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DOES SOCIAL MEDIA SENTIMENT DURING TELEVISED POLITICAL DEBATES
INFLUENCE STOCK MARKET BEHAVIOUR? – EVIDENCE FROM PORTUGAL

DIOGO SIMON BEJA DA COSTA

Work project carried out under the supervision of:

José Tavares

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Abstract

This study analyses the impact of televised political debates and social media reactions on PSI20 prices in February 2024. Using OLS regressions, we examine normalised and absolute favourability measures, focusing on debates between left and right-wing parties, particularly PS and AD. Results suggest that, when grouped into left and right, the first negatively influences PSI20 prices while the latter has a positive impact. Proportional favourability exerts a stronger effect, better reflecting how markets perceive political competition and performance. Despite limitations, namely omitted variable bias, findings provide valuable insights into the relationship between politics, social media sentiment, and stock market performance.

Keywords: *Televised Political Debates, Social Media, Stock Market, Finance and Politics, Political Campaigns, Elections, Portugal, PSI20, Artificial Intelligence*

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1. Introduction

Televised political debates have long been a cornerstone of democratic processes, providing citizens the opportunity to witness first-hand how at least two candidates from different political backgrounds, with non-identical perspectives, address critical issues. Such affairs often encompass domains which are crucial for a modern society's health and evolution, namely public policy, economics, and financial markets. People have a chance to assess candidates' policy positions but also to get a measure of their rhetorical skills and attitude (Druckman 2003). Due to the nature of a political debate, which is, from the politicians' perspective, a chance to gain the maximum votes possible, it would not be strange to observe that they are able to shape public opinion, at least to some extent (Brierley, Kramon, and Ofoosu 2019; Kulachai, Lerdtomornsakul, and Homyamyen 2023).

While televised political debates had a narrower audience some decades ago, limited to television viewers, social media has transformed how people engage with these events. Indeed, in recent years, the rise of social media platforms such as Twitter, Facebook, and Instagram has provided real-time avenues for public discourse, enabling users to share opinions, create viral discussions, and react to candidates' live performances. In fact, social media have transformed political engagement, emphasising instantaneous reactions and the viral nature of public speeches (Gorrell et al. 2019). Now, it is essential to understand that public opinion, which is, at least, partially shaped by these debates and then magnified through social media, can unlock greater potential economic consequences. Specifically, as public sentiment spreads across social platforms, it can influence market actors and provoke a change in investor sentiment, possibly causing fluctuations in financial markets.

Various studies have looked at how political statements affect the economy and financial markets (e.g. Lei 2017), with fewer focusing specifically on political debates (e.g. Carcani

2019). Research also links political statements and social media to stock market uncertainty (Fan, Talavera, and Tran 2020; Ortiz 2023). However, to the best of the author's knowledge, no study has been conducted on the connection between social media sentiment during televised political debates and immediate stock market reactions, yet. This study seeks to fill this gap. Given the increasing role of political uncertainty in market volatility, amplified by social media-driven responses, this research will contribute to a better understanding of financial markets and hopefully allow policymakers to be better equipped to deal with oscillations in such markets, given an increasingly digital world.

We will examine the televised political debates that were held in Portugal during February 2024. The latter originated from the need to call early elections, due to a corruption scandal involving public contracts and figures close to the Prime Minister (Euronews 2023). Also, the outcome of the election was highly uncertain, as the two main parties were expected to be neck-and-neck in the final vote count (*The Portugal News* 2024). Thus, given the nature and context of those elections, these debates were probably more susceptible to ignite political and economic reactions, translated both on social media and in financial markets.

We will therefore aim to answer the following question: Does social media sentiment during televised political debates influence stock market behaviour in Portugal?

To conduct this analysis, we used data from two sources: the first was provided by Augusta Labs, a private and non-politically affiliated firm focused on Artificial Intelligence (AI) solutions, which developed an AI tool for Cable News Network (CNN) to analyse public sentiment on the Portuguese 2024 election candidates and debates. Advanced AI techniques were applied for sentiment analysis, introducing a ground-breaking approach to understanding public sentiment during televised political debates. Traditional sentiment analysis methods often involve time-consuming manual coding or basic keyword tracking, limiting their depth in

capturing nuanced opinions and real-time reactions. In contrast, this study leveraged Large Language Models (LLMs) to process vast amounts of social media data quickly and accurately, enabling real-time insights that would be unattainable through conventional methodologies. The second dataset corresponds to major stock market indices in Portugal, specifically the PSI20, which we will use to understand variations in Portuguese financial markets given the debates and social media sentiment.

The rest of the paper is organised as follows. Section 2 discusses the current state of the literature. In section 3 we will describe the dataset further, as well as the employed methodology. Section 4 presents the empirical results. Section 5 concludes.

2. Literature Review

Political events, such as elections, policy announcements, and televised debates, often influence public sentiment and, by extension, stock market behaviour. However, the role of social media platforms in amplifying and shaping public reactions to political events adds a new dimension to this relationship. This section will examine the existing research on how political interventions and events, including televised debates, influence the stock market. Additionally, it will explore the role of social media platforms in shaping political decisions and inducing stock market oscillations.

Previous research has established that political activity affects economic outcomes, namely inflation and unemployment (Alesina and Rodrik 1994; Fowler 2006). It has also been proved that the state of the economy influences politics, namely elections (Van Der Brug, Van Der Eijk, and Franklin 2001; Andrew Leigh 2005; Duch and Stevenson 2005). There is, however, mixed evidence in what concerns politics' effect on financial markets. For instance, Döpke and Pierdzioch (2006) analyse the interaction between political activity and stock

market movements in Germany and find that, contrary to results from the US, there is no election cycle in German stock market returns. Moreover, they do not find significant evidence of the political process influencing the stock market. However, there is a greater body of literature that supports the opposite thesis. Several articles find that there is indeed evidence of political events, specifically elections, influencing the US stock market (e.g., Foerster and Schmitz 1997; Pástor and Veronesi 2010; Snowberg, Wolfers, and Zitzewitz 2007; Reilly et al. 2020). Such evidence is also verified in other countries, both developed and developing (Brander 1989; Pantzalis, Stangeland, and Turtle 2000; Zach 2003; Cunha 2024). More interesting, perhaps, is the fact that such oscillations in financial markets are uneven. Boutchkova et al. (2011) show that political events trigger volatility changes, with varying effects across industries based on their political sensitivity. Nieminen (2020) confirms that industries closely tied to government policies are more sensitive to political uncertainty, and thus more significantly affected during presidential elections.

While elections significantly influence the stock market, political speeches also play a key role in shaping investor expectations. Indeed, public statements by political leaders may provide some insights into economic orientation and thus ignite market reactions. However, not only the content of such speeches matters: Maligkris (2017) finds that the tone of presidential candidates' speeches affects the stock market. In fact, an informative tone increases returns and trading volume while reducing volatility, whereas a negative tone has the opposite effect. Lei (2017) supports these findings.

Understanding that political speeches influence stock market behaviour, it is essential to grasp the specific impact of political debates. Some studies show that televised debates impact election results and that the evaluation of the candidates by the voters depends on the means of communication, as seen in the Kennedy-Nixon debate (Druckman 2003). Others find no evidence of debates affecting vote choice (e.g., Le Pennec and Pons 2023), suggesting they

mainly shape voters' impressions of candidates' character. Watching debates is more likely to reinforce existing preferences than changing voting intentions (Benoit and Hansen 2004). Thus, if televised debates do not always influence voting decisions, they certainly shape perceptions of candidates' personalities, which may be sufficient to stimulate financial markets. Carcani (2019) studied the three debates between Hillary Clinton and Donald Trump, Obama and John McCain, and George W. Bush and Al Gore, and found that no less than seven out of these nine debates provoked a significant reaction in the stock market.

Having established that political debates can spark stock market reactions, it is important to consider the role of social media in amplifying these effects. First, it is crucial to acknowledge the part that social media plays in political processes. Boulianne (2015) conducted a meta-analysis of 36 studies examining the relationship between social media usage and civic and political engagement and concluded that the two are positively linked overall. Social media platforms have become a key tool in shaping public opinion and political decisions, as demonstrated by Maruyama et al. (2014), who detected that individuals who frequently tweeted altered their voting decisions to match the prevailing opinion expressed on Twitter. Zheng and Shahin (2018) reinforce this idea, uncovering that Twitter may have played a role in shifting the US political landscape during the 2016 election, as Donald Trump was seen as the "winner" of the second and third debates on the platform. This aligned with exit poll data showing a connection between the timing of vote decisions and the three debates. Moreover, not only have social media platforms become key in shaping public opinion and political decisions, but they also constitute a valid source of information to extract political sentiment and behaviour, as uncovered by DiGrazia et al. (2013).

The increasing importance of social media platforms in shaping public opinion has not gone unnoticed in financial markets. Ortiz (2023) conducted research on Donald Trump's tweets and found evidence that the political elite has a massive impact on social media, which

translates into a market response. Indeed, it appears that market uncertainty significantly increases in response to tweets about foreign policy and trade, monetary policy, and immigration policy. He also uncovered that the frequency and intensity of tweet sharing impact stock uncertainty, regardless of the content. Other studies have examined the effects of sentiment analysis on platforms such as Twitter, revealing that social media sentiment can provide early indicators of market movements (Bollen et al. 2011). Tumasjan et al. (2010) analysed around 250,000 daily stock-related tweets and found that bullish sentiment tweets correlate with abnormal returns, while message volume predicts next-day trading activity. As so, there is proof that social media networks do massively influence the stock market.

However, there remains a distinct gap in the literature when it comes to real-time reactions to televised political debates. While social media platforms are extensively used by the public to express immediate reactions to debates, there is no detailed analysis of how this specific type of sentiment influences financial markets. Unlike other political events, televised debates offer live and spontaneous engagement, prompting rapid and volatile market sentiment shifts.

This study seeks to fill this gap by focusing specifically on the connection between social media sentiment during televised political debates and stock market reactions. By leveraging AI-driven sentiment analysis of social media reactions, this research will provide new insights into how real-time public discourse during televised debates can influence market behaviour.

3. Dataset and Methodology

3.1 Political Context

It is important to have a general idea of Portugal's political landscape several months before the 2024 elections to understand the need for early elections.

In mid-2023, members of the Socialist Party (PS), including figures close to Prime Minister António Costa, were implicated in a corruption scandal involving public contracts (Euronews 2023). While Costa himself was not directly involved, the scandal damaged the government's credibility and fuelled internal divisions within the PS. Tensions with coalition partners worsened, further destabilising the government. Opposition parties called for Costa's resignation, amid rising inflation and energy prices. With the government losing its majority and public trust, Costa resigned as Prime Minister in late 2023.

On 9 November 2023, President Marcelo Rebelo de Sousa announced the dissolution of parliament, calling for early elections on 10 March 2024. He officially signed the dissolution decree on 15 January 2024. Several political debates were held between 5 February and 23 February in anticipation of the legislative elections and were broadcasted through television on several channels, some public whereas others private, with different politically leaning views and audiences, namely RTP, RTP3, SIC, SIC Notícias, TVI and CNN. All the leaders debated with each other, and there were two debates with all parties, respectively with and without parliamentary representation. In total, 30 debates occurred, with a duration of 30 to 40 minutes, except the debate between the two main candidates, Pedro Nuno Santos (PS) and Luís Montenegro (AD - Democratic Alliance), with a duration of 75 minutes.

PS and AD, the leading left and right-wing contenders, were favourites to win the election. One would suspect debates involving them to be more likely to trigger reactions in social media and financial markets, as they carry greater weight and credibility in their potential to shape the election outcome. Thus, they will be the main focus of our analysis.

3.2 Dataset

3.2.1 Dataset Description

Our investigation will be conducted using data collected from two sources.

The first pool of data was provided by Augusta Labs and contains information relative to users’ immediate and subsequent reactions to a given political debate on social platforms, specifically Facebook, Instagram, Twitter, Reddit and YouTube. This research leverages LLMs for real-time analysis of vast social media data, surpassing traditional methods like manual coding or keyword tracking. AI’s efficiency in processing large datasets offers deeper insights into public sentiment during and after televised political debates, enabling a comparison of stock market activity with social media reactions. First, it is crucial to examine how Augusta Labs handled data collection, processing, and analysis. At the start of each debate, data started being collected from neutral sources (users not associated with any party) using web scraping, a technique that automatically extracts data from websites and exports it into a structured format. The collection process differed across platforms, using different functions designed to navigate and extract data from each one. For Instagram and Facebook, AI was used to select relevant posts for extracting comments, leveraging LLMs that identified pertinent content based on specified keywords, such as party names, candidates’ names, and relevant abbreviations (e.g. “AD”). On Twitter, AI filtered and gathered data from tweets found through global searches using the candidates’ names, particular acronyms, and party names. Meanwhile, data collection on Reddit and YouTube focused on comments posted in the debate threads and on debate-related videos, respectively. The data was uniformly formatted for analysis using standard programming processes before recurring to AI. Each collected interaction was analysed to identify which side of the debate the user seemed to think had won, using the LLM “GPT-4-turbo”, the most advanced model at the time. This analysis produced three possible outputs, revealing users’ preferences:

Table 1: AI Sentiment Analysis of Social Media Interactions

“s1”	indicates that the author believes side 1 of the debate won
“s2”	indicates that the author believes side 2 of the debate won
<i>Inconclusive</i>	for interactions with neutral sentiment or those unrelated to the debate

Augusta Labs tested this model against representative samples of over 50 interactions by four different humans, showing an accuracy of around 96%. The errors were not biased, meaning they did not occur more often for one side than the other (no candidate was being favoured). Moreover, around 500 to 2000 interactions were collected per debate, depending on the latter's popularity, and it is important to mention that Augusta Labs implemented several methods to limit the effect of agents that would want to influence the results (e.g., by setting a limit and thus considering only one interaction per user, and even by discarding interactions from users that had reacted "favourably" for both sides of a given debate).

The second data source contains the absolute prices and volume of the most relevant Portuguese Stock Indexes (PSI), specifically the PSI20, which encompasses the 20 largest companies in Portugal. This data was extracted from Bloomberg Terminal for every 10 minutes in February 2024, alongside other relevant stock indexes across Europe and the World, namely London (ASX), Frankfurt (DAX) and the S&P500 (SPX). This allows us to understand the stock market's behaviour every 10 minutes during the immediate and following hours (up to 18 hours) of a particular political debate and, therefore, determine whether the former is in any way influenced by the latter. We will focus on prices exclusively since the volume (total number of shares traded on a security on the current day) of PSI20 shares did not significantly vary in the timeframe we are analysing.

3.2.2 Dataset Treatment

The social media reactions dataset contains key variables translating social media activity related to Portuguese political debates held from February 5 to February 20, 2024. In total, it contains 1017 observations across all debates that were considered, which is a bit scarce for inference purposes. Augusta Labs did not collect data from debates with all parties present, with and without parliamentary representation, implying there are no observations regarding them. The same applies to the debate between AD and BE. Also, it is important to state that

social media observations were not collected evenly: data was usually heavily collected at the start of the debate and during the subsequent hours, but with uneven gaps between them, sometimes seconds apart and other times several hours (e.g., 2 am to 9 am). Such data extraction method could not be employed regarding stock market data. Indeed, the latter was consistently gathered every 10 minutes throughout February 2024. Moreover, since stock markets are closed on weekends and overnight, the dataset included observations with both social media and stock market data and others with only social media data. This led to many missing stock market values, which were addressed using linear interpolation, estimating values based on available data (the nearest preceding and subsequent data points). After cleaning and formatting the dataset, key variables provided by Augusta Labs were used, such as *alls1*, *alls2*, *percl*, and *percr*, to generate new ones for the analysis. The first two represent the number of comments across all five platforms (Facebook, Instagram, Twitter, Reddit and YouTube), where one can infer which side of the debate the user considered to be superior. Table 2 shows how comments were assessed by AI for variables *alls1* and *alls2*.

Table 2: Example of AI Sentiment Analysis with PS and AD Related Comments

Side 1	Side 2	User’s Comment	Impact on <i>alls1</i>	Impact on <i>alls2</i>
AD	PS	“The leader of AD performed well”	+1	No impact
		“The leader of PS did not clearly explain their position on healthcare”	+1	No impact
		“I enjoyed the debate”	No impact	No impact

Therefore, the latter represent the absolute volume and favourability of social media reactions *vis-à-vis* a given debate. In turn, *percl* and *percr* correspond to the standardised values of *alls1* and *alls2*, respectively, from a scale of 0 to 100. In other words, they correspond to the percentage of social media reactions that favour either side 1 or 2 of the debate. By generating dummy variables for each of the parties to identify whether they

participated in a given debate, and using variables *alls1*, *alls2*, *percl* and *percr*, we were able to generate the two core variables of our analysis: *favourability* and *absolute_favourability*. These were created individually for each party, allowing for a detailed analysis of their performance across debates. For example, *fav_AD* reflects the proportion of comments supporting AD compared to the total number of comments that favour either party in the debate. Similarly, *abs_fav_AD* represents the raw count of comments explicitly supporting AD, regardless of the total comments concerning that debate or the opposing party's performance. We created variables *abs_fav_LEFT* and *abs_fav_RIGHT* for absolute favourability counts and *fav_LEFT* and *fav_RIGHT* for relative favourability. *abs_fav_LEFT* reflects the total comments supporting left-leaning parties (BE, CDU, PAN, LIVRE, PS), while *abs_fav_RIGHT* reflects those supporting right-leaning parties (AD, IL, CHEGA). Similarly, *fav_LEFT* and *fav_RIGHT* represent the proportions of comments favouring left- and right-leaning parties, respectively. These variables provide a comparative perspective on the public's reactions to left and right-aligned candidates/parties during the debates.

3.3 Methodology

Before tackling data examination, recognising the specific nature of our merged dataset is crucial to avoid mistaken interpretations.

Due to the different time dynamics of the data sources (continuous social media reactions and stock market data limited to trading hours), the dataset is treated as cross-sectional. Each observation represents a single point in time, and each debate is considered an independent event, assuming no overlap in effects. This approach ensures that the analysis focuses on the relationship between social media reactions and stock market performance without being constrained by continuity or dependencies typical of time-series data across debates. In fact, it is unlikely that a debate between two left-wing parties depends on one between two right-wing parties, for instance, as discussed topics and the tone of the debate are likely different.

Our analysis aims to confirm the following set of hypotheses:

- H1: PSI20 prices behave differently to the performance of the main parties on the left and the right, PS and AD, respectively.
- H2: The stock market responds differently to reactions regarding candidates from different political spectrums, i.e. from the left and the right.

To verify whether the latter hold or not, we developed two models, each designed to explain PSI20 prices using different measures of party favourability. Both incorporate the UK FTSE All-Share Index (*ASX_LP*) as a control variable to account for broader international market trends that could influence PSI20, given the integration of capital markets, independently of debate-related factors. In fact, the correlation in stock returns between the Lisbon and London stock exchanges is 0.7797. The decision to use an index from London as a control variable over indices from the Frankfurt or New York stock exchanges is primarily due to its alignment with the Portuguese time zone, ensuring more synchronised trading hours and market movements. This also helps regarding the number of observations we can use in our regressions.

- Model 1: Normalised Favourability

This specification uses each party's normalised favourability (*fav_*) as an explanatory variable. Normalised favourability represents the proportion of comments supporting a party relative to the total number of favourability-related comments for that debate. For example, for PS, model 1 is specified as:

$$PSI20_{LP_{imputed}} = \beta_0 + \beta_1 * fav_{PS} + \beta_2 * ASX_{LP_{imputed}} + \epsilon \quad (1)$$

- Model 2: Absolute Favourability

This specification employs the absolute favourability (*abs_fav_*) of each party.

It represents the raw count of comments supporting the party, regardless of the total number of comments or other parties' favourability. For example, for PS, model 2 is specified as:

$$PSI20_{LP_{imputed}} = \beta_0 + \beta_1 * abs_fav_PS + \beta_2 * ASX_{LP_{imputed}} + \epsilon \quad (2)$$

Model 1 captures the relative influence of a party's favourability compared to others during a debate, providing insights into proportional dynamics. Model 2 focuses on the absolute volume of support a party receives, reflecting the total magnitude of reactions without considering the relative performance of other parties. For both models, we performed several specifications of the regressions to account for different types of effects on PSI20 prices: each party versus all other parties, each party versus parties of the opposite political spectrum and left versus right (grouping parties into two political groups). These approaches allowed us to capture not only individual party-specific effects but also broader ideological influences on the PSI20 index. Note that coefficients from both models are different, despite same labelling.

3.4 Descriptive Statistics

The descriptive statistics presented in this subsection provide a foundational understanding of the dataset, highlighting the key patterns and relationships that will be further explored in the subsequent regression analysis.

Table 3 highlights the variability in stock market performance and social media metrics across debates. Figure 1 is a scatterplot representing each party's position vis-à-vis the absolute and proportional volumes of support a party receives. It allows us to have a global sense of users' preferences regarding the debates and candidates' performances. One could read, for instance, that PS is one of the parties with more absolute support. But, when confronted with other political parties, it is less performant. One possible explanation is that, after approximately eight years in power, PS faced criticism for challenges like sluggish

economic growth, persistent public debt, and social dissatisfaction, contributing to a perception of ineffective governance (Katanich 2023).

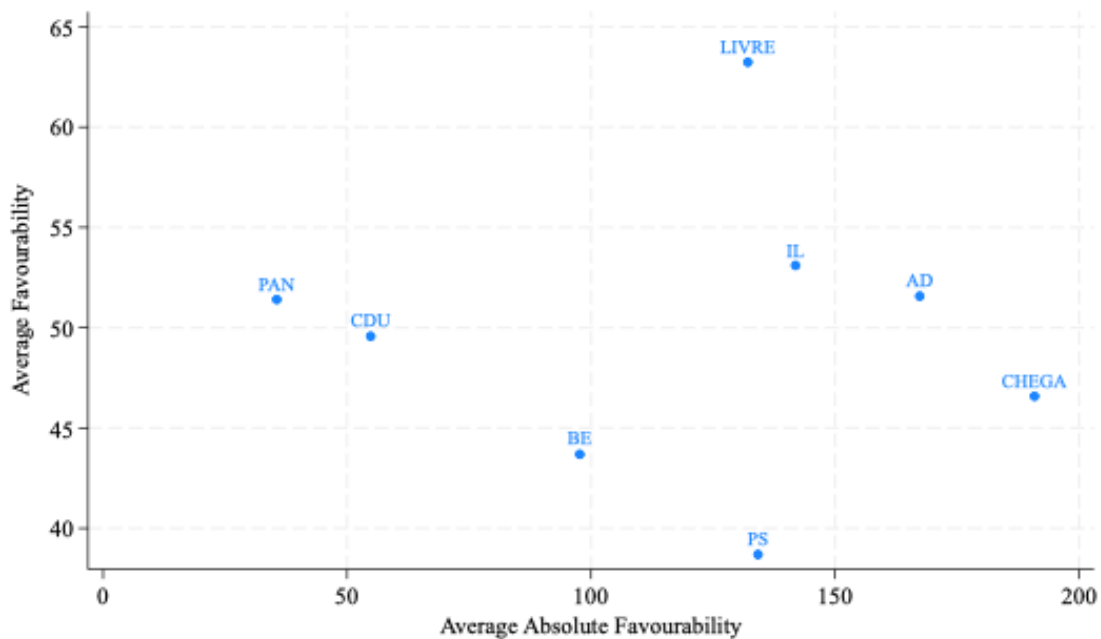
Table 3: Descriptive Statistics of Key Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
fav PS	268	38.694	9.991	0	100
fav AD	213	51.573	9.417	0	80
fav BE	235	43.689	17.554	0	100
fav CDU	205	49.571	12.701	0	100
fav PAN	168	51.405	12.911	0	100
fav LIVRE	318	63.236	14.289	0	100
fav IL	301	53.106	16.277	22	100
fav CHEGA	326	46.583	11.922	0	73
fav LEFT	1017	58.549	31.694	0	100
fav RIGHT	1017	41.451	31.694	0	100
abs fav PS	268	134.213	146.715	0	708
abs fav AD	213	167.352	240.507	0	1057
abs fav BE	235	97.685	116.36	0	484
abs fav CDU	205	54.829	64.26	0	305
abs fav PAN	168	35.595	46.161	0	242
abs fav LIVRE	318	132.142	125.3	0	635
abs fav IL	301	141.92	139.145	1	615
abs fav CHEGA	326	190.88	178.309	0	855
abs fav LEFT	1017	116.191	124.873	0	708
abs fav RIGHT	1017	138.241	195.657	0	1057
ASX LP imputed	957	4159.217	27.492	4102.02	4217.26
PSI20 LP imputed	957	6169.221	42.658	6095.87	6249.83

Note: *ASX_LP_imputed* and *PSI20_LP_imputed* refer to UK FTSE All-Share Index and PSI20 Index prices, respectively, adjusted using linear interpolation to overcome the many missing stock market values, given the structure of the dataset. Normalised favourability (*fav*) represents the proportion of comments supporting a party relative to the total number of favourability-related comments for that debate, whereas absolute favourability (*abs_fav*) represents the raw count of comments supporting the party, regardless of the total number of comments or other parties' favourability. All eight parties, as well as left and right-wing statistics are presented.

These factors likely influenced public sentiment and shaped market reactions, as they eroded confidence in the government's ability to address key issues, particularly during politically charged debates. It is also interesting to see that all three right-wing parties have a greater absolute favourability than all five left-wing parties. This means that, on average, the total number of comments supporting each right-wing party is greater than that of each left-wing party, in absolute terms. Again, this may be because PS governed for the majority of its eight years in power with most left-wing parties' support (Admin 2017; Maxnl 2022).

Figure 1: Scatter Plot of Average Absolute Favourability and Favourability for All Parties



Note: Data reflects average favourability (0-100) and absolute favourability of all parties. Hence the scale of the Y-axis.

However, when looking at the average favourability, that is, when considering the proportion of comments supporting a party relative to the total number of favourability-related comments, we observe that this discrepancy between left and right is not as pronounced and is, in fact, much more balanced. This likely occurs namely due to two factors. First, CHEGA's tone and type of speech during the debates are predominantly negative and lack substantive proposals for addressing the country's problems (*The Straits Times* 2024). Consequently, debates involving CHEGA generate an abnormally high volume of reactions, but the proportion of reactions in the party's favour is smaller than that of other parties, which drags right-wing parties' averages down. Second, LIVRE's position suggests that while having lower absolute favourability, the proportion of favourable reactions relative to total reactions (normalised favourability) is significantly higher. LIVRE might have a smaller but highly supportive base of followers, leading to a higher favourability score despite fewer overall comments (even if it is the left-wing party with the most volume of comments, on average). With these descriptive statistics in mind, let's proceed to our regression results.

4. Empirical Results

4.1 Model 1 – Normalised Favourability

This subsection provides insights into the relative influence of public sentiment regarding political debates on PSI20 prices.

Table 4: AD vs PS - Model 1

VARIABLES	(1) PS vs All	(2) AD vs All	(3) PS vs Right	(4) AD vs Left	(5) PS vs AD
fav_PS	-0.602*** (0.119)		-1.165*** (0.247)		0.000376 (0.0119)
fav_AD		1.013*** (0.139)		0.0476 (0.177)	
ASX_LP_imputed	1.676*** (0.0414)	0.892*** (0.0389)	1.689*** (0.0543)	1.252*** (0.0466)	0.666*** (0.0674)
o.fav_AD					-
Constant	-787.3*** (171.6)	2,423*** (159.9)	-816.8*** (223.1)	962.4*** (187.8)	3,440*** (284.1)
Observations	208	213	128	165	61
R-squared	0.890	0.794	0.896	0.919	0.628

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 4 presents the coefficients and their statistical significance regarding debates with either PS or AD (and the specific debate between them), not only against all other parties (e.g. AD vs All) but also against parties from the opposite political spectrum (e.g. PS vs Right). It is important to mention that the coefficient *fav_AD* is omitted in the debate between AD and PS, which is normal given the nature of the variable ($fav_AD = 100 - fav_PS$, for this specific debate). We can see that all coefficients concerning PS are negative (except *fav_PS* in the debate between PS and AD), and those concerning AD are positive. This indicates that regardless of considering debates against all other parties or against parties from the opposite political spectrum, PS seems to have a negative effect on PSI20 prices, and AD a positive one. Such effects are not of the same intensity, as depicted by the magnitude of each

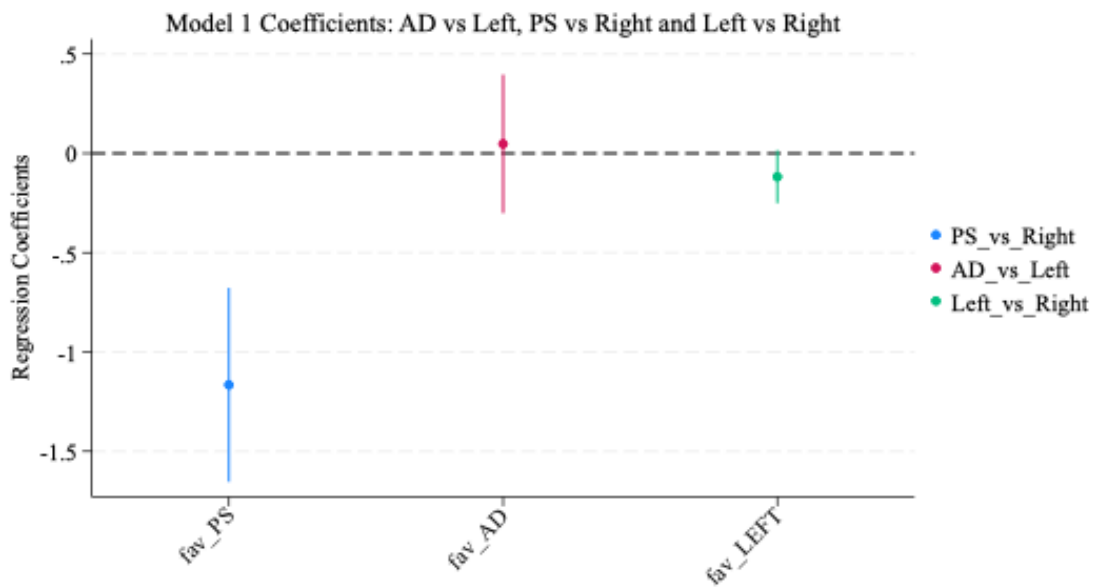
coefficient for each regression specification, as can be seen below in Figure 2. For example, considering the specification of PS and AD against all other parties, on average, a one-unit increase in the normalised favourability of PS is associated with a decrease of 0.602 units in PSI20 prices, whereas a one-unit increase in the normalised favourability of AD is associated with an increase of 1.013 in PSI20 prices, holding all other variables constant. Putting it differently, if *fav_PS* takes its mean value, which is 38.694 (see Table 1), then its impact on PSI20 prices will be, on average, *ceteris paribus*, equal to approximately -23.294. Conversely, if *fav_AD* takes its mean value, which is 51.573 (see Table 1), then its impact on PSI20 prices will be, on average, *ceteris paribus*, equal to approximately 52.243. Hence, the impact of *fav_PS* on PSI20 prices is approximately half the standard deviation of PSI20 prices (i.e. 42.658 – see Table 1), whereas the impact of *fav_AD* exceeds one standard deviation. It is important to notice that the weight of the UK FTSE All-Share Index (*ASX_LP*) is, in general, considerably greater than that of other variables, implying a stronger effect on PSI20 prices, on average. These results are in line with those of Table 5, which considers all parties, grouped into left and right-wing parties. The latter suggests that as the proportion of comments supporting a left-wing party increases, PSI20 prices tend to decrease.

Table 5: Left vs Right - Model 1

VARIABLES	(1) Left vs Right
fav_LEFT	-0.118* (0.0679)
o.fav_RIGHT	-
ASX_LP_imputed	1.153*** (0.0316)
Constant	1,377*** (131.6)
Observations	564
R-squared	0.706

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 2: Coefficient Plot 1



Note: 95% Confidence Intervals are also displayed. We are assuming that Gauss-Markov assumptions are satisfied.

For model 1, results concerning parties other than AD and PS can also be checked in Tables 6 and 7 (see Appendix). These tables represent debates between those parties and all other parties, as well as with parties from the opposite political spectrum, respectively. Figure 3 (see Appendix) visually represents selected results from Table 7, for clarity.

4.2 Model 2 – Absolute Favourability

This subsection provides insights into the absolute influence of public sentiment regarding political debates on PSI20 prices.

Table 8 coefficients are mainly in accordance with results from model 1. In fact, the raw count of comments supporting each party, regardless of proportional considerations, indicates that, on average and *ceteris paribus*, AD positively impacts PSI20 prices, unlike PS, specifically when the latter debates against right-wing parties. Indeed, considering the specification of PS and AD against parties from the opposite political spectrum, on average, a one-unit increase in the absolute favourability of PS is associated with a 0.0215 units decrease

in PSI20 prices, whereas a one-unit increase in the absolute favourability of AD is associated with a 0.0164 units increase in PSI20 prices, holding all other variables constant.

Table 8: AD vs PS - Model 2

VARIABLES	(1) PS vs All	(2) AD vs All	(3) PS vs Right	(4) AD vs Left	(5) PS vs AD
abs_fav_PS	0.0113 (0.00889)		-0.0215* (0.0112)		-0.00110 (0.00413)
abs_fav_AD		0.0262*** (0.00604)		0.0164*** (0.00408)	0.000584 (0.00264)
ASX_LP_imputed	1.604*** (0.0474)	0.915*** (0.0431)	1.610*** (0.0550)	1.189*** (0.0334)	0.696*** (0.116)
Constant	-509.9** (197.2)	2,377*** (179.3)	-521.2** (229.3)	1,227*** (139.3)	3,314*** (490.6)
Observations	208	213	128	165	61
R-squared	0.877	0.763	0.881	0.927	0.629

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

In other words, if *abs_fav_PS* takes its mean value, which is 134.213 (see Table 1), then its impact on PSI20 prices will be, on average, *ceteris paribus*, equal to roughly -2.889. Conversely, if *abs_fav_AD* takes its mean value, which is 167.352 (see Table 1), then its impact on PSI20 prices will be, on average, *ceteris paribus*, equal to approximately 2.745. Hence, the impact of *abs_fav_PS* and *abs_fav_AD* on PSI20 prices is quite reduced. Moreover, since *abs_fav_PS* is positive during PS debates against all parties but turns negative when PS faces right-wing parties, this suggests that the impact of absolute favourability on PSI20 prices depends not only on PS itself but also on the political alignment of its opponents. Again, this may be due to the recent governing history of the country. Table 9 shows that the direction of results regarding Left and Right are the same as for model 1, but less pronounced. For model 2, one can also check results concerning parties other than AD and PS in Tables 10 and 11 (see Appendix), which represent debates between those parties and all other parties, as well as with parties from the opposite political spectrum. Figures 4 and 5 (see Appendix) visually represent selected results from Tables 8, 9 and 11.

Table 9: Left vs Right - Model 2

VARIABLES	(1) Left vs Right
abs_fav_LEFT	-0.0199* (0.0111)
abs_fav_RIGHT	0.0364*** (0.00742)
ASX_LP_imputed	1.118*** (0.0316)
Constant	1,511*** (131.0)
Observations	564
R-squared	0.723

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

It is worth noting that the social-media-related coefficients in model 1 are generally larger in absolute terms than those in model 2. This indicates that proportional favourability exerts a stronger influence on PSI20 prices than absolute favourability. This difference can be attributed to model 1's emphasis on the relative importance of a party's support compared to its competitors in a debate, which better reflects how markets perceive political competition and performance. In contrast, model 2 focuses solely on the raw count of supportive comments, failing to capture the broader context of debate dynamics, which likely results in a smaller impact on market outcomes, in this case, prices.

4.3 Limitations

4.3.1 Description of Statistical and Dataset Limitations

This study employs Ordinary Least Squares (OLS) regressions as the estimation method. If the Gauss-Markov assumptions are satisfied, that is, linearity (the true model is linear in parameters), exogeneity (the average value of the error term does not depend on the independent variables), homoskedasticity (errors have constant variance), and no autocorrelation (errors are uncorrelated), then OLS estimators are Best Linear Unbiased Estimators (BLUE). This ensures estimators are unbiased, consistent, and efficient. However,

some of these assumptions are not satisfied in our dataset. The data collected by Augusta Labs is cumulative, as the count of comments supporting a party grows over time, influencing favourability calculations. Consequently, values at each time point depend on past data from the same debate, likely leading to autocorrelated errors. Therefore, it is prudent to cluster observations by debates to account for autocorrelation. Also, we tested for heteroskedasticity using the Breusch-Pagan test, which assumes a null hypothesis of constant variance under normally distributed errors. Most regressions in both models showed heteroskedasticity, so we imposed robust standard errors to correct for non-constant error variance, ensuring unbiased and valid coefficient estimates. Moreover, we conducted Ramsey's test for omitted variable bias, a key source of potential endogeneity in our analysis, rejecting the null hypothesis of no bias in nearly all regressions. A possible solution would be adding a control or instrumental variable for Portugal-specific news and events affecting PSI20 prices, absent from debate-related variables or the London Stock Exchange. Without the possibility to compile such data, omitted variable bias might impact the unbiasedness and consistency of our estimations. Nonetheless, it is important to mention that other sources of endogeneity are unlikely to apply. Indeed, simultaneity is not relevant in our case, as we don't expect PSI20 prices to influence normalised or absolute favourability measures (it is a one-way direction in terms of influence, not reciprocal). Also, we expect the measurement error to be slim, given the 96% accuracy of AI sentiment analysis of social media interactions in Augusta Labs' dataset. Furthermore, the linearity assumption is likely violated, as checked by plotting residuals against fitted values and each independent variable with the dependent one. We attempted to address this by adding higher-order terms to capture non-linear dynamics, but without success. The omitted variable bias likely affects the model's linearity, as its absence distorts the true functional form if it interacts with included variables or influences PSI20 prices non-linearly.

Other limitations include the time misalignment between social media reactions and stock market activity, as some debates occurred on weekends, allowing public reactions to dissipate before markets reopened. Additionally, back-to-back debates involving PS or AD on two days (see Figure 6, Appendix) complicate isolating the impact of each debate on the stock market due to overlapping timings and cumulative market reactions. Finally, social media data may introduce self-selection bias, as its users may not fully represent financial market participants.

These limitations suggest the results, while insightful, require cautious interpretation.

4.3.2 Results adjusted for Heteroskedasticity and Autocorrelation

Tables 12 to 19 (see Appendix) show that standard errors change for each model and regression specification when accounting for and correcting for heteroskedasticity and autocorrelation, which diminishes statistical significance, even if coefficient values do not change. In fact, UK FTSE All-Share Index coefficient estimates are generally the only coefficients whose statistical significance is not severely impoverished by these adjustments, revealing it is a solid control variable. In contrast, the significance of variables linked to social media reactions, whether from model 1 or model 2, is considerably impacted by these modifications. Nevertheless, these results remain valuable, as they consistently indicate the direction of the relationship between social media reactions and PSI20 prices, even if the exact magnitude of these effects is less precise. Specifically, left-wing parties appear to have a negative impact on PSI20 prices, particularly in debates against right-wing parties, whereas right-wing parties tend to exert a positive influence on the said index. LIVRE and CHEGA emerge as notable outliers, with both parties consistently displaying negative coefficients, indicating a persistent negative effect on PSI20 prices. LIVRE's negative impact persists even in debates against other left-wing parties, suggesting the stock market's aversion to the party's policies, even within its ideological alignment. Meanwhile, CHEGA drags down both

absolute and normalised favourability averages for right-wing parties, likely due to the tone of its candidate's debates, aligning with findings from Maligkris (2017) and Lei (2017).

5. Conclusion

There are two main conclusions to be drawn from this study. The first is that the direction of the impact of social media reactions on PSI20 prices is, most of the time, consistent across models and even within each model's specifications. Specifically, results suggest that, whether using normalised favourability or absolute favourability, left-wing parties tend to have a negative effect on PSI20 prices when grouped into left and debating against right-wing parties, while right-wing parties appear to exert a positive influence on the index. This is particularly true regarding PS and AD, the main political forces and parties on the Portuguese left and right, respectively. Thus, both H1 and H2 are confirmed: the stock market responds differently to reactions regarding candidates from different political alignments (i.e., left-wing and right-wing), including from PS and AD. However, it is important to note that when left-wing parties debate against parties from across the political spectrum, and even against parties from the opposite political spectrum, but as individual parties (e.g. BE) and not as a political group (e.g. Left), their impact is not always negative. This might be explained by differences in the tone, content, or perceived significance of these debates. Indeed, the market reaction might not be negative if the debate focuses on topics that markets perceive as less risky (e.g., social issues rather than fiscal policy). The second conclusion we can make is that proportional measures of favourability, which highlight the relative strength of support for a party compared to its competitors, are more influential in explaining PSI20 price movements than absolute favourability measures. This is likely because proportional measures better align with how investors interpret competitive political signals, offering a clearer indication of a party's standing within the broader context of a debate.

Although most results are statistically non-significant, likely due to omitted variable bias from the lack of control for Portugal-specific news and events, findings remain valuable. Indeed, results provide relevant insights into the relationship, namely the direction of effects, between political debates, social media dynamics, and the Portuguese stock market's performance. Such insights should guide policymakers in addressing market oscillations in an increasingly digital world.

It is crucial to bear in mind that the PSI20 and Portuguese stock markets are relatively small, with limited price fluctuations due to their size and investor diversity, resulting in fewer pronounced reactions to external factors like political debates or social media sentiment. In contrast, larger markets like the U.S., with greater price volatility and a more dynamic investor base, would likely yield more evident and statistically significant results.

For future research, incorporating a variable that captures country-specific news and events, independent of social-media-related variables and other stock index controls, would provide a more comprehensive understanding of market dynamics. Additionally, increasing the number of social media observations and conducting a similar study in a country with a larger and more active stock market, such as the U.S., could further enhance the robustness and precision of the analysis, and maybe even yield more explicit results.

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7. Appendix

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Table 6: Other Parties vs All - Model 1

VARIABLES	(1) BE vs All	(2) CDU vs All	(3) PAN vs All	(4) LIVRE vs All	(5) IL vs All	(6) CHEGA vs All
fav_BE	1.122*** (0.0673)					
fav_CDU		0.187 (0.130)				
fav_PAN			0.337*** (0.122)			
fav_LIVRE				-0.591*** (0.0588)		
fav_IL					0.835*** (0.0678)	
fav_CHEGA						-1.065*** (0.118)
ASX_LP_imputed	0.845*** (0.0437)	1.472*** (0.0731)	1.749*** (0.0647)	1.046*** (0.0441)	2.278*** (0.0695)	0.914*** (0.0555)
Constant	2,594*** (182.3)	44.84 (303.1)	-1,115*** (270.8)	1,836*** (182.8)	-3,360*** (290.4)	2,422*** (231.2)
Observations	235	205	168	318	241	326
R-squared	0.676	0.673	0.819	0.658	0.825	0.578

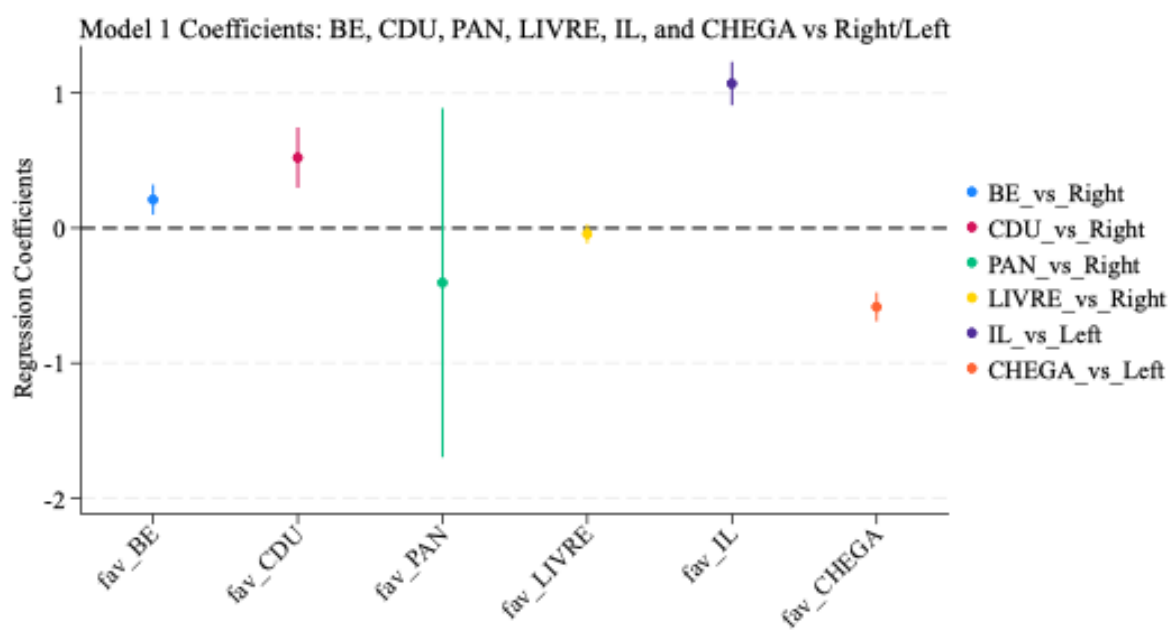
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Other Parties vs Parties of Opposite Political Spectrum - Model 1

VARIABLES	(1) BE vs R	(2) CDU vs R	(3) PAN vs R	(4) LIVRE vs R	(5) IL vs L	(6) CHEGA vs L
fav_BE	0.211*** (0.0561)					
fav_CDU		0.522*** (0.113)				
fav_PAN			-0.405 (0.642)			
fav_LIVRE				-0.0427 (0.0360)		
fav_IL					1.070*** (0.0814)	
fav_CHEGA						-0.584*** (0.0545)
ASX_LP_imputed	-0.625*** (0.0636)	0.538*** (0.172)	-2.419*** (0.882)	2.126*** (0.0564)	2.587*** (0.0916)	0.341*** (0.0314)
Constant	8,699*** (264.2)	3,882*** (710.6)	16,194*** (3,683)	-2,702*** (236.1)	-4,661*** (383.8)	4,756*** (130.0)
Observations	109	100	50	177	166	233
R-squared	0.788	0.275	0.366	0.896	0.831	0.504

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 3: Coefficients Plot 2 (selected results from Table 7)



Note: 95% Confidence Intervals are also displayed. We are assuming that Gauss-Markov assumptions are satisfied.

Table 10: Other Parties vs All - Model 2

VARIABLES	(1) BE vs All	(2) CDU vs All	(3) PAN vs All	(4) LIVRE vs All	(5) IL vs All	(6) CHEGA vs All
abs_fav_BE	0.0622*** (0.0168)					
abs_fav_CDU		-0.117*** (0.0245)				
abs_fav_PAN			0.224*** (0.0305)			
abs_fav_LIVRE				-0.00563 (0.00832)		
abs_fav_IL					0.0762*** (0.0088)	
abs_fav_CHEGA						-0.0546*** (0.00807)
ASX_LP_imputed	0.742*** (0.0724)	1.460*** (0.0695)	1.822*** (0.0579)	0.991*** (0.0547)	1.975*** (0.0784)	0.991*** (0.0569)
Constant	3,063*** (301.1)	109.2 (288.8)	-1,407*** (241.1)	2,028*** (227.3)	-2,066*** (326.7)	2,061*** (236.0)
Observations	235	205	168	318	241	326
R-squared	0.327	0.703	0.857	0.548	0.781	0.536

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 11: Other Parties vs Parties of Opposite Political Spectrum - Model 2

VARIABLES	(1) BE vs R	(2) CDU vs R	(3) PAN vs R	(4) LIVRE vs R	(5) IL vs L	(6) CHEGA vs L
abs_fav_BE	0.0320*** (0.00243)					
abs_fav_CDU		0.0388*** (0.0123)				
abs_fav_PAN			0.208*** (0.0178)			
abs_fav_LIVRE				-0.0187*** (0.00274)		
abs_fav_IL					0.116*** (0.00869)	
abs_fav_CHEGA						-0.0140*** (0.00412)
ASX_LP_imputed	-0.750*** (0.0274)	0.565*** (0.181)	-1.411*** (0.194)	2.054*** (0.0509)	1.528*** (0.0831)	0.354*** (0.0377)
Constant	9,219*** (113.1)	3,793*** (750.3)	11,984*** (802.4)	-2,398*** (212.8)	-212.9 (345.8)	4,679*** (155.8)
Observations	109	100	50	177	166	233
R-squared	0.909	0.198	0.835	0.917	0.834	0.292

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Figure 4: Coefficients Plot 3 (selected results from Tables 8 and 9)



Figure 5: Coefficients Plot 4 (selected results from Table 11)

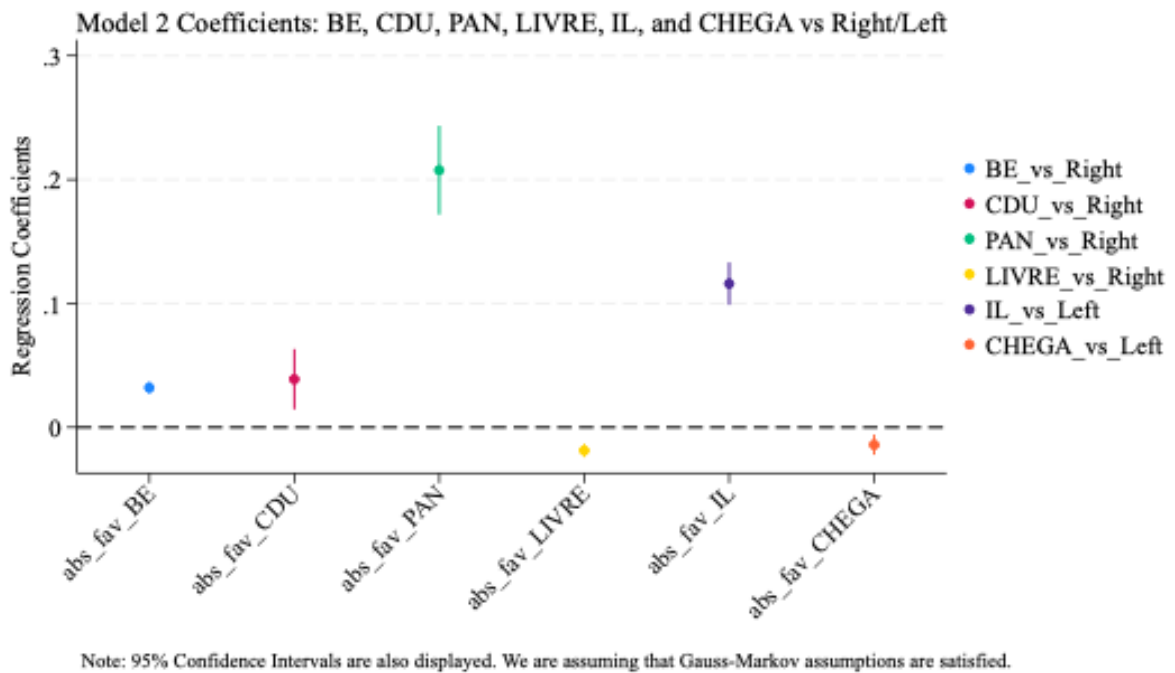


Figure 6: Timeline of Political Debates and Post-Debate Periods with either PS or AD

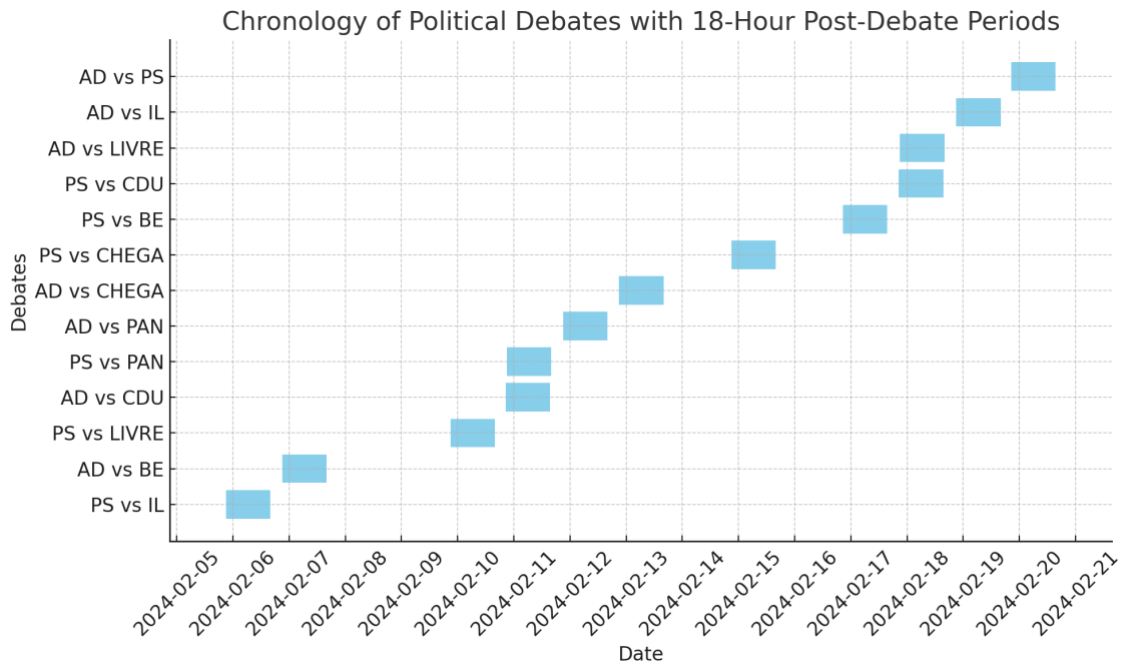


Table 12: AD vs PS - Model 1 (Corrected for Heteroskedasticity and Autocorrelation)

VARIABLES	(1) PS vs All	(2) AD vs All	(3) PS vs Right	(4) AD vs Left	(5) PS vs AD
fav_PS	-0.602 (0.481)		-1.165 (1.239)		0.000376 (0)
fav_AD		1.013 (0.661)		0.0476 (0.248)	
ASX_LP_imputed	1.676*** (0.114)	0.892** (0.229)	1.689** (0.213)	1.252*** (0.208)	0.666 (0)
o.fav_AD					-
Constant	-787.3 (467.9)	2,423** (933.3)	-816.8 (867.9)	962.4 (859.8)	3,440 (0)
Observations	208	213	128	165	61
R-squared	0.890	0.794	0.896	0.919	0.628

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 13: Left vs Right - Model 1 (Corrected for Heteroskedasticity and Autocorrelation)

VARIABLES	(1) Left vs Right
fav_LEFT	-0.118 (0.400)
o.fav_RIGHT	-
ASX_LP_imputed	1.153*** (0.248)
Constant	1,377 (1,030)
Observations	564
R-squared	0.706

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 14: Other Parties vs All - Model 1 (Corrected for Heteroskedasticity and Autocorrelation)

VARIABLES	(1) BE vs All	(2) CDU vs All	(3) PAN vs All	(4) LIVRE vs All	(5) IL vs All	(6) CHEGA vs All
fav_BE	1.122** (0.281)					
fav_CDU		0.187 (0.137)				
fav_PAN			0.337 (0.278)			
fav_LIVRE				-0.591 (0.314)		
fav_IL					0.835** (0.260)	
fav_CHEGA						-1.065* (0.420)
ASX_LP_imputed	0.845** (0.238)	1.472** (0.476)	1.749*** (0.336)	1.046** (0.332)	2.278*** (0.350)	0.914** (0.322)
Constant	2,594** (995.3)	44.84 (1,973)	-1,115 (1,395)	1,836 (1,387)	-3,360* (1,465)	2,422 (1,328)
Observations	235	205	168	318	241	326
R-squared	0.676	0.673	0.819	0.658	0.825	0.578

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 15: Other Parties vs Parties of Opposite Political Spectrum - Model 1 (Corrected for Heteroskedasticity and Autocorrelation)

VARIABLES	(1) BE vs R	(2) CDU vs R	(3) PAN vs R	(4) LIVRE vs R	(5) IL vs L	(6) CHEGA vs L
fav_BE	0.211 (0.0938)					
fav_CDU		0.522 (0.445)				
fav_PAN			-0.405 (0.403)			
fav_LIVRE				-0.0427 (0.0195)		
fav_IL					1.070** (0.368)	
fav_CHEGA						-0.584 (0.274)
ASX_LP_imputed	-0.625 (0.179)	0.538 (0.737)	-2.419 (0.449)	2.126** (0.294)	2.587*** (0.457)	0.341 (0.167)
Constant	8,699* (732.4)	3,882 (3,062)	16,194* (1,836)	-2,702 (1,228)	-4,661* (1,915)	4,756*** (696.0)
Observations	109	100	50	177	166	233
R-squared	0.788	0.275	0.366	0.896	0.831	0.504

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: AD vs PS - Model 2 (Corrected for Heteroskedasticity and Autocorrelation)

VARIABLES	(1) PS vs All	(2) AD vs All	(3) PS vs Right	(4) AD vs Left	(5) PS vs AD
abs_fav_PS	0.0113 (0.0229)		-0.0215 (0.0213)		-0.00110 (0)
abs_fav_AD		0.0262 (0.0197)		0.0164 (0.0193)	0.000584 (0)
ASX_LP_imputed	1.604*** (0.0980)	0.915** (0.245)	1.610** (0.254)	1.189** (0.217)	0.696 (0)
Constant	-509.9 (409.3)	2,377* (1,025)	-521.2 (1,059)	1,227 (903.7)	3,314 (0)
Observations	208	213	128	165	61
R-squared	0.877	0.763	0.881	0.927	0.629

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Left vs Right - Model 2 (Corrected for Heteroskedasticity and Autocorrelation)

VARIABLES	(1) Left vs Right
abs_fav_LEFT	-0.0199 (0.0699)
abs_fav_RIGHT	0.0364 (0.0548)
ASX_LP_imputed	1.118*** (0.247)
Constant	1,511 (1,029)
Observations	564
R-squared	0.723

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Other Parties vs All - Model 2 (Corrected for Heteroskedasticity and Autocorrelation)

VARIABLES	(1) BE vs All	(2) CDU vs All	(3) PAN vs All	(4) LIVRE vs All	(5) IL vs All	(6) CHEGA vs All
abs_fav_BE	0.0622 (0.0720)					
abs_fav_CDU		-0.117 (0.0701)				
abs_fav_PAN			0.224*** (0.0324)			
abs_fav_LIVRE				-0.00563 (0.0319)		
abs_fav_IL					0.0762* (0.0351)	
abs_fav_CHEGA						-0.0546* (0.0220)
ASX_LP_imputed	0.742 (0.533)	1.460** (0.406)	1.822*** (0.309)	0.991* (0.409)	1.975*** (0.303)	0.991** (0.346)
Constant	3,063 (2,211)	109.2 (1,685)	-1,407 (1,282)	2,028 (1,702)	-2,066 (1,257)	2,061 (1,429)
Observations	235	205	168	318	241	326
R-squared	0.327	0.703	0.857	0.548	0.781	0.536

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Other Parties vs Parties of Opposite Political Spectrum - Model 2 (Corrected for Heteroskedasticity and Autocorrelation)

VARIABLES	(1) BE vs R	(2) CDU vs R	(3) PAN vs R	(4) LIVRE vs R	(5) IL vs L	(6) CHEGA vs L
abs_fav_BE	0.0320 (0.00524)					
abs_fav_CDU		0.0388* (0.00914)				
abs_fav_PAN			0.208*** (0.00202)			
abs_fav_LIVRE				-0.0187 (0.0164)		
abs_fav_IL					0.116** (0.0301)	
abs_fav_CHEGA						-0.0140 (0.0227)
ASX_LP_imputed	-0.750* (0.0676)	0.565 (0.852)	-1.411 (0.351)	2.054*** (0.137)	1.528*** (0.196)	0.354 (0.259)
Constant	9,219** (277.2)	3,793 (3,535)	11,984* (1,451)	-2,398* (569.4)	-212.9 (818.7)	4,679** (1,074)
Observations	109	100	50	177	166	233
R-squared	0.909	0.198	0.835	0.917	0.834	0.292

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1