*mas*" (but), "*nem*" (neither), "*não*" (no), "*sem*" (without), and "*fora*" (out). In addition, we anonymize Twitter mentions as "@user" and links as "URL." We keep "#Hashtags" in the native Twitter format. Finally, we do not transform text to lowercase for consistency with the architecture of Souza et al. (2020) 's BERT model.

Model fine-tuning. We divide the dataset between 80% for training, 10% for validation, and 10% for testing. In NLP applications, the performance of a model in a given task is directly influenced by the characteristics of the training sample. In the case of Fortuna et al. (2019)'s dataset, as in other datasets on hate speech or offensive comments detection, a class imbalance exists. 31.5% of tweets were annotated as "hate speech" under the binary classification, being this a minority class. As class imbalance may affect the model's performance, we use a Random Oversampling technique to equalize the number of tweets in the minority and majority classes in the training sample (80% of the tweets). The random oversampling approach randomly adds examples from the minority class to the original training dataset, with replacement.

Training results. The hate-speech BERT model we train attains an overall accuracy of 77% in both the validation and test datasets. Table 4 summarizes additional statistics (Precision, Recall, and F1-score) to characterize the model performance fully.

Table 4: Training results

Validation sample				
	Precision	Recall	F1	Support
0	0.86	0.76	0.81	365
1	0.64	0.78	0.71	202
W. Avg.	0.79	0.77	0.77	567
Test sample				
	Precision	Recall	F1	Support
0	0.88	0.79	0.83	406
1	0.58	0.72	0.64	161
W. Avg.	0.79	0.77	0.78	567

A.2.2 Dictionary method

In this paper, we employ a dictionary method to detect hate speech, leading to a multi-level classification of it. The dictionary enables us to distinguish hate speech based on its targets and to analyze the dynamics of each hate type separately. We distinguish five different categories of hate, namely: "political hate," "homophobia," "racism," "sexism," and "insult". While the latter are traditional types of hate speech in the literature, the former is less common. We decide to include it given its relevance in the context under study. In addition to the five categories, we construct a binary variable, "hate speech," which takes the value of one if the corresponding tweet is classified as having at least one of the hate targets. This variable is used to compare the dictionary and the BERT model performance and to perform a series of robustness checks on the main results of the paper.

For the categories "homophobia," "racism," "sexism," and "insult," we consider the top-frequency words for each type of hate speech in three different papers: Fortuna et al. (2019), Leite et al. (2020), and Pereira (2018). First, we rely on the hierarchical classification of Fortuna et al. (2019). To construct it, the authors followed a Rooted Directed Acyclic Graph (DAG) in which "hate speech" is the graph's root. The second level of classes relates to the target of hate, and it comprises: "sexism," "body," "origin," "homophobia," "racism," "ideology," "religion," "health," and "lifestyle." We use a subset of these hate targets, namely: "sexism," "homophobia," "racism," and "religion" and "origin" (both included in "racism").

Second, we use Leite et al. (2020), which presents a large-scale dataset of tweets in Brazilian Portuguese. Tweets are annotated as either toxic or non-toxic and, if toxic, classified with a type of toxicity. The authors considered the following toxicity types: "LGBTQ+phobia," "Obscene," "Insult," "Racism," "Misogyny," and "Xenophobia." In Table 3 of the paper, the authors present the most common words of each class and their occurrence. We use a subset of these words as input for our hate targets classification, namely: "LGBTQ+phobia" ("homophobia"), "Obscene" and "Insult" (both included in "insult"), "Racism" and "Xenophobia" (both included in "racism"), and "Misogyny" ("sexism").

Third, we employ the work of Pereira (2018) to improve our hate target "homophobia." The paper focuses on the detection of homophobic tweets in Brazilian Portuguese, and it applies diverse NLP techniques to identify them. In Figure 3.6.3 of the paper, the author reports an offensive vocabulary to LGBT individuals, which we consider to construct the class "homophobia" in this paper.

Table 5 presents the list of words considered for each type of hate speech in our dictionary. Additionally, Table 6 illustrates a list of tweets present in our dataset. For each of them,

we report the classification obtained by the BERT model and the dictionary method. These examples were manually chosen to illustrate scenarios in which the two classification methods coincide and scenarios in which they do not. Although neither method performs with perfect accuracy, at least one of them is able to detect instances of hate speech.

Table 5: Dictionary method

Political hate					
corrupta	corrupto	esquerda	esquerdista	esquerdopata	facha
facho	fascista	feminista	feminazi		
Homophobia					
baitola	baitolo	bicha	bichona	bixa	boiola
boiolice	fufa	gayzada	gayzismo	marica	mariquinha
sapata	sapatao	sapatão	traveca	traveco	viadagem
viadao	viadinho	viado			
Xenophobia					
branco	carioca	islão	latino	mesquita	muçulmano
nego	nordest	paulista	povo	preto	sulista
Sexism					
burra	feia	gorda	louca	mulher	mulheres
mulherdeverdade		piranha	puta	putinha	vagabunda
Insults					
caralho	fuder	idiota	lixo	merda	porra
puta					

Table 6: Classification of tweets: BERT and dictionary method.

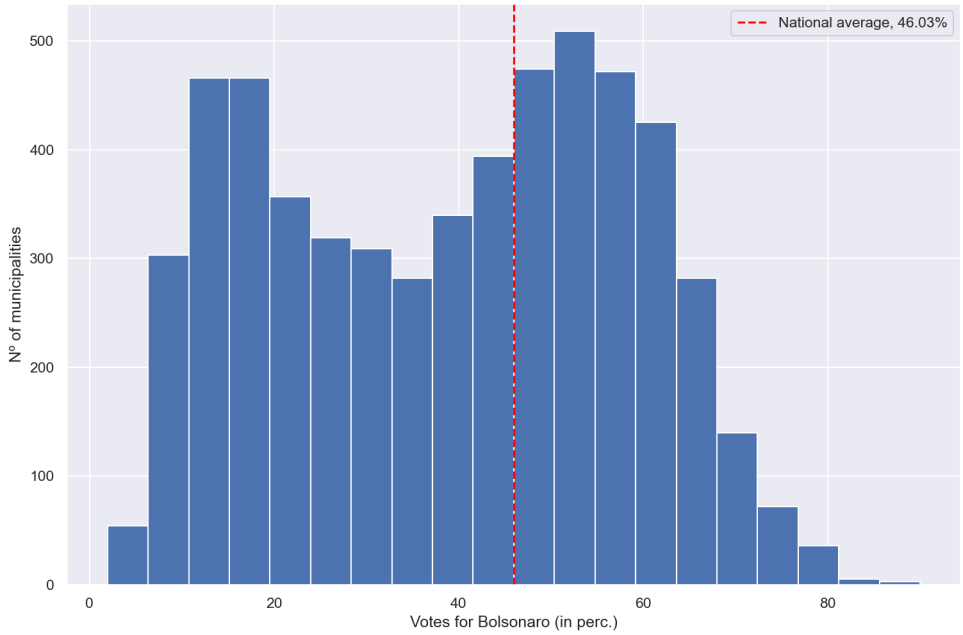
Tweets in Portuguese (in English)	BERT	Dictionary
Direitos humanos? Vai a merda seus porcos URL (Human rights? Fuck you pigs URL)	1	1
Puta merda esqueci livro (Holy shit I forgot the book)	1	1
Aquele medo de ser só mais um fudido sem nada na vida voltou a me perseguir (That fear of being just another fuck-up with nothing in life came back to haunt me)	1	0
Esses caras da @user só falam m..., bando de fdp vermelhos... (These @user guys are full of shit, a bunch of red fucks. . .)	1	0
Oh seus filhos das putas, a porra da esquerda é livre URL (Oh you sons of bitches, the fucking left is free URL)	0	1
40 fucking dias pra eu ver o amor da minha vida puta merda eu nao to acreditando (40 fucking days for me to see the love of my life holy shit I can't believe it)	0	1

Note: Example of tweets belonging to our database posted on 12/03/2018 and their classification by the BERT model and the dictionary method. User mentions and web links were anonymized.

A.3 Tables and Figures

Figure 9: Bolsonaro's vote share at the municipality level. 2018 Presidential Election.

a. 1º Round, October 7th.



b. 2º Round, October 28.

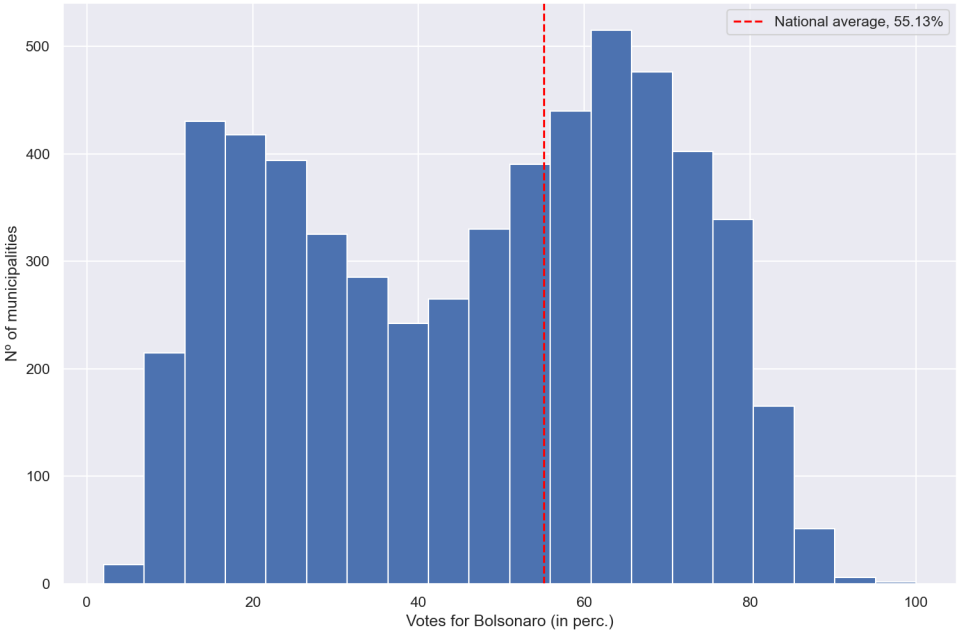
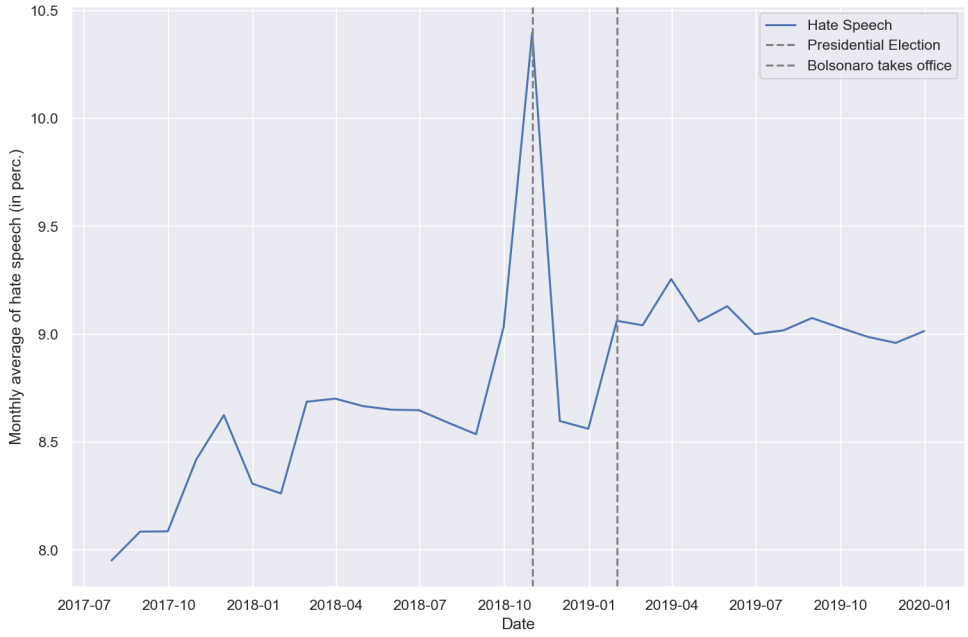
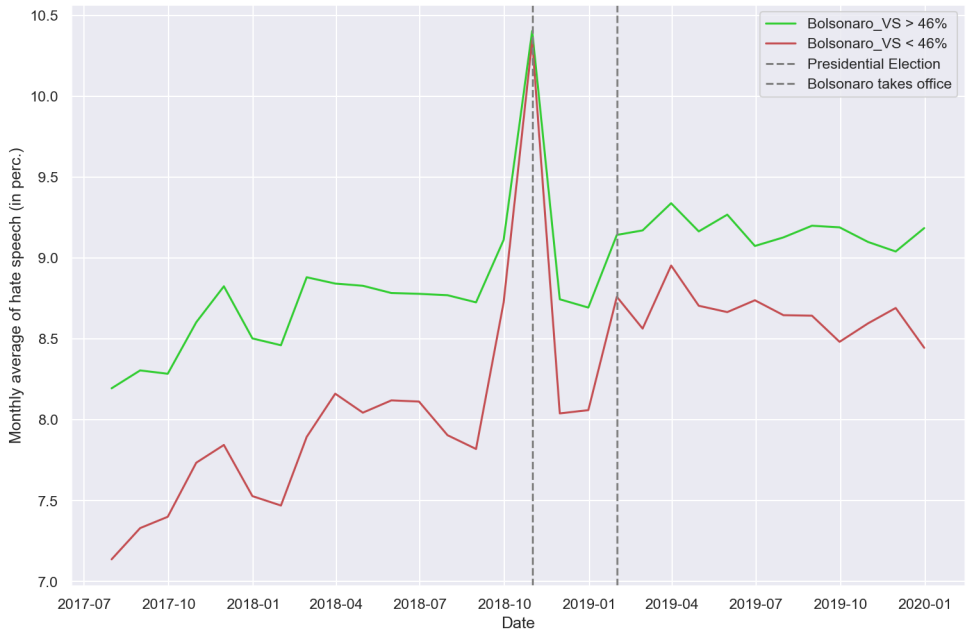


Figure 10: Evolution of hate speech in Brazilian tweets, 2017-2019. Monthly average.

a. All municipalities.

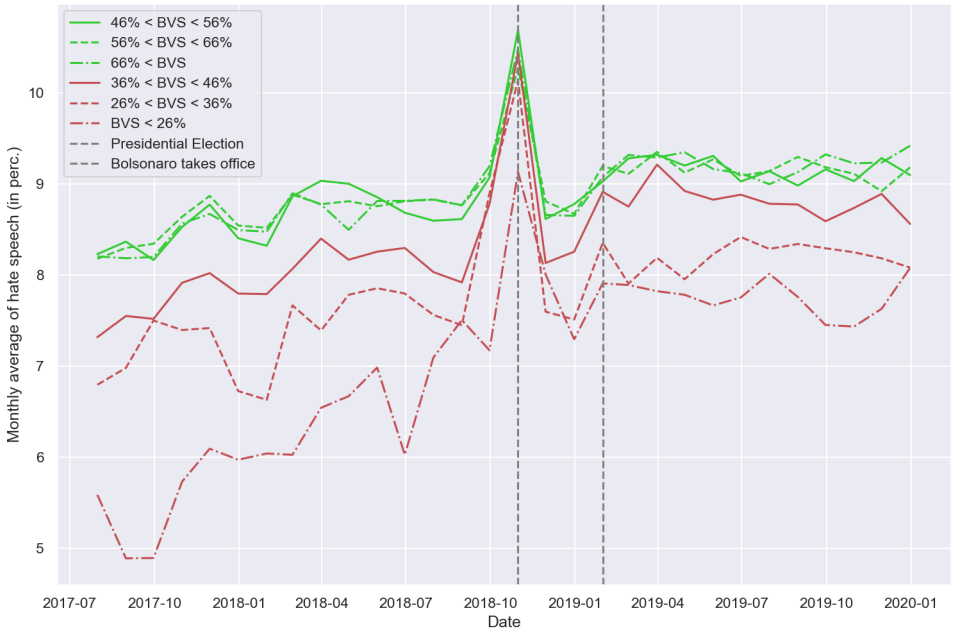


b. Municipalities, by the 2018 election result.



Note: Hate speech variables were aggregated by month. The BERT model classified the tweets.

Figure 11: Evolution of hate speech in Brazilian tweets, 2017-2019. Heterogeneity analysis by margins of difference in the 2018 election result.



Note: Hate speech trends are constructed separately for each group of municipalities. "BVS" stands for Bolsonaro's vote share in the 1º round of the 2018 election.

Table 7: Descriptive Statistics, by the 2018 election result. Municipalities in the tweets' sample.

Variable	$Lost_m$	Won_m	Difference
urban	0.828	0.738	0.089***
income_pc	755.3	478.3	277.0***
cellphone	0.891	0.810	0.081***
computer	0.427	0.241	0.186***
internet	0.735	0.693	0.042***
primary	0.382	0.368	0.013***
tertiary	0.435	0.474	-0.039***
no_religion	0.058	0.070	-0.012***
catholic	0.678	0.721	-0.043***
pentecostal	0.128	0.117	0.010***
black	0.052	0.082	-0.029***
indigenous	0.003	0.006	-0.003**
brown	0.286	0.489	-0.202***
born_mun	0.567	0.673	-0.106***
born_state	0.673	0.747	-0.075***
vs_pt_2006	0.351	0.528	-0.177***
vs_pt_2010	0.378	0.524	-0.146***
vs_pt_2014	0.310	0.507	-0.197***

Note: N = 1482 (municipalities for which Twitter data is available, after data cleaning). All variables are aggregated at the municipality level. Column "$Lost_m$" refers to the municipalities where Bolsonaro's vote share was $> 46\%$, whereas column "Won_m" refers to where his vote share was $< 46\%$. The third column reports the statistical difference between the respective means. Variables "cellphone," "computer," and "internet" are the proportion of households reported to have such goods in the 2010 Population Census. Variables "no_religion," "catholic," "pentecostal," "black," "indigenous," and "brown" are the proportion of individuals registered to have such demographic characteristics in the 2010 Population Census. Variables "primary" and "tertiary" refer to the population with (at most) primary and tertiary education. Variables "bornhere_mun" and "bornhere_state" refer to the proportion of individuals born in the municipality and state where they answered the 2010 Population Census. Variables "vs_pt_2006," "vs_pt_2010," and "vs_pt_2014" are the proportion of votes obtained by the Workers' Party (Partido dos Trabalhadores, PT) in the 1º round of the 2006, 2010, and 2014 Presidential Elections, respectively.

Table 8: Descriptive Statistics, by the 2018 election result. All Brazilian municipalities.

Variable	$Lost_m$	Won_m	Difference
urban	0.569	0.735	-0.166***
income_pc	346.8	680.4	-333.6***
cellphone	0.697	0.869	-0.173***
computer	0.140	0.363	-0.223***
internet	0.610	0.703	-0.094***
primary	0.383	0.407	-0.023***
tertiary	0.495	0.425	0.070***
no_religion	0.052	0.052	-0.001
catholic	0.793	0.705	0.087***
pentecostal	0.098	0.126	-0.028***
black	0.075	0.048	0.027***
indigenous	0.009	0.005	0.004***
brown	0.558	0.304	0.255***
born_mun	0.710	0.556	0.154***
born_state	0.742	0.675	0.068***
vs_pt_2006	0.553	0.344	0.210***
vs_pt_2010	0.575	0.391	0.184***
vs_pt_2014	0.585	0.331	0.254***

Note: N = 5570 (municipalities). All variables are aggregated at the municipality level. Column "$Lost_m$" refers to the municipalities where Bolsonaro's vote share was $> 46\%$, whereas column "Won_m" refers to where his vote share was $< 46\%$. The third column reports the statistical difference between the respective means. Variables "cellphone," "computer," and "internet" are the proportion of households reported to have such goods in the 2010 Population Census. Variables "no_religion," "catholic," "pentecostal," "black," "indigenous," and "brown" are the proportion of individuals registered to have such demographic characteristics in the 2010 Population Census. Variables "primary" and "tertiary" refer to the population with (at most) primary and tertiary education. Variables "bornhere_mun" and "bornhere_state" refer to the proportion of individuals born in the municipality and state where they answered the 2010 Population Census. Variables "vs_pt_2006," "vs_pt_2010," and "vs_pt_2014" are the proportion of votes obtained by the Workers' Party (Partido dos Trabalhadores, PT) in the 1º round of the 2006, 2010, and 2014 Presidential Elections, respectively.

A.3.1 Regression results at the municipality level.

Table 9: Municipality level regressions.

	(1)	(2)
Variables	$Hate_{mt}$	$Hate_{mt}$
$Post_t$ X $Lost_m$	0.062***	
	(0.021)	
$Post_t$ X $VoteShare_m$		-0.025***
		(0.011)
Constant	-0.019***	-0.010***
	(0.002)	(0.001)
Municipality FE	Yes	Yes
Date FE	Yes	Yes
Municipalities	1,482	1,482
Observations	89,865	89,865
R-squared	0.074	0.073

Note: Standardized variables. Standard errors clustered at the municipality level are in parentheses. $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to July 2018 and a value of 1 from January to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Municipality level regressions. Monthly data.

	(1)	(2)
Variables	$Hate_{mt}$	$Hate_{mt}$
$Post_t$ X $Lost_m$	0.063**	
	(0.029)	
$Post_t$ X $VoteShare_m$		-0.032**
		(0.014)
Constant	-0.019***	-0.010*
	(0.007)	(0.006)
Municipality FE	Yes	Yes
Date FE	Yes	Yes
Municipalities	1,482	1,482
Observations	27,324	27,324
R-squared	0.144	0.144

Note: Standardized variables. Robust standard errors are in parentheses. $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to July 2018 and a value of 1 from January to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Municipality level regressions. Redefining $Post_t$.

	(1)	(2)
Variables	$Hate_{mt}$	$Hate_{mt}$
$Post_t$ X $Lost_m$	0.054***	
	(0.015)	
$Post_t$ X $VoteShare_m$		-0.020**
		(0.008)
Constant	-0.019***	-0.012***
	(0.004)	(0.003)
Municipality FE	Yes	Yes
Date FE	Yes	Yes
Municipalities	1,482	1,482
Observations	100,375	100,375
R-squared	0.072	0.072

Note: Standardized variables. Robust standard errors are in parentheses. $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to August 2018 and a value of 1 from November 2018 to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Municipality level regressions. Results by hate targets.

	(1)	(2)	(3)	(4)	(5)
Variables	$Political_{mt}$	$Homophobia_{mt}$	$Racism_{mt}$	$Sexism_{mt}$	$Insult_{mt}$
Panel A: Binary Treatment					
$Post_t$ X $Lost_m$	-0.016	0.036*	0.038	0.040**	0.018
	(0.026)	(0.021)	(0.025)	(0.020)	(0.021)
Constant	-0.022***	-0.005**	-0.024***	-0.009***	-0.006***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	89,865	89,865	89,865	89,865	89,865
R-squared	0.094	0.036	0.131	0.038	0.075
Panel B: Continuous Treatment					
$Post_t$ X $VoteShare_m$	0.003	-0.021**	-0.021*	-0.018*	-0.007
	(0.017)	(0.011)	(0.013)	(0.010)	(0.010)
Constant	-0.024***	0.001	-0.018***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	89,865	89,865	89,865	89,865	89,865
R-squared	0.094	0.036	0.131	0.038	0.075

Note: Standardized variables. Standard errors clustered at the municipality level are in parentheses. $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to July 2018 and a value of 1 from January to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

A.3.2 Regression results at the individual level.

Table 13: Intensive margin of hate speech. Individual level regressions. Sub-sample of Twitter users, restricted by their activity.

	(1)	(2)	(3)	(4)
Variables	$Hate_{imt}$	$Hate_{imt}$	$Hate_{imt}$	$Hate_{imt}$
$Post_t$ X $Lost_{im}$	0.008*		0.011**	
	(0.004)		(0.005)	
$Post_t$ X $VoteShare_{im}$		-0.002		-0.002
		(0.002)		(0.002)
Constant	0.047***	0.047***	0.061***	0.062***
	(0.001)	(0.001)	(0.002)	(0.001)
Individual FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Individuals	52,518	52,518	24,180	24,180
Observations	342,732	342,732	210,565	210,565
R-squared	0.260	0.260	0.226	0.226

Note: Standardized variables. Robust standard errors are in parentheses. Columns (1)-(2): all Twitter users who posted at least 25 tweets over the period, from which at least 5 are classified as hate speech. Columns (3)-(4): all Twitter users who posted at least 50 tweets over the period, from which at least 10 are classified as hate speech. $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to August 2018 and a value of 1 from November 2018 to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Individual level regressions.

Variables	(1) $Hate_{imt}$	(2) $Hate_{imt}$
$Post_t$ X $Lost_{im}$	0.006	
	(0.004)	
$Post_t$ X $VoteShare_{im}$		-0.001
		(0.002)
Constant	-0.009***	-0.009***
	(0.001)	(0.000)
Individual FE	Yes	Yes
Month FE	Yes	Yes
Individuals	113,127	113,127
Observations	523,458	523,458
R-squared	0.342	0.342

Note: Standardized variables. Robust standard errors are in parentheses. All Twitter users in the sample. $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to August 2018 and a value of 1 from November 2018 to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Individual level regressions. Sub-sample of Twitter users, restricted by their activity.

Variables	(1) $Hate_{imt}$	(2) $Hate_{imt}$	(3) $Hate_{imt}$	(4) $Hate_{imt}$
$Post_t$ X $Lost_{im}$	0.007*		0.008**	
	(0.004)		(0.004)	
$Post_t$ X $VoteShare_{im}$		-0.001		-0.002
		(0.002)		(0.002)
Constant	-0.009***	-0.008***	-0.006***	-0.007***
	(0.001)	(0.000)	(0.001)	(0.001)
Individual FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Individuals	90,355	90,355	50,329	50,329
Observations	475,402	475,402	357,506	357,506
R-squared	0.315	0.315	0.270	0.270

Note: Standardized variables. Robust standard errors are in parentheses. All Twitter users in the sample who posted (i) at least 25 tweets over the period in columns (1)-(2) and (ii) at least 50 tweets in columns (3)-(4). $Post_t$ is a dummy variable that takes a value of 0 from July 2017 to August 2018 and a value of 1 from November 2018 to December 2019. $Lost_m$ is a dummy variable that takes a value of 1 for the municipalities where Bolsonaro's vote share was lower than 46% and a value of 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.