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Is there anything Left?: A Global Analysis on Changes in Engagement with Political Content on Twitter in the Musk Era

Brahmani Nutakki

Saarland Informatics Campus, I2SC, Saarland University, Germany

Rosa M. Navarrete

Giuseppe Carteny

Department of European Social Research, I2SC, Saarland University, Germany

Ingmar Weber

Saarland Informatics Campus, I2SC, Saarland University, Germany

Over the past few years, Twitter (now X) has become an influential platform for political discourse. However, prior research suggests that Twitter may be biased towards right-wing content. Following the change in ownership in October 2022, there have been several changes to Twitter's policies, particularly in content flagging and Twitter Blue Verification. Understanding how any shifts in outcomes vary across different political ideologies is important for comprehending the evolving political discourse, especially given recent developments. To explore this issue, we examine shifts in engagement (characterized by likes and retweets) for political figures before and after November 2022, focusing on describing how engagement has changed over time. We perform a global analysis by collecting tweets from 6550 accounts belonging to political leaders and parties from twelve countries among the ones with the highest user activity on the platform, namely, Argentina, Brazil, Canada, Colombia, France, Germany, India, Japan, Mexico, Spain, the United Kingdom, and the United States, between June 2021 and June 2023. Our findings indicate that the number of likes on political tweets increased after November

Brahmani Nutakki: bnutakki@cs.uni-saarland.de
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2022. However, we observe that the number of retweets decreased significantly, along with a marginal decrease in the likes-to-retweet ratio, with no statistically significant difference between the Left and the Right. Our study is the first to offer a global perspective by examining how platform engagement has shifted over time during the Musk Era. These observations contribute to the ongoing discussion on the role of social media platforms in political dialogue, highlighting the importance of monitoring policy developments and trends in the digital media landscape. To support further research, we release the data on politicians and parties used in this study, with their Twitter data available upon request.

Keywords: Social Media and Politics, Political Bias, Twitter

Introduction

Social Media has become an integral part of our lives, playing a significant role in our day-to-day activities and enabling discussions with people beyond one's immediate social network. However, a growing body of research points to the challenges social media presents, as it can be used as a tool to foster partisan animosity, amplify polarization, spread radical messages and increase misinformation (Van Bavel et al., 2021; Tucker et al., 2018; Chen et al., 2023; Ramaciotti Morales et al., 2023).

Twitter (now X)[1] is one of the most widely used social media platforms with over 410 million monthly active users and over 370 million advertiser-reachable users in 2023 (Statista, 2023b; DataRePortal, 2023). Over time, it has emerged as a hotspot for political discussions, with the Pew Research Center finding that around 33% of tweets generated by American users are political in nature (Mitchell, 2022), with evidence suggesting that using Twitter affects electoral results by altering political opinions (Fujiwara et al., 2021). Research also shows that politicians have increasingly adopted platforms such as Twitter for strategic purposes, such as easily broadcasting messages to their audience and responding to unrest. By leveraging

[1]The analysis in this paper focuses on a period when the platform was still called Twitter, which is why we refer to it under that name.

Twitter's immediacy and reach, politicians can bypass traditional media gatekeepers, engage directly with their constituents, and shape narratives in real-time (Barberá and Zeitzoff, 2017). These features make Twitter a powerful platform for political mobilization and influence, while its ability to amplify polarizing content might significantly increase social divides. Against this backdrop, Twitter was acquired by Elon Musk[2] on October 28, 2022. In the period following the acquisition, there have been many policy changes regarding content flagging and moderation, along with introducing Twitter Blue (X, 2022; Novak, 2023) as seen in Figure 1. Twitter Blue is a paid premium subscription that includes a blue check mark on the profile and offers various features, including prioritized ranking in conversations and searches (X, 2022). Whereas previously blue check marks were given based on the authenticity, notability, and activity of the accounts (X, 2023), now a confirmed phone number and a monthly subscription of 8$ is sufficient[3]. This feature was initially rolled out in November 2022 and was immediately removed after an influx of impersonators. It was later reintroduced on December 11, 2022. Similarly, Twitter previously had rules against Hateful Conduct that prohibited attacks on individuals based on their characteristics. However, following the acquisition, these specific rules have been altered, as evident when comparing archived snapshots[4] with the current website[5].

[2]https://twitter.com/elonmusk

[3]As of June 2023

[4]https://web.archive.org/web/20230407140923/https://help.twitter.com/en/rules-and-policies/hateful-conduct-policy

[5]https://help.twitter.com/en/rules-and-policies/hateful-conduct-policy

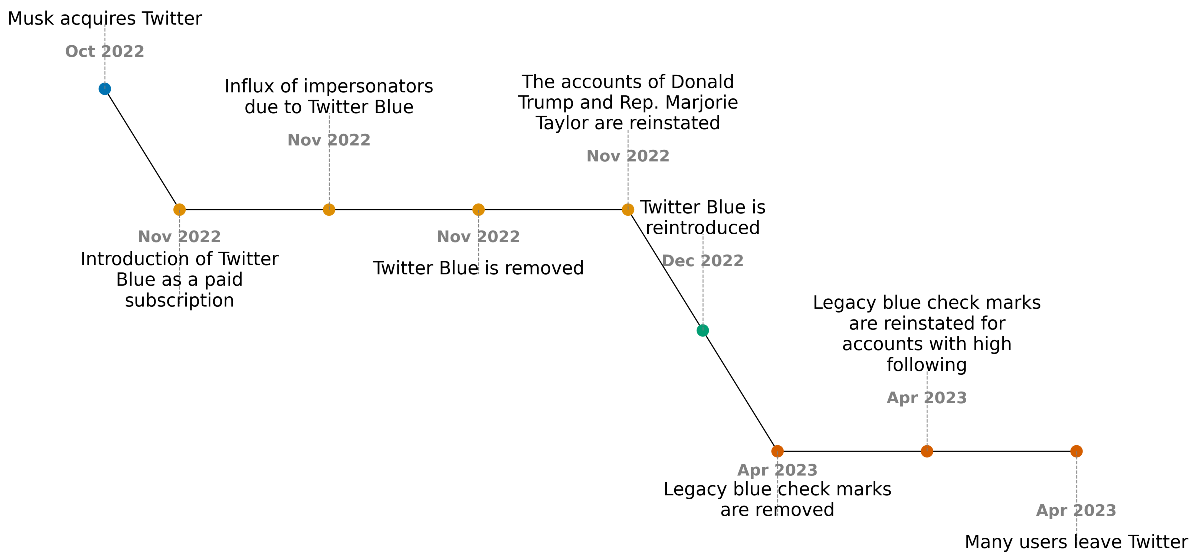

Figure 1. Timeline of events following Musk's acquisition of Twitter. The plot highlights significant changes that have occurred during this period.

Researchers have observed major shifts in the platform content, network dynamics, and the time users spend on the platform since November 2022. Rathje et al. (2024) found in their survey and field experiments that both the conservative and liberal users reported their Twitter feeds to be less positive, with an increased percentage of less reliable content and a decrease in their usage post changes. They also found that the average News Guard[6] quality rating of shared news links and news accounts and other liked URLs went down after the acquisition. A report by the Washington Post shows that top-tweeting Republicans are posting more, enjoying higher views and are followed more than their top-tweeting counterparts, although they did not find any evidence of platform censorship (Harwell et al., 2024). Twitter also saw an overall 30% decline in its usage by 2024 (Research, 2024), but Republicans report feeling more comfortable expressing their views as they feel welcome on the platform (Gelles-Watnick and Risa, 2024). There are also reports of increased shared content tied to radical ideologies, such as right-wing extremism (SPL Center, 2022). The CCDH (Center for Countering Digital Hate) and ADL (Anti-Defamation League) reported that the lack of removal of more than 99% of the reported

[6]https://www.newsguardtech.com

hateful tweets and reinstating banned accounts fosters a troubled space (CCDH, 2023; ADL, 2023). Recent research also points to an increased presence of bots acting on Twitter since the purchase (Hickey et al., 2023). Furthermore, in addition to the changes happening to Twitter's "black box", Musk actively engaged in the political debate, promoting right-wing political actors or ideologies[7], and implementing controversial decisions, such as reinstating the previously suspended accounts of Donald Trump[8] and the far-right Rep Marjorie Taylor[9] (AP News, 2022). Reports also mention his contributions of around 200 million dollars to Trump's 2024 US election campaign, a significant amount that underscores Musk's potential influence in politics[10].

Given Twitter's global reach and influence, understanding how these recent changes relate to political actors is crucial for understanding the evolution of political discourse around the globe. Our research provides detailed information about how engagement has shifted over time during a study period that coincides with (i) several changes to the platform and (ii) major shifts in its usage. As a result, we focus on *describing* changes in engagement, thus investigating the following research questions: 1) How has the political landscape on Twitter changed since the recent changes to the platform? 2) How do the changes in engagement compare between the political Right and the political Left? This analysis is particularly relevant considering the recent changes to the platform and in the context of Musk's increasing influence and the platform's role in political discourse.

To address these research questions, we analyze public metrics such as likes and retweets of politicians and their respective parties in twelve countries. Along with these, we also focus on the likes-to-retweets ratio to understand the difference in engagement a politician receives. We consider that a tweet receiving a higher number of likes indicates greater attention by a broader audience. Meanwhile, a lower likes-to-retweets ratio (fewer likes needed per retweet) reflects that a significant portion of the audience is not just liking the content but also actively re-

[7]https://www.theatlantic.com/technology/archive/2022/12/elon-musk-twitter-far-right-activist/672436/, https://www.reuters.com/world/europe/elon-musk-wades-into-german-debate-over-migration-2023-09-29/, https://www.latimes.com/business/story/2022-11-28/column-elon-musks-engagement-with-nazis-and-the-far-right-on-t

[8]https://x.com/realDonaldTrump

[9]https://x.com/RepMTG

[10]https://www.theguardian.com/us-news/2024/nov/12/elon-musk-america-pac-donald-trump-campaign

sharing it, thereby endorsing and amplifying the message[11]. Conversely, a higher ratio suggests that the audience is more inclined to like the content but not share it. We stick to these metrics instead of considering 'views', 'quotes' or 'replies' since 1) 'views' were only introduced in December 2022 and can not be collected using Twitter v1 API and 2) as mentioned 'quotes' or 'replies' do not always signify support. Although there are varying motives for liking and retweeting as discussed in Section 2, we believe that these metrics are broadly used to show silent approval vs public endorsement, particularly given the large sample size in our study. To demonstrate that these metrics effectively capture these notions (as seen in Figure 2), we manually collected and tested posts with varying expected engagement behaviours—such as adult content (which users tend to like rather than retweet for privacy reasons) and job postings (which users tend to retweet to reach a broader audience). Our analysis confirms that the ratio is significantly different for these categories, aligning with expected behaviours. More details on this can be found in the Appendix.

Figure 2. Comparison of two tweets with similar likes but different likes-to-retweets ratios (2.5 and 4.4).

[11] We are only looking at verbatim retweet-as-is retweets, which are consistently found to be a marker of political alignment (Wong et al., 2016; Metaxas et al., 2021). This does not hold for quoting adding-a-comment retweet, which can also be used to mock a message (Garimella et al., 2016).

To the best of our knowledge, this is the first study that offers a *global* perspective by examining how platform engagement has shifted over time during the Musk Era. Details of the politicians and parties included in our analysis are available in the GitHub repository[12] with data collected from Twitter available for academic research upon request.

Related Work

Social media platforms, particularly Twitter have become pivotal in shaping political discourse, communication and engagement. To contextualize our study within the existing body of research, we explore three key areas in this literature review: the role of Twitter in politics, user engagement actions on the platform, and the auditing of biases in social media algorithms.

Twitter and Politics

There has been a lot of prior research on how Twitter influences the political landscape and affects real-life scenarios. Twitter has emerged as a powerful tool for organizing political movements and protests due to its ability to facilitate rapid communication and coordination. Studies have shown its use in significant events such as the Occupy Wall Street and Indignados movements in 2011 (Theocharis et al., 2015), demonstrating how users leverage the platform to disseminate information efficiently. More recently, Twitter played a role in the events surrounding the US Capitol riot in January 2021, highlighting its continued influence on real-world political scenarios (Lee et al., 2022).

The platform's open nature has also been associated with the spread of political bias and misinformation. Research indicates that certain groups have utilized Twitter to disseminate biased or misleading information. For example, supporters of politically Right Trump were found to be active in spreading misinformation and fake news (Bovet and Makse, 2019). Additionally, studies have shown that Twitter can contribute to the amplification of politicized information and misinformation by conservative media outlets (Yini Zhang and Lukito, 2023). There is also evidence suggesting that many right-wing accounts circulate content from sources with questionable factuality scores (Guimaraes et al., 2021).

Garimella and Weber (2017) reported a 10% to 20% rise in polarization in the U.S. over

[12]https://github.com/Societal-Computing/TwitterDataofPoliticians

an eight-year period. They looked at 679,000 Twitter users for signs of polarization based on their network, tweeting behaviours, and content. Another Twitter study shows that although the far-right thinking changed from anti-religion and racist views to anti-immigration over time, far-right groups use this change as an excuse to distance themselves from right-wing extremism (Ahmed and Pisoiu, 2021).

Previous research also shows the existence of segregated partisan structures in Twitter's political networks. Conover et al. (2021) found that the network of political retweets exhibits limited connectivity between left- and right-leaning users, whereas the user-mentioned network, created by looking at who mentions who in their posts, is characterized by a heterogeneous cluster where users with differing political views interact more frequently. At the same time, some studies suggest that right-leaning users display higher levels of activity and maintain more interconnected networks, which may enhance their capacity to disseminate information rapidly (Conover et al., 2012). They might also be more likely to follow and be followed by automated accounts, increasing their exposure to Right content (Chen et al., 2021).

Collectively, these studies suggest that Twitter might exhibit a right-wing bias or at least an ideological imbalance in how information is disseminated and engaged with on the platform. Evidence points to higher levels of activity among right-leaning users, more interconnected networks that facilitate the rapid spread of right-leaning content, and the circulation of information from less credible sources predominantly by right-wing accounts. This raises questions about the platform's role, either directly or indirectly, in amplifying certain political ideologies over others, connecting to our central inquiry: "Is there anything Left?"

While existing literature has extensively examined Twitter's influence on political communication, less attention has been paid to how significant changes in platform policies and governance might correlate with shifts in political amplification and user engagement. Recent changes in Twitter's ownership and subsequent policy adjustments have the potential to alter these dynamics. Based on prior findings, alterations in content moderation and algorithmic policies could be associated with changes in the amplification of certain messages and user engagement patterns.

Our study seeks to explore these aspects by investigating temporal changes in political amplification and engagement across twelve countries. By analyzing the differential outcomes of left- and right-leaning political actors over time, we aim to contribute to a deeper understanding of how shifts in platform governance might relate to broader political discourse.

Twitter User Actions

User interactions on Twitter significantly influence the platform's content dissemination and user experience. Engagement features such as likes and retweets are not only indicators of user preferences but also integral components of Twitter's recommendation algorithm, affecting the visibility and reach of tweets (Twitter, 2023).

Such engagement-based ranking algorithms can alter the type of content users see and interact with. Milli et al. (2023) found that these algorithms may amplify emotional content and contribute to increased polarization among users. In their pre-registered randomized experiment, participants reported a preference for a reverse chronological feed over the algorithmically curated timeline, indicating skepticism toward the recommendations provided by the platform. The study also observed that certain accounts, including that of Elon Musk, appeared to receive higher amplification compared to others.

User motivations can vary significantly between passive actions, such as viewing, and more active ones, such as clicking (any click such as liking, sharing, commenting), highlighting the complexity of online interactions (Ellison et al., 2020). Within these interactions, understanding why users engage with tweets through likes and retweets is essential for interpreting these metrics accurately. Meier et al. (2014) explored user awareness of the favouriting feature (now known as liking) and the motivations behind its use. They discovered that users employ the like feature for various reasons, such as expressing approval, supporting the author, or bookmarking content for later reference. While liking and retweeting share similarities in expressing agreement or interest, their expressive functions can differ. Liking a tweet may serve as a more private form of endorsement, whereas retweeting publicly shares the content with one's followers, signalling a stronger or more public level of support.

Engagement features also play a role in identifying spam or inauthentic accounts. Research indicates that suspended accounts often exhibit excessive interactions, such as frequent replies and mentions, which are characteristic of spamming behaviour (Pierri et al., 2023).

Additionally, the characteristics of an account's followers can influence engagement dynamics. Grabowicz et al. (2021) found that early followers tend to be more engaged and are often considered credible users, such as verified or expert accounts. It should be noted that, in this context, verified refers to legacy verification but not Twitter Blue.

Drawing from these insights, metrics like likes and retweets can serve as proxies for gauging the level of engagement for tweets across different users. They help in understanding how content resonates with audiences and how it spreads within the network. By analyzing these engagement actions, researchers can gain insights into user behaviour, content popularity, and the potential reach of tweets.

In the context of our study, examining likes and retweets allows us to assess engagement patterns among politicians' tweets over time. By analyzing these metrics across various users and comparing them before and after significant platform changes, we aim to observe trends in user interactions.

Twitter Auditing/Social Media Auditing

Extensive research has been conducted to audit platforms like Twitter for potential biases in content and user engagement, utilizing various methods such as sock puppet approaches and agent-based testing. Sock puppet audits involve creating automated accounts (bots) that mimic human behaviour to analyze how different feeds present content to users. For instance, Bartley et al. (2021) utilized this approach to compare reverse chronological feeds with personalized algorithmic feeds. Their findings indicated that personalized feeds display popular tweets but may distort users' perceptions of their friends' activity levels by selectively sampling displayed tweets.

Similarly, during the COVID-19 pandemic, a sock puppet audit revealed that algorithmic curation slightly amplified political tweets while suppressing health and COVID-19-related content (Bandy and Diakopoulos, 2021b). Agent-based testing, as conducted by Bandy and Diakopoulos (2021a), compared chronological and algorithmic feeds, discovering that chronological timelines contain twice as many external links and fewer junk news sites than algorithmic feeds.

Research has also highlighted that algorithmic biases can lead to the amplification of certain types of content or political ideologies. An internal study by Twitter examined the political content amplification in seven countries and found that, in six of them, tweets from the political Right were amplified more than those from the political Left (Huszár et al., 2022). This study employed a treatment-control design, comparing users exposed to the algorithmic feed with those viewing the reverse chronological feed. Amplification was measured using "linger impressions," which occur when at least 50% of a tweet is visible on a user's screen for at least 500 milliseconds.

Further investigations revealed that algorithmic feeds might amplify users' friends' tweets based on political leanings, potentially diverging from the content users actively subscribe to (Bouchaud et al., 2023). These studies suggest that algorithmic content curation can inadvertently introduce biases that affect users' exposure to diverse viewpoints.

In addition to algorithmic factors, user behaviour plays a significant role in shaping biases on social media platforms. Kulshrestha et al. (2017) examined user searches and queries to differentiate between biases introduced by algorithms and those stemming from user actions. Their research on political queries on Twitter indicated that user-generated queries contribute substantially to the overall bias on the platform. This finding underscores the interplay between user behaviour and algorithmic curation in influencing content exposure.

The closest work to our study is the internal analysis conducted by Twitter (Huszár et al., 2022), which explored the amplification of politicians from multiple countries using internal metrics like linger impressions. However, our research distinguishes itself by utilizing publicly accessible engagement metrics such as likes and retweets to examine user-level changes over time. By analyzing such data, we seek to enhance the transparency of research on social media platforms and provide insights that are accessible to a broader audience.

Data Collection

An extensive data collection process was performed to obtain the data required for our analysis (Figure 3). We initially started by considering the top twenty countries in terms of user activity on Twitter from (World Poplulation Review, 2023) and (Statista, 2023a). Out of these, we had to remove countries such as South Korea, the Philippines, and Turkey that do not have proper data on current parliamentarians or enough politicians on Twitter. After this filtering process, we restricted our analysis to twelve countries, namely Argentina, Brazil, Canada, Colombia, France, Germany, India, Japan, Mexico, Spain, the United Kingdom, and the United States.

Figure 3. Details of the Data Collection Process

For these countries, we collected the names and the Twitter profiles of the parliamentarians in both upper and lower houses or their equivalent, the ministers of the cabinet, and the political parties (together, referred to as politicians from here on, since most accounts are of politicians) in the parliament/government as of April 2023. Most of the Twitter profiles were obtained from official government sites[13]. In cases where this was not possible, we looked for Twitter lists made by the Twitter accounts of the Parliament Houses[14]. For India, where there is no official information on the Twitter profiles of the members of the parliament, we manually searched Twitter using their names and picked accounts that had words such as 'MP', 'Rajya

[13]See e.g. https://members.parliament.uk/parties/Lords for members of the House of Lords, UK and https://www.house.gov/representatives for House of Representatives, US.

[14]See, e.g., https://twitter.com/i/lists/1691734501162881488 for the Spanish Senate

Sabha', or 'Lok Sabha'. We conducted a validation round by randomly picking 20 profiles and double-checking their correctness. All the profiles checked in this validation round from all the countries were found to be correct.

For the 8603 politicians across all countries, we successfully identified 6550 Twitter accounts, accounting for protected accounts for which data could not be collected. We then focused on gathering tweet metrics for the most recent 3200 tweets per account, as limited by the Twitter API, excluding retweets, replies and quotes. Although the earliest date of these tweets varies for each user, our dataset ensures coverage starting from at least June 2021 for all users. Table 1 contains the percentage of politicians on Twitter for each country, their Twitter Blue Verification Status and other details. Although these details do not directly look at engagement and support, they are still helpful in understanding the high-level Twitter behaviour of politicians in each country. For instance, nearly all politicians in the United States are classified as government organizations/entities, whereas this is significantly less common in other countries, underscoring cross-country differences in policy adoption.

Table 1: This table provides information on the number of parliament members and those with Twitter accounts within our collected data. It also shows the percentage split of left- and right-leaning politicians among these collected Twitter accounts. Additionally, it includes the percentages of these accounts that have government verification badges and blue verification status.

Country	Num. of Politicians in Parliament	Num. of Politicians on Twitter	% of Left-wing Politicians on Twitter	% of Right-wing Politicians on Twitter	% of Government verified accounts	% of Blue verified accounts
Argentina	352	299	56%	44%	13%	12%
Brazil	646	616	54%	46%	10%	11%
Canada	429	401	10%	90%	47%	9%
Colombia	333	205	64%	36%	8%	20%
France	961	662	29%	71%	32%	12%
Germany	949	702	53%	48%	2%	5%
India	853	683	30%	70%	47%	21%
Japan	726	588	25%	75%	1%	10%
Mexico	647	581	65%	35%	11%	17%
Spain	704	553	60%	40%	5%	8%
UK	1437	715	54%	46%	55%	4%
US	564	545	49%	51%	97%	14%
Total	8603	6550	46%	54%	29%	11%

Given the extensive scope of our research, covering twelve countries with varying political systems, identifying the ideological positions of political actors in each country posed a considerable challenge. This task required us to draw information from distinct sources, the details of which can be found in Table 2. To accomplish this, we first employed the Chapel

Hill Expert Survey (CHES) (Jolly et al., 2022) to gather information on the ideological positions of political parties in European countries and Argentina, Brazil, and Colombia. The CHES data offers measurements of the ideological position of each party, derived from the collective input of international experts specializing in political parties. For other countries, we resorted to data from the Manifestos Project Dataset (Lehmann et al., 2023), a component of the Manifesto Research on Political Representation project, also known as MARPOR. This dataset analyzes the electoral manifestos of political parties, providing left-right positions of political actors based on the coded content of party electoral programs. Nonetheless, there were still instances where we could not determine the ideological position of certain parties from our previous sources, as seen in Table 2. To complement our collection, we also utilized the Varieties of Party Identity and Organization Dataset (V-Party) (Coppedge et al., 2024), the Global Party Survey (GPS) (Norris, 2019) and the World Values Survey (EVS, 2022). We used the ideology indicated in their Wikipedia pages for parties that were still missing data in any of these sources as Herrmann and Döring (2023) showed that this method leads to reliable results similar to those obtained using traditional expert-based coding methods.

In cases of conflicting scores, we resolved discrepancies by prioritizing expert-coded surveys or the majority-supported score. Importantly, since we focus only on binary ideological labels (left-right), the number of cases with conflicting binary labels was relatively small. By incorporating data from these distinct sources, we successfully assigned left-right labels to most political parties with parliamentary representation in all the countries included in our research. In the case of coalitions, the parties that did not have a left-right label were assigned the same label as the major party in the coalition. For simplicity, we assigned politicians the same value as the party they belong to, as we are interested in high-level patterns of amplification and potential biases. This would remove independent politicians or those in parliament that do not belong to any party, such as the Bishops in the House of Lords, UK[15]. More details on the distribution of Left and Right politicians in the Parliaments can be found in Table 1.

[15]https://www.parliament.uk/site-information/glossary/bishops/

Table 2: Coverage of left-right scores by various datasets for parties in Parliament as of April 2023. The column CHES constitutes both CHES Europe and CHES Latin America.

Country	CHES	MARPOR	VPARTY	GPS	WVS
Argentina	75%	-	75%	25%	25%
Brazil	38%	8%	77%	46%	46%
Canada	-	100%	100%	100%	100%
Colombia	39%	-	50%	33%	33%
France	100%	100%	100%	80%	80%
Germany	62%	62%	54%	54%	54%
India	-	-	34%	20%	20%
Japan	-	71%	86%	86%	57%
Mexico	-	100%	100%	71%	71%
Spain	56%	56%	44%	33%	22%
UK	64%	64%	36%	64%	-
US	-	100%	100%	100%	100%

Empirical Analysis and Results

This section details the approaches used and the insights they provide on how the platform evolved over time.

Pre vs Post-Musk Analysis

We begin by calculating the daily median metrics for each politician within the specified time period, focusing on likes, retweets, and the likes-to-retweets ratio. These daily medians serve as the basis for subsequent analysis steps.

To analyze the overall trends, we examine the monthly median-of-median values for the above-mentioned metrics. Using the daily median, we determine the monthly median for each politician. Finally, we compute the country-level median-of-median metric for each month by taking the median of these monthly medians across all politicians in the country. We consider medians rather than means to avoid outlier effects and make the analysis more robust. As mentioned, Musk acquired Twitter at the end of October 2022, with most changes implemented in November 2022. Noticeable changes for all countries are observed in Figure 4, from November to December 2022, coinciding with the period when policy changes were introduced. The exception is Brazil, but this is likely due to the elections and protests during this period[16]. The uniform spike in all plots at the same time period for all countries is likely associated with external factors, such as policy changes that may have affected politicians globally. The consistent and marginal increase in likes and retweets, respectively, from November to December 2022, reflects an observed rise in the engagement of political tweets. The increase in the likes-to-retweets ratio means a higher share of people liking the tweets but not actively sharing them. However, these results indicate the *overall* monthly change for each country but do not necessarily signify changes at the level of individual politicians.

[16]https://www.bbc.com/news/world-latin-america-64206220

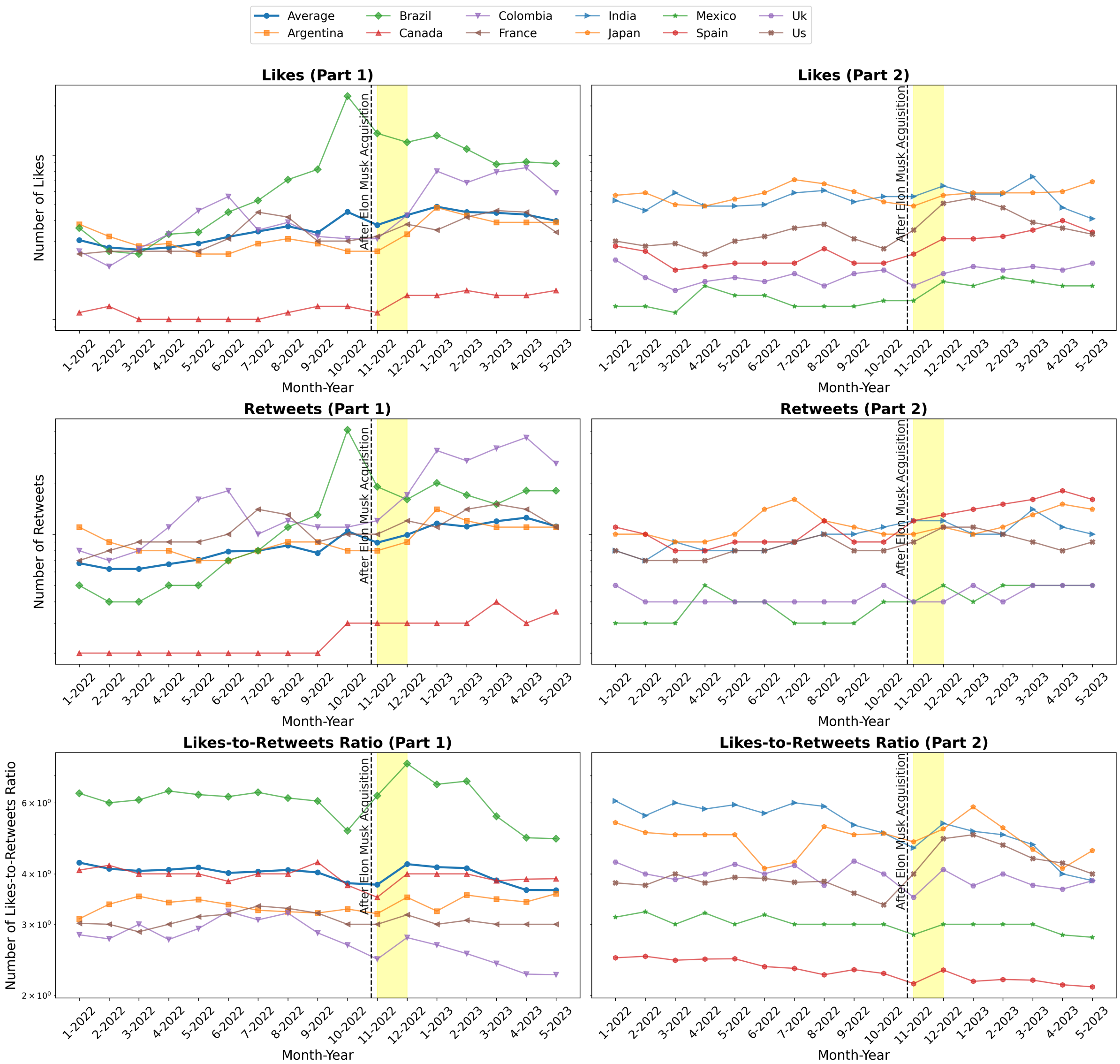

Figure 4. Temporal Analysis of Median-of-Median Metrics from January 2022 to June 2023 (Values before January 2022 are excluded to enhance readability). The spikes highlighted in all plots in all countries from November to December 2022 suggest that these changes are likely associated with external action.

To understand the changes at a user level, each politician is tested to see if they had a statistically significant increase or decrease in their engagement using their likes, retweets and likes-to-retweets ratio. For each politician, pre- and post-Musk values of daily medians are obtained for each metric, considering November 5, 2022, as the cutoff. This date is chosen not as a definitive marker for observable changes, but rather to approximate a period around which engagement patterns might have shifted, providing a structured way to examine potential variations before and after this time frame. Many reports show signs of increased extreme content within one week of acquisition, making this as a useful reference point for the analysis. Politicians with less than ten tweets, either pre- or post-Musk, are excluded from the analysis. Since most users exhibit autocorrelation at different lags and overdispersion in the metrics (Figure 5), we use Generalized Additive Models for Location, Scale, and Shape (GAMLSS) (Rigby and Stasinopoulos, 2005) to account for these factors. Autocorrelation is tested using simple ACF graphs, with a maximum of 10 lags considered. If autocorrelation is detected, the lagged dependent variable (DV) at the identified lag is included in the model. GAMLSS extends generalized linear models (GLMs) by allowing for flexible distributional assumptions, enabling the modelling of location (mean), scale (variance), and shape (skewness and kurtosis) parameters as functions of independent variables. We fit a model for each metric for each politician to understand differences at the politician level and refrain from using a combined model due to the varying lag levels (most accounts have different lag structures and intensity of violations) for each politician, meaning that a single model would fail to adequately capture the unique autocorrelation patterns and engagement dynamics of individual politicians.

To ensure robustness, we tested alternative models, including ARIMA, which effectively handle autocorrelation but do not account for overdispersion, and negative binomial regression, which accommodates overdispersion but does not model autocorrelation, resulting in poorer convergence. Additionally, we tried fitting a Bayesian hierarchical model with a spline for time to partially address both autocorrelation and overdispersion. However, it was not useful since this approach required significant computational resources.

Figure 6 shows that at least 80% of the individual models converge for the three metrics. Focusing on the models that converged, we now assess whether the changes in likes, retweets, and likes-to-retweets are statistically significant or not. Figure 7 illustrates the proportion of politicians in all countries with significant and non-significant changes in each metric, categorized by the direction of change: whether there is an increase or decrease in the metric following Musk's acquisition. The plot reveals that overall, 45% of politicians experienced a significant change in their likes, 63% in retweets, and only 20% in their likes-to-retweets ratio. Among these, a higher proportion of politicians experienced an increase in their likes and likes-to-retweets ratio, but a decrease in the number of retweets. This suggests that the content of these politicians may be reaching a larger audience, as reflected in more likes, though it is not being actively shared (retweeted).

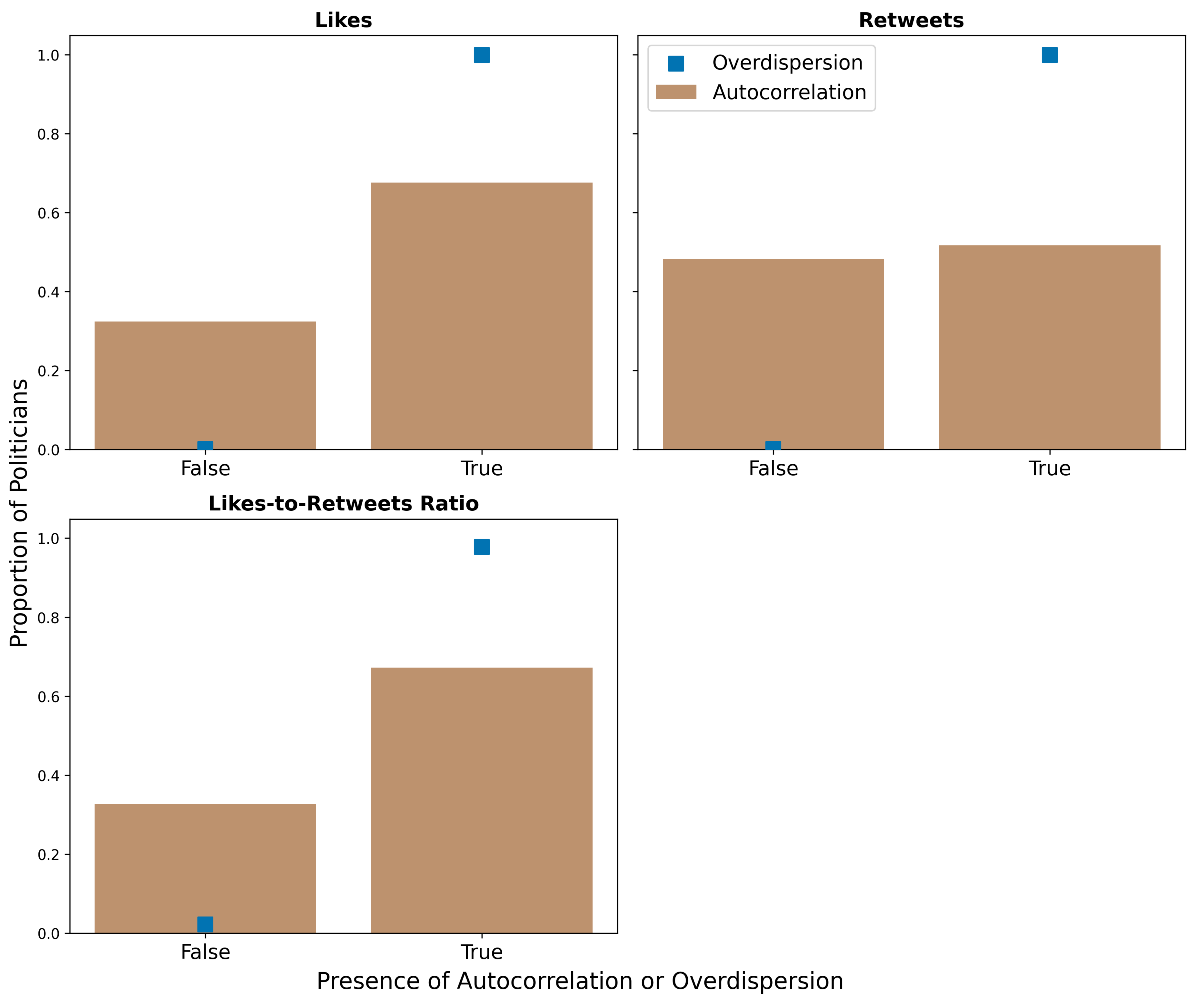

Figure 5. Plots illustrating the proportion of politicians exhibiting autocorrelation and overdispersion.

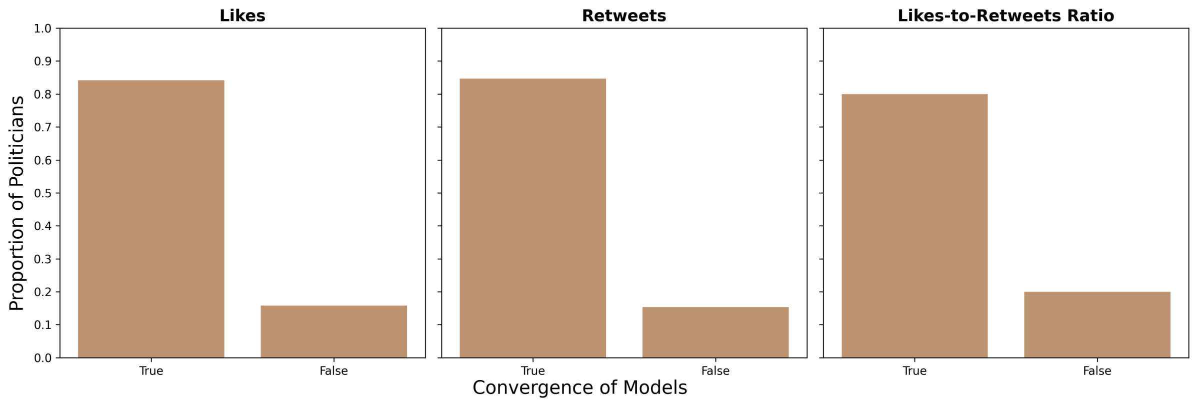

Figure 6. Proportion of politicians for whom the models successfully converged.

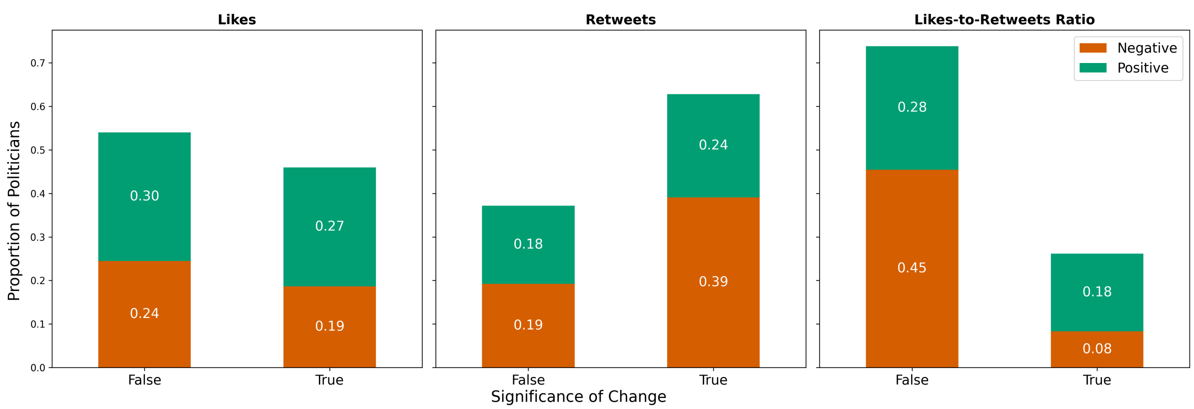

Figure 7. Plots illustrating the proportion of politicians who exhibited significant changes across all metrics, along with the direction—positive or negative—of these changes.

Similarly, examining the politicians of each country separately, we observe that a higher proportion of U.S. politicians experienced significant changes across the three metrics compared to politicians from other countries, as seen in Table 3. This highlights cross-country variations in the patterns of change, which could relate to differences in platform dynamics or engagement trends in each context.

Table 3: Percentage of politicians exhibiting significant changes across various metrics for each country.

Country	Likes	Retweets	Likes-to-Retweets Ratio
Argentina	42%	69%	20%
Brazil	54%	59%	31%
Canada	49%	65%	24%
Colombia	46%	65%	28%
France	45%	63%	25%
Germany	46%	59%	26%
India	38%	56%	22%
Japan	41%	66%	21%
Mexico	46%	61%	24%
Spain	37%	57%	18%
UK	44%	65%	27%
US	64%	77%	46%

Left vs Right Analysis

As discussed in the previous section, the politicians in each country are classified into two groups, the Left and the Right, based on the ideological position of their affiliated party. We opted for this binary distinction for the sake of simplicity and because the use of 'left' and 'right' to designate certain political positions is mostly universal. The left-right schema provides the overarching political code that promotes political orientation among citizens and facilitates political communication between the elites and the mass public. In general, it can be said that the ideals of progress and equality are more associated with the Left, while conservatism and defense of the status quo are mostly linked with the Right (Bobbio, 1996; Mair, 2007; Noël and Thérien, 2008; Lindqvist, 2024). However, we are aware that left-right ideology is a continuum and that the ideological alignment of politicians is much more complex. Moreover, the meanings associated with each of these ideological labels can vary from one context to another because political actors are interested in inserting new societal conflicts onto the left-right

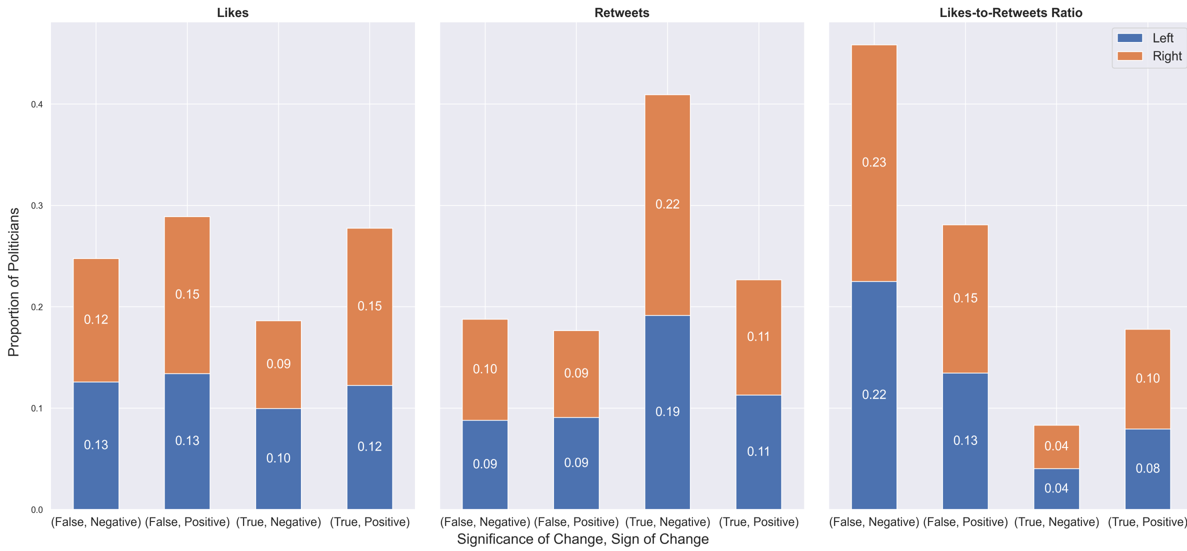

Figure 8. Plots illustrating the proportion of politicians, categorized by ideology, who exhibited significant changes across all metrics, along with the direction—positive or negative—of these changes.

scale (de Vries et al., 2013). This means there are ideological differences between politicians from different countries who are situated under the same ideological label. Therefore, we had to set aside the discussions and nuances over politicians' ideology in order to offer a global overview, distinguishing based on a global concept, such as the Left and the Right, although we understand that works focused on one or two more homogeneous countries could offer a more complex view. We now perform a similar analysis as before but separately on the left and right-leaning politicians. Looking at the proportion of politicians in all countries in Figure 8, the trends across the Left and Right with significant change largely remain the same; in that, we see an increase in likes and likes-per-retweet and a decrease in retweets. However, our analysis does not indicate any relationship between political ideology and whether politicians benefit from the observed changes. Similarly, the country-specific analysis did not reveal any additional patterns or deviations from the overarching trends.

Discussion

In this study, we examine how changes to Twitter following Elon Musk's acquisition corresponded with shifts in political engagement and platform evolution. We perform a *global analysis* by analyzing user-level changes in engagement using likes and retweets. Overall, our results show that tweets from politicians exhibited a considerable increase in likes and a decrease in retweets, along with a slight increase in the likes-to-retweets ratio. This aligns with the notion proposed in (Grabowicz et al., 2021) that early followers are more aligned and engaged, supporting content more actively. As content spreads to a broader audience, it is more likely to reach beyond its "core" supporters, resulting in higher likes and lower retweets. From the Left vs. Right analysis, it can be observed that, in most countries, there are no significant differences between the two, suggesting that political ideology is not an indicator of engagement changes during this time period.

Various factors may be associated with the observed changes, such as differences in tweeting activity and shifts in network dynamics. For example, if a politician reduces their tweeting frequency, this could correlate with changes in their per-tweet engagement. Another possibility is that users unfollow politicians or delete their accounts, changing engagement patterns. Additionally, since we consider politicians in parliament as of April 2023 but consider data from November 2022 to June 2023 for post-Musk analysis, there is a possibility that politicians who came into power after November 2022 might have gained sudden popularity and thus influence the analysis. To address this, we collected a list of such politicians[17] and tested whether excluding them alters the trends. We found that there were not many such politicians (less than ten), and excluding them did not change the overall trends.

This study comes with its set of caveats due to issues with data collection and the dynamic changes occurring on the platform between November 2022 and June 2023. As shown in Figure 1, several factors—including the removal and reintroduction of legacy blue check marks and changes to content exposure—likely influenced the results. This period also saw a large number of users leaving the platform, all of which changed the exposure of the content

[17] From official sites such as https://www.parliament.uk/about/how/elections-and-voting/by-elections/by-elections-2019/, https://sansad.in/ls/members etc.

received[18]. As previously discussed, we refrain from attributing observed changes to specific causes, focusing instead on describing the observed trends.

Another consideration is determining who to include in the analysis. For example, should figures like Donald Trump[19] be weighted as a de facto spokesperson for their party? Currently, we include only parliamentarians in office, excluding non-parliamentary opposition, which can be highly active on social media.

Regarding engagement data, we lack information on *who* liked or retweeted posts, making it unclear whether the engagement came from in-network or out-of-network audiences. Although the newly introduced view count metric[20] could provide insights into tweet reach, it was not available for the entire study period[21], as discussed in Section 1.

To get the Twitter data of the politicians for the analysis, we used our Twitter v1.1 API and the GRAPHQL API endpoints[23], adhering to Twitter's rate limits. Twitter's decision to deprecate v1.1 API keys along with Academic APIs and restrict access to the platform (Reuters, 2023) deeply affected our data collection process. It came to a complete stop by mid-June 2023, after which we could not collect any data. In a time where social media is a vital part of our lives, data availability, in particular for public figures, is of utmost importance, and we urge that the API restrictions be lifted or made available at adequate costs, fostering data transparency. Although legislation like the Digital Services Act[24] aims to systematically provide data access to researchers, it is not yet fully functional, to the best of our knowledge[25]. Transparency in algorithmic and policy decisions is of equal importance. For instance, Meta (in particular Instagram and Threads)[26] allows users to opt out of political content suggestions,

[18] https://www.theguardian.com/technology/2022/dec/13/twitter-lose-users-elon-musk-takeover-hate-speech

[19] Donald Trump was not the President of the United States during the time of data collection but remains a key Republican figure.

[20] https://help.x.com/en/using-x/view-counts

[21] View counts were introduced on December 22, 2022, and are accessible through the v2 API[22].

[23] e.g API endpoint to search the user by their screen name https://twitter.com/i/api/graphql/G3KGOASz96M-Qu0nwmGXNg/UserByScreenName?

[24] https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/digital-services-act_en

[25] https://dsa40collaboratory.eu

[26] https://about.instagram.com/blog/announcements/continuing-our-approach-to-political-content-on-instagram-and

while reports suggest that X does not provide this option and may prioritize political content even when users prefer otherwise [27]. Independent oversight or similar mechanisms could help ensure informed discourse on the influence of platform policies.

Conclusion

To the best of our knowledge, this is the first study to conduct a *temporal* and *global* analysis of political engagement trends following recent changes to Twitter. Our findings show that political content has been reaching a broader audience, with an increase in likes and likes-to-retweets ratio but a decrease in retweets. However, we do not find any evidence that shows a significant difference in engagement patterns between the Left and the Right. Given the continued reach of Twitter (now X) and the observable changes under Elon Musk's leadership, we view examining shifts in political discourse during this period as necessary and valuable.

Future research could benefit from a more comprehensive profile collection and an in-depth analysis of tweet content to better understand patterns of visibility and amplification. However, such analyses remain challenging due to limitations in API access and data availability. Legislation such as Article 40 of the Digital Services Act could play a crucial role in enabling greater access to data for research into this area.

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[27] https://www.washingtonexaminer.com/policy/technology/3207324/x-algorithm-shows-political-content/

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Robustness Checks for Likes-to-Retweets Ratio

As mentioned in Section 1, we use the likes-to-retweets ratio to understand differences in tweet engagement. A lower ratio suggests that users actively retweet the tweet, while a higher ratio indicates that the tweet is liked more often than it is retweeted. As discussed in Section 2, although the literature highlights varying motives for these actions, we assume that likes generally reflect silent approval, whereas retweets signify strong support or public endorsement.

To validate this assumption, we analyzed the likes-to-retweets ratio of tweets from categories with distinct engagement behaviours, such as adult (pornographic) content and job postings. Using related hashtags (#xxx, #postdocjobs etc.) and relevant communities, we manually collected fifty tweets from each category. The box plots in Figure 9 show that tweets containing adult content have a higher likes-to-retweets ratio (users are more likely to like but not retweet), while job postings exhibit a lower ratio (users are more likely to retweet for broader dissemination). These results validate our assumption that these metrics can characterize differences in engagement patterns.

We extended this analysis to two groups of politicians within the same country but with differing follower counts, based on the notion that early followers are more engaged, while a larger following reaches less-engaged audiences, resulting in fewer retweets (Grabowicz et al., 2021). Box plots of manually collected tweets from these politicians confirm that those with higher follower counts tend to have higher likes-to-retweets ratios than those with smaller followings. While individual tweets may vary due to factors like content or media type (e.g., videos), the broader trends still support our assumptions.

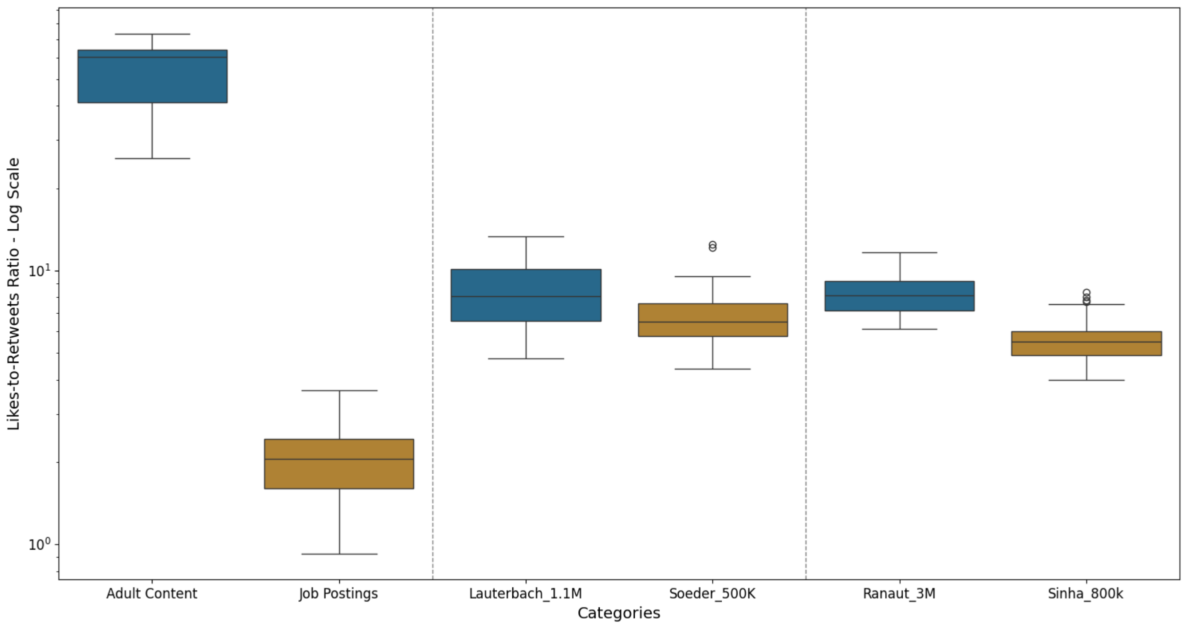

Figure 9. Box plots displaying the variations in the likes-to-retweets ratio among different groups. The first comparison is between Adult Content and Job Postings, while the second and third compare politicians from the same country but with different follower counts. The blue box plots represent a higher ratio, whereas the brown ones represent a lower ratio.

Effect Sizes of Changes in Engagement Metrics for Politicians, Country-Wise

These graphs (Figures 10, 11, 12) present the distribution of coefficients representing the estimated effect sizes of metrics (percentage changes) derived from fitting GAMLSS models for politicians across various countries. Each panel corresponds to a specific country, and the x-axis represents the effect sizes with their 95% confidence intervals, while the y-axis lists politicians (not explicitly labeled here). Coefficients with high standard errors (>5) have been excluded for clarity.

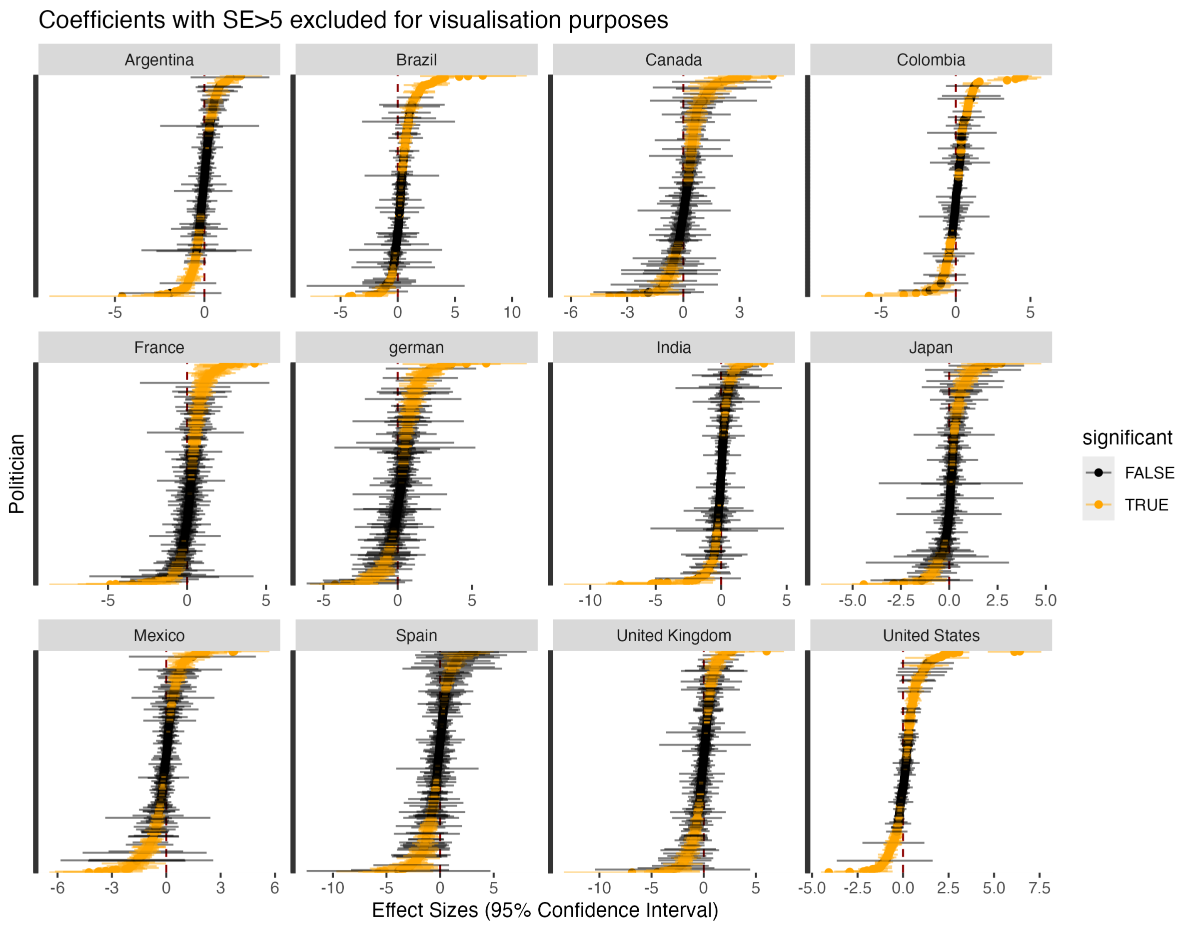

Figure 10. Effect sizes derived from fitting GAMLSS on Likes. Points in orange indicate statistically significant effects, where the confidence interval does not include zero, while points in black represent non-significant effects. The dashed vertical line at zero represents no change.

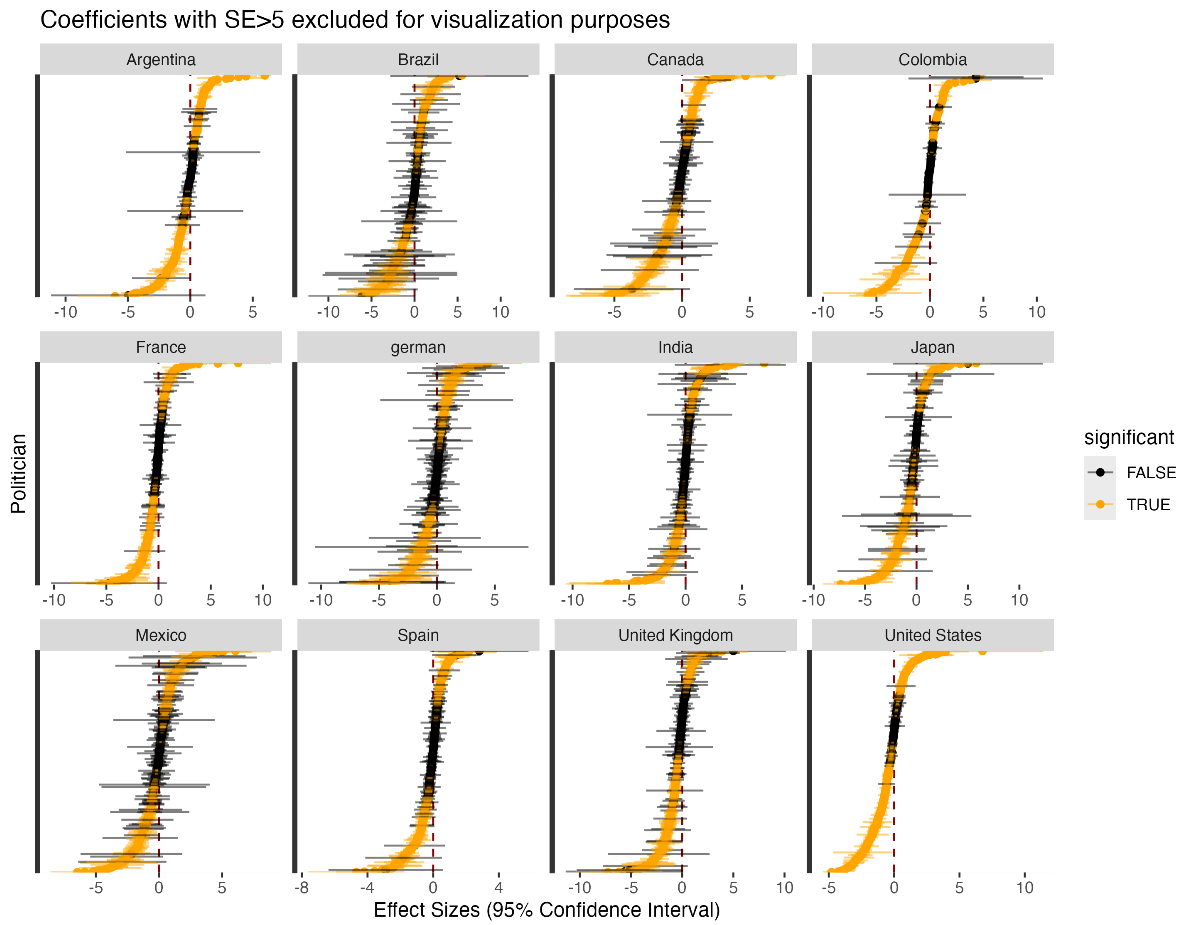

Figure 11. Effect sizes derived from fitting GAMLSS on Retweets. Points in orange indicate statistically significant effects, where the confidence interval does not include zero, while points in black represent non-significant effects. The dashed vertical line at zero represents no change.

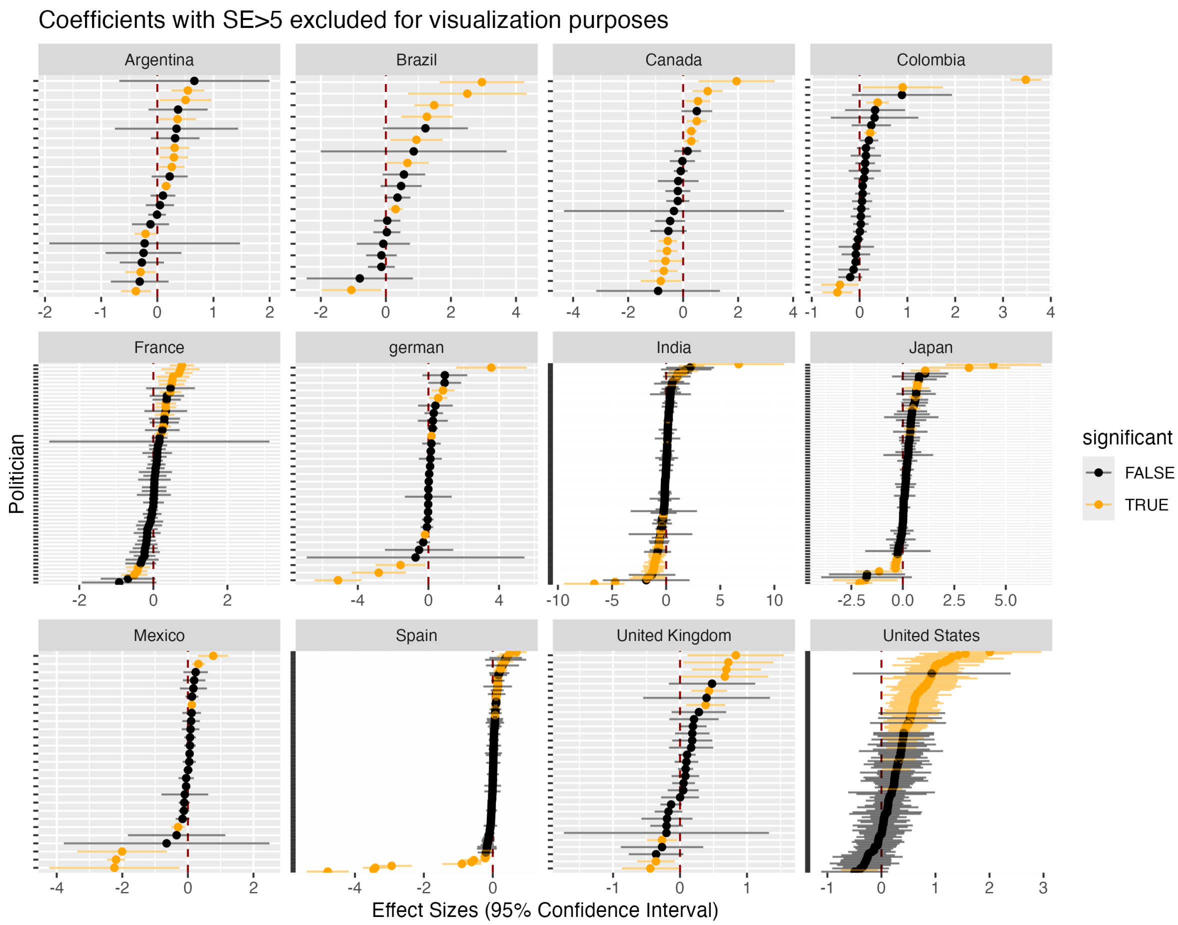

Figure 12. Effect sizes derived from fitting GAMLSS on likes-to-retweets ratio. Points in orange indicate statistically significant effects, where the confidence interval does not include zero, while points in black represent non-significant effects. The dashed vertical line at zero represents no change.