Political Bias in the Media
Evidence from the Universe of French Broadcasts, 2002-2020*

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Abstract

How does the media bias the news? And in particular, how do journalist preferences interact with owner slant? We compile a unique dataset of journalists and guests appearing on French television and radio shows between 2002 and 2020 to quantify the role played by journalist selection and compliance in political coverage. First, we leverage the movements of thousands of journalists between media outlets, and estimate a model in which the share of coverage for each political group is determined both by journalist and outlet components. We find that outlet-level decisions account for three-fourth of the differences in political coverage; on the contrary, journalists' personal editorial preferences play only a minor role. Second, we examine how journalists respond to a major takeover-induced editorial change. Using a difference-in-differences strategy, we show that while many journalists left in response to the shock, those who stayed largely adapted to the new editorial direction. Notably, exploiting unique data on journalist salary, we show that this compliance came at nearly no cost for the new owner, reflecting journalists' low bargaining power in an industry in crisis.

Keywords: media bias; slant; journalists; media ownership; media concentration; pluralism; media capture; news organizations; wage compensation; monopsony power
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1 Introduction

In both the United Kingdom and France, the editorial positioning of television channels like GB News and CNews has tested in recent years the boundaries of regulations designed to ensure fair and balanced coverage in broadcast media. This has raised questions about how editorial lines take shape, and in particular the role played by journalists. While prior research has established that ownership can influence content (e.g. Martin and McCrain, 2019; Mastrorocco and Ornaghi, 2025), owners do not make daily editorial decisions – journalists do. This disconnect points to a deeper puzzle: through what mechanisms does ownership influence media content? Unpacking this process is key to understanding how media content is produced – and how ownership shapes political coverage.

In this article, we examine the inner workings of media organizations to uncover how slant emerges. One possibility is that slant is primarily a matter of selection – media organizations may hire journalists whose editorial preferences naturally align with an outlet's vision.[1] Alternatively, slant may be a matter of incentives: even when journalists' own editorial preferences diverge from their employer's stance, professional incentives may encourage compliance. We use novel data from French broadcasts between 2002 and 2020 to measure the share of coverage devoted to each political group in each program, and assess the costs of compliance. By tracking journalists as they move between outlets, we quantify how much of the variation in political representation is shaped by journalists' personal editorial choices versus their adaptation to their employer's editorial decisions. To complement this analysis, we study the editorial shift that occurred after Vincent Bolloré – often dubbed the 'French Murdoch' – acquired three television channels in 2015. We investigate how journalists reacted to the new management: whether they adjusted their show content to align with the new editorial direction or left, either voluntarily or otherwise, and for what salary.

French broadcast media offers an ideal setting to examine how journalists shape content. First, as in many countries, radio and television form the core of the news ecosystem. They dominate media power rankings (Kennedy and Prat, 2019; Cagé and Huet, 2021) and the outlets topping the list of news sources are television channels, ahead of social media.[2] Second, the programs of all the major radio and television outlets have been archived by the INA (*National Audiovisual Institute*) from 2002 to 2020. Our data encompass 2.1 million shows across various formats – from newscasts to talk shows and documentaries – offering a comprehensive view of media content.[3] Third, the INA rigorously recorded every individual whose speech is featured, whether they are in the studio or appear via broadcast content (e.g., a politician's statement at a town hall or a pre-recorded interview with an executive). We refer to these individuals who make up 2.3 million appearances as guests, and we systematically collect data on their political leaning when applicable. Lastly, the extensive time frame allows us to track journalists as they move

[1] For instance, in the context of the US federal bureaucracy, ideological alignment between politicians and bureaucrats has been shown to impact performance (Spenkuch et al., 2023).

[2] In 2019, 71% of French respondents (respectively 53%) get their daily news from television (respectively radio), compared to only 47% online and 4% on Facebook (Sumida et al., 2019).

[3] Only fiction shows, reality shows, sports shows and games shows are excluded.

between outlets, observing how their political coverage shifts in response to changes in their employer. The granularity of the data also allows us to control for both audience composition and concurrent news events at the time each show airs.

To measure editorial slant, we quantify the coverage given to different political opinions by calculating the time share devoted to each political group, following the approach of Durante and Knight (2012). Media coverage of politicians indeed has a causal impact on voting behaviors (Chiang and Knight, 2011; Caprini, 2023) and is closely monitored by regulatory agencies in many countries due to its influence on the electoral process. To this end, we assign each guest a political leaning, when applicable.[4] This classification is time-varying and based on two main sources. First, we classify politicians using lists of election candidates and government appointees. Second, we extend this classification to politically-vocal individuals who are not professional politicians (e.g., commentators, activists) by using lists of think tank contributors, participants in party events, and public figures who endorse presidential candidates.[5] This additional step is motivated by the increasing airtime these individuals receive in talk shows; we label them 'politically engaged non-politicians' (PENOPs). As a result, we classify 13,418 distinct guests, accounting for 602,914 appearances.[6]

We find that political groups are unevenly represented across television and radio channels and explore the potential mechanisms. The first relates to journalist composition: outlets may hire journalists who, on average, are more likely to cover certain political opinions. The second involves compliance: journalists may adjust their political coverage to align with the editorial strategy of the outlet they work for. These two mechanisms may reinforce each other if the composition of journalists varies according to the outlet's editorial line – e.g. if journalists sort on outlets whose editorial stance matches their own inclinations.

To assess the relative contribution of these mechanisms, we leverage the movements of 4,456 journalists observed across different media outlets and estimate a two-way fixed effects model. By analyzing changes in coverage as journalists switch outlets, we can quantify how much they adapt to their new employer. We model the time share devoted to each political group by a given journalist on a specific outlet as the sum of three components: (i) a journalist component, capturing the journalist's inclination to cover a political group; (ii) a media outlet component, reflecting how journalists adjust their coverage to align with the outlet's editorial policy; and (iii) time components, controlling for audience composition changes and news events at a high frequency. Since outlets periodically revise their editorial strategies, we estimate a model that allows media-outlet effects to vary every two seasons, following the approach of Lachowska et al. (2022).[7]

[4]We consider six political groups (radical left, green, left, liberal, right, radical right) and rely on the Chapel Hill Expert Survey to match political parties to these political groups.

[5]This category includes individuals like Jacques Généreux, a politically active economist who crafted the economic platform for *La Fance Insoumise* (a radical-left party) in both the 2017 and 2022 elections. Another example is Nicolas Bouzou, an essayist and vice president of the right-wing think tank *Cercle Turgot*.

[6]Politically classified guests account for about a quarter of all appearances. Guests who are not politically classified are typically journalists, entertainment professionals (actors, singers, etc.) and sport professionals.

[7]Specifically, we regress the time share devoted to each political group on journalist fixed effects, channel-by-period fixed effects, and time-by-platform (radio or television) fixed effects. Each period spans two seasons, with a season defined as a

We then decompose the variance in outlet-level slant using a method similar to that of Finkelstein et al. (2016). First, we examine the share of time dedicated to politically active guests as a share of all guests. We find that journalist composition accounts for around 20% of the variance in political coverage across outlets, while outlet-level factors such as the editorial strategy account for 40%. The remaining 40% is attributed to sorting, as journalists inclined to cover politics are more likely to work on outlets emphasizing political guests. When focusing on the share of coverage given to a specific political group among political guests, we find that compliance with channel-level decisions is the primary factor explaining differences across outlets. Whether considering the coverage share dedicated to the left or the right, channel-level factors account for about 75% of the variance, while journalist composition contributes less than 10%. The remaining 15% are explained by sorting, as journalist are more likely to work on outlets whose editorial line aligns with their own inclinations.

In other words, our results indicate that differences in political coverage across media outlets are not primarily due to the selection of journalists with distinct editorial preferences, but rather stem from outlet-level decisions – such as the channels' editorial strategies – to which journalists adapt. Consequently, journalists' own political views, which may diverge from those of the broader population (e.g. Hassell et al., 2020), do not drive variations in coverage across outlets. Instead, journalists adjust their reporting largely irrespective of their personal inclinations. Furthermore, we illustrate that the editorial lines of outlets under the same parent company often prioritize similar political forces. This suggests that owners may establish editorial directions reflecting their own preferences, rather than horizontally differentiating on slant to maximize audience share across their outlets.

We also show that, over the period studied, outlet effects explain a growing share of the cross-outlet variance in coverage: the share of the variance explained by media outlets increased from around 25% in 2005-2010 to up to 62% in 2015-2019. This may be related to the increasing concentration of the news industry over the same time period, and in particular to the observed drop in the number of journalist positions. Possibly, making journalists comply to outlet-level editorial lines has become easier over the period.

Given that outlet-level decisions largely account for cross-outlet differences in coverage, the second part of this paper further explores the relationship between ownership and editorial strategy, and the role played by the sate of the journalists' labor market in explaining their compliance. We focus on a significant owner-induced shift in outlet slant and examine two response options for journalists: adapt or leave. In 2015, Vincent Bolloré – a French billionaire often likened to Rupert Murdoch – became the main shareholder of the Vivendi conglomerate, the parent company of the Canal Plus Group, which owns several television channels. Journalistic accounts have noted his close ties to conservative figures and reported a swift rightward shift in programming (see also Capozzi, 2016; Cagé, 2022).

We begin by quantifying the magnitude of the editorial shift at the outlet level through an event-study

one-year period from September to August, aligning with the scheduling cycles used by broadcast media. Time is measured at the hourly level, and for each journalist and time slot, we aggregate all shows broadcast during that time slot on a weekly basis.

design, comparing Bolloré channels to the other outlets in our sample. The takeover resulted in a 5.5 percentage-point increase in the time share devoted to radical right guests, compared to a 7.6% baseline on control channels. We find no pre-trends, which supports a causal interpretation of the results. The shift is more pronounced when we consider politically-vocal guests who are not professional politicians, and whose speaking time is not subject to regulatory oversight. Outlets may leverage these PENOPs to slant their content while circumventing existing pluralism regulations. Furthermore, we observe no increase in viewership in the short to medium run, suggesting that the editorial change did not evidently align better with audience preferences.

Turning to the mechanisms, we first examine compliance. Using an event-study specification with journalist-channel pair fixed effects, we find that journalists who remained on the acquired outlets increased their coverage of the radical right by 3.2 percentage points. This suggests that continuing journalists largely complied with the new editorial line by adapting their political coverage. We next analyze whether journalists cease to have shows on the channel in response to the change in editorial line. We find that the probability of a journalist leaving increases by 15 percentage points following the takeover, up from a 40% baseline. This effect is driven by journalists who are younger, lesser known, lesser paid, i.e. by journalists who likely have less bargaining power. This suggests that these journalists had no option but to leave. Notably, journalists who had a tendency to cover the right or radical right (as indicated by the fixed effects estimated using the two-way fixed effects framework in the first part of the paper) were just as likely to leave as their peers. Journalists' departure therefore does not seem primarily driven by ideological motives.

We further discuss why this ownership-driven change in editorial line largely operated through compliance rather than selection. Using novel annual individual-level data on journalist salary, we show that the complying journalists receive no compensation for adapting the content of their shows – they do not get higher wages nor more airtime. Rather, it appears that the extent of the downsizing of the newsroom disciplined the journalists who were able to keep their job. Five years after the takeover, they appear to fare better than those who leave – among whom many appear to have left the journalism career they had initially embraced – as their wages remain comparable to the wage of journalists at other outlets. In other words, in a shrinking job market, media outlets seem to discipline journalists by using the extensive margin – whether or not to have a job – stick rather than the intensive margin – how much you are paid – carrot. This implies that, even in a country like France where labor protection is generally considered as high, journalists are not in a position to push back on the editorial line set by the owner. The principle of editorial independence seems like a distant ideal in an industry in crisis were securing a stable journalist job is difficult.

Literature This article contributes to the literature on how the ownership structure impacts media content. Previous studies have demonstrated that changes in media control can impact content in the context of local private TV network acquisitions (Martin and McCrain, 2019; Miho, 2020; Mastrorocco

and Ornaghi, 2025) or shifts in public broadcasters' partisan control (Durante and Knight, 2012). Our paper is the first to explore journalist-level consequences, documenting how journalists respond to ownership changes and how this alters the editorial slant of acquired outlets. Specifically, we analyze journalists' adaptation to new guidelines and the shifts in journalist composition at the outlet level, and use novel career and salary information to investigate the price of compliance.

Our research adds to the broader discussion on media ownership, concentration, and reporting. We find that differences in media coverage across outlets are largely driven by channel-level decisions, underscoring the need to understand the rationale behind these editorial strategies (Mullainathan and Shleifer, 2005; Gentzkow and Shapiro, 2006, 2010; Martin and Yurukoglu, 2017).[8] Gentzkow and Shapiro (2010) find that local newspapers' media slant mostly reflected readers' political makeup rather than ownership. In contrast and consistently with Martin and McCrain (2019), our findings show that ownership changes directly impact the editorial slant, with no resulting audience increase.[9]

Additionally, our research engages with studies on journalist-level reporting bias. From a theoretical standpoint, Baron (2006) models the amount of discretion that owners give to career-motivated journalists in slanting their piece. He argues that tolerating bias may allow news organizations to hire journalists at lower wage. On the contrary, our empirical results indicate that journalists do not receive monetary compensation for complying with the organization editorial line. Few empirical works has sought to measure bias at the journalist level. Hassell et al. (2020) show that U.S. journalists, on average, lean liberal; yet, this does not result in gatekeeping bias when reporting on electoral candidates. This is consistent with our findings that allow us to rationalize why, despite the general perception that the majority of the journalists lean left, many media outlets emerge as conservative. We indeed show that journalists largely comply with their outlet's editorial guidelines rather than report based on personal preferences.[10] Moreover, we are the first to investigate whether this compliance comes at a cost to employers, both in terms of increased monetary compensation or visibility given to the journalists.

Finally, our work builds on recent studies that leverage geographic, institutional, or organizational moves to distinguish individual effects from contextual ones. This approach has been used to study outcomes like wage earnings (Abowd et al., 1999; Card et al., 2013; Song et al., 2019; Lachowska et al., 2022; Babet et al., 2022, among others), health care use (Finkelstein et al., 2016), political participation (Cantoni and Pons, 2022), bureaucratic productivity (Best et al., 2023; Fenizia, 2022) and teacher performance

[8] See Puglisi and Snyder Jr (2015) for a review of the empirical literature on the causes of media bias.

[9] Our work builds on the extensive literature on measuring media bias, which has relied on various methods such as endorsements(Ansolabehere et al., 2006; Chiang and Knight, 2011; Puglisi and Snyder, 2015), think tank citations (Groseclose and Milyo, 2005), editorials (Ho et al., 2008), language (Gentzkow and Shapiro, 2010; Garz and Rickardsson, 2023), and issue coverage (Puglisi and Snyder, 2015; Galvis et al., 2016). Closest to ours are Durante and Knight (2012) and Knight and Tribin (2021), who also use time shares to measure political representation. However, we extend this approach by including a wider range of show types, incorporating politically vocal figures beyond professional politicians, and providing a show-level measure. This also draws on research into 'celebrity politics' (West and Orman, 2003; Wood and Herbst, 2007; Wheeler, 2013), and aligns with efforts to quantify political representation on Vivendi channels (Sécail, 2022).

[10] Xu (2024) examines how financial journalists' social networks influence M&A coverage. DellaVigna and Hermle (2017) explore conflict-of-interest bias in movie reviews. Bursztyn et al. (2020) study slant differences on Fox News shows and their impact on viewers' distancing behavior at the time of the Covid-19 crisis.

(Chetty et al., 2014). To the extent of our knowledge, our paper is the first to adapt the methodology of Finkelstein et al. (2016) to examine cross-outlet differences in media coverage. Concomitant work by Srinivasan (2021) and Boxell and Conway (2022) also examine journalist transitions in U.S. newspapers.[11] But we uniquely leverage a natural experiment to study whether journalists comply or exit after a takeover-induced change in editorial line, and the extent to which this depends on journalists' characteristics, including their pre-takeover editorial preferences. Further, we are the first to quantify the price of compliance, considering both monetary and non-monetary compensations, as well as to disentangle between the extensive margin (the propensity to cover politics) and the intensive margin (the coverage devoted to different political groups conditional on covering politics) when investigating differences in political coverage. Last, our measure of bias takes into account both the politicians and the PENOPs, and we consider the exhaustive set of show broadcast on the main television and radio channels, the key news sources in many countries.

The rest of the paper is organized as follows. Section 2 outlines the institutional setting, while Section 3 describes the data and provides descriptive statistics. Section 4 decomposes the differences in political representation across channels, showing that outlet-level decisions account for most of the variation, a tendency that has gained strength in recent years. Section 5 examines journalists' reactions to Vincent Bolloré's takeover and the role played by career-related concerns. Finally, Section 6 discusses policy implications and concludes.

2 Institutional setting

News sources in France Television and radio are the primary sources of news in France, as in most Western countries. In 2017, 71% of French adults reported getting daily news from television, 53% from radio, 47% online, and 23% from print. Further, 16% cited TF1 (private television) as their main news source, 15% mentioned BFM TV (private television), 15% France TV (public television), 6% *Le Monde* (newspaper), 6% Radio France (public radio), while only 4% Facebook (Sumida et al., 2019). [12] Additionally, 25% of individuals rely on a single type of source for daily news, with television being the most common. Notably, the most recognized media figures in France are predominantly television and radio journalists, with nine of the top ten journalists named in open-ended surveys working in broadcast media (Newman et al., 2022).[13] Appendix Section B provides details on the main French television and

[11] See also Goldman et al. (2024) who compare the *Wall Street Journal* and the *New York Times* coverage of corporate financial news, and document a changing tone of the articles written by journalists who switch between these two newspapers. Braghieri et al. (2024) also propose a variance decomposition to explore how slanted article-level online media consumption is, and in particular whether it is driven by within- or across-outlet variation.

[12] In a 2024 survey, 66% of French respondents reported using television to inform themselves on a daily basis, 51% reported using radio, and 47% social media. Source: Arcom, 'Les Français et l'information,' 2024.

[13] In 2022, when asked to name up to five journalists they pay attention to, respondents most frequently mentioned these three presenters: Pascal Praud (CNews and RTL), Anne-Claire Coudray (TF1), and Jean-Jacques Bourdin (BFMTV and RMC) (Newman et al., 2022). This was based on an open-ended question in the Digital News Report survey. Journalists from national newspapers like *Le Monde* and *Le Figaro* were rarely mentioned, accounting for only 6% of responses, with digital media journalists were mentioned even less frequently (3%) (Newman et al., 2022).

radio outlets and includes information on their ownership.[14]

Broadcast regulation and pluralism The 1986 Law on Freedom of Communication established the framework for broadcast regulation in France.[15] Its first article highlights the constitutional principle of ensuring the 'pluralist nature of the expression of currents of thought and opinion' as a key objective. To achieve this, the law introduced measures to limit ownership concentration (external pluralism), based on the premise that diversified ownership promotes media independence and ensures a variety of editorial content. This reasoning echoes the conclusions of the 1947 Hutchins Commission report in the United States. These regulations specifically target the broadcast sector and operate alongside broader anti-concentration laws.[16]

The 1986 Law also led to the establishment of an independent regulatory body, now known as Arcom (*Autorité de régulation de la communication audiovisuelle et numérique*).[17] It is the French counterpart to the FCC (Federal Communications Commission) in the United States and Ofcom in the United Kingdom. One of its key responsibilities is to 'ensure respect for the pluralist expression of currents of thought and opinion' in radio and television programming, particularly in political and general information programs (Article 3).[18] In practice, Arcom mandates that one-third of speaking time be allocated to the president and members of the government, while the remaining two-thirds must be distributed among all political parties (including the governing party), proportionate to electoral results, the number of elected officials, popularity in the polls, and the party's contribution to public debate.[19] However, because 'public debate contribution' and 'popularity' are not precisely measurable, this guideline serves as a broad principle left largely to the discretion of media outlets, rather than a strict rule. Indeed, as we document in this article, there are significant differences in the speaking time allotted to each party across various outlets. Notably, Arcom only monitors the time given to politicians, not politically vocal individuals who are not formally

[14]Appendix Table B.1 lists the main 30 national television channels in France (excluding cable and satellite channels) with the corresponding audience share over the period studied. The most watched television channels are all included in our dataset and account for two thirds of overall television viewership in 2020 (at the end of our sample). Appendix Table B.2 lists the main radio stations, excluding music-only stations and local stations. Those with the largest audience are France Inter (public) and RTL (private); both of them are included in our sample.

[15]Loi 86-1067 du 30 septembre 1986.

[16]In the Unites States, the Federal Communications Commission (FCC), designed regulations in line with its mission to ensure "*the diversity of viewpoints from antagonistic forces*." The US Supreme Court has supported the "*assumption that diversity of ownership would enhance the possibility of diversity of viewpoints*" (Fisch, 2010). The European Commission writes that: "*independent media, and in particular news media, provide access to a plurality of views and are reliable sources of information to citizens and businesses alike. They contribute to shaping public opinion and [...] are essential for the functioning of our democratic societies and economies.*" In case of mergers or acquisitions, the Commission recommends assessing "*the impact of the concentration on media pluralism, including its effects on the formation of public opinion*" (COM/2022/457).

[17]Established in 1989 as the *Conseil supérieur de l'audiovisuel* (CSA), Arcom is the regulatory body responsible for allocating broadcast frequencies, overseeing mergers and acquisitions in the media sector, setting standards for diversity and pluralism, and labeling content suitability for young audiences. Arcom also has the authority to impose sanctions for hate speech or discrimination. For more details on the regulatory environment of French broadcasting, see Cagé and Huet (2021).

[18]In the U.S., the 1949 FCC Fairness Doctrine required broadcasters to provide the public with 'a reasonable opportunity to hear different opposing positions on public issues of importance and interest in the community' (Fisch, 2010). Most European countries have implemented some form of internal pluralism regulations (see '*Internal Media Plurality in Audiovisual Media Services in the EU: Rules and Practices*,' ERGA Report, 2018).

[19]See the Arcom's website for additional details.

politicians – whom we refer to as PENOPs.

Political parties The French political landscape features a wide range of parties, spanning from the radical left to the radical right.[20] Given that parties frequently split, merge, or change names, we classify them into ideology-based groups according to the Chapel Hill Expert Survey (CHES). The six resulting political groups are: (i) Radical Left (*Parti Communiste*, *La France Insoumise*); (ii) Greens (*Europe Écologie-Les Verts*); (iii) Left (*Parti Socialiste*, 'other left'); (iv) Liberals (*MoDem*, *La République en Marche*); (v) Right (*Les Républicains*, *Union des démocrates et indépendants*, 'other right'); and (vi) Radical Right (*Rassemblement National*, *Debout La France*). For our analysis, we further aggregate these into 'all left' (combining the Radical Left, Greens, and Left) and 'all right' (combining the Right and Radical Right), while also providing results at the individual political group level.

3 Data and descriptive statistics

We build a novel dataset on television and radio shows using INA archives, supplemented by various additional sources.[21] In this section, we briefly describe the data, explain how we define the estimation sample, and present descriptive statistics. More details are provided in the online Appendix.

3.1 Content and coverage

Our data on shows come from the INA, where staff have manually recorded since 2002 the journalists and guests featured in the shows of all the main television and radio outlets. Notably, the data include information on specific segments within longer shows, meaning the individuals in our sample are not limited to headline journalists and guests. The INA documents a very broad range of programs – including newscasts, talk shows (such as late-night shows), investigative programs, and more – whether or not they feature politicians. The only shows that are not included are fiction shows, reality shows, sports events and game shows. This comprehensive coverage extends beyond that of most previous studies.

Sample definition Our sample includes 12 television channels and six radio stations, all available for free to the entire French market. For television, we focus on digital channels that feature shows featuring political guests each season.[22] These channels accounted for 83.6% of total viewership in 2007 and 67.4% in 2020. For radio, we concentrate on national, non-local, non-music stations, which captured 46.3% of the total audience in 2020 (with all national non-music stations accounting for 54.9%).[23] As such, our

[20] For a recent overview, see Cagé and Piketty (2023).

[21] Show data can be accessed via the following interface: `http://inatheque.ina.fr/`. For previous research using INA data, see Cagé et al. (2020) and Cagé et al. (2022).

[22] More specifically, the sample includes the following television outlets: ARTE, BFM TV, C8, Canal+, CNews, France 2, France 3, France 5, LCI, LCP/Public Sénat, M6 and TF1. Canal+ is not entirely free as some segments are only available to subscribers, but the large majority of their shows with guests and journalists are available for free.

[23] The six stations in the sample are France Culture, France Info, France Inter, Europe 1, RMC, and RTL.

sample covers a significant share of both television and radio audiences and includes nearly all shows with journalists broadcast on national outlets.

The INA data span the years 2002 to 2020, which we consider to describe the evolution of the speaking time shares below. For estimation, in Sections 4 and 5, we focus on shows broadcast between September 1, 2005, and August 31, 2019. This is because the year 2005 marks the transition of French television from analog to digital, when new national channels became freely available.[24] The sample ends in 2019 because, after that date, the number of documented shows declines significantly due to budget cuts at the INA, making the data incomplete. This sub-sample covers 14 seasons, with each season defined as the period from September to August.

3.2 Measuring editorial slant using data on guests

The 261,993 unique individuals listed as guests in our sample account for 2.3 million appearances. The INA defines a guest as someone who speaks during a show, regardless of whether they are physically present in the studio. For example, a politician giving a campaign speech or a lawyer being interviewed in their office are both considered guests if their words are broadcast. Under this definition, multiple media outlets can feature the President of the Republic as a guest simultaneously by broadcasting the same press conference. This allows journalists to cover prominent figures who are sought by multiple outlets or who rarely agree to in-studio interviews. This broad definition of a guest also enables us to closely track which individuals receive media coverage. Additionally, the data include information on recurring guests, such as their gender, birth year, country of origin, and a time-invariant description of their profession.[25]

We use the amount of coverage each show dedicates to various political groups – providing them with opportunities to promote their views – as our measure of slant. The level of media coverage politicians receive can indeed have a causal impact on voting behavior (Caprini, 2023), making it a crucial area of scrutiny.[26] For that matter, regulators in many countries monitor the speaking time allocated to each party this way, especially during election campaigns (Holtz-Bacha, 2014; Cagé, 2018). More precisely, we compile detailed data on the featured individuals and create a time-varying measure of each guest's political affiliation, if applicable. We then calculate the share of coverage devoted to political guests as a whole, as well as the proportion allocated to each political group, following the approach of Durante and Knight (2012).

Guests classified as politicians Our classification procedure relies on two sets of data. The first focuses on elections and government appointments. We track the political party a guest ran for and in which

[24]This is for example the case of C8 or BFM TV in our sample.

[25]Using keywords, we create indicator variables for whether each guest falls into a given professional category (see Appendix Section A.3 for details). Appendix Table C.1 provides descriptive statistics on guests' appearances. The majority concern male guests (76%) and guests born in the 1960s or earlier. The most common professions include politicians, professions in the media or publishing industry (writer, columnist, etc.), and professions in the entertainment industry (singer, actor, etc.).

[26]Many parties indeed employ communication experts to design events that attract media attention and politicians often undergo media training to ensure they deliver their messages as persuasively as possible.

elections (house, senate, E.U., regional, cantonal, or municipal), whether they were affiliated with a parliamentary group, and whether they held a government position under a specific majority. Appendix Section A.2.1 details how we combine these data sources. This first set of sources allows us to closely monitor changes in the political affiliations of guests who are professional politicians over time.

Guests classified as PENOPs Motivated by the presence of guests who express political views on shows like talk shows but are not professional politicians, we turn to a second set of data sources. Our goal is to identify tangible indicators of political leanings for guests who neither run for office nor serve in government but frequently share their political opinions in the media – whom we refer to as PENOPs. A notable example in the French context is Eric Zemmour, who appeared as a panelist on CNews' daily show *Face à l'info* from 2019 to 2021, where he played the 'literary reactionary' role.[27]

To systematically classify these guests, we draw from three data sources. First, we gather lists of speakers from political parties' summer events (*universités d'été*), which typically include politicians as well as non-politicians like experts, columnists, and activists. Second, we collect the names of individuals who publicly endorsed a candidate in the first round of the presidential elections. Third, we track think tank participation by compiling a list of French think tanks and mapping them to political groups where relevant.[28] For think tanks with clear political leanings, we use their archives and archived versions of their websites to identify members and contributors (reports, blog posts, etc.). By combining these sources, we create a time-varying measure of each guest's political leaning.

Classification results Appendix Figure D.3 summarizes the results of our classification. Overall, 25.9% of appearances (602,914 in absolute value) are by guests who have been politically classified. Among the 23.9% of appearances by guests identified as "politicians" in the INA time-invariant profession categorization, 91.9% are matched to a political leaning. The remaining 8.1% typically consist of retired or future politicians observed during politically inactive periods.[29] Thus, we classify nearly all the guests who are politicians and are expected to be classified. Additionally, we classify 5.1% of appearances by individuals whose profession is not designated as 'politician' by the INA. Some of these individuals are classified as politicians using our first set of sources (e.g., Bernard Laporte, a rugby coach who later became a Minister of Sports), while others are identified as PENOPs using the second set of sources.

The remaining 74.1% of appearances are by guests who are not politically classified. This reflects the

[27] "In this role, Zemmour has defended the bloody conquest of Algeria and the French general who led the slaughter. He has castigated unaccompanied minors: 'They are thieves, they are murderers, they are rapists, that's all they are. They must be sent back,' he declared [...]." In "The Fox News of France", Valentine Faure, *Nieman Reports*, January 20, 2024.

[28] Think tanks are linked to a political party based on four criteria: (i) whether their founders or top leaders were politicians from that party, (ii) which politicians or parties provide them with funding, (iii) their stated goals, and (iv) the composition of their Twitter community. Appendix Section A.2.2 provides a detailed list of party summer events with participant numbers, a breakdown of think tanks and their political leanings, statistics on their Twitter communities, and the number of names collected. It also outlines how we combine these data sources to create a single measure of political leaning.

[29] One example is criminal defense lawyer Éric Dupond-Moretti, who was frequently invited to the media before his appointment as Minister of Justice. Another is Dominique de Villepin, former Prime minister who made several media appearances long after retiring from politics and transitioning to a career as a lawyer.

richness of the INA data, which includes a wide variety of shows, some featuring political guests only occasionally. As shown in Appendix Figure D.4, approximately one million appearances are indeed by guests from the media/publishing (writers, invited reporters, etc.), entertainment, or sports industries.[30]

Time share We aim to measure the relative amount of time each outlet dedicates to covering different political groups. Since we lack data on the precise amount of time allocated to each guest, we base our approach on the premise that, for a given number of guests, a longer show results in more coverage for each invited guest. Conversely, for a fixed show length, coverage becomes more diluted with more guests. Therefore, we calculate that each guest receives coverage equal to the length of the show (or sub-show) divided by the number of guests on the show.[31]

In Appendix Section A.2.5, we further demonstrate that the guests featured in shows significantly influence the content discussed. For a subset of shows, we transcribe the content and investigate whether the relative frequency of specific words or expressions is systematically higher when guests from a particular political group are present compared to when they are not. We document clear differences in the language used by guests from each group. For example, radical-right politicians often uses expressions such as 'massive immigration,' 'Islamic fundamentalism,' and 'monetary sovereignty,' while radical-left guests mention more frequently issues related to lay-offs, 'social struggle' and 'ecological planning'. While this might not seem surprising, it validates the relevance of our measure of slant.

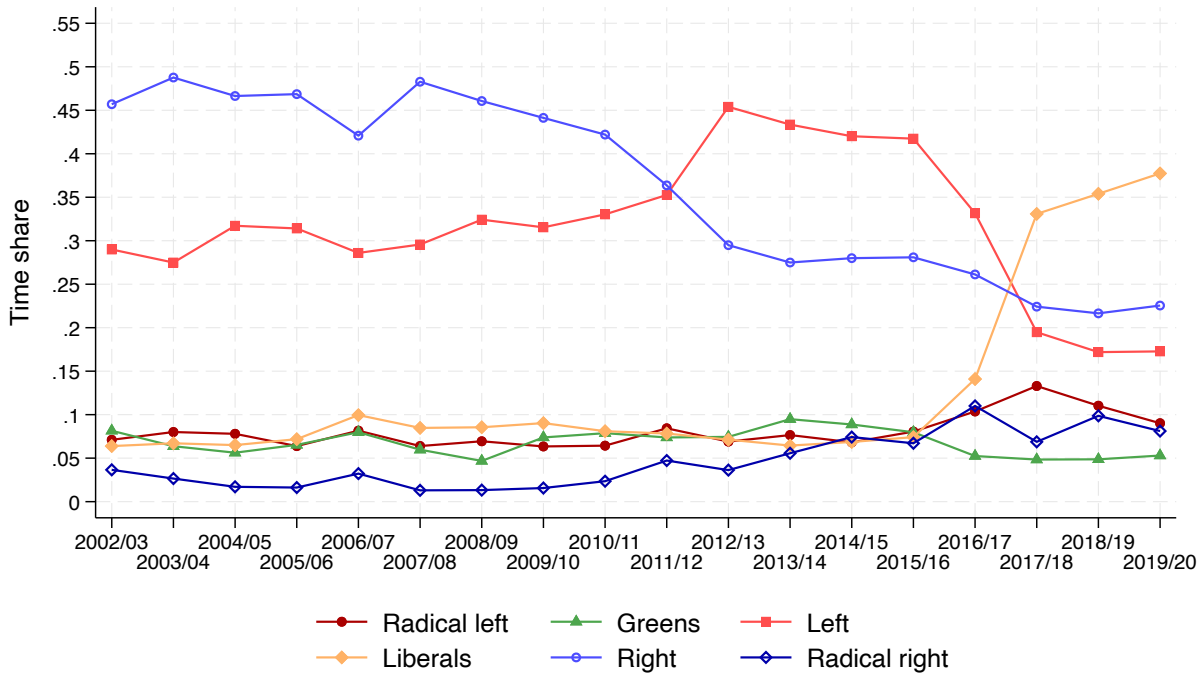
Overall, we measure the coverage dedicated to each political group across the 2.3 million shows in our dataset using the guests appearing on the shows. This approach offers a transparent measure of political coverage that can be flexibly adapted to multiparty systems and is comparable to the metrics used by most agencies responsible for regulating ideological diversity in the media.

Descriptive statistics From there, we can compute the time share dedicated to each type of guests – non-politicians, politicians, and PENOPs – as well as to each political group. Appendix Figure D.5 shows that over time, the total screen time allocated to politically active guests has increased by more than 15 percentage points, with notable growth in the time dedicated to both politicians and PENOPs. The latter group has come to represent a growing share of the overall time devoted to political guests during our period of interest (see Appendix Figure D.1),[32] a tendency that can be partly explained by the fact that

[30]Note also that foreign politicians (e.g. Barack Obama and Angela Merkel) are not classified, as we do not attempt to match guests who are not French to a French political group.

[31]If a guest appears in a show that includes sub-segments, we exclude the duration of those sub-segments that do not feature the guest from our calculations (e.g. the weather report during a talk show). To assess the validity of our measure, we compare the time share assigned to each guest in a show with the share of frames containing the guest's face, using a subset of television shows where a face-recognition algorithm has been implemented by Petit et al. (2021). The right panel of Appendix Figure A.2.4 plots our time share measure against the image frame share for this subset. Our measure explains 87% of the variation in screen time share as measured by image frames. We observe a strong positive linear relationship between the frame share and the computed time share, indicating that our measure effectively approximates the time share of each guest.

[32]While this share was approximately 8% at the beginning of our time period, it has since doubled and now exceeds 15%. This trend is primarily driven by radio and generalist television outlets, whereas the share has remained more stable on news and entertainment television stations. This increase mirrors the growing time dedicated to talk shows, as illustrated in Appendix Figure D.2. It may be partly due to cost-cutting measures (Cagé, 2015).



Notes: The Figure plots the evolution of the speaking-time share devoted to each political group among politically classified guests for each season, aggregated over all the outlets in our sample. The speaking-time share of the political groups includes the speaking time of both politicians and PENOPs.

Figure 1: Evolution of the speaking-time share devoted to guests depending on their political group, 2002-2020

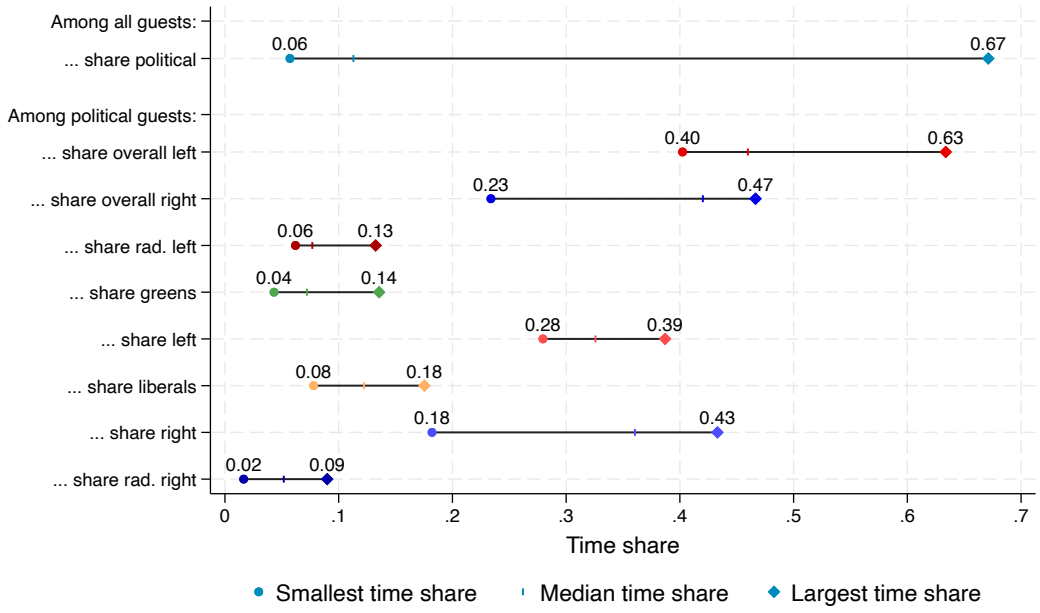
their speaking time is not monitored by the regulator.[33] Figure 1 focuses specifically on political guests.[34] The electoral cycles are clearly visible: the right held office until 2012, followed by the left from 2012 to 2017, and then the liberals gaining power in 2017. The government party is consistently more represented, reflecting the Arcom guideline that requires one-third of political speaking time to be allocated to the government.[35]

We next explore variation in the coverage of political groups across channels. For each group of guests, Figure 2 plots the time share dedicated to this group on the outlet covering it the most and the outlet covering it the least. Reflecting the fact that some outlets prioritize news while others emphasize entertainment,

[33]Furthermore – though measuring this is beyond the scope of this paper – the speech of PENOPs may be perceived as more persuasive than that of politicians, either because audiences place greater trust in them or are less able to filter out their ideological bias (see e.g. Afrouzi et al., 2023; Banerjee et al., 2020).

[34]Including both politicians and PENOPs. See Appendix Figure D.6 for a similar plot that considers only politicians (sub-Figure D.6a). While the overall trends are comparable, we will see below that the inclusion of PENOPs by certain channels can lead to increasing slant.

[35]Appendix Figure D.6 presents the same time shares but excludes government officials (sub-figure D.6b). In this case, both the right and the left are similarly represented until 2017, when the liberal party emerges victorious in the presidential elections, overshadowing the left and, to a lesser extent, the right. Additionally, we observe a significant rise in the speaking-time share of the radical right in recent years.



Notes: The figure plots the time share dedicated to each group on the different channels in our sample. For each group, dots report the time share dedicated to this group on the channel covering this group the least, diamonds represent the time share on the channel covering this group the most, and the pipes indicate the median time share dedicated to this group. The period considered ranges from September 2002 to August 2020.

Figure 2: Across-outlet differences in the time share dedicated to each political group

the time share dedicated to political guests ranges between 6% and 67%.[36] When considering the share of political coverage each political group receives, we also find substantial variation across outlets. The time share dedicated to right-wing parties (combining both right and radical right) ranges between 23% and 47%, which is more than twice as much. Similarly, the time share dedicated to left leaning groups (including the left, greens, and radical left) varies between 40% and 63%, showing a 23 percentage-point difference. There are therefore substantial disparities in how outlets cover politics, despite the regulatory framework described above. The goal of this article is to understand the drivers of these differences, and in particular the role played by journalists.

3.3 Journalists

The INA data identify the journalists credited in each show. The term 'journalist' is used broadly here, encompassing hosts, reporters, correspondents, columnists, and others, regardless of whether they hold a press card or specialize in political news.[37]

[36]The 24-hour news channels (LCP, BFM TV, CNews and LCI) devote more time to politicians than other channels that are more focused on entertainment (M6 or C8 for instance). This is also the case of the public radio France Info – which provides continuous live news and information – compared to other radio stations.

[37]In France, the press card is issued annually by the CCIJP (*Commission de la Carte d'Identité des Journalistes Professionnels* – Professional Journalists Identity Card Commission). See below for details.

The role of journalists in media organizations Journalists must regularly decide which stories and individuals to feature in their shows, as editorial planning is a key aspect of the broadcast production process (see Cagé et al., 2022, for example).[38] Salhia Brakhlia, a radio morning show journalist, explains her approach to selecting show content: 'We choose our guests ourselves, considering the legitimacy of those we want to hear and the timing of their invitations. That responsibility rests with us.'[39] Moreover, in France, many journalists also produce their own shows (Pasquier, 2008), further influencing the selection of stories and guests.[40]

Journalist characteristics Table 1 presents descriptive statistics for the journalists in our sample. The dataset includes 21,468 distinct journalists (Column 1), of whom 16,637 have participated in at least one show with guests (Column 2). To filter out those who appear only in exceptional circumstances (e.g., during the Olympic Games), we exclude journalists who have made fewer than four appearances and hosted fewer than three guests on a given channel in a given season. Consequently, the estimation sample consists of 16,385 distinct journalists (Column 3). Among these, 8,782 are observed across multiple two-season periods (Column 4), and 4,455 (27%) appear on at least two distinct outlets (Column 5). Columns 6 to 8 focus on similarly defined sets of journalists, but only include shows with at least one politically classified guest. In this political guest estimation sample, there are 12,365 distinct journalists, of whom 6,599 are tracked over multiple periods, and 3,206 are observed across different outlets.

For each show, INA data provide information on journalists' gender – around 40% of them are female – as well as their profession. In the estimation sample, 63% are described as 'reporters', 13% as 'directors', 6% as 'hosts' (*présentateur*) and 6% as 'producers'. To proxy for journalists' prominence, we search whether journalists have a Wikidata entry or a *Les Biographies* (LesBios) entry, the French equivalent of the *Who's Who*.[41] Notably, our identification relies on journalists observed on multiple outlets (Column 5) or staying for multiple time periods on a given outlet (Column 4), and these journalists do not systematically dedicate more or less time to the right or to the left compared to others.

Journalist salary To better understand the consequences of the takeover we analyze in Section 5 and estimate the price of compliance, we manually collected novel annual data data on journalists' employers and wage earnings from the CCIJP, the committee that delivers press cards to journalists. While it should

[38] Bradshaw et al. (2009) examine the role of local television news anchors in the U.S. and how they contribute to the newscast beyond their on-air performances. Most local TV news anchors are actively involved in the news production process, handling many of the essential tasks required for a daily broadcast. Notably, over two-thirds of them participate in scheduling interviews.

[39] In "Choix des invités et des questions, indépendance : comment sont préparées les interviews politiques de franceinfo." *France Info*, 11/22/2023. For additional evidence covering Australia, the U.K. and the U.S. on the central role played by journalists – including in the choice of participants – see Neil (2015).

[40] This is also true in the U.S., where several late-night talk show hosts, such as David Letterman, Trevor Noah, and Jay Leno, produce their shows. Similarly in the U.K., television personalities like Simon Cowell and Jonathan Ross take on similar roles (see e.g. Bennett, 2010).

[41] Appendix Sections A.3.2 and A.4.1 provide details on how we compiled data from these sources that allow us to gather information on renown journalists. Around 7% (resp. 12%) of journalists in the estimation sample have a *Les Biographies* (resp. Wikidata) entry.

Table 1: Descriptive statistics on journalists

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All shows	All shows with guests				Shows with political guests		
	All journ. Mean	All journ. Mean	Est. sample Mean	Dist. periods Mean	Dist. channels Mean	Est. sample Mean	Dist. periods Mean	Dist. channels Mean
Descriptive characteristics								
% female	38.3	39.0	39.0	39.0	38.1	40.3	39.8	39.1
% with profession	90.3	94.2	94.5	98.7	99.2	95.8	99.1	99.3
% *reporter*	53.9	61.9	62.1	71.7	74.8	68.2	76.7	80.6
% *host*	5.3	5.9	6.0	7.1	8.4	6.5	7.3	8.6
% *producer*	6.1	6.0	6.1	6.3	4.5	5.6	5.7	4.1
% *director*	17.8	13.2	13.1	12.0	11.0	11.0	10.2	8.0
% w/ LesBios entry	5.6	6.6	6.7	9.1	12.3	8.2	10.9	14.8
% w/ Wikidata entry	12.0	12.4	12.5	15.1	19.1	13.3	16.0	20.7
% w/ press card (CCIJP)	21.3	26.0	26.1	37.2	40.6	31.6	43.7	47.9
Birth year (CCIJP)	1971.6	1971.8	1971.8	1971.8	1974.0	1972.0	1971.8	1974.1
1st press card year (CCIJP)	1999.2	1999.3	1999.3	1999.1	2000.8	1999.3	1999.0	2000.8
Average annual wage (CCIJP)	56835.9	57102.2	57196.6	59094.0	60795.7	57657.0	59764.7	61587.5
Media presence								
# distinct days	161.9	202.7	205.7	360.6	416.1	264.0	451.9	515.0
# dist. days w/ pol guest	47.3	47.3	47.4	70.3	91.5	47.4	84.7	112.3
# dist. seasons	4.0	4.6	4.7	7.3	7.5	5.5	8.2	8.4
# dist. seasons w/ pol. guest	4.1	4.1	4.1	5.6	5.9	4.1	6.5	6.8
# distinct channels	1.4	1.5	1.6	1.8	2.7	1.7	1.9	2.9
# dist. channels w/ pol. guest	1.4	1.4	1.4	1.6	2.2	1.4	1.6	2.5
% at least 2 channels	27.5	34.0	34.4	47.6	100.0	40.5	52.0	100.0
% at least 2 chan. w/ pol. guest	26.7	26.7	26.7	36.3	77.3	26.7	40.2	100.0
% has any guest	82.6	100.0	100.0	100.0	100.0	100.0	100.0	100.0
# guests	279.8	361.0	366.5	652.4	830.5	478.3	837.7	1051.8
Show time (hours)	64.8	83.6	84.9	150.9	197.7	110.6	193.1	250.6
Time per guest (min)	14.7	14.2	14.2	13.3	13.7	13.3	12.5	13.3
Political guests								
% has any pol. guest	58.9	75.0	75.9	91.7	94.1	100.0	100.0	100.0
# politic. guests	62.8	81.0	82.3	148.2	195.9	109.0	195.8	254.6
Time w/ pol. guest (hrs)	12.4	16.0	16.2	29.1	42.7	21.5	38.5	55.9
Time per pol.guest (min)	13.3	13.3	13.3	12.9	13.7	13.3	12.3	13.3
% time w/ pol. guest	15.3	15.6	15.7	17.0	18.8	20.7	21.0	22.7
% time rad. left	8.8	8.8	8.8	8.8	8.7	8.8	8.6	8.5
% time greens	8.4	8.4	8.4	8.2	7.8	8.4	8.1	7.6
% time left	31.7	31.7	31.7	32.7	32.8	31.8	33.6	33.1
% time liberals	11.0	11.0	11.0	10.3	11.1	11.0	10.4	11.3
% time right	33.0	33.0	33.0	32.9	33.0	32.9	32.4	32.8
% time rad. right	5.2	5.3	5.3	5.5	5.3	5.3	5.4	5.6
# journalists	21,468	16,637	16,385	8,782	4,455	12,364	6,599	3,206
# journalist-channel pairs	30,890	25,528	23,274	14,689	11,344	17246	10,777	8,088
# journalist-show pairs	5,587,296	2,191,391	2,182,190	2,088,896	1,299,508	695,347	665,665	434,598

Notes: The Table provides descriptive statistics on journalists. An observation is a journalist. Column 1 considers all the journalists in our data, irrespective of whether their shows feature guests. Columns 2 to 5 consider journalists who have at least one show with at least one guest, irrespective of whether featured guests are politically classified or not. Column 2 describes all the journalists thus defined ("All journalists"), Column 3 those who are in the estimation sample of equation (2), i.e. we exclude observations of journalists having less than three guests and who appear fewer than four times on a given channel in a given season ("Est. sample"). Column 4 focuses on journalists, among those in Column 3, who are observed on the same outlet in at least two distinct periods ("Dist. periods"), while Column 5 looks at journalists in the estimation sample who are observed on at least two distinct outlets ("Dist. channels"). Columns 6 to 8 do the same but only consider shows with at least one guest who is politically classified. More details are provided in the text.

be noted that not all the journalists observed in the INA dataset are found in the CCIJP archives – as not all of them meet the criteria to be awarded a press card[42] – our new data on salary includes information for 4,576 journalists over 19 years. The resulting data set includes all the journalists we searched and who have a press card, making it exhaustive in this regard. Specifically, the sample includes information on all the journalists observed in the INA data in 2014[43] and who have a press card, and report for each year between 2002 and 2020 how much they earned as well as their job title (even if they no longer work for one of the broadcast media in our sample). Importantly, we also observe these journalists the years when they are unemployed but still apply for a press card. We can also identify journalists who retire if they apply for an emeritus press card, as well as working-age individuals who leave journalism (and thus stop applying for a press card). We provide a detailed description of this data in Appendix Section A.4.2. Table 1 indicates that we have CCIJP data for 25.2% of the journalists in our main estimation sample; this figure increases to 30.5% among journalists observed at least once with a political guest.

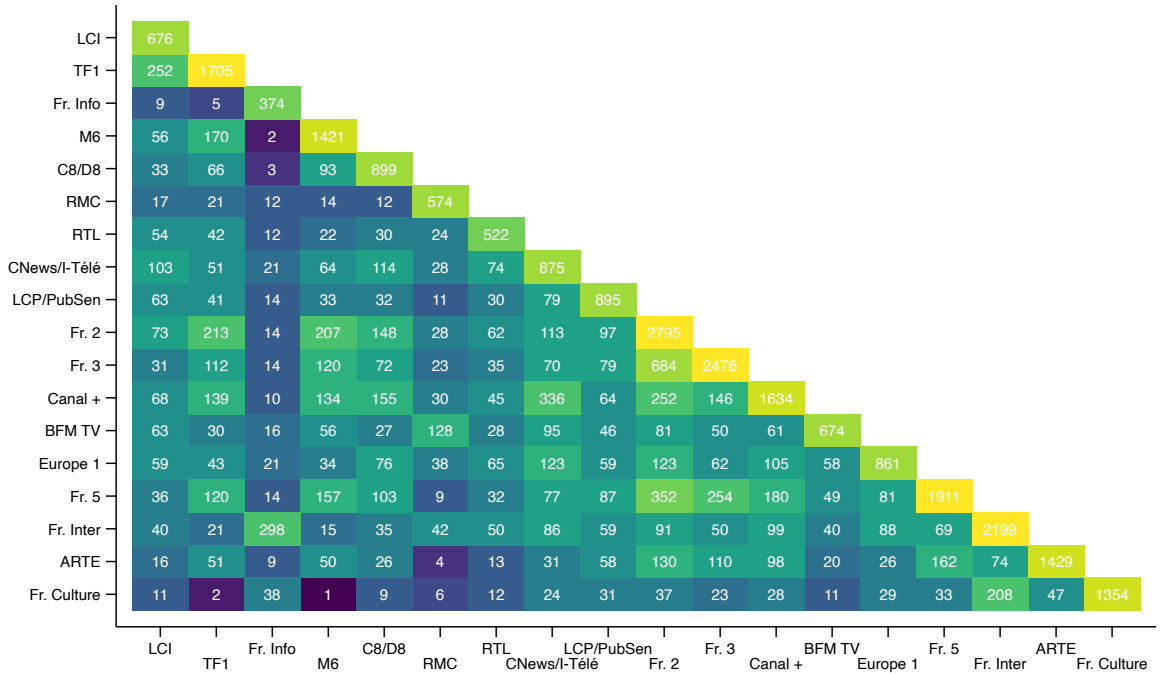
Movers More than a quarter of journalists in the estimation sample are observed on at least two distinct outlets – we refer to these journalists as 'movers'. All the outlets in our sample are interconnected to each other by movers, creating a densely connected network. This is illustrated in Figure 3. It considers the estimation sample (see Column 3 of Table 1) and reports for each outlet pair how many journalists are observed on both outlets. The diagonal reports the number of journalists observed at least once on the considered outlet, irrespective of whether they are also observed on another outlet. Notably, outlets are ranked based on the time share dedicated to left-wing guests: even outlets with largely different political coverage are linked by multiple movers.

The large number of journalists moving across outlets can be explained by several features of the labor market of journalists. First, a large proportion of journalists in French broadcast media do not hold open-ended contracts, which compels them to switch outlets from one season to the next and facilitates the cancellation of programs by media companies.[44] Second, in an increasingly competitive media landscape, the cost of top journalistic talent has risen sharply (Newman et al., 2022). Each year, a 'mercato TV' (TV transfer market) occurs between seasons. Media outlets primarily focus on ratings when negotiating moves, while journalists appear chiefly motivated by compensation. Notably, even well-known journalist-producers, despite their high salaries, often lack stable contracts. Leroux and Riutort (2006) observe that

[42]In France, the profession of journalist was formalized with the creation of the CCIJP in 1935 (see Cagé, 2016). This committee follows the French labor code to deliver the press card. The French labor code defines a professional journalist as "any person whose primary, regular, and remunerated professional activity is associated with one or more daily or periodical publications or news agencies, which provide essential resources." As an example, Laurence Ferrari – who appears in the INA dataset – had her press card denied when working on C8 for *Le Grand 8*, as the talk show was considered an 'infotainment' program, rather than an information program (see Cabot E., "Ferrari et Pulvar, privées de carte de presse", 05/31/2013, *Le Journal du Dimanche*).

[43]We use 2014 as the reference year given that it is the last pre-takeover year (see Section 5 for details on the 2015 ownership change we study).

[44]Many journalists are either temporary show business workers (*"intermittents du spectacle"*) or on fixed-term contracts (the majority practice of the *"contrats de grille"* means that journalists – who also often produce their shows as highlighted above – are hired for a given season, from September to June).



Notes: This Figure plots, for each outlet pair, the number of distinct journalists observed on both outlets in the estimation sample. Figures on the diagonal report the number of distinct journalists observed at least once on the considered outlet, irrespective of whether they are observed on another outlet. Outlets are ordered based on the time share they dedicate to the right, from most (top, left) to least (bottom, right).

Figure 3: Journalists observed on multiple outlets

'the counterpart to the inflation in the compensation of journalists (...) seems to lie in the intrinsic fragility of (their) position,' highlighting 'the maximum duration granted to a program is one season, and those that fail to meet expected audience numbers can be discontinued very quickly.' We further discuss journalists' labor market conditions and bargaining power in Section 5 below.

4 Explaining differences in political coverage across outlets

In this section, we aim to measure the extent to which differences in political coverage across outlets are explained by (i) variations in the composition of journalists, who may on average have differing editorial preferences, and (ii) journalists' adaptation to channel-level editorial policies. Doing so, we also account for the fact that journalists may sort on channels whose editorial policy aligns with their personal editorial preferences.

4.1 Changes in coverage patterns around moves

Descriptive evidence To motivate our approach, we start by showing that journalists adjust their coverage of politics to the outlet they work for, suggesting that they adapt to its editorial policy. To this end, we

focus on movers. We collapse our data at the journalist-outlet-week level, and define a move as a journalist being observed at least two weeks on an outlet c before being observed at least two weeks on another outlet c'.[45] For each of the 8,845 moves, we compute the difference in the time share dedicated to a political group during the journalists' first two weeks on destination outlet c' compared to their last two weeks on the origin outlet c.[46] We then plot this difference against the variation in time share allocation to the same political group between outlets c' and c. If movers dedicate the same amount of time to a political group regardless of the outlet, this indicates that they do not adapt their coverage to their employer, and the slope should be zero. Conversely, if they fully align their coverage with their current outlet's coverage patterns, the slope should be equal to one.[47]

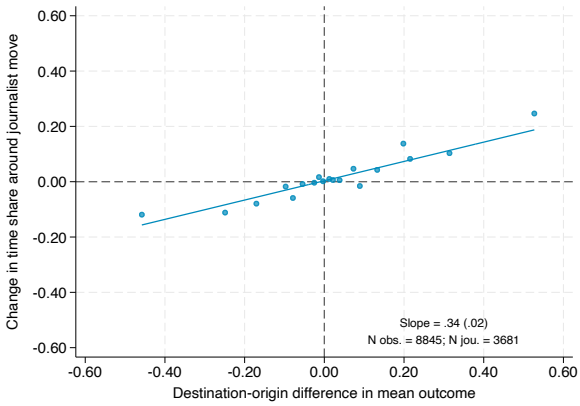
Figure 4 plots the relationship. Panels 4a, 4b and 4c consider the time share when all guests are considered, while Panels 4d and 4e, focus exclusively on political guests. In all cases, the binned scatter plots show a positive, linear relationship. First, when considering the time devoted to political groups as a share of all guests, the slope coefficients range between 0.34 and 0.39, indicating that more than a third of the time movers devote to political guests depends on the channel they currently works for. When focusing solely on political guests, the slope coefficients are higher, ranging from 0.42 for the time spent on left-wing guests (Panel 4d) to 0.71 for right-wing guest (Panel 4e). This suggests that, conditional on featuring political guests, around two-thirds of the time devoted to a political group is shaped by the media outlet. Journalists, therefore, appear to adapt more strongly when deciding which political group to feature than in determining the overall presence of political figures on their shows.

Event study A potential concern is that journalists might switch outlets as their editorial preferences evolve over time. For example, a journalist developing a stronger preference for right-wing guests might move to an outlet known for frequently featuring right-wing figures. To address this, we employ an event-study design to test for pre-trends. Specifically, we consider the move of journalist i at time τ, where τ denotes the first week after the move. Journalist i moves from an origin outlet, $o(i,\tau)$, to a destination outlet, $d(i,\tau)$. We define $\delta(i,\tau)$ as the difference in the channel-level average time share dedicated to a given group between the destination and origin channels: $\delta_{(i,\tau)} = \bar{y}_{d(i,\tau)} - \bar{y}_{o(i,\tau)}$. We then estimate the

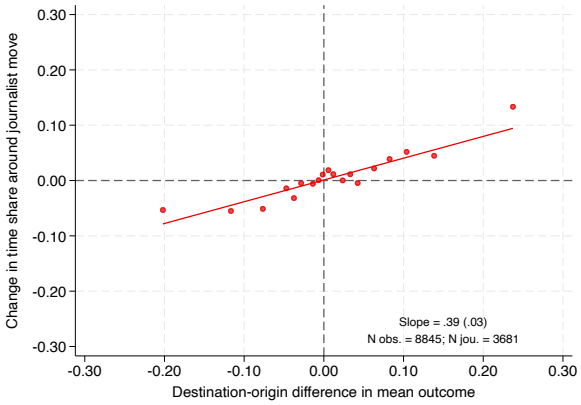
[45] In our preferred specification, we exclude moves for which the last week on the origin outlet is the same as the first week on the destination outlet as it often reflects journalists being simultaneously employed on distinct outlets. In our estimation sample, 1,786 distinct journalists are indeed observed working on multiple outlets over a single week (1,784 on two distinct outlets). One example is Patrick Cohen, who hosted a daily morning show on France Inter (*Le Sept Neuf*) while co-hosting a daily evening show on France 5 (*C à vous*) between 2011 and 2017. Such moves are not helpful to assess the presence of pre-trends, but we provide additional estimation results specifically using those within-week moves below and show below that our results are very similar.

[46] We use a two-week window around the move – rather than, for example, the last pre-move and the first post-move shows – to account for the possibility that journalists may balance their political coverage across multiple shows. For instance, they might invite a right-wing guest at the end of the week after hosting a left-wing one earlier in the same week.

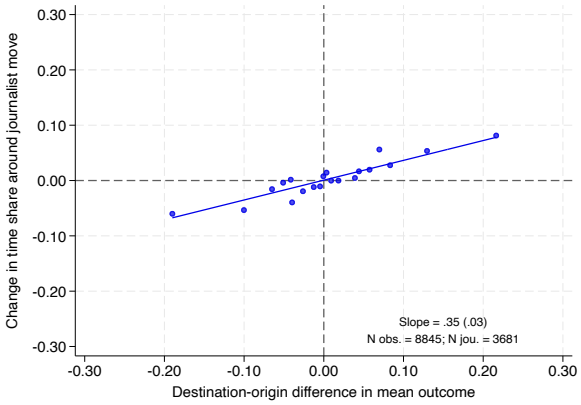
[47] Appendix Figure D.7 plots the distribution of differences in time share between destination and origin outlets. The distribution is roughly symmetric, and while many moves entail modest time-share differences, we observe a substantial number of moves across channels with very distinct coverage patterns.



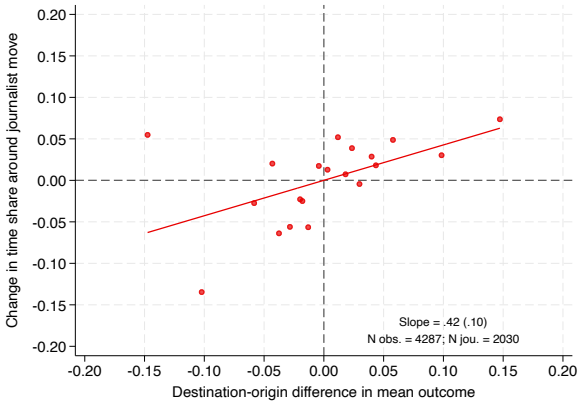
(a) Political guests among all guests



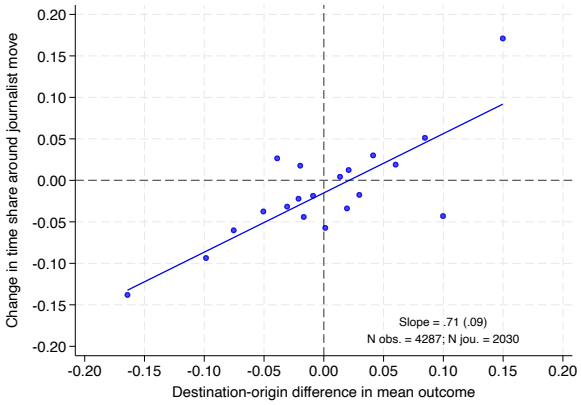
(b) Left-wing guests among all guests



(c) Right-wing guests among all guests



(d) Left-wing guests among political guests



(e) Right-wing guests among political guests

Notes: The Figure shows how the political time share of a given journalist changes before and after a move against the difference in average outcomes across destination and origin channels. The x-axis shows the difference in average speaking-time share between destination and origin channels. The y-axis shows the average speaking-time share difference for a moving journalist between the first two post-move weeks and the last two pre-move weeks. The dots are averages computed by vintiles. The line is the best linear fit from an OLS regression. The slope and the corresponding robust standard error, as well as the number of moves and the number of journalists are reported at the bottom of each figure.

Figure 4: Change in moving journalists' political time share against destination-origin channel differences

following model:

$$y_{i,\tau+r} = \sum_{t=-3, t\neq -1}^{3} \theta^t 1(t = r) \times \delta_{(i,\tau)} + \mu_{(i,\tau)} + \nu_r + \epsilon_{i,\tau+r} \quad (1)$$

where $y_{i,\tau+r}$ is the time share devoted to a given group in shows hosted by journalist i during relative week r, where $r \in (-3, 3)$. $\mu_{(i,\tau)}$ are move fixed effects and ν_r are relative time fixed effects. Standard errors are clustered at the move level. The coefficients of interest are the θ^t and capture the change in the time share around the move.

Figure 5 presents the results. Whether considering the extensive margin – the time share devoted to different groups among all guests – or the intensive margin – the time share devoted to the different political groups among political guests – the invitation patterns change sharply following the move, with no evidence of pre-trends. This suggests that moves are not driven by drifting journalist preferences or temporary shocks, supporting the idea that they can be seen as exogenous. The magnitude of the post-move adjustments are in line with the slope coefficients observed in Figure 4 and remains stable after the move.[48] In other words, journalists do not exhibit gradual adaptation; instead, they seem to adjust immediately to the editorial environment of their new outlet.

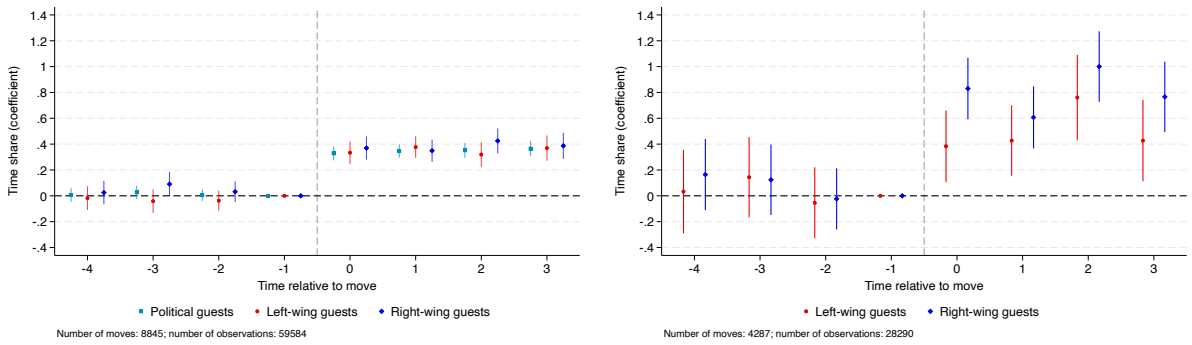
We also test for pre-trends among various subsets of journalists. While some journalists may have little control over their moves due to precarious work conditions, others may indeed move voluntarily, potentially driven by changes in their editorial preferences. To address this, we estimate equation (1) for shows hosted by different types of journalists, distinguishing them based on fame. As shown in Appendix Figure D.8, pre-move estimates are close to zero and not statistically significant, both for the journalists who can be considered famous (given that they have a Wikipedia and/or a *Les Bios* entry) and for the others. Notably, the magnitude of the post-move adjustments is similar across journalist groups, supporting a causal interpretation of the estimates and suggesting that the work environment influences journalists in a broadly consistent manner. Furthermore, we track journalists working on two distinct outlets within the same week, as it is unlikely their political preferences would change in such a short time frame. Doing so means that we focus on journalists who work for two outlets in parallel.[49] Appendix Figure D.9 shows that the slope coefficients from these binned scatter plots are close to those reported in Figure 4.

4.2 Two-way fixed effects model

Model Next, to assess the relative importance of journalists' individual editorial preferences versus their compliance with outlet-level editorial policies in shaping coverage patterns, we estimate the following

[48]The standard errors are larger when the estimation is restricted to shows with at least one political guest. This is because many shows feature no political guests, reducing the number of shows, journalists, and moves available for estimation.

[49]This is for example the case of Frédéric Taddei who used to have a show on Europe 1 (Europe 1 Social Club) and on France 2 (Ce soir ou jamais) from 2014 to 2107. There are 1,784 distinct journalists observed at least once on two distinct outlet during the same week, for a total of 32,282 journalist-week pairs – i.e. these journalists are seen about 18 times on two distinct outlets within a single week.



(a) Extensive margin: Share of all guests

(b) Intensive margin: Share of political guests

Notes: The Figure plots the event-study estimates from equation (1). The dependent variable is the time share devoted by a journalist to a given group in the weeks before and after the move. Sub-figure 5a expresses the time shares as a share of the total speaking time of guests. Sub-figure 5b expresses these shares as a share of the total speaking time of the political guests alone. Light-blue diamonds report the time share of the political guests, red dots the time share of the left-wing guests, and blue squares report that of the right-wing guests. Vertical bars indicate 95% confidence intervals. Standard errors are clustered at the move level.

Figure 5: Event study: Change in the time share devoted to different groups around the move

model, drawing on the approach used by Lachowska et al. (2022):

$$y_{ict} = \alpha_i + \gamma_{c,s(t)} + \tau_{p(c),t} + \epsilon_{ict} \tag{2}$$

where y_{ict} is the time share devoted to guests belonging to a specific group (such as politically classified guests or left-wing guests) in the shows of journalist i on outlet c at time t. Time t is defined as the interaction between weekly date and one-hour time slots (e.g. between 7am and 8am in the first week of 2010).[50] Our observations are structured as follows: for each week and time slot, we aggregate all the shows broadcast on outlet c by journalist i. Since different journalists have varying air times (some may be on air for several hours a week, while others may only appear for a few minutes), we weight observations by the weekly air time of each journalist in the given time slot. As before, we consider both the extensive and intensive margins. In the first case, y_{ict} is defined as the time dedicated to a specific group of guests as a share of all guests. In the second case, we narrow our focus to shows with at least one political guest, computing the time dedicated to guests of a particular political group as a share of the total time dedicated to politically classified guests.

We assume that this time share can be modeled as the sum of three components: (i) a time component that controls for news pressure and audience characteristics ($\tau_{p(c),t}$); (ii) a journalists component (α_i); and (iii) a premium attributed to the outlet ($\gamma_{c,s(t)}$). More specifically, $\tau_{p(c),t}$ consists of time fixed effects at the week $\times$ hourly time slot $\times$ platform level, where platform p refers to either television or radio. This component controls for time shocks (e.g., a news event making a political group more newsworthy) and audience characteristics for each hour of each week on each platform.[51] Thus, these time fixed effects

[50] We use the midpoint of a show to assign it to a given hourly time slot.

[51] It is important to consider the platform, as audience peaks do not occur simultaneously on radio and television, and both

non-parametrically control for demand characteristics at a high frequency. α_i is a set of journalist fixed effects. It reflects an individual journalist's propensity to cover guests from specific groups after accounting for time shocks. It captures time-invariant characteristics, such as preferences or specialization, which may influence their likelihood of covering certain guests. $\gamma_{c,s(t)}$ is a set of channel fixed effects that measures how journalists adapt their coverage based on their outlet. These fixed effects account for channel-level decisions and can be seen as capturing the editorial policy of each outlet.[52] ϵ_{ict} is the error term.

Importantly, since each outlet may periodically adjust its editorial strategy, channel effects are allowed to change every two-season period (indexed by s) following the approach of time-varying AKM models (Lachowska et al., 2022). Assuming that channels' editorial lines remain fixed over long periods is likely unrealistic, especially considering potential changes in ownership and top management. This flexibility allows for the identification of channel effects not only with the 4,456 movers but also with the 8,783 stayers who are observed on the same outlet over multiple time periods (see Table 1).[53]

Identifying assumption We can obtain unbiased estimates of the components in equation (2) using OLS under the conditional random mobility assumption. This assumes that, conditional on journalist effects, time-varying channel effects, and time effects, journalist moves can be considered exogenous. While the model allows for journalists sorting based on their fixed characteristics and channel components, it assumes the additive separability of each component, implying that journalists are not expected to move based on a match component. If a match component were present, the channel effect estimates from equation (2) would reflect a mix of the true effect and the average complementarity of journalist-channel matches.

We assess the plausibility of this assumption in two ways. First, Figure 4 shows that the relationship between journalists' post-move adjustments and the coverage gaps between origin and destination outlets is linear and symmetric. If journalists were moving based on a match component, a transition to an outlet with a higher time share would produce an effect of a different magnitude compared to a symmetric move in the opposite direction. Second, in the presence of match components, the residuals may be particularly large if, for example, journalists who devote substantial time to political guests are paired with a channel that emphasizes political coverage. To investigate this, we split the estimated channel-season and journalist effects into quartiles and compute the mean residual for each quartile pair. Appendix Figure D.10 presents the results. First, residuals are not systematically larger (or smaller) for top or bottom quartile journalist-channel pairs, and the mean residuals for each cell are very small. If match effects are indeed present, they thus appear to be quantitatively negligible.

A second type of endogenous mobility may occur if moves are triggered by changes in journalist

platforms cater to different sets of consumers.

[52]These channel effects capture the influence of peers and management within the outlet that may affect content choices.

[53]Compared to Finkelstein et al. (2016) and Cantoni and Pons (2022), our model does not include relative year fixed effects controlling for adjustment costs. This is motivated by two features of our setting. First, journalists can move several times, and are sometimes observed working on distinct outlets in the same week. Second, Figure 4 shows that journalists moving to similar outlets in terms of coverage exhibit no change in show content, implying that adjustment costs do not seem to play a role here.

preferences.[54] However, the absence of systematic pre-trends in Figure 5 supports the notion that journalists do not switch outlets due to preference shocks.

Variance decomposition We next examine the factors driving differences in editorial slant across outlets. We focus on variations between outlets since, within an outlet, individual journalists may have differing propensities to cover politics or certain parties due to various reasons, including preferences, specialization, skills, or networks.[55] Such differences may cancel each other out, leading to coverage that is not necessarily slanted. We here ask whether the journalists hired by a specific outlet have, on average, a baseline tendency to prioritize certain political groups. If this were the case despite all outlets facing the same news shocks and operating within the same national media market, it would suggest that outlets selectively hire journalists based on their propensity to cover certain parties.

More specifically, we consider the variation across outlet $\times$ period pairs and draw from the methodology developed by Finkelstein et al. (2016) to decompose it. Let $y_{ict}^{net} = y_{ict} - \tau_{p(c),t}$ denote the time share dedicated to a specific group at time t in shows hosted by i on channel c, net of time effects $\tau_{p(c),t}$ that account for political cycles, news shocks and audience characteristics during each show's broadcast.[56] Let $\bar{y}_{cs}^{net}$ and $\bar{\alpha}_{cs}$ represent the expectation of y_{ict}^{net} and α_i across shows on outlet c in period s, respectively. It follows that $\bar{y}_{cs}^{net} = \bar{\alpha}_{cs} + \gamma_{cs}$. After removing time effects, the time share dedicated to a given group is the sum of two components: one attributed to outlet-specific factors (such as editorial policy and management), and the other due to the composition of journalists at that outlet. From this, we can decompose variance across channel $\times$ period as:

$$var(\bar{y}_{cs}^{net}) = var(\gamma_{cs}) + var(\bar{\alpha}_{cs}) + 2cov(\gamma_{cs}, \bar{\alpha}_{cs}) \tag{3}$$

The three terms account for (i) the variance in channel-level decisions, reflecting differences in editorial policies ($var(\gamma_{cs})$); (ii) the variance in average journalist-level decisions, which reflects the differences in journalist composition across outlets ($var(\bar{\alpha}_{cs})$); and (iii) the covariance between the two, which measures the extent to which journalists sort on channels that align with their personal inclination ($2cov(\gamma_{cs}, \bar{\alpha}_{cs})$).[57]

[54] The model however allows journalists to sort based on their fixed preferences, which are captured by journalist fixed effects.

[55] There are many reasons why journalists, within an outlet, may differ in their propensity to cover a particular political group. It can stem from individual preferences, but also specialization (such as expertise in certain policy issues or in reporting on a specific party, or a focus on a politically conservative geographic area), skills (some may be better as entertainers than as political interviewers) or their network (certain journalists may have easier access to specific political figures). Consequently, a media outlet may intentionally hire journalists who complement each other's strengths and perspectives, rather than employing journalists with uniform reporting styles.

[56] Finkelstein et al. (2016) first aggregate their outcome variable at the year level, and then take the average across years, effectively netting out year fixed effects. Given that we have higher frequency time fixed effects to finely control for news and demand shocks, and that not all outlets schedule their shows with guests at the same time, we directly net out time components from our outcome variable.

[57] Finkelstein et al. (2016) propose two main decomposition methods. One of them is a variance decomposition similar to the one presented in equation (3). The second one is a linear decomposition comparing two sets of observations. We focus on the variance decomposition for two reasons. First, the covariance term of the variance decomposition indicates whether journalists sort across outlets, which is of interest in the present setting. Second, it has the advantage that it does not require choosing specific sets of outlets to be compared (e.g. top versus bottom halves or quarters.).

In estimating the variance and covariance terms, we correct for sampling error which may lead to underestimating sorting (Andrews et al., 2008, 2012), using a split-sample approach akin to Finkelstein et al. (2016), Cantoni and Pons (2022) and Best et al. (2023).[58]

4.3 Decomposition of cross-channel variations in coverage

4.3.1 Variance decomposition

Estimation Appendix Table C.2 presents details on the estimation. There are 1,257,785 observations when the coverage share is expressed as a percentage of all guests (Columns 1 to 3) and 481,635 observations when it is expressed as a percentage of political guests only (Columns 4 and 5). The model explains between 44% and 60% of variance in the dependent variable. For all dependent variables, an F-test strongly rejects the null hypothesis that all channel effects are jointly zero (p-value = 0.000), indicating that channel-level decisions significantly contribute to explaining coverage patterns.

Results We next estimate the decomposition of the variation in coverage shares following equation (3). Table 2 presents the results. We first consider the coverage dedicated to political guests as a percentage of all guests (Column 1). Channel-period effects ($var(\gamma_{cs})$) account for nearly 40% of the total variance in coverage share, indicating that journalists adapt the intensity of their political coverage based on the outlet they work for. Regardless of their specialization or preferences, journalists tend to dedicate more time to political guests when they move to an outlet that put more emphasis on politics. Around 20% of the variance is explained by journalist composition ($var(\bar{\alpha}_{cs})$), while 40% is attributed to sorting. Outlets thus appear to selectively hire journalists: those that prioritize political coverage tend to hire journalists with a high propensity to feature political guests. This aligns with the idea that political journalists are more likely to work for outlets specializing in politics, highlighting the importance of this specialization in the hiring process. Further, a similar breakdown is observed when considering the share of coverage dedicated to the left (Column 2) and to the right (Column 3). The proportion of coverage dedicated to a political group among all guests therefore largely depends on whether the show covers politics at all, i.e., on the extensive margin.

We next turn our focus to the intensive margin, examining the share of coverage dedicated to the left (Column 4) and right (Column 5) among political guests. When focusing on which political groups outlets cover – conditional on covering political guests – journalist composition matters much less, explaining only around 6% of the cross outlet-period variance. Outlet-period effects account for approximately 77% of the variance, and sorting for the remaining 17%. This means that differences across outlets regarding which party is covered in political shows are largely driven by outlet-level decisions, with journalists adapting significantly to these editorial choices. While outlets that prioritize the left (resp. right) tend to hire

[58] We randomly split the estimation sample into two subsamples of approximately identical size, stratifying by outlet-period-journalist. We estimate the components of equation (3) by taking the covariance between noisy estimates of the two subsamples, with the idea that the sampling errors are orthogonal.

Table 2: Explaining differences in political coverage: Variance decomposition

	(1)	(2)	(3)	(4)	(5)
	Among all guests			Among political guests	
	Political	Left-wing	Right-wing	Left-wing	Right-wing
Cross outlet-period variance of average:					
Time share, $var(\bar{y}_{cs}^{net})$	0.02572	0.00587	0.00480	0.00349	0.00378
Outlet-period effects, $var(\gamma_{cs})$	0.00989	0.00225	0.00205	0.00261	0.00302
Journalist effects, $var(\bar{\alpha}_{cs})$	0.00557	0.00125	0.00101	0.00026	0.00024
Sorting, $2 \times cov(\gamma_{cs}, \bar{\alpha}_{cs})$	0.01026	0.00237	0.00174	0.00062	0.00052
Correlation:					
Sorting, $cor(\gamma_{cs}, \bar{\alpha}_{cs})$	0.687	0.700	0.595	0.258	0.223
s.e.	0.014	0.021	0.028	0.093	0.099
Share of variance explained by:					
Outlet-period effects	0.384	0.382	0.427	0.748	0.800
s.e.	0.008	0.012	0.017	0.082	0.079
Average journalist effect	0.216	0.213	0.210	0.074	0.063
s.e.	0.006	0.011	0.012	0.035	0.026
Sorting	0.399	0.404	0.362	0.178	0.137
s.e.	0.005	0.007	0.012	0.089	0.083
Observations					
Number of outlet-periods	126	126	126	126	126

Notes: The Table reports components of the variance decomposition proposed in equation (3) based on the parameters estimated using equation (2). Columns 1 to 3 consider the time coverage dedicated to, respectively, political guests, left-wing guests and right-wing guests as a share of the time dedicated to all guests. Columns 4 and 5 focus on the time coverage dedicated to left-wing guests and right-wing guests as a share of the time dedicated to political guests. The first row reports the variance of $\bar{y}_{cs}^{net}$. The second, third and fourth rows report the components of equation (3) (decomposing variance across channel x period), i.e. the variance of γ_{cs}, the variance of $\bar{\alpha}_{cs}$, and twice the covariance between γ_{cs} and $\bar{\alpha}_{cs}$. The fifth row reports the correlation between γ_{cs} and $\bar{\alpha}_{cs}$, and the sixth row indicates the corresponding standard errors. Rows seven to twelve indicate the variance explained by each of the components as a share of the variance of $\bar{y}_{cs}^{net}$, along with the corresponding standard errors. Standard errors are calculated using a bootstrap with 100 repetitions. We follow Best et al. (2023) and randomly resample the residuals, stratifying by outlet-period-journalist triple to preserve the match structure of the observations. The time period is September 1, 2005-August 31, 2019.

journalists more likely to cover the left (resp. right), the degree of selective hiring is small, as journalist composition explains a minor share of the variance. Overall, these results suggest that outlets do not primarily cover politics differently due to hiring journalists with specific editorial or political preferences. Instead, journalists seem to adapt their political coverage to their employer's editorial line, regardless of their own preferences or specialization. We come back to this point in Section 5 below, when documenting the extent of compliance following an ownership change.

Change over time We next assess how this decomposition varies over time. To this end, we estimate equation (2) considering three distinct periods: 2005-2010, 2010-2015, and 2015-2019. We focus on coverage measures expressed as shares of all guests, as the larger number of observations allows for more statistical power. Appendix Figure D.12 shows the results: while the share of variance explained by channel effects was near 25% in the first period, it exceeded 30% in the second one and reached around

50% in the most recent years. The share of variance explained by channel effects has thus more than doubled between 2005 and 2019, indicating that journalists' adaptation to channel-specific editorial lines plays an increasing role in explaining differences in coverage across media. This trend coincides with a decline in the number of journalist positions in France, suggesting that limited job opportunities may be driving journalists to align more closely with their employers' editorial expectations (see Section 5.4 below).

Journalist fixed effects We further investigate whether journalist fixed effects systematically vary based on journalist characteristics (Appendix Figure D.11). Panel D.11a, shows that journalists dedicating more time to political guests are often described as 'reporters' and appear more during prime time. On the other hand, Panel D.11b finds no clear predictors for covering right-wing guests more frequently, suggesting that political coverage depends more on a journalist's specialization or the outlet's editorial line than personal traits. Panel D.11c considers the absolute value of journalist fixed effects, thus focusing on journalists whose coverage of the right deviates significantly from the coverage expected given time shocks. Journalists with less airtime and only occasional appearances tend to deviate more from expected coverage patterns. These journalists likely work on short-term contracts or as freelancers to cover specific events.

4.3.2 Robustness checks

We show that our results are robust to various changes in the specification and sample. First, excluding time periods before elections with stricter political representation rules yields similar results (Appendix Table C.3). Second, our findings remain consistent, both quantitatively and qualitatively, when observations are not weighted by the time dedicated to guests (Appendix Table C.4). We also explore whether the variance explained by channel components decreases if we assume that channel effects are fixed across periods (rather than allowing these effects to change every two-season period as in equation (2); we find no significant change (Appendix Table C.5). Lastly, high-profile journalists may behave differently than others and may not comply to the same extent. Restricting the sample to the 500 most visible journalists (approximately the top 3%[59]) shows that channel effects still account for the largest share of the variance (Appendix Table C.6).

4.4 Channel effects and ownership

Our results indicate that outlet-level editorial strategies significantly influence how journalists cover politics. To explore the relationship between these editorial strategies and ownership, we plot the channel effects by parent company in Figure 6.[60] Notably, all the channels considered are freely accessible nationwide,

[59]The 500 most visible journalists are the 500 journalists with the highest number of appearances in our sample.

[60]For each outlet-owner pair, we take the average fixed effect of the outlet over the ownership period. For example, Vivendi has been the parent company of Canal+, CNews and C8 since 2015. For Canal+, CNews and C8, we take the average of channel-period and of owner-period fixed effects in the periods 2015-2017 and 2017-2019.

meaning that differences in editorial policies cannot be attributed to variations in audience characteristics, such as political leanings or willingness to pay for content.

Considering the share of political guests (Panel 6a), we find that nearly all private parent companies owning multiple outlets have varying degrees of political emphasis among their channels. Typically, one outlet focuses more on political content, while others prioritize non-political guests. This pattern suggests that parent companies adopt a product differentiation strategy by creating specialized outlets to cater to audiences distinctly interested in politics.[61]

In contrast, when examining the share of right-wing guests among political guests (Panel 6b), the outlet effects – reflecting outlet-level editorial decisions – are much more similar and often share the same sign within the same private parent company. Instead of segmenting the market to specialize each outlet for a specific political segment (as would be suggested by a product differentiation model where slant is considered as a product characteristic[62]), owners seem to establish comparable editorial guidelines for political coverage across all their outlets. This suggests that owners may have particular preferences for the type of political content they wish to present and set editorial guidelines accordingly (see, for example, Mastrorocco and Ornaghi, 2025, regarding the Sinclair group in the U.S.). We further explore the relationship between ownership and channel editorial lines in Section 5 below.

5 The case of an owner-induced change in editorial line: adapt or leave?

The results so far quantify the sources of variation in political coverage over the main outlets of the French broadcast sector as a whole. They show that compliance with outlet-level editorial policies is the main driver of slant. To understand why compliance rather than selection appears to be the main force underlying differences in coverage, we now consider the case of the 2015 takeover by Vincent Bolloré of three television channels: Canal+, C8, and CNews.

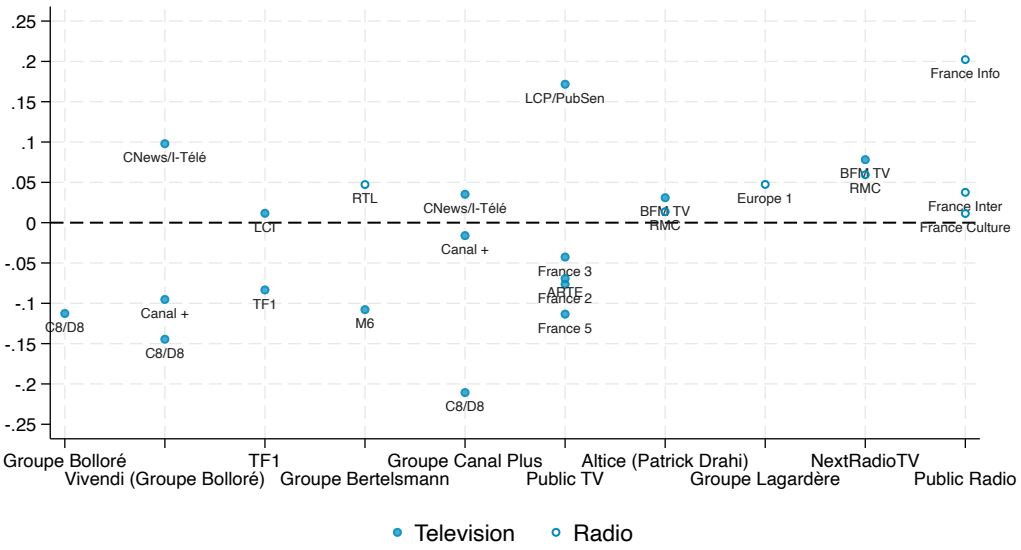
5.1 The impact of Bolloré's takeover on the editorial line

Context Vivendi is a conglomerate in advertising, entertainment, media, and publishing, with a market value of approximately 10 billion euros in 2024. It is the parent company of the Canal Plus Group, which includes major channels like Canal+, CNews, and C8. Vincent Bolloré, the main owner of the Bolloré Group valued at 17 billion euros in 2024, previously owned several free newspapers and two television channels – Direct Star (renamed CStar, dedicated to music) and Direct 8 (renamed C8, focused on entertainment).[63] In 2012, he sold 60% of these channels to the Canal Plus Group in exchange for 1.7% of Vivendi shares.

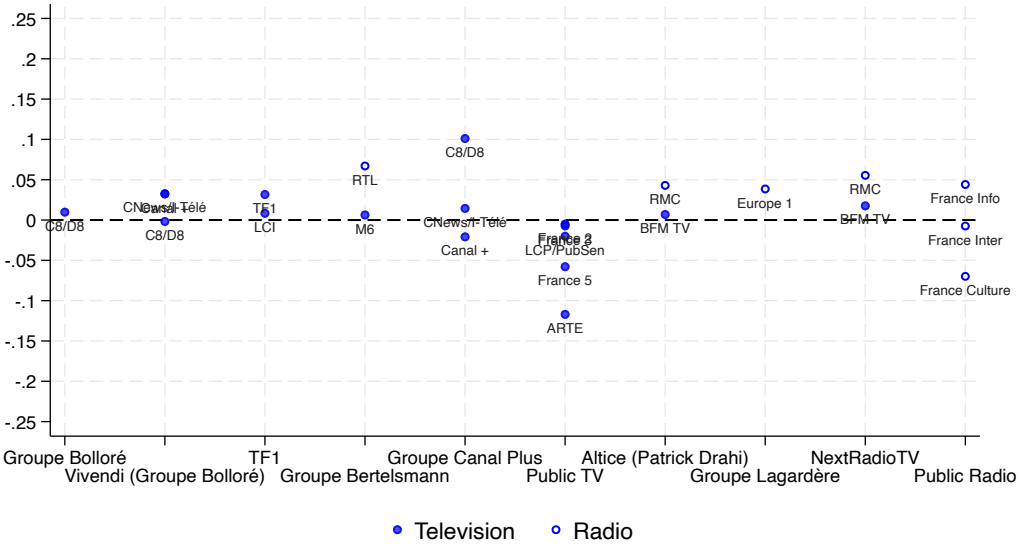
[61] An exception is NextRadioTV that has two outlets that appear to be specialized in politics, but one is a radio channel and the other one a television station, meaning that they already cater to distinct sets of consumers. On product variety in the media industry, see e.g. Berry and Waldfogel (2001); Berry et al. (2016); Fan (2013).

[62] See e.g. Anand et al. (2007); Chan and Suen (2008); Anderson and McLaren (2012); Gentzkow et al. (2014); Cagé (2020)

[63] The Bolloré Group operates in a variety of industries – transport and logistics, plastics, energy, telecommunications, advertising – and in several countries, mostly in Europe and Africa.



(a) Share of political guests among all guests



(b) Share of right-wing guests among political guests

Notes: The Figure reports mean channel-period fixed effects from equation (2) by parent company. Sub-figure 6a reports the results when we consider the share of political guests among all guests, and sub-figure 6b when we consider the share of right-wing guests among political guests. The time period is September 1, 2005-August 31, 2019.

Figure 6: Media outlet fixed effects depending on the parent company

Bolloré took control of Vivendi in 2015, increasing his stake from 5.1% at the beginning of the year to over 14.4% by April. Using a French law designed to benefit long-term investors, he secured 26% of the voting shares, de facto gaining control of the group. In July 2015, Rodolphe Belmer, the CEO of Canal+, was replaced by Maxime Saada, and Ara Apkarian, who managed C8 and CNews, also departed. Vincent Bolloré became chairman of the supervisory board of Canal+ in September 2015. D8 was rebranded as C8 in September 2016. In July 2016, several executives at CNews (formerly I-Télé) were fired, followed by a major strike at the channel in October. CNews officially changed its name from I-Télé in February 2017.

Change in editorial line We first examine whether the coverage of politics on these three channels changed after the takeover when compared to other channels, using a difference-in-differences framework. Our specification is as follow:

$$\begin{aligned} y_{ct} = &\beta_1 1[Treated]_c \times 1[t \in (Apr.2015, Aug.2017)]_t \\ &+ \beta_2 1[Treated]_c \times 1[t \in (Sept.2017, Aug.2019)]_t \\ &+ \delta_c + \tau_{p(c),t} + \gamma X_{ct} + \epsilon_{ict} \end{aligned} \tag{4}$$

where y_{ct} is the coverage share devoted to a given group – either political guests as a share of all guests (extensive margin) or different political groups among politically active guests (intensive margin) – in the shows on channel c during week $\times$ time slot t. $1[Treated]_c$ is an indicator variable for whether the channel is part of Vivendi (Canal+, C8, and CNews). $1[t \in (Apr.2015, Aug.2017)]_t$ and $1[t \in (Sept.2017, Aug.2019)]_t$ are indicator variables for whether shows are broadcast between April 2015 and August 2017, or between September 2017 and August 2019, respectively. The coefficients of interest, β_1 and β_2, capture short- and medium-term changes post-takeover, with the split motivated by the gradual nature of changes occurring on channels, including executive turnover and rebranding between 2015 and 2017. By September 2017, most changes had been implemented. X_{ct} is an indicator variable for C8 from 2005 to 2011, addressing potential differences from previous ownership. Finally, δ_c and $\tau_{p(c),t}$ represent channel and platform-week-time slot fixed effects, respectively. We weight observations by the time dedicated to guests and cluster standard errors at the outlet level.

Table 3 Panel A presents estimates from equation (4). Column 1 looks at the extensive margin (the outcome is the share of political guests among all guests), while Columns 2 to 7 consider guests from each political group as a share of political guests. The takeover had no significant effect on the overall share of political guests. The point estimates are positive, and are suggestive of a 10% increase in the time share devoted to political guests, but they are not statistically significant. For individual political groups, coverage of the radical right increased by 2.0 percentage points in the short run and 5.5 percentage points in the medium run (Column 7), compared to a 7.6% baseline in control channels. In the medium run, this reflects a 70% higher time share for the radical right on Bolloré's channels compared to other

outlets, aligning with the widely reported rise of the radical right on CNews post-acquisition.[64] We find no significant changes for other political groups, but negative point estimates for liberal and right-wing politicians suggest the radical right may have crowded out their coverage.

Table 3: Effect of the takeover on the coverage share of each political group: Difference-in-differences estimates

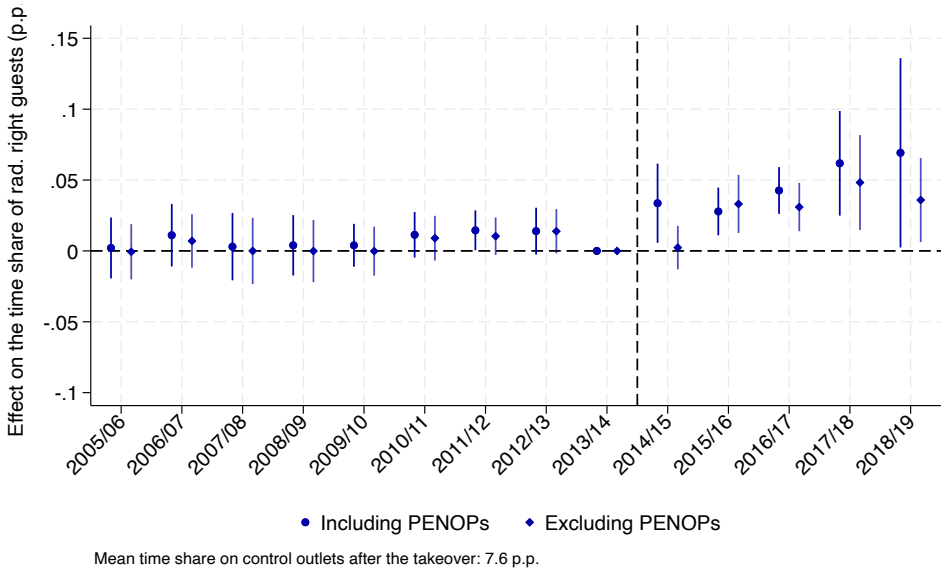
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. With channel fixed effects						
	Political	Rad. left	Greens	Left	Liberal	Right	Rad. right
Treated×2015/17	0.0199	0.00487	-0.00116	-0.0106	-0.00493	-0.00593	0.0198**
	(0.0254)	(0.00756)	(0.00429)	(0.0147)	(0.00608)	(0.00663)	(0.00874)
Treated×2017/19	0.0220	0.00351	-0.00413	0.00368	-0.0294	-0.0297	0.0553*
	(0.0277)	(0.0117)	(0.00360)	(0.0136)	(0.0283)	(0.0184)	(0.0290)
Observations	150036	79537	79537	79537	79537	79537	79537
R^2	0.622	0.433	0.413	0.477	0.540	0.502	0.466
$\bar{y}$(control, post)	.216	.101	.06	.304	.202	.246	.076
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel B. With journalist-channel fixed effects						
	Political	Rad. left	Greens	Left	Liberal	Right	Rad. right
Treated×2015/17	0.00618	-0.0130	-0.000875	-0.00985	-0.00547	0.0153	0.0165***
	(0.0191)	(0.0104)	(0.00335)	(0.0151)	(0.00704)	(0.0109)	(0.00435)
Treated×2017/19	0.0531	-0.0220	-0.0103	-0.00861	0.0120	0.000495	0.0319*
	(0.0307)	(0.0205)	(0.00714)	(0.0161)	(0.0241)	(0.0207)	(0.0175)
Observations	1268239	478200	478200	478200	478200	478200	478200
R^2	0.626	0.452	0.441	0.466	0.529	0.477	0.465
$\bar{y}$(control, post)	.216	.101	.06	.304	.202	.246	.076

Notes: The outcome variable is the time share of distinct groups: political guests as a share of all guests (Column 1), radical left (Column 2), greens (Column 3), left (Column 4), liberals (Column 5), right (Column 6), and radical right (Column 7) as a share of political guests. Panel A estimates correspond to equation (4) (observations are at the channel-week-time slot level), and Panel B estimates to equation (6) (observations are at the journalist-channel-week-time slot level). Standard errors are clustered at the outlet level and stars indicate significance at the 1, 5, and 10% levels with ***, **, and *, respectively. The time period is September 1, 2005-August 31, 2019.

The identifying assumption underlying our difference-in-differences framework is that trends are parallel before the takeover. Slightly amending equation (4), we test this assumption by interacting the treatment indicator with a set of season indicator variables. Figure 7 plots the coefficients for the coverage share of the radical right. We find no evidence of diverging pre-trends; the pre-2015 estimates are not statistically significant and are close to zero. In contrast, the radical-right coverage share increases visibly after 2015, strengthening over time. This supports the validity of the difference-in-differences design,

[64]This was particularly evident during the 2022 presidential campaign when CNews gave a platform to far-right candidate Éric Zemmour. See for example, "Vincent Bolloré, Éric Zemmour and the rise of 'France's Fox News'?," *Financial Times*, October 5, 2021, and "A Fox-Style News Network Rides a Wave of Discontent in France," *The New York Times*, September 14th, 2021. Section 6 discusses the impact of this shift to the radical right on electoral outcomes.

allowing for a causal interpretation of the estimates.[65]



Notes: The Figure plots estimates from the event-study specification corresponding to equation (4). The dependent variable is the speaking-time share of radical-right guests. The vertical line marks Vincent Bolloré taking control of the channels. Standard errors are clustered at the channel level, and vertical bars indicate 95% confidence intervals. The time period is September 1, 2005-August 31, 2019.

Figure 7: Event-study regression: Radical-right time shares around Bolloré takeover

The role of PENOPs Table 3 includes both politicians and PENOPs in the measure of coverage given to each political party. While regulators monitor the speaking time given to politicians under pluralism rules, this does not apply to PENOPs. Figure 7 thus also reports event-study estimates excluding PENOPs. Although we still observe a statistically significant increase in the radical right's time share after Bolloré's takeover, the increase is smaller. This suggests that outlets may find it easier to slant content by featuring PENOPs, allowing them to bypass pluralism regulations.

Extensive margin response We investigate whether political figures from certain partisan groups became more or less likely to receive coverage after the takeover. This shift could occur if guests began accepting or declining interview requests from Bolloré outlets based on their opinion of the new editorial direction. For instance, if figures from a particular group started boycotting Bolloré outlets, they would be featured less frequently post-takeover. To analyze this, we consider all possible guest-outlet-week combinations and explore whether the takeover influenced the likelihood of political guests being featured, reflecting

[65]Appendix Figure D.13 reports similar event studies for the other political groups, it similarly shows no pre-trend.

either a narrowing or broadening of the guest pool. We estimate the following specification:

$$\begin{aligned} y_{jct} = &\beta_1 1[Treated]_c \times 1[t \in (Apr.2015, Aug.2017)]_t \\ &+ \beta_2 1[Treated]_c \times 1[t \in (Sept.2017, Aug.2019)]_t \\ &+ \alpha_{jc} + \mu_{jt} + \epsilon_{jct} \end{aligned} \tag{5}$$

where y_{jct} indicates whether political guest j appeared on outlet c in week t. α_{jc} captures the baseline likelihood of a guest appearing on a given outlet, while μ_{jt} accounts for their newsworthiness. Coefficients β_1 and β_2 capture whether political guests became more likely to appear on acquired outlets post-takeover. We further interact these estimates with political group indicators to investigate whether guests from specific political groups became relatively more or less likely to be featured. For example, if radical-right politicians were less likely to decline interviews, these interaction terms should be positive. Appendix Table C.8 reports the results.[66] Acquired outlets do not become more nor less likely to feature political guests at least once per week. This effect remains similarly close to zero regardless of the political group. This suggests that the takeover did not make it harder to cover guests from a specific political group.[67] Rather, the rise in radical-right coverage appears to be due to radical right guests being featured more lengthily than others.

Viewership Finally, we explore whether this shift to the radical right led to increased viewership, as the new management may have aimed to boost profits by catering to viewer preferences (Gentzkow and Shapiro, 2010). Using quarterly viewership data, we compare acquired outlets to others in an event-study design. Appendix Figure D.15 reports the results. The takeover had a short run negative impact on audience numbers for Vincent Bolloré's channels before a return to normal. This suggests that the editorial change was not evidently better fitted to audience tastes.[68]

5.2 Adapt

The results show a sharp increase in radical-right coverage following the takeover. How did journalists respond? We here examine whether those who remained at the newly-acquired outlets adapted to the new editorial line by analyzing changes in the time shares devoted to each group for each journalist-channel

[66] Appendix Figure D.14 reports event study estimates for each interaction term; it shows no pre-trend.

[67] Remember furthermore that, as already highlighted, the guests include both the individuals who are are physically present in the studio and thus who are not, as long as they speak during a show. Thus, even if a given individual was unwilling to attend a show, the media outlet would still be able to broadcast him/her, e.g. by broadcasting images of his/her meetings or of an interview given on another channel.

[68] Fully assessing whether this editorial change was profitable would require additional data on shows' production costs and advertising price, which may increase with ratings but may also vary based on audience characteristics. This is beyond the scope of this study.

pair. We estimate the following specification:

$$\begin{aligned} y_{ict} = &\beta_1 1[Treated]_c \times 1[t \in (Apr.2015, Aug.2017)]_t \\ &+ \beta_2 1[Treated]_c \times 1[t \in (Sept.2017, Aug.2019)]_t \\ &+ \alpha_{ic} + \tau_{p(c),t} + \gamma X_{ct} + \epsilon_{ict} \end{aligned} \tag{6}$$

y_{ict} is the time share for a specific group in the shows of journalist i on channel c during week $\times$ time slot t. Compared to equation (4), we control for channel-journalist fixed effects (α_{ic}) rather than only for channel fixed effects. We thus exploit within journalist-channel pair variation. As before, observations are weighted by air time.

Panel B of Table 3 presents the estimates for the share of political guests among all guests (Column 1) and for each political group among political guests (Columns 2 to 7).[69] For journalists who stayed, the time share of radical-right guests increased by 1.65 percentage points in the short run and 3.19 percentage points in the medium run (compared to 7.6% on control channels). No significant changes are found for other parties or the overall share of political guests (Column 1).[70] The coefficients in Panels A and B are quite similar, just slightly lower for radical-right guests in Panel B, suggesting that continuing journalists nearly fully complied with the new editorial line.

Robustness We test the robustness of our specification in Appendix Table C.7. Column 1 reports baseline estimates. In Column 2, we focus exclusively on prime-time hours, finding somewhat stronger effects, suggesting that the increase in radical-right guests was at least as visible during peak viewership hours. When analyzing journalist-channel pairs, the effects are stronger in the short run but weaker in the medium run, likely due to prime-time journalists shifting to less-watched slots. Dropping pre-election periods during which the time dedicated to candidates is strictly monitored by Arcom (equal speaking and air time rules) yields similar results (Column 3). In Column 4, replacing platform-week-hour fixed effects by week fixed effects shows consistent results, though slightly lower in Panel B. In Column 5, again using week fixed effects, we only use radio stations as a comparison group. Unlike other television channels – which may have reacted to Bolloré's outlets by either mimicking them with more radical-right coverage or by differentiating themselves with less radical-right content – radio stations do not directly compete with these outlets and are less likely to have been influenced by the takeover. The estimates remain very similar to the baseline results. In Column 6, the outcome variable is defined excluding guests who are PENOPs. Consistently with the above results, the effect tends to be smaller, plausibly because pluralism rules only apply for politicians.

[69] See Appendix Figure D.16 for the corresponding figure documenting the absence of pre-trends.

[70] Although radical-right guests may have crowded out those from the radical left and greens, the effects are not statistically significant.

5.3 Leave

Results so far show that journalists who stayed on Bolloré's channels complied with the new editorial guidelines. In this section, we explore whether journalists left – voluntarily or not – the acquired channels after the takeover, as only those in line with the new editorial line may have stayed.

Probability of leaving To do so, for each journalist-channel pair, we define an indicator variable equal to one if a journalist appearing on a given channel in quarter t is no longer observed on the same channel in quarter $t+4$, i.e., one year later. We then compare the likelihood that a journalist leaves the channel across treated channels (Canal+, C8 and CNews) and control channels. The specification is as follows:

$$y_{ict} = \sum_{q \neq 2013q1} \beta_q 1[Treated]_c \times 1[t=q]_t + \alpha_{ic} + \delta_t + \epsilon_{ict} \tag{7}$$

where y_{ict} indicates whether journalist i observed on channel c in quarter t is no longer on that channel in quarter $t+4$. As before, α_{ic} are journalist-channel pair fixed effects, and δ_t are quarter fixed effects. $1[Treated]_c$ indicates whether the considered channel is one of those controlled by Vincent Bolloré in 2015. $1[t=q]_t$ are quarter indicator variables. The coefficients of interest, β_q, capture the difference in the probability of a journalist leaving across treated and control channels.

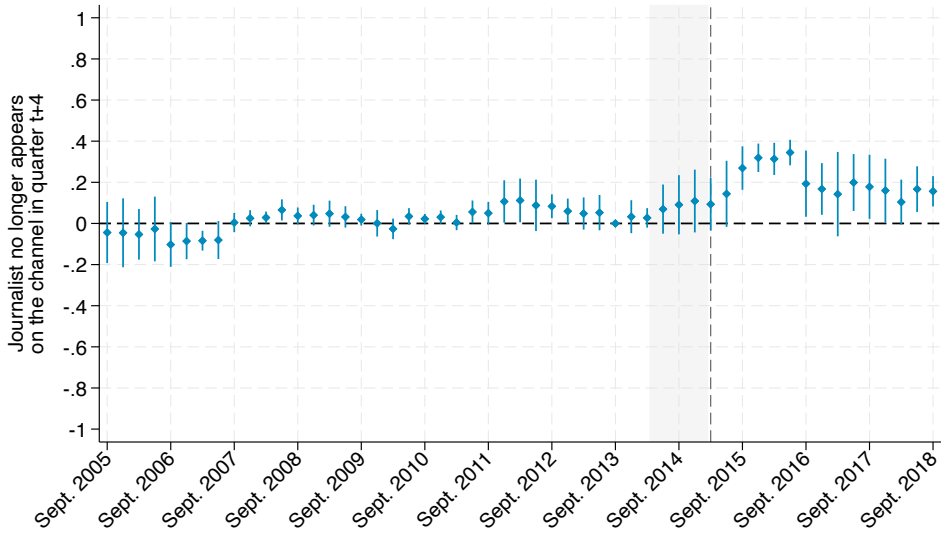
Figure 8 displays the estimates. Prior to the takeover, the likelihood of journalists leaving their network showed similar trends across both treated and control channels (Panel 8a), supporting the causal interpretation of our findings. However, beginning around September 2015, journalists on acquired channels became significantly more likely to stop appearing on screen. For instance, journalists working on one of Bolloré's channels in 2016 were about 20 percentage points more likely to stop being on the channel the following year (see also Table 4, Column 1). As a reference point, the baseline probability that journalists would cease to appear on a control channel at the same time was around 50%, meaning that the probability of journalists leaving increased by 40% after the takeover.[71]

Composition Were the journalists who stayed those most aligned with the new editorial guidelines? Journalists may value producing content that aligns with their editorial preferences.[72] As such, we find that those who were the most exposed to the change in editorial line were the most likely to leave and that there is a positive correlation between outlet effects and average journalist effects (Section 4), implying that journalists tend to work on outlets whose editorial line aligns with their own preferences.

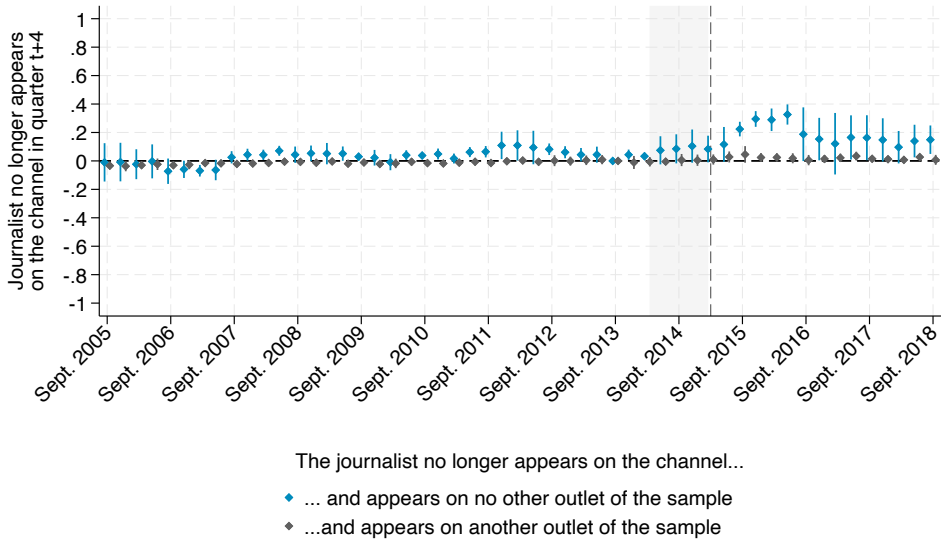
From there, we ask whether the journalists who stayed had editorial preferences differing from those who left, as measured using the individual fixed effects estimated in equation (2). We interact the difference-

[71] Appendix Table C.9 reports the difference-in-differences estimates. Appendix Table C.10 provides the breakdown by channel; the effect is present on all three channels. CNews saw the largest outflow (with a 32 percentage-point increase both in the short and medium run), followed by Canal+ (16 percentage-point increase in the short run) and C8 (4 percentage-point increase in the short run and 11 in the medium run).

[72] For instance, Spenkuch et al. (2023) study bureaucrats and show that they are less motivated to pursue the organizational mission when they are ideologically misaligned with the presidency.



(a) Whether journalists leave



(b) Whether journalists leave and are observed on another outlet

Notes: The Figure plots estimates from event-study regressions corresponding to equation (7). The dependent variable is an indicator variable equal to one if a given journalist-channel pair observed in quarter t is still observed in quarter $t+4$. In Panel a, we consider the likelihood of journalists leaving. In Panel b, we consider whether a journalist left and is seen on another outlet of the sample (grey) or on no other outlet of the sample (blue). The shaded area corresponds to the season running from March 2014 to March 2015, when Vincent Bolloré took control of the channels. Standard errors are clustered at the channel level, vertical bars indicate 95% confidence intervals. The time period is September 1, 2005-August 31, 2019.

Figure 8: Event-study regression: Whether journalists leave – probability of staying on Bolloré's channels after the takeover

Table 4: Probability that journalists are no longer observed on the same channel a year later, Depending on the journalists' characteristics: Difference-in-differences estimates

	(1) Baseline	(2) 1(Reporter)	(3) 1(Newscaster)	(4) 1(High wage)	(5) 1(Older)	(6) 1(Producer)	(7) 1(Famous)	(8) 1(Male)
Treated × 2015/17	0.187***	0.138**	0.125**	0.286***	0.268***	0.218***	0.187***	0.287***
	(0.0499)	(0.0521)	(0.0566)	(0.0557)	(0.0489)	(0.0463)	(0.0523)	(0.0617)
Treated × 2017/19	0.117*	0.0495	0.0778	0.181**	0.134**	0.139**	0.150*	0.264***
	(0.0665)	(0.0503)	(0.0643)	(0.0729)	(0.0561)	(0.0652)	(0.0819)	(0.0489)
Treated × 2015/17 × Inter=1		0.155***	0.315**	-0.0791*	-0.0792	-0.197***	-0.00473	-0.136***
		(0.0382)	(0.122)	(0.0396)	(0.0523)	(0.0455)	(0.0262)	(0.0352)
Treated × 2017/19 × Inter=1		0.412***	0.365***	-0.161***	-0.126**	-0.0958	-0.112**	-0.191***
		(0.0610)	(0.108)	(0.0556)	(0.0503)	(0.0614)	(0.0468)	(0.0553)
R^2	0.496	0.497	0.497	0.432	0.431	0.497	0.496	0.495
Observations	278,493	278,493	278,493	106,590	106,590	278,493	278,493	276,956
$\bar{y}$ (treated, pre)	0.396							
$\bar{y}$ (treated, pre, inter=0)		0.404	0.403	0.316	0.300	0.386	0.423	0.420
$\bar{y}$ (treated, pre, inter=1)		0.382	0.369	0.272	0.273	0.457	0.337	0.384

Notes: The outcome variable is an indicator for whether a given journalist-channel pair existing in quarter t no longer exists in quarter $t + 4$. Column 1 presents the baseline specification. The interaction variable indicates whether the journalist is credited as a reporter in t (Column 2), whether the journalist works for a newscast in t (Column 3), whether the journalist has an above-median wage (Column 4), whether the journalist has an above-median age (Column 5), whether the journalist is credited as a producer in t (Column 6), whether the journalist has a *Les Biographies* or Wikidata entry (Column 7), whether the journalist is a male (Column 8). The number of observations is lower in Columns 4 and 5 given that the salary and age information come the CCIJP data, and not all the journalists have a press card (see the text for details). The last rows report the mean of the outcome variable on control channels for the period ranging from April 2015 to August 2019. Standard errors are clustered at the outlet level and stars indicate significance at the 1, 5, and 10% levels with ***, **, and *, respectively. The time period is September 1, 2005-August 31, 2019.

in-differences term of equation (7) with indicator variables for whether these journalists had a positive individual fixed effect regarding the coverage of each political group. Appendix Table C.11 reports the results. Journalists who have a higher propensity of covering political figures in general were much more likely to leave (Column 2). However, when considering each political group separately, whether journalists tend to dedicate more coverage to a certain group is at best only weakly influencing their propensity to leave.[73] In particular, journalists who tend to cover the right or radical right more were equally likely to leave (Columns 7 and 8). In other words, while the journalists covering politics more were much more likely to leave, their slant did not play a major role in their decision.

Taken together, the results so far show that the shift to the radical right was not primarily the result of a change in the composition of journalists, as the ones staying were not specifically those favoring this political group. Instead, the journalists who stayed adapted by increasingly featuring radical-right voices in their shows. This is very much consistent with the results presented in Section 4 showing that, when it comes to which political groups receive coverage, differences across outlets are largely driven by channel-level decisions, rather than by the composition of their employees.

[73]The journalists more inclined to covering the radical left and the liberals were slightly more likely to leave in the short run.

5.4 Why compliance rather than composition?

To rationalize why changes in slant appear driven by compliance rather than by a change in the composition of journalists, we finally investigate the costs associated with making journalists comply to the new editorial line.

Who are those who left If journalists' baseline compatibility with their employer's editorial guideline does not predict them leaving or staying, then what does? Table 4 reports the difference-in-differences estimates interacted with several journalist characteristics to explore the characteristics of those leaving. Journalists working as reporters (Column 2) or in charge of a newscast (Column 3) were at least twice as likely to leave. The increase is strikingly large – around 30 percentage points in the short run for newscasters. These journalists were potentially those who were the most impacted by the change in editorial line, which mostly affected the composition of political guests covered, rather than their overall presence.

In contrast, journalists with higher wages (Column 4), who are older (Column 5), working as producers (Column 5), who are better known[74] (Column 6) and who are male (Column 7) were comparatively more likely to stay. To the extent that these characteristics are associated with a higher bargaining power, one may hypothesize that these journalists reached an agreement with the new management regarding the continuation of their position. But – at least for the better payed and older journalists – it may also reflect the fact that it is more costly for them to leave, as they have more to lose. Everything else equal, there is indeed evidence of a negative age bias during recruitment (Carlsson and Eriksson, 2019; Neumark et al., 2019; Neumark, 2024), and it might be difficult for a relatively-well paid journalist to find a similar position that pays equally well. Hence, they may be more inclined to comply.

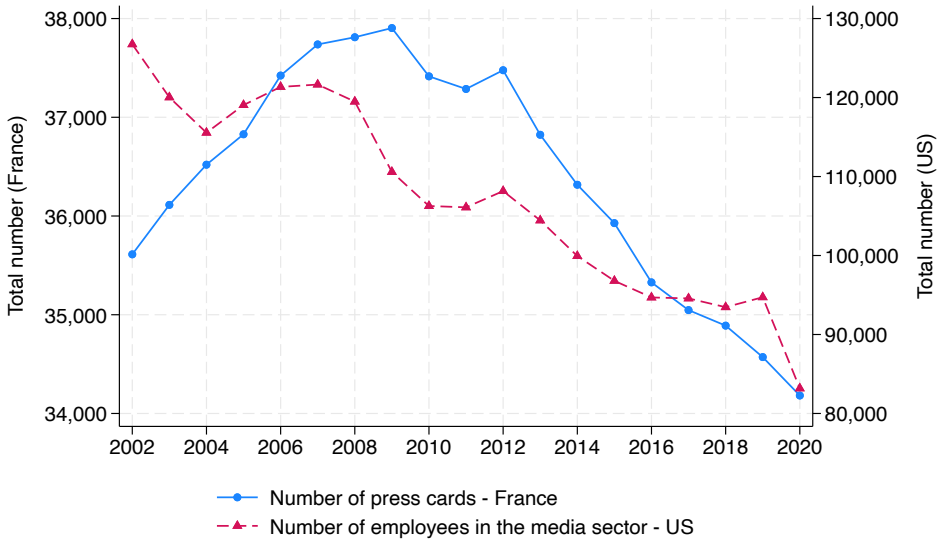
Where do they go? We next ask where the journalists who left the acquired outlets went, and in particular whether they move to a similar position as this is indicative of whether they left voluntarily. Figure 8b indicates that, among those who no longer appear on acquired outlets, nearly all of them are seen on no other outlet in our sample – which includes all the leading French television and radio stations.[75] Appendix Table C.9 reports the corresponding difference-in-differences estimates. In the short run, the takeover caused a 16 percentage-point increase in the number of journalists not observed on any channel in our sample in quarter $t + 4$. Compared to the share of journalists who left acquired channels before the takeover – 33.6%[76] – this is a 48% increase. Possibly, the journalists who left acquired outlets had no option of staying and had to find a job soon after, even if in a different kind of media outlet (print, online, etc.) or out of the media industry altogether.

[74] As before, we use the presence of a *Les Biographies* or a Wikidata entry as a sign that the journalist is well known.

[75] For the subset of journalists who have a press card, we follow them below across all outlets, including for instance print newspapers, and document a similar pattern.

[76] While this baseline probability to leave may seem high, it reflects the fact that – as highlighted above – many journalists are temporary show business workers and on fixed-term contracts. The media industry is thus characterized by a very high turnover, a tendency reinforced by the fact that the number of journalist positions is declining (see below).

It may indeed be difficult for journalists to find a similar position in a competing outlet in a context of declining number of positions. Indeed, as illustrated in Figure 9, the number of press cards delivered each year in France has declined since 2009, with a 10% drop between 2009 and 2020. This reflects an increasingly competitive job market for journalists (blue line with dots). As detailed in a 2024 comparative Reuters Institute's analysis, "every year seems to be the worst year for journalism lately (...). Very few [journalists] manage to get a stable and well-paying job."[77] The shrinking of the journalist job market is indeed far from being specific to France, and we observe mergers, closures and layoffs in many other Western democracies. In the U.S., between 2007 and 2020, the newsroom employment declined by 31% (dashed red line with triangles).



Notes: The Figure plots the evolution of the number of journalists in France and the U.S. between 2002 and 2020. For France, this number corresponds to the total number of press cards delivered by the CCIJP. For the U.S., the newsroom employment was computed by the authors using the "Occupational Employment and Wage Statistics" (OEWS) tables provided on the Bureau of Labor Statistics (BLS)' website. We consider as employed in the media sector News Analysts, Reporters, and Correspondents, Radio operators and Photographers.

Figure 9: Evolution of the number of journalists, France and the U.S., 2002-2020

Furthermore, it is important to note that this drop in newsroom employment also reflects an important number of journalists being unemployed – i.e. still looking for a job as a journalist but unable to find one. In France, following a job loss, journalists can still request a press card as "unemployed"; in 2020, nearly 5% of the press cards delivered were delivered to unemployed journalists. This can indicate either (or both) journalists' attachment to their career as a journalist and so unwilling to change sector, or the lack of adaptability of journalists' competencies to other sectors.

The monetary cost of compliance: Wage and employment To further understand the long-term consequences of the takeover for journalists, we analyze the probability that they are still awarded a press

[77] https://reutersinstitute.politics.ox.ac.uk/news/shrinking-path-ten-young-journalists-open-about-their-struggles-break-news-industry

card up to five years after Bolloré took over their media outlet (compared to the journalists working for the media outlets in the control group at the time of the takeover) and how their earnings evolve. No longer receiving a press card directly indicates a job change, as it means that the individual is no longer working as a "professional journalist" as defined by the CCIJP (i.e. she no longer collaborates with a news media as defined by law and/or that she no longer performs a journalistic function). To this end, we use the dataset compiled from the CCIJP archives in which we track the exhaustive work history of the journalists who had a press card in 2014 and were working on one of the outlets in our main sample.[78] We estimate the following specification:

$$y_{it} = \sum_{q \neq 2014} \beta_q 1[Treated]_i \times 1[t = q]_t + \alpha_i + \delta_t + \gamma X_{it} + \epsilon_{it} \tag{8}$$

where y_{it} is the annual gross wage earnings or the press card status of individual i in year t, and $1[Treated]_i$ indicates whether this journalist was working for one of the Bolloré channel at the time of the takeover. α_i is a set of journalist fixed effects and δ_t a set of year fixed effects. With X_{it}, we control for the age and age squared of journalists (everything else equal, more experience can indeed be associated to a higher salary). Standard errors are clustered at the journalist level.

Figure 10 reports the results. In Panel a, the outcome of interest is the annual wage earnings of the individual, expressed in 2020 euros. It is equal to zero if the individual has no earnings as a journalist, which may be due to the fact that the individual is unemployed, or that she is employed, but no longer as a journalist.[79] The figure shows that, in 2015 and 2016, the takeover translated in a €$5,000$ to €$10,000$ drop in annual earnings for journalists, down from an average of about €$52,000$. It took three years to the individuals to then recover. This drop may be driven either by the fact that the treated journalists have a higher probability to stop working as journalists (extensive margin) or by the fact that, while still working as journalists, their salary decreases compared to the one of the journalists in the control group.

Panel b considers whether individuals continue working as a journalist. By 2020, the journalists who worked on an acquired outlet in 2014 were about 5 percentage points less likely to still be in journalism, down from an average of 73.1% among journalists who were working on control outlets (-7%). For departing journalists, the takeover thus implied a drastic career change; not only did they have to work for a different type of employer, but many appear to have left the journalism career they had initially embraced.

In Panel c, we focus on the subset of individuals who are observed working as journalists, and take the logarithm of their annual wage earnings. We find no evidence of a wage increase following the takeover (while one might have expected such an increase either if the novel owner had to compensate the

[78] We have collected data on the exhaustive work history of journalists who had a press card and who were working in 2014 on one of the following outlets: Arte, BFM TV, C8, Canal +, CNews, Europe 1, LCI, LCP, M6, RMC, RTL, and TF1. As detailed in Appendix Section A.4.2, we do not have exhaustive data on journalists working for Radio France and France Télevision, and we therefore exclude them from this part of the analysis. We further focus on journalists we observe having a press card in at least two years before 2015, the year of the takeover (doing so, we exclude journalists who have a press card only once before the takeover and thus do not appear to work as journalists on a stable basis).

[79] A third possibility can come from the fact that the individual retired (see below).

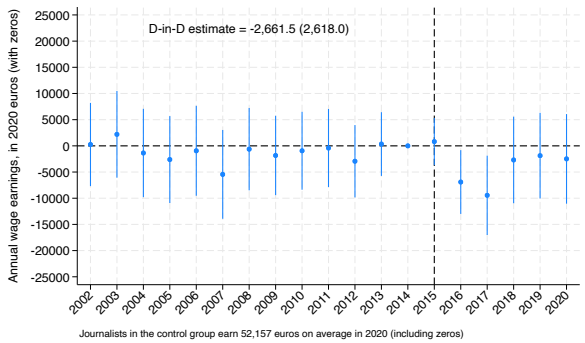
journalists for complying with the novel editorial line, or if the journalists who left did so to increase their compensation). Focusing more specifically on those who are observed during the 2018/2019 season on an outlet owned by the same parent company as in 2013/2014, we find that the journalists who stayed on Bolloré outlets had wages that kept pace with those of journalists on other outlets (Panel 10d).

As a robustness check, we consider the fact that some individuals stop working as journalists because they retire. In the later case, the decision not to stay is driven by very different motivations. Appendix Figure D.17 reports the same estimates as in Figure 10 but, for the subset of journalists who retired (and that we observe given that they obtain an emeritus press card), we exclude them for the sample at the time of retirement (rather than considering that their wage as a journalist is equal to zero). In the same spirit, Appendix Figure D.18 excludes journalists older than 62 and younger than 20. The results are very similar.

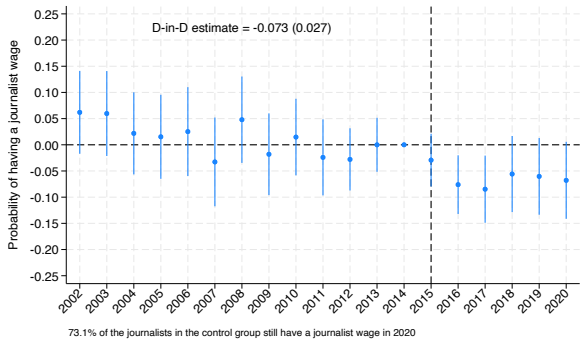
Taken together, these results indicate that the journalists who stayed following the takeover fare comparatively well compared to those who left. Their wage remains competitive, and they are advancing in the journalist career they had initially embraced. This is not the case of those who left, who appear to leave the profession altogether. It additionally indicates that implementing the new editorial line entailed no wage bill cost to the owner; the mere risk of having to leave seems to have been enough to discipline the stayers.

Figure 11 further provides evidence of newsroom downsizing. It compares the number of journalists with a press card and their payroll between Bolloré-owned outlets and control outlets. While the number of journalists slightly increased at control outlets, Bolloré outlets experienced a sharp decline – over 25% on average – between 2014 and 2020. By 2020, only about half of the pre-takeover journalists were still employed at Bolloré outlets, compared to nearly 80% at control outlets. This underscores the extent of internal reorganization and explains why existing employees may have feared for their job, potentially driving them to adapt to the new editorial guidelines. At control outlets, inexperienced journalists made up less than a third of new hires, whereas they represented 55% of new hires at Bolloré outlets. These less experienced hires are not only cheaper, but may also be more pliable than their experienced counterparts. Furthermore, among the outlets considered, the number of press cards dropped by 122 between 2014 and 2020 (-6%), of which 108 were formerly attributed to journalists working on Bolloré outlets. This downsizing may therefore have had broader consequences, as journalists working at other outlets saw their set of outside options shrink, further lowering their own bargaining power.

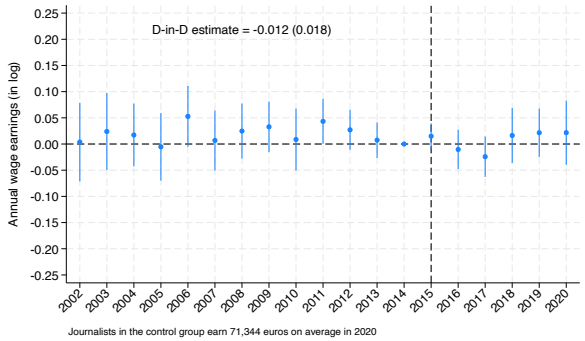
The non-monetary costs of compliance: Notoriety Alternatively, if not through better wages, journalists may have been compensated in other ways. While it is difficult to measure all the non-pecuniary aspects of a journalism job, we here consider airtime. Indeed, journalists may value having longer shows or shows aired during high-ratings hours as it may bring them notoriety with the public. To explore this, we estimate equation (6) on the subsample of journalist-outlet pairs that existed both in the last pre-takeover season (2013-2014) and the last season of our sample (2018-2019) – i.e. we focus on the journalist-outlet pairs that kept existing after the takeover. For each journalist-outlet pair ic, we consider the airtime, the



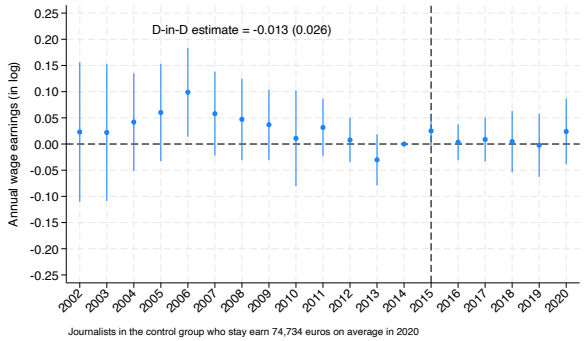
(a) Annual wage earnings as a journalist, including zeros (in 2020 euros)



(b) Probability of working as a journalist



(c) Annual wage earnings as a journalist (in log), conditional on working as a journalist



(d) Annual wage earnings as a journalist (in log), conditional on working as a journalist – Stayers only

Notes: The Figure uses CCIJP data and therefore only considers journalists who hold a press card (see Appendix Section A.4.2 for details). It plots estimates from event-study regressions corresponding to equation (8). The treated journalists are those who appeared on a Bolloré outlet during the 2013/14 season. In Panels 10c and 10d, the dependent variable is the logarithm of the wage earnings of journalist i in year t, conditional on being employed as a journalist. In Panel 10d, we restrict the sample to individuals who, during the 2018/19 season, have shows on the same outlet (or a sister outlet) as in 2013/14. We refer to them as stayers. In Panel 10b, the dependent variable is an indicator variable equal to one if individual i has a press card in year t, and to zero otherwise. In Panel 10a, the dependent variable is the annual gross wage of individual i in year t expressed in 2020 euros. The wage is equal to zero if the individual does not work as a journalist. Standard errors are clustered at journalist level, vertical bars indicate 95% confidence intervals.

Figure 10: The monetary cost of compliance: Wage and employment as journalists

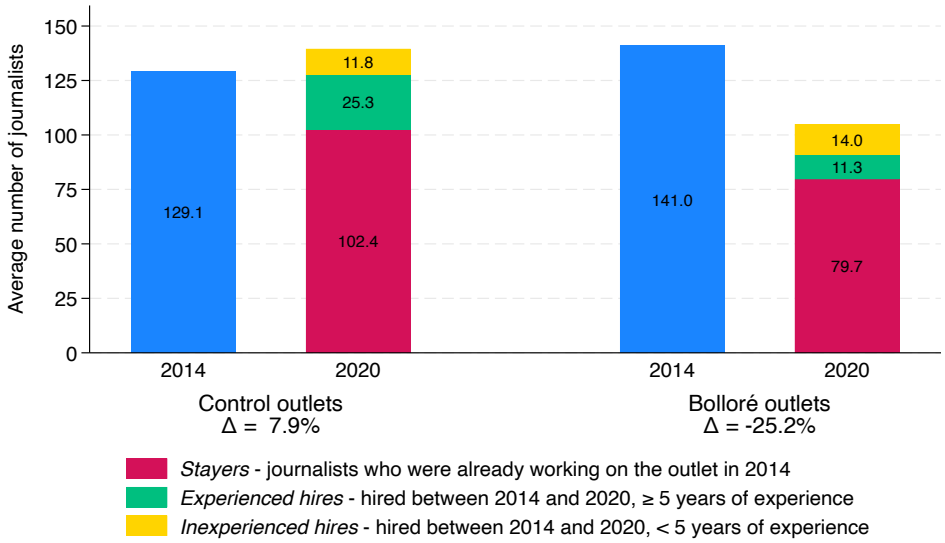
number of days on air, and whether the journalist's show aired in peak-audience time slots during week t.[80]

Table 5 reports the results. The journalists who stayed on acquired outlets were not more likely to appear in a given week, nor did they appear more days, nor did they have more airtime. Rather, we find that they were less likely to have a show during a peak audience time slot.[81] Overall, this suggests that the journalists who stayed on the acquired outlets did not benefit from more airtime, nor from more high-audience time slots.

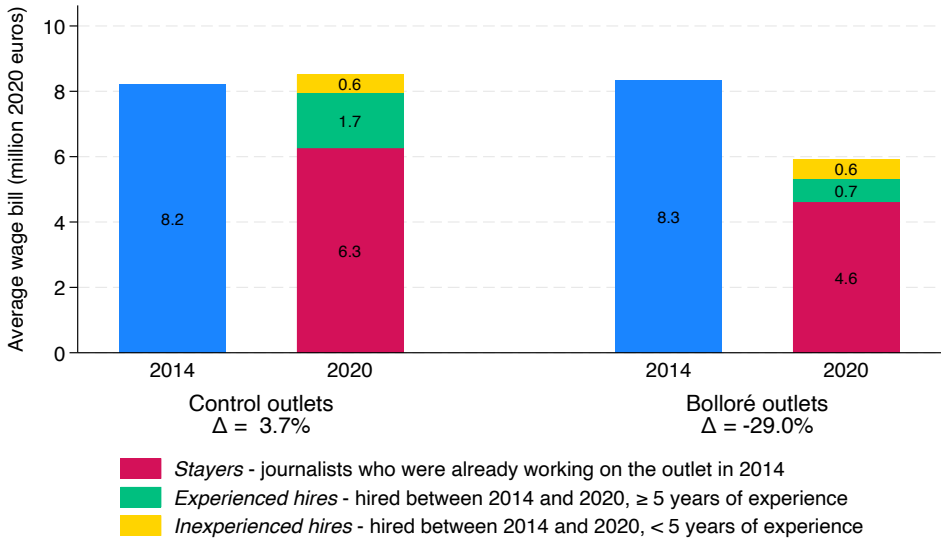
We further explore whether the journalists who stay receive more press coverage as notoriety may boot a journalist's career. To this end, we query the Europresse database with the name of each journalist

[80] Peak-audience time slots are defined as follows: 7:00am to 9:00am for radio, 7:00pm to 10:00pm for television.

[81] Appendix Figure D.19 plots the corresponding event study coefficients.



(a) Head count



(b) Wage bill

Notes: The Figure uses CCIJP data and therefore only considers journalists who hold a press card. A hire is a journalist holding a press card working for an outlet in 2020 who did not have a press card in 2014 and/or was not working on this outlet in 2014. The number of years of experience is the number of years elapsed since the journalist was first granted a press card. It is measured at the time the journalist first appears on the outlet. The control outlets are Arte, BFM TV, Europe 1, LCI, LCP, M6, RMC, RTL and TF1.

Figure 11: Head count and wage bill on Bolloré and control outlets

Table 5: Effect of the takeover on the airtime of journalists who stay on the same outlet: Difference-in-differences estimates

	(1) 1(Airtime>0)	(2) Airtime, min	(3) # days	(4) 1(Peak time)
Treated × 2015/17	0.0205	13.03	-0.00919	-0.0270***
	(0.0311)	(29.75)	(0.124)	(0.00746)
Treated × 2017/19	0.0568	12.31	0.00193	-0.0513***
	(0.0393)	(30.82)	(0.240)	(0.0122)
R-squared	0.313	0.461	0.370	0.204
Observations	1,813,426	1,813,426	1,813,426	1,813,426
$\bar{y}$ (control, post)	0.0880	12.22	0.215	0.0326

Notes: The Table plots the estimates of equation (6). The estimation sample uses all the journalist-outlet pairs that existed both in the last pre-takeover season (2013-2014) and in the last season of our sample (2018-2019) and spans all the possible journalist-outlet × week combinations, with airtime being zero in the weeks in which the journalist does not appear. In Column 1, the outcome variable is an indicator variable for whether journalist i on outlet c had strictly positive airtime in week t. In Column 2, it is the airtime in minutes of journalist i on outlet c in week t. In Column 3, it is the number of days that journalist i appears on outlet c in week t. In Column 4, it indicates whether journalist i appears in a peak-audience time slot on outlet c in week t. Standard errors are clustered at the outlet level and stars indicate significance at the 1, 5, and 10% levels with ***, **, and *, respectively. The time period is September 1, 2005-August 31, 2019.

working on one of the outlets of our sample during the 2013-2014 season, along with the names of the main French television and radio outlets.[82] For each week and journalist, we consider whether there are press articles containing journalists' names. As our goal is to explore whether those who stayed gained in press coverage, we focus on the journalists who by 2018-2019 had stayed on the outlet they we working for during the 2013-2014 season.

Appendix Figure D.20 plots the event-study coefficients. We do not find any increase in the press coverage of journalists who stay on acquired outlets compared to journalists who stay on comparison ones. This is the case across various measures: whether journalists receive coverage at all, the number of articles citing them, or the number of newspapers citing them. This suggests that they did not become more notorious by staying on acquired outlets.

5.5 Journalists' reduced bargaining power in a monopsony

Taken together, the results indicate that the journalists who stayed on acquired outlets fare relatively well compared to those who are gone. Their wages seem to keep up with those of others in the profession, and – even if they do not benefit from additional air time – they are at least still active in the career they had initially embraced. In other words, securing their career progression may be the main reason why journalists accept to change the content of their shows. Their bargaining power appears minimal, even in a setting where there are unions and specific labor protection measures (such as the 'conscience clause' that

[82]The goal is to narrow down searches to articles linked to the journalists with this name, rather than to other persons with the same name. We additionally require that the name of the journalist does not appear in the 'author' field as our goal is to count the number of article about these journalists, not by them. Appendix Section A.4.3 provides additional details on how we create this dataset.

allows journalists to leave their media company on their own initiative, without notice and with severance pay[83]) as they adapt to even drastic editorial changes not in exchange of a better wage or better working conditions, but solely to avoid being worse off. Despite the principle of editorial independence, journalists are not in a position to push back on the editorial line set by the owner, which explains why the editorial change largely operates through compliance, rather than through selection.

Our findings can be illustrated by the career path of Laurence Ferrari, born in 1966, who was the anchor of the most-watched evening newscast until 2012 and whose face has appeared on numerous magazine covers. In 2014, at the eve of Bolloré's takeover, she was working on I-Télé. Ten years later, in 2024, she had a two hour-long daily debate show titled 'Punchline' on the same channel, since then rebranded as CNews. In interviews, when asked about the conservative stances she takes in the opening of her show, she explains that she "can no longer remain silent" and "must speak for [her]self." Yet, some of her former peers doubt it reflects her opinions.[84] One commented: "She's like a broken puppet playing the role of the reactionary journalist without even seeming to believe it. Deep down, that's not her."[85] In 2016, when Bolloré reshuffled the top management, while not on strike herself, she was said to be in solidarity with the striking newsroom. One of her former close associates confides: "She was unhappy. In private, she would tell me, 'I want to leave', and she was looking for other opportunities, but without success." A former colleague explained that "staying at CNews wasn't her heart's choice, but she was willing to swallow bitter pills to remain on air. Her only concern was to be there." Another added: "She didn't align at all with the CNews editorial line, but it's hard to judge – she has bills to pay like everyone else."[86]

Hence, rather than giving bonuses to existing journalists in exchange for their compliance, downsizing – on top of cutting costs – may have been a way for the owner of disciplining the remaining employees and making them implement the new editorial line.[87] The apparently low bargaining power of journalists is consistent with a shrinking labor market segment in which a small number of large firms operate, the number of vacancies is low but the number of journalists aspiring for a job is high (Azar and Marinescu, 2024).

[83]This clause can be used in the event of a sale, merger, change in the group of shareholders involving a change in editorial line, or a significant change in the direction of the media outlet that would be detrimental to their honor, reputation or moral interests.

[84]In 2013, she hosted a gala evening in favor of the legalization of same-sex marriage, which was supported by the socialist government. She explained at the time that "it was logical at some point to get involved, to stand up for the values that drive me. Namely: tolerance, equal rights, and solidarity." In "Laurence Ferrari veut 'être aux côtés de ceux qui se mobilisent' pour le mariage pour tous" *Closer*, 01/27/2013.

[85]Another said: "She throws out categorical statements, acting like a know-it-all, when I remember her as being so moderate– it's strange." In Rousseaux, François, "Laurence Ferrari, pasionaria de CNews : son grand virage au pays de Bolloré." *Télérama*, 02/19/2024.

[86]In Rousseaux, François, "Laurence Ferrari, pasionaria de CNews : son grand virage au pays de Bolloré." *Télérama*, 02/19/2024.

[87]A former CNews employee noted: "If a far-left billionaire had come in with the same politically reversed project, they would have all signed on." In Chaffanjon, Charlotte "Comment CNews s'est hissé au sommet des audiences : enquête sur le mégaphone de l'extrême droite," *Libération*, 06/03/2024.

6 Discussion and conclusion

This paper examines the personnel economics behind media outlets to better understand the dynamics at work between owners and journalists, and how they shape media slant. We use new data on the content of television and radio shows of the leading French outlets over more than 15 years. Leveraging the thousands of journalists switching outlets as well as an ownership change, we show that across-outlet differences in political coverage are largely driven by journalists complying to outlet-level decisions, such as the editorial guidelines set by the top management. Further, we document that, despite the principle of editorial independence, journalists do not have the bargaining power to push back on the decisions of the owners. In the case of Bolloré's takeover, making journalists change their coverage required no compensation from the new owner – either through higher wages or increase airtime – as keeping their job seems to have been a sufficient motive for the remaining journalists – including notorious ones – to comply.

Our findings have significant implications for both viewers and journalists. For viewers, the results underscore the role of media pluralism regulations, such as the UK's impartiality regime.[88] Despite the abundance of information sources available today, media concentration and audience consumption patterns indeed often limit the diversity of perspectives to which voters are exposed (Prat, 2018; Kennedy and Prat, 2019). Besides, suggestive evidence points to the role of media content in shaping electoral outcomes. Although the causal impact cannot be quantified,[89] the 2015 Bolloré takeover and its subsequent editorial changes are likely to have influenced the 2022 French presidential election, especially the rise of radical-right candidate Éric Zemmour.[90] There was indeed a noticeable shift in the political preferences of CNews viewers, as shown in Appendix Figure D.21, which uses survey data to offer suggestive evidence of the channel's impact. While CNews viewers were initially more left-leaning than the general population in 2013, they shifted to the right following Bolloré's takeover. Although this shift cannot be causally attributed to CNews due to the inability to track whether these were the same individuals whose views changed, or if they were different viewers drawn to the channel by its new editorial direction, the timing is striking. Over the same period, electoral support for the radical right in France notably increased, further suggesting a potential link between the editorial change and broader political trends.

For journalists, our results emphasize the importance of labor market dynamics and media industry concentration for the content they produce. The extent of the downsizing at Bolloré outlets may have had

[88] See in particular "Section 5: Due impartiality and due accuracy" of The Ofcom Broadcasting Code. We mentioned earlier the US "fairness doctrine," but it was ended in 1987.

[89] Unfortunately, since there is no geographic heterogeneity we can exploit in the penetration of Bolloré's channels, we cannot quantify the causal impact of the shift to the radical right on electoral results due to the change in ownership (Della Vigna and Kaplan, 2007; Martin and Yurukoglu, 2017; Martin and McCrain, 2019).

[90] Zemmour was indeed a regular debater on CNews before running for elections. See e.g. "Behind the Scenes, Billionaires Shape French Presidential Campaign," *The New York Times*, March 10, 2022. While they do not specifically consider Bolloré's channels, Schneider-Strawczynski and Valette (2021) provide interesting evidence of the impact of media coverage – and more specifically of the coverage of immigration on French television channels – on attitudes toward immigration. Note also that promoting viewpoint diversity matters beyond political attitudes. The lack of internal pluralism might also indeed have negative consequences, e.g. regarding trust in media or how well people are informed.

broader industry-level consequences. It contributed to a decline in the number of press cards delivered to radio and television outlets, further reducing the set of outside options that journalists at other outlets have and their bargaining power. Further, while we study France, a country where labor protection is generally considered high, the collapse in the overall number of journalists as well as the increasing concentration of the media industry, lined with the closure of newsrooms – phenomena that likely undermine journalists' bargaining power – are far from specific to France nor to broadcast media. Our results for instance echo the recent internal conflict at *The Washington Post* over its decision not to endorse a candidate in the US 2024 presidential election. This decision, attributed to owner Jeff Bezos, led to the departure of several staff members.[91] and was upheld despite strong opposition within the newsroom. Future research may ask whether the wave of unionization taking place in American newsrooms will change the leverage journalists have vis-à-vis their owners' editorial decisions.

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[91] For instance, columnists Michele Norris and Robert Kagan left the Washington Post. Source: Laurence Edmonds, "Washington Post columnist quits, calling the decision to 'withhold' endorsement a 'terrible mistake'," *Business Insider*, 10/27/2024.

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Online Appendix to the Paper: Political Bias in the Media. Evidence from the Universe of French Broadcasts, 2002-2020

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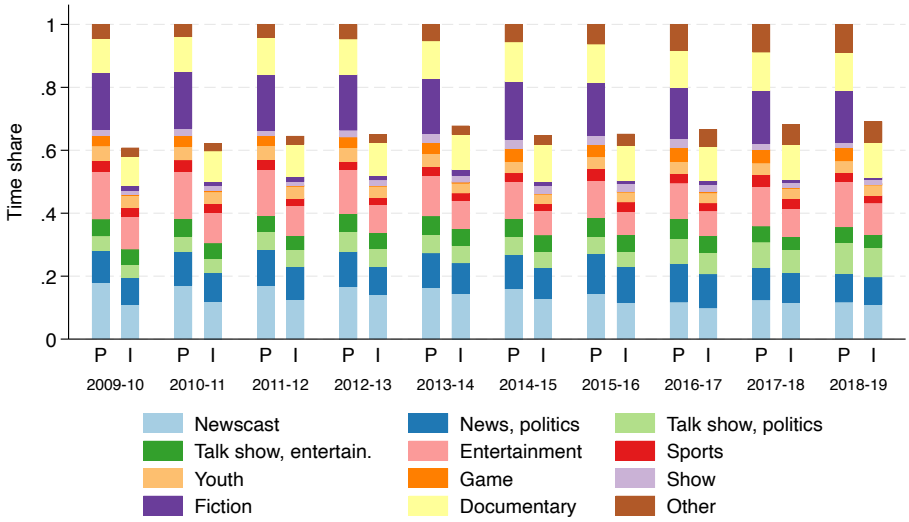
A Dataset

A.1 INA data coverage benchmark

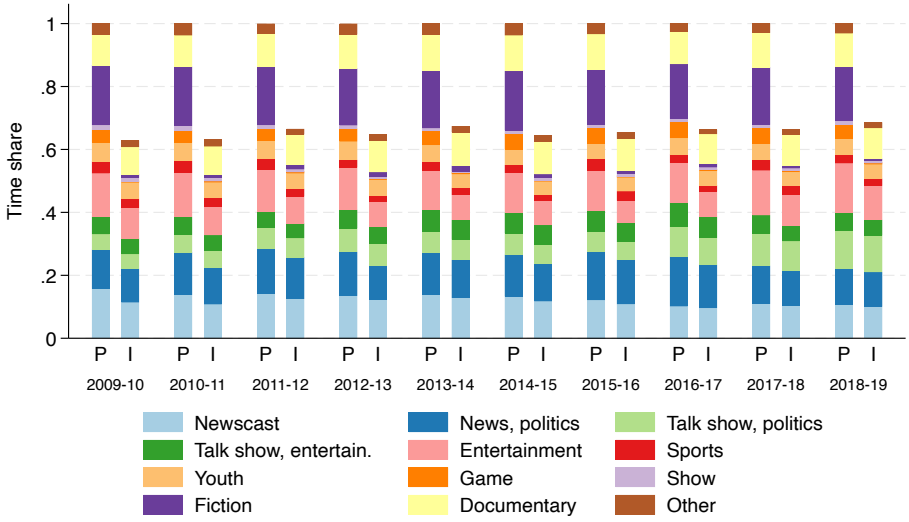
To benchmark the range of shows covered in INA data, we use data provided by another source, Plurimedia. Plurimedia is a company that collects metadata on scheduled television shows before they are broadcast, and sells them to websites and magazines publishing television schedules. The dataset includes all shows, 24 hours a day, for all the television channels from September 2009 to December 2020. For each show, the data provide information on the channel, date, scheduled start time, length and title.

Building on Plurimedia show classification, we devise 12 show categories: (i) newscasts, (ii) shows about news and politics (interviews, in-depth analysis of specific news topics, etc.), (iii) talk shows about politics (debates, news commentary with pundits or commentators), (iv) entertainment talk shows (which also include infotainment talk shows such as late shows), (v) entertainment shows (reality TV, home makeover shows, cooking shows, etc.), (vi) sports shows, (vii) youth shows (cartoons, educational programs), (viii) games, (ix) performance shows (concerts, plays, etc.), (x) fiction, (xi) documentaries, and (xii) other shows (weather forecast, lottery, undetermined night-time programs, etc.).

We match shows in Plurimedia data with shows in INA data, and determine for each category the time length of shows that are in both datasets as a share of the length of shows in the Plurimedia dataset. Figure A.1 contrasts the coverage of shows by type across Plurimedia and INA data. While newscasts, shows about news and politics, and talk shows are nearly all included in INA data, only a subset of entertainment, sports, youth programs and documentaries are covered. Most of the difference between INA and Plurimedia data coverage can be explained by fiction shows. Overall, the figure shows that INA data provide a broad coverage of shows that have journalists, which makes it ideal to measure political slant using guest speaking-time shares. Notably, while most studies in the media bias literature only focus on news shows, we cover a much broader range of programs, whose total length far exceeds that of newscasts only.



(a) All programs



(b) Excluding programs starting between 11pm and 5am

Notes: "P" refers to Plurimedia data, and "I" refers to INA data. The vertical bars show the breakdown of programs by type for the 12 television channels in our sample. Bars denoted "P" depict the time dedicated to programs of each category, divided by the total screen time in the considered semesters as documented in Plurimedia data. Bars denoted "I" depict the time dedicated to programs of each category in INA data, divided by the total screen time in the corresponding categories in Plurimedia data. Shorter "I" bars reflect that some shows are not documented in INA data. Sub-figure A.1 considers all shows in Plurimedia data, while sub-figure A.1b excludes shows aired during the night, as they can be imprecisely described in Plurimedia data (e.g. 'night shows').

Figure A.1: Data coverage comparison between Plurimedia data and INA data

A.2 Classifying guests

In this section, we provide details on the methodology we use to classify the guests in our sample. We distinguish between politicians on the one hand, and politically engaged non-politicians, whom we call PENOPs, on the other hand.

A.2.1 Politicians

To classify politicians, we use several data sources:

- **Arcadie project**. The Arcadie project is an open data website that gathers information on elected officials. For instance, their age, gender, profession, place of birth, spouse job, electoral district, committee assigned to, social media accounts, etc. We collect data on the group affiliation of MPs. Each year, they are required to pay a membership fee to the parliamentary group they are assigned to. Some of them, when they switch party during their term start paying their membership to another group. We collect all this information and can therefore track the party affiliation of MPs, who are major political figures in the French political landscape.

- **Elections data**. We then collect election data for several elections: legislative elections (National Assembly), senate elections, European elections, regional elections, departmental elections and municipal elections.[1] If candidates run by lists, we collect all the names on the list (European elections for example). One exception are municipal elections. Given some municipalities are very small, the last candidate on a municipal election list almost never gets elected and never appears in the media. In this case, we keep the top five candidates of each list in municipalities with at least $100,000$ registered voters, and the first on the list for municipalities with at least $20,000$ registered voters. For elections, we consider candidates to be affiliated to the party whose label they are running with three months before the election date (to account for the campaign period), and three months before the end of the mandate (they might be running again with a different affiliation).

- **Government**. We use the list of government members (*ministres*, *secrétaires d'état*, and *directeur de cabinet du président*), and consider them to be affiliated to the president's party.

Next, for each person in a given month, we search the aforementioned datasets for a political affiliation. We give some data sources precedence over others. The first one is the Arcadie dataset, as party affiliation is allowed to change within terms. Next, we use legislative elections (National Assembly elections), Senate elections, and then whether the person is in the government. Government data comes after legislative and senate elections data because the government sometimes includes politicians from politically close but distinct parties. For instance, politicians from the Green party have worked under the socialist president, although not affiliated to the socialist party. We then use

[1] *Régions* and *départements* are intermediate tiers of government in France. Municipalities are the lowest.

other election data sources in the following order: European, regional, departmental, and municipal elections. If some politicians have gaps in their electoral careers, we extend their past affiliation in the future.

A.2.2 Politically engaged non-politicians (PENOPs)

To determine the political leaning (if any) of guests who are not politicians, we use data from three different sources: (i) the annual summer meetings organized by political parties (*universités d'été*), (ii) think tank staff and contributors, (iii) endorsements of politicians in op-eds published in the press. Our goal is to collect data on behaviors that we consider, when aggregated, are indicative of the political leaning of a person. These behaviors are analyzed with a probabilistic model in which the recurrence of such behaviors is considered indicative of a given political leaning.

Summer meetings of political parties We collect data on the participants of political party summer meetings. These meetings typically gather politicians and party executives but also academics, media personalities, businessmen, activists, or union representatives. By participant, we here mean people whose name was on the program and who were invited to give a speech or take part in a round table. Although taking part in such events does not imply that the person is affiliated to a party, we consider it to be suggestive of a person's political leaning.

We collect data from various sources. For recent meetings, we retrieve the program on the party website (typically, events from 2021 and sometimes 2020). For older events, we used the Wayback machine search engine (Web archive). We also directly contacted parties and requested the program of their past meetings. Some answered positively to our requests and shared copies of the programs from their own archives (UMP/LR, Modem and Les Verts/EELV).

Overall, we have extensive coverage of the French political landscape: close to one hundred programs (n=97), from the radical right to the radical left. It should be noted, however, that the information was scarcer on the right than on the left: Parti socialiste, Parti communiste and Les Verts/EELV nearly account for 50% of the programs (49%, and 54% if including the more recently created LFI), while liberal parties account for 15% of the sample (15 programs for the Modem and LREM). Meanwhile, important right-wing parties such as FN, UMP/LR and UDI account for about 16% of the sample, with 16 programs retrieved for the three parties combined. As a general observation, summer meetings of left-wing parties are large events aimed at a substantial audience, reaching beyond the circle of political activists, hosting hundreds of speakers from the party leadership and civil society; they are also generally held every year. Right wing parties' events are different, however. Their audience is mostly restricted to political activists, and sometime include the youth section of the party, with the goal of training young political activists and letting them meet important party figures. These parties hold summer meetings less regularly, with many blank years (especially in presidential election years), and there are fewer speakers. These discrepancies may be explained by historical and ideological

reasons, given that summer universities or large instructional events are a traditional tool used by the progressive political forces to reach a broader audience, as opposed to conservative parties that tend to center on a network of local elites, without needing to promote their ideology to large segments of the population. For this reason, we also collect data on the summer meetings of smaller right-wing parties: *Action Française* (a nationalist and royalist micro-party), *La Manif pour Tous* (a political movement created in opposition to same-sex marriage in 2013 which later morphed into a political party), *Chrétienté-Solidarité* (a Catholic traditionalist political organization close to the *Rassemblement National*), *Oser la France* (socially and economically conservative Christian political movement), *Acteurs d'Avenir* (Christian organization aimed at educating "tomorrow's Christian leaders"), and *La Convention de la Droite* (a summer meeting organized by radical-right politicians to foster alliances with traditional right-wing parties).

- **La France Insoumise** (radical left). 4 summer meetings, 2017-2020. Programs found online.
- **Parti de Gauche** (radical left). 6 summer meetings, 2011-2013, 2015-2017. Online and Wayback machine.
- **Parti Communiste Français** (radical left). 12 summer meetings, 2008, 2009, 2011-2020. Found with the Wayback machine.
- **Europe Ecologie Les Verts** (greens). 20 summer meetings, 2002-2021. Received from party's archivists, and online.
- **Mouvement Républicain Citoyen** (left). 6 summer meetings, 2008-2012, 2014.
- **Les Radicaux de Gauche** (left). 2 summer meetings, 2018-2019. Online.
- **Parti socialiste** (left). 16 summer meetings, 2002-2015 and 2020-2021. Received from the Fondation Jean Jaurès, and found with the Wayback machine.
- **Le Vent se Lève** (left). 2 summer meetings, 2018-2019. Online.
- **Mouvement Démocrate** (liberals). 13 summer meetings, 2008-2020. Received from party's archivists, and online.
- **La République En Marche** (liberals). 2 summer meetings, 2019, 2020. Found online.
- **Union des Démocrates et Indépendants** (right). 3 summer meetings, 2018-2020. Obtained from Wayback machine and online.
- **Union pour la Majorité Présidentielle/Les Républicains** (right). 9 summer meetings, 2003, 2006, 2008, 2009, 2011, 2015, 2017, 2020, 2021. Received from party's archivists.

- **Acteurs d'Avenir** (right). 11 summer meetings, 2010-2015 and 2017-2021. Online and Wayback machine.
- **Osons la France** (radical right). 3 summer meetings, 2018-2020. Online and Wayback machine.
- **La Manif pour Tous** (radical right). 7 summer meetings, 2013-2019. Online and Wayback machine.
- **Chrétienté et Solidarité** (radical right) 10 summer meetings. 2008-2013, 2015, 2016, 2019, 2021. Online and Wayback machine.
- **Front National/Rassemblement National** (radical right). 4 summer meetings, 2011, 2013 and 2016. Found with the Wayback machine.
- **Convention de la droite** (radical right). 1 summer meeting, 2019. Online.
- **Action Française** (radical right). 4 summer meetings, 2017-2019, 2021. Found online.

Think tanks Next, we collect data on staff members and contributors of think tanks. Many intellectual figures, pundits, or more generally policy commentators regularly contribute to think tanks publications. These publications can be long and detailed reports, or posts on recent news events on the think tank's website. Our goal is to collect the name of contributors and staff members as, plausibly, choosing to associate one's name with a think tank reflects some form of political alignment.

We start by identifying the main French think tanks. To do so, we start with the list compiled by the Open Think Tank Directory, and sort them according to their number of Twitter followers, as documented in the dataset. We focus on think tanks that have more than $5,000$ followers, as others are generally very niche. We then discard the think tanks that have no website or publications. For example, this is the case of the *Fondation Danielle-Mitterrand - France Libertés*, which mostly raises funds and financially supports targeted projects. We also discard think tanks that can be assimilated to research centers (INRAE, CERI, etc.) and do not exhibit a particular political leaning, or that are affiliated to an administration (France Stratégie, CEPII, etc.) as their leaderships change with elections. We also rule out very recent think tanks, such as Hemisphère Gauche and Institut La Boétie (both created in 2020). We decided to include all organizations, whether a foundation or a non-profit organization, whose stated goal is to inform the political debate and which, for that purpose, produces reports and (or) organizes conferences. Some of these think tanks are generalists, others focus on economic, geopolitical, judicial or environmental issues for example.

For each think tank, we map them to political parties based on several criteria. First, founders or top management staff are sometimes clearly politically involved. For instance the *Fondapol*'s founder, Jérôme Monod, was the chief of staff of Jacques Chirac, and its current director, Dominique Reynié, is a right-wing elected official. The *Fondation Gabriel-Péri*, named after a communist politician, was

created by the Communist Party itself. *Terra Nova* was created by Olivier Ferrand, a Socialist Party executive. Next, we rely on the think tank's own stated goal. For example, *Polemia*, founded by far-right politician Jean-Yves Le Gallou, claims on its "About us" web page that its work is structured around "defending identity, criticizing the oligarchy, and fighting media tyranny," which is typical of far-right rhetoric. ATTAC, a radical left organization, states that it fights for "social and environmental justice and conducts actions against the power of finance and multinational companies," which in this case is ideologically typical of radical-left movements. We also study the funding of these think tanks. We have data on the organization(s) to which members of parliament decided to grant part of their discretionary budget line (known as *réserve parlementaire*).[2] Finally, we collect the Twitter handle of each think tank and of members of parliament. Using simple retweets (retweets without comments), we situate each think tank in the French political space. This is illustrated in Figure A.2. If, with these methods, the political positioning of think tanks is still ambiguous, or if they do not seem to be politicised, then we consider them not to be political and do not classify them.

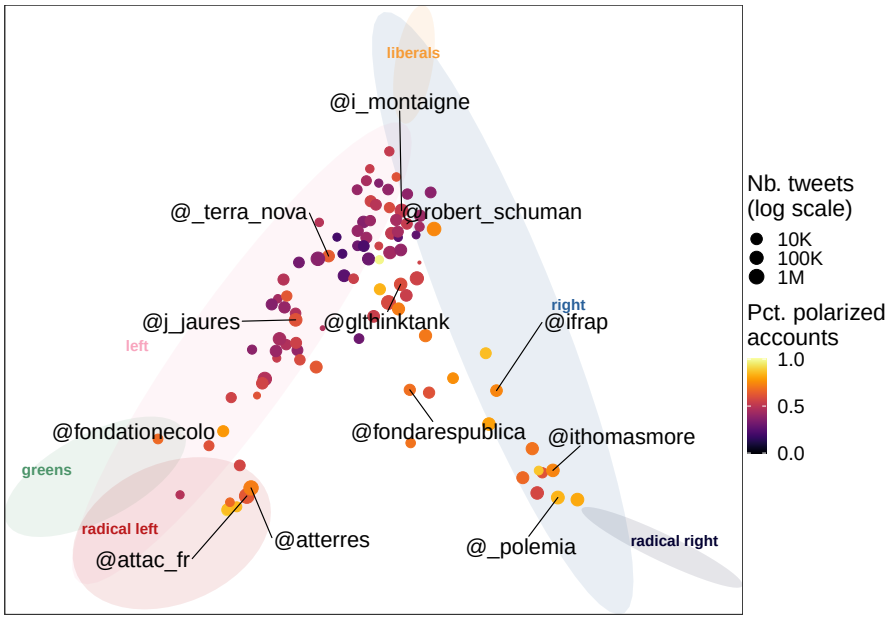


Figure A.2: Think tanks projected on the French political Twitter space

We then collect data on staff members and contributors. For staff members, we use the think tank's web page "Our team" (or the equivalent). Using the Wayback machine, we collect all the names of people on this web page for every year since 2002, or for as many years as possible. For contributors, we scrape publication title, dates and authors. Table A.1 reports the list of think tanks for which we collect data, their creation date and political family. The next two columns present the number of

[2]This dataset is called "Réserve Parlementaire" and is available from 2013 to 2017. We look at the party affiliation of the MPs who granted money to think tanks drawing from their own budget line that they can use at discretion for either fund non-profit organizations or local governments.

staff members and contributors that we found for each think tank. The same person can be counted several times if they have been part of the staff for several years, or contributed to several publications. For some think tanks, no staff were found. This is the case of Polémia, which does not disclose this information on its website. For some think tanks, there are no contributors (Fondation Copernic, Fondation pour la Nature et l'Homme, and The Shift Project). This is either because no publication is signed, or publications are signed as a team (Copernic). Sometimes, when the format of publication is very ad hoc and different each time, we were not able to scrape author names (Fondation pour la Nature et l'Homme and The Shift Project). We also exclude contributors who work for polling companies. Think tanks often hire them to conduct surveys and credit them as contributors, but that may not be indicative of pollsters' leaning. In the last two columns, the Table reports the number of occurrences of staff members and contributors that were matched with INA data. The figures are always smaller, which is because some people never appear in the media. Overall, we match nearly 9,000 occurrences of staff members, and more than 18,000 occurrences of contributors.

Table A.1: Think tanks staff and contributors: descriptive statistics

			Number found		Once merged with INA data	
Name	Creation	Family	Staff	Contributor	Staff	Contributor
Fondation Gabriel Peri	2004	Radical left	373	814	238	447
ATTAC	1998	Radical left	1,029	2,708	807	1,857
Fondation Copernic	1998	Radical left	1,898	–	1,292	–
Les Economistes Atterres	2011	Radical left	458	210	335	188
Fondation pour la nature et l'homme	1990	Greens	1,295	–	817	–
Fondation de l'ecologie politique	2012	Greens	412	53	348	36
Fondation Jean Jaures	1992	Left	878	3,904	634	2,728
Institut Jacques Delors	1996	Left	429	1,793	334	1,098
Republique des Idées	2002	Left	123	121	95	118
Fondation Res Publica	2005	Left	590	82	479	65
Terra Nova	2008	Left	1,488	1,392	1,117	861
The Shift Project	2010	Left	287	–	110	–
Fabrique de l'Ecologie	2013	Left	386	803	307	388
Fondation Robert Schuman	1991	Liberals	518	1,568		
Institut Montaigne	2000	Liberals	632	3,678	501	2,327
Generation Libre	2013	Liberals	178	57	123	32
IFRAP	1985	Right	75	3,220	65	2,661
Fondapol	2004	Right	595	1,785	449	824
Groupement de recherches et d'études pour la civilisation européenne	1969	Radical right	58	2,140	27	1,007
Fondation Polemia pour l'identité la sécurité et les libertés européennes	2002	Radical right	–	3,723	–	1,111
Institut Thomas More	2004	Radical right	527	946	271	702
Institut des Libertés	2012	Radical right	76	1,069	50	946
		Total	12,405	30,066	8,921	18,609

Notes: This table reports the number of staff and contributors. The figures refer to the number of occurrences in our data, not the unique number of staff members or contributors. An individual who contributes once a year between 2010 and 2019 will account for 10 occurrences of contributors. The number of occurrences after the merge with INA data is smaller because some contributors and staff members never appear in the media.

Endorsements in newspapers We collect the names of people who signed opinion pieces in newspapers in which they endorse a candidate running in the first round of the presidential elections. Such opinion pieces are generally signed by several people and detail the reasons why they support a given candidate. We only focus on endorsements published before the first round. Support decisions expressed between the first and second round of elections might be driven by a desire to defeat the opponent (especially when a radical-right politician qualified in the second round, as in 2002 and 2017), rather than real endorsement of the candidate's platform and values.

Combining party meetings, think tanks and endorsements data We finally combine the data described above in a probabilistic model. Using the Chapel Hill Expert Survey, we place each political family on a left-right scale, ranging from 0 to 100. Each behavior (summer meetings attendance, think tank participation, and endorsement) is mapped to a political family, and is attributed a left-right score between 0 and 100. For each behavior, we extend it temporally with a decay using an asymmetric Gaussian distribution: its intensity decays very fast before the event, and slowly after. When the intensity slips below a threshold, we consider that the individual is not classified.

When an individual has taken part in events matched to distinct families (for example, attended summer meetings of the Green party, and contributed to a socialist think tank), we compute a decay-weighted average of their left-right placement. In the end, we discretize this left right placement using the midpoint between political families. For example, if in a given month, an individual has a left-right placement of 40, then we consider them to belong to the party whose left-right placement is the closest.

Figure A.3 illustrates the procedure for Daniel Cohn-Bendit, a Green politician who was a member of the European Parliament from 1994 to 2014. The x-axis represents time, the y-axis the left-right scale, from 0 to 100. Yellow lines correspond to the midpoint between political families' left-right placement as computed from the Chapel Hill Expert Survey. They define each political family's political space over time. Blue lines are contour lines of the asymmetric Gaussian distributions. Red dots represent the monthly weighted average of the political placement on the left-right scale, and green dots represent the variance of the placement.

A.2.3 Manual checks

As a last step, we manually check that guests accounting for the largest time share for each channel-season are correctly classified. For each of them, we check whether their identity and political affiliation are consistent with the profession listed in the INA dataset, as well as the data sources on political activity. One source of errors is the presence of homonyms. The concern is that frequently invited guests who are not described as politicians in the INA data (e.g. cooks, comedians, etc.) share the same name as (local) politicians, and are mistakenly politically classified as a result. For example, Isabelle Mercier, the Canadian poker player, appeared for 121 minutes on the channel ARTE in 2006-2007. She was mistakenly classified as 'radical left' for she had a homonym who was part of the staff of the

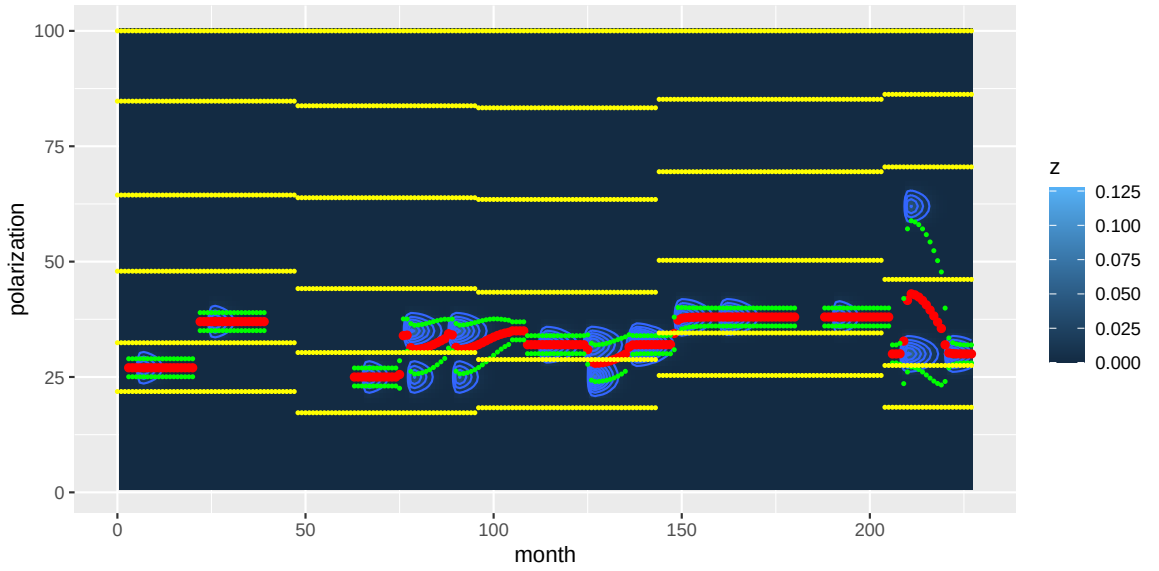


Figure A.3: Political classification using endorsements, party events and think tanks

think tank ATTAC (Association for the Taxation of Financial Transactions and for Citizens' Action) at that time. Manually checking the consistency of data sources allowed us to correct this error. We proceed as follows: for the guests accounting for more than 1 percent of the political time share at the channel-season level (1,216 distinct individuals), we manually check whether homonyms exist in the INA dataset, what the profession of the guest is, as reported by the INA, the source that allowed us to classify the guest (regional elections, think tanks, etc.) and check whether the sources are consistent. If not, we further check at the show level whether the identity of the guest matches the identity of the person politically involved. If needed, we further check online whether a given individual has indeed taken up an active political role. As a result, for each individual-month pair of top guests, we either remove the political classification if the initial classification was incorrect and the guest is not politically active, correct it, or leave it unchanged if correct.

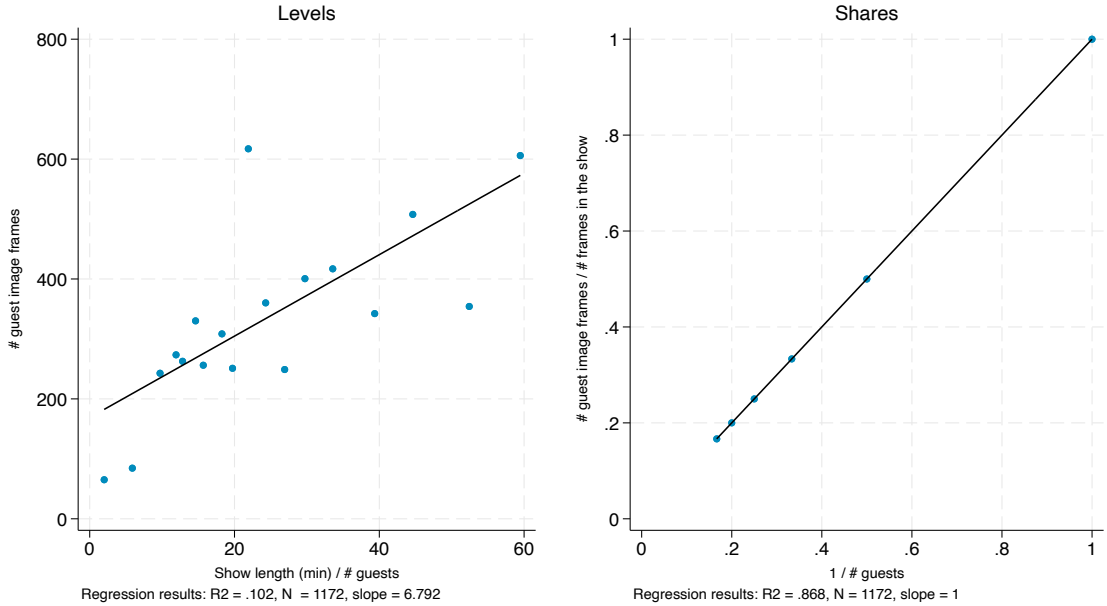
A.2.4 Precision of the time share measure

To check how much our time share measure – emission length divided by the number of guests – captures actual variation in coverage time shares, we rely on a subset of shows for which we have data from a facial recognition algorithm provided by Petit et al. (2021). Petit et al. (2021) develop a tool to recognize image frames of guests on television, allowing us to proxy the actual screen time presence of a person in a show with the number of recognized frames. This measure itself is a proxy for actual *speaking* time shares. First, one frame can correspond to 1-3 seconds since they are cut based on changes in the image on screen. Second, screen time presence of a person's face does not always coincide with their speaking time, as sometimes people's faces are superimposed while another person

is speaking. This measure is still very granular on the show level. We restrict the analysis to shows for which all the show's guests are in the face recognition face dictionary and can therefore potentially be detected, leaving us with a sample of 1180 shows.

Figure A.4 shows the correlation between the actual screen time presence as proxied by recognized image frames with our measure of speaking time. The left panel compares imputed levels of speaking time. In levels, our measure explains 10% of variation in image frames, and the slope suggests that one additional minute in our measure translates into 7 more image frames of a person in a show (approximately 21 seconds). The relationship appears linear.

The right panel correlates *relative* screen time presence of a guests (among other guests) with our outcome, the speaking-time share of the guest. Our measure explains 87.3 % of the observed variation in screen time presence with a slope of 1, making us confident that our measure proxies screen time shares sufficiently well.



Notes: The left figure plots the number of image frames in which guests of a given show appear against the length of the show divided by the number of guests. A frame accounts for between 1 and 3 seconds. The right figure plots the share of frames matching each guest among the total number of frames matching one of the show's guests against the time share attributed to each guest.

Figure A.4: Comparing time share computed based on show length to face recognition data

A.2.5 Speech of politically classified guests

We next assess whether guests classified as being part of one of the political groups have a speech that effectively reflects their political leaning. To this end, we analyze the transcripts of shows in which a

politically classified guest is featured. The shows are transcribed using a software developed by the LIUM (Informatics Laboratory of the University of Le Mans). Unfortunately, they do not indicate who is speaking – whether it is the journalist, the guest, or another guest if there are multiple guests. As such, we choose to focus on shows that regularly feature only one guest per show (or per sub-show). Appendix Tables A.2, A.3 and A.4 list the shows used in the transcript analysis.

For each transcribed show, we stem words and remove those referring to named entities using the spacy Python library. It should be noted that doing performs reasonably well but fails to remove all the words referring to named entities, especially if they are first or family names similar to nouns (e.g. 'Marine' is a French first name, but it can also mean 'navy'). This is in part because transcribed texts have only lower case letters and no punctuation. We then identify all the *n*-grams occurring at least three times with *n* ranging between one and three.

We follow Ferrario and Stantcheva (2022) to identify the *n*-grams that are the most specific to shows featuring guest from a given political group compared to shows featuring no one from this group. We compare the relative frequency of each *n*-gram in the transcripts of two sets of shows. We conduct a χ^2 test to test the independent between the two groups' frequency distribution. The null hypothesis is rejected at the 1% level when $|\chi^2| > 6.63$.

Tables A.5 and A.6 compare shows featuring a radical left guest to others. They feature the words and top bi-grams (respectively) with the largest χ^2 test statistics. We filter out *n*-grams related to named entities that the spacy library failed to remove or containing stopwords ('a', 'an', 'the', 'this', 'that', etc.) and numbers (they often refer to dates or presidential elections years). Among the top words, many refer to radical left parties (Communist party, Unbowed France, Workers' Struggle, New Anti-capitalist Party, etc.), to wealth and capitalism (e.g. 'big business', 'tax heaven', 'capitalist class', 'dividend'), to the working class (e.g. 'worker', 'lay off', 'wage') and policies they oppose (e.g. 'austerity') or support ('ecological planning').

Tables A.7 and A.8 do the same for green guests. Many words refer to environmental issues (e.g. 'climate', 'warming', 'climate change', 'global warming', 'ecological crisis', 'pollution'), to power sources ('nuclear plant', 'fossil fuel', 'renewable energy', 'energy transition', 'diesel', 'renewable, gas'), or to policies they support ('heavy trucks tax', 'energy-efficiency improvements').

Tables A.9 and A.10 compare words in shows featuring a left-wing guest to those in shows featuring no such guests. The left was in power from 2012 to 2017, that is during most of the sample of shows we consider here. It is therefore not surprising that many words relate to governance (e.g. 'minister', 'government', 'president', 'reform', 'prime minister', 'socialist house representative', 'National Assembly', 'socialist group', 'law'). Other words relate to the main issues the left sought to address when in power ('unemployment', 'recovery', 'growth', 'energy transition') or reforms they implemented ('taxes', 'public bank').

Tables A.11 and A.12 compare shows featuring a liberal guest to others. This political group reached power in 2017 and between this year and the end of our sample in 2020, their rule was heavily

marked by the 'Yellow Vests' movement and the subsequent 'Great Debate' (Grand Débat) meant to allow protesters to voice their grievances. The period was also characterized by the negotiation following the 2016 Brexit referendum, hence the references to the United Kingdom, to Brexit or the the conservative party. Other keywords refer to policies implemented (or at least discussed) by the liberals when in government: changes in unemployment insurance criteria (e.g. 'unemployment insurance'), the creation of a voluntary civil conscription (the universal national service), cuts in the transfers to local governments (e.g. 'local government'), a reform of the pension system aborted due to the Yellow Vests and then COVID (e.g. 'retirement'), stricter rules regarding elected officials hiring family members and referred to as rules aimed at 'moralizing public life' (e.g. 'public life'), the abolition of the wealth tax named ISF (e.g. 'wealth tax'), and the creation of the 'prime d'activité' meant to boost the income of low-wage employees on the grounds that work should pay (e.g. 'work pay').

Tables A.13 and A.14 compare shows featuring a right-wing guest to others. This party has not been in power since 2012, that is for most of the considered period. It was nonetheless characterized by a conflict between the two self-proclaimed winners of the internal vote for the main right wing party's presidency in 2012, by open primary elections in 2016, and by a disappointing electoral result in the 2017 presidential race as the main right-wing candidate was directly linked to a favoritism scandal. Many words refer to the party (e.g. UMP, Republican, UMP group, UMP house representative), to elections (e.g. candidate, election, primary, presidential elections, open primary, campaign, debate, vote), and to party institutions (e.g. political bureau).

Finally, Tables A.15 and A.16 do the same for radical right guests. Several words relate to immigration, one of the main issue of this political group (e.g. immigration, border, undocumented, massive immigration, national borders, complete opening). Others relate to sovereignty and currency as pulling France out of the EU and re-introducing the franc was one of the main items of the platform of the National Rally (formerly National Front, FN). This is echoed by words like 'national currency', 'national sovereignty', 'European Union', 'franc', 'euro', 'currency', or 'sovereignty'. Other words relate to economic protectionism (e.g. 'unfair competition', 'economic patriotism') or to Islam ('Islamic fundamentalism').

Table A.2: Sample of transcribed shows (part 1)

Outlet	Show name	# (sub-)shows	Time span
BFM TV	20H Week-end	311	2015–2020
BFM TV	20H30 Live	2243	2014–2020
BFM TV	Bourdin direct	999	2011–2016
BFM TV	Journal de 18 heures	54	2011–2020
BFM TV	Journal de 20h	150	2011–2016
BFM TV	Journal de 20h30	2021	2011–2020
BFM TV	Journal de 21h	2737	2011–2020
BFM TV	L'invité de Jean Jacques Bourdin	415	2016–2020
CNews/I-Télé	Journal	3909	2011–2017
CNews/I-Télé	Le JT	1519	2014–2016
CNews/I-Télé	On ne va pas se mentir	621	2012–2016
CNews/I-Télé	Punchline	1	2017–2017
Europe 1	Europe 1 vous répond	1	2014–2014
Europe 1	L'interview	346	2011–2017
Europe 1	L'interview culture	1	2017–2017
Europe 1	L'interview d'Alexandre Kara	12	2014–2014
Europe 1	L'interview d'Europe 1 soir	390	2012–2013
Europe 1	L'interview de 8h20	28	2013–2013
Europe 1	L'interview de Caroline Roux	2	2013–2013
Europe 1	L'interview de Jean Philippe Balasse	4	2014–2014
Europe 1	L'interview de Jean Pierre Elkabbach	1100	2011–2016
Europe 1	L'interview de Nikos Aliagas	200	2011–2012
Europe 1	L'interview de Thierry Guerrier	14	2011–2012
Europe 1	L'interview de Thomas Sotto	7	2014–2015
Europe 1	L'interview du dimanche	2	2018–2018
Europe 1	L'interview découvertes	12	2015–2016
Europe 1	L'interview politique	225	2014–2018
Europe 1	L'interview politique de 08h15	169	2016–2018
Europe 1	L'interview vérité	858	2013–2017
Europe 1	L'invité	182	2011–2017

Table A.3: Sample of transcribed shows (part 2)

Outlet	Show name	# (sub-)shows	Time span
Europe 1	L'invité d'Europe matin	8	2018–2018
Europe 1	L'invité d'Europe soir	139	2013–2018
Europe 1	L'invité de Patrick Cohen	94	2017–2018
Europe 1	L'invité du week end	20	2017–2018
Europe 1	Le grand rendez vous Europe 1	244	2012–2018
France 2	13h15 le dimanche	162	2012–2020
France 2	20 heures	19281	2011–2020
France 2	Complément d'enquête	1	2011–2011
France 2	Des paroles et des actes	39	2011–2016
France 2	L'émission politique	23	2016–2018
France 2	Les 4 vérités	2141	2012–2020
France 2	On n'est pas couché	1	2016–2016
France 2	Un jour, un destin	2	2014–2015
France 2	Vivement dimanche	105	2012–2020
France 3	12 13 Edition nationale	8585	2011–2020
France 3	19 20 Edition nationale	2325	2011–2020
France 3	Dimanche en politique	229	2016–2020
France 3	Soir 3 journal	4	2012–2012
France 5	C dans l'air	6462	2013–2019
France 5	C à dire	1419	2013–2019
France Info	L'invité	625	2011–2015
France Inter	5 minutes avec	197	2011–2012
France Inter	Invité de la semaine	17	2011–2012
France Inter	L'interview politique	242	2014–2017
France Inter	L'invité	2	2011–2011
France Inter	L'invité actu	44	2013–2015
France Inter	L'invité d'Inter	1587	2011–2019
France Inter	L'invité de 6h20	546	2017–2020
France Inter	L'invité de 7h50	1473	2013–2020
France Inter	L'invité de 8h20	487	2014–2020

Table A.4: Sample of transcribed shows (part 3)

Outlet	Show name	# (sub-)shows	Time span
France Inter	L'invité du 5/7	762	2013–2017
France Inter	L'invité du 5/9	1	2012–2012
France Inter	L'invité du week end	223	2015–2020
France Inter	Le grand invité du samedi	63	2013–2014
France Inter	Tous politiques	115	2012–2015
LCI	L'invité d'Audrey	200	2017–2018
LCI	L'invité de Julien Arnaud	289	2011–2013
LCI	L'invité de LCI Matin	263	2016–2017
LCI	L'invité de la matinale	38	2018–2018
LCI	L'invité du matin	1	2016–2016
LCI	L'invité politique	658	2013–2017
LCI	Le grand jury RTL Le Figaro LCI	139	2011–2016
LCI	Oui ou non	396	2011–2015
M6	Le 1945	6506	2012–2020
RMC		115	2012–2013
RMC	Bourdin direct	610	2011–2015
RMC	L'invité de Jean Jacques Bourdin	570	2013–2018
RMC	L'invité en studio	689	2015–2018
RTL	L'Homme du jour	319	2015–2017
RTL	L'invité actu	559	2012–2015
RTL	L'invité de RTL	1419	2011–2020
RTL	L'invité de RTL Matin	10	2017–2019
RTL	L'invité de RTL Midi	918	2012–2019
RTL	L'invité de RTL Soir	1167	2012–2019
RTL	Le choix de RTL	3	2015–2015
RTL	Le choix de Yves Calvi	675	2011–2015
RTL	Le grand jury RTL Le Figaro LCI	188	2012–2018
RTL	RTL et vous	322	2013–2014
TF1	Le 20H	20088	2011–2020
TF1	Sept à huit	614	2012–2020

Table A.5: Top words in shows featuring a radical left guest

Top 20 words	χ^2 test statistic	In French	In English
insoum	5619.2	insoumis	unbowed (refers to rad. left party name)
gauch	5221.1	gauche	left
travailleur	3872.6	travailleur	worker
commun	2617.6	commun (or communiste)	common (or communist)
fiscal	2521.4	fiscal	fiscal
russ	1942.4	russe	Russian
mpa	1928.1	NPA (probable transcription error)	NPA (refers to rad. left party)
salair	1685.6	salaire	wage
licenci	1653.2	licencier	lay off
gen	1497.1	gens	people
impot	1496.6	impôt	tax
monsieur	1470.2	monsieur	sir
austerit	1382.4	austérité	austerity
ouvrier	1357.5	ouvrier	worker
polit	1319.5	politique	politics
social	1215.4	social (or socialiste)	social (or socialist)
insoumis	1121.1	insoumis	unbowed (refers to rad. left party name)
ouvri	1107.4	ouvrier	worker
dividend	1072.3	dividende	dividend
vot	1069.7	voter	vote

Table A.6: Top bi-grams in shows featuring a radical left guest

Top 20 bigrams	χ^2 test statistic	In French	In English
part:commun	5030.2	Parti Communiste	Communist Party (rad. left party)
franc:insoum	3730.7	France Insoumise	Unbowed France (rad. left party)
lutt:ouvrier	3153.9	Lutte Ouvrière	Workers' Struggle (rad. left party)
sixiem:republ	1705.9	sixième république	Sixth republic
commun:franc	1202.2	Communiste Français	French Communist (rad. left party)
franc:insoumis	1100.5	France Insoumise	Unbowed France (rad. left party)
assemble:constitu	1022.4	assemblée constituante	Constituent assembly
monarch:presidentiel	754.4	monarchie présidentielle	presidential monarchy
mobilis:social	722.8	mobilisation sociale	social mobilization
planif:ecolog	699	planification écologique	ecological planning
servic:public	698.5	service public	public service
grand:patronat	688.1	grand patronat	big business
part:anticapital	681.4	Parti Anticapitaliste	Anticapitalist Party (rad. left party)
candidat:commun	668.6	candidat communiste	communist candidate
quand:mem	660.8	quand même	anyway
lutt:social	657.7	lutte sociale	social struggle
etat:unis	653.9	Etats-Unis	United States
parad:fiscal	586	paradis fiscal	tax haven
candidatur:commun	576.1	candidature communiste	communist candidacy
class:capital	545.4	classe capitaliste	capitalist class

Table A.7: Top words in shows featuring a green guest

Top 20 words	χ^2 test statistic	In French	In English
ecolog	59598.3	ecologie	ecology
vert	9704.8	vert	green
nucleair	7451.1	nucléaire	nuclear
climat	7176.9	climat	climate
energet	5590.9	énergétique	energetic
energ	3598.7	énergie	energy
transit	3234.5	transition	transition
pollut	2616.7	pollution	pollution
rechauff	2576.5	rechauffement	warming
ecolo	2165.8	ecologique	ecological
log	2161.9	logement	housing
deregl	2111.2	dérèglement	disruption
diesel	1788.9	diesel	diesel
renouvel	1519.7	renouvelable	renewable
sevran	1463.9	Sevran	Sevran (green stronghold)
polit	1400	politique	politics
environnemental	1385.8	environnemental	environmental
question	1377.5	question	question
gaz	1140	gaz	gas
accord	1135.5	accord	agreement

Table A.8: Top bi-grams in shows featuring a green guest

Top 20 bigrams	χ^2 test statistic	In French	In English
europ:ecolog	15201.5	Europe Ecologie	Europe Ecologie (green party)
transit:energet	3703	transition énergétique	energy transition
energ:renouvel	3433.3	énergies renouvelables	renewable energy
deregl:climat	2670	dérèglement climatique	climate change
rechauff:climat	2156	réchauffement climatique	global warming
chang:climat	1500.3	changement climatique	climate change
group:ecolog	1488.3	groupe écologiste	ecologist group
europeen:europ	1421.1	européen Europe	European Europe
candidat:ecolog	1343.2	candidat écologiste	ecologist candidate
cris:ecolog	1253.5	crise écologique	ecological crisis
deput:ecolog	942.1	député écologiste	environmentalist representative
secretair:national	904.7	secrétaire national	national secretary
renov:thermiqu	854.5	rénovation thermique	energy-efficiency improvements
ecolog:polit	821.2	écologie politique	political ecology
energ:fossil	798.3	énergie fossile	fossil fuel
fiscalit:ecolog	794.4	fiscalité écologique	ecological tax
tax:poid	763.8	taxe poids	heavy trucks tax
central:nucleair	714.9	centrale nucléaire	nuclear plant
group:europ	703.8	groupe Europe	Europe group
efficacit:energet	699.8	efficacité énergétique	energy efficiency

Table A.9: Top words in shows featuring a left-wing guest

Top 20 words	χ^2 test statistic	In French	In English
gauch	13065.2	gauche	left
social	12761.4	social (or socialiste)	social (or socialist)
ministr	11383.1	ministre	miniter
gouvern	6037.2	gouvernement	government
republ	5175.5	république	republic
croissanc	4655.2	croissance	growth
film	4181.4	film	movie
debat	3358.5	débat	debate
responsabilit	3243	responsabilité	responsabilité
reform	3193.7	reforme	reform
p	3113.3	PS	PS (left-w. party)
president	3103.1	président	president
loi	2939.1	loi	law
redress	2781.3	redressement	recovery
econom	2729.8	economie	economy
impot	2388.1	impôt	tax
polit	2309.8	politique	politics
an	1969.4	an	year
engag	1945.2	engagement	commitment
chomag	1913	chômage	unemployment

Table A.10: Top bi-grams in shows featuring a left-wing guest

Top 20 bigrams	χ^2 test statistic	In French	In English
part:social	7341	parti socialiste	Parti Socialiste (left-w. party)
premi:ministr	3381.3	premier ministre	prime minister
deput:social	2104.2	député socialiste	socialist representative
premi:secretair	1411	premier secrétaire	first secretary
certain:nombr	1250.3	certain nombre	certain number
assemble:national	1213.3	Assemblée Nationale	National Assembly
group:social	1206.3	groupe socialiste	socialist group
social:democrat	892.2	social démocrate	social democrat
partenair:social	874.2	partenaires sociaux	social partners
banqu:publiqu	780.5	banque publique	public bank
impot:sur	701.7	impôt sur	tax on
transit:energet	683	transition énergétique	energy transition
mem:temp	676.8	même temps	same time
aujourd:hui	653.1	aujourd'hui	today
dialogu:social	622.3	dialogue social	social dialogue
candidat:social	621.1	candidat socialiste	socialist candidate
lutt:contr	612.7	lutte contre	fight against
front:national	597.3	Front National	Front National (rad. right party)
i:tel	570.2	I-Télé	I-Télé (television outlet)
etat:unis	562.5	Etats-Unis	United States

Table A.11: Top words in shows featuring a liberal guest

Top 20 words	χ^2 test statistic	In French	In English
modem	4947.8	Modem	Modem (centrist party)
ministr	3596.4	ministre	miniter
deput	3010.4	deputé	representative
europeen	2762.8	européen	European
republ	2687.1	république	republic
gilet	2260.7	gilet	vest (as in Yellow Vests)
reform	2027.5	reforme	reform
assemble	1941.1	assemblée	assembly
britann	1940.2	britannique	British
royaum	1782.4	royaume	Kingdom
jaun	1763	jaune	yellow (as in Yellow Vests)
film	1740.4	film	movie
president	1538.4	président	president
union	1514	union	union
gouvern	1479.8	gouvernement	government
majorit	1479.4	majorité	majority
sujet	1477.2	sujet	subject
parlementair	1414.2	parlementaire	parliamentary
isf	1377.7	ISF (impôt sur la fortune)	wealth tax
retrait	1068.3	retraite	retirement

Table A.12: Top bi-grams in shows featuring a liberal guest

Top 20 bigrams	χ^2 test statistic	In French	In English
gilet:jaun	2464.2	gilets jaunes	Yellow Vests (social movement)
royaum:uni	2097	Royaume Uni	United Kingdom
assemble:national	1594.1	Assemblée Nationale	National Assembly
union:europeen	1590.6	Union Européenne	European Union
premi:ministr	1300.9	premier ministre	prime minister
voi:bien	842.7	vois bien	see well
grand:debat	772.8	Grand Débat	Great Debate
transit:ecolog	633.9	transition écologique	transition écologique
grand:bretagn	569.4	Grande Bretagne	Great Britain
fonction:publiqu	480	fonction publique	public service
vi:publiqu	459.3	vie publique	public life
break:sit	447.1	Brexit (likely transcription error)	Brexit (likely transcription error)
bras:exit	387.5	Brexit (likely transcription error)	Brexit (likely transcription error)
travail:pay	385.3	travail paye	work pays
collectivit:local	383.9	collectivité locale	local government
point:fr	383	point fr	dot fr (website suffix)
assur:chomag	382.5	assurance chômage	unemployment insurance
servic:national	350.9	service national	National Service (civil conscription service)
respect:autrui	345.2	respecter autrui	respect others
part:conserv	335.5	parti conservateur	conservative party

Table A.13: Top words in shows featuring a right-wing guest

Top 20 words	χ^2 test statistic	In French	In English
ump	47182	UMP	UMP (right-w. party)
polit	11174.6	politique	politics
droit	10312.9	droite	right
primair	8741.9	primaire	primary
candidat	8368.2	candidat	candidate
republicain	8367.6	républicain	republican (refers to right-w. party name)
national	5266.5	national	national
mair	5052.4	maire	mayor
front	4958.9	front	front
vot	4952.8	voter	vote
pas	4901.5	pas	not
sujet	4861.8	sujet	subject
elect	4324.7	élection	election
debat	4098.1	débat	debate
moi	3931.2	moi	me
president	3843.9	président	president
republ	3214.7	république	republic
film	2944.5	film	movie
campagn	2920.4	campagne	campaign
opposit	2906.2	opposition	opposition

Table A.14: Top bi-grams in shows featuring a right-wing guest

Top 20 bigrams	χ^2 test statistic	In French	In English
famill:polit	7255.1	famille politique	political family
front:national	5830.4	Front National	Front National (rad. right party)
bureau:polit	2638.1	bureau politique	political bureau
deput:ump	2108.8	député UMP	UMP representative (right-w. party)
aujourd:hui	1343.4	aujourd'hui	today
lign:polit	1204.2	ligne politique	political line
elect:presidentiel	1156	élections présidentielles	presidential elections
premi:tour	816.7	premier tour	first round
part:polit	789.9	parti politique	political party
vi:polit	784.6	vie politique	political life
ancien:president	780.6	ancien président	former president
primair:ouvert	758.7	primaire ouverte	open primaries
assemble:national	747.2	Assemblée Nationale	National Assembly
group:ump	738.3	groupe UMP	UMP group (right-w. party)
elect:municipal	708.3	élections municipales	municipal elections
grand:edit	648.3	grande édition	grande édition (television show)
part:social	646.4	parti socialiste	Parti Socialiste (left-w. party)
dis:simpl	634.1	dis simplement	simply say
droit:republicain	620.8	droite républicaine	republican right
premi:ministr	619.8	premier ministre	prime minister

Table A.15: Top words in shows featuring a radical right guest

Top 20 words	χ^2 test statistic	In French	In English
front	38626.6	front	front
national	28414.7	national	national
patriot	13740.3	patriote	patriotic
immigr	9945.2	immigration	immigration
fn	8209.2	FN	FN (rad. right party)
monsieur	6750.8	monsieur	sir
union	5503.2	union	union
europeen	4731.5	européen	European
franc	4713.4	franc	franc
frontier	3617.7	frontière	border
monnai	3467.8	monnaie	currency
souverainet	3297.4	souveraineté	sovereignty
candidat	3254.8	candidat	candidate
polit	3210	politique	politics
peupl	2719.9	peuple	people
euro	2716.4	euro	euro
ump	2504.1	UMP	UMP (right-w. party)
electeur	2485.9	électeur	voter
clandestin	2210.7	clandestin	undocumented
deloyal	2025.2	déloyal	unfair

Table A.16: Top bi-grams in shows featuring a radical right guest

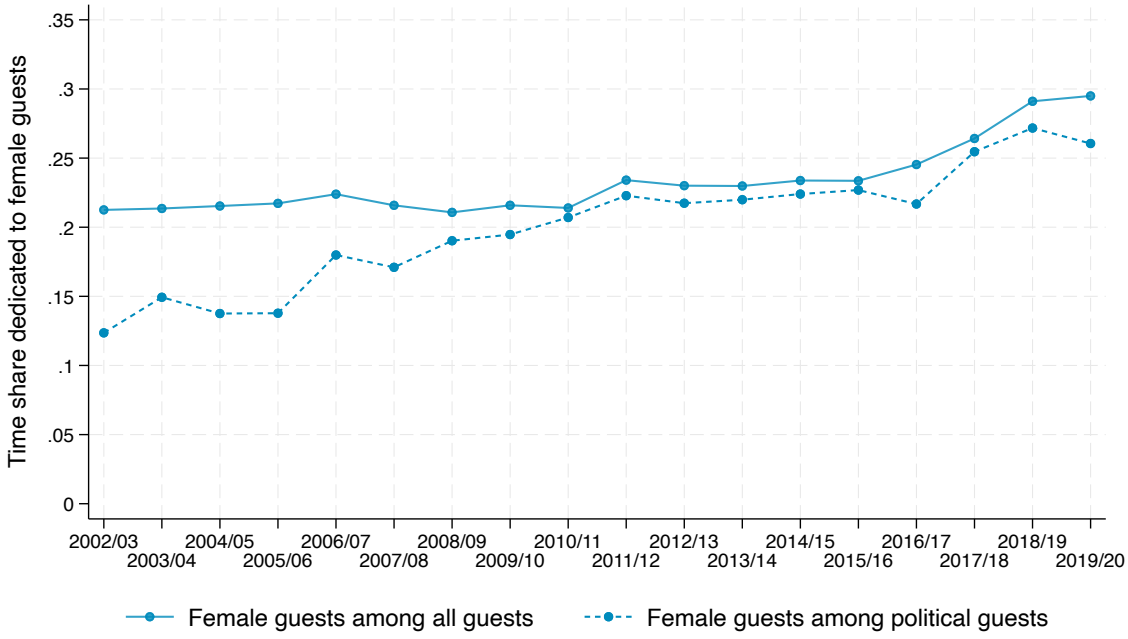
Top 20 bigrams	χ^2 test statistic	In French	In English
front:national	44151.9	Front National	Front National (rad. right party)
union:europeen	6641.6	Union Européenne	European Union
rassembl:bleu	4114	Rassemblement Bleu	Rassemblement Bleu (rad. right coalition)
fondamental:islam	3785.9	fondamentalisme islamique	Islamic fundamentalism
rassembl:national	3617.9	Rassemblement National	Rassemblement National (rad. right party)
patriot:econom	3442.2	patriotisme économique	economic patriotism
immigr:massiv	3233	immigration massive	massive immigration
frontier:national	3157.3	frontières nationales	national borders
monnai:national	3070.3	monnaie nationale	national currency
peupl:franc	2378	peuple français	French people
second:tour	2169.3	second tour	second round
henin:beaumont	2005.5	Henin-Beaumont	Henin-Beaumont (rad. right stronghold)
ouvertur:total	1692.3	ouverture totale	complete opening
concurrent:deloyal	1443.1	concurrence déloyale	unfair competition
protection:intelligent	1391.8	protection intelligente	intelligent protection
souverainet:national	1312.5	souveraineté nationale	national sovereignty
international:deloyal	1215.2	international déloyal	international unfair
souverainet:monetair	1211.9	souveraineté monétaire	monetary sovereignty
bureau:execut	1159.4	bureau exécutif	executive committee
premi:tour	1144.5	premier tour	first round

A.3 Additional data on guests

In addition to political classification, we use several data sources to describe guests' demographic and professional characteristics.

A.3.1 INA data

We first use INA data which, for each individual, provide a short description of the guest's profession, gender, year of birth, and country. For gender, INA data indicate whether the person is male or female. Figure A.5 plots the share of women across seasons, for all appearances, and only for appearances that we classify politically. It increased between 2002 and 2020, from 22% to 29%.



Notes: The Figure plots the evolution of the share of the guest appearances who are marked as women in the INA data. The continuous line with dots reports this share among all appearances, and the dashed line among the guests who are politically classified.

Figure A.5: Evolution of the share of women among the guests, 2002-2020

INA data also provide a short description of guests' age and profession. This information is rather general ("politician" rather than "mayor of Paris" for instance) and not time-varying. If, however, an individual had several professions during their career, both are generally detailed. For example David Douillet, a judo gold medalist who later became Minister of Sports, has "judoka, politician" listed as his profession. We then classify professions into groups by searching keywords in the guest description. A given guest can fall in multiple categories if their description contains keywords corresponding to distinct categories. The categories are the following:

- **Politicians**: “homme politique,” “femme politique,” and “personnalité politique.”
- **Activists/philanthropists**: union leader, think tank director or member, foundation director, NGO director, etc.
- **Media/publishing**: any profession related to the media and publishing sector.
  - **Journalist**: journalist, reporter, editor, newspaper director, etc.
  - **Director and producer**: director, producer, assistant producer but also film editor (“monteur”), audiovisual technician, etc.
  - **Host**
  - **Opinion**: columnist, critic, etc.
  - **Writer**: writer, novelist, poet, essayist, etc.
  - **Director**: publication director, program director, production director, channel director, etc.
- **Business and finance**: businessman, CEO, market analyst, banker, asset manager, etc.
- **Administration**: top civil servant (“haut fonctionnaire”), supreme court justice, prosecutor, diplomat, military officer, judge, etc.
- **Entertainment**.
  - **Cinema and theater**: actor, actress, stage director, screenwriter, etc.
  - **Music**: singer, musician, songwriter, opera singer, DJ, etc.
  - **Dance**: dancer, choreographer, etc.
  - **Visual arts**: painter, photographer, etc.
  - **Festival**: festival director, etc.
  - **Other**: clown, magician, model, ‘Miss France’, etc.
- **Sports**.
  - Football
  - Rugby
  - Tennis
  - Cycling
  - Etc.

- **Pundits**. It should be noted that people classified with these key words are by no means all academics. Some hold PhDs and now work in consulting or think tanks. Others, for example, are described as 'economist' because they have written books on economic issues. Overall, these guests should be seen as people invited for their expertise, with the notion of expertise being somewhat loosely defined.
  - **Social sciences and humanities**: economist, sociologist, political scientist, geopolitics specialist, demographer, philosopher, historian, archaeologist, etc.
  - **Hard sciences and medicine**: medical doctor, surgeon, climatologist, physicist, chemist, etc.
- **Polls and communication**: opinion polls, communication consultant, publicist, etc.

We have data on people's profession for 85% of appearances. Appendix Table C.1 depicts the appearance share of guests for the main profession categories.

A.3.2 Wikidata

We also use Wikidata to collect data on people in the INA dataset (journalists and guests). We collect data on: date of birth, place of birth, education, profession, employers and citizenship. The procedure is as follows: for each name in our dataset (first name and last name), we search Wikidata and get the top 10 results, of which we discard those that do not refer directly to a person (i.e. a book, a place, etc.). For each name, we get between 0 and 10 results.

We then merge each Wikidata search result with the INA dictionary of name (*thesaurus*) and assess match quality. To do so, we create a score. A match's score is obtained as follows:

- Whether the first name and last name match. While the first Wikidata result might refer to the right person, the second might refer to a sibling or parent. There might be false negatives if the person uses a different name (Léa Salamé vs. Hala Salamé), or only their first name (Arthur, Magloire).
- Whether the birth year matches. Unfortunately, birth year is often missing in INA data.
- Whether the birth year is plausible. We give a higher score to Wikidata matches whose birth year is in the top 90% of the distribution (born after 1937). It helps discard people who have common names and have a homonym in history (military officer in the 19th century, etc.)
- Whether the gender matches.
- Whether the country of citizenship matches.
- Whether there is overlap between Wikidata's label and profession fields and INA's the profession field.

For each name, we keep the Wikidata match that has the best score. In the event of a tie, we keep the highest ranked in the Wikidata search results (likely more famous). We then drop all search results in the bottom decile, as the low score often indicates that most data fields were missing, and assessing the match quality is impossible. Of the around $40,000$ with at least 10 appearances that were searched in Wikidata, we find $21,048$ valid matches, a fraction of them being journalists.

A.4 Data on journalists

INA data, as for guests, also provide information on journalists' characteristics (gender, year of birth, country). Similarly, we collect data from Wikidata and match it to our dataset for both guests and journalists. Because, in the case of journalists, we are particularly interested in their work experience, we additionally collect data from *Les Biographies* (Section **??**) as well as information on their annual compensation and job title (Section A.4.2).

A.4.1 Les Biographies

Data on journalists come from the online version of a publication, akin to *Who's Who*, which contains concise biographical information on notable people in France. Each notice generally indicates the date and place of birth, the education and professional career (position, firm, start and end date) of the considered individual.

We focus on journalists, and for this reason we only retrieve notices of people related to the media industry. To do so, we use a keyword search on the *Les Biographies* website using a premium account. The keywords refer to channel names or media groups. They are the following: Arte, BFM, BFMTV, C8, Canal +, CNews, Europe 1, France 2, France 3, France 4, France 5, France Bleu, France Classique, France Culture, France Info, France Inter, France Télévision, I-télé, Groupe Les Echos, Groupe RTL, Groupe TF1, Groupe M6, Lagardère Active, LCI, M6, Mediawan, NextRadioTV, Radio France, RMC, RMC Sport, RTL, TF1, TMC, Vivendi, and W9. We collect the notice content of any person whose description contains at least one of these tokens.

We then focus on these people's careers. For each job entry, we disentangle the firm from the job title, and divide the classified job titles into several categories.

- Journalists. This category is broadly defined and refers to all positions related to media content: journalist, reporter, host, editor, columnist, etc.
- Participants. This category gathers people who regularly participate in shows, typically talk shows or debate shows.
- Top executives. This includes people that have a C-level position in a media outlet (CEO, CFO, etc.). We also create an indicator variable for whether the person was the CEO.

- Others. This generally includes people whose job is neither C-level, nor directly related to content creation, such as for instance head of marketing, head of advertising, etc.

As a result, for each person that has a notice on *Les Biographies*, we have their professional time line, with the duration of each position, the firm, and the job type. Of course, young journalists who rarely appear on screen are less likely to have a *Les Biographies* entry. Overall, we collect data on $5,001$ individuals.

A.4.2 CCIJP data

We collect novel data on journalists' wage earnings from the paper archives of the CCIJP (Committee of professional journalists identity card). In France, the profession of journalist was formalized with the creation of the CCIJP in 1935. This committee delivers press cards to journalists, which they can for example use to be accredited to cover events or to obtain a press armband. The French labor code defines a professional journalist as "any person whose primary, regular, and remunerated professional activity is associated with one or more daily or periodical publications or news agencies, which provide essential resources." To be able to establish whether a person meets these criteria, the committee collects data on journalists' employers and wage on a yearly basis.

It should be noted that not all the journalists in the INA dataset have been awarded a press card. For example, Laurence Ferrari – who appears in the INA dataset – had her press card denied when working on C8 for *Le Grand 8*, as the talk show was considered an 'infotainment' program, rather than an information program.[3] To obtain the press card, one indeed needs to show that she practices a "journalistic activity" (see Cagé, 2016, for details).

When digitizing this non-publicly available data, we have collected data on all the journalists who appeared at least once in our sample between 2002 and 2020. For France Télévision and Radio France – the two public broadcasters – we focused our data collection effort on the years 2014 (the last pre-takeover year), 2005, 2010, 2015, 2016 and 2017 rather than annually. The reason is that these two entities hire a very large number of journalists – more than 700 for Radio France and more than 2,000 for France Télévision –, which makes collecting data on their wage annually an incredibly costly task (knowing that access to this very sensitive data has only been granted to one of the co-authors and cannot be delegated to any research assistant). We further collect data on the careers of these journalists, even if their employer is not one of the 18 outlets in our sample. In this case, for the years until 2017 (included), we consider a broader group of employers: other main television outlets, other main radio stations, national and local daily newspapers, national weekly newspapers, and press agencies.

For each journalist in each year, we collect her gross wage earnings as well as her position title. We then clean the job titles and divide them into the following 13 categories:

[3] In Cabot E., "Ferrari et Pulvar, privées de carte de presse," 05/31/2013, *Le Journal du Dimanche*.

- CEO, deputy CEO: job titles including 'directeur général', 'président-directeur général', 'PDG', 'DG', etc., as well as deputy CEOs (e.g. 'directeur général adjoint').
- Managing director: job titles including the word 'directeur' (director), but not 'directeur général'. This can include 'directeur des programmes', 'directeur de l'information', 'directeur de la publication', 'directeur des sports', 'directeur des magazines', etc.
- Editorialist, columnist: job titles including the words 'éditorialiste' or 'chroniqueur'.
- Editor in chief: job titles including 'rédacteur en chef', i.e. the lead editor of the media. This category also includes 'rédacteur en chef adjoint' for example.
- Correspondent: job titles including 'envoyé spécial', 'envoyé permanent' or 'correspondant'.
- Host: job titles including 'présentateur'.
- Senior reporter: job titles including 'grand reporter'.
- Section editor: job titles including 'chef d'édition', 'chef de service', 'chef de rubrique', 'chef de bureau', 'chef de l'information', etc.
- Coordinator: job titles including 'coordinateur', e.g. 'coordinateur d'édition'.
- Video-journalist: job titles including 'reporter image', 'reporter photo', 'reporter video', 'journaliste spécialisé image' or 'cameraman'.
- Freelance: job titles including 'pigiste'.[4]
- Intern: job titles including 'stagiaire' or 'apprenti'.[5]
- Reporter: job titles including 'journaliste', 'redacteur', 'reporter' that do not fall in the above-mentioned categories.

Figure A.6 illustrates the hierarchical interweaving of the various positions within the newsrooms. Figure A.7 show the headcount and wage share associated to each position for the journalists in our sample. Figure A.8 plots the distribution of gross annual wage earnings by job position. The figure in parentheses indicates the number of observations associated with each position. The largest groups are 'editor in chief', 'senior reporter', 'section editor' and 'reporter'.

[4]When they apply annually to the CCIJP to obtain their press cards, journalists have to specify whether they are monthly-paid salaried workers ("journalistes appointés au mois") or freelancers ("journalistes rénumérés à la pige").

[5]Once she receives her first press card, a journalist is considered as an "intern" during two years (only one if she has studied in one of the twelve recognized journalism schools). At the end of the "internship" period, she obtains the tenured press card.

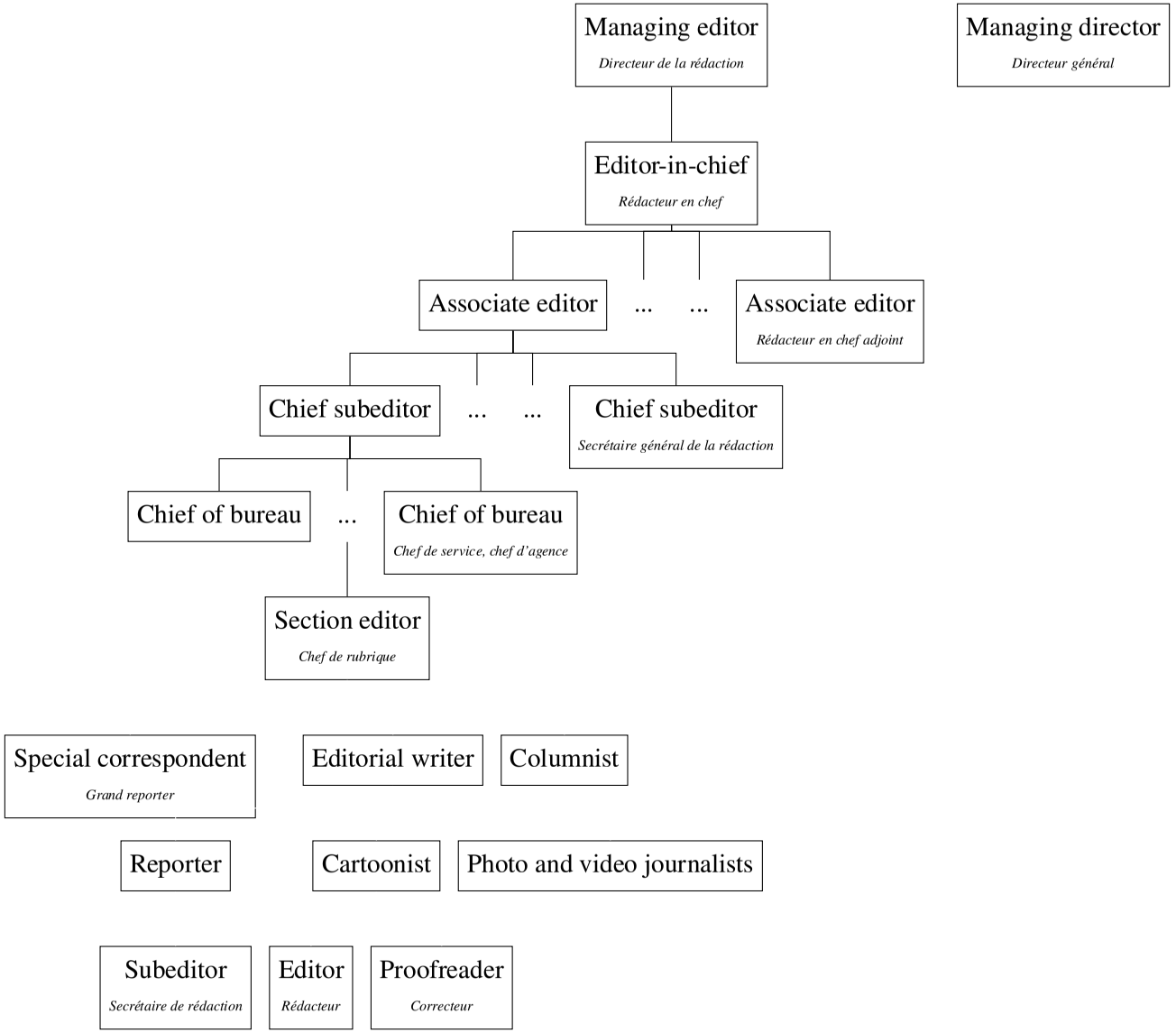
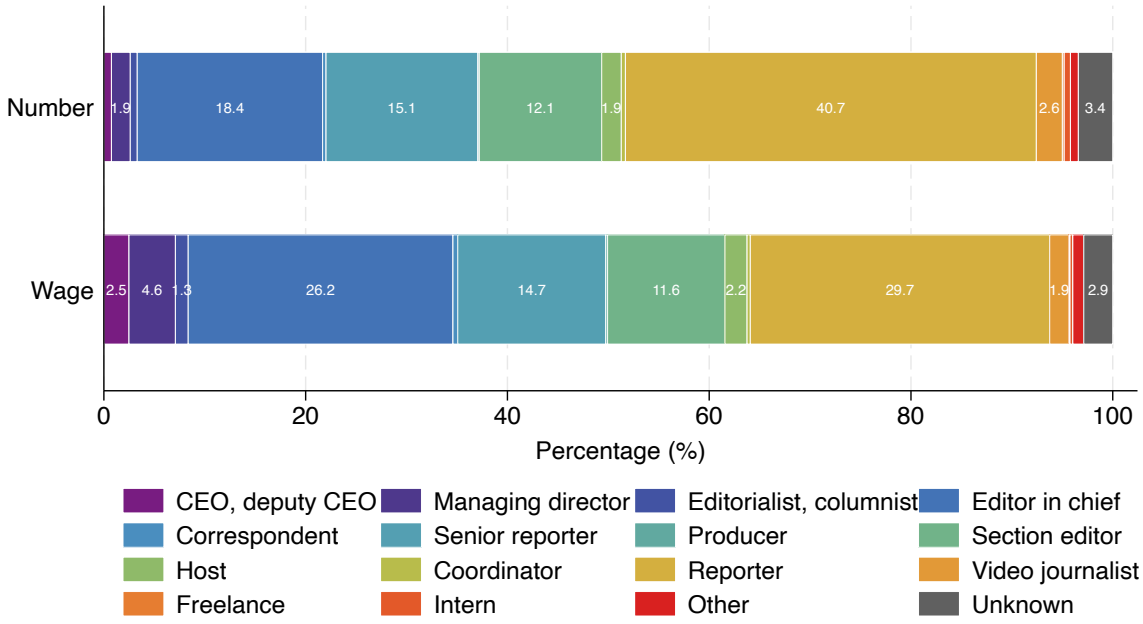
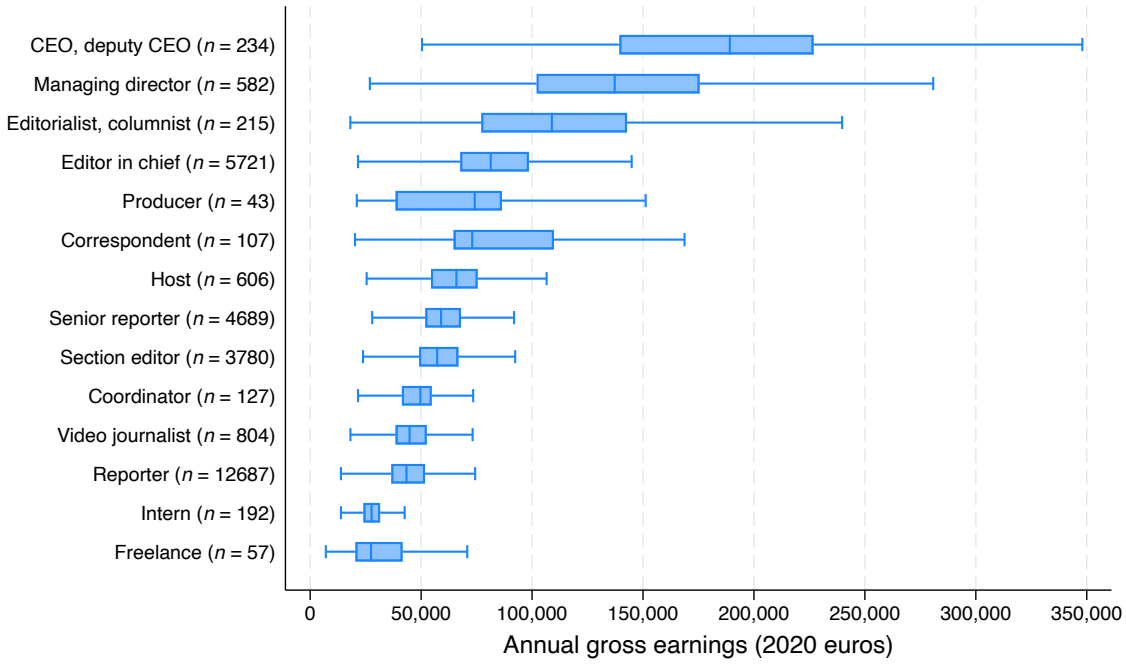


Figure A.6: Job titles: Hierarchical interweaving



Notes: The figure plots the headcount and wage share associated to each position for the journalists in the data we manually collected from the CCIJP archives.

Figure A.7: Headcount and wage share, by position



Notes: The figure plots the distribution of gross annual wage earnings in our wage estimation sample by job title groups. Figures in parenthesis indicate the number observations corresponding to each job title. The data comes from the CCIJP archives and was manually collected by the authors.

Figure A.8: Wage of journalists, by position

A.4.3 Data on journalist names' mentions in the press

We additionally collect data on press articles citing the name of journalists who are working on one of the 18 outlets in our INA data set during the 2013/2014 season.

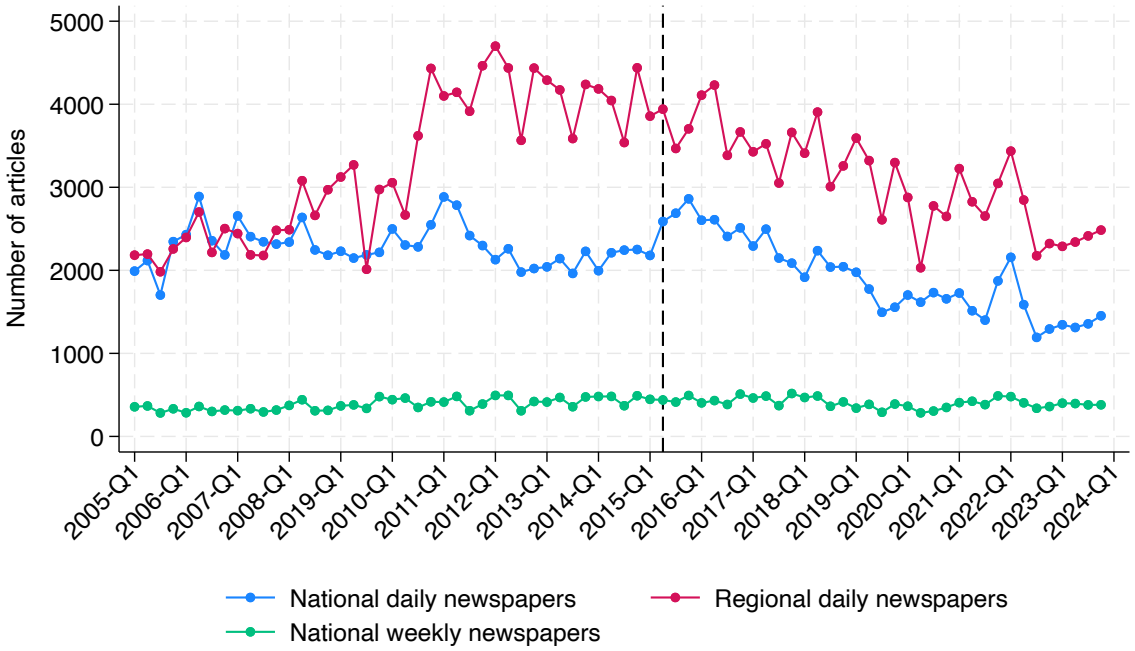
We consider the French press outlets, whose content is continuously available on Europresse between at least 2010 and 2020, that is in a five year window around the takeover. When both the print and the online versions are available, we collect data for the print version. They are the following:

- National daily: Aujourd'hui en France, La Croix, La Tribune, Le Monde, Le Figaro, Libération, Les Échos, L'Humanité.
- National weekly: L'Express, Le Figaro Magazine, Le Point, Valeurs Actuelles, Télérama.
- Local daily: L'Est Républicain, Midi Libre, La Nouvelle République, Ouest-France, Le Parisien, Paris-Normandie, Le Progrès, La Provence, Sud Ouest, Le Télégramme, La Voix du Nord.

For this set of source, we search the number of articles containing the name of each of the journalists who appear in the INA data set during the 2013/2014 season (the last season before the takeover) as well as at least one of the following keywords: show, television, telly, tv, radio, TF1, France 2, France 3, Canal+, France 5, M6, Arte, Direct 8, D8, C8, W9, TFX, NRJ12, LCP, Public Sénat, France 4, BFM, I-Télé, CNews, LCI, Franceinfo, Franceinfotv, France Info, France Télévision, Radio France, France Inter, France Culture, France Bleu, RMC, RTL, Europe 1, Radio Classique, Sud Radio. The goal is to exclude articles about other persons with the same name.

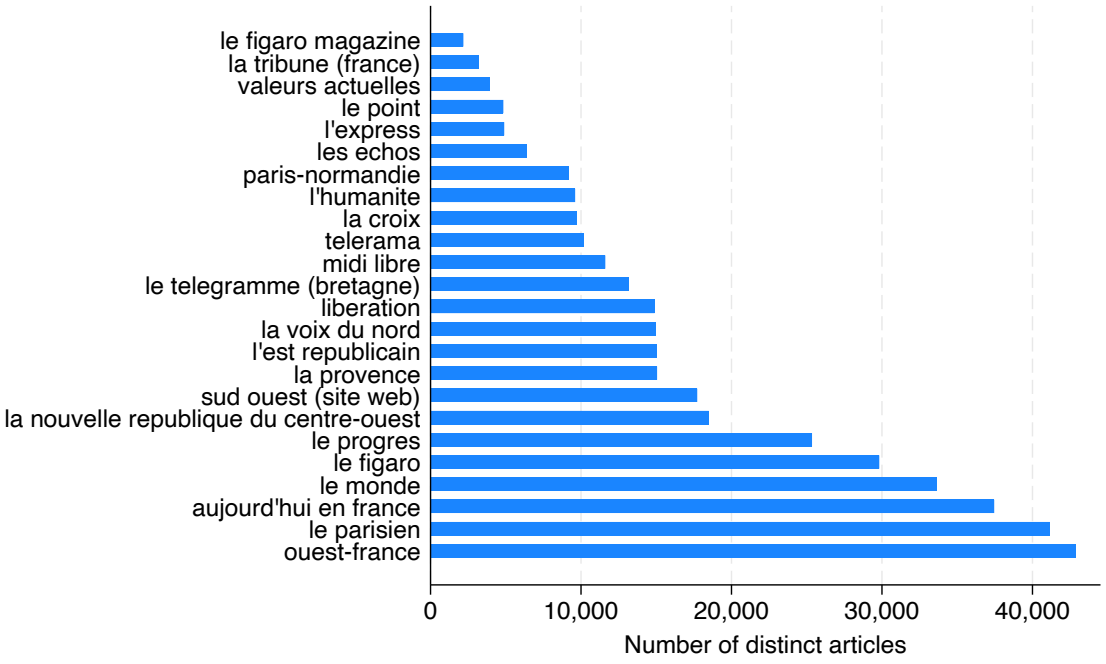
We exclude from this search the articles that are authored by the considered journalist, as our goal is to measure the amount of attention received by a given broadcast journalists, rather than to measure whether this journalist also writes for print media.[6] For each journalist, we collect the title, date and publisher of all the articles citing their name issued between January 1st 2005 and December 31st 2023. Appendix Figure A.9 plots the quarterly number of press articles in the estimation sample, by source type. Appendix Figure A.10 reports the number of press articles by source.

[6]It should however be noted that the name of photo reporters do not appear in the 'author' field, but in the caption of the article's photograph.



Notes: The figure plots the number of press articles in the estimation sample over time and by source type.

Figure A.9: Number of press articles over time, by source type



Notes: The figure plots the number of press articles in the estimation sample by source.

Figure A.10: Number of press articles by source

B Details on the French media and political landscape

B.1 Media landscape

In this section, we provide details on the French media landscape. Table B.1 provides information on television channels and Table B.2 does the same for radio stations.

Table B.1: French national digital terrestrial television channels

					Ownership		Audience share		
#	Channel	Sample	Free/Pay	Creation	2002 (or inception)	2020	2002	2007	2020
1	TF1	Yes	Free	1935	Bouygues	Bouygues	32.7	30.7	19.2
2	France 2	Yes	Free	1964	Public	Public	20.8	18.1	14.1
3	France 3	Yes	Free	1972	Public	Public	16.4	14.1	9.4
4	Canal+	Yes	Mixed	1984	Canal Plus	Bolloré	3.7	3.4	1.2
5	France 5	Yes	Free	1986	Public	Public	2.3	3.3	3.5
6	M6	Yes	Free	1987	Bertelsmann	Bertelsmann	13.2	11.5	9.0
7	Arte	Yes	Free	1992	Public	Public	1.6	1.8	2.9
8	C8	Yes	Free	2005	Bolloré	Bolloré	–	0.2	2.6
9	W9		Free	2009	Bertelsmann	Bertelsmann	–	0.9	2.6
10	TMC		Free	1954	AB & Bouygues	Bouygues	–	1.2	3.0
11	TFX		Free	2005	AB	Bouygues	–	0.6	1.6
12	NRJ 12		Free	2005	NRJ	NRJ	–	0.4	1.3
13	LCP	Yes	Free	2000	Public	Public	–	–	–
14	France 4		Free	2005	Public	Public	–	0.4	1.2
15	BFM TV	Yes	Free	2005	Weill	Altice	–	0.2	2.9
16	CNews	Yes	Free	1999	Canal Plus	Bolloré	–	0.3	1.4
17	CStar		Free	2005	Lagardère	Bolloré	–	0.4	1.1
18	Gulli		Free	2005	Lagardère & Public	Bertelsmann	–	0.8	1.3
20	TF1 Séries Films		Free	2012	Bouygues	Bouygues	–	–	1.8
21	L'Equipe		Free	1998	Amaury	Amaury	–	–	1.3
22	6ter		Free	2012	Bertelsmann	Bertelsmann	–	–	1.7
23	RMC Story		Free	2012	Diversite TV	Altice	–	–	1.5
24	RMC Découverte		Free	2012	Weill	Altice	–	–	2.3
25	Cherie 25		Free	2012	NRJ Group	NRJ Group	–	–	1.1
26	LCI	Yes	Free	1994	Bouygues	Bouygues	–	–	1.2
27	Franceinfo		Free	2016	Public	Public	–	–	0.7
41	Paris Première		Pay	1986	Paris & L. des eaux	Bertelsmann	–	–	–
42	Canal+ Cinéma		Pay	1996	Canal Plus	Bolloré	–	–	–
43	Canal+ Sport		Pay	1998	Canal Plus	Bolloré	–	–	–
	Planète+		Pay	1988	Canal Plus	Bolloré	–	–	–
	Total viewership of the 30 national digital terrestrial television channels (if available)						90.5	88.4	90.4
						Total sample viewership	90.7	83.6	67.4

Notes: As of today in Metropolitan France, there are 30 national digital terrestrial television channels: 7 public channels, 18 free national private channels, and 5 national pay channels. The Table provides information on each of them. Audience data from Médiamétrie. Data is missing either when the channel did not exist yet, or when Médiamétrie reports does not report the information (mostly for smaller channels).

Table B.2: French radio stations, excluding music only and local stations

Station	Sample	Creation	Ownership 2002	Ownership 2020	Audience share 2003	Audience share 2020
France Inter	Yes	1947	Public	Public	9.8	14.7
France Info	Yes	1947	Public	Public	4.9	4.7
France Bleu		1947	Public	Public	5.7	5.8
France Culture	Yes	1947	Public	Public	–	2.7
RTL	Yes	1933	Bertelsmann	Bertelsmann	11.5	12.6
Europe 1	Yes	1955	Lagardère	Lagardère	7.8	3.9
RMC	Yes	1943	Weill	Altice	2.8	5.3
Radio Classique		1983	LVMH	LVMH	–	2.4
BFM Business		1992	Altice	Altice	–	–
Audience share of non-local, non-music only stations					–	54.9
Audience share of our sample					36.8	46.3

Notes: Audience data from Mediametrie.

B.1.1 Public broadcasters

In France, there are eight public television stations: France 2, France 3, France 4, France 5, France Ô, Franceinfo, Arte, and LCP-Public Sénat. The first six of these – France 2, France 3, France 4, France 5, France Ô, Franceinfo – are operated by *France Télévisions*, while Arte is jointly operated by French and German public broadcasters. LCP-Public Sénat shares similarities with C-Span in the US. It is managed by the upper and lower houses; it primarily covers parliamentary activity. Our dataset includes information for the main ones: France 2, France 3, France 5, and Arte. In March 2020, France 2 had an audience share of 14.4%, France 3 had 9.1%, France 5 had 3.3% and Arte had 2.9%. Franceinfo was created in 2016, while France Ô, which is dedicated to overseas territories, became available nationally through digital terrestrial television in 2010.

We also have information for four public radio channels: France Bleu, France Culture, France Info and France Inter, which are the four main public radio stations with news programs. In 2020, France Inter had an audience share of 14.7%, France Info had 4.7%, and France Bleu had 5.8%. There are other public radio channels, mostly focused on music (France Musique, Fip, and the Mouv'); they are not in our sample. They are all managed by *Radio France*.

Appointment of public media group directors The French public broadcasting service is made up of *France Télévisions* for television on the one hand (i.e. in our dataset France 2, France 3, France 5), and *Radio France* for radio on the other hand (France Culture, France Info, and France Inter). As of today, the heads of *France Télévisions* and of *Radio France* are appointed by Arcom. However, this has

not always been the case during our period of interest. Indeed, between 2009 and 2013, the President of the Republic was legally responsible for appointing the president of *France Télévisions*, after receiving Arcom's approval. This law was strongly criticized for placing the nominally independent public sector media under direct state control. In 2013, this provision was reversed and Arcom was once again given authority to appoint the director of *France Télévisions* (see e.g. Benson et al., 2017).

B.1.2 Private broadcasters

Regarding private television, our dataset covers all national digital terrestrial television channels that have at least some programs with political guests in each season.

It excludes channels that specialize in entertainment – e.g. CStar (music), Gulli (children), NRJ TV, TFX, W9, TF1 Séries Films, 6ter, Chérie 25, which mostly have fiction or reality TV shows. L'Equipe TV is devoted to sport. RMC Story and RM Découverte essentially show documentaries. Furthermore, as reported in Table B.1, these television stations tend to have a rather low audience.

Our dataset also includes the three 24-hour news channels: BFM TV, CNews/I-Télé, LCI, as well as three private radio channels broadcasting news programs: Europe 1, RMC and RTL, which are the three private general-interest radio services in France.

These different television channels and radio stations changed hands a number of times during our period of interest. For the sake of the presentation here, we regroup them depending on their shareholder.

Groupe TF1 **TF1**, which was a public channel at the time of its creation, became private in 1987 after its acquisition by Bouygues (an industrial group specialized in construction, real estate development, telecommunications, and transportation). As of today, Bouygues owns 43.90% of the channels' capital, with the rest of the capital divided as follows: 28.80% floating stock abroad, 20.00% floating stock in France, and 7.30% for TF1 employees (TF1 shares are listed on the Premier Marché of the Paris Stock Exchange – Euroclear code 005490). The audience share of TF1 in March 2021 was 20.5%.

LCI was launched in 1994 on behalf of the media group TF1 as a pay television channel. It became a free channel in 2016. It is still owned by the "Groupe TF1". The audience share of M6 in March 2021 was 1.1%

The Groupe TF1 also owns the channel **TMC**. Launched in 1954, TMC is selected in 2003 by the CSA to be broadcast free-to-air on preselection No. 10 of the free TNT. This allowed it to obtain maximum coverage of the French territory as soon as it was launched on TNT in 2005. In 2005, the Groupe TF1, together with the Groupe AB (a business group in the field of broadcasting), bought the capital shares owned by Pathé in the channel (80% of the capital, the remaining 20% been owned by the Principality of Monaco. In 2010, the Groupe TF1 bought the shares owned by the Groupe AB (a transaction allowed by the CSA). In 2016, the Groupe TF1 finally bought the capital shares owned by the Principality of Monaco and became the unique shareholder of TMC.

Groupe M6 **M6** (Métropole Télévision) was launched in 1987. 48.26% of its capital is own by the "SA Immobilière Bayard d'Antin", i.e. RTL Group (Bertelsmann). The rest of the capital is divided as follows: 7.24% is owned by the "Compagnie nationale à portefeuille" (a family-owned professional shareholder), and 43.35% corresponds to floating stock. The audience share of M6 in March 2021 was 9.5%

RTL Group (Bertelsmann) also owns the radio station **RTL**.[7] The audience share of RTL in November-December 2020 was 12.6%.

NextRadioTV NextRadioTV, founded in 2000 by Alain Weill, is a company consisting of BFM TV and RMC. In 2015, Altice (a multinational telecommunications corporation founded and headed by Patrick Drahi, and the parent company of SFR) bought 49% of NextRadioTV, 51% of the capital been still held by Alain Weill.[8] In 2016, SFR Group / Altice took exclusive control of Groupe News Participations, which holds 99.7% of NextRadioTV's capital (a transaction permitted in 2017 by the competition authority[9] and approved in 2018 by the CSA).

BFM TV was launched in 2005 by NextRadioTV. As of today, 100% of the capital of BFM TV is owned by NextRadioTV whose 99.7% of the capital is owned directly or indirectly by the company "Groupe News Participations" (GNP), 99.7% of the capital of the latter being owned by "Altice Content Luxembourg", i.e. SFR (Patrick Drahi). The audience share of BFM TV in March 2021 was 2.8%

NextRadioTV also fully owns the private radio station **RMC**. RMC, founded in 1943, was bought in 2001 by NextRadioTV. The audience share of RMC in November-December 2020 was 6.1%.

Groupe Canal Plus As of today, the "Groupe Canal Plus" is made of the following television channels: Canal+, C8, and CNews.[10] A limited company, the "Groupe Canal Plus" is itself 100% owned by Vivendi. Since 2015, the "Groupe Bolloré" (with Vincent Bolloré) is the main shareholder of Vivendi with 26.28% of the capital (all the other shareholders own less than 5% of the capital).

C8 (formerly Direct 8 – D8) was launched in 2005 by Vincent Bolloré[11], and bought by the "Groupe Canal Plus" in 2011. As of today, 100% of the capital of C8 is owned by the "Groupe Canal Plus". The audience share of C8 in March 2021 was 2.7%.

CNews (formerly I-Télé), a 24-hour news channel, was launched in 1999 by the "Groupe Canal Plus". Initially a subscription-based television services, it became a free channel as of its arrival on French digital terrestrial television in October 2005. 99.8% of CNews is owned by the "Groupe Canal

[7]Founded in 1933 as Radio Luxembourg, the station's name was changed to RTL in 1966. It broadcast from outside France until 1981, because only public stations had been allowed until then. In 1981, privately run radio stations were allowed to broadcast in France and RTL has since then broadcast in France.

[8]As part of this operation, two new companies were created: one the one hand, News Participation, which owns NextRadioTV – 51% controlled by Alain Weill and 49% by Altice –, and on the other hand, Altice content, whose goal is to invest in media companies.

[9]Décision n° 17-DCC-76 en date du 13 juin 2017.

[10]As well as CStar, which is not included in our sample given it is not a general-interest channel.

[11]The official creation of the channel took place in 2001, with a number of tests. It was officially launched in 2005 with the "Télévision numérique terrestre" – digital terrestrial television platform.

Plus SA" (the remaining 0.20% is owned by Canal+ Finance SA). The audience share of France 2 in March 2021 was 1.9%.

Canal+ was launched in 1984 as the first French premium television (and the first private national television company.[12]) At the time of its launch, its main shareholder was the "Groupe Havas", a publicly-traded company whose main shareholder was the State itself. The capital share owned by Havas – the company was privatized in 1987 – in Canal Plus progressively decreased, and in 1987 the channel was listed on the stock exchange. At the time, its two main shareholders were Havas and the Compagnie Générale des Eaux.[13]

The audience share of Canal+ in March 2021 was 1.1% (but we must remember that Canal+ is a premium television channel).

Europe 1 Europe 1 is a privately owned radio station created in 1955, owned and operated by Lagarère since 1974 (Lagarère SCA at the beginning of the period, Lagarère Active as of today). The audience share of Europe 1 in November-December 2020 was 3.9%.

Radio Classique Launched in 1983 by Christian Pellerin,, Radio Classique broadcast mainly classical music, but also segments of economic and political news. In 1986, the station was 25% owned by RTL and 75% by the real estate company Lucia (a land holding company created by Christian Pellerin). In 1992, Pellerin sold Radio Classique to Sagem, a group specialized in professional and military electronics. In 1999, Desfossés International, a subsidiary of Bernard Arnault's group, LVMH (and media division of LVMH), bought 100% of the capital of Radio Classique. In 2000, Desfossés International became DI Group.[14] In 2008, as a result of the buyout of the economic daily *Les Echos* Bernard Arnault, DI Group renamed "Groupe les Echos" (with Nicolas Beytout as the CEO).

Note that all the private television channels have to establish a convention with Arcom.

[12]In 1984, the government initially granted Canal-Plus a public service concession for twelve years. The concession was renewed in 1994.

[13]More precisely, in 1984, more than 60 percent of the capital of the channel was held by state-controlled shareholders: Havas (42.13%) and nationalized banks (the Société Générale, the Banque Nationale de Paris (BNP), the Crédit Lyonnais, the Crédit Commercial de France (CCF), and the Banque Régionale d'Escompte et de Dépôt (Bred), 18.18 % in all).The other (private) shareholders were the Compagnie générale des eaux, L'Oréal, the Garantie Mutuelle des Fonctionnaires (GMF) (5%) and the regional daily newspaper *Ouest-France* (1.66%). Agence Havas, while remaining the largest shareholder in Canal Plus, held only 25% of its capital at the end of March 1986, through a number of capital increases and the sale of 12.5% of its shares. Furthermore, thanks to a capital increase, Perrier became a shareholder in 1986 with 5% of the capital, as well as Gilbert Gross's SGGMD (5%), the British group Granada (3%), and the Compagnie Financière Saint-Germain (2%), a holding company. In March 1986, the Compagnie Générale des Eaux (CGE) was still the leading private partner of the channel with 15.65% of its capital. It was followed by L'Oréal (10.41%), the Société Générale (10%), the Garantie Mutuelle des Fonctionnaires (GMF) (5.21%) and a group of banks (12.5%). The balance was held by various mutual funds and regional press groups associated with the creation of Canal Plus from the outset. In 1987, the CGE strengthened its position in the capital of Canal Plus, increasing its capital share from 15.65% to 21.49% (through the purchase of 5.21% of the shares held by the GMF and the acquisition of the shares (0.63%) of the Bred). At the time Canal Plus went public (in November 1987), its main shareholder were Havas (24.23%), CGE (20.72%), L'Oréal (7.7%), Société Générale (8.08%), CCF (6.82%), and Perrier (5%).

[14]Bernard Arnault bought Desfossés International (that edited the financial dailies *La Tribune* and l'*Agefi)* in 1994.

B.1.3 Pluralism and equal-time rules

A 1990 decision of the *Conseil Constitutionnel* – the French equivalent of the US Supreme Court – states that pluralism "is one of the conditions for democracy."[15] A 1986 law provides that media outlets' freedom of communication to the public should be reconciled with pluralism. Outside of electoral campaigns, the *Autorité de régulation de la communication audiovisuelle et numérique* (Arcom) requires television and radio outlets to represent a plurality of viewpoints in their programs. In practice, the Arcom guidelines state that a third of the political speaking time relative to the national political debate must be devoted to the president and the government. The remaining two-thirds should be split across political forces based on vote shares, elected officials' count, parliamentary groups' size, opinion polls, and political groups' contribution to public debate. Arcom asks each outlet to tabulate speaking time of politicians. This is done quarterly to average out news events. All programs are taken into account since 2018, previously, only shows on news and politics were subject to this rule. Only elected politicians or party members are accounted for.

In the context of elections, the pluralism principle is replaced by an equal-time rule that is strictly enforced.

Regarding presidential elections, we need to distinguish between the so-called *intermediate period* (from the publication of candidate lists to official start date of the campaign) and the 30-day *official campaign* itself (two weeks before the first round, then another two between the first and second rounds). The official campaign begins on the second Monday preceding the first round of voting and comes to a halt at midnight on the eve of the ballot. It then resumes on the day when the two front-runners are announced and comes to a final halt at midnight on the eve of the second round. Today, the principle of "equitable" speaking time prevails during the intermediate period.[16] Under the supervision of Arcom, the speaking time of the various parties during the "intermediate" campaign must reflect the extent to which they are representative of the French political landscape, as well as their capacity to demonstrate their intention to run candidates. There are three criteria of a party's "representativeness": its results in the most recent elections; the number and position of elected officials that it claims to have; and the evidence of opinion polls.[17] During the official campaign, an equal-time rule applies, by which each candidate should be granted the same speaking time.

With regard to parliamentary elections, the French electoral code states that – for the broadcasting of video clips – the parties with formally constituted groups in the National Assembly shall together

[15] CC, 86-217 DC, 18 septembre 1986, cons. 11

[16] The organic law of April 25, 2016, updated the rules governing presidential elections, including the allocation of speaking time. Previously, strict equality had been stipulated for candidates and their supporters throughout the "intermediate" period, which was naturally advantageous to the "smallest" campaigns. (Note, however, that this strict equality related only to speaking time, not to total airtime, and that the latter included TV and radio editorial material on candidates and their supporters.) On the rules governing pluralism during and outside election periods, see the information available on the CSA website, https://www.csa.fr.

[17] See the CSA recommendation no. 2016-2 of September 7, 2016 to the radio and television services for the presidential elections: `https://www.legifrance.gouv.fr/affichTexte.do?cidTexte=JORFTEXT000033104095&categorieLien=id`.

have a total of three hours for the first round, while parties without such groups may each have seven minutes' broadcasting time provided they can show that at least 75 candidates are running in their name.

B.2 Political landscape

There are many political parties in France, ranging from far left to far right. The political landscape has historically been dominated by two parties: the socialist party on the left (PS), and a conservative party (RPR, then UMP and now *Républicains*). A liberal party (REM, now *Renaissance*) emerged in 2016 and won both presidential and parliamentary elections in 2017. There are many other smaller parties – communist parties, green parties, centrist parties, anti-immigration parties, etc. – whose names changed and that merged or split over time. For this reason, we aggregate parties in six political groups using the Chapel Hill Expert Survey party classification (Bakker et al., 2015). They define several so-called families: radical left, green, socialist (left), liberal, conservative (right) and radical right.

Table B.3 reports the main French parties, along with their Chapel Hill family, their general left-right score (averaged over time), their economic left-right score and their social left-right score. Parties in bold are parties that were in power over the period we study.

We sometimes aggregate political groups in more aggregated groups. In this case, we combine radical left, green and socialist parties into a 'left-wing parties' group. Similarly, we group conservative and radical right parties in a 'right-wing parties' group.

Table B.3: Main Political Parties

Party	Family	L-R general	L-R economics	L-R social
Parti Communiste Francais	Radical left	1.1	1.1	3.8
La France Insoumise	Radical Left	1.7	1.1	2.4
Europe Ecologie-Les Verts	Greens	2.5	1.9	1.6
Parti Socialiste	Socialists	3	3.1	2.8
Mouvement Démocrate	Liberal	6.1	6.2	4.5
La République En Marche	Liberal	6.3	6.3	3.2
Les Républicains	Conservatives	7.9	8.1	6.9
Debout la France	Radical Right	9	7	8.3
Front National	Radical Right	9.6	5.9	8.9

Notes: L-R values are drawn from the Chapel Hill Expert Survey and range from 0 (Left) to 10 (Right). When available, 2019 data is used, 2014 otherwise. L-R general corresponds to a general placement on a left-right scale from 0 to 10. L-R economics refers to the party's ideological stance on economic issues such as privatization, taxes, regulation, etc. Parties on the economic left advocate for the government taking an active role in the economy, the right, a reduced role. L-R social corresponds to the variables "galtan", the party positioning on social and cultural values, from 0 - Libertarian or postmaterialists in favor of the expansions of personal freedoms to 10 - Traditional or authoritarian in favor of order, tradition and stability. The political parties in bold are those that have been in power at least once over the past two decades.

C Additional tables

Table C.1: Descriptive statistics of guest appearances

	(1) All app. Mean	(2) Non-political Mean	(3) Political Mean	(4) Politicians Mean	(5) PENOPs Mean
Descriptive characteristics					
% male	76.44	75.66	78.65	78.27	82.64
% female	21.86	22.10	21.16	21.57	16.92
% has birth year	67.08	57.57	94.32	95.30	84.20
% born 1940s or before	17.17	15.20	22.79	22.83	22.42
% born 1950s	19.07	13.46	35.15	35.67	29.76
% born 1960s	16.10	13.92	22.36	22.95	16.29
% born 1970s	9.40	8.81	11.08	10.98	12.09
% born 1980s or after	5.34	6.18	2.93	2.87	3.64
Profession					
% any profession	84.69	80.07	97.91	98.30	93.97
% politician	26.40	5.91	85.07	93.01	3.21
% politician, France	23.89	2.53	85.07	93.01	3.21
% media, publishing	24.85	30.46	8.81	6.65	31.09
% entertainment	13.73	17.98	1.57	1.49	2.35
% academics, pundits	11.55	12.56	8.65	4.39	52.51
% sports	8.69	11.20	1.50	1.54	1.06
% activists	4.07	4.56	2.64	1.73	11.95
% business men/women	3.09	3.49	1.97	1.60	5.81
% top bureaucrats	2.79	2.56	3.47	3.39	4.31
% pollsters, PR	0.33	0.43	0.05	0.05	0.04
Media presence					
% appears once	5.76	7.63	0.43	0.44	0.35
% appears 10+ times	79.19	72.98	96.97	97.03	96.34
% appears 100+ times	47.97	36.18	81.71	82.89	69.63
% appears 1,000+ times	12.83	2.91	41.26	44.76	5.22
% appears on one channel	9.21	12.12	0.88	0.90	0.67
% appears on all channels	19.91	7.35	55.87	58.40	29.83
Political leaning					
% unclassified	74.12	100.00	0.00	0.00	0.00
% classified as politician	23.60	0.00	91.16	100.00	0.00
% classified as PENOP	2.29	0.00	8.84	0.00	100.00
% radical left	1.83	0.00	7.09	6.58	12.34
% greens	1.56	0.00	6.02	5.24	14.08
% left	9.03	0.00	34.88	34.45	39.39
% liberals	2.82	0.00	10.90	10.15	18.67
% right	9.38	0.00	36.23	38.78	9.92
% radical right	1.09	0.00	4.21	4.08	5.60
# guest appearances	2,329,309	1,726,398	602,911	549,614	53,297
# distinct guests	261,993	254,357	13,418	11,003	2,583

Notes: This Table reports descriptive statistics on guest appearances in INA data. Columns 1 describes all appearances in the sample. Column 2 only considers appearances to which no political leaning is matched. Column 3 only considers politically classified appearances. Column 4 considers appearances classified as politicians, i.e. using election candidates' lists and using government appointees lists. Column 5 considers appearances classified as PENOPs, i.e. using lists of think tank staff members and contributors, of participants in party summer meetings, and of endorsements. For some guests, no gender is provided either because the data is missing, or because the guest is in fact a group of guests, such as a band. Data on the profession of guests is time-invariant. It can be missing for some guests, typically guests appearing vary rarely. 'politician, France' excludes guests whose profession is politician but whose country, if indicated, is not France (e.g. Donald Trump).

Table C.2: Analysis of the variance of time shares devoted to different groups

	All guests			Political guests	
	(1) Political guests	(2) All left	(3) All right	(4) All left	(5) All right
Journalist FE	Yes	Yes	Yes	Yes	Yes
Channel-Period FE	Yes	Yes	Yes	Yes	Yes
Week-Hour-Platform FE	Yes	Yes	Yes	Yes	Yes
F-stat	370.9	197.4	169.4	21.3	23.9
R-sq.	0.599	0.440	0.435	0.465	0.453
Adj. R-sq.	0.584	0.419	0.414	0.420	0.406
RMSE	0.188	0.139	0.126	0.266	0.258
Observations	1,257,785	1,257,785	1,257,785	481,635	481,635

Notes: The Table reports the F-statistics associated with testing for channel-period effects being jointly equal to zero, the R-square, adjusted R-square, root mean squared error (RMSE) and number of observations corresponding OLS regressions of equation (2), using respectively the share of political guests among all guests (Column 1), the share of left-wing guests among all guests (Column 2), the share of right-wing guests among all guests (Column 3), the share of left-wing guests among political guests (Column 4) and the share of right-wing guests among right-wing guests (Column 5).

Table C.3: Explaining differences in political coverage: Variance decomposition – Robustness, Excluding pre-election periods

	(1)	(2)	(3)	(4)	(5)
	Among all guests			Among political guests	
	Political	Left-wing	Right-wing	Left-wing	Right-wing
Cross outlet-period variance of average:					
Time share, $var(\bar{y}_{cs}^{net})$	0.02588	0.00629	0.00444	0.00434	0.00528
Outlet-period effects, $var(\gamma_{cs})$	0.01058	0.00262	0.00190	0.00349	0.00459
Journalist effects, $var(\bar{\alpha}_{cs})$	0.00517	0.00116	0.00094	0.00006	-0.00012
Sorting, $2 \times cov(\gamma_{cs}, \bar{\alpha}_{cs})$	0.01013	0.00251	0.00159	0.00079	0.00082
Correlation:					
Sorting, $cor(\gamma_{cs}, \bar{\alpha}_{cs})$	0.681	0.709	0.584	0.218	0.202
s.e.	0.017	0.021	0.027	0.085	0.091
Share of variance explained by:					
Outlet-period effects	0.409	0.417	0.429	0.804	0.868
s.e.	0.011	0.015	0.018	0.073	0.072
Average journalist effect	0.200	0.184	0.213	0.013	-0.023
s.e.	0.007	0.011	0.011	0.033	0.024
Sorting	0.392	0.399	0.359	0.183	0.155
s.e.	0.007	0.008	0.013	0.081	0.075
Observations					
Number of outlet-periods	126	126	126	126	126

Notes: The Table reports components of the variance decomposition proposed in equation (3) when excluding from the estimation sample of equation (2) pre-election periods during which candidates' air and speaking-time shares are tightly monitored by Arcom. Other notes as in Table 2.

Table C.4: Explaining differences in political coverage: Variance decomposition – Robustness, Without weights

	(1)	(2)	(3)	(4)	(5)
	Among all guests			Among political guests	
	Political	Left-wing	Right-wing	Left-wing	Right-wing
Cross outlet-period variance of average:					
Time share, $var(\bar{y}_{cs}^{net})$	0.01734	0.00394	0.00325	0.00267	0.00301
Outlet-period effects, $var(\gamma_{cs})$	0.00484	0.00121	0.00101	0.00239	0.00254
Journalist effects, $var(\bar{\alpha}_{cs})$	0.00590	0.00129	0.00112	0.00018	0.00022
Sorting, $2 \times cov(\gamma_{cs}, \bar{\alpha}_{cs})$	0.00660	0.00144	0.00111	0.00009	0.00026
Correlation:					
Sorting, $cor(\gamma_{cs}, \bar{\alpha}_{cs})$	0.612	0.568	0.512	0.053	0.123
s.e.	0.012	0.017	0.021	0.065	0.057
Share of variance explained by:					
Outlet-period effects	0.279	0.307	0.312	0.898	0.842
s.e.	0.006	0.008	0.010	0.048	0.041
Average journalist effect	0.340	0.327	0.345	0.067	0.072
s.e.	0.006	0.009	0.010	0.016	0.014
Sorting	0.381	0.366	0.343	0.035	0.086
s.e.	0.005	0.007	0.009	0.046	0.038
Observations					
Number of outlet-periods	126	126	126	126	126

Notes: The Table reports components of the variance decomposition proposed in equation (3) when not weighting observations by the time dedicated to guests when estimating equation (2). Other notes as in Table 2.

Table C.5: Explaining differences in political coverage: Variance decomposition – Robustness, Time-invariant channel fixed effects

	(1)	(2)	(3)	(4)	(5)
	Among all guests			Among political guests	
	Political	Left-wing	Right-wing	Left-wing	Right-wing
Cross outlet variance of average:					
Time share, $var(\bar{y}_{cs}^{net})$	0.02547	0.00540	0.00474	0.00256	0.00320
Outlet effects, $var(\gamma_c)$	0.00935	0.00179	0.00190	0.00187	0.00224
Journalist effects, $var(\bar{\alpha}_c)$	0.00571	0.00127	0.00102	0.00020	0.00016
Sorting, $2 \times cov(\gamma_c, \bar{\alpha}_c)$	0.01041	0.00234	0.00182	0.00049	0.00080
Correlation:					
Sorting, $cor(\gamma_c, \bar{\alpha}_c)$	0.711	0.771	0.648	0.330	0.567
s.e.	0.016	0.023	0.028	0.175	0.164
Share of variance explained by:					
Outlet effects	0.367	0.332	0.402	0.731	0.701
s.e.	0.010	0.017	0.021	0.134	0.103
Average journalist effects	0.224	0.235	0.215	0.078	0.049
s.e.	0.007	0.014	0.014	0.039	0.031
Sorting	0.409	0.433	0.384	0.192	0.250
s.e.	0.006	0.008	0.012	0.134	0.095
Observations					
Number of outlets	18	18	18	18	18

Notes: The Table reports the components of variance due to time, journalists and channels estimated by implementing the following variance decomposition across outlets: $var(\bar{y}_c^{net}) = var(\gamma_c) + var(\bar{\alpha}_c) + 2cov(\gamma_c, \bar{\alpha}_c)$ after estimating the following model: $y_{ict} = \alpha_i + \gamma_c + \tau_{p(c),t} + \epsilon_{ict}$. Other notes as in Table 2.

Table C.6: Explaining differences in political coverage: Variance decomposition – Robustness, Only using the 500 journalists appearing the most

	(1)	(2)	(3)	(4)	(5)
	Among all guests			Among political guests	
	Political	Left-wing	Right-wing	Left-wing	Right-wing
Cross outlet-period variance of average:					
Time share, $var(\bar{y}_{cs}^{net})$	0.03123	0.00697	0.00615	0.00297	0.00503
Outlet-period effects, $var(\gamma_{cs})$	0.01467	0.00324	0.00299	0.00142	0.00466
Journalist effects, $var(\bar{\alpha}_{cs})$	0.00654	0.00143	0.00130	0.00035	0.00054
Sorting, $2 \times cov(\gamma_{cs}, \bar{\alpha}_{cs})$	0.01002	0.00230	0.00186	0.00120	-0.00018
Correlation:					
Sorting, $cor(\gamma_{cs}, \bar{\alpha}_{cs})$	0.501	0.519	0.451	0.307	-0.035
s.e.	0.026	0.033	0.043	0.091	0.114
Share of variance explained by:					
Outlet-period effects	0.470	0.465	0.486	0.479	0.928
s.e.	0.018	0.025	0.031	0.109	0.119
Average journalist effect	0.209	0.205	0.212	0.117	0.108
s.e.	0.009	0.015	0.015	0.080	0.069
Sorting	0.321	0.331	0.302	0.405	-0.035
s.e.	0.013	0.018	0.025	0.120	0.153
Observations					
Number of outlet-periods	126	126	126	126	126

Notes: The Table reports components of the variance decomposition proposed in equation (3) based on the parameters estimated using equation (2) when only using the 500 journalists with the highest number of appearances. Other notes as in Table 2.

Table C.7: Effect of the takeover on the radical-right guests time share: Difference-in-differences estimates, Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. With channel fixed effects					
	Baseline	Only prime time	Not regulated	Week FE	Radio	No PENOPs
Treated×2015/17	0.0198**	0.0199**	0.0176**	0.0245***	0.0219**	0.0180**
	(0.00874)	(0.00927)	(0.00786)	(0.00644)	(0.00849)	(0.00632)
Treated×2017/19	0.0553*	0.0585**	0.0555*	0.0493**	0.0560***	0.0284**
	(0.0290)	(0.0205)	(0.0291)	(0.0179)	(0.0108)	(0.00990)
Observations	79537	24772	77044	86106	42686	38066
R^2	0.466	0.399	0.453	0.122	0.109	0.101
$\bar{y}$(control, post)	.076	.076	.076	.076	.076	.076
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel B. With journalist-channel fixed effects					
	Baseline	Only prime time	Not regulated	Week FE	Radio	No PENOPs
Treated×2015/17	0.0165***	0.0227***	0.0147***	0.0159***	0.0168*	0.0100
	(0.00435)	(0.00725)	(0.00373)	(0.00467)	(0.00851)	(0.00843)
Treated×2017/19	0.0319*	0.00969	0.0360*	0.0179	0.0328**	0.0232*
	(0.0175)	(0.0153)	(0.0178)	(0.0108)	(0.0113)	(0.0108)
Observations	478200	190161	461661	479902	203234	177141
R^2	0.465	0.351	0.462	0.149	0.171	0.170
$\bar{y}$(control, post)	.076	.076	.076	.076	.076	.076

Notes: The outcome variable is the time share of radical-right guests as a share of political guests. Column 1 reports the baseline specification (corresponding to Column 7 of Table 3). In Column 2, we restrict the sample to television prime time (between 7:00pm and 11:00 pm). In Column 3, we drop pre-election periods during which the speaking-time share of candidates is tightly monitored (equal air and speaking time periods). In Column 4, we use week fixed effects instead of week-time slot-platform fixed effects, effectively accounting for radio outlets in the control group. In Column 5, we use only radio outlets in the control group and use week fixed effects. In Column 6, we exclude PENOPs from the computation of time shares. Panel A estimates correspond to the estimation of equation (4) and Panel B estimates to the estimation of equation (6). Standard errors are clustered at the outlet level and stars indicate significance 1, 5, and 10% with ***, **, and *, respectively. The time period is September 1, 2005-August 31, 2019.

Table C.8: Effect of the takeover on whether outlets feature political guests, by political group: Difference-in-differences estimates

	(1) Baseline	(2) 1(Rad. left)	(3) 1(Greens)	(4) 1(Left)	(5) 1(Liberals)	(6) 1(Right)	(7) 1(Rad. right)
Treated × 2015/17	-0.0108	-0.0105	-0.0112	-0.0105	-0.0103	-0.0126	-0.0101
	(0.0117)	(0.0116)	(0.0119)	(0.0131)	(0.0115)	(0.0114)	(0.0113)
Treated × 2017/19	0.00955	0.00979	0.0100	0.0103	0.0100	0.00893	0.00855
	(0.0108)	(0.0106)	(0.0110)	(0.0115)	(0.0110)	(0.0110)	(0.0105)
Treated × 2015/17 × 1.Inter		-0.00435	0.00751	-0.000750	-0.00453	0.00585	-0.0162
		(0.00456)	(0.00447)	(0.00544)	(0.00329)	(0.00555)	(0.00952)
Treated × 2017/19 × 1.Inter		-0.00294	-0.00413	-0.00315	0.000184	0.00228	0.0128
		(0.00848)	(0.00884)	(0.00448)	(0.0147)	(0.00699)	(0.0213)
Observations	4403286	4403286	4403286	4403286	4403286	4403286	4403286
R^2	0.341	0.341	0.341	0.341	0.341	0.341	0.341
$\bar{y}$ (control, post)	.098						
$\bar{y}$ (control, post, inter=0)		0.098	0.098	0.096	0.097	0.099	0.097
$\bar{y}$ (control, post, inter=1)		0.093	0.087	0.102	0.101	0.093	0.107
Guest-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outlet-Guest FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variable is an indicator variable for whether guest j is observed on outlet c in week t. The analysis only considers politically-classified guests. Column titles refer to the political leaning of the guests and indicate which interaction term is used for the estimation of equation (5). Standard errors are clustered at the outlet level and stars indicate significance 1, 5, and 10% with ***, **, and *, respectively. The time period is September 1, 2005-August 31, 2019.

Table C.9: Journalists leaving after the takeover: Difference-in-differences estimates

	(1)	(2)	(3)
	Leaves	To no other channel	To another channel
Treated × 2015/17	0.187***	0.158***	0.0295***
	(0.0499)	(0.0497)	(0.00865)
Treated × 2017/19	0.117*	0.0971	0.0198***
	(0.0665)	(0.0631)	(0.00585)
R^2	0.496	0.511	0.469
Observations	278,493	278,493	278,493
$\bar{y}$ (treated, pre)	0.396	0.336	0.0600

Notes: The outcome variable in Column 1 is an indicator variable for whether a given journalist-channel pair existing in quarter t no longer exists in quarter $t + 4$. In Column 2, the outcome variable indicates whether a given journalist-channel pair existing in quarter t no longer exists in quarter $t + 4$ and journalist i is seen on no other channel in $t + 4$. In Column 3, the outcome variable indicates whether a given journalist-channel pair existing in quarter t no longer exists in quarter $t + 4$ but journalist i is seen on another channel in $t + 4$. Standard errors are clustered at the outlet level and stars indicate significance at the 1, 5, and 10% with ***, **, and *, respectively. The time period is September 1, 2005-August 31, 2019.

Table C.10: Journalists leaving after the takeover, by channel: Difference-in-differences estimates

	(1) Leaves	(2) To no other channel	(3) To another channel
C8/D8 × 2015/17	0.0424***	0.0437***	-0.00135
	(0.0104)	(0.00922)	(0.00247)
C8/D8 × 2017/19	0.106***	0.0884***	0.0178***
	(0.0257)	(0.0241)	(0.00450)
CNews/I-Télé × 2015/17	0.326***	0.299***	0.0279***
	(0.00962)	(0.00814)	(0.00327)
CNews/I-Télé × 2017/19	0.322***	0.293***	0.0294***
	(0.0262)	(0.0244)	(0.00524)
Canal+ × 2015/17	0.164***	0.124***	0.0399***
	(0.0103)	(0.00877)	(0.00353)
Canal+ × 2017/19	0.0446	0.0291	0.0155***
	(0.0261)	(0.0243)	(0.00499)
R^2	0.497	0.511	0.469
Observations	278,493	278,493	278,493
$\bar{y}$ (treated, pre)	0.396	0.336	0.0600

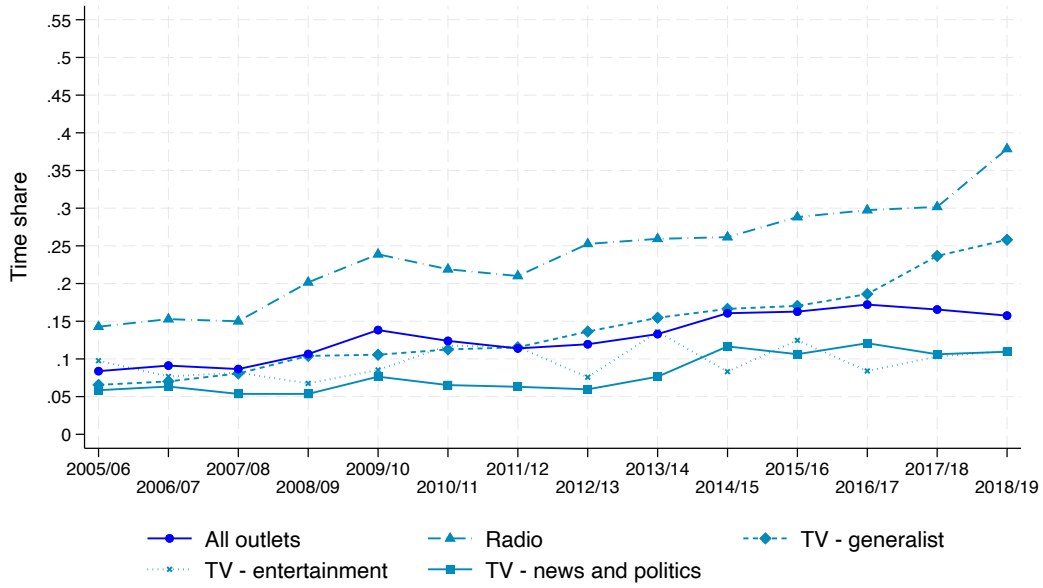
Notes: The outcome variables are the same as those described in Table C.9. Standard errors are clustered at the outlet level and stars indicate significance at the 1, 5, and 10% with ***, **, and *, respectively. The time period is September 1, 2005-August 31, 2019.

Table C.11: Journalists leaving after the takeover, by editorial preferences: Difference-in-differences estimates

	(1) Baseline	(2) Pol. guests	(3) Rad. left	(4) Greens	(5) Left	(6) Liberals	(7) Right	(8) Rad. right
Treated × 2015/17	0.187***	0.0572	0.192***	0.213***	0.210***	0.177***	0.192***	0.210***
	(0.0499)	(0.0355)	(0.0503)	(0.0572)	(0.0523)	(0.0499)	(0.0450)	(0.0478)
Treated × 2017/19	0.117*	0.0617	0.102	0.111**	0.115*	0.108	0.137**	0.0900
	(0.0665)	(0.0641)	(0.0924)	(0.0497)	(0.0572)	(0.0644)	(0.0594)	(0.0896)
Treated × 2015/17 × (Host FE>0)=1		0.314***	0.0313**	-0.0223	-0.0111	0.0814***	0.0272	-0.0104
		(0.0276)	(0.0145)	(0.0332)	(0.0169)	(0.0240)	(0.0288)	(0.0130)
Treated × 2017/19 × (Host FE>0)=1		0.0928*	0.0286	0.00261	-0.00477	0.0236	-0.0577	0.0538
		(0.0528)	(0.0799)	(0.0757)	(0.0379)	(0.0220)	(0.0394)	(0.0534)
R^2	0.496	0.479	0.458	0.458	0.458	0.458	0.458	0.458
Observations	278,493	263,227	242,345	242,345	242,345	242,345	242,345	242,345
$\bar{y}$ (treated, pre)	0.396							
$\bar{y}$ (treated, pre, inter=0)		0.404	0.366	0.353	0.382	0.350	0.348	0.394
$\bar{y}$ (treated, pre, inter=1)		0.354	0.343	0.362	0.331	0.371	0.366	0.319

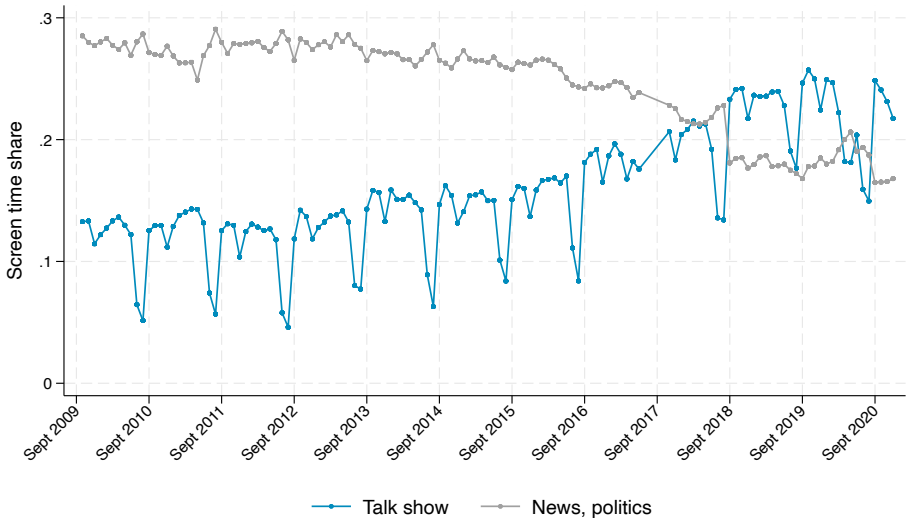
Notes: The outcome variable is an indicator for whether a given journalist-channel pair existing in quarter t no longer exists in quarter $t+4$. Column 1 presents the baseline specification. Other columns present difference-in-differences estimates interacted with whether or not the considered journalist has a positive individual fixed effect when estimating equation (2). The dependent variable used when estimating equation (2) is the share of political guests among all guests in Column 2, and the share of, respectively, radical left, greens, left, liberal, right, and radical right guests as a share of political guests in Columns 3 to 8. The last rows report the mean of the outcome variable on control channels for the period ranging from April 2015 to August 2019. Standard errors are clustered at the outlet level and stars indicate significance at the 1, 5, and 10% with ***, **, and *, respectively. The time period is September 1, 2005-August 31, 2019.

D Additional figures

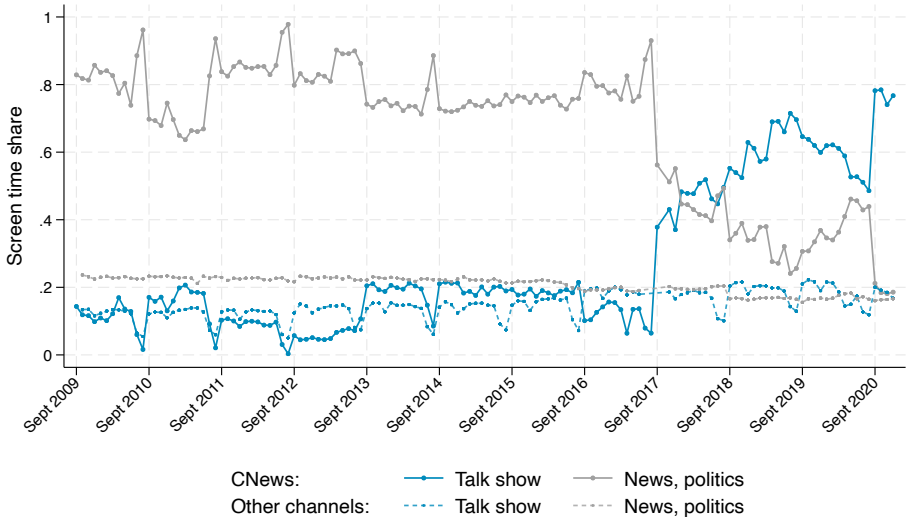


Notes: The Figure plots the evolution of the speaking-time share of PENOPs among the overall time share of politically-classified guests in our sample. Generalist TV outlets are TF1, France 2, France 3, France 5 and ARTE. Entertainment TV outlets are M6 and C8. News and politics TV outlets are BFM TV, CNews, LCI and LCP/PublicSenat.

Figure D.1: Share of coverage dedicated to PENOPs among politically classified guests



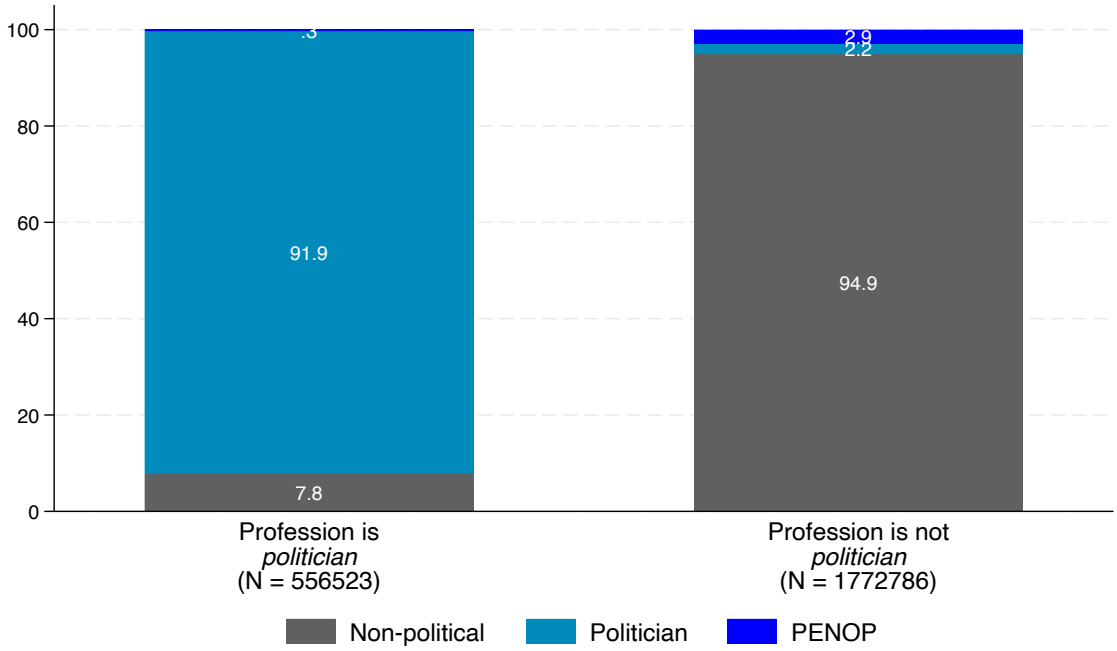
(a) Time share dedicated to talk shows and to shows on news and politics



(b) Comparison between CNews and other television channels

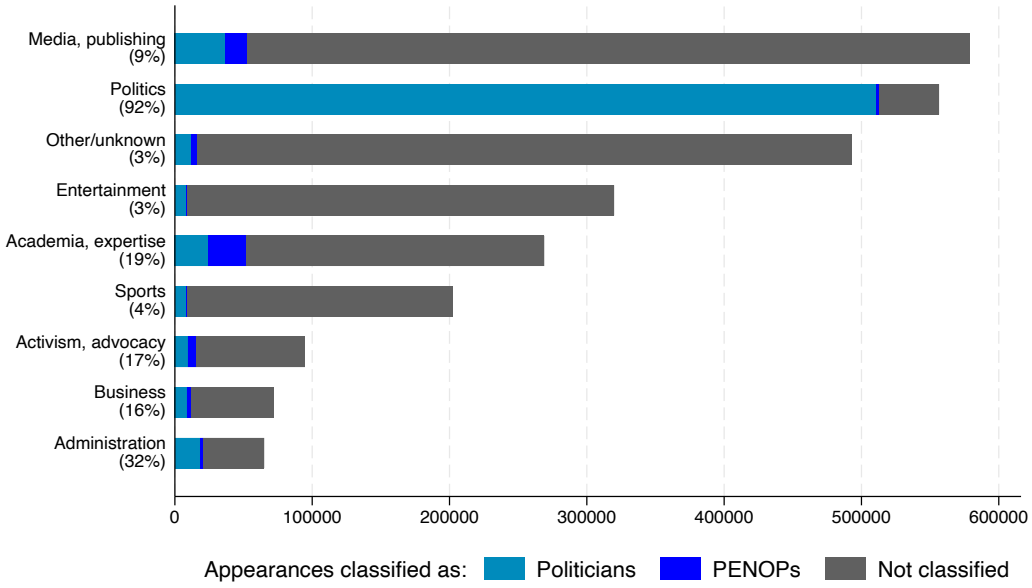
Notes: The Figure plots the evolution of the type of shows broadcast on television over time. Sub-figure D.2a reports the time share dedicated to shows that are talk shows (blue) and shows dedicated to news and politics (gray). There are seasonal drops in the time devoted to talk shows during the summer season (July and August). Sub-figure D.2b reports the same shares but compares CNews (continuous line) to the other television channels in the sample (dashed lines). Data are from Plurimedia.

Figure D.2: Types of television shows over time



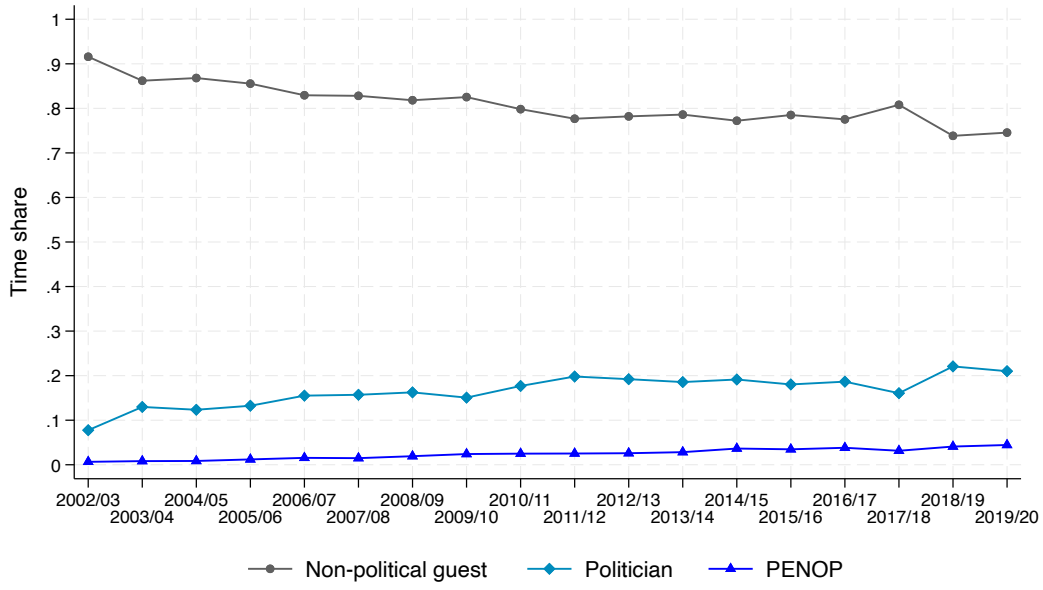
Notes: The Figure reports the share of appearances that are politically classified for two subsets of appearances based on whether or not the guests' INA description (which is time-invariant) includes 'politician' and 'France' (to exclude foreign politicians). Gray areas account for the share of appearances that are not politically classified. Light blue ones are appearances classified politically based on the set of sources used to classify professional politicians (i.e. government position, candidate lists, parliamentary groups). The darker blue share indicates the share of appearances classified politically based on the set of sources meant to classify politically engaged non-politicians (PENOPs) (i.e. party summer meeting attendants, think tank staff and contributors, and candidate endorsements).

Figure D.3: Output of appearance classification



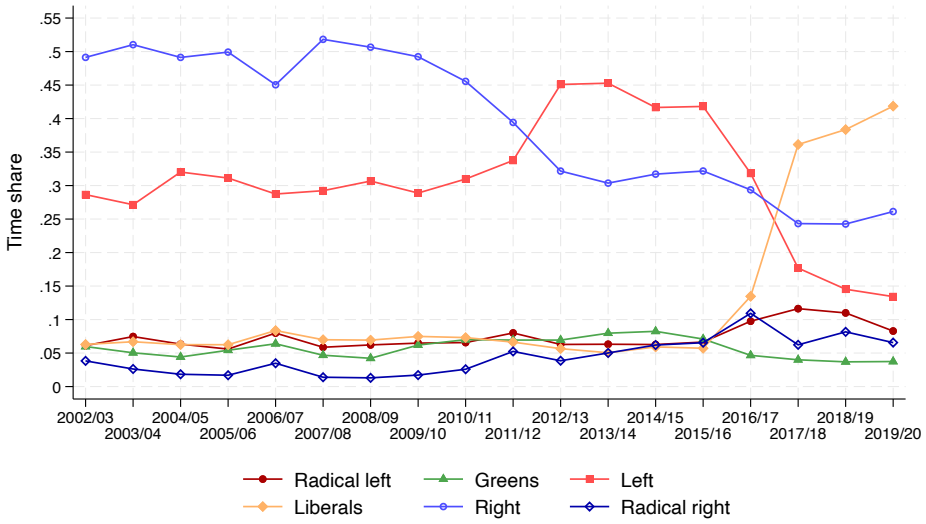
Notes: The Figure plots the number of appearances by profession that are classified as politicians, as PENOPs or are not classified. The professions are defined using guests' time-invariant description (see Section A.3 for details on professional categories). One guest can have several professions, and can thus fall into multiple categories. Figure in parentheses indicate the share of appearances that are politically classified, either as politician or as PENOPs. Other notes as in Figure D.3.

Figure D.4: Appearances classified as politicians or PENOPs by profession

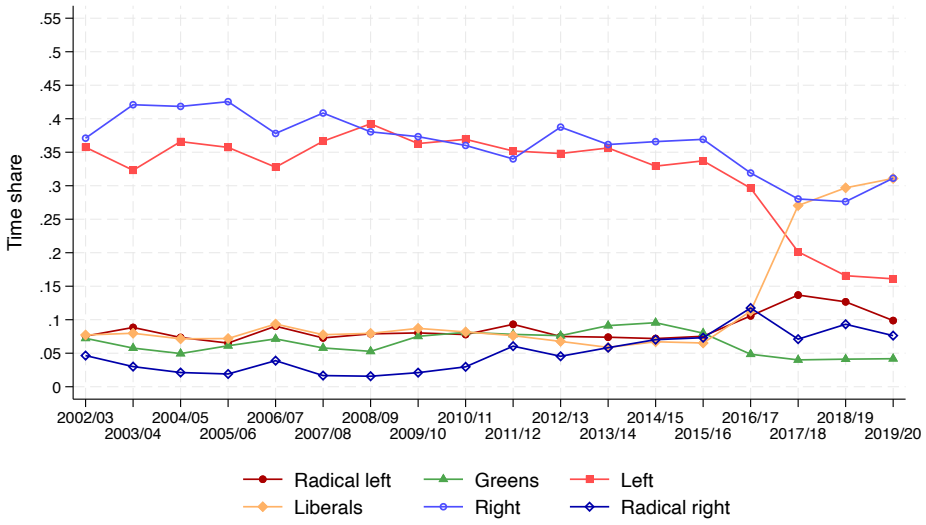


Notes: The Figure plots the evolution of the speaking-time share devoted to each group of guests for each season, aggregated over all the outlets in our sample.

Figure D.5: Evolution of the speaking-time share devoted to guests depending on their group, 2002-2020



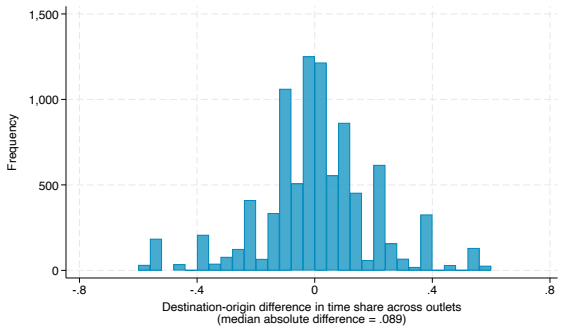
(a) Politically-classified appearances excluding PENOPs



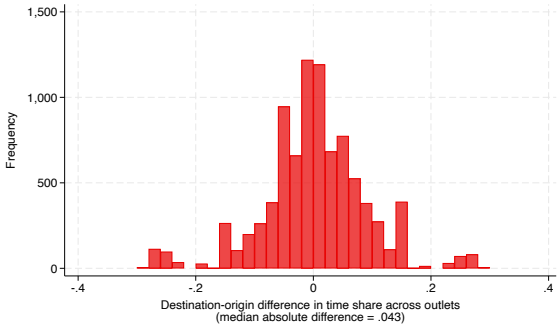
(b) Politically-classified appearances excluding PENOPs and government officials

Notes: The Figure plots the time share of each political group for each season, aggregated over all the outlets in our sample. Sub-Figure D.6a includes all the political groups, while sub-Figure D.6b excludes the government members. The speaking-time share of the political groups only includes the speaking time of the politicians.

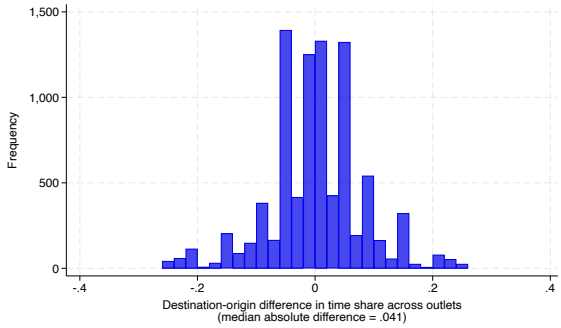
Figure D.6: Evolution of the speaking-time share devoted to the different political groups, 2002-2020, Excluding PENOPs



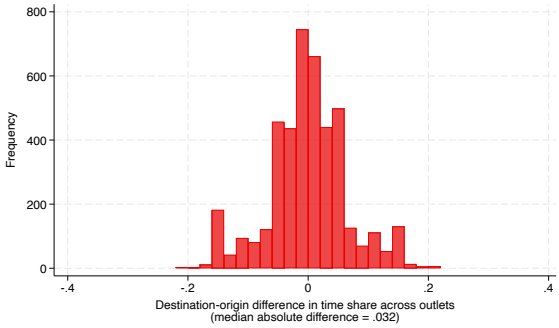
(a) Political guests among all guests



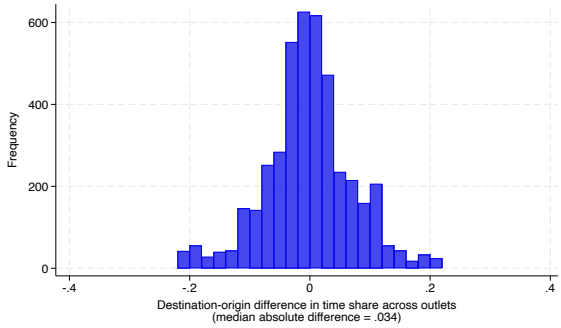
(b) Left-wing guests among all guests



(c) Right-wing guests among all guests



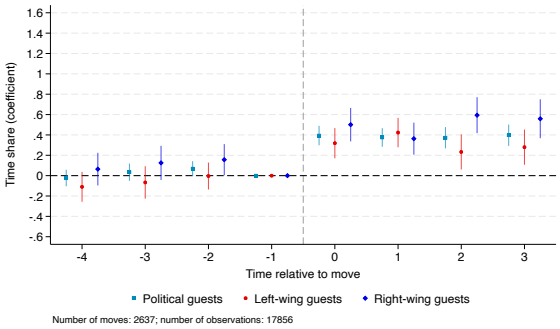
(d) Left-wing guests among political guests

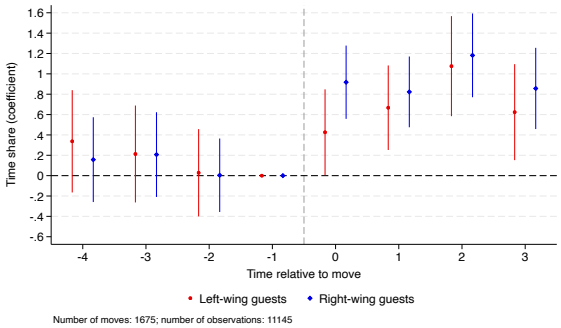


(e) Right-wing guests among political guests

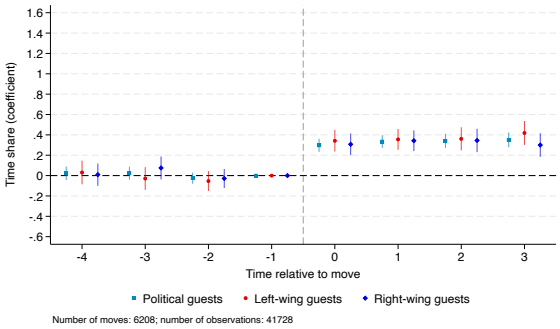
Notes: The Figure plots the distribution of the differences in the time share devoted to different groups between the destination and the origin outlets at the time of the move. Sub-figure D.7a reports this difference for the time devoted to the political guests among all the guests, and sub-figure D.7b (respectively D.7c) for the time devoted to the left-wing (respectively right-wing) guests among all guests. Sub-figure D.7d (respectively D.7e) reports the time share of left-wing (respectively right-wing) guests among political guests. The time period is September 1, 2005-August 31, 2019.

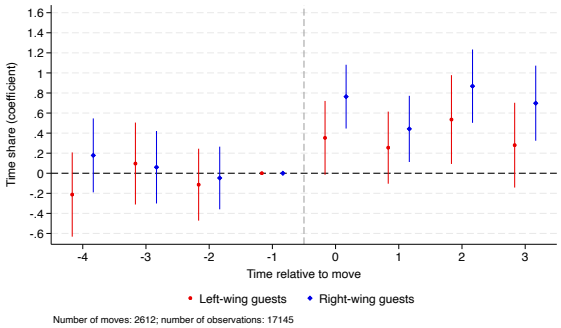
Figure D.7: Distribution of the difference in the time share devoted to different groups between the destination and the origin outlets





(a) Famous (*Les Bios* or Wikidata entry)

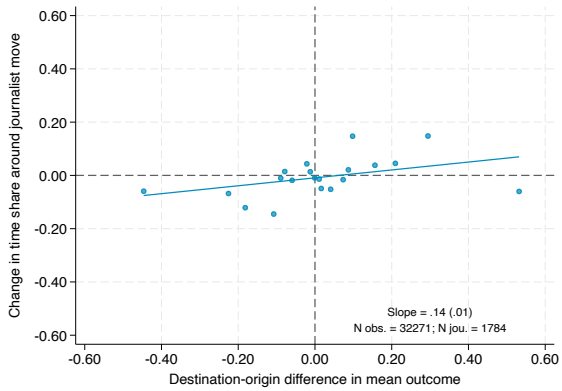




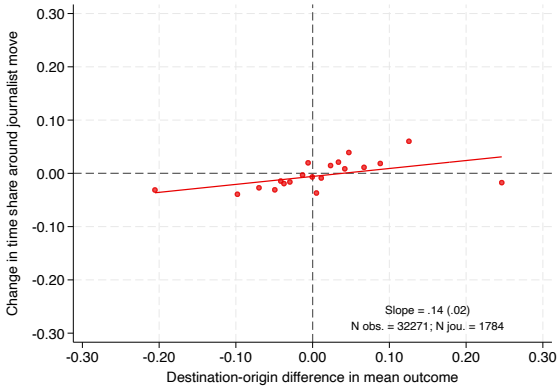
(b) Not famous (no *Les Bios* or Wikidata entry)

Notes: The figure plots the event-study estimates from equation (1) when focusing on several subsets of shows: shows of journalists who are famous (D.8a), shows journalists who are not famous (D.8b). Figures on the left consider the share of guests from a given group as a share of all guests; figures on the right consider the share of guests of a given group as a share of political guests. Other notes as in Figure 5. The time period is September 1, 2005-August 31, 2019.

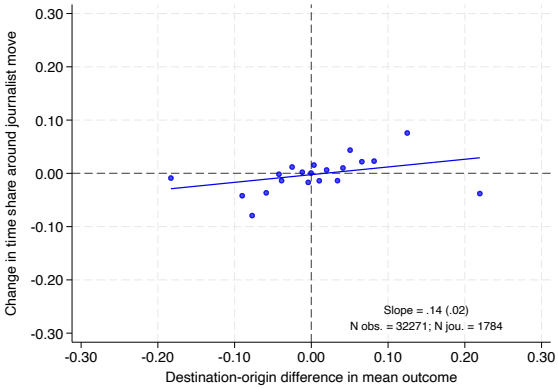
Figure D.8: Event study: Change in the time share devoted to different groups around the move, Heterogeneity depending on the type of journalists



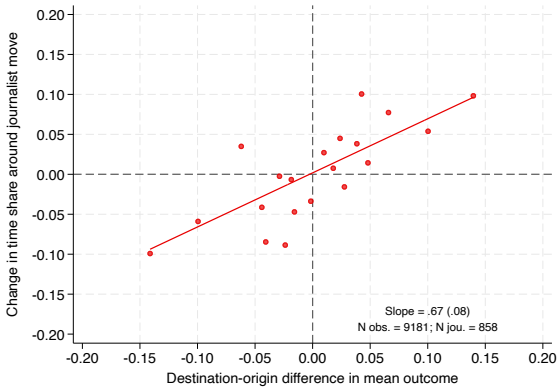
(a) Political guests among all guests



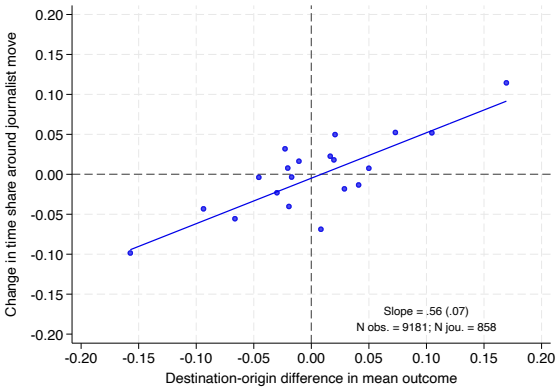
(b) Left-wing guests among all guests



(c) Right-wing guests among all guests



(d) Left-wing guests among political guests

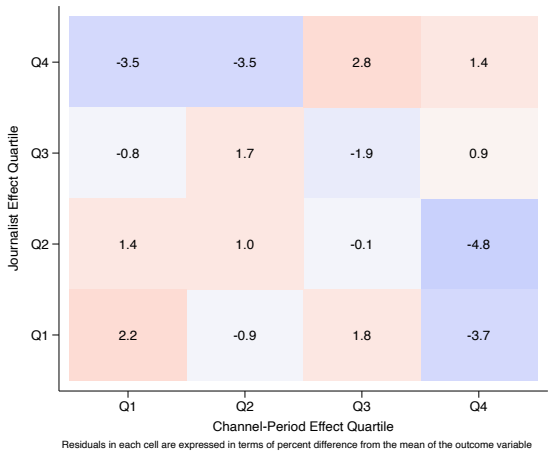


(e) Right-wing guests among political guests

Notes: The Figure shows how the political time share of a given journalist changes before and after a move against the difference in average outcomes across destination and origin channels. The x-axis shows the difference in average speaking-time share between destination and origin channels. The y-axis shows the average speaking-time share difference for a moving journalist between the first two post-move weeks and the last two pre-move weeks. The dots are averages computed by vintiles. The line is the best linear fit from an OLS regression. The slope and the corresponding robust standard error, as well as the number of moves and the number of journalists are reported at the bottom of each figure. Journalists observed on multiple outlets within week tend to have regular shows on distinct outlets during the same season, which explains the large number of observations compared to the number of journalists. The time period is September 1, 2005-August 31, 2019.

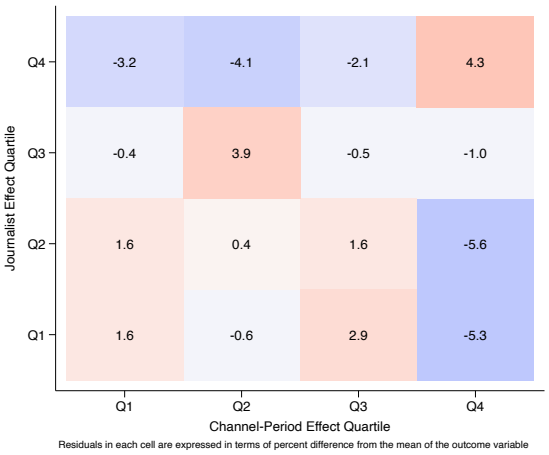
Figure D.9: Difference in political time shares between shows hosted by journalist appearing on different outlets within the same week

(a) Political guests among all guests

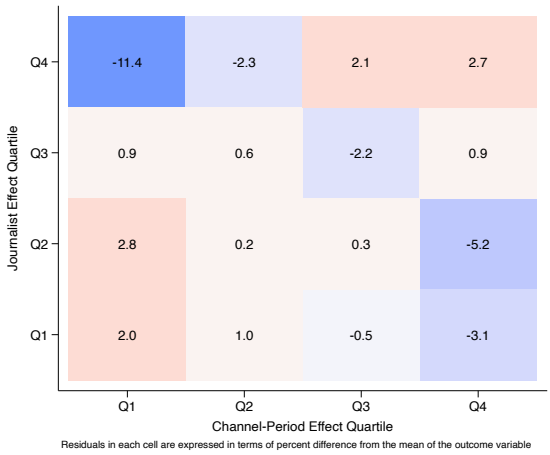


(b) Left wing guests among all guests

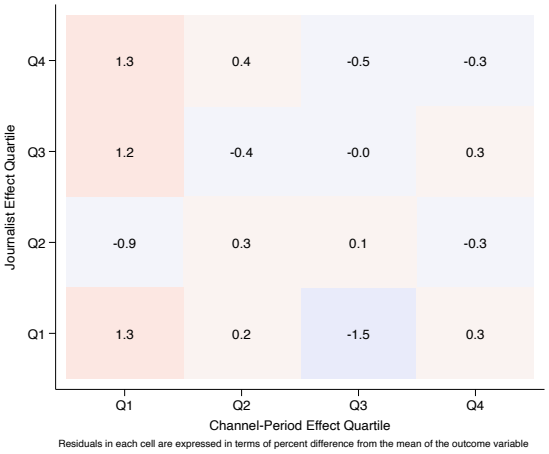
(c) Right wing guests among all guests

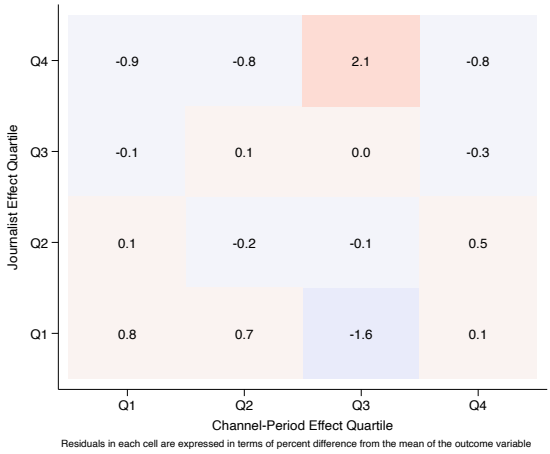


(d) Left wing guests among political guests



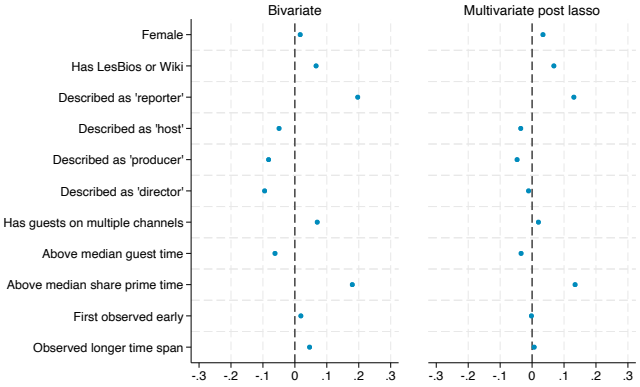
(e) Right wing guests among political guests



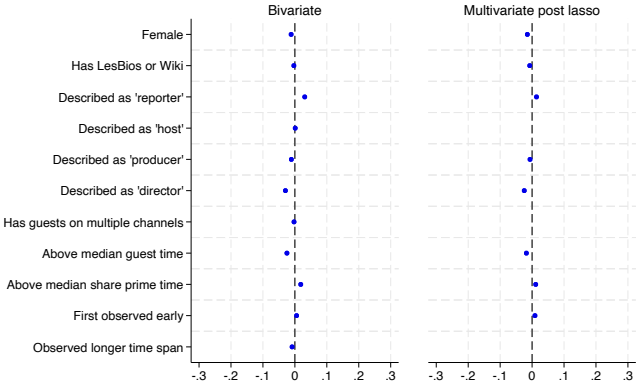


Notes: The figure plots mean residuals from equation (2) with cells defined by quartiles of estimated channel-season effects, interacted with quartiles of estimated host effects. The mean residuals are expressed in percent difference from the mean of the outcome variable. The time period is September 1, 2005-August 31, 2019.

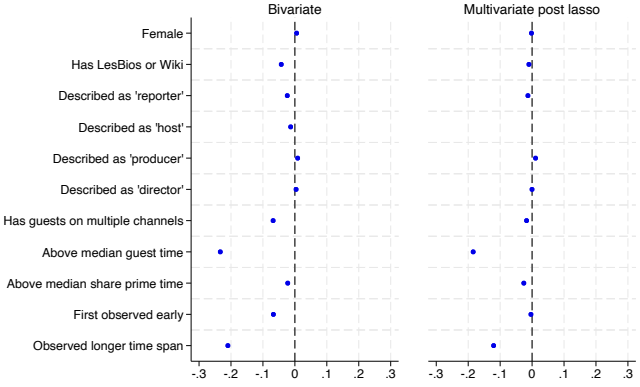
Figure D.10: Mean residual by channel-period $\times$ journalist quartiles



(a) Share of political guests among all guests



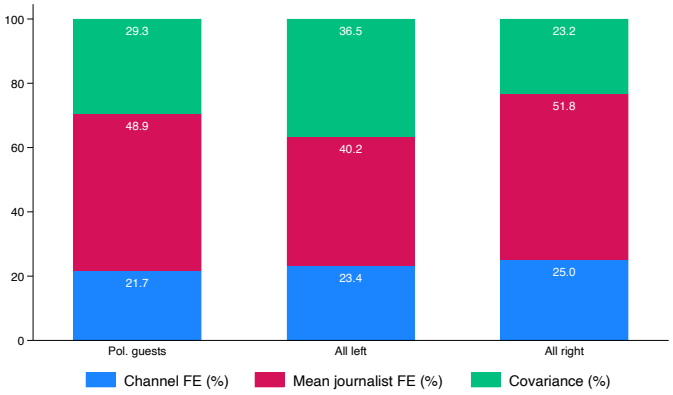
(b) Share of right-wing guests among political guests



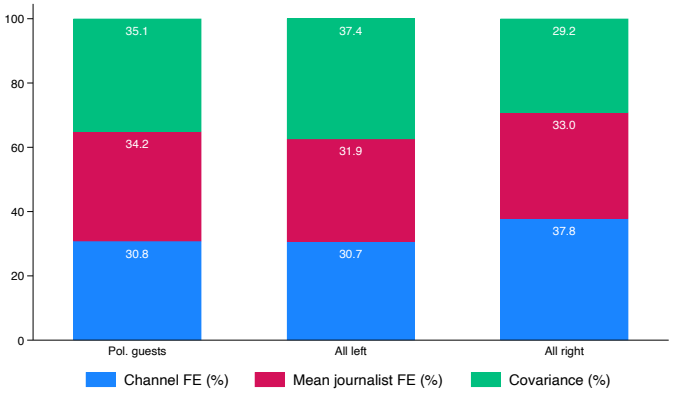
(c) Share of right-wing guests among political guests – Fixed effects absolute value

Notes: The Figures report estimates and robust 95% confidence intervals from bivariate (left) and multivariate (right) OLS regressions of standardized journalist fixed effects on standardized covariates. In the upper Figure D.11a, journalist fixed effects are obtained when estimating equation (2) with the share of political guests among all guests as the outcome variable. In the middle and bottom Figures D.11b and D.11c, journalist fixed effects are obtained using the share of right-wing guests among political guests as the outcome of equation (2). The bottom Figure D.11c uses the absolute values of the estimated fixed effects. The time period is September 1, 2005-August 31, 2019.

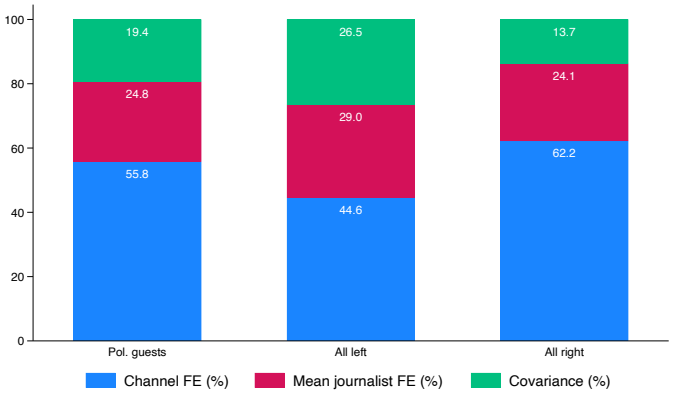
Figure D.11: Correlates of journalist fixed effects



(a) September 2005-August 2010



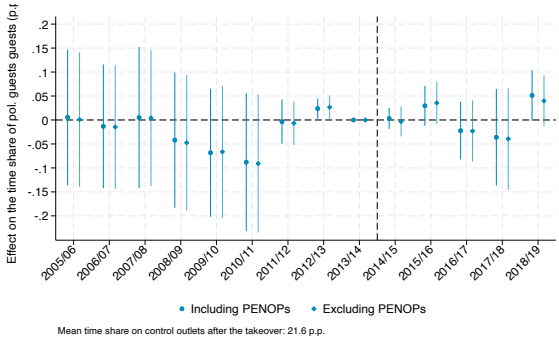
(b) September 2010-August 2015



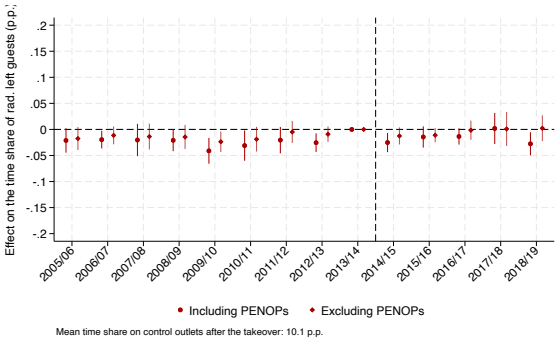
(c) September 2015-August 2019

Notes: The Figure reports components of the variance decomposition proposed in equation (3) based on the parameters estimated using equation (2). Panel D.12a reports the shares of variance when estimating equation (2) with shows between September 2005 and August 2010, Panel D.12b does the same when estimating equation (2) with shows between September 2010 and August 2015, and Panel D.12c when estimating equation (2) with shows between September 2015 and August 2019. The outcome variables used in equation (2) are, respectively, the share of political guests among all guests, the share of all left-wing guests among all guests, and the share of all right-wing guests among all guests. The time period is September 1, 2005-August 31, 2019.

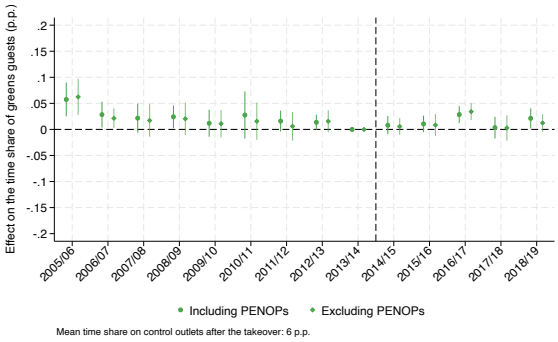
Figure D.12: Variance decomposition across time periods



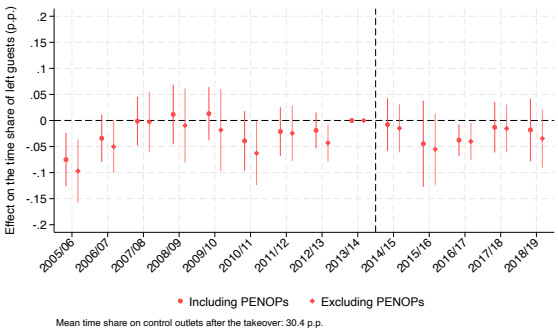
(a) Political guests among all guests



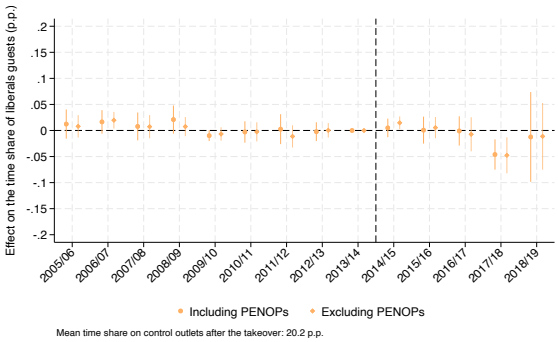
(b) Radical left among political guests



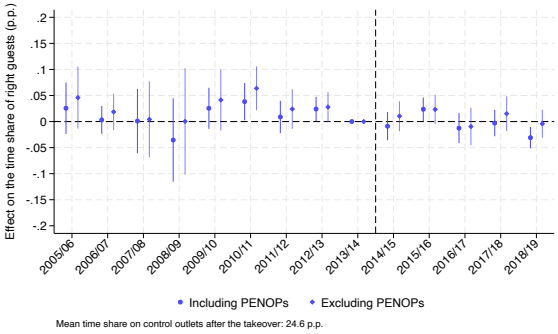
(c) Greens among political guests



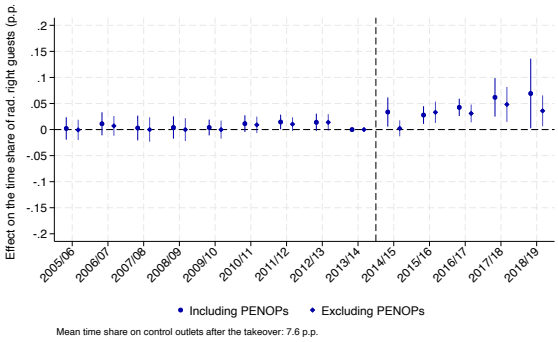
(d) Left among political guests



(e) Liberals among political guests



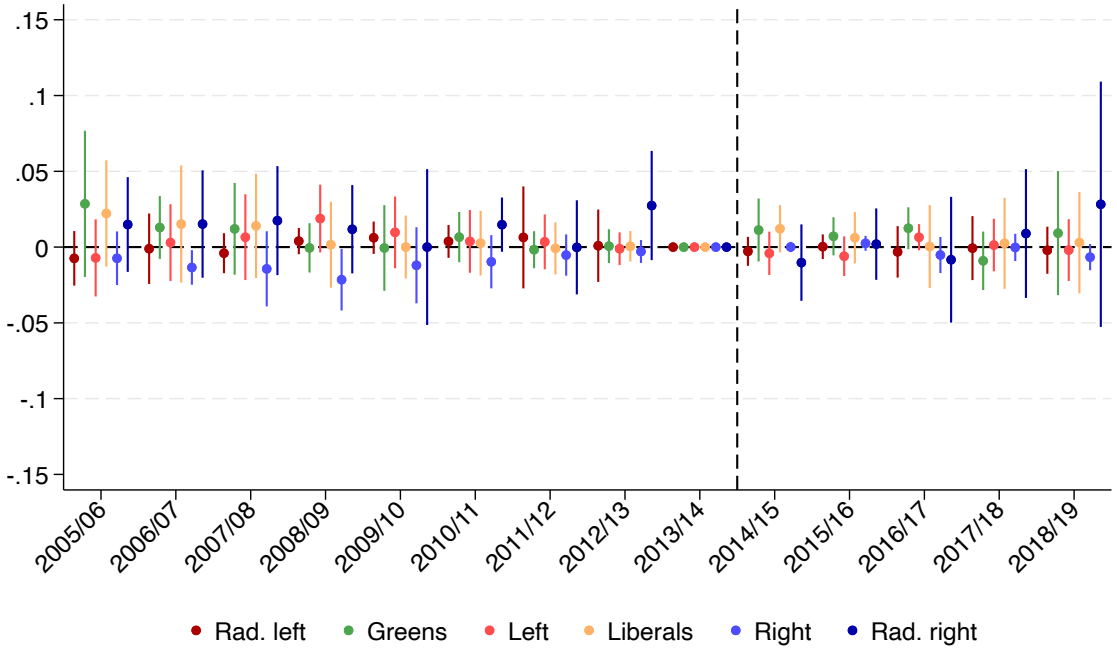
(f) Right among political guests



(g) Radical right among political guests

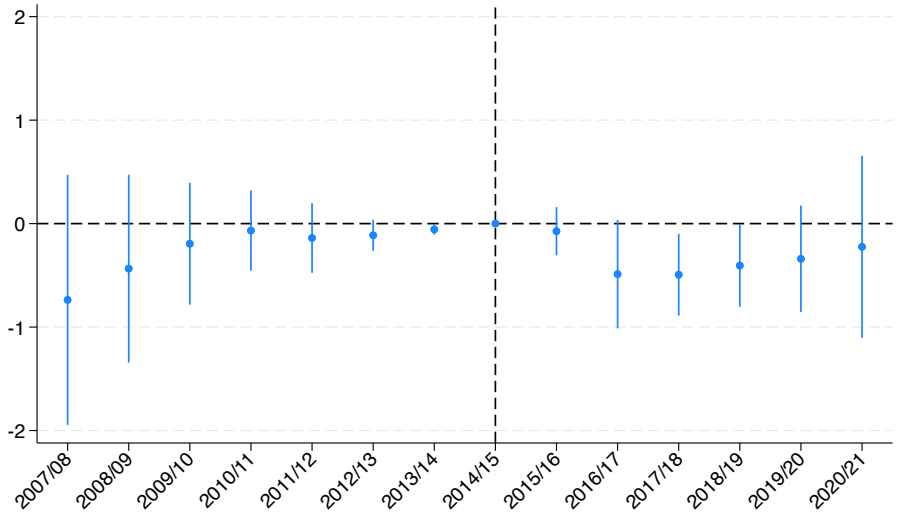
Notes: The Figure plots estimates from the event-study specification corresponding to equation (4). The dependent variables are the time share of political guests among all guests in sub-figure D.16a, of the radical left in sub-figure D.16b, of the greens in sub-figure D.16c, of the left in sub-figure D.16d, of the liberals in sub-figure D.16e, of the right in sub-figure D.16f, and of the radical right in sub-figure D.16g as a share of political guests. Other notes as in Figure 7. The time period is September 1, 2005-August 31, 2019.

Figure D.13: Event-study regression: Speaking-time shares of the different political groups around Bolloré's takeover, Controlling for channel fixed effects



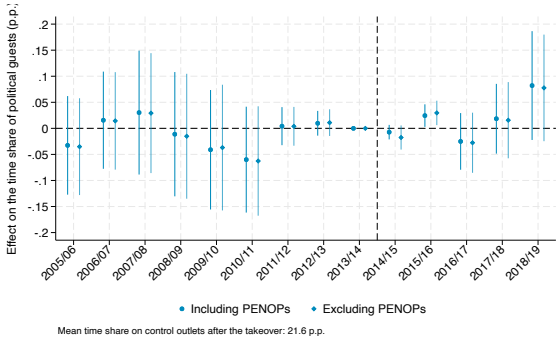
Notes: The outcome variable is an indicator variable for whether guest i is observed on outlet c in week t. The sample spans all the possible guest-outlet-week combinations and only considers politically classified guests. The Figure plots the interaction terms estimated from a specification similar to equation (5) where the treatment variable is interacted with season indicator variables (season 2013-2014 is the reference year) and an indicator variable corresponding to each political group. Standard errors are clustered at the channel level. Vertical bars indicate 95% confidence intervals. The time period is September 1, 2005-August 31, 2019.

Figure D.14: Effect of the takeover on whether outlets feature political guests, by political leaning: Event-study regression

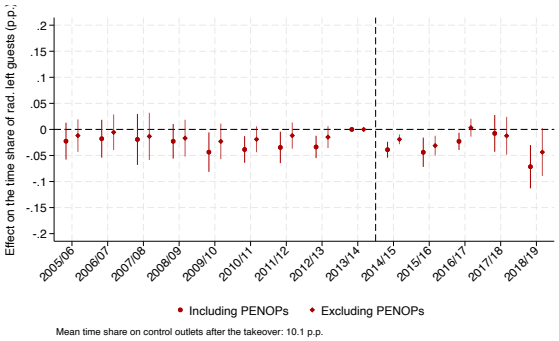


Notes: The Figure plots estimates from an event-study regression in which the dependent variable is the logarithm of the viewership share measured at the monthly level. Data collected from the newsletter *La Correspondance de la Presse*. The outlets included in the sample are Arte, BFM TV, C8/D8, CNews/ITélé, Canal+, France 2, France 3, France 5, M6 and TF1. C8/D8, CNews/ITélé, Canal+ are the channels acquired by Bolloré, other channels are part of the control group. We estimate the following specification: $y_{ct} = \sum_s 1[t \in s] \times 1[Treated]_c + \alpha_c + \tau_t + +\epsilon_{ct}$. Standard errors are clustered at the channel level. Vertical bars indicate 95% confidence intervals. The time period is September 1, 2005-August 31, 2019.

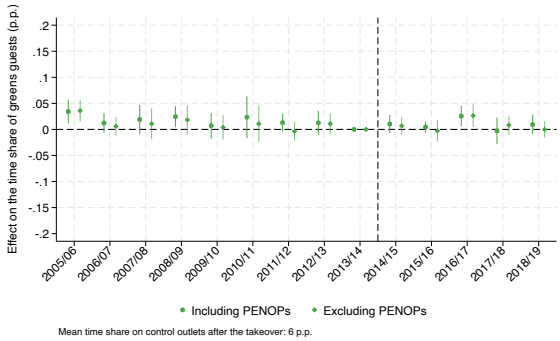
Figure D.15: Change in viewership following Bolloré's takeover: Event-study regression



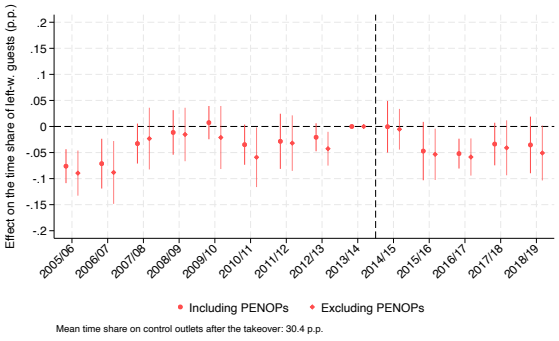
(a) Political guests among all guests



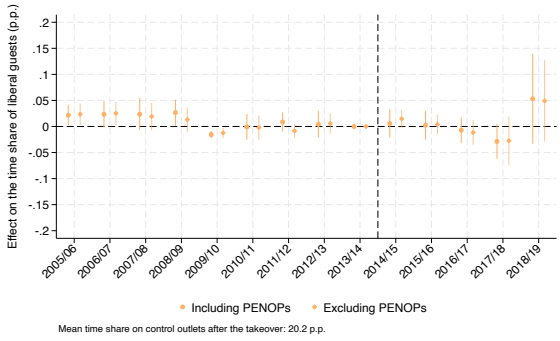
(b) Radical left among political guests



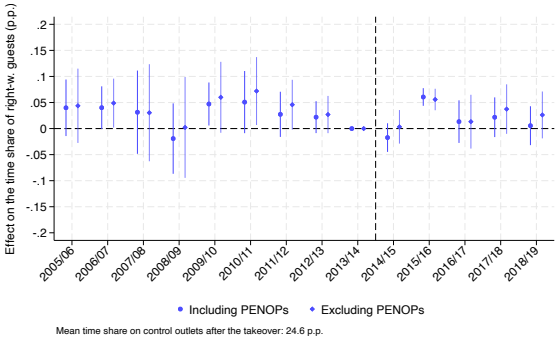
(c) Greens among political guests



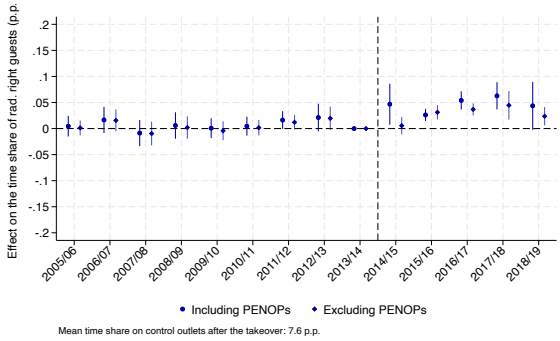
(d) Left among political guests



(e) Liberals among political guests



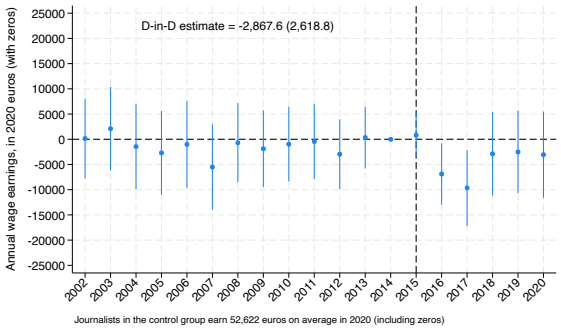
(f) Right among political guests



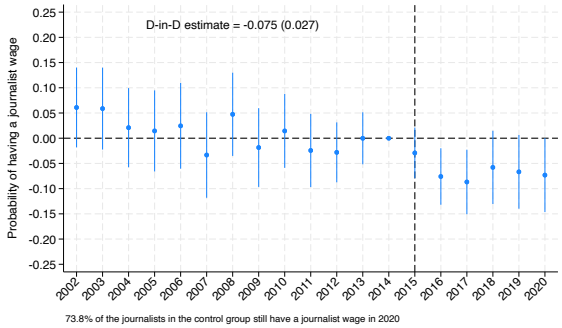
(g) Radical right among political guests

Notes: The Figure plots estimates from the event-study specification corresponding to equation (6). The dependent variables are the time share of political guests among all guests in sub-figure D.16a, the time share of the radical left in sub-figure D.16b, of the greens in sub-figure D.16c, of the left in sub-figure D.16d, of the liberals in sub-figure D.16e, of the right in sub-figure D.16f and of the radical right in sub-figure D.16g among political guests. Other notes as in Figure 7. The time period is September 1, 2005-August 31, 2019.

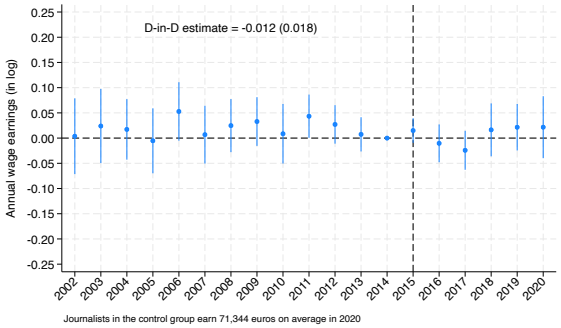
Figure D.16: Event-study regression: Speaking-time shares of the different political groups around Bolloré's takeover, Controlling for channel-journalist fixed effects



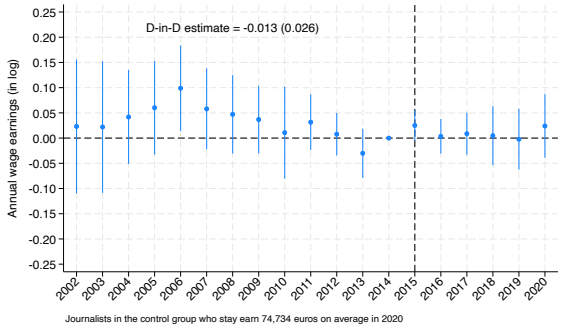
(a) Annual wage earnings as a journalist, including zeros (in 2020 euros)



(b) Probability of working as a journalist



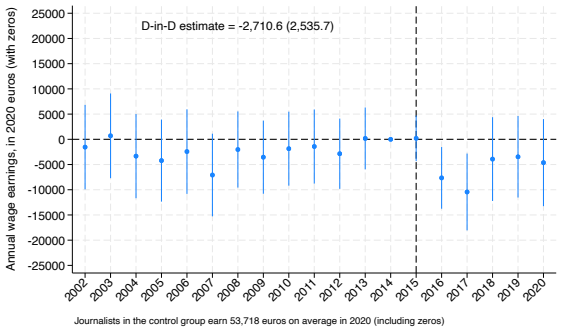
(c) Annual wage earnings as a journalist (in log), conditional on working as a journalist



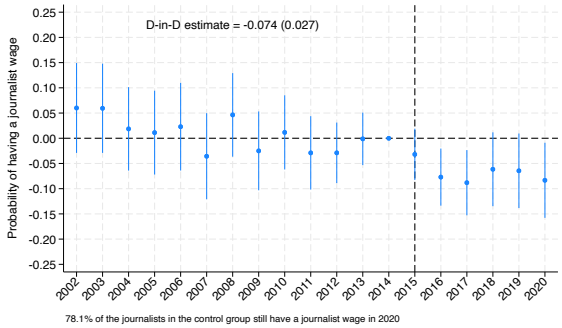
(d) Annual wage earnings as a journalist (in log), conditional on working as a journalist – Stayers only

Notes: The Figure plots estimates from event-study regressions corresponding to equation (8). We drop from the sample the journalists who have an 'emeritus' (*honoraire*) press card. Other notes as in Figure 10.

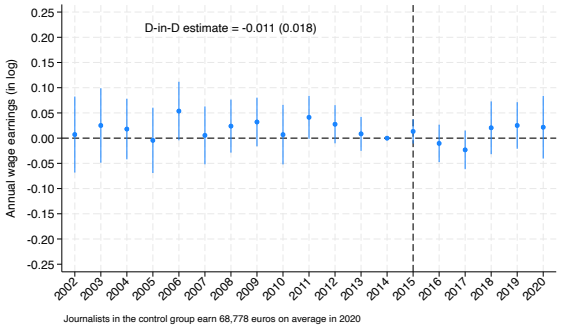
Figure D.17: The monetary cost of compliance: Wage and employment as journalists, Excluding 'emeritus' journalists



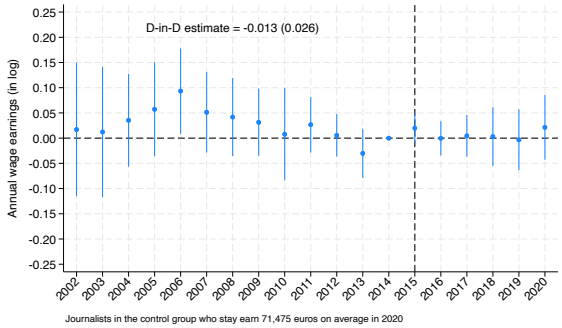
(a) Annual wage earnings as a journalist, including zeros (in 2020 euros)



(b) Probability of working as a journalist



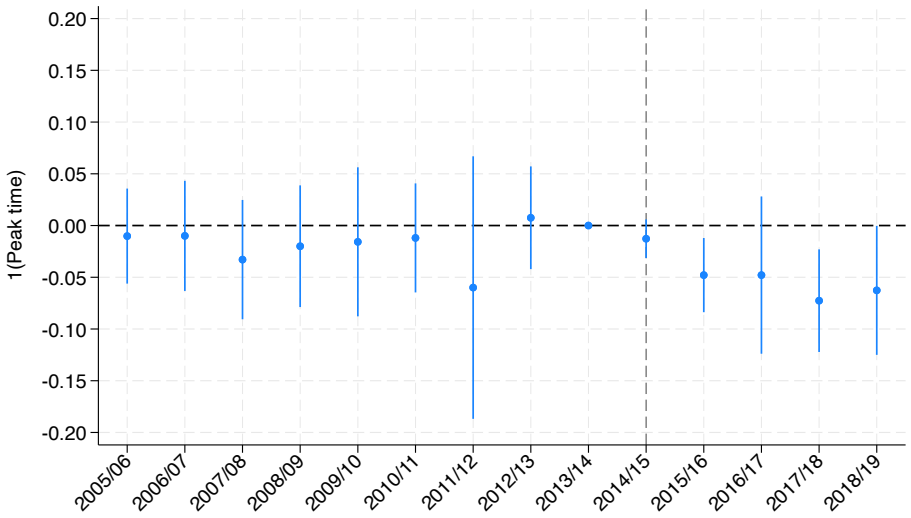
(c) Annual wage earnings as a journalist (in log), conditional on working as a journalist



(d) Annual wage earnings as a journalist (in log), conditional on working as a journalist – Stayers only

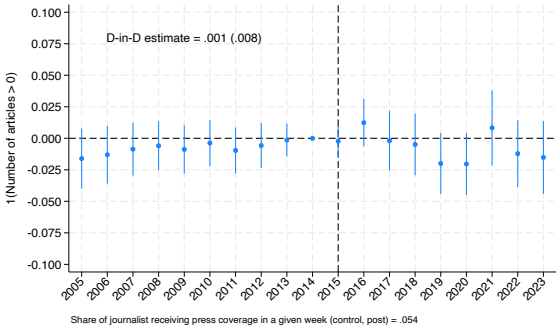
Notes: The Figure plots estimates from event-study regressions corresponding to equation (8). We drop from the sample the journalists who are older than 62 and younger than 20. Other notes as in Figure 10.

Figure D.18: The monetary cost of compliance: Wage and employment as journalists, Excluding journalists younger than 20 and older than 62

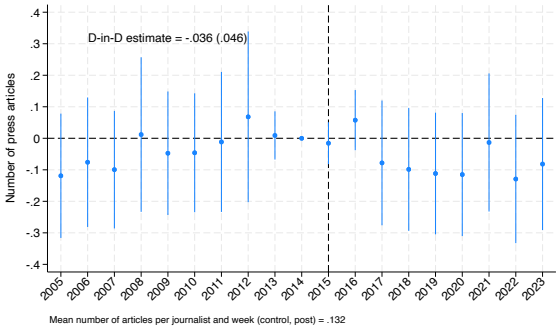


Notes: The Figure plots estimates from the event-study specification corresponding to equation (6). Vertical bars are 95% confidence intervals. The estimation sample uses all the journalist-outlet pairs that existed both in the last pre-takeover season (2013-2014) and in the last season of our sample (2018-2019). The outcome variable indicates whether journalist i appears in a peak-audience time slot on outlet c in week t. Other notes as in Table 5. The time period is September 1, 2005-August 31, 2019.

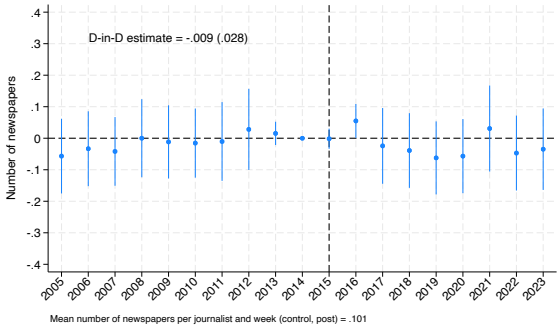
Figure D.19: Event-study regression: Effect of the takeover on the probability that journalists who stay have a show during peak-audience time slots



(a) Whether the journalist is cited in the press



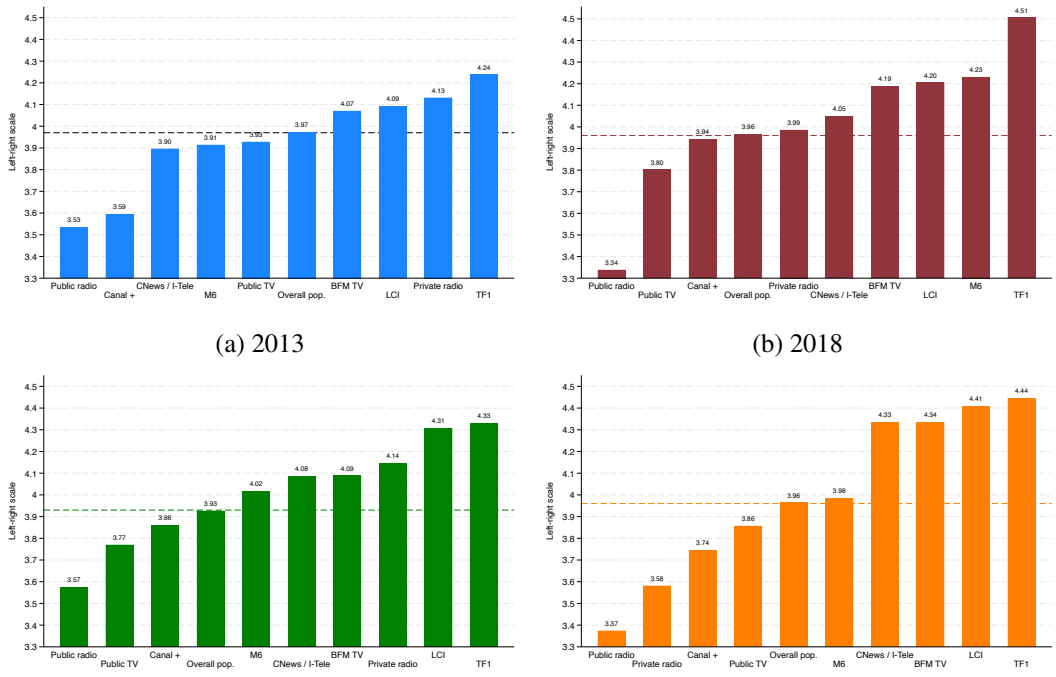
(b) Number of press articles citing the journalist



(c) Number of press articles citing the journalist

Notes: The Figure plots estimates from the event-study specification corresponding to equation (8), but without age controls as this information is only available for the subset of journalists who have had a press card. Vertical bars are 95% confidence intervals. The estimation sample uses all the journalist-weeks combinations. The outcome variables are measured at the journalist i week t level. They measure: (a) whether journalist i receives press coverage in week t, (b) the number of press articles citing journalist i in week t and (c) the number of newspapers citing journalist i in week t. Standard errors are clustered at the channel level.

Figure D.20: Event-study regression: Effect of the takeover on the press coverage received by the journalists who stay



(a) 2013

(b) 2018

(c) 2019

(d) 2020

Notes: The Figure plots the average political preferences of the audience of the different television channels / radio stations in our data. The data come from the Reuters Institute's *Digital News Report*. The sample includes $1,016$ individuals for France for the year 2013, $2,006$ for 2018, $2,005$ for 2019, and $2,038$ for 2020. Among the survey questions, respondents are asked whether they watch public television, Canal+, I-Télé, LCI, BFM TV, TF1, and M6, and whether they listen to public radio or private radio. They are also asked about their "political ideology": *"Some people talk about 'left', 'right' and 'centre' to describe parties and politicians. (Generally socialist parties would be considered 'left wing' whilst conservative parties would be considered 'right wing'). With this in mind, where would you place yourself on the following scale?"*, with a 1 (very left-wing) to 7 (very right-wing) scale.

Figure D.21: Political preferences of the audience

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Ferrario, Beatrice and Stefanie Stantcheva, "Eliciting people's first-order concerns: Text analysis of open-ended survey questions," in "AEA Papers and Proceedings," Vol. 112 American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203 2022, pp. 163–169.

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