The Impact of Political Campaigns on Demand for Partisan News*

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Abstract

I explore how electoral campaigns affect the market for partisan news in Spain. I use machine learning and large language models (LLMs) to build a novel slant index that I match to high-frequency audience-meter data on television consumption. This allows me to compare how the same story is framed across outlets and how many people watched it. I integrate these measures into a structural model of news demand and supply. Outlets choose the political framing of the news and viewers select their preferred information source based on it. To identify viewers' preferences for political content, I exploit exogenous changes in the mix of political events that constrain what outlets can cover. During the campaign period, demand becomes more polarized: viewers strongly screen out favorable coverage of the party they oppose. On the supply side, outlets specialize and face lower costs of producing slanted coverage that aligns with their political stance. I evaluate the effects of a proportional airtime requirement, the standard rule in television regulation during campaigns. Outlets comply by becoming more partisan, resulting in a more polarized media environment.

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1 Introduction

Political polarization has intensified in recent years in both the United States and Europe (Reiljan, 2019). Evidence consistently points to news media consumption as a contributing factor, particularly among audiences of traditional outlets (Martin and Yurukoglu, 2017; Boxell et al., 2024; Schneider-Strawczynski and Valette, 2025). The way political information is framed and consumed is especially concerning around electoral periods. Before elections, the selection of leaders depends on what voters learn during the campaign; after elections, higher polarization is usually associated with lower electoral accountability and reduced acceptance of democratic results (Besley, 2005; Graham and Svolik, 2019). Yet the role of the market for political information during these periods remains underexplored, largely due to data limitations and the difficulty of credibly identifying demand and supply.

This paper investigates how the market for political news changes during electoral campaigns and evaluates the effects of media regulation intended to ensure pluralism. To do so, I develop and estimate a structural model of demand and supply for television news. Outlets choose how much and the way they talk about political parties and based on it, viewers select their preferred outlet. I fit the model to a novel dataset that combines viewership records with a daily slant index of television news during Spain's 2023 general election. I find that, during the election campaign, demand for political news was more polarized than in comparable non-campaign periods: viewers strongly screen out favorable content about the party they oppose and favor their own. On the supply side, the estimated model reveals that channels specialize in political content and face higher costs when slanting against their ideological stance. I then use the estimated supply and demand models to evaluate the effects of the most common media regulation in Europe—proportional airtime across parties. The counterfactual results show that the regulation leads to unintended effects. Channels comply with the rule by adopting a more negative tone, resulting in greater media polarization.

Two central challenges hinder the estimation of demand for news. The first is slant measurement: constructing scalable and comparable indicators of partisan slant for hundreds of broadcast hours is intrinsically difficult. Second, even with good measures, market equilibrium creates endogeneity—outlets tailor content to viewers, and viewers gravitate toward congenial outlets—making it hard to disentangle demand from supply. The methodology developed in this paper addresses both issues by (i) generating a high-frequency, story-level slant index comparable across outlets and (ii) proposing a novel identification strategy that exploits exogenous variation in the daily news pool that allows me to distinguish audience preferences from editorial decisions.

To tackle the measurement problem, I construct a unique dataset that captures both the supply and demand for political content on television news. As concerns the demand side, high-frequency audience-meter data overcome well-known limitations of survey evidence (Prior, 2009). As for the supply side, I design a scraping pipeline that monitors live newscasts and archives the footage. I then process more than 500 hours of video and use machine-learning techniques to generate transcripts. Next, I apply high-dimensional clustering to split each day's coverage into more than 20,000 *stories*—segments that discuss the same issue—and use LLMs to classify each story's tone toward each party. This design allows me to document novel facts about political news coverage, such as the way outlets differ in their treatment of major political events and how such shocks affect their editorial line over time. I compare this slant index with alternative measures used in previous works and with the metrics used by most media regulators, which track leaders' on-screen minutes. To replicate the latter, I train a face-recognition model on broadcast imagery to quantify each leader's screen time. The LLM-based index is more informative: by capturing thematic framing, it uncovers the political tone even when the corresponding parties or politicians are not explicitly mentioned. This reveals strong partisan differences across outlets, whereas previous metrics suggest a balanced coverage.

To address the endogeneity problem, I use supply shocks to identify demand preferences. Specifically, I exploit exogenous variation in the daily composition of the news landscape that constrains outlets' feasible slant choices. In order to characterize the news landscape, I collect all stories distributed by the largest newswire that serves these broadcasters, apply the same text-classification pipeline and use the resulting corpus as a proxy for the set of stories broadcasters can draw upon each day. I show that when the pool of either right- or left-leaning stories grows for exogenous reasons, the aligned channels expand their coverage in that direction. Moreover, the way they adapt their coverage is consistent with an *issue intensity* approach (Puglisi and Snyder, 2015). Newsworthy political events for either party are not ignored and lead all outlets to increase coverage. The difference lies in how much time they devote to these events. For example, on a day highly favorable to the left, the right-leaning outlet raises its share of positive coverage of left parties by 10%, compared with 18% at the left-leaning outlets. This variation identifies a BLP-style demand model (Berry et al., 1995), in which viewers' preferences for slant vary with ideology, allowing me to test the degree of polarization in information consumption.

The demand estimation results show that, outside the campaign period, there is no systematic asymmetry in political content demand between right- and left-leaning audiences. Viewers generally prefer negative political news, consistent with an entertainment-seeking type of consumption in which conflict and scandals attract more attention. During the campaign, however, affective polarization emerges: right-leaning viewers increasingly seek negative coverage of the left and more positive coverage of the right, with the mirror pattern among left-leaning viewers. A one-minute increase in positive coverage of right-wing parties yields a net gain of approximately 3,000 viewers (0.03 stdev.) in right-leaning regions. The model results align with survey-based evidence of polarization. First, in regions where the model implies a higher polarization in news consumption, electorates are also more polarized in their voting intentions. Second, after a year of decline, survey-based polarization exhibits a trend break at the start of the campaign, matching the timing of the break in news demand from my model estimates.

Given the demand estimates, I then model and estimate content supply. Outlets play a differentiation game choosing the distribution of airtime and tone across parties to maximize viewership. The costs of producing slant depend on the composition of any given day's news landscape. Unobserved factors—such as owner bias or reporter absences—can shift these costs, thereby creating endogeneity. In order to identify the cost parameters, I exploit high-frequency variation in the newscast editions. Due to the fact that midday and evening editions are separated by only a few hours, differences in content offered between them stem from unexpected story arrivals in the interim. I show that outlets adjust slant to these unexpected arrivals with responses that align with their stance. The estimated cost parameters reveal heterogeneity across content types and outlets. Outlets specialize in producing content that matches their ideological point of view. For instance, making coverage on the left 1 p.p. more positive (relative to the median) entails an audience share loss of 8 p.p. for the right-wing outlet, compared with only 3 p.p. for the left-leaning outlets. This corresponds to about 50% (20%) of the drop observed when a major football match overlaps the newscast.

Finally, I test the effectiveness of existing interventions aimed at promoting content diversity and fighting polarization in television news. The most common campaign-period regulation is the proportional-airtime rule, which requires broadcasters to allocate coverage of political parties according to their vote shares in previous elections. Despite its prominence, there are concerns that this measure is not adequate in practice, largely due to poor measurement and weak enforcement (Assemblée nationale, 2024), but there is a lack of formal evidence regarding its effects. I use the estimated demand and supply parameters to simulate a campaign-period counterfactual in which Spanish outlets are subject to this rule and quantify its effects.

Contrary to the policy's objective, the result is a more polarized political coverage. Since the most recent election delivered a balanced vote share to the right and left blocs, the rule assigns a similar share of campaign minutes to both parties. In the baseline scenario, however, all channels devote so much more relative time to the left that enforcing the regulation requires them to rebalance minutes from the left to the right. Accordingly, outlets then readjust on two margins: the amount of political coverage aired and the partisan tone within those minutes. They primarily adjust the tone by intensifying negative coverage, which is the category from which they enjoy larger payoffs. This leads to more extreme slanting; the resulting spread in outlets' optimal slant positions is roughly three times larger after the implementation of the rule. The mechanism behind this change stems from the design of the rule itself: since the regulation limits only the total airtime for each party, channels adjust through slant to maintain their preferred political inclination, something that could not be tracked with previous metrics. This highlights the fact that different slant metrics—and regulations built on them—can backfire when tone is ignored, yielding higher rather than lower media polarization.

Related Literature My first contribution is to the literature on slant measurement. Puglisi and Snyder (2015) divide measures of bias into *comparison*, *intensity*, and *tone* approaches. Comparison measures—such as Groseclose and Milyo (2005), based on think-tank mentions and Gentzkow and Shapiro (2010), based on lexical proximity to congressional speeches, locate outlets by how closely their language matches partisan references. In contrast, my index does not require any explicit party mentions nor baseline partisan speech. Intensity measures such as those using newspapers endorsements (Chiang and Knight, 2011) or television airtime (Durante and Knight, 2012; Cagé et al., 2022), track how much attention outlets devote to any given topic or actor. I retain an intensive margin by accounting for airtime spent, while simultaneously adding tone within that exposure. My metric improves upon existing indicators by capturing greater nuances in slant.

The second strand studies political news consumption. I take a revealed-preference, structural approach. Building on Gentzkow and Shapiro (2010), I use the text to quantify outlet slant and model heterogeneous preferences for like-minded news. Closely related, Simonov and Rao (2022) estimate a structural model of demand for government-controlled online news. I extend this demand framework by incorporating a competitive model of supply, which allows me to test heterogeneity in slant production costs and to do counterfactual policy evaluations. My approach also advances the identification of preferences for political content. Puglisi and Snyder (2011b) show that exogenous scandal shocks shift newspapers' coverage asymmetrically, but their design cannot discern the salience of these scandals prior to their news coverage, which is essential knowledge in order to assess how constrained outlets are in their reporting decisions. To address this, I rely on newswire agencies with the purpose of creating a baseline for the pool of political content on a given day. Since these agencies already supply content to outlets, variation in the composition of their stories provides exogenous shocks that constrain outlets' ability to slant the daily news (i.e., supply shocks), which I use to identify demand.[1] This identification strategy applies in settings where previous instruments like cable-dial positions (Martin and Yurukoglu, 2017) are not applicable.

Third, this paper contributes to the literature on media persuasion. Experimental

[1]For an alternative use of downstream aggregators as shocks in content supply see Djourelova (2023).

evidence is mixed: some studies find limited scope for persuasion because self-selection dominates (Arceneaux and Johnson, 2013), whereas others document reinforcement among strongly committed partisans, polarizing attitudes (Levendusky, 2013). Complementing these experiments, recent work in political economy shows sizable media effects on polarization. In democracies, Schneider-Strawczynski and Valette (2025) show that television coverage of immigration polarizes attitudes in France, and Martin and Yurukoglu (2017) attribute a large share of rising U.S. voter polarization to cable news. In autocratic settings, Enikolopov et al. (2025) find that access to an independent TV channel polarizes electoral outcomes, reducing regime support among traditional-media users and mobilizing pro-regime voters among social-media users, suggesting that persuasion depends on the surrounding information environment. I enrich this literature by studying media's production decisions, also showing correlational links between media consumption and ideological polarization.

Fourth, the paper contributes by importing IO estimation tools into the political economy literature. On the demand side, recent work uses text embeddings and imagery to build product characteristics in demand models (Compiani et al., 2025). I leverage LLMs to construct slant-based product characteristics, capturing differentiation in goods that might otherwise seem homogeneous, such as news programs. However, if firms were to compete in differentiation, this richer product space raises concerns about endogeneity. Standard instruments such as demographic shifts across pricing zones (Fan, 2013) or candidate positions across electoral precincts (Longuet-Marx, 2025) rely on cross-market variation and they are not applicable for high-frequency settings such as mine, where each day's slant decision is endogenous and content is broadcast uniformly nationwide. I instead exploit supply shocks in upstream news content, which provide exogenous variation in setups with high-frequency dynamics and allow me to identify demand preferences.

On the supply side, I build on the media IO literature on spatial competition. Closest to my setting, Goettler and Shachar (2001) study optimal schedule choices by television networks that only maximize audience ratings without considering costs. In contrast, I estimate a daily content-positioning game with explicit slant production costs. Cost identification in prior work relies either on many local, isolated markets (e.g., Draganska et al., 2008; Fan, 2013) or on exogenous demand shifters over time in a single national market (Wollmann, 2018). Neither is available with nationally broadcast newscasts observed over a short time horizon. I therefore use high-frequency timing variation: unexpected story arrivals between the midday and evening editions shift the relative cost of producing specific party–tone content without plausibly affecting same-day unobservables.

Finally, this paper contributes to the literature that evaluates policy interventions in media markets. Previous work has studied interventions aimed at reducing polarization in online media. Exposure to opposing views has been shown to increase, rather than decrease, polarization (Bail et al., 2018). Temporary shutdowns of Facebook during campaign periods have been found to modestly reduce polarization, though often at the cost of lower political knowledge (Allcott et al., 2024). Policy interventions in television markets have instead focused on market structure and ownership—for instance, bundling (Crawford and Yurukoglu, 2012), vertical integration (Crawford et al., 2018), ownership changes (Martin and McCrain, 2019), and entry of commercial television (Prat and Strömberg, 2005). To the best of my knowledge, this is the first paper evaluating the effectiveness of content regulations within a structural model of supply and demand for news.

Rest of the Paper The remainder of the paper is organized as follows. Section 2 briefly summarizes the Spanish political and television landscape. Section 3 introduces the data, describes the text-analysis techniques employed, and reports descriptive statistics on content and audiences. Section 4 describes the market setting and demand model, addresses endogeneity and the identification strategy, and presents its results. Section 5 details the identification and estimation of the supply-side cost parameters. Section 6 develops the counterfactual analysis. Section 7 concludes.

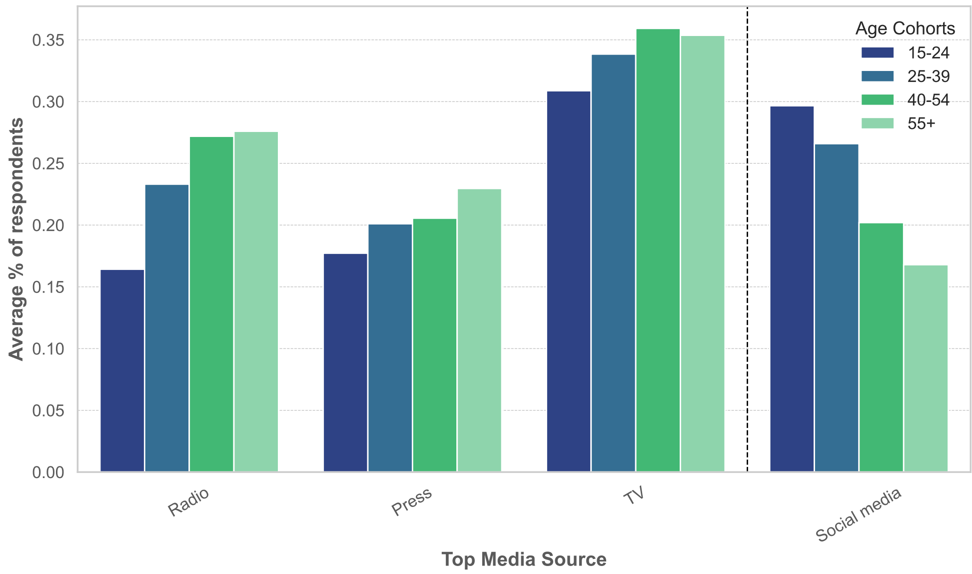
2 Context

In this section, I provide context by comparing Spain with Europe and the United States along three dimensions. First, I document patterns of media use and credibility, showing that traditional media—especially television—remain the primary source of political information in Europe. Second, I summarize the Spanish party system and describe the main national TV newscasts and the ideology of their audiences during the sample period. Third, I compare audience sorting on television with sorting in radio and the press within Spain, and with recent estimates for France and the United States, showing that newspapers and radio are generally more segmented than broadcast TV and that Spain is the more segregated environment overall. Altogether, these results motivate that television's comparatively mixed audiences are precisely where campaigns and policy can still affect their attitudes.

2.1 Traditional Media and Political Information

Traditional media remain the primary source of information in most European countries (European Parliament, 2025). Figure 1 shows the main media used to acquire political information in Europe by age group, as reported by the 2022 Eurobarometer survey under the question *"What media have you used the most to access news in the past 7 days?"*. Traditional media are represented to the left of the vertical, dashed line as radio, press, and television. Television remains the dominant source of political information and surpasses social media across all age cohorts.[2]

Figure 1: Preferred Media for Political Information in Europe



Note: Share of respondents selecting radio, press, TV, or social media as the main source of political news in the past 7 days, by age cohort. Using data for the EU-27 countries ($N = 112059$). Source: Eurobarometer, 2022.

Similarly, traditional media still enjoy higher credibility than digital-only outlets or news encountered on social platforms. Nearly half of survey participants (49%) say they trust public TV and radio—well above printed newspapers (39%) or news found on social networks and messaging apps (each below 15%) (European Commission, 2022). This credibility premium is closely linked to rising concern about fake news: respondents who worry most about disinformation are also the likeliest to turn to traditional broadcasters when verifying what is true. In the era of AI-enabled misinformation, audiences therefore continue to see traditional outlets—especially prime-time newscasts—as the primary source of political information, highlighting the importance of analyzing these markets.

[2] This pattern is also consistent for Spain under different surveys. Figure C.17 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). Television is preferred to social media for all but the youngest cohort (15-35 y.o.).

2.2 Spanish Politics and TV News

Spanish Political Context

Political power in Spain has historically been dominated by a two-party system, with government alternating between the Socialist Party (*Partido Socialista*-PSOE) and the People's Party (PP). During the sample period (December 2022–July 2023), Spain was governed by a PSOE-led coalition under President Pedro Sánchez, first in alliance with Unidas Podemos (UP) and, after its relaunch, SUMAR, with the main opposition led by PP and the far-right party VOX.[3] Although regional and independentist parties play a major role in the political environment, they are excluded from this analysis. For the remainder of the paper, parties are pooled into two blocs—right (PP and VOX) and left (PSOE and UP).

During the sample period analyzed in this work, the far-right party VOX made notable gains in the May 28, 2023 regional elections, fueling speculation of a PP–VOX coalition. In response to these results, the day after the regional elections, President Sánchez decided to bring forward the general elections to July 23, 2023. In that election, the PP became the largest parliamentary group, though without the possibility of forming an absolute majority, which led the left coalition to maintain power.

Spanish TV News

The product analyzed in this paper is television news broadcasts. I focus on the four largest national channels: *Televisión Española*, the state-owned public broadcaster; *Antena 3* and *La Sexta* (Atresmedia group); and *Telecinco* (Mediaset).[4] Altogether, their evening news editions capture around 50 % of viewership—about 4.5 million viewers[5], or 10 % of Spain's population.

What is the political composition of these audiences? Figure 2 shows the correlation between individuals' preferred political party (left or right) and their preferred channel for acquiring political information under the question *"What is your preferred TV channel for political content?"*. I condition only on *partisan* individuals, i.e., those who report

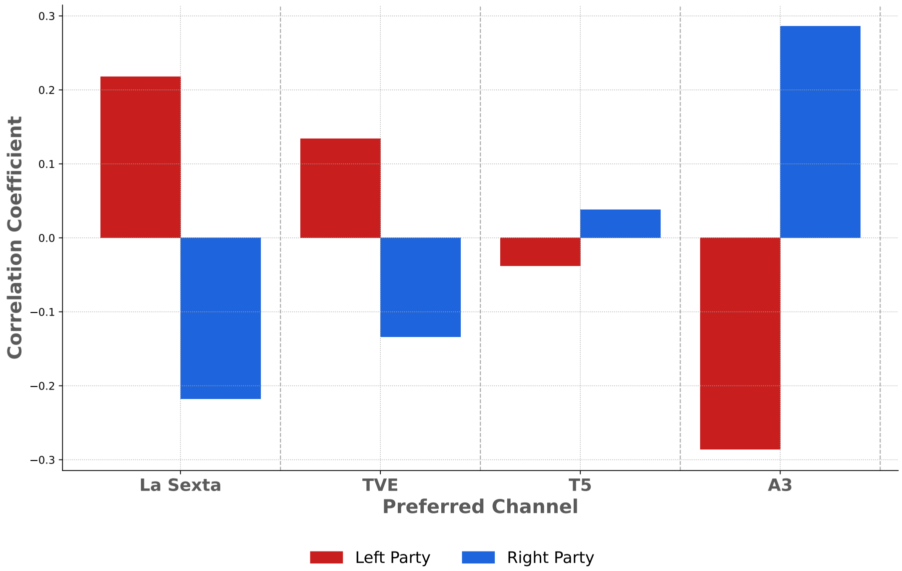
[3]Relevant for this sample period is the integration of Podemos into the new electoral coalition SUMAR. All classification metrics account for this transition, but throughout the text I refer to UP as either Podemos or SUMAR after its creation.

[4]While these outlets drive the national news agenda, data limitations prevent inclusion of regional networks—most notably Catalonia's TV3, which commands a substantial local audience and may exhibit distinct partisan dynamics. Future work can extend this framework to incorporate TV3 and other region-specific channels.

[5] By comparison, the most-watched U.S. cable-news program (Fox News) averages roughly 2.2 million viewers.

a preferred political party. Right-wing individuals tend to watch A3 more, whereas left-leaning individuals are divided between La Sexta and the public channel TVE. T5 appears in the middle, with weak correlations. This is consistent with the Mediaset group offering more entertainment oriented content as previously documented for Italy in Durante et al. (2019).

Figure 2: Correlation Between Preferred Channel and Political Party



Note: Correlation between viewers' declared party bloc (Left/Right) and preferred TV channel for political news among respondents who (i) say TV is their main news source and (ii) report a preferred party. Positive values indicate greater popularity within that bloc. Source: CIS, Encuesta Pre-electoral 2023.

To benchmark the degree of partisan sorting in television news against other media and prior studies, I compute the *isolation index* (Gentzkow and Shapiro, 2011) for TV, radio, and the press. In a binary left–right setting, the index measures how much more likely a right-wing user is to encounter a co-partisan in the outlets that right-wing audiences visit than a left-wing user would in the outlets left-wing audiences visit. An isolation index of zero indicates no additional clustering by ideology (i.e., right- and left-leaning viewers consume the same outlets), while an index of one corresponds to complete segregation, where each group encounters only its own members.[6] Television is the least isolated medium (11 pp), followed by the press (18 pp) and radio (29 pp).

To contextualize these results, I compare them with the most recent estimates available for France (Dejean et al., 2022) and the U.S. (Gentzkow and Shapiro, 2011) (Table E.22).

[6]The formal definition appears in Appendix Section E. Results of the isolation index and its decomposition by party bloc and can be seen in Appendix Table E.21. On television, right-leaning viewers face 41% right exposure vs. 30% for left-leaning viewers (11 pp). In the press: 43% vs. 25% (18 pp). On radio: 52% vs. 24% (29 pp).

Spanish TV is about 8 p.p. more isolated than French TV and nearly 10 p.p. more than U.S. broadcast TV. This higher media segregation aligns with cross-country surveys that place Spain among the top most polarized electorates worldwide (Edelman, 2023).

Taken together, the previous evidence reveals several facts. Television is the predominant and most trusted source to acquire political information in Europe. Additionally, the cross-country ranking reveals a common pattern: newspapers and radio are more ideologically segmented than broadcast TV. Since media effects are limited when audiences are already sorted, this pattern suggests greater potential for television to influence attitudes and less for radio or newspapers, where audiences are already politically aligned. This distinction is crucial when considering the external validity of my results for other media environments.

3 Data, Text Analysis and Descriptive Evidence

In this section, I describe the data and text-analysis pipeline I use to link news content to viewership. I assemble audience-meter records and prime-time newscast transcripts, build a slant index with machine learning and LLMs, and benchmark it against prior slant measures. I then present descriptive facts showing how political coverage varies during the campaign and how major political events shift outlets' coverage over time. These facts motivate the model in Section 4.

3.1 Data

I assemble a unique dataset that captures both the demand and supply sides of TV news. For the demand side, I have minute-by-minute viewership data for the four main channels that offer daily news programs: TVE, A3, La Sexta, and T5. 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 congress speeches, survey and weather data.

TV Content

I record daily videos for both the midday and evening news editions. This leads to a total of 563 hours of content. I rely on 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 summary of the entire downloading pipeline is provided in Appendix Section A.

News programs offer a unique environment to test substitutability for several reasons. Even though channels offer other political programs, the homogeneity of these products allows for very clean comparisons. These programs are broadcast every day at almost the same time and all share a very similar structure, with a presenter introducing the main stories of the day. Their lengths are similar, with the shortest show (A3) averaging 32 minutes and the longest (TVE) 42 minutes.

TV news programs are also highly fact-checked and they remain the most trusted source of information in Spain.[7] This fact is important as it ensures a cleaner interpretation of the audience choice data as revealed preferences for the content consumed and limits the extent of fake news as an additional dimension in the editorial strategy of the outlets.

Audience Data

I use Audimeter, a high-frequency audience data source provided by Kantar Media. I observe the total amount of viewers for each channel each day and minute. Variation over minutes will not be exploited. Instead, I rely on the initial audience at the beginning of the shows each day (i.e., minute-zero audience). For the model estimation, I compute the audience share variable as the number of viewers divided by the potential number of TV-viewing households within a given region also provided by Kantar Media. Although I do not have individual-level data on choices, I have geographical disaggregation for 15 autonomous regions in Spain (also referred to as regions hereinafter), which I match to survey demographics.[8] The shares for the demand estimation correspond to the evening TV news shows, which, with the exception of La Sexta at 20:00, start at 21:00 daily. For the supply side identification, I also consider the midday editions, which analogously take place at 14:00 and 15:00. For this analysis, La Sexta's program is treated as if it occurred simultaneously with the others.

Agencia EFE

I obtain all news stories published in Spanish by one of the largest news agencies in the world, Agencia EFE (or henceforth, EFE). I have information on the title of each story along with a short summary segment for 32,525 stories in the period under study.

Similar to Reuters or Associated Press, this agency mainly sells content and images to third-party newscasts. All the outlets in the sample are clients of EFE.[9]

[7]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 A3 Noticias continue to rank as the most trusted news sources, with trust levels of 48% and 51%, respectively. La Sexta registers approximately 42%, and T5 follows at 41% (Newman et al., 2023).

[8]The Canary Islands and La Rioja are excluded due to different time zones and zero market shares, respectively. Similarly, peak days with sports events that altered the news schedule were also removed.

[9]See collaborations with Mediaset, Atresmedia, and RTVE.

Congress Speeches

I collect the complete set of plenary session transcripts from the Spanish Congress of Deputies during the XV Legislature. The official Diarios de Sesiones del Pleno are published in PDF format on the Congress website.[10] There are a total of 1411 interventions. Each of them is linked to the corresponding speaker, and I match speakers to their parliamentary group using official records. This dataset is used for robustness of the text classification.

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. These data are monthly and are in cross-sectional format.

Weather

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

3.2 Text Classification

As noted above, news programs present a very similar structure in length, broadcast time, and format. This homogeneity allows for cleaner comparisons as opposed to general opinion shows, where characteristics differ starkly, but at the same time makes them almost perfect substitutes; the key differentiation (aside from vertical, quality components) being the way they treat the information. Here I describe how text analysis techniques can provide robust measures of political slant and effectively differentiate the outlets' treatment of information.

Building Content Characteristics

Each day d, 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. This leads to a total of 20,674 stories. The subset of political stories, $P_{jd} \subseteq S_{jd}$, is the set of all stories that mention national parties or prominent politicians in addition to general words related to politics, identified by keyword matches from Table D.15.

[10] Available at: https://www.congreso.es/es/busqueda-de-intervenciones.

Each $s \in P_{jd}$ is fed into ChatGPT and assigned a score: $t(s) \in \{-1, 0, 1\}$[11] with $t(s) = 1$ ($t(s) = -1$) denoting a positive (negative) tone. Stories with a stance (i.e., $t(s) \in \{-1, 1\}$) also receive a party label $p(s) \in \{L(eft), R(ight)\}$, whereas neutral stories do not.

Notice that the broad classification of what is *political* allows for stories without explicit mentions of political actors to be classified as partisan. Table D.19 contains text examples of this. Positive Left stories include, for instance, an economic forecast from the European Commission and the opening of a new gigafactory, while Negative Left stories include court officers barricading courthouses for pay raises and fuel-price surges driven by the Ukraine war. These cases show how the classifier infers slant from thematic framing alone, assigning a political slant to national parties without explicit references to them.

Additionally, a story can be mapped to its length in minutes, $\ell(s)$, with total length of the news programs denoted by L_{jd}. I then define:

$$\begin{aligned}
x_{jd}^{party+} &= \frac{1}{L_{jd}} \sum_{s \in P_{jd}} \Big(\mathbb{1}\{t(s) = 1\} \times \mathbb{1}\{p(s) = party\} \times \ell(s) \Big) \qquad \forall party \in \{L, R\} \\
x_{jd}^{party-} &= \frac{1}{L_{jd}} \sum_{s \in P_{jd}} \Big(\mathbb{1}\{t(s) = -1\} \times \mathbb{1}\{p(s) = party\} \times \ell(s) \Big) \quad \forall party \in \{L, R\} \\
x_{jd}^{political} &= \frac{1}{L_{jd}} \sum_{s \in P_{jd}} \ell(s).
\end{aligned} \tag{1}$$

Combining all these characteristics—i.e., party label, tone, and minutes— Equation (1) represents the shares of positive and negative minutes, as well as the share of airtime devoted to politics. Similarly, I proxy the daily news landscape with all stories published in Spanish by the newswire agency EFE—$N \approx 32.5K$ items over the sample. Mirroring the content covariates in (1), I classify every story with the same pipeline and construct daily measures of the political mix in the set of stories available as:

$$\begin{aligned}
z_d^{party+} &= \frac{1}{|\mathcal{N}_d|} \sum_{s \in \mathcal{P}_d} \Big(\mathbb{1}\{t(s) = 1\} \times \mathbb{1}\{p(s) = party\} \Big) \qquad \forall\, party \in \{L, R\}, \\
z_d^{party-} &= \frac{1}{|\mathcal{N}_d|} \sum_{s \in \mathcal{P}_d} \Big(\mathbb{1}\{t(s) = -1\} \times \mathbb{1}\{p(s) = party\} \Big) \quad \forall\, party \in \{L, R\}, \\
z_d^{\text{political}} &= \frac{|\mathcal{P}_d|}{|\mathcal{N}_d|},
\end{aligned} \tag{2}$$

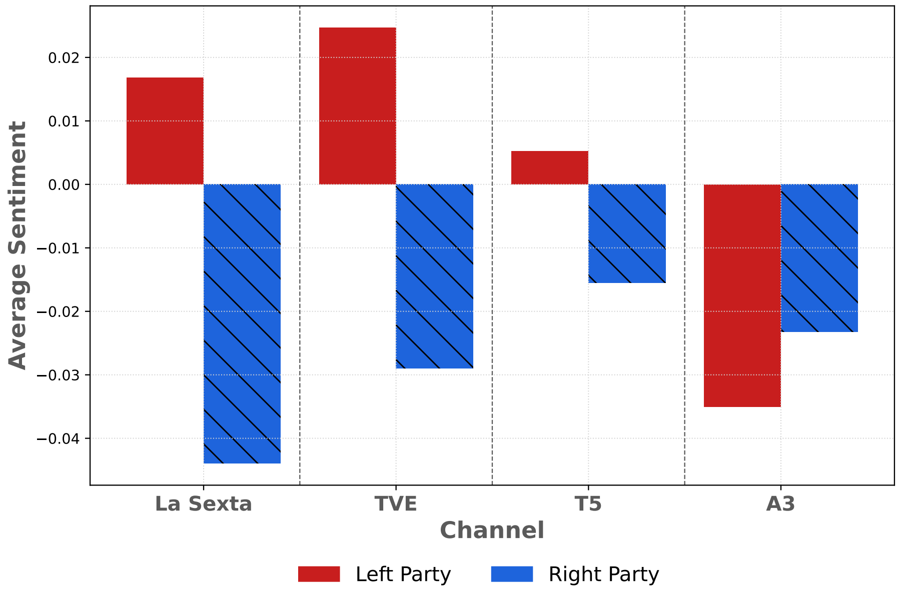
where now $\mathcal{N}_d$ denotes the total number of stories on day d, and $\mathcal{P}_d$ the subset of them classified as political under the same criteria as before. These variables will constitute the main controls and instruments for the empirical application in the next section.

[11] More details about the prompt and classification results can be found in Appendix Section A.

Results of the Slant Classification

Figure 3 plots each channel's net average tone toward left- and right-wing parties, calculated as the difference between positive and negative coverage from Equation (1) over the entire sample period.[12] Positive (negative) values indicate a net (un)favorable tone toward a party by that outlet.

Figure 3: Average Tone Across Channels and Parties



Note: The figure shows the average net tone toward left- and right-wing parties for each TV channel, computed as the difference between positive and negative minutes of coverage ($\bar{x}_j^{party+} - \bar{x}_j^{party-}$) as defined in Eq. (1). Positive (negative) values indicate a net (un)favorable tone toward a party by that outlet.

La Sexta and TVE tilt strongly pro-left, T5 sits near the center with a mild leftward bias, and A3 is the only channel with a slight pro-right balance. Every channel exhibits a net negative tone toward the right-wing bloc, reflecting the fact that the left coalition held office throughout the period under study. As can be seen in some of the text examples in Tables D.3 and D.19, the classifier interprets the passage of new laws or institutional visits as something positive for the incumbent. In practice, this meant an abundance of positive policy stories on the left and comparatively few favorable stories on the opposition, which pushes the average right-wing tone to be negative.

To validate these results, I compare outlets' slant classification with the ideological composition of their viewers that comes from survey data. I assign each channel a *slant index* calculated as

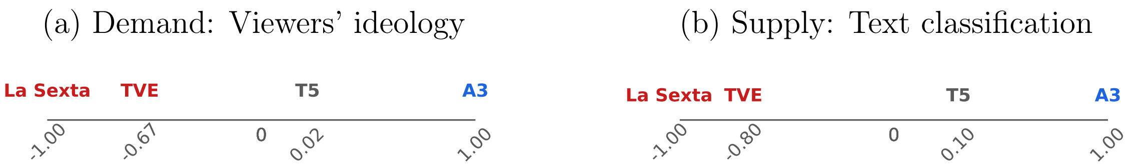
[12] Specific examples of stories with their tone classification can be seen in Appendix Table D.3.

$$Slant_j \equiv \left(\bar{x}_j^{R+} - \bar{x}_j^{R-}\right) - \left(\bar{x}_j^{L+} - \bar{x}_j^{L-}\right). \tag{3}$$

The slant index captures the party balance of each channel both in terms of their tone and proportion of time spent on each party. More positive values indicate coverage more favorable to right parties relative to left, and negative values the reverse. To assess whether the text-based slant is consistent, I compare it with each outlet's predicted left–right position derived from survey data on viewers' ideology described in the previous section (Figure 2). Under a demand-driven equilibrium, we expect the content offered to match viewers' political orientation.

Figure 4 displays the normalized scores: panel (a) shows outlets' positions based on viewers' ideology, and panel (b) based on their text-based slant. The consistent left-to-right ranking and the close dispersion of the values in both panels confirms that the LLM-based content classification of the channel's slant is similar to the ideological distribution of their viewers.

Figure 4: Left–right Positions of Channels from Demand vs. Supply



Note: The figure compares normalized left–right positions for the outlets in the sample. Panel (a) uses viewer ideology data from CIS survey data, using the difference in correlation coefficients between right and left; panel (b) uses GPT-based slant index as described in Equation (3). Values are normalized so that the two most extreme channels take values -1 and 1 to enable comparisons across the two different metrics.

Robustness of the text classification. The use of LLMs as classifiers has gained popularity for the classification of political stances, with even higher accuracy scores for ideological classification compared to human annotators (see, e.g., Le Mens and Gallego, 2023; Törnberg, 2023; Gilardi et al., 2023). However, two main concerns arise. First, LLMs have been shown to suffer from prompt instability, producing inconsistent results across multiple runs of the same query. Second, the performance of LLMs in discerning political stance compared to other text classification methods. In Appendix Section B, I address these concerns. I first demonstrate that the classification remains stable under repeated queries. Second, I compare my results with previous methods used to assess slant: similarity to congress speeches an politicians time on screen. Specifically, methods based on similarity to congressional speeches (Gentzkow and Shapiro, 2010; Laver et al., 2003) yield a consistent ideological ranking of the outlets although the spread of the ideological spectrum differs. Finally, I compare the LLM-based slant measure with the exposure metric used by regulatory agencies that tracks party leaders' on-screen time. To replicate this metric, I train a face-recognition model on images of national party leaders and apply it to a stratified subsample of broadcasts; for each outlet, I compute the share of minutes in which any leader appears. This exposure measure yields markedly different ideology scores: it portrays outlets as far more homogeneous and fails to recover the observed left–right ranking or its cross-outlet dispersion. In short, airtime is highly sensitive to event-driven appearances and production choices, making it a poor proxy for editorial slant.

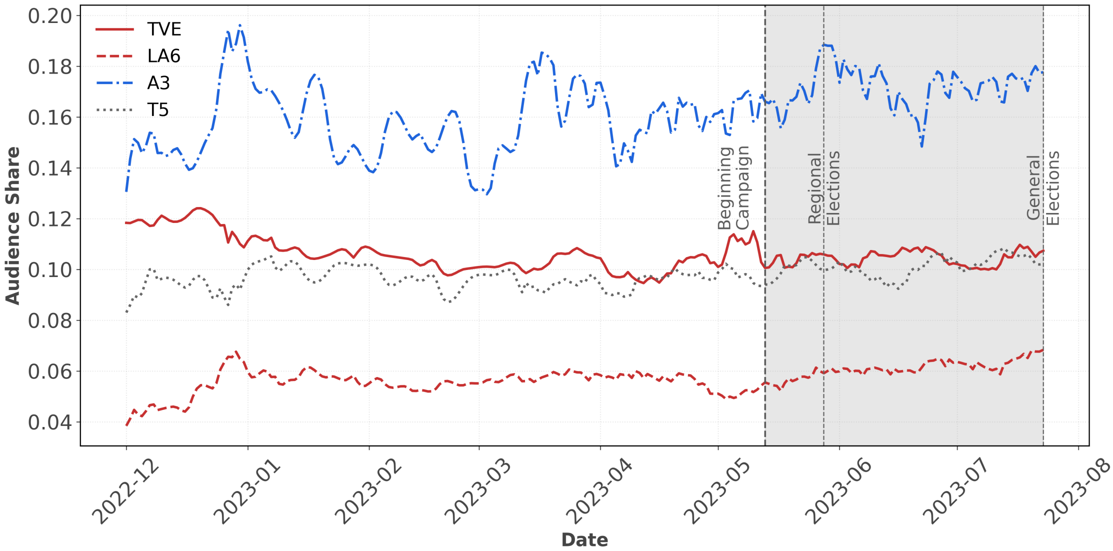
3.3 Descriptive Evidence

TV News Consumption and the Election Campaign

I divide the sample into two periods. The *off-campaign* period runs from the start of data collection (December 2022) to May 13, 2023, the date of the first publicly announced campaign for the regional elections. The *campaign* period covers both the regional and general election campaigns and ends on July 23, 2023 (general election day).

The campaign period coincided with the summer months, which usually coincide with low audience levels across outlets. However, Figure 5 shows a different scenario: due to the presence of a salient political event, all the outlets retained their audience shares. A3 moves from 17.2% to 16.9%, T5 from 9.4% to 10.1%, La Sexta from 5.6% to 6.0%, and TVE from 10.2% to 10.3%. This stability of the audience share numbers contrasts with the evolution in the total viewership. All channels lose audience levels in this period—on the order of 15–25%—with A3 still the largest (roughly 2.2M viewers off-campaign vs. 1.7M during the campaign) and the remaining channels experience similar proportional declines (see Figure C.20). This suggests that information seeking helps outlets maintain their slice of attention even as overall viewing falls in summer months.

Figure 5: TV Audience over Time



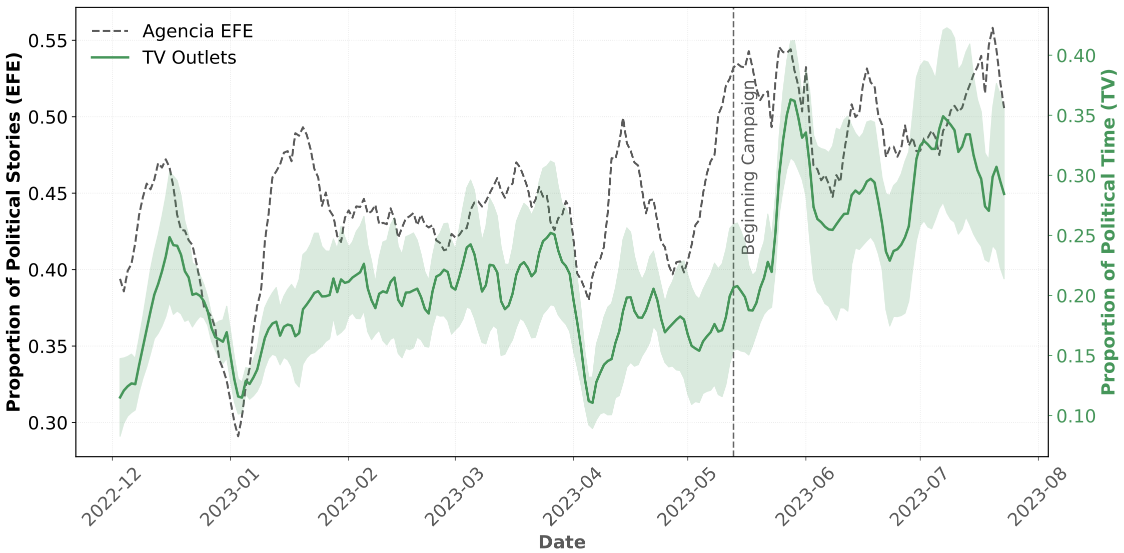
Note: The figure represents the share of audience for the TV outlets in the sample. Vertical, dashed lines indicate the date of the beginning of the campaign, the regional and the general elections, respectively. The shaded area represents the *campaign* period considered. All series are smoothed using a centered rolling mean with a 9-day window.

Political Coverage and the Election Campaign

Election campaigns concentrate public attention on politics and shift newsroom priorities. Consistent with this, Figure 6 shows that the share of political content rises sharply for both television and the EFE newswire. On average, TV channels devote 18% of airtime to politics off-campaign, rising to 30% during the campaign. For EFE, the share of political stories increases from 43% to 51%. Both series display similar seasonality (Pearson correlation $r = 0.59$), dipping in non-political periods such as Christmas and Easter.[13]

[13] There is, however, heterogeneity in how closely outlets follow the agency in terms of political coverage. A3 exhibits the strongest co-movement with EFE in political coverage ($r = 0.67$), followed by T5 ($r = 0.48$), TVE ($r = 0.38$), and La Sexta ($r = 0.26$). Figure C.21 in the Appendix shows the time series decomposition of political coverage by outlet.

Figure 6: Proportion of Political Coverage over Time



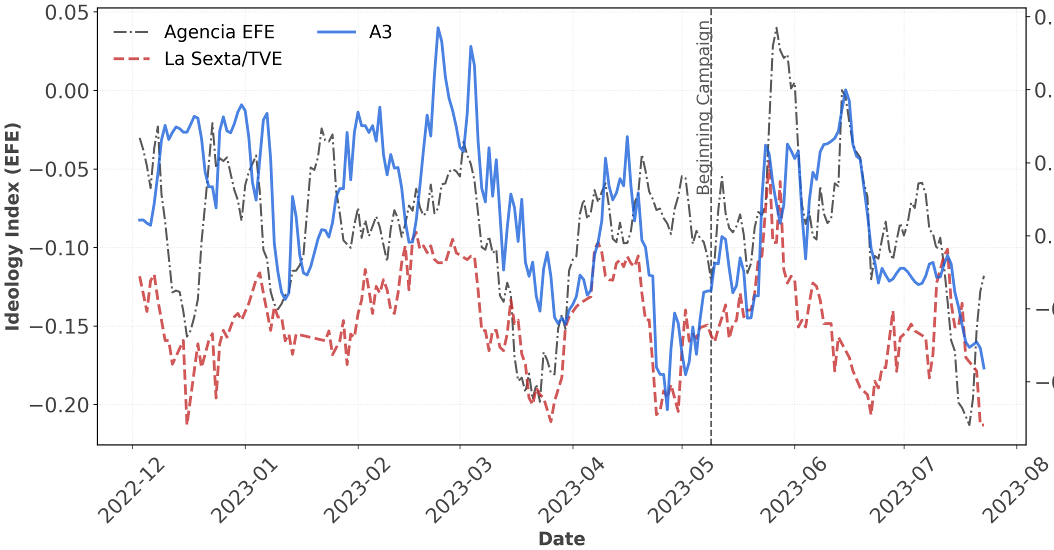
Note: The figure represents the proportion of political content for the TV outlets (solid) and EFE (dashed) as defined in Eqs. (1) and (2), respectively. All series are smoothed using a centered rolling mean with a 9-day window.

Campaigns shift attention toward politics; the next natural question to ask then is which party benefits from this. Figure 7 shows the evolution of slant index defined in Eq. (3) for the newswire agency EFE and the TV outlets.[14] Positive (negative) values indicate coverage more favorable to the right (left). EFE's series is predominantly negative, indicating a systematic tilt toward the left on average. As noted earlier, this pattern largely stems from the governing left-bloc coalition, which, by holding power, receives greater visibility through coverage of official meetings, legislation, and related activities.

There are clear structural breaks in outlets' trends. In March 2023, the right-leaning channel A3 experienced a marked shift in its slant index, with its previously conservative orientation converging toward that of the left-leaning outlets. This break coincided with a surge of negative stories about the right and positive coverage of the left. At that time, coverage turned more negative for the right and more positive for the left. A failed no-confidence vote launched by the far-right party VOX exposed splits on the right and weakened the opposition. Right parties were also on the defensive over several issues: opposing new laws on gender identity, assisted dying, and gender equality; being accused of blocking judicial reform; and disputes over pensions. Meanwhile, the governing left highlighted favorable news—record employment, a new housing law, and major industrial investment announcements. The right wing outlet A3 did not return to its previous level of conservatism until June, when the right's strong performance in the May regional elections brought back the

[14]Time series for all the individual outlets are shown in Appendix Figure C.22.

Figure 7: Evolution of the Slant Index



Note: The figure represents the time series of slant index defined in Eq. (3) for both the TV outlets (right y-axis) and the newswire agency EFE (left y-axis). Positive values denote pro-right coverage; negative values denote pro-left coverage. TV channels are grouped into left-leaning (La Sexta and TVE) and the right-leaning (A3). All series are smoothed using a centered rolling mean with a 9-day window.

divergence and partisan polarization between left- and right-leaning outlets.

For the analysis that follows, I take the entire off-campaign period as the baseline to better capture the underlying conservatism of A3. To illustrate how slant changed between the two periods of analysis, I decompose tone by party in Appendix Figure C.19. During the campaign, all outlets adopted a common approach to the parties at the extremes: they became more negative toward the far-right party VOX and more positive toward the left-wing party SUMAR. As a result, cross-channel slant became slightly less dispersed, and outlets' ideological positions converged.[15]

4 Demand for News

In this section, I introduce the market setting for demand. I first develop a mixed logit (BLP) model (Berry et al., 1995) where individuals choose the channel to watch depending

[15] Appendix Figure C.30 shows changes in left–right positions. Dispersion is summarized using three complementary statistics: the cross-channel range (distance between the most right- and most left-leaning outlet), the standard deviation (spread around the mean), and the left–right bloc gap (A3 versus the average of La Sexta, TVE, and T5). The cross-channel range declined from 0.088 to 0.083, the standard deviation from 0.032 to 0.030, and the bloc gap from 0.063 to 0.051.

on the content characteristic offered by the outlets (i.e., political slant). I then describe the endogeneity problem that arises from the simultaneity between editorial decisions and viewers' choices and introduce my identification strategy. Finally, I present the main estimation results and evidence linking media polarization to political polarization.

4.1 Demand Model

Viewers choose a single outlet to watch the news or else choose the outside option, defined as not consuming any of them. The single-product choice assumption might be particularly strong in television markets, where viewers can easily switch programming during the broadcasts—something that cannot be identified from daily aggregate data. To mitigate this concern, I restrict attention to the initial (i.e., minute-zero) audience for each day.[16] This makes the outlet choices mutually exclusive since they coincide in their broadcast emission times and thus cannot be simultaneously chosen.

I consider a market where both firms and products coincide. Formally, an individual i in region r chooses between any outlet $j \in \mathcal{J} \equiv \{La\ Sexta, TVE, T5, A3\}$ to watch at the beginning of day d or the outside option ($j = 0$). I define the expected utility of j as:

$$U_{ijrd} = \underbrace{\sum_k x^k_{jd-1}\beta^k + w_{rd}\gamma + \xi_{jrd}}_{\delta_{jrd}} + \underbrace{\sum_k x^k_{jd-1}\left(\sigma^k\nu^k_{ird} + \pi^k y_{irm}\right)}_{\mu_{ijrd}} + \epsilon_{ijrd} \tag{4}$$

and the one for the outside option is assumed to be $U_{i0} = \epsilon_{i0}$. The observed characteristics x^k_{jd} represent the proportion of time on channel j and day d devoted to characteristic $k \in \{R+, R-, L+, L-, political\}$ as defined in Eq. (1). w_{rd} measures the precipitation level on a given day-region. Weather shocks raise the utility of the inside options relative to the outside option, making viewers more likely to engage in indoor activities such as TV consumption (Wilbur, 2008). Individual taste shocks follow a standard normal distribution, $\nu^k_{ird} \sim N(0, 1)$, with mean shifted by demographics, y_{irm}, that represent whether individual i in region r is right-wing in month m according to survey data. Thus δ_{jrd} captures the mean utility for the baseline type (left-viewers) and the parameters π^k allow for asymmetric tastes of politics based on ideology, enabling to test the degree of polarization in news consumption.

The unobserved (to the econometrician) product characteristics are decomposed into three components $\xi_{jrd} = \xi_j + \xi_{dow} + \Delta\xi_{jrd}$. The first two represent product dummies that

[16] Previous works have documented the importance of inertia from previous shows in TV news consumption (Richter, 2025). During the period of analysis, there were no changes in the preceding slot's programming agenda, which minimizes this concern given the inclusion of day of the week fixed effects. Results are robust to the estimation using the first five minutes of the shows.

account for unobserved quality factors such as outlet loyalty, and day of the week dummies to control for seasonal variation in the value of TV consumption. The final term $\Delta\xi_{jrd}$ account for other unobserved product shocks that might include higher valuation of a given type of story that comes from knowledge of it through social media, specific regional taste shocks due to local events, etc. By assumption, viewers have full information about all the product characteristics when making decisions.

The market share for the jth product is computed as the integral over the individual choice indicators as:

$$s_{jrd} = \int d_{ijrd}(\boldsymbol{\delta_{rd}}, \boldsymbol{\mu_{ird}}) d\boldsymbol{\mu}_{ird} d\boldsymbol{\epsilon}_{ird} \tag{5}$$

where d_{ijrd} equals 1 if $U_{ijrd} > U_{ikrd} \quad \forall j \neq k$ and 0 otherwise. The shocks ϵ_{ird} are assumed to be i.i.d. drawn from a type I extreme-value distribution.[17]

Under the assumption of no individual heterogeneity in preferences ($\boldsymbol{\sigma} = 0$) and a homogeneous ideology distribution ($y_{ir} = \bar{y}_r$), Eq. (4) collapses to a plain logit model:

$$ln\left(\frac{s_{jrd}}{s_{0rd}}\right) = \sum_k x^k_{jd-1}\beta^k + w_{rd}\gamma + \sum_k \left(x^k_{jd-1} \times y_r\right)\phi^k + \xi_{jrd} \tag{6}$$

I report results for both BLP and logit models in Section 4.3.

4.2 Endogeneity and Identification Strategy

Models of demand estimation have often treated product characteristics as exogenous and used them as instruments for estimating price elasticities. That can be reasonable when characteristics are costly to adjust and competition is mostly price-based after product launch. In news markets, however, slant is easy to change, and is chosen by the outlets taking into account the same unobserved demand shocks that move audience shares, which makes it endogenous.

Formally, viewers form expectations about each channel's utility to start watching the news on day d based on exogenous variables—weather, individual attributes, and an unobserved (to the econometrician) shock ξ—as well as yesterday's realized slant content $\boldsymbol{x}_{jd-1}$. Channels already choose day's $d-1$ slant while forming expectations about next-day utility shocks $\Delta\xi_{jrd}$. These shocks have two components. On the one hand, there are day d taste shocks that outlets did not foresee when they set yesterday's slant. These include information people acquire on the day through social media about political events, which

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

can raise the immediate payoff from starting the news on a particular outlet. The timing difference partially addresses this concern because at minute–0 viewers choose a channel to start consuming the news based on exogenous factors and on yesterday's slant $\boldsymbol{x}_{j,d-1}$, which has already occurred. Hence these unanticipated shocks that shift minute–0 utility are orthogonal to $\boldsymbol{x}_{j,d-1}$ due to timing differences and do not create endogeneity in the estimation of the preferences for slant coefficients. On the other hand, there are predictable components—ongoing scandals, pre-show information—that outlets can anticipate and incorporate when planning and setting slant. As a result, optimal content decisions are functions of these anticipated taste shocks, implying $\mathbb{E}[\mathbf{x}_{jrd-1}\,\Delta\xi_{jrd}] \neq \mathbf{0}$.

I address endogeneity using random variation in the daily composition of the story pool available to produce the news. Each day's newswire feed is a proxy for the set of stories editors can draw on to build the newscast. The political mix of this set determines what is newsworthy and thus constrains what outlets can speak about. Although these shocks are common to all outlets, they affect outlets asymmetrically. Since events are not predictable and outlets wish to maintain their stance, they need to take advantage of politically "favorable" days where they can increase the coverage of events that match their political leaning. I therefore use the *news shock* $\mathbf{z}_d$ defined in Eq. (2) as instruments for outlet–day slant $\mathbf{x}_{jd}$. The key identification assumption is that $\mathbf{z}_d$ affects audience shares only through its impact on the cost of supplying slanted content, not through direct shifts in viewers' tastes.

The following examples illustrate the mechanism.[18] On 27 February 2023 (the most negative day for left-wing parties), a loophole in a law sponsored by the left party UP led to early releases of convicted sexual offenders and corruption scandals hurt the Socialist Party. Airtime given to negative left-wing stories differed markedly across channels: A3 (right) devoted almost 19%, TVE (left) and T5 each gave roughly 4%, and La Sexta (left) about 2%. The mirror image occurred on 17 May 2023 (the most negative day for right-wing parties): stories included a payments scandal involving the right-wing People's Party, the defeat of a conservative motion in the Senate, and police-abuse allegations during a march against the far-right party VOX. Left-leaning outlets devoted about 15% of airtime to negative right-wing content, whereas the right one devoted roughly 4%.

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

$$x_{jd}^{party,tone} = \sum_k \sum_{j'} \left(d_j(j') \times z_d^k \right) \alpha_j^k + \gamma_{dow} + \epsilon_{jd}, \tag{7}$$

where $k \in \{L+, R+, L-, R-, political\}$. As defined in Eq. (1), $x_{jd}^{party,tone}$ is outlet j's

[18]The full breakdown of the text examples is shown in Tables D.13 and D.14.

share of airtime with positive or negative tone about $party \in \{L, R\}$; z_d^k is the corresponding news shock from Eq. (2), and $d_j(j')$ is a dummy with value one if $j = j'$ and γ_{dow} are day of the week fixed effects. Controlling for the whole news landscape, I estimate how outlets increase the production of each type of content. A positive coefficient α_j^{R+} means that, ceteris paribus, a 1 p.p. increase in positive right-wing news shock increases outlet j's coverage of the right by α_j^{R+} p.p.

Figure 8 presents added-variable plots for regression Equation (7) pooling left channels for simplification.[19] Outlets generally respond to news shocks by increasing their coverage, independently on whether these affect right or left parties. The difference therefore, lies on the intensive margin: when the share of positive-right stories rises by one standard deviation, the right-leaning A3 lifts its own positive-right airtime by about 0.24 stdev., whereas the left-leaning outlets TVE and La Sexta react hardly at all. Symmetrically, a one-stdev. increase in positive-left stories leads TVE to expand favorable coverage of the left by roughly 0.26 stdev, while A3's response is 0.13 stdev. By contrast, the adjustment on the negative right content is small and non-significant. This is consistent with a saturation effect. Since all outlets already use negative tone on the right (e.g., see Figure 3) this leaves them with less margin to adjust on this category.

The existence of exogenous variation in outlets' response to the common news' shock is required by the rank condition in the estimation (Berry and Haile, 2014). Table 1 shows the F test for equality of coefficients across all outlets and the t-test for equality between right- and left-leaning outlets. The largest and most significant differences occur for pro-right content, followed by negative left, positive left and, the less significant negative right.

Table 1: Tests for Differences in Coefficients

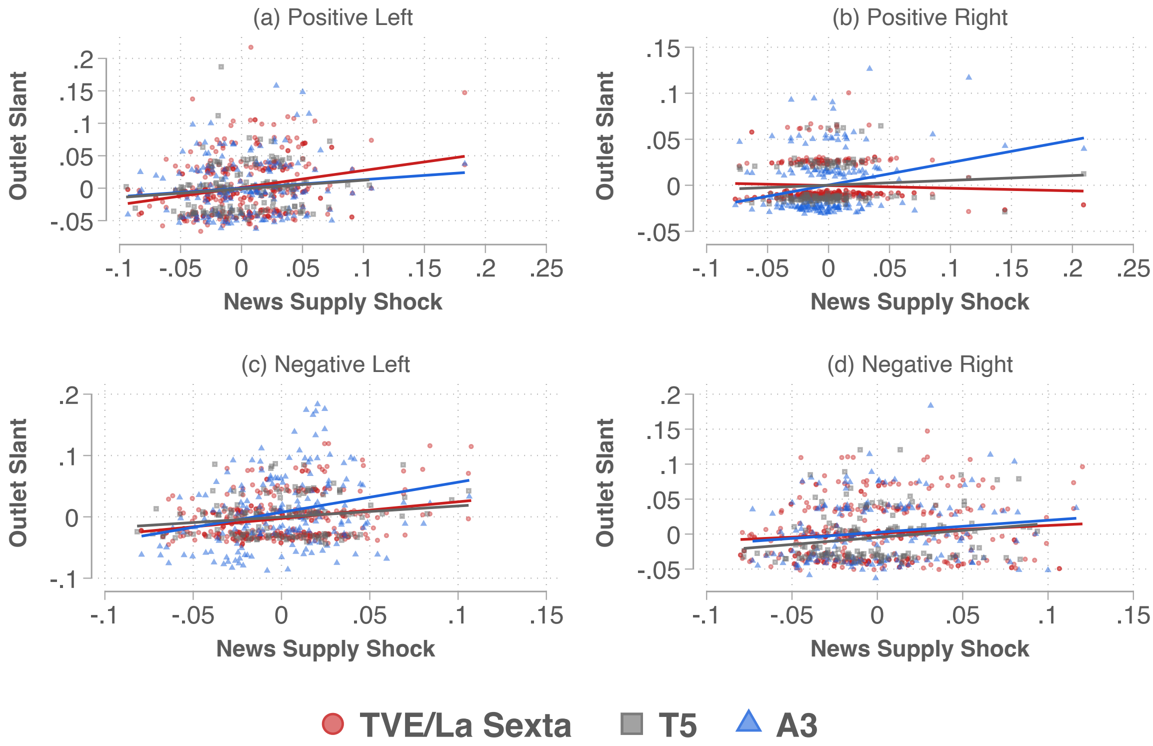
Characteristic	F-test	F-test p-value	T-test	T-test p-value
$L-$	2.69	0.07	3.51	0.06
$L+$	1.31	0.27	1.87	0.17
$R-$	0.42	0.66	0.34	0.56
$R+$	8.78	0.00	17.55	0.00

Note: Summary of F- and T-test results for equality of coefficients across channels from regression Equation (7). The F-test evaluates overall equality across channels, while the T-test compares the coefficient of the main independent variable between A3 and TVE/La Sexta.

Accordingly, I use $\boldsymbol{z}_d$ as instruments for the linear content characteristics $\boldsymbol{x}_{jd}$. For the K non-linear parameters governing preference heterogeneity $\boldsymbol{\sigma}$, I follow Gandhi and Houde (2019) and use instruments of the form $\left(\hat{x}_{jd}^k - \sum_{l \neq j} \hat{x}_{ld}^k\right)^2$, where $\hat{x}_{jd}^k$ is the predicted slant

[19] I also present a non-linear LOWESS version to mitigate concerns of outliers in Appendix Figure C.23. Full results of the estimation are shown in Table D.9.

Figure 8: Added Variable Plots for Production of Political Content



Note: The figure shows the added variable plots from the estimation of regression Equation (7). The x-axis represents the news shocks z_d^k residuals and the y-axis the corresponding outlet's slant x_{jd}^k residuals for each party-tone combination. Channels are pooled into left (TVE and La Sexta), middle (T5) and right (A3) for visualization purposes.

based on the reduced-form regression Eq. (7). To identify the demographic interaction coefficients π, I multiply these instruments by the average share of right-wing votes, $\bar{y}_{mr}\, \hat{x}_{jd}^k$.

4.3 Results of the Demand Estimation

I present the results of the BLP estimation for the off-campaign and campaign periods in Table 2. I show the preferred specification with both outlet and day-of-week fixed effects, and standard errors clustered at the regional level. Because the political division in demographics is only between left- and right-leaning viewers, the βs represent the mean tastes of left-leaning viewers and the πs are deviations for right-leaning audiences.

Most of the heterogeneity is captured by the demographics (i.e ideology). The estimated taste-dispersion parameters (σs) are small and imprecisely estimated. The high standard errors on these coefficients arise by construction. The identification of the random-coefficients relies on variation across markets in the choice set, which is null in my case given that the

Table 2: BLP Estimation Results with Standard Errors

Coefficient	**Parameter**	**Estimate**	**Std. Error**
	Off-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)

Note: The table shows the results of the BLP estimation of model (4). The estimations are divided into the off-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 $N_{off-campaign} = 6604$.

same products are present across regions and dates.[20] The low values of the estimated σs naturally link to the similar results that I obtain under the multinomial logit specification shown in Table D.10.

In order to give a better interpretation of the content-taste parameters I present the mean own elasticities 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 mean elasticity for the k-th characteristic as:

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

where aggregation is taken over outlets (j), regions (r) and days (d). Both left and right parties were almost equally disliked during off-campaign (Table D.5.). An increase of 1 percent in net tone towards right (left) parties results in drops of 0.98 (1.00) percentage points in audience share; corresponding to a decrease of nearly 13,000 viewers.[21] This is consistent with a taste for scandals or entertainment-like type of political content. During the campaign, aversion to right-leaning tone persists but weakens (-0.60 pp), and higher net tone on the left yields a small audience gain of 0.09 p.p. (867 viewers). Furthermore, Table D.11 computes the diversion ratios to get a sense of where viewers go when a channel's political content shifts—i.e., a loss-normalized decomposition of exits across destinations. Most of the substitution occurs to the outside option, indicating viewers mainly switch to non-tv news consumption.

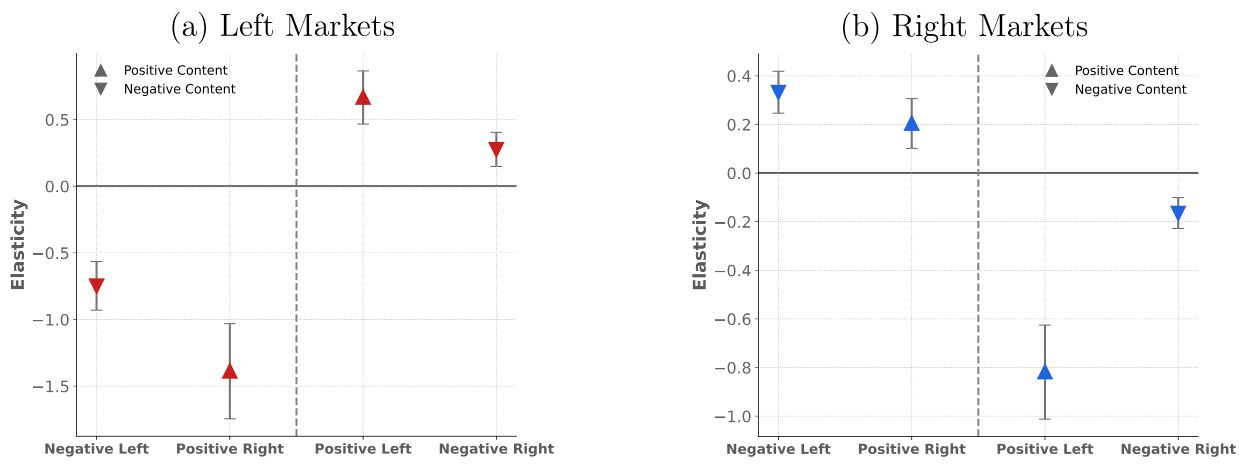
I focus now on the results for the main period of analysis, the election campaign. To see the extent of polarization in news consumption, I compute elasticities for right and left markets separately. I define a "right market" as any region whose mean intention-to-vote to the right ($\bar{y}_r$) lies above the median. Figure 9 plots the estimated elasticities for that period for left markets (panel a) and right markets (panel b).[22] Polarization becomes now evident. Left viewers present negative taste for content that harms their party and positive taste for content that benefits it. The analogous pattern is present in the taste of right-wing viewers. This campaign pattern contrasts with the off-campaign "scandal/negativity" taste, where both blocs reacted similarly to net partisan tone.

[20]A similar result was documented by Nevo (2001) for the cereal industry. Consistent with his findings, the relative importance of demographics versus random shocks—computed as the ratio of variance explained by demographics to the total variance in the distribution of estimated coefficients—exceeds 90% in my model.

[21]A 1 p.p. increase in airtime on characteristic k changes audience share by $\Delta S = S \times \frac{\epsilon}{100}$. Given an average total audience of $\bar{L}$, the level change in viewers is $\Delta V = \Delta S \times \bar{L}$. Since 1 p.p. of airtime corresponds to $0.01\,\bar{T}$ minutes (where $\bar{T}$ is the average broadcast length), $\frac{\Delta V}{\Delta t} = \left(S \times \frac{\epsilon}{100} \times \bar{L}\right) \times \frac{1}{0.01\,\bar{T}}$ gives the change in viewers per extra minute of coverage.

[22]Table D.6 and Figure C.24 show full results also for the off-campaign period.

Figure 9: Estimated Elasticities for Left and Right Markets During Campaign



Note: Each panel shows estimated mean own elasticities for consumer responses as described in Eq. (8) during the campaign period. Panel (a) shows elasticities for left-leaning regions (defined as regions with below-median right-wing vote intention), and Panel (b) for right-leaning regions (above-median). Whiskers represent 95% confidence intervals of the mean across markets.

Furthermore, favorable partisan reactions are asymmetric across right and left markets. In-party affinity is relatively stronger in left markets (a larger reward for positive-left than for negative-right). In right markets, by contrast, out-party aversion dominates (a larger penalty for positive-left and a stronger response to negative-right). For example, a 1 p.p. increase in negative-right tone during the campaign is associated with a net loss of 8,015 viewers in right markets relative to the off-campaign period. Across both right- and left-leaning markets, audiences consistently screen out coverage that favors the opponent, and this is the content that provokes the largest reactions.

4.4 Demand for News and Electoral Polarization

Does higher polarization in the demand for partisan content link to more polarized electoral attitudes? In the spirit of Martin and Yurukoglu (2017), I compute the Esteban–Ray (ER) polarization index and link it to the way people consume partisan news according to my demand estimates.

I compute ER on party vote intentions, which can be consistently tracked over time across survey waves for the four main parties in the sample $\mathcal{P} = \{\text{UP}, \text{PSOE}, \text{PP}, \text{VOX}\}$. Define v_{prm} as the share of intention to vote towards party p on region r in month m; where I renormalize within $\mathcal{P}$ so that $\sum_{p\in\mathcal{P}} v_{prm} = 1$. The ER index is defined as:

$$ER_{rm} = \sum_{p\in\mathcal{P}} \sum_{q\in\mathcal{P}} v_{prm}^{1+\alpha}\, v_{qrm}\, d_{pq}, \tag{9}$$

where α is set to the standard value of 1.5 and d_{pq} denotes the ideological distance between parties.[23] The index ER_{rm} is low when support concentrates on a single party and rises as mass is split across parties that are farther apart on the ideology scale.

In order to capture partisan-selective news consumption, I measure news-demand polarization as the out-party negativity gap in audience reactions to slanted content. Specifically, I calculate the elasticity gap between reactions to congenial and uncongenial coverage during the campaign period and define *media polarization* for a given region as:

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

For right-wing regions ($p(r) = R$), media polarization refers to the difference in taste for negative content on the left versus positive on the left and analogously for the left-wing regions. Because the estimates satisfy $\bar{\epsilon}_r^{(L-)} > \bar{\epsilon}_r^{(L+)}$ in right-leaning regions and $\bar{\epsilon}_r^{(R-)} > \bar{\epsilon}_r^{(R+)}$ in left-leaning ones, the index in Eq. (10) is always non-negative and therefore comparable across regions. Higher values indicate more partisan-selective news consumption: audiences respond more to negative than positive news about the party they oppose.[24] I then divide regions into *high* and *low* groups according to their news demand polarization relative to the median and plot their ER index for an extended period over the year before and after the 2023 election. Results are shown in Figure 10.

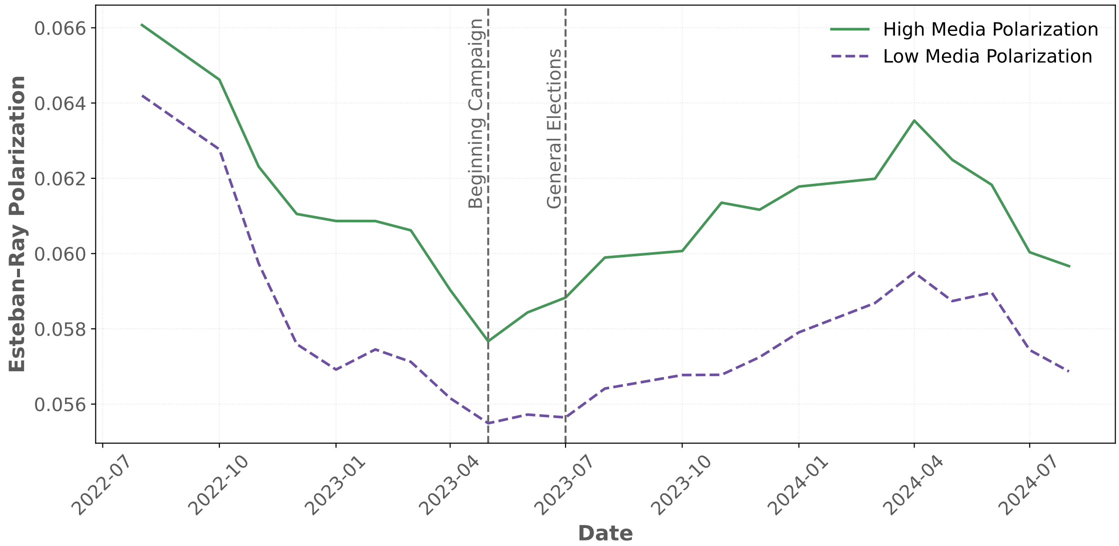
Regions with high polarization in news demand (solid line) have significantly higher ER polarization[25]; thus, consuming political information in a more partisan-selective way is associated with electorates whose vote intentions are concentrated in ideologically distant parties. Similar to the demand-side results, the political campaign constitutes a structural break of one year of declining ER polarization levels that persists for over a year. This persistence contrasts with prior work that found short-lived effects of polarization after campaigns lose salience (Hernández et al., 2020). While descriptive, this pattern is consistent with persuasion mechanisms in the media literature and it motivates future work that explores the causal link between media consumption and political polarization.

[23] Baseline ideology scores used to compute distances: $i_{\text{UP}} = -1.0$, $i_{\text{PSOE}} = -0.5$, $i_{\text{PP}} = 0.5$, $i_{\text{VOX}} = 1.0$ Distances are defined as $d_{pq} = |i_p - i_q| / \max_{i,j} |i_i - i_j| \in [0, 1]$.

[24] This interpretation aligns with in–out party evaluation gaps commonly used to capture affective polarization (Iyengar et al., 2019).

[25] The coefficient from a regression on the ER polarization index on the high-media polarization dummy is positive and significant with $t - val \approx 5$ with and without the inclusion of date fixed-effects.

Figure 10: Electoral Polarization by Regions with High vs. Low Media-Demand Polarization



Note: The figure shows the evolution of the Esteban–Ray polarization index as defined in Eq. (9), plotted separately for regions with high (i.e. above the median) versus low media polarization according to Eq.(10). Vertical dashed lines marking the start of the campaign and election periods are shifted one to match the survey's timing. The series covers the year before and after the 2023 general election. All series have been smoothed under a three-month centered moving average.

Limitations. To conclude the results section for demand, it is important to discuss some limitations of my analysis.

First, the use of aggregate data cannot rule out selection effects at the individual level. Campaigns might change audience composition toward news seekers, who have been shown to have asymmetric effects on polarization relative to entertainment seekers (Levendusky, 2013; Arceneaux and Johnson, 2013). This could lead to an overestimation of preference polarization. To partly address this concern, I test compositional changes in audience based on complementary data on demographics. Appendix Table D.7 shows no significant compositional differences along the age and sex dimensions from off- to on-campaign.

Second, the link between media and political polarization naturally raises the question of how much of the shift in preferences is driven by changes in ideological polarization. I re-estimate the model in Equation (4) using initial ideology measures (i.e., December) rather than monthly ones; the results are robust. However, this does not mitigate the concern about the potential endogeneity of ideology, which remains a limitation of this paper. Future work might address this concern using individual panel data or by allowing more flexible dynamics between ideology and media consumption, as in Martin and Yurukoglu (2017).

5 Supply of News

The demand estimates in Section 4.3 show that viewers react sharply to partisan tone, especially during the campaign. This leads to the complementary question: How do broadcasters decide the way they frame the news? The following remark from the news director of one of the channels illustrates their behavior:

> "Even a news program 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, A3 News (2014)[26]

Producers therefore aim to maximize the audience shares and adapt their coverage to do so on a daily basis. In order to capture this behavior, I build a model of news slant decisions.

5.1 Supply Model

Within each day's news broadcast, outlets choose the slant of the news in order to maximize national audience, but face costs of producing the slant that depend on the news pool that is available. Formally, channel $j \in \{La\ Sexta, TVE, T5, A3\}$[27] on day d and edition hour $h \in \{0 \text{ (midday)}, 1 \text{ (evening)}\}$ solves the following problem:

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

where $\boldsymbol{z}_{dh}$ measures the pool of stories available at edition h, meaning the stories available up until the beginning of the midday ($h = 0$) and evening editions ($h = 1$) of the newscasts. $\boldsymbol{x}_{jdh}$ is the proportion of minutes to each tone category as defined in Eq. 1. L_r refers to the total potential audience in region r. Notice that I have now incorporated the midday dimension in this analysis. The reason for this will become apparent below in the description of the identification strategy.

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

[27]Although both La Sexta and A3 belong to the same media company, AtresMedia; the short period span considered here considers them as independent products. That is, firms and products coincide.

The first term in the payoff captures outlets' incentives to retain audience. Although this motive differs between the private (for-profit) and the public broadcasters, I abstract from pricing considerations and—following Goettler and Shachar (2001)—focus on predicted audience only. This standardizes payoffs and allows the public, ad-free broadcaster to be included in the same competition game. The second term in the payoff captures the cost of producing slant as a function of the exogenous pool of stories available on a given day. I parameterize the marginal cost function of a given channel j for content category k as:

$$mc(x_{jdh}^k, z_{dh}^k, \eta_{jd}^k, \nu_{jdh}^k; \phi, \lambda_j^k) \equiv \phi + 2\lambda_j^k \frac{x_{jdh}^k}{z_{dh}^k} + \eta_{jd}^k + \nu_{jdh}^k.$$

Marginal costs depend on the ratio between the airtime share devoted to each tone category, x_{jdh}^k, and the share of available stories, z_{dh}^k. I use a flexible specification and allow the slope parameters $\boldsymbol{\lambda}_j$ that govern production costs to vary across outlets and content types. This can capture, for example, greater efficiency when journalists produce slant aligned with the outlet's preferred ideological position. The last two components represent unobserved cost factors and are divided in: (i) η_{jd}^k, a day-specific marginal-cost shock (e.g., a key reporter is on sick leave, a satellite link fails, or legal review delays a segment) that is known to outlets; and (ii) ν_{jdh}^k, a mean-zero, outlet–day–edition idiosyncratic supply shock that is unknown to the players.

The first-order conditions (ignoring the constraints for estimation) are

$$\underbrace{\sum_r \frac{\partial \widehat{s_{jrd+1}}}{\partial x_{jdh}^k} L_r}_{\equiv g_{jd+1h}(x_{jdh}^k)} = \phi + 2\lambda_j^k \frac{x_{jdh}^k}{z_{dh}^k} + \underbrace{\eta_{jd}^k + \nu_{jdh}^k}_{\equiv u_{jdh}^k} \quad \forall (j,k) \tag{12}$$

where the derivative for all the tone characteristics also includes the marginal effect on $x^{political}$ but is omitted from the formulation for notational simplicity. The predicted audience share comes from the evening newscasts estimation but is also used to predict the midday audience share due to data limitations. This is consistent under the assumption of stable audience composition, and therefore tastes, on a given day. I show empirically that the estimated game has a unique Nash equilibrium for the majority of the days in the sample.

5.2 Endogeneity and Identification Strategy

Channels choose the day's slant $\mathbf{x}_{jdh}$ after observing the same-day cost shifter $\boldsymbol{\eta}_{jd}$. Events like a reporter's sick leave, a technical broadcast issue or owner bias[28] might shift these

[28]Endogenous factors such as outlet's private interests will be taken care of by my identification strategy if they enter linearly in the payoff specification. For instance, in the specification proposed by (Anderson

unobserved factors thus affecting the optimal slant $\mathbf{x}_{jdh}$ and thereby the demand gradient $g_{jd+1h}(\mathbf{x}_{jdh})$. Formally, from Equation (12), $\mathbb{E}\left[\boldsymbol{u}_{jdh} \times \frac{\boldsymbol{x}_{jdh}}{\boldsymbol{z}_{dh}}\right] \neq \mathbf{0}$.

I exploit within-day timing for identification. The day-specific cost shock η^{k}_{jd} is assumed to be realized before content production decisions and to be constant across the midday ($h = 0$) and evening ($h = 1$) editions. It thus captures newsroom frictions that persist throughout the day. Under this assumption, changes in chosen content between the two editions are driven by new stories arriving in the interim, $\Delta \boldsymbol{z}_d \equiv \boldsymbol{z}_{d1} - \boldsymbol{z}_{d0}$. These arrivals shift the optimal slant $\mathbf{x}_{jdh}$ by altering the marginal-cost term $\boldsymbol{x}_{jdh}/\boldsymbol{z}_{dh}$, while leaving $\boldsymbol{\eta}_{jd}$ unchanged.

Text examples illustrate this mechanism (Table D.20). 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, the biggest swing in negative-left coverage (+41 p.p.) occurred on 29 May 2023: the arrival of the overseas-ballot recount after the regional elections effectively tipped a key seat, opening a right-bloc majority, and channels incorporated those items in the evening. Analogously, on 31 May 2023 negative-right coverage rose (+22.6 p.p.) and positive-left increased (+28.2 p.p.) after afternoon legal developments unfavorable to the right and pro-government organizational updates entered between editions, shifting the evening mix the other way. These within-day arrivals of politically slanted stories are precisely the exogenous movements in content composition that I use to trace audience responses and identify λ.

To document this variation empirically, I first regress the evening on the midday slant of the stations controlling for outlet fixed-effects. The residuals of these regressions are the variation in the evening programming not explained by the midday slant and channel-specific attributes. I then regress these residuals on the news shocks that enter between those two time slots, $\Delta \boldsymbol{z}$. Figure C.26 shows the scatter of the regression. The positive relationship 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. Unlike the pattern shown in the demand shocks, outlets do not respond homogeneously to these arrivals (Figure C.25).[29] Right and left outlets respond by increasing coverage when the content is positive, whereas they reduce the evening airtime minutes if the unexpected arrivals are negative political news. As before, asymmetries in their responses are consistent with their political positions.

and McLaren, 2012), owner bias would enter as a multiplicative term between owners' private ideology and the content characteristics, governed by a coefficient that captures its strength.

[29]To decompose this variation by outlet, I also run regressions of the form described in (7) done on within-day differences Δx_{jd} and Δz_d. Although there is significantly less power now, the main mechanism still holds. Right (left) outlets increase their production of stories of a given party-tone from midday to the evening editions conditional on those stories being aligned with their stances.

These exogenous shocks can therefore be exploited in the cost estimation to address endogeneity. Differencing (12) eliminates the unobserved shock:

$$\underbrace{\sum_r \left(\frac{\partial \widehat{s_{jrd+1}}}{\partial x^k_{jd1}} - \frac{\partial \widehat{s_{jrd+1}}}{\partial x^k_{jd0}} \right) L_r}_{\Delta g^k_{jd+1}} = 2\lambda^k_j \Delta \left(\frac{x^k_{jd}}{z^k_d} \right) + \Delta \nu^k_{jd}, \quad \forall (j,k). \tag{13}$$

Intuitively, the evening–midday change in the gradient, Δg^k_{jd+1}, is driven by the change in story availability $\Delta \frac{x^k_{jd}}{z^k_d}$, while the day-persistent cost shock cancels out. The system of equations in (12) can be estimated under GMM with conditions $\mathbb{E}\left[\Delta\left(\frac{\boldsymbol{x}_{jd}}{\boldsymbol{z}_d}\right)\Delta\boldsymbol{\nu}_{jd}\right] = \mathbf{0}$.

Notice that the parameters $(\phi, \boldsymbol{\eta})$ cancel out in the differentiation and thus cannot be identified but they are part of the overall cost and thus needed to interpret them. They can be recovered by rearranging from the first-order condition in (12). Define the residual as:

$$r^k_{jdh} \equiv \phi + \eta^k_{jd} + \nu^k_{jdh} = g_{jd+1h} - 2\,\lambda^k_j \frac{x^k_{jdh}}{z^k_{dh}}.$$

Since $\mathbb{E}(\nu^k_{jdh}) = 0$, an unbiased estimate of the unobserved marginal cost shifter $\boldsymbol{\eta} + \phi$ is obtained by averaging across the midday and evening editions of r_{jdh},

$$\widehat{\phi + \eta^k_{jd}} = \tfrac{1}{2}\big(\hat{r}^k_{jd0} + \hat{r}^k_{jd1}\big).$$

In the counterfactual problem (14), I treat this estimate as given (fixed by day and channel) and solve for best responses under the policy constraints, so changes arise from the policy, not from altering day-specific costs.

5.3 Results of the Supply Estimation

The sign of λ^k_j is theoretically ambiguous ex ante. If, as suggested in Simonov and Rao (2022), high availability of stories of a given type will make production easier since the journalist need not expend effort to investigate, z might act as a simple input into production costs and $\lambda > 0$. On the other hand, since outlets are news aggregators, having more stories available of a given type might increase production costs, since they would need to process and filter the stories they prefer. This mechanism is consistent under $\lambda < 0$. I therefore do not restrict the λ to be positive in the estimation and show robustness under stricter version of $\lambda \geq 0$.

Table 3 reports the estimated λ_j^k.[30] There is heterogeneity both across outlets and content types, and it partly lines up with editorial positions. For instance, left outlets face higher costs for negative-left content, whereas the right-leaning channel does not. Producing content that favors the right is intrinsically beneficial across outlets ($\lambda < 0$), but especially so for right channel. Negative-right content is beneficial or less costly for left outlets, while A3 faces the highest cost in that category. The main deviation from this pattern is positive-left content, where signs match with the negative left one and thus do not reflect the expected asymmetries.

Table 3: Estimated Cost Parameters (λ) by Channel and Content Type

	La Sexta (Left)	TVE (Left)	Telecinco (T5) (Middle)	Antena 3 (A3) (Right)
Positive Right	-89.09	-103.74	-13.87	-240.52
	(85.99)	(121.36)	(91.62)	(77.50)
Negative Right	4.07	-8.88	31.13	35.16
	(4.80)	(11.41)	(36.16)	(53.89)
Positive Left	12.82	6.27	108.34	-38.96
	(44.44)	(2.63)	(60.39)	(23.79)
Negative Left	36.11	3.36	24.03	-40.03
	(52.70)	(13.12)	(43.99)	(84.81)
Political	-0.35	0.32	1.50	1.45
	(0.61)	(0.62)	(1.05)	(1.25)

Note: The table shows the estimated coefficients from the unconstrained GMM for the system in Equation (13) for the campaign period. Robust standard errors in parentheses.

Costs are measured in thousands of viewers and map directly into audience values, so they can be read as "how much audience a channel gives up" to shift tone. A 1 p.p. increase (from the median) in positive coverage of the left is relatively expensive for the right-leaning channel A3: it costs 8 p.p. of audience share more than moving the same amount toward negative coverage of the left. For left-leaning outlets, the same shift is far smaller, only 3 p.p. more than going negative. This corresponds to roughly 50% (right) and 20% (left) of the audience-share loss observed when major football matches coincide with the newscast.[31]

[30]Processing of the midday broadcasts for the pre-campaign period could not be completed after the Google Cloud and OpenAI credits ended; consequently, the cost estimates here cover only the campaign window.

[31] During the sample period, three dates held football matches on the public broadcaster TVE: UEFA Champions League (2023-06-10), Copa del Rey (2023-04-05), and UEFA Nations League (2023-06-15). For each date, I compare the news share loss of the rest of the outlets relative to the same-weekday mean. The

In contrast, a 1 p.p. increase in positive coverage of the right is 6 p.p. less costly than going negative for the right-leaning outlet, while for left-leaning outlets it is 1 p.p. more costly than going negative.

Given the demand and supply estimates, I recover the total payoffs for each outlet and tone. Figure C.27 plots the payoff functions (in thousands of viewers) [32] For both parties, negative-tone categories dominate: the right-leaning channel obtains a maximum of around 500 thousand viewers with negative-left content (vs. 400 thousand at the maximum positive-left tone), while the left-leaning outlets get a maximum of around 300 thousand with negative-right content (vs. 90 thousand with positive-right). To better illustrate this negativity premium, Figure C.29 plots the payoff surface for each channel varying the right and left tones. It becomes apparent that the outlets obtain higher viewership by becoming more negative on the opposing party, with the middle channel reaching a maximum with a balanced coverage.

6 Proportional Air Time Rule

Across Europe, election coverage is commonly regulated by proportional-time rules tied to party representativeness. In France, for instance, the broadcast regulator ARCOM monitors the speaking time and airtime of political actors in news bulletins, news magazines and other programs on TV and radio to enforce political pluralism. During campaigns these rules apply to all programs covering the election. ARCOM requires equitable coverage (proportional to representativeness) and, in the presidential election, strict equality of speaking time and airtime from the start of the official campaign. In Italy, the communications authority AGCOM enforces the par condicio law, which governs access to programs of information and political communication on television and radio. During electoral periods, AGCOM requires that news and political programs allocate speaking and news time proportionally to each party's representativeness. These rules apply explicitly to news bulletins and current-affairs programs.[33]

My model estimates allow me to assess the implications of the proportional-airtime rule for all broadcasters. I take the proportion of votes in the past general elections for each party ($vote^R, vote^L$) and estimate the new equilibrium under the following problem:

average audience share loss was 17.91 p.p.

[32] Figure C.28 shows the payoffs under the non-negativity constraint. The ranking of payoffs is stable across the two specifications.

[33] More details about the regulations can be checked at https://www.arcom.fr/nous-connaitre-nos-missions/garantir-le-pluralisme-et-la-cohesion-sociale/proteger-le-pluralisme-politique for ARCOM and at https://www.agcom.it/sites/default/files/migration/delibera/Delibera%20122-24-CONS.pdf for AGCOM.

$$
\begin{aligned}
&\max_{\{\boldsymbol{x}_{jd}\}} \left\{ \sum_r \widehat{s_{jrd+1}}(\boldsymbol{x}_{jd}, \boldsymbol{x}_{-jd}) L_r - \sum_k \left(\hat{\lambda}_j^k \frac{(x_{jd}^k)^2}{z_d^k} + \widehat{(\phi + \eta_{jd}^k)} x_{jd}^k \right) \right\} \\
&s.t. \quad \frac{x_{jd}^{R+} + x_{jd}^{R-}}{x_{jd}^{political}} = vote^R \equiv 0.49 \\
&\qquad \frac{x_{jd}^{L+} + x_{jd}^{L-}}{x_{jd}^{political}} = vote^L \equiv 0.51 \\
&\qquad x_{jd}^k \in [0,1] \quad \forall k
\end{aligned} \tag{14}
$$

I assume that the policy is enforced; that is, all outlets must devote the proportion of political time given by vote shares from the previous election $(vote^R, vote^L)$ (i.e, constraints bind). This simplifies the choice set to $\left(x_{jd}^{L+}, x_{jd}^{R+}, x_{jd}^{political}\right)$. According to my measurement, a minute is attributable to a party only when it carries a detectable stance; neutral political minutes are therefore not counted toward the quota. For computational constraints I i) pool left channels as a single player using their average payoffs and ii) discretize the action space and solve for the pure Nash equilibrium after converting the problem into a normal form game.[34]

6.1 Effects of the Regulation

Results of the counterfactual estimation are shown in Table 4. I present the results for dates with a unique Nash equilibrium (63% of the total dates). The left columns report the baseline, average minutes for each category during the campaign and the right column reports the results from the counterfactual equilibrium.

Several facts emerge from the counterfactual exercise. First, in terms of political coverage, the left-leaning outlets slightly reduce it, whereas the middle (T5) and right (A3) sharply increase it to 90 percent. These responses are consistent with the model's supply and demand estimates. With low marginal costs of producing political content (Table 3), the optimal political share, $x^{\text{political}}$, is mainly driven by viewer preferences. From the demand estimates (Table 2), right-wing viewers value political content positively, while left-wing viewers value it negatively. This makes it profitable for the right-leaning outlet to expand political minutes, though less so for outlets with left-leaning audiences. Second, the increase in political content comes almost entirely in the form of negative tone of the opposing party.

[34] I build a discrete grid with values on $[0, 0.3, 0.6, 0.9]$. I then filter only feasible choices. In the original normal form game, the joint action space from this setting consists of $20^4 = 160,000$ pure strategy profiles even under the simplest grid of 3 points per action. The counterfactual constraints simplify the action space to 2197 strategy profiles. The code was run under a Google Cloud "n2d-standard-224" virtual machine (224 vCPUs, 896 GB RAM).

Table 4: Baseline and Counterfactual Slant by Channel

	La Sexta/TVE (Left)		Telecinco (T5) (Middle)		Antena 3 (A3) (Right)	
	Baseline	Count.	Baseline	Count.	Baseline	Count.
Negative Left	0.06	0.05	0.04	0.36	0.09	0.45
Positive Right	0.03	0.00	0.03	0.00	0.04	0.01
Positive Left	0.09	0.10	0.04	0.10	0.06	0.01
Negative Right	0.09	0.15	0.04	0.44	0.07	0.43
Political	0.42	0.30	0.18	0.90	0.39	0.90

Note: The table reports the average share of minutes per content category under the baseline and counterfactual equilibria. Baseline values refer to observed campaign broadcasts; counterfactual values are predicted from solving the counterfactual optimization problem in Equation (14). Channels are grouped as: left-leaning (La Sexta, TVE), middle (T5), and right-leaning (A3).

The right-leaning outlet increases negative coverage equally for both parties and the left-leaning outlets do so only for the right. The "negativity" in the equilibrium is consistent with the payoffs shown in Figure C.29, where each outlet enjoys significantly more viewers from raising negative rather than positive tone on the opposed party.

Taken together, these adjustments generate a more polarized landscape. Figure C.31 illustrates the resulting shifts in outlets' ideological positions: left-leaning and centrist outlets move further left, while A3 strengthens its rightward tilt. Dispersion across channels' slant positions increased from 0.06 to 0.20, leading to a much more polarized media environment.[35]

Evaluating demand at the counterfactual equilibrium shows that, naturally, since content offered is more partisan, the effects on overall viewership escalates with it. In right-leaning regions, a 1 p.p. increase in net right tone attracts on the order of 60 thousand more viewers more than the baseline. Similar, symmetric responses occur in left-leaning markets.[36] Fixing airtime while leaving tone unconstrained therefore first makes outlets go more negative and then amplifies affective polarization on the demand for political content.

To sum up, proportional-airtime rules increase cross-outlet slant dispersion by inducing outlets to shift toward more negative tone. With polarized viewing preferences, this, in turn, amplifies polarization in media demand—an especially concerning pattern given evidence that negative campaign content heightens affective polarization (Lau et al., 2017).

[35]See footnote 15 for details on the computation of dispersion.

[36]Table D.8 shows the estimated elasticities for both the Baseline and Counterfactual estimations.

Limitations Finally, the counterfactual results should be interpreted with caution. First, as noted before, I discretize each outlet's action space on a coarse grid; best responses can be pushed to grid boundaries, yielding corner solutions that may over- or understate the continuous-choice equilibrium. Second, the binding constraints force the neutral stories to be zero in the equilibrium (i.e. $x^{\emptyset} = 0$). Although this implies that those minutes will be allocated between the share of politics and the tone categories, it does not necessarily force the outlets to become more negative. To check this substitution towards negative content, I also run a robustness counterfactual where I fix the proportion of political time to be that of the baseline. Outlets consistently substitute towards more negative tone. Third, I retain only equilibria for which a unique pure-strategy Nash equilibrium is found. This excludes realizations with multiple (or mixed-strategy) equilibria and may bias inference toward stability. If multiplicity matters, equilibrium selection could depend on unmodeled factors. Finally, for tractability I pool La Sexta and TVE into a single left player with averaged payoffs. This removes within-bloc competition and coordination frictions; in the full four-player game, left outlets might either undercut one another on tone or differentiate strategically, altering the comparative statics. Relaxing these assumptions could dampen or reshape the effects.

7 Conclusion

This paper studies how election campaigns reshape the market for political news using a structural model of demand and supply. I construct a story-level slant index for Spanish prime-time TV newscasts by combining machine learning with large language models (LLMs) and match it to high-frequency audience-meter data. This lets me track over time both the partisan tone viewers are exposed to and their viewing responses.

On the demand side, I estimate a BLP-style model in which viewers choose their preferred information source depending on the political slant it offers. I identify demand using supply shocks. I exploit exogenous shocks in the news landscape's partisan mix that constrain how much outlets can slant the news. During the campaign, viewers polarize their consumption of political news, screening out coverage favorable to the opposing party and favoring their own. Furthermore, I show that regions with higher polarization in political news consumption also have electorates that are more polarized in their voting intentions. On the supply side, the estimated cost parameters show substantial heterogeneity: outlets specialize and face lower costs when slanting the news toward their ideological positions.

Building on the demand and supply estimates, I evaluate the effects of implementing proportional-airtime rules for broadcasters during campaigns. The counterfactual results show that, while channels deliver balanced airtime across parties, this masks an increase in the polarization of the slant they supply. The mechanism follows from the rule's design. Because only total exposure in minutes is constrained, outlets comply by adjusting the most profitable tone—negative. This increases cross-outlet dispersion in supplied slant and strengthens audience responses to partisan content.

This paper highlights two main points. First, surges in ideological polarization during periods of high political conflict—such as election campaigns—are mirrored in how voters consume news. While campaigns serve an informational role, the way this information is consumed and framed can intensify polarization in media markets, which might have important consequences for voting outcomes. Second, widely used metrics for monitoring media bias overlook tone, which can lead to poorly targeted interventions. The framework developed in this work provides a more robust basis for media monitoring and a path for evaluating regulatory measures.

Several avenues for future research emerge from the present work. The unique features of the dataset—which allows to compare the tone and coverage of the same story across outlets on a given date—can inform and test prior theoretical work on sources of media bias, such as distortion and filtering (Gentzkow et al., 2014). Another promising direction is to study the role of newswire agencies as upstream providers of information. Because these services are broadly accessible across countries, the same benchmark can be applied in both democracies and autocracies to estimate media bias and analyze polarization in news markets.

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Appendix

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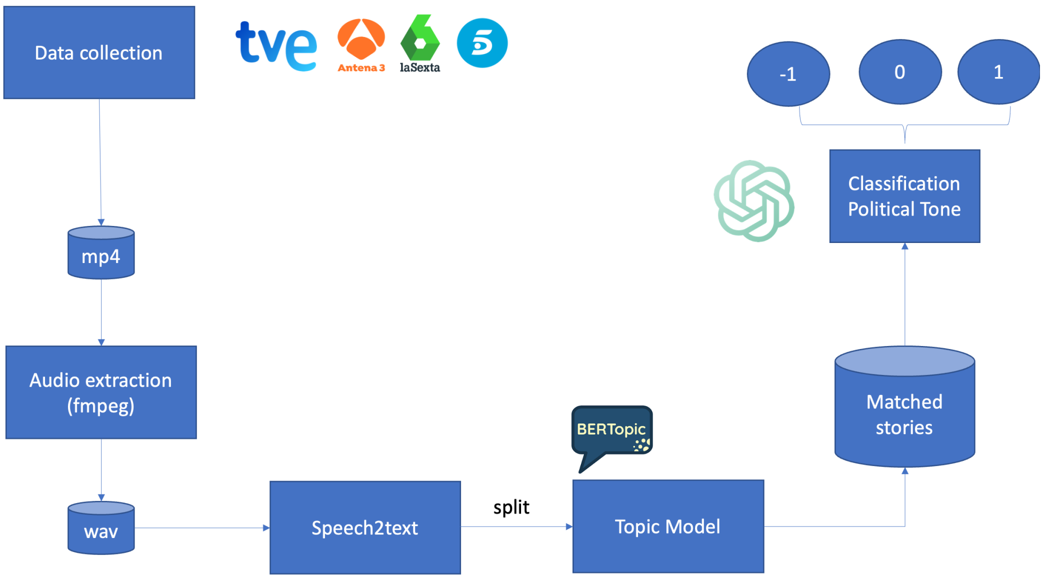
A Data Pipeline Details

This appendix describes the end-to-end pipeline used to collect, process, and analyze Spanish prime time newscasts. The workflow follows Figure A.11: daily recordings are stored, audio is extracted and transcribed, text is segmented into minute-level stories, topics are estimated with a topic model, and political tone is classified with a large language model. The corpus comprises the midday and evening national newscasts of TVE, A3, La Sexta, and T5, totaling 563 hours of programming stored and versioned in Google Cloud Storage (GCS) [37]

Figure A.11: Pipeline for Content Downloading and Classification



Note: 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, GPT4 is used to classify political tone.

Audio and transcription. Each broadcast is converted from MP4 to mono PCM WAV to standardize the input for automatic speech recognition. Transcripts are obtained with *Google Cloud Speech-to-Text* (language `es-ES`, long-running recognition with automatic punctuation). The service returns time-stamped transcripts; for each show I archive the raw JSON and a lightly normalized plaintext transcript.

Segmentation and alignment. Newscasts are split into minute-level stories using program timestamps and textual cues (anchor transitions and title cards).

Topic discovery. Topics are estimated with *BERTopic* using multilingual sentence embeddings (`paraphrase-multilingual-MiniLM-L12-v2`). After fitting, outlier reduction

[37] This project has been supported by Google Cloud for Education credits and OpenAI research credits.

and topic updates are applied; residual or incoherent clusters are flagged and excluded from matched comparisons.

LLM-based ideology classification. Story-level political tone is obtained with ChatGPT on a discrete grid per party. To reduce computational and monetary costs, I first filter the set of minute-level stories using a dictionary of political keywords (Table D.15); the final classification set contains 15,406 stories. The prompt used in the classifier is:

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*. Story-level tones are aggregated to the program–day level with duration weights (seconds per story). Channel-level summaries are constructed by averaging across program–days, and matched-story comparisons are restricted to aligned topic–day pairs.

B Robustness of the Text Classification

B.1 Comparison with Previous Approaches

One concern with LLMs classification is whether they can consistently capture meaningful patterns in text to distinguish tone. Table D.17 shows the most frequent three-word sequences across each sentiment–ideology category. The trigrams in the "Positive Right" column center on leadership titles and formal roles, reflecting an organizational focus; those in "Negative Right" cluster around legal and procedural language, indicating contexts of investigation or trial. The "Positive Left" trigrams emphasize policy areas and sectoral initiatives, suggesting substantive, topic-driven framing, while the "Negative Left" sequences feature judicial and procedural terms, pointing to oversight and legal scrutiny. Specific examples of stories can be seen in Appendix Table D.3.

To assess robustness, I also compare the LLM's classifications with those obtained using methods from previous works (Gentzkow and Shapiro, 2010; Laver et al., 2003). I use all Spanish congress speeches during the sample period and exploit party labels to assess similarities with the outlets' content.

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 the 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:

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

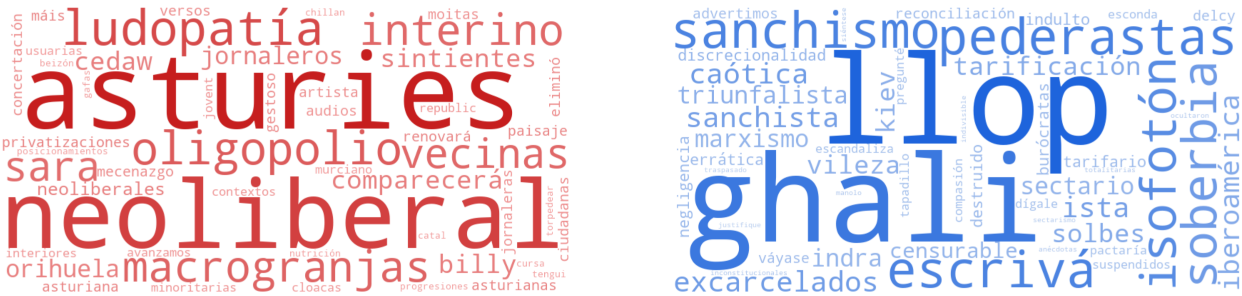
where:

- $\text{freq}(w,\text{Left})$ 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 Figure B.12.

Figure B.12: Word Cloud Congress Speeches

(a) Top Left Words **(b) Top Right Words**



Note: The wordclouds represent the top words with lowest (left) and highest (right) scores as defined in Eq. (15). Size is weighted by word TF-IDF value.

The word clouds make clear the distinctive use of language by parties in congress. On the left, for example, the large term "neoliberal" (neoliberalism) underscores an ongoing critique of market-driven reforms, while "oligopolio" (oligopoly) highlights concerns about concentrated economic power. On the right, "sanchismo" (literally "Sánchez-ism") signals frequent reference to the governing style of Prime Minister Sánchez as a political brand, and "pederastas" (pederasts) reveals the use of morally charged scandal language with the ley solo sí es si scandal.

Figure B.13 shows the left–right positions derived from this method. Although the overall ranking of the outlets from left to right is consistent with the ChatGPT classification in Figure 3, the middle channel is now classified as left-wing, close to the public channel.

Two remarks are worth mentioning. First, it is important to note that this comparison against survey data might entail some issues. Declared preferences can serve as validation under the assumption of channels' decisions being heavily driven by demand preferences rather than other factors. Cross-validation of human annotators on the labels of political stories would be an alternative way to verify the results.

Second, reducing each story to a single left–right score aids interpretation, but ignores the multidimensional nature of politics highlighted by Puglisi and Snyder (2011a). Economic versus cultural cleavages, or regional versus national frames, may evolve differently and deserve separate tracking. I leave extending the LLM classifier to a low-dimensional vector of ideological dimensions for future work.

Figure B.13: Normalized Ideology Index by Channel

(a) Demand: Viewers' ideology (b) Supply: Text classification

Note: The figure compares normalized left–right positions for the outlets in the sample. Panel (a) uses viewer ideology data from CIS survey data, using the difference in correlation coefficients between right and left; panel (b) uses Congress-speech-based text classification net tone as described in Equation (15). Values are normalized so that the two most extreme channels take values -1 and 1.

B.2 Stability of the Classifier

Due to their inherent stochasticity, repeated queries using the same prompt may yield different classifications (Atil et al., 2024). As shown in (Boehnke et al., 2024), this variability can introduce noise in tasks that require high consistency, particularly in content classification. To mitigate this issue, I leverage OpenAI's "functions" tool, which constrains the classifier's responses to predefined discrete numerical outputs, reducing potential inconsistencies. Table B.1 presents the mean classification scores from 100 iterations of a random sample of political stories [38], along with the corresponding standard errors. The relatively small standard errors suggest that, despite the model's stochastic nature, the classification remains stable.

Table B.1: 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.

B.3 Text vs. Image

Imagery is a key component of television. This may be especially relevant for political actors, for whom televised coverage has been shown to magnify the impact of candidates' physical appearance on voter perceptions and electoral outcomes (Lenz et al., 2011). Imagery in the

[38] Good practices recommend to run the classification multiple times and average out the results (Törnberg, 2023). Financial costs, however, impede me from doing the whole approach multiple times

form of time devoted to candidates further constitutes the main metric used by regulatory agencies. For example, the French media authority ARCOM publishes monthly "pluralism" reports that track each political actor's share of speaking time on national television; Italy's Osservatorio di Pavia produces similar statistics for the national regulator AGCOM. These metrics have also been used extensively in research as measures of slant (see, e.g., Cagé et al., 2022; Durante and Knight, 2012).

Here I compare some of these approaches to my text-based measure. 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. 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.e. see images in Figure B.14). 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, which I aggregate at the daily level for each channel and party leader.

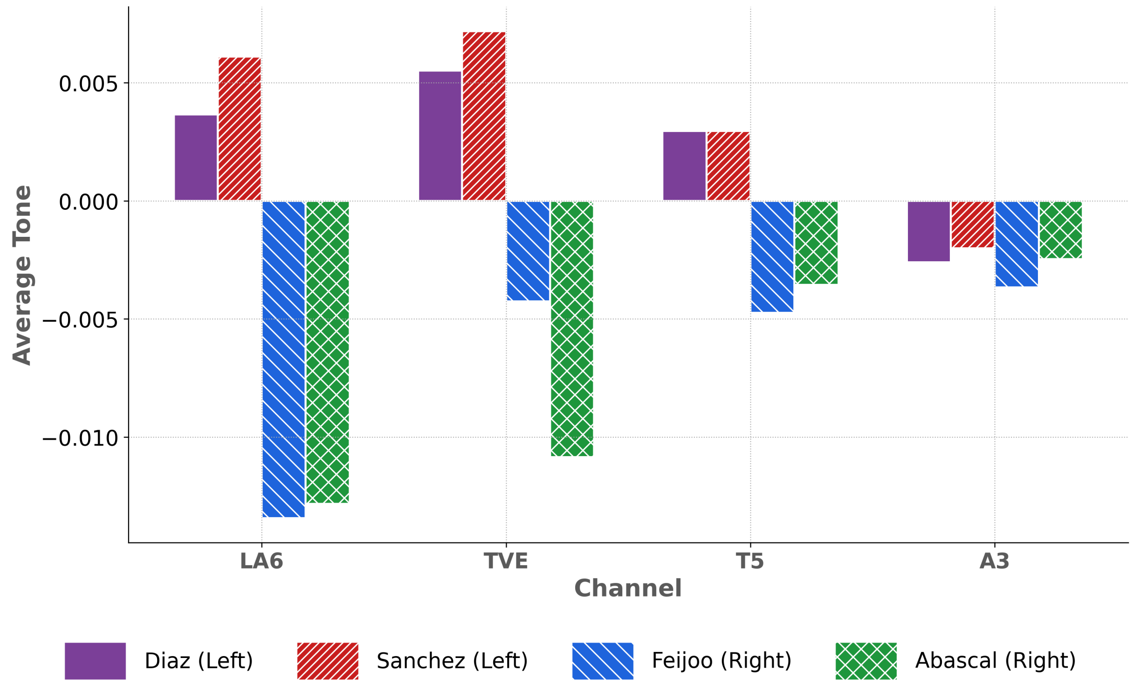
Figure B.14: Images Used for Training the Image Classifier

Note: The figure shows the example of the politicians' images used in the training of the face recognition algorithm.

The net tone on the sample of days for each channel and political leader is shown in

Figure B.15. As expected, significant differences appear, positioning channels in the left-right spectrum shown before.

Figure B.15: Net Tone per Channel and Politician



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

Next, I compare if visuals or tone follow a similar scenario. Figure B.16 panel a) shows the proportion of image appearances by channel and political leader. All channels coincide in their ranking, giving more air to PP, followed by PSOE, UP, and VOX. The two most extreme channels—La Sexta on the left and A3 on the right—give very similar coverage to the right-wing politician Feijóo, appearing in nearly 2% of the frames. Panel b) reveals a similar pattern for text mentions of the party leaders.

To further 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. Table B.2 reports results under different specifications, including date and channel fixed effects.

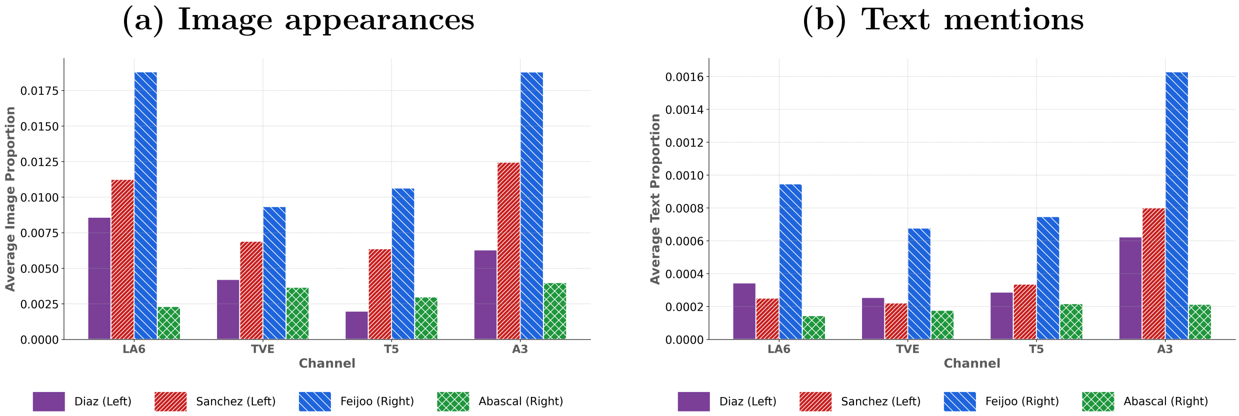
Column (4) reports the specification with both channel and day of the week fixed effects, so the coefficients reflect pure within–channel–day fluctuations in coverage. The pattern is heterogeneous across politicians. For Abascal (VOX), a one-standard-deviation increase in word mentions predicts a decrease of 0.39 standard deviations in tone, whereas the same increase in on-screen images predicts an increase of 0.06 standard deviations. Both left-leaning politicians present positive correlations between image appearances and tone, although nei-

Table B.2: Effect of Mentions on Tone toward Party Leaders

	Outlet Slant (x)			
	(1)	(2)	(3)	(4)
Feijóo (PP)				
Text Mentions	-1.956	-3.038	0.364	-1.342
	(2.063)	(2.134)	(2.391)	(2.584)
Image Appearances	-0.065	0.003	-0.275	-0.189
	(0.147)	(0.151)	(0.179)	(0.189)
Abascal (VOX)				
Text Mentions	-42.813	-44.024	-46.659	-49.989
	(7.855)	(7.832)	(9.609)	(9.471)
Image Appearances	0.963	0.933	0.565	0.437
	(0.470)	(0.470)	(0.600)	(0.595)
Sánchez (PSOE)				
Text Mentions	4.131	11.634	2.648	13.515
	(6.020)	(6.992)	(6.494)	(7.909)
Image Appearances	0.023	-0.045	0.033	0.032
	(0.239)	(0.244)	(0.356)	(0.377)
Díaz (UP)				
Text Mentions	-0.576	1.276	-0.714	3.365
	(3.158)	(3.280)	(4.080)	(4.405)
Image Appearances	0.473	0.485	0.290	0.321
	(0.197)	(0.206)	(0.232)	(0.247)
Channel FE	No	Yes	No	Yes
Date FE	No	No	Yes	Yes
Observations	231	231	231	227

Note: Robust standard errors in parentheses. Each block shows coefficients from regressing net tone on text mentions and image appearances of the party leader.

Figure B.16: Proportion of appearances by political actor and channel. Panel (a) shows image appearances and panel (b) shows text mentions for a random sample of 67 days.



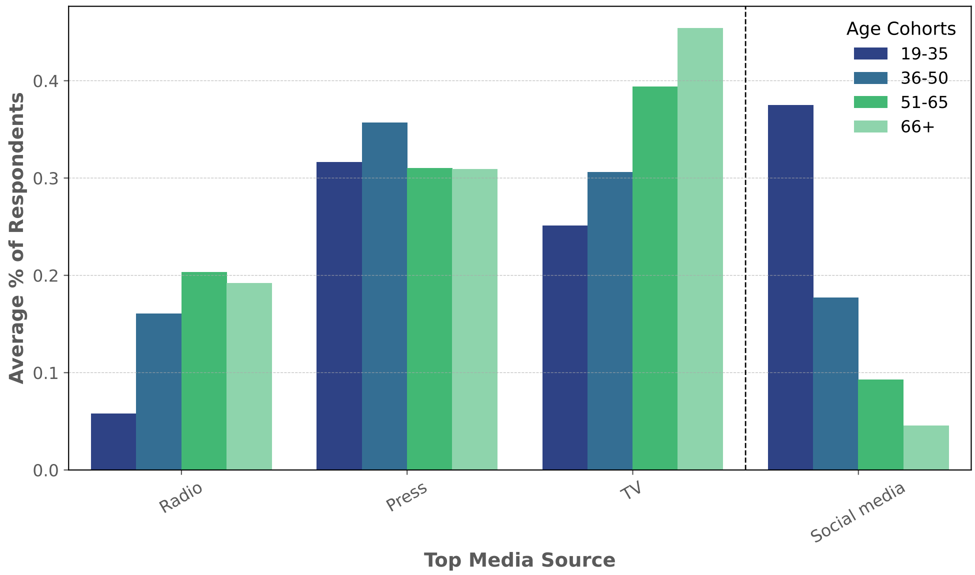
Note: The proportions are computed per channel and political actor over the same random sample of 67 days.

ther appears to be a strong predictor.

Taken together, the results indicate that text-based and image-based measures of salience relate to tone in systematically different ways. Outlets appear much more homogeneous under this metric, with extreme channels showing similar values. This poses concerns regarding the interpretation of previous metrics based on airtime.

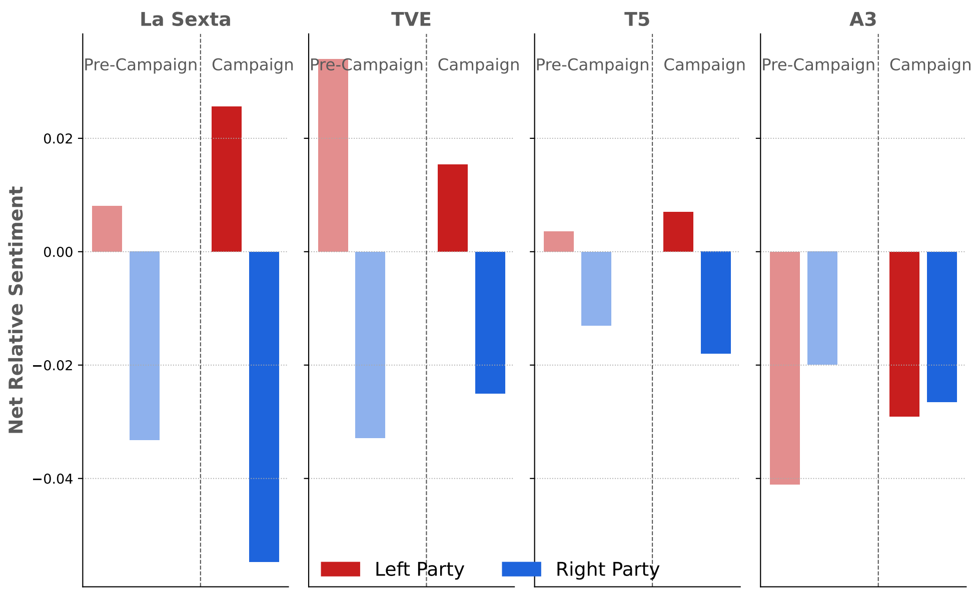
C Figures

Figure C.17: Top Media Source to Acquire Political Information in Spain



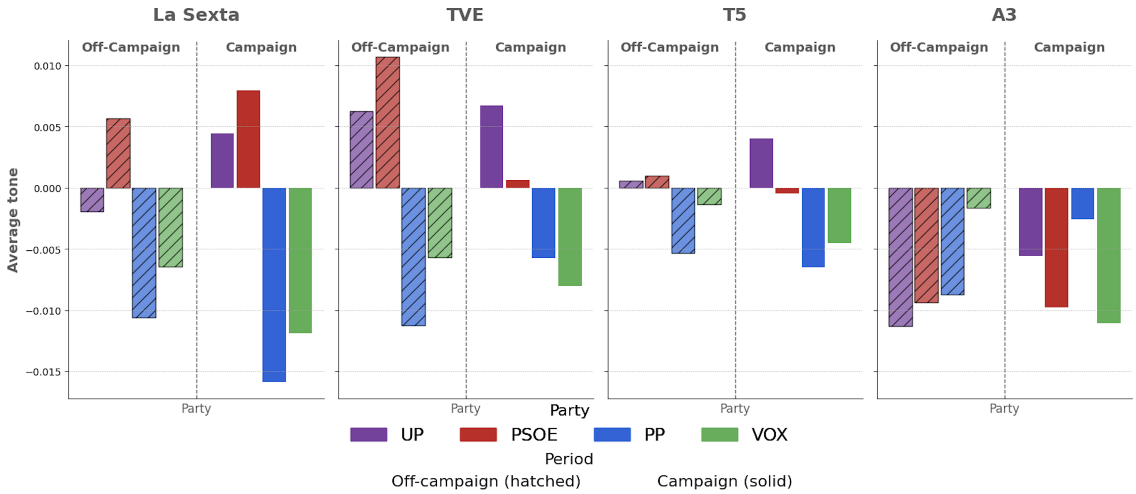
Note: Histogram on the preferred media used for political information by age cohorts in Spain. Source: Barómetro CIS, 2023.

Figure C.18: Tone across Channels and Parties off and during Campaign



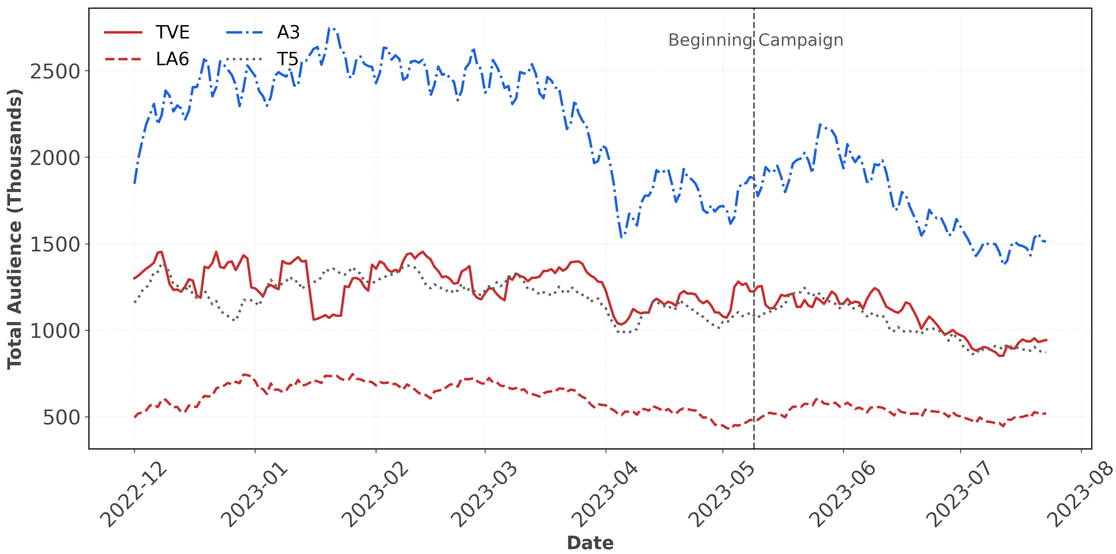
Note: The figure shows the relative tone calculated as the average sentiment over right and left parties. The vertical dashed line delimits results off and during campaign periods, respectively.

Figure C.19: Decomposition of Tone across Channels and Parties pre and during Campaign



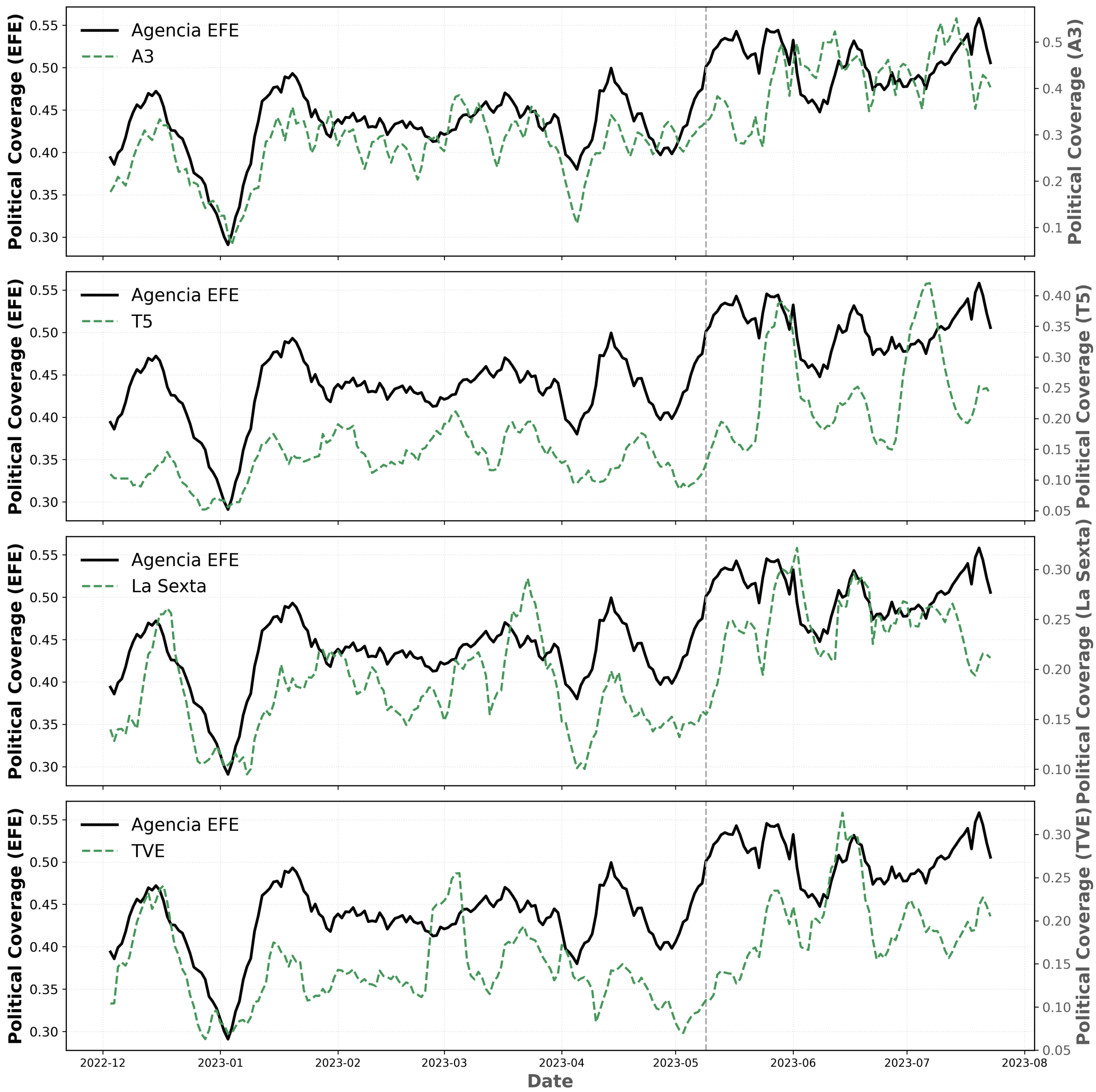
Note: The figure shows the relative tone calculated as the average sentiment over each political party. The vertical dashed line delimits results off and during campaign periods, respectively.

Figure C.20: TV Audience over Time



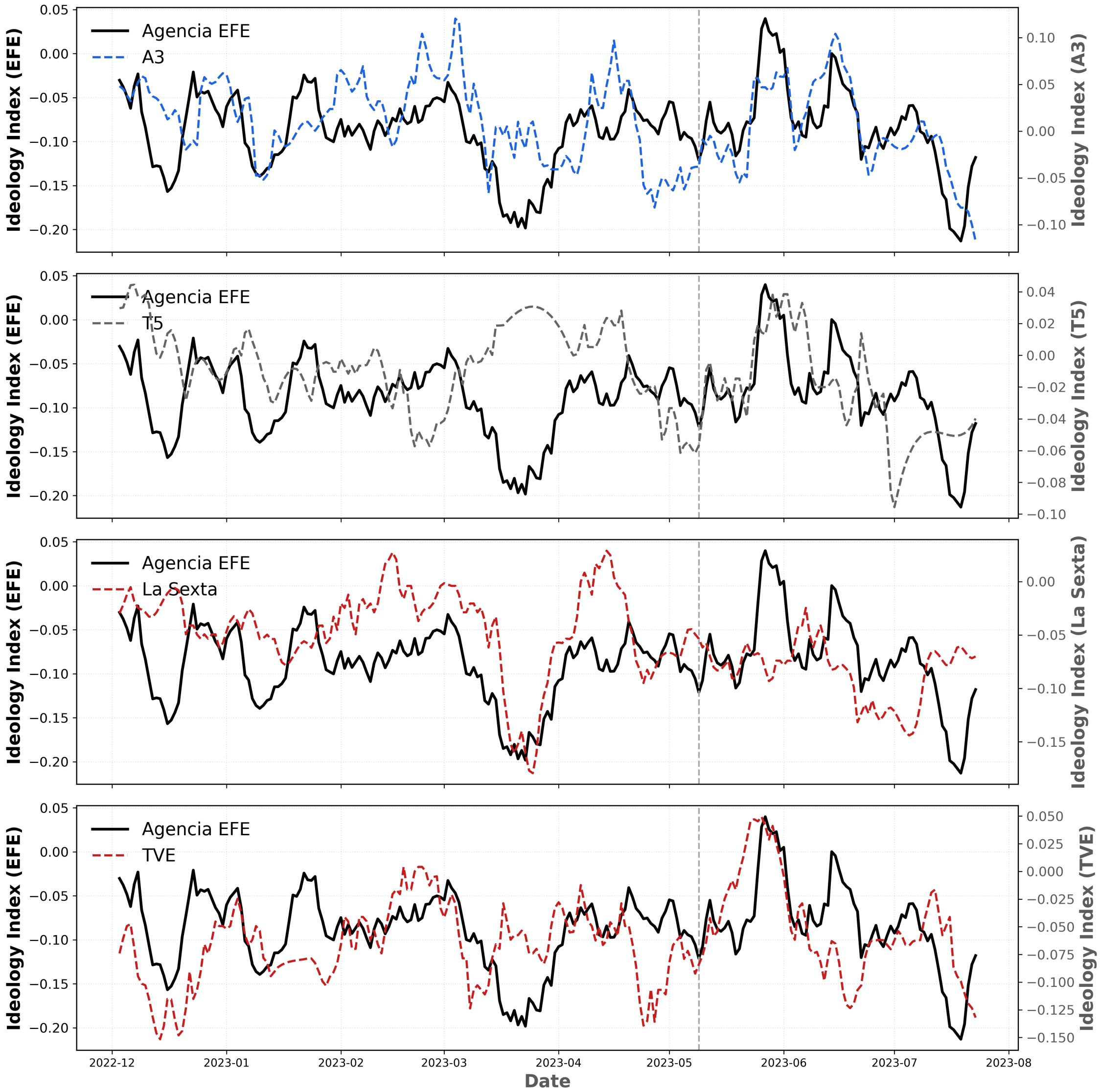
Note: The figure represents the total audience in thousands of viewers for TV outlets. All series are smoothed using a centered rolling mean with a 9-day window.

Figure C.21: Evolution of the Political Coverage by Outlet



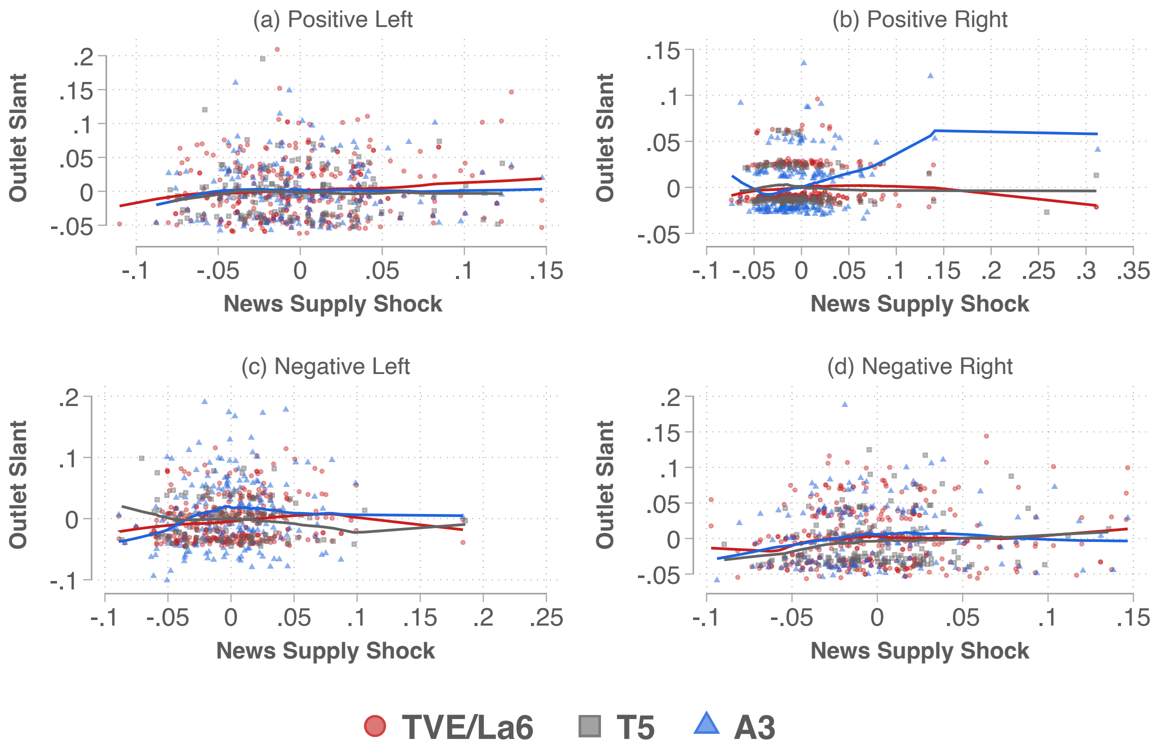
*Note:*The figure represents the smoothed time series of the political coverage for TV channels (right y-axis) and the analogous formula for EFE (solid) on the left axis. The left axis represents the proportion of political stories. All series are smoothed using a centered rolling mean with a 9-day window.

Figure C.22: Evolution of the Ideological Index by Outlet



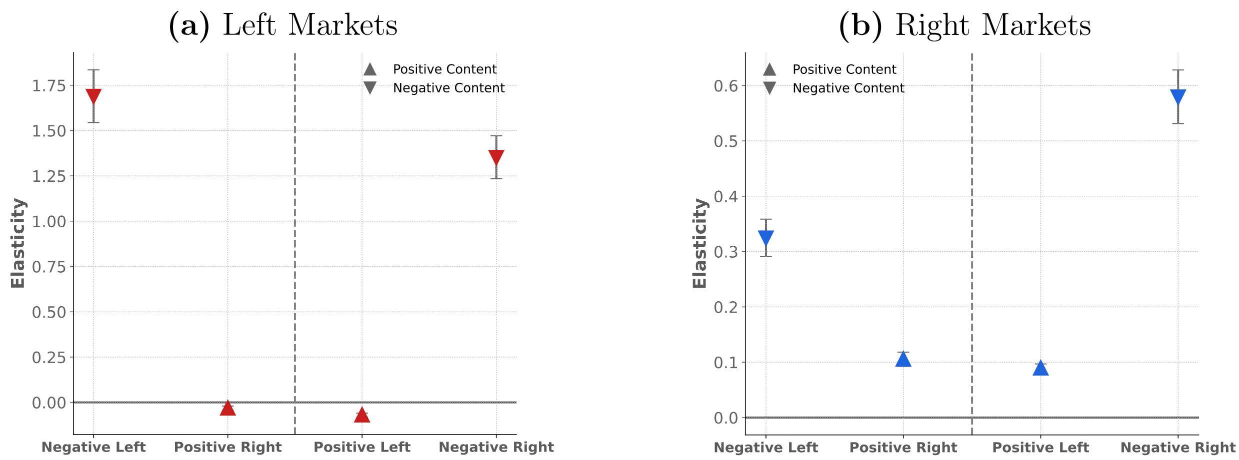
*Note:*The figure represents the smoothed time series of the ideology index in Equation (3) for TV channels (right y-axis) and the analogous formula for EFE (solid) on the left axis. The left axis represents the ideological score of the outlets. All series are smoothed using a centered rolling mean with a 9-day window.

Figure C.23: Added Variable Plots for Production of Political Content (non-parametric fit)



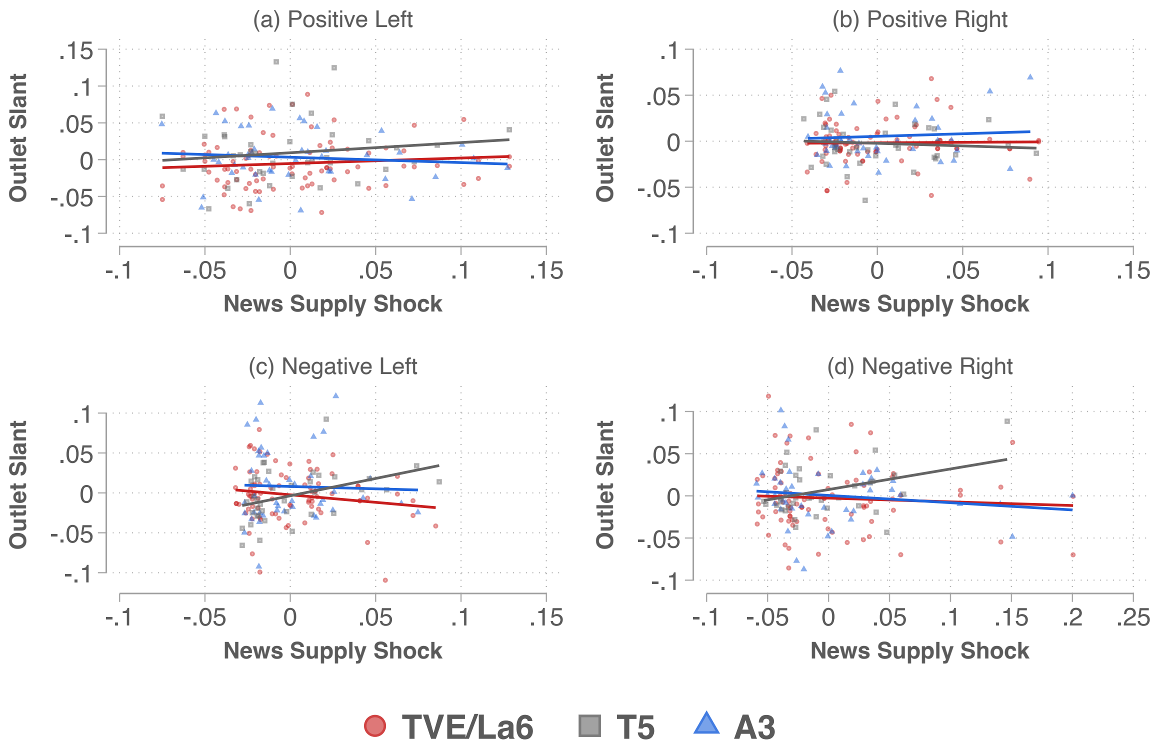
Note: The figure shows the added variable plots from the estimation of Eq. (7). The x axis represents $(z_d^{party,+}, z_d^{party,-})$ and the y axis the corresponding $(x_{jd}^{party,+}, x_{jd}^{party,-})$. Channels are pooled into left (TVE and La Sexta), middle (T5) and right (A3) for visualization purposes.

Figure C.24: Estimated Elasticities for Left and Right markets off-Campaign



Note: Each panel shows estimated mean own elasticities for consumer responses as described in Eq. (8) for the off-campaign period. Panel (a) reports results for the left-leaning markets, while Panel (b) shows the results for the right-leaning markets. Right markets are defined as regions with proportion of right-wing voters above the median. Whiskers represent the 95% confidence intervals of the mean across markets.

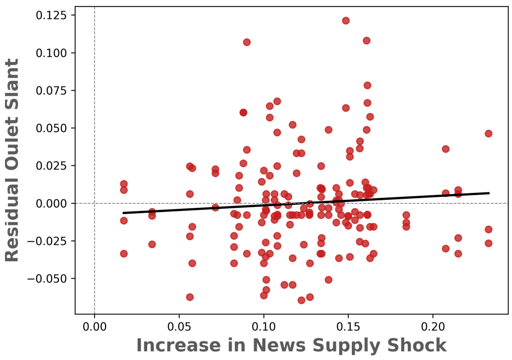
Figure C.25: Added Variable Plots for Production of Political Content (within day)



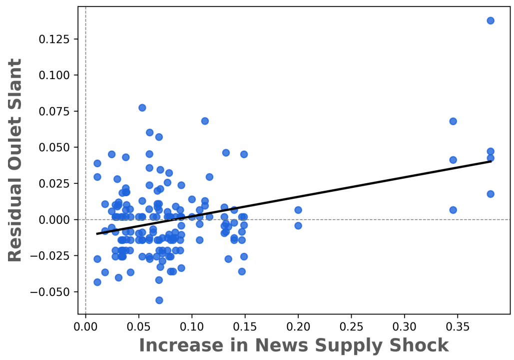
Note: The figure shows the added variable plots from the analogous estimation of Eq. (7) using within day differences. The x axis represents $\left(\Delta z_d^{party,+}, \Delta z_d^{party,-}\right)$ and the y axis the corresponding $\left(\Delta x_{jd}^{party,+}, \Delta x_{jd}^{party,-}\right)$. Channels are pooled into left (TVE and La Sexta), middle (T5) and right (A3) for visualization purposes.

Figure C.26: Within-day Relationship Between Editorial Content Share and News Supply Shock

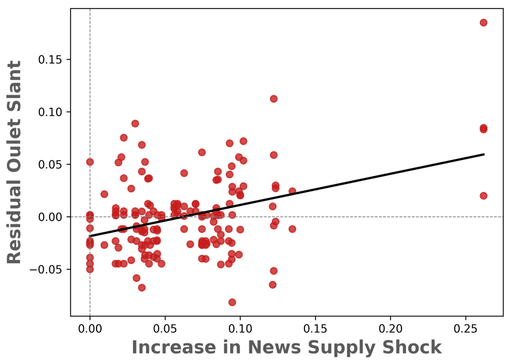
(a) Positive Left



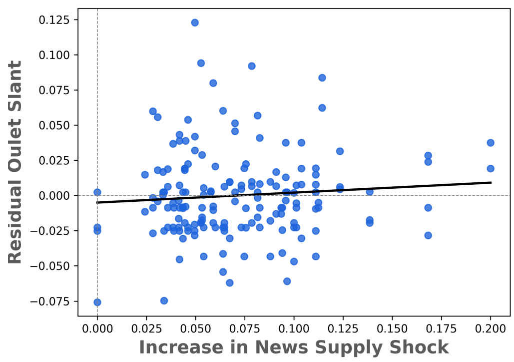
(b) Positive Right



(c) Negative Left

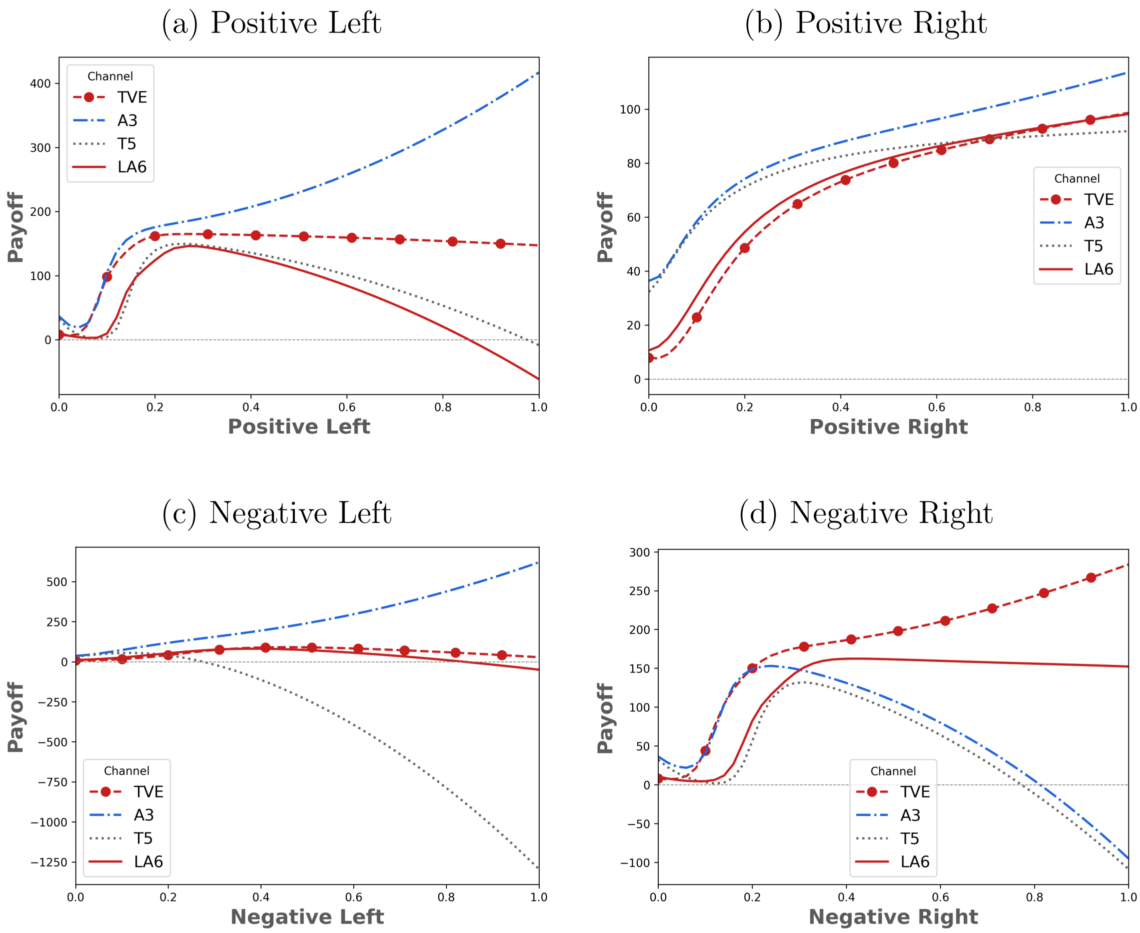


(d) Negative Right



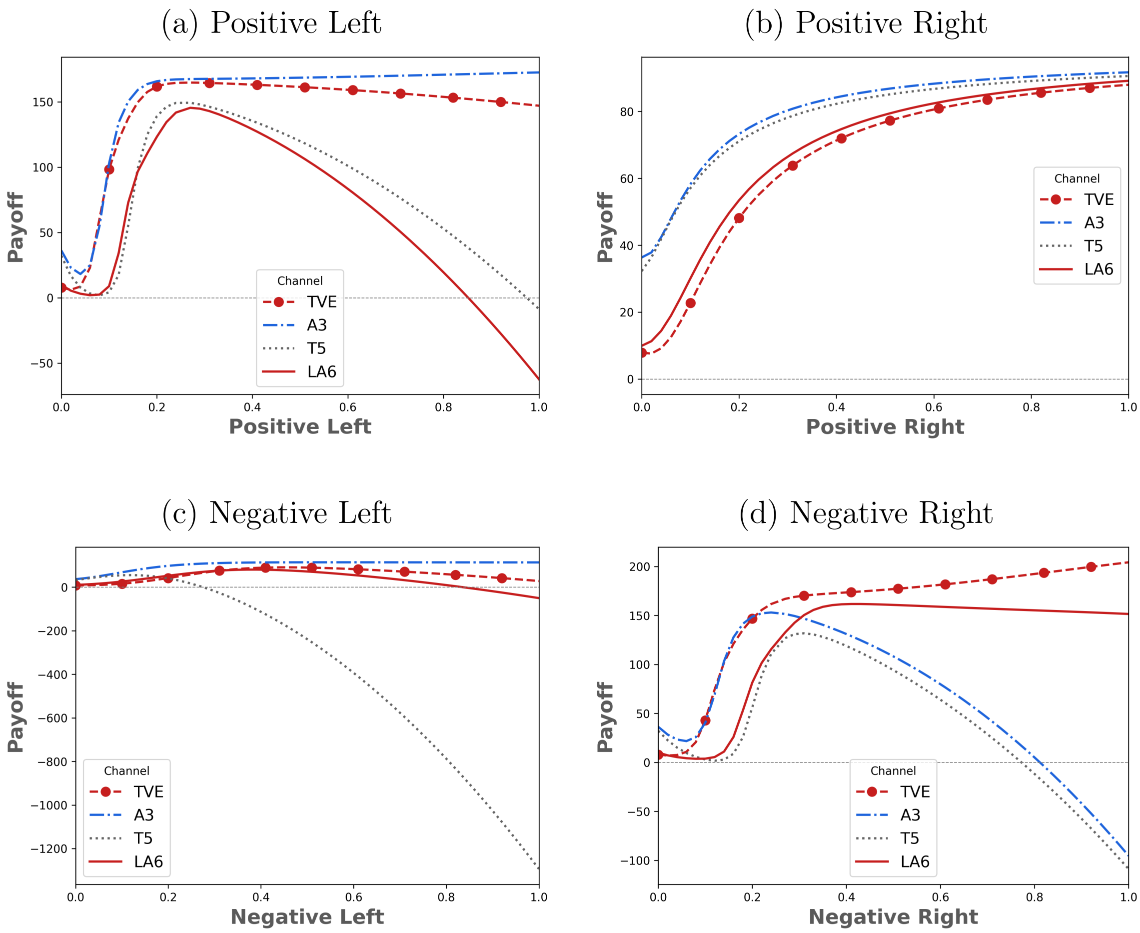
Note: Scatterplots of the within-day relationship between channels' editorial content share (x) and the corresponding news supply shock (z) from Agencia EFE. Each panel corresponds to one type of coverage: (a) positive-left, (b) positive-right, (c) negative-left, and (d) negative-right. The y-axis plots the residuals from a regression of evening content share on midday content share with outlet fixed effects, capturing variation in evening coverage not explained by earlier coverage. The x-axis shows the share of EFE stories of the corresponding type published between midday and evening. Lines represent fitted values from ordinary least squares.

Figure C.27: Outlet's Payoffs for each Tone Category



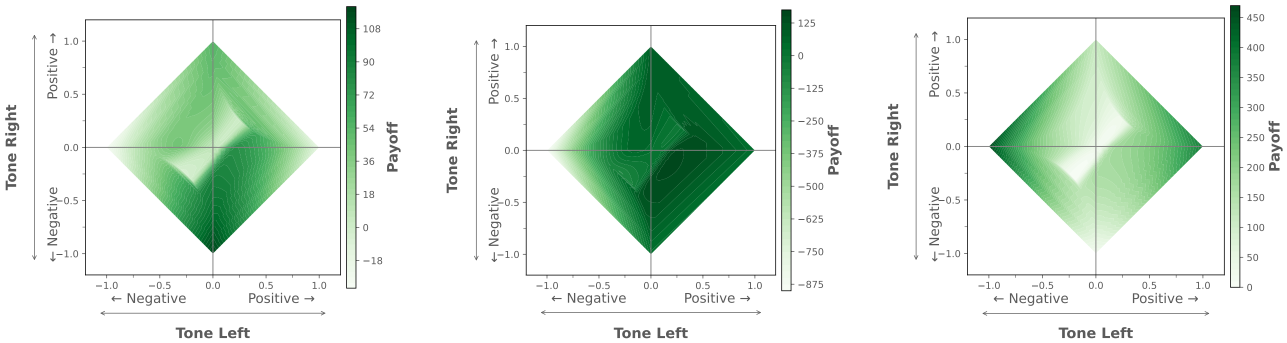
Note: Figures shows the average payoffs of the supply game after estimation. y-axis values represent thousands of viewers. Average are taken over days. Each panel corresponds to one type of coverage: (a) positive-left, (b) positive-right, (c) negative-left, and (d) negative-right.

Figure C.28: Outlet's Payoffs for each Tone Category (Constrained)



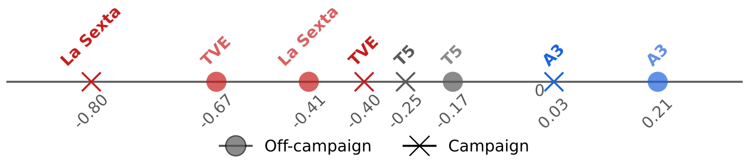
Note: Figures shows the average payoffs of the supply game after estimation. y-axis values represent thousands of viewers. Average are taken over days. Each panel corresponds to one type of coverage: (a) positive-left, (b) positive-right, (c) negative-left, and (d) negative-right.

Figure C.29: Outlet's Surface Payoffs by Tone



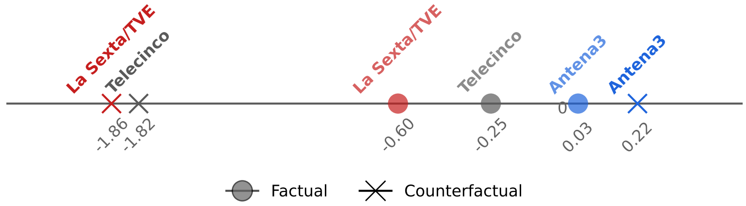
Note: Each panel shows predicted payoff from the model estimates as a function of net left tone (x-axis) and net right tone (y-axis). Moving right (up) means more favorable coverage of the left (right) party. Payoff is measured in thousands of viewers. Each pane represents the payoffs for Left (La6 and TVE), Middle (T5) and Right (A3) outlets.

Figure C.30: Change in Positions Off-campaign to Campaign



Note: The figure shows the relative change in slant positions according to the ideological index in Equation (3) from off-campaign to campaign.

Figure C.31: Change in Positions Baseline vs Counterfactual Scenario



Note: The figure shows the relative change in slant positions according to the ideological index in Equation (3) from the baseline to the counterfactual scenario during the campaign period.

D Tables

D.1 Descriptive Evidence

Table D.3: Proportion of Political Content and Sentiment by Channel

Outlet	**Category**	**Pre-campaign**	**During campaign**
	Negative Left	0.106	0.090
	Negative Right	0.043	0.066
A3	Positive Left	0.065	0.061
	Positive Right	0.023	0.039
	Political	0.277	0.387
	Negative Left	0.041	0.032
	Negative Right	0.047	0.067
La Sexta	Positive Left	0.049	0.057
	Positive Right	0.013	0.012
	Political	0.207	0.277
	Negative Left	0.038	0.037
	Negative Right	0.045	0.046
TVE	Positive Left	0.072	0.052
	Positive Right	0.012	0.021
	Political	0.175	0.212
	Negative Left	0.043	0.039
	Negative Right	0.025	0.044
T5	Positive Left	0.047	0.046
	Positive Right	0.012	0.026
	Political	0.111	0.183
	Negative Left	0.076	0.073
	Negative Right	0.058	0.094
EFE	Positive Left	0.138	0.145
	Positive Right	0.043	0.099
	Political	0.438	0.515

Note: The table shows the proportion of political minutes and the breakdown by tone/party for each channel, off- and during campaign. For EFE it shows the proportion of stories of each category (Eqs. (1)).

Table D.4: Proportion of Positive/Negative Minutes by Channel

Outlet	**Category**	**Pre-campaign**	**During campaign**
A3	Positive Left	0.065	0.061
	Positive Right	0.023	0.039
	Negative Left	0.106	0.090
	Negative Right	0.043	0.066
La Sexta	Positive Left	0.049	0.057
	Positive Right	0.013	0.012
	Negative Left	0.041	0.032
	Negative Right	0.047	0.067
T5	Positive Left	0.047	0.046
	Positive Right	0.012	0.026
	Negative Left	0.043	0.039
	Negative Right	0.025	0.044
TVE	Positive Left	0.072	0.052
	Positive Right	0.012	0.021
	Negative Left	0.038	0.037
	Negative Right	0.045	0.046

Note: The table shows the proportion of positive and negative minutes for each channel, off- and during campaign (Eqs. (1).

D.2 Additional Results

Table D.5: Estimated Elasticities

Characteristic	**Pre-campaign**	**Campaign**
Positive Right	0.036	-0.531
Negative Right	1.012	0.070
Net Right (Positive - Negative)	-0.976	-0.601
Positive Left	0.006	-0.062
Negative Left	1.009	-0.150
Net Left (Positive - Negative)	-1.003	0.088

Note: The table shows the average elasticities for each characteristic in Eq. (8).

Table D.6: Estimated Elasticities for Right and Left Markets

	Pre-campaign		Campaign	
Characteristic	Left Market	Right Market	Left Market	Right Market
Negative Left	1.705	0.313	-0.747	0.333
	(0.022)	(0.005)	(0.093)	(0.044)
Positive Left	-0.073	0.085	0.666	-0.819
	(0.002)	(0.001)	(0.102)	(0.099)
Negative Right	1.443	0.580	0.277	-0.164
	(0.019)	(0.008)	(0.065)	(0.032)
Positive Right	-0.036	0.108	-1.388	0.204
	(0.002)	(0.002)	(0.182)	(0.052)

Note: The table shows the average elasticities for each characteristic by right and left markets as defined in Eq. (8). Right markets are defined as regions with proportion of right-wing voters above the median. Standard errors in parentheses are calculated as the standard error of the mean across markets.

Table D.7: Audience Compositional Change Tests

Channel	Age										Sex	
	4-9	10-12	13-15	16-24	25-29	30-34	35-44	45-54	55-64	65+	Female	Male
	-0.03	-0.12	-0.07	0.19	0.18	0.11	-0.03	0.00	0.03	-0.07	-0.04	0.03
TVE	(0.67)	(0.66)	(0.63)	(0.52)	(0.66)	(0.63)	(0.63)	(0.56)	(0.52)	(0.47)	(0.53)	(0.50)
	-0.24	0.03	-0.34	-0.13	0.06	-0.05	-0.09	-0.09	-0.06	-0.02	-0.05	-0.02
A3	(0.63)	(0.52)	(0.49)	(0.53)	(0.54)	(0.49)	(0.51)	(0.49)	(0.45)	(0.43)	(0.45)	(0.47)
	0.15	-0.00	0.03	0.01	-0.23	-0.18	0.15	0.05	0.15	0.06	0.07	0.06
T5	(0.73)	(0.70)	(0.63)	(0.63)	(0.67)	(0.63)	(0.58)	(0.61)	(0.65)	(0.65)	(0.59)	(0.71)
	-0.21	-0.78	-0.20	-0.10	0.07	0.43	0.12	0.05	0.03	0.02	0.04	0.05
La Sexta	(1.03)	(1.22)	(0.93)	(0.87)	(0.82)	(0.68)	(0.69)	(0.66)	(0.69)	(0.77)	(0.80)	(0.67)

Note: Each cell reports the campaign profile coefficient from a logit testing audience share changes from the off- to the campaign periods. Robust standard errors in parentheses.

Table D.8: Estimated Elasticities for Right and Left Markets (Baselline and Counterfactual)

Characteristic	Baseline		Counterfactual	
	Left Market	Right Market	Left Market	Right Market
Negative Left	-0.747	0.333	-6.742	2.163
Positive Left	0.666	-0.819	1.255	-2.407
Negative Right	0.277	-0.164	3.950	-5.726
Positive Right	-1.388	0.204	-0.158	0.043

Note: The table shows the average elasticities for each characteristic by right and left markets as defined in Eq. (8). Right markets are defined as regions with proportion of right-wing voters above the median. Left column shows the elasticities from the model estimation and the right column from the counterfactual Problem (14).

Table D.9: First Stage Regressions for Demand

	(1) Positive Right	**(2) Negative Right**	**(3) Positive Left**	**(4) Negative Left**
News-Shock (z)				
Positive Right				
TVE	-0.0246	0.0104	0.0507	-0.0856
	(0.0506)	(0.0837)	(0.0855)	(0.0862)
A3	0.244***	-0.0395	0.0732	0.0118
	(0.0538)	(0.0889)	(0.091)	(0.0917)
T5	0.0499	0.0539	-0.0688	-0.114
	(0.0572)	(0.0945)	(0.0966)	(0.0974)
La Sexta	-0.0283	0.0556	0.0818	-0.108
	(0.0535)	(0.0884)	(0.0904)	(0.0912)
Negative Right				
TVE	-0.0407	0.0604	-0.0641	0.0283
	(0.0425)	(0.0702)	(0.0718)	(0.0724)
A3	0.0175	0.166*	0.0126	-0.00300
	(0.0477)	(0.0787)	(0.081)	(0.0812)
T5	-0.0530	0.199*	0.0769	0.0466
	(0.0562)	(0.0929)	(0.095)	(0.0957)
La Sexta	-0.0281	0.179**	-0.0266	-0.224**
	(0.0465)	(0.0769)	(0.0786)	(0.0792)
Positive Left				
TVE	0.0498	0.253***	0.394***	0.122
	(0.0446)	(0.0737)	(0.0754)	(0.0760)
A3	0.154**	0.0572	0.132	0.202*
	(0.0468)	(0.0773)	(0.0790)	(0.0797)
T5	0.00992	0.0324	0.126	0.126
	(0.0589)	(0.0974)	(0.0996)	(0.100)
La Sexta	-0.0536	-0.0424	0.118	0.0943
	(0.0472)	(0.0780)	(0.0797)	(0.0804)
Negative Left				
TVE	0.0829	0.119	-0.00250	0.344***
	(0.0520)	(0.0859)	(0.0878)	(0.0885)
A3	0.174**	0.00666	-0.0501	0.492***
	(0.0570)	(0.0941)	(0.0962)	(0.0970)
T5	-0.0649	0.167*	0.0275	0.182*
	(0.0606)	(0.100)	(0.102)	(0.103)
La Sexta	-0.0519	-0.0869	-0.0741	0.187*
	(0.0581)	(0.096)	(0.0981)	(0.099)
Political				
TVE	-0.00269	-0.0666	-0.0470	-0.0686
	(0.0287)	(0.0475)	(0.0485)	(0.0489)
A3	-0.0883**	0.0295	0.0418	-0.0496
	(0.0308)	(0.0509)	(0.0520)	(0.0524)
T5	0.0468	-0.0543	0.00609	-0.0231
	(0.0360)	(0.0595)	(0.0608)	(0.0613)
La Sexta	0.0653*	0.0738	0.0506	0.0445
	(0.0306)	(0.0505)	(0.0516)	(0.0521)
$\mathbf{R}^2$	0.3539	0.5025	0.5511	0.5573

Note: Robust standard errors in parentheses. $p < 0.05$, *$p < 0.01$, **$p < 0.001$, ***Total observations: $N = 687$.

Table D.10: Logit Estimation Results with Standard Errors

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)

Note: The table shows the results of the logit estimation of model (6). The estimations are divided into the off-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 D.11: Diversion Ratios by Characteristic and Outlet (Campaign period)

	Positive Left				Positive Right				Negative Left				Negative Right				Political			
Destination ↓	TVE	T5	A3	La6	TVE	T5	A3	La6	TVE	T5	A3	La6	TVE	T5	A3	La6	TVE	T5	A3	La6
TVE	0.00	0.03	0.01	0.01	0.00	0.02	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.02	0.01	0.00
T5	0.01	0.00	0.02	0.03	0.05	0.00	0.15	0.10	0.02	0.00	0.26	0.03	0.00	0.00	0.03	0.06	0.06	0.00	0.17	0.02
A3	0.04	0.05	0.00	0.50	0.00	0.04	0.00	0.01	0.00	0.03	0.00	0.00	0.01	0.10	0.00	0.91	0.01	0.07	0.00	0.01
La6	0.00	0.01	0.23	0.00	0.01	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Outside	0.94	0.90	0.74	0.45	0.94	0.93	0.84	0.88	0.98	0.95	0.72	0.96	0.99	0.88	0.94	0.04	0.93	0.91	0.82	0.97

Note: The table reports diversion ratios: for a 1% increase in outlet j's characteristic x_j^k, the entry is the fraction of j's audience loss (columns) that diverts to outlet destination l (rows). With the share changes Δs_l^t from a 1% change in x_j^k, I define $D_{j\to l}^{k,t} = \frac{\max\{\Delta s_l^t, 0\}}{-\Delta s_j^t}$ for $\Delta s_j^t < 0$. as the diversion rate from alternative j to l and characteristic k on market t. Then, conditioning on markets that loose audience I compute $D_{j\to l}^k = \frac{\sum_{t:\,\Delta s_j^t<0}(-\Delta s_j^t)\, D_{j\to l}^{k,t}}{\sum_{t:\,\Delta s_j^t<0}(-\Delta s_j^t)}$, $\sum_{l\neq j} D_{j\to l}^k + D_{j\to 0}^k = 1.$ which is the reported loss-weighted averages across markets.

Table D.12: Robustness for the Estimated Cost Parameters (λ) by Channel and Estimator

	La Sexta			TVE			Telecinco (T5)			Antena 3 (A3)		
	Unconstr.	NNLS	NLLS	Unconstr.	NNLS	NLLS	Unconstr.	NNLS	NLLS	Unconstr.	NNLS	NLLS
Positive Right	-89.09	0.00	0.00	-103.74	0.00	0.00	-13.87	0.00	0.00	-240.52	0.00	0.00
	(85.99)	(97.60)	(0.00)	(121.36)	(112.30)	(0.00)	(91.62)	(88.67)	(0.00)	(77.50)	(94.67)	(0.00)
Negative Right	4.07	0.00	2.62	-8.88	2.21	0.00	31.13	38.43	25.78	35.16	2.71	4.44
	(4.80)	(4.80)	(1.86)	(11.41)	(11.39)	(0.00)	(36.16)	(36.27)	(26.73)	(53.89)	(53.70)	(20.13)
Positive Left	12.82	8.17	10.38	6.27	5.68	6.69	108.34	83.23	112.34	-38.96	0.00	0.00
	(44.44)	(44.45)	(8.50)	(2.63)	(2.64)	(1.66)	(60.39)	(60.31)	(53.00)	(23.79)	(24.65)	(0.00)
Negative Left	36.11	11.38	14.88	3.36	11.53	7.89	24.03	47.67	16.62	-40.03	0.00	0.00
	(52.70)	(52.71)	(14.68)	(13.12)	(13.12)	(5.71)	(43.99)	(43.95)	(23.57)	(84.81)	(81.40)	(0.00)
Political	-0.35	0.00	0.00	0.32	0.21	0.23	1.50	1.39	1.64	1.45	0.52	0.00
	(0.61)	(0.60)	(0.00)	(0.62)	(0.65)	(0.21)	(1.05)	(1.13)	(0.87)	(1.25)	(1.36)	(0.00)

Note: Robust standard errors in parentheses. Each column shows the results under unconstrained GMM, non-negative least squares (NNLS), and nonlinear least squares (NLLS), respectively.

D.3 Text Examples

Table D.13: Top Stories for Negative Left and Outlet's Production

Stories
-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
A3	0.184
T5	0.037
La Sexta	0.01

Note: 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.

Table D.14: Top Stories for Negative Right and Outlet's Production

Stories
-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
A3	0.038
T5	0.067
La Sexta	0.148

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

Table D.15: Political Terms

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

Note: The table shows the political words included to filter the stories into national politics. The bottom section lists all the general political terms used for filtering.

Table D.17: Top trigrams by sentiment and ideology in the EFE dataset

Pos. Right	**Neg. Right**	**Pos. Left**	**Neg. Left**
vox secretary general	gürtel national service	agriculture fisheries food	ere court sevilla
vox ignacio garriga	gürtel trial service	minister agriculture fisheries	social rights ione
general vox ignacio	valencia francisco camps	dec gov president	social ione belarra
núñez feijóo called	gürtel trial gürtel	fisheries food luis	andalusian government josé
pp candidate elections	former president valencian government	food luis planas	andalusia josé antonio
vox parties madrid	valencian government francisco	jan gov president	enforcement only yes law
josé sáenz buruaga	psoe deputy secretary general	psoe deputy secretary general	former president andalusian gov
núñez feijóo requested	gürtel trial madrid	council ministers approved	mediator case las palmas
maría josé sáenz	abortion law reform	minister economic affairs	mediator las palmas gran
may pp president	former valencian president francisco	first vice president minister	núñez feijóo accused

Note: The table shows the top trigrams for Positive and Negative sentiment by ideology in the EFE dataset using ChatGPT-based classification.

Table D.18: Examples of Stories and Party–Tone

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

Feijóo Criticizes Government Size and Alliances “In Zaragoza Feijóo says Spain ‘doesn’t need 22 ministries and three vice-presidencies’, proposes 13–14 portfolios, and likens PSOE’s fiscal plan to Podemos. Sánchez counters that PP votes in Brussels match Vox on women’s rights. . . ”	A3	2023-06-01	positive PP (Right)
Vox Holds Key Role in Regional Talks “After 28-M gains, Vox negotiators press PP for cabinet seats in Valladolid and Burgos. In Aragón, Santiago Abascal meets Jorge Azcón to discuss immigration and farm policy in exchange for a coalition vote of confidence. . . ”	LA6	2023-06-13	positive Vox (Right)
Vox and PP May Enter Extremadura Parliament “Latest Extremadura poll shows PSOE at 32%, short of a majority, while PP and Vox together could secure an absolute 34 seats. Socialist premier Fernández Vara warns a ‘reactionary pact’ would end rural-health rollout. . . ”	T5	2023-05-23	positive Vox (Right)
Podemos Faces Coalition Tensions with Díaz “In Madrid, Podemos brands Sumar talks ‘frozen’ and urges Vice-PM Yolanda Díaz to join its 28-M campaign rallies or risk splitting the left. Spokeswoman Ione Belarra says voters ‘deserve clarity’ on joint lists before June. . . ”	A3	2023-04-09	negative UP (Left)
Díaz–Podemos Division Widens Post-Launch “One day after Díaz launched Sumar without Podemos ministers on stage, both sides trade barbs. Podemos keeps open the door to running alone; Díaz insists a Sumar without Podemos ‘would not be a failure but a pity’. . . ”	T5	2023-04-03	negative UP (Left)
PSOE Suspends Deputy in Corruption Case “Socialists suspend Canary Islands MP Juan B. Fuentes and force him to relinquish his seat after police allege he led a livestock-subsidy racket. PSOE spokesman Patxi López demands swift judicial clarification to ‘protect the institution’. . . ”	TVE	2023-02-27	negative PSOE (Left)

Coalition Fractures over 'Only Yes is Yes' Law "Podemos accuses PSOE of 'rolling back feminism' by rewriting consent law with PP votes. After a week of insults across the aisle, both parties pivot to 28-M agendas, downplaying talk of an early split..."	A3	2023-04-21	negative PSOE (Left)
Residents Protest Metro Damage in Madrid "Evacuated families in San Fernando de Henares block cement-injection works they blame for subsidence cracks. They chant 'Ayuso, listen!' and demand full buy-outs; regional officials say repairs are safe and urge calm..."	LA6	2023-01-05	negative PP (Right)
Gürtel Scheme Sentences Upheld by Court "Supreme Court confirms 13-year term for Francisco Correa and 15 for Pablo Crespo over rigged contracts for Pope Benedict's 2006 Valencia visit, rejecting all appeals. PP says it 'respects the ruling' and notes offences pre-dated Rajoy..."	A3	2023-04-10	negative PP (Right)
Ayuso Strategy Aims to Outflank Vox "Leaked memo shows Madrid PP will 'turn up the volume' on culture-war issues to lure Vox voters and secure an outright majority for Isabel Díaz Ayuso. Critics warn rhetoric could deepen polarisation..."	A3	2023-05-18	negative VOX (Right)
Díaz Warns of Right-Wing Coalition Risks "Campaigning in Gijón, Díaz tells women a Feijóo–Abascal government would bring austerity 'back to black-and-white Spain'. She urges progressives to unite under Sumar to stop Vox entering La Moncloa..."	LA6	2023-07-15	negative VOX (Right)

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

Table D.19: Examples International News with Party Tone

Story	Channel	Date	Tone-party
Justice Officials Lock In Courts "After a month of fruitless negotiations, court clerks barricade themselves inside dozens of courthouses for 24 h, demanding the same one-off pay rise recently granted to judges and prosecutors. The unions warn of massive case backlogs if talks do not resume. Strasbourg will monitor whether Spain abides by any future judgement on the dispute..."	TVE	2023-06-22	negative Left
Prices Rise, but Economy Outperforms EU "Headline inflation ticks up to 4.1 percent in April, yet quarterly GDP expands by 0.5 percent—double the euro-area pace—thanks to booming exports and a rebound in machinery investment. Core inflation eases to 6.6 percent, prompting the government to claim its 'targeted' anti-price measures are working..."	La Sexta	2023-04-28	positive Left
Opening of a New Gigafactory "King Felipe VI and Prime Minister Sánchez lay the first stone of Volkswagen's battery plant in Sagunto. The three-billion-euro project is slated to create three thousand direct and thirty thousand indirect jobs and anchor a full electric-vehicle supply chain on the Mediterranean corridor by 2026..."	La Sexta	2023-03-17	positive Left
Ukraine War Triggers Fuel Price Surge "Russia's blockade of Black Sea corridors and soaring gas prices push petrol above two euros per litre during the summer peak. Madrid extends a twenty-cent per litre rebate, caps basic energy tariffs and opens talks with Brussels on a broader Iberian price exception..."	A3	2023-02-24	positive Left
Gov't Approves Student Housing Aid "Cabinet earmarks two-point-five billion euros for grants and scholarships; rural students forced to leave home will now receive up to two thousand five hundred euros per academic year. Education Minister Alegría says the measure tackles both depopulation and unequal access to university..."	TVE	2023-02-21	positive Left

Story	Channel	Date	Sentiment
Spain Secures EU Recovery Funds "European Commission releases a further six billion euros after Madrid meets forty milestones on labour, pension and digital reforms. Vice-President Calviño hails the country as the 'frontrunner' of Next Generation EU implementation and vows to accelerate project selection in the regions..."	La Sexta	2023-02-17	positive Left
Spain Pushes Green Tax in EU "During an informal Ecofin in Stockholm, Spain floats a climate levy on private jets and luxury yachts, arguing that the richest one percent emit far more than the poorest fifty percent. The plan will be tabled formally once Spain assumes the rotating Council presidency in July..."	La Sexta	2023-02-01	positive Left
Spain Proposes Tax on Ultra-Rich "Environment Minister Ribera outlines a two-percent wealth tax on fortunes above one hundred million euros to finance a permanent EU climate-adaptation fund. Analysts say the levy could raise eight billion euros annually across the bloc if adopted..."	La Sexta	2023-02-01	positive Left
Spain Asks US to Remove Plutonium "Foreign Affairs sends an official note to Washington urging removal of fifty thousand cubic metres of soil still contaminated by the 1966 Palomares nuclear accident. Local mayors say the clean-up would revive agriculture and tourism; the US has yet to reply..."	La Sexta	2023-03-06	positive Left
Spain Leads in EU Recovery Program "Another six billion euros disbursed as Spain confirms ninety-nine of one hundred and two commitments under Next Generation EU. A ten-member European Parliament mission will audit project rollout in Madrid, Andalusia and Catalonia next week..."	TVE	2023-02-17	positive Left
Justice Protests as EU Ministers Meet "Hundreds of justice-office clerks rally outside Logroño's conference hall, accusing the government of 'stonewalling'. Inside, EU ministers debate cyber-crime, organised crime and victim protection under Spain's rotating presidency..."	TVE	2023-07-21	negative Left

Story	Channel	Date	Sentiment
Self-Employed Hit by Rising Costs "New survey finds sixty-seven percent of freelancers have raised their prices after business expenses jumped almost twenty percent in a year. Trade groups call for lower advance tax withholdings and more flexible social-security contributions..."	TVE	2023-07-10	negative Left
Bank of Spain Cuts Forecasts "The central bank trims 2023 growth to 1.3 percent as household spending weakens and interest rates stay high. It warns inflation will remain elevated 'longer than anticipated' but sees a rebound to 1.7 percent in 2024 if anti-inflation measures expire..."	TVE	2022-12-20	positive Left

Note: International and economic stories whose framing implies a partisan slant even without explicit party names. Texts shortened, translated to English, and headlines created with the help of ChatGPT.

Table D.20: EFE case studies

Date	Characteristic	Δx	Top 3 Stories
2023-05-29	Negative Left	0.412	**Overseas votes Count gives victory to PP** "Final overseas ballots leave the Partido Popular only nine-hundred-and-thirty-four votes short of wresting a seat from the PSOE in Asturias, which would hand a PP–Vox–Foro bloc an outright majority in the regional assembly; the definitive recount on Wednesday could tip the balance..."
			Abascal(VOX) Urges Pact to Oust Sánchez "Cheered by the snap-election call, Vox leader Santiago Abascal appeals to Alberto Núñez Feijóo to show 'statesmanship', seal postelection pacts and 'repeal sanchismo'—labelling the PSOE's record on crime and the economy 'disastrous'..."
			PP's regional president criticizes Sanchez "Andalusian premier Juanma Moreno calls the early vote 'an act of political survival', adding that the PM feels cornered by Sunday's heavy losses and hopes to reset the narrative before Spain takes over the EU Council presidency."

Date	Characteristic	Δx	Top 3 Stories
2023-05-31	Negative Right	0.226	**IMF Chief denounces Corruption on PP** "Ex–IMF chief Rodrigo Rato denounces the 'impunity' of the prosecutor's office after fresh money-laundering indictments and says he is confident the Supreme Court will keep him out of prison pending appeal..." **PSOE Minister defends economic policies** "First Vice-President Nadia Calviño touts a 'centrally balanced' economic policy that lifted jobs and wages, rebutting Feijóo's claim that Spain faces rising uncertainty and fiscal drift under the coalition..." **Sanchez Rallies against the Right** "In a closed-door call, the PM urges the party machine to mobilise against 'an emboldened PP backed by the far right' and warns of a campaign based on 'smears and fake data' ahead of the twenty-three-July vote."
2023-05-31	Positive Left	0.282	**PSOE New Legislation on Education** "Universities Minister Joan Subirats says the early election is 'the only sensible path' and pledges to clear decrees on accreditation and staff tenure before the parliamentary freeze later this month..." **PSOE obtains millions in subsidies** "Interior Ministry figures show the Partido Popular will receive six-point-three-million euros for its twenty-three-thousand councillors elected on 28 May, while the PSOE will draw five-point-six million euros for its twenty-thousand local officials..." **PSOE gains votes in Basque Country** "Basque PP chairman Iturgaiz says his party will support PNV–PSE mayoral nominees 'gratis et amore' to deny EH Bildu key councils but will demand policy input and committee seats for day-to-day governing."

Date	Characteristic	Δx	Top 3 Stories
2023-05-29	Positive Right	0.276	**PP Close to Win regional elections** "Expatriate ballots, to be counted Wednesday, could swing the last seat in Asturias and allow a PP–Vox–Foro coalition to unseat the Socialists after thirty-eight years of left-wing dominance. . . " **VOX starts coalition with PP** "'We must agree as we did on 28 May,' Abascal says, vowing to dismantle 'gender ideology' laws and roll back tax hikes if Vox enters a national coalition with the PP after July's general election. . . " **PP Questions Election Timing** "Andalusian president Moreno describes the PM's dissolution of parliament as 'a sign of weakness', insisting that regional governments now need clarity on the next state budget before autumn."

Note: 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 EFE between the two editions. Texts shortened, translated to English, and headlines created with the help of ChatGPT.

E Isolation Index

E.1 Definition

For a medium $m \in \{TV, Radio, Press\}$, the isolation index is computed as:

$$\text{Isolation}_m = \sum_j \left(\frac{\text{Right}_j}{\text{Right}_\text{m}}\right)\left(\frac{\text{Right}_j}{\text{Audience}_j}\right) - \sum_j \left(\frac{\text{Left}_j}{\text{Left}_\text{m}}\right)\left(\frac{\text{Right}_j}{\text{Audience}_j}\right), \tag{16}$$

where Right_j and Left_j denote the numbers of right- and left-leaning viewers of outlet j, $\text{Audience}_j = Right_j + Left_j$ is its total audience of that outlet and R_m are the total right-wing viewers in that medium.

The isolation index takes value of 1 if and only if, for every outlet that right people visit ($Right_j > 0$), then all other visitors are also right-wing, $\frac{Right_j}{Audience_j} = 1$ and the analogous for outlets consumed by left-wing users. This reflects a scenario of perfect segregation.

E.2 Results

Table E.21: Ideological Segregation by Medium (CIS Survey)

	Right exposure to		
	Right	Left	Isolation index
TV	0.414	0.299	0.115
Radio	0.527	0.240	0.287
Press	0.437	0.251	0.186

Note: The table reports the isolation index from Equation (16) using the CIS survey (Spain). "Right exposure" for Right (Left) is the average share of Right users on outlets visited by Right (Left) respondents. The isolation index is the difference.

Table E.22: Comparison of Isolation Indices

	CIS Survey (Spain,2023)	**Dejean et al.** (France, 2022)	**Gentzkow & Shapiro** (U.S., 2008)
TV	0.115	0.035	0.033 (Cable)
			0.018 (Broadcast)
Radio	0.287	0.039	—
Press	0.186	0.072	0.104

Note: The table reports the isolation index from Equation (16) and comparisons with previous results. The first column reports the isolation-style index computed from my data using the CIS survey (Spain). The second column reproduces the offline (traditional-media) partisan selective exposure measures from Dejean et al. (2022) on French data. The third column shows the replicated isolation index from Gentzkow and Shapiro (2011) for offline TV and newspapers (radio was not reported).