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Abstract

For democracies to function, voters need to be exposed to a variety of views, and media outlets play a key role in this process. Using novel data on hosts and guests appearing in millions of French television and radio shows over 20 years, this article shows that media largely differ in how much attention they devote to different political groups. We investigate the inner workings of media organizations leading to such differences, and in particular quantify the role played by hosts when it comes to deciding who to invite. Thanks to thousands of hosts moving across outlets, we first estimate a two-way fixed effects model and decompose the across-outlet variance in political group representation into three factors: (i) differences in host composition, (ii) host compliance with distinct editorial lines, and (iii) host sorting on outlets. We show that channel-level decisions and sorting largely explain across-outlet differences. Overall, hosts have little agency, but we document heterogeneity depending on their characteristics. To complement this analysis, we then study how hosts adapt to a major ownership-driven change in the editorial line, relying on a difference-in-differences framework. We find that hosts who stayed after the takeover largely complied with the new editorial line, but that many others left the acquired outlets. Our findings have important implications for the optimal regulation of the media industry and highlight the limitations of existing legislation on media pluralism.

Keywords: Media bias; Slant; Journalists; Pluralism; Media ownership; Media capture
JEL No: L15, L82, J40

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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 promote pluralism in news media. With the idea that media ownership may influence editorial lines, they have encouraged ownership diffusion across competing outlets (external pluralism). They have also created rules requiring that each outlet feature 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 people are actually exposed to a reduced set of news sources, themselves controlled by a small number of conglomerates (Prat, 2018; Kennedy and Prat, 2019). This has raised concerns that some media tycoons may disproportionately influence the political process, and has 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 the Internet may, for example, give them leverage and independence,[1] while employment insecurity may be a disciplining force, pushing them to conform to the editorial policy of their outlet. Furthermore, journalists may choose their employers based on political affinity (and vice versa), which may amplify each outlet's tendency to prioritize certain views.

In this paper, we study the extent to which hosts have agency in opinion representation in their shows. We examine an important recurring choice they have to make: who to invite.[2] To do so, we use novel show-level data on French broadcasts between 2002 and 2020 and track hosts as they work for distinct outlets over time. We estimate to what extent differences 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 so-called "French Murdoch," Vincent Bolloré.

The French broadcast media provides an ideal setting to understand the inner workings of media outlets. First, as in many countries, media power is concentrated in a relatively small number of news outlets, with television and radio being at the center of the news ecosystem

[1] Respectively, 21% of US and 29% of French respondents report paying more attention to the journalist than to the news brand when consuming news online (Newman et al., 2022).

[2] As discussed in Section 4.4, news anchors play an active part in the broadcast production process. On the one hand, most of them tend to participate in the selection process of their guests (a phenomenon that we observe in many other countries, including the US). On the other hand, in France, a large share of the hosts are also the producers of their shows, and as such are in charge of the guest invitations.

(Kennedy and Prat, 2019; Cagé and Huet, 2021). Outlets topping the list of main news sources among French citizens are television channels, ahead of social media. In 2019, 71% of them (respectively 53%) get their daily news from television (respectively radio), compared to only 47% online and 4% on Facebook (Sumida et al., 2019). Second, our dataset 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 from the *Institut National de l'Audiovisuel* (National Audiovisual Institute) archives. The 2.1 million shows in our data are not restricted to newscasts, but also include other programs such as talk shows and entertainment shows. They feature 21,469 distinct hosts and more than 261,993 distinct guests.[3] Third, with the ample time frame covered, we can track hosts as they move from one outlet to another and observe how they adapt to their new work environment after the move. Data granularity ensures that we can finely control for viewership composition and news events at the time each show airs.

As a first step, we map each guest appearance to a political leaning,[4] if applicable. To do so, we rely on two sets of sources. First, to classify politicians we use lists of candidates running in elections and of government appointees. Second, we go one step further and classify guests who are politically vocal but are not professional politicians – e.g. activists, think tank commentators, public intellectuals, etc.[5] – using lists of think tank contributors, participants at party events, and public figures endorsing presidential candidates.[6] This extra step is motivated by the increasing speaking time these guests receive in talk shows;[7] we label them 'politically engaged non-politicians' (PENOPs). Importantly, each guest's political leaning is allowed to change over time. As a result, we classify 13,418 distinct guests, which account for 602,914 appearances.[8] Building on this classification, we document that political forces are unevenly represented across channels, despite the existence of broadcast regulation meant to ensure respect for the pluralist expression of currents of thought.[9] For instance, on average

[3]We include all the shows with at least one host. Only fiction, sports and games are not included. The large number of hosts derives from the broad coverage of our dataset, both regarding the time frame and the variety of shows documented. It should also be noted that our data not only includes news anchors, but also reporters, columnists, special correspondents, etc. who are in charge of segments within longer shows. In our empirical analysis below, we will focus on hosts observed with guests.

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

[5]We call "public intellectuals" here all the intellectuals that are publicly "engaged", in the sense of the French expression *'intellectuels engagés'*.

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

[7]Appendix Figure C.1 shows that the time share dedicated to talk shows nearly doubled between 2009 and 2021. This increase in talk shows may be used to reduce costs (Cagé, 2015), but also to escape broadcast regulation on pluralism.

[8]Politically classified guests account for about a quarter of all appearances. Guests who are not politically classified are typically writers, actors, singers, athletes, etc.

[9]See Section 2 for a detailed presentation of the existing regulation.

during our time period, left-wing parties account for around 40% of the speaking time of political guests on the 24-hour news channel LCI, but for more than 60% on the television channel ARTE.

What drives the differences in political coverage across channels? We seek to measure the relative role played by three factors. First, channels may have distinct editorial policies, to which hosts comply by adapting who they invite depending on the outlet they work for (*compliance*). Second, channels employ distinct hosts, who may invite distinct types of guests, potentially due to their preferences or specialization (*composition*). Finally, hosts inclined to invite guests from a given group may be more likely to work on an outlet whose editorial line prioritizes this group (*sorting*).

To this end, we estimate a two-way fixed effects model. The time share dedicated to a political group by a given host on a given outlet at a given time is assumed to be the sum of (i) a host component – reflecting the host's baseline propensity to cover a political group; (ii) a channel component – accounting for the extent to which a host's work environment influences how much they cover a certain group; and (iii) time components – which capture changes in audience characteristics and news shocks. Channel effects are identified thanks to the $4,456$ hosts observed on distinct channels in our sample. Changes in guest composition as they move from one channel to another reveal how much outlet-level decisions impact who is invited. Importantly, we follow Lachowska et al. (2022) and estimate a model that allows channel effects to change every two seasons so as to reflect the fact that channels' editorial lines may be periodically adjusted.[10] Furthermore, thanks to the granularity of our data, we can use time fixed effects to finely control for news shocks and changes in audience characteristics at a high frequency.

We then follow the approach pioneered by Abowd et al. (1999) to decompose the variance in political group representation across outlets and periods. The variance of channel components reflects compliance with outlet-level decisions; that of host components accounts for host composition; and the covariance between host and channel effects captures sorting. The first outcome we consider is the time share dedicated to guests of given groups among all guests. Doing so accounts for two decision margins: whether to invite political guests (extensive margin), and if so, of what leaning (intensive margin). We show that, after netting out the time effects, channel editorial lines account for around 40% of the differences in guest invitation patterns across channels, while sorting accounts for another 40% and host composition for 20%.

Focusing exclusively on the intensive margin – i.e. which political group to represent conditional on having a political guest – we show that channel-level decisions play an even

[10]Specifically, we regress the time share devoted to each group on host fixed effects, channel × period fixed effects, and time × platform (radio or television) fixed effects. Each period corresponds to two seasons, where seasons are one-year periods running from September to August, so as to match the time frame media outlets use to plan their shows or to adjust their programs. Time is defined at the hourly level and, for each host and each time slot, we aggregate for each week all the shows broadcast by the host during the time slot.

more important role. Whether we consider the speaking-time share devoted to the left or to the right, we see that, once we take into account the time effects, channel components account for around 80% of the variance in the speaking times. Host composition only accounts for a small share of the variance (less than 10%), just like host sorting. Hosts therefore largely comply with 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. Furthermore, we also show that, within owner, outlets often tend to prioritize the same political forces, suggesting that owners want *all* their channels to prioritize certain views, most probably corresponding to their own preferences.

In the second part of the paper, we focus on a large owner-induced change in editorial policy, and investigate the role played by hosts in this change. In particular, we 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 of the event have highlighted the proximity of Vincent Bolloré to conservative figures, and noted shows swiftly moved rightwards following the takeover (see also Capozzi, 2016; Cagé, 2022). First, we compare Vivendi channels to others in our sample around the takeover to quantify the magnitude of the editorial shift. After documenting the absence of pre-trends, we show that, controlling for channel and time fixed effects, Bolloré's takeover led to a 5.53 percentage-point increase in the speaking time of the radical right, compared to a 7.6% baseline on control channels. We also show that the magnitude of the shift toward the radical right following Bolloré's takeover is stronger when PENOPs are included than when we only consider the speaking-time share of the strictly defined politicians (the effect is also both statistically and economically significant in the latter case, however). This is of particular importance because it suggests that PENOPs may be used by the channels to bypass the existing pluralism regulation.

We then ask whether this change in editorial line was (partly) driven by hosts complying with the new editorial line. In an event-study specification with host-channel fixed effects, we explore whether invited guests changed within host-channel pairs. The magnitude of the estimated coefficients we obtain with this specification is very close to the one obtained when simply using channel fixed effects. It implies that changes in the mix of guests on Bolloré's channels are not entirely driven by hosts being replaced by others but, instead, that hosts who stayed nearly fully adjusted their choice of guest to comply with the new editorial policy.

We next 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 51% baseline. The effect is driven by hosts who invite political guests, 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 those most likely to leave. Male hosts, famous hosts, and hosts credited as producers were more likely to stay. This is also the case of hosts who already tended to invite more radical-right guests (as measured by the host fixed estimated using the AKM framework) and were thus probably more compatible with the new editorial line. Regarding hosts who leave, most are no longer observed on any of the channels in our sample following the takeover, suggesting that 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. Finally, we provide suggestive evidence indicating that this shift to the radical right impacts electoral results.

Our findings have important policy implications for the optimal regulation of the media sector. First, when measuring pluralism, it is important not to focus only on politicians as narrowly defined as candidates at elections, party officials and elected politicians. Channels indeed increasingly rely on PENOPs to bias content; by doing so, they avoid existing regulations and may limit the range of views voters are exposed to. Second, given that the impact of ownership changes on editorial policies varies with the characteristics of the journalists, and in particular with their bargaining power, there may be a need for policies that reinforce the agency of journalists. We come back to these points at the end of the article.

Literature Our paper first contributes to the ongoing discussion on media ownership, media concentration and news reporting. Gentzkow and Shapiro (2010), studying local newspapers, ask whether differences in political reporting across outlets are explained by owners responding to local readers' demands, or rather by owners' ideological views. They find support for the former. Since then, several papers have documented that changes in media control can impact media content, in the context of private television network acquisition (Martin and McCrain, 2019; Miho, 2020; Mastrorocco and Ornaghi, 2020) or public broadcasters' control (Durante and Knight, 2012). Furthermore, 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, 2021; Bursztyn et al., 2020; Djourelova, 2022; Simonov and Rao, 2022, among others).[11] Our paper helps explain the potential consequences of a change in media ownership by studying the response from hosts, and documents that journalists are largely constrained by their environment. Studying a takeover-induced change

[11]Our work also 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 Milyo, 2005), language (Gentzkow and Shapiro, 2010), and issue coverage (Puglisi and Snyder, 2015; Galvis et al., 2013). Our work is closest to Durante and Knight (2012) and Knight and Tribin (2021) as we also use time shares to measure political representation on screen. Yet, we build this measure (i) for a broader range of shows – including entertainment, (ii) at the show-level, and (iii) for a broader variety of guests. In particular, 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).

in editorial line, we then find that hosts either comply or leave, the latter potentially disrupting their careers.[12]

Second, 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. Such a strategy has been used to explain a variety of outcomes, which include wage earnings (Abowd et al., 1999; Card et al., 2013; Song et al., 2019; Lachowska et al., 2022; Babet et al., 2022, among others), health care consumption (Finkelstein et al., 2016), political participation (Cantoni and Pons, 2022), bureaucrats' productivity (Best et al., 2023; Fenizia, 2022), 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.[13]

By doing so, our work finally sheds light on the inner workings of media outlets. Some 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. Furthermore, our article improves our understanding of the mechanisms through which owners bias the news.

The rest of the paper is organized as follows. Section 2 below provides details on the institutional setting, and Section 3 describes the data. Section 4 presents the decomposition of across-channel differences in political representation and shows 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, as in the majority of Western democracies. In 2017, 71% of French adults reported getting their news at least

[12] Our paper also builds on attempts within other disciplines to quantify political representation on Vivendi channels (Sécail, 2022).

[13] Work in progress by Boxell and Conway (2022) similarly leverages journalist transitions between outlets to study the role played by journalists in determining the political slant of the news they produce (see also Srinivasan, 2021, who likewise exploits a within-journalist across-firm design in a working paper). Compared to our article, these studies are limited in that the importance of journalist preferences is estimated on the movers – who are not representative of the overall population of journalists – while our approach allows us to rely on both stayers and movers. Furthermore, we are the very first to disentangle between the extensive and the intensive margins when investigating differences in political representation, to take into account both politicians and PENOPs, and – thanks to the natural experiment used in the second part of our paper – to distinguish between the compliers and the leavers and to study their characteristics. See also Xu (2023) who focuses on M&A news and studies how financial journalists' personal social networks shape their editorial content.

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). 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, when asked to name up to five specific journalists they pay attention to, French respondents first mentioned the following 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).[14]

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, including information on their ownership.

Broadcast regulation and pluralism The 1986 Law on Freedom of Communication[15] 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 (external pluralism), 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.[16]

The 1986 Law also led to the creation of an independent regulatory agency, which is known

[14] This was done using an open-ended question in the *Digital News Report* survey. Nine out of ten journalists named work in broadcast media, primarily in television outlets. Journalists from national newspapers like *Le Monde* and *Le Figaro* are rarely mentioned, with only 6% of names coming from print media, and journalists from digital media outlets even less so (3%) (Newman et al., 2022).

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

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

today as the *Autorité de régulation de la communication audiovisuelle et numérique* (Arcom).[17] Arcom is the French equivalent of the Federal Communications Commission (FCC) in the United States or Ofcom in the United Kingdom. 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).[18] In practice, Arcom requires that a third of the speaking time be dedicated to the President of the Republic and the members of 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.[19] Given that public debate contribution and popularity are not unambiguously measurable, it is a general principle, left to the discretion of the media outlets, rather than a working rule. Indeed, in this article we document large differences in the speaking time of each party across outlets. Channels are required to record the speaking time of each politician and communicate aggregate quarterly figures to Arcom.

Stricter equal-time rules apply during presidential and parliamentary electoral campaigns. As a robustness check, we drop the periods during which equal time rules. Doing so does not impact our main findings.

Political parties The French political landscape has many parties, ranging from radical left to radical right (for a recent overview, see Cagé and Piketty, 2023). 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 (*Parti Communiste*, *La France Insoumise*); (ii) greens (*Europe Écologie-Les Verts*); (iii) left (*Parti Socialiste*, "other left"); (iv) liberals (*MoDem*, *La République en Marche*); (v) right (*Les Républicains*, *Union des démocrates et indépendants*, "other right"); and (vi) radical right (*Rassemblement National*, *Debout La France*).

[17] Created in 1989 under the name *Conseil Supérieur de l'Audiovisuel* (CSA), Arcom is the regulatory agency in charge of delivering frequencies, overseeing mergers and acquisitions in the media market, setting rules on diversity and pluralism, and 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.

[18] In 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, Arcom monitors the equity and diversity of political expression on broadcast media. Most European countries have some kind of internal pluralism rules (see "*Internal Media Plurality in Audiovisual Media Services in the EU: Rules and Practices*," ERGA Report, 2018).

[19] See Arcom's website for additional details: `https://www.csa.fr/web/index.php/Proteger/Garantie-des-droits-et-libertes/Proteger-le-pluralisme-politique`.

3 Data and descriptive statistics

In this article, we build a novel dataset on television and radio shows from the archives of the *Institut National de l'Audiovisuel* (INA), which we assemble and complement using a number of additional sources.[20] In this section, we describe the data, explain how we define the sample and outcomes of interest, and present descriptive statistics.

3.1 Content and coverage

Source data Our data on shows come from the INA, whose staff has manually documented the hosts and guests appearing in television and radio shows since 2002 for all the main television and radio outlets. For each show, the title, date, start and end time, genre, and the list of persons related to the show have been manually annotated. For each person, we have their first and last name, as well as a time-invariant description of their profession (e.g. politician, journalist, singer, etc.), and a show-specific role, which we use to identify hosts and guests. Notably, the data are very detailed and include information on segments within longer shows. This is typically the case for newscasts, where the main show credits the main host, and each sub-show credits the reporter in charge of a specific news story as host, and the persons who are interviewed as guests. Our data are therefore not restricted to headline hosts and guests.

Regarding coverage of shows, the INA collects data on all shows with hosts, which accounts for a large variety of shows: not only newscasts, but also talk shows and infotainment shows in the style of late shows, investigation shows, etc. As a result, our data cover the universe of shows to the exclusion of fiction shows, reality shows, sports, games and documentaries. In Appendix Section A.1, we compare the time length of the television shows present in the INA data to shows documented in data provided by Plurimedia and show that INA data coverage is very high for news shows and both political and entertainment talk shows.[21] We can therefore reliably analyze the content of a broad range of shows, where most previous works only focused on a narrower set of shows.[22]

[20]The 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 INA data, see Cagé et al. (2020, 2022).

[21]To benchmark INA data coverage, we use information from Plurimedia, a company that compiles scheduled television shows before they are broadcast with nearly no information on guests. Nearly all the newscasts, shows about news and politics, and talk shows are included in the INA data. As expected given the absence of hosts in many of those shows, the coverage is lower for shows in the entertainment (including games), sports, youth, and documentary categories. See to Appendix Section A.1 for more details.

[22]Most papers in the existing literature focus on newscasts (see Durante and Knight, 2012; 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 that the consumption of content that might influence political knowledge and behavior is not limited to the news broadcasts.

Sample definition Our sample includes 12 television channels and six radio stations. For television, we focus on country-wide digital television channels (not cable, not satellite) that have shows with hosts and political guests in each season. More specifically, the sample includes the following television outlets: ARTE, BFM TV, C8, Canal+, CNews, France 2, France 3, France 5, LCI, LCP/Public Sénat, M6 and TF1. They accounted for 67.4% of viewership in 2020 (83.6% in 2007). For radio, we focus on non-local, non-music radio outlets. The six stations in the sample are France Culture, France Info, France Inter, Europe 1, RMC, and RTL. These stations accounted for 46.3% of the total audience in 2020 (the audience share of all country-wide non-music radio stations was 54.9% in that year). In other words, television and radio outlets in our sample account for a large share of audience on both platforms, and for nearly all shows with hosts broadcast on country-wide outlets.

Our data on French television and radio shows covers 2002-2020. However, for the estimation sample, we focus on shows broadcast between September 1st, 2005 and August 31st, 2019. The reason we start in 2005 is that, in that year, 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 that date, the number of documented shows sharply decreases due to budget cuts at the INA; data are thus incomplete. As a result, our sample includes 14 seasons, which are one-year periods from September to August.

3.2 Guests

The $261,993$ unique guests in our sample account for 2.3 million appearances. The INA considers that a guest appears in a show if they speak during the show, whether or not they are in the studio.[23] This way, we can finely track the coverage dedicated to top politicians, who appear as guests very frequently in our sample as they regularly make public statements even though they are less frequently in the studio.[24]

The data include each guest's gender, birth year, country, and a time-invariant description of their profession. Using keywords, we create indicator variables for whether each guest falls into a given profession (see Appendix Section A.3 for details). Appendix Table C.1 provides descriptive statistics on guests' appearances. The majority concern male guests (76%) and guests born in the 1960s or earlier. The most common professions include politicians, professions in the media or publishing industry (writer, columnist, etc.), and professions in the entertainment industry (singer, actor, etc.). 94% of appearances are by guests who appear at least twice, and 48% by guests who appear at least 100 times.

[23] E.g. if a minister gives a press conference and clips of the event are broadcast during a newscast, then the minister is listed as guest, even though they are not in the studio during the show.

[24] The top five guests in number of appearances are François Hollande (14,281 appearances, politician, left), Nicolas Sarzoky (13,173 appearances, politician, right), Manuel Valls (7,859 appearances, politician, left), François Fillon (6,284 appearances, politician, right) and Marine Le Pen (5,597 appearances, politician, radical right). They account for 2.0% of all appearances, and 7.8% of politically classified appearances.

Guests classified as politicians We next map each guest appearance to a political group – if applicable. This measure of political leaning is allowed to vary over time: a guest might become a politician, leave politics or change political affiliation over time. Our classification procedure relies on 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, senate, EU, *région*, *canton*, municipality), whether they were affiliated to a political group in parliament, and whether they worked for the government under a given majority. Appendix Section A.2.1 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 professional politicians change over time.[25]

Guests classified as PENOPs Motivated by the presence of guests who express their political views in shows like talk shows but are not professional 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. We call these guests 'politically engaged non-politicians' (PENOPs). To identify them, 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 such as 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 the presidential elections.

For the third source, we focus on think tanks and proceed in two stages. First, 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. Second, 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.2.2 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.

Appearance classification As a result, we get a time-varying measure of the political leaning (if any) of each guest. Figure 1 summarizes the results. Overall, 25.9% of appearances

[25]Given the complexity of the French political landscape, and the creation of novel political parties, it is not rare to observe politicians changing affiliation (e.g., after Emmanuel Macron's election win in 2017, a number of former Socialist Party members lined up to join his political party, *En Marche!*).

(602, 914 in absolute value) are by guests who are politically classified. Among the 23.9% of the appearances of guests whose profession indicates 'politician' and whose country is France, 91.9% are matched to a political leaning. Appearances of politicians who are not classified are typically appearances of retired or of future politicians observed when they were not active.[26] This means that we classify nearly all the guests who are politicians and are therefore expected to be classified.

We further classify 5.1% of the appearances of people whose profession, as indicated by the INA, is not 'politician'. Some are classified using the first set of sources (e.g. Bernard Laporte, a rugby player and rugby coach who became a sports minister), while others are classified with the second set of sources as PENOPs (e.g. Agnès Verider-Molinié, who heads a think tank). This latter group accounts for a growing share of the time devoted to political guests during our period of interest, as illustrated in Appendix Figure C.2. While this share was around 7% at the beginning of our time period, it has more than doubled since then and now exceeds 15%.

Other appearances – 74.1% – are not politically classified. This is a direct implication of the richness of INA data, which not only include news shows – which largely cover politics – but also entertainment or infotainment shows that invite political guests more occasionally. Guests who are not politically classified often have a profession related to publishing (e.g. writers on a book tour), entertainment (e.g. singers, actors, etc.), academia, or sports (Didier Deschamps, a football coach, is one of the non-classified guests appearing the most). Foreign politicians are also not classified (e.g. Barack Obama and Angela Merkel) as we do not attempt to match guests who are not French to a political group.

[Figure 1 about here.]

Time share After classifying guests politically, we seek to measure the relative amount of time that each outlet dedicates to guests of each political group. To this end, we take into account the length of the shows (or sub-shows) in which these guests appear. The idea is to account differently for guests appearing in short segments, and guests invited for longer interviews. We use the length of the show or sub-show[27] and divide it by the number of guests. If a one-hour show features two guests, we consider that each guest gets 30 minutes.

A possible caveat comes from the fact that this measure does not take into account how long the host speaks, or whether the guest is often interrupted. To check the validity of our measure, we compare the time share we attribute to each guest in a show (50% for instance)

[26]One example is the criminal defense lawyer Éric Dupond-Moretti who was regularly invited in the media before he was appointed minister of justice. Another is Dominique de Villepin who appeared several times in the media long after retiring from politics and becoming a lawyer.

[27]If a guest takes part in a show that contains sub-shows – which 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.

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. Our measure explains 87% of the variation of screen time share measured by image frames. We document a linear relationship between the frame share and the computed time share, indicating that our time share measure is a good approximation of the time share of each guest.

While our measure does not account for the tone of the host or the charisma of the guest, we believe that measuring the time that political guests are given to express their views – which is the basic requirement for the public to be exposed to them – is a good way to measure the extent to which an outlet covers a certain political group.

Time shares over time From there, we can compute the time share dedicated to each type of guest (non-politicians, politicians and PENOPs) and each political group. Figure 2 plots these time shares aggregated across all the outlets in our sample for each season. Figure 2a shows that over time, the total screen time devoted to the non-politicians has decreased by more than 15 percentage points, in favor of politically active guests, with an increase in the time devoted to both politicians and PENOPs.

Figure 2b focuses on politicians and PENOPs, whom we refer to as political guests.[28] 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 (see Section 2 above).[29]

[Figure 2 about here.]

Time shares across channels We next explore variation in time shares across channels in Figure 3. Figure 3a plots the time share dedicated to non-political guests, politicians and PENOPs. Unsurprisingly, the 24-hour news channels (LCP, BFM TV, CNews and LCI) devote more time to politicians than the other channels that are more focused on entertainment (M6 or C8 for instance). This is also the case of the public radio France Info – which provides continuous live news and information – compared to other radio stations.

[28]See Appendix Figure C.3 for a similar plot but only taking into account politicians. The overall trends – averaged over all the different channels – are similar but, as we will see below, the use of PENOPs by certain channels can increase their political polarization.

[29]Appendix Figure C.3 reports the same time shares but 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 in recent years a significant rise in the speaking-time share of the radical right.

Figure 3b plots the time share dedicated to each political group, when only considering politicians and PENOPs. There are substantial differences in coverage across outlets despite the regulation described above. For example, the 24-hour news channel LCI devotes 40.2% of the time share to left-wing guests, compared to 63.4% for France Culture. Comparing outlets within platforms, there are still substantial differences across networks, even though they all operate on the same country-wide television market, and therefore all cater to the same set of potential consumers. There is a 21.0 percentage-point difference in left-wing parties' representation between the TV channel that represents the left the least and the one that represents it the most. The figure for radio is 20.3 percentage points.[30]

[Figure 3 about here.]

3.3 Hosts

Hosts and invitation decisions The goal of this paper is to determine the relative agency hosts have when deciding who to invite in their shows. Before turning to the empirical framework, it is worth briefly describing the role hosts play when choosing their guests. First, it is important to note that in France, a number of hosts also produce their shows (see e.g. Pasquier, 2008) and, as such, unambiguously play a part in selecting guests. Further, although this dual role is widespread in France, it is not specific to France. In the US for example, a number of top hosts of late-night talk shows also produce their shows (e.g. John Oliver, David Letterman, Trevor Noah, Jay Leno, etc.), a phenomenon that we also observe in the UK for a number of television personalities such as Simon Cowell (see e.g. Bennett, 2010) or Jonathan Ross.

Second and more generally, a key dimension of the broadcast production process is editorial planning. Newsrooms have dedicated teams of journalists, producers and editors who collaborate to identify and prioritize news stories (see e.g. Cagé et al., 2022). As highlighted by Rodier (2020), "at the editorial conference, each and every programmer, host and news director agrees daily on the topics to be covered." While one might think that the responsibility for selecting news stories mainly falls to the news producers, anchors also actually have some influence. According to Bradshaw et al. (2009) – who consider the case of the US and analyze how local television news anchors contribute to the newscast beyond their on-air performances – the majority of local TV news anchors contribute to the news produced and perform most of the tasks necessary to produce a daily news broadcast – which, for over two-thirds of them, includes scheduling interviews. Similarly, in the Italian context, Bonini and

[30] Appendix Figure C.4 plots the same time shares across channels when only considering peak audience hour slots. These time slots are 7:00-9:00 am for radio outlets and 7:00-11:00 pm for television outlets. The share of politically classified guests is higher for all outlets, while the time share of each party is quite similar and the ranking of channel is nearly the same.

Gandini (2016) note that "every program is created by a team of people who work together every day, including hosts, producers, assistant producers and authors." These findings are consistent with what Salhia Brakhlia (France Info's morning show host) has said about the way her political interviews are prepared: "we choose our guests ourselves, because we think about the legitimacy of the guests we want to hear and when we choose to invite them. And that's up to us."[31]

[Table 1 about here.]

Host characteristics Table 1 presents descriptive statistics regarding the hosts in our sample for several sub-samples. The dataset includes $21,469$ distinct hosts (Column 1), many of whom – $16,631$ – have hosted at least one show with guests (Column 2). To exclude hosts who appear only in exceptional circumstances (Olympic Games, Eurovision song contest, election nights, etc.), we drop the observations of hosts who appear fewer than four times and had fewer than three guests on a given channel in a given season for the corresponding channel and season. As a result, the estimation sample counts $16,386$ distinct hosts (Column 3). Among them, $8,783$ are observed on an outlet in at least two distinct two-season time periods (Column 4), and $4,456$ are observed on at least two distinct outlets (Column 5). Columns 6 to 8 present similarly defined sets of hosts, but only focus on shows with at least one politically classified guest. There are $12,365$ distinct hosts in this political guests estimation sample, of whom $6,600$ stay over multiple periods, and $3,207$ are observed on distinct outlets.

For each show, INA data includes information on hosts' gender – around 40% of hosts are female – and profession. For more than 90% of hosts, the data feature a time-invariant text description of their profession. In the estimation sample, 63% are described as 'journalist', 13% as 'director', 6% as 'presenter' (*présentateur*) and 6% as 'producer'. We complement this information by indicating whether hosts have a Wikidata entry or a *Les Biographies* (LesBios) entry, the French equivalent of the *Who's Who*.[32] This is an indicator of their fame, and the share of hosts with such profiles increases as we focus on hosts who stay on an outlet for several periods or are observed on several outlets.

Importantly, as our identification relies on hosts moving across outlets or staying for long periods of time on a given outlet, we make sure that hosts who are observed in distinct periods (Column 4) or on multiple outlets (Column 5) do not systematically differ from others when

[31] In "Choix des invités et des questions, indépendance : comment sont préparées les interviews politiques de franceinfo." *France Info*, 11/22/2023, `https://www.francetvinfo.fr/economie/medias/choix-des-invites-et-des-questions-independance-comment-sont-preparees-les-interviews-politiques-de-franceinfo_6199632.html`. For additional evidence covering Australia, the UK and the US on the central role played by hosts – including in the choice of participants – see Neil (2015).

[32] Appendix Sections A.3.2 and A.4 provide details on how we compiled data from these sources that allow us to gather information on renown hosts. Around 7% (resp. 12%) of hosts in the estimation sample have a *Les Biographies* (resp. Wikidata) entry.

it comes to which political groups they invite in their shows. They are not more right-wing or left-wing than hosts that do not move, or that are observed more briefly on a given outlet.

Hosts moving across outlets Identifying the effect of hosts' work environment on who they invite crucially relies on hosts moving across outlets. We refer to hosts observed on multiple outlets during our sample period as 'movers'. Figure 4 considers the estimation sample (see Column 3 of Table 1) and reports for each outlet pair how many hosts are observed on both outlets. Figures on the diagonal account for the number of hosts observed at least once on the considered outlet, irrespective of whether they are also observed on another outlet. Outlets are ranked according to the time share dedicated to left-wing politicians. Leading broadcasters typically have more hosts (TF1, France 2, France Inter for instance), and there are more hosts co-occurring on outlets that belong to the same parent company (TF1 and LCI, France Inter and France Info for instance). Overall, all outlets are connected to each other by a large number of movers, even across outlets that largely differ in terms of time share dedicated to political groups.[33]

[Figure 4 about here.]

From there, one may wonder why hosts move across media outlets. In Section 4, we run a number of empirical exercises supporting the conditional random mobility assumption, on which our two-way fixed effects approach relies. Here, we first provide qualitative evidence – based on our informed knowledge of the industry – in support of this assumption.

First, note that in the French context, a sizable share of the journalists working in broadcast media do not have an open-ended contract (a so-called "CDI") – i.e. a lasting attachment to the media they work for – but are in more precarious situations, at least from a contractual point of view. This pushes them to move between outlets from one season to the other, but also makes it easier for a media outlet to decide to cancel a program at the end of a season. Many journalists are either temporary show business workers (*"intermittents du spectacle"*) or on fixed-term contracts (the majority practice of the *"contrats de grille"* means that hosts – who also often produce their shows as highlighted above – are hired for a given season, from September to June).

A specific case is that of the famous broadcast journalists; as appears clearly in Table 1, movers tend to be on average more known than stayers, as proxied by the fact that they have an entry in Wikidata and/or *Les Biographies*. In an increasingly competitive media landscape, the price of top journalist talent has risen substantially (Newman et al., 2022); every year, a so-called "mercato TV" (TV transfer) takes place between seasons and gives rise to news coverage. When negotiating a move, media outlets are mostly motivated by ratings, while

[33] This is also true within shorter time periods, as illustrated in Appendix Figure C.5.

hosts are chiefly motivated by compensation. But it is important to note that even famous host-producers are – despite their high compensation – in a precarious situation (see e.g. Leroux and Riutort, 2006, who note that "the counterpart to the inflation in the compensation of hosts (...) seems to lie in the intrinsic fragility of (their) position"; "the maximum duration granted to a program is one season, and those that do not meet their expected audience numbers can be discontinued very quickly.").

Last, with respect to our analysis, it is important to note that the observed moves do not seem to be driven by political considerations; in the many news articles covering the annual mercato, the issue of the editorial line of the channels never appears as a driver of the switch. This is consistent with the event-study evidence presented below.

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 channels (host compliance), or (iii) the sorting of hosts across channels, which may magnify the other two effects (host sorting).

4.1 Changes in invitation patterns around moves

To motivate our approach, we start by showing that, when hosts move from one media outlet to another, they change who they invite in their shows.

Moves As our goal is to study how invitation patterns change when a host moves, we start by identifying moves in our sample. We collapse our dataset at the host-outlet-week level, and here define a move as a host being observed at least two weeks on an outlet c before being observed at least two weeks on another outlet c'.[34] Doing so results in $8,851$ moves that we use to study how guest invitation patterns adjust after a move.

Changes around moves We hypothesize that hosts moving to a destination outlet that dedicates more time to a given group of guests than the origin outlet will start inviting guests who are part of this group more than they did when they worked for the origin outlet. Appendix Figure C.6 plots the difference between destination and origin outlets when considering

[34] We exclude moves for which the last week on the origin outlet is the same as the first week on the destination outlet as it often reflects hosts being simultaneously employed on distinct outlets. In our estimation sample, $1,757$ distinct hosts are indeed observed working on distinct outlets during the same week. One example is Patrick Cohen, who hosted a daily morning show on France Inter (*Le Sept Neuf*) while co-hosting a daily evening show on France 5 (*C à vous*) between 2011 and 2017.

several groups' time share. The distribution is roughly symmetric, and while many moves entail modest differences in time share, we nonetheless observe a substantial number of moves across channels with very distinct invitation patterns.

For each group, we compute the difference in the time share a host dedicates to this group in the shows they host in their first two weeks on destination outlet c' and in the shows they host in their last two weeks on origin outlet c.[35] We next plot it against the difference in the time share dedicated to this group between outlet c' and outlet c. If the mover has similar guests irrespective of the outlet, then the slope should be equal to zero. Conversely, if they fully adapt to the new media's editorial line, it should be equal to one.

Figure 5 plots the relationship. In sub-figures 5a, 5b and 5c, the time share is normalized by the speaking time of all the guests, and in sub-figures 5d and 5e, only by the one of the political guests. If we first consider the extensive margin, we obtain slope coefficients that vary between 0.34 (for the time share devoted to the political guests) and 0.39 (for the time share of the left-wing guests), suggesting that channels explain a little over one-third of the observed variation in the time share devoted to these guests.

When we turn to the intensive margin (i.e. normalize the time share by the speaking time of the political guests), we observe larger slope coefficients: 0.42 for the time share devoted to the left-wing guests (sub-figure 5d) and 0.71 for the one devoted to the right-wing guest (sub-figure 5e). In other words, the channel environment seems to explain a larger share of the variation in which a political group is represented among the political guests than in the propensity to cover politics. While hosts adapt their choice of guests to the outlet they work for as they move, they thus appear to comply more strongly on the intensive than on the extensive margin.

[Figure 5 about here.]

Event study A potential concern is that hosts may switch to another outlet because, over time, their preferences shift with regard to their choice of guests. They may want to work for a channel whose guests' political leaning better matches their evolving preferences. For instance, a journalist who becomes more right-wing over time may at some point decide to join a more right-wing newsroom. If this were to be the case, Figure 5's slope coefficients would not solely reflect the effect of moving to another outlet on guest invitation patterns, but also the evolving preferences of hosts.

To test whether hosts moving from one media outlet to another already exhibit invitation patterns that converge toward those of the destination's editorial line, we use an event-study

[35] We use a two-week window around the move – rather than for example the last pre-move and the first post-move shows – to take into account the fact that hosts may balance their political invitations over several shows, e.g. invite a right-wing guest at the end of the week if they have hosted a left-wing one earlier in the week.

specification. We consider the move of host i at time τ, with τ denoting the time of the first post-move week. The host moves from an origin outlet $o(i,\tau)$ to a destination outlet $d(i,\tau)$. We denote by $\delta(i,\tau)$ the difference in the channel-level average speaking-time share of a given group between the destination and origin channels: $\delta_{(i,\tau)} = \bar{y}_{d(i,\tau)} - \bar{y}_{o(i,\tau)}$. $\delta_{(i,\tau)}$ is positive (resp. negative) for hosts who move to an outlet that represents a given group more (resp. less) than the origin outlet. We estimate the following model:

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

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

Figure 6 reports the results. Whether considering the extensive or the intensive margin, invitation patterns sharply change after a move. No pre-trend is visible. Moves do not seem triggered by drifting host preferences or by temporary shocks. This supports the idea that they can be seen as exogenous.

Regarding the magnitude of the effects, we see that, at the extensive margin, moving from a channel that devotes 0% of the total speaking-time share to the right to a channel that devotes 100% of this share to the right increases by 35 percentage points the time share that the host devotes to the right in their shows (sub-figure 6a). The magnitude of the effect is similar when we consider the time share devoted to the left or to political guests overall, and does not vary significantly following the move. In other words, there is no sign of gradual adaptation following the move; instead, hosts appear to immediately adapt to their new environment. The magnitude of the effect is larger at the intensive margin (sub-figure 6b), consistent with the results of Figure 5 above.[36] Considering right-wing guests for instance, moving from a channel that devotes 0% of the political speaking-time share to the right to a channel that devotes 100% of this share to the right increases by 80 percentage points the political time share that the host devotes to the right in their shows.

We further check whether the absence of pre-trends also holds for several sub-sets of hosts. Indeed, while some hosts may not be in a position to decide when or to which outlet they move given their precarious work conditions, others may only move if they wish to do so. For this latter group, changes in ideology may still be triggering moves. To assess whether this is the case, we estimate equation (1) using shows hosted by distinct types of guests. In particular, we

[36] The standard errors are also larger in this case, reflecting the fact that, because some channels only devote little time to politics, the estimates are noisier when we normalize the time share by the speaking time of the political guests alone.

compare hosts who are famous (i.e. have a *LesBios* or a Wikidata entry) to those who are not, as well as hosts who are working as producers or directors to those who are simply presenters or journalists. Appendix Figure C.7 plots the results. Pre-move estimates are nearly all close to zero and not statistically significant. The magnitude of the effects, which reflect to what extent hosts adapt to their environments, is overall very similar across sub-samples. This lends support to a causal interpretation of the estimates.

[Figure 6 about here.]

4.2 Two-way fixed effects model: Empirical strategy

Next, to quantify the relative importance of host composition, of hosts complying to distinct editorial lines, and of host sorting in explaining differences in political coverage across channels, we estimate the following model, in the spirit of Lachowska et al. (2022):

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

where y_{ict} is the time share devoted to guests who belong to a given group (politically classified guests, left-wing guests, etc.) in the shows hosted by host i on outlet c at time t. Time t is defined as a one-hour time slot (e.g. 7am to 8am, or 8pm to 9pm)[37] and, for each host and each time slot, we aggregate for each week all the shows broadcast by the host during the time slot. For example, an observation thus corresponds to all the shows broadcast by host i on channel c from 7am to 8am during the first week of January 2018. Given that different hosts have different air times (some may be on air for several hours a week, while others may only appear for a few dozen minutes), observations are weighted by the weekly time-slot air time of each host.

As before, we consider both the extensive and the intensive margin. In the first case, y_{ict} is defined as the time dedicated to a given group of guests over the total length of the show. In the second case, we narrow our focus to shows with at least one political guest and compute the time dedicated to guests of a given political group as a share of the time dedicated to politically classified guests.

As appears in equation (2), we assume that this time share can be modeled as the sum of the following three components: (i) a time component that captures news pressure and viewers' characteristics at a given point in time ($\tau_{p(c),t}$); (ii) a host component (α_i); and (iii) a premium due to the outlet ($\gamma_{c,s(t)}$). More specifically, $\tau_{p(c),t}$ is a set of time fixed effects at the week $\times$ hourly time slot $\times$ platform level, where platform p is either television or radio. It controls for time shocks (e.g. a news event making a political group more newsworthy at a

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

given point in time) as well as for viewers' characteristics in each hour of each week.[38] These time fixed effects therefore control non-parametrically for demand characteristics at very high frequency. α_i is a set of host fixed effects. It reflects the host's propensity to invite guests from a given group after accounting for time shocks. In other words, it captures hosts' time-invariant characteristics, such as preferences or specialization, which could make them more or less susceptible to invite certain guests. $\gamma_{c,s(t)}$ is a set of channel fixed effects that accounts for how a host changes her invitation pattern based on the outlet they work on; these fixed effects capture channel-level decisions and can be seen as measuring the editorial line of each outlet.

Importantly, channel effects are allowed to change every two-season period (indexed by s), in the spirit of time-varying AKM models (Lachowska et al., 2022). Assuming that channels' editorial lines are fixed over long periods of time would indeed be likely unrealistic – to begin with because there might be changes in channel ownership. Rather, our model allows channel effects to vary over time, reflecting that their editorial line might be periodically adjusted. This flexibility also implies that channel effects are identified both with the $4,456$ movers who switch across media outlets (see Table 1),[39] and with the $8,783$ stayers who are observed in distinct time periods on a given outlet. The latter help track changes in the channel environment. ϵ_{ict} is the error term and represents transitory fluctuations in the time share dedicated to each group.

Identifying assumption We can obtain unbiased estimates of the components of equation (2) using OLS under the conditional random mobility assumption, i.e. that conditional on host effects, time-varying channel effects and time effects, moves can be considered exogenous. Importantly, this means that hosts can sort based on their own characteristics and channel components (e.g. hosts specialized in interviewing politicians can sort on channels that feature many interviews with politicians). However, as the model assumes the additive separability of each component, hosts are not supposed to move based on a match component. If this were the case, the channel effect estimates from equation (2) would indeed capture a mixture of the true effect and the average complementarity of host-channel matches. We discuss the plausibility of this assumption in two ways.

First, we can see from Figure 5 – which plots, for each group, the change in the time share devoted to this group between the shows presented by a host on the origin media and on the destination media against the destination-origin difference in the time share for the considered group – that the relationship is linear and symmetric around zero. This suggests that a host

[38] It is important to take into account the platform given that audience peaks do not occur at the same time on radio as on television, and that both platforms cater to different sets of consumers.

[39] As shown in Figure 4 above, all the outlets in the sample are connected to each other and form one single densely connected set.

moving from c to c' or, symmetrically, from c' to c, would experience the same change in political time shares in absolute terms. If hosts were moving to a destination outlet based on a match component, a move to a higher left-wing (resp. right-wing) time share channel should on the contrary have a different effect than a move in the opposite direction.

Next, we explore whether the mean residuals are abnormally large or small for some host-channel pairs. For example, in the presence of match components, the residuals may be particularly large for hosts that devote a lot of time to political guests when paired with a channel that has a lot of political guests. To assess whether this is the case, we split the estimated channel-season and host effects into quartiles and compute the mean residual for each quartile pair. Appendix Figure C.9 reports the results. Two findings emerge. First, residuals are not systematically larger (or smaller) for top or bottom quartile host-channel pairs. Second, for each cell, mean residuals are very low, at most within +5% or -5% with respect to the mean of the outcome variable, which means that if match effects are present at all, they are quantitatively very small.

A second type of endogenous mobility may occur if hosts move from one outlet to another due to a change in their baseline propensity to invite a given type of guest, because their political preferences or their specialization changes, for instance. Such moves may lead to an over-estimation of channel effects, as they would partly capture drifts in the host component. However, the absence of systematic pre-trends in Figure 6 lends support to the idea that hosts do not transfer to another outlet because the destination channel better suits their evolving inclinations.

Finally, another form of endogenous mobility could arise if transitory shocks in coverage systematically triggered moves between high and low time share outlets. Again, the absence of a systematic dip or spike in coverage before the move in Figure 6 suggests that it is not a concern in the present setting. Overall, these results bolster our confidence that our identification assumption can be considered valid.

Variance decomposition We seek to understand what drives the differences in the profile of guests across channels. To this end, we decompose the share of variation in invitation patterns and focus on 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 such as specialization or preferences. We also analyze how hosts sort across channels, i.e. whether they tend to work on channels whose guidelines fit their personal inclination.

Let $\bar{y}_{cs}$ be the expectation of y_{ict} across shows on outlet c in period s. $\bar{\alpha}_{cs}$ and $\bar{\tau}_{cs}$ denote the analogous expectations for the part of the time share imputable to host characteristics and time effects, respectively. $\bar{\alpha}_{cs}$ captures the differences in average hosts characteristics across outlets $\times$ periods, while $\bar{\tau}_{cs}$ accounts for news pressure and viewership characteristics at the time each channel broadcasts its shows.

$$\bar{y}_{cs} = \bar{\alpha}_{cs} + \gamma_{cs} + \bar{\tau}_{cs} \tag{3}$$

From there, we can express the variance across channel $\times$ period pairs as:

$$var(\bar{y}_{cs}) = var(\gamma_{cs}) + var(\bar{\alpha}_{cs}) + 2cov(\gamma_{cs}, \bar{\alpha}_{cs}) + var(\bar{\tau}_{cs}) + 2cov(\gamma_{cs} + \bar{\alpha}_{cs}, \bar{\tau}_{cs}) \tag{4}$$

The first three terms account for (i) the variance in channel-level decisions, reflecting differences in editorial lines ($var(\gamma_{cs})$); (ii) the variance in average host characteristics, which can be seen as the difference in host composition across outlets ($var(\bar{\alpha}_{cs})$); and (iii) the covariance between the two, which measures the extent to which hosts sort on channels whose editorial line fits their personal inclination ($2cov(\gamma_{cs}, \bar{\alpha}_{cs})$). In addition, $var(\bar{\tau}_{cs})$ is the variance explained by time effects and $2cov(\gamma_{cs} + \bar{\alpha}_{cs}, \bar{\tau}_{cs})$ the covariance between time components and the other components.

Sampling error While our estimation sample features media outlets that are densely connected by a large number of hosts moving across channels (including within-period), a potential concern may come from the fact that the limited number of observations for each component may lead us to estimate them with error. The variance of components may reflect the variance of both the parameters and the sampling error. Further, our estimates of the covariance term $cov(\gamma_{cs}, \bar{\alpha}_{cs})$ may be downward biased (Andrews et al., 2008, 2012). In other words, the so-called "limited mobility bias" may lead us to underestimate sorting.

We address this issue in two ways. First, we estimate standard errors for our variance decomposition using the bootstrap procedure implemented by Best et al. (2023). We resample partial residuals stratifying at the outlet-period-host level to preserve the match structure of the data. This way, we can build empirical confidence intervals for our estimates. Second, we implement a split-sample approach as in Finkelstein et al. (2016); Cantoni and Pons (2021); Best et al. (2023). We randomly split the estimation sample into 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, with the idea that the sampling errors are orthogonal.

4.3 Decomposition of cross-channel variations in political time shares: Results

4.3.1 Estimation

Table 2 reports details on the estimations, both at the extensive (Columns (1) to (3)) and at the intensive (Columns (4) and (5)) margins. At the extensive (respectively intensive) margin, there are $1,257,932$ (respectively $481,671$) observations. The model explains between 44% and 60% of the dependent variable variance. For all dependent variables, a F-test strongly rejects the null hypothesis that all the channel effects are jointly zero (p-value = 0.000), which supports the idea that channel environments do play a part in explaining invitation patterns.

[Table 2 about here.]

4.3.2 Variance decomposition

We next follow equation (4) and estimate the decomposition of the variation in speaking-time shares. As before, we do so both at the extensive and at the intensive margin, and present the results in turn.

Extensive margin Table 3 reports the results when we express the time dedicated to different groups of guests as a share of the total time dedicated to guests. In Columns 1 to 4, we consider the time share devoted to the political guests as a share of all guests. In Columns 5 to 8 (resp. 9 to 12), the outcome of interest is the time share of left-wing (resp. right-wing) guests among all guests. Row 1 reports the variance of the outcome variable across channel-period pairs, and rows 2 to 7 show the components of the variance due to time effects, channel effects and host effects. Row 8 presents the correlation between channel-period effects and average host effects. To account for the bias in the estimation of variance components stemming from sampling error, we further report in rows 9 to 13 the variance components estimated using the split sample approach described above. Columns 2, 6 and 10 report the bootstrapped standard errors of each component. Columns 3, 7 and 11 show the variance explained by each component as a share of the variance of the outcome variable (row 1), while Columns 4, 8 and 12 do the same as a share of the sum of the host and channel components (rows 4 and 9, respectively), i.e. after netting out time effects.

Several findings emerge. First, channel-period effects ($var(\gamma_{cs})$) account for about a third of the total variance, a result that is consistent across outcomes. The composition of host ($var(\bar{\alpha}_{cs})$) accounts for a smaller share of the variance – about 20% – while sorting ($2cov(\gamma_{cs}, \bar{\alpha}_{cs})$) accounts for another third of the variance. The remaining part – about 15% – is accounted for by time effects. When focusing on host and channel components, both compliance with channel editorial lines (channel effects) and sorting (covariance) account for 40%

of the variance, while host composition only account for 20% of differences across channels. These patterns are similar whether we consider plug-in estimates (rows 1 to 8) or split-sample estimates (rows 9 to 13). Components are precisely estimated, as reflected by the standard errors. The latter are larger, however, when considering split-sample variance estimates, which is expected given that the procedure relies on using two sets of noisy estimates to deal with sampling error bias.

Second, these results are quite stable across outcomes, as each component accounts for similar variance shares across groups. Appendix Figure C.10 reports the variance decomposition shares when considering each group separately. Sorting components and host effects tend to account for larger share of variance when considering historically dominant groups (left and right). Potentially, since these parties account for a larger time shares, hosts are more likely to sort based on these political groups than on ones that are less represented. Further, we find that the share of each component is quite stable over time, as shown in Appendix Figure C.11.

Overall, the results are consistent with the idea that each channel is characterized by an editorial line that emphasizes political coverage or, conversely, entertainment or other types of content. Hosts appear to specialize – some regularly interview political guests while others never do – and work on outlets that match their specialization. After netting out time shocks, channel editorialization accounts for around 40% of the differences in the guest invitation patterns across channels.

[Table 3 about here.]

Intensive margin We next focus on which political groups are represented, conditional on inviting political guests. Table 4 presents the results. Time effects account for a large share of differences across outlet-periods, as differences in representation of each group across periods is very much influenced by electoral cycles. Interestingly, compared to what we observe at the extensive margin, we see that channel components account for a larger share of the variability across channel-periods – around 80% – after accounting for time effects. Host composition only accounts for a small share of the variance – less than 10% – and host sorting for around 10%.

This implies that channel-level decisions play a major role in explaining which political groups are represented in broadcast media, conditional on inviting political guests. Hosts covering politics appear much more constrained by channels' editorial lines when deciding which group to invite than when deciding to what extent to cover politics. They seem to have minimal agency, as reflected by the small share of the variance explained by the differences in average host fixed effects. There is, however, some degree of sorting. This means that hosts, when covering politics, are essentially left with two options: either complying with editorial guidelines, or moving to another channel that better fits their inclinations.

[Table 4 about here.]

4.3.3 Robustness checks

We first explore whether our results are robust to excluding periods before elections in which stricter rules apply regarding political representation. Indeed, invitation patterns in these periods may not accurately match channels' editorial guidelines. Appendix Tables C.3 and C.4 present the results. The shares associated with each variance component are very similar. If anything, channel effects tend to account for a slightly larger share of variance.

Next, we explore whether our results are different when we do not weight observations by the time dedicated to guests, i.e. hosts with very short occasional shows are given the same weight as hosts with longer daily shows. Average host effects are also not weighted by how long the host is on air, but instead by how many weeks $\times$ time slot they appear on the channel. Appendix Tables C.5 and C.6 report the results. When considering all guests, each variance component now accounts for about a third of net-of-time-effects variance. When only considering shows with political guests, channel components tend to account for a slightly larger share of variance, and sorting tends to be smaller. Overall, these results are similar to those presented in our preferred specification.

Finally, we explore whether the share of variance explained by channel components is lower if they are not allowed to change every period. We estimate a two-way fixed effects model in which both host components and channel components are fixed for the whole sample period (i.e. channel effects are not interacted with period effects). Appendix Tables C.7 and C.8 report the results of the variance decomposition across outlets. The variance share explained by channel effects slightly decreases, but the variance associated with each component is very similar to that obtained before.

4.4 Host effects

We now analyze what distinguishes hosts who differ in how much time they give to political guests. The left panel of Figure 7a reports the estimated coefficients of bivariate regressions of host fixed effects on a series of covariates when using the share of political guests among all guests as the outcome variable. Both the outcome and explanatory variables are standardized and set to have mean zero to help the interpretation and comparability of estimates. The right panel of the figure reports regression coefficients from a multivariate regression after selecting the most relevant covariates using a LASSO procedure. To account for the fact that the outcome variable is itself estimated with error, both bivariate and multivariate regressions are weighted by the inverse of the bootstrapped sampling variance of the outcome variable, as in Finkelstein et al. (2016).

We see that hosts who dedicate relatively more time to political guests are hosts whose professional description includes the word 'journalist', hosts who are more often on prime time than others, and hosts who are more famous (as proxied by the presence of a *LesBios* or Wikidata entry). In contrast, those who are less likely to dedicate time to political guests are hosts whose profession includes the words 'presenter', 'producer' or 'director'.

Figure 7b reports similar results, but with host fixed effects estimated when using the share of right-wing guests among political guests as the outcome variable (i.e. when focusing on the intensive margin). There is no salient predictor of hosts being inclined to give more time to right-wing guests. Potentially, female hosts, hosts described as 'directors' and hosts accounting for large amounts of time with guests tend to represent the right a little less, but the magnitudes are small.

Figure 7c instead considers the absolute value of the host fixed effects when considering right-wing guest time share, as it represents how much a host deviates from the time share dictated by time shocks. Hosts who deviate more are those who have guests on a single channel, who only account for a small amount of time spent with guests, and who are observed on a shorter time span in our sample. Potentially, they are hosts working under a short-term contract or freelancers who are tasked with covering a specific event, rather than hosts who have guests on a very regular basis and interact with a variety of them. Interestingly, when conditioned on other characteristics, hosts who are observed earlier in the sample (and may have more experience) and hosts who are 'directors' or 'producers' tend to deviate more. Remember that, as we discussed in Section 4.4 above, a significant share of hosts in France are also the producers of their shows. This is particularly true of star presenters, and we can thus expect them to have more agency, which allows them to deviate more.

[Figure 7 about here.]

4.5 Channel effects and ownership

So far, we have evidenced that channel editorial guidelines largely influence guest invitation patterns. From there, we seek to understand how these guidelines relate to ownership. To this end, we estimate a specification similar to equation (2) but use owner-period fixed effects instead of channel-period fixed effects. Figure 8 uses diamonds to report the fixed effects associated with each owner when considering the share of political guests among all guests (sub-figure 8a) and the share of right-wing guests among political guests (sub-figure 8b) as the outcome variable. We further report channel-period effects against the parent owner effect.[40]

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

If we first consider the extensive margin (upper Figure 8a), we see that several parent companies own media outlets that are quite different in their coverage of politics. For instance, in the Bertelsmann group, M6 gives little coverage to political guests while RTL does so more. Similarly, in the Vivendi group, C8 has a focus on non-political guests, while the opposite is true for CNews. Public broadcasters also differ in the intensity of their political coverage, with France Culture and France 5 being less focused on politics than France Info and LCP. Overall, conglomerates with multiple outlets often appear to have a portfolio of outlets that are diverse in the intensity of their political coverage, even though they are all available to the same nation-wide audience for free.[41] This suggests that owners seek to segment channels on this dimension.

In contrast, if we turn to the intensive margin, we see that channels' fixed effect tend to be much closer to the fixed effect of their parent company (bottom Figure 8b). In other words, while there is within-parent company diversity in the intensity of political coverage, partisan leaning is more homogeneous. This is most probably due to the fact that owners might have specific views on the type of content they want. For this reason, rather than segmenting the market and specializing each outlet in their portfolio such that it serves a specific political segment,[42] they impose a similar editorial line on all the outlets they own so that they reflect those views (see e.g. Mastrorocco and Ornaghi, 2020, on the example of the Sinclair group in the US).

[Figure 8 about here.]

We further explore the relationship between owner preferences and channel editorial lines in Section 5 below, when studying the case of the takeover of three television channels by Vincent Bolloré.

5 Case study: the Bolloré takeover

To understand the role played by hosts in an owner-driven editorial change, we study how they adapted their choice of guests and whether they switched to another outlet around the time Vincent Bolloré took control of the Vivendi Group, the parent company of three television channels in our sample – Canal+, C8 and CNews.

take the average of channel-period and of owner-period fixed effects in the periods 2015-2017 and 2017-2019.

[41] With the exception of Canal+ for some time slots.

[42] Differentiating channels based on politics might indeed be one way to limit competition between outlets ultimately owned by the same group.

5.1 Bolloré's takeover of Vivendi in a nutshell

Vivendi is an advertising, entertainment, media and publishing conglomerate whose market value stood at around 11 billion euros in 2024. It is the parent company of the Canal Plus Group – a television group that owns several outlets, the leading ones being Canal+, CNews and C8.

Vincent Bolloré is the main owner of the Bolloré Group (valued at 17 billion euros in 2024), 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) in 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,[43] 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 became chairman of the supervisory board of Canal+ in September 2015. D8 was rebranded as C8 in September 2016. Several C-level executives at the 24-hour news channel CNews (then known as I-Télé) were fired in July 2016, and a major strike occurred at the channel in October 2016 in response to a change in editorial line. The channel changed name from I-Télé to CNews in February 2017. As of March 2022, the Bolloré Group owned 29% of Vivendi, and had effective control of the company.

5.2 Compliance

Measuring the change in editorial line In a first step, we explore whether the guest composition on these three channels changed after the takeover when compared to guests on other channels in a difference-in-differences framework. Our specification writes as follow:

$$\begin{aligned} y_{ct} = &\beta_1 1[Treated]_c \times 1[t \in (Apr.2015, Aug.2017)]_t \\ &+ \beta_2 1[Treated]_c \times 1[t \in (Sept.2017, Aug.2019)]_t \\ &+ \delta_c + \tau_{p(c),t} + \gamma X_{ct} + \epsilon_{ict} \end{aligned} \tag{5}$$

[43] The law grants double voting rights to established shareholders.

where y_{ct} is the time share devoted to a given group (either political guests as a share of all guests for the extensive margin, or different political groups among politically active guests when we focus on the intensive margin) in the shows broadcast on channel c in the week $\times$ time slot t. $1[Treated]_c$ is an indicator variable for whether the channel belongs to Vivendi (Canal+, C8, and CNews). $1[t \in (Apr.2015, Aug.2017)]_t$ and $1[t \in (Sept.2017, Aug.2019)]_t$ are indicator variables for whether shows are broadcast between April 2015 and August 2017, or between September 2017 and August 2019, respectively. The two coefficients of interest are β_1, which captures short-term changes after the takeover, between April 2015 and August 2017; and β_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. By September 2017, most changes had already been implemented. X_{ct} is an indicator variable equal to one for C8 from 2005 to 2011. It accounts for potential differences due to C8's past ownership. Finally, δ_c and $\tau_{p(c),t}$ are respectively channel and platform-week-hour of the day fixed effects. We weight observations by the amount of time dedicated to guests, and cluster the standard errors at the level of the media outlets.

Table 5 Panel A reports estimates from equation (5). Column 1 considers the extensive margin: the outcome is the share of political guests among all guests. Columns 2 to 7 consider guests from each political group separately, as a share of political guests.[44] The takeover did not have a significant effect on the share of political guests. The point estimates are positive, and are suggestive of a 10% increase in the time share devoted to political guests, but they are not statistically significant. Turning to each political group separately, we find that the speaking-time share of the radical right increased by 1.98 percentage points in the short run and 5.33 percentage points in the medium run (Column 7), compared to a 7.6% baseline in control channels. This means that, in the medium run, the time share of the radical right was 70% higher in the shows broadcast on Bolloré's channels than in the shows on other outlets. This is consistent with the much-publicized rise of the radical right on CNews following its acquisition by Vincent Bolloré (in particular during the 2022 presidential campaign when CNews gave a platform to the far-right candidate Éric Zemmour[45]). We do not detect significant changes for other political groups, but point estimates are negative for liberal and right-wing politicians, suggesting that radical-right coverage may have crowded out the coverage of these other groups.

Appendix Table C.9 further investigates whether there is heterogeneity in the effect de-

[44] We include in our definition of the speaking-time share of each political party both politicians and PENOPs. Below we discuss what happens when the PENOPs are not included and present the results.

[45] See e.g. "Vincent Bolloré, Éric Zemmour and the rise of 'France's Fox News'?," *Financial Times*, October 5, 2021, and "A Fox-Style News Network Rides a Wave of Discontent in France," *The New York Times*, September 14th, 2021. We discuss in Section 6 below the impact of this shift to the radical right on electoral results.

pending on which Bolloré's channel we consider. We observe a rise in the speaking-time share of the radical right on both C8 and on the 24-hour news channels CNews in the short as well as in the medium run. This increase is statistically significant at the one-percent level. On Canal+, the takeover leads to a decrease in the overall speaking time devoted to politics.

[Table 5 about here.]

The identifying assumption underlying our difference-in-difference framework is that trends are parallel before the takeover. Slightly amending equation (5), we test it by interacting the treatment indicator with a set of season indicator variables. Figure 9 plots the coefficients on the interaction terms between season indicators and the treatment status of channels for the speaking time of radical-right guests. We find no evidence of diverging pre-trends; nearly all of the pre-2015 estimates are indeed not statistically significant and hover around zero. In contrast, there is a visible increase in the share of the radical-right speaking-time share after 2015, which becomes even stronger over time. This lends support to the validity of the difference-in-differences design, meaning that estimates can have a causal interpretation.[46]

[Figure 9 about here.]

Compliance The results so far show that the takeover led to a sharp increase in the coverage of radical-right guests. How did hosts react to such a change? We here explore the mechanisms underlying this editorial line shift. First, the documented changes in political time shares may be due to composition effects – some hosts leave and are replaced by new ones who invite more radical-right guests – or, second, to compliance, with continuing hosts adapting to the new editorial policy.

To assess whether the hosts who stayed on the same channel adapted to the new editorial line, we study how the time shares dedicated to each group changed for each host-channel pair. We estimate the following specification:

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

We compute the time share dedicated to a given group in the shows of host i on channel c in week $\times$ time slot t. Compared to equation (5), we now control for channel-host fixed effects (α_{ic}) rather than simply for channel fixed effects. This way, we exploit within host-channel pair variation. As before, observations are weighted by the amount of time dedicated to guests.

[46]Online Appendix Figure C.12 reports similar event studies for the other political groups, and similarly shows that there is no pre-trend.

Table 5 Panel B reports the estimates for the share of political guests among all guests (Column 1) and for each political group among political guests (Columns 2 to 7).[47] For hosts who stayed, the time share of radical-right guests increased by 1.65 percentage points in the short run and 3.19 percentage points in the medium run (compared to 7.6% on control channels). As before, we find no statistically significant change for other parties, nor in the time share devoted to political guests (Column 1). Among continuing hosts, radical-right guests may have crowded out guests from the radical left and greens, as the effects are negative for these two parties (they are not statistically significant, however).

Importantly, note that the coefficients reported in Panel A and Panel B of Table 5 are very similar. Their absolute value is slightly lower for radical-right guests in Panel B than in Panel A, reflecting the fact that continuing hosts may not have fully complied with the new channel's editorial line, but they are nonetheless very close. This implies that changes in the mix of guests on Bolloré's channels is at least in part driven by continuing hosts complying with the new editorial policy.

The growing importance of PENOPs Note that all the results presented in this section until now include both the guests classified as politicians and those classified as PENOPs in our measure of the speaking-time share of each political party. As highlighted above, this is of particular importance given that, contrarily to the speaking-time share of politicians, that of PENOPs is not subject to pluralism rules, and so might thus be used by owners willing to bias the news as a way to bypass regulation.

This is indeed what we observe in the data. Appendix Figure C.14g reports coefficients similar to those presented in Figure 9 above for the speaking-time share of the radical-right guests, but highlights the estimated results when PENOPs are not included in this time share. While we observe a statistically significant increase in the speaking-time share of the radical right following Bolloré's takeover event absent PENOPs, the magnitude of this increase is lower.

Robustness We check the robustness of our specification to several changes in Appendix Table C.10. Baseline estimates are reported in Column 1. First, we check in Column 2 whether our results differ if we focus exclusively on prime time hours (between 7pm and 11pm on television) as a channel may change its overall composition of guests without altering guests in most watched shows, meaning that the guests to whom most viewers are exposed remain unchanged. If anything, the reported effects are stronger. They are as significant despite the lower number of observations when observations are at the channel level. This suggests that the increase in radical-right guests was at least as visible during peak viewership hours.

[47]See online Appendix Figure C.14 for the corresponding figure documenting the absence of pre-trends.

Considering the analysis at the host-channel pair level, effects are stronger in the short run, but weaker in the medium run. This may be explained by former prime-time hosts moving to other less-watched time slots. In Column 3, we drop pre-election periods during which the time dedicated to candidates is strictly monitored by Arcom (equal speaking and air time rules). The results are very similar. In Column 4, we replace platform-week-hour of the day fixed effects by week fixed effects, meaning that we no longer control for variations in viewership across the time slots and platforms. The results are very similar in Panel A. They are slightly lower when considering within host-channel effects. In Column 5, again using week fixed effects, we only use radio stations as a comparison group. The idea is that other television channels may have responded to the increased radical-right coverage on Bolloré's outlets by either copying them and also increasing radical-right coverage, or on the contrary by trying to further differentiate themselves by reducing radical-right coverage. If the takeover 'contaminates' the control group, we may under- or overestimate the impact of the takeover. Using only radio outlets in the control group – and assuming that these outlets cannot have been contaminated given that radio stations are not directly competing with television channels – we find estimates that are very similar to the baseline ones. In Column 6, we compute the outcome variable excluding guests who are PENOPs. As mentioned above, the effect tends to be smaller, plausibly because pluralism rules are not binding for PENOPs while they are for politicians. Overall, our results appear robust to a number of specification changes, lending support to the idea that our estimates capture the causal impact of the takeover on slant.

Furthermore, one may wonder whether the time share dedicated to the radical right may have increased because guests from other parties were no longer willing to take part in shows broadcast on Bolloré's channels. If this were to be the case, the interpretation of our findings would be completely different, given that the estimated effects of the takeover would no longer reflect a change in the demand for guests but rather in the supply of guests. To address this potential concern, we ask whether some guests stopped appearing on the acquired channels after the takeover, as this may be a sign that some of them were no longer willing to appear in shows or were no longer invited. To this end, we indicate for each guest-outlet pair whether a guest who is observed in a given quarter is observed again in quarter $t+4$, i.e. a year later. We then explore whether the propensity that a guest keeps appearing drops for acquired channels when compared to other channels after the takeover. More formally, we estimate the following specification:

$$y_{ict} = \sum_{q \neq 2013q1} \beta_q 1[Treated]_c \times 1[t=q]_t \times 1[Guest\ characteristics]_i + \alpha_{ic} + \delta_t + \epsilon_{ict} \quad (7)$$

where y_{ict} indicates whether guest i observed on channel c in quarter t is still on the channel in quarter $t+4$. α_{ic} are guest-channel pair fixed effects, which capture any fixed characteristics that are specific to the match between a guest and a channel. δ_t are quarter fixed effects which control for the aggregate propensity of a guest to appear. $1[Treated]_c$ indicates whether the considered channel is one of those controlled by Vincent Bolloré in 2015. $1[t = q]_t$ are quarter indicator variables. $1[Guest\ characteristic]_i$ is an indicator variable for whether a guest has a certain characteristic (e.g. whether they are politically involved, or whether they are left-wing).

Appendix Figure C.15 plots the results. First, if we consider all the guests we find that there was no major drop in the propensity that hosts are still observed a year later on acquired outlets (sub-figure C.15a). Most coefficients are close to zero and not statistically significant. Further, the interaction term is almost never statistically significant, implying that if guests stopped appearing on the channel, this was not specific to political guests, but rather impacted them all. Second, if we focus on politically classified guests and allow for an interaction with an indicator variable for whether the guest is left-leaning, we similarly find no significant drop (sub-figure C.15b). If some political figures were boycotting Bolloré's channels due to the change in editorial line, one may expect guests' propensity to keep appearing on these channels to be lower for left-wing guests than for political guests from other parties. This is not what we observe. While some politicians may have chosen to boycott Bolloré's channels, this behavior thus seems to have been limited to a relatively small set of politicians and is far from systematic. Further, it may have been bypassed by the channels showing clips from press conferences or rallies rather than having the guest on set. Overall, we do not think that our results are supply-driven, with a shortage of guests from a given leaning causing the increased representation of other groups.

5.3 Sorting

Results so far show that hosts who stayed on Bolloré's channels complied with the new editorial guidelines. In this section, we assess whether hosts reacted to the owner-induced change in editorial line by leaving – voluntarily or not – the acquired channels.

Probability of staying To do so, for each host-channel pair, we define an indicator variable equal to one if a host observed on 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:

$$y_{ict} = \sum_{q \neq 2013q1} \beta_q 1[Treated]_c \times 1[t = q]_t + \alpha_{ic} + \delta_t + \epsilon_{ict} \tag{8}$$

where y_{ict} indicates whether host i observed on channel c in quarter t is still on the channel in quarter $t+4$. As before, α_{ic} are host-channel pair fixed effects, δ_t are quarter fixed effects and $1[Treated]_c$ indicates whether the considered channel is one of those controlled by Vincent Bolloré in 2015. $1[t = q]_t$ are quarter indicator variables. The coefficients of interest are β_q, which account for the difference that existing host-channel matches are continued across treated and control channels.

Figure 10 plots the estimates. Before the takeover, the propensity of hosts to continue working for their network followed similar trends across treated and control channels (sub-figure 10a). This lends support to the causal interpretation of our estimates. Starting around September 2015, we find that hosts on acquired channels were significantly less likely to continue appearing on screen. Hosts who worked on one of Bolloré's channels in 2016 were nearly 25 percentage points less likely to still be on the channel the following year (see also Table 6, Column 1). As a reference point, the probability that hosts would continue to appear on a control channel at the same time was around 51%, meaning that the probability of hosts staying was halved after the takeover. Sub-figure 10b reports similar estimates, but exclusively focuses on hosts working as journalists at time t (as opposed to presenter, producer or director). The drop is strikingly large – -50 percentage points in 2016 and 2018 – implying that journalists were especially likely to leave.[48]

[Figure 10 about here.]

Table 6 reports the difference-in-differences estimates interacted with several host characteristics. Hosts with political guests (Column 3), working as journalists (Column 4) and/or in charge of a newscast (Column 6) were at least twice as likely to leave. They were potentially those who were the most impacted by the change in editorial line, which mostly affected the composition of political guests, rather than their overall presence. Hosts working as producers (Column 5) and male hosts (Column 7) were relatively more likely to stay. Famous hosts – as proxied by the presence of a *Les Biographies* or a Wikidata entry – were initially just as likely to leave, but relatively more likely to stay in the longer run. Potentially, being a producer, being male, and being famous is associated with a higher bargaining power and one may hypothesize that these hosts reached an agreement with the new management.

Finally, building on the estimations presented in Section 4.4 above, we investigate whether the propensity to stay varies with the host fixed effects. We show that, when considering the time share dedicated to the radical right as a share of political guests, hosts with positive fixed effects were slightly more likely to stay (Column 11), especially if they had political guests in

[48]Table C.11 provides the breakdown by channel; the effect is present on all three channels. CNews saw the largest drop (with a 32 percentage-point decrease both in the short and medium run), followed by Canal+ (16 percentage-point decrease in the short run) and C8 (4 percentage-point drop in the short run and 11 in the medium run).

quarter t (Column 12). Potentially, hosts with a higher baseline propensity to represent the radical right were more compatible with the editorial line change.

[Table 6 about here.]

Where hosts go We next ask where the hosts who left the acquired channels went. Figure 11 plots event-study estimates for several outcomes. Sub-figure 11a shows that the takeover caused a 30 percentage-point increase in 2016 in the number of hosts 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 – 46.2% – this is a 30 to 60% increase in the probability of stopping working on one of the channels in our sample, which includes all the main French television and radio stations.

[Figure 11 about here.]

This suggests that, for many departing hosts, the takeover implied a drastic career change, potentially leading hosts to take up a job in other types of media organizations (online media, newspapers, etc.) or leave journalism altogether. To investigate the extent to which these departing hosts actually left journalism following the takeover, we looked up 282 of them by manually searching[49] their names first on LinkedIn and then, for those who did not appear on the platform (39%), on Wikipedia (where we did find 41% of the remaining hosts), Twitter and Google.[50] We concentrated on the first job taken by the journalists following the takeover. Of the 252 departing hosts for whom we were able to recover information, more than 16% completely left the media industry and 15% took a job in the audiovisual production sector broadly defined.[51] As expected, a number of the departing hosts also disappear from our dataset following the takeover either because they joined print media (6%), online media (2.4%), or television channels such as 'L'Équipe' that are not included in our dataset because they are not general-interest (8.33%).[52]

Furthermore, some of them are still working on television or radio channels that are included in our dataset but no longer as hosts – and so logically no longer appear in our data either – or as hosts of shows with no guests.[53] Finally, note that a substantial share of the

[49]We focus on hosts who met the following conditions: hosts observed at least four times on a Bolloré's channel during the 2014/2015 season and who were last observed on a Bolloré channel before September 2020 (when our dataset ends).

[50]Doing so, we recover information on 87% of the leaving hosts with certainty, and 7% with some uncertainty.

[51]For instance, Marc Sauvourel was a senior reporter at Canal+ and then worked as freelance director-producer for the audiovisual company 'Little Darwin Films'. Jean-Baptiste Rivoire was editor-in-chief at Canal+ before setting up his own production company, 'Socrate productions'.

[52]This is the case of Pierre Tremblay, for example, who was working as a journalist for the 'Grand Journal' show on Canal+ before joining the print media *Le Devoir*, and of Tangi Kerhoas, who left I-Télé/CNews following the takeover to join 'L'Équipe'.

[53]For example, Eléonore Boccara, previously a host on I-Télé/CNews, who then began presenting national lottery games on France 3.

departing hosts in our data are still working for the Bolloré Group following the takeover, but are no longer part of broadcast shows and thus no longer appear in our data. For instance, Bérengère de Termont, who was news editor on D8/C8 before the takeover, then became head of cinema investments for the channel. Adrienne de Malleray, who was a news editor at Canal+, then became head of brand content.

Sub-figures 11b, 11c and 11d study the share of hosts who left and began working on another channel in our sample. Sub-figure 11b considers hosts working on channels in the bottom tertile of the right-wing time share distribution. Sub-figures 11c and 11d do the same for outlets in the middle and top tertile of the right-wing time share distribution. Among the hosts who left Bolloré's channels and went to work on another one in our sample, most appear to have moved to bottom and middle tertile outlets. We see no increase in the propensity that they are observed on one of the top six right-wing time share channels of the sample. This suggests that the hosts who left Bolloré's channels disproportionately joined channels that invite relatively fewer right-wing guests, hinting at a potential sorting based on political preferences.

Taken together, the results show that as acquired channels experienced a shift in editorial policy to the radical right, many hosts left these channels. The majority of them did not appear on any of the channels in our sample a year later, meaning that their careers could have been negatively impacted (along with the overall supply of journalism at the national level). 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 host. For those who stayed, as evidenced in the previous section, they largely complied with the new editorial policy, with a significant increase in the radical-right time share from 2017-2018, after most hosts had already left.

Finally, note that the shift to the radical right had a negative impact on audience numbers for Vincent Bolloré's channels, at least in the short run. Online Appendix Figure C.16 reports the results of an event study where we investigate the change in audience due to the takeover for Bolloré's channels compared to other channels. We observe a drop in audience for both CNews and Canal+ following the takeover, and a small decline for C8.[54] Furthermore, Canal+ never recovered from this drop. Hence, it seems difficult to argue that the shift to the radical right may be driven by a willingness to better adapt channel supply to audience preferences.[55] It rather seems to reflect the owner's own preferences.

[54]CNews and C8 became available for free through digital terrestrial television (DTT) in 2005 and gradually gained popularity in subsequent years as households acquired DTT box sets. That potentially explains why viewership for these outlets increased more than for control channels in the early years of the sample.

[55]Fully assessing whether this editorial change was profitable would require additional data on shows' production costs and advertising price, which may increase with ratings but may also vary based on audience characteristics.

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.

Our article is the first to quantify the contributions of media outlet and journalist-specific factors in slanting the news. Contrarily to existing papers in the literature (e.g. DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017; Martin and McCrain, 2019, among others), and because there is no geographic heterogeneity we can exploit in the penetration of Bolloré's channels, we cannot quantify the impact of the shift to the radical right on electoral results due to the change in ownership. However, there is a lot of suggestive evidence pointing to the impact of this change in editorial line on the 2022 presidential election results, and primarily on the electoral success of Éric Zemmour, a radical-right candidate who saw his support level peak at 18 percent for the elections and who finally ranked fourth.[56] Zemmour was promoted by Vincent Bolloré, in particular as part of the show he co-hosted on CNews, "Face a l'info"[57]; as highlighted by *The New York Review of Books*, he is "a contemporary media creation, foisted onto the public by CNews, France's equivalent of Fox News, which is backed by the right-wing billionaire Vincent Bolloré."[58] In the online Appendix, we provide further suggestive evidence of the impact of CNews on voters' preferences. We compute information on the characteristics of the viewers/listeners of each channel – in particular their political preferences – from the *Digital News Report*'s 2013, 2018, 2019 and 2020 surveys (Reuters Institute, 2013, 2018). For each year, we compute the average ideology of the viewers of the different channels and compare it to the one reported overall by all the surveyed individuals. Figure C.17 reports the results. We see that, while the individuals who report consuming CNews were on the left of the overall population in 2013, they shifted to the right following Bolloré's takeover. Of course, this cannot be interpreted as a causal effect of CNews on voters' opinions, in particular given

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

[57]CNews was fined several times by Arcom for broadcasting Zemmour's comments, e.g. his diatribe against child migrants and the asylum system for which he was found to have "incited hatred toward isolated foreign minors and spread a number of degrading stereotypes that could encourage discriminatory behavior."

[58]"Who does Éric Zemmour speak for?", James McAuley, *The New York Review of Books*, January 13th, 2022.

that we cannot determine whether these are the same viewers whose mind changed because of their exposure to CNews or whether they are different viewers who turned to CNews because of the new editorial line. However, it is of interest to note that, over the time period, the electoral support for the radical right strongly increased in France. It is also worth keeping in mind that, as we just saw, the shift to the radical right had a negative impact on audience numbers for Bolloré's channels; hence, it seems unlikely that the change occurred to better suit existing audience preferences.

Yet, this paper's contribution does not relate to the consequences of media slant, but rather to the determinants of the political slant of media outlets. To the extent of our knowledge, we are the first to disentangle and quantify how slant is generated. Our results have important policy implications regarding the relevance of existing media pluralism regulations – e.g. the UK broadcasting regulator's impartiality regime.[59] 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-politicians who are nonetheless politically involved guests from the same side. The most likely explanation for such behavior is that the latter are not accounted for by existing pluralism regulations (neither in France nor in other democracies). Hence, a first policy implication is that – as long as the regulator cares about internal pluralism – a broader range of guests should be considered when monitoring speaking-time shares.[60] Further, not only news programs should be regulated, but also entertainment shows that can be used as a way to slant content.

Note also that our findings regarding the importance of PENOPs and of non-news content should matter not only for policymakers but also 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 aspect of slant, and thus also of its consequences.

Second, the results shown in Section 5.3 on the probability of leaving following the takeover, but also the findings in Section 4.4 on the correlation between hosts' characteristics and the extent to which hosts deviate from their channel editorial policy, point toward the need to introduce rules to reinforce journalists' agency, independently of their experience or popularity. Article 6 of the European Media Freedom Act (EMFA) – a proposed regulation adopted by the European Commission that has not yet been formally adopted by the European Parliament – notes that "media service providers providing news and current affairs content shall

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

[60]Of course, one might also want to take into account other dimensions that are overlooked by existing regulations and that we do not take into account either in this article because of the limitations of existing data. There are indeed many subtle ways bias can enter into news coverage. In particular, analyzing the content of the shows might be of particular interest for future research.

take measures that they deem appropriate with a view to guaranteeing the independence of individual editorial decisions." Such measures shall aim to "guarantee that editors are free to take individual editorial decisions in the exercise of their professional activity." Based on our results, it might be useful for such projects to include rules that will better protect journalists' independence in their choice of guests (or more broadly of media content) (see e.g. the discussion in Cagé and Huet, 2021).

Finally, note that none of our findings – nor their implications – can be considered specific to France. First, as already mentioned, CNews is often seen as the French Fox News – and we could also highlight Murdoch's grip on Australian media. In the UK, the overtly right-wing broadcaster GB News (launched in 2021) is nowadays following a similar path to CNews, despite the existence of pluralism rules in both countries. Further, the collapse in the overall number of journalists as well as the increasing concentration of the media industry, lined with the closure of newsrooms – phenomena that undermine journalists' agency – are similarly not specific to France. Hence, the future of media ownership and pluralism rules is under discussion in many countries, and we hope our research will inform this debate.

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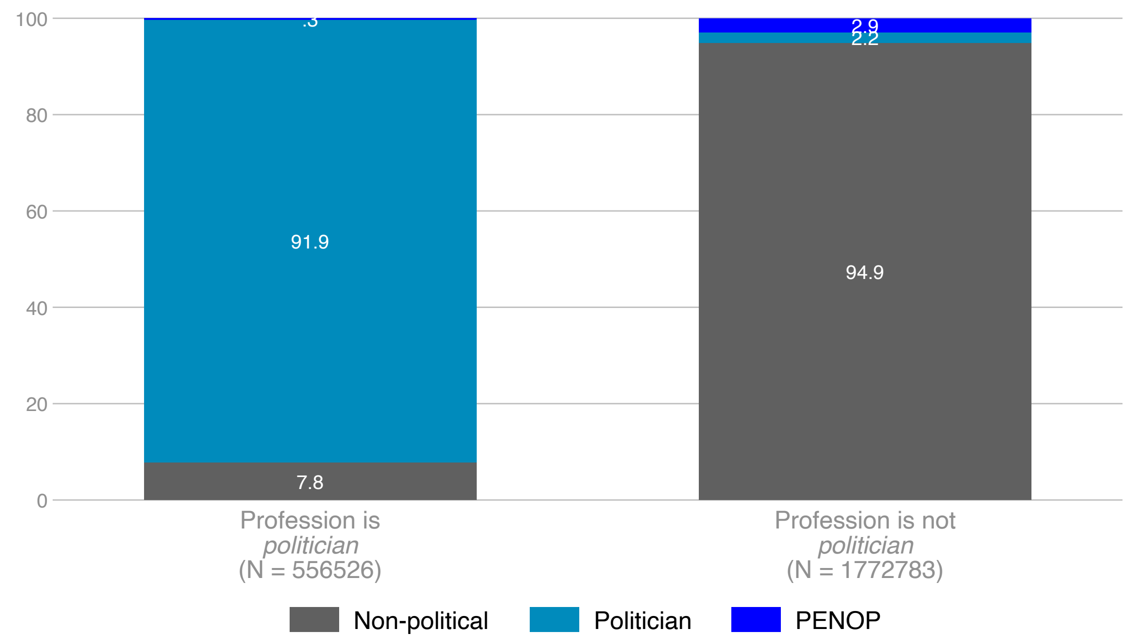
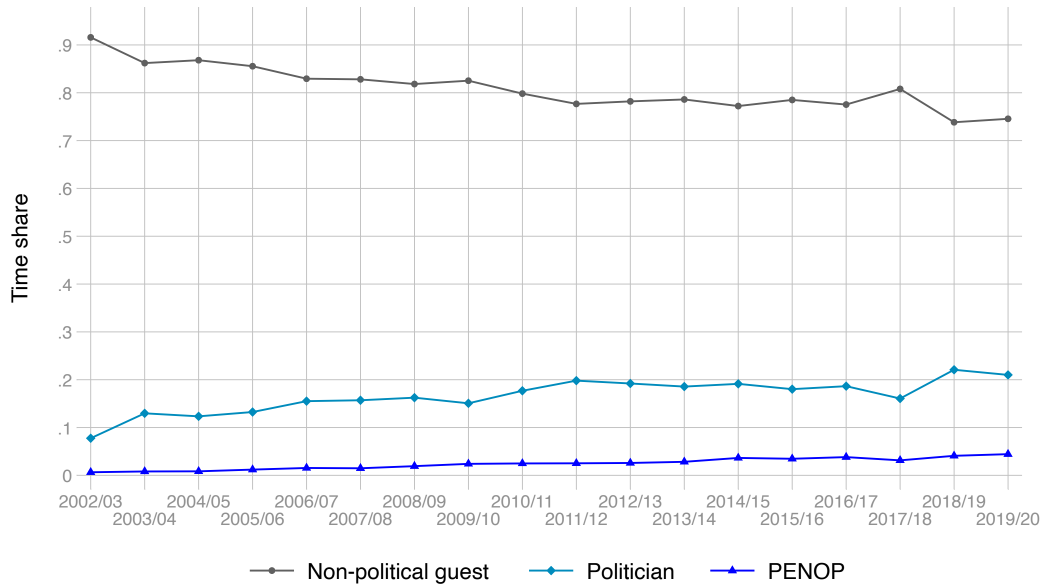
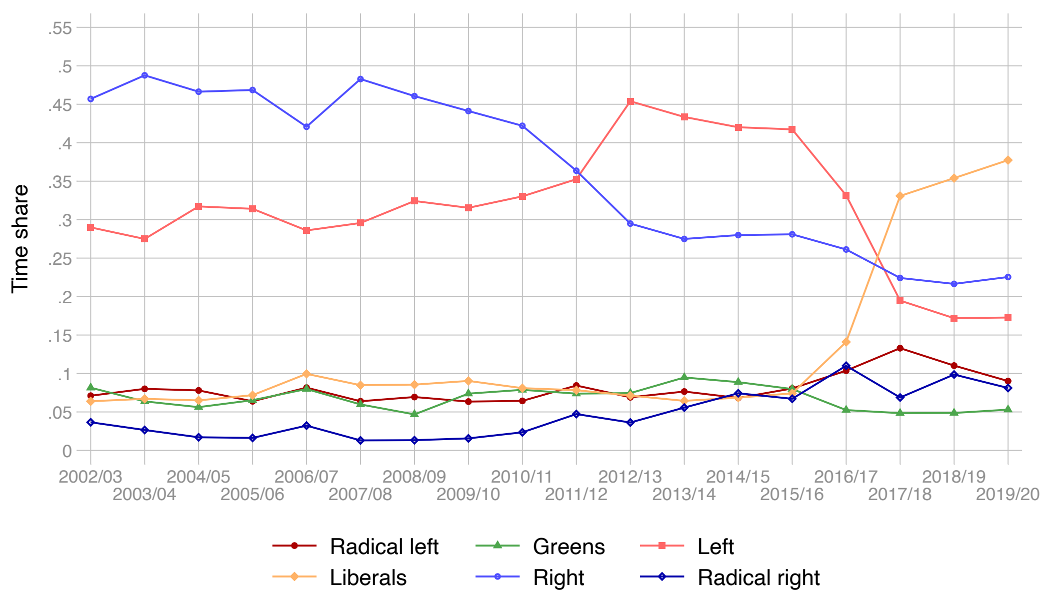


Notes: The Figure reports the share of appearances that are politically classified for two subsets of appearances based on whether or not the guests' INA description (which is time-invariant) includes 'politician' and 'France' (to exclude foreign politicians). Gray areas account for the share of appearances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

Figure 1: Output of appearance classification



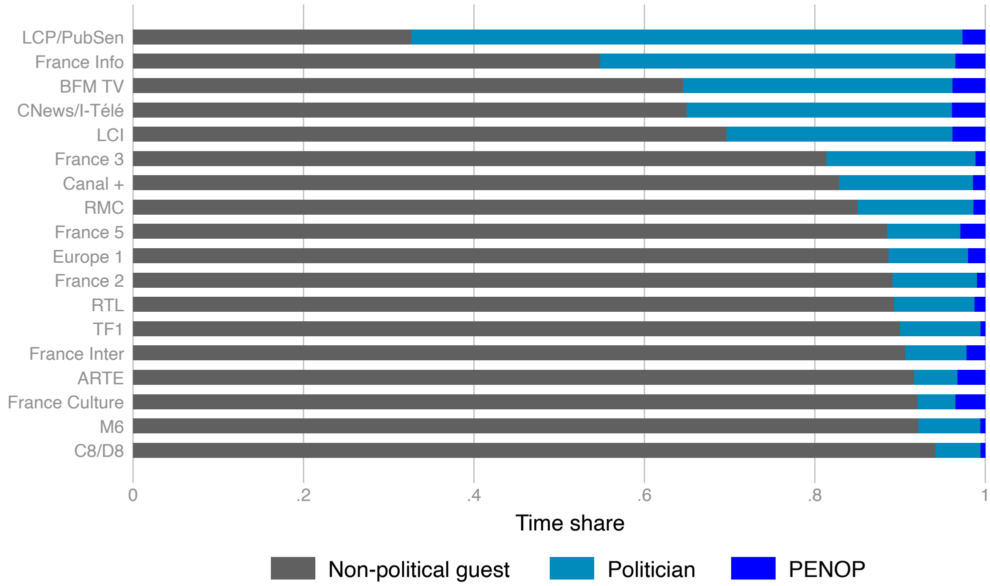
(a) All guests



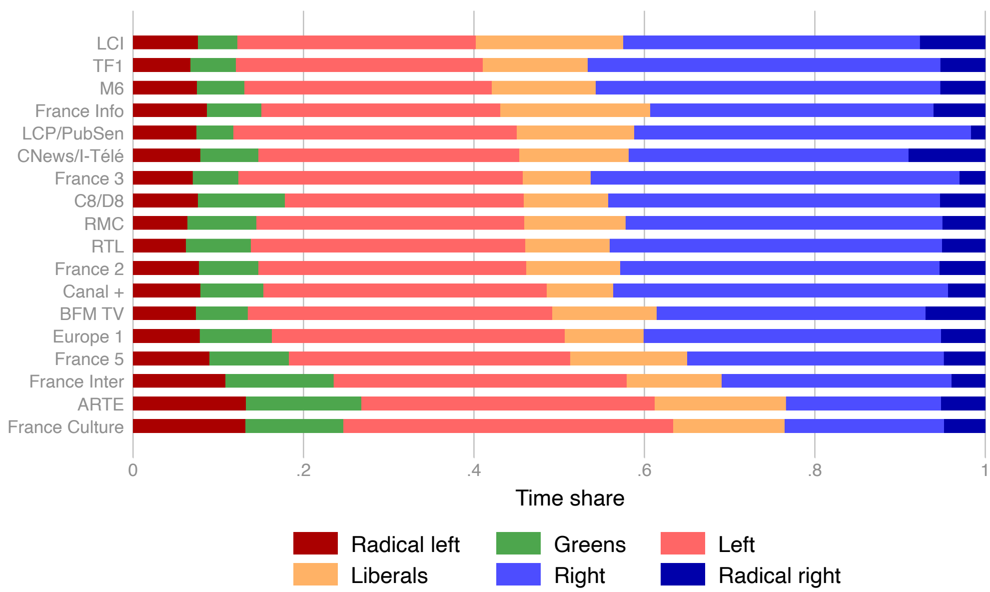
(b) Politically classified guests

Notes: The Figure plots the evolution of the speaking-time share devoted to each group of guests for each season, aggregated over all the outlets in our sample. Sub-figure 2a includes all the guests and sub-figure 2b only the politically-classified guests. The speaking-time share of the political groups includes the speaking time of both politicians and PENOPs.

Figure 2: Evolution of the speaking-time share devoted to guests depending on their group, 2002-2020



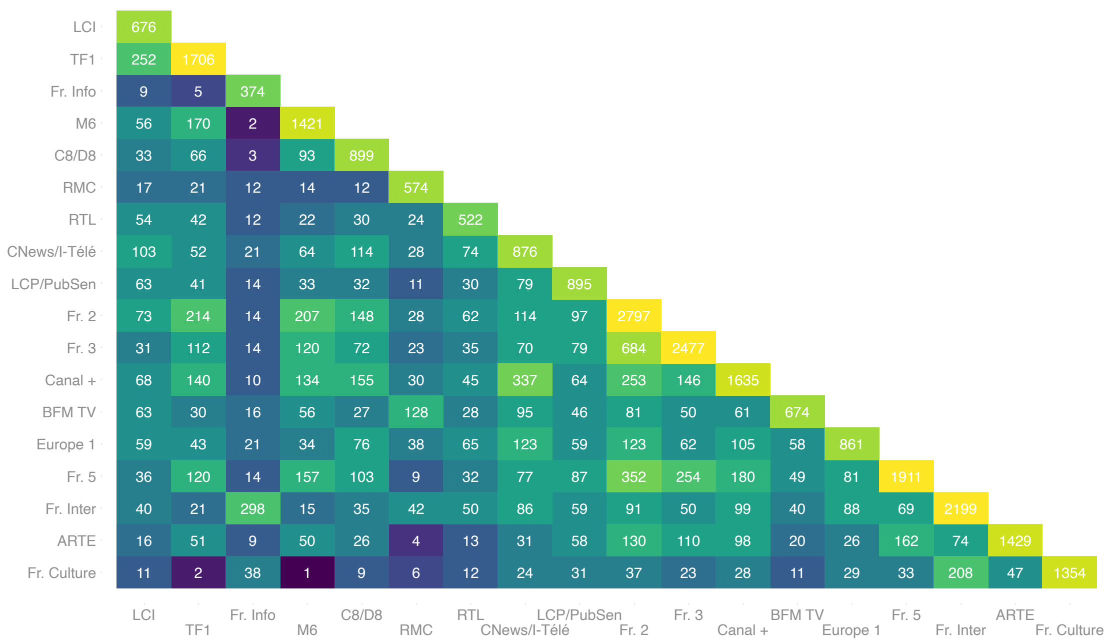
(a) All guests



(b) Politically classified guests

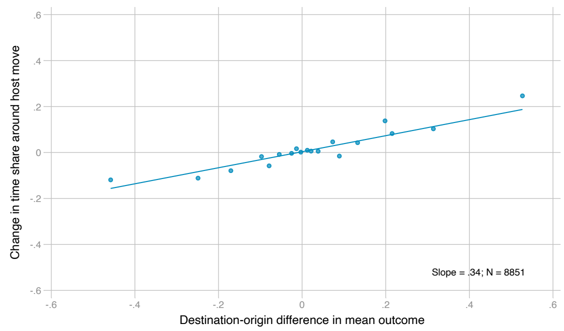
Notes: The Figure plots the speaking-time share dedicated to each group, depending on the media outlet. Sub-figure 3a includes all the guests, while sub-figure 3b only includes the politically classified guests. Media outlets are ranked depending on the time share they devote to the left-wing parties.

Figure 3: Speaking-time share devoted to the different groups of guests, depending on the media outlet

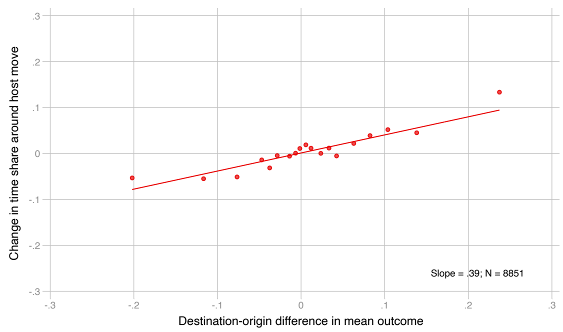


Notes: This Figure plots, for each outlet pair, the number of distinct hosts observed on both outlets in the estimation sample. Figures on the diagonal report the number of distinct hosts observed at least once on the considered outlet, irrespective of whether they are observed on another outlet.

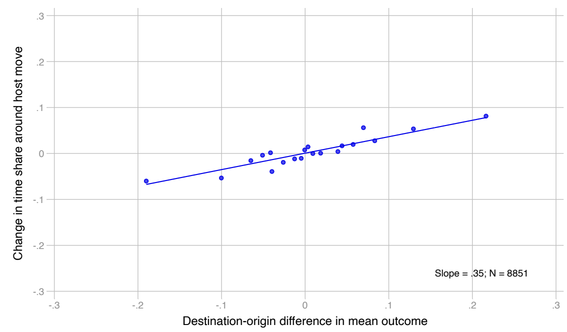
Figure 4: Hosts observed on multiple outlets



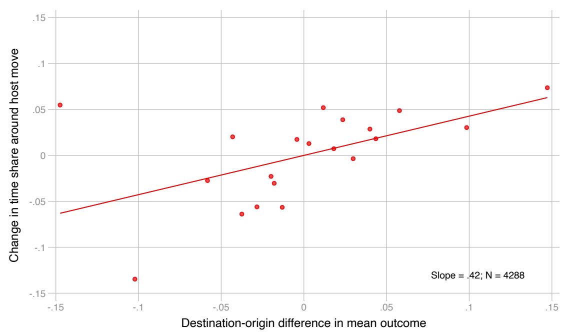
(a) Political guests among all guests



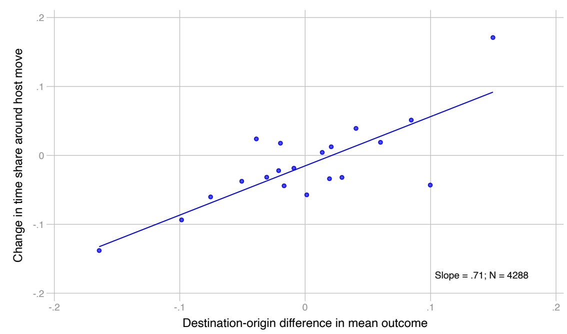
(b) Left-wing guests among all guests



(c) Right-wing guests among all guests



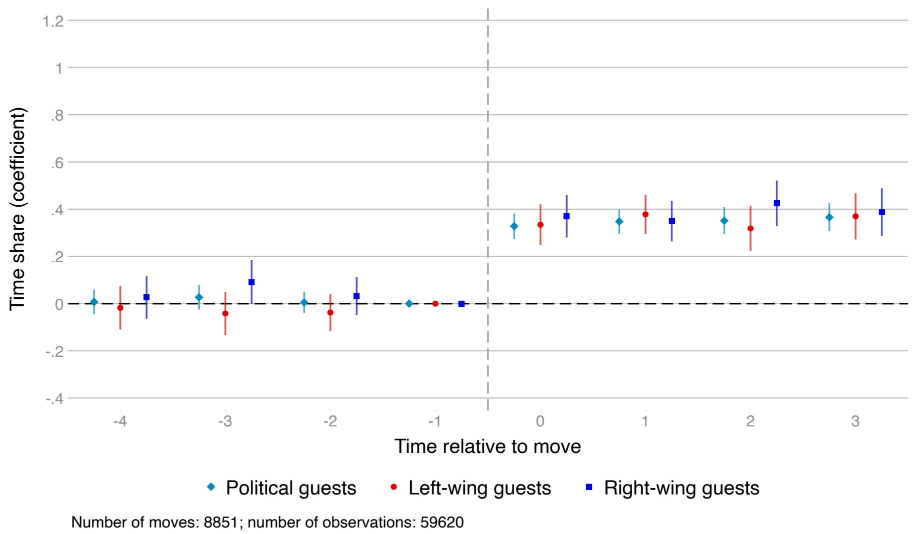
(d) Left-wing guests among political guests



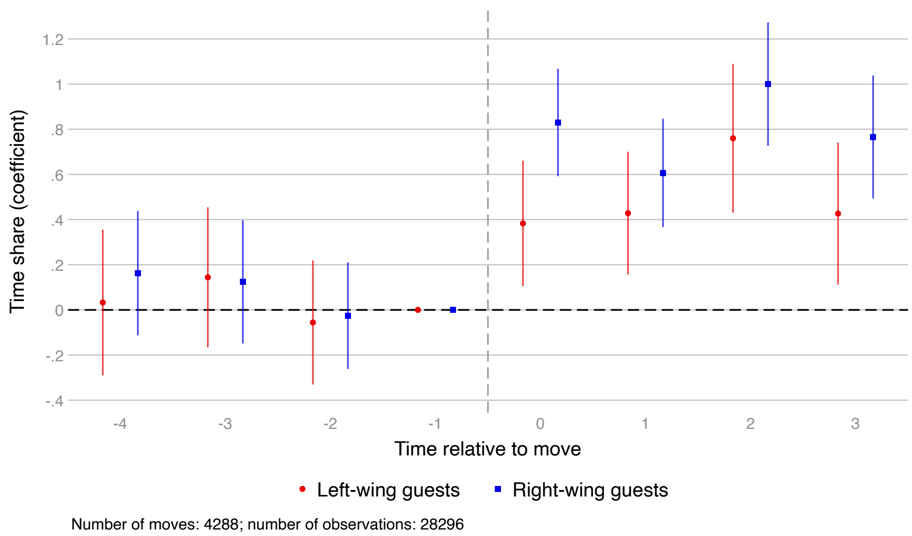
(e) Right-wing guests among political guests

Notes: The Figure shows how the political time share of a given 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 host between the first two post-move weeks and the last two pre-move weeks. The dots are averages computed by vintiles. The line is the best linear fit from an OLS regression. The slope and the number of moves are reported at the bottom of each figure.

Figure 5: Change in moving hosts' political time share against destination-origin channel differences



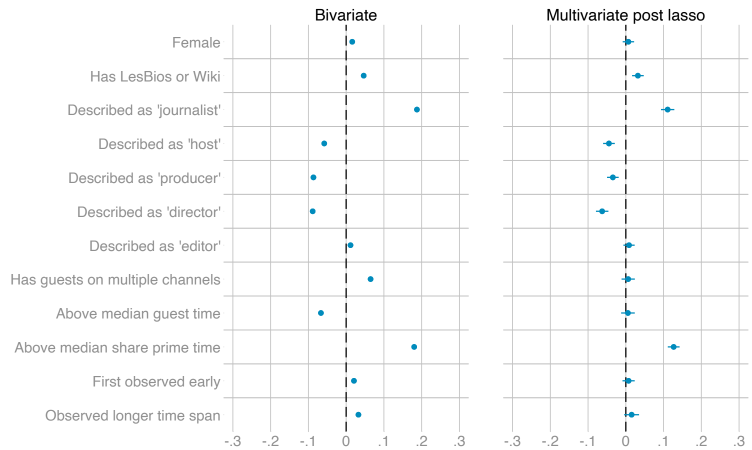
(a) Extensive margin: Share of all guests



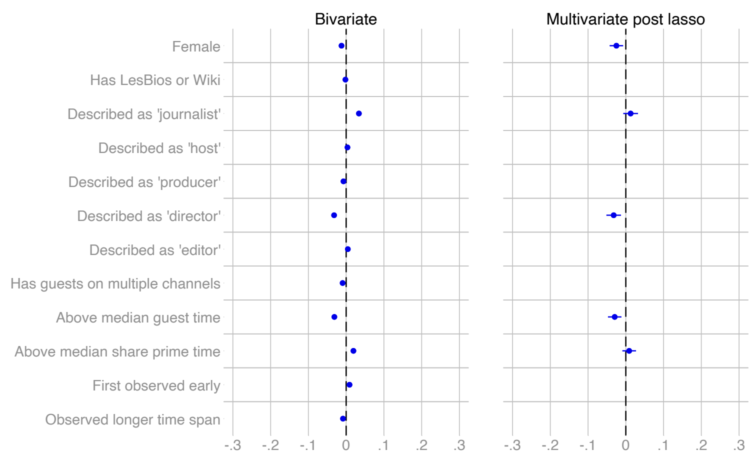
(b) Intensive margin: Share of political guests

Notes: The Figure plots the event-study estimates from equation (1). The dependent variable is the time share devoted by a host to a given group in the weeks before and after the move. Sub-figure 6a expresses the time shares as a share of the total speaking time of guests. Sub-figure 6b expresses these shares as a share of the total speaking time of the political guests alone. Light-blue diamonds report the time share of the political guests, red dots the time share of the left-wing guests, and blue squares report that of the right-wing guests. Vertical bars indicate 95% confidence intervals. Standard errors are clustered at the move level.

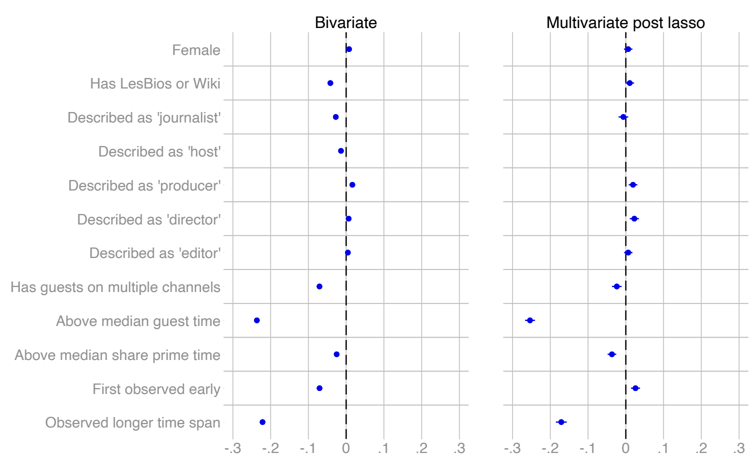
Figure 6: Event study: Change in the time share devoted to different groups around the move



(a) Share of political guests among all guests



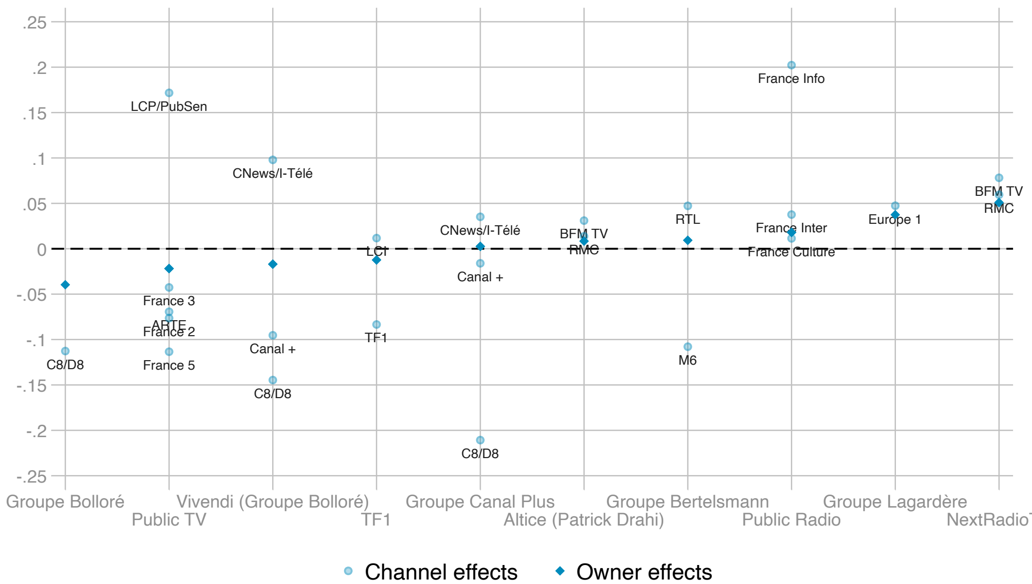
(b) Share of right-wing guests among political guests



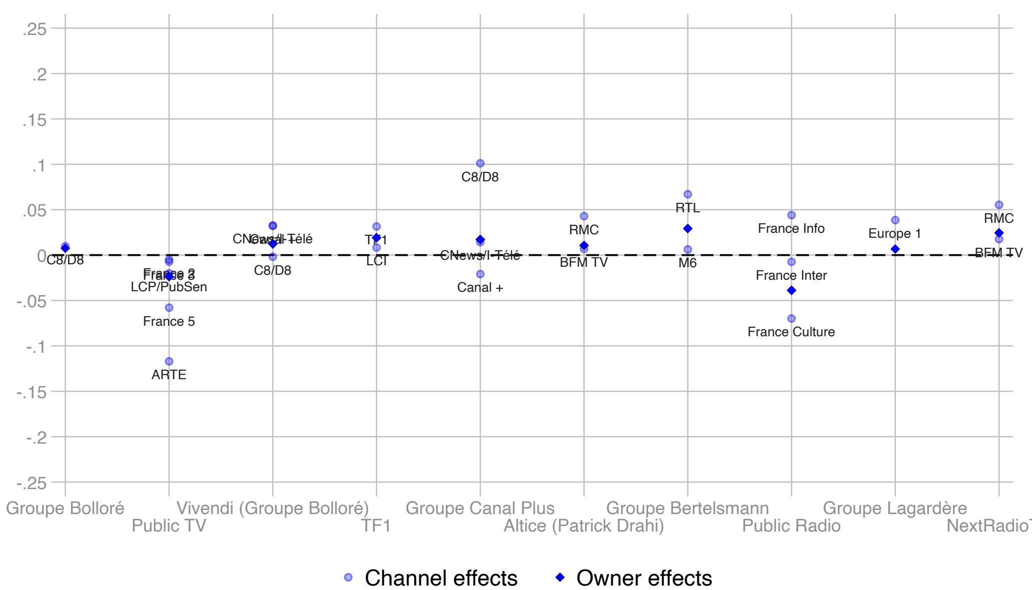
(c) Share of right-wing guests among political guests – Fixed effects absolute value

Notes: The Figures report estimates and robust 95% confidence intervals from bivariate (left) and multivariate (right) OLS regressions of standardized host fixed effects on standardized covariates. In the upper Figure 7a, host fixed effects are obtained when estimating equation (2) with the share of political guests among all guests as the outcome variable. In the middle and bottom Figures 7b and 7c, host fixed effects are obtained using the share of right-wing guests among political guests as the outcome of equation (2). The bottom Figure 7c uses the absolute values of the estimated fixed effects.

Figure 7: Correlates of host fixed effects



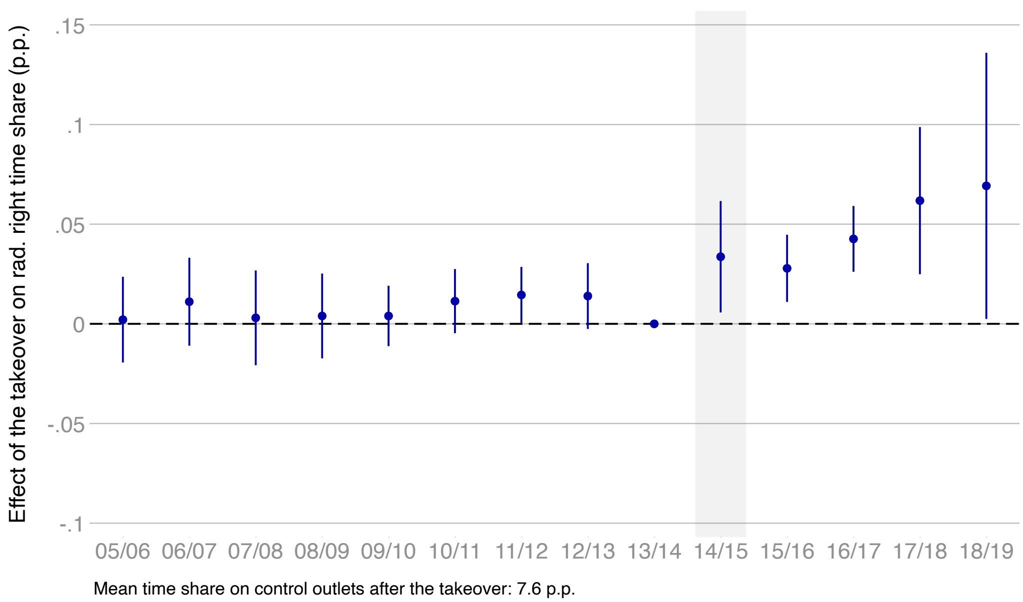
(a) Share of political guests among all guests



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

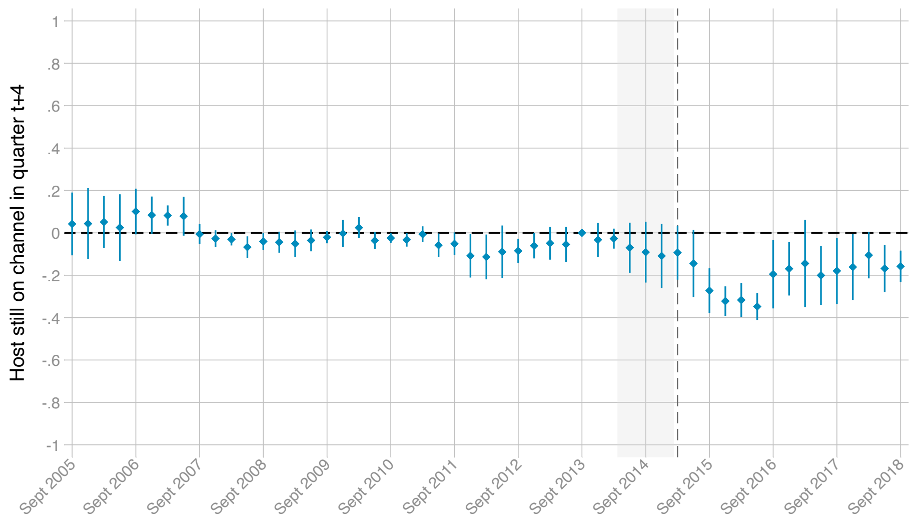
Notes: The Figure reports owner fixed effects estimates from a specification including time fixed effects, host fixed effects, and owner fixed effects (dark-blue diamonds) and mean channel-period fixed effects from equation (2) (light-blue dots). Sub-figure 8a reports the results when we consider the share of political guests among all guests, and sub-figure 8b when we consider the share of right-wing guests among political guests.

Figure 8: Media outlet fixed effects depending on the parent company

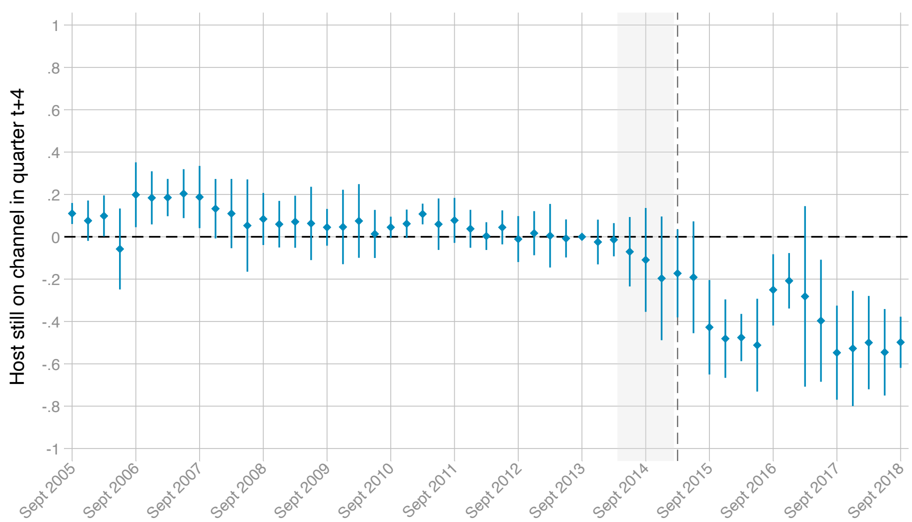


Notes: The Figure plots estimates from the event-study specification corresponding to equation (5). The dependent variable is the speaking-time share of radical-right guests (both politicians and PENOPs are included). The shaded area corresponds to the season running from September 2014 to August 2015 during which Vincent Bolloré took control of the channels. Standard errors are clustered at the channel level, vertical bars indicate 95% confidence intervals.

Figure 9: Event-study regression: Radical-right time shares around takeover



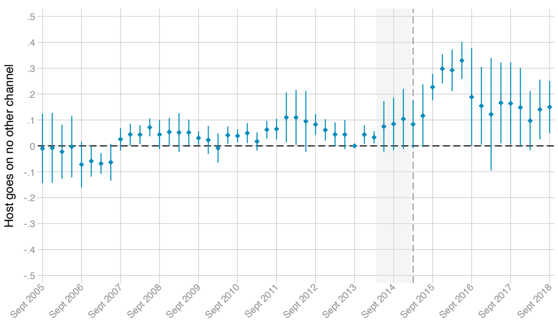
(a) All hosts



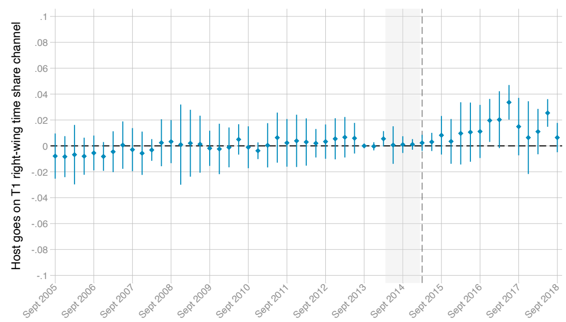
(b) Hosts working as journalists

Notes: The Figure plots estimates from event-study regressions corresponding to equation (8). Sub-figure 10a includes all the hosts, while only the hosts working as journalists are included in sub-figure 10b. The dependent variable is an indicator variable equal to one if 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, when Vincent Bolloré took control of the channels. Standard errors are clustered at the channel level, vertical bars indicate 95% confidence intervals.

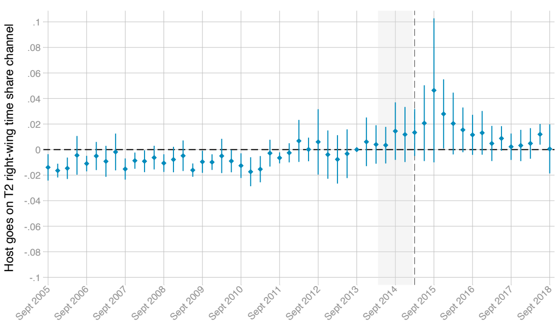
Figure 10: Whether hosts leave – probability of staying on Bolloré's channels after the takeover



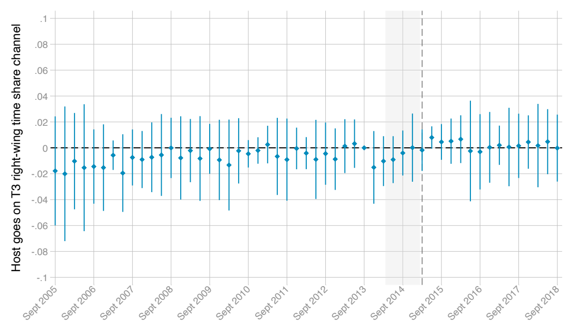
(a) Seen on no other outlet



(b) Seen on T1 of right-wing time share outlet



(c) Seen on T2 of right-wing time share outlet



(d) Seen on T3 of right-wing time share outlet

Notes: The Figure plots estimates from event-study regressions corresponding to equation (8). In sub-figure 11a, the outcome is an indicator variable for whether the host is no longer observed on the channel in quarter $t + 4$ and is observed on no other channel in the sample. In sub-figure 11b (respectively 11c and 11d), the outcome is an indicator variable for whether the host is no longer observed on the channel in quarter $t + 4$ but is observed on channels in the bottom tertile of right-wing time share (respectively the middle tertile and the top tertile). Other notes are as in Figure 10.

Figure 11: Where hosts go – probability of being observed on another outlet following the takeover

Table 1: Descriptive statistics on hosts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All shows	All shows with guests				Shows with political guests		
	All hosts Mean	All hosts Mean	Est. sample Mean	Dist. periods Mean	Dist. channels Mean	Est. sample Mean	Dist. periods Mean	Dist. channels Mean
Descriptive characteristics								
% female	38.25	38.97	39.01	38.97	38.12	40.32	39.75	39.09
% has profession description	90.32	94.29	94.48	98.72	99.19	95.78	99.12	99.35
% prof. *journalist*	54.67	62.84	63.01	72.77	76.26	69.20	77.80	82.13
% prof. *presenter*	5.34	6.02	6.08	7.23	8.51	6.59	7.47	8.67
% prof. *producer*	6.14	6.13	6.16	6.44	4.53	5.69	5.83	4.18
% prof. *director*	18.09	13.49	13.44	12.36	11.42	11.27	10.62	8.45
% w/ LesBios entry	5.64	6.68	6.73	9.13	12.32	8.18	10.91	14.78
% w/ Wikidata entry	11.97	12.47	12.54	15.09	19.05	13.34	16.02	20.67
Media presence								
# distinct days	161.90	202.84	205.75	360.61	416.10	263.99	451.86	515.02
# dist. days w/ pol guest	47.30	47.30	47.40	70.31	91.53	47.40	84.70	112.28
# dist. seasons	3.97	4.64	4.69	7.27	7.53	5.53	8.21	8.37
# dist. seasons w/ pol. guest	4.06	4.06	4.06	5.59	5.88	4.06	6.49	6.77
# distinct channels	1.44	1.55	1.56	1.82	2.75	1.67	1.93	2.90
# dist. channels w/ pol. guest	1.41	1.41	1.41	1.57	2.20	1.41	1.65	2.55
% at least 2 channels	27.52	34.01	34.43	47.58	100.00	40.51	51.97	100.00
% at least 2 chan. w/ pol. guest	26.67	26.67	26.73	36.34	77.33	26.73	40.26	100.00
% has any guest	82.59	100.00	100.00	100.00	100.00	100.00	100.00	100.00
# guests	279.82	361.12	366.49	652.36	830.40	478.31	837.62	1051.57
Political guests								
% has any pol. guest	58.92	74.99	75.89	91.67	94.10	100.00	100.00	100.00
# political guests	62.80	81.06	82.26	148.23	195.83	109.01	195.78	254.52
% time w/ pol. guest	15.31	15.61	15.69	17.04	18.80	20.71	20.95	22.68
% time rad. left	8.83	8.79	8.79	8.82	8.66	8.77	8.61	8.46
% time greens	8.37	8.41	8.42	8.21	7.76	8.42	8.09	7.63
% time left	31.71	31.75	31.75	32.69	32.86	31.77	33.65	33.08
% time liberals	10.95	10.95	10.95	10.27	11.08	10.98	10.39	11.33
% time right	33.04	32.98	32.98	32.87	32.97	32.94	32.35	32.82
% time rad. right	5.24	5.28	5.26	5.52	5.34	5.29	5.43	5.58
# hosts	21,469	16,631	16,386	8,783	4,456	12,365	6,600	3,207
# host-channel pairs	30,894	25,532	23,278	14,693	11,348	17250	10,781	8,092
# host-show pairs	5,587,688	2,191,475	2,182,273	2,088,980	1,299,602	695,364	665,682	434,617

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

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

	All guests			Political guests	
	(1) Political guests	(2) All left	(3) All right	(4) All left	(5) All right
Host FE	Yes	Yes	Yes	Yes	Yes
Channel-Period FE	Yes	Yes	Yes	Yes	Yes
Week-Hour-Platform FE	Yes	Yes	Yes	Yes	Yes
F-stat	371.1	197.5	169.5	21.3	23.9
R-sq.	0.599	0.440	0.435	0.465	0.453
Adj. R-sq.	0.584	0.419	0.414	0.420	0.406
RMSE	0.188	0.139	0.126	0.266	0.258
Observations	1,257,932	1,257,932	1,257,932	481,671	481,671

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

Table 3: Variance decomposition – All guests (extensive margin)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Political guests				All left-wing guests				All right-wing guests			
		SE	%	%		SE	%	%		SE	%	%
Plug-in												
1. $Var(\bar{y}_{cs})$	0.030595	.	100.0	.	0.007316	.	100.0	.	0.005900	.	100.0	.
2. $Var(\bar{\tau}_{cs})$	0.004395	0.000062	14.4	.	0.001253	0.000028	17.1	.	0.000999	0.000021	16.9	.
3. $2Cov(\bar{\tau}_{cs}, \bar{\alpha}_{cs} + \gamma_{cs})$	0.000417	0.000200	1.4	.	0.000159	0.000068	2.2	.	0.000093	0.000053	1.6	.
4. $Var(\bar{\alpha}_{cs} + \gamma_{cs})$	0.025783	0.000310	84.3	100.0	0.005905	0.000105	80.7	100.0	0.004808	0.000093	81.5	100.0
5. $Var(\bar{\alpha}_{cs})$	0.005509	0.000165	18.0	21.4	0.001249	0.000062	17.1	21.2	0.001000	0.000051	16.9	20.8
6. $Var(\gamma_{cs})$	0.010051	0.000290	32.9	39.0	0.002281	0.000104	31.2	38.6	0.002103	0.000098	35.6	43.7
7. $2Cov(\bar{\alpha}_{cs}, \gamma_{cs})$	0.010223	0.000216	33.4	39.7	0.002375	0.000068	32.5	40.2	0.001706	0.000076	28.9	35.5
8. $Corr(\bar{\alpha}_{cs}, \gamma_{cs})$	0.686984	0.015934	.	.	0.703344	0.022878	.	.	0.588305	0.031134	.	.
Split-sample												
9. $Var(\bar{\alpha}_{cs} + \gamma_{cs})$	0.025790	0.000319	84.3	100.0	0.005877	0.000103	80.3	100.0	0.004815	0.000097	81.6	100.0
10. $Var(\bar{\alpha}_{cs})$	0.005525	0.000166	18.1	21.4	0.001244	0.000063	17.0	21.2	0.001000	0.000049	16.9	20.8
11. $Var(\gamma_{cs})$	0.010026	0.000286	32.8	38.9	0.002253	0.000103	30.8	38.3	0.002103	0.000096	35.6	43.7
12. $2Cov(\bar{\alpha}_{cs}, \gamma_{cs})$	0.010239	0.000223	33.5	39.7	0.002380	0.000067	32.5	40.5	0.001713	0.000080	29.0	35.6
13. $Corr(\bar{\alpha}_{cs}, \gamma_{cs})$	0.683897	0.031984	.	.	0.701841	0.044436	.	.	0.584562	0.064335	.	.
Observations												
14. N channel-period pairs	126	.	.	.	126	.	.	.	126	.	.	.

Notes: The Table reports components of the variance decomposition proposed in equation (4) based on the parameters estimated using equation (2). Columns 1 to 4 (resp. 5 to 8 and 9 to 12) consider the variance in the share of political guests (resp. left-wing guests and right-wing guests) among all guests. The first row reports cross outlet-period variance in time share, the second reports the variance of time components and the third reports the covariance between time components and channel and host components. Row 4 reports the variance of channel and host components. Rows 5 and 6 show the variance of host components and of channel-period components, respectively. Row 7 reports the covariance between channel-season and host components, times two. Row 8 reports the correlation between host and channel-period components. Rows 9 to 13 use a split-sample method to report the same components as rows 4 to 8. Columns 2, 6 and 10 report bootstrapped standard errors for each component. Columns 3, 7 and 11 express the variance of each component as a share of total variance while Columns 4, 8 and 12 do the same as a share of net-of-time variance.

Table 4: Variance decomposition – Political guests (intensive margin)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All left-wing guests				All right-wing guests			
		SE	%	%		SE	%	%
Plug-in								
1. $Var(\bar{y}_{cs})$	0.009428	.	100.0	.	0.009875	.	100.0	.
2. $Var(\bar{\tau}_{cs})$	0.005258	0.000207	55.8	.	0.005365	0.000228	54.3	.
3. $2Cov(\bar{\tau}_{cs}, \bar{\alpha}_{cs} + \gamma_{cs})$	0.000480	0.000276	5.1	.	0.000462	0.000282	4.7	.
4. $Var(\bar{\alpha}_{cs} + \gamma_{cs})$	0.003691	0.000224	39.1	100.0	0.004048	0.000248	41.0	100.0
5. $Var(\bar{\alpha}_{cs})$	0.000331	0.000102	3.5	9.0	0.000281	0.000104	2.8	6.9
6. $Var(\gamma_{cs})$	0.003023	0.000329	32.1	81.9	0.003353	0.000392	34.0	82.8
7. $2Cov(\bar{\alpha}_{cs}, \gamma_{cs})$	0.000336	0.000246	3.6	9.1	0.000414	0.000324	4.2	10.2
8. $Corr(\bar{\alpha}_{cs}, \gamma_{cs})$	0.167792	0.091007	.	.	0.213454	0.120330	.	.
Split-sample								
9. $Var(\bar{\alpha}_{cs} + \gamma_{cs})$	0.003531	0.000243	37.4	100.0	0.003916	0.000268	39.7	100.0
10. $Var(\bar{\alpha}_{cs})$	0.000288	0.000125	3.1	8.1	0.000222	0.000117	2.2	5.7
11. $Var(\gamma_{cs})$	0.002759	0.000369	29.3	78.1	0.003214	0.000426	32.6	82.1
12. $2Cov(\bar{\alpha}_{cs}, \gamma_{cs})$	0.000484	0.000292	5.1	13.7	0.000481	0.000353	4.9	12.3
13. $Corr(\bar{\alpha}_{cs}, \gamma_{cs})$	0.198175	0.171270	.	.	0.208395	0.205277	.	.
Observations								
14. N channel-period pairs	126	.	.	.	126	.	.	.

Notes: The Table reports components of the variance decomposition proposed in equation (4) based on the parameters estimated using equation (2). Columns 1 to 4 (resp. 5 to 8) consider the variance in the share of left-wing guests (resp. right-wing guests) among political guests. Other notes are as in Table 3.

Table 5: Effect of the takeover on the time share of each political group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. With channel fixed effects						
	Political	Rad. left	Greens	Left	Liberal	Right	Rad. right
Treated×2015/17	0.0198	0.00487	-0.00116	-0.0106	-0.00493	-0.00593	0.0198**
	(0.0254)	(0.00756)	(0.00429)	(0.0147)	(0.00608)	(0.00663)	(0.00874)
Treated×2017/19	0.0220	0.00351	-0.00413	0.00368	-0.0294	-0.0297	0.0553*
	(0.0277)	(0.0117)	(0.00360)	(0.0136)	(0.0283)	(0.0184)	(0.0290)
Observations	150036	79537	79537	79537	79537	79537	79537
R^2	0.622	0.433	0.413	0.477	0.540	0.502	0.466
$\bar{y}(control, post)$	.216	.101	.06	.304	.202	.246	.076
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel B. With host-channel fixed effects						
	Political	Rad. left	Greens	Left	Liberal	Right	Rad. right
Treated×2015/17	0.00610	-0.0130	-0.000879	-0.00985	-0.00547	0.0153	0.0165***
	(0.0191)	(0.0104)	(0.00335)	(0.0151)	(0.00704)	(0.0109)	(0.00435)
Treated×2017/19	0.0531	-0.0220	-0.0103	-0.00862	0.0120	0.000515	0.0319*
	(0.0308)	(0.0205)	(0.00714)	(0.0161)	(0.0241)	(0.0206)	(0.0175)
Observations	1268386	478235	478235	478235	478235	478235	478235
R^2	0.626	0.452	0.441	0.466	0.529	0.477	0.465
$\bar{y}(control, post)$	.216	.101	.06	.304	.202	.246	.076

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

Table 6: Probability that hosts are observed on the same channel a year later

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline	1(Has guests)	1(Has pol. guests)	1(Journalist)	1(Producer)	1(Newscast)	1(Male)	1(LesBios/Wiki)	1(2y ago)	1(Prime)	1(FE rad right>0)	1(FE rad right>0)
Treated × 2015/17	-0.189***	-0.193***	-0.119***	-0.138**	-0.220***	-0.125**	-0.284***	-0.189***	-0.109**	-0.168***	-0.231***	-0.339***
	(0.0502)	(0.0468)	(0.0381)	(0.0522)	(0.0466)	(0.0568)	(0.0608)	(0.0528)	(0.0477)	(0.0464)	(0.0563)	(0.0341)
Treated × 2017/19	-0.117*	-0.152**	-0.107	-0.0491	-0.139**	-0.0777	-0.259***	-0.150*	-0.178***	-0.102*	-0.157	-0.250*
	(0.0667)	(0.0651)	(0.0666)	(0.0506)	(0.0653)	(0.0644)	(0.0490)	(0.0821)	(0.0418)	(0.0550)	(0.103)	(0.143)
Treated × 2015/17 × Interaction=1		0.00281	-0.149***	-0.159***	0.198***	-0.317**	0.132***	0.00647	-0.0670***	-0.0618**	0.0523*	0.0774***
		(0.0396)	(0.00897)	(0.0379)	(0.0458)	(0.120)	(0.0333)	(0.0263)	(0.0106)	(0.0250)	(0.0292)	(0.0233)
Treated × 2017/19 × Interaction=1		0.0412	-0.00343	-0.414***	0.0963	-0.366***	0.186***	0.113**	0.154***	-0.0479	0.0851	0.196*
		(0.0258)	(0.0443)	(0.0610)	(0.0615)	(0.109)	(0.0524)	(0.0470)	(0.0344)	(0.0571)	(0.0764)	(0.106)
Observations	278566	278566	278566	278566	278566	278566	278566	278566	278566	278566	242418	116564
R^2	0.496	0.497	0.497	0.497	0.497	0.497	0.496	0.496	0.501	0.496	0.458	0.495
$\bar{y}$ (control, post)	0.505											
$\bar{y}$ (control, post, inter=0)		0.391	0.441	0.513	0.514	0.470	0.491	0.493	0.363	0.488	0.534	0.587
$\bar{y}$ (control, post, inter=1)		0.542	0.588	0.496	0.461	0.562	0.515	0.554	0.607	0.535	0.551	0.594

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. The interaction variable indicates whether the host has guests in t (Column 2), whether the host has political guests in t (Column 3), whether the host is working as a journalist in t (Column 4), whether the host works as a producer in t (Column 5), whether the host works for a newscast (Column 6), whether the host is male (Column 7), whether the host has a *Les Biographies* or Wikidata entry (Column 8), whether the host was observed on the channel two years ago (Column 9), whether the host has a show in prime time (Column 10), whether the host has a strictly positive host FE when estimating equation (2) using the time share dedicated to radical-right guests as a share of political guests as the dependent variable (Column 11), and whether this host FE is strictly positive among hosts who have political guests in t (Column 12). The last rows report the mean of the outcome variable on control channels for the period ranging from April 2015 to August 2019. Standard errors are clustered at the outlet level and stars indicate significance at the 1, 5, and 10% with ***, **, and *, respectively.