

The Impact of Political Campaigns on Demand for Partisan News*

Luis Menéndez

Universitat Autònoma de Barcelona, CSIC and Barcelona School of Economics

September 23, 2025

Job Market Paper

[Latest version here](#)

Abstract

I explore how electoral campaigns fuel the appetite for partisan news and how that, in turn, links to political polarization. I construct a daily, story-level measure of slant in Spanish TV news using machine learning and Large Language Models (LLMs) and match it to high-frequency audience-meter records. I then develop and estimate a structural model of news demand and supply. I propose a novel identification strategy that relies on exogenous shocks to the salience of political events that constrain outlets' slant production decisions. Polarization in news consumption intensifies only when the electoral campaign begins, with out-party animosity dominating. Furthermore, regions with more polarized media consumption patterns also exhibit a higher and persistent level of political polarization in their electorates. Finally, I evaluate the effects of a media regulation policy that enforces proportional-airtime rule during campaigns. Implementing the regulation has unexpected effects: outlets comply by hardening their editorial stance, resulting in a more polarized media landscape.

*I am very grateful to my supervisors Hannes Mueller and Rosa Ferrer for their continuous support and mentorship during my doctoral studies. This paper benefited from a visit to the University of Cambridge's Department of Economics, supported by Christopher Rauh, to whom I am especially grateful. I also want to thank Antoine Zerbini, Hanna Wang, Julian Hidalgo, Joan Llull and Matthew Ellman for their insightful comments and seminar participants and discussants at the BSE Jamboree, the Applied Seminars at UAB, the ENTER seminars, the Monash-Warwick-Zurich Text-as-Data Workshop, the Workshop in Networks and Political Economy in PSE and the Barcelona Supercomputing Center. I acknowledge funding from the Spanish Ministry of Science and Innovation through FPI Grant PRE2021-099556. All remaining errors are mine.

1 Introduction

Political polarization has surged in recent years in both the United States and Europe (Boxell et al., 2020; Reiljan, 2019). This matters for democracy, as it undermines electoral accountability and erodes norms of competition and acceptance of defeat (Graham and Svolik, 2019). Information segregation is therefore especially concerning during electoral campaigns, when the selection of leaders depends on what voters learn and how issues are framed (Besley, 2005). A growing literature links rising polarization to news media consumption—particularly among audiences of traditional outlets—which, in the era of AI and misinformation, continue to be the primary and most credible source of political information.

This paper investigates how demand for political information changes during election campaigns and evaluates the effect of media regulation intended to ensure pluralism. To answer this, I develop and estimate a structural model of news demand and supply. The demand follows a BLP-style specification (Berry et al., 1995), in which viewers choose among channels based on content characteristics—airtime and tone by political party—endogenously set by outlets in equilibrium. The analysis draws on a newly assembled dataset of television news in Spain, currently Europe’s most polarized country (Edelman, 2023). I construct a daily, outlet-comparable slant index by applying machine learning and large language models (LLMs) to the text transcripts of each broadcast. I then match this to real-time audience-meter data on television consumption. This enables me to track both the slant of content aired and how many people consume it across outlets and over time. My main finding is that, during Spain’s 2023 general-election campaign, demand for political news was more polarized than in comparable non-campaign periods. Consistent with affective polarization, viewers were more responsive to content about the party they oppose—especially by screening out favorable coverage of it. Furthermore, I show that the most common media regulation in Europe—proportional airtime across parties—would have undesirable effects: outlets comply by raising negative coverage, pulling them farther apart in slant.

Two central challenges hinder the estimation of demand for news. First, constructing scalable, outlet-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 here addresses both issues by (i) generating a high-frequency, story-level slant index comparable across channels and (ii) proposing a novel identification strategy that exploits exogenous variation in the daily news pool to distinguish audience preferences from editorial decisions.

First, to tackle the measurement problem, I construct a unique dataset that captures both the supply of and demand for political content on TV news. On the demand side, high-frequency audience-meter data overcome well-known limitations of survey evidence (Prior, 2009). On the supply side, I assemble a new dataset of daily TV newscasts that enables me to compare the same story across outlets. I process more than 500 hours of video content and, using machine-learning techniques, generate text transcripts. I then apply high-dimensional clustering to split each day’s coverage into more than 20,000 stories. Finally, I use LLMs to classify each story’s political tone with respect to each political party.

I compare this index with alternative slant measures from the literature trained on congressional speeches and with the one used by most media regulatory agencies, which tracks leaders’ on-screen minutes as a measure of balance. To replicate the latter, I train a face-recognition model on broadcast imagery to quantify each leader’s screen time. Across these benchmarks, the LLM-based index is more informative: by capturing thematic framing, it uncovers political tone even when parties or politicians are not explicitly mentioned. This measure reveals strong partisan differences across outlets, while airtime-based metrics or speech-trained classifiers suggest balanced coverage. This ability to detect divergence makes the LLM-based index directly useful for media plurality evaluations and for demand estimation, enabling differentiation among products that would otherwise appear to be close substitutes.

Second, to address the identification problem, I exploit exogenous shocks to the salience of political events that constrain outlets’ news production. I collect all stories distributed by the largest newswire serving these broadcasters, apply the same text-classification pipeline, and use the resulting corpus as a proxy for the daily set of stories broadcasters can draw upon each day. I show that when the pool of pro-right (pro-left) stories grows for exogenous reasons, right-leaning (left-leaning) channels expand coverage accordingly. This variation identifies a structural random-coefficients model of news demand in which viewers’ preferences vary with ideology. The estimated model allows me to test the degree of confirmation bias and, because the slant metric distinguishes both party and tone, the specific form of polarization in news consumption.

The demand estimation results show that, outside campaign periods, 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 campaigns, 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 from off- to on-campaign. These findings align with prior evidence on polarized news consump-

tion during presidential campaigns in the United States ([Peterson et al., 2017](#)). Next, I relate this polarization in news demand to survey-based electoral polarization: in those regions where people react more to negative coverage of the opposing party, the electorate also tends to polarize, with voting intentions concentrated in parties that are more ideologically distant. Moreover, electoral polarization shows a trend break consistent with the demand estimates. After a year of decline, it rises sharply at the start of the campaign and remains elevated for about a year.

Given the demand estimates, I model and estimate content supply. Outlets play a differentiation game, choosing the distribution of airtime across parties and political tone to maximize viewership, with production costs depending on the mix of stories available each day. Unobserved marginal cost factors create endogeneity in slant choices. Identification relies on timing: I exploit the short interval between the midday and evening newscasts. Because these editions are separated by only a few hours, differences in the content aired are driven by unexpected story arrivals in the interim, which shift production costs without directly affecting same-day unobservables. Outlets adjust slant to these arrivals, with responses that are outlet-specific and shaped by the stories' partisan orientation. The results of the cost estimation are consistent with outlets' political positions: producing left-favoring content is costly for all channels—particularly right-leaning ones—while right-favoring content generally increases payoffs, though less so for left-leaning outlets.

Finally, I test the effectiveness of existing policy interventions aimed at promoting diversity and fighting polarization in television news. The most common campaign-period intervention is the proportional-airtime rule, which requires broadcasters to allocate coverage to political parties according to their results 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 on it.

To assess the impact of this regulation, I use the estimated demand and supply parameters to simulate a counterfactual in which Spanish outlets are regulated under proportional airtime during the campaign. Perhaps strikingly—and contrary to the policy's primary goal—the result is more polarized political coverage. Because the most recent election delivered a larger vote share to the right bloc, the rule assigns a larger share of campaign minutes to those parties. In the baseline scenario, however, all channels devote more relative time to the left, so enforcement requires every outlet to rebalance minutes from left to right. Outlets then adjust on two margins: the amount of politics they air and the tone within those minutes—primarily by intensifying negative coverage. The resulting spread in outlets' optimal slant positions is roughly three times larger after enforcement. The mechanism behind the change stems from the rule itself: since the regulation limits only total airtime for each party, channels adjust through slant to maintain their preferred tone

positions. This highlights that airtime-based metrics—and regulations built on them—can backfire when they ignore tone, yielding higher rather than lower media polarization.

Related Literature The first strand of the literature that my paper contributes to is that on the measurement of media slant. I contribute to this literature by proposing a new methodology that combines tone and intensity, using LLMs to discern both sentiment and airtime. [Puglisi and Snyder \(2015\)](#) divide measures of bias into *comparison*, *intensity*, and *tone* approaches. Comparison measures—such as [Groseclose and Milyo \(2005\)](#) (think-tank citations) and [Gentzkow and Shapiro \(2010\)](#) (lexical proximity to congressional speeches)—locate outlets by how closely their language matches partisan references; my index instead does not require explicit party mentions nor baseline partisan speech. Intensity measures—[Chiang and Knight \(2011\)](#) using endorsements for newspapers and [Durante and Knight \(2012\)](#); [Cagé et al. \(2022\)](#) using airtime for television—track how much attention outlets devote to topics or actors. I retain intensive margin via time spent but add tone within that exposure, allowing me to see how much time and tone were devoted to the same exact story across outlets on a given date. 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 text to quantify outlet slant and model heterogeneous tastes for like-minded news while also accounting for competitive behavior in the supply of information. Closely related, [Simonov and Rao \(2022\)](#) estimate a structural model of demand for government-controlled online news in Russia. This paper proposes a novel framework for structural estimation of content preferences, combining LLM-based slant measures with an integrated model of demand and supply of news. Furthermore, I propose an identification strategy that exploits shocks in upstream news content. Newswire companies that supply content to outlets provide a way to proxy for exogenous shocks to the news landscape that constrain outlets' ability to slant the day's news.¹ My identification strategy can be applied in settings where previous instruments like cable-dial positions ([Martin and Yurukoglu, 2017](#)) are not applicable.

Third, a growing body of literature studies media persuasion. Experimental evidence shows mixed conclusions: some studies find limited scope for persuasion because self-selection dominates ([Arceneaux and Johnson, 2013](#)), whereas others document reinforcement effects among strongly committed partisans ([Levendusky, 2013](#)). Complementing these results, more recent works in political economy have shown consistent media persuasion effects on polarization attitudes; [Schneider-Strawczynski and Valette \(2025\)](#) show how TV coverage of immigration polarizes attitudes toward immigrants in France, and [Martin and Yurukoglu \(2017\)](#) show that cable-news polarization can explain a large share of the rise in U.S. voter

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

polarization. I complement this literature by studying media’s production decision of polarized news, also showing correlational links between media consumption and ideological polarization.

Fourth, this article contributes by bringing tools from IO estimation to the political economy literature. 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 TV news programs. However, this richer product space raises concerns about endogeneity in characteristics. Prior studies address this with instruments based on demographic shifts across pricing zones (Fan, 2013) or candidate positions across electoral precincts (Longuet-Marx, 2025). However, these instruments are difficult to adapt to media environments with high-frequency data and with national coverage of content such as mine. I instead exploit supply shocks in upstream news content, which provide exogenous variation in setups with high-frequency dynamics. On the supply side, I build on the media IO literature on spatial competition in television. Closest to my setting, Goettler and Shachar (2001) study optimal schedule choices by profit-maximizing networks; in contrast, I estimate a daily content-positioning game and introduce an identification strategy that leverages high-frequency variation in news broadcasts to pin down cost parameters even when credible demand shocks are unavailable.

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 social media platforms (e.g., Facebook during pre-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; Cagé et al., 2022), and entry (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 TV 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 the demand model, addresses endogeneity and the identification strategy, and presents results. Section 5 details identification and estimation of the supply-side parameters. Section 6 develops the counterfactual

analysis. Section 7 concludes.

2 Context

Before detailing the data and text-classification methodology, 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 quantify audience sorting across outlets, benchmarking audience sorting in TV, radio, and the press for Spain against recent estimates for France and the United States. This motivates my focus on television and frames the external validity of the results.

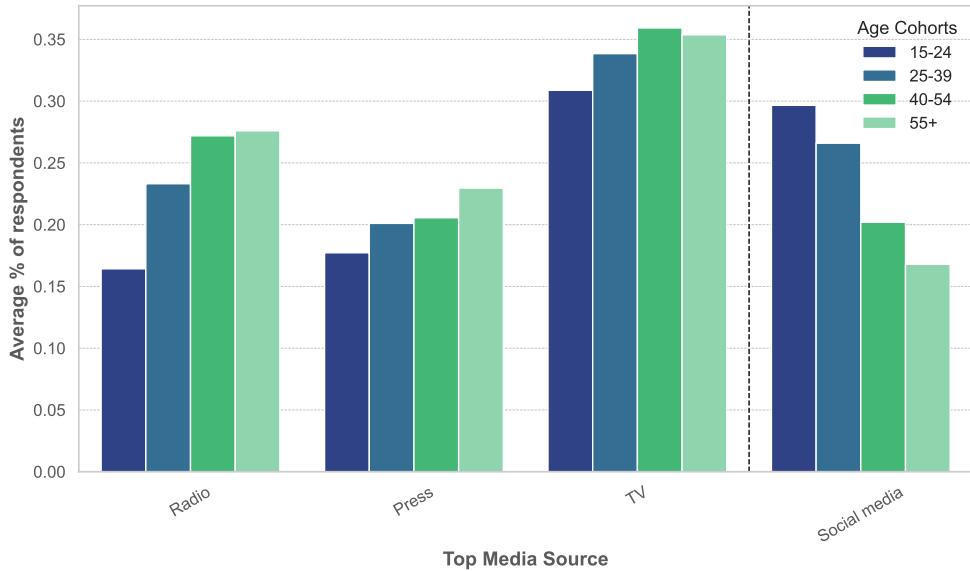
2.1 Traditional Media and Political Information

Traditional media remain the primary source of information in most European countries ([Parliament, 2024](#)). Figure 1 shows the main media used to acquire political information in 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

Traditional media still enjoy higher credibility than digital-only outlets or news encountered on social platforms. Europeans continue to cite television as their main source of current affairs information, and nearly half (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 safest gatekeepers of political information, highlighting the importance of analyzing these markets.

²This pattern is also consistent in different surveys for Spain. Figure C.16 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).

Figure 1: Preferred Media for Political Information in Europe



Note: Histogram of the preferred media used for political information in Europe. Using data for the 27 countries in Eurobarometer survey under the question "*What media have you used the most to access news in the past 7 days?*" . $N = 112059$. Source: Eurobarometer, 2022.

2.2 Spanish Politics and TV News

Here, I provide context on the Spanish political party system to situate television news and the ideology of their audiences.

Spanish Political Context

Political power in Spain has historically been dominated by a two-party system, with government alternating between the Socialist Party (PSOE) and the People's Party (PP). During my 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,³ with the main opposition led by PP and the extreme-right party VOX. 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).

The extreme-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

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

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). Altogether, their evening news editions capture around 50 % of viewership—about 4.5 million viewers, or 10 % of Spain’s population. By comparison, the most-watched U.S. cable-news program (Fox News) averages roughly 2.2 million viewers. 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.

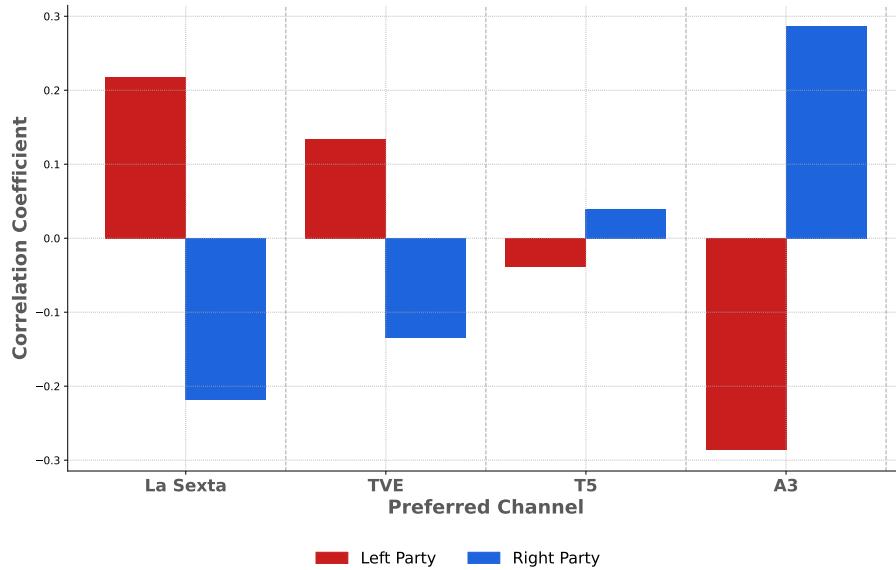
What is the political composition of these audiences? Figure 2 shows the correlation between individuals’ preferred political party (left or right) and their preferred channel for acquiring political information. I condition only on *partisan* individuals, i.e., those who report a preferred political party. Right-wing individuals tend to watch Antena 3 (A3) more, whereas left-leaning individuals are divided between La Sexta and the public channel Televisión Española (TVE). Telecinco (T5) appears in the middle, with weak correlations. This is consistent with the Mediaset group offering more pro-entertainment content as previously documented for Italy in [Durante et al. \(2019\)](#).

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. The formal definition appears in Section E. Television is the least isolated medium (11 pp), followed by the press (18 pp), with radio the most isolated (29 pp).⁴

To contextualize these results, I compare them with recent estimates for France in 2022

⁴Results of the isolation index its decomposition by party bloc and can be seen in Table E.19. 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).

Figure 2: Correlation Between Preferred Channel and Political Party



Note: Bars show correlation coefficients between individuals' declared preferred political party (left or right) and their preferred TV news channel for political information. The question was only asked for those that marked television as their preferred source of political information. Sample restricted to partisan respondents (those reporting a preferred political party). Survey question: 'What is your preferred TV channel for political content?' Source: CIS, Encuesta Pre-electoral 2023.

(Dejean et al., 2022) and the U.S. in 2008 (Gentzkow and Shapiro, 2011) (Table E.20). Spain exhibits higher levels of partisan isolation across all media, consistent with the high levels of political polarization documented elsewhere (Edelman, 2023). Television in Spain is about 8 percentage points more isolated than French TV and nearly 10 pp above U.S. broadcast TV.

Taken together, the cross-country ranking reveals a common pattern: newspapers and radio are more ideologically segmented than broadcast TV, while Spain shows overall higher segregation. Since media effects are limited when audiences are already sorted, this pattern suggests greater potential for television to influence attitudes (given its comparatively mixed audience) 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 and Descriptive Evidence

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.

3.1 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.⁵ 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 share 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). Although I do not have individual-level data on choices, I have geographical disaggregation for 15 autonomous regions in Spain (also referred to as

⁵The 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](#)).

regions hereinafter), which I match to survey demographics.⁶ The shares are specific to the evening TV news shows, which, with the exception of La Sexta at 20:00, start at 21:00 daily. For this analysis, this channel's program is treated as if it occurred simultaneously with the others.

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 my sample period.

Similar to Reuters or Associated Press, this agency mainly sells content and images to third-party newscasts. All the outlets in my sample are clients of EFE.⁷

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.⁸ 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

⁶The 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.

⁷See collaborations with Mediaset, Atresmedia, and RTVE.

⁸Available at: <https://www.congreso.es/es/busqueda-de-intervenciones>.

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.13.

Each $s \in P_{jd}$ is fed into ChatGPT and assigned a score: $t(s) \in \{-1, 0, 1\}$ ⁹ 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 $p(s) \in \{L, R\}$, whereas neutral stories do not.

Notice that the broad classification of what is *political* allows for stories without explicit mentions of Spanish political actors to be classified as partisan. Table D.17 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:

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

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

⁹More details about the prompt and classification results can be found in Appendix Section A.

by EFE— $N \approx 32,000$ items over the sample. Mirroring the content covariates in (1), I classify every story with the same NLP pipeline and construct daily measures of the political mix in the set of stories available as:

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

where now \mathcal{N}_d denotes the total number of EFE 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.

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 ¹⁰. Positive (negative) values indicate a net (un)favorable tone toward a party by that outlet.

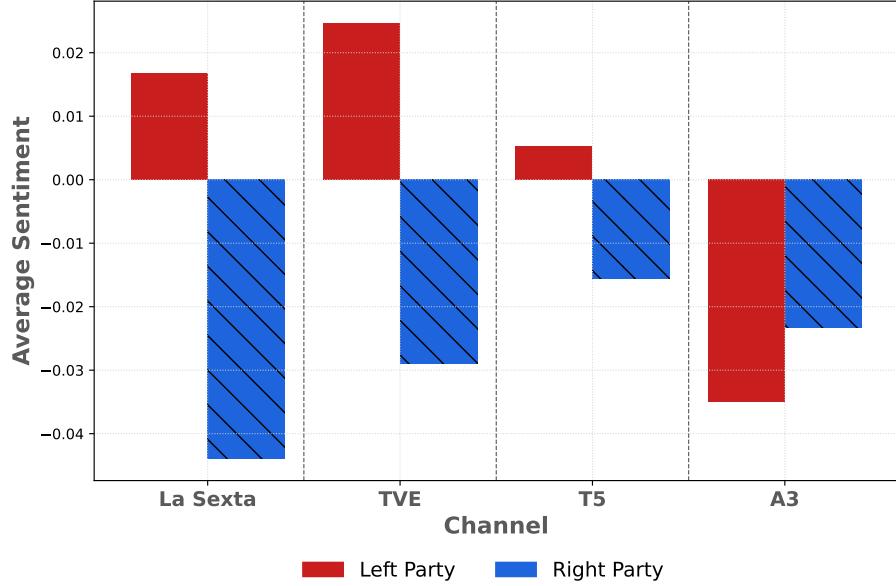
La Sexta and TVE tilt strongly pro-left, T5 sits near the center with a mild leftward bias, and A3 is the only channel with a slight pro-right balance. Perhaps strikingly, every channel exhibits a net negative tone toward the right-wing bloc, reflecting the fact that the left coalition held office throughout my sample period. As can be seen in some of the text examples in Tables D.3 and D.17, 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 channels that comes from survey data. I assign each channel a *slant index* calculated as

$$Slant_j \equiv (\bar{x}_j^{R+} - \bar{x}_j^{R-}) - (\bar{x}_j^{L+} - \bar{x}_j^{L-}), \quad (3)$$

¹⁰Specific examples of stories with their tone classification can be seen in Appendix Table D.3.

Figure 3: Average Tone Across Channels and Parties



Note: Bars show 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.

and, in parallel, compute each region’s left-right position from survey data (Figure 2). I then normalize both series so that the most extreme channels take values of -1 and 1 to enable comparisons across the two different measures and different classification methods. Figure 4 displays these 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 close scores in both panels confirms that the LLM-based classification is similar to the distribution of audience preferences, as one would expect in a demand-driven market equilibrium. Below, I also show robustness of the classification and comparisons with other methodologies previously used in the literature.

Figure 4: Normalized Slant Index by Channel



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.

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, one may question the performance of alternative 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. 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. I also apply face recognition to compare the slant measure with the standard metric based on politicians’ airtime. This metric, widely used by regulatory agencies and in prior research, produces a completely different scenario, in which all channels appear more homogeneous, and it fails to predict actual slant.

Taken together, these results show the robustness of LLMs for slant classification and raise concerns about the use of traditional measures—such as image-based metrics—to assess plurality. Nevertheless, empirical validation with human annotators remains advisable for future work.

3.3 Descriptive Evidence

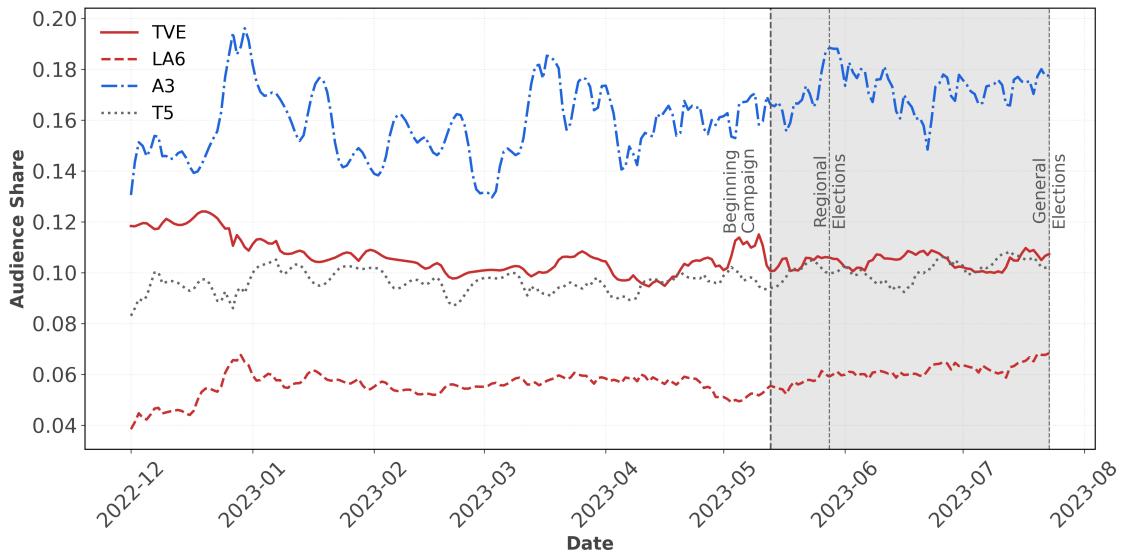
TV News Consumption and the Election Campaign

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, in which seasonality drives audience numbers down. However, salient political events typically retain audience numbers. To see these effects, Figure 5 shows the time series evolution of the audience shares for each of the four channels in my sample. All outlets nearly maintain their share during the campaign: 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%.

Figure 5: TV Audience over Time



Note: The figure represents the share of audience for the TV outlets in my 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 to reduce noise and highlight underlying trends over time.

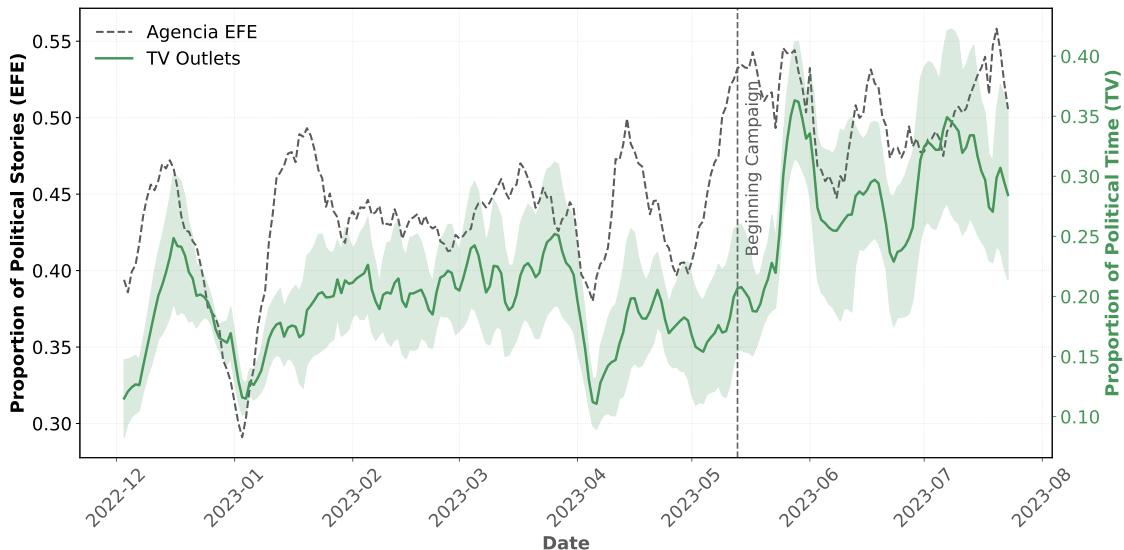
This stability of the audience share numbers contrasts with summer seasonality. All channels lose audience levels in this period—on the order of 15–25%—with A3 still the largest (roughly 2.2M viewers off-campaign vs. 1.7M during the campaign) and the remaining channels experience similar proportional declines (see Figure C.19). This suggests that information seeking helps outlets maintain their slice of attention even as overall viewing falls in summer months. ¹¹

¹¹ Due to data limitations, I cannot benchmark these patterns against prior years to quantify the effect of the campaign per se on TV consumption.

Political Coverage and the Election Campaign

Election campaigns concentrate public attention on politics and shift newsroom priorities. Consistent with this, political content rises sharply for both television and the EFE newswire. Figure 6 plots the share of political content over time. The dashed line is the average across the four TV channels (with a shaded band for one standard deviation) represented on the right y-axis, and the solid black line is EFE with the left y-axis representing the proportion of political stories on a given day. 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 when non-political events dominate (Christmas, Easter). ¹²

Figure 6: Proportion of Political Coverage over Time



Note: The figure represents the proportion of political content for the TV outlets (dashed) and EFE (solid). Political content defined by dictionary matches to political terms (Table D.13). For TV outlets, measure is minutes of political coverage over total minutes; for EFE, share of political stories. All series are smoothed using a centered rolling mean with a 9-day window.

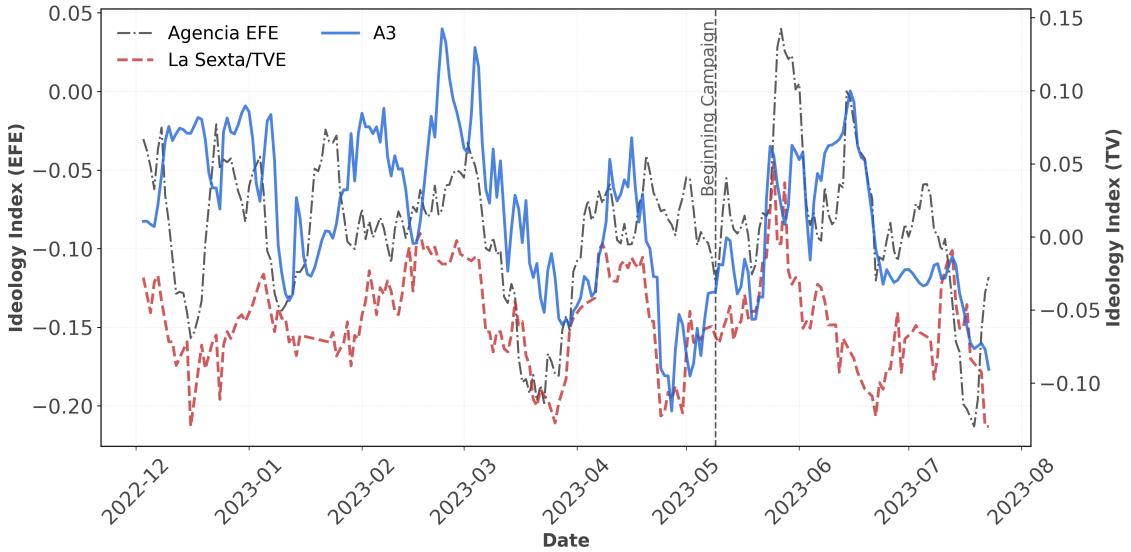
Political Slant and the Election Campaign

If campaigns shift attention toward politics, the next question is who benefits from that attention. To track net tone, I use the slant index in Equation 3. Figure 7 shows the

¹² 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.20 in the Appendix shows the time series decomposition of political coverage by outlet.

evolution of slant for EFE (dashed gray line) and the main outlets.¹³ 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.

Figure 7: Evolution of the Slant Index



Note: The figure represents the time series of ideological index (Eq. 3) for Spanish TV evening news channels and Agencia EFE. Positive values denote pro-right coverage; negative values denote pro-left coverage. TV channels (right y-axis) are grouped into left-leaning (La Sexta, TVE) and the right-leaning (A3). EFE ideology index shown on left y-axis. All series are smoothed using a centered rolling mean with a 9-day window.

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. During this period, Spanish politics was dominated by a failed no-confidence motion initiated by the far-right party Vox, which exposed divisions on the right and left the opposition weakened. At the same time, conservative parties were on the defensive over a series of symbolic and institutional controversies—ranging from opposition to progressive laws on gender identity, euthanasia, and feminism, to accusations of obstructing judicial reform and mishandling pensions. In contrast, the governing left bloc emphasized favorable developments, including record employment figures, new housing legislation, and major industrial investments. 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 divergence and partisan polarization

¹³Time series for all the outlets are shown in Appendix Figure C.21.

between left- and right-leaning outlets.

For the analysis that follows, I take the entire pre-campaign period as the baseline to better capture the underlying conservatism of A3. To illustrate how slant evolved in these two periods, I decompose tone by party in Appendix Figure C.18. During the campaign, outlets adopted a common strategy: all became more negative toward the far-right party VOX and more positive toward the left-wing party SUMAR. As a result, the political slant appeared less segregated, with outlets' ideological positions converging modestly.¹⁴

4 Demand for News

In this section, I introduce the market setting for demand. Supply will be explicitly modeled in Section 5. I first develop a mixed logit (BLP) model (Berry et al., 1995) where individuals choose the channel to watch depending 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

Newscasts carry no advertising, so I abstract from two-sided market considerations. Channels differentiate primarily by how they present the day's stories. Viewers choose one outlet or the outside option, defined as not consuming news on any of the sampled outlets. The single-product choice assumption might be particularly strong in television markets, where viewers can switch programming during the same day—something that cannot be identified from daily aggregate data. To mitigate this concern, I restrict attention to the initial (i.e., minute-zero) audience each day.¹⁵

An individual i in region r chooses an outlet $j \in \mathcal{J} \equiv \{La\ Sexta, TVE, T5, A3\}$ to

¹⁴ Quantitatively, dispersion across channels narrowed slightly during the campaign. Appendix Figure C.27 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.

¹⁵ Previous works have documented the importance of inertia from previous shows in TV news consumption (Richter, 2025). During my sample period, there were no changes in the preceding slot's programming agenda, which minimizes this concern. Results are robust to the estimation using the first five minutes of the shows.

watch at the beginning of day d based on the following expected utility :

$$U_{ijrd} = \underbrace{\sum_k x_{jd-1}^k \beta^k}_{\delta_{jrd}} + w_{rd} \gamma + \xi_{jrd} + \underbrace{\sum_k x_{jd-1}^k (\sigma^k \nu_{ird}^k + \pi^k y_{irm})}_{\mu_{ijrd}} + \epsilon_{ijrd} \quad (4)$$

where x_{jd}^k represents the proportion of time on channel j and day d devoted to characteristic $k \in \{R+, R-, L+, L-, political\}$ as defined in Eq. 1. w_{rd} measures the precipitation level on a given day-region. Weather shocks rise 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). In my model, this happens with a common shift in the valuation of the inside options. Taste shocks follow a standard normal distribution, $\nu_{ird}^k \sim N(0, 1)$, 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. The parameters π^k allow for asymmetric tastes of politics based on ideology. Thus, they capture polarization in news consumption: More right-wing individuals might screen out opposed content.

The unobserved (to the econometrician) product characteristics are decomposed into $\xi_{jrd} = \xi_j + \xi_{dow} + \Delta \xi_{jrd}$, where I include product dummies that account for unobserved quality factors and day of the week dummies to control for seasonal variation in the value of TV consumption. Unobserved product tastes can take the form of higher valuation of a given type of story that comes from knowledge of it through social media, specific regional taste shocks due to local events, etc. By assumption, both the outlets and the viewers have full information about all the product characteristics. Due to timing differences, this assumption comes in the form of a correct expectation formation for next day unobserved preferences ξ_{jrd+1} in the moment of setting today's content \mathbf{x}_{jd} .

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

Market shares are computed as the integral over the individual choice indicators from 4:

$$s_{jrd} = \int d_{ijrd}(\boldsymbol{\delta}_{rd}, \boldsymbol{\mu}_{ird}) d\boldsymbol{\mu}_{ird} d\epsilon_{ird} \quad (5)$$

where d_{ijrd} equals 1 if $U_{ijrd} > U_{ikrd} \quad \forall j \neq k$ and 0 otherwise. The shocks ϵ_{ird} are distributed i.i.d. with a Type I extreme-value distribution.¹⁶

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

¹⁶The model is estimated using the *pyblp* package (Conlon and Gortmaker, 2020).

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

I report results for both the 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. While this might be realistic for markets where characteristics are costly to change and competition relies mainly on price after products are launched, the assumption of exogenous content is not credible in my setup: channels tilt the day’s slant according to their audiences’ preferences.

Formally, viewers form expectations about each channel’s utility to start watching the news based on exogenous variables—weather, individual attributes, and an unobserved (to the econometrician) shock ξ —as well as yesterday’s slant \mathbf{x}_{jd} . Channels, in turn, choose today’s slant while forecasting next-day utility shocks $\Delta \xi_{j,d+1}$. Hence, their optimal content decisions are functions of unobserved taste shocks, implying $\mathbb{E}[\mathbf{x}_{jrd} \Delta \xi_{jrd+1}] \neq \mathbf{0}$.

I address this endogeneity by using the daily composition of the newswire as an exogenous supply shock. Each day’s wire composition shifts which stories—and thus which tones toward left or right—are easier to produce. Formally, I use the *news shock* \mathbf{z}_d defined in Eq. 2 as instruments for outlet–day slant \mathbf{x}_{jd} . Outlets aim to maintain preferred slant positions, but in the short run the available story mix constrains coverage, so they smooth shocks and take advantage of “favorable” days. 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.

Consider the following examples. On 27 February 2023 (the highest z_d^{L-} in the sample), a loophole in a law sponsored by 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 extreme-right party VOX. Left-leaning outlets devoted about 15% of airtime to negative right-wing content, whereas the right one devoted roughly 4%. The full breakdown appears in Tables D.11 and D.12.

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

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

where $k \in \{L+, R+, L-, R-, political\}$. As was described before, $x_{jd}^{party,tone}$ is outlet j 's share of airtime with positive or negative tone about $party \in \{L, R\}$; z_d^k is the corresponding 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)¹⁷ pooling left channels for simplification. When the share of positive-right stories rises by one standard deviation, the right-leaning A3 lifts its own positive-right airtime by about 0.30 stdev., whereas the left-leaning outlets TVE and La Sexta react hardly at all. Symmetrically, a one-stdev. increase in positive-left stories leads TVE to expand favorable coverage of the left by roughly 0.38 stdev, while A3's response is not statistically different from zero. By contrast, the adjustment on the negative right content is small. 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

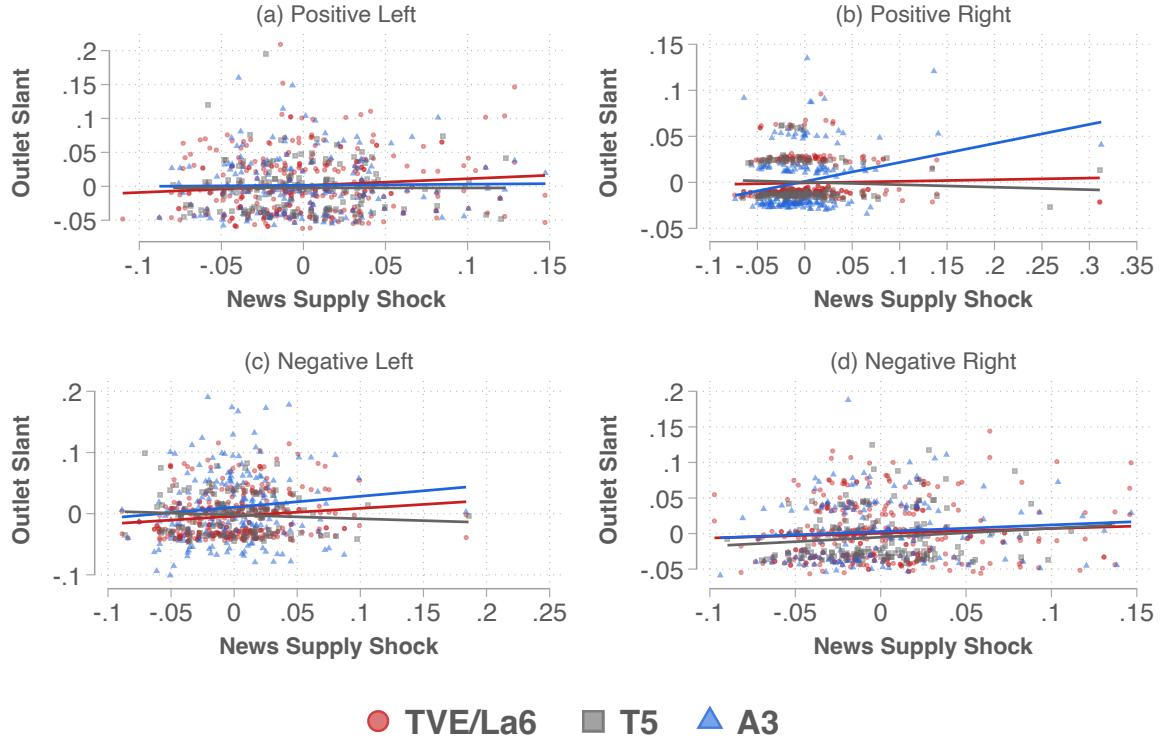
Characteristic	F-test	F-test p-value	T-test	T-test p-value
$L-$	2.69	0.07	3.51	0.06
$L+$	1.31	0.27	1.87	0.17
$R-$	0.42	0.66	0.34	0.56
$R+$	8.78	0.00	17.55	0.00

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 \mathbf{z}_d as instruments for the linear content characteristics \mathbf{x}_{jd} . For the K

¹⁷I also present a non-linear LOWESS version to mitigate concerns of outliers in Appendix Figure C.22. 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 and the y-axis the corresponding outlet's slant x_{jd}^k for each party-tone combination. Channels are pooled into left (TVE and La Sexta), middle (T5) and right (A3) for visualization purposes.

non-linear parameters governing preference heterogeneity, I follow [Gandhi and Houde \(2019\)](#) and use instruments of the form $(\hat{x}_{jd}^k - \sum_{l \neq j} \hat{x}_{ld}^k)^2$, where \hat{x}_{jd}^k is the predicted slant based on the reduced-form regression Eq. (7) constructed from the news shocks and outlet fixed effects. To identify demographic interactions, 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 β s represent the mean tastes of left-leaning viewers and the π s are deviations for right-leaning audiences.

Most of the heterogeneity is captured by the demographics (i.e ideology). The estimated

Table 2: BLP Estimation Results with Standard Errors

Coefficient	Parameter	Estimate	Std. Error
Pre-campaign			
Positive Left	β^{L+}	-16.90	(11.73)
Positive Right	β^{R+}	-25.53	(31.03)
Negative Left	β^{L-}	28.29	(25.89)
Negative Right	β^{R-}	56.44**	(28.45)
Political	$\beta^{political}$	11.49***	(4.28)
Weather	γ	0.00	(0.03)
Positive Left	σ^{L+}	0.44	(296.90)
Positive Right	σ^{R+}	0.68	(715.26)
Negative Left	σ^{L-}	12.64	(8.68)
Negative Right	σ^{R-}	21.99	(13.83)
Political	$\sigma^{political}$	0.00	(46.79)
Right-Wing \times Positive Left	π^{L+}	46.26	(48.70)
Right-Wing \times Positive Right	π^{R+}	77.81	(95.92)
Right-Wing \times Negative Left	π^{L-}	-70.09	(57.97)
Right-Wing \times Negative Right	π^{R-}	-103.71	(97.76)
Right-Wing \times 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 \times Positive Left	π^{L+}	-421.99**	(176.15)
Right-Wing \times Positive Right	π^{R+}	334.94***	(127.41)
Right-Wing \times Negative Left	π^{L-}	288.65**	(116.22)
Right-Wing \times Negative Right	π^{R-}	-280.33***	(104.44)
Right-Wing \times 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 $N_{off-campaign} = 6604$.

taste-dispersion parameters (σs) are small and very imprecise. 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 same products are present across regions and dates.¹⁸ These low values of heterogeneity 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 elasticity for the k -th characteristic as:

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

Both left and right parties were almost equally disliked during off-campaign (Table D.5.). An increase of 1 percent in net tone ($\bar{\epsilon}^{\text{party}+} - \bar{\epsilon}^{\text{party}-}$) towards right (left) results in drops of 0.98 (1.00) percentage points in audience share; corresponding to a decrease of nearly 13,000 viewers.¹⁹ This is consistent with a taste for scandals or entertainment-like type of political content, which is more likely to happen off-campaign. During the campaign, audiences remain averse to right-leaning tone—though less so, with only a 0.60 pp loss—but the effect of net left-leaning tone flips to 0.09 pp increase (867 viewers).

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.

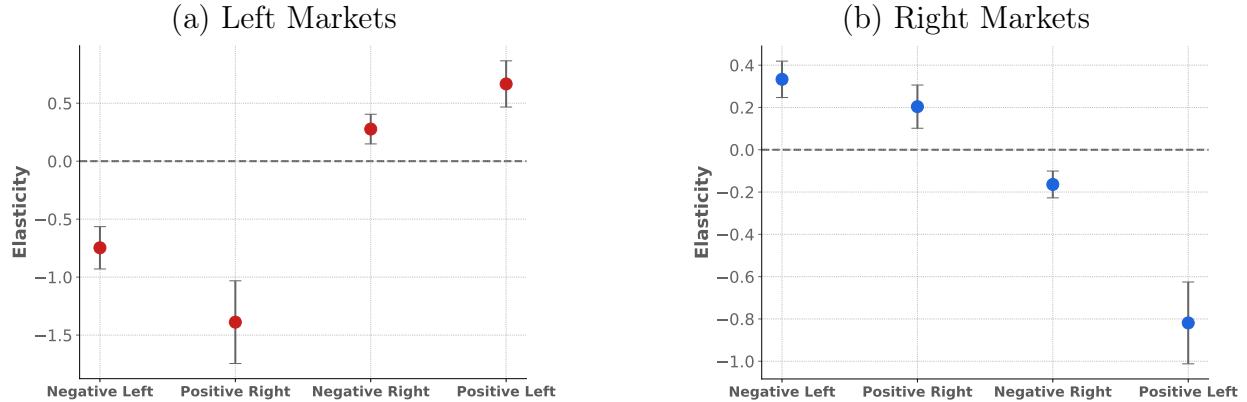
I focus now on the results for the main period of analysis, the election campaign. Figure 9 plots the estimated elasticities for that period²⁰ for left markets (panel a) and right markets (panel b). Polarization becomes now evident. Left viewers present negative taste for content that harms their party 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.

¹⁸A similar result was documented by [Nevo \(2001\)](#). 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.

¹⁹A 1 pp 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 pp of airtime corresponds to $0.01 \bar{T}$ minutes (where \bar{T} is the average broadcast length), $\frac{\Delta V}{\Delta t} = (S \times \frac{\epsilon}{100} \times \bar{L}) \times \frac{1}{0.01 \bar{T}}$ gives the change in viewers per extra minute of coverage.

²⁰Table D.6 and Figure C.23 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). Content categories are negative-left, positive-right, negative-right, and positive-left coverage. Whiskers represent 95% confidence intervals of the mean across markets.

Furthermore, decomposing by party–tone shows that partisan reactions are asymmetric. In left markets, in-party affinity is relatively stronger (a larger reward for positive-left than for negative-right). In right markets, out-party aversion dominates (a larger penalty for positive-left and a stronger response to negative-right). For example, a 1 pp 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. The consistent dislike is clear: both blocs screen out coverage that favors the opponent, and this out-party penalty is the dominant effect.

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 polarization in the way people consume partisan news that comes from my demand model estimates.

I compute ER on *party vote intentions*²¹ for the four main parties $\mathcal{P} = \{\text{UP}, \text{PSOE}, \text{PP}, \text{VOX}\}$, renormalizing within \mathcal{P} so that $\sum_{p \in \mathcal{P}} s_{prm} = 1$ for region r and month m . The ER index is defined as:

²¹The CIS survey lacks a direct ideology question persistent over time.

$$ER_{rm} = \sum_{p \in \mathcal{P}} \sum_{q \in \mathcal{P}} s_{prm}^{1+\alpha} s_{qrm} d_{pq}, \quad (9)$$

where *alpha* is set to the standard value of 1.5 and d_{pq} denotes the normalized ideological distance between parties²². 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. 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 right and analogously for left-wing regions:

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

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 (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.²³

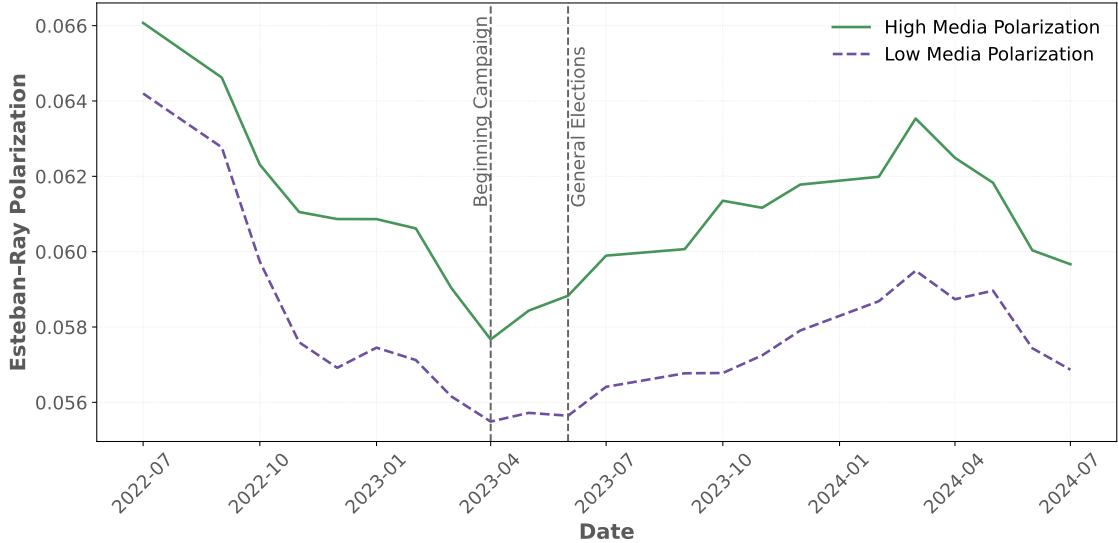
I divide regions into *high* and *low* groups according to their news demand polarization relative to the median and plot their ER index for an extended period over the year before and after the 2023 election. Results are shown in Figure 10.

Regions with high polarization in news demand (solid line) consistently show higher ER polarization; 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.

²²Baseline ideology scores used to compute distances: $i_{UP} = -1.0$, $i_{PSOE} = -0.5$, $i_{PP} = 0.5$, $i_{VOX} = 1.0$. Distances are defined as $d_{pq} = |i_p - i_q| / \max_{i,j} |i_i - i_j| \in [0, 1]$.

²³This interpretation aligns with in-out party evaluation gaps commonly used to capture affective polarization (Iyengar et al., 2019).

Figure 10: Esteban-Ray Polarization by Level of Media Polarization



Note: The figure shows the Esteban–Ray polarization index of vote intentions over time, plotted separately for regions with high versus low media polarization. High-polarization regions are those above the median in the media polarization index, defined as the difference between audience reactions to out-party versus in-party coverage during the campaign (Eq. 10). Vertical dashed lines marking the start of the campaign and election periods are shifted one month earlier to match the timing of 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 which mix of stories and tones to air each day? Spanish prime-time newscasts are developed under tight time constraints, with producers constantly monitoring real-time ratings and the incoming news wire. The following remark from the news director of one of the channels captures this:

“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)²⁴

Producers therefore aim to maximize the audience handed off to the next slot—despite the bulletin itself carrying no advertising—and fine-tune slant before each edition. They furthermore do these adjustments on a daily basis.

5.1 Supply Model

I capture this behavior with a competitive model of news slant decisions. Outlets choose the slant of their news editions to maximize total (national) audience, but face costs of producing the slant that depend on the information set available. Formally, channel $j \in \{La Sexta, TVE, T5, A3\}$ ²⁵ on day d and edition hour $h \in \{0 \text{ (midday), } 1 \text{ (evening)}\}$ solves the following problem:

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

where \mathbf{z}_{dh} measures the pool of stories available at edition h and \mathbf{x}_{jdh} is the proportion of minutes to each tone category as defined above. L_r refers to the total potential audience in region r . Following Goettler and Shachar (2001), I model each network’s payoff as the

²⁴Source: https://cadenaser.com/ser/2014/12/03/television/1417630810_539829.html

²⁵Although 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.

predicted audience rate without considering asymmetric pricing schedules across outlets. I parameterize the marginal cost function as:

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

The λ_j parameters are channel-specific and govern the slope of the production costs. The unobserved cost factors depend on two key components: i) η_{jd}^k , a *day-specific* marginal-cost shock (e.g. a key reporter is on sick leave, satellite link fails, or legal concerns delay a segment) known to the outlets, and ii) ν_{jdh}^k is a mean zero channel-day-hour specific idiosyncratic supply shock unknown to the players. By assumption, these unobservables enter as linear terms.

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

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

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.

5.2 Endogeneity and Identification Strategy

Channels choose the day's slant \mathbf{x}_{jdh} after observing the same-day cost shifter η_{jd}^k . Events like a reporter's sick leave or a technical broadcast issue might shift these unobserved factors thus affecting the optimal slant \mathbf{x}_{jdh} and thereby the demand gradient $g_{jd+1h}(\mathbf{x}_{jdh})$. Furthermore

Formally, from Equation 12, $\mathbb{E} \left[u_{jdh}^k \times \frac{x_{jdh}^k}{z_{dh}^k} \right] \neq 0$.

The identification strategy exploits within-day timing. I assume that the day-specific cost shock η_{jd}^k is constant across editions (midday and evening), reflecting newsroom frictions that persist throughout the day. Under this assumption, changes in the chosen content mix between editions are driven by new stories coming between the midday and evening editions. These shifts move \mathbf{x}_{jdh} through the marginal cost term x_{jdh}^k/z_{dh}^k without affecting η_{jd}^k , providing cost shifters that are orthogonal to the unobserved cost component.

Text examples illustrate this mechanism (Table D.18). 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 pp) 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 pp) and positive-left increased (+28.2 pp) 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 z that enter between those two time slots. Figure C.25 shows the scatter of the regression. There is a positive association for all content categories. This indicates that entry of new content between midday and night is associated with an increase in editorial production of that content in the evening news shows.²⁶

Differencing (12) eliminates the unobserved shock:

$$\underbrace{\sum_r \left(\widehat{\frac{\partial s_{jrd+1}}{\partial x_{jd1}^k}} - \widehat{\frac{\partial s_{jrd+1}}{\partial x_{jd0}^k}} \right) L_r}_{\Delta g_{jd+1}^k} = 2\lambda_j^k \Delta \frac{x_{jd}^k}{z_d^k} + \Delta \nu_{jd}^k, \quad \forall(j, k). \quad (13)$$

Notice that (ϕ, η) cancel out in the differentiation and thus cannot be identified. Intuitively, the evening–midday change in the gradient, Δg_{jd+1}^k , is driven by the change in story availability $\Delta \frac{x_{jd}^k}{z_d^k}$, while the day-persistent cost shock cancels out. Endogenous factors such as outlet’s private interests will also be canceled out if they enter linearly in the payoff specification (see e.g. [Anderson and McLaren, 2012](#)). The system of equations in 12 can be estimated under GMM with conditions $\mathbb{E} \left[\Delta \left(\frac{x_{jd}^k}{z_d^k} \right) \Delta \nu_{jd}^k \right] = 0$.

5.3 Results of the Supply Estimation

The sign of λ_j^k 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

²⁶To 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 . Figure C.24 shows the added variable plots. 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.

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 outlets 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 .²⁷ The estimated cost slopes are heterogeneous across outlets and content types, and they partly line 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 cell. 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)
Negative Left	12.782 (44.512)	6.614 (3.107)	108.985 (60.695)	-38.135 (24.006)
Positive Right	-89.175 (85.860)	-105.658 (121.713)	-13.868 (91.624)	-238.018 (77.314)
Positive Left	36.094 (52.716)	3.368 (13.110)	25.984 (43.586)	-38.962 (84.390)
Negative Right	4.059 (4.788)	-8.694 (11.057)	30.280 (36.013)	34.624 (53.835)
Political	-0.349 (0.610)	0.317 (0.622)	1.498 (1.049)	1.455 (1.248)

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

To assess this, Figure C.26 plots the implied payoff functions using the estimated demand and supply parameters. The payoff functions are single-peaked or monotone, indicating that the observed choices correspond to maxima or corner solutions. The right-leaning outlet enjoys higher payoffs for producing positive-right content and negative-left content,

²⁷Processing 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.

whereas the left-leaning outlets obtain higher payoffs for negative-right content. The only inconsistency arises in the positive-left category, where the right-leaning outlet's payoff is strictly increasing; this pattern reflects the cost parameters for this category reported in Table 3.

6 Proportional Air Time Rule

Across Europe, the most common rule for election coverage is proportional airtime. France's ARCOM times every political segment and enforces near balance during the official campaign for both public and private broadcasters. Similarly, Germany or Italy's *Par Condicio* tie lengths to past vote shares. Spain, by contrast, remains unregulated.

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

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

where, in a logic consistent with my measurement strategy, time to a political party can only be discerned if that story has some specific slant. I assume that the policy is enforced; that is, all outlets must devote the proportion of political time given by vote shares from the previous election ($\text{vote}^R, \text{vote}^L$) (i.e, constraints bind). This simplifies the choice set to $(x_{jd}^{L+}, x_{jd}^{R+}, x_{jd}^{political})$. 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.²⁸

Rearranging from the first-order condition in (12), define the residual

²⁸ In the original normal form game, the joint action space consists of $20^4 = 160,000$ pure strategy profiles under the simplest grid of 3 points per action. The counterfactual constraints simplify the action space to 4,096 strategy profiles. The code was run under a Google Cloud “n2d-standard-224” virtual machine (224 vCPUs, 896 GB RAM).

$$r_{jdh}^k \equiv \phi_1 + \eta_{jd}^k + \nu_{jdh}^k = g_{jd+1h} - 2\lambda_j^k \frac{x_{jdh}^k}{z_{dh}^k},$$

The parameters ϕ and η cannot be separately identified. Because $\mathbb{E}(\nu_{jdh}^k) = 0$, and unbiased estimate of the unobserved marginal cost shifter $\eta + \phi$ is obtained by averaging across the midday and evening editions of r_{jdh} ,

$$\widehat{\phi + \eta_{jd}^k} = \frac{1}{2}(\hat{r}_{jd0}^k + \hat{r}_{jd1}^k).$$

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.

6.1 Effects of the Regulation

Results of the counterfactual estimation are shown in Table 4. The left columns report the factual, average minutes for each category during the campaign and the right column reports the results from the counterfactual estimation.

Table 4: Factual 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 category. Baseline values refer to observed campaign broadcasts; counterfactual values are predicted from solving from solving the counterfactual optimization problem in Equation 14. Channels are grouped as: left-leaning (La Sexta, TVE), middle (T5), and right-leaning (A3).

Several facts emerge from the counterfactual exercise. First, left-leaning outlets (La Sexta/TVE) reduce the overall share of political coverage from 42% to 30% when constrained to allocate airtime proportionally. Since they are forced to spend more time on right-wing

coverage, they cut back on politics altogether and shift toward a more negative tone of the right (from 0.09 to 0.15). At the same time, their positive coverage of the left remains broadly unchanged, implying that compliance is achieved primarily by eliminating right-positive content and compensating with hostile tone.

Second, the centrist outlet (T5) responds by dramatically expanding its political content, from 18% of airtime in the factual data to 90% in the counterfactual. The strong responses on politics can be explained by the combination of supply and demand parameters. With low marginal costs of producing politics (Table 3), optimal political share $x^{political}$ will mainly be driven by demand tastes. From the demand estimation results (Table 2), right-(left-)wing viewers demand positive (negative) amount of political content. The combination of cheap politics on the cost side and strong campaign-period demand asymmetries on the viewer side thus delivers the large increases (decreases) in political airtime for right- and left-wing outlets in the counterfactual.

This increase in political content comes almost entirely in the form of negative tone: coverage harming the right grows more than tenfold (from 0.04 to 0.44), and coverage harming the left rises sharply as well (from 0.04 to 0.36). In other words, proportional airtime regulation induces T5 to turn heavily partisan, despite its relatively neutral baseline position.

Third, the right-leaning outlet (A3) also amplifies its use of negative tone. Its political coverage rises from 39% to 90%, with negative coverage of both left and right parties soaring (0.09 to 0.45 and 0.07 to 0.43, respectively). Positive coverage, by contrast, collapses to near zero.

Taken together, these adjustments generate a markedly more polarized landscape. Figure C.28 illustrates the resulting shifts in outlets' ideological positions: left-leaning and centrist outlets move further left, while A3 strengthens its rightward tilt. Importantly, the regulation compresses the space for balanced coverage by forcing all outlets to increase political airtime but leaving tone unconstrained. Dispersion across channels increased from 0.06 to 0.20, with a notable rise in the standard deviation from 0.03 to 0.1, leading to a much more polarized media environment.

Evaluating demand at the counterfactual equilibrium shows that viewers become much more sensitive to net partisan tone, especially in ideologically aligned markets. Because outlets comply with proportional airtime mainly by raising negative coverage, marginal audience gains concentrate in those tone categories while positive tone loses traction. In right-leaning regions, a 1 pp increase in net right tone attracts on the order of 60,000 additional viewers (versus only a few thousand in the factual data); in left-leaning regions, the response to net left tone is several times larger than factually, around 80,000 viewers. By contrast, extra positive minutes yield little upside for the in-party and are punished

more when they flatter the out-party.²⁹ Fixing airtime while leaving tone unconstrained therefore makes small shifts in tone move audiences at scale, strengthening incentives to go negative and amplifying affective polarization on the demand side.

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, 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. Third, 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 either assumption could dampen or reshape the effects.

7 Conclusion

This paper studies how election campaigns reshape demand for political news using a structural model of television news supply and demand. I construct a story-level slant index for prime-time broadcasts by combining machine learning with large language models (LLMs), and match it to high-frequency audience data. This allows me to track the slant content offered in the news in parallel to the amount of people consuming it.

I apply the framework to Spain’s 2023 general election. On the demand side, I estimate a BLP-style random-coefficients model identified by exogenous variation in set of stories available to produce slant. The results show that political news consumption polarizes sharply during the campaign and the information pattern is consistent with affective polarization: viewers dislike negative news about their own party but they particularly screen out any content that benefits the opposing party. Furthermore, I show that polarization in demand for political content links tightly to ideological polarization, where election campaigns triggered a surge in the latter that lasts for over a year.

Building on the demand and supply estimates, I evaluate the most common media regulation to foster pluralism during campaigns: proportional-airtime rules. The counterfactual results show that, while channels offer a balanced coverage of the political parties, this obscures increases in the polarization of the slant they offer. The reason for this stems from the design of the policy: since only total exposure in minutes aired is enforced, outlets comply by adjusting the tone, widening cross-outlet dispersion in supplied slant and strengthening

²⁹Table D.8 shows the estimated elasticities for both the Factual and Counterfactual estimations.

audience responses to partisan content.

This paper highlights two main points. First, surges in ideological polarization during periods of intense political conflict are closely mirrored by the way voters consume information. Second, widely used metrics for monitoring media bias—such as airtime balance—often overlook crucial differences in political tone, leading to interventions and regulations with unintended consequences. When policy is designed using incomplete or misaligned measures, regulation can inadvertently amplify polarization along dimensions it fails to capture, such as editorial slant. The methodological framework developed here provides a more robust basis for media monitoring and a path for evaluating regulatory measures that effectively reduce polarization in information acquisition.

Several avenues for future research emerge from the present work. Leveraging the unique feature of the dataset—which allows to compare the tone and coverage of the same story across outlets on a give date—future work could micro-found editorial decisions from the underlying news landscape to distinguish between different forms of bias, such as selection, and framing, as theorized in previous works (e.g. [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, this benchmark can be applied comparably in democracies and autocracies to estimate media bias.

References

- Allcott, H., Gentzkow, M., Mason, W., Wilkins, A. S., Barberá, P., Brown, T., Cisneros, J. C., Crespo-Tenorio, A., Dimmery, D., Freelon, D., González-Bailón, S., Guess, A. M., Kim, Y. M., Lazer, D., Malhotra, N., Moehler, D., Nair-Desai, S., Nait El Barj, H., Nyhan, B., de Queiroz, A. C. P., Pan, J., Settle, J., Thorson, E. A., Tromble, R., Velasco Rivera, C., Wittenbrink, B., Wojcieszak, M., Zahedian, S., Franco, A., Kiewiet de Jonge, C., Stroud, N. J., and Tucker, J. A. (2024). The Effects of Facebook and Instagram on the 2020 Election: A Deactivation Experiment. *Proceedings of the National Academy of Sciences of the United States of America*, 121.
- Anderson, S. P. and McLaren, J. (2012). Media Mergers And Media Bias With Rational Consumers. *Journal of the European Economic Association*, 10(4):831–859.
- Arceneaux, K. and Johnson, M. (2013). *Changing Minds or Changing Channels? Partisan News in an Age of Choice*. Chicago Studies in American Politics. University of Chicago Press, Chicago, IL.
- Assemblée nationale (2024). Compte Rendu N 6 — Table Ronde (Ouverte à la Presse) Réunissant Julia Cagé et Claire Sécaïl. Compte rendu 6, Commission d’Enquête sur l’Attribution, le Contenu et le Contrôle des Autorisations de Services de Télévision à Caractère National sur la Télévision Numérique Terrestre, Paris. Séance du 18 janvier 2024; Session ordinaire 2023–2024.
- Atil, B., Chittams, A., Fu, L., Ture, F., Xu, L., and Baldwin, B. (2024). LLM Stability: A Detailed Analysis with Some Surprises. *CoRR*, abs/2408.04667.
- Bail, C. A., Argyle, L. P., Brown, T. W., Bumpus, J. P., Chen, H., Hunzaker, M. B. F., Lee, J., Mann, M., Merhout, F., and Volfovsky, A. (2018). Exposure to Opposing Views on Social Media Can Increase Political Polarization. *Proceedings of the National Academy of Sciences*, 115(37):9216—9221.
- Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. *The RAND Journal of Economics*, 25(2):242—262.
- Berry, S. T. and Haile, P. A. (2014). Identification in Differentiated Products Markets Using Market Level Data. *Econometrica*, 82(5):1749—1797.
- Berry, S. T., Levinsohn, J. A., and Pakes, A. (1995). Automobile Prices in Market Equilibrium. *Econometrica*, 63:841–890.
- Besley, T. (2005). Political Selection. *Journal of Economic Perspectives*, 19(3):43–60.

- Boehnke, J., Pontikes, E., and Bhargava, H. (2024). Decoding Unstructured Text: Enhancing LLM Classification Accuracy with Redundancy and Confidence. *Conference on AI Applications in NLP*.
- Boxell, L., Gentzkow, M., and Shapiro, J. M. (2020). Cross-Country Trends in Affective Polarization. *Review of Economics and Statistics*, 106:557—565.
- Cagé, J., Hengel, M., Hervé, N., and Urvoy, C. (2022). Hosting Media Bias: Evidence from the Universe of French Broadcasts, 2002–2020. SSRN Electronic Journal. Working paper; later issued as CEPR Discussion Paper No. 18905 (2024).
- Chiang, C.-F. and Knight, B. (2011). Media Bias and Influence: Evidence from Newspaper Endorsements. *The Review of Economic Studies*, 78(3):795—820. Accessed 19 June 2025.
- Compiani, G., Morozov, I., and Seiler, S. (2025). Demand Estimation with Text and Image Data.
- Conlon, C. and Gortmaker, J. (2020). Best Practices for Differentiated Products Demand Estimation with PyBLP. *The RAND Journal of Economics*, 51(4):1108—1161.
- Crawford, G. S., Lee, R. S., Whinston, M. D., and Yurukoglu, A. (2018). The Welfare Effects of Vertical Integration in Multichannel Television Markets. *Econometrica*, 86(3):891—954.
- Crawford, G. S. and Yurukoglu, A. (2012). The Welfare Effects of Bundling in Multichannel Television Markets. *American Economic Review*, 102(2):643—685.
- Dejean, S., Lumeau, M., and Peltier, S. (2022). Partisan Selective Exposure in News Consumption. *Information Economics and Policy*.
- Djourelova, M. (2023). Persuasion Through Slanted Language: Evidence from the Media Coverage of Immigration. *American Economic Review*, 113(3):800—835.
- Durante, R. and Knight, B. (2012). Partisan Control, Media Bias, and Viewer Responses: Evidence from Berlusconi’s Italy. *Journal of the European Economic Association*, 10(3):451—481.
- Durante, R., Pinotti, P., and Tesei, A. (2019). The Political Legacy of Entertainment TV. *American Economic Review*, 109(7):2497—2530.
- Edelman (2023). Edelman Trust Barometer 2023: Global Report.
- Esteban, J. and Ray, D. (1994). On the Measurement of Polarization. *Econometrica*, 62(4):819—851.

- European Commission (2022). Media Use in the European Union: Standard Eurobarometer 96, Winter 2021–2022. Fieldwork: 18 Jan – 14 Feb 2022.
- Fan, Y. (2013). Ownership Consolidation and Product Characteristics: A Study of the U.S. Daily Newspaper Market. *American Economic Review*, 103(5):1598—1628.
- Gandhi, A. and Houde, J.-F. (2019). Measuring Substitution Patterns in Differentiated Products Industries. Technical Report 26375, National Bureau of Economic Research.
- Geitgey, A. (2017). face_recognition: Simple Facial Recognition API for Python. https://github.com/ageitgey/face_recognition.
- Gentzkow, M. and Shapiro, J. M. (2010). What Drives Media Slant? Evidence from U.S. Daily Newspapers. *Econometrica*, 78(1):35—71.
- Gentzkow, M. and Shapiro, J. M. (2011). Ideological Segregation Online and Offline. *The Quarterly Journal of Economics*, 126(4):1799—1839.
- Gentzkow, M., Shapiro, J. M., and Stone, D. F. (2014). Media Bias in the Marketplace: Theory. NBER Working Paper 19880, National Bureau of Economic Research.
- Gilardi, F., Alizadeh, M., and Kubli, M. (2023). ChatGPT Outperforms Crowd Workers for Text-Annotation Tasks. *Proceedings of the National Academy of Sciences of the United States of America*, 120.
- Goettler, R. L. and Shachar, R. (2001). Spatial Competition in the Network Television Industry. *Antitrust: Antitrust Law & Policy*.
- Graham, M. H. and Svolik, M. W. (2019). Democracy in America? Partisanship, Polarization, and the Robustness of Support for Democracy in the United States. *American Political Science Review*, 114:392–409.
- Groseclose, T. and Milyo, J. (2005). A Measure of Media Bias. *The Quarterly Journal of Economics*, 120(4):1191—1237.
- Hernández, E., Anduiza, E., and Rico, G. (2020). Affective Polarization and the Salience of Elections. *Electoral Studies*.
- Iyengar, S., Lelkes, Y., Levendusky, M., Malhotra, N., and Westwood, S. J. (2019). The Origins and Consequences of Affective Polarization in the United States. *Annual Review of Political Science*, 22:129—146.
- Laver, M., Benoit, K., and Garry, J. (2003). Extracting Policy Positions from Political Texts Using Words as Data. *American Political Science Review*, 97(2):311—331.

- Le Mens, G. and Gallego, A. (2023). Positioning Political Texts with Large Language Models by Asking and Averaging. *arXiv e-prints*, page arXiv:2311.16639.
- Lenz, G. S., Sekhon, J., Snowberg, E., Snyder, J. M. J., Song, B. K., and Todorov, A. (2011). Looking the Part: Television Leads Less Informed Citizens to Vote Based on Candidates' Appearance. *American Journal of Political Science*, 55:574—589.
- Levendusky, M. S. (2013). Why do Partisan Media Polarize Viewers? *American Journal of Political Science*, 57(3):611—623.
- Longuet-Marx, N. (2025). Party Lines or Voter Preferences? Explaining Political Realignment. Presented at the Spring 2025 IOG-BFI Conference, March 28–30, 2025.
- Martin, G. J. and McCrain, J. (2019). Local News and National Politics. *American Political Science Review*, 113(2):372—384.
- Martin, G. J. and Yurukoglu, A. (2017). Bias in Cable News: Persuasion and Polarization. *American Economic Review*, 107(9):2565—2599.
- Nevo, A. (2001). Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica*, 69(2):307–342.
- Newman, N., Fletcher, R., Schulz, A., Andi, S., Robertson, C. T., and Nielsen, R. K. (2023). Digital News Report 2023. Accessed: 2025-05-13.
- Parliament, E. (2024). Audiovisual and Media Policy.
- Peterson, E., Goel, S., and Iyengar, S. (2017). Echo Chambers and Partisan Polarization: Evidence from the 2016 Presidential Campaign. In *Proceedings of the Annual Meeting of the American Political Science Association*.
- Prat, A. and Strömberg, D. (2005). Commercial Television and Voter Information. *Public Choice & Political Economy eJournal*.
- Prior, M. (2009). Improving Media Effects Research Through Better Measurement of News Exposure. *The Journal of Politics*, 71(3):893—908.
- Puglisi, R. and Snyder, J. M. (2011). Newspapers and Party Polarization. *Journal of Public Economics*, 95(7–8):547—555.
- Puglisi, R. and Snyder, J. M. (2015). Empirical Studies of Media Bias. In Anderson, S. P., Waldfogel, J., and Strömberg, D., editors, *Handbook of Media Economics*, volume 1 of *Handbook of Media Economics*, pages 647—667. North-Holland.
- Reiljan, A. (2019). Fear and Loathing Across Party Lines (Also) in Europe: Affective Polarisation in European Party Systems. *European Journal of Political Research*.

- Richter, P. O. (2025). *Structural and Theoretical Approaches to Modeling Information Choices and Media Markets*. PhD thesis, Universitat Pompeu Fabra, Barcelona, Spain. Doctoral dissertation, Doctorat en Economia, Finances i Empresa.
- Schneider-Strawczynski, S. and Valette, J. (2025). Media Coverage of Immigration and the Polarization of Attitudes. *American Economic Journal: Applied Economics*, 17(1):337—368.
- Simonov, A. and Rao, J. (2022). Demand for Online News Under Government Control: Evidence from Russia. *Journal of Political Economy*, 130(2):259—309.
- Törnberg, P. (2023). ChatGPT-4 Outperforms Experts and Crowd Workers in Annotating Political Twitter Messages with Zero-Shot Learning. *arXiv*, abs/2304.06588.
- Wilbur, K. C. (2008). A Two-Sided, Empirical Model of Television Advertising and Viewing Markets. *Marketing Science*, 27(3):356—378.

Appendix

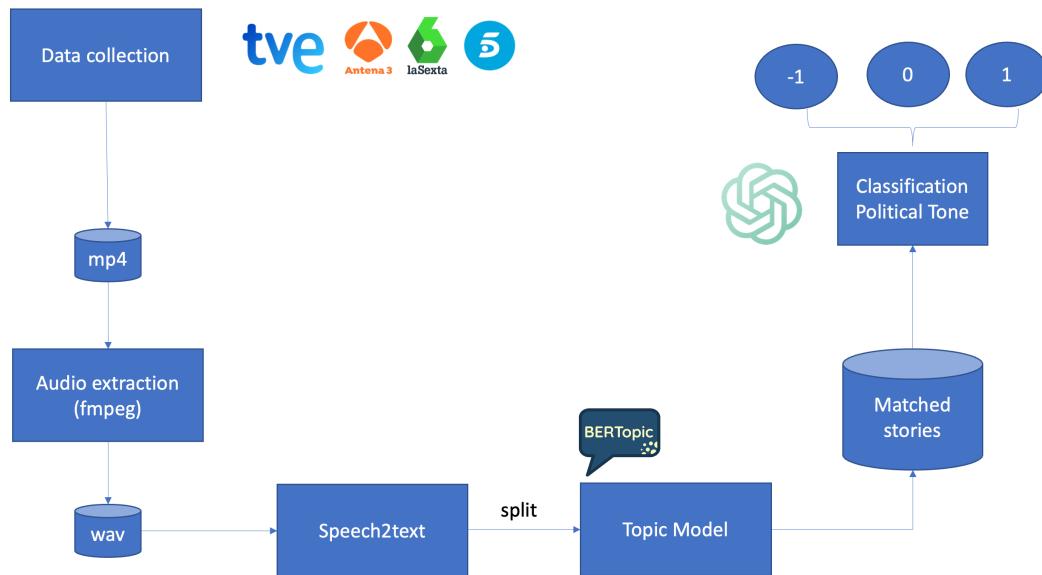
Table of Contents

A Data Pipeline Details	44
B Robustness of the Text Classification	46
B.1 Comparison with Previous Approaches	46
B.2 Stability of the Classifier	48
B.3 Text vs. Image	48
C Figures	52
D Tables	63
D.1 Descriptive Evidence	63
D.2 Additional Results	65
D.3 Text Examples	69
E Isolation Index	80
E.1 Definition	80
E.2 Results	80

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) ³⁰

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

³⁰This 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.13); 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.15 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 my 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 my sample period and associate each speaker with their respective political party, filtering to retain the set of relevant parties.

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

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

where:

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

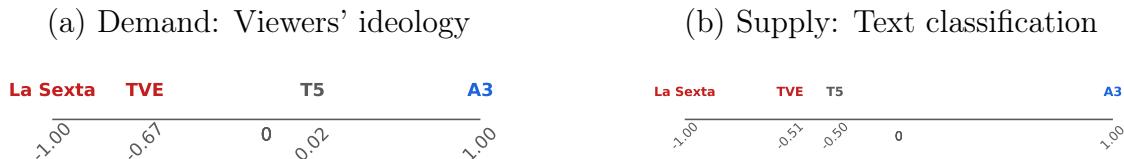


Note: The wordclouds represent the top words with lowest (left) and highest (right) scores as defined in Eq. 15. Size is weighted by word TF-IDF value.

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.

Figure B.13: Normalized Ideology Index by Channel



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 ChatGPT-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.

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 \(2011\)](#). 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.

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 ³¹, 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

³¹Good 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 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.

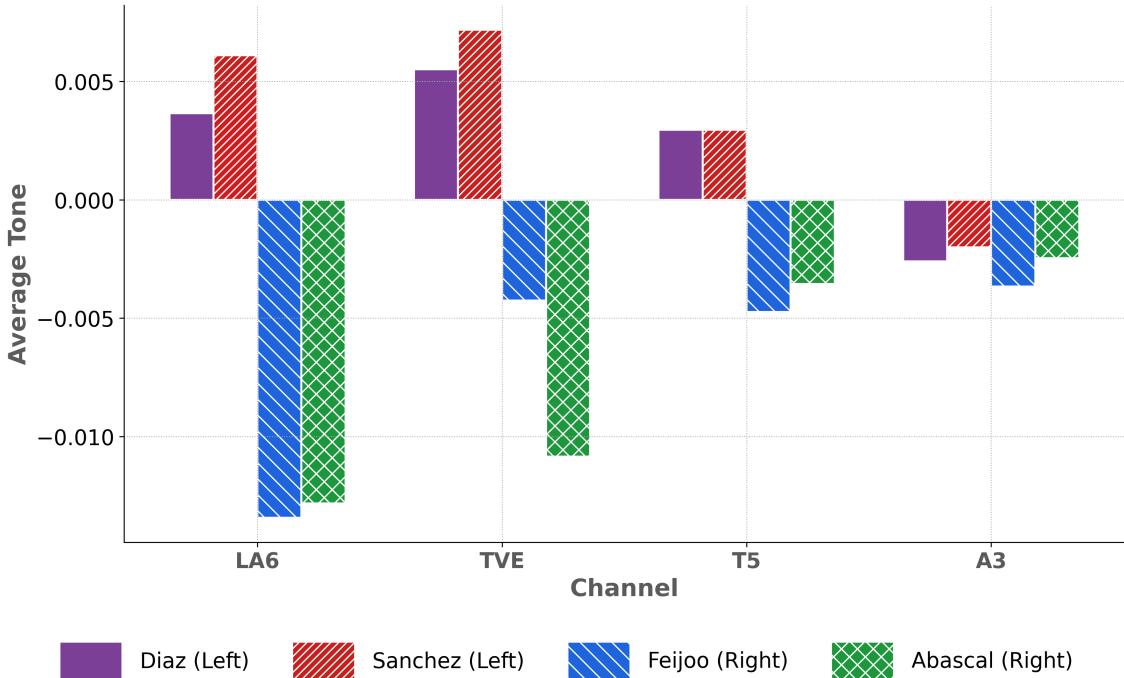
The net tone on the sample of days for each channel and political leader is shown in Figure [B.14](#). As expected, significant differences appear, positioning channels in the left-right spectrum shown before.

Next, I compare if visuals or tone follow a similar scenario. Figure [B.15](#) 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.

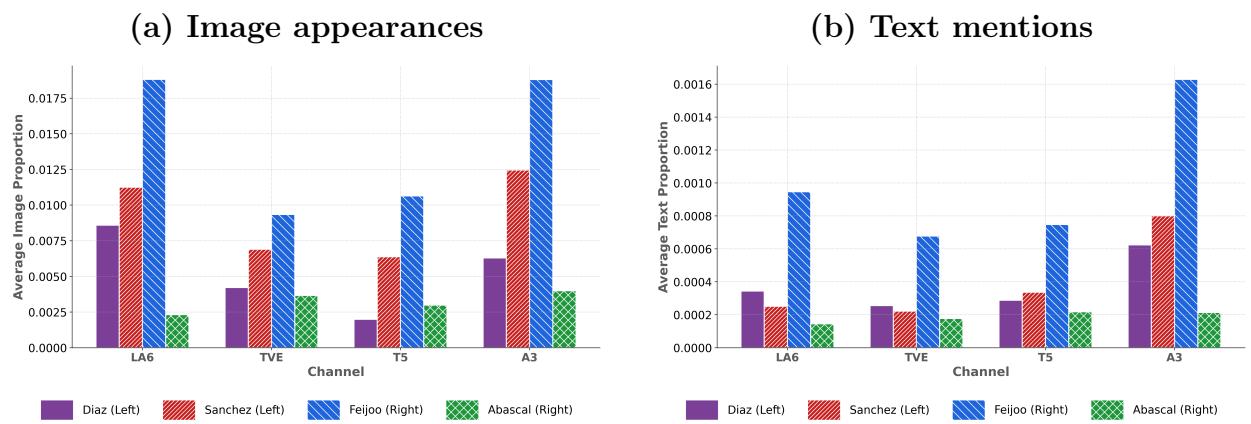
Column (4) reports the specification with both channel and day of the week fixed effects, so the coefficients reflect pure within-channel-day fluctuations in coverage. The pattern is heterogeneous across politicians. For Abascal (VOX), a one-standard-deviation increase in word mentions predicts a decrease 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 neither appears to be a strong predictor.

Figure B.14: 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.

Figure B.15: 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.

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

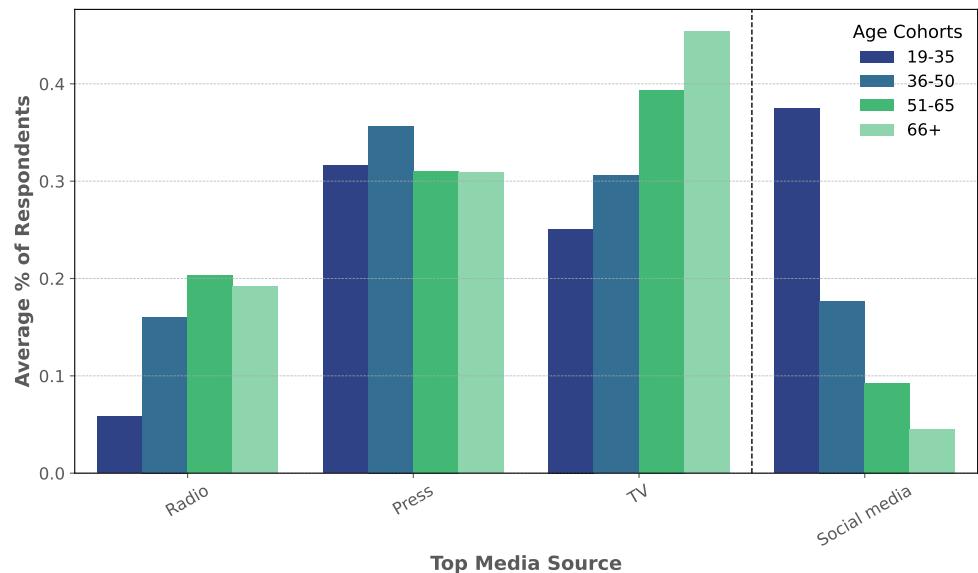
	<i>Outlet Slant (x)</i>			
	(1)	(2)	(3)	(4)
Feijóo (PP)				
Text Mentions	-1.956 (2.063)	-3.038 (2.134)	0.364 (2.391)	-1.342 (2.584)
Image Appearances	-0.065 (0.147)	0.003 (0.151)	-0.275 (0.179)	-0.189 (0.189)
Abascal (VOX)				
Text Mentions	-42.813 (7.855)	-44.024 (7.832)	-46.659 (9.609)	-49.989 (9.471)
Image Appearances	0.963 (0.470)	0.933 (0.470)	0.565 (0.600)	0.437 (0.595)
Sánchez (PSOE)				
Text Mentions	4.131 (6.020)	11.634 (6.992)	2.648 (6.494)	13.515 (7.909)
Image Appearances	0.023 (0.239)	-0.045 (0.244)	0.033 (0.356)	0.032 (0.377)
Díaz (UP)				
Text Mentions	-0.576 (3.158)	1.276 (3.280)	-0.714 (4.080)	3.365 (4.405)
Image Appearances	0.473 (0.197)	0.485 (0.206)	0.290 (0.232)	0.321 (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.

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.

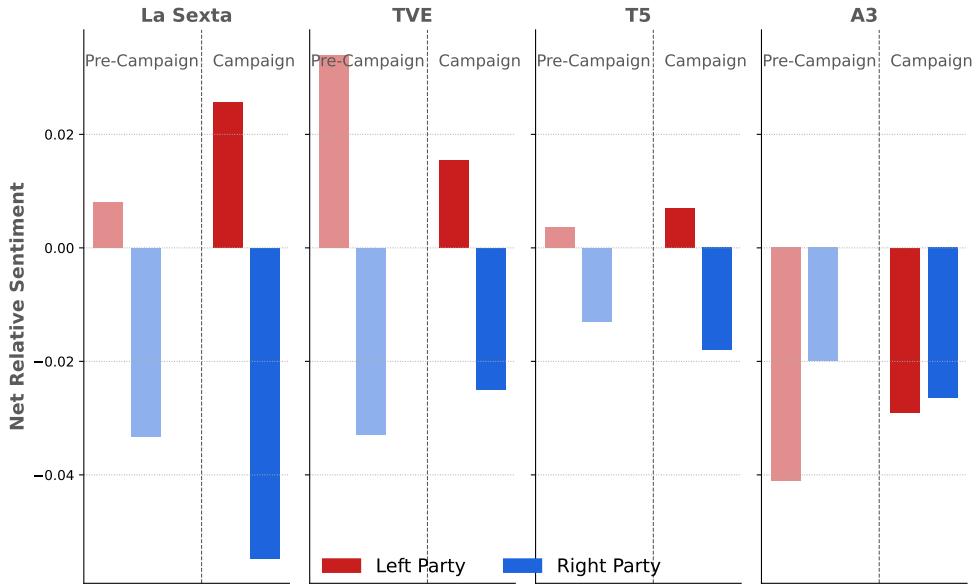
C Figures

Figure C.16: Top Media Source to Acquire Political Information in Spain



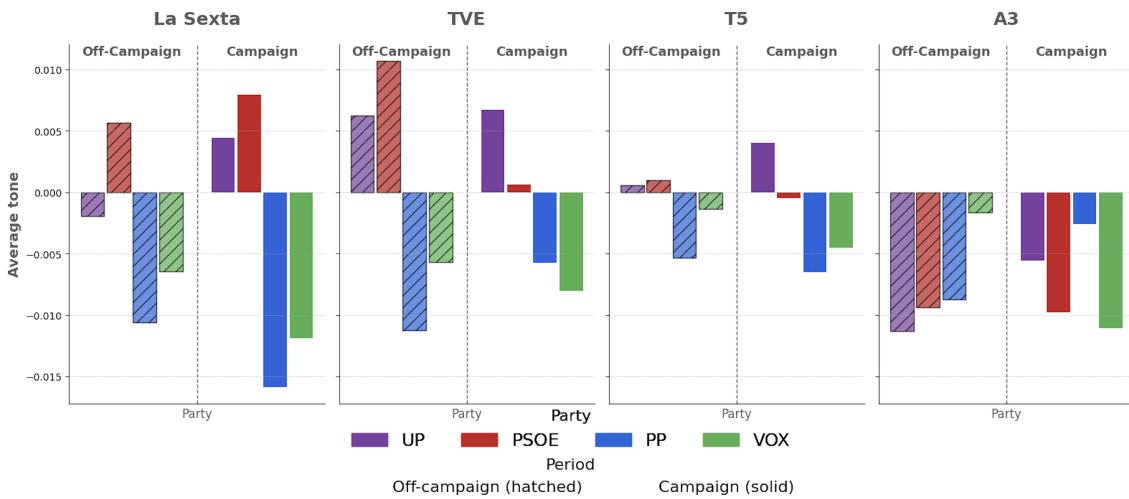
Note: Histogram on the preferred media used for political information by age cohorts in Spain.
Source: Barómetro CIS, 2023.

Figure C.17: Tone across Channels and Parties off and during Campaign



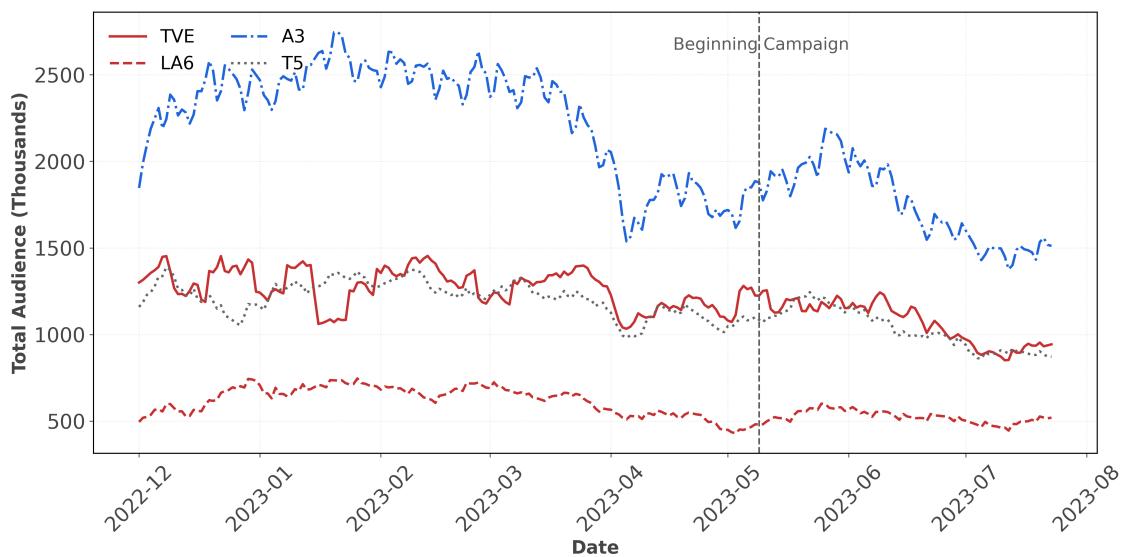
Note: The figure shows the relative tone calculated as the average sentiment over right and left parties. The vertical dashed line delimits results off and during campaign periods, respectively.

Figure C.18: Decomposition of Tone across Channels and Parties pre and during Campaign



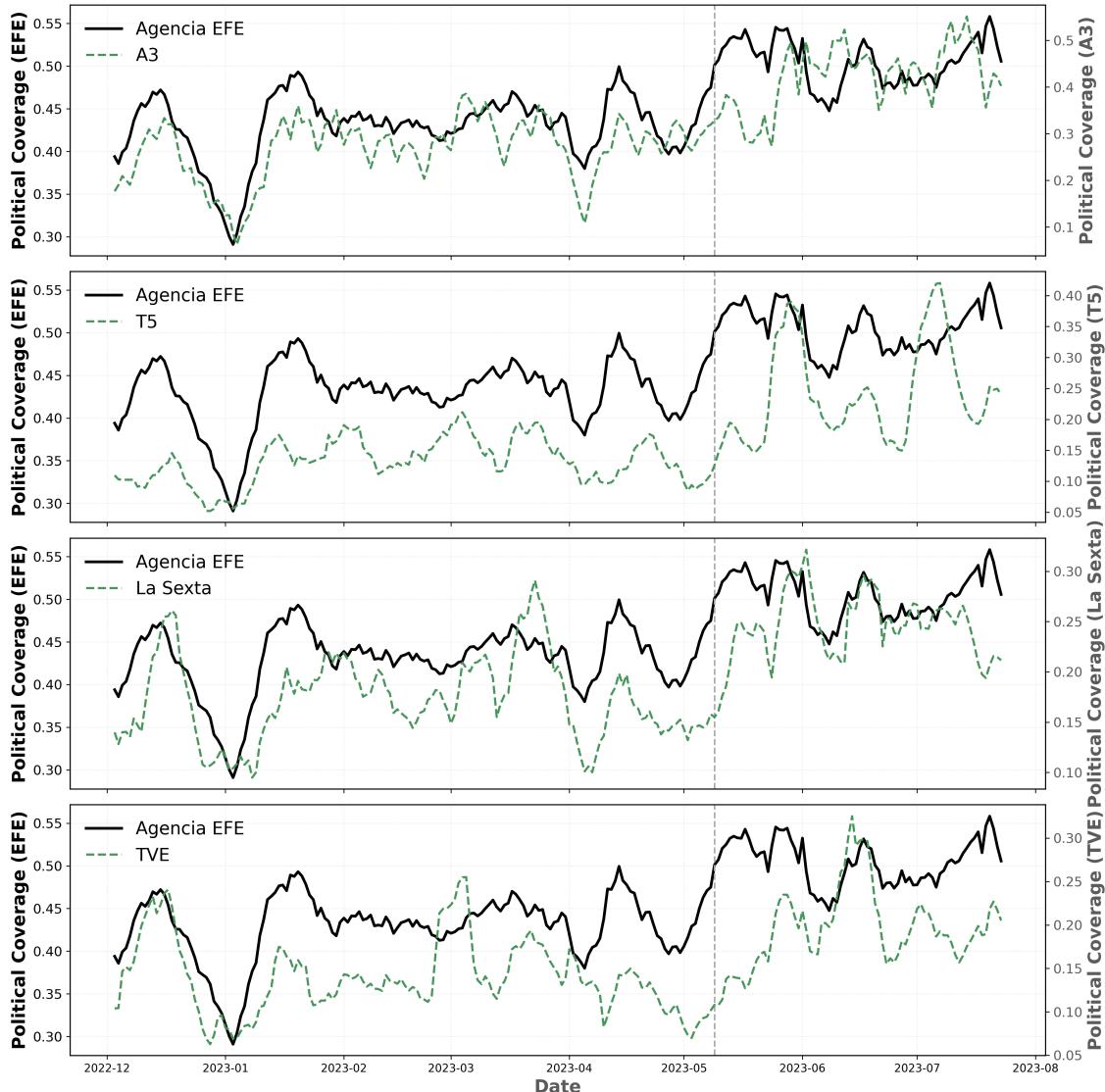
Note: The figure shows the relative tone calculated as the average sentiment over each political party. The vertical dashed line delimits results off and during campaign periods, respectively.

Figure C.19: TV Audience over Time



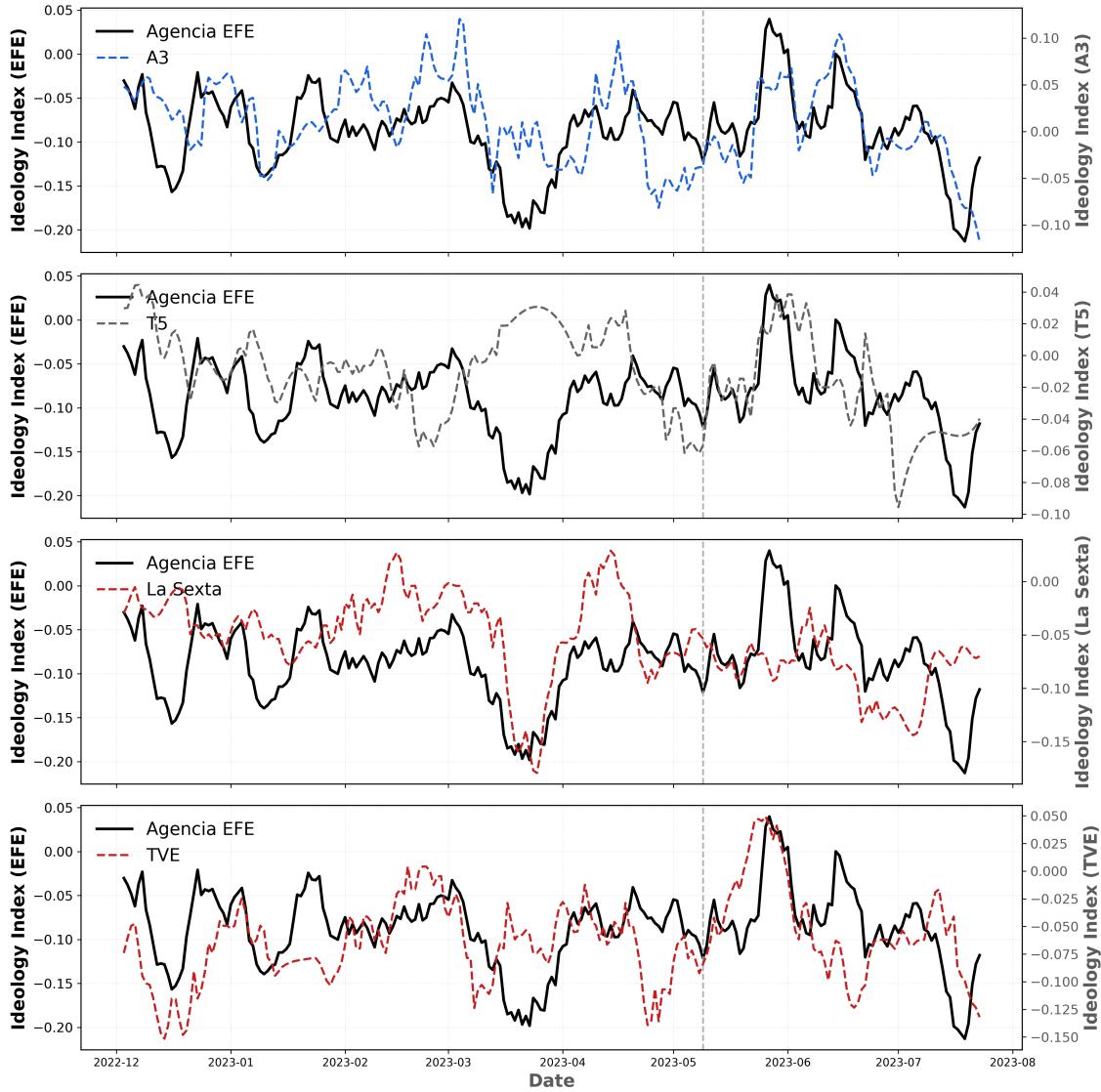
Note: The figure represents the total audience in thousands of viewers for TV outlets. All series are smoothed using a centered rolling mean with a 9-day window.

Figure C.20: Evolution of the Political Coverage by Outlet



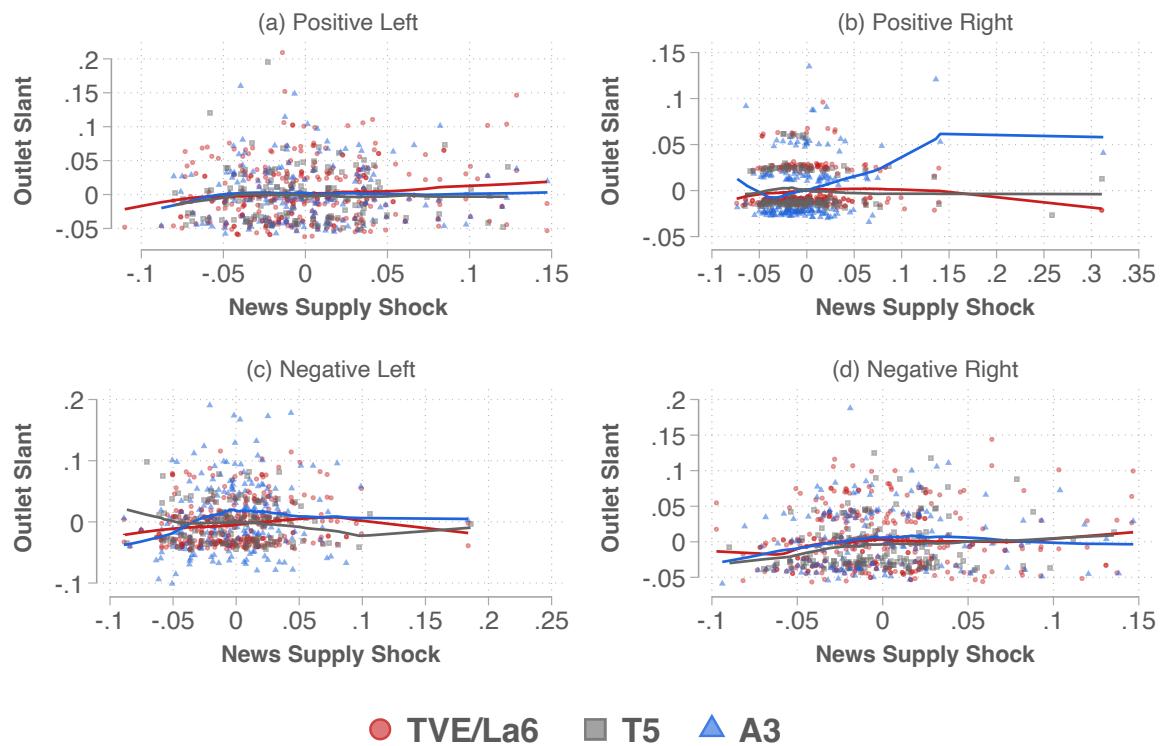
Note: The figure represents the smoothed time series of the political coverage for TV channels (right y-axis) and the analogous formula for EFE (solid) on the left axis. The right axis represents the proportion of political minutes of the outlets. The right axis represents the proportion of political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

Figure C.21: Evolution of the Ideological Index by Outlet



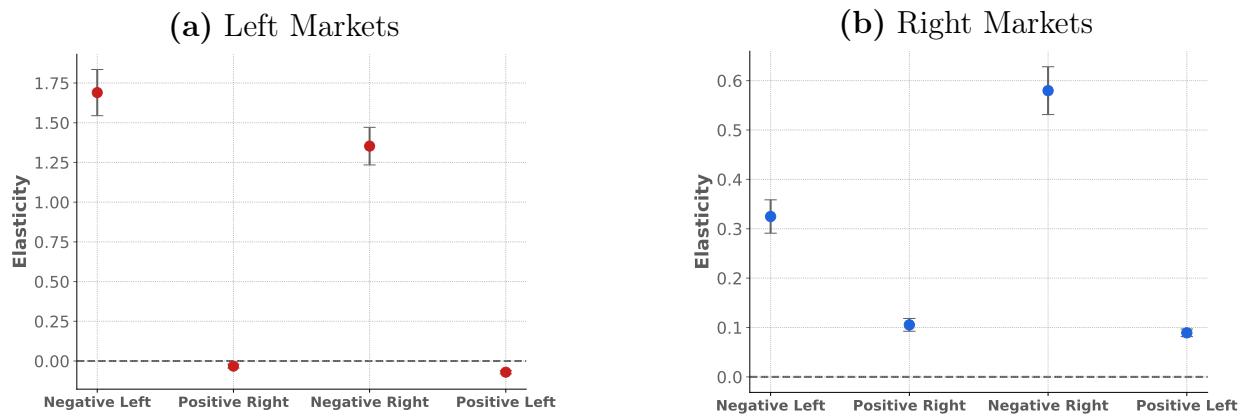
Note: The figure represents the smoothed time series of the ideology index in Equation 3 for TV channels (right y-axis) and the analogous formula for EFE (solid) on the left axis. The left axis represents the ideological score of the outlets . All series are smoothed using a centered rolling mean with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

Figure C.22: Added Variable Plots for Production of Political Content (non-parametric fit)



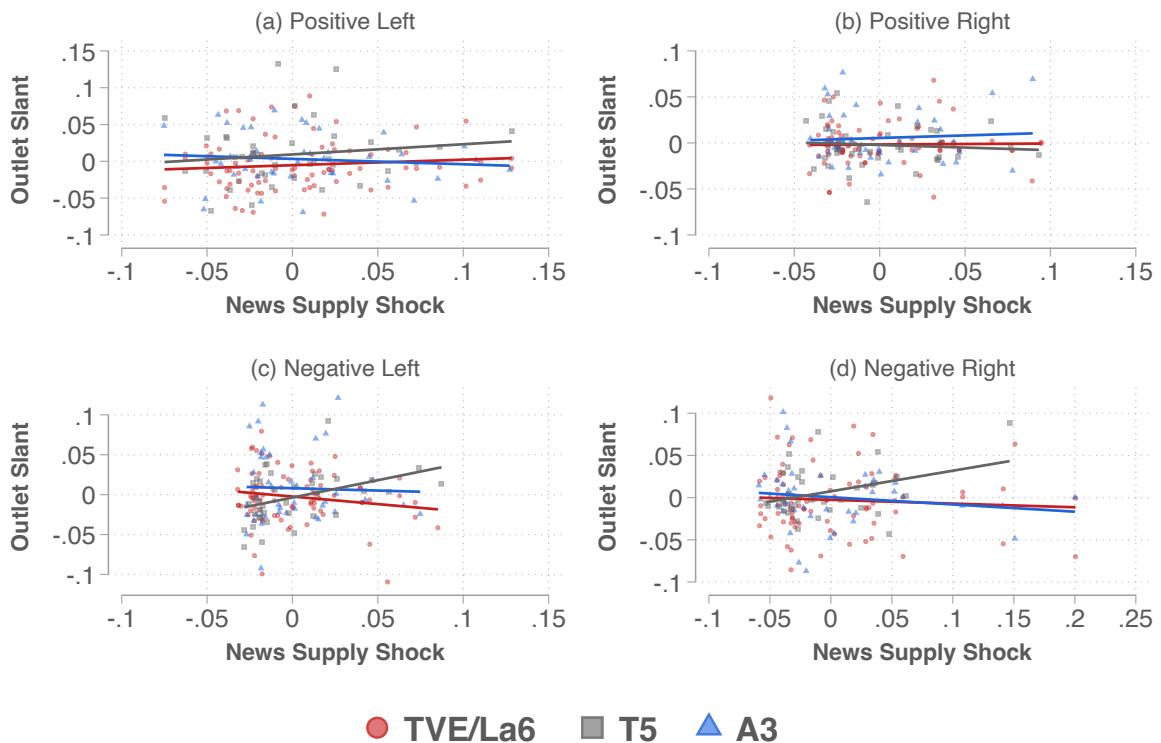
Note: The figure shows the added variable plots from the estimation of equation 7. The x axis represents $(z_d^{party,+}, z_d^{party,-})$ and the y axis the corresponding $(x_{jd}^{party,+}, x_{jd}^{party,-})$. Channels are pooled into left (TVE and La Sexta), middle (T5) and right (A3) for visualization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

Figure C.23: Estimated Elasticities for Left and Right markets off-Campaign



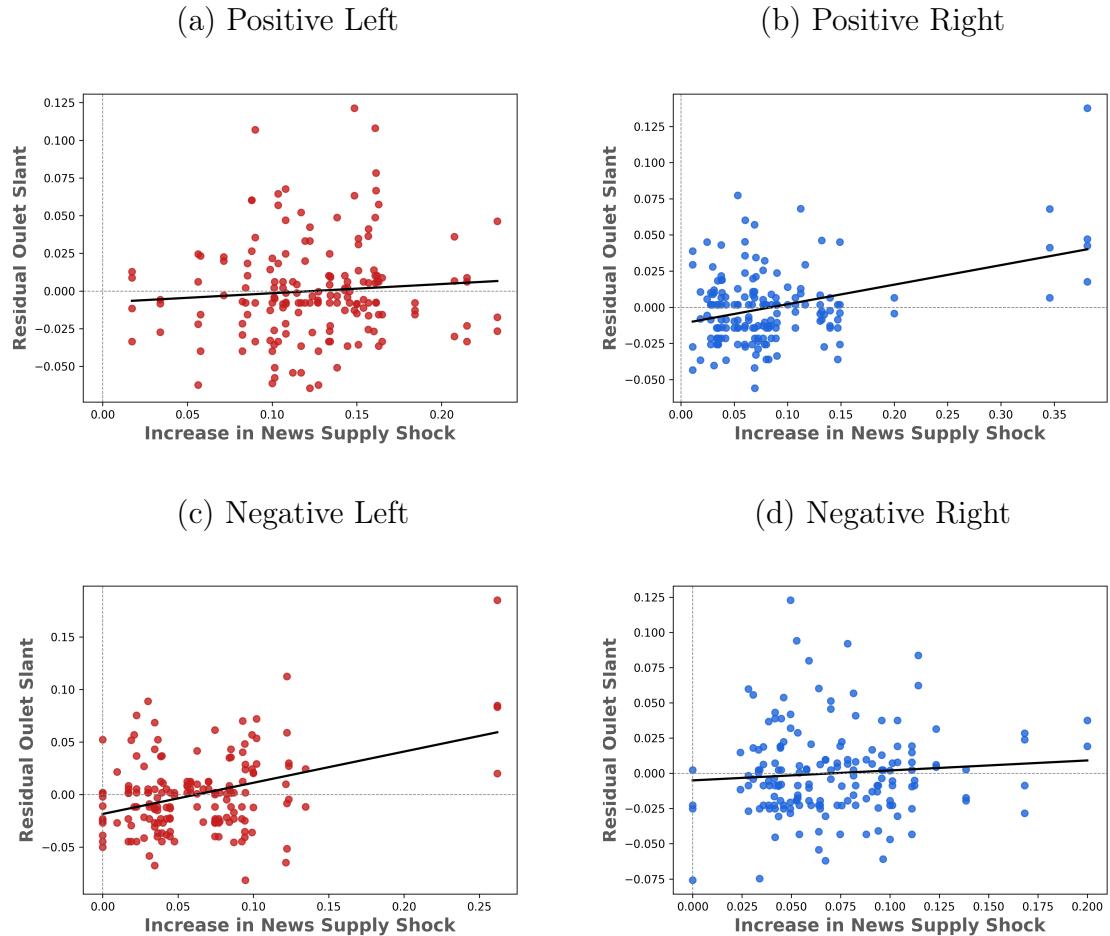
Note: Each panel shows estimated mean own elasticities for consumer responses as described in equation 8 for the off-campaign period. Panel (a) reports results for the left-leaning markets, while Panel (b) shows the results for the right-leaning markets. Right markets are defined as regions with proportion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

Figure C.24: Added Variable Plots for Production of Political Content (within day)



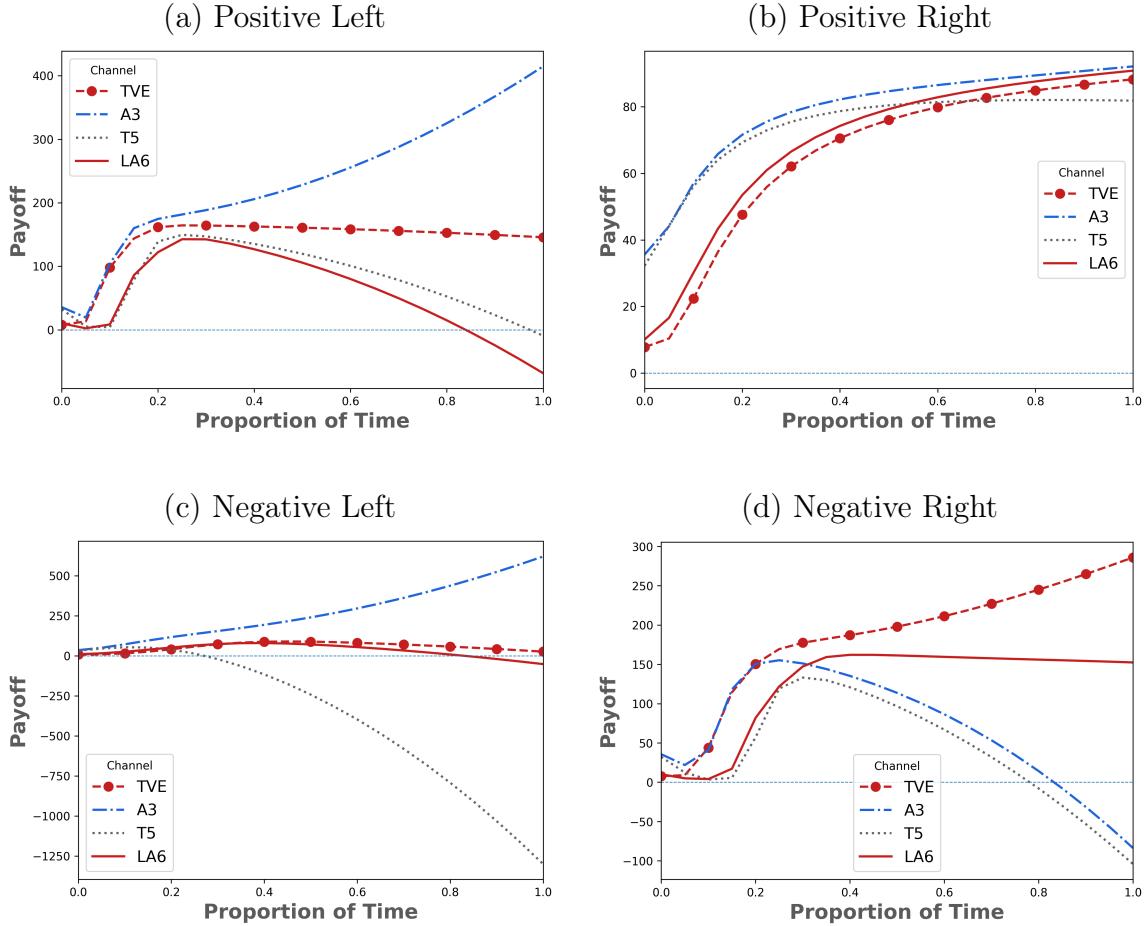
Note: The figure shows the added variable plots from the analogous estimation of equation 7 using within day differences. The x axis represents $(\Delta z_d^{party,+}, \Delta z_d^{party,-})$ and the y axis the corresponding $(\Delta x_{jd}^{party,+}, \Delta x_{jd}^{party,-})$. Channels are pooled into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

Figure C.25: Within-day Relationship Between Editorial Content Share and News Supply Shock



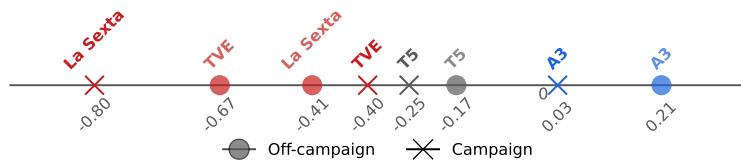
Note: Scatterplots of the within-day relationship between channels' editorial content share (x) and the corresponding news supply shock (z) from Agencia EFE. Each panel corresponds to one type of coverage: (a) positive-left, (b) positive-right, (c) negative-left, and (d) negative-right. The y -axis plots 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.26: Outlet's Payoffs for each Tone Category



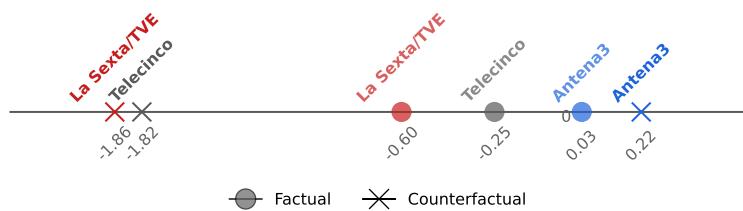
Note: Figures shows the average payoffs of the supply game after estimation. Average are taken over days. Each panel corresponds to one type of coverage: (a) positive-left, (b) positive-right, (c) negative-left, and (d) negative-right.

Figure C.27: 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.28: Change in Positions Factual vs Counterfactual



Note: The figure shows the relative change in slant positions according to the ideological index in Equation 3 from the factual to the counterfactual 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
A3	Negative Left	0.106	0.090
	Negative Right	0.043	0.066
	Positive Left	0.065	0.061
	Positive Right	0.023	0.039
	Political	0.277	0.387
La Sexta	Negative Left	0.041	0.032
	Negative Right	0.047	0.067
	Positive Left	0.049	0.057
	Positive Right	0.013	0.012
	Political	0.207	0.277
TVE	Negative Left	0.038	0.037
	Negative Right	0.045	0.046
	Positive Left	0.072	0.052
	Positive Right	0.012	0.021
	Political	0.175	0.212
T5	Negative Left	0.043	0.039
	Negative Right	0.025	0.044
	Positive Left	0.047	0.046
	Positive Right	0.012	0.026
	Political	0.111	0.183
EFE	Negative Left	0.076	0.073
	Negative Right	0.058	0.094
	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.

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.

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 Equation 8.

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

Characteristic	Pre-campaign		Campaign	
	Left Market	Right Market	Left Market	Right Market
Negative Left	1.705 (0.022)	0.313 (0.005)	-0.747 (0.093)	0.333 (0.044)
Positive Left	-0.073 (0.002)	0.085 (0.001)	0.666 (0.102)	-0.819 (0.099)
Negative Right	1.443 (0.019)	0.580 (0.008)	0.277 (0.065)	-0.164 (0.032)
Positive Right	-0.036 (0.002)	0.108 (0.002)	-1.388 (0.182)	0.204 (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
TVE	5.58	6.12	6.58	8.31	5.02	5.89	6.31	7.99	9.07	11.40	8.86	9.65
A3	8.94	10.91	15.21	11.69	10.03	12.96	11.95	13.21	15.50	16.42	15.27	13.91
T5	6.13	7.34	8.82	8.95	9.20	10.11	9.75	9.56	7.90	8.29	10.04	6.81
La Sexta	3.47	3.84	4.22	4.50	4.50	5.27	6.13	7.08	6.54	5.28	4.91	6.88

Notes: The table reports the test statistics for changes in daily *cuota* by profile (age, sex) between the pre-campaign (Dec 1, 2022–May 12, 2023) and campaign (May 13–Jul 23, 2023) periods, by channel. Higher values indicate larger estimated shifts.

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

Characteristic	Factual		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

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

Note: Results of the estimation of the regression equation 7. Robust standard errors in parentheses; $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 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 \times Right-Mean	ϕ^{L+}	47.67	(36.262)
Positive Right \times Right-Mean	ϕ^{R+}	111.13**	(50.798)
Negative Left \times Right-Mean	ϕ^{L-}	-81.40	(51.195)
Negative Right \times Right-Mean	ϕ^{R-}	-151.24*	(89.249)
Political \times 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 \times Right-Mean	ϕ^{L+}	-619.77**	(303.679)
Positive Right \times Right-Mean	ϕ^{R+}	461.19*	(242.882)
Negative Left \times Right-Mean	ϕ^{L-}	398.26*	(211.132)
Negative Right \times Right-Mean	ϕ^{R-}	-413.87**	(187.584)
Political \times 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 $N_{pre_campaign} = 6604$.

D.3 Text Examples

Table D.11: Top Stories for Negative Left and Outlet's Production

Stories	
<hr/>	
-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.12: 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.13: 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.15: 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.16: 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.17: 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 6	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 6	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 ‘front-runner’ of Next Generation EU implementation and vows to accelerate project selection in the regions...”	La 6	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 6	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 6	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 6	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 for display.

Table D.18: EFE case studies

Date	Characteristic	Δx	Top 3 Stories
2023-05-29	Negative Left	0.412	<p>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...”</p> <p>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’...”</p> <p>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.”</p>

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

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.

E Isolation Index

E.1 Definition

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

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

where Right_j and Left_j denote the numbers of right- and left-leaning viewers of outlet j , $\text{Audience}_j = \text{Right}_j + \text{Left}_j$ 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 iff, for every outlet that right people visit ($\text{Right}_j > 0$), then all other visitors are also right-wing, $\frac{\text{Right}_j}{\text{Audience}_j} = 1$ and the analogous for outlets consumed by left-wing users. This reflects an scenario of perfect segregation.

E.2 Results

Table E.19: Ideological Segregation by Medium (CIS Survey)

	Right exposure to		Isolation index
	Right	Left	
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.20: 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 / Newspapers	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).