The Impact of Political Campaigns on Demand for Partisan News

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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 horizontal-differentiation game. Finally, I run counterfactual simulations to assess the effect of policies regulating campaign airtime. My framework offers a tractable tool for evaluating media policies aimed at content fairness or fighting misinformation.

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1 Introduction

Political polarization has surged in both the United States and Europe over the past decade (Boxell et al., 2020; Reiljan, 2019). Extensive research highlights the role of social media in driving this trend (Zhuravskaya et al., 2020). However, far less is known about polarization on TV, which remains the primary source of political information across Europe. While television 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 methods based on congress speeches, dictionary counts, and image appearances of political leaders.

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. This variation, which is not driven by viewer demand, allows me to identify the parameters of the demand model. 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 fight political plurality have often been found to be insufficient due to 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 forcing outlets to devote relative political time to a party according to past election results. Consistent with the way this policy is enforced, I only regulate total airtime, thus letting channels adjust through tone.

This paper is the first existing effort to quantitatively monitor media 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. Earlier studies measure media bias using candidate endorsements (Chiang and Knight, 2011), textual analysis (Gentzkow and Shapiro, 2010; Gentzkow et al., 2019), or the share of speaking time allocated to each side (Durante and Knight, 2012; Cagé et al., 2022). I introduce a new methodology that merges slant and airtime by employing large language models (LLMs) for text classification. Validation with survey data on political preferences shows that this approach outperforms previous text-based methods that rely on congressional speeches. In addition, the machine-learning framework pinpoints both the tone and the time devoted to the same story on a given day across outlets, allowing me to track the topics on which outlets converge. The measure thus unifies several approaches previously treated separately in the literature (Puglisi and Snyder, 2015) and complements theoretical work on the sources of media bias. By using upstream news providers as proxies for the overall news landscape, the analysis also speaks to bias generated by *filtering* versus outright *distortion* (Gentzkow et al., 2014).

The closest empirical work estimates demand for like-minded political news. Simonov and Rao (2022) classify government-sensitive content and match it to individual browsing data to estimate a structural model of news acquisition; they find that outlet-specific factors drive demand and create inertia in sensitive-news consumption. Other studies document sizable demographic differences in news choices across content types (Gambaro et al., 2021; Bang et al., 2023).

Evidence on the media's role in political polarization is mixed. Laboratory experiments suggest that already-polarized viewers self-select into polarized news sources, with media having limited effects (Arceneaux and Johnson, 2013), but there is evidence of polarizing effects by affecting those already away from the political center (Levendusky, 2013). Martin and Yurukoglu (2017) show that cable-news polarization can account for much of the rise in voter polarization: using channel positions as instruments for U.S. TV consumption, they estimate a dynamic model in which ideology evolves with the slant consumed and conclude that roughly two-thirds of the observed increase stems from cable news. I introduce a new identification strategy that isolates short-run effects in settings where their instrument is infeasible. Although data limitations prevent me from modeling belief updating directly, I present correlational evidence linking media and political polarization: regions with more polarized media consumption are also more politically polarized, and the latter series exhibits a clear break during campaign periods.

The identification strategy exploits supply-chain flows from news aggregators. A similar mechanism appears in Djourelova (2023), who study how an Associated Press keyword ban altered U.S. newspaper coverage. I show that news-aggregator feeds provide a credible proxy for the daily news landscape and yield exogenous variation in story availability.

Social media is known to amplify polarization by creating online echo chambers (Bail et al., 2018; Zhuravskaya et al., 2020). I add to newer evidence on traditional media (Schneider-Strawczynski and Valette, 2025) by showing that television can likewise intensify polarization during election campaigns—a critical period for voting decisions.

Methodologically, the paper relates to work that estimates complete market structures in political contexts. Longuet-Marx (2025) embed a BLP-style demand for candidate positions in a positioning game, while recent studies incorporate text embeddings and imagery to build product characteristics in demand models (Compiani et al., 2025). I contribute a scalable method for constructing slant characteristics from text that captures both coverage intensity and ideological tone, offering a market-differentiation index for products that might otherwise appear homogeneous.

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.

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. Finally, Section 6 presents the estimation of the supply-side parameters.

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 based on survey data for both Spain and Europe. 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.

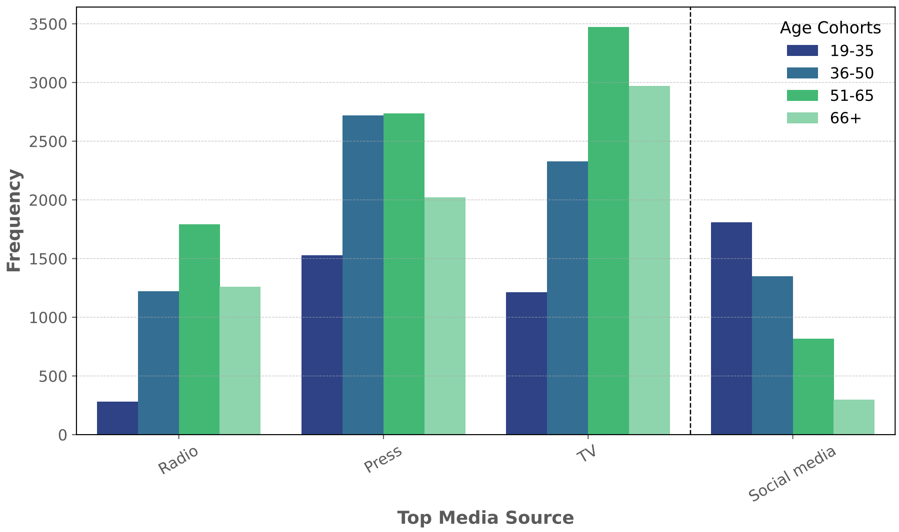
Spanish TV market

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 in the left panel 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.13 shows that 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.

Figure 1: Top media source to acquire political information by age cohorts in Spain



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

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 the party began to attract a substantial portion of the electorate.[1] 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

[1]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.

forward the general elections to June 23, 2023.[2] For the rest of the analysis, parties will be pooled into right (PP and VOX) and left (PSOE and Podemos).

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 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[3]. 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.[4]

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.12.

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

[2] I refer readers to the Spanish Media Monitor webpage to explore various metrics of coverage across political parties and actors.

[3] 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.

[4] This might pose problems in the substitutions toward the outside option. If people do not substitute LaSexta for the other channels due to timing differences, this might bias the elasticity of substitution toward the other outlets.

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.[5]

Agencia EFE

I obtain all news stories provided in Spanish by one of the largest news agencies in the 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.[6] 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 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.

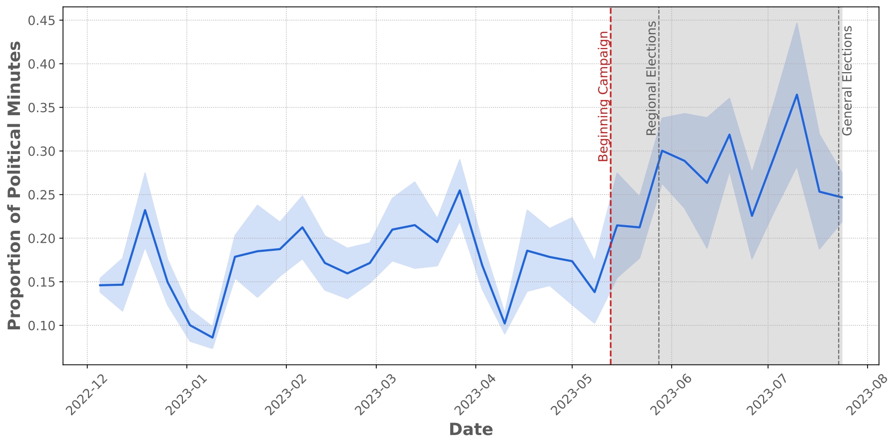
Figure 2 shows the weekly average proportion of time devoted to national politics over time, where the *campaign* period corresponds to the shaded span and vertical dashed lines mark the beginning of the campaign, the regional elections, and the national elections, respectively. A channel is defined to spend one minute on national politics if the associated

[5]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).

[6]See, e.g., collaborations with Mediaset, Atresmedia, and RTVE.

text for that minute contains any of the party matches in the dictionaries in Table 20. Off-campaign, channels spend on average nearly 18% of their daily time on politics. Naturally, this increases to 30% during campaign periods.

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 20. Vertical, dashed lines indicate the date of the regional and general elections, respectively. The shaded area represents the "campaign" period considered.

3.2 Political Tone

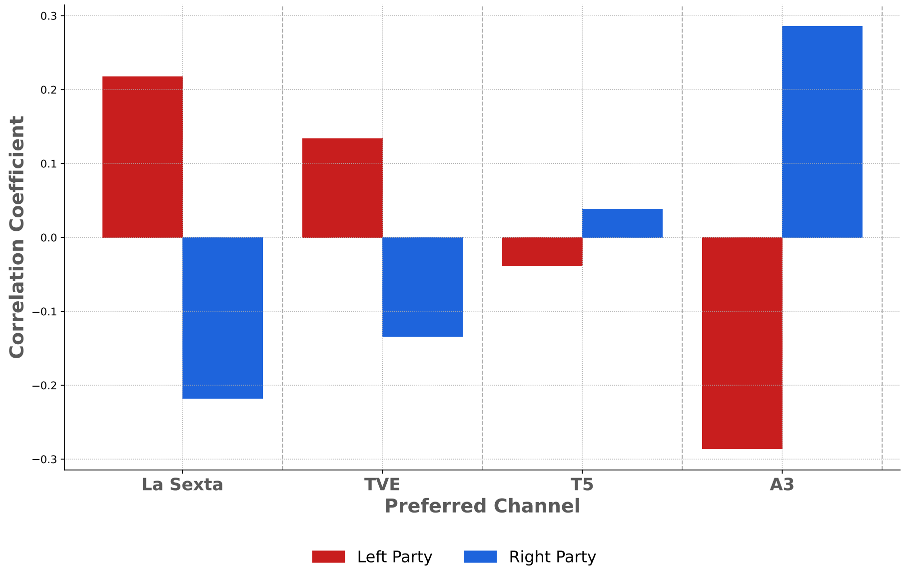
Here I describe the methodology used to classify the political tone of the content broadcast. Under market equilibrium, an outlet's slant should match its audience's political leaning. Because the slant classification is unsupervised, I use survey data to evaluate the ideology of each channel's viewers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

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 appears in the middle, with weak correlations.

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

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

outlets are consistent with those shown in Figure 3. Bearing this in mind, I now present the content classification for the outlets' slant (supply) and compare it with the ideology of their viewers.

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-4o, 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 C. 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, identified by keyword matches from Table 20 in addition to general words related to politics.

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 18 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.

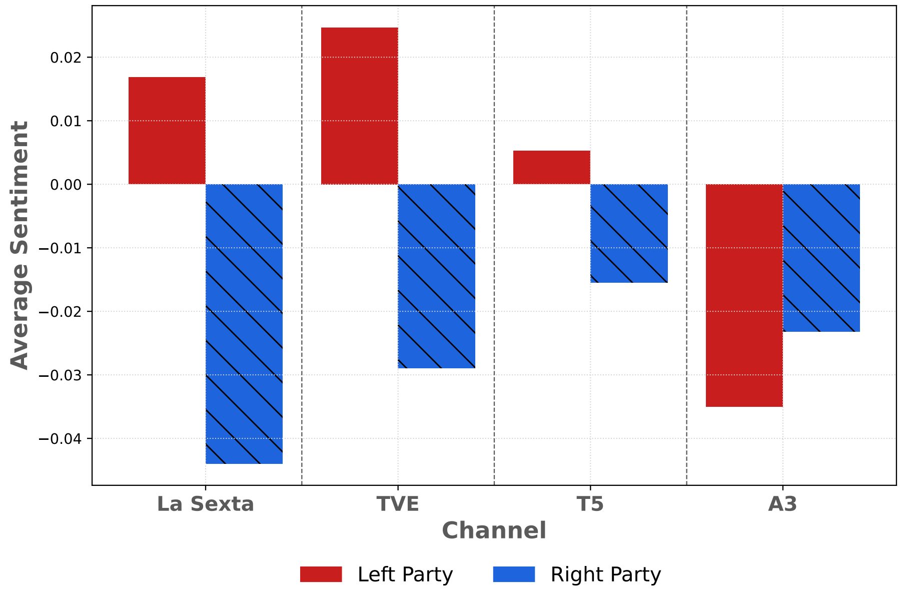
A story can be mapped to its duration in minutes, $min(s)$. This is key to accounting for the intensive margin. Combining all these characteristics—i.e., party label, tone, and minutes—I define the shares of positive and negative minutes, as well as the share of airtime devoted to politics, as follows:

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

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.

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

Figure 4: Average sentiment across channels and parties



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

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

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, respectively.

Figure 5 panes a) and b) shows the scores according to viewer's ideology and channels slant; respectively. 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

(a) Demand: Viewers' ideology *(b) Supply: ChatGPT text classification*

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 11 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. I use all Spanish congress speeches during my sample period and exploit party labels to assess similarities with the outlets' content (Gentzkow and Shapiro, 2010; Laver et al., 2003). Appendix D details the methodology. Importantly, Figure D.25 shows the left–right positions derived from this method, which consistently map to the ChatGPT classification in Figure 4, confirming the approach's validity.

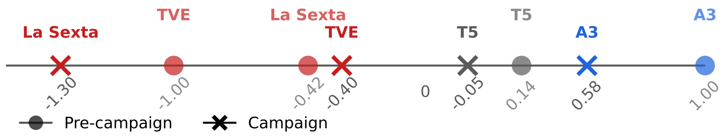
Political Tone and Electoral Campaign

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.14. 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.

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

Figure 6: Change in positions off-campaign to campaign



Notes: The figure shows the relative change in positions of the slant from off-cmapaign 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.

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.15 and A.16 show the proportions of image appearances and word mentions by channel and political leader. Figure A.17 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.16 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 4 through 7 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 my 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, 1994) (BLP) estimation[7]. 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 $j \in \mathcal{J} \equiv \{La6, TVE, T5, A3\}$ [8] to watch at the beginning of day d based on the following expected utility :

$$U_{ijrd} = \underbrace{\sum_k x^k_{jd-1}\beta^k + w_{rd}\gamma + \xi_{jrd}}_{\delta_{jrd}} + \underbrace{\sum_k x^k_{jd-1}\left(\sigma^k \nu^k_{ird} + \pi^k y_{irm}\right)}_{\mu_{ijrd}} + \epsilon_{ijrd} \tag{3}$$

where x^k_{jd} 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

[7] The model is estimated under the *pyblp* package (Conlon and Gortmaker, 2020).

[8] 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.

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 π^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 or specific regional taste shocks due to local events. 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 expectation formation for next day unobserved preferences ξ_{jrd+1} in the moment of setting todays' content $\boldsymbol{x_{jd}}$.

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:

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

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 (i.e $\boldsymbol{\sigma} = 0$) and there is no heterogeneity in the distribution of ideology in a given region $y_{ir} = \bar{y_r}$, equation 3 is consistent with a plain logit model as:

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

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

4.1 Content endogeneity and news shocks

Previously, demand estimation has often treated content characteristics as exogeneous 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 7 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 ξ—as well as on yesterday's content slant $\boldsymbol{x}_{jd}$. 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≈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*:

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

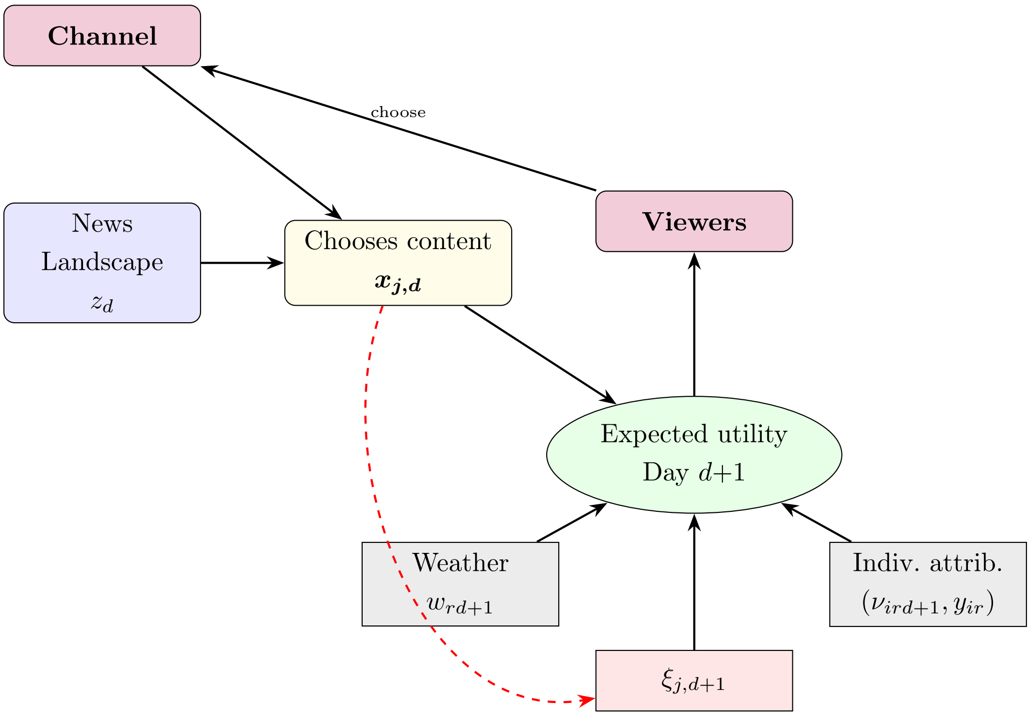
Here S_d denotes the total number of EFE stories on day d, and $\mathcal{P}_d$ the subset classified as political. The *news landscape* is common for all the outlets but will affect them asymmetrically due to their ideal positions. Channels would like to produce at their steady state, average positions (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.

Tables 13 and 14 illustrate the content–supply mechanism. 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

Figure 7: 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 $\boldsymbol{x}_{j,d}$ are made with knowledge of the future utility shock $\xi_{j,d+1}$.

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 %.

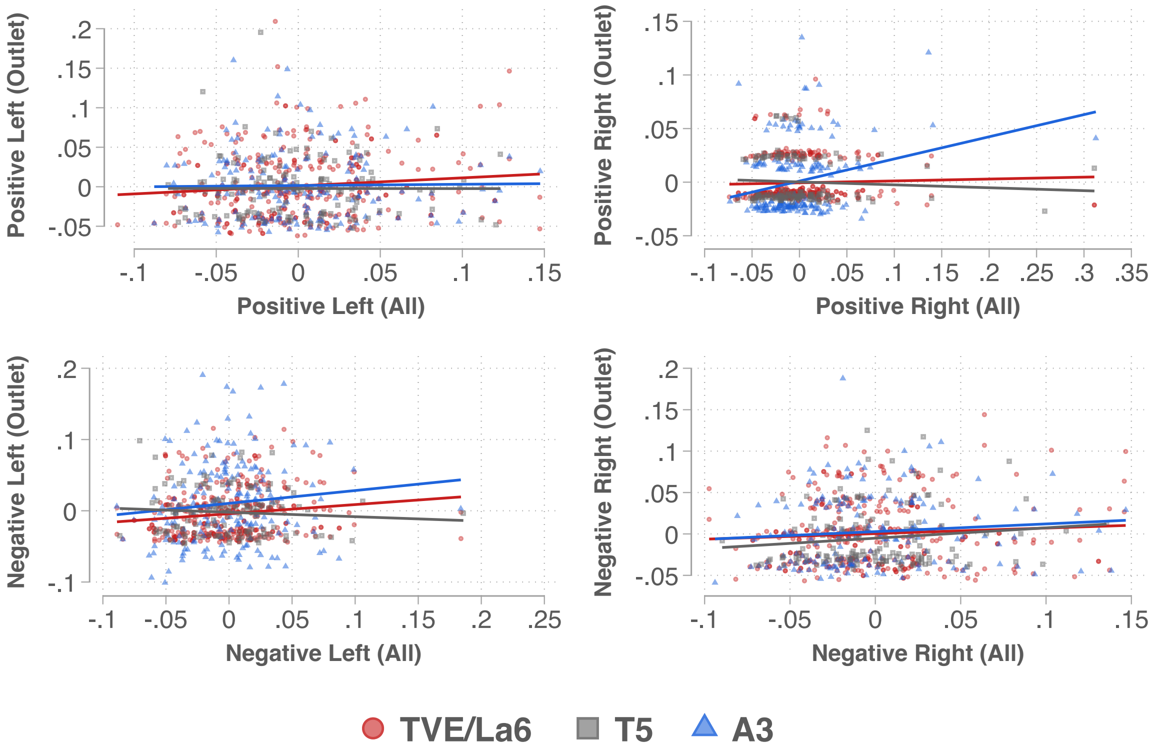
In order to show formal evidence of the previous mechanism, I estimate, for each $(party, tone)$ pair, separate regressions of the form:

$$x_{jd}^{party,tone} = \sum_k \left(\boldsymbol{d}_j \times z_d^k\right) \alpha_j^k + \left(\boldsymbol{d}_j \times z_d^{political}\right) \alpha_j^{political} + \epsilon_{jd}, \tag{7}$$

where $k \in \{L+, R+, L-, R-\}$. As was described before, $x_{jd}^{party,tone}$ is outlet j's share of airtime with positive or negative tone about *party*, $z_d^{party,tone}$ is the corresponding share among all EFE stories, and $\boldsymbol{d}_j$ is a vector of outlet dummies. 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 $\alpha_j^{R,+}$.

Figure 8 presents added-variable plots for regression equation (7) (a LOWESS version appears in Appendix Figure A.19). A one-percentage-point rise in negative left-wing stories is associated with a 0.49 pp increase in Antena 3's negative left coverage, compared with 0.27 pp for the left-leaning channels. The pattern reverses for positive left coverage: left-leaning outlets expand output more than the right-leaning one. As shown in figure 4, all outlets on average speak negatively about the right. The fact that there are not significance differences for the negative right tone is consistent with a crowding out effect that limits channel's adaptation ability in this category.

Figure 8: 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 $\left(z_d^{party,+}, z_d^{party,-}\right)$ and the y axis the corresponding $\left(x_{jd}^{party,+}, x_{jd}^{party,-}\right)$. Channels are pooled into left (TVE and La6), middle (T5) and right (A3) for visualization purposes.

Accordingly, I use $\left(z_d^{party+}, z_d^{party-}, z_d^{political}\right)_{party\in\{L,R\}}$ 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.

For the K non-linear parameters governing preference heterogeneity I follow Gandhi and Houde (2019). Instruments take the form $\left(\hat{x}_{jd}^k - \sum_{l\neq j}\hat{x}_{ld}^k\right)^2$, 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, $\bar{y}_r\,\hat{x}_{jd}^k$.

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.

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 average, unattractive. Third, there is no sizable dispersion in the taste parameters captured by the estimated σ. 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).

Table 2: BLP Estimation Results with Standard Errors

Coefficient	**Parameter**	**Estimate**	**Std. Error**
	Pre-campaign		
Positive Left	β^{L+}	-16.90	(11.73)
Positive Right	β^{R+}	-25.53	(31.03)
Negative Left	β^{L-}	28.29	(25.89)
Negative Right	β^{R-}	56.44**	(28.45)
Political	$\beta^{political}$	11.49***	(4.28)
Weather	γ	0.00	(0.03)
Positive Left	σ^{L+}	0.44	(296.90)
Positive Right	σ^{R+}	0.68	(715.26)
Negative Left	σ^{L-}	12.64	(8.68)
Negative Right	σ^{R-}	21.99	(13.83)
Political	$\sigma^{political}$	0.00	(46.79)
Right-Wing × Positive Left	π^{L+}	46.26	(48.70)
Right-Wing × Positive Right	π^{R+}	77.81	(95.92)
Right-Wing × Negative Left	π^{L-}	-70.09	(57.97)
Right-Wing × Negative Right	π^{R-}	-103.71	(97.76)
Right-Wing × Political	$\pi^{political}$	-25.17**	(12.59)
	Campaign		
Positive Left	β^{L+}	134.16**	(65.57)
Positive Right	β^{R+}	-129.79***	(48.43)
Negative Left	β^{L-}	-104.84**	(41.32)
Negative Right	β^{R-}	92.62**	(41.63)
Political	$\beta^{political}$	-6.43**	(3.26)
Weather	γ	0.00	(0.01)
Positive Left	σ^{L+}	0.00	(320.36)
Positive Right	σ^{R+}	19.25*	(10.89)
Negative Left	σ^{L-}	0.00	(134.33)
Negative Right	σ^{R-}	0.02	(73.18)
Political	$\sigma^{political}$	0.00	(19.55)
Right-Wing × Positive Left	π^{L+}	-421.99**	(176.15)
Right-Wing × Positive Right	π^{R+}	334.94***	(127.41)
Right-Wing × Negative Left	π^{L-}	288.65**	(116.22)
Right-Wing × Negative Right	π^{R-}	-280.33***	(104.44)
Right-Wing × 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 $N_{pre\_campaign} = 6604$.

Elasticities

I present the estimated 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 kth characteristic as:

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

The estimated elasticities for right and left-markets [9] across tones are shown in figure 9 for the pre-campaign and campaign periods; respectively. Estimate results are also shown in Table 12 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 campaign periods vs a 0.31 per cent decline in pre-campaign.

This means that an in crease 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.

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.

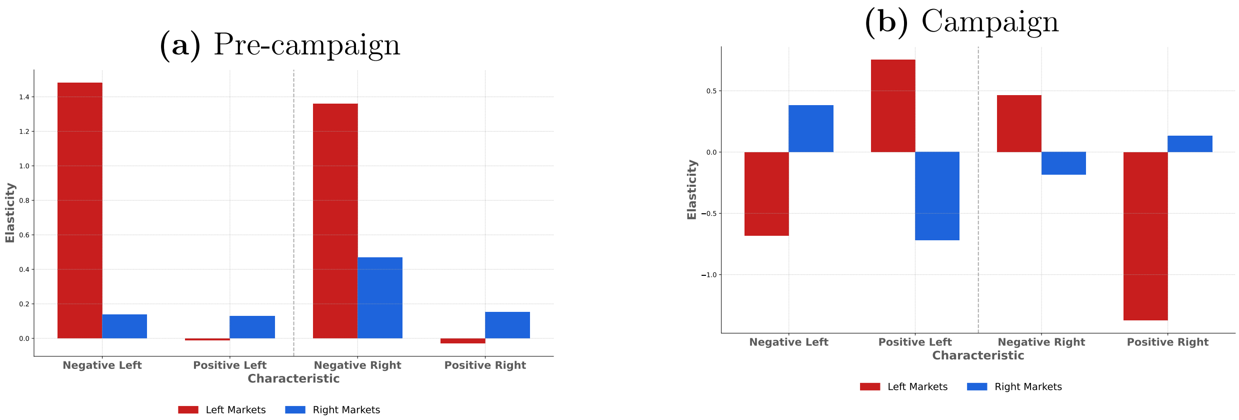
Political Polarization

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:

$$ER_{rm} = \sum_p \sum_q s^{1+\alpha}_{prm} \, s_{qrm} \times 1, \qquad \alpha = 1.5, \tag{9}$$

[9] Where a region is define as right if the proportion of right-wing voters is above the median.

Figure 9: Estimated Elasticities for Right and Left markets, Pre-campaign and Campaign



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

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:

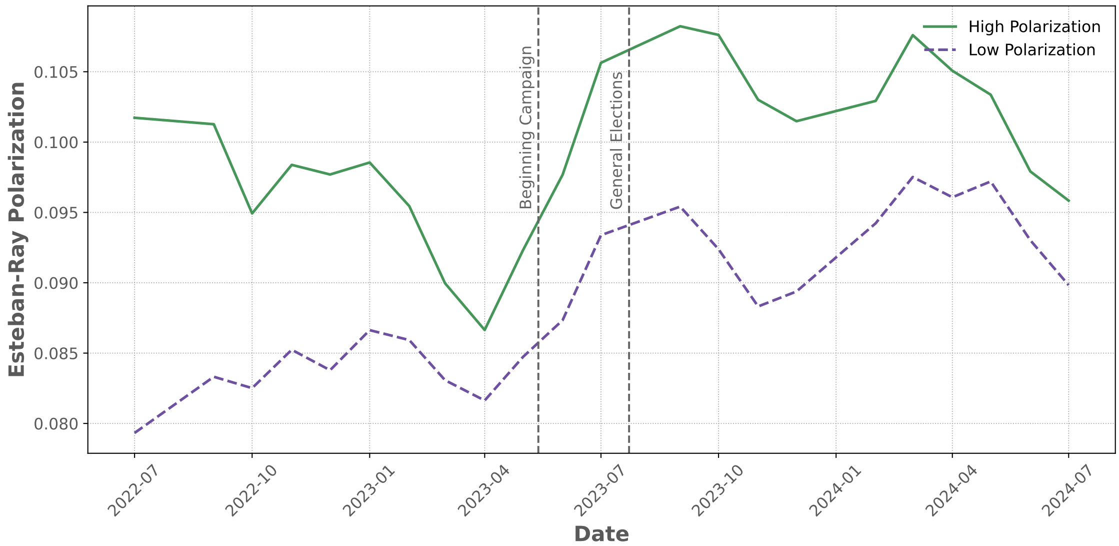
$$MediaPol_r = \begin{cases} \bar{\epsilon}_r^{(L-)} - \bar{\epsilon}_r^{(L+)} & if \quad p(r) = R \\ \bar{\epsilon}_r^{(R-)} - \bar{\epsilon}_r^{(R+)} & if \quad p(r) = L \end{cases} \tag{10}$$

I divide regions in *high* and *low* groups according to their media polarization index relative to the median. Figure 10 plots the smoothed ER_{rm} for both groups over the year before and after the 2023 general election [10]. 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.

In order to check weather 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. Results are robust. However, the use of aggregate data cannot rule out selection effects. Campaigns might change audience composition to news seekers that have been shown to be

[10]Raw time series are shown in appendix figure A.22.

Figure 10: 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.

the ones more affected by media polarization in prior work (Levendusky, 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)[11]

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

[11] Source: https://cadenaser.com/ser/2014/12/03/television/1417630810_539829.html

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

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

$$
\mathcal{C}(x^k_{jdh}, z^k_{dh}, \omega^k jdh; \lambda^k_j) \equiv \lambda^k_j \frac{(x^k_{jdh})^2}{z^k_{dh}} + F(\omega^k_{jdh})
$$

where there is a channel-characteristic specific parameter that governs the slope of the production cost and unobserved (to the econometriciaan) cost factors other than the stories available; $F(\omega^k_{jdh})$. By assumption, these unobservables will enter as linear terns in the marginal costs. The sign of λ^k_j 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 production easier since the journalist need not do much effort to find them. This will imply $\lambda^k_j > 0$. 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 $\lambda^k_j < 0$.

First-Order Conditions and Endogeneity

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

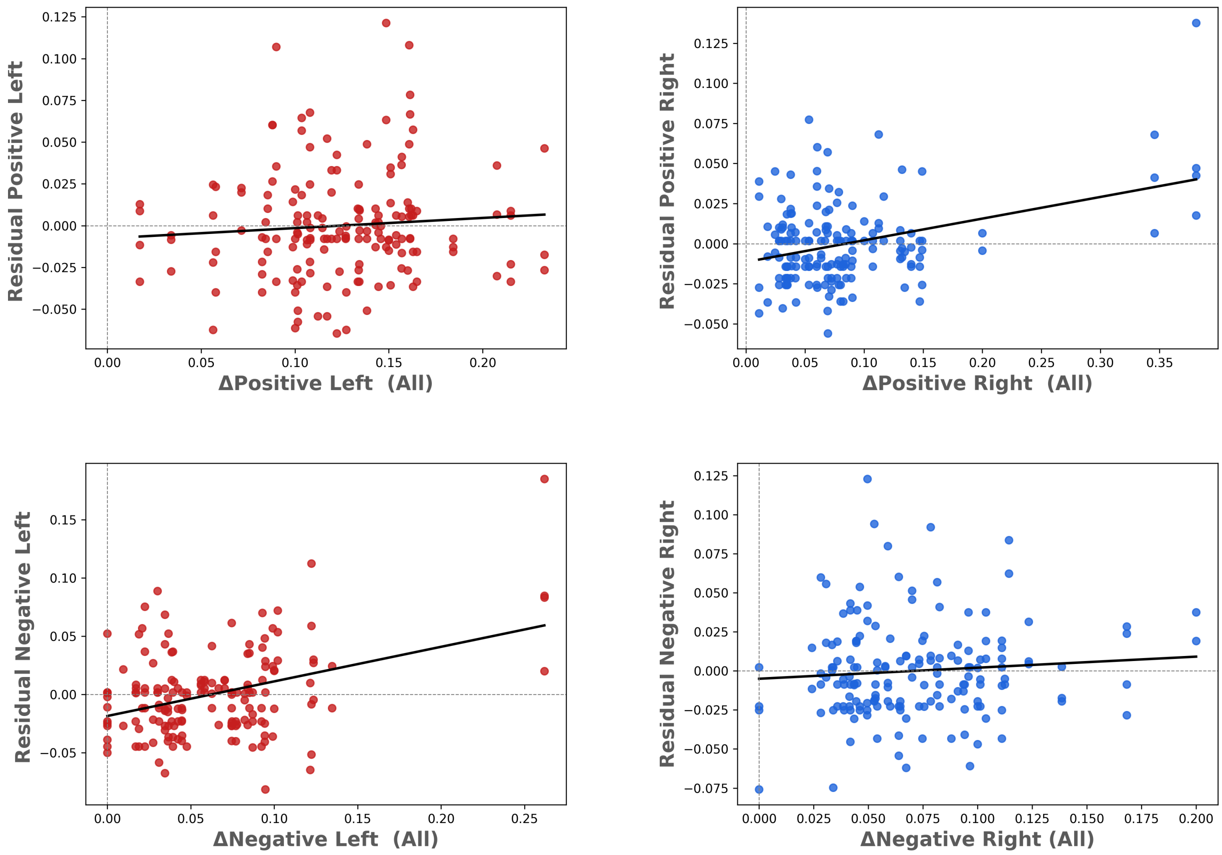
$$
\sum_r \frac{\partial s_{jrd+1}}{\partial x^k_{jdh}} \frac{L_r}{L} = 2\lambda^k_j \frac{x^k_{jdh}}{z^k_{dh}} + \underbrace{\eta^k_{jd} + \nu^k_{jdh}}_{\equiv F'(\omega^k_{jdh})}, \tag{12}
$$

I decompose the unobserved cost factors into η^k_{jd}, 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 ν^k_{jdh} is transitory noise. Because η^k_{jd} influences both marginal cost and the share gradient $g^k_{jdh} \equiv \sum_r \partial s_{jrd+1}/\partial x^k_{jdh}\,(L_r/L)$, λ^k_j would be biased in a naive regression: $\mathbb{E}[g^k_{jdh}\,\eta^k_{jd}] \neq 0$.

The key identification strategy is that η^k_{jd} 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 11 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.

Figure 11: 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.

To decompose this variation by outlet, I run regressions of the form 6 done on within day differences Δx_{jd} and Δz_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 19 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, nn 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 in story mix create the variation we use to measure viewers' taste for like-minded versus opposing content.

Differencing (12) eliminates the unobserved shock:

$$\underbrace{\sum_r \left(\frac{\partial s_{jrd+1}}{\partial x^k_{jd1}} - \frac{\partial s_{jrd+1}}{\partial x^k_{jd0}} \right) \frac{L_r}{L}}_{\Delta g^k_{jd}} = 2\lambda^k_j \left(\frac{x^k_{jd1} - x^k_{jd0}}{z^k_{d1} - z^k_{d0}} \right) + \Delta\nu^k_{jd}. \tag{13}$$

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

6.1 Results

Table 3 reports the estimated λ^k_j. 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 (λ) by Channel and Content Type

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

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

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.

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:

$$
\begin{aligned}
&\max_{\{\mathbf{x}_{jd}\}} \left\{ \sum_r s_{jrd+1}(\boldsymbol{x}_{jd}, \boldsymbol{x}_{-jd}) \frac{L_r}{L} - \sum_k \lambda_j^k \mathcal{C}(x_{jd}^k, z_d^k) + \boldsymbol{\eta}_{jd} \boldsymbol{x}_{jd} \right\} \\
&s.t. \quad \frac{x_{jd}^{R+} + x_{jd}^{R-}}{x_{jd}^{political}} = vote^R \\
&\qquad \frac{x_{jd}^{L+} + x_{jd}^{L-}}{x_{jd}^{political}} = vote^L \\
&\qquad x_{jd}^k \geq 0 \quad \forall k
\end{aligned}
\tag{14}
$$

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).

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.

References

Arceneaux, K. and Johnson, M. (2013). *Changing Minds or Changing Channels? Partisan News in an Age of Choice*. Chicago Studies in American Politics. University of Chicago Press, Chicago, IL.

Assemblée nationale (2024). Compte rendu n6 : Commission d'enquête sur l'attribution, le contenu et le contrôle des autorisations de services de télévision à caractère national sur la télévision numérique terrestre – table ronde, ouverte à la presse, réunissant mme julia cagé et mme claire sécail. https://www.assemblee-nationale.fr/dyn/opendata/CRCANR5L16S2024PO831733N006.html. Compte rendu n6, séance du jeudi 18 janvier 2024 à 10 h 30 (session ordinaire 2023–2024, présidence de M. Quentin Bataillon).

Atil, B., Chittams, A., Fu, L., Ture, F., Xu, L., and Baldwin, B. (2024). Llm stability: A detailed analysis with some surprises. *CoRR*, abs/2408.04667.

Bail, C. A., Argyle, L. P., Brown, T. W., Bumpus, J. P., Chen, H., Fallin Hunzaker, M. B., Lee, J., Mann, M., Merhout, F., and Volfovsky, A. (2018). Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences*, 115(37):9216–9221.

Bang, M., L'Heude, L., Postlewaite, A., and Sieg, H. (2023). Access and exposure to local news media in the digital era: Evidence from u.s. media markets. NBER Working Paper 31436, National Bureau of Economic Research.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 25(2):242–262.

Berry, S. T. and Haile, P. A. (2014). Identification in differentiated products markets using market level data. *Econometrica*, 82(5):1749–1797.

Boehnke, Jörn, P. E. and Bhargava, H. (2024). Decoding unstructured text: Enhancing llm classification accuracy with redundancy and confidence. *Conference on AI Applications in NLP*.

Boxell, L., Gentzkow, M., and Shapiro, J. M. (2020). Cross-country trends in affective polarization. *Review of Economics and Statistics*, 106:557–565.

Cagé, J., Hengel, M., Hervé, N., and Urvoy, C. (2022). Hosting media bias: Evidence from the universe of french broadcasts, 2002–2020. SSRN Electronic Journal. Working paper; later issued as CEPR Discussion Paper No. 18905 (2024).

Chiang, C.-F. and Knight, B. (2011). Media bias and influence: Evidence from newspaper endorsements. *The Review of Economic Studies*, 78(3):795–820. Accessed 19 June 2025.

Compiani, G., Morozov, I., and Seiler, S. (2025). Demand estimation with text and image data.

Conlon, C. and Gortmaker, J. (2020). Best practices for differentiated products demand estimation with pyblp. *The RAND Journal of Economics*, 51(4):1108–1161.

Crawford, G. S., Lee, R. S., Whinston, M. D., and Yurukoglu, A. (2018). The welfare effects of vertical integration in multichannel television markets. *Econometrica*, 86(3):891–954.

Crawford, G. S. and Yurukoglu, A. (2012). The welfare effects of bundling in multichannel television markets. *American Economic Review*, 102(2):643–85.

DellaVigna, S. and Kaplan, E. (2007). The fox news effect: Media bias and voting. *The Quarterly Journal of Economics*, 122(3):1187–1234.

Djourelova, M. (2023). Persuasion through slanted language: Evidence from the media coverage of immigration. *American Economic Review*, 113(3):800–835.

Durante, R. and Knight, B. (2012). Partisan control, media bias, and viewer responses: Evidence from berlusconi's italy. *Journal of the European Economic Association*, 10(3):451–481.

Edelman (2023). Edelman trust barometer 2023: Global report.

Esteban, J. and Ray, D. (1994). On the Measurement of Polarization. *Econometrica*, 62(4):819–851.

Gambaro, M., Larcinese, V., Puglisi, R., and Snyder Jr, J. M. (2021). The revealed demand for hard vs. soft news: Evidence from italian tv viewership. *National Bureau of Economic Research*, Working Paper 29020.

Gandhi, A. and Houde, J.-F. (2019). Measuring substitution patterns in differentiated products industries. Technical Report 26375, National Bureau of Economic Research.

Geitgey, A. (2017). face_recognition: Simple facial recognition api for python. https://github.com/ageitgey/face_recognition.

Gentzkow, M. (2006). Television and voter turnout*. *The Quarterly Journal of Economics*, 121(3):931–972.

Gentzkow, M. and Shapiro, J. M. (2008). Preschool television viewing and adolescent test scores: Historical evidence from the coleman study. *The Quarterly Journal of Economics*, 123(1):279–323. Available at https://web.stanford.edu/~gentzkow/research/TV_QJE_2008.pdf.

Gentzkow, M. and Shapiro, J. M. (2010). What drives media slant? evidence from us daily newspapers. *Econometrica*, 78(1):35–71.

Gentzkow, M., Shapiro, J. M., and Stone, D. F. (2014). Media bias in the marketplace: Theory. NBER Working Paper 19880, National Bureau of Economic Research.

Gentzkow, M., Shapiro, J. M., and Taddy, M. (2019). Measuring group differences in high-dimensional choices: Method and application to congressional speech. *Econometrica*, 87(4):1307–1340.

Jensen, R. T. and Oster, E. (2009). The power of tv: Cable television and women's status in india. *The Quarterly Journal of Economics*, 124(3):1057–1094. Also available as NBER Working Paper No. 13305.

Laver, M., Benoit, K., and Garry, J. (2003). Extracting policy positions from political texts using words as data. *American Political Science Review*, 97(2):311–331.

Le Mens, G. and Gallego, A. (2023). Positioning political texts with large language models by asking and averaging. *arXiv e-prints*, page arXiv:2311.16639.

Lenz, G. S. and Lawson, C. (2011). Looking the part: Television leads less informed citizens to vote based on candidates' appearance. *American Journal of Political Science*, 55(3):574–589.

Levendusky, M. S. (2013). Why do partisan media polarize viewers? *American Journal of Political Science*, 57(3):611–623.

Longuet-Marx, N. (2025). Party lines or voter preferences? explaining political realignment. Presented at the Spring 2025 IOG-BFI Conference, March 28–30, 2025.

Martin, G., Pfiffer, C., and Vasserman, S. (2024). What do news readers want? Technical report.

Martin, G. J. and McCrain, J. (2019). Local news and national politics. *American Political Science Review*, 113(2):372–384.

Martin, G. J. and Yurukoglu, A. (2017). Bias in cable news: Persuasion and polarization. *American Economic Review*, 107(9):2565–99.

Newman, N., Fletcher, R., Schulz, A., Andı, S., Robertson, C. T., and Nielsen, R. K. (2023). Digital news report 2023. Accessed: 2025-05-13.

Parliament, E. (2024). Audiovisual and media policy.

Peterson, E., Goel, S., and Iyengar, S. (2017). Echo chambers and partisan polarization: Evidence from the 2016 presidential campaign. In *Proceedings of the Annual Meeting of the American Political Science Association*.

Prat, A. and Strömberg, D. (2005). Commercial television and voter information. CEPR Discussion Paper DP4989, Centre for Economic Policy Research. Available at SSRN: https://ssrn.com/abstract=772002.

Prior, M. (2009). Improving media effects research through better measurement of news exposure. *The Journal of Politics*, 71(3):893–908.

Puglisi, R. and Snyder, J. M. (2015). Chapter 15 - empirical studies of media bias. 1:647–667.

Reiljan, A. (2019). 'fear and loathing across party lines' (also) in europe: Affective polarisation in european party systems. *European Journal of Political Research*.

Schneider-Strawczynski, S. and Valette, J. (2025). Media coverage of immigration and the polarization of attitudes. *American Economic Journal: Applied Economics*, 17(1):337–368.

Simonov, A. and Rao, J. (2022). Demand for online news under government control: Evidence from russia. *Journal of Political Economy*, 130(2):259–309.

Törnberg, P. (2023). Chatgpt-4 outperforms experts and crowd workers in annotating political twitter messages with zero-shot learning.

Wilbur, K. C. (2008). A two-sided, empirical model of television advertising and viewing markets. *Marketing Science*, 27(3):356–378.

Zhuravskaya, E., Petrova, M., and Enikolopov, R. (2020). Political effects of the internet and social media. *Annual Review of Economics*, 12(1):415–438.

Appendix

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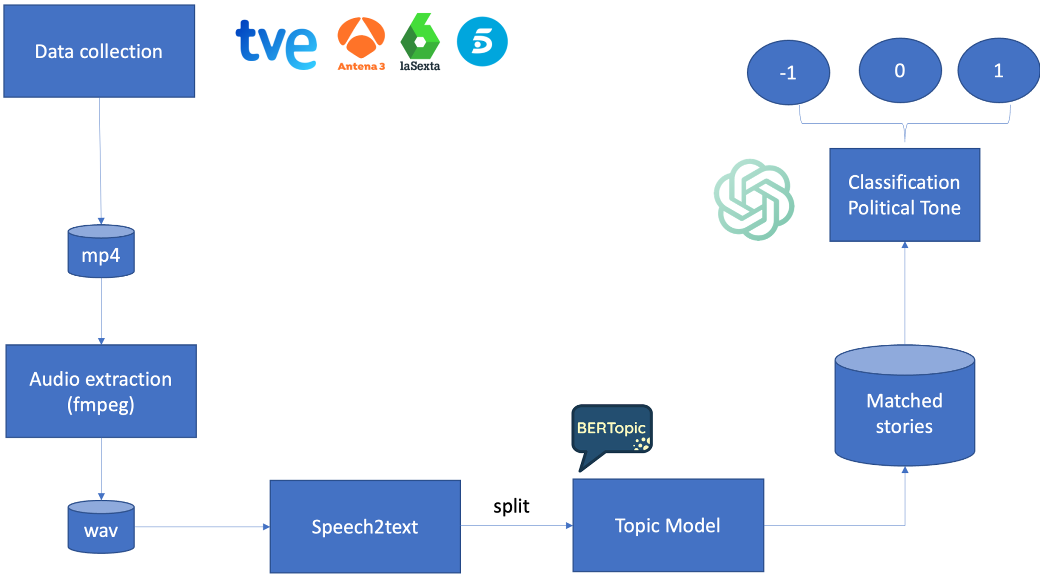
D Digression: LLMs Stability and Alternative Ideology classifications **55**

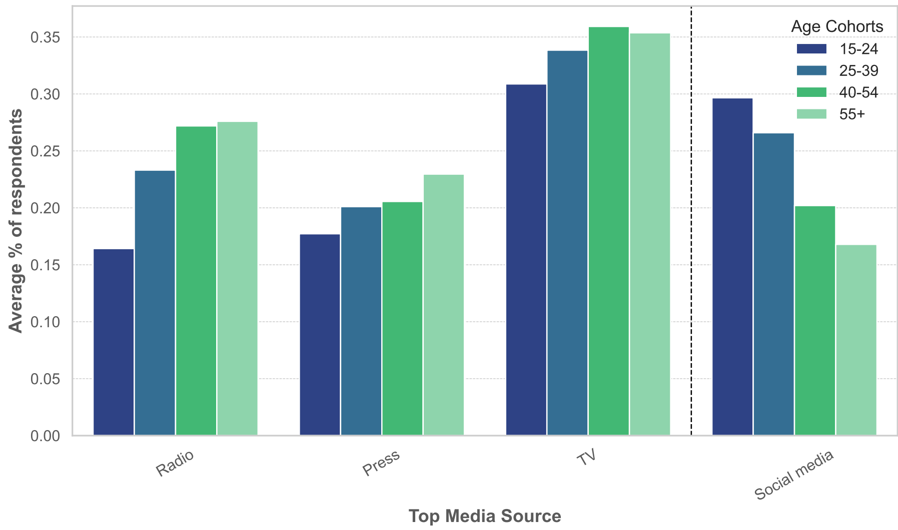
A Figures

Figure A.12: Pipeline for content downloading and classification



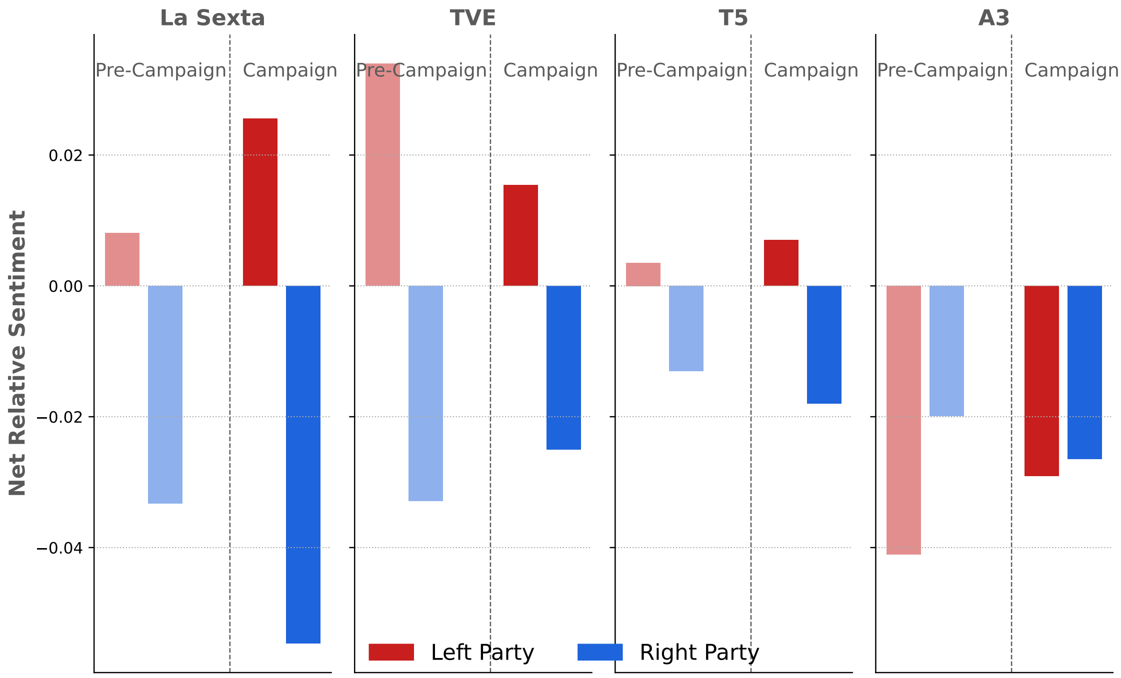
Notes: Pipeline for the text downloading. First videos are downloaded daily from the main TV channels. Google engine is used to convert the audio to text. I then split the stories by minute and use BERTopic to classify and match them. Finally, ChatGPT4 is used to classify political tone.

Figure A.13: Preferred Media for Political Information in Europe



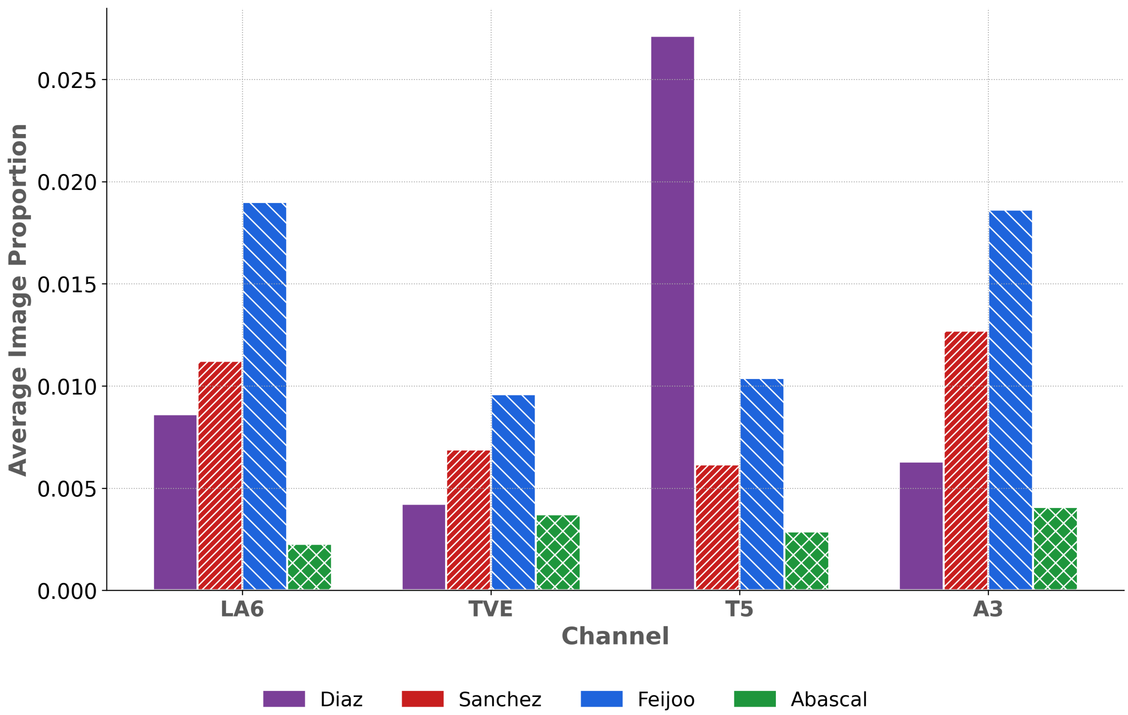
Notes: Histogram of the preferred media used for political information in Europe. Using data for the 27 countries in Eurobarometer with $N = 112059$. Source: Eurobarometer, 2022.

Figure A.14: Net sentiment across channels and parties pre and during campaign



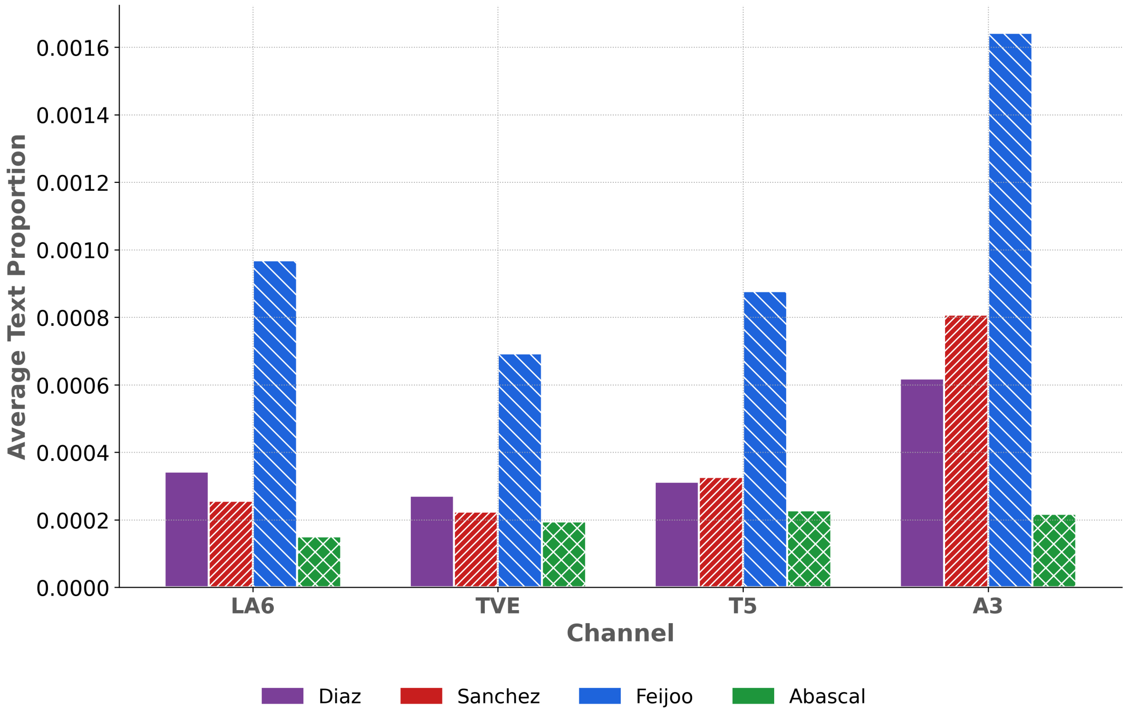
Notes: The figure shows the relative tone calculated as the average sentiment over right and left parties. The vertical dashed line delimits results pre and during campaign periods, respectively.

Figure A.15: Proportion of Image appearances per channel and politician



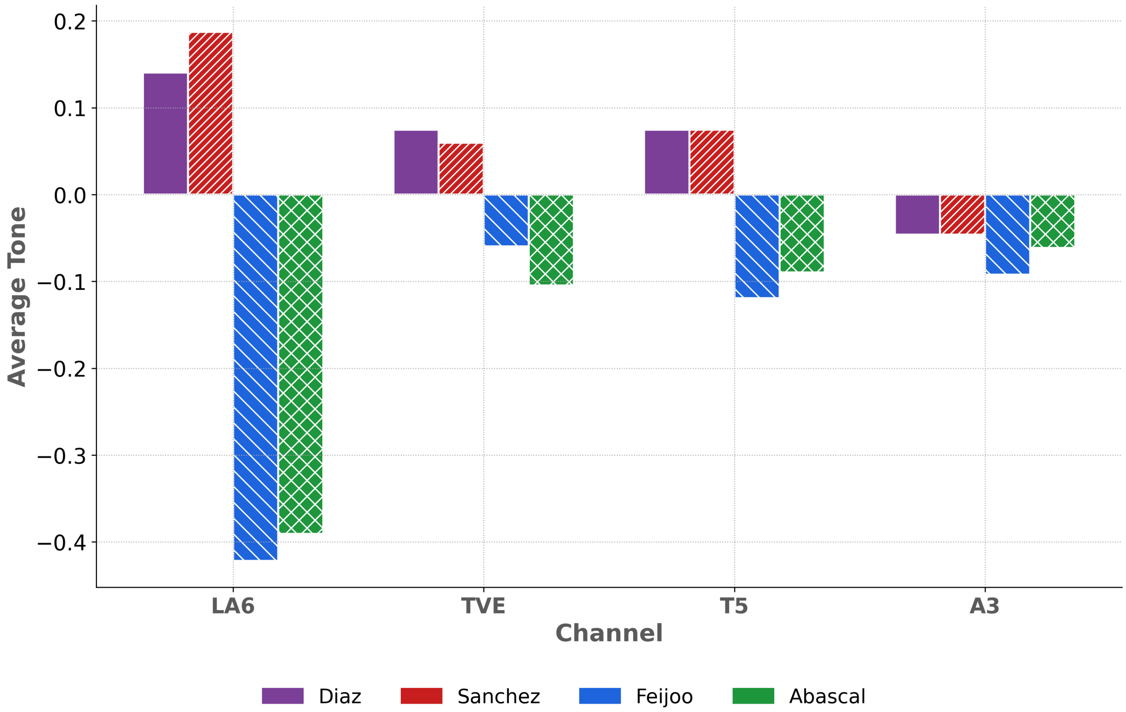
Notes: The figure shows the relative proportion of appearances by political actor and channel for a random sample of 67 days.

Figure A.16: Proportion of text mentions per channel and politician



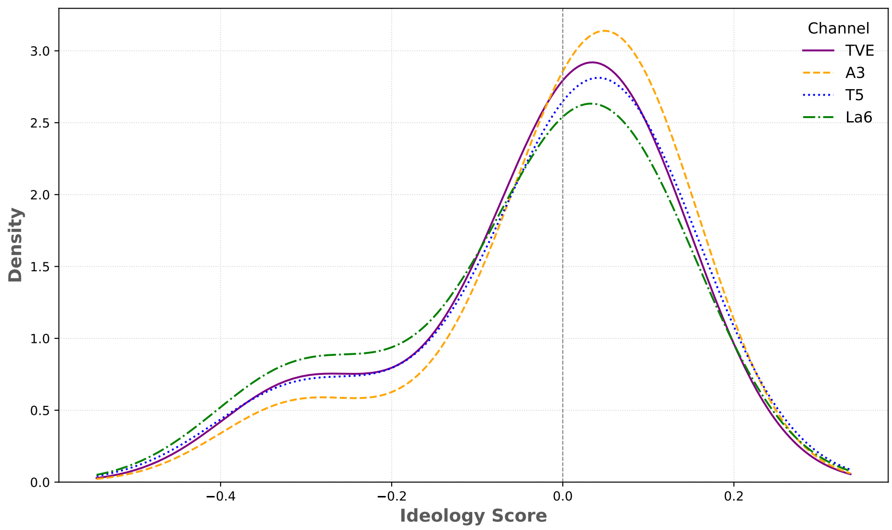
Notes: The figure shows the relative proportion of text mentions by political actor and channel for a random sample of 67 days.

Figure A.17: Net tone per channel and politician



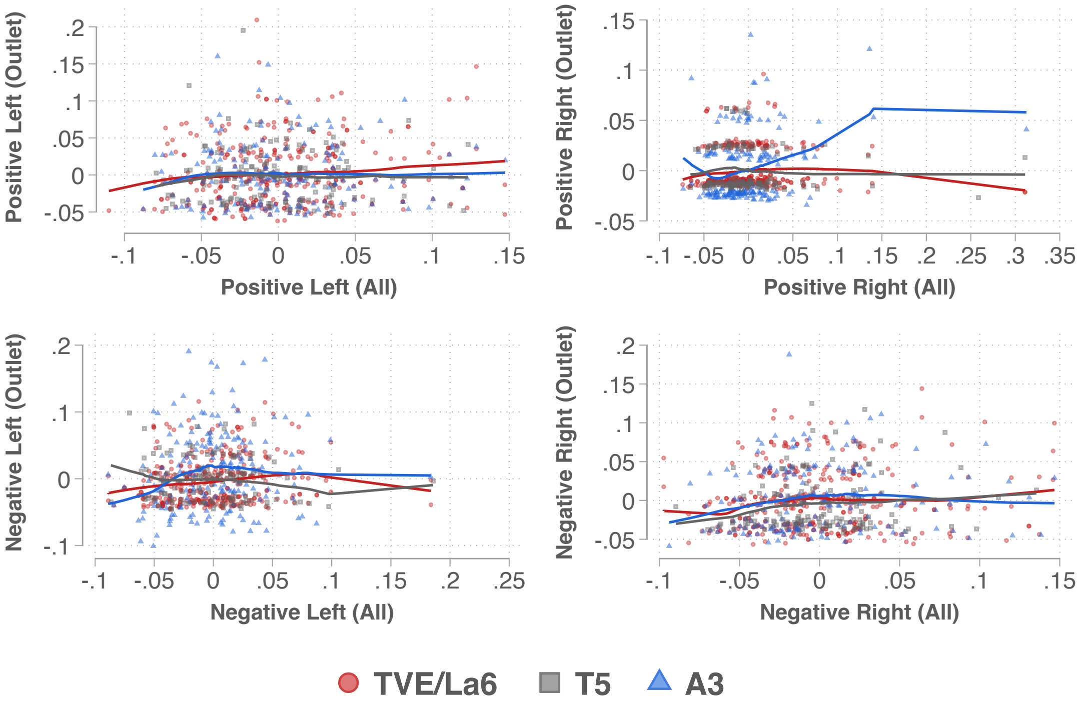
Notes: The figure shows the net tone based on the ChatGPT classification by political actor and channel for a random sample of 67 days.

Figure A.18: Density estimation for channels ideology based on audience share data



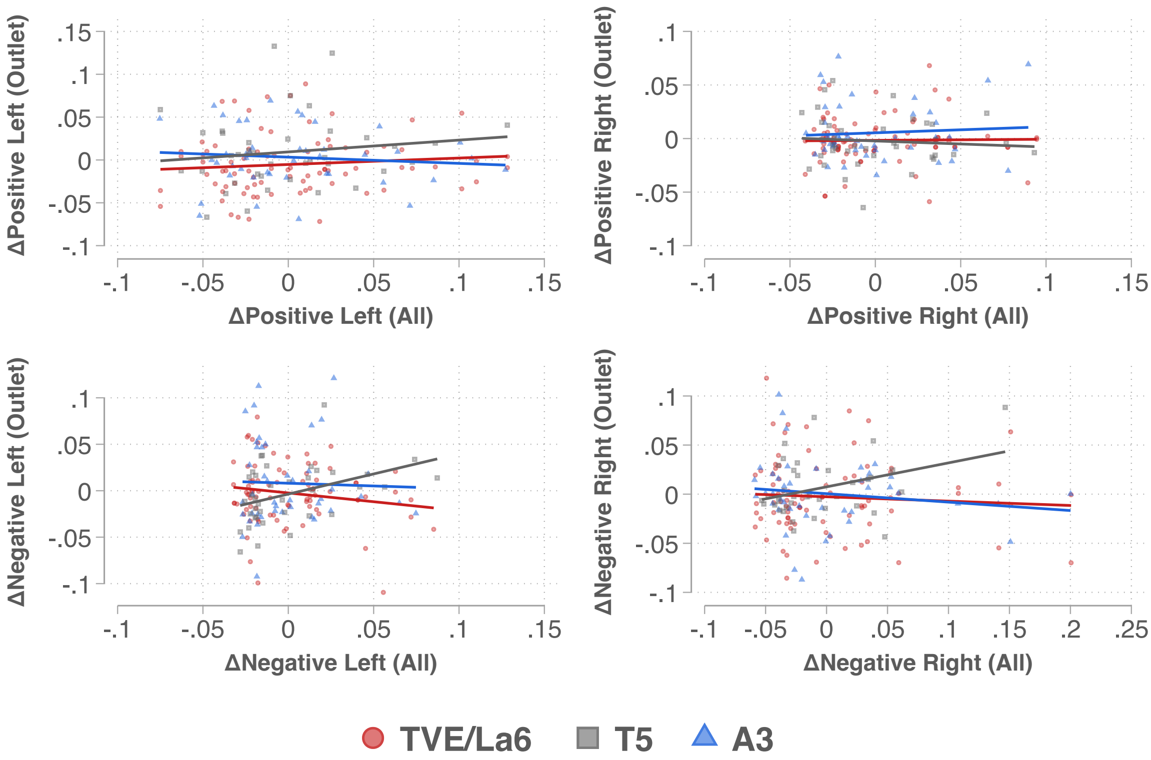
Notes: Estimated density of channels' audience ideology. The figure shows a kernel density estimate on the ideology score constructed using survey daa and weighted by channels' share of audience for each autonomous region.

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 equations **??** and 7. 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.

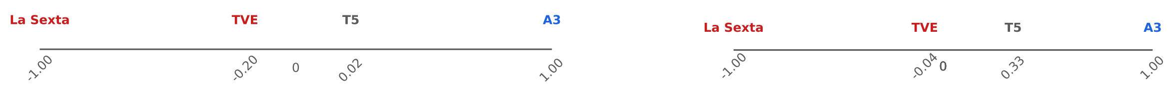
Figure A.20: Added variable plots for production of political content (within day)



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

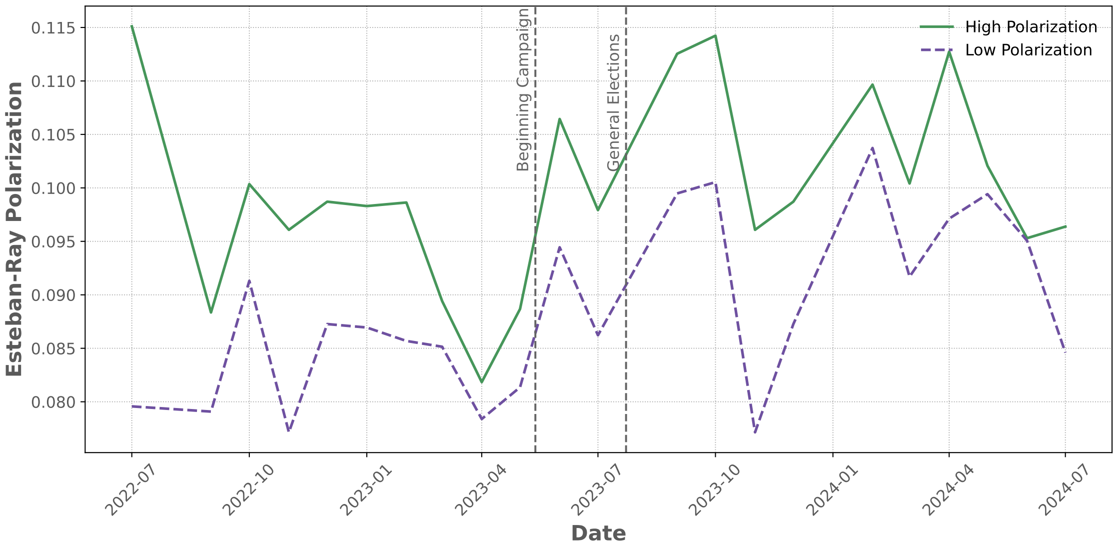
Figure A.21: Normalized Ideology Scores by Channel

(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 4: Effect of Mentions on Tone toward Feijóo

	(1)	(2)	(3)	(4)
Text Mentions	-25.763	-51.515	42.517	6.957
	(50.044)	(51.028)	(61.383)	(64.934)
Image Appearances	-4.373	-2.024	-12.421**	-9.379*
	(3.785)	(3.852)	(4.815)	(5.112)
constant	-0.088	-0.093	-0.049	-0.053
	(0.076)	(0.077)	(0.093)	(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, Feijoo. Results are for a random sample of 67 days.

Table 5: Effect of Mentions on Tone toward Abascal

	(1)	(2)	(3)	(4)
Text Mentions	-506.623***	-534.081***	-539.867***	-609.038***
	(148.973)	(147.122)	(161.979)	(156.866)
Image Appearances	18.013**	15.994*	22.023**	17.193*
	(9.077)	(8.996)	(10.119)	(9.898)
constant	-0.122**	-0.109*	-0.130**	-0.099*
	(0.057)	(0.056)	(0.057)	(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 6: Effect of Mentions on Tone toward Sánchez

	(1)	(2)	(3)	(4)
Text Mentions	61.471	196.424	27.282	193.827
	(106.565)	(123.145)	(119.969)	(145.161)
Image Appearances	-2.352	-4.286	-7.639	-10.754
	(4.253)	(4.331)	(6.583)	(6.971)
constant	0.054	0.014	0.120	0.077
	(0.063)	(0.067)	(0.075)	(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 7: Effect of Mentions on Tone toward Díaz

	(1)	(2)	(3)	(4)
Text Mentions	-11.990	21.235	-78.607	-19.353
	(67.519)	(69.918)	(91.794)	(99.632)
Image Appearances	0.019	-0.072	-0.861	-1.032*
	(0.512)	(0.517)	(0.595)	(0.603)
constant	0.064	0.051	0.103**	0.080
	(0.044)	(0.045)	(0.051)	(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.

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

Table 8: Logit Estimation Results with Standard Errors

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 9: Top 5 Topics by party-tone category on Agencia EFE after BERTopic.

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

Table 10: 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 11: 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 12: Estimated Elasticities by Left and Right markets

	Pre-campaign		**Campaign**	
Characteristic	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

Top stories for Negative Left
-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**
TVE	0.037
Antena 3	0.184
Telecinco	0.037
La Sexta	0.01

Table 13: 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.

Top stories for Negative Right
-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**
TVE	0.074
Antena 3	0.038
Telecinco	0.067
La Sexta	0.148

Table 14: 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.

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

Table 15: Top trigrams for Positive Right and Negative Right in the Agencia EFE dataset using ChatGPT-based classification.

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

Table 16: Top trigrams for Positive Left and Negative Left in the Agencia EFE dataset using ChatGPT-based classification.

Story	Channel	Date	Sentiment
Teen Survey Shows Growing LGBT Identity "26% of teens don't identify as heterosexual; Minister urges action against hate speech..."	TVE	2023-04-14	positive UP
Podemos Frames Vote as Housing Referendum "Podemos defends housing law and blames partners for delays during the term..."	A3	2023-05-15	positive UP
Sánchez Pauses Campaign for NATO Summit "Sánchez attends NATO summit during Spain's EU Council presidency; Biden also present..."	A3	2023-07-09	positive PSOE
Sánchez Visits Wildfire Zone, Reshuffles Cabinet "Sánchez links fire to climate change and appoints new ministers in key portfolios..."	TVE	2023-03-27	positive PSOE
PP Demands Return of Sedition Charges "PP leader attacks Penal Code reform, calling Sánchez's decisions opportunistic..."	TVE	2023-02-14	positive PP
Feijóo Criticizes Government Size and Alliances "Feijóo says PSOE is aligned with Podemos; suggests cutting ministries from 22 to 13..."	A3	2023-06-01	positive PP
PP Lowers Taxes in Balearic Islands "New PP government cuts inheritance and property taxes for young and relatives..."	A3	2023-07-18	positive PP
Vox Holds Key Role in Regional Talks "Vox could tip balance in cities like Valladolid; coalition talks underway in Aragón..."	LA6	2023-06-13	positive Vox
Vox Launches Second No-Confidence Motion "Vox files another no-confidence motion, this time with an external candidate..."	A3	2023-02-27	positive Vox
Vox and PP May Enter Extremadura Parliament "PSOE risks majority in Extremadura; PP and Vox may tip the balance..."	T5	2023-05-23	positive Vox

Podemos Faces Coalition Tensions with Díaz "Podemos criticizes coalition tensions; urges Díaz to support May campaign..."	A3	2023-04-09	negative UP
Díaz–Podemos Division Widens Post-Launch "Díaz and Podemos exchange criticism over platform launch and campaign unity..."	T5	2023-04-03	negative UP
PSOE Suspends Deputy in Corruption Case "PSOE suspends deputy Fuentes after corruption probe; demands public explanation..."	TVE	2023-02-27	negative PSOE
Coalition Fractures over 'Only Yes is Yes' Law "Podemos and PSOE clash over law reform; campaign focus now takes over..."	A3	2023-04-21	negative PSOE
Residents Protest Metro Damage in Madrid "San Fernando residents halt metro works; blame Ayuso's gov for property cracks..."	LA6	2023-01-05	negative PP
Gürtel Scheme Sentences Upheld by Court "Supreme Court confirms sentences for Gürtel leaders over public contract fraud..."	A3	2023-04-10	negative PP
Ayuso Strategy Aims to Outflank Vox "Madrid PP raises tension to win votes from Vox; polls show majority not secured..."	A3	2023-05-18	negative VOX
Díaz Warns of Right-Wing Coalition Risks "Díaz urges women to vote to block Abascal–Feijóo coalition and austerity return..."	LA6	2023-07-15	negative VOX

Table 17: The table shows examples of story summaries by political sentiment. Texts have been shortened, translated to English, and headlines made with the help of ChatGPT.

Story	Channel	Date	Sentiment
Justice Officials Lock In Courts "Justice staff stay locked inside courts seeking wage talks; Council of Europe will monitor compliance..."	TVE	2023-06-22	Negative Left

Story	Channel	Date	Sentiment
Prices Rise, but Economy Outperforms EU "Inflation rises to 4.1%, but GDP growth of 0.5% exceeds EU average thanks to exports..."	La6	2023-04-28	Positive Left
Gigafactory Launched in Sagunto "King and PM lay foundation for battery plant expected to create jobs and lead EU mobility shift..."	La6	2023-03-17	Positive Left
Ukraine War Triggers Fuel Price Surge "War-induced supply shocks push fuel over 2euros/L; Spain intervenes with price discounts..."	A3	2023-02-24	Positive Left
Gov't Approves Student Housing Aid "Cabinet increases rural student grants to 2,500 euros/year; 125,000 students to benefit..."	TVE	2023-02-21	Positive Left
Spain Secures EU Recovery Funds "Brussels approves 6B euros disbursement as Spain meets targets; reforms praised..."	La6	2023-02-17	Positive Left
Spain Pushes Green Tax in EU "Gov't promotes climate tax on private jets and wealthy emitters ahead of EU presidency..."	La6	2023-02-01	Positive Left
Spain Proposes Tax on Ultra-Rich "New green tax on fortunes over 100M euros could fund EU climate action; Spain takes lead..."	La6	2023-02-01	Positive Left
Spain Asks US to Remove Plutonium "Gov't requests US remove 50,000 square meters of toxic soil from 1960s incident; no reply yet..."	La6	2023-03-06	Positive Left
Spain Leads in EU Recovery Program "Spain receives 6B euros more as Brussels confirms compliance; 10 MEPs to audit..."	TVE	2023-02-17	Positive Left
Justice Protests, EU Ministers Meet "Officials protest lack of talks on pay; EU ministers debate cybercrime under Spain's presidency..."	TVE	2023-07-21	Negative Left
Self-Employed Hit by Rising Costs "Inflation, taxes raise expenses; 67% of self-employed increase prices to stay afloat..."	TVE	2023-07-10	Negative Left
Bank of Spain Cuts Forecasts "Slow consumption, persistent inflation lead to downward revision; rebound if policies fade..."	TVE	2022-12-20	Positive Left

Story	Channel	Date	Sentiment

Table 18: Examples of political stories that do not contain party matches of Spanish politicians but have a slant towards some of them.

Table 19: Case studies: Examples of Agencia EFE stories for each date and content type with largest overall $|\Delta x|$ (all channels combined).

Date	Characteristic	Δx	Top 3 Stories
2023-05-29	Negative Left	0.412	**PP Eyes Asturias Seat with Expat Votes** "PP is 934 votes from taking a seat from PSOE in Asturias and forming gov with Vox..."
			Abascal Urges Pact to Oust Sánchez "Vox leader celebrates snap elections and calls on PP's Feijóo to forge pact..."
			Moreno Says Sánchez Acts to Save Himself "Moreno claims Sánchez calls early elections out of fear, not strength..."
2023-05-31	Negative Right	0.226	**Rato Criticizes Prosecutors** "Rato attacks Anti-Corruption prosecutors and says he hopes to avoid prison..."
			Calviño Defends Government's Record "VP Calviño argues economic policy is balanced, counters Feijóo's criticism..."
			Sánchez Rallies Against Emboldened Right "Sánchez tells PSOE to fight 'bold' right ahead of July elections..."
2023-05-31	Positive Left	0.282	**Subirats Pushes University Decrees** "Minister Subirats says early elections right call; aims to pass decrees..."
			PP and PSOE Get Millions in Subsidies "PP to receive 6.3M euros and PSOE 5.6M euros after 28M municipal elections..."
			Basque PP Supports PNV-PSE Investiture "Basque PP to back PNV-PSE mayors to block EH Bildu, with no gov deal..."

Date	Characteristic	Δx	Top 3 Stories
2023-05-29	Positive Right	0.276	**PP Close to Win in Asturias** "Expat votes could flip one Asturias seat to PP-Vox-Foro coalition..."
			Abascal Backs Pact to Oust PSOE "Vox's Abascal pushes pact with PP to remove Sánchez and undo policies..."
			Moreno Criticizes Election Timing "Andalusian PP's Moreno says Sánchez is calling early vote out of weakness..."

Table 19: 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 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 20 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 20: 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	lópez de uralalde	
	isabel rodríguez	rosa martínez	

Table 21: Party-specific political terms

política	democracia	partido político	gobierno	elecciones	votación
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 22: 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*.

D 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 avere 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 11 shows the mean and standard dviation 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:

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

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
- α 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 ??.

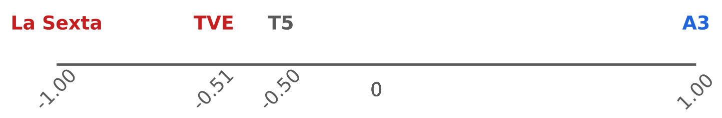
Figure D.23: Word Cloud Top Left Words

Figure D.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 D.25: Normalized Ideology Scores



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