Hosting Media Bias: Evidence from the Universe of French Broadcasts, 2002-2020*

Julia Cagé1, Moritz Hengel1, Nicolas Hervé2, and Camille Urvoym

1Sciences Po Paris, 2Institut National de l’Audiovisuel, 3University of Mannheim

February 16, 2023

Abstract

Democracies need informed voters – voters who are exposed to a diverse range of views. News media take an active role in the process of informing voters; yet, they vary in their coverage of political parties. In this paper, we explore whether differences in political coverage are mainly driven by the editorial choices of (a few) owners, or by the preferences of diverse journalists, provided that they have some agency. To do so, we build a novel dataset on millions of French television and radio shows over 20 years, with information on the identity of hosts, guests, and guests’ political leaning. We estimate a two-way fixed effects model identified thanks to the many hosts that we observe working on multiple channels. We show that hosts largely comply with outlet-level decisions, which account for 85% of cross-channel differences in political representation. Complementing these results, we study how hosts adapted to a major ownership-driven change in editorial line, and find that the hosts who stayed after the takeover complied with the new owner’s preferences.

Keywords: Media bias; Slant; Journalists; Pluralism; Media ownership; Media capture

JEL No: L15, L82, J40

* We are grateful to Davide Cantoni, Kerstin Holmheu, Marco Palladino, Maria Petrova, Carlo Schwarz, Guo Xu, Noam Yuchtman and Ekaterina Zhuravskaya, to seminar participants at CERGE-EL, HEC Liège, King’s College, the London School of Economics, the University of Mannheim, the Paris School of Economics, Princeton University (Political Economy Workshop), Sciences Po Paris, the Stockholm School of Economics (SITE), and Trinity College, and to conference participants at the CEPR Workshop on Media, Technology, Politics and Society, the MYPEERs workshop, and the EEA-ESEM Conference for very helpful comments and suggestions. We thank Nicolas Cizel and Albin Soares-Couto from the CSA for their help with the data; Dominique Fackler, Anne Couteux and Laetitia Larcher from the INA for always taking the time to answer our (numerous!) questions; and Richard Fletcher for providing us the survey data from the Reuters’ Digital News Reports. We thank Agathe Denis, Sacha Martinelle, Léanne Martinez and Romane Surel for outstanding research assistance. We gratefully acknowledge financial help from the Paris Région PhD program. The research leading to this paper has received funding from the European Research Council under the European Union’s Horizon 2020 research and innovation program (Grant Agreement no. 948536). This work has been supported by a public grant overseen by the French National Research Agency (ANR) as part of the “Investissements d’Avenir” program within the framework of the LIEPP center of excellence (ANR11LABX0091, ANR 11 IDEX000502). Responsibility for the results presented lies entirely with the authors.
1 Introduction

For democracies to function, voters need to be exposed to a plurality of views (Pariser 2011). For this reason, regulators in many countries have sought to preserve pluralism in news media. With the idea that media ownership may influence editorial lines, they have promoted ownership diffusion across competing outlets (external pluralism). They have also created rules requiring that each outlet features a balanced representation of political forces, thereby setting bounds to channel editorial policies (internal pluralism). While today people can access a virtually infinite number of opinions, reach and attention patterns are such that they are actually exposed to a reduce set of news sources, themselves controlled by a small number of conglomerates (Prat 2018; Kennedy and Prat 2019). It has raised concerns that some media tycoons may disproportionately influence the political process, and renewed discussions on media concentration and polarization.

Contrasting with the small number of owners, there are many journalists and hosts in charge of the daily production of media content. Their diversity – in terms of specialization, views or backgrounds – is a potential source of pluralism, provided that they have some agency vis-à-vis their employers’ editorial policies. In today’s world, engaging directly with their audience on Internet may for example give them leverage and independence while employment insecurity may be a disciplining force, pushing them to conform to the editorial policy of their outlet. Furthermore, journalists may chose their employers based on political affinity, which may amplify each outlet’s tendency to prioritize certain views.

In this paper, we ask how much agency hosts have regarding opinion representation in their shows. We examine an important choice they have to make on a recurrent basis: who to invite. To do so, we use novel show-level data on French broadcast between 2002 and 2020 and track hosts as they work for distinct outlets over time. We estimate to what extent differences

---

1In 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 to assess “the impact of the concentration on media pluralism, including its effects on the formation of public opinion” (COM/2022/457).

2In the US, the 1949 FCC fairness doctrine required that media with a broadcast license give the public “a reasonable opportunity to hear different opposing positions on the public issues of importance and interest in the community” (Fisch 2010). In France, the Regulatory Authority for Audiovisual and Digital Communication (ARCOM) monitors the equity and diversity of political expression on broadcast media. Most European country have some kind of internal pluralism rules (see “Internal Media Plurality in Audiovisual Media Services in the EU: Rules and Practices,” ERGA Report, 2018).

3The literature provides evidence that media content can be impacted by ownership (Durante and Knight 2022b; Martin and McCrain 2019; Mastorocco and Ornaghi 2020, for instance), and that media content impacts voters’ behaviors (DellaVigna and Kaplan 2007; Bursztyn et al. 2020; Moreno-Medina et al. 2022, among others).

4Respectively, 21% of US and 29% of French respondents report paying more attention to the journalist than to the news brand when consuming news online (Reuters Institute, Digital News Report, 2022).
in representation of political views across channels are driven by host-level decisions on the one hand, and hosts adapting to the channel they work for on the other hand. We complement this quantification exercise with a case study. We track how hosts reacted to a major owner-induced change in editorial line around the 2015 takeover of three television channels by the Vivendi conglomerate, owned by the so-called “French Murdoch,” Vincent Bolloré.

As in many countries, media power in France is concentrated in a relatively small number of news outlets, with television and radio being at the center stage of the news ecosystem (Kennedy and Prat, 2019). Outlets topping the lists of main news source among French respondents are television channels, ahead of social media like Facebook (4%). In 2019, 71% and 53% of the respondents reported that they got their daily news from television and radio respectively, compared to only 47% online (Sumida et al., 2019). Our data includes all the major news sources: it comprises all the most consumed television and radio outlets from 2002 to 2020, with detailed show-level information compiled and enriched by the National Audiovisual Institute (INA) archives. The 2.1 million shows in our data are not restricted to newscasts, but also include talk and entertainment shows. They feature 39,322 distinct hosts and more than 260,413 distinct guests. With the ample time frame covered, we can track hosts as they move from an outlet to the other and observe how they adapt to their new work environment upon move. Data granularity ensures we can finely control for viewership composition and news events at the time the show airs.

We first document that political forces are unevenly represented across channels. For instance, on average during our time period, left-wing parties account for 40% of the speaking time on LCI, but 60% on France 4. To show this, we classify guests by political leaning in six groups (radical left, green, left, liberal, right, radical right). We use lists of candidates running in elections and lists of government appointees to identify politicians. Given the increasing coverage they receive in talk shows, we also classify guests who are not politicians in a strict sense, but are politically vocal (activists, think tank commentators, public intellectuals, etc.). To do so, we rely on think tank contribution or affiliation, endorsements, and party-event participation. Overall, we classify 16,380 distinct individuals, accounting for 661,295 appearances (of course, we allow the political leaning of the guests to vary over time). From there, we can compute the screen time share of each political group at the show- or channel-level.

---

5See also Newman et al. (2022).
6We include all the shows with at least one host and one guest. We do not include fictions and sport games.
7The diversity in coverage is clearly visible despite the regulatory agency’s guidelines requiring channels to represent political forces ‘equitably,’ which here means in proportion to their contribution to the political debate (see Section 2 for more details on the institutional background). The differences that prevail nonetheless partly reflect the ambiguity and weak enforcement of this rule.
8We call “public intellectuals” here all the intellectuals that are publicly “engaged”, in the sense of the French expression “intellectuels engagés”. As will appear clearly from our empirical results, in recent years, media owners have increasingly substituted talk shows to news programs, both to reduce costs (Cagé, 2015), but also as a way to escape broadcast regulation on pluralism.
level.

What explains the differences in political coverage across channels? One explanation is that channels have distinct editorial policies, to which hosts comply by adapting their invitations to the channel they work for (contextual factors). Another is that channels employ distinct hosts on average, who invite distinct guests, potentially due to the hosts’ preferences or specialization (individual factors). We estimate the relative role of contextual and individual factors in a two-way fixed effects model that allows channel effects to vary over time (Lachowska et al., 2022). We regress the political time share of a given host at the show level on host fixed effects, channel-times-period fixed effects, and media platform (radio or television), date, and hour fixed effects. Time fixed effects capture news shocks, potentially making one party more news-worthy than the others at a given moment of time (e.g. because there is a change in the leadership of the party), as well as viewership by controlling for the characteristics of potential viewers or listeners for each hour of each day, by media type. Among the 14,492 hosts in our data who invited politically-classified guests, 9,810 are observed working on at least two of the 20 channels in our sample. Changes in who they invite as they move from one channel to the other reveals to what extent they adapt the content of their shows to their employer. In other words, if hosts moving from channel C to channel C’ systematically invite more left-wing guests upon move, everything else equal, we interpret it as a sign that channel C’ prioritizes left-wing guests with respect to C. We can also estimate the extent to which hosts have agency with respect to their outlet’s editorial policy. If hosts keep inviting an above average share of right- or left-wing guests as they move from one outlet to the other, it implies that they also partly contribute to slanting shows, potentially based on their own preferences or specialization.

We show that hosts largely adapt who they invite based on which channel they work for. According to our estimations, when moving to a channel that grants 1 extra percentage point of screen time to a political group than their origin channel, they increase their coverage of this group by 0.63 percentage points on average. We decompose differences in political representation across channel-period pairs using our two-way fixed effects model. Based on the linear decomposition, channel-level decisions are crucial and explain 87% (respectively 90%) of the differences in left-wing (respectively right-wing) parties time share. Host characteristics account for the remaining 13% (10%). A variance-decomposition exercise leads to similar conclusions – channels account for around 82% (85%) of the difference for the left (right) – while highlighting host sorting: covariance between channel and host effects account for 16% (13%) of the variance. Host effects only explain the remaining 2.2% (2.1%).

---

9Distinct editorial policies can be driven either or both by supply-driven or demand-driven factors. We come back to this point below.

10Here, each period corresponds to two ‘seasons’, where seasons are one-year periods from September to August, so as to match the time frame media outlets use to plan their shows or to adjust their programs.
therefore largely comply to channel-level editorial policies. This finding sheds new light on the mechanisms through which media slant happens, by quantifying the relative role played by owners and hosts.

Analyzing trends over time, we find that the dispersion of channel effects increased over the sample period, which can be seen as reflecting polarization in editorial policies. One reason for this may be that profit-maximizing owners specialize each channel ideologically; another is that owners want their channels to prioritize certain views (Gentzkow and Shapiro 2010). We find that, within owner, channels often tend to prioritize the same political forces, suggesting that the latter explanation might be at play.

We then explore the what predicts hosts over- or under-representing certain political groups. Female hosts and hosts who are more central to the political guest-host network tend to deviate more to the left relative to their channel, but the effect is small. Interestingly, when looking at absolute deviations from the channel line, we find that hosts tend to deviate more if they are more famous as proxied by their total screen time, the existence of a Wikipedia entry or the number of shows with the President of France. At the same time, hosts who work as journalists on channels, who are more central to the political host-guest network and who have more political screen time tend to deviate less in absolute terms from the channel line. This suggests that journalists specialize in politics follow more closely the outlet’s editorial line, while more famous hosts are allowed to deviate more from it.

In the second part of the paper, we focus on a large owner-induced change in editorial policy, and study two hosts’ response margins: complying or leaving. In 2015, Vincent Bolloré – a French billionaire often compared 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 on the event have highlighted the proximity of Vincent Bolloré with conservative figures, and noted shows swiftly moved rightwards (see also Capozzi 2016, Cagé 2022). We compare Vivendi channels to others in our sample before and after the takeover. Our event-study specification includes host-channel fixed effects, meaning that we exploit within host-channel variation. After the takeover, we show that right-wing parties’ screen time share increased by 5.5 percentage points, and that of left-wing parties decreased by 6.8 percentage points. We find no evidence of diverging pre-trends. Hosts who remained on the acquired channels adapted the content of their show to the new editorial policy implemented after the takeover.

We further analyze whether hosts left the channel in response to the change in editorial policy. We find that the probability that a host stays decreases by 15 percentage points following the takeover, from a 38% baseline. The effect is driven by hosts who invite political guests, who have above median political screen time, who are credited as ‘journalists’ and whose shows are newscasts. It suggests that hosts who were the most exposed to the change
in editorial policy were precisely the ones most likely to leave. Male hosts, famous hosts, and hosts with higher ratings are more likely to stay in the medium run. Regarding hosts who leave, a majority of them is no longer observed on one of the channels in our sample following the takeover, suggesting their career has been negatively impacted. Those who work on another channel are more likely to work on a channel that represents the right relatively less, hinting at potential sorting on editorial policy.

**Literature** Our work sheds light on the inner workings of media outlets. A burgeoning literature studies how journalists’ work is impacted by new technologies (Cagé et al., 2020a; Hatte et al., 2020) or by the resources of their outlets (Djourelova et al., 2021). Some empirical papers have focused on reporting bias at the journalist level, but essentially from a theoretical perspective Dyck and Zingales (2003); Baron (2006). Our paper contributes to this literature by studying host invitation decisions, and the extent to which these decisions are determined by the outlets hosts work for.

Our paper also contributes to the ongoing discussion on media ownership, media concentration and news reporting. Gentzkow and Shapiro (2010), studying local newspapers, asks whether differences in political reporting across outlets is explained by owners responding to local readers’ demand, or rather by owners’ ideological views. They find support for the former. Since, several papers have documented that changes in media control can impact media content, in the context of private television networks acquisition (Martin and McCrain, 2019; Miho, 2020; Mastrorocco and Ornaghi, 2020), or public broadcasters’ control (Durante and Knight, 2012b); and a large body of work shows that media content impacts attitudes and behaviors down the line (DellaVigna and Kaplan, 2007; Chiang and Knight, 2011; Martin and Yurukoglu, 2017; Knight and Tribin, 2019; Bursztyn et al., 2020; Djourelova, 2022; Simonov and Rao, 2020; among others). This paper helps understand the potential consequences of media ownership change by studying the response from hosts. We document that journalists are largely constrained by their environment. Studying a takeover-induced change in editorial line, we find that hosts either comply or leave, the latter potentially disrupting their careers. Our paper also adds to works in other disciplines on political representation on Vivendi channels (Sécail, 2022).

---

11 This is consistent with existing anecdotal evidence documenting that a large share of the former journalists working for the news channel acquired by Bolloré have quit journalism (which is unfortunately not a surprise in a context where the overall number of journalists in France is declining).

12 Our work builds on the large literature measuring media bias. Some articles have relied on endorsements (Ansolabehere et al., 2003; Chiang and Knight, 2011), think tank quotes (Groseclose and Millyo, 2005), language (Gentzkow and Shapiro, 2010), issue coverage (Puglisi and Snyder, 2011; Galvis et al., 2013). Our work is closest to Durante and Knight (2012a) and Knight and Tribin (2019) as we also use time shares to measure political representation on screen. Yet, we build this measure for a broader range of shows, including entertainment, at the show-level, and for a broader variety of guests. Beyond professional politicians, we also include other politically vocal guests, taking into account the literature on “celebrity politics” (West and Orman, 2003; Wood and Herbst, 2007; Wheeler, 2013).
Finally, our empirical strategy draws on recent work on two-way fixed effects models meant to tease out effects of individual characteristics from context effects using moves across geographic areas, institutional environments or organizations. They have been used to explain a variety of outcomes, which include wage earnings (Abowd et al., 1999; Card et al., 2013a; Lachowska et al., 2022), health care consumption (Finkelstein et al., 2016), political participation (Cantoni and Pons, 2022), bureaucrats’ productivity (Best et al., 2017; Fenizia, 2022), or teachers’ performance (Chetty et al., 2014). Our paper is the first to use this type of model to study the relative role of hosts and their environment in media content creation.

The rest of the paper is organized as follows. Section 2 below provides details on the institutional setting, and Section 3 on the data. Section 4 presents the decomposition of across-channel differences in political representation and show that channel-level decisions account for the largest share of differences across outlets. Section 5 focuses on hosts reaction to Vincent Bolloré’s takeover. Finally, Section 6 discusses the policy implications of our results and concludes.

2 Institutional background

**News sources** Television and radio are the main sources of news in France. In 2017, 71% of French adults reported getting their news at least daily from television, 53% from radio, 47% online, and 23% from print. When asked about their main news source, 16% answer TF1 (private television), 15% BFM TV (private television), 15% France TV (public television), 6% Le Monde (newspaper), 6% Radio France (public radio), and 4% Facebook (Sumida et al., 2019). The list is largely dominated by television networks, social media being far behind. 25% of the surveyed individuals get their news daily from only one type of source, with television also being the most common source among those individuals. In 2022, the three most mentioned journalists are three presenters (either on television and/or on radio): Pascal Praud (CNews and RTL), Anne-Claire Coudray (TF1), and Jean-Jacques Bourdin (BFMTV and RMC) (Newman et al., 2022).

**Channels** 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 in 2020 (at the end of our sample) are TF1 (private), France 2 (public), France 3 (public), M6 (private), and France 5 (public), and are all included in our dataset. 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). Appendix Section B provides additional details on each channel.
Ownership  Public broadcast in France counts several channels among the most influential ones (France 2 and France Inter, among others). Public broadcasters fall under the umbrella of France Télévision for television channels and Radio France for radio stations. ARTE is jointly run by the French and German public broadcasts, and LCP is overseen by the French parliament. Regarding private outlets, four major groups dominate the market: the TF1 Group (property of Bouygues), the Bertelsmann group, NextRadioTV (property of Altice) and the Canal Plus group (Vivendi). These groups often own media outlets of different types. E.g. NextRadioTV owns television channels, radio stations, and some magazines; Vivendi, the parent company of Canal Plus, also owns the publishers Editis and Prisma media. Bertelsmann owns both radio stations and television channels.

Broadcast regulation and pluralism  The 1986 Law on Freedom of Communication laid the foundation of broadcast regulation in France. Its first article explicitly mentions the constitutional principle of “the pluralist nature of the expression of currents of thought and opinion” as one of its objectives. To this end, it has set rules limiting ownership concentration, with the idea that diffused ownership helps preserve media independence and diversity of editorial content – a reasoning similar to that developed in the 1947 Hutchins Commission report in the US. These rules are specific to the broadcast sector and apply on top of anti-concentration rules. They consider each platform separately (television, radio, etc.). For instance, according to the law, a given group cannot own more than 7 national television channels (excluding cable and satellite); a natural person cannot own more than 49% of a national television channel whose mean viewership exceeds 8%; etc.

The 1986 Law is also at the origin of the creation of an independent regulatory agency, which is known today as the Autorité de régulation de la communication audiovisuelle et numérique (Arcom). The Arcom is the French equivalent of the Federal Communications Commission (FCC) in the United States. One of its missions is to “ensure respect for the pluralist expression of currents of thought and opinion in the programs of radio and television services, in particular for political and general information programs” (article 3). In practice, the Arcom requires that a third of the speaking time be dedicated to the president and the

---

13 The TF1 Group belongs to Bouygues and encompasses several television channels, including TF1 (general), TMC (general), TFX (entertainment), and LCI (news). The Bertelsmann conglomerate owns several television channels – M6 (generalist), W9, 6ter (entertainment), Gulli (youth) – and the radio station RTL. NextRadioTV (owned by Patrick Drahi’s Altice) owns several television channels including BFM TV (news), and several radio stations among which RMC. The Canal Plus group (property of Vincent Bolloré’s Vivendi) owns several channels, including Canal+ (general), C8 (general) and CNews (news). Appendix Section B provides more details on each of these channels, their ownership structure and ownership changes during our period of interest.


15 Created in 1989 under the name Conseil Supérieur de l’Audiovisuel (CSA), the Arcom is the regulatory agency in charge of delivering frequencies, of overseeing mergers and acquisitions in the media market, of setting rules regarding diversity and pluralism, of labeling whether programs are appropriate for young audiences. It can also impose sanctions in case of hate speech or discrimination. See Cagé and Huet (2021) for more details on the regulatory environment of French broadcast.

Electronic copy available at: https://ssrn.com/abstract=4036211
government. The remaining two thirds should be dedicated to all political parties (including the government party), in proportion to the electoral results, the number of elected officials, popularity in the polls and a party’s contribution to the public debate. Public debate contribution and popularity not being unambiguously measurable, it is a general principle, left to the discretion of the media outlets, not a working rule. We indeed document in this article large differences in the speaking time of each party across outlets. Channels have to record the speaking time of each politician and communicate aggregate quarterly figures to the Arcom.

Stricter equal-time rules apply during presidential and parliamentary electoral campaigns. As a robustness check, we drop those periods when equal time rules apply as the time share of each political group is artificially balanced across candidates and does not necessarily reflect the decisions of hosts or of channels.

Political parties The French political landscape counts many parties, ranging from radical left to radical right. For clarity, and because parties split, merge, and change name over time, we aggregate them in ideology-based groups following the Chapel Hill Expert Survey (CHES) classification. The resulting six political groups are: i. radical left (communist party, France insoumise); ii. greens (Europe Écologie-Les Verts); iii. left (socialist party, “other left”); iv. liberals (MoDem, République en Marche); v. right (les Républicains, Union des démocrates et indépendants, “other right”); and vi. radical right (Rassemblement National, Debout La France).

3 Data and descriptive statistics

In this article, we build a novel dataset on television and radio shows from the Institut National de l’Audiovisuel (INA) archives that we clean and complement using a number of different resources. In this section, we describe the data, explain how we define the sample and outcomes of interest, and present descriptive statistics. In Section 4, we will then study the factors behind the documented differences in relative political representation across channels.

16See the Arcom’s website for additional details: https://www.csa.fr/web/index.php/Proteger/Garantie-des-droits-et-libertes/Proteger-le-pluralisme-politique
17Only professional politicians are monitored, not commentators, activists, or union leaders. We will come back to this point in the Data section below.
18Speaking times are added up irrespective of whether the show is broadcast during “prime time” or in the middle of the night. Anecdotal evidence suggests that some channels sometimes broadcast several times during the night interviews of politicians belonging to parties they under-represent (see e.g. https://www.arretsurimages.net/articles/quotas-31-fois-yannick-jadot-sur-lci). In our analysis, when studying speaking time shares, we take into account the average audience of the different time slots.
19See online Appendix Section [B.1] for a precise description.
20The INA collects and archives television and radio shows. Show data can be accessed via the following interface: http://inatheque.ina.fr/. For previous research using the INA data, see Cagé et al. 2020b,a.
Content and coverage The INA manually documented hosts and guests appearing in television and radio shows starting in 2002, focusing on the main television and radio stations. For each show, INA staff indicated the title of the show, the date, the start time, the end time, the show type, and the list of persons related to the show. For each person, we have her first name and last name, as well as a show time-invariant description of her profession (politician, journalist, singer, actor, etc.), and a show-specific role. Most common roles are ‘host’ and ‘guest’, but there are other labels, such as ‘voice-over’ (common for documentaries), ‘musician’ (if the show has a band for instance), etc. The data also includes information on segments within longer shows. That is typically the case for newscasts, where the main show credits the main host, and each sub-show references the reporter who went on the grounds as host of the sub-show, and the persons she interviewed as guests. Sub-shows therefore help measuring how much time is dedicated to each host or guest.

Regarding coverage, the INA collected data on a large variety of shows with hosts and guests: not only newscasts, but also talk shows, infotainment shows (in the style of late shows), investigation shows, etc. The shows that are not included are fiction, sports, games, and documentaries that feature no guests. In Appendix Section A.1 we compare the time length of the television shows in the INA data to shows documented in another dataset.21 We document that newscasts, shows about news and politics, and talk shows are nearly all included in INA data. The coverage is lower in the entertainment shows (including games), sports shows, youth programs, and documentaries categories. It is expected, since many of those shows do not feature guests. Overall, with INA data, we can reliably analyze the content of a broad range of shows, while most previous works only focused on a specific type of shows.22

Sample definition Our dataset covers French television and radio shows between 2002 and 2020. However, in our preferred empirical specification, we are going to focus on the sub-period September 1st 2005 - August 31st 2019, including 14 seasons (which are one-year periods from September to August).23 In 2005, the French TV system transitioned from analog to digital, and new country-wide channels became available for free. The sample ends in 2019 since, after

---

21 To benchmark the INA data coverage, we use information from Plurimedia, a company that collects scheduled television shows before they are broadcast.

22 Most papers in the existing literature focus on newscasts (see Durante and Knight 2012b, Gambaro et al. 2021, for instance). Some have also specifically focused on entertainment shows (see e.g. Jensen and Oster 2009, La Ferrara et al. 2012, DellaVigna and Ferrara 2015). To the extent of our knowledge, our article is the first to take into account all the different kinds of shows consumed by citizens on both television and radio, which seems of particular importance given the consumption of content that might influence political knowledge and behavior is not limited to the news broadcasts.

23 Seasons match the time frame outlets use to plan their shows or to adjust their programs. They typically hire new hosts between seasons, around the summer. With the data at our disposal, we could have included the programs broadcast during the summer. However, we have decided not to do so for several reasons. First, there are many more reruns of shows during the summer than during the rest of the year. While channels decide which shows to rerun, this is not up to the hosts’ decision. Second, most of the programs do not run during the summer and tend to be replaced by shows with both less hosts and guests.
that date, the number of documented shows sharply decreases due to budget cuts at the INA; less staff is since then in charge of show referencing and data on guests are entirely missing for certain channels past that date. As a result, we have a balanced sample of channels ranging from September 2005 to August 2019.

There are 14 television networks and six radio channels in our sample. For television, we focus on country-wide digital television networks (not cable, not satellite) that have shows with hosts and guests each season (see Appendix Section A.2 for more details on the sample), i.e. the following channels: ARTE, BFM TV, C8, Canal+, CNews, France 2, France 3, France 4, France 5, LCI, LCP/PublicSénat, M6, TF1 and TMC. The included channels accounted for 71.6% of viewership in 2020 (85.2% in 2007). The six radio stations included in the sample are France Culture, France Info, France Inter, Europe 1, RMC, and RTL. While the audience share of country-wide non-music radio station was 54.9% in 2020, the stations in our sample accounted for 46.3%. As a result, television and radio networks in our sample account for a large share of audience on both platforms, and for nearly all shows with hosts and guests broadcast on country-wide channels.

Guests The 260,413 unique guests in our sample account for 2.3 million appearances. The INA considers that a guest appears in a show if she speaks during the show, whether or not she is in the studio. The top five guests in number of appearances are François Hollande (14,278 appearances, politician, left), Nicolas Sarzoky (13,169 appearances, politician, right), Manuel Valls (7,860 appearances, politician, left), François Fillon (6,279 appearances, politician, right) and Marine Le Pen (5,592 appearances, politician, radical right). They account for 2.0% of all appearances, and 7.1% of politically-classified appearances.

The data include each guest’s gender, birth year, country, and a time-invariant description of the profession. Using keywords, we create indicator variable for whether each guest falls into a given category (one guest can fit several categories). The keywords and categories are precisely described in Appendix Section A.4 and Appendix Figure A.5 plots the relative frequency of each category. One in four appearances is by a guest who is a politician, meaning that a majority of guests are not involved in politics. Their job can be related to entertainment (actor, comedian, singer, etc.) or sports (player, coach, etc.) for instance.

Political leaning of guests We next map each guest appearance to a political group (if any). This measure of political leaning is allowed to vary over time: a guest might become a politician during our period of study, leave politics or change political affiliation over time. We use two sets of data sources. The first set of sources centers on elections and government appointments. We track for which party a given guest ran and in which elections (house, 24E.g. if a minister gives a press conference and snippets from the conference are broadcast during a newscast, then the minister is listed as guest, even though she is not present in the studio during the show.
senate, EU, région, canton, municipalities), whether when in parliament she was affiliated to a political group, and whether she worked for the government under a given majority. Appendix Section A.3.1 describes in detail how we combine these different data sources. With this first set of sources, we finely track how the affiliations of guests who are explicitly involved in politics change over time.

Motivated by the presence of guests who express their political views in shows like talk shows but are not politicians, we use a second set of data sources. Our goal is to find tangible signs of political leaning for guests who do not run in elections or work for the government but might still regularly be in the media. To this end, we collect data from three different sources. The first one is the list of speakers in political parties’ summer events (universités d’été). These events typically gather politicians and non-politicians like experts, columnists, activists, etc. Second, we collect the names of people who endorsed in the press one of the candidates running in the first round of presidential elections. For the third source, we focus on think tanks and proceed in two steps. We compile a list of French think tanks, and map them to a political group when relevant. Think tanks are linked to a party based (i) on whether founders or top managers were politicians in this party, (ii) on which politicians or political party grants them funds, (iii) on their stated goal, and (iv) on their community on Twitter. For the think tanks that have a political leaning, we use archives and archived versions of their websites to collect the list of members and contributors (report, blog post, etc.). We then combine these data sources and obtain a time-varying measure of the political leaning of guests. Appendix Section A.3.2 lists all the party summer events along with the number of participants, all the think tanks with their corresponding political leaning, statistics on their Twitter community, and the number of names collected. It also describes in detail how we combine these data sources in a single measure of political leaning.

As a result, we get a time-varying measure of political leaning for each guest. We classify 28.6% of appearances (661,295 in absolute value). Among the 24.1% of appearances by guests whose profession indicates ‘politician’ and whose country is France, 95.9% are matched to a political leaning. Appearances that are not classified are typically appearances of retired politicians or of not-yet politicians observed when they were not active (e.g. the criminal defense lawyer Eric Dupond-Moretti before he was appointed Minister of Justice). It means that we classify virtually all the guests who are politicians and are therefore expected to be classified. We also classify 7.2% of appearances of people who are not considered to be politician (e.g. Bernard Thibault, a union leader, or Bernard Laporte, a rugby player and rugby coach who became in charge of sports in a government). The remaining 71.4% appearances are by guests who are in the media/publishing sector (36.1%), in the entertainment industry (20%), are experts/academics (14.8%), or whose profession is missing in the data (24.8%). The most common guests who are not politically classified are Barack Obama (4,228 times),
Screen time share  To measure the relative amount of time that each outlet dedicates to guests with given political views, we take into account show (or sub-show) length. The idea is to account differently for guests appearing in short segments, and guests giving longer interviews. To this end, we use the length of the show or sub-show and divide it by the number of guests. For example, if a one-hour show features two guests, we consider that each guest gets 50% of the speaking time share, i.e. 30 minutes. This measure does not take into account several margins: how long the host speaks, whether the guest is interrupted often, or the tone of the interviewer. To check the validity of our measure, we compare the time share we attribute to each guest in a show (50% for instance) to the share of frames that contain the face of the guest using a subset of television shows for which a face-recognition algorithm has been implemented in the context of a machine learning study by [Petit et al. (2021)]. The right panel of Appendix Figure A.4 plots the computed time share against image frame share for this subset of shows. We find that our measure explains 87% of the variation of screen time share measured by image frames with a slope coefficient of 1. In other words, our time share measure proxies very precisely the screen time of each guest. Even if our measure does not take into account interruptions, cutaways, or the tone of the host, we still believe that it captures how much time political actors are given to express their views, which is the basic requirement for the public to be exposed to them. In this sense, our measure of political representation is similar to that of [Durante and Knight (2012a)].

From there, we have a measure of the screen time of each political group for each show, that we aggregate at the season level. Figure 1 plots the time share of each political group aggregated across all outlets in our sample. Panel (a) includes all the guests who are politically classified. We can clearly observe the electoral cycles, with the right being in power until 2012, the left from 2012 to 2017, and the liberals gaining power in 2017. The government party is systematically more represented, which echoes the Arcom guideline requiring that a third of the political speaking time be dedicated to the government. Panel (b) excludes government officials. In this case, both the right and the left are similarly represented, until 2017 when the liberal party emerges as winner of the presidential elections and eclipses the left and, to a lesser extent, the right. We also observe a in recent years a significant rise in the speaking-time share of the radical right.

Figure 2 juxtaposes the speaking time share of political groups on each outlet, which are sorted by the time share of all left-wing parties combined. We can see that there are substantial

---

25 Regarding Obama and Merkel, note that this is due to the fact that we do not classify the guests who are not French.
26 If a guest takes part in a show that contains sub-shows – that could be the case if a guest is invited in a talk show that includes segments like a live performance, a book review, a cooking demonstration, etc. – we net out the length of the sub-shows that do not feature the guest.

Electronic copy available at: https://ssrn.com/abstract=4036211
(a) All politically-classified appearances (b) Excluding government officials

Notes: The figures plot the time share of each political group for each season, aggregating over all the outlets in our sample. Panel (a) includes all the political groups, while Panel (b) excludes the government members.

Figure 1: Time share of political groups over time

differences across outlets. For example, the 24-hour news channel LCI devotes 40.7% of the time share to left-wing guests, compared to 60.2% for France Culture. Comparing outlets within platforms, there are still substantial differences across networks, even though they all operate on the country-wide television market (and so all potentially serve the same set of consumers). There is a 19.3 percentage-point difference in left-wing parties representation between the TV network representing the left the least and that representing it the most. The figure for radio is 15.8 percentage points. In the rest of the paper, we seek to tease out the relative contribution of host characteristics and of outlet-level decisions, while finely controlling for demand.

Hosts  INA data also includes information on show hosts. We have the name and gender of each host. We complement this information by collecting data online from two sources: Wikidata and Les Biographies (LB), which is the French equivalent to the Who’s Who. Appendix Sections A.4.2 and A.5 provide details on how we compiled data from these sources.

To estimate the relative impact of host- vs. outlet-level decisions on show content, we track hosts as they move from outlet to outlet. Table 1 presents descriptive statistics for several sub-samples. Column (1) includes all the hosts included in our sample, and Column (2) only hosts that have at least two shows featuring guests who are politically classified. Column (3) focuses on hosts who have at least two shows with political guests and are observed in distinct outlet-season pairs. Finally, Column (4) features hosts who have at least two shows with political guests and are observed on at least two distinct outlets.

The dataset includes 39,322 distinct hosts (Column (1)). Among them, more than a third (14,492) have hosted at least two shows featuring guests who are politically classified (either
Notes: The figures plot the time share of each political group for each season, depending on the media outlets. Media outlets are ranked depending on the time share they devote to the left-wing parties. Panel (a) includes all political groups, while Panel (b) excludes government members.

Figure 2: Time share of political groups across channels

on the same or on different media outlets) and are thus in the estimation sample (Column (2)). Among those, 6,884 are observed on at least two distinct outlets (Column (4)), and 9,810 are observed on an outlet in at least two distinct 2-season time periods (Column (3)). As detailed in Section [4], our model thus estimates 140 channel-time effects with leveraging 6,884 movers (49 per estimate), and 9,810 stayers (70 per estimate).

Hosts in the estimation sample are more likely to have a description in INA data, and that description is more likely to include the word ‘journalist’. Indeed, some hosts exclusively invite guests related to entertainment or sports; journalists by contrast are generally trained to analyze political developments and interview politicians. Hosts in the estimation sample, and a fortiori those observed on distinct channels, are more known, as proxied by the existence of a Les Biographies or a Wikidata entry. They have more screen time, are observed on more days, have more guests, dedicate more time to political guests, etc. This is in line with the idea that hosts observed across longer periods of time or across channels are more visible and more advanced in their careers.

Regarding other characteristics such as gender, age, but also the time share dedicated to each political group, we find that hosts are very similar across samples. It means that the hosts whose shows we use to identify channel effects do not systematically differ from others when it comes to which political group they invite in their shows. They are not more right-wing or left-wing than hosts that do not move, or are observed more briefly on a given outlet.
Table 1: Descriptive statistics on hosts

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All hosts</td>
<td>Est. sample</td>
<td>Dist. 2y-s</td>
<td>Dist. channels</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>sd</td>
<td>mean</td>
<td>sd</td>
</tr>
<tr>
<td><strong>Descriptive characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% female</td>
<td>36.30</td>
<td>(48.09)</td>
<td>39.17</td>
<td>(48.81)</td>
</tr>
<tr>
<td>Birth year (pred)</td>
<td>1967.07</td>
<td>(18.47)</td>
<td>1968.64</td>
<td>(17.81)</td>
</tr>
<tr>
<td>% with description</td>
<td>82.31</td>
<td>(38.16)</td>
<td>94.43</td>
<td>(22.93)</td>
</tr>
<tr>
<td>% 'journalist'</td>
<td>44.29</td>
<td>(49.67)</td>
<td>65.73</td>
<td>(47.46)</td>
</tr>
<tr>
<td>% 'host'</td>
<td>3.57</td>
<td>(18.54)</td>
<td>5.73</td>
<td>(23.24)</td>
</tr>
<tr>
<td>% 'producer'</td>
<td>17.32</td>
<td>(37.84)</td>
<td>16.15</td>
<td>(36.80)</td>
</tr>
<tr>
<td>% w/ LesBios entry</td>
<td>4.65</td>
<td>(21.06)</td>
<td>7.78</td>
<td>(26.78)</td>
</tr>
<tr>
<td>% w/ Wikidata entry</td>
<td>8.85</td>
<td>(28.40)</td>
<td>12.57</td>
<td>(33.16)</td>
</tr>
<tr>
<td><strong>Media presence</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># distinct days</td>
<td>46.13</td>
<td>(174.60)</td>
<td>120.12</td>
<td>(272.01)</td>
</tr>
<tr>
<td># distinct channels</td>
<td>1.60</td>
<td>(1.17)</td>
<td>2.31</td>
<td>(1.57)</td>
</tr>
<tr>
<td># dist. chan x 2y s</td>
<td>3.97</td>
<td>(5.06)</td>
<td>7.94</td>
<td>(6.41)</td>
</tr>
<tr>
<td>% has any pol. guest</td>
<td>59.49</td>
<td>(49.09)</td>
<td>100.00</td>
<td>(0.00)</td>
</tr>
<tr>
<td># guests</td>
<td>158.35</td>
<td>(713.52)</td>
<td>415.20</td>
<td>(1129.69)</td>
</tr>
<tr>
<td>Screen time (hours)</td>
<td>37.47</td>
<td>(197.45)</td>
<td>98.22</td>
<td>(316.07)</td>
</tr>
<tr>
<td>Time per guest (min)</td>
<td>17.06</td>
<td>(21.76)</td>
<td>13.33</td>
<td>(13.63)</td>
</tr>
<tr>
<td><strong>Political guests</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># politic. guests</td>
<td>39.67</td>
<td>(285.15)</td>
<td>106.50</td>
<td>(462.13)</td>
</tr>
<tr>
<td>Time w/ pol. guest (hrs)</td>
<td>8.30</td>
<td>(64.78)</td>
<td>22.28</td>
<td>(105.25)</td>
</tr>
<tr>
<td>Time per pol. guest (min)</td>
<td>14.10</td>
<td>(16.44)</td>
<td>13.48</td>
<td>(15.19)</td>
</tr>
<tr>
<td>% time w/ pol. guest</td>
<td>17.81</td>
<td>(25.98)</td>
<td>26.47</td>
<td>(23.14)</td>
</tr>
<tr>
<td>% time rad. left</td>
<td>9.73</td>
<td>(20.53)</td>
<td>9.35</td>
<td>(14.14)</td>
</tr>
<tr>
<td>% time greens</td>
<td>8.53</td>
<td>(19.40)</td>
<td>8.63</td>
<td>(14.40)</td>
</tr>
<tr>
<td>% time left</td>
<td>29.60</td>
<td>(30.57)</td>
<td>30.10</td>
<td>(22.23)</td>
</tr>
<tr>
<td>% time liberals</td>
<td>9.58</td>
<td>(20.04)</td>
<td>9.86</td>
<td>(15.01)</td>
</tr>
<tr>
<td>% time right</td>
<td>32.14</td>
<td>(31.91)</td>
<td>32.03</td>
<td>(23.25)</td>
</tr>
<tr>
<td>% time rad. right</td>
<td>5.84</td>
<td>(16.01)</td>
<td>5.86</td>
<td>(11.54)</td>
</tr>
<tr>
<td>Observations</td>
<td>39322</td>
<td></td>
<td>14492</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The Table provides descriptive statistics on the hosts. An observation is a host. Column (1) includes all the hosts included in our sample ("all hosts"). Column (2) only includes hosts who are in the estimation sample, meaning those who have at least two shows featuring guests who are politically classified ("est. sample"). Column (3) focuses on hosts, among those in the estimation sample, who are observed on the same outlet in at least two distinct 2-season periods ("Dist. 2y-s"). Finally, Column (4) features hosts in the estimation sample who are observed on at least two distinct outlets ("Dist. channels"). "% description" reports the share of the hosts for which the INA data provides a short description. More details are provided in the text.
4 What explains the differences in relative political representation across channels?

In this section, we ask to what extent the differences in relative political representation across channels are driven by: (i) the preferences or specialization of hosts working on each channel (host composition), (ii) the editorial guidelines of each channel (host compliance), or (iii) the sorting of hosts across channels which could potentially magnify the other two effects or, conversely, mute them (host sorting).

4.1 Specification

**Two-way fixed effects model** To decompose the relative influence of each mechanism, we use the following model, in the spirit of Lachowska et al. (2022):

\[ y_{it} = \alpha_i + \gamma_{c(i,t)} + \tau_t + \epsilon_{it} \] (1)

where \( c \) indexes the channels, \( i \) the hosts and \( t \) the time. \( y_{it} \) is the time share of a given political group in shows hosted by host \( i \) at time \( t \). In our preferred specification, we define this share by using as the numerator the time dedicated to guests of a given political group, and as the denominator the total time dedicated to political guests. This share varies between 0, if that political group was not represented at all, and 1, if all political guests in the show were from that political group. The unit of observation is the triple of host \( i \), channel \( c \) and time \( t \), where time is measured at the date × hour level.

\( \tau_t \) is a time fixed effect at the date × hour × platform level, where platform is either television or radio. It controls for time shocks such as news events as well as viewers’ characteristics in each hour of each day. These time fixed effects therefore control for demand characteristics non-parametrically at very high frequency. \( \alpha_i \) is a host fixed effect. It accounts for the hosts fixed characteristics, including his preferences or specialization, that could make him susceptible of over- or under-representing a given political group. \( \gamma_{c(i,t)} \) is a channel fixed effect that accounts for how a host changes his invitation pattern based on which channel he works on. In other words, it reflects the editorial guidelines promoted on this particular channel. Channel effects are allowed to change every two seasons, in the spirit of time-varying AKM models Lachowska et al. (2022). It follows from the idea that assuming that channels’ editorial lines are fixed over long periods of time is likely unrealistic (to begin with because there might be changes in channel ownership). Rather, our model allows channel effects to vary, reflecting that their editorial line might be periodically adjusted. This flexibility also implies that channel effects are identified both with movers, switching from one media outlet...
to the others, and by stayers who are observed in distinct time brackets. Together with the large number of hosts observed on distinct channels, the fact that stayers also contribute to the identification of channel fixed effects ensures that they are estimated with a sufficient number of observations.

**Model assumptions**  With this two-way fixed effects model, we implicitly assume additive separability of host, channel and time components. Identification requires that hosts’ moves are as good as random, conditional on host fixed effects, 2-season $\times$ channel fixed effects, and date $\times$ hours $\times$ platform fixed effects. More formally, we assume that $E(\epsilon_{it}) = 0$; this orthogonality condition means that hosts can sort based on their fixed characteristics and 2-season $\times$ channel effects. For instance, hosts tend to over-represent the right can sort into right-leaning channels without violating the identifying assumption.

Card et al. (2013b) identify three types of endogenous mobility in a standard two-way fixed effect models. One would be hosts sorting on channels based on match quality. The second would be that mobility is associated with trends in channel effects. Our specification flexibly allows channel effects to vary every two seasons. Only moves triggered by short-term changes in channel editorial lines would violate the identifying assumption. Finally, moves should not be triggered by transitory changes in editorial line.

**Movers and stayers**  We estimate the parameters of Equation 1 observing the guest composition of shows hosted by movers – hosts observed on distinct channels – and stayers – hosts observed on the same channel in distinct time brackets. Regarding movers, Figure 3 plots a matrix reporting the number of moves for each origin-destination pair in the estimation sample. We consider that a host moves if his next show is on a channel that is distinct from the channel of its current show. By that definition, there are 65,666 moves in the data set. Outlets are ranked according to the time share dedicated to left-wing parties, from highest (top, right) to lowest (bottom, left). We observe moves across all outlets, with relatively more moves between similar outlets – as illustrated by lighter shades close to the diagonal. The number of moves is particularly high within outlets of the same group (TF1 and LCI, France 2 and France 3 for instance), which is expected since sometimes hosts have shows on both channels in a given season. The two outlets with the least moves are TMC and France 4, but these two channels only have a few shows including political guests.27

Appendix Figure C.1 plots the distribution of the differences in the time share devoted to politicians from the right and from the left between destination and origin channels at the time of the move. The distribution is roughly symmetric, meaning that there is a similar number

---

27TMC’s coverage of politics was initially very limited and expanded around 2015. Later estimates are indeed more precise. Regarding France 4, the channel was close to being interrupted around 2017 and now largely prioritizes youth and educational content. Later periods effects are more imprecise.
Figure 3: Number of moves, by origin and destination outlets

Notes: The figure plots the number of moves for each origin and destination pair in the estimation sample. Only shows with at least one politically classified guests are included. We consider that a host moves if his next show is on a channel that is distinct from the channel of its current show. By that definition, there are 65,666 moves in the data set. Outlets are ranked according to the time share dedicated to left wing parties, from highest (top, right) to lowest (bottom, left).
of moves from channels that devote relatively more time to the left than to the right than the opposite. Many moves entail small destination-origin differences, meaning that hosts move between “similar” outlets from this point of view. Yet, for 50% of the moves, the absolute difference exceeds 5.0 percentage points for the left and 4.9 percentage points for the right, meaning that we observe a substantial number of moves across channels with very distinct invitation patterns.

Hosts staying on a given channel over time help identify how the environment impacts show content, holding hosts time-invariant characteristics fixed, and how the effect of this environment may change over time. Appendix Figure C.2 plots the distribution of the number of days elapsed between the first and last show with a political guest hosted by a journalist on a given channel. We exclude host-channel pairs where the host had a show with a political guest on only one day. There are 19,219 remaining host-channel pairs. The distribution is skewed, with many pairs being short lived (25% of pairs last less than 9 months). Yet, a substantial number of hosts stay for a rather long period, with the median spell length being 943 days, more than two years and a half. Appendix Table C.2 reports descriptive statistics on spell length by channel. These hosts staying for longer periods help track changes in the channel environment. Again, the two outlets with the shortest median spells are TMC and France 4. For this reason, as a robustness check, we also report our main variance decomposition estimates excluding these two outlets in the Appendix.

**Variance decomposition** To understand differences in observed political group representation across channels, we want to decompose the share of variation in invitation patterns between two broad sets of factors: on the one hand, channel-specific characteristics, such as the guidelines set by the editorial board, and on the other hand, host-characteristics like specialization or preferences. We also want to analyze how hosts sort across channels, that is whether they tend to work on channels whose guidelines fit their personal inclination.

Our decomposition between those two types of factors follows Finkelstein et al. (2016) and Cantoni and Pons (2021). Let \( y_{it}^{\text{net}} = y_{it} - \tau_t \) denote the time share of a given political group at time \( t \) with host \( i \) net of time effects \( \tau_t \), which reflect news pressure, political cycles, and media viewership. Let \( \bar{y}_{cs} \) and \( \bar{y}_{cs}^{\text{net}} \) respectively denote the raw and net-of-time-effects expectations of speaking time share on channel \( c \) in season \( s \), weighted by political time length. Let \( \bar{\alpha}_{cs} \) be the channel-season level expectation of host characteristics \( \alpha_i \), also weighted by political time length. Then, the difference in net time share dedicated to a given political group between two outlets \( c \) and \( c' \) is the sum of the differences of the channel and host components:

\[
\bar{y}_{cs}^{\text{net}} - \bar{y}_{cs'}^{\text{net}} = (\gamma_{cs} - \gamma_{cs'}) + (\bar{\alpha}_{cs} - \bar{\alpha}_{cs'})
\]

The share of the difference between outlets \( c \) and \( c' \) that is attributable to channel-level decisions is:
\[ S_{\text{channel}}(c, c') = \frac{\gamma_{cs} - \gamma_{c's}}{\bar{y}_{cs} - \bar{y}_{c's}} \] (2)

It represents by how much the representation gap between two channel-season pairs would fall if the channel level editorial decisions were the same. The share attributable to hosts is:

\[ S_{\text{host}}(c, c') = \frac{\bar{\alpha}_{cs} - \bar{\alpha}_{c's}}{\bar{y}_{cs} - \bar{y}_{c's}} \] (3)

It can be interpreted as by what share would the gap in representation between two channel-season pairs fall if hosts characteristics where the same on average. Note that although the two shares sum to 1, they need not be between 0 and 1, as \( \bar{\alpha}_{cs} - \bar{\alpha}_{c's} \) and \( \bar{y}_{cs} - \bar{y}_{c's} \) might have opposite sign. That might arise if the average host working on a given channel tends to over-represent a party while the editorial guideline would suggest otherwise.

We can use an alternative decomposition of cross-channel variance in political time share across channel-period pairs. It follows from \( \bar{y}_{cs}^{\text{net}} = \gamma_{cs} + \bar{\alpha}_{cs} \) that:

\[ \text{Var}(\bar{y}_{cs}^{\text{net}}) = \text{Var}(\gamma_{cs}) + \text{Var}(\bar{\alpha}_{cs}) + 2\text{Cov}(\gamma_{cs}, \bar{\alpha}_{cs}) \] (4)

From there, we can express the variance across channel-season pairs as the sum of (i) the variance in channel-level decisions, reflecting differences in editorial views (\( \text{Var}(\gamma_{cs}) \)), (ii) the variance in average host characteristics which can be seen as differences in host composition across outlets (\( \text{Var}(\bar{\alpha}_{cs}) \)), and (iii) the covariance between the two, which measures the extent to which hosts sort on channels whose editorial line fits their personal inclination (\( 2\text{Cov}(\gamma_{cs}, \bar{\alpha}_{cs}) \)). This way, we can assess the role played by sorting across hosts and outlets.

We estimate each component of equation (4) using a split-sample approach to account for the fact that channel and host effects are themselves estimates. Otherwise, the variance of these estimates would indeed be inflated by the sampling error variance. We thus randomly split the sample in two subsamples of approximately identical size, stratifying by outlet-period-host. We estimate the components of equation (4) by taking the covariance between noisy estimates of the two subsamples, assuming that the sampling errors are orthogonal.

**Event study** To test whether hosts moving from one media outlet to another might already exhibit invitation patterns in line with the destination’s editorial line, we use an event-study specification. We focus on the shows of a host \( i \) just around a move from an origin outlet \( o(i) \)
to a destination outlet $d(i)$. We denote by $\delta$ the difference in channel-level average speaking time share of a given political family between the destination and origin at the time of the last pre-move show: $\delta_i = \bar{y}_{d(i)} - \bar{y}_{o(i)}$.

$\delta_i$ is positive (respectively negative) for hosts who move to an outlet that represents a given political group more (respectively less) than the origin outlet. The specification writes as follows:

$$y_{ir} = \sum_{t=-2,t\neq-1}^{2} \theta^t 1(r = t) \times \delta_i + \mu_i + \nu_r + \epsilon_{ir}$$

where $y_{ir}$ is the time share of a given political group in a show hosted by host $i$ at relative time $r$, with $r \in (-2, 2)$. $\mu_i$ is a set of host fixed effects and $\nu_r$ of relative time effects. Standard errors are clustered at the host level.

### 4.2 Changes around move

As a first step, we plot how the time share of a given political group changes in the shows hosted by a journalist as the host moves from an outlet to another. For each move, we compute the change in time share as the difference between the average time share in the last two shows on the origin channel, and the first three shows on the destination channel. This difference is plotted against the destination-origin difference in time share for the considered political group at the time of the last pre-move show. If the mover invites similar guests, irrespective of which channel he works for, then the slope should be zero. Conversely, if the fully adapts to outlets’ editorial lines, the slope should be one.

Figure 4 shows the relationship for all left-wing parties (Panel A) and all right-wing parties (Panel B). The slopes are around 0.63, meaning that channel-level decisions explain around two-third of the observed variation in channel-level representation of political groups.

The relationship appears linear and symmetric around zero, suggesting that a host moving from $c$ to $c'$ or, symmetrically, from $c'$ to $c$ would experience the same change in political time shares in absolute value. If hosts were sorting based on match quality, a high left-wing (right-wing) time share channel would have a different effects on hosts than a low left-wing (right-wing) time share channel. Here, the effect of moving from a low to a high left-wing (right-wing) representation channel appears similar and opposite to that of moving from a high to a low left-wing (right-wing) representation channel.

Figure 5 plots estimates of $\theta^t$ from Equation 5. The reference show is the last show before the move ($r = -1$). Invitation patterns sharply change upon move. Point estimates are similar across political groups and stable after move. They are statistically significant and range between .5 and .8 for post-move shows, which is consistent with the slopes reported above. By contrast, pre-move estimates are close to zero and not statistically significant,
Figure 4: Change in moving hosts’ political time share against destination channel - origin channel differences

(a) Left-wing parties
Slope = 0.625

(b) Right-wing parties
Slope = 0.631

Notes: The figure shows how the political time share of a given host 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 hosts between the three first post-move shows and the last two pre-move shows. The grey dots are averages computed by vintiles. The line is the best linear fit from an OLS regression. The slope is reported in the bottom right-hand corners of the graph.

illustrating the absence of pre-trends. When still working for their origin outlets, movers do not exhibit signs that they are gradually becoming more in line with the destination editorial line. Moves do not appear to be triggered by changes in hosts preferences, or temporary shocks. Instead, it lends support to the idea that moves in the present framework can be seen as exogenous.

4.3 Decomposition of cross-channel variation in political time share

Estimation We estimate Equation 1 with the time share of several political groups as dependent variables. The estimation sample includes 725,785 shows with at least one politically classified guest, weighted by the time dedicated to political guests. The model explains between 72.9% and 75.1% of the dependent variable variance. For all dependent variables, a F-test strongly rejects the null hypothesis that all the channel effects are zero (p-value = 0.000). In their shows, hosts comply with the channel editorial policy and adapt the composition of their guests to the channel they work for.

Channel and host shares We follow equations 2 and 3 to measure the overall and relative contribution of channel and host effects across channel groups. We do so for distinct groups of channel-season pairs, C and C’, with respectively a high and low time share dedicated to the political group under consideration.
<table>
<thead>
<tr>
<th>Outlet-period pairs from the top and bottom</th>
<th>Difference in time share</th>
<th>Share of difference due to</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>0.148</td>
<td>0.071</td>
</tr>
<tr>
<td>Overall, net of time effects</td>
<td>0.082</td>
<td>0.010</td>
</tr>
<tr>
<td>Due to channels</td>
<td>0.071</td>
<td>0.010</td>
</tr>
<tr>
<td>Dues to hosts</td>
<td>0.010</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>0.166</td>
<td>0.069</td>
</tr>
<tr>
<td>Overall, net of time effects</td>
<td>0.077</td>
<td>0.008</td>
</tr>
<tr>
<td>Due to channels</td>
<td>0.069</td>
<td>0.008</td>
</tr>
<tr>
<td>Dues to hosts</td>
<td>0.008</td>
<td></td>
</tr>
</tbody>
</table>

| All left                                  | All left                 | All left                  | All left                  |
|-------------------------------------------|--------------------------|---------------------------|
| Overall                                   | 0.148                    | 0.071                     |
| Overall, net of time effects              | 0.082                    | 0.010                     |
| Due to channels                           | 0.071                    | 0.010                     |
| Dues to hosts                             | 0.010                    |                           |
| Overall                                   | 0.166                    | 0.069                     |
| Overall, net of time effects              | 0.077                    | 0.008                     |
| Due to channels                           | 0.069                    | 0.008                     |
| Dues to hosts                             | 0.008                    |                           |

Notes: Each column reports the linear decomposition of the difference in average political time share across two sets of outlet-season pairs. Reported shares in rows 5 (“Channels (%))“ and 7 (“Hosts (%)“) correspond to shares presented in Equations 2 and 3 respectively. Column (1) compares outlet-periods pairs whose time share dedicated to left-wing guests (upper part) and right-wing guests (bottom part) are in the top 50% to those in the bottom 50%. Columns (2), (3) and (4) compare the top and bottom 25%, 10% and 5% respectively. Standard errors are the standard deviation of the corresponding shares bootstrapped with 100 replications.
Figure 5: Change in moving hosts’ political time share around move

(a) Aggregates

(b) Breakdown by party

Notes: The figure plots the event-study estimates from Equation (5). The dependent variable is the time share of a given political group in the shows before and after the move. It is regressed on the difference in average outcome between destination and origin channels interacted with relative time indicator variables. The sample includes all hosts who moved to another channel for their last two shows on the origin channel and the first three on the destination channel.

Table 2 reports the results. Column (1) compares outlet-periods pairs whose time share dedicated to left-wing guests (upper part) and right-wing guests (bottom part) are in the top 50% to those in the bottom 50%. Columns (2), (3) and (4) compare the top and bottom 25%, 10% and 5% respectively. Channel effects consistently account for around 90% of the difference between outlets. In contrast, hosts account for only 10%. In other words, equalizing hosts across channel would only reduce the difference in political time share across channels by 10%. Appendix Table C.3 reports results of the linear decomposition when excluding TMC and France 4, whose effects are more noisily estimated. Results are unchanged. Hosts therefore largely adapt to which channel they work for, and show content is largely dictated by channel-level decisions.

**Variance decomposition** We next follow Equation (4) and report an alternative decomposition of the variation in political time shares. Doing so, we can test for the presence of sorting between host and channel effects.

Table 3 reports the results for distinct political groups – left-wing parties, right-wing parties, radical parties (i.e. the sum of the radical left and the radical right) and government parties. Again, we find that channel effects account for the largest share of variance – between 81.7% and 86.1%. The remaining variance is almost entirely explained by sorting, as covariance between host effects and channel effects accounts for between 12.7% and 16%. Hosts composition only account for a residual part, meaning that who hosts are matter only minimally to
Table 3: Variance decomposition of political time share differences

<table>
<thead>
<tr>
<th></th>
<th>All left</th>
<th>All right</th>
<th>Radical</th>
<th>Government</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total variance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance, raw</td>
<td>0.0111</td>
<td>0.0134</td>
<td>0.0059</td>
<td>0.0103</td>
</tr>
<tr>
<td>Variance, net of time effects</td>
<td>0.0091</td>
<td>0.0083</td>
<td>0.0048</td>
<td>0.0093</td>
</tr>
<tr>
<td><strong>Channel effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>0.0074</td>
<td>0.0071</td>
<td>0.0042</td>
<td>0.0080</td>
</tr>
<tr>
<td>% variance, net of time effects</td>
<td>81.7</td>
<td>85.0</td>
<td>86.1</td>
<td>85.6</td>
</tr>
<tr>
<td>Bootstrapped s.e.</td>
<td>8.9</td>
<td>10.9</td>
<td>6.7</td>
<td>5.9</td>
</tr>
<tr>
<td><strong>Host Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>0.0002</td>
<td>0.0002</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>% variance, net of time effects</td>
<td>2.2</td>
<td>2.1</td>
<td>1.3</td>
<td>1.6</td>
</tr>
<tr>
<td>Bootstrapped s.e.</td>
<td>3.3</td>
<td>4.2</td>
<td>1.8</td>
<td>1.7</td>
</tr>
<tr>
<td><strong>Covariance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 × Covariance</td>
<td>0.0015</td>
<td>0.0011</td>
<td>0.0006</td>
<td>0.0012</td>
</tr>
<tr>
<td>% variance, net of time effects</td>
<td>16.0</td>
<td>12.9</td>
<td>12.7</td>
<td>12.8</td>
</tr>
<tr>
<td>Bootstrapped s.e.</td>
<td>10.6</td>
<td>13.1</td>
<td>5.9</td>
<td>5.5</td>
</tr>
</tbody>
</table>

Notes: The table reports components of the variance decomposition laid out in Equation 4. The first row reports cross outlet-period variance in time share, the second one does the same, netting out time fixed effects from the time shares. The third row reports the split sample variance of channel-period effects, the fourth row expresses channel effects variance as a share of total variance, net of channel effects. The fifth row reports the standard deviation of bootstrapped shares (100 replications). Rows 6 to 8 do the same for host effects, rows 9 to 11 for the covariance between host and channel-period effects.

explain differences in political coverage.

Appendix Table C.4 reports the same variance decomposition when excluding France 4 and TMC. Variance shares are of the same magnitude but are more precisely estimated. The two main options hosts seem to have are either complying with the editorial policy or work on an outlet more compatible with their baseline inclinations.

4.4 Host effects

To better understand the determinants of host fixed effects, we next correlate them with a broad set of individual characteristics. We are interested in the standardized value of the host fixed effects. A more positive (negative) value indicates the host tends to over-represent (under-represent) a given group, potentially due to preferences or specialization. We also look at the absolute value of standardized host effects, as we want to know which hosts tend to deviate from the channels’ editorial policies.

Figure 6 presents the result of a multivariate OLS regression of various host characteristics for the 14,492 hosts in the estimation sample (Column 2 in table 1) for both left and right wing fixed effects of hosts. The left panel indicates that female hosts’ fixed effects are
Figure 6: Correlation between host effects and characteristics

Notes: The figure reports estimates and robust 95% confidence intervals from multivariate OLS regressions on standardised host fixed effects for left and right wing parties (left side) and their absolute values (right side).

associated with a deviation to the left from the channel editorial line. Moreover, hosts who are more central to the political host-guest network – as measured by their degree centrality – are somewhat more left-wing relative to their channel. Similarly, host who invite more government guests represent the left relatively less. In terms of individual’s professions, estimates are rather imprecise. Moreover, Figure C.3 in the appendix further shows that in a lasso regression that accounts for potential over-fitting most profession dummies are deselected. However, hosts who work as artists or producer tend to deviate more to the left of the channel line. All estimated correlations are rather small and less than 0.1 standard deviations of the estimated host fixed effects (1 SD = 0.18% ).

The right panel of Figure 6 looks at absolute values of the host fixed effect, indicating whether hosts tend to systematically deviate from the average political mix, whether by over- or under-representing a given group. Whether we look at fixed effects estimated with the left or the right time share as the dependent variables, the patterns are very similar. Hosts who work on several channels, who have more screen and who have had a French president as a guest tend to deviate more. The same applies to hosts who are more known, as proxied by having an entry on Wikipedia and Les Biographies. In short, more popular hosts deviate more. They may derive this agency from their notoriety.

Interestingly, conditional on total screen time, hosts who are more central in the political
guest-host network and hosts who have more political screen time deviate less from the channel line. The same applies to hosts whose identified profession is 'journalist' (rather than 'host'). Channel may select well-situated journalists to cover political issues close to the editorial line of the channel, while hosts who are per se not specialised on political journalism have a greater ability to deviate from the channel line.

4.5 Channel effects and ownership

So far, we have evidenced that hosts largely comply with their channel’s editorial line. We further explore how these editorial lines evolve over time. Appendix Figure C.4 plots for each channel in our sample how its channel effects has evolved from the first period in our sample to the last. We report 95% confidence intervals bootstrapped with 100 replications, and ranked channels based on their last period effect.

For the representation of left-wing parties, channel effects ranged from -8 to 9 percentage points in the first period, and from -12 to 12 percentage points in the last. The split-sample standard deviation of channel effects, reported in the legend, has increased from 0.04 to 0.07. A similar pattern, albeit more muted, is visible when using the time share of right-wing parties as a dependent variable. Channels’ editorial lines, when it comes to politics, has been diverging over time and are now more polarized.

Appendix Tables C.5 and C.6 report the variance decomposition following Equation 4 for three distinct periods: September 2005-August 2011, September 2011-August 2015 and September 2015-August 2019. Both for left and right-wing time shares, the share of variance explained by channel effects has been increasing over time, while both host effects and covariance have decreased. It suggests that over the considered period channels have strengthened their grip over show content.

Why have editorial guidelines changed over time? Over the same period, the French media landscape has experienced growing ownership concentration (see e.g. Cagé and Huet 2021). The documented divergence in editorial lines may be linked to ownership changes. Oftentimes, a takeover is followed by changes in the top management and editorial board. There are several reasons why ownership may impact the editorial line (Gentzkow and Shapiro 2010). On the one hand, owners that have several outlets might seek to segment the market and specialize each outlet in their portfolio such that it serves a specific political segment. For instance, two television channels operating in the same market have the same potential viewer – whoever switches on television at a given point in time. Differentiating channels based on politics might be one way to limit competition between outlets ultimately owned by the same group. On the other hand, owners might have specific views on the type of content they want

---

28For instance, when Bolloré gained control of Vivendi and Canal+ channels, he started by replacing the incumbent top management.
Figure 7: Correlation between channel effects and ownership groups

Notes: The figure reports estimates and robust 95% confidence intervals from multivariate OLS regressions of channel-period fixed effects on indicator variables for owner identity.

and the outlets they own might all have similar editorial lines, reflecting those views.

Figure 7 plots estimates from a regression of channel effects on ownership indicator variables. Media outlets belonging to some owners systematically have editorial lines pointing in a specific direction (some are favorable to the right, others to the left, etc.). The regression R-squared are around 30%, meaning that ownership explains a non-trivial share of differences in channels’ editorial policies. We explore the relationship between ownership change and channel effects into more details in Section 5 when studying the case of the takeover of three television channels by Vivendi.

5 Case study: the Bolloré takeover

5.1 Bolloré’s takeover of Vivendi in a nutshell

Vivendi is an advertising, entertainment, media and publishing conglomerate whose market value fluctuated around 12 billion euros in 2022. It is the parent company of the Canal Plus Group – a television group that owns several television outlets, the leading ones being Canal+, CNews and C8.

Vincent Bolloré is the main owner of the Bolloré Group (valued 15 billion euros in 2022), which operates in a variety of industries – transport and logistics, plastics, energy, telecommunications, advertising – and in several countries, mostly in Europe and Africa. Until 2012, the
Bolloré Group owned several free newspapers and two television channels: Direct Star (later renamed CStar, a channel dedicated to music) and Direct 8 (later renamed C8). It sold 60% of its television channels to the Canal Plus Group (owned by Vivendi), 2012, in exchange for 1.7% of Vivendi shares.

Bolloré then took control of Vivendi in 2015. While the Bolloré Group owned 5.1% of Vivendi at the start of 2015, it owned more than 14.4% by April 2015. Leveraging a French law (loi Florange) aimed at favoring long-term investors, he obtained 26% of the vote shares of Vivendi, thereby taking control of the group. Rodolphe Belmer, who was the CEO of Canal+ at the time was replaced by Maxime Saada in July 2015. Ara Apkarian, who was in charge of C8 and CNews, also left in July 2015. Vincent Bolloré himself becomes chairman of the supervisory board of Canal+ in September 2015. C8 is rebranded, its name changes from D8 to C8 in September 2016. Several C-level executives of CNews (called at the time I-Télé) are fired in July 2016, where a major strike breaks out in October 2016 in response to a change in editorial line. The channel changes name, from I-Télé to CNews and is completely rebranded in February 2017. As of March 2022, the Bolloré Group owned 29% of Vivendi, and has effective control of the company.

5.2 Compliance

In this section, we seek to understand more precisely how ownership affects hosts and invitation patterns. To this end, we study shows around the time when Vincent Bolloré took control of the Vivendi Group, the parent company of three television channels in our sample – Canal+, C8 and CNews. In a first step, we explore whether shows on these three channels features a different mix of guests compared to others in our sample in a difference-in-differences framework. Our specification writes as follow:

\[
y_{ict} = \beta_1 [\text{Treated}]_c \times 1[t \in (\text{Apr. 2015, Aug. 2017})]_t + \beta_2 [\text{Treated}]_c \times 1[t \in (\text{Sept. 2017, Aug. 2019})]_t + \delta_c + \tau_t + \gamma X_{it} + \epsilon_{ict}
\]

where \(y_{it}\) is the time share of a given political group in a show hosted by host \(i\), on channel \(c\), at time \(t\). \(\delta_c\) are channel fixed effects, and \(\tau_t\) are date-hour time fixed effects. \(1[\text{Treated}]_c\) is an indicator variable for whether the channel belongs to Vivendi (Canal+, C8, and CNews). $1[t \in$
and $1[t \in (\text{Sept.}2017, \text{Aug.}2019)]_t$ are indicator variables for whether the show is broadcast between April 2015 and August 2017, or between September 2017 and August 2019, respectively. The two coefficients of interest are $\beta_1$, – which captures short-term changes after the takeover, between April 2015 and August 2017 – and $\beta_2$ – accounting for medium run changes, observed from September 2017 until the end of our sample in August 2019. Splitting the ‘post’ period between a short- and a medium-run is motivated by the fact that changes occurring on channels were gradual, with each experiencing changes in C-level executives and rebranding between 2015 and 2017 (I-Télé became CNews in February 2017 for instance. By September 2017, most changes had already been implemented. $X_{it}$ includes an indicator variable equal to C8 from 2005 to 2011. It accounts for potential differences due to C8’s past ownership.

To get a sense of whether changes in political time share are due to composition effects – some hosts leave and are replaced by new ones who invite other guests – or, rather, to continuing hosts complying with new editorial policies, we include channel-host fixed effects. The idea is to study changes in invited guests within channel-host pairs. This specification writes:

$$y_{ict} = \beta_1 1[Treated]_c \times 1[t \in (\text{Apr.}2015, \text{Aug.}2017)]_t$$
$$+ \beta_2 1[Treated]_c \times 1[t \in (\text{Sept.}2017, \text{Aug.}2019)]_t$$
$$+ \alpha_{ic} + \tau_t + \epsilon_{ict}$$  \hspace{1cm} (7)$$

For our estimates to have a causal interpretation, the parallel trend assumption needs to hold. We test it by interacting the treatment indicator with a set of season indicator variables. Figure 8 plots the coefficients on the interaction terms between season indicators and the treatment status of channels. Panel (a) corresponds to Equation (6) and Panel (b) to Equation (7). We find no evidence of diverging pre-trends. Nearly all of the pre-2015 estimates are not statistically significant and hover around zero. In contrast, there is a visible increases (decrease) in the share of right (left) wing guests time share after 2015. It brings support to the validity of the difference-in-differences design, meaning that estimates can have a causal interpretation.

Table 4 reports estimates from Equations (6) and (7). Comparing Bolloré channels to others, we find that in the medium run, the time share of left-wing parties declined by 6.8 percentage points (Column 1) compared to a 46.4% baseline in control channels. In contrast, that of right-wing parties increased by 5.5 percentage points (Column 3), while it was equal to 32.7% on control channels after April 2015. In both cases, it implies an increase (decrease) by more than 10% of the time share dedicated to right-wing (left-wing) guest. In the short run, the
time share of radical parties increased by 1.3 percentage points (Column 5). The channels controlled by Vincent Bolloré clearly started to prioritize right-wing guests to the expense of left-wing guests after he took control of Vivendi.

Estimates in Columns (2), (4) and (6) report the change in time shares within channel-host pairs. Compared to coefficients reported in Columns (1), (3) and (5) respectively, we find that estimates are very similar. Their absolute value is slightly lower for left-wing parties, and slightly larger for right wing and radical parties, but are qualitatively the same. It implies that changes in the mix of guests on Bolloré channels is not entirely driven by hosts being replaced by others. Instead, hosts who stayed adjusted who they invite to the new editorial policy in the same proportions as the overall change. It shows that compliance was one of the mechanisms underlying the ownership-induced change in editorial line.

Appendix Table C.7 reports estimates for each political group. For hosts who stayed, the time share of radical right guests decreased by 2.5 percentage points (10.8% on control channels), and that of left-wing hosts decreased by 2.6 percentage points (28.9% on control channels). On the right, the increase is largely driven by an increase in the radical right time share: +5.3 percentage points, with respect to an average 7.9% on control channels. The increase in the right-wing guest time share is therefore driven by far-right guests who crowded out left and radical-left guests.

Appendix Table C.8 reports baseline estimates separately for each Bolloré channel. Coefficients are less precisely estimated. The time share of radical parties increased by 9.4 percentage points on C8. That of right-wing guests increased by 5.9 percentage points on CNews, while that of left-wing guests decreased by 8.0 percentage points. On Canal+, left-wing time share decreased by 3.4 percentage points, that of right-wing parties increased by 3.6 percentage points, and that of radical parties decreased by 3.6 percentage points. Point estimates are overall similar when including channel-host fixed effects, but standard errors are larger.

Appendix Tables C.9, C.10 and C.11 report robustness checks. We estimates the same specification with distinct time fixed effects, excluding equal-time period mandated by the ARCOM, using an inverse hyperbolic sine transformation of the outcome variable, excluding government members, excluding the guests who are not politicians but who we classify politically, and excluding summer months. Overall, point estimates remain very stable across specification, are are nearly all statistically significant.

5.3 Sorting

Results so far show that hosts who stayed on the Bolloré channels complied to the new editorial guidelines. In this section, we explore whether hosts reacted to the owner-induced change in editorial line by leaving treated channels. To do so, we collapse our data set at the host-channel-quarter level and define an indicator variable equal to one if a host observed on
Figure 8: Event-study regressions: time shares around takeover

Notes: The Figures plots estimates from event-study specifications corresponding to Equation 6 (Panel a) and to Equation 7 (Panel b). The dependent variables are the time share of left wing parties (red diamonds), of right-wing parties (blue dots), and of radical parties (grey triangles). The shaded area corresponds to the season running from September 2014 to August 2015 during which Vincent Bolloré took control of the channels. Standard errors are clustered at the channel level, vertical bars indicate 95% confidence intervals.

Table 4: Effect of the takeover on the time share of political groups

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated × 2015/17</td>
<td>0.00597</td>
<td>0.00389</td>
<td>0.00504</td>
<td>0.0108</td>
<td>0.0132*</td>
<td>0.0174**</td>
</tr>
<tr>
<td></td>
<td>(0.0107)</td>
<td>(0.0100)</td>
<td>(0.00914)</td>
<td>(0.00971)</td>
<td>(0.00719)</td>
<td>(0.00783)</td>
</tr>
<tr>
<td>Treated × 2017/19</td>
<td>-0.0676***</td>
<td>-0.0594**</td>
<td>0.0550***</td>
<td>0.0645***</td>
<td>0.00668</td>
<td>0.0281</td>
</tr>
<tr>
<td></td>
<td>(0.0227)</td>
<td>(0.0245)</td>
<td>(0.00954)</td>
<td>(0.0111)</td>
<td>(0.0339)</td>
<td>(0.0276)</td>
</tr>
<tr>
<td>Observations</td>
<td>771080</td>
<td>754993</td>
<td>771080</td>
<td>754993</td>
<td>771080</td>
<td>754993</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.623</td>
<td>0.638</td>
<td>0.621</td>
<td>0.637</td>
<td>0.619</td>
<td>0.635</td>
</tr>
<tr>
<td>Channel FE</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Channel-host FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>$\bar{y}$ (control, post)</td>
<td>.464</td>
<td>.464</td>
<td>.327</td>
<td>.327</td>
<td>.187</td>
<td>.187</td>
</tr>
</tbody>
</table>

Notes: The outcome variable is the time share of distinct political groups: left-wing parties (radical left, greens and left) in Columns (1)-(2), right-wing parties (right and radical right) in Columns (3)-(4), radical parties (radical left and radical right) in Columns (5)-(6). Estimates in odd-numbered columns correspond to Equation 6, estimates in even-numbered columns correspond to Equation 7. The last row reports the mean of the outcome variable on control channels during for the period ranging from April 2015 to August 2019. Standard errors are clustered at the outlet level and indicate significance 1, 5, and 10% with ***, **, and *, respectively.
a given channel in quarter $t$ is still observed on this channel in quarter $t+4$ – i.e. one year later. We compare the likelihood that a host stays on the channel across treated (Canal+, C8 and CNews) and control channels in our data. The specification writes as follows:

$$y_{ict} = \sum_{q \neq 2013q_1} \beta_q 1[Treated]_c \times 1[t = q] + \alpha_{ic} + \delta_t + \epsilon_{ict} \quad (8)$$

where $y_{ict}$ indicates whether host $i$ observed on channel $c$ in quarter $t$ is still on the channel in quarter $t+4$. $\alpha_{ic}$ are host-channel pair fixed effects, which capture any fixed characteristics that are specific to the match between a host and a channel. $\delta_t$ are quarter fixed effects. $1[Treated]_c$ indicates whether the channel considered is one of those controlled by Vincent Bolloré in 2015. $1[t = q]_t$ are quarter dummy variables. The coefficients of interest are $\beta_q$, which account for the difference that existing host-channel matches are continued across treated and control channels.

Figure 9: Hosts’ probability to stay on the channel after the takeover

(a) Unweighted
(b) Weighted by guest screen time

**Notes:** The Figures plots estimates from event-study regressions corresponding to Equation (8). In Panel b, observations are weighted by guest screentime, the are not weighted in Panel a. The dependent variable is a dummy for whether a given host-channel pair observed in quarter $t$ is still observed in quarter $t+4$. The shaded area corresponds to the season running from March 2014 to March 2015, which is when Vincent Bolloré took control of the channels. Standard errors are clustered at the channel level, vertical bars indicate 95% confidence intervals.

Figure 9 plots the event-study estimates. Before the takeover, the propensity of hosts to continue working for their network followed similar trends across treated and control channels in our sample. The absence of diverging pre-trends lends support to the causal interpretation of our estimates. Starting around September 2015, we find that hosts on acquired channels are significantly more likely to discontinue their work. Hosts who worked on one of the Bolloré
channel in 2016 were 20 percentage points less likely to still be on the channel the next year. As a reference point, the probability to keep working on at control channel at the same time was around 38%, meaning that the probability that hosts stay was halved after the takeover. Panel (b) of Figure 9 reports similar estimates, weighted by the speaking time of guests. Doing so, estimates are more negative around 2016, nearing -40 percentage points. It suggests that hosts with many guests were especially likely to leave.

Table 5 shows the difference-in-difference estimates interacted with several hosts characteristics. We first find that the hosts more likely to leave were also those most exposed to changes in the editorial line: those that had politically classified guests, and among them those who have an above-median share of politically-classified guests. Hosts whose shows were newscasts and hosts described as ‘journalists’ in the credits were also more likely to leave. Table C.12 provides the breakdown by channel; the effect is present on all three channels.

We also find that male hosts were much more likely to stay on treated channels than their female counterparts. Famous hosts, as proxied by a LesBiographies entry, were more likely to leave in the short run, but much more likely to stay in the medium run. It suggests that some of them decided to leave early after the takeover, but that past the first wave, renowned hosts were more likely to stay. Similarly, we find that hosts who have been on the channel for at least two years – potentially flagship hosts – were initially more likely to leave (-6pp) – but ultimately more likely to stay (+12pp). Although estimates are less precise, we find that hosts whose shows were during prime time and whose ratings were higher were more likely to stay. One potential explanation is that these hosts have more bargaining power. Some might have decided to leave early on, confident that they could work somewhere else, or decided to stay, thinking that their bargaining power was such that they could negotiate favorable conditions.

We next turn to the destination channels of the hosts who left following the takeover. Appendix Figure C.5 plots event study estimates for several outcomes. Panel (a) shows that the takeover caused a 30 percentage-point increase in 2016 of the number of host not observed on any channel in our sample in quarter $t + 4$. This figure is around 15 percentage points in 2017 and 2018. Compared to the corresponding figure on control channels at the same time – 58.3% – this is a 25-50% increase in the probability of stopping working on one of the sample channels. It suggests that, for many departing hosts, the takeover implied a drastic change in career, potentially leading hosts to take up a job in other types of media organizations (pure players, newspapers, etc.) or simply leaving journalism. Panel (b) studies the share of hosts who leave and who are working on another channel of the sample. This fraction increases by about 3 percentage points, nearly doubling the 3.8% share on control channels. Panels (c) to (f) split destination channels across quartiles of right-wing time share. Most hosts leaving

31Regarding the last find, it may partly be driven by the Brachard law (1935) that allows in France journalists (defined as employees with a carte de presse) to resign from their job and receive benefits (one month of wage per year of seniority) in case of ownership change and/or major change in editorial line.
Bolloré channels went to work on one of the 5 channels with the smallest right-wing time share (+2 percentage points, with respect to 1.2% on control channels). Inflows are smaller for outlets in the second quartiles, and close to zero for other networks. It suggests that the hosts who left Bolloré channels for another one when the editorial policy was pushing for more right-wing guests disproportionately joined channels that invite relatively fewer right-wing guests, hinting at a potential sorting based on political preferences.

In Appendix Tables C.13 and C.14 we study the characteristics of hosts who left and appeared on any or no other channel. Being a journalist largely increases the probability to be observed on no other channel, but has no effect on the probability to be observed on another channel. Conversely, male hosts are equally likely to be observed on another channel, but are much less likely to be observed on no other channel. Being more renowned is associated with a higher probability of being observed on another channel, and a negative probability of being observed on no other channel. Overall, it suggests that while some journalists were the most likely to exit, either because they are those for whom the labor market is the most precarious, or because their skills are more portable to other platforms (newspapers, pure players, etc.). Renowned hosts may react more quickly precisely because they can find a position on another media outlet more easily.

Taken together, the results show that as acquired channels experienced a shift in editorial policy to the right, many hosts left these channels. The majority appeared on none of the channels of our sample a year later, meaning that their careers could have been negatively impacted. Those who started working on other channels in our sample went to work on those giving relatively less speaking time to the right. They may have left due to disagreements with the new editorial policy and found those destination channels more compatible with the type of shows they want to create. For those who stayed, as evidenced in the previous section, they largely complied with the new editorial policy, with a significant increase in right wing time share from 2017-2018, after most hosts had already left.

6 Discussion and Conclusion

In a context of decreasing advertising revenues and increased media competition, business tycoons’ appetite for traditional media outlets does not seem to wane. Recent empirical evidence has shown that changes in ownership can affect media content, therefore potentially impacting the set of information viewers have and their ability to hold elected officials accountable. These concerns warrant a better understanding of the mechanisms through which owners may impact media slant. This paper opens the black box of news production and highlights the mechanisms through which slant happens.

32Channels in the first quartile in terms of right-wing parties time share are ARTE, France Culture, France Inter, France 5 and France 4.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>-0.154***</td>
<td>-0.0823***</td>
<td>-0.182***</td>
<td>-0.113**</td>
<td>-0.113**</td>
<td>-0.246***</td>
<td>-0.149***</td>
<td>-0.0931***</td>
<td>-0.138**</td>
<td>-0.168***</td>
<td>-0.155***</td>
</tr>
<tr>
<td>(0.0429)</td>
<td>(0.0209)</td>
<td>(0.0503)</td>
<td>(0.0412)</td>
<td>(0.0414)</td>
<td>(0.0475)</td>
<td>(0.0411)</td>
<td>(0.0291)</td>
<td>(0.0510)</td>
<td>(0.0366)</td>
<td>(0.0445)</td>
<td></td>
</tr>
<tr>
<td>Treated × 2015/17</td>
<td>-0.151</td>
<td>-0.140*</td>
<td>-0.173</td>
<td>-0.0888</td>
<td>-0.119</td>
<td>-0.296***</td>
<td>-0.164*</td>
<td>-0.190***</td>
<td>-0.152</td>
<td>-0.245</td>
<td>-0.198*</td>
</tr>
<tr>
<td>(0.0883)</td>
<td>(0.0705)</td>
<td>(0.107)</td>
<td>(0.0879)</td>
<td>(0.0883)</td>
<td>(0.0837)</td>
<td>(0.0920)</td>
<td>(0.0643)</td>
<td>(0.0927)</td>
<td>(0.148)</td>
<td>(0.103)</td>
<td></td>
</tr>
<tr>
<td>Treated × 2015/17 × 1.Inter</td>
<td>-0.122***</td>
<td>-0.0848***</td>
<td>-0.118***</td>
<td>-0.253***</td>
<td>0.125***</td>
<td>-0.0428**</td>
<td>-0.0663**</td>
<td>-0.0535</td>
<td>-0.0290</td>
<td>0.0359</td>
<td></td>
</tr>
<tr>
<td>(0.0269)</td>
<td>(0.0244)</td>
<td>(0.0182)</td>
<td>(0.0840)</td>
<td>(0.0201)</td>
<td>(0.0185)</td>
<td>(0.0249)</td>
<td>(0.0700)</td>
<td>(0.0879)</td>
<td>(0.0527)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treated × 2017/19 × 1.Inter</td>
<td>-0.0127</td>
<td>-0.00915</td>
<td>-0.231***</td>
<td>-0.337***</td>
<td>0.193***</td>
<td>0.175**</td>
<td>0.116***</td>
<td>0.0212</td>
<td>0.0549</td>
<td>0.0515**</td>
<td></td>
</tr>
<tr>
<td>(0.0380)</td>
<td>(0.0331)</td>
<td>(0.0179)</td>
<td>(0.0734)</td>
<td>(0.0348)</td>
<td>(0.0695)</td>
<td>(0.0294)</td>
<td>(0.0305)</td>
<td>(0.0700)</td>
<td>(0.0208)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>263832</td>
<td>263832</td>
<td>143131</td>
<td>263832</td>
<td>263832</td>
<td>263832</td>
<td>263832</td>
<td>263832</td>
<td>146100</td>
<td>154436</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.468</td>
<td>0.470</td>
<td>0.469</td>
<td>0.469</td>
<td>0.469</td>
<td>0.469</td>
<td>0.469</td>
<td>0.469</td>
<td>0.468</td>
<td>0.492</td>
<td></td>
</tr>
<tr>
<td>$\bar{y}$ (control, post)</td>
<td>0.579</td>
<td>0.579</td>
<td>0.579</td>
<td>0.579</td>
<td>0.579</td>
<td>0.579</td>
<td>0.579</td>
<td>0.579</td>
<td>0.579</td>
<td>0.579</td>
<td></td>
</tr>
<tr>
<td>$\bar{y}$ (control, post, inter=0)</td>
<td>0.280</td>
<td>0.399</td>
<td>0.388</td>
<td>0.338</td>
<td>0.379</td>
<td>0.372</td>
<td>0.242</td>
<td>0.349</td>
<td>0.298</td>
<td>0.337</td>
<td></td>
</tr>
<tr>
<td>$\bar{y}$ (control, post, inter=1)</td>
<td>0.145</td>
<td>0.145</td>
<td>0.145</td>
<td>0.145</td>
<td>0.145</td>
<td>0.145</td>
<td>0.145</td>
<td>0.145</td>
<td>0.145</td>
<td>0.145</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The outcome variable is an indicator for whether a given host-channel pair existing in quarter $t$ is still existing in quarter $t + 4$. Column (1) presents the baseline specification. Column (2) includes an indicator for whether the host has guests who are politically classified. In Column (3), the indicator is for, among hosts who have political guests, those that have an above channel-quarter specific median share of political guests. In Column (4) the indicator is for whether the host is credited as a journalist for the show. The dummy in Column (5) indicates whether the host’s show is a newscast. In Column (6), the indicator indicates whether the host is male and in Column (7) whether he has a ‘Les Biographies’ entry. The indicator variable in Column (8) is for whether the host was already on the channel two years ago. The indicator variable in Column (9) is for whether the host’s shows are during prime time (7:00-9:00am for radio, 19:00-21:00 for TV). In Column (10), the indicator is for whether the host has above median viewership (within channel-quarters). The indicator in Column (11) is similar, except that the viewership share is residualized on date-hour FEs and channel-season FEs, to measure whether the host tends to over- or under-perform. 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 indicate significance 1, 5, and 10% with ***, **, and *, respectively.

Electronic copy available at: https://ssrn.com/abstract=4036211
Our article is the first to quantify the contributions of media outlet and journalist-specific factors in slanting the news. Of course, our analysis suffers from a number of caveats. Not least, we only consider media slant using information on the guests and do not study the content of the shows. While analyzing content could be of interest for future research – and keeping in mind the fact that doing so would raise important technical challenges, given it would require not only to use the transcripts of millions hours of shows but also to determine who says what – we nonetheless believe that the platform given to political parties through the presence of guests in the media is an important component of media slant as of today.

The main contribution of our article is with respect to the political economy literature studying pluralism and how (well) voters are informed. However, we think that our work can also inform policy-makers on the relevance of existing media pluralism regulations. In particular, from a descriptive point of view, we show that media owners tend to bias the content of broadcast shows not only by disproportionately inviting politicians from one side of the political spectrum, but also by inviting non-politician yet politically-involved guests from the same side. The most likely explanation for such a behavior is that the later are not accounted for by existing pluralism regulations (not in France nor in other democracies).

Note that this also has consequences for the existing literature on media bias that, by only considering politicians – i.e. by not taking into account the guests who are not politicians but nonetheless politically vocal – may miss an important part of slant, and thus also of its consequences.
References


Durante, Ruben and Brian Knight, “Partisan Control, Media Bias, And Viewer Responses: Evidence From Berlusconi’s Italy,” *Journal of the European Economic Association*, 2012, 10 (3), 451–481.


