Social Media vs. Surveys: A New Scalable Approach to Understanding Legislators' Discourse

Valentina González-Rostani* José Incio† Guillermo Lezama‡

This paper explores how legislators use social media, specifically investigating whether their posts reflect the concerns expressed by their legislative party peers in an anonymous survey. Utilizing data from Twitter, we compare legislators' social media posts with their responses in a survey of legislators in Latin America. We propose a novel, and scalable method for analyzing political communications, employing OpenAI for topic identification in statements and BERTopic analysis to identify clusters of political communication. This approach enables a thorough and detailed examination of these topics over time and across political parties. Applying our method to statements made by members of the Chilean Congress, we observe a general alignment between the preferences stated in surveys by elites and the prominence of these issues on Twitter. This result validates social media platforms (particularly Twitter) as a tool for predicting politicians' preferences. Our methodological approach offers a scalable tool for analyzing political rhetoric over time.

Key words: OpenAI, Legislators, Political Communication, Text-as-data, Elites Survey, PELA

*University of Pittsburgh, Department of Political Science. Email: mag384@pitt.edu.
†Pontificia Universidad Católica del Perú, Department of Sociology. Email: jincio@pucp.pe.
‡University of Pittsburgh, Department of Economics. Email: guillermo.lezama@pitt.edu.

Introduction

Social media has revolutionized how elected representatives communicate with their constituencies, fellow legislators, and the media. This paradigm shift from traditional communication methods to digital platforms presents a unique intersection of transparency and strategy within political discourse.[1] While these platforms facilitate a more direct and immediate connection with the public, they also introduce a nuanced battlefield for politicians. This digital arena compels them to continually balance between voicing their genuine policy preferences and molding their rhetoric to align with what is electorally advantageous. As highlighted by Alesina and Cukierman (1990), politicians often face a dilemma between advocating for their core values and pursuing policies that maximize reelection prospects.

The complexity of this scenario has increased in the digital age. Blum, Cormack, and Shoub (2023) point out that the wide range of communication channels available to politicians, especially social media, greatly expands their ability to influence public perception and gain support. However, a critical question arises: Do these digital interactions reflect politicians' genuine policy preferences and priorities, or are they strategic tactics aimed at winning votes and retaining office? This research note explores this dilemma by comparing digital-era political communication with the priorities expressed in an anonymous survey of parliamentary elites.

Surveys focusing on the political elite, such as the Parliamentary Elites in Latin America Observatory (PELA hereafter, PELA-USAL 2018), offer valuable insights into the preferences and priorities among political leaders. However, these surveys often fail to capture legislators' communicated policy priorities to their constituents. In addition, since the sample is taken once per legislature, it does not allow us to observe changes in legislators' priorities or reactions to events between surveys.

Fortunately, the extensive social media data collection allows us to observe politicians' communicated priorities in real time, providing a new avenue for exploring these communication strategies and broader aspects of elite political behavior and public policy formulation. Politicians widely use social networks. For example, every U.S Congress member maintains a Twitter account (Golbeck et al. 2018), with similarly high usage rates observed in Europe (Scherpereel, Wohlgemuth, and Lievens 2018) and Latin America (Munger et al. 2019).[2] Understanding these political communications is crucial as even ostensibly cheap talk political speeches can have profound implications (Farrell 1995). They can

[1] Refer to Siegel et al. (2022), Blum, Cormack, and Shoub (2023), and Cormack (2016)

[2] These digital platforms serve as a critical platform for politicians, enabling them to engage in policy discussions, disseminate updates about their activities (Golbeck, Grimes, and Rogers 2010; Golbeck et al. 2018), communicate with the electorate (Hemphill, Otterbacher, and Shapiro 2013), and enhance their visibility in various media outlets (Graham et al. 2013).

shape public attention, influence policy actions (Jones and Baumgartner 2004), and affect how the electorate perceives their representatives' performance in the legislature (Grimmer 2013).

This study makes two key contributions. First, we analyze social media data as a proxy for communicated policy priorities and contrast it with elites' survey preferences. This approach provides insights into legislators' daily strategic communications, revealing an overall convergence of their private and communicated policy priorities. Second, using state-of-the-art natural language processing techniques (Laurer et al. 2024; Wolf et al. 2020), we implement a scalable methodological approach for identifying issues in political communications. This represents a tool for analyzing party dynamics with temporally disaggregated data and for identifying issues beyond those covered in elite surveys conducted every five years.

To achieve this, we classify legislators' social media statements into political topics using the OpenAI API's chat completion feature, aligning them with issues from the PELA survey. We compare issue salience on social media with relevance assigned in PELA. Next, using BERT-based topic analysis (BERTopic, Grootendorst 2022), a deep transfer learning technique, we identify emerging clusters in political discourse, suggesting additional topics for future PELA questionnaires. We test our approach by mapping the daily communications of Chilean members of Congress from March to December 2014,[3] utilizing Twitter as our data source. We provide descriptive plots to illustrate how elite strategic communication evolves over time and diverges from stated preferences.

Our findings demonstrate the efficacy of using social media, particularly Twitter, as a proxy for legislators' privately stated priorities. First, we show that a substantial proportion (24%) of public statements on Twitter align with the topics in PELA's questionnaire. This observation suggests that legislators indeed use social media platforms to convey their opinions on issues that are relevant to them. For example, in the Chilean case, the degree of importance (rankings) that legislators expressed in the anonymous survey largely coincides with the importance they assign to it in their public statements. Second, the analysis using unsupervised clustering of statements demonstrates additional clusters of political communication, such as international affairs. Lastly, many tweets involve greetings and interactions rather than policy topics, similar to findings for US congress members' tweets (Hemphill, Russell, and Schöpke-Gonzalez 2021; Barberá et al. 2019).

Our results and methodological proof of concept highlight the value of analyzing political communications on social media, which provides high-time granularity. This study is the first to comprehensively juxtapose legislators' declared preferences with their actual communication strategies. Our scalable

[3]This year coincides with the most recent PELA survey available.

approach maps strategic communication tendencies, allowing for the examination of daily variations in policy preferences across parties and legislators, complementing sporadic data from surveys or roll call votes. Additionally, we demonstrate that GPT-3.5 is an effective and affordable tool for researchers to identify policy issues, emphasizing the efficiency and multi-language applicability of modern Large Language Models compared to traditional human coding methods (Gilardi, Alizadeh, and Kubli 2023; Laurer et al. 2024).

Policy-seeking or Vote-seeking?

While surveys highlight the policy preferences of parliamentary elites, social media analysis reveals their political communication strategies. These strategies may fall into three categories: championing preferred policies (policy-seeking), communicating party policy preferences to core supporters, and deviating from their actual policy priorities to address electorate-relevant issues (vote-seeking behavior). If politicians are policy-seeking, alignment between their private and public policy priorities is expected. However, if they are office-seeking, a divergence between their views and social media statements is likely.

Building on the notion of politicians as policy-seeking, their communications should align with their stated preferences and priorities. Scholars like Jacobs and Shapiro (2000) and Shapiro and Jacobs (2000) argue that many politicians prioritize specific policy outcomes over reelection. These policy-driven politicians exploit lapses in public engagement to steer the agenda towards their preferences (Shapiro and Jacobs 2000) and strive to align public opinion with their views by explaining any inconsistencies (Grose, Malhotra, and Parks Van Houweling 2015).

Another plausible reason for the alignment between stated policy positions and political communication could be the legislators' focus on catering to their core party supporters (e.g., Wright 1989). For instance, these supporters play an important role in nomination processes and primaries (Bawn et al. 2012; Fenno 1978; Gerber and Morton 1998) as well as in general elections (Holbrook and McClurg 2005). Moreover, as Egan (2013) and Kastellec et al. (2015) note, the policy preferences of highly engaged party members are more likely to coincide with those of policy-oriented politicians.

Though there are incentives to maintain alignment of preferences and actions, legislators do not always act to support their own views. Deviations may occur as they adapt to avoid losing electoral support. For instance, Mayhew (2004) emphasizes Congress members' constant pursuit of reelection, which, in our analysis, could lead them to use social media platforms for direct communication with constituents. This need to remain electorally relevant may cause politicians to adapt their

communication to suit changing public sentiments (Stimson, MacKuen, and Erikson 1995). Barberá et al. (2019) show that legislators often align their discourse with public concerns, following rather than leading on issues. Similarly, Canes-Wrone and Shotts (2004) highlight how shifts in public opinion directly influence the preferences and behaviors of political figures.

Moreover, the need for strategic positioning can lead to selective communication. Politicians might avoid discussing topics that are important to them but potentially unfavorable in the public eye. Milita et al. (2017) suggest that remaining silent on certain issues can be more beneficial than creating ambiguity, which would increase saliency. Additionally, Cormack (2013) and Gonzalez-Rostani (2023) demonstrate that politicians can either portray themselves ideologically or focus on specific issues, such as pro-redistributive policies, in their campaign communications, depending on the coverage of swing districts and the targeting of certain audiences. This nuanced approach reflects a calculated effort to balance personal policy preferences with the demands of vote-seeking and maintaining a favorable public image.

EMPIRICAL STRATEGY AND DATA

Our case focuses on the members of the Chilean Congress who were elected during the 2013 election, including all members of the House of Representatives and the Senate. They assumed their legislative roles in March 2014. We utilize two primary data sources for our analysis. First, to gauge legislators' preferences, we rely on the PELA-USAL (2018), which provides a comprehensive anonymous survey of legislators' characteristics and policy positions gathered after each legislative election.[4] Surveys are a conventional method for exploring voters' policy preferences, and the PELA survey has over 30 years of experience applying this methodology to legislators.

Chile is known for its stable party system in Latin America (Mainwaring and Scully 1995). The electoral system uses open-list proportional representation, creating a multi-party landscape across the ideological spectrum. Party labels are crucial in elections and coalition-building. At the left end of the ideological spectrum is the Communist Party (PC), while at the right end is the Independent Democratic Union (UDI). In 2014, the center-left coalition "Nueva Mayoría" elected Michelle Bachelet as President, comprising the Socialist Party (PS), Party for Democracy (PPD), Social Democrat Radical Party (PRSD), and the Communist Party (PC). The Christian Democratic Party (PDC) is center-right,

[4]The 54th Congress is the most recent data available in the PELA survey and was conducted in 2014. For more details, refer to Appendix B.

positioned between centrist and right-wing factions, with National Renewal (RN) and UDI further to the right.[5]

We analyze legislators' responses to a question about the relevance assigned to 12 critical issues, including inflation, education, health, and corruption. Legislators rated the importance of these issues on a scale from 1 to 10. For example, a rating of 10 for education and 8 for health indicates higher significance for education. We examine if a politician's stated concern for an issue aligns with its salience in their communicated policy priorities.

Due to PELA's anonymity, we could not directly match legislators' responses to their Twitter postings. Instead, we compared responses aggregated at the party level. We quantified the importance each party assigns to each issue by ranking the relevance of each topic for each legislator and averaging these rankings by party. For example, if education is the top issue for legislator A and the fourth for legislator B, the party's average ranking for education would be 2.5 (refer to Appendix B.2).

Second, to investigate elite public communication, we implement a scalable method to analyze politicians' social media activity. We compiled a list of elected officials and their Twitter handles, finding that 92% of legislators had an account at the time we collected the data. Using these handles, we downloaded legislators' past tweets through the Twitter API,[6] generating a dataset of 122,245 tweets from March 2014 to December 2014.[7] We rely on Twitter statements as reliable indicators of the significance legislators assign to different political issues (Barberá et al. 2019).

Our approach uses an innovative method to categorize tweet content based on the issues assessed in the PELA survey. We use OpenAI technology to identify these issues.[8] We developed a prompt to recognize the issues of interest and validated it by randomly sampling tweets from our dataset. This validation, conducted by human coders, ensured accurate identification and minimized omissions and mislabeling. Once we generated a reliable prompt, we applied it across all statements, resulting in a categorical classification for each tweet. Finally, to verify the reliability of our classification, we selected 1,000 random tweets and asked independent annotators to determine if they aligned with any PELA issues, instructing them with ChatGPT's prompt. The annotators and ChatGPT disagreed in less than

[5]See Appendix A for further details.

[6]Data retrieved in February 2023.

[7]We focused exclusively on legislators from the seven political parties represented in PELA (141 legislators). Out of these, 129 politicians possessed Twitter accounts. Among them, 97 actively tweeted during the analyzed period.

[8]As suggested by Palmer, Smith, and Spirling 2023, researchers should justify the use of closed models. We believe that OpenAI's LLM, although closed, is justified for use as it represents a state-of-the-art tool for classification. It simplifies a process that would otherwise be very time- and resource-consuming. Researchers, especially those studying developing nations, often lack the grants and human resources needed to train their own language models. Using resources like OpenAI's LLM can help them build future knowledge. For transparency and to assist others, our prompt is detailed in the Appendix.

10% of the cases. Additionally, as a visual check, we present the word clouds for each PELA issue (Figure D.1). Appendix C presents detailed notes for replicability (OpenAI prompt), rationale of its use, and validation.

This method significantly advances previous methodologies, which relied on hand-coded content analysis or automated text analysis using dictionaries (Laurer et al. 2024). Hand-coding, while insightful, is time-consuming, resource-intensive, and prone to human bias. Dictionary-based methods require extensive case knowledge and risk researcher arbitrariness in word selection, making them highly context-specific. Politicians often reference topics in varied ways, making predefined seed words or dictionaries problematic for capturing the true context of discussions.

Moreover, recent studies have shown that ChatGPT can match or even outperform hand coding. For example, it can be more accurate than crowd-workers (especially M-Turk) in annotation and topical classification tasks (Gilardi, Alizadeh, and Kubli 2023; Kocoń et al. 2023). Additionally, ChatGPT-3 has proven highly efficient in identifying latent topics, such as hate speech (Ji et al. 2023) and populism (Bellodi et al. 2023).

To determine the relevance of each topic to legislators, we categorize every Twitter statement as either pertaining to one (or more) of the predefined issues (as identified by PELA) or as unrelated.[9] This method aligns with our approach to the PELA data, assessing the salience of each topic in legislators' tweets. We calculate the proportion of tweets dedicated to each topic by each legislator and use this to rank the topics by importance. Finally, we average legislators' rankings for all legislators in each party, providing an overall indicator of how each party prioritizes the topics.

We then employ BERTopic analysis with OpenAI to classify tweets into topic clusters without imposing pre-defined structures. This approach enables us to automatically identify clusters that may not be included in the PELA options but still demonstrate significant saliency. Our analysis focuses on uncovering these topics, as they may be more indicative of the interconnections within social media discourse. Additionally, this method informs the designers of elite surveys about potentially important issues, such as international affairs and immigration, which are currently not covered in the survey but could be considered for future inclusion.

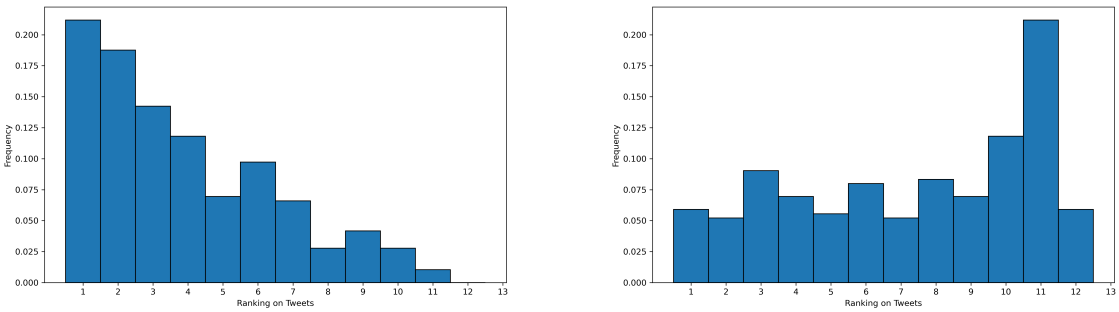
These strategies provide the necessary tools to construct a tracker for monitoring issue salience, such as the daily ratio of legislators' tweets on topics like corruption and assessing each issue's significance by party affiliation. We first present plots comparing survey preferences with political

[9]Although we use multinomial labeling, in most cases, only a single issue was identified.

communication, then illustrate our methods' potential by showing the dynamics over time for a specific issue and the content of some top-discussed issues.

Discussion

Figure 1 displays the distribution of legislators' rankings on Twitter for the top three and bottom three topics based on their parties' responses in PELA. For example, in Figure 1a, we can see that 21.2% of the legislators tweet most frequently about a topic that ranks among the top three for their own party according to PELA. This is followed by 18.8% of legislators whose second most-tweeted topic and 14.2% whose third most-tweeted topic also align with the top three topics for their party. Figure 1a shows a descending pattern, indicating that topics ranked among the top three in PELA are more likely to be salient on Twitter. Conversely, Figure 1b shows an ascending pattern for the least relevant issues. This means the topics ranked among the least three relevant issues in PELA are less salient on Twitter. This alignment between private survey responses and public Twitter statements suggests a convergence between the policy preferences expressed privately and those shared publicly. This finding has two implications. First, it suggests that politicians' private and public stances are generally aligned, indicating they may be more policy-driven or less strategic in their public communications. Second, it validates the use of social media, particularly Twitter, as a reliable tool for assessing policy preferences, providing more time-sensitive and granular data.



(a) Twitter ranking among PELA top 3

(b) Twitter ranking among PELA bottom 3

Figure 1: Histogram of Twitter Ranking Values for the Most Relevant Issues on PELA (Relative Terms).
Note: These figures show the frequency distribution of Twitter rankings for the three most relevant topics (a) and the three least relevant topics (b) as ranked by parties in the PELA survey. The x-axis represents their rankings on Twitter, and the y-axis represents their relative frequency. The data include all tweets by members of Congress from March to December 2014, classified using OpenAI.

We then compare the issues' ranking given by the legislators (grouped by parties) in PELA versus the issue's saliency in Twitter.[10] Figure 2 shows for each topic the average distance between legislators' Twitter rankings (grouped by parties) and their respective parties' rankings in PELA. Positive values indicate worse rankings (higher number) on Twitter than in PELA, implying less salience of the topic on

[10]Refer to Table C.4 for the saliency of each issue.

Twitter than its measure of party concern in PELA. The dotted lines between -2 and 2 aim to highlight when rankings are similar, as a difference of 2 in a ranking is likely not meaningful.

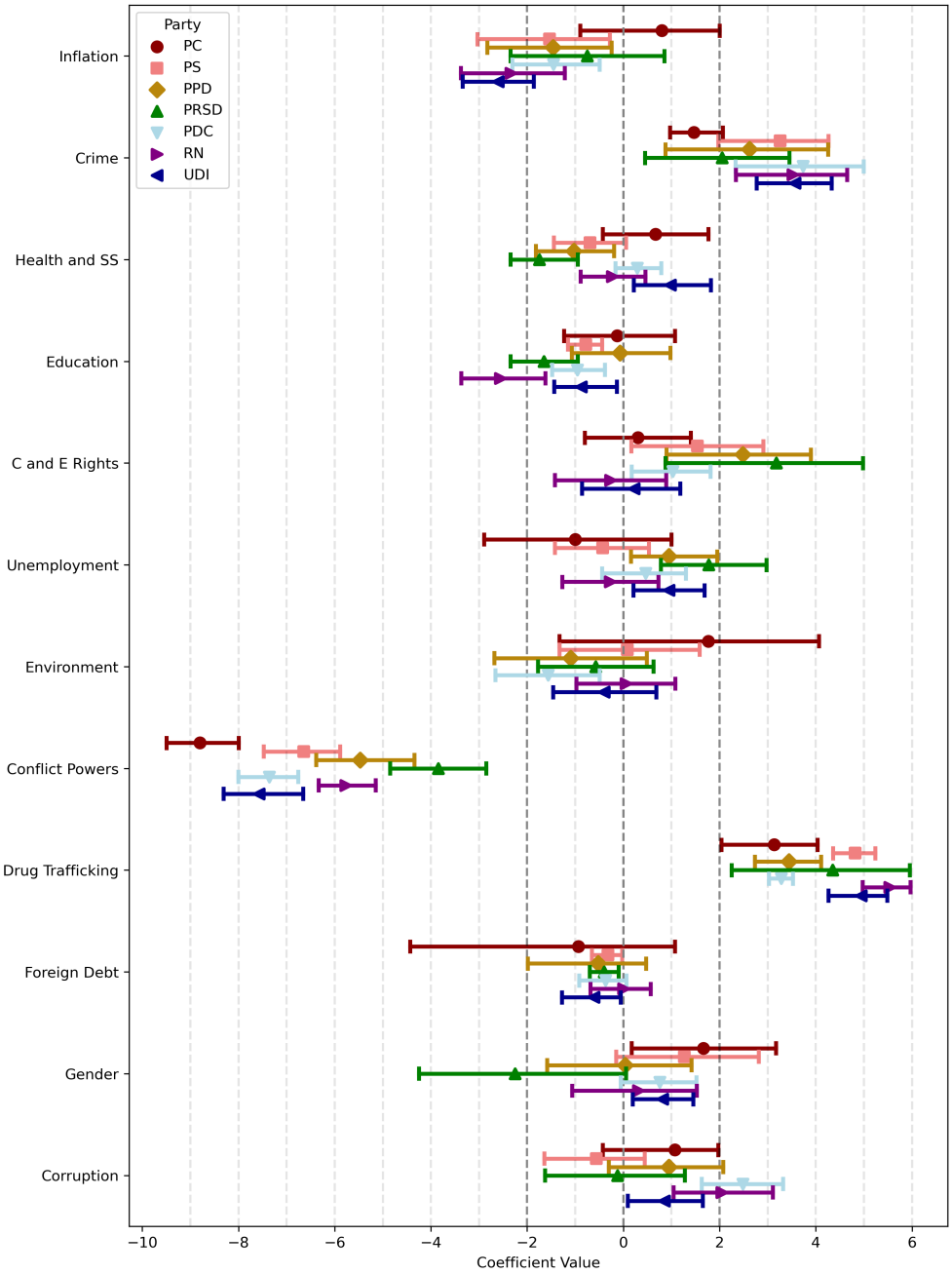


Figure 2: Coefficient Plot with Difference between Twitter and PELA Rankings

Note: This figure plots the distance between Twitter rankings and PELA (2014) rankings on the x-axis. It calculates each legislator's distance from their respective party's average ranking in PELA. A value of 0 indicates no difference between the rankings; positive numbers signify greater relevance on PELA than on Twitter; negative numbers indicate lesser relevance on PELA than on Twitter. The lines represent the 95% confidence intervals obtained through bootstrapping with 1000 simulations. The y-axis lists the issues included in the PELA survey, with different colors representing the various parties. The order of parties is based on ideology, ranging from the leftist (PC) to the rightist (UDI) See Table A.1. The data comprise all tweets produced by members of Congress, posted from Twitter from March 2014 to December 2014, and collected on February 2023. Tweets have been classified as relevant to these issues using OpenAI.

While there is not much divergence, this plot reveals variations across specific topics and parties. Notably, crime and drug trafficking appear as concerns for legislators in survey responses but are less salient in their daily political communications. Interestingly, this applies to parties in PELA regardless

of their focus on crime, with the left-wing PS averaging 5.07 and the right-wing RN at 2.35. This evidence suggests that while legislators recognize the importance of some issues privately, they do not publicly address them.

Meanwhile, conflict between powers (e.g., executive and legislative) seems less relevant in survey responses but is frequently addressed on Twitter, indicating higher saliency. Other significant divergences, nearly two ranking levels apart, include inflation, where the right-wing parties RN and UDI highlight more on Twitter despite not considering it a primary issue (8.75 and 7.91) in PELA. RN's Twitter emphasis on education also differs from its lower PELA ranking of 5.5, compared to other parties' ratings below 3.75. This reflects the extensive Twitter dialogue on education in 2014, indicating RN's alignment with prevailing trends.

To further support these findings, we perform Spearman's rank correlation analysis to compare Twitter and survey rankings, tested for non-negative correlations, and combined individual and partisan p-values using Fisher's method to assess overall similarity in dispersion across all parties (Appendix H). We implement this at the party level (averaging rankings within parties) and at the individual level (comparing each politician's Twitter ranking to their party's PELA ranking). The analysis reveals a significant overall alignment between the Twitter rankings and survey rankings, with combined p-values indicating strong similarity in both cases. Specifically, the combined p-value at the party-level analysis is 0.0051, and at the individual-level analysis, it is 2.08e-07, demonstrating a robust correlation, particularly for the parties PS, PDC, PC, PPD, and PRSD.

Thus far, we have demonstrated an overall alignment between private and communicated policy priorities. Are there other salient issues beyond those covered in the PELA questionnaire? To identify these, we employ BERTopic with labels from OpenAI. Table F.9 shows the results of this analysis. Twitter statements predominantly focus on social media engagement (31.6%),[11] government issues and reforms (29.6%) and the sharing of national news (10.6%). Our analysis identifies several issue-related clusters that are not covered by PELA, such as 'Venezuela and Human Rights,' 'Tax Reforms,' 'Natural Resources,' 'Labor Rights and Domestic Workers,' 'Public Transport,' and international affairs such as the Middle East conflict. These insights indicate the growing importance of international affairs to politicians and other domestic areas of interest, such as taxes and labor rights, providing crucial information for survey designers. For instance, 'Venezuela and Human Rights' reflects the international

[11] Here are included social media interactions such as greetings to their followers, promotion of events, statements regarding national holidays, etc.

condemnation of violence in Venezuela in 2014, and 'Tax Reforms' aligns with the significant tax reform of that year (Law N° 20.780).

TRACING THE EVOLUTION OF ISSUE SALIENCE ACROSS TIME

To demonstrate the application and potential of our analysis, Figure 3 illustrates how our approach facilitates the evaluation of issue salience over time. We detail the daily proportion of tweets on education (left panel) and gender (right panel) from members of Congress. The plot indicates that education is more salient than gender, with noticeable peaks in salience at specific times.

Regarding education, there is a peak of 25% daily tweets at the beginning of August, coinciding with the publication of Bachelet government's educational reform roadmap. Another peak occurred on October 21, aligning with the legislative approval of the "Ley de Inclusión Escolar" (School Inclusion Law; Law No. 20.845), which reformed student admissions, terminated shared financing in state-funded schools, and prohibited profit-making by these institutions. Similarly, tweets related to gender issues represented 20% on March 8th, International Women's Day, and increased again on October 10th, following the creation of the Ministry of Women and Gender Equity by the Chamber of Deputies. Thus, our analysis effectively identifies temporal shifts in legislators' focus. These shifts reveal important political actions, such as creating a new ministerial cabinet, even if the issue is generally low-salient.

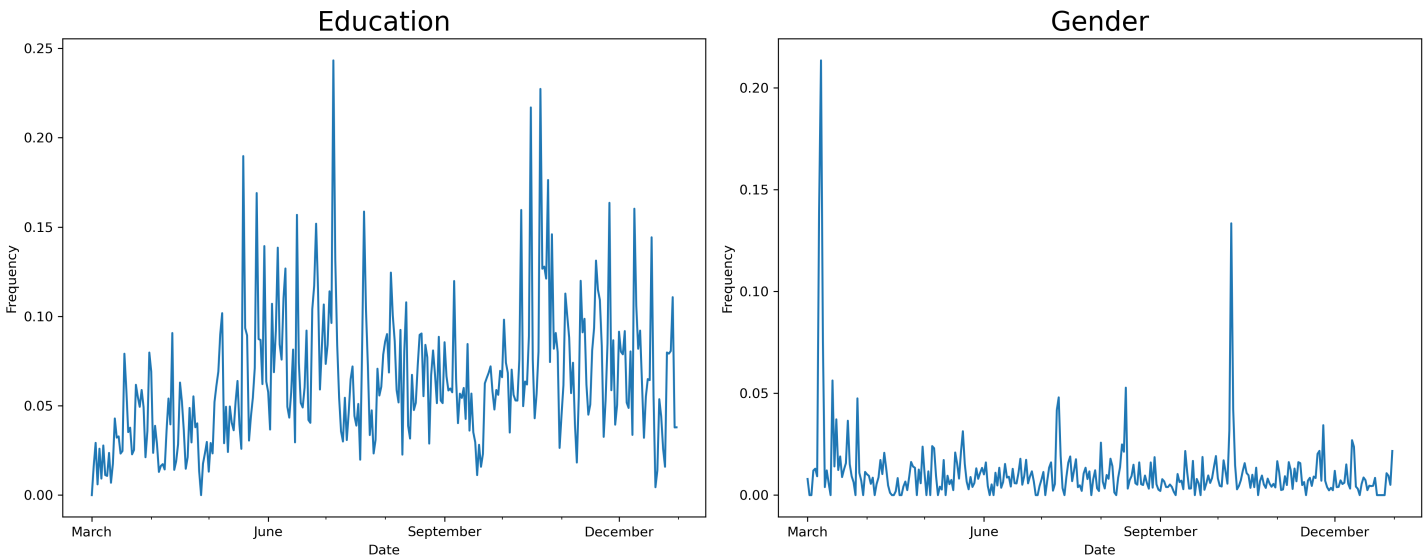


Figure 3: Salience of Education, and Gender in Members of Congress' tweets.
Note: This figure illustrates the shifting salience of education (Panel a) and gender issues (Panel b) over time in legislators' tweets. The data comprise all tweets produced by Members of Congress, posted on Twitter from March 2014 to December 2014 and collected on February 2023. Tweets have been classified as relevant to these issues using OpenAI. Saliency is calculated as the ratio of the number of tweets on a given day about topic i to the total tweets of that day. The x-axis represents time, while the y-axis represents frequency. See the evaluation of all topics in Appendix (Figure E.2).

Conclusion

This study has demonstrated that analyzing legislators' daily social media communications provides timely, scalable insights into political elites' microdynamics. We have contributed to previous work emphasizing the usefulness of social media in studying politicians' policy agendas (Hemphill, Russell, and Schöpke-Gonzalez 2021; Barberá et al. 2019). Moreover, by comparing these communications with PELA's stated priorities, we have identified alignment between private and public stances on various topics and across different parties. A word of caution: this alignment relies on the validity of issues deemed relevant by Latin American experts on the PELA scientific board. Our approach enables a detailed analysis of public agenda dynamics, modeling factors that determine issue relevance over time, and identifying new issues that elite surveys like PELA should consider incorporating in their field planning.

Although our proof of concept focused on the members of the 54th Chilean Congress, we believe this methodology has broader applications given the global prevalence of social media use among politicians. Furthermore, while our analysis focused on Twitter, we foresee its applicability to other platforms like YouTube, Facebook, TikTok, and Instagram, which are also widely used by politicians and readily accessible for research. We expect that our findings will be consistent across these platforms.

Our methodology offers a research template with high temporal precision, adaptable to various legislative contexts and social media platforms. Due to space constraints, we limited the scope of our analysis; however, this method can be extended to investigate other significant questions. For instance, it could examine whether specific events, such as elections, lead to greater divergence and explore issue ownership over time. Future work could also utilize our measures of communicated preferences to examine alignment with parliamentary activities, such as initiating or supporting bills, thereby highlighting instances where communicated salience diverges from parliamentary actions. Moreover, future studies could analyze factors such as age and gender as determinants of alignment between private and public communicated priorities. Additionally, while our focus has been on issue salience, another important research avenue involves identifying pro and anti-stances on various issues. OpenAI can be a useful tool for this exploration.

This study has contributed to a small but growing group of scholars using deep learning transformer models to analyze political text (Laurer et al. 2024; Wolf et al. 2020). We are among the first to apply OpenAI to political speeches, demonstrating its effectiveness in classifying non-English text. This approach saves time and resources while enabling a more inclusive examination of political discourse

across different cultural contexts due to its multi-language capabilities. We expect these tools to provide reserchers, policymakers, and the public with a deeper understanding of how political elites address key policy issues.

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Online Appendix

Contents

A The Chilean Case and its Party System

Chile is renowned for having one of the most stable party systems in Latin America (e.g., Coppedge 1998; Mainwaring and Scully 1995; Payne 2003). Even more recent studies acknowledge its high level of institutionalization despite recognizing changes (Luna and Altman 2011). The country's electoral system is based on open-list proportional representation, creating a multi-party landscape with a broad ideological spectrum.

In Chilean politics, both parties and politicians play significant roles. Despite the open-list system, political parties remain influential by strategically selecting candidates to maximize electoral success and rewarding loyal members with nominations (Luna and Altman 2011).

Media coverage of political activities, including tweets from congress members, is common. Tweets on significant issues or controversies often receive widespread attention, influencing public discourse. For example, "La Tercera," a Chilean news outlet, recently provided full coverage of two years of Boric's Twitter account (La Tercera, March 10, 2024).

For a detailed overview of the ideological scores of each party, see the following table.

	L-R Ideology.
Partido Comunista de Chile (PC)	1.22
Partido Socialista de Chile (PS)	3.11
Partido por la Democracia (PPD)	3.61
Partido Radical Socialdemócrata (PRSD)	3.88
Partido Demócrata Cristiano (PDC)	5.00
Renovación Nacional (RN)	7.11
Unión Demócrata Independiente (UDI)	8.94

TABLE A.1: Parties Chile
Note: The ideological position goes from 1 (extreme left) to 10 (extreme right). Source: Author's own elaboration based on data from Chapel Hill Expert Survey: Latin America (CHES:LA, Martínez-Gallardo et al. 2022)

B PELA

B.1 Data Description

A few databases help us understand the positions of legislators and parties in Latin America. The most notable effort is the Latin American Parliamentary Elites Project (PELA), which has collected legislators' opinions in 18 countries in the region since 1994 (PELA-USAL 2018).

PELA is a valuable resource that has enhanced our understanding of Latin American legislators, their positions, and their relationships with parties. It has been the foundation of extensive academic literature, with over 100 research papers utilizing PELA data from across Latin America.[12]

The survey is conducted once per legislative term in each country through in-person interviews with a sample of legislators. For our analysis, we relied on the PELA survey administered to 68 out of 120 deputies and 38 senators legislators in the 54th Chilean Congress. While this does not represent full coverage, the sampling was carefully weighted to ensure major political parties were represented based on their presence in the national legislature (PELA-USAL 2018; Barragán, Rivas Pérez, and Rivas Otero 2020; Alcántara, García Montero, and Rivas Pérez 2020) . This ensures that the PELA data provides a reliable and comprehensive portrait of the Chilean political landscape.

[12]For more information, see: https://oir.org.es/pela/en/publications/

Party	Number of legislators	Mean ideology
UDI	17	7.65
RN	10	7.50
PDC	11	4.73
PRSD	4	4.25
PPD	9	3.75
Otros	7	3.57
PS	7	2.29
PC	3	1.00

TABLE B.2: PELA's coverage
The number of legislators represents the legislators by party interviewed during the PELA survey. The Mean Ideology column represents the average self-ratings of legislators on the left-right continuum, where one is left and ten is right. Source: PELA-USAL (2018)

B.2 Ranking

For the ranking construction, the scores given by each legislator to the problems included in the PELA questionnaire were averaged by party.

Let n_i be the number of legislators in party i, and let r_{ij} be the ranking assigned to issue j by legislator k in party i. The average ranking $\bar{r}_{ij}$ of issue j for party i is given by:

$$\bar{r}_{ij} = \frac{1}{n_i} \sum_{k=1}^{n_i} r_{ijk}$$

where:

- $\bar{r}_{ij}$ is the average ranking of issue j for party i.
- n_i is the number of legislators in party i.
- r_{ijk} is the ranking of issue j by legislator k in party i.

For example, if party i has two legislators, and their rankings for education (issue j) are 1 and 4 respectively, the average ranking for education for party i would be:

$$\bar{r}_{ij} = \frac{1}{2}(1+4) = 2.5$$

Topic	Other	PC	PDC	PPD	PRSD	PS	RN	UDI
Inflation	9.07	8.50	8.50	8.33	9.25	9.29	8.75	7.91
Crime	5.71	8.33	3.36	4.17	5.75	5.07	2.35	2.35
Health and SS	1.86	2.83	2.05	3.61	3.75	3.07	2.95	2.71
Education	2.50	2.83	3.36	2.61	3.75	2.57	5.50	3.00
C and E Rights	6.57	5.50	6.55	4.56	6.13	5.71	8.30	8.56
Unemployment	6.36	7.50	6.23	6.89	5.13	6.43	6.65	5.35
Enviroment	6.71	5.33	6.09	7.39	4.88	6.00	7.20	7.50
Conflict Powers	10.36	10.50	10.45	8.89	6.25	10.14	7.90	10.74
Corruption	6.43	3.83	6.09	5.89	8.63	7.64	4.80	5.59
Drug Trafficking	6.50	7.17	7.95	7.22	5.75	6.14	5.50	5.24
Foreign Debt	11.57	10.83	11.23	10.78	10.50	11.57	10.75	11.18
Gender	4.36	4.83	5.82	6.83	8.25	4.36	7.35	7.65

TABLE B.3: Distribution of topics by party
Note: The scores by topic represent the average ranking legislators gave to each topic. Source: PELA

C Empirical strategy

Our Python function configures ChatGPT-3.5 with a few instructions (detailed in the next section) and connects to the OpenAI API. The function processes all tweets and executes the given instructions. Approximately 23% of the tweets are classified into pre-set topics (based on the topics proposed by PELA), while the remaining 77% remain unclassified. We ran our analysis using the free version of Google Colab[13]. The function processes all tweets and executes the given instructions. Based on the prompt in subsection C.1, the tweets were classified into one of the topics queried by PELA. The cost of using the OpenAI API for this project was 197 USD.

We applied BERTopic to perform a latent topic analysis in the second step. Then, we connected to the OpenAI API to generate readable descriptions for the latent topics based on the most relevant words of these topics.

C.1 Open AI Prompt

The prompt we used to configure the language model parameters is detailed below. It is a complete list of instructions to avoid ambiguities during classification.

"Please classify the content of tweets from Chilean congressmen. Assign a number from the following list of topics based on the central theme or issue of the tweet. If the tweet's content does not align with any of these topics, assign a 0. The topics, along with some indicative keywords, are:

1. Inflación (Inflation) - Keywords: precios, costo de vida, aumento, economía, alza de precios, incremento, subida, devaluación, alza de canasta básica

2. Inseguridad Ciudadana y delincuencia (Public insecurity and crime) - Keywords: seguridad, delitos, policía, crimen, desconfianza, delincuencia, vulnerabilidad, temor

3. Salud/Seguridad Social (Health/Social Security) - Keywords: hospitales, médicos, pensiones, salud pública, jubilaciones, covid, virus, vacunas, bienestar, paciente, essalud

4. Educación (Education) - Keywords: escuelas, universidades, estudiantes, reforma educativa, alfabetización, profesor, enseñanza, aprendizaje

[13]Google Colab is an online Jupyter Notebook environment that requires no setup. It runs on Python 3.7 and provides 12 GB of RAM, access to CPU and GPUs, and 100 GB of storage

5. Derechos de los grupos étnicos y culturales (Rights of ethnic and cultural groups) - Keywords: indígenas, cultura, lengua, diversidad, minorías, discriminación, pluricultural, identidad
6. Desempleo y Subempleo (Unemployment and Underemployment) - Keywords: trabajo, empleo, economía laboral, oportunidades, tasa de desempleo, crisis laboral, subempleo, informal
7. Medio Ambiente (Environment) - Keywords: naturaleza, contaminación, protección ambiental, cambio climático, árboles, aves, incendios, sostenibilidad, biodiversidad, conservación
8. Conflictos entre los poderes del Estado (Conflicts between the powers of the State) - Keywords: congreso, gobierno, ley, constitución, separación de poder, institucional, autonomía, legislativo, ejecutivo, judicial
9. Narcotráfico (Drug trafficking) - Keywords: drogas, narcóticos, fronteras, policía, narcotráfico, pandillas, delincuencia organizada, cocaína
10. Deuda Externa (External Debt) - Keywords: préstamos, FMI, crédito, finanzas, deuda externa, préstamo, banco mundial, financiamiento
11. Las desigualdades entre hombre y mujeres (Gender Inequality) - Keywords: género, igualdad, derechos de la mujer, brecha salarial, empoderamiento, feminismo, roles, equidad
12. Corrupción (Corruption) - Keywords: sobornos, corrupción, deshonestidad, malversación, comisiones ilegales, nepotismo, fraude, escándalo, corrupto

Analyze the tweets provided below, and for each, indicate only the topic number(s) it pertains to (NEVER A TEXT), based on the central theme of the tweet in relation to the topics and keywords listed. If the tweet is unrelated to these topics, or if you're unable to determine the topic due to lack of context or clarity, assign a 0. Ensure to provide a classification only for tweets that have a clear and definite relation to the topics.

Remember, the classification should be based on concrete policy or political issues referenced in the tweet, not on general expressions or sentiments. Do it from a Chilean perspective. Provide only the number(s) of the relevant topic(s), nothing else."

C.2 Open AI descriptive

The following table shows the frequency of tweets for each topic. The "Other" category includes all tweets that were not classified into any of the PELA topics.

Topic	Frequency (%)
Education	6.82%
Health and SS	4.36%
Conflict Powers	4.18%
Environment	1.68%
Corruption	1.22%
Crime	1.22%
Inflation	1.20%
Unemployment	1.16%
Gender	1.12%
C and E Rights	0.86%
Drug Trafficking	0.13%
Foreign Debt	0.08%
Other	76.77%

TABLE C.4: Frequency of Issues Over the Total Number of Tweets in the Period.
Note: This table illustrates the share of each issue that appeared in PELA 2014. The data comprises all tweets produced by Members of Congress, collected from Twitter from March 2014 to December 2014. Tweets have been classified as relevant to these issues using OpenAI. Source: Tweets

C.3 Ranking Calculation using Twitter

To determine the relevance of each topic to legislators, we categorize every Twitter statement t_i as either related to one or more of the predefined issues P_k (identified by PELA) or as unrelated (P_0).

$$t_i \in \{P_0, P_1, P_2, \ldots, P_n\}$$

Although we use multinomial labeling, in most cases, only a single issue P_k was identified. This method aligns with our approach to the PELA data, where we assess the salience of each topic P_k in legislators' tweets. For each legislator L_j, we calculate the proportion π_{jk} of tweets dedicated to each topic P_k over the entire period:

$$\pi_{jk} = \frac{\text{number of tweets by } L_j \text{ on } P_k}{\text{total number of tweets by } L_j}$$

We then rank the topics for each legislator L_j based on these proportions π_{jk}. This ranking R_{jk} serves as an indicator of the importance legislators place on each topic:

$$R_{jk} = \text{rank}(\pi_{jk})$$

Finally, we calculate the average ranking $\overline{R}_{pk}$ for each topic P_k by averaging the rankings R_{jk} across all legislators L_j belonging to each party p:

$$\overline{R}_{pk} = \frac{1}{|L_p|} \sum_{j \in L_p} R_{jk}$$

where $|L_p|$ is the number of legislators in party p.

	PC	**PDC**	**PPD**	**PRSD**	**PS**	**RN**	**UDI**
Inflation	9.30	7.05	6.88	8.50	7.75	6.41	5.30
Crime	9.80	7.10	6.79	7.80	8.33	5.88	5.92
Health and SS	3.50	2.33	2.58	2.00	2.38	2.72	3.68
Education	2.70	2.40	2.54	2.10	1.79	2.94	2.12
C and E Rights	5.80	7.57	7.04	9.30	7.25	8.03	8.78
Unemployment	6.50	6.69	7.83	6.90	6.00	6.38	6.30
Environment	7.10	4.52	6.29	4.30	6.08	7.25	7.10
Conflict Powers	1.70	3.10	3.42	2.40	3.50	2.12	3.16
Drug Trafficking	10.30	11.24	10.67	10.10	10.96	11.03	10.18
Foreign Debt	9.90	10.86	10.25	10.10	11.25	10.75	10.56
Gender	6.50	6.57	6.88	6.00	5.62	7.66	8.46
Corruption	4.90	8.57	6.83	8.50	7.08	6.84	6.44

TABLE C.5: Average Ranking by Party
Note: We averaged the legislators' rankings for each topic on Twitter by party. Source: Tweets

D VALIDATION OPENAI TOPICS

The OpenAI API allows access to language models and image generation through different Python packages. ChatGPT's large language model has over 175 billion parameters, trained using a vast amount of text from the Internet and other sources. The model has been trained using Reinforcement Learning from Human Feedback (RLHF).

We employed two strategies to validate OpenAI's tweet classifications. First, we created a reference classification and compared it with OpenAI's. To create the reference classification, we randomly sampled 1,000 tweets and had two research assistants, both sociology graduates, independently classify them into PELA's subjects, including a "none" category. A coauthor then reviewed the classifications and resolved any discrepancies between the research assistants to establish the final reference classification.

D.1 Annotators vs. Open AI

Table D.6 presents the inter-code reliability between the two research assistants and OpenAI. The table above summarizes the inter-coder reliability. The results demonstrate high statistical significance levels of agreement (Kappa >0.8).

Annotator	Percentage Disagreement	Cohen's Kappa value	P-value
Annotator 1	5	0.9	Sig
Annotator 2	9	0.82	Sig

TABLE D.6: Disagreement analysis
This table shows disagreement percentages, Cohen's Kappa values, and P-values for annotators vs OpenAI

Next, Table D.7 presents the confusion matrix that compares the binary version of the reference category (1 if the tweet references one of the PELA's topics, 0 otherwise) with OpenAI's classification.

	Reference	
Prediction	0	1
0	477	41
1	15	467

TABLE D.7: Confusion Matrix
This table compares the "reference" classification constructed by humans vs the classification made by OpenAI

Besides the binary classification, we also tested the accuracy in the two most frequent PELA's topics present in our validation sample. Table Table D.8 demonstrates that OpenAI's accuracy is very high, not only in the binary classification but also within PELA's topics, providing evidence for the pertinence of this approach.

	Measure	PELA's topics	Education	Health
1	Accuracy	0.94	0.98	0.98
2	Precision	0.92	0.99	0.99
3	Recall	0.97	0.99	0.99
4	F1 Score	0.94	0.99	0.99

TABLE D.8: Accuracy measures
This table presents various accuracy measures comparing the "reference" classification constructed by humans with the classification made by OpenAI. The first column displays the results for the binary classification (PELA's topic vs. Non-PELA's topic), while the second and third columns are for the two most frequent PELA topics in our sample.

D.2 World Cloud w/Content by Each Category

For our second strategy, we plotted the frequencies of the most important words for each topic using word clouds. As shown visually, the most frequent words in the corpus of each subgroup of tweets relate to the topic to which they were classified.

Figure D.1: Most Frequent Words by Issue

Note: These figures plot the most frequent words for each of the topics in the analyzed period. The data comprises all tweets produced by Members of Congress, collected from Twitter from March 2014 to December 2014. Tweets have been classified as relevant to these issues using OpenAI.

E Mapping Issues Over Time

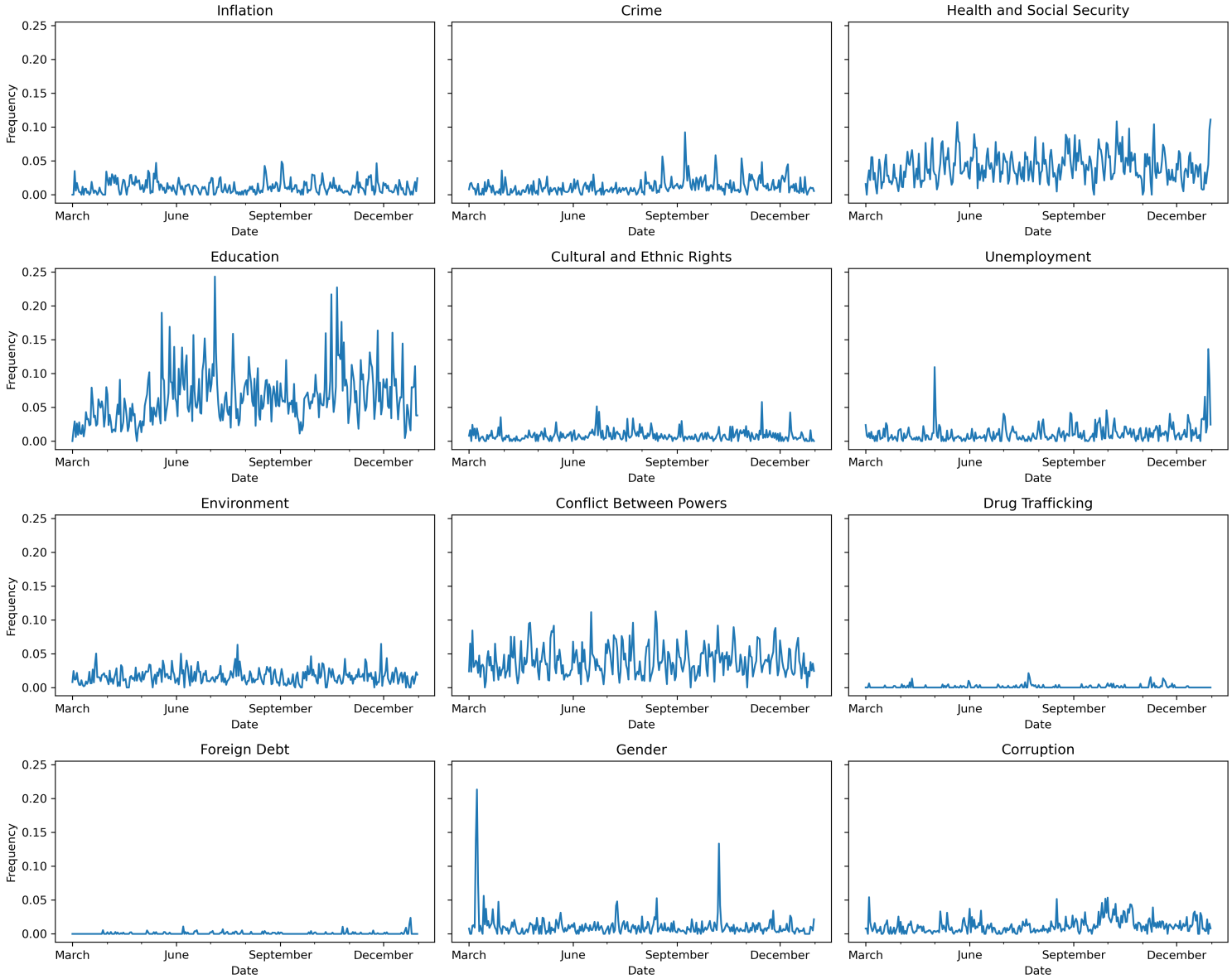

Figure E.2: Salience of PELA issues in Members of Congress' Tweets.
Note: This figure illustrates the shifting salience of every issue that appeared in PELA 2014 over time in legislators' tweets. The data comprise all tweets produced by Members of Congress, collected from Twitter from March 2014 to December 2014. Tweets have been classified as relevant to these issues using OpenAI. Saliency is calculated as the ratio of the number of tweets on a given day about topic i to the total tweets of that day. The x-axis represents time, while the y-axis represents frequency.

F BERTopic

F.1 Theoretical justification

BERTopic is an advanced transfer learning technique designed to identify hidden themes within text. It generates document embeddings using pre-trained transformer-based language models, which are then clustered to create topic representations. In contrast to traditional unsupervised learning models like Latent Dirichlet Allocation (LDA Blei, Ng, and Jordan 2003) or Non-Negative Matrix Factorization (NMF Févotte and Idier 2011), which rely on bag-of-words representations, BERTopic retains the semantic relationships between words. As an example of a previous work highlighting the better performance of BERT models over LDA you can refer to Uthirapathy and Sandanam (2023) and Egger and Yu (2022)

Deep learning model transformers have been proven to outperform classical models that do not incorporate transfer learning (e.g., Laurer et al. 2024). The use of such models for analyzing political texts is a recent development and has only been applied in a few studies to date (Bestvater and Monroe 2023; Licht 2023; Widmann and Wich 2023; Burst et al. 2023; Laurer et al. 2024; González-Rostani, Incio, and Lezama 2024; González-Rostani 2024).

F.2 Implementation

We employed a clustering technique that leverages HuggingFace transformers and TF-IDF, as demonstrated (BERTopic, Grootendorst 2022), to identify the underlying semantic structure and latent themes within the discourse of immigration. BERTopic, built upon the Bidirectional Encoder Representations from Transformers (BERT) architecture, offers an advanced approach to extracting and categorizing latent topics from textual data. Unlike conventional methods, BERTopic captures contextual relationships between words, resulting in more coherent and interpretable topics. We perform clustering using Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN). The language is set to 'multilingual,' and the number of topics we determined was 40. This means that after training the topic model, the number of topics was reduced to 40 using a c-TF-IDF calculation.

Once clusters are established, we employ the OpenAI API to retrieve topic representations from the documents within each cluster and identify keywords for each cluster.

TABLE F.9: Distribution of Topics by Share

Topic	Share
Social Media Engagement	31.6%
Reform and Policy Discourses	29.6%
National News Distribution	10.6%
Venezuela and Human Rights	6.9%
Tax Reforms and its implications	6.6%
Natural resources (e.g., water)	6.2%
Congress and sport initiatives	3.1%
Free Software and Technology	2.9%
Public Health Infrastructure	2.5%
Gender Equity and Women's Ministry	2.4%
Enhancing Quality of Life	2.3%
Labor Reform and Domestic Workers	2.3%
Disaster Response and Aid	2.1%
Radio Broadcasts and Interviews	2.1%
Media Engagement and Interviews	2.0%
Middle East Conflict	1.8%
Public Transport Discussions	1.8%
Pet Ownership Responsibility	1.4%
Community Support and Assistance	1.4%
Food Industry and Health	1.2%
Cannabis Legalization Debate	1.1%
Broadcasting Pre-Announcements	1.1%
Energy Policy Discussions	1.1%
Civic Engagement and Public Safety	1.0%
Remote Areas and Environmental Protection	1.0%
Civil Union and Equality Rights	0.9%
Therapeutic Abortion Debate	0.6%
Disability Rights and Inclusion	0.6%
Organ Donation Awareness	0.4%
Electoral System Analysis	0.4%
Breast Cancer Awareness	0.4%
Expressions of Gratitude	0.4%
Cultural and Social Reflections	0.4%
Cultural Programs and Tributes	0.4%
Educational Disruptions	0.2%
Taxation and Fiscal Policy	0.2%
Public Health Preparedness	0.2%
Protests and Indigenous Rights	0.2%
Health and Public Service Announcements	0.2%

Note: This table showcases the most relevant topics identified using BERT OpenAI topic analysis. The data comprise all tweets produced by Members of Congress, collected from Twitter from March 2014 to December 2014. 'Topics' refers to the automatic labels generated by OpenAI, based on representative terms and documents; 'Share' denotes the proportion of tweets in each cluster relative to the total number of tweets.

G Use of Twitter

G.1 Replication

Given the recent changes to Twitter's API policies and costs Allem (2023), we recognize the importance of these issues and propose several viable solutions that still make it possible for a researcher to use the approach suggested in this article. To replicate this study or use our approach to explore other subjects further, we suggest these options to access the data:

1. **Scraping tools:** We can utilize web scraping tools like Selenium to collect tweet data rather than relying solely on the Twitter API. This approach may be more labor-intensive, but it can provide a cost-effective alternative to the API's increasing fees. Other packages are available that help retrieve tweets from web.archive (GitHub - ChRauh/PastTwitter: Functions to scrape Twitter account info for past points in time via archive.org).

2. **Tweet ID repositories:** We will publish the tweets' IDs used in this paper in a public repository. This would allow other researchers to "hydrate" the tweets using tools like Twarc, which can retrieve the full tweet content based on the IDs. This approach respects Twitter's terms of service.

3. **Sampling approach:** Instead of attempting to collect the entire dataset of tweets, we could adopt a sampling approach. By carefully selecting a representative sample of tweets, we may be able to address the research questions while minimizing the costs associated with API usage or scraping.

4. **Exploring alternative platforms:** It is possible to explore other platforms' data access, such as Facebook, Reddit, or even newer emerging platforms. While the data may not be as readily available as Twitter, there may be opportunities to develop novel approaches.

G.2 Concerns about account deactivation

To ensure no bias resulted from legislators deleting tweets during the period under analysis, we randomly selected 10 accounts and reviewed the snapshots stored by the Wayback Machine (WBM). Unfortunately, the WBM did not save snapshots for all legislators for every day. However, we gathered data for two legislators over eight days in 2015. The number of tweets reported by the WBM for these days matched the number reported in our database. In some cases, our database showed a larger number of tweets than the WBM, likely due to WBM's snapshots not capturing all tweets because of rendering issues or the need to scroll down to view additional tweets.

We complemented this analysis by reviewing Gabriel Boric's tweets, who has remained active in politics and even became president in 2022. We found similar results, indicating no systematic deletion of tweets by Chilean legislators during the period under analysis. Therefore, we do not have evidence to suggest that Chilean legislators have systematically erased their tweets from the term under analysis.

G.3 Discussion of External Validity (Twitter and other Social Media) and Alternative Sources

The authors acknowledge the increased costs and challenges in accessing Twitter data. However, we anticipate that our methodology and findings will be replicated across other social media platforms like YouTube, Instagram, TikTok, and Facebook. Politicians often share similar messages across these platforms, making our approach relevant for broader social media analysis.

Following, we mention examples of alternative social media data sources:

- **YouTube**: The YouTube API is free and accessible to researchers. YouTube, with 4.95 billion monthly active users, is a significant platform for consuming online media and a growing news source. Recent studies have explored YouTube's political impact from viewership perspective (Mohsin 2020; Hosseinmardi et al. 2021; Hosseinmardi et al. 2024; Haroon et al. 2023; Ibrahim et al. 2023; Mamié, Horta Ribeiro, and West 2021) and party dynamics during electoral campaigns (González-Rostani 2024).

- **Meta's Content Library API**: Integrated with the Social Media Archive (SOMAR) at ICPSR, this API allows researchers to analyze real-time public data from Facebook and Instagram. As of November 2023, researchers can apply for access to this data, providing a robust alternative to Twitter. Applications are reviewed by the ICPSR at the University of Michigan's Institute for Social Research (ISR).[14].

- **TikTok**: TikTok provides data access through a research-developers agreement, offering another valuable source for political science research (refer to Research tools).

- Furthermore, for retrieving past **Tweets**, researchers can utilize:

  - Selenium: For web scraping.
  - Twarc: For data hydration using tweet IDs researchers have shared.
  - PastTwitter: A GitHub package for scraping past Twitter data from web.archive.

H Statistical Methods for Analyzing Rankings Similarity Between Survey and Twitter Data

H.1 Spearman's Rank Correlation Analysis

Spearman's rank correlation coefficient (ρ) was used to measure the strength and direction of the monotonic relationship between two ranked variables: the survey rankings and the Twitter rankings. The analysis was performed in the following steps:

H.1.1 Aggregated Party Rankings vs. Survey Rankings. For each party, the average Twitter rankings for each topic were computed. Spearman's rank correlation was calculated between the average Twitter rankings and the survey rankings for each party using the formula:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

where d_i is the difference between the ranks of each observation and n is the number of observations.

H.1.2 Individual Rankings vs. Survey Rankings. For each individual politician, Spearman's rank correlation was calculated between their Twitter rankings and the survey rankings.

H.2 Formal Test for Non-Negative Correlation

To formally test whether the Spearman's rank correlation coefficients were non-negative, a one-tailed hypothesis test was conducted for each individual and for each party. The steps involved were:

H.2.1 Calculation of One-Tailed p-Values. The two-tailed p-values from the Spearman's rank correlation test were divided by two to obtain one-tailed p-values. These p-values were retrieved from the package *spearmanr* from the Python's library *Scipy*.'

$$\text{one-tailed p-value} = \frac{\text{two-tailed p-value}}{2}$$

H.2.2 Rejection of Null Hypothesis. For each individual or party, the null hypothesis (H_0) that the correlation is less than or equal to zero ($\rho \leq 0$) was tested against the alternative hypothesis (H_1) that the correlation is greater than zero ($\rho > 0$). The null hypothesis was rejected if the Spearman's ρ was greater than zero and the one-tailed p-value was less than 0.1.

H.3 Fisher's Method for Combining p-Values

To assess the overall similarity of rankings across all parties, Fisher's method was used to combine the p-values from the individual tests. Fisher's method combines the p-values from independent tests to

[14] See more information at META-ICPSR communication release

produce an overall test statistic, which follows a chi-squared distribution. The test statistic is calculated as:

$$-2\sum_{i=1}^{k}\ln(p_i)$$

where p_i are the p-values from the individual tests and k is the number of p-values being combined. This statistic follows a chi-squared distribution with $2k$ degrees of freedom. The overall p-value from Fisher's method was used to test the global null hypothesis that there is no correlation between the Twitter rankings and survey rankings across all parties.

H.4 Statistical Analysis and Implementation

The statistical analysis was implemented in Python using the `scipy.stats` module. The steps included:

H.5 Results

H.5.1 Aggregated Party Rankings vs. Survey Rankings.

Party	Spearman's rho	One-tailed p-value	Significance
PS	0.510	0.045	Significant
RN	0.382	0.110	Not Significant
PDC	0.512	0.044	Significant
UDI	0.371	0.118	Not Significant
PC	0.474	0.060	Significant
PPD	0.462	0.065	Significant
$PRSD$	0.639	0.013	Significant

H.5.2Summary Statistics for Individual Rankings vs. Survey Rankings by Party.

Party	Average Spearman's rho	Median Spearman's rho	Min Spearman's rho	Max Spearman's rho
PC	0.395	0.419	0.094	0.628
PDC	0.431	0.460	0.168	0.703
PPD	0.371	0.359	0.165	0.573
$PRSD$	0.547	0.520	0.462	0.682
PS	0.438	0.441	0.084	0.669
RN	0.263	0.291	−0.091	0.507
UDI	0.292	0.337	0.057	0.538

H.5.3Combined p-Values Using Fisher's Method.

Level	Combined p-value
$Party$	0.0051
$Individual$	$2.08e-07$

H.5.4 Interpretation of Results.

- **Aggregated Party Rankings vs. Survey Rankings**: The significant p-values for PS, PDC, PC, PPD, and PRSD indicate a strong alignment between the Twitter rankings and survey rankings for these parties. RN and UDI did not show significant correlations, suggesting a weaker alignment for these parties.

- **Individual Rankings vs. Survey Rankings**: The average Spearman's rho values further support the alignment for PS, PDC, PC, PPD, and PRSD. The lower average Spearman's rho values for RN and UDI indicate a weaker alignment at the individual level as well.
- **Combined p-Values**: The combined p-value using Fisher's method at the party level (0.0051) and individual level (2.08e-07) strongly indicate an overall significant similarity in the rankings across the parties.

The statistical analysis demonstrates a significant overall similarity in the rankings between Twitter data and survey data, particularly for PS, PDC, PC, PPD, and PRSD. These p-values were retrieved from the *spearmanr* function from Python's *Scipy* library.

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