Political and economic uncertainty indicator for Peru based on Twitter and GTP-3.5 Turbo

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Abstract

This study examines the impact of political-economic uncertainty on key macroeconomic variables, focusing on the Lima Stock Exchange (BVL) and the USD/PEN exchange rate. We construct an uncertainty index based on social media analysis, using tweets from influential Peruvian figures (2018-2023). These tweets are analyzed and classified by GPT-3.5 Turbo to assess their stance on Peru's political and economic situation, generating a political-economic uncertainty time series.

We then test the correlation between this index, BVL returns, and exchange rate fluctuations. To capture the effects of uncertainty on market volatility, we consider GARCH models, which allow for a robust analysis of conditional variance dynamics.

Keywords: Political Uncertainty, Twitter Exchange Rate, Peruvian Economy, GPT-3.5 Turbo.

JEL Classification: C33, C55, E32, F41, H11.

1 Introduction

2 Methods and Data Collection

2.1 Data Ingestion

Twitter. In our study, we utilized Twitter, a platform where users interact through brief messages called tweets, to gain insights into Peruvian politics and economy. We focused on a curated set of 98 Twitter accounts, selected for their significant influence in these spheres. The owners of these accounts range from economists and political analysts to private sector representatives, politicians, and prominent journalists. Each plays a vital role in shaping public discourse and policy within Peru. Our data collection, conducted via Twitter API, spanned from January 23, 2018, to January 31, 2023, resulting in a comprehensive panel dataset of 225 925 tweets; after filtering, resulting in 216 273(see Table C). See Table A and Figure 1.

2.2 Tweets Analysis and Labeling

To develop our political uncertainty index time series, we gathered classifications from GPT-3.5 turbo by employing a specific prompt tailored for labeling tweets into one of the following categories: Unrelated, In Favor, Against, or Neutral. These classifications aimed to mirror the stance conveyed in tweets toward the incumbent president and active government policies on the date of the tweet.

State-of-the-art LLMs like GPT-4 and GPT-3.5 turbo Brown et al. (2020); OpenAI (2023) demonstrate exceptional performance across a wide range of applications, including classification tasks that previously required custom-built, task-specific models designed by specialized engineers using domain-specific data. Our findings consistently demonstrate a high degree of concurrence between the responses generated by GPT-3.5 turbo and those provided by human evaluators. In cases where uncertainties arise, both entities tend to offer similar interpretations, while in clearer contexts, their responses align as anticipated.

In the development of our methodology, special consideration was given to the unique challenges of tweet content analysis. Acknowledging insights from related research Lan et al. (2023), our approach was formulated with an awareness of the intricacies involved in parsing tweets, which often feature domain-specific terminology, cultural nuances, and the idiosyncratic language of social media. To address these challenges effectively, the prompt used in our study was meticulously designed to not only recognize but also accurately interpret these complex elements, ensuring a more robust and nuanced understanding of tweet content.

The prompt used for classifying each tweet is available in Appendix B. For labelling examples, see Figure 2.

In our comprehensive analysis, we processed a dataset comprising 216 273[1] using the

[1]Initially we processed 225 928 tweets, but 9577 corresponded to tweets from entities and not individuals: GRADE, the Lima Chamber of Commerce, and CONFIEP; 75 corresponded to error cases (see Tables of

OpenAI GPT-3.5 Turbo via the OpenAI API. This approach was distinctively zero-shot, relying on the inherent capabilities of GPT-3.5 Turbo without any fine-tuning or model-specific adjustments. The dataset encompassed a total of 144,090,355 tokens, with an average of 637 tokens per analysis instance. This figure includes the token count for the prompts and the tweet content. Financially, the stance detection process was efficiently conducted, totaling a cost of $216.33. This cost-effectiveness demonstrates the feasibility of employing advanced language models for large-scale text analysis in a budget-conscious research environment.

Anomalies were found in 81 instances (75 after removing GRADE, CONFIEP and Lima Chamber of Commerce) where the labels did not align with the predefined categories. Further examination of these anomalies revealed the distribution of Table C. We finished filtering by removing the misprocessed tweets and obtained the statistics from Figure 3.

The visual representation of Twitter data through pie charts offers insightful revelations into public stance over the past six years. Figure 3 illustrates the distribution of tweets and retweets, categorized by stances such as Against, Neutral, In Favor, and Unrelated for the period 2018-2023. A clear trend emerges from the data: Unrelated content dominates retweets in all years, though its prevalence gradually decreases over time. In earlier years (2018-2020), Unrelated retweets accounted for 45.6%, 58.4%, and 54.3%, respectively. In contrast, in the later years (2021-2023), Unrelated retweets decline to 46.5%, 46.8%, and 41.0%, respectively, suggesting a shift toward more politically engaged retweeting behavior.

A notable shift occurs in 2022 and 2023, where Against tweets become significantly more prominent, reflecting increasing political polarization and a rise in critical engagement on social media platforms. This is also visible in retweets, where the proportion of Against and In Favor retweets rises, reducing the share of Unrelated content.

Overall, this pattern suggests a progressive increase in political engagement, where more tweets and retweets explicitly express a stance rather than remaining neutral or unrelated to political discourse. The decline in Unrelated content in retweets underscores a growing tendency toward opinion-driven sharing, as Twitter users increasingly engage with political narratives over time.

This trend may be partially attributed to the COVID-19 pandemic, during which social media usage, including platforms like Twitter, saw a significant increase, see Figure 4. Studies have indicated that the pandemic led to heightened activity on social media, as individuals sought information, connection, and outlets for expression during periods of social distancing and lockdowns Sharma et al. (2020). The increased reliance on social media during the pandemic likely contributed to the observed rise in politically engaged content, as users turned to platforms like Twitter to discuss and disseminate information about political developments and policies related to the crisis.

Appendix C) and 3 to corrupted tweets. Finally, these were removed from the list since the remaining list focuses on individuals and well classified tweets.

2.3 Limitations of our methodology

2.3.1 Benchmarking with human subjectivity

One of the fundamental limitations of our methodology is rooted in the subjective nature of the labeling process. Our reliance on annotators possessing a profound comprehension of the prevailing political biases and orientations within the Twitter accounts under scrutiny remains a critical aspect. It is imperative for these annotators to have active engagement within Peruvian politics and the economy to ensure the precision of the labels assigned to each tweet. This aspect warrants further exploration to substantiate the robustness of our findings.

2.3.2 Labeling utilizing GPT-3.5 turbo

The labeling outcomes generated by GPT-3.5 turbo exhibit sensitivity to several factors, including variations in prompt wording, the arrangement and structure of the prompt, examples and the level of detail provided Zhang et al. (2023). Through iterative adjustments to the prompt, guided by observations from a small validation set, subtle alterations can influence the degree of alignment between the labels assigned by GPT-3.5 turbo and our human benchmark.

2.3.3 Impact of new Twitter API access tiers

Our study encountered a substantial limitation in data collection through the Twitter API, notably influenced by transformative changes detailed in a March 29, 2023 announcement from the X Dev team. The tweet heralded the rollout of novel Twitter API access tiers, ushering in self-serve access with varied options, including Free, Basic, Pro, and Enterprise tiers. However, this restructuring omitted the provision of a comprehensive free tier, obliging academic users to opt for paid tiers, notably the Pro plan, priced at $\$5,000$ per month. This unavailability of an extensive free tier significantly hindered our study, constrained by financial limitations. Consequently, our ability to access a balanced and comprehensive dataset was compromised, resulting in a marked disparity in the volume of tweets collected between earlier and subsequent years.

3 The uncertainty indicator

The major challenge we face once the data has been processed is determining how to aggregate it. In Figures 11-18 , we present the distribution and histograms of tweets classified as *In Favor*, *Against*, and *Neutral* for selected individuals in the sample over the observed time horizon. Notably, some individuals did not post or retweet during certain periods.

Regarding the aggregation, let V_{it} denote the number of *In Favor* tweets by individual i on day t. Similarly, let A_{it} represent the number of *Against* tweets by individual i on day t. Define U_{it} as the average stance of individual i on day t, using $+1$ for In Favor tweets, 0 for Neutral and -1 for Against. Using these series, we construct the aggregated measures $\Omega_t = \sum_{i=1}^{N} U_{it}$ (see Figure 5), $D_t = \sum_{i=1}^{N}(A_{it} - V_{it})$ (see Figure 6), $M_t = [\min\{\Omega_t, 0\}]^2$ (see Figure 7), $\Delta M_t = (1-L)M_t$ (see Figure 9), and $\Delta(D_t^2) = (1-L)D_t^2$ (see Figure 10). Here L denotes the lag operator.

4 Draft ideas

- Use Twitter data in a count model to estimate the probability of macroeconomic downturns (1 if a downturn occurs, 0 otherwise), in line with techniques in Cameron and Trivedi (2005) or Hastie et al. (2009).

- We have graphs similar to Figure 1 in *The Role of Uncertainty Index in Forecasting Volatility of Bitcoin: Fresh Evidence from GARCH-MIDAS Approach* and Figures 2-3 in *Forecasting Stock Volatility with Economic Policy Uncertainty: A Smooth Transition GARCH-MIDAS Model*.

- It is possible to manually collect information from Twitter accounts and generate weights.

- The usual aggregations are not yet refined or definitive. In particular, those squared exhibit excessively large values. In all cases, except for the differenced ones, a trend is observed in the second part, along with a clear structural break at the onset of the COVID-19 pandemic (in tweet count).

- My hypothesis, based on the daily series of the Lima Stock Exchange (BVL) and Forex data from BCRP, is that our indicator reflects percentage variations when the incumbent government is anti-establishment and strong (elections 2021). When it is weak (November 2022 crisis), it has no impact. However, this series might be more correlated with another variable, such as the Business Confidence Index (although I have not found a daily frequency in BCRP).

A List of Twitter accounts

Table 1: List of curated Twitter accounts relevant to Peruvian politics and economy.

Username	Name	Category
RosanaCuevaM	Rosana Cueva	Journalist
NicolasLucar	Nicolas Lucar	Journalist
PolloFarsantePe	Beto Ortiz	Journalist
MilagrosLeivaG	milagrosleiva	Journalist
DeltaMdelta	Monica Delta	Journalist
MavilaHuertasC	Mavila Huertas C	Journalist
SolCn	Sol Carreño	Journalist
VertizPamela	Pamela Vértiz	Journalist
claudia cisneros	claudiacisneros	Journalist
recisneros	Renato Cisneros	Journalist
larryportera	Paola Ugaz	Journalist
tuesta	Fernando Tuesta Soldevilla	Journalist
Federicoagust	Federico Salazar B.	Journalist
julianaoxenford	Juliana Oxenford	Journalist
mariateguiperu	Aldo Mariategui	Journalist
JaimeChincha	Jaime Chincha	Journalist
VeroLinaresC	Verónica Linares	Journalist
tenoriopedro	Pedro Tenorio	Journalist
JBCPERU	José Barba Caballero	Journalist
jdealthaus	Jaime de Althaus	Journalist
ensustrece	Semanario Hildebrandt en sus trece	Journalist
BaylyOficial	Jaime Bayly	Journalist
jctafur	Juan Carlos Tafur	Journalist
cparedesr	Carlos Paredes	Journalist
PCaterianoB	Pedro Cateriano B	Politician
Carlos_Bruce	Carlos Bruce - Techito	Politician
JuanSheput	Juan Sheput	Politician
VLADIMIR_CERRON	Vladimir Cerrón	Politician
anibaltorresv	Aníbal Torres V.	Politician
pedrofrancke	Pedro Francke	Politician
Ollanta_HumalaT	Ollanta Humala Tasso	Politician
sigridbazan	Sigrid Bazán	Politician
MirtyVas	Mirtha Vásquez	Politician
FlorPabloMedina	Flor Pablo Medina	Politician
rlopezaliaga1	Rafael López Aliaga	Politician

Table 1: List of curated Twitter accounts relevant to Peruvian politics and economy.

Username	Name	Category
patarevalo	Patricia Arévalo	Politician
George_Forsyth	George Forsyth	Politician
JorgeMunozPe	Jorge Muñoz	Politician
DanielUrresti1	Daniel Urresti	Politician
VictorAndresGB	Vitocho	Politician
KeikoFujimori	Keiko Fujimori	Politician
MartinVizcarraC	Martín Vizcarra	Politician
JorgeDCG	Jorge del Castillo	Politician
Mauriciomulder	Mauricio Mulder	Politician
nidiavilchez	Nidia Vilchez	Politician
FSagasti	Francisco Sagasti	Politician
AlbertoBelaunde	Alberto de Belaunde	Politician
MaricarmenAlvaP	Maricarmen Alva	Politician
PattyChirinos1	Patricia Chirinos	Politician
adrianatudelag	Adriana Tudela Gutiérrez	Politician
CesarAcunaP	César Acuña Peralta	Politician
MesiasGuevara	Mesías Guevara	Politician
vozdelatierra	Marco Arana	Politician
MarisaGlave	Marisa Glave	Politician
GuilleBermejoR	Guillermo Bermejo Rojas	Politician
robertochiabra	Roberto Chiabra	Politician
RichardArcePeru	Richard Arce	Politician
Alm_Montoya	Jorge Montoya	Politician
AlejandroCavero	Alejandro Cavero	Politician
HectorValer_PER	Héctor Valer Pinto	Politician
RosselliAmuruz	Rosselli Amuruz	Politician
HDeSotoPeru	Hernando de Soto	Politician
UrsulaLetonaP	Ursula Letona	Politician
AlvaroVargasLl	Álvaro Vargas Llosa	Politician
AlbertoOtarolaP	Alberto Otárola	Politician
HPerezDeCuellar	Hania Pérez de Cuéllar	Politician
alosegura	Alonso Segura Vasi	Economist
BustamantePao18	Paola Bustamante S.	Economist
aethorne	Alfredo E Thorne	Economist
WaldoMendozaB	Waldo Mendoza Bellido	Economist
JuanManuelGarc3	Juan Manuel García C	Economist

Table 1: List of curated Twitter accounts relevant to Peruvian politics and economy.

Username	Name	Category
CarlosAnderso1	Carlos A. Anderson	Economist
hugonopo	Hugo Ñopo	Economist
tuestadavid	David Tuesta	Economist
pablo_lavado	Pablo Lavado	Economist
OswaldoMolinaC	Oswaldo Molina	Economist
CParodiT	Carlos Parodi Trece	Economist
psecadae	Pablo Secada	Economist
DWinkelried	Diego Winkelried	Economist
romerocaroperu	Manuel Romero Caro	Economist
manupulgarvidal	Manuel Pulgar Vidal	Economist
BancalariA	Antonella Bancalari	Economist
eljorobado	Carlos Meléndez	Political analyst
DargentEduardo	Eduardo Dargent	Political analyst
DelaPuenteJuan	Juan De la Puente	Political analyst
lauermirko	Mirko Lauer	Political analyst
rmapalacios	Rosa María Palacios	Political analyst
Frospigliosi	Fernando Rospigliosi	Political analyst
BetoAdrianzen	Alberto Adrianzen	Political analyst
ocram	Marco Sifuentes	Political analyst
brunoschaaf	Bruno Schaaf	Political analyst
luisbenaventegi	Luis Benavente	Political analyst
camcesar	Cesar Campos	Political analyst
AlfredoMTorres	Alfredo M.Torres G.	Political analyst
gonza_banda	Gonzalo Banda	Political analyst
Roque_Benavides	Roque Benavides	Private sector
CayetanaAljovin	Cayetana Aljovín	Private sector

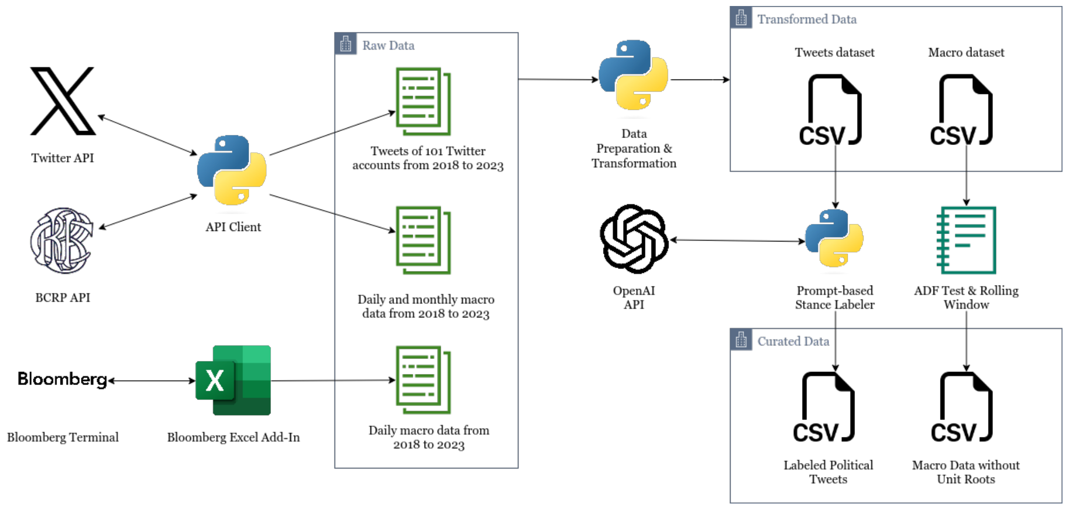

Figure 1: Data ingestion.

B Prompt: classification instructions

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Instructions for classification:
You are a politics expert and linguist tasked with analyzing the stance of tweets
from Peruvian influencers.
Each tweet is contextualized by the date it was posted and the president in office
at that time, providing a snapshot of the political sentiment during their
administration. Your assessment should consider Peru's political structure and the
interplay of its executive, legislative, and judicial branches.

Context:
Peru's political landscape operates within a constitutional democracy with a
separation of powers among the executive, legislative, and judicial branches.
Political parties in the legislative assembly play a pivotal role in formulating
laws that protect citizen rights and public interests.
Presidents such as Kuczynski, Vizcarra, Merino, Sagasti, Castillo, and Boluarte
have steered policies amid various economic and political pressures.
The Bank of the Republic of Peru (BCRP) is instrumental in managing inflation and
exchange rate policies, which are critical for economic stability and influence
the nation's fiscal health and living costs.
The judiciary, along with MINDEF and MINITER, ensures justice and societal order,
reflecting the country's law enforcement framework.
Election integrity is vital for maintaining the essence of democracy in Peru, with
ONPE being the guardian of this process.
Sound economic governance through fiscal responsibility and tax strategies is
essential for Peru's progress and alignment with international economic standards.
This scenario, involving past and current presidents, illustrates the dynamic and
complex interactions of governance, economic policy, and the country's path towards
a sustainable democracy.

Tweet Labelling Rules:
- Unrelated label: Assign this label to tweets that do not discuss or reference
Peru's governmental structure, economic management, legislative developments,
judicial actions, security policies, the impact of presidential terms, or election
practices.
- Stance-Based Labels:
    - In Favor: Use this label for tweets expressing support for the aformentioned
    aspects of Peru's democracy, policies, economic development or growth.
    - Against: Assign this label to tweets that express opposition or criticism
    towards Peru's governmental structure, economic management, legislative
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developments, judicial actions, and election practices. This includes tweets highlighting corruption, government-linked crimes, terrorism, political instability, human rights violations, poor economic management, legislative and judicial failures, or problematic election practices.

- Neutral: Apply this label to tweets that either discuss these aspects without taking a side or weigh both sides evenly.

Task:

Label the following tweet with one of the provided categories: "Unrelated", "In Favor", "Against", or "Neutral". The classification should reflect the tweet's stance towards the president and government policies active at the tweet's date.

Date(YYYY-MM-DD): {created_at}

<tweet>

{tweet_text}

</tweet>

Provide ONLY the label (e.g., "Against") as your response and NOTHING ELSE.

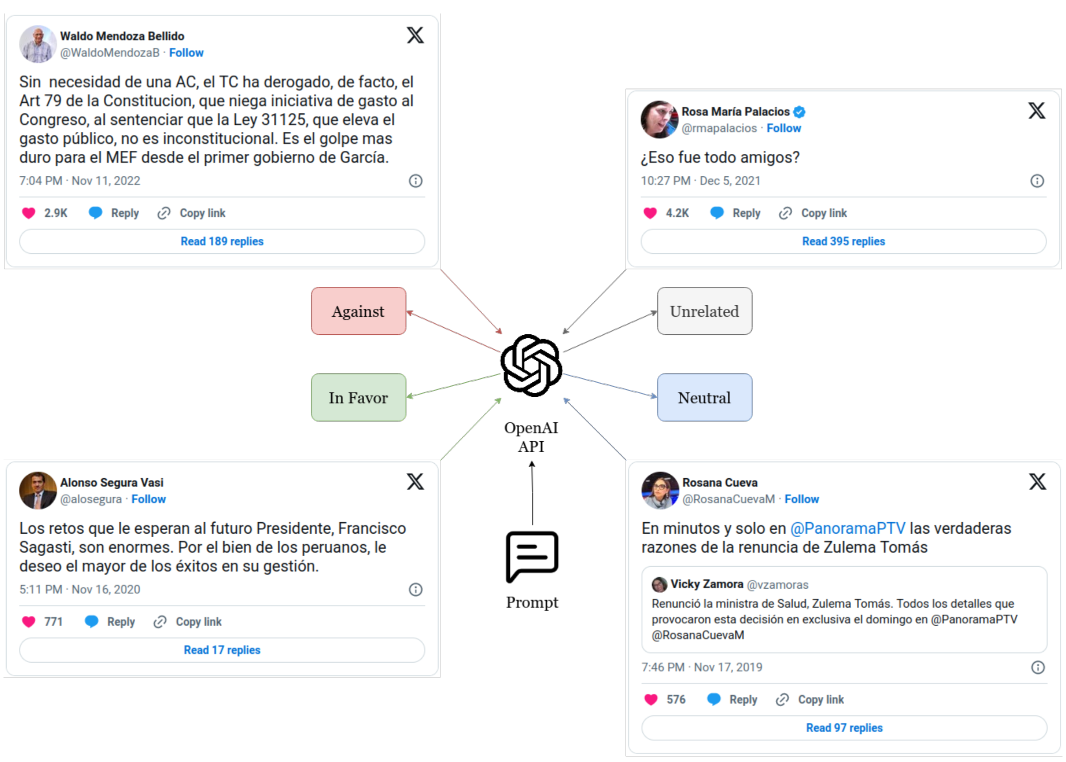

Figure 2: Labeling diagram.

C Key statistics

Table 2: Updated Distribution of Tweet Stances without filtering.

Stance	**Frequency**
Unrelated	88367
Against	78962
In Favor	36178
Neutral	12766
In favor	47
Unrelated.	16
Related	3
In Favor.	2
None	1
With the given information, it is not possible to determine the tweet's stance towards the president and government policies. Therefore, the label is "Unrelated." (1)	
Neutrall	1
Unaffected	1
Related.	1
Related to Tweet Categorization Instructions: Given the instructions provided, the tweet does not discuss or reference Peru's governmental structure, economic management, legislative developments, judicial actions, security policies, the impact of presidential terms, or election practices. Therefore, the appropriate label for this tweet is "Unrelated". (1)	
In Favour	1

Table 3: Updated Distribution of Tweet Stances

Stance	**Frequency**
Unrelated	88367
Against	78962
In Favor	36178
Neutral	12766

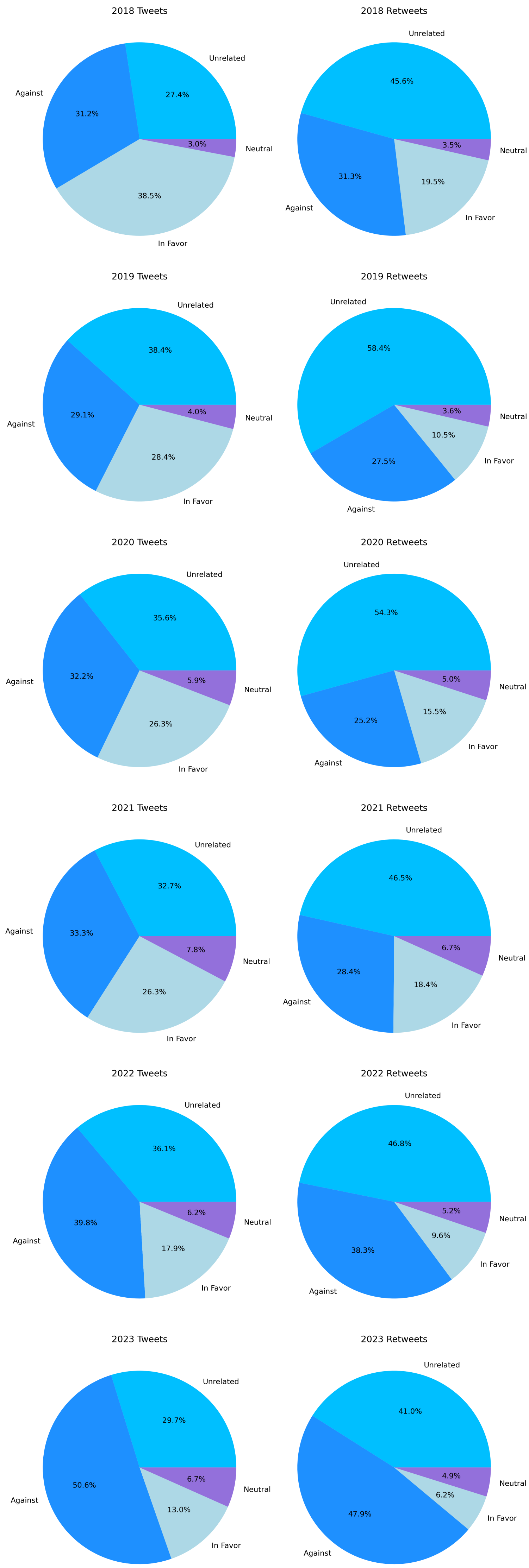

Figure 3: Tweet and Retweet Stance Distribution by Year.

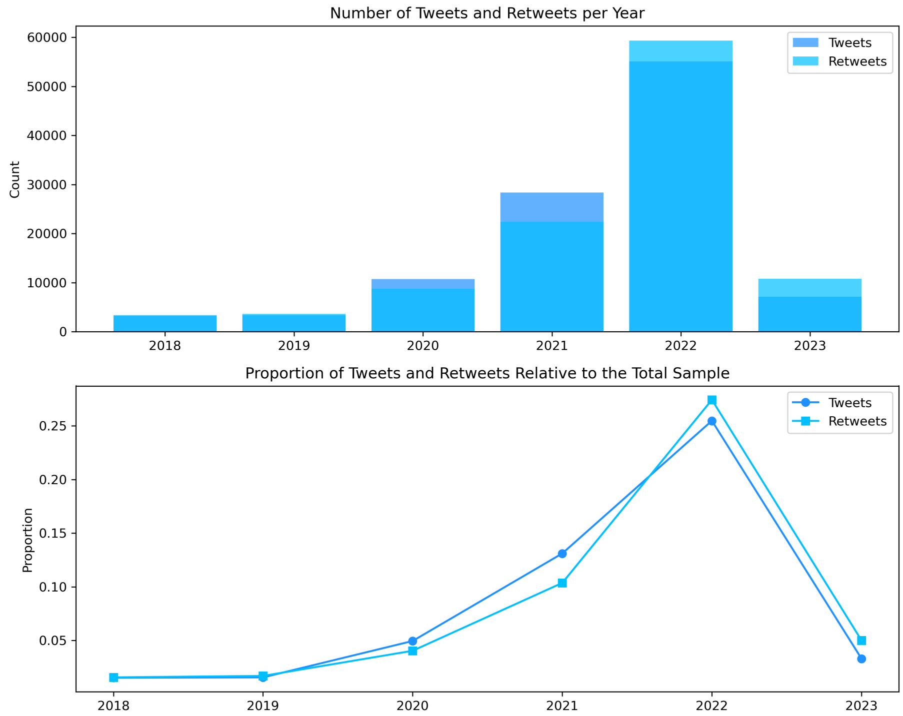

Figure 4: Tweets and retweets progression analysis.

Aggregation

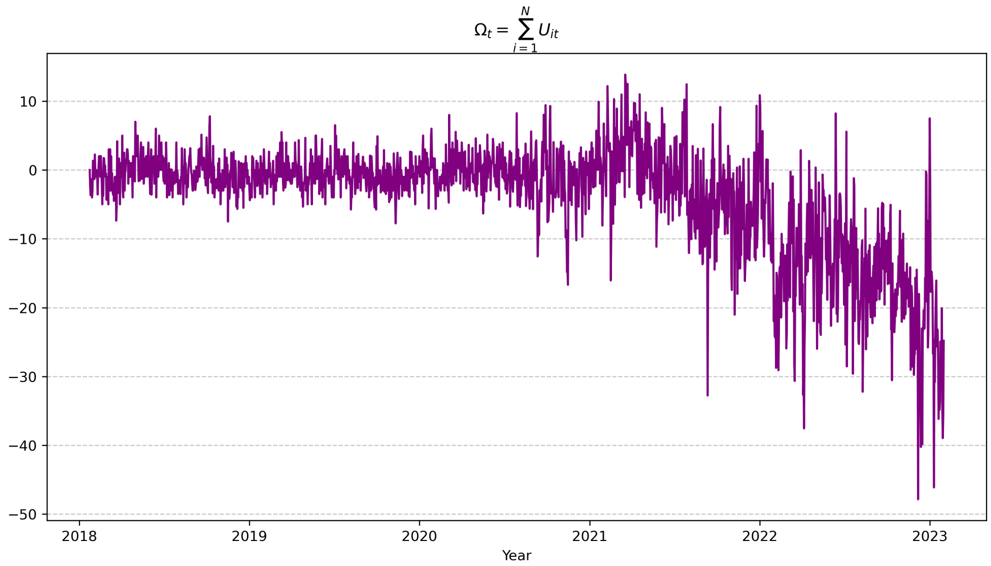

Figure 5: Evolution of $\Omega_t = \sum_{i=1}^{N} U_{it}$

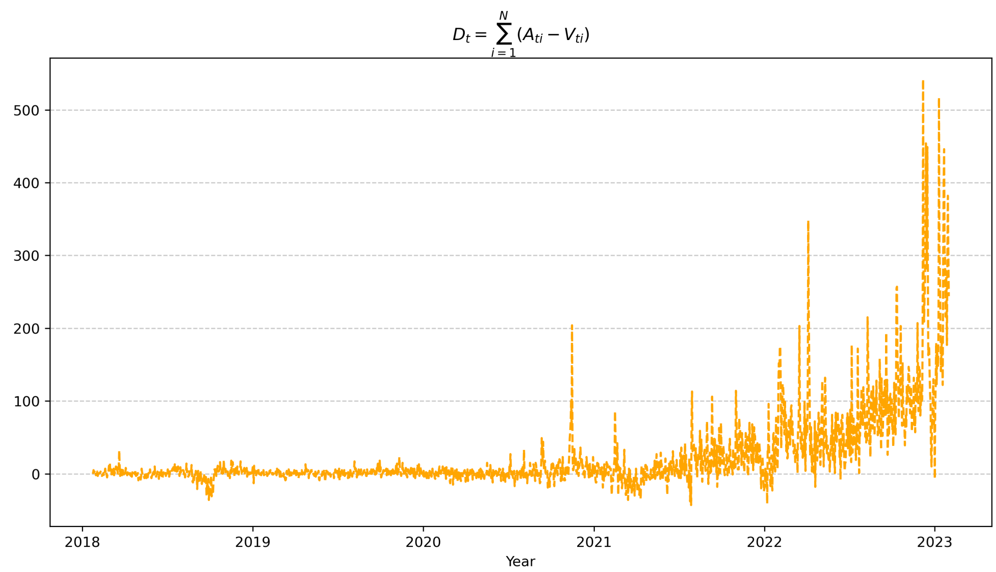

Figure 6: Evolution of $D_t = \sum_{i=1}^{N}(A_{it} - V_{it})$

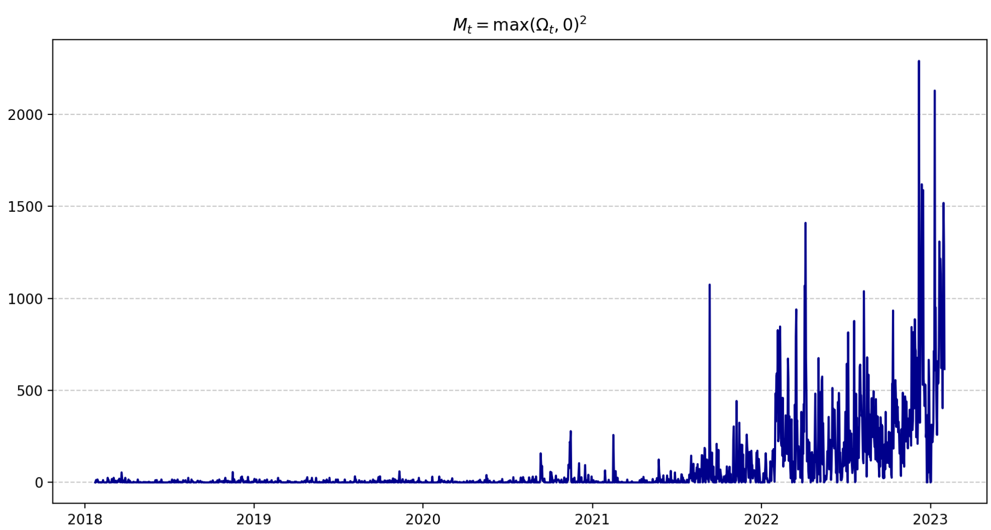

Figure 7: Evolution of $M_t = \min(\Omega_t, 0)^2$

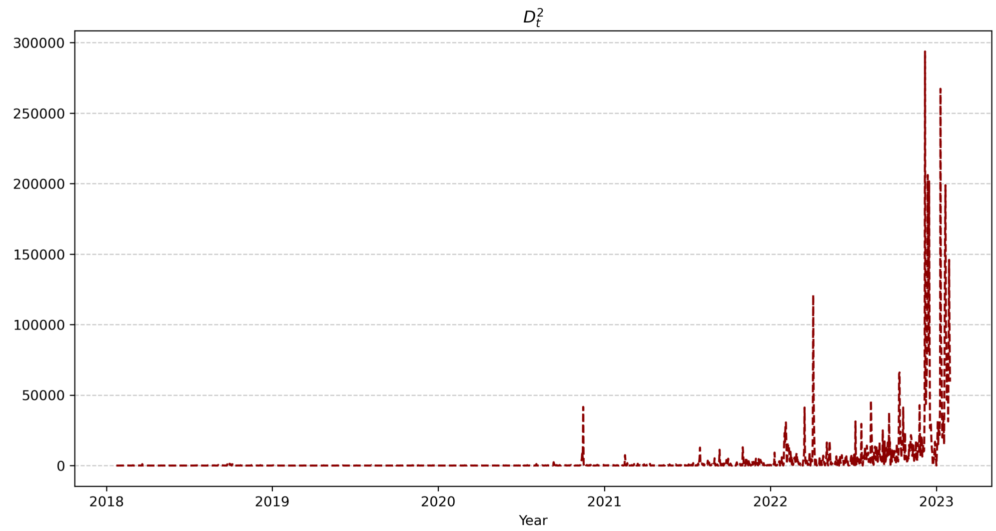

Figure 8: Evolution of D_t^2

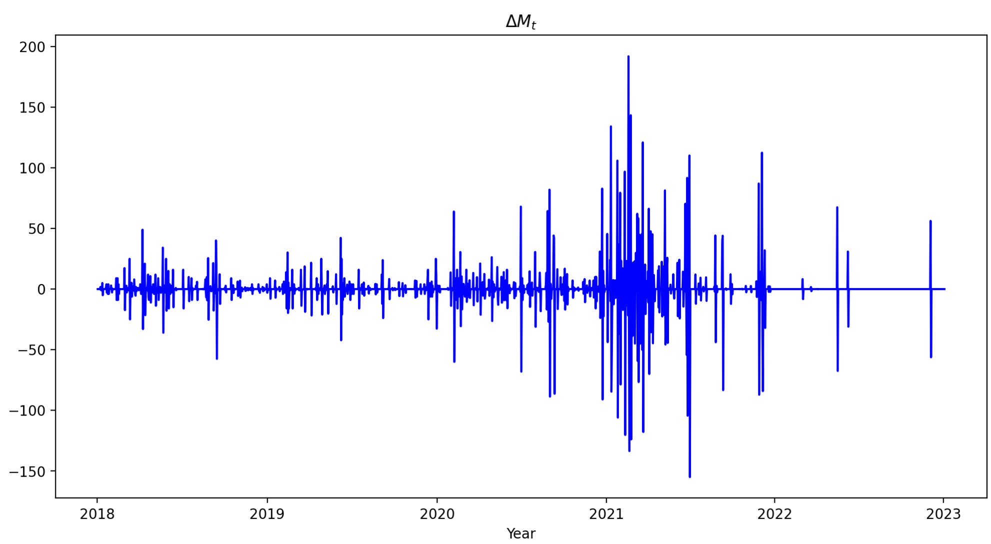

Figure 9: Evolution of ΔM_t

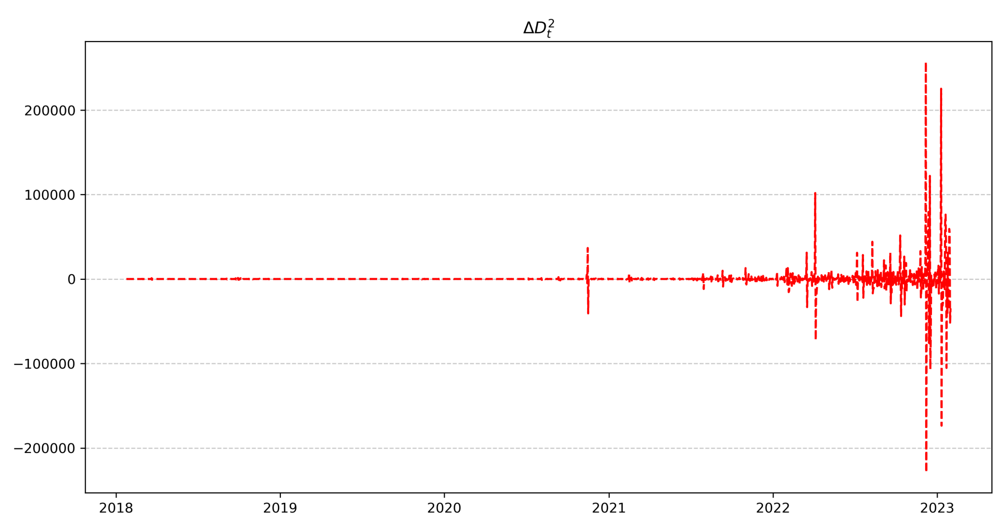

Figure 10: Evolution of ΔD_t^2

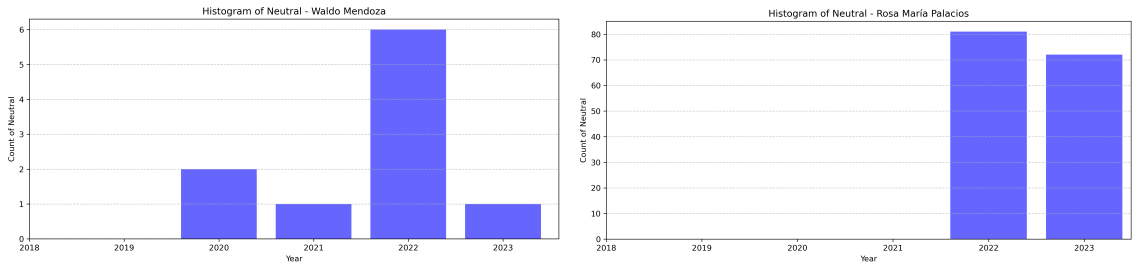

Figure 11: Histogram of Neutral Tweets for Waldo Mendoza and Rosa María Palacios

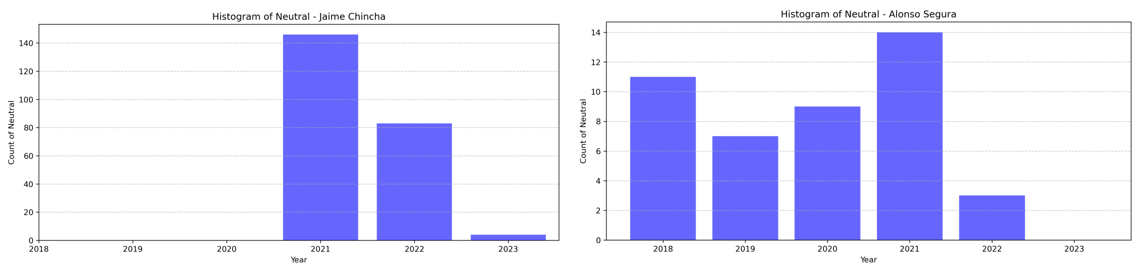

Figure 12: Histogram of Neutral Tweets for Jaime Chincha and Alonso Segura

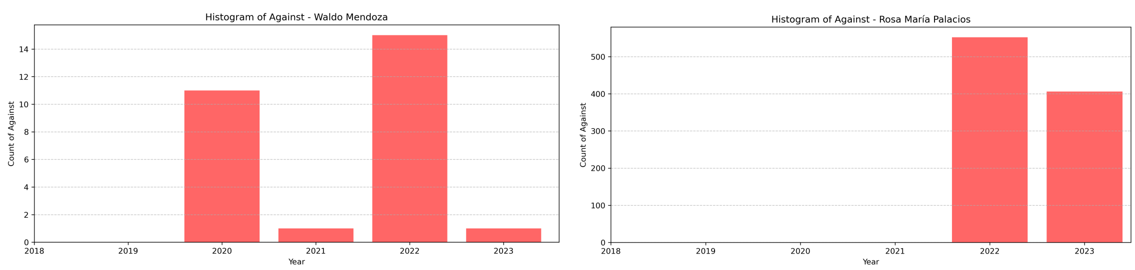

Figure 13: Histogram of Against Tweets for Waldo Mendoza and Rosa María Palacios

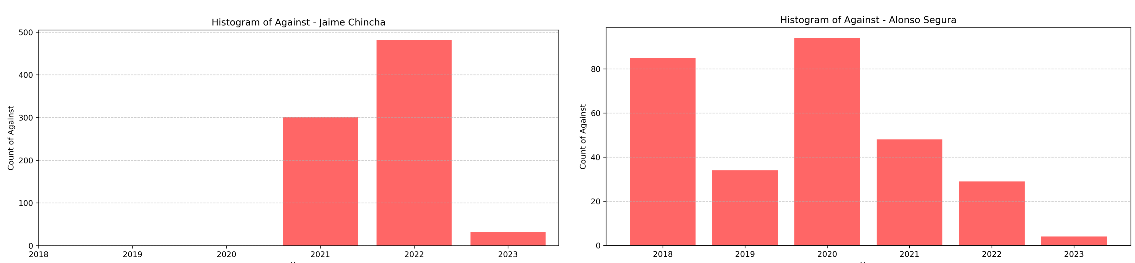

Figure 14: Histogram of Against Tweets for Jaime Chincha and Alonso Segura

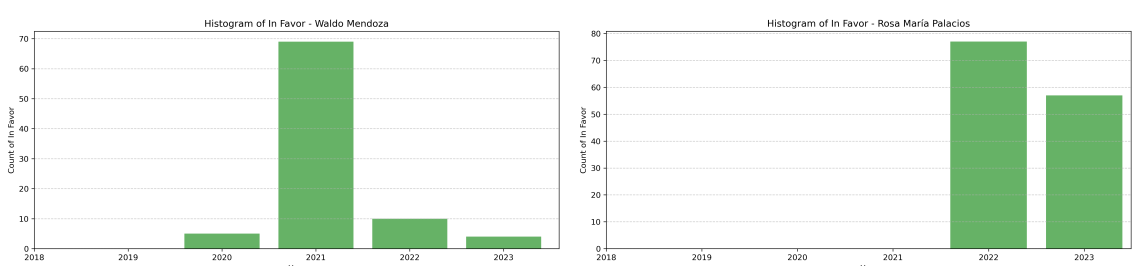

Figure 15: Histogram of Against Tweets for Waldo Mendoza and Rosa María Palacios

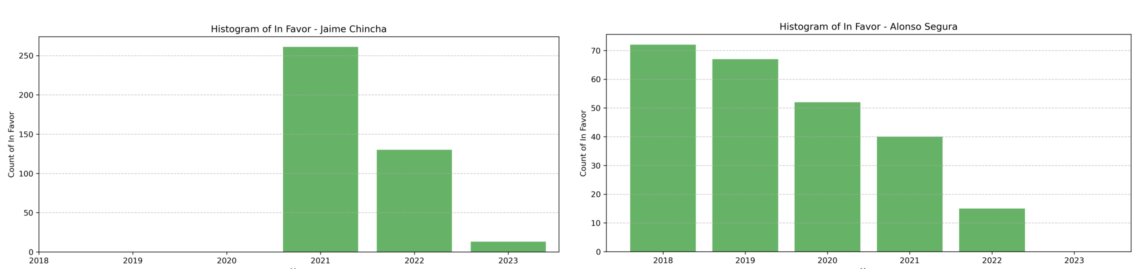

Figure 16: Histogram of Against Tweets for Jaime Chincha and Alonso Segura

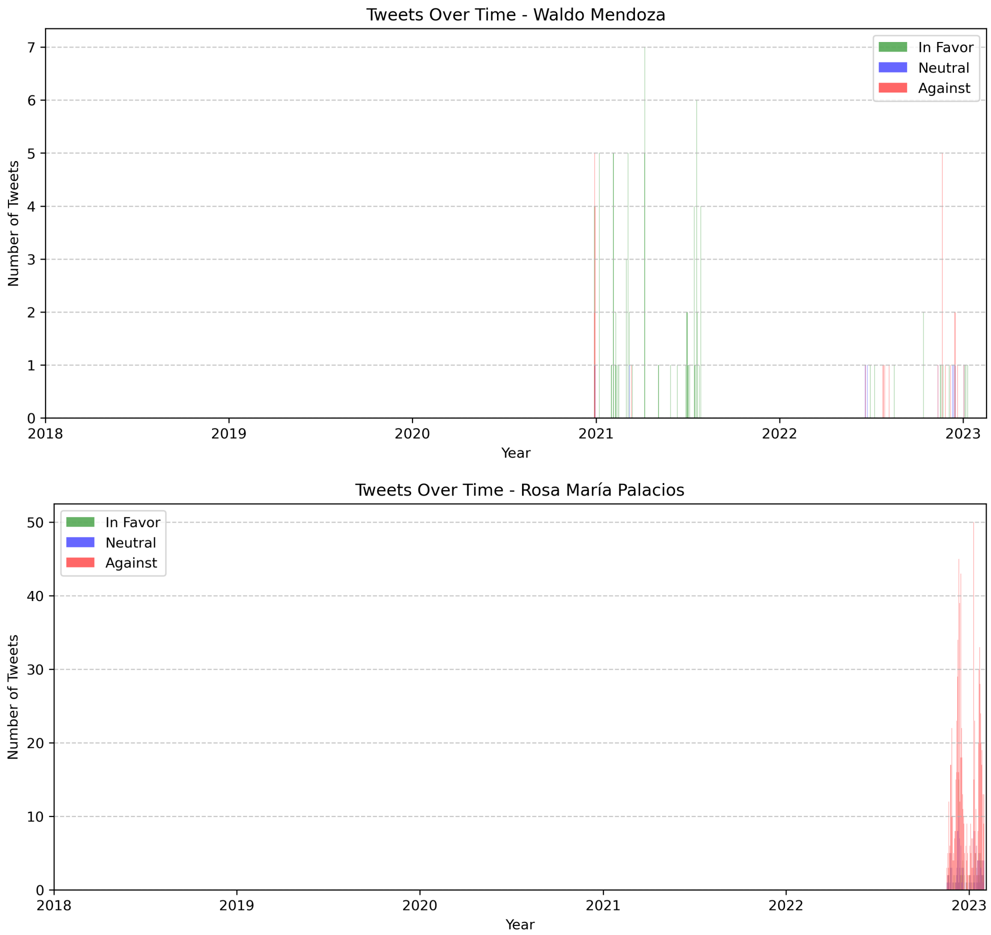

Figure 17: Number of tweets per day for Waldo Mendoza and Rosa María Palacios

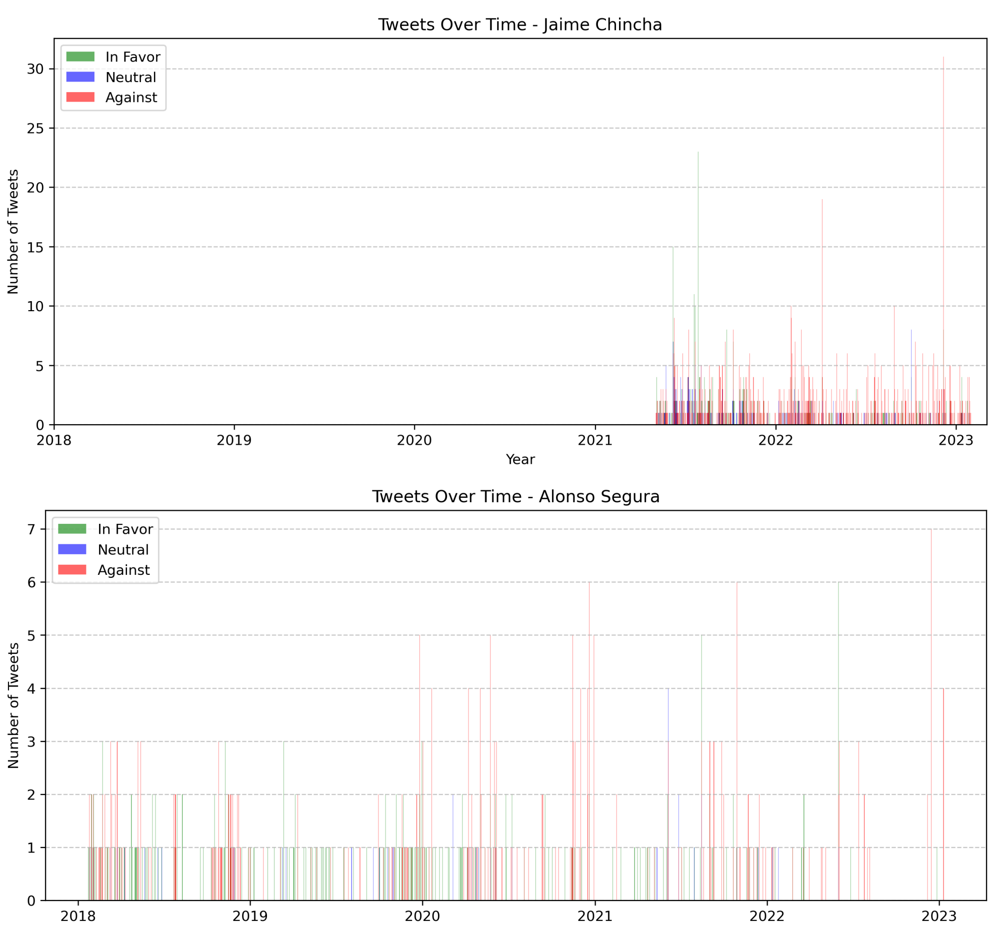

Figure 18: Number of tweets per day for Jaime Chincha and Alonso Segura

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