

# The Impact of Political Campaigns on Demand for Partisan News

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## **Job Market Paper**

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### **Abstract**

Political polarization in news consumption has recently gained attention, yet policies to limit it are hard to evaluate. This paper introduces a novel, self-collected dataset on Spanish prime-time TV news. I identify stories minute-by-minute and match them across newscasts to compare editorial treatment. Combining machine-learning methods with large language models, I classify the partisan slant of each story and use the resulting data to document changes in news coverage during the 2023 presidential campaign. I then match these data to high-frequency audience-meter records and estimate a random-coefficients demand model, using shifts in the daily wire-service story mix as instruments for slant. I find significant evidence of affective polarization only after the election campaign begins. Given the demand estimates, I back out outlets' content preferences from a competition game. Finally, I run counterfactual simulations to assess the effect of policies regulating campaign airtime.

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# 1 Introduction

Political polarization has surged in both the United States and Europe over the past decade ([Iyengar et al., 2019](#); [Reiljan, 2019](#)). Extensive research highlights the role of social media in driving this trend ([Zhuravskaya et al., 2020](#)). However, [Boxell et al. \(2020\)](#) find that polarization in the United States has increased the most precisely among groups that are more likely to consume traditional, rather than social, media. Even now, television remains the primary source of political information across Europe, and it is known to have large effects on voting outcomes ([DellaVigna and Kaplan, 2007](#); [Gentzkow, 2006](#); [Martin and Yurukoglu, 2017](#)), education ([Gentzkow and Shapiro, 2008](#)), and culture ([Jensen and Oster, 2009](#)). The mechanisms through which this influence operates—specifically, the preferences driving viewer demand—remain understudied.

In response, regulators have tightened rules in media markets, but designing and evaluating effective policies remains challenging. The first obstacle is measurement: developing indicators of partisan slant that are both scalable to thousands of hours of content and comparable across outlets is inherently difficult. Second, even with good measures, there is a fundamental identification problem. Market equilibrium introduces endogeneity: the content an outlet provides is a strategic response to viewer preferences, while viewers choose outlets that align with their views. This feedback loop makes it difficult to separate viewer demand from the editorial decisions of the channels. This paper proposes a novel methodology to address these two challenges. I estimate the extent of confirmation bias and polarization in the demand for political content and examine how these dynamics evolve during electoral campaigns in Spain, the most polarized country in Europe ([Edelman, 2023](#)).

To tackle the measurement challenge, I construct a unique dataset that integrates the supply and demand of political content in Spanish TV news. On the demand side, high-frequency audience-meter data address well-known limitations of survey-based studies ([Prior, 2009](#)). On the supply side, I compile a text corpus of all news segments and employ Large Language Models (LLMs) and machine learning to classify their political tone. This approach provides a granular, daily measure of the airtime and tone allocated to each political party. I further show how my stance measure compares with previous text-classification methods based on congressional speeches, dictionary counts, and face-recognition measures of political leaders' screen time.

To overcome the identification problem, I propose a strategy that leverages exogenous shocks to the daily news supply. I collect all stories from the largest news aggregator that supplies these outlets, using it as a proxy for the day's available news landscape. While outlets aim to maintain their long-term ideological positions, these daily news shocks constrain their broadcasts, making some days exogenously more favorable to one ideological side. Descriptive evidence supports this mechanism: right-wing (left-wing) channels expand coverage

when the pool of favorable right-wing (left-wing) stories is larger.

My findings align with prior evidence on polarized news consumption in the United States ([Peterson et al., 2017](#)). Outside of campaign periods, there is no systematic asymmetry in political-content demand between right- and left-leaning audiences; viewers generally prefer negative political tone. During campaigns, however, affective polarization emerges: right-leaning viewers increasingly seek negative coverage of the left and more positive coverage of the right, with a mirror pattern among left-leaning viewers. Using these demand estimates, I model and estimate news production. Outlets engage in a differentiation game, choosing daily slant to maximize viewership. Production costs depend on the mix of stories available each day. Identification relies on timing: I exploit variation in news stories between midday and evening broadcasts to estimate outlets' slant-production costs. Producing left-favoring content is costly for all channels, particularly for right-leaning ones, while right-favoring content generally increases payoffs, though less so for left-leaning outlets.

Existing media regulations to foster political plurality have often proved insufficient because of poor measurement and, consequently, lack of enforcement ([Assemblée nationale, 2024](#)). I run a counterfactual in which Spain adopts a policy already used in several European countries: proportional airtime during election campaigns. I estimate the equilibrium of the game while forcing outlets to devote relative political time to each party according to past election results. Consistent with the way this policy is enforced, I regulate only total airtime, allowing channels to adjust through tone.

This paper is the first effort to quantitatively monitor media slant in Spain and contributes to the debate on regulation in media markets.

## Related Literature

This paper contributes to several strands of the media- and political-economics literature. The first is the measurement of media slant. [Puglisi and Snyder \(2015\)](#) divide measures of bias into two broad categories: the *comparison* and the *intensity* approach. The former relies on text-analysis techniques to benchmark media slant to partisan language. [Groseclose and Milyo \(2005\)](#) and [Gentzkow and Shapiro \(2010\)](#) compare, respectively, citations of think tanks and similarities in language between U.S. newspapers and congressional speeches. Direct measures of candidates' visibility have also been applied to newspapers via endorsements ([Chiang and Knight, 2011](#)) or to television via airtime ([Durante and Knight, 2012](#); [Cagé et al., 2022](#)). This last approach further constitutes the main slant metric employed by public regulatory agencies.<sup>1</sup> I contribute to this literature by proposing a new method-

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<sup>1</sup>For example, the French media authority ARCOM publishes monthly “pluralism” reports that track each political actor’s share of speaking time on national television; Italy’s Osservatorio di Pavia produces similar statistics for the national regulator AGCOM.

ology that unifies both approaches, using LLMs to discern the tone and minutes of airtime devoted to each issue to account for intensity. I also document comparisons with some of these existing metrics highlighting some of their main drawbacks. My method constitutes a scalable, unsupervised way to compare the treatment of the same issue across different outlets. By further proxying the news landscape with an external news aggregator, this paper might complement empirically previous theoretical work modeling the sources of bias stemming from *filtering* versus *outright* distortion ([Gentzkow et al., 2014](#)).

The second strand of the literature studies how audiences choose among news products. Initial work documents sizeable demographic heterogeneity: older, less-educated Italians watch different mixes of hard and soft news than younger, high-skill viewers ([Gambaro et al., 2021](#)), and comparable gaps appear in U.S. local-media markets ([Bang et al., 2023; Bang and Sieg, 2025](#)). I complement this literature by focusing on content rather than broad topic labels as a way to infer tastes for political stories, highlighting the importance of accounting for content endogeneity.

Moving beyond demographics, a parallel line of research embeds ideology as the source of preference heterogeneity, asking whether consumers actively seek like-minded sources. Experimental evidence offers mixed results, with some work pointing to limited media persuasion because of self-selection into news ([Arceneaux and Johnson, 2013](#)) and other work documenting reinforcement effects among extreme partisans ([Levendusky, 2013](#)). My work offers a revealed-preference approach to study the extent of confirmation bias and thus links directly to articles that estimate structural models of demand for news.

My approach follows the seminal work of [Gentzkow and Shapiro \(2010\)](#) in several aspects. I use text to quantify outlets' slant, showing how LLMs can outperform their content-classification method. I also model heterogeneity in preferences over slant to study the taste for like-minded news and recover parameters from a competition game. [Simonov and Rao \(2022\)](#) also estimate a structural model of demand for government-controlled online news in Russia. Unlike them, who treat the supply side as fixed and recover audiences' tastes from random day-to-day swings in the share of government-sensitive stories, I rely on product-level cost shifters that move each station's slant differently within the same day. This approach follows the logic of downstream news aggregators such as the Associated Press for U.S. newspapers ([Djourelova, 2023](#)). These instruments provide exogenous variation in settings where classic instruments such as cable-dial positions ([Martin and Yurukoglu, 2017](#)) cannot be applied.

Some of this work has further explored the effects of media polarization on attitudinal polarization. [Martin and Yurukoglu \(2017\)](#) show that cable-news slant can account for much of the rise in voter polarization in the United States. [Schneider-Strawczynski and Valette \(2025\)](#) also show how television exposure to coverage of immigration polarizes attitudes towards immigrants in France. I present correlational evidence linking media consump-

tion and political polarization. Specifically, ,this work highlights the role of political campaigns—beyond ownership changes alone (Durante and Knight, 2012)—as another driver of preference change and polarization.

Third, this article contributes methodologically to IO demand estimation. Recent work has explored the use of text embeddings and imagery to construct product characteristics in demand models (Compiani et al., 2025). I introduce a scalable index of media slant that incorporates both tone and coverage intensity and compare it with slant measures based on facial recognition. This tool makes it possible to capture differentiation in products that might otherwise seem homogeneous, such as TV news programs. However, this richer product space raises standard concerns about endogeneity in product characteristics. These concerns have previously been addressed with instrument designs based on demographic changes over pricing zones (Fan, 2013) or candidate positions across electoral precincts (Longuet-Marx, 2025). I propose a novel identification strategy that exploits supply shocks in news content drawn from upstream aggregators. On the supply side, my paper leverages high-frequency data to identify cost parameters. This might be used in setups where credible demand shocks are not available.

Finally, prior research evaluates policy interventions in television markets—bundling (Crawford and Yurukoglu, 2012), vertical integration (Crawford et al., 2018), ownership changes (Martin and McCrain, 2019; Cagé et al., 2022), and entry (Prat and Strömberg, 2005). I extend this literature by assessing content regulations aimed at enhancing political plurality, which constitute the main regulatory tool for campaign content in several countries.

## Rest of the Paper

The rest of the paper is organized as follows. In Section 2, I briefly summarize the Spanish political and TV landscape. Section 3 introduces the data and describes the text analysis techniques I employ, along with descriptive statistics on both the content and audience sides. In Section 4, I first describe the market setup and the demand model and then discuss the endogeneity problem and the instrumental-variables approach. Results from the demand estimation are shown in Section 5. Section 6 presents the identification and estimation of the supply-side parameters. Finally, section 7 shows the counterfactual estimation.

## 2 Context

Before detailing the data used and the text classification methodology, I provide a brief context on the Spanish TV market. To compare the use of TV versus other media for political information, I provide descriptive evidence and compare Spain to Europe and the

US markets. Finally, I describe the political context in Spain by introducing the main parties considered in the analysis and the changes in party structure leading to the general elections of 2023.

## Spanish TV Market

The Spanish TV market is a competitive mix of public and private broadcasters, with Televisión Española (TVE) positioned as the state-owned provider of news, cultural programs, and entertainment. The two primary private conglomerates, Atresmedia and Mediaset, dominate the market. Atresmedia operates Antena 3 and LaSexta, while Mediaset controls Telecinco. Altogether, their evening TV news editions (the product analyzed in this paper) capture around 50% of the market share, equating to 4.5 million viewers, which represents 10% of the Spanish population. For comparison, the average number of viewers for the most popular news program in the U.S., Fox News, is around 2.2 million.

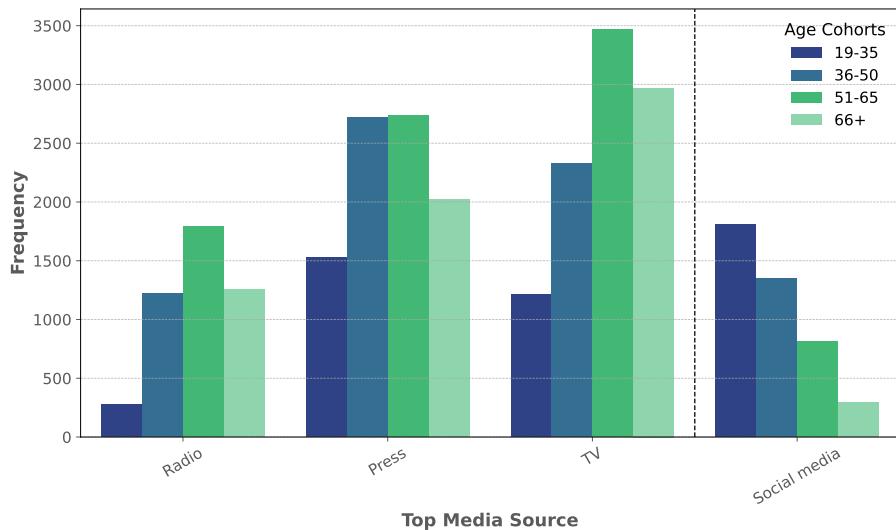
## Traditional Media and Political Information

Traditional media remain the primary source of information in most European countries ([Parliament, 2024](#)). Figure 1 shows the main media used to acquire political information in Spain by age group, as reported by the 2023 survey from the Centro de Investigaciones Sociológicas (CIS) under the question: *"Through which media do you usually get information about news in Spain?"*. Traditional media are represented to the left of the vertical, dashed line as radio, press, and television. Television remains the dominant source of political information for those aged 50 and older and dominates social media for all but the youngest cohort. This pattern, however, is not specific to Spain. Figure A.12 shows the analogous comparison using now data from the Eurobarometer survey. Television remains the dominant source of political information in Europe, particularly among older age groups. While younger cohorts (15–24, 25–39) rely more on social media, TV consistently outweighs social media among those aged 40 and above, with the gap widening significantly in the 55+ age group. This pattern highlights television's enduring influence in European media landscapes, especially for older demographics, despite the rise of digital platforms.

## Political Context

Political power in Spain has historically been dominated by a two-party system, with either the Socialist Party (PSOE) or the Conservative Party (PP) in power. The emergence of the left-wing party Podemos (UP) following the 15M movement marked a significant shift, as

**Figure 1:** Top Media Source to Acquire Political Information in Spain



Notes: Histogram on the preferred media used for political information by age cohorts in Spain.  
Source: Barómetro CIS, 2023.

the party began to attract a substantial portion of the electorate.<sup>2</sup> Of particular interest is the rise of the far-right party VOX, which made notable gains in the regional elections held on May 28, 2023, raising the possibility of forming a coalition with the Popular Party (PP). In response, the day after the regional elections, President Pedro Sánchez decided to bring forward the general elections to June 23, 2023.<sup>3</sup>

Although regional and independentist parties play a major role in certain regions, they are excluded in the present work. I leave their consideration for future work that integrates additional ideological dimensions beyond the left-right one. For the rest of the analysis, parties will be pooled into right (PP and VOX) and left (PSOE and Podemos/Sumar).

### 3 Data and Descriptive Statistics

I build a unique dataset that captures both the demand and supply sides of TV news in the Spanish market. For the demand side, I use minute-by-minute viewership data for the four main channels that offer daily TV news programs: TVE, Antena 3, LaSexta, and Telecinco. On the content side, I build a scraping pipeline that records the daily news programs live and processes this information into text. This dataset spans from December 2022 to July

<sup>2</sup>Relevant for this period of study is the integration of Podemos into the new political party SUMAR. All classification metrics account for this transition, but throughout the text, I refer to UP as either Podemos or SUMAR after its creation.

<sup>3</sup>I refer readers to the [Spanish Media Monitor](#) webpage to explore various metrics of coverage across political parties and actors.

2023 on a daily basis. It is complemented by all the stories published in Spanish by the largest news provider. Finally, I make use of survey and weather data as controls.

## Audience Data

I use Audimeter, a high-frequency audience data source provided by Kantar Media, to observe the share of viewers for each channel at each day and minute. Although I do not have individual-level data on choices, I have geographical disaggregation for the 16 autonomous regions in Spain (also referred to as regions hereinafter), which I match to survey demographics<sup>4</sup>. The shares are specific to the evening TV news shows, which, with the exception of LaSexta at 20:00, start at 21:00 daily. For this analysis, this channel's program is treated as if it occurred simultaneously with the others.<sup>5</sup>

## TV Content

I record daily TV news videos and use Google Cloud infrastructure to store and process the data. Videos are converted to audio, and I use machine learning (*speech-to-text*) to obtain text transcripts. Although visuals are not used in the main estimation due to computational constraints, I show comparisons between image and text metrics below. A more detailed explanation of the entire downloading pipeline can be seen in Appendix Figure A.11.

I consider both the evening and midday editions of TV news programs. This product offers a unique environment to test substitutability for several reasons. First, even though channels offer other political programs, the homogeneity of TV news allows for very clean comparisons. These programs are broadcast every day at almost the same time and all share a very similar structure, with a presenter introducing the main stories of the day. The fact that the structure is so similar makes them almost perfect substitutes and the key differentiation (aside from vertical, quality components) is therefore the way they present the information. Third, TV news is highly fact-checked and remains the most trusted source of information in Spain<sup>6</sup>. This fact is important as it ensures a cleaner interpretation of the audience choice data as revealed preferences for the content consumed and limits the extent of fake news as an additional dimension in the editorial strategy of the outlets.

## Agencia EFE

I obtain all news stories published in Spanish by one of the largest news agencies in the

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<sup>4</sup>The Canary Islands and La Rioja are excluded due to different time zones and zero market shares; respectively. Similarly, peak days with sport events that altered the news schedule were also removed.

<sup>5</sup>This might pose problems in the substitutions toward the outside option and specifically with *connected substitutes* assumption in [Gandhi and Houde \(2019\)](#).

<sup>6</sup>The Digital News Report 2023 reveals notable patterns in public trust towards news media across Europe, with Spain reflecting a stable but modest level of confidence. According to the report, the public service broadcaster RTVE and Antena 3 Noticias continue to rank as the most trusted news sources, with trust levels of 53% and 52%, respectively. LaSexta registers a trust increase of 2.7 percentage points over the previous year, reaching approximately 47%, and Telecinco follows at 39% ([Newman et al., 2023](#)).

world, Agencia EFE. Similar to Reuters or AP, this agency mainly sells content and images to third-party newscasts. I document that all the outlets in my sample are clients of Agencia EFE.<sup>7</sup> I have information on the title of each story along with a short summary segment. There are around 41K stories for my sample period.

## Survey Data

To understand polarization behavior, I use survey data gathered from the Centro de Investigaciones Sociológicas (CIS). Specifically, I rely on the "intention to vote" question and map it onto my binary left-right spectrum according to the parties described above. This data is monthly and cross-sectional.

## Weather

I use meteorological data on daily rainfall deviations per region for the time span matching the TV news programs (18:00–00:00) from the Spanish Meteorological Agency (AEMET).

### 3.1 Political Coverage and Elections

I divide the time span into two periods. The *off-campaign* period starts at the beginning of data collection in December 2022 and extends to the start of the first publicly announced political campaign on May 13, 2023. The *campaign* period covers both regional and general election campaigns and lasts until July 17, 2023, the day of the general elections.

Figure 2 shows the weekly average proportion of time devoted to national politics over time, where the *campaign* period corresponds to the shaded span and vertical dashed lines mark the beginning of the campaign, the regional elections, and the national elections, respectively. A channel is defined to spend one minute on national politics if the associated text for that minute contains any of the party matches in the dictionaries in Table D.19. Off-campaign, channels spend on average nearly 18% of their daily time on politics. Naturally, this increases to 30% during campaign periods.

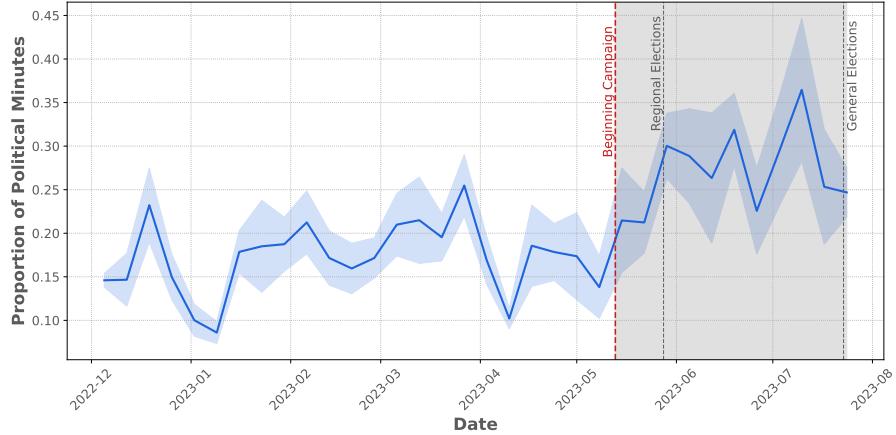
### 3.2 Political Tone

Here I describe the methodology used to classify the political tone of the content broadcast. Under market equilibrium, an outlet's slant should match its audience's political leaning. Because the slant classification is unsupervised, I use survey data to evaluate the ideology of each channel's viewers and then use this benchmark to validate the slant classification.

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<sup>7</sup>See, e.g., collaborations with [Mediaset](#), [Atresmedia](#), and [RTVE](#).

**Figure 2:** Proportion of Time Devoted to Politics over Time



Notes: Average daily proportion of political terms relative to overall words with shaded standard deviations. Political time is measured by dictionary matches to terms in Table D.19. Vertical, dashed lines indicate the date of the regional and general elections, respectively. The shaded area represents the "campaign" period considered.

## Political Orientation of the Audience

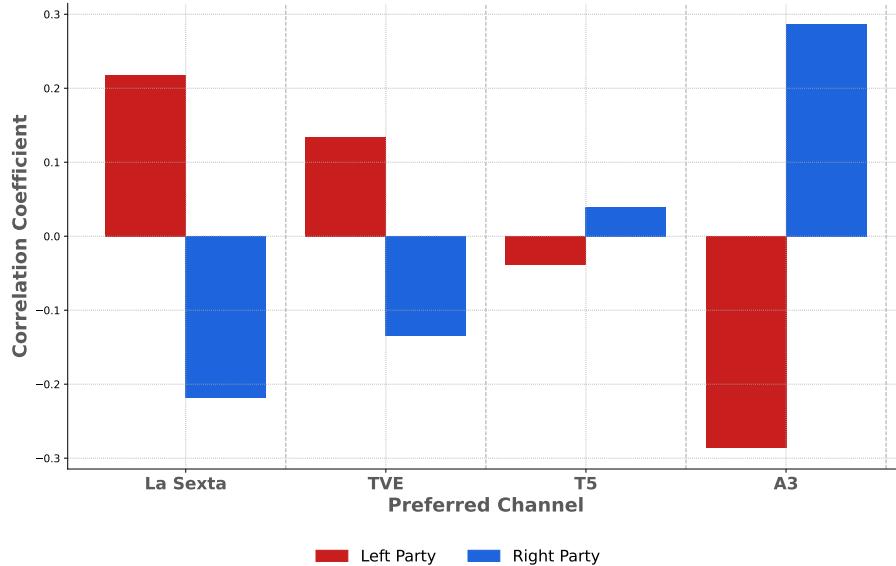
Figure 3 shows the correlation between individuals' preferred political party and their preferred channel for acquiring political information, based on survey data from the Centro de Investigaciones Sociológicas (CIS). Right-wing individuals (PP and VOX) tend to watch Antena 3 more, whereas left-leaning individuals are divided between LaSexta and the public channel TVE. Telecinco (Mediaset) appears in the middle, with weak correlations. This is consistent with the Mediaset group offering a more pro-entertainment content as previously documented in [Durante et al. \(2019\)](#).

Given the well-known issues with survey data for media consumption ([Prior, 2009](#)), I rely on audience shares together with regional intention-to-vote pools. Figure A.18 shows the political density on the left-right spectrum of each channel. The left-right positions of the outlets are consistent with those shown in Figure 3.

## Isolation Index

To benchmark the partisan sorting of Spanish prime-time newscasts against earlier work, I compute the *isolation index* for TV, Radio and Press. The formula and results are shown in Appendix Section C. In a binary left-right setting, the index measures how much more often a right-wing viewer finds herself surrounded by right-wing co-viewers than a left-wing viewer does. [Gentzkow and Shapiro \(2011\)](#) report values of 0.018 for U.S. broadcast and 0.033 for U.S. cable news in 2008. The corresponding value for my sample period is 0.10,

**Figure 3:** Correlation Between Preferred Channel and Political Party



Notes: Bars represent a correlation coefficient between the declared preferred political party (pooling left and right parties) and the most watched channel. The survey ask respondents if they watch TV for political content and what is their preferred channel. Source: Built using data from CIS's Encuesta Pre-electoral 2023

almost 3 to 5 times larger.

In addition to television, I compute the isolation index for radio and press using the same methodology. The results, reported in Table C.18, reveal even higher levels of partisan sorting in these media. The isolation index for radio is 0.30, and for press it is 0.18, both substantially above the corresponding values for U.S. broadcast and cable news reported by Gentzkow and Shapiro (2011). This suggests that, in Spain, listeners and readers of radio and press are even more ideologically segregated than TV. The magnitude of these indices indicates a much stronger degree of ideological segregation in Spanish offline media than in the U.S. context studied before.

The isolation index, however, operates at the outlet level. Viewers can self-select into the political segments that match their tastes while sharing the channel with ideologically mixed audiences at other times. Hence, a high outlet-level isolation score may still mask substantial cross-cutting exposure within channels. To capture this finer within-outlet sorting, the next section builds a slant metric that combines machine-classified slant with the airtime spent.

### 3.3 Text Classification

Text analysis methods, such as party mentions or sentiment analysis, cannot reliably discern named entities. To discern slant in a given story, there must be sufficient context on the

theme, political actors involved, irony, etc. The use of LLMs as classifiers has gained popularity in recent years for various contexts, such as the classification of political stances ([Le Mens and Gallego, 2023](#)), and has even been found to achieve higher precision and accuracy scores for ideological classification compared to human annotators ([Törnberg, 2023](#)). I use ChatGPT-4, feeding it all of our political stories and asking it to classify the tone associated with each political party. Notably, I distinguish between positive and negative tones toward each party, and I provide a flexible query that allows the classifier to remain neutral if the content is ambiguous. More details about the prompt and classification results can be found in Appendix D. I describe below how I combine airtime with tone to build content characteristics.

## Building Content Characteristics

Each day, channel  $j$  produces a set of stories  $S_{jd}$  indexed by  $s$ . Empirically, these segments result from BERTopic clustering on the unstructured transcripts, which ensures that the LLM has enough context by feeding it the entire text of a given story. The subset of political stories,  $\mathcal{P}_{jd} \subseteq S_{jd}$ , is the set of all stories that mention national parties or prominent politicians in addition to general words related to politics, identified by keyword matches from Table D.19.

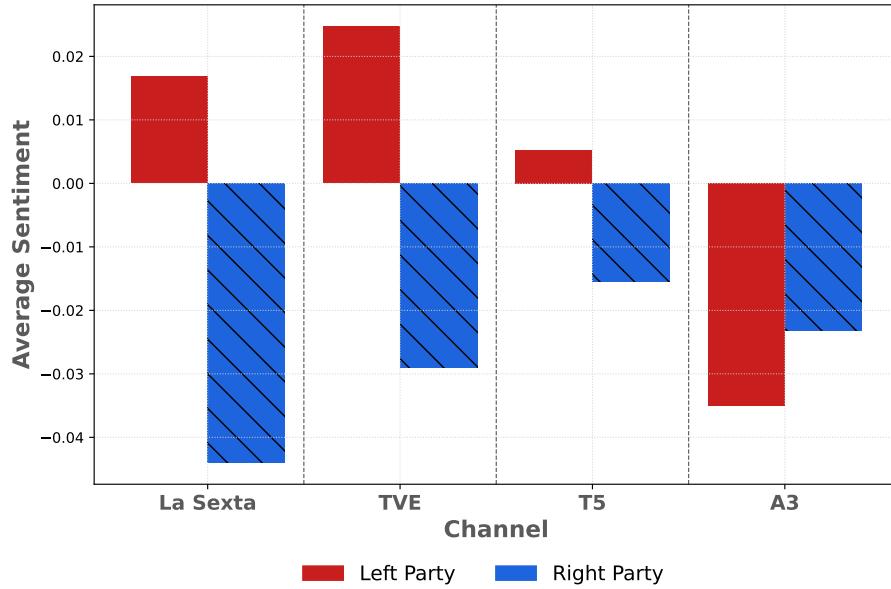
Each  $s \in \mathcal{P}_{jd}$  is fed into ChatGPT and is assigned a tone  $tone(s) \in \{-1, 0, 1\}$ . Stories with a stance (i.e.,  $tone(s) \in \{-1, 1\}$ ) also receive a party label  $p(s) \in \{L, R\}$ , whereas neutral stories do not. Notice that the broad classification of what is *political* allows for stories that do not contain any specific mention of Spanish politics to have an associated slant toward some party. Table B.16 contains examples of stories that do not match any Spanish political term but still have an associated slant toward a political party. These include favorable economic forecasts from the European Commission, international visits by the Spanish King, or European funds.

A story can be mapped to its duration in minutes,  $min(s)$ . This is key to accounting for the intensive margin. Combining all these characteristics—i.e., party label, tone, and minutes—I define the shares of positive and negative minutes, as well as the share of airtime devoted to politics, as follows:

$$\begin{aligned}
x_{jd}^{party+} &= \frac{1}{min_{jd}} \sum_{s \in S_{jd}} \left( \mathbb{1}\{tone(s) = 1\} \times \mathbb{1}\{p(s) = party\} \times min(s) \right) \quad \forall party \in \{L, R\} \\
x_{jd}^{party-} &= \frac{1}{min_{jd}} \sum_{s \in S_{jd}} \left( \mathbb{1}\{tone(s) = -1\} \times \mathbb{1}\{p(s) = party\} \times min(s) \right) \quad \forall party \in \{L, R\} \\
x_{jd}^{political} &= \frac{1}{min_{jd}} \sum_{s \in P_{jd}} min(s)
\end{aligned} \tag{1}$$

These variables will constitute the main controls on the empirical application in the next section. Figure 4 shows the net average tone relative to total time spent on politics for each party-outlet. Whilst all channels present a negative net tone on the right, there are still significant differences that allow to map them into a different political spectrum. Both La Sexta and the public channel, TVE, offer more pro-left content. Telecinco appears in the middle but still maintains a pro-left stance and Antena 3 is the only one with a more pro-right balance.

**Figure 4:** Average Tone Across Channels and Parties



Notes: Average tone for each channel-party as classified by Chat GPT 4 from the whole sample period.

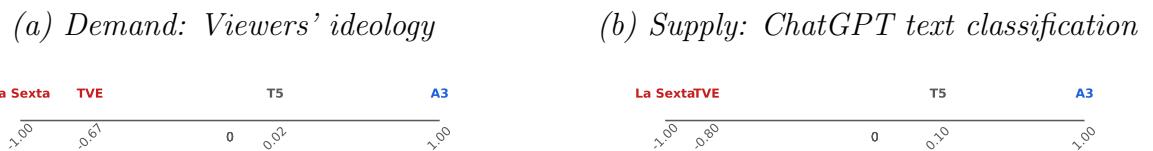
The results match closely those from declared survey data. To simplify the comparison, I assign each channel an ideological score from text as :

$$\frac{\bar{x}_j^{R+} - \bar{x}_j^{R-} - \bar{x}_j^{L+} - \bar{x}_j^{L-}}{\bar{x}_j^{political}} \tag{2}$$

and, similarly, from the individual survey data, I use the differences in correlation coefficients between right parties. To enable comparisons in positions across scales; I normalize the values of the most to extreme channels to  $-1$  and  $1$ .

Figure 5 panes a) and b) shows the scores according to viewer’s ideology and channels slant. As expected, the slant offered in the TV news closely matches the viewer’s political preferences as one would expect in equilibrium. Below, I show robustness of the text classification and comparison with other methodologies previously used in the literature.

**Figure 5:** Normalized Ideology Scores by Channel



*Notes:* The figure compares normalized left-right audience positions for Spanish television channels. Panel (a) uses ChatGPT-based text classification from equation 2; panel (b) uses viewer ideology data from CIS survey data using the difference in correlation coefficients between right and left. The two most extreme channels are normalized into the  $-1$  and  $1$  values.

## Robustness of the Text Classification

Two main concerns arise with the use of LLMs as text classifiers. First, LLMs have been shown to suffer from potential stochasticity, making results unstable when using multiple runs of the same prompt. Second, one may question the performance of alternative text classification methods.

Due to their inherent stochasticity, repeated queries using the same prompt may yield different classifications (Atil et al., 2024). As shown in (Boehnke and Bhargava, 2024), this variability can introduce noise in tasks that require high consistency, particularly in content classification. To mitigate this issue, I leverage OpenAI’s “functions” tool, which constrains the classifier’s responses to predefined discrete numerical outputs, reducing potential inconsistencies. Table B.9 presents the mean classification scores from 100 iterations of a random sample of political stories, along with the corresponding standard errors. The relatively small standard errors suggest that, despite the model’s stochastic nature, the classification remains stable.

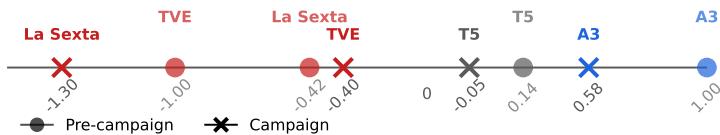
The second concern challenges the validity of LLM reasoning as a tool for political classification. To assess robustness, I compare the LLM’s classifications with those obtained using methods from previous works (Gentzkow and Shapiro, 2010; Laver et al., 2003). I use all Spanish congress speeches during my sample period and exploit party labels to assess

similarities with the outlets' content. Appendix E details the methodology. Figure E.25 shows the left-right positions derived from this method. Although the overall ranking of the outlets from left to right is consistent to the ChatGPT classification in Figure 4, the middle channel is classified now as left wing close to the public TV.

## Political Tone and Electoral Campaign

The nature of political news during campaigns differs markedly from that off-campaign. Off-campaign stories might cover scandals, international summits, etc., whereas during campaigns politicians specifically aim to gain votes through public speeches. To examine how this affects channels' slant positions, I decompose the relative tone before and during campaign periods in Figure A.13. The left-leaning channel, LaSexta, significantly reinforced its position by increasing its positive tone toward left-wing parties and decreasing it toward right-wing parties. A similar strengthening occurs in the middle channel. Both the public channel and the right-wing outlet significantly moderated their relative slants. Figure 6 shows the change in positions relative to off-campaign. Dots mark the normalized  $-1$  to  $1$  positions from the pre-campaign period, and crosses mark those from the campaign period. The ranking shifts: LaSexta is now the most left-leaning channel, followed by TVE. All but the public channel moderated their tones toward more left-wing-favorable coverage. There is thus no clear, homogenous polarization in outlets' positions during the campaign.

**Figure 6:** Change in Positions Off-campaign to Campaign



*Notes:* The figure shows the relative change in positions of the slant from off-campaign to campaign according to the ChatGPT classification. Channels are mapped into the  $[-1, 1]$  scale using their correlation (tone) and normalizing values into this scale.

## Text vs. Image

Imagery is a key component of TV. Previous work has linked politicians' appearances on TV to voting outcomes (Lenz and Lawson, 2011). Below, I compare different metrics of image appearances, politician mentions, and tone.

Due to computational constraints, I cannot perform image detection across my full video sample. Instead, I compare image-based and text-based metrics using a random sample of

67 days. The image-based metric approximates screen time—i.e., the number of seconds a political leader appears visually—and is conceptually similar to the measures constructed in [Cagé et al. \(2022\)](#) and [Durante and Knight \(2012\)](#).

Specifically, I train a state-of-the-art face recognition system ([Geitgey, 2017](#)) using labeled images of the main party leaders: Pedro Sánchez (PSOE), Alberto Núñez Feijóo (PP), Santiago Abascal (VOX), and Yolanda Díaz (UP). I then extract frames from the first 25 minutes of each prime-time news broadcast across major channels, resulting in a sample of 79,788 images. Using the `face_recognition` library, I detect and identify faces in each frame. This allows me to construct a frame-level dataset of visual exposure and emotional tone, which I aggregate at the daily level for each channel and party leader.

Figures [A.14](#) and [A.15](#) show the proportions of image appearances and word mentions by channel and political leader. Figure [A.16](#) shows the net tone by political party over the same sample period.

All channels except Telecinco coincide in their ranking of politician visual appearances, with Feijóo first, followed by Sánchez, Díaz, and finally Abascal. Telecinco shows the greatest airtime devoted to Díaz, with her appearing in 3% of the news. The comparison with the text mentions in Figure [A.15](#) reveals a different scenario: left-leaning channels mention Díaz relatively more than Sánchez, but this pattern does not hold for the right-leaning channel.

To examine the relationship between tone—based on the LLM classification—and coverage, I regress net tone by political actor on both the proportion of image appearances and word mentions. Tables [B.1](#) through [B.4](#) report results under different specifications, including date and channel fixed effects.

Column (4) reports the specification with both channel and date fixed effects, so the coefficients reflect pure within-channel-day fluctuations in coverage. The pattern is heterogeneous across politicians. For Abascal (VOX), a one-standard-deviation increase in word mentions predicts a decrease of 0.28 standard deviations in tone, whereas the same increase in on-screen images predicts an increase of 0.13 standard deviations. Sánchez (PSOE) exhibits the reverse pattern: additional text is linked to a 0.11 standard-deviation softening of tone, while extra images correspond to a 0.13 increase. Taken together, the results indicate that text-based and image-based measures of salience relate to tone in systematically different ways. This poses concerns regarding the interpretation of previous metrics based on airtime; whereas basic count matches naturally present a noisier predictor of tone, image appearances seem to be consistently associated with a negative, rather than a positive, tone. Further research might explore the integration of imagery and stance.

## 4 Market Set Up

In this section I introduce the market set up for demand. Supply will be explicitly modeled in section 6. There are no adds during the TV news programs so I abstract from two sided market considerations. Channels differentiate themselves through the way they present the stories of the day. I follow a mixed logit model (Berry et al., 1998) (BLP) estimation<sup>8</sup>. A key assumption in this type of models is single product choice. TV, however, has strong switching behavior where viewers can explore different alternatives and this cannot be identified from daily, aggregate data. To minimize this concern, I make use of the initial (i.e minute-0) audience of each day. Since 3 out of 4 outlets coincide in their airing times, this makes the single product choice assumption less problematic under the initial audience.

An individual  $i$  a region  $r$  chooses an outlet  $j \in \mathcal{J} \equiv \{La6, TVE, T5, A3\}$ <sup>9</sup> to watch at the beginning of day  $d$  based on the following expected utility :

$$U_{ijrd} = \underbrace{\sum_k x_{jd-1}^k \beta^k + w_{rd}\gamma + \xi_{jrd}}_{\delta_{jrd}} + \underbrace{\sum_k x_{jd-1}^k (\sigma^k \nu_{ird}^k + \pi^k y_{irm})}_{\mu_{ijrd}} + \epsilon_{ijrd} \quad (3)$$

where  $x_{jd}^k$  represents the proportion of time on channel  $j$  and day  $d$  devoted to characteristic  $k \in \{R+, R-, L+, L-, political\}$  as defined in Equation 1.  $w_{rd}$  measures the precipitation level on a given day-region. Weather conditions alter the value of the outside option and make viewers more prone to engage in indoor activities like TV consumption (Wilbur, 2008). In my model, this happens with a common shift in the valuation of the inside options.

I model the distribution of viewer's content taste parameters using the standard normal random shocks  $\nu_{ird}^k \sim N(0, 1)$  with mean shifted by demographics,  $y_{irm}$ , that represent whether individual  $i$  is right wing in month  $m$  according to survey data. The parameters  $\pi^k$  allow for asymmetric tastes of politics based on ideology. Thus, they capture polarization in news consumption: More right wing individuals might screen out opposed content.

The unobserved (to the econometrician) product characteristics are decomposed into  $\xi_{jrd} = \xi_j + \xi_{dow} + \Delta\xi_{jrd}$ , where I include product dummies that account for unobserved quality factors and day of the week dummies to control for seasonal variation in the value of TV consumption. Unobserved product tastes can take the form of higher valuation of a given type of story that comes from knowledge of it through social media, specific regional taste shocks due to local events, non-controlled amplification due to visuals and appearance etc. By assumption, both the outlets and the viewers have full information about all the product characteristics. Due to timing differences, this assumption comes in the form of a correct

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<sup>8</sup>The model is estimated under the *pyblp* package (Conlon and Gortmaker, 2020).

<sup>9</sup>Although both LaSexta and A3 belong to the same media company, AtresMedia; the analysis here is based on short run profit maximization and they are assumed to be different, independent products.

expectation formation for next day unobserved preferences  $\xi_{jrd+1}$  in the moment of setting todays' content  $\mathbf{x}_{jd}$ .

The outside option is modeled in terms of *potential* audience (Berry, 1994) and its mean utility value is normalized to 0 .

Market shares are just the integral over the individual choice indicators from 3:

$$s_{jrd} = \int d_{ijrd}(\boldsymbol{\delta}_{rd}, \boldsymbol{\mu}_{ird}) d\boldsymbol{\mu}_{ird} d\boldsymbol{\epsilon}_{ird} \quad (4)$$

where  $d_{ijrd}$  equals 1 if  $U_{ijrd} > U_{ikrd} \quad \forall j \neq k$  and 0 otherwise. Survey weights are included in the integration.

Under the assumption of no individual heterogeneity in preferences (i.e  $\boldsymbol{\sigma} = 0$ ) nor in the distribution of ideology in a given region  $y_{ir} = \bar{y}_r$ , equation 3 is consistent with a plain logit model as:

$$\ln \left( \frac{s_{jrd}}{s_{0rd}} \right) = \sum_k x_{jd-1}^k \beta^k + w_{rd} \gamma + \sum_k (x_{jd-1}^k \times y_r) \phi^k + \xi_{jrd} \quad (5)$$

I show results under both the BLP and plain logit in section 5.

## 4.1 Content Endogeneity and News Shocks

Previously, demand estimation has often treated content characteristics as exogenous and use them to instrument for prices. However, my set up precisely shows the adaptation of content to audience preferences: channels tilt the slant of the day and viewers choose their preferred content accordingly. Figure A.17 depicts the core trade-offs. Viewers form expectations about the utility of each channel based on exogenous variables—weather, individual attributes, and an unobserved (to the econometrician) shock  $\xi$ —as well as on yesterday's content slant  $\mathbf{x}_{jd}$ . Channels, in turn, choose today's slant while forecasting tomorrow's utility shock  $\Delta \xi_{j,d+1}$ . Hence their optimal content decisions are functions of unobserved taste shocks, implying  $\mathbb{E}[\mathbf{x}_{jrd-1} \Delta \xi_{jrd}] \neq \mathbf{0}$ .

To overcome this problem I instrument, for every endogenous product characteristic  $k$ , with exogenous supply shocks. I proxy the daily news landscape with all stories published in Spanish by *Agencia EFE*—around  $N \approx 41,000$  items over the sample. Television stations rely heavily on third-party wire services for footage, text, and images, a downstream flow documented and exploited in earlier work (Djourelova, 2023). The fact that all outlets in my sample contract with EFE, mitigates concerns that the agency is systematically biased or poorly informed.

Mirroring the content covariates in (1), I classify every EFE story with the same NLP pipeline and construct daily measures of the political mix in the *news landscape*:

$$\begin{aligned} z_d^{\text{party}+} &= \frac{1}{|S_d|} \sum_{s \in S_d} [\mathbb{1}\{\text{tone}(s) = 1\} \mathbb{1}\{p(s) = \text{party}\}] \quad \forall \text{party} \in \{L, R\}, \\ z_d^{\text{party}-} &= \frac{1}{|S_d|} \sum_{s \in S_d} [\mathbb{1}\{\text{tone}(s) = -1\} \mathbb{1}\{p(s) = \text{party}\}] \quad \forall \text{party} \in \{L, R\}, \\ z_d^{\text{political}} &= \frac{|\mathcal{P}_d|}{|S_d|}. \end{aligned} \quad (6)$$

Here  $S_d$  denotes the total number of EFE stories on day  $d$ , and  $\mathcal{P}_d$  the subset classified as political. The *news landscape* is common for all the outlets but will affect them asymmetrically due to their ideal positions. Channels would like to produce at their steady state, average positions (i.e those depicted in 5), but in the short run the available story mix constrains what they can speak about. When the news landscape tilts toward a given party-tone combination, stations are either helped to move closer to—or forced away from—their ideals, depending on how well the available content aligns with those targets. Since days are independent, outlets know they need take profit of a favorable day as newsworthy events might crowd out the news the day after. This setup therefore mirrors the classic BLP strategy of using product-specific cost shifters: the common EFE shock enters each channel's cost function but, because editorial lines differ, it shifts channels' content choices differentially within the same day, generating cross-sectional variation that the rank condition requires for identification (Berry and Haile, 2014).

Outlets' coverage of scandals or economic have been extensively documented for the U.S. press (see e.g. Puglisi and Snyder (2011); Larcinese et al. (2007)). Tables B.11 and B.12 illustrate this mechanism linking the news landscape to outlet's reporting. The most unfavourable day for left-wing parties in my sample is 27 February 2023. On that date a technical flaw a law sponsored by the left party Podemos; motions and corruption scandals towards the Socialist party hurt the coalition government.

Airtime devoted to negative left-wing stories therefore spiked: Antena 3 (right) devoted almost 19 %, while TVE (left) and Telecinco each gave roughly 4 %, and La Sexta (left) only 2 %.

The mirror image occurred on 17 May 2023, the day with the most negative coverage of right-wing parties. Stories included a payments scandal involving the People's Party, the defeat of a conservative motion in the Senate, and police abuse allegations during an anti-VOX march.

This time the left wing outlets lead the production of negative right-wing content with 15 % of the time, whereas Antena 3 devoted barely 4 %.

In order to show formal evidence of the previous mechanism, I estimate, for each  $(party, tone)$  pair, separate regressions of the form:

$$x_{jd}^{party,tone} = \sum_k \sum_{ch} (d_j(ch) \times z_d^k) \alpha_j^k + \epsilon_{jd}, \quad (7)$$

where  $k \in \{L+, R+, L-, R-, political\}$ . As was described before,  $x_{jd}^{party,tone}$  is outlet  $j$ 's share of airtime with positive or negative tone about  $party \in \{L, R\}$ ;  $z_d^k$  is the corresponding share among all EFE stories, and  $d_j(ch)$  dummy with value one if  $j = ch$ . Controlling for the whole news landscape, I estimate how outlets increase the production of content of each type. A positive coefficient  $\alpha_j^{R+}$  means that, ceteris paribus, one additional positive right-wing story in the wire increases outlet  $j$ 's own positive coverage of the right by  $\alpha_j^{R+}$ .

Results of the estimation are shown in table B.5. Figure 7 presents added-variable plots for regression equation (7) (a LOWESS version appears in Appendix Figure A.19). Table 1 shows the F and t-test for overall differences and pairwise comparisons between right and left outlets showing how the highest differentiation occurs for content in favor of the right (positive right and negative left).

When the share of positive-right stories rises by one standard deviation, the right-leaning Antena 3 lifts its own positive-right airtime by about 0.30 stdev., whereas the left-leaning outlets TVE and La Sexta react hardly at all. Symmetrically, a one-stdev. increase in positive-left stories leads TVE to expand favourable coverage of the left by roughly 0.38 stdev, while Antena 3's response is indistinguishable from zero. By contrast, none of the channels shows more than a "small" ( $< 0.15$  stdev) adjustment to extra negative-right news, consistent with the idea that hostile coverage of the right is already close to saturation (eg. see figure 4).

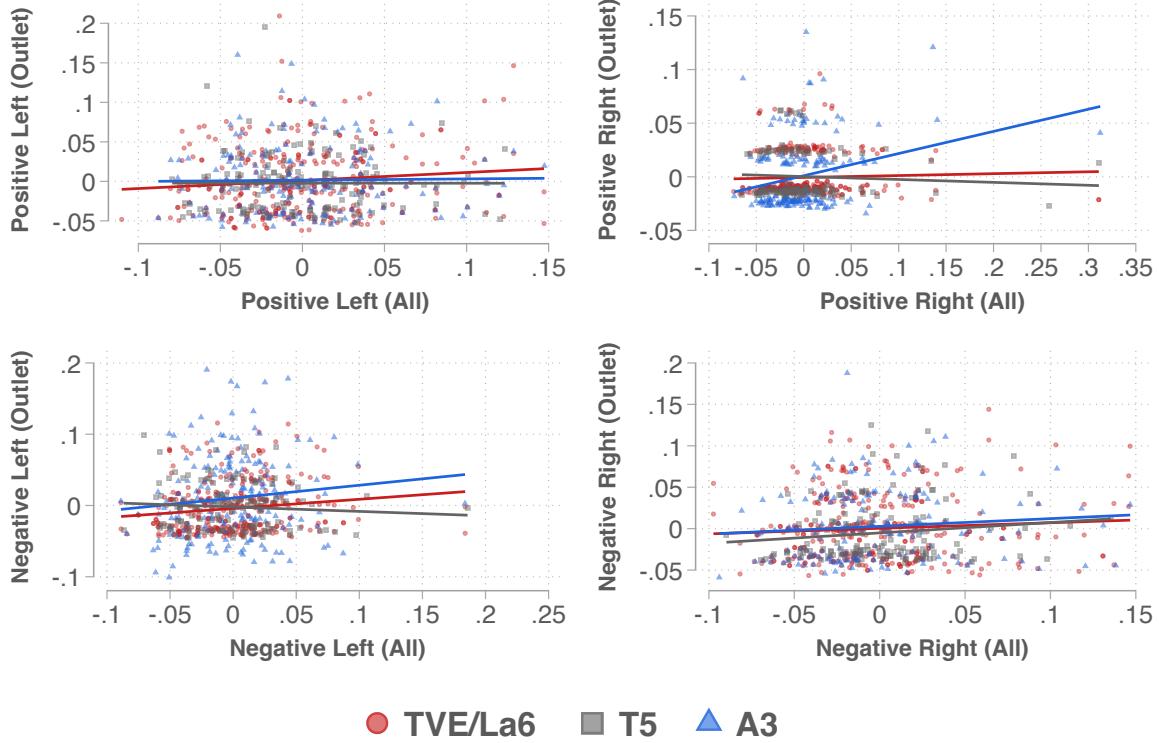
Table 1: F and t-tests for Regression Coefficients

Characteristic	F-test	F-test p-value	T-test	T-test p-value
$L-$	2.69	0.0686	3.51	0.0613
$L+$	1.31	0.2711	1.87	0.1715
$R-$	0.42	0.6594	0.34	0.5592
$R+$	8.78	0.0002	17.55	0.0000

Notes: Summary of F- and T-test results for equality of news variable coefficients across channels. The F-test evaluates overall equality across channels, while the T-test compares the coefficient of the main independent variable between A3 and TVE/La6.

Accordingly, I use  $(z_d^{party+}, z_d^{party-}, z_d^{political})_{party \in \{L, R\}}$  as instruments for the linear content characteristics. The goal is not to proxy the outlet-specific news landscape perfectly, but to exploit exogenous variation in story supply that shifts slant decisions. The short sample window limits any strategic adaptation of EFE's editorial line to individual channels.

**Figure 7:** Added Variable Plots for Production of Political Content



Notes: The figure shows the added variable plots from the estimation of equation 6. The x axis represents  $(z_d^{party,+}, z_d^{party,-})$  and the y axis the corresponding  $(x_{jd}^{party,+}, x_{jd}^{party,-})$ . Channels are pooled into left (TVE and La6), middle (T5) and right (A3) for visualization purposes.

For the  $K$  non-linear parameters governing preference heterogeneity I follow [Gandhi and Houde \(2019\)](#). Instruments take the form  $(\hat{x}_{jd}^k - \sum_{l \neq j} \hat{x}_{ld}^k)^2$ , where  $\hat{x}_{jd}^k$  is the first-stage prediction from (7). To identify demographic interactions, I multiply these instruments by the local share of right-wing votes,  $\bar{y}_r \hat{x}_{jd}^k$ .

## 5 Results

I present the results of the BLP estimation for the pre-campaign and campaign periods in Table 2. I show the preferred specification with outlet and day-of-week fixed effects and standard errors clustered at the regional level.

The pre-campaign estimates reveal four main facts. First, there is a strong, statistically precise mean taste for stories about national politics, indicating that political coverage per se draws audience attention before the campaign begins. Second, conditional on this baseline, viewers demand a negative tone toward both parties, but the pull is considerably stronger when the right-wing bloc is the target, whereas positive-toned stories are, on aver-

age, unattractive. Third, there is no sizable dispersion in the taste parameters captured by the estimated  $\sigma$ . This is expected, as identification of these parameters requires exogenous changes in the choice sets (Berry and Haile, 2014), which do not apply in my market setup. Fourth, the ideology–content interaction terms are small and imprecise, so the heterogeneity cannot be explained by viewers’ ideology.

During the campaign window, the same specification paints a markedly different picture. The average taste for political coverage becomes negative, suggesting that audiences experience political saturation once the race officially begins. Conditional on this baseline, valence preferences reverse and intensify: viewers now reward positive stories about the left and negative stories about the right while penalising the opposite frames, producing an aggregate tilt toward left-leaning parties. Ideology–content interactions, however, reveal stark polarisation. Right-wing audiences actively seek favourable coverage of their own side and avoid negative stories about it, yet the dominant force is out-group animosity: they exhibit a particularly strong demand for negative coverage of the opposition. This pattern is consistent with *affective polarisation* and echoes evidence from the United States showing that exposure to presidential campaigns makes partisans increasingly hostile toward their opponents (Peterson et al., 2017).

## Elasticities

I present the mean own elasticities across right and left markets for both the off campaign and campaign periods. Given that increasing the positive relative minutes to a party also implies increasing the overall total minutes on politics, I compute the elasticity for the  $k$ th characteristic as:

$$\bar{\epsilon}^k = \frac{1}{J \times R \times D} \sum_j \sum_r \sum_d \left( \frac{\partial s_{jrd}}{\partial x_{jt}^k} + \frac{\partial s_{jrd}}{\partial x_{jt}^{political}} \right) \frac{x_{jd}^k}{s_{jrd}} \quad \forall k \in \{R+, R-, L+, L-\} \quad (8)$$

The estimated elasticities for right and left-markets <sup>10</sup> across tones are shown in figure 8 for the pre-campaign and campaign periods; respectively. Estimate results are also shown in Table B.10 on the Appendix.

The polarization in preferences clearly emerges in the right pane (b), where it is shown how the right and left markets present opposed elasticities for the tones that opposed their ideological views.

To give a size effect of this change; an increase of 1 per cent on net tone towards a party (i.e  $\bar{\epsilon}^{party+} - \bar{\epsilon}^{party-}$ ) is associated with a 0.31 per cent increase in audience share during

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<sup>10</sup>Where a region is define as right if the proportion of right-wing intention to vote is above the median.

Table 2: BLP Estimation Results with Standard Errors

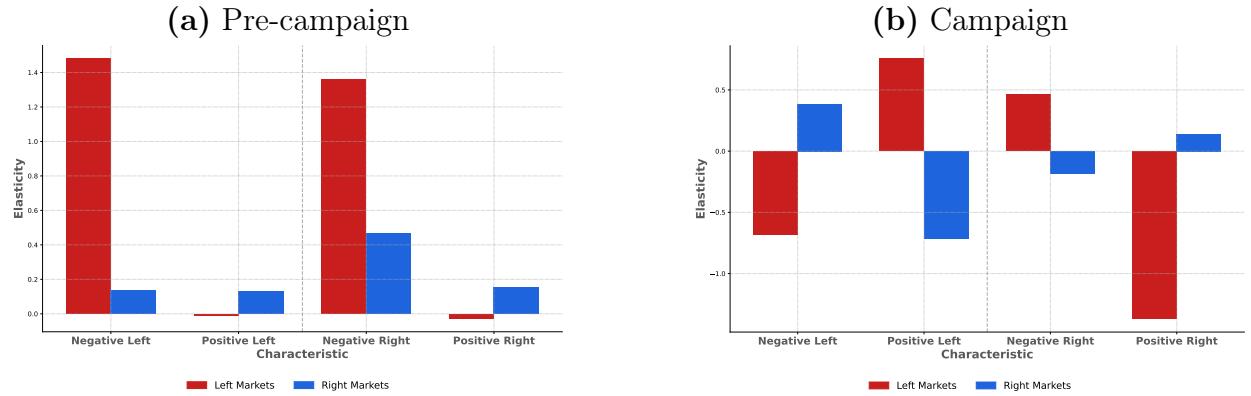
Coefficient	Parameter	Estimate	Std. Error
Pre-campaign			
Positive Left	$\beta^{L+}$	-16.90	(11.73)
Positive Right	$\beta^{R+}$	-25.53	(31.03)
Negative Left	$\beta^{L-}$	28.29	(25.89)
Negative Right	$\beta^{R-}$	56.44**	(28.45)
Political	$\beta^{political}$	11.49***	(4.28)
Weather	$\gamma$	0.00	(0.03)
Positive Left	$\sigma^{L+}$	0.44	(296.90)
Positive Right	$\sigma^{R+}$	0.68	(715.26)
Negative Left	$\sigma^{L-}$	12.64	(8.68)
Negative Right	$\sigma^{R-}$	21.99	(13.83)
Political	$\sigma^{political}$	0.00	(46.79)
Right-Wing $\times$ Positive Left	$\pi^{L+}$	46.26	(48.70)
Right-Wing $\times$ Positive Right	$\pi^{R+}$	77.81	(95.92)
Right-Wing $\times$ Negative Left	$\pi^{L-}$	-70.09	(57.97)
Right-Wing $\times$ Negative Right	$\pi^{R-}$	-103.71	(97.76)
Right-Wing $\times$ Political	$\pi^{political}$	-25.17**	(12.59)
Campaign			
Positive Left	$\beta^{L+}$	134.16**	(65.57)
Positive Right	$\beta^{R+}$	-129.79***	(48.43)
Negative Left	$\beta^{L-}$	-104.84**	(41.32)
Negative Right	$\beta^{R-}$	92.62**	(41.63)
Political	$\beta^{political}$	-6.43**	(3.26)
Weather	$\gamma$	0.00	(0.01)
Positive Left	$\sigma^{L+}$	0.00	(320.36)
Positive Right	$\sigma^{R+}$	19.25*	(10.89)
Negative Left	$\sigma^{L-}$	0.00	(134.33)
Negative Right	$\sigma^{R-}$	0.02	(73.18)
Political	$\sigma^{political}$	0.00	(19.55)
Right-Wing $\times$ Positive Left	$\pi^{L+}$	-421.99**	(176.15)
Right-Wing $\times$ Positive Right	$\pi^{R+}$	334.94***	(127.41)
Right-Wing $\times$ Negative Left	$\pi^{L-}$	288.65**	(116.22)
Right-Wing $\times$ Negative Right	$\pi^{R-}$	-280.33***	(104.44)
Right-Wing $\times$ Political	$\pi^{political}$	19.34**	(8.93)

The table shows the results of the BLP estimation of model 3. The estimations are divided into the pre-campaign and campaign period. Both day-of-the-week and outlet fixed effects are included. Standard errors are clustered at the region level. The total number of observations are  $N_{campaign} = 2307$  and  $N_{pre\_campaign} = 6604$ .

campaign periods vs a 0.31 per cent decline in pre-campaign.

This means that an increase of 1 per cent of negative right tone during the campaign is associated with a loss of 8015 total viewers in right markets with respect to the pre-campaign period.

**Figure 8:** Estimated Elasticities for Right and Left markets, Pre-campaign and Campaign



*Note:* Each panel shows estimated mean own elasticities for consumer responses in right- and left-leaning markets as described in equation 8. Panel (a) reports results for the pre-campaign period, while Panel (b) covers the campaign period.

In order to replicate the outlets' positions shown in figure 5; I do the analogous comparison ranking them according to their estimated demand elasticities. Figure A.21 on the appendix shows the comparison. Panel a) ranks channels in the -1,1 segment according to the campaign elasticities. Panel (b) shows their positions for the same period according to their slant. Both rankings agree and the relative scores of the middle channels are similar indicating the consistent equilibrium between supply and demand.

## Political Polarization

Does the polarization in media consumption link to electoral attitudes? In this section I show correlational evidence between political and media polarization from my demand estimates. As in [Martin and Yurukoglu \(2017\)](#), I compute the Esteban-Ray (ER) polarization index ([Esteban and Ray, 1994](#)) using the intention to vote by region as:

$$ER_{rm} = \sum_p \sum_q s_{prm}^{1+\alpha} s_{qrm} \times 1, \quad \alpha = 1.5, \quad (9)$$

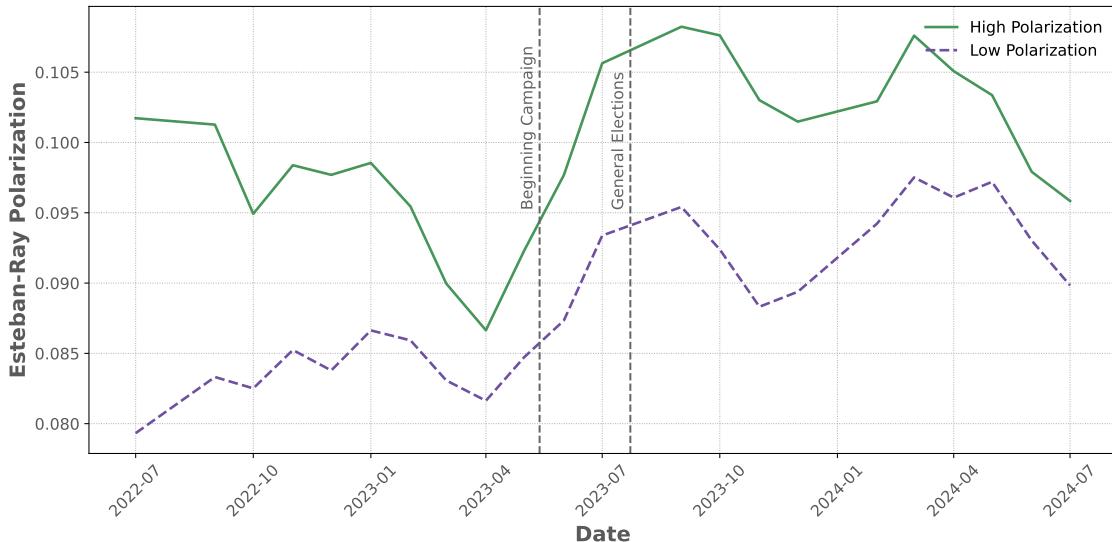
where  $s_{pm}$  is the share of intention to vote for party  $p \in \{L, R\}$  on month  $m$  and I set  $\alpha = 1.5$ . Since there are only two blocks, the distance between political parties is normalized to one.

Media polarization is captured by the *elasticity gap* between reactions to congenial and uncongenial coverage during the campaign. For right wing regions,  $p(r) = R$ , media polarization refers to the difference in taste for negative content on the left versus positive and viceversa:

$$MediaPol_r = \begin{cases} \bar{\epsilon}_r^{(L-)} - \bar{\epsilon}_r^{(L+)} & \text{if } p(r) = R \\ \bar{\epsilon}_r^{(R-)} - \bar{\epsilon}_r^{(R+)} & \text{if } p(r) = L \end{cases} \quad (10)$$

I divide regions in *high* and *low* groups according to their media polarization index relative to the median. Figure 9 plots the smoothed  $ER_{rm}$  for both groups over the year before and after the 2023 general election <sup>11</sup>. Places that present higher polarized media consumption coincide with a highly divided electorate. Moreover, consistent with the results in the demand estimation, polarization intensifies close to the moment where the campaign begins. The gap between both high and low regions also widens after the trend break. This feedback reinforces the link between media consumption and voting outcomes.

**Figure 9:** Political and Media Polarization



*Note:* The figure shows the mean Esteban-Ray polarization index under a smoothed rolling mean of 3 months computed as in equation 9. Solid (dashed) line represents the regions above (below) the median in terms of their media polarization consumption according to index 10.

In order to check whether political polarization is driving the results of the demand estimation; I run my model in 3 using the initial (i.e December) rather than the monthly ideology.

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<sup>11</sup>Raw time series are shown in appendix figure A.22.

Results are robust. However, the use of aggregate data cannot rule out selection effects. Campaigns might change audience composition towards news seekers, who have been shown to have asymmetric effects relative to entertainment seekers in terms of polarization (Levendusky, 2013; Arceneaux and Johnson, 2013). Future work might address this concern with the use of individual panel data or allowing more flexible dynamics between ideology and media consumption as in Martin and Yurukoglu (2017).

## 6 Supply Side

News directors explicitly link editorial choices to real-time audience figures:

“Even a news programme is deeply subject to the day-to-day swings of audience share. A drop of half a point when covering a topic can lead us to drop that topic altogether.”

—Vicente Vallés, Director and Presenter, Antena 3 News (2014)<sup>12</sup>

Two facts follow from this quote. First, although the newscast contains no adverts, outlets maximise the audience they hand over to subsequent slots. Second, editorial decisions are taken at high frequency: producers meet before the *midday* and *evening* editions and update slant in response to fresh stories and the latest ratings.

For channel  $j$  on day  $d$  and edition  $h \in \{0 \text{ (mid-day)}, 1 \text{ (evening)}\}$  the problem is

$$\begin{aligned} & \max_{\{\mathbf{x}_{jdh}\}} \left\{ \sum_r \mathbf{s}_{jrd+1}(\mathbf{x}_{jdh}, \mathbf{x}_{-jdh}) \frac{L_r}{L} - \mathcal{C}(\mathbf{x}_{jdh}, \mathbf{z}_{dh}, \boldsymbol{\omega}_{jdh}; \boldsymbol{\lambda}_j) \right\} \\ & \text{s.t. } x_{jdh}^{L+} + x_{jdh}^{R+} + x_{jdh}^{L-} + x_{jdh}^{R-} + x_{jdh}^{\emptyset} = x_{jdh}^{political} \\ & \quad x_{jdh}^k \in [0, 1] \quad \forall k \end{aligned} \tag{11}$$

where  $\mathbf{z}_{dh}$  measures the pool of stories available at edition  $h$ . I parameterize the cost function as:

$$\mathcal{C}(x_{jdh}^k, z_{dh}^k, \omega_{jdh}^k; \lambda_j^k) \equiv \lambda_j^k \frac{(x_{jdh}^k)^2}{z_{dh}^k} + F(\omega_{jdh}^k)$$

where there is a channel-characteristic specific parameter that governs the slope of the production cost and unobserved (to the econometrician) cost factors other than the stories available;  $F(\omega_{jdh}^k)$ . By assumption, these unobservables will enter as linear terms in the marginal costs. The sign of  $\lambda_j^k$  is theoretically ambiguous. On the one hand,  $z$  might act as a simple input in any production costs. High availability of stories of a given type will make

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<sup>12</sup>Source: [https://cadenaser.com/ser/2014/12/03/television/1417630810\\_539829.html](https://cadenaser.com/ser/2014/12/03/television/1417630810_539829.html)

production easier since the journalist need not do much effort to find them. This will imply  $\lambda > 0$ . On the other hand, outlets are news aggregators. Having more stories available of a given type might increase the cost of producing them since they would need to process and filter the ones that they prefer. This mechanism is consistent under  $\lambda < 0$ .

## First-Order Conditions and Endogeneity

The first-order condition (ignoring the summation constraint for estimation) is

$$\sum_r \frac{\partial s_{jrd+1}}{\partial x_{jdh}^k} \frac{L_r}{L} = 2\lambda_j^k \frac{x_{jdh}^k}{z_{dh}^k} + \underbrace{\eta_{jd}^k + \nu_{jdh}^k}_{\equiv F'(\omega_{jdh}^k)}, \quad (12)$$

I decompose the unobserved cost factors into  $\eta_{jd}^k$ , a *persistent, day-specific* marginal-cost shock (e.g. a key reporter is on sick leave, satellite link fails, or legal concerns delay a segment), and  $\nu_{jdh}^k$  is transitory noise. Because  $\eta_{jd}^k$  influences both marginal cost and the share gradient  $g_{jdh}^k \equiv \sum_r \partial s_{jrd+1}/\partial x_{jdh}^k (L_r/L)$ ,  $\lambda_j^k$  would be biased in a naive regression:  $\mathbb{E}[g_{jdh}^k \eta_{jd}^k] \neq 0$ .

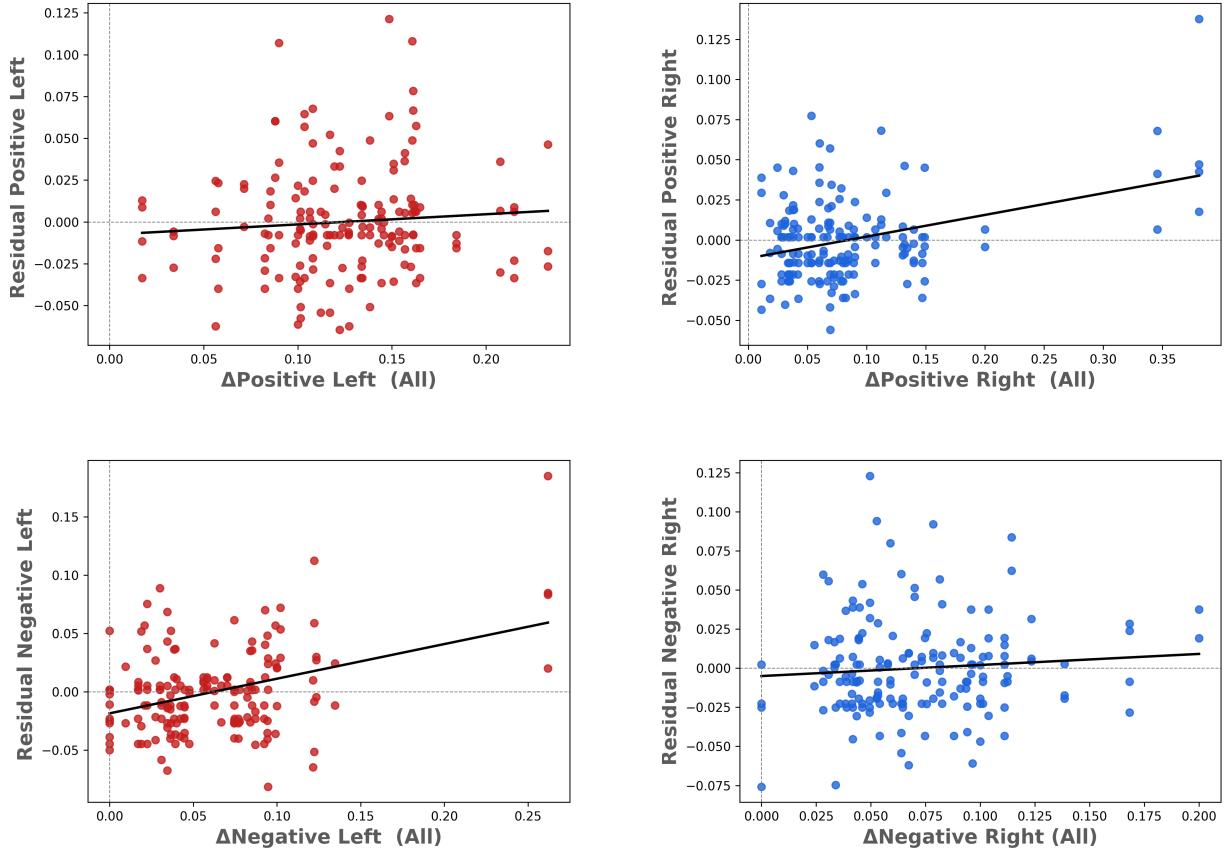
The key identification strategy is that  $\eta_{jd}^k$  is constant within the day. This allows me to rely on variation in news production within day that is only due to new stories coming in between the midday and evening editions that alter production. To show the variation that I will exploit, I first regress the evening on the midday editions controlling for outlet fixed-effects. The residuals of these regression are the variation in the evening programming not explained by the midday slant and channel specific attributes. I then regress these residuals on the stories that enter between those two time slots in EFE. Figure 10 shows the scatter of the regression.

There is a positive association for all content categories. This indicates that entry of new content between midday and night is associated with an increase in editorial production of that content in the evening news' shows.

To decompose this variation by outlet, I run regressions of the form 6 done on within day differences  $\Delta x_{jd}$  and  $\Delta z_d$ . Figure A.20 on the appendix shows the added variable plots. Although there is significantly less power now, the main mechanism still holds. Right (left) outlets increase more their production of stories of a given party-tone from midday to the evening editions conditional on those stories being aligned with their stances.

Table B.17 shows examples on the text. I filter the days with the highest within-day increase in coverage by all channels and report the new stories that entered between midday and evening editions for each content type. For instance, on 29 May 2023, stories criticizing the left pushed evening coverage sharply toward a pro-right tone; on 31 May 2023, stories criticizing the right swung coverage the opposite way. These sudden, within-day shifts

**Figure 10:** Within Day Increase in News Production



*Note:* Scatter with fitted line from the regression of the residual from a regression of the evening tone on the midday tone with outlet fixed effects on the tone of the stories in EFE between midday and evening.

in story mix create the variation we use to measure viewers' taste for like-minded versus opposing content.

Differencing (12) eliminates the unobserved shock:

$$\underbrace{\sum_r \left( \frac{\partial s_{jrd+1}}{\partial x_{jd1}^k} - \frac{\partial s_{jrd+1}}{\partial x_{jd0}^k} \right) \frac{L_r}{L}}_{\Delta g_{jd}^k} = 2\lambda_j^k \left( \frac{x_{jd1}^k - x_{jd0}^k}{z_{d1}^k - z_{d0}^k} \right) + \Delta \nu_{jd}^k. \quad (13)$$

Intuitively, the evening–mid-day change in the gradient,  $\Delta g_{jd}^k$ , is driven by the change in story availability ( $z_{d1}^k - z_{d0}^k$ ), while the day-persistent cost shock cancels out.

## 6.1 Results

Table 3 reports the estimated  $\lambda_j^k$ <sup>13</sup>. Producing content favourable to the left (positive-L or negative-R) is costlier for the right-leaning Antena 3, while the reverse holds for left-leaning La Sexta and TVE. Telecinco, a centrist outlet, faces the lowest absolute costs in every category.

Table 3: Estimated Cost Parameters ( $\lambda$ ) by Channel and Content Type

	La Sexta	TVE	Telecinco	Antena 3
Negative Left	12.782 (44.512)	6.614 (3.107)	108.985 (60.695)	-38.135 (24.006)
Positive Right	-89.175 (85.860)	-105.658 (121.713)	-13.868 (91.624)	-238.018 (77.314)
Positive Left	36.094 (52.716)	3.368 (13.110)	25.984 (43.586)	-38.962 (84.390)
Negative Right	4.059 (4.788)	-8.694 (11.057)	30.280 (36.013)	34.624 (53.835)
Political	-0.349 (0.610)	0.317 (0.622)	1.498 (1.049)	1.455 (1.248)

*Note:* Robust standard errors in parentheses. Table shows the estimated coefficients under GMM for equation 13.

The signs confirm the interpretation: left-favourable content is costlier for right-leaning outlets, and vice versa for all characteristics but for positive left content. These outlet–slant asymmetries feed directly into the counterfactuals in Section 7.

## 7 Counterfactuals: Work in progress

Across Europe, broadcast regulators increasingly impose proportional-air-time rules to curb partisan imbalances in election coverage: France’s ARCOM stopwatches every political segment to enforce strict minute-for-minute equality during the “période officielle”; Italy’s Par Condicio law compels both public and private stations to “balance and compare” exposure for all lists; and Germany grants each registered party free television slots whose length scales with its prior vote share. Spain, by contrast, still relies on a voluntary pluralism. The public network TVE issues a proportional airtime manifesto while commercial groups—Atresmedia and Mediaset—entirely unconstrained.

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<sup>13</sup>Due to computational issues with the pre-processing of the midday shows for the pre-campaign period; this section presents the cost estimation only for the campaign period.

My model estimates allow to test what would be the implications of enforcing such policy to all the broadcasters. I take the proportion of votes in the past general elections for each party and estimate the new equilibrium under the following problem:

$$\begin{aligned}
& \max_{\{\mathbf{x}_{jd}\}} \left\{ \sum_r s_{jrd+1}(\mathbf{x}_{jd}, \mathbf{x}_{-jd}) \frac{L_r}{L} - \sum_k \lambda_j^k \frac{(x_{jd}^k)^2}{z_d^k} \right\} \\
& \text{s.t. } \frac{x_{jd}^{R+} + x_{jd}^{R-}}{x_{jd}^{political}} = vote^R = 0.51 \\
& \quad \frac{x_{jd}^{L+} + x_{jd}^{L-}}{x_{jd}^{political}} = vote^L = 0.49 \\
& \quad x_{jd}^{L+} + x_{jd}^{R+} + x_{jd}^{L-} + x_{jd}^{R-} \leq x_{jd}^{political} \\
& \quad x_{jd}^k \in [0, 1] \quad \forall k
\end{aligned} \tag{14}$$

where, in a logic consistent with my measurement strategy, time to a political party can only be discerned if that story has some specific slant. I assume that the policy is enforced; that is all outlets must devote the proportion of political time given by previous proportions of votes ( $vote^R, vote^L$ ) (i.e constraints bind). This simplifies the choice set to  $(x_{jd}^{L+}, x_{jd}^{R+}, x_{jd}^{political})$ . I discretize the action space and solve for the pure Nash equilibrium after converting the game into normal form.

## 8 Conclusion

Understanding the demand of political information is crucial to understand political polarization and media market regulation. However, endogeneity concerns often impede classical demand estimation techniques due to the lack of valid instruments. In this paper, I introduce a novel dataset that comprises the Spanish TV market, where I match daily transcripts of the TV news to audimeter data on viewership. I propose a new methodology that makes uses of text analysis and Large Language Models (LLMs) to analyze the production of political content in TV news. This methodology extracts the political tone and intensity of the daily TV news and exploits the random availability of political events, together with channel's long-run ideological positions, to measure supply shocks that allow the estimation of demand preferences.

I show that channels face asymmetric constraints in their production of political content depending on whether the composition of the day is more or less favorable to their ideological stance. I estimate a structural BLP demand model where I split my sample into both pre-campaign and during political campaign periods. This model allows me to introduce heterogeneity into the demand estimation and decompose political preferences based on the ideological composition of the audience. My results reveal that while there is no significant

asymmetric demand for political content during the pre-campaign period, affective polarization emerges during the political campaign, with right-wing viewers demanding more negative content about the opposing party and more favorable content about their own. Finally, I model the competition game into channels' daily content production and estimate their cost structures. Right wing media enjoy higher benefits/costs on producing content that goes against their editorial line.

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# Appendix

## Table of Contents

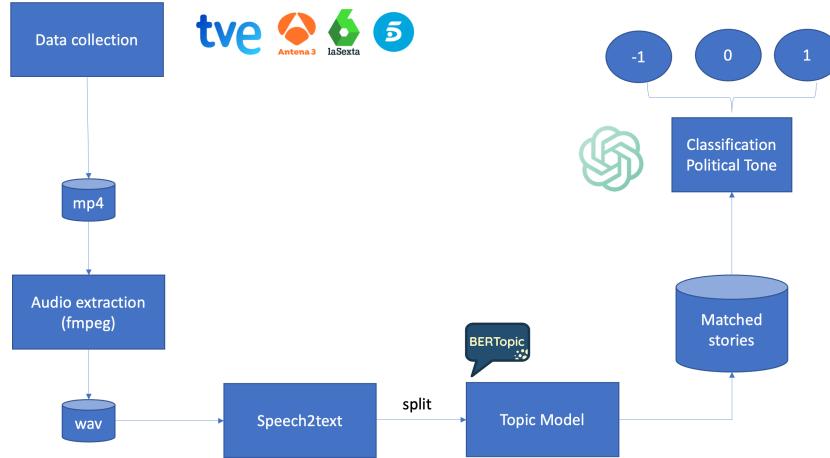
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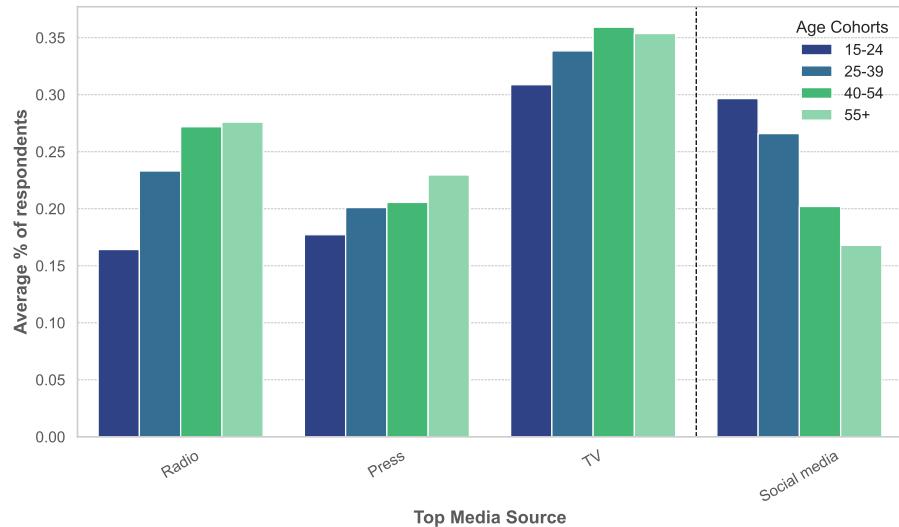
## A Figures

**Figure A.11:** Pipeline for Content Downloading and Classification



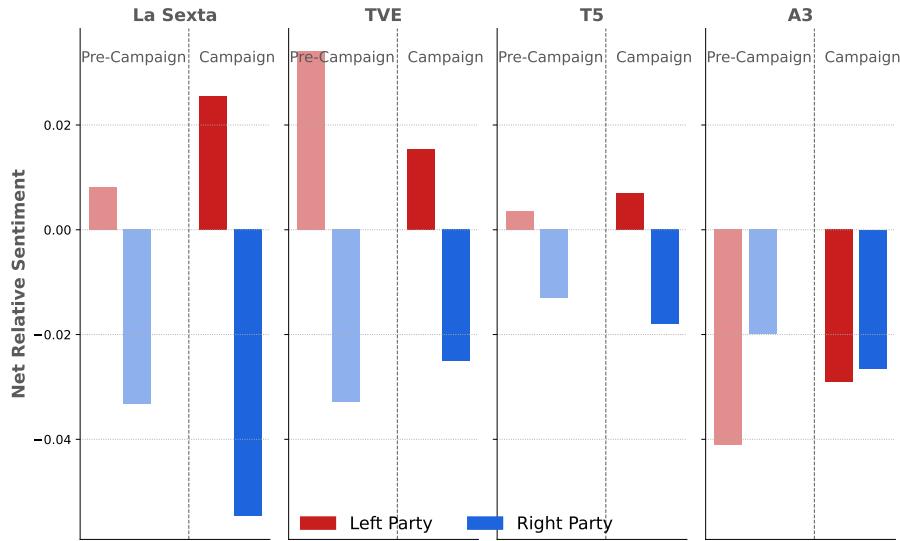
Notes: Pipeline for the text downloading. First videos are downloaded daily from the main TV channels. Google engine is used to convert the audio to text. I then split the stories by minute and use BERTopic to classify and match them. Finally, ChatGPT4 is used to classify political tone.

**Figure A.12:** Preferred Media for Political Information in Europe



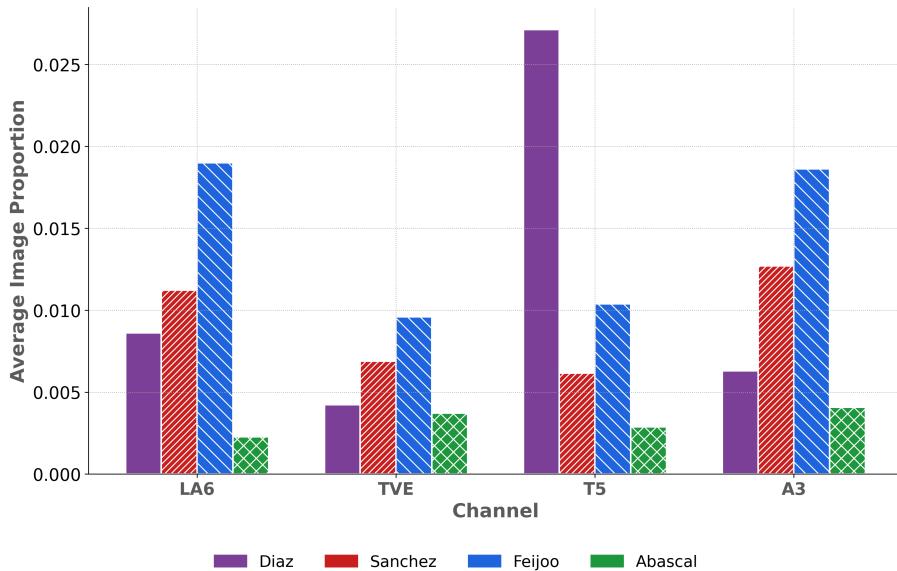
Notes: Histogram of the preferred media used for political information in Europe. Using data for the 27 countries in Eurobarometer with  $N = 112059$ . Source: Eurobarometer, 2022.

**Figure A.13:** Tone across Channels and Parties pre and during Campaign



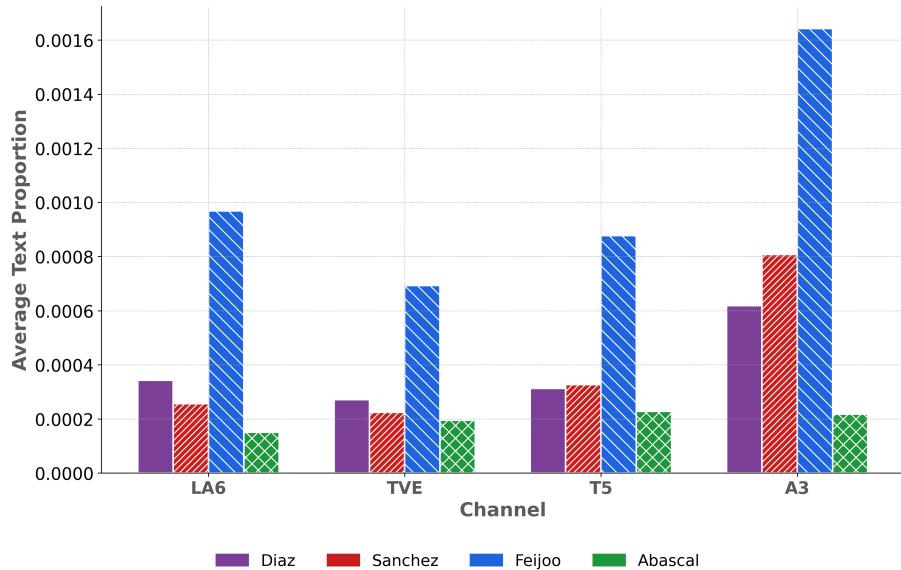
Notes: The figure shows the relative tone calculated as the average sentiment over right and left parties. The vertical dashed line delimits results pre and during campaign periods, respectively.

**Figure A.14:** Proportion of Image Appearances per Channel and Politician



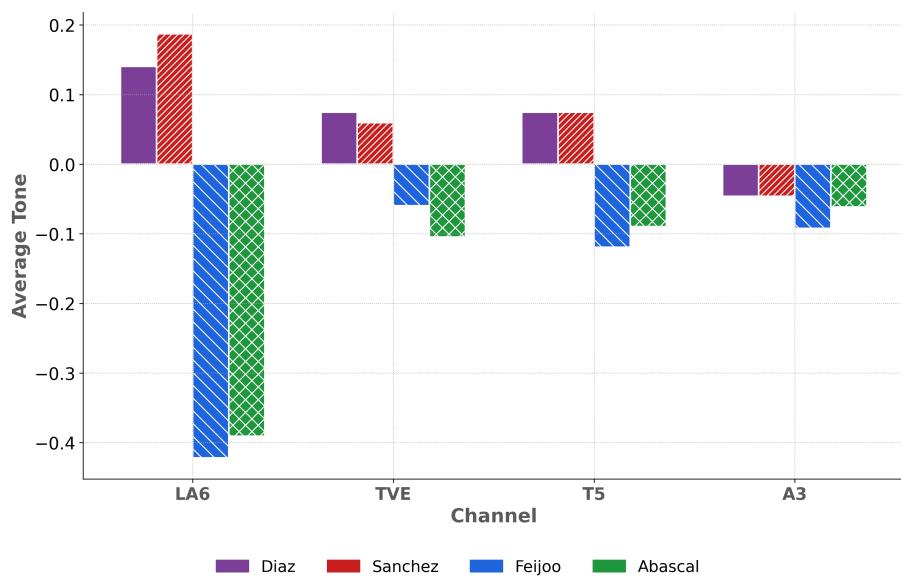
Notes: The figure shows the relative proportion of appearances by political actor and channel for a random sample of 67 days.

**Figure A.15:** Proportion of Text Mentions per Channel and Politician



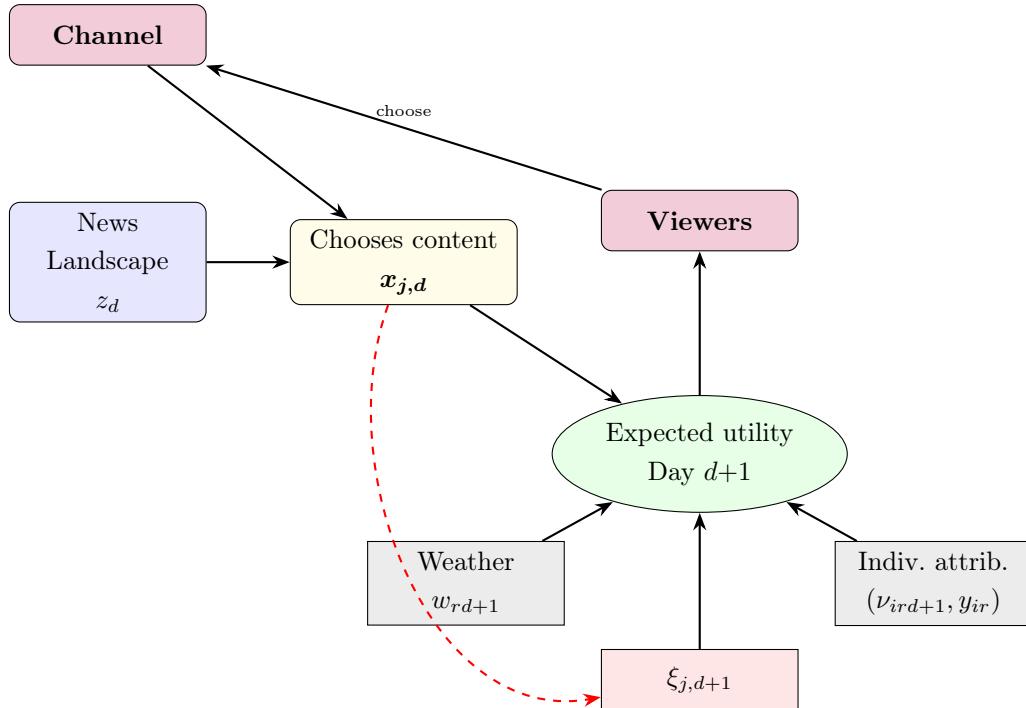
Notes: The figure shows the relative proportion of text mentions by political actor and channel for a random sample of 67 days.

**Figure A.16:** Net Tone per Channel and Politician



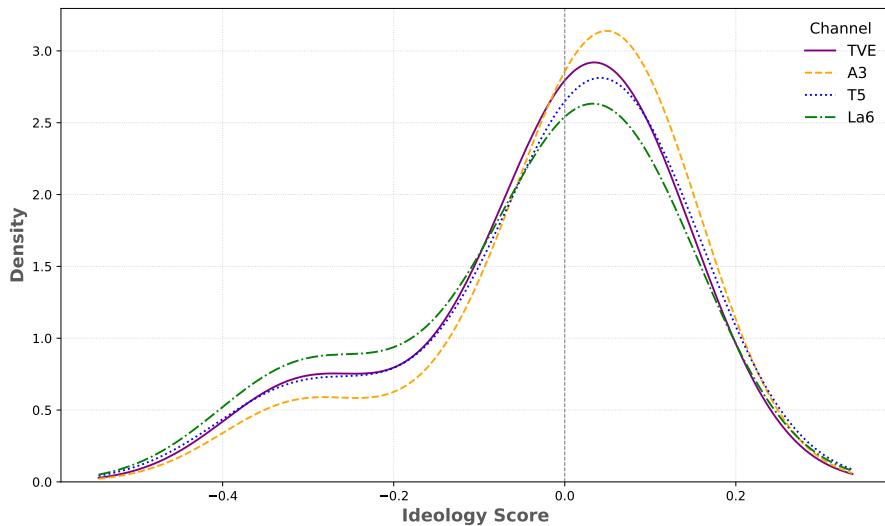
Notes: The figure shows the net tone based on the ChatGPT classification by political actor and channel for a random sample of 67 days.

**Figure A.17:** Trade-offs in the Model



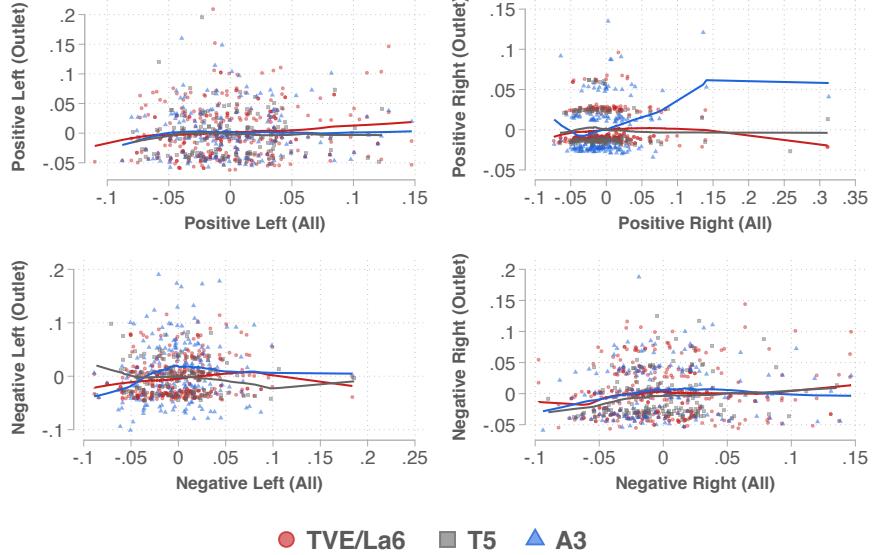
Notes: This diagram illustrates the structure of the model. Solid black arrows indicate causal and temporal dependencies among variables. The red dashed arrow emphasizes the simultaneity problem: content decisions  $x_{j,d}$  are made with knowledge of the future utility shock  $\xi_{j,d+1}$ .

**Figure A.18:** Density Estimation for Channels' Ideology (Audience Share)



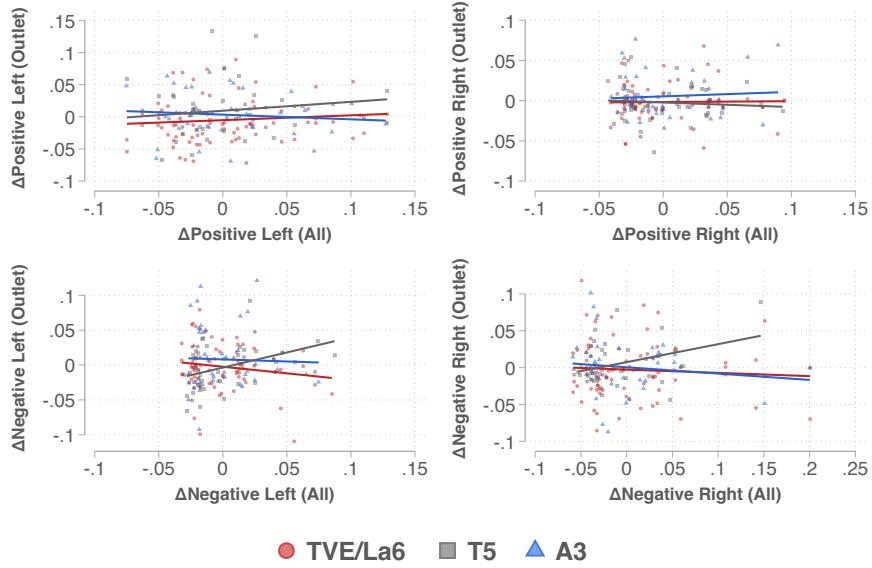
Notes: Estimated density of channels' audience ideology. The figure shows a kernel density estimate on the ideology score constructed using survey data and weighted by channels' share of audience for each autonomous region.

**Figure A.19:** Added Variable Plots for Production of Political Content (non-parametric fit)



Notes: The figure shows the added variable plots from the estimation of equation 6. The x axis represents  $(z_d^{party,+}, z_d^{party,-})$  and the y axis the corresponding  $(x_{jd}^{party,+}, x_{jd}^{party,-})$ . Channels are pooled into left (TVE and La6), middle (T5) and right (A3) for visualization purposes.

**Figure A.20:** Added Variable Plots for Production of Political Content (within day)



Notes: The figure shows the added variable plots from the analogous estimation of equation 6 using within day differences. The x axis represents  $(\Delta z_d^{party,+}, \Delta z_d^{party,-})$  and the y axis the corresponding  $(\Delta x_{jd}^{party,+}, \Delta x_{jd}^{party,-})$ . Channels are pooled into left (TVE and La6), middle (T5) and right (A3) for visualization purposes.

**Figure A.21:** Normalized Ideology Scores by Channel

(a) Demand: Viewers' Elasticities

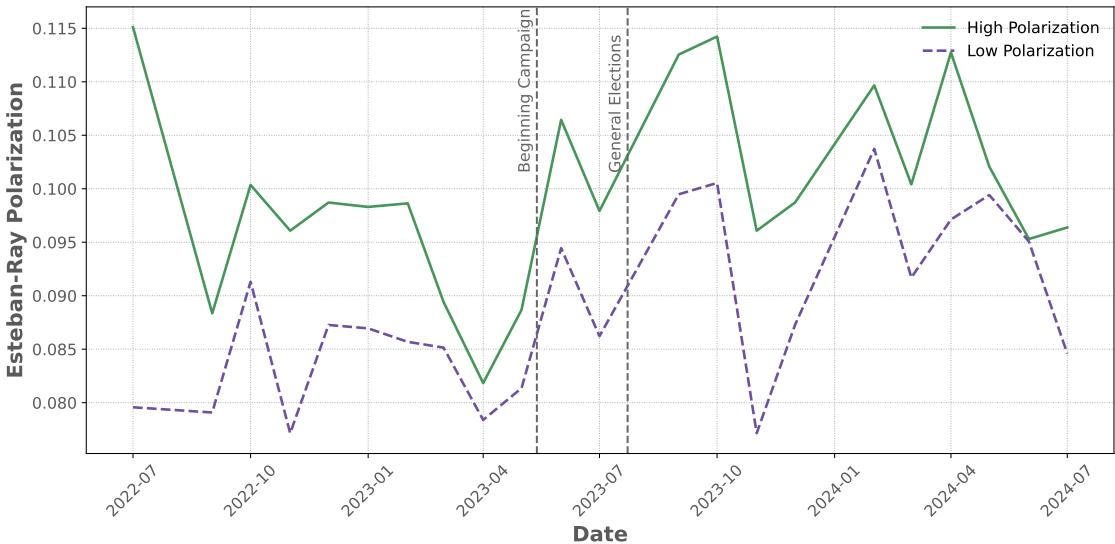


(b) Supply: ChatGPT text classification



*Notes:* The figure compares normalized left-right audience positions for Spanish television channels. Panel (a) positions channels according to the demand elasticities from the BLP estimation. Panel (b) shows the relative positions of the slant for the campaign according to the ChatGPT classification. Channels are mapped into the  $[-1, 1]$  scale using their correlation (tone) and normalizing values into this scale.

**Figure A.22:** Political and Media Polarization (no-smoothing)



*Note:* The figure shows the mean Esteban-Ray polarization index computed as in equation 9. Solid (dashed) line represents the regions above (below) the median in terms of their media polarization consumption according to index 10.

## B Tables

### B.1 Additional Results

Table B.1: Effect of Mentions on Tone toward Feij  o

	(1)	(2)	(3)	(4)
Text Mentions	-25.763 (50.044)	-51.515 (51.028)	42.517 (61.383)	6.957 (64.934)
Image Appearances	-4.373 (3.785)	-2.024 (3.852)	-12.421** (4.815)	-9.379* (5.112)
constant	-0.088 (0.076)	-0.093 (0.077)	-0.049 (0.093)	-0.053 (0.101)
Channel FE	No	Yes	No	Yes
Date FE	No	No	Yes	Yes
Observations	238	238	234	234

*Note:* Robust standard errors in parentheses. The table shows the estimated coefficients for a regression of net tone on the People's Party calculated as in 1, on the proportion of image appearances and text mentions of its party leader, Feij  o. Results are for a random sample of 67 days.

Table B.2: Effect of Mentions on Tone toward Abascal

	(1)	(2)	(3)	(4)
Text Mentions	-506.623*** (148.973)	-534.081*** (147.122)	-539.867*** (161.979)	-609.038*** (156.866)
Image Appearances	18.013** (9.077)	15.994* (8.996)	22.023** (10.119)	17.193* (9.898)
constant	-0.122** (0.057)	-0.109* (0.056)	-0.130** (0.057)	-0.099* (0.056)
Channel FE	No	Yes	No	Yes
Date FE	No	No	Yes	Yes
Observations	238	238	234	234

*Note:* Robust standard errors in parentheses. The table shows the estimated coefficients for a regression of net tone on VOX calculated as in 1, on the proportion of image appearances and text mentions of its party leader, Abascal. Results are for a random sample of 67 days.

Table B.3: Effect of Mentions on Tone toward Sánchez

	(1)	(2)	(3)	(4)
Text Mentions	61.471 (106.565)	196.424 (123.145)	27.282 (119.969)	193.827 (145.161)
Image Appearances	-2.352 (4.253)	-4.286 (4.331)	-7.639 (6.583)	-10.754 (6.971)
constant	0.054 (0.063)	0.014 (0.067)	0.120 (0.075)	0.077 (0.085)
Channel FE	No	Yes	No	Yes
Date FE	No	No	Yes	Yes
Observations	238	238	234	234

*Note:* Robust standard errors in parentheses. The table shows the estimated coefficients for a regression of net tone on PSOE calculated as in 1, on the proportion of image appearances and text mentions of its party leader, Sánchez. Results are for a random sample of 67 days.

Table B.4: Effect of Mentions on Tone toward Díaz

	(1)	(2)	(3)	(4)
Text Mentions	-11.990 (67.519)	21.235 (69.918)	-78.607 (91.794)	-19.353 (99.632)
Image Appearances	0.019 (0.512)	-0.072 (0.517)	-0.861 (0.595)	-1.032* (0.603)
constant	0.064 (0.044)	0.051 (0.045)	0.103** (0.051)	0.080 (0.054)
Channel FE	No	Yes	No	Yes
Date FE	No	No	Yes	Yes
Observations	238	238	234	234

*Note:* Robust standard errors in parentheses. The table shows the estimated coefficients for a regression of net tone on UP calculated as in 1, on the proportion of image appearances and text mentions of its party leader, Díaz. Results are for a random sample of 67 days.

Table B.5: First Stage Regressions

	(1) Positive Right	(2) Negative Right	(3) Positive Left	(4) Negative Left
<b>Positive Right (All)</b>				
TVE	0.00342 (0.08)	-0.00456 (-0.07)	-0.0498 (-0.71)	-0.0916 (-1.30)
A3	0.207*** (4.62)	-0.139 (-1.89)	-0.0615 (-0.81)	-0.113 (-1.47)
T5	-0.0372 (-0.88)	-0.0746 (-1.08)	-0.0943 (-1.31)	-0.166* (-2.28)
La Sexta	0.0334 (0.73)	-0.0129 (-0.17)	0.0290 (0.37)	-0.0256 (-0.33)
<b>Negative Right (All)</b>				
TVE	-0.0296 (-0.74)	0.00590 (0.09)	-0.0707 (-1.04)	0.0738 (1.08)
A3	-0.0333 (-0.79)	0.0929 (1.34)	-0.0104 (-0.14)	-0.0440 (-0.61)
T5	-0.0585 (-1.05)	0.131 (1.44)	0.0327 (0.35)	-0.0166 (-0.17)
La Sexta	-0.0185 (-0.42)	0.143* (1.97)	-0.0399 (-0.53)	-0.123 (-1.63)
<b>Positive Left (All)</b>				
TVE	0.0261 (0.68)	0.0634 (1.01)	0.200** (3.07)	-0.0511 (-0.78)
A3	0.00911 (0.22)	-0.0626 (-0.92)	0.0154 (0.22)	-0.0845 (-1.19)
T5	-0.0712 (-1.43)	-0.159 (-1.95)	-0.00405 (-0.05)	-0.0572 (-0.67)
La Sexta	0.00655 (0.16)	-0.0906 (-1.33)	-0.00875 (-0.12)	0.0718 (1.01)
<b>Negative Left (All)</b>				
TVE	0.0144 (0.32)	-0.0603 (-0.81)	-0.176* (-2.26)	0.149 (1.90)
A3	0.0446 (0.93)	-0.133 (-1.69)	-0.173* (-2.11)	0.184* (2.23)
T5	-0.141** (-2.66)	0.0136 (0.16)	-0.00461 (-0.05)	-0.0569 (-0.63)
La Sexta	0.0262 (0.53)	-0.141 (-1.73)	-0.139 (-1.65)	0.111 (1.31)
<b>Political (All)</b>				
TVE	0.0167 (0.82)	0.0680* (2.03)	0.0828* (2.38)	0.0494 (1.41)
A3	0.0187 (0.84)	0.145*** (3.98)	0.137*** (3.62)	0.175*** (4.59)
T5	0.0975*** (3.69)	0.0981* (2.26)	0.0837 (1.86)	0.125** (2.77)
La Sexta	0.0145 (0.63)	0.132*** (3.47)	0.123** (3.12)	0.0393 (0.99)

Note: Robust standard errors in parentheses; \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . The table shows the results of the first stage regressions in equation 6. The total number of observations is  $N = 687$

Table B.6: Logit Estimation Results with Standard Errors

Coefficient	Parameter	Estimate	Std. Error
<b>Pre-campaign</b>			
Positive Left	$\beta^{L+}$	-17.62	(14.344)
Positive Right	$\beta^{R+}$	-41.16**	(18.718)
Negative Left	$\beta^{L-}$	27.24	(20.268)
Negative Right	$\beta^{R-}$	66.04*	(34.668)
Political	$\beta^{political}$	14.28*	(7.465)
Weather	$\gamma$	0.01	(0.655)
Positive Left $\times$ Right-Mean	$\phi^{L+}$	47.67	(36.262)
Positive Right $\times$ Right-Mean	$\phi^{R+}$	111.13**	(50.798)
Negative Left $\times$ Right-Mean	$\phi^{L-}$	-81.40	(51.195)
Negative Right $\times$ Right-Mean	$\phi^{R-}$	-151.24*	(89.249)
Political $\times$ Right-Mean	$\phi^{political}$	-30.80	(18.952)
<b>Campaign</b>			
Positive Left	$\beta^{L+}$	222.18**	(110.419)
Positive Right	$\beta^{R+}$	-177.76**	(88.006)
Negative Left	$\beta^{L-}$	-153.39**	(76.074)
Negative Right	$\beta^{R-}$	147.85**	(69.428)
Political	$\beta^{political}$	-10.37**	(5.107)
Weather	$\gamma$	0.80***	(0.287)
Positive Left $\times$ Right-Mean	$\phi^{L+}$	-619.77**	(303.679)
Positive Right $\times$ Right-Mean	$\phi^{R+}$	461.19*	(242.882)
Negative Left $\times$ Right-Mean	$\phi^{L-}$	398.26*	(211.132)
Negative Right $\times$ Right-Mean	$\phi^{R-}$	-413.87**	(187.584)
Political $\times$ Right-Mean	$\phi^{political}$	28.91**	(14.181)

The table shows the results of the logit estimation of model 5. The estimations are divided into the pre-campaign and campaign period. Both day-of-the-week and outlet fixed effects are included. Standard errors are clustered at the region level. The total number of observations are  $N_{campaign} = 2307$  and  $N_{pre\_campaign} = 6604$ .

Table B.7: Top 5 Topics by Party-Tone Category on Agencia EFE after BERTopic.

Topic Words	Count
<b>Positive Right</b>	
vox, motion, abascal, censure, pp, tamames, santiago, garriga, parties, party feijoo, nñez, alberto, pp, leader, gamarra, parties, party, general, cuca guardiola, extremadura, mrida, mara, vara, extremeo, council, assembly, candidate mazn, valencian, president, corts, valencian, valencians, government, carlos electoral, elections, general, jec, board, campaign, 28m, 23j, vote	312 113 68 64 63
<b>Negative Right</b>	
vox, motion, abascal, censure, pp, tamames, santiago, garriga, parties, party abortion, castilla, healthcare, anti-abortion, pregnancy, abortions, law, mañueco code, criminal, sedition, embezzlement, reform, crime, penalties, amendments electoral, elections, general, jec, board, campaign, 28m, 23j, vote sánchez, pedro, feijoo, president, government, nñez, leader, alberto, pp, executive	369 112 81 71 69
<b>Positive Left</b>	
yes, only, reform, sexual, law, is, violence, reform, just, podemos sánchez, pedro, feijoo, president, government, nñez, leader, alberto, pp, executive yolanda, díaz, vice president, sumar, second, podemos, labor, leader, minister sumar, podemos, errejón, iu, íñigo, yolanda, parties, coalition, díaz, left-wing psoe, socialists, federal, secretary, parties, socialist, lobato, espadas, congress	200 183 179 142 129
<b>Negative Left</b>	
yes, only, reform, sexual, law, is, violence, reform, just, podemos sánchez, pedro, feijoo, president, government, nñez, leader, alberto, pp, executive vox, motion, abascal, censure, pp, tamames, santiago, garriga, parties, party sexual, assault, sexually, sexual, minor, violence, assault, convicted, abuse psoe, socialists, federal, secretary, parties, socialist, lobato, espadas, congress	182 153 129 108 72

Table B.8: Table shows the top 5 topics associated with the top stories that provided more positive/negative coverage for each party in the Agencia EFE corpus. words were translated to English with the help of ChatGPT.

Table B.9: Mean and Standard Error for 100 Rounds of ChatGPT Classification

Statistic	PP	PSOE	VOX	UP
Mean	-0.014	0.106	-0.053	0.024
Standard Error	0.003	0.004	0.001	0.002

Note: The table shows the mean and standard error for 100 rounds of ChatGPT classification of political content with 40 random political stories.

Table B.10: Estimated Elasticities by Left and Right markets

Characteristic	Pre-campaign		Campaign	
	Left Market	Right Market	Left Market	Right Market
Negative Left	1.481	0.136	-0.681	0.380
Positive Left	-0.011	0.129	0.754	-0.716
Negative Right	1.358	0.469	0.462	-0.182
Positive Right	-0.029	0.152	-1.371	0.133

*Note:* The table shows the average elasticities for each characteristic by right and left markets as defined in equation 8. Right markets are defined as regions with proportion of right wing voters above the median.

## B.2 Text Examples

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### Top Stories for Negative Left

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- Reduction of a convicted rapist's sentence in Salamanca under the "Solo sí es sí" law
  - Seville Court reduces a murder and sexual assault sentence by 5 years due to the "Solo sí es sí" law
  - Vox formally submits a motion of no confidence against Prime Minister Pedro Sánchez
  - Madrid's regional president, Isabel Díaz Ayuso, predicts that the "Mediator Case" will bring down the government
- 

### Channel Proportion of Negative Left

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TVE	0.037
Antena 3	0.184
Telecinco	0.037
La Sexta	0.01

---

Table B.11: Top table shows the main stories contributing to negative left content on 2023-02-27, the highest day with negative left content, summarized and translated to English by ChatGPT. Bottom table shows the proportion of minutes devoted to negative left content per channel on the same date.

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### Top stories for Negative Right

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- Congress declarations against Ayuso over alleged "bribes" to her brother
  - Marinaleda criticizes the "abusive" arrest of two residents during a protest against Vox
  - The Senate rejects a PP motion on the government's alleged partisan use of the Falcon jet
- 

### Channel Proportion of Negative Right

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TVE	0.074
Antena 3	0.038
Telecinco	0.067
La Sexta	0.148

---

Table B.12: Top table shows the main stories contributing to negative right content on 2023-05-17, the highest day with negative right content, summarized and translated to English by ChatGPT. Bottom table shows the proportion of minutes devoted to negative right content per channel on the same date.

Table B.13: Top trigrams for Positive Right and Negative Right in the Agencia EFE

Positive Right	Negative Right
vox secretary general	gürtel national service
vox ignacio garriga	gürtel trial service
general vox ignacio	valencia francisco camps
núñez feijóo called	gürtel trial gürtel
pp candidate elections	former president valencian government
vox parties madrid	valencian government francisco
josé sáenz buruaga	psoe deputy secretary general
núñez feijóo requested	gürtel trial madrid
maría josé sáenz	abortion law reform
may pp president	former valencian president francisco

The table shows the top trigrams for Positive Right and Negative Right in the Agencia EFE dataset using ChatGPT-based classification.

Table B.14: Top trigrams for Positive Left and Negative Left in the Agencia EFE

Positive Left	Negative Left
agriculture fisheries food	ere court sevilla
minister agriculture fisheries	social rights ione
dec gov president	social ione belarra
fisheries food luis	andalusian government josé
food luis planas	andalusia josé antonio
jan gov president	enforcement only yes law
psoe deputy secretary general	former president andalusian gov
council ministers approved	mediator case las palmas
minister economic affairs	mediator las palmas gran
first vice president minister	núñez feijóo accused

The table shows the top trigrams for Positive Left and Negative Left in the Agencia EFE dataset using ChatGPT-based classification.

Table B.15: Examples of Stories and Party-Tone

Story	Channel	Date	Tone-Party
<b>Teen Survey Shows Growing LGBT Identity</b>  “26 % of Madrid-area teenagers now identify outside the heterosexual label. 3 % identify as trans. Equality Minister Irene Montero warns that hate-speech ‘normalisation’ at school is making many hide their identity and calls on teachers and parents to defend new anti-bullying protocols...”	TVE	2023-04-14	positive UP
<b>Podemos Frames Vote as Housing Referendum</b>  “On Mallorca, Podemos declares 28-M a ‘referendum on the right to housing’. Party leaders claim credit for Spain’s first rent-control law, accuse coalition partners of stalling passage, and promise faster social-housing construction next term...”	A3	2023-05-15	positive UP
<b>Sánchez Pauses Campaign for NATO Summit</b>  “Fresh from taking over the EU Council, PM Pedro Sánchez suspends rallies to join NATO leaders in Vilnius. He will brief allies on Ukraine and Spain’s defence boost; the White House confirms President Biden will attend after a stop in London with King Charles III...”	A3	2023-07-09	positive PSOE
<b>Sánchez Visits Wildfire Zone, Reshuffles Cabinet</b>  “Touring the Teruel command centre, the PM links the massive blaze to climate change and urges ‘serious adaptation’. Minutes later La Moncloa announces a mini-reshuffle: José Miñones to Health and Héctor Gómez to Industry, Commerce”	TVE	2023-03-27	positive PSOE
<b>PP Demands Return of Sedition Charges</b>  “Opposition leader Feijóo brands the Penal Code reform ‘ridiculous’, calls for full reinstatement of sedition, and accuses Sánchez of weakening Spain to buy separatist votes. PP deputies will table their own text next week...”	TVE	2023-02-14	positive PP

<b>Feijóo Criticizes Government Size and Alliances</b>  “In Zaragoza Feijóo says Spain ‘doesn’t need 22 ministries and three vice-presidencies’, proposes 13-14 portfolios, and likens PSOE’s fiscal plan to Podemos. Sánchez counters that PP votes in Brussels match Vox on women’s rights...”	A3	2023-06-01	positive PP
<b>PP Lowers Taxes in Balearic Islands</b>  “First bill of the new PP-led Balearic cabinet scraps inheritance and donation tax for close relatives, cuts transfer tax to 2 % for first-time buyers under 30, and extends credits for green renovations. Regional PSOE says the move ‘starves’ public services...”	A3	2023-07-18	positive PP
<b>Vox Holds Key Role in Regional Talks</b>  “After 28-M gains, Vox negotiators press PP for cabinet seats in Valladolid and Burgos. In Aragón, Santiago Abascal meets Jorge Azcón to discuss immigration and farm policy in exchange for a coalition vote of confidence...”	LA6	2023-06-13	positive Vox
<b>Vox Launches Second No-Confidence Motion</b>  “Vox registers a fresh censure motion against Sánchez – this time fronted by 89-year-old economist Ramón Tamames rather than Abascal. PP says it will abstain, calling the move ‘electoral theatre’; socialists predict easy defeat...”	A3	2023-02-27	positive Vox
<b>Vox and PP May Enter Extremadura Parliament</b>  “Latest Extremadura poll shows PSOE at 32 %, short of a majority, while PP and Vox together could secure an absolute 34 seats. Socialist premier Fernández Vara warns a ‘reactionary pact’ would end rural-health rollout...”	T5	2023-05-23	positive Vox
<b>Podemos Faces Coalition Tensions with Díaz</b>  “In Madrid, Podemos brands Sumar talks ‘frozen’ and urges Vice-PM Yolanda Díaz to join its 28-M campaign rallies or risk splitting the left. Spokeswoman Ione Belarra says voters ‘deserve clarity’ on joint lists before June...”	A3	2023-04-09	negative UP

<b>Díaz–Podemos Division Widens Post-Launch</b>  “One day after Díaz launched Sumar without Podemos ministers on stage, both sides trade barbs. Podemos keeps open the door to running alone; Díaz insists a Sumar without Podemos ‘would not be a failure but a pity’...”	T5	2023-04-03	negative UP
<b>PSOE Suspends Deputy in Corruption Case</b>  “Socialists suspend Canary Islands MP Juan B. Fuentes and force him to relinquish his seat after police allege he led a livestock-subsidy racket. PSOE spokesman Patxi López demands swift judicial clarification to ‘protect the institution’...”	TVE	2023-02-27	negative PSOE
<b>Coalition Fractures over ‘Only Yes is Yes’ Law</b>  “Podemos accuses PSOE of ‘rolling back feminism’ by rewriting consent law with PP votes. After a week of insults across the aisle, both parties pivot to 28-M agendas, downplaying talk of an early split...”	A3	2023-04-21	negative PSOE
<b>Residents Protest Metro Damage in Madrid</b>  “Evacuated families in San Fernando de Henares block cement-injection works they blame for subsidence cracks. They chant ‘Ayuso, listen!’ and demand full buy-outs; regional officials say repairs are safe and urge calm...”	LA6	2023-01-05	negative PP
<b>Gürtel Scheme Sentences Upheld by Court</b>  “Supreme Court confirms 13-year term for Francisco Correa and 15 for Pablo Crespo over rigged contracts for Pope Benedict’s 2006 Valencia visit, rejecting all appeals. PP says it ‘respects the ruling’ and notes offences pre-dated Rajoy...”	A3	2023-04-10	negative PP
<b>Ayuso Strategy Aims to Outflank Vox</b>  “Leaked memo shows Madrid PP will ‘turn up the volume’ on culture-war issues to lure Vox voters and secure an outright majority for Isabel Díaz Ayuso. Critics warn rhetoric could deepen polarisation...”	A3	2023-05-18	negative VOX

<b>Díaz Warns of Right-Wing Coalition Risks</b>	LA6	2023-07-15	negative VOX
"Campaigning in Gijón, Díaz tells women a Feijóo–Abascal government would bring austerity ‘back to black-and-white Spain’. She urges progressives to unite under Sumar to stop Vox entering La Moncloa..."			

The table shows examples of story summaries by political sentiment. The header has been produced by ChatGPT as a summary of the story and stories have been translated to English with the help of ChatGPT.

Table B.16: Examples International News with Party Tone

Story	Channel	Date	Tone-party
<b>Justice Officials Lock In Courts</b>  "After a month of fruitless negotiations, court clerks barricade themselves inside dozens of courthouses for 24 h, demanding the same one-off pay rise recently granted to judges and prosecutors. The unions warn of massive case backlogs if talks do not resume. Strasbourg will monitor whether Spain abides by any future judgement on the dispute..."	TVE	2023-06-22	negative Left
<b>Prices Rise, but Economy Outperforms EU</b>  "Headline inflation ticks up to 4.1 percent in April, yet quarterly GDP expands by 0.5 percent—double the euro-area pace—thanks to booming exports and a rebound in machinery investment. Core inflation eases to 6.6 percent, prompting the government to claim its ‘targeted’ anti-price measures are working..."	La 6	2023-04-28	positive Left
<b>Gigafactory Launched in Sagunto</b>  "King Felipe VI and Prime Minister Sánchez lay the first stone of Volkswagen’s battery plant in Sagunto. The three-billion-euro project is slated to create three thousand direct and thirty thousand indirect jobs and anchor a full electric-vehicle supply chain on the Mediterranean corridor by 2026..."	La 6	2023-03-17	positive Left
<b>Ukraine War Triggers Fuel Price Surge</b>  "Russia’s blockade of Black Sea corridors and soaring gas prices push petrol above two euros per litre during the summer peak. Madrid extends a twenty-cent per litre rebate, caps basic energy tariffs and opens talks with Brussels on a broader Iberian price exception..."	A3	2023-02-24	positive Left

Story	Channel	Date	Sentiment
<b>Gov't Approves Student Housing Aid</b> “Cabinet earmarks two-point-five billion euros for grants and scholarships; rural students forced to leave home will now receive up to two thousand five hundred euros per academic year. Education Minister Alegría says the measure tackles both depopulation and unequal access to university...”	TVE	2023-02-21	positive Left
<b>Spain Secures EU Recovery Funds</b> “European Commission releases a further six billion euros after Madrid meets forty milestones on labour, pension and digital reforms. Vice-President Calviño hails the country as the ‘front-runner’ of Next Generation EU implementation and vows to accelerate project selection in the regions...”	La 6	2023-02-17	positive Left
<b>Spain Pushes Green Tax in EU</b> “During an informal Ecofin in Stockholm, Spain floats a climate levy on private jets and luxury yachts, arguing that the richest one percent emit far more than the poorest fifty percent. The plan will be tabled formally once Spain assumes the rotating Council presidency in July...”	La 6	2023-02-01	positive Left
<b>Spain Proposes Tax on Ultra-Rich</b> “Environment Minister Ribera outlines a two-percent wealth tax on fortunes above one hundred million euros to finance a permanent EU climate-adaptation fund. Analysts say the levy could raise eight billion euros annually across the bloc if adopted...”	La 6	2023-02-01	positive Left
<b>Spain Asks US to Remove Plutonium</b> “Foreign Affairs sends an official note to Washington urging removal of fifty thousand cubic metres of soil still contaminated by the 1966 Palomares nuclear accident. Local mayors say the clean-up would revive agriculture and tourism; the US has yet to reply...”	La 6	2023-03-06	positive Left
<b>Spain Leads in EU Recovery Program</b> “Another six billion euros disbursed as Spain confirms ninety-nine of one hundred and two commitments under Next Generation EU. A ten-member European Parliament mission will audit project rollout in Madrid, Andalusia and Catalonia next week...”	TVE	2023-02-17	positive Left

Story	Channel	Date	Sentiment
<b>Justice Protests as EU Ministers Meet</b> “Hundreds of justice-office clerks rally outside Logroño’s conference hall, accusing the government of ‘stonewalling’. Inside, EU ministers debate cyber-crime, organised crime and victim protection under Spain’s rotating presidency. . .”	TVE	2023-07-21	negative Left
<b>Self-Employed Hit by Rising Costs</b> “New survey finds sixty-seven percent of freelancers have raised their prices after business expenses jumped almost twenty percent in a year. Trade groups call for lower advance tax withholdings and more flexible social-security contributions. . .”	TVE	2023-07-10	negative Left
<b>Bank of Spain Cuts Forecasts</b> “The central bank trims 2023 growth to 1.3 percent as household spending weakens and interest rates stay high. It warns inflation will remain elevated ‘longer than anticipated’ but sees a rebound to 1.7 percent in 2024 if anti-inflation measures expire. . .”	TVE	2022-12-20	positive Left

International and economic stories whose framing implies a partisan slant even without explicit party names. Texts shortened, translated to English, and headlines created for display.

Table B.17: Agencia EFE case studies

Date	Characteristic	$\Delta x$	Top 3 Stories
2023-05-29	Negative Left	0.412	<p><b>PP Eyes Asturias Seat with Expat Votes</b></p> <p>“Final overseas ballots leave the Partido Popular only nine-hundred-and-thirty-four votes short of wresting a seat from the PSOE in Asturias, which would hand a PP–Vox–Foro bloc an outright majority in the regional assembly; the definitive recount on Wednesday could tip the balance...”</p> <hr/> <p><b>Abascal Urges Pact to Oust Sánchez</b></p> <p>“Cheered by the snap-election call, Vox leader Santiago Abascal appeals to Alberto Núñez Feijóo to show ‘statesmanship’, seal postelection pacts and ‘repeal sanchismo’—labelling the PSOE’s record on crime and the economy ‘disastrous’...”</p> <hr/> <p><b>Moreno Says Sánchez Acts to Save Himself</b></p> <p>“Andalusian premier Juanma Moreno calls the early vote ‘an act of political survival’, adding that the PM feels cornered by Sunday’s heavy losses and hopes to reset the narrative before Spain takes over the EU Council presidency.”</p>
2023-05-31	Negative Right	0.226	<p><b>Rato Blasts Anti-Corruption Prosecutors</b></p> <p>“Ex–IMF chief Rodrigo Rato denounces the ‘impunity’ of the prosecutor’s office after fresh money-laundering indictments and says he is confident the Supreme Court will keep him out of prison pending appeal...”</p> <hr/> <p><b>Calviño Defends Government’s Record</b></p> <p>“First Vice-President Nadia Calviño touts a ‘centrally balanced’ economic policy that lifted jobs and wages, rebutting Feijóo’s claim that Spain faces rising uncertainty and fiscal drift under the coalition...”</p> <hr/> <p><b>Sánchez Rallies Against ‘Emboldened’ Right</b></p> <p>“In a closed-door call, the PM urges the party machine to mobilise against ‘an emboldened PP backed by the far right’ and warns of a campaign based on ‘smears and fake data’ ahead of the twenty-three-July vote.”</p>

Date	Characteristic	$\Delta x$	Top 3 Stories
2023-05-31	Positive Left	0.282	<p><b>Subirats Pushes Two University Decrees</b></p> <p>“Universities Minister Joan Subirats says the early election is ‘the only sensible path’ and pledges to clear decrees on accreditation and staff tenure before the parliamentary freeze later this month...”</p> <hr/> <p><b>PP and PSOE Secure Millions in Subsidies</b></p> <p>“Interior Ministry figures show the Partido Popular will receive six-point-three-million euros for its twenty-three-thousand councillors elected on 28 May, while the PSOE will draw five-point-six million euros for its twenty-thousand local officials...”</p> <hr/> <p><b>Basque PP Offers ‘Free’ Investiture Votes</b></p> <p>“Basque PP chairman Iturgaiz says his party will support PNV–PSE mayoral nominees ‘gratis et amore’ to deny EH Bildu key councils but will demand policy input and committee seats for day-to-day governing.”</p>
2023-05-29	Positive Right	0.276	<p><b>PP Close to Win in Asturias</b></p> <p>“Expatriate ballots, to be counted Wednesday, could swing the last seat in Asturias and allow a PP–Vox–Foro coalition to unseat the Socialists after thirty-eight years of left-wing dominance...”</p> <hr/> <p><b>Abascal Backs Pact to Oust PSOE</b></p> <p>“‘We must agree as we did on 28 May,’ Abascal says, vowing to dismantle ‘gender ideology’ laws and roll back tax hikes if Vox enters a national coalition with the PP after July’s general election...”</p> <hr/> <p><b>Moreno Questions Election Timing</b></p> <p>“Andalusian president Moreno describes the PM’s dissolution of parliament as ‘a sign of weakness’, insisting that regional governments now need clarity on the next state budget before autumn.”</p>

The table shows days with highest increase in news production between midday and night editions for each content type together with the stories of that type that appeared on Agencia EFE between the two editions.

## C Isolation Index for Spanish Media

The isolation index is computed as:

$$\text{Isolation} = \sum_j \left( \frac{\text{Right}_j}{\text{Right}} \right) \left( \frac{\text{Right}_j}{\text{Audience}_j} \right) - \sum_j \left( \frac{\text{Left}_j}{\text{Left}} \right) \left( \frac{\text{Right}_j}{\text{Audience}_j} \right),$$

where  $\text{Right}_j$  and  $\text{Left}_j$  denote the numbers of right- and left-leaning viewers of outlet  $j$  and  $\text{Audience}_j$  is its total audience

Table C.18: Ideological Segregation by Medium (CIS Survey)

	Right exposure to		Isolation index
	Right	Left	
TV	0.425	0.322	0.103
Radio	0.484	0.181	0.303
Press	0.373	0.194	0.179

*Notes:* “Right exposure” for Right (Left) is the average share of Right users on outlets visited by Right (Left) respondents. The isolation index is the difference.

## D Chat GPT Ideology Classification

In this section I summarize the usage of ChatGPT as a text classifier for political tone. We detail the prompt and specification details used for the text classification together with final results.

To reduce both computational and monetary costs, I first filter our split stories using a simple dictionary based approach into those that might contain any relevant political information. Table D.19 shows the key terms used to filter the political stories. After the match, I obtain a final number of 15406 political stories that I feed into the chat GPT classifier.

Political	PP	PSOE	SUMAR/UP	VOX
política	pp	psoe	unidas podemos	vox
democracia	partido popular	partido socialista	podemos	abascal
partido político	feijoo	sanchez	ione belarra	de los monteros
gobierno	alberto nunez feijoo	federico buyolo garcia	pablo iglesias	macarena olona
elecciones	ayuso	maria jesus montero	yolanda diaz	ortega smith
votación	cuca gamarra	carmen calvo	irene montero	rocio monasterio
constitución	pablo casado	jose luis abalos	alberto garzon	ignacio garriga
legislación	esperanza aguirre	felix bolanos	iona errejon	jose alcaraz
senado	ana pastor	francina armengol	monica garcia	herminio campillo
congreso	pilar barreiro	sanchez mato	jaume asens	zambrano garcia
dictadura	rafael hernando	margarita robles	noelia vera	luis gestoso
soberanía	alvarez de toledo	marlaska	raul camargo	
estado	javier maroto	jose manuel albares	lopez de uralde	
ciudadanía		isabel rodriguez	rosa martinez	
derechos				
libertades				

Table D.19: The table shows the political words included to filter the stories into national politics. We included both general terms that refer to politics as well as party specific terms.

PP	PSOE	SUMAR/UP	VOX
pp	psoe	unidas podemos	vox
partido popular	partido socialista	podemos	abascal
feijoo	sanchez	ione belarra	de los monteros
alberto núñez feijoo	federico buyolo garcía	pablo iglesias	macarena olona
ayuso	maría jesús montero	yolanda díaz	ortega smith
cuca gamarra	carmen calvo	irene montero	rocío monasterio
pablo casado	josé luis ábalos	alberto garzón	ignacio garriga
esperanza aguirre	félix bolaños	íñigo errejón	josé alcaraz
ana pastor	francina armengol	mónica garcía	herminio campillo
pilar barreiro	sanchez mato	jaume asens	zambrano garcía
rafael hernando	margarita robles	noelia vera	luis gestoso
álvarez de toledo	marlaska	raúl camargo	
javier maroto	josé manuel albares	lopez de uralalde	
	isabel rodríguez	rosa martínez	

Table D.20: Party-specific political terms

política	democracia	partido político	gobierno	elecciones	votación
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constitución	legislación	senado	congreso	dictadura	soberanía
estado	ciudadanía	derechos	libertades	campaña	debate
reforma	corrupción	transparencia	poder judicial	poder ejecutivo	poder legislativo
demagogia	burocracia	ideología	socialismo	capitalismo	anarquismo
populismo	liberalismo	conservadorismo	totalitarismo	autoritarismo	nacionalismo
federalismo	municipalismo	diplomacia	alianza	tratado	cumbre
embajada	consulado	acuerdo	plebiscito	referéndum	presidente
ministro	formación	votar	candidato	candidatura	programa electoral
propuesta	ley	oposición	mayoría		

Table D.21: General political terms arranged in six columns

### Prompt

Analyze the sentiment of the following news article with respect to the political parties (and their members) in Spain: PP, Podemos/Sumar, PSOE, VOX. Only use numeric values from the set [-1, -0.5, 0, 0.5, 1].

Evaluate the sentiment towards each party with a number between -1 and 1, where -1 indicates an extremely negative perception, 0 indicates neutrality or irrelevance for the party, and 1 indicates an extremely positive perception.

Consider only the values -1, -0.5, 0, 0.5, and 1.

Base your evaluation solely on the explicit content of the news article. If the article does not mention or imply any sentiment towards a party, assign a 0 to that party.

The format must always be a list [PP , PSOE , UP , VOX ] where X represents the numeric sentiment value.

Note: Prompt used under *gpt-4-0125-preview*.

## E Digression: LLMs Stability and Alternative Ideology classifications

### Stability of the classifier

Due to the stochasticity in LLMs predictions, good practices recommend to run the classification multiple times and average out the results (Törnberg, 2023). Financial costs, however, impede me from doing the whole approach multiple times but I show results on stability below on a random subset of 40 stories. Table B.9 shows the mean and standard deviation of the classification output for 100 rounds of classification.

Results of the final classification for the non neutral stories are shown in figure ???. Each bar represents the percentage of stories of that given sentiment associated to each political party. We can see that the classification reserved the extreme values 1 and -1 for few stories and focused on the -0.5 and 0.5 values.

## Alternative Ideology Classification

Similar to [Gentzkow and Shapiro \(2010\)](#) and [Laver et al. \(2003\)](#) I exploit party ideology in congress speeches to calculate similarity measures of the outlet's speech. I make use of all congressional speeches produced during my sample period and associate each speaker with their respective political party, filtering to retain the set of relevant parties.

I follow a similar, non-linear version of [Laver et al. \(2003\)](#) and create a score for each word  $w$  in the congress speech as:

$$\text{Score}(w) = \ln \left( \frac{\text{freq}(w, \text{Left}) + \alpha}{\text{Total}_{\text{Left}} + \alpha} \right) - \ln \left( \frac{\text{freq}(w, \text{Right}) + \alpha}{\text{Total}_{\text{Right}} + \alpha} \right), \quad (15)$$

where:

- $\text{freq}(w, \text{Left})$  is the number of times word  $w$  appears in the speeches of left-leaning parties (PSOE and UP),
- $\text{Total}_{\text{Left}}$  is the total word count in left-party speeches,
- $\text{freq}(w, \text{Right})$  and  $\text{Total}_{\text{Right}}$  are defined analogously for right-leaning parties (PP and Vox), and
- $\alpha$  is a small smoothing parameter.

I select the value of alpha that maximizes accuracy of label prediction in the congress dataset;  $\alpha = 0.9$ . Words with high positive scores are used disproportionately in left-leaning speeches, while those with high negative scores are more characteristic of right-leaning speeches. I rank all words by their computed score and select the top 100 left-coded words and top 100 right-coded words, represented in wordcloud figures ?? and ??.

**Figure E.23:** Word Cloud Top Left Words



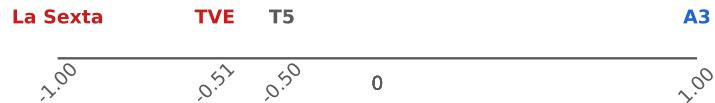
**Figure E.24:** Word Cloud Top Right Words



Notes: The wordclouds represent the Top Words with lowers (left) and highest (right) scores as defined in equation 15. Size of the word is weighted by word frequency appearance.

Finally, to classify the channel data, I calculate for each channel the fraction of tokens that appear in the left-coded list versus the right-coded list. This yields an index of ideological slant that reflects which side's language is more prevalent in the channel's content. The

**Figure E.25:** Normalized Ideology Scores



Notes: The figure shows the normalized ideology positions of the channels after the text classification based on congress speeches.