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ABSTRACT

Media Coverage of Immigration and the Polarization of Attitudes*

This paper investigates the effect of media coverage on immigration attitudes. It combines data on immigration coverage in French television with individual panel data from 2013 to 2017 that records respondents' preferred television channel and attitudes toward immigration. The analysis focuses on within-individual variations over time, addressing ideological self-selection into channels. We find that increased coverage of immigration polarizes attitudes, with initially moderate individuals becoming more likely to report extremely positive and negative attitudes. This polarization is mainly driven by an increase in the salience of immigration, which reactivates preexisting prejudices, rather than persuasion effects from biased news consumption.

JEL Classification: D8, F22, L82

Keywords: immigration, media, polarization, salience

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"The news media isn't just an actor in politics. It's arguably the most powerful actor in politics". Klein (2020), *Why We're Polarized*, pp. 240.

Against the backdrop of the 2015 refugee crisis and rising migration flows, immigration has emerged as a highly contentious and politically charged issue, particularly in Europe and the United States. This surge in public and media attention coincided with the rise of nationalist and populist movements, such as Germany's AfD, Italy's Lega, France's Front National, and the Republicans under Donald Trump's leadership, who took a strong anti-immigration stance (Guriev and Papaioannou, 2022). Drawing on accessibility-based models from media theories, such as agenda-setting and priming,[1] one can hypothesize that increased media attention on immigration has heightened viewers' focus on the issue and reactivated preexisting prejudices against immigrants.

This paper aims to investigate the relationship between media coverage of immigration and the formation of attitudes toward immigration. To accurately capture the prevalence of immigration on television, we use data from the French National Audiovisual Institute (INA), which records a detailed description of all subjects covered by French television channels. This allows us to provide a comprehensive picture of immigration's overall prominence and representation in French evening television news over time, including its framing toward specific topics or sentiments. These television data are then combined with individual panel data from the ELIPSS survey (Longitudinal Internet Studies for Social Sciences) to track individuals' attitudes toward immigration in 12 distinct waves between January 2013 and December 2017. Unlike most papers that use geographical or experimental variations in media coverage, this paper links respondents to their preferred television channel for political information, and thus to their actual media exposure. The richness of our panel dataset also allows us to control for individual, channel, and wave fixed effects in the main empirical specification, effectively mitigating concerns related to self-selection *i.e* individuals watching television channels that align with their ideology.[2]

The main result of this paper is that increased news coverage of immigration polarizes attitudes. There is a shift in the distribution of attitudes toward both extremes, as individuals with initially moderate attitudes become more likely to

[1]See Scheufele and Tewksbury (2007) for a detailed review of media theories.

[2]Durante et al. (2019), for instance, demonstrate that Italian viewers changed their favorite news programs in response to a change in news content on public television after the 2001 national elections. Other empirical tests in the paper support our findings that the results are not sensitive to self-selection on observables and unobservables, and are unlikely to be driven by an endogenous adjustment of TV channels or time-varying shocks correlated with individual unobservables that would be not absorbed by fixed effects.

report extremely positive and negative attitudes. This asymmetric change results from initial belief heterogeneity; those with initially moderately positive attitudes become extremely positive, while those with initially moderately negative attitudes become more concerned about immigration. In terms of magnitude, we find that a one-standard-deviation increase (1.9%) in the share of immigration-related subjects in overall broadcasting is associated with a five percentage point increase in the likelihood that individuals with moderate attitudes report extreme attitudes. These results translate to the political level, with a polarization of voters toward parties with the most extreme positive and negative immigration stances.

Consistent with polarization at both ends of the distribution of attitudes, an increase in immigration coverage has no effect on the average immigration attitude in the population. This supports previous findings by Baysan (2022) who studied a randomized door-to-door informational campaign in Turkey designed to warn voters about the threat posed by a referendum aimed at reducing executive power constraints. She showed that the null average effect on vote shares concealed polarization on both sides of the political spectrum, particularly in areas with a high concentration of moderate voters. We confirm the importance of looking beyond average effects when investigating how exposure to the same information affects individual attitudes and beliefs. We focus on situations in which individuals are exposed to information about immigration, through media consumption rather than direct contact,[3] and not through a single shock, but rather through repeated exposure to information over time. Unlike Baysan (2022), who uses ballot-box-level data, we precisely characterize individuals who polarize as those with initially moderate attitudes toward immigration who move to the extremes of the distribution based on their initial inclination.

Several tests in the paper support interpreting our results through the lens of salience. Salience must be understood here as the psychological process by which an individual's limited attention is increasingly drawn to a prominent topic, resulting in the topic being overweighted in subsequent decisions (Kahneman, 2011; Bordalo et al., 2013).[4] Within our framework, increased immigration coverage raises the prominence of this subject in the minds of TV viewers, causing them to place greater emphasis on the immigration topic when forming their opinion, thereby amplifying their initial position on the distribution of attitudes

[3]Baysan (2022) specifies that the goal of the door-to-door campaign was to inform voters by specifically circumventing the government's strict media censorship.

[4]See Eisensee and Strömberg (2007) or Snyder Jr and Strömberg (2010) for striking examples of the role of the press in driving the salience of a specific topic.

from moderate to extreme.[5] Consistent with this interpretation, polarization of moderates occurs even when they are exposed to the same topic, a neutral tone, or information from the same channel, namely for viewers exposed to the same information.

We provide further evidence that the polarization of moderates is not explained by i) motivated reasoning, when TV viewers seek and accept information that aligns with their pre-existing beliefs while discounting or dismissing contradictory information, or ii) persuasion, when TV viewers exposed to differing information sets and framing update their attitudes in different directions depending on the bias of the news, resulting in the so-called "echo-chamber" effect (Zhuravskaya et al., 2020). We find motivated thinking to be only relevant for individuals who already have extremely positive or negative attitudes, and not for individuals who have moderate attitudes, as this strategic adjustment requires strong initial attitudes (Swire et al., 2017).[6]

This paper contributes to the fast-growing literature on the impact of salience on political attitudes. Existing papers in the context of migration manipulates the salience of the topic using experimental settings (Dennison and Geddes, 2019; Hopkins et al., 2019; Grigorieff et al., 2020; Dylong and Silke, 2022).[7] Alesina et al. (2022) randomize the order in which respondents receive questions about immigration and redistribution in an online survey experiment and find that i) priming immigration without any additional information deteriorates natives' attitudes toward immigration and ii) this salience effect overcomes the positive impact of exposure to positive anecdotes about immigrants. Similarly, Barrera et al. (2020) used an online survey experiment during the 2017 French presidential election campaign to randomly expose respondents to fact-checking on far-right statements. The results show that i) fact-checking successfully corrects people's misconceptions and beliefs about immigration but ii) has no effect on their voting preferences because the negative impact of fact-checked erroneous statements on far-right support is compensated by the salience effect of fact-checking exposure. Our paper provides additional out-of-the-lab evidence on the

[5] Similarly, Baysan (2022) suggests that the information campaign may have increased the salience of authoritarianism, causing individuals to pay more attention to this topic.

[6] Specifically, pro-immigration individuals are more likely to maintain extremely favorable attitudes when exposed to neutral and positive information but not when exposed to negative information, which aligns with motivated reasoning. There is also a significant backlash toward more negative attitudes when anti-immigration viewers are exposed to positive immigration coverage that sharply contradicts their initial beliefs.

[7] This paper does not cover the literature on the direct impact of immigration on natives' attitudes and votes; refer to Alesina and Tabellini (2022) for a review. Similarly, see Barber and Odean (2007); Chetty et al. (2009); Finkelstein (2009); Bordalo et al. (2013, 2015); Ochsner and Roesel (2023) for examples of the impact of salience on individuals' decisions and beliefs.

relevance and importance of salience in determining natives' attitudes toward immigration.

Other papers use quasi-natural experiments to capture meaningful variations in the salience of migration, such as Gagliarducci and Tabellini (2021) with the construction of Catholic churches in the U.S. between 1890 and 1920 that increased the salience of the Italian community, Ochsner and Roesel (2023) with Austrian far-right populist campaigns that reactivated anti-Muslim sentiments in the mid-2000s, or Giavazzi et al. (2020) with the salience of immigration in German social networks following criminal events or terrorist attacks between 2013 and 2017. These papers find that priming immigration sways natives' attitudes in a particular direction, mostly increasing anti-immigration attitudes. A notable exception that does not identify an average effect is Colussi et al. (2021), who find that the increased salience of the Muslim population during Ramadan is associated with increased support for extreme parties (both left and right) in German municipalities with mosques. Compared to this paper, which cannot distinguish whether the effect occurs as a result of media exposure or direct contact with immigrants, our study systematically associates individuals with their exposure to television news. Similarly, we show that short-term variations in the salience of immigration are a strong driver of political polarization.

This paper also speaks to the emerging literature on the cultural and political polarization (DiMaggio et al., 1996; Fiorina and Abrams, 2008; Desmet et al., 2017; Martin and Yurukoglu, 2017; Gentzkow et al., 2019; Alesina et al., 2020). Unlike most studies focusing on the United States, we provide evidence for polarization in a European country. Additionally, while existing works suggest that social media may drive polarization by creating echo chambers that exacerbate political divisions (Bail et al., 2018; Levy, 2020; Allcott et al., 2020; Zhuravskaya et al., 2020; Cinelli et al., 2021), this paper shows that traditional media, such as television, can also contribute to polarization by simply making a topic more salient. This result is important, as television news is less ideologically targeted and more frequently fact-checked than information spread on social media.

Finally, this paper also contributes to a lesser extent to the literature on the role of media in shaping political attitudes where seminal papers use exogenous variation in broadcasting or penetration to derive causality.[8] This paper specifi-

[8]See DellaVigna and Kaplan (2007); Gerber et al. (2009); Enikolopov et al. (2011); DellaVigna et al. (2014); Barone et al. (2015); Martin and Yurukoglu (2017); Mastrorocco and Minale (2018) for causal inference and DellaVigna and Gentzkow (2010); DellaVigna and La Ferrara (2015); Enikolopov and Petrova (2015) for extended reviews of the literature on the impact of media on political outcomes.

cally focuses on attitudes toward immigration (Boomgaarden and Vliegenthart, 2009; De Philippis, 2009; Héricourt and Spielvogel, 2014; de Coulon et al., 2016; Facchini et al., 2017; Benesch et al., 2019; Couttenier et al., 2021; Keita et al., 2023; Djourelova, 2023) but does so without an experimental design. Instead, we use systematic within-channel variations in the coverage of immigration to investigate the effect of differential monthly exposure to immigration through television, and the panel dimension allows us to focus on intra-individual variability rather than local average effects.

The rest of the paper is organized as follows. Section I describes the data on individuals' attitudes and media reporting on immigration. Section II describes the empirical and identification strategies. Section III reports the main results and Section IV discusses additional tests that discriminate between alternative interpretations of the results. Finally, Section V concludes the paper.

I Data

This section describes and provides descriptive statistics for the main datasets used in this paper. First, we present attitudes toward immigration from the ELIPSS panel survey and document the extent to which viewers self-select into TV channels. Then, using data from the French National Audiovisual Institute (INA), we characterize the coverage of the immigration topic on French television between January 2013 and December 2017.

A Attitudes Toward Immigration and Self-Selection into TV Channels

Individual attitudes toward immigration are measured with the ELIPSS survey (Tiberj and Goujou, 2020). In this representative panel study, respondents are asked to complete a 30-minute self-administered questionnaire using a touch-screen tablet. The 2013 pilot study included 1,039 individuals, 80% of whom remain in the 2016 sample, alongside 2,514 new individuals who joined the panel.

This paper employs 12 specific waves of the ELIPSS panel that measure individual attitudes toward immigration in France between September 2013 and November 2017 (see Table 1). We focus on French citizens aged 18 to 79 years who report television to be one of their two main sources of political information and watch news programs at least one day per week.[9] Taking into account

[9]Of the respondents, 69% report television as a source of political information, well ahead of

missing information for specific waves and controls, our final sample for analysis consists of 6,776 observations from 1,312 unique respondents.[10]

Table 1: Number of Individual Observations per Wave

Wave	Year	Month	Obsv.	%	Q1	Q2	Q3
1	2013	September	464	6.83	x	x	x
2	2013	December	447	6.58		x	x
3	2014	April	405	5.96	x		
4	2014	June	406	5.97	x	x	x
5	2014	December	412	6.0	x		x
6	2015	March	382	5.62	x	x	x
7	2015	April	417	6.14		x	
8	2015	June	393	5.78	x	x	x
9	2015	December	393	5.78	x	x	x
10	2016	September	1,068	15.72	x	x	x
11	2017	May	982	14.45	x	x	x
12	2017	November	1,027	15.11	x	x	x
Total:			6,796	100			

Notes: This table reports the number of individual observations per wave in the benchmark sample. Q1, Q2, and Q3 indicate whether the three statements used in the analysis, namely *"There are too many immigrants in France"*, *"France's cultural life is enriched by immigrants"*, and *"French Muslims are French citizens same as any others"*, respectively, are recorded in each specific wave.
Source: Authors' elaboration on ELIPSS data.

Respondents are asked to answer to what extent they agree or disagree with the following statements (Q1) *There are too many immigrants in France*, (Q2) *France's cultural life is enriched by immigrants* and (Q3) *French Muslims are French citizens same as any others*. Respondents specify their level of agreement with each statement on a four-point Likert scale ranging from strongly agree (1) to strongly disagree (4). To ensure comparability between answers, we first recode answers from different questions such that higher values always represent more negative attitudes toward immigration or Muslim citizens. Then, we compute $Attitudes_{it}$ as the average attitude of individual i in wave t on the three aforementioned dimensions.[11]

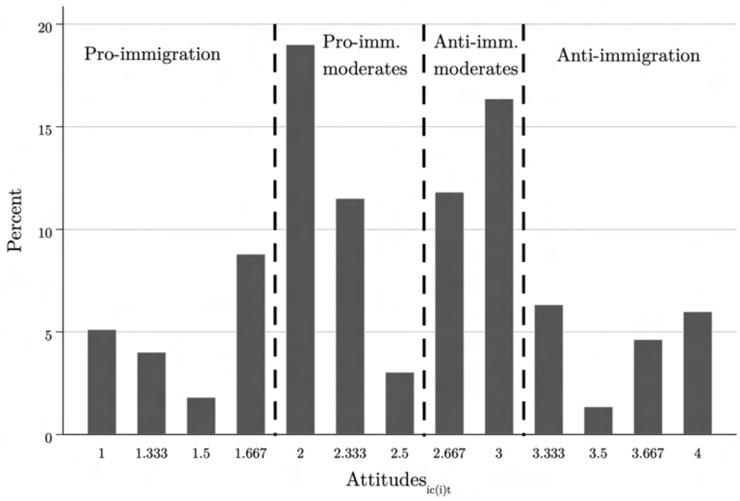
radio (44%), internet (42%), or newspapers (26%). Among TV viewers, 75% declared watching television at least five days a week. These numbers are consistent with findings by Kennedy and Prat (2019) who report that all "three top media organizations in France are primarily television-based" and that citizens mainly obtain their information from these media. It also echoes the 2021 Reuters Institute Digital News Report, which shows that despite a slight decline in favor of online information, TV remained the first source of information for news in France between 2013 and 2021.

[10]See Figure A1 for a detailed description of sample selection.

[11]Note that not all three questions are included in every survey wave, as detailed in Table 1. Consequently, the average is consistently computed based on the available questions.

Figure 1 depicts the distribution of pooled $Attitudes_{it}$ within our sample, which closely follows a normal distribution, with the majority of respondents reporting moderate attitudes toward immigration. Following Fisher (1958), we categorize respondents' attitudes toward immigration into four groups using bins constructed by minimizing the sum of squared deviations from the group mean. Then, we define the categorical variable $Attitudes_{it}^{Cat.} \in$ {Pro-immigration, Pro-immigration moderate, Anti-immigration moderate, Anti-immigration}, which assigns each observation to one of the groups. Approximately 33.60% of the respondents are considered *pro-immigration moderates* with $Attitudes_{it} \in [2; 2.5]$, while 28.22% of them are *anti-immigration moderates* with $Attitudes_{it} \in]2.5; 3]$. For the two tails of the distribution, 19.81% of respondents hold very positive attitudes toward immigration with $Attitudes_{it} \in [1; 2[$), while 18.37% of them exhibit strong negative attitudes with $Attitudes_{it} \in]3; 4]$).[12] Throughout the rest of the empirical analysis, individuals with extreme political attitudes are referred to as *pro-immigration* and *anti-immigration* respondents, respectively.

Figure 1: Individuals' Attitudes Toward Immigration, 2013-2017



Notes: $Attitudes_{it}$ is the average attitude of individual i toward immigration. Pro-immigration corresponds to $Attitudes_{it} \in [1; 2[$, Pro-immigration moderates to $Attitudes_{it} \in [2; 2.5]$, Anti-immigration moderates to $Attitudes_{it} \in]2.5; 3]$, and *Anti-immigration* to $Attitudes_{it} \in]3; 4]$.
Source: Authors' elaboration on ELIPSS data (2013-2017).

Unsurprisingly, individual characteristics differ strongly across the four groups of immigration attitudes. Table A1 reports that, on average, respondents with

In Appendix C3, we offer evidence of the robustness of our results by assessing the impact of excluding any of the three dimensions used for the index and by employing a composite index generated through principal component analysis (PCA).

[12] This classification is robust to the use of the distribution of attitudes in the first wave of respondents (September 2013 or September 2016 for the refreshment sample) or the first wave (September 2013).

more (less) positive attitudes toward immigration are significantly more (less) likely to be highly educated, employed, and have higher incomes. The characteristics of pro-immigration moderates largely follow the patterns as of pro-immigration individuals; similarly, the characteristics of anti-immigration moderates are close to those of anti-immigration individuals.

The transition matrix of attitudes in Figure C3 demonstrates significant variability in respondents' attitudes toward immigration across waves, with variations notably toward adjacent categories of attitudes. For instance, pro-immigration moderates' (anti-immigration moderates) attitudes are more likely to transition to pro-immigration (anti-immigration) in the next period, rather than making drastic shifts to the opposite ends of the attitude spectrum. Figure C4 also shows that over the course of our four-year panel, approximately 50% of respondents did not maintain the same attitudes toward immigration at the end of the panel that they had at the start of the panel.

Respondents in the ELIPSS panel are also asked about their "usual preferred channel to watch political news programs".[13] This allows us to connect each respondent to the content they have been exposed to during the study period. The analysis is restricted to seven channels, namely TF1, France 2 (FR2), France 3 (FR3), Arte, M6, BFM TV, and CNews due to the limited sample size for other channels.[14] This channel information is available in two waves, in September 2013 and 2016. This means that for the first nine waves, we assign each individual his or her baseline 2013 channel, and the possibility of switching channels only applies to the last three waves. The channel transition matrix in Figure C2 shows that viewers tend to show strong loyalty to their preferred news channels within four years and that channel changes are relatively infrequent. This makes the assumption that the preferred channel is largely time-invariant plausible.[15]

Regarding self-selection into channels, the literature provides sound evidence that viewers tend to choose media platforms that conform to their ideology (see Mullainathan and Shleifer, 2005; Gentzkow, 2006; Durante and Knight, 2012, among others). We provide detailed evidence of self-selection into channels in

[13]Respondents only indicate their main preferred channel, which potentially restricts our understanding of their television consumption. However, our focus is solely on political information from evening news programs. In this context, it appears reasonable to assume that individuals do not simultaneously watch multiple channels; if they do, it would decrease the likelihood of detecting effects in our analysis.

[14]See Table A2 in the Appendix for a breakdown of individual observations across channels. Specifically, we exclude channels such as Canal+, France 5, LCP, and LCI for which we have fewer than 150 observations over time or 35 distinct respondents in the ELIPSS data. These minor channels account for only 5% of the original TV viewer sample.

[15]Of those who reported their preferred TV channel for political information in both 2013 and 2016, 17.89% change their preferred TV channel between the two periods.

Appendix A1. Overall, we find that individuals opposed to immigration tend to favor TF1 for political information, while immigration supporters are more likely to choose Arte, France 2, or CNews.[16] As shown in Figure A6, this selection results in varying distributions of attitudes for each channel, although the majority of them attract a diverse set of respondents with mixed attitudes toward immigration.

B Immigration in the Media and the 2015 Refugee Crisis

We use media data provided by the French National Audiovisual Institute (INA), which archives news broadcasts for France's main national television channels (Philippe and Ouss, 2018; Cagé et al., 2019) to provide a comprehensive picture of immigration's overall prominence and representation in evening news over time. The analysis is restricted to all the news covered by evening news programs between 6:45 p.m. and 9:30 p.m. from January 2013 to December 2017 on TF1, France 2, France 3, Arte, M6, BFM TV and CNews (I-Tele before February 2017). All programs in our analysis mainly focus on events and information with national resonance. During our analysis period, the two leading news programs by TF1 and France 2 had 6.1 million and 4.8 million viewers per evening, respectively (25 and 20% of the French audience).

To identify whether subject s on channel c in year-month t is related to the immigration topic ($Immigration_{sct} = 1$), we exploit INA's descriptors and account of news, which provides a comprehensive description of each broadcasted subject.[17] We build a lexicon that includes keywords associated with immigration and their variations in spelling (see Appendix B1). Using a bag-of-words model, a subject is classified as immigration-related if it includes at least one word from the lexicon. For instance, the following subject in the data, from the BFM TV evening news program on September 16, 2015, is classified as immigration-related since it includes keywords from the lexicon such as "migrants" and "refugees".

*Speakers: Ruth Elkrief, Nathalie Schuck (Le Parisien), Thierry Arnaud. According to an ELABE poll survey, 80% of the respondents ask for an increase in border controls. Interview of Bernard Sananès, president of the ELABE institute. Fear increased following the pictures of **migrants** in Hungary or Germany.*

[16] CNews's alignment with more positive immigration attitudes may come as a surprise, but note that this channel shifted its political stance after Vincent Bolloré's takeover in July 2015, which affects only the last four waves of our sample (Cagé et al., 2022).

[17] This is the most comprehensive information on television broadcasting available because there is no systematic transcription of all television programs.

European leaders are in a panic. The reversal of opinion was predictable. The question of border control arises outside Schengen. Syrian ***refugees*** *are not so interested in France.*

The empirical analysis exploits this unique framework to compute a measure of the salience of immigration on French TV news channels. First, information on immigration news is collapsed at the channel-month level to match the time dimension provided by the ELIPSS survey.[18] Then, we define $ShareSubj_{ct}$, the share of subjects devoted to the immigration topic in year-month t on the evening news program of channel c, as follows:

$$ShareSubj_{ct} = (\#Subj_{sct}|Immigration_{sct} = 1) \,/\, (\#Subj_{sct}) \tag{1}$$

where $\#Subj_{sct}$ is the total number of subjects broadcast in year-month t during the evening news program of channel c. This variable captures the prevalence of the immigration topic in the overall broadcasting of political information on French television channels. As reported in Table B1, the average share of immigration-related news for all months from 2013 to 2017 is 4.50%, with a standard deviation of 4.80% and a maximum of 38,10% (Arte in September 2015).[19] In descending order, the channels with the greatest average coverage of migration in the sample are Arte, France 2, CNews, BMF TV, France 3, TF1, and M6.

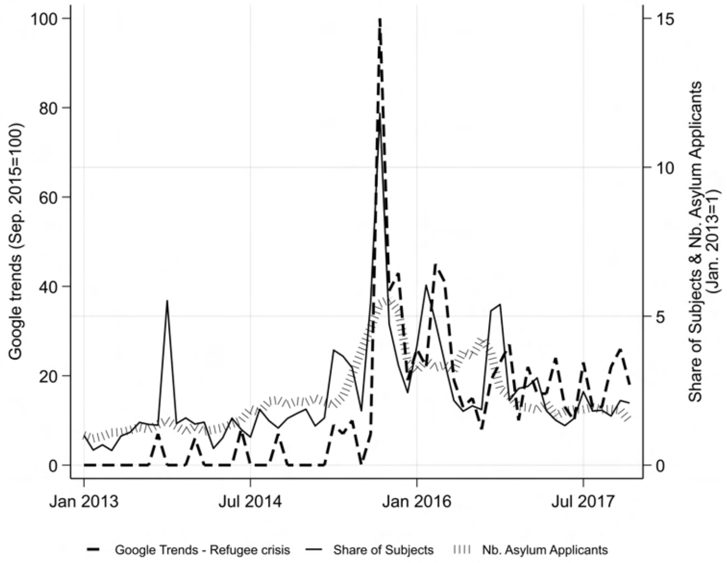
The empirical analysis exploits channel deviations from the average coverage of immigration over time that is mostly driven by world events. Figures 2, B2 and Table B1 display a significant rise in immigration coverage that coincides with the substantial influx of asylum seekers into Europe following the 2015 refugee crisis. The average share of immigration subjects increased from 3.30% prior to September 2015 to 5.90% thereafter. Additional data from Google Trends on the refugee crisis category also illustrate how natives' attention to immigration shifted in response to this increased salience of immigration.

Figure B3 provides descriptive evidence that the data capture meaningful and sufficient variation at the channel level for the 12 available waves of the ELIPSS

[18] Unfortunately, only the month of the survey and not the exact date of the interview is available for all respondents. This implies that we cannot rule out the possibility that the impact of the media on attitudes is a short-term effect that lasts only a few days. Nonetheless, the within-channel variability at the month level corresponds to 75% of the within variability when information is considered at the day level, and focusing on monthly variations allows us to capture the effect of repeated exposure to immigration-related subjects.

[19] The corresponding numbers in our benchmark sample used in the empirical analysis are 2.73%, 1.91%, and 18.80%, as we only use the month preceding the 12 ELIPSS waves and individual observations are not distributed evenly across waves.

Figure 2: Media Coverage of Immigration and the 2015 Refugee Crisis



Notes: "Share of Subjects" is the average share of subjects on French TV evening news programs devoted to immigration-related topics. "Google Trends - Refugee crisis" reports the monthly frequency of search queries associated with the refugee crisis, namely how often a refugee-related term is entered into the Google search engine. "Nb. Asylum Applicants"is the monthly total number of asylum seekers in Europe as reported by Eurostat. The data from Google Trends are scaled such that the highest peak is set at 100. Scaling for the other two series is relative to the initial period in January 2013.
Sources: Authors' elaboration on INA, Google trends, and Eurostat data.

survey. Even after absorbing common monthly shocks and channel-specific time-invariant characteristics, there are still appreciable variations over time in the coverage of immigration across the various French evening news programs (see Figure B4). These channel-specific fluctuations in immigration coverage can be attributed to various factors, including changes in editorial staff, and board preferences for specific subjects. For instance, Cagé et al. (2022) report that political representation across French channels is influenced by journalists' decisions and their adaptation to the channel they work for. Thus, we provide additional estimates in Section IIIB to ensure that our effects are not solely driven by channel adaptation to audience attitudes. Additionally, idiosyncratic shifts in news priorities, such as coverage and special editions on other topics, or channel-specific contractual agreements (e.g., for sporting events), can impact the time available for immigration news (Eisensee and Strömberg, 2007; Durante and Zhuravskaya, 2018; Djourelova and Durante, 2022). To this end, we demonstrate the robustness of our findings by using 2SLS estimates, as outlined in Appendix C11, which leverage news pressure from sports and disaster-related news to predict exogenous changes in immigration coverage.

As stated in Section IA, we can only track individual attitudes for a subsample of 12 months. In Appendix B3, we show that the subsample of media data for the months preceding each wave of the ELIPSS survey is, however, representative of the variation recorded in the full INA database.

II Empirical Strategy

This section presents the main empirical strategy in Subsection A and discusses its identification challenges in Subsection B.

A Empirical Specifications

The first benchmark empirical model tests the hypothesis that an increase in immigration coverage increases the likelihood of reporting extreme attitudes toward immigration. We use $Pol_{ic_{(i)}t}$ as a dependent variable, which equals one if an individual i in wave t, watching evening news programs on his or her preferred channel c, reports extreme attitudes (pro- or anti-immigration), and zero otherwise (moderates). We estimate the following specification:

$$Pol_{ic_{(i)}t} = \beta_1 ShareSubj_{ct-1} + \boldsymbol{\beta' X_{it}} + \gamma_i + \gamma_c + \gamma_t + \varepsilon_{it} \tag{2}$$

where $ShareSubj_{ct-1}$ is the aforementioned measure of the coverage of immigration on channel c during the month preceding the month of the interview. γ_t stands for wave fixed effects that absorb time-varying shocks that are common to all individuals, such as the impact of the 2015 refugee crisis in Europe, which unambiguously affected natives' attitudes toward immigration (Hangartner et al., 2019; Schneider-Strawczynski, 2020; Steinmayr, 2021), while γ_i and γ_c are the individual and channel fixed effects, respectively.[20] A vector of time-varying covariates, $\boldsymbol{X_{it}}$, that includes age, marital status, education, household size, number of children, employment status, occupation, and income categories, improves the precision of the estimates.[21] The coefficient of interest β_1 captures the marginal impact of an increase in the coverage of immigration on the likelihood of polarization. It can be interpreted as the percentage-point increase in the likelihood of reporting extreme attitudes toward immigration for a one percentage point increase in immigration coverage.

[20]Channel fixed effects (γ_c) can be estimated separately from individual fixed effects (γ_i) because the preferred channel for political information is updated in 2016.

[21]A detailed description of control variables is available in Table C1.

Second, to test whether polarization occurs on both sides of the distribution of attitudes, we replace the dependent variable $Pol_{ic_{(i)}t}$ in equation (2) with Pro-Pol$_{ic_{(i)}t}$, which is equal to one for individuals with pro-immigration attitudes and zero otherwise, and symmetrically with Anti-Pol$_{ic_{(i)}t}$, which is equal to one for individuals with anti-immigration attitudes and zero otherwise.[22] We also report unconditional quantile estimates as a robustness check (Firpo et al., 2009).

Third, we interact the treatment variable with preexisting attitudes to determine whether the direction of the shift of moderate individuals at the two extremes of the distribution is stochastic or the result of latent heterogeneity within this group. The benchmark specification becomes as follows:

$$\begin{aligned} Pol_{ic_{(i)}t} = {} & \beta_1 ShareSubj_{ct-1} + \beta_2 Attitudes^{Cat.}_{it-1} + \boldsymbol{\beta' X_{it}} + \gamma_i + \gamma_c + \gamma_t \\ & + \beta_3 ShareSubj_{ct-1} \times Attitudes^{Cat.}_{it-1} + \varepsilon_{it} \end{aligned} \tag{3}$$

where $Attitudes^{Cat.}_{it-1} \in$ {Pro-immigration, Pro-immigration moderate, Anti-immigration moderate, Anti-immigration} is a categorical variable that classifies the individual i into groups of attitudes at $t-1$. Marginal effects are obtained through:

$$\partial Pol_{ic_{(i)}t} / \partial ShareSubj_{ct-1} = \beta_1 + \beta_3 Attitudes^{Cat.}_{it-1} \tag{4}$$

The omitted category is "Pro-immigration", such that $Attitudes^{Cat.}_{it-1} = 0$ and β_1 is the marginal effect of an increase in the coverage of immigration for $i \in$ {Pro-immigration} at $t-1$.

Including $Attitudes^{Cat.}_{it-1}$ on the right-hand side could make equation (3) susceptible to Nickell bias (Nickell, 1981), as it shares similar variations with $Pol_{ic_{(i)}t}$, both being derived from $Attitudes_{it}$ with a one-month lag for the former. Thus, we also always report the results of estimating equation (3) with time-invariant baseline attitudes, defined as the attitudes of individuals when they enter the panel. The main effect of attitudes (β_2) is absorbed by the individual fixed effects in this robustness check. Note, however, that using initial attitudes rather than attitudes at $t-1$ is a less desirable option because it does not allow respondents' attitudes to evolve over time.[23]

Given that the sampling process is not clustered, we follow Abadie et al. (2022) and report standard errors clustered at the individual level to account for within-individual serial correlation over time in all estimates. In Appendix C7, we also report that our conclusions remain virtually unchanged when clustering

[22] See Figure C1 for a graphical representation of the coding process for the various dependent variables.

[23] In Appendix C1 we document substantial shifts in attitudes over time.

standard errors at the channel level or when computing wild cluster bootstrapped standard errors to address the issue of the small number of clusters when clustering at the TV channel level (See Cameron and Miller, 2015; MacKinnon and Webb, 2017; MacKinnon et al., 2020).[24]

B Identification Assumptions

The main concern with the empirical strategy is the possibility of individuals self-selecting into television channels that align with their immigration attitudes, which would confound the estimates. The benchmark specification includes individual fixed effects, γ_i, to address the possibility that TV consumption choices are endogenous to immigration views. This means that the identifying variability stems solely from the correlation between an individual's attitudes toward immigration and the monthly variation in the salience of immigration on his or her preferred TV channel.

Individual fixed effects absorb the impact of any time-invariant individual characteristics on immigration views but not the effects of shocks correlated with these characteristics. Concerns may arise if variations in immigration news coverage are entirely demand driven, and if channels perfectly adjust their content based on what they anticipate about their audience's changing interests and beliefs about immigration over time (Gentzkow and Shapiro, 2010). We devote Section IIIB to this threat to identification and present several pieces of evidence demonstrating that this issue is unlikely to affect our main results. Among other tests, we find no significant effects when assigning non-TV viewers to a television-based immigration coverage by matching them to a TV viewer based on several characteristics. More importantly, when we estimate a model that simultaneously includes all leads and lags of our variable of interest, we find non-significant correlations between current and future variations in immigration coverage and individual attitudes.

Finally, given that different exposure to immigration may result from individuals changing their preferred TV channel due to a shift in their attitudes, we provide additional evidence, in Section IIIB, that our estimates remain robust to interacting channel and individual fixed effects (γ_{ic}). While this approach mitigates the issue of ideological self-selection across channels, it does shift the

[24]We use the Stata `boottest` package (Roodman, 2015) to perform the wild cluster bootstrap with Webb weights and 999 replications. Our main conclusions are also robust to clustering standard errors at the channel-month level. However, MacKinnon et al. (2020) emphasize that when working with panel data, "it is never to cluster below the cross-section level"; and this is why we do not report these results, which are available upon request to the authors.

identifying variability to the correlation between monthly variations in immigration coverage on a specific French TV channel and an individual's attitudes toward immigration watching this channel during a particular year. In terms of policy implications, it restricts the relevance of the results to individuals who opt not to change their preferred TV channel. Given that individuals are particularly attached to their TV news and that channel changes are relatively rare, as shown in Section I, it is both reassuring and unsurprising to see that the results are robust to the inclusion of these fixed effects.

III Main Results

This section covers the main findings regarding the impact of immigration coverage on the polarization of attitudes. Section IIIA reports the estimates of the benchmark equations (2) and (3), as well as the robustness checks associated with these specifications. Section IIIB presents additional identification results, and Section IIIC focuses on political preferences rather than immigration attitudes. Finally, Section IIID studies which types of framing drive the results.

A Attitudes Toward Immigration

Table 2 reports the results of the benchmark equation (2) estimated with different structures of fixed effects and controls. Overall, it shows that an increase in immigration coverage significantly increases the polarization of those with moderate attitudes toward the extremes. In the most comprehensive specification, in Column (4), we find that a one percentage point increase in the share of immigration subjects ($ShareSubj_{ct-1}$) is associated with a 2.60 percentage point increase in the likelihood of individuals reporting extreme attitudes. In terms of standard deviations (0.019 in the estimation sample), this corresponds to an approximately five percentage point increase.

We extensively discuss and challenge the robustness of this result in Appendix C. Specifically, we report that the polarization effect is robust to excluding channels or waves one by one (Figures C5 and C6), using alternative dependent variables (Table C3), or employing alternative independent variables to measure the coverage of immigration in TV channels (Table C5).[25] In Appendix C5, we

[25]The results are also robust to alternative subsamples, such as restricting the empirical analysis before the 2016 refreshment sample, to the set of respondents who have non-missing answers on all of the questions in the index, or to the waves that ask all three questions simultaneously. However, we find no effect of immigration coverage on attitudes when we restrict the analysis to non-citizen respondents. This result should be interpreted with caution

Table 2: Coverage of Immigration and Polarization of Immigration Attitudes

	(1)	(2)	(3)	(4)
$ShareSubj_{ct-1}$	1.640***	1.747***	2.171***	2.603***
	(0.459)	(0.361)	(0.554)	(0.613)
Controls	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes
Wave FE	No	No	Yes	Yes
Channel FE	No	No	No	Yes
Nb. Observations	6,796	6,796	6,796	6,796
Adjusted R^2	0.018	0.431	0.449	0.450
Std. coefficient	0.031	0.033	0.042	0.050

Notes: The dependent variable is Polarization, $Pol_{ic_{(i)}t}$, which takes value one for individuals with extreme attitudes and zero otherwise. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient). Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

also investigate whether the polarization response of an increase in the coverage of immigration on natives' attitudes varies across individual characteristics and sources of political information. Our findings reveal that the unemployed, older, and those with lower levels of education are less likely than others to change their attitudes, often remaining entrenched in their positions. We find little evidence of heterogeneity in the responses of individuals who also consume political information from other secondary sources such as radio, newspapers, or the internet.

As discussed in Section II, polarization may be concentrated only on one side of the attitude distribution if moderate respondents increased their likelihood of reporting either extremely positive or extremely negative attitudes but not both. In such a case, average or median immigration attitudes would shift in one direction, but as shown in Table C2, increased immigration coverage has no effect on both. This finding is consistent with previous research by Baysan (2022), which suggests that a null effect on the average or median may reflect changes in opposite directions within the distribution of attitudes, masking an overall polarization effect. While Baysan (2022) demonstrates that this occurred through direct contact for information provision, this paper demonstrates that it can occur through traditional media exposure. In Table 3, we reestimate equa-

because the number of non-citizens in the ELIPSS survey is very small, making it impossible to draw any firm conclusions. All of these results are available upon request.

Table 3: Direction of the Polarization

	(1) Pol	(2) Pro-Pol	(3) Pro-Pol moderates	(4) Anti-Pol moderates	(5) Anti-Pol
$ShareSubj_{ct-1}$	2.603***	1.677***	-1.739**	-0.865	0.926**
	(0.613)	(0.443)	(0.677)	(0.576)	(0.393)
Nb. Observations	6,796	6,796	6,796	6,796	6,796
Adjusted R^2	0.450	0.585	0.370	0.350	0.557
Std. coefficient	0.050	0.032	-0.033	-0.017	0.018

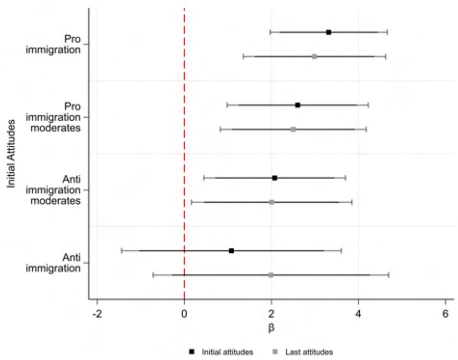
Notes: The dependent variable in Column (1) is Polarization, which takes value one for individuals with extreme attitudes and zero otherwise. The dependent variable in Column (2) is a dummy equal to one for pro-immigration attitudes and zero otherwise. The dependent variable in Column (3) is a dummy equal to one for pro-immigration moderate attitudes and zero otherwise. The dependent variable in Column (4) is a dummy equal to one for anti-immigration moderate attitudes and zero otherwise. The dependent variable in Column (5) is a dummy equal to one for anti-immigration attitudes and zero otherwise. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient). Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

tion (2) with alternative dependent variables to investigate this phenomenon. In Column (2), we use *Pro-pol*, a dummy variable equal to one for individuals with pro-immigration attitudes and zero otherwise, and in Column (5), we use *Anti-pol*, a dummy variable equal to one for individuals with anti-immigration attitudes and zero otherwise. By construction, the sum of the two separately estimated coefficients for these new dependent variables equals the previously estimated coefficient for Pol. Columns (2) and (5) show that polarization exists on both sides of the attitude distribution, as both coefficients are positive and statistically significant. In Columns (3) and (4), we present estimates for pro-immigration moderates and anti-immigration moderates to provide a comprehensive overview. These coefficients are nearly perfectly symmetric with those estimated in Columns (2) and (5), with quantitatively similar but opposite signs. In both cases, the negative signs indicate a lower likelihood of expressing moderate attitudes as immigration coverage increases.

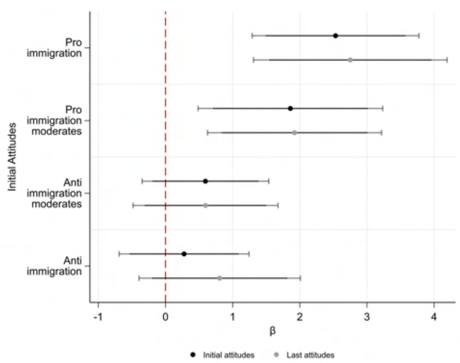
These findings are corroborated by unconditional quantile estimates (Firpo et al., 2009) reported in Figure C10. Quantile estimates allow us to exploit the full variability of our measure of immigration attitudes without the need for separate dummies, such as pro- or anti-polarization indicators. The estimated coefficients support previous results that increased immigration coverage impacts the likelihood of displaying extreme attitudes on both ends of the distribution. It is associated with both an increase in the likelihood of having more positive attitudes toward immigrants at the left-hand side of the distribution (quantiles 10 to 30) and a significant increase in the likelihood of having more negative attitudes toward immigrants at the right-hand side of the distribution (quantiles 70 to 90).

Finally, Figure 3 reports the marginal effects of increased immigration coverage on the likelihood of polarization to demonstrate that the increase in attitudes at both ends of the distribution is not arbitrary but rather reflects underlying heterogeneity in initial immigration attitudes. These marginal effects, estimated as described in Section II, show two main patterns. First, Figure 3a reveals that

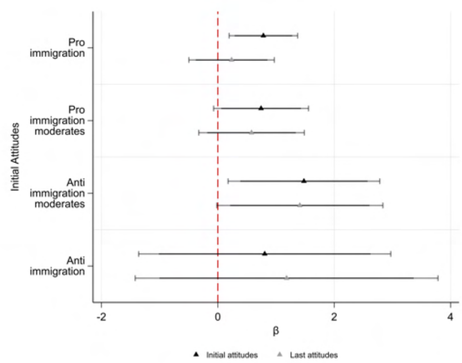
Figure 3: Coverage of Immigration Interacted with Preexisting Attitudes



(a) *Pol* as Dependent Variable



(b) *Pro-Pol* as Dependent Variable



(c) *Anti-Pol* as Dependent Variable

Notes: The figures show the marginal effect of $ShareSubj_{ct-1}$ on *Pol*, *Anti-pol* and *Pro-pol*, conditional on preexisting attitudes defined either in the last wave or at baseline, and estimated separately from Equation (3). All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

polarization results from changes in attitudes among all individuals, with the exception of anti-immigration individuals whose attitudes remain stable regardless of the level of immigration coverage. This echoes previous findings in the literature that changing the attitudes of those who already have strong exclusionary attitudes may be more difficult (Kalla and Broockman, 2021). At the other end of the attitude distribution, pro-immigration individuals strongly respond to changes in immigration coverage by significantly increasing their likelihood of remaining on the extreme left-hand side of the distribution rather than returning to moderate positions. Second, compared to Baysan (2022), the use of data at the individual level allows us to characterize switchers as mainly coming from the middle of the attitude distribution. When immigration coverage on TV increases, anti-immigration moderates become more anti-immigration (Figure 3c), while pro-immigration moderates become more pro-immigration (Figure 3b).

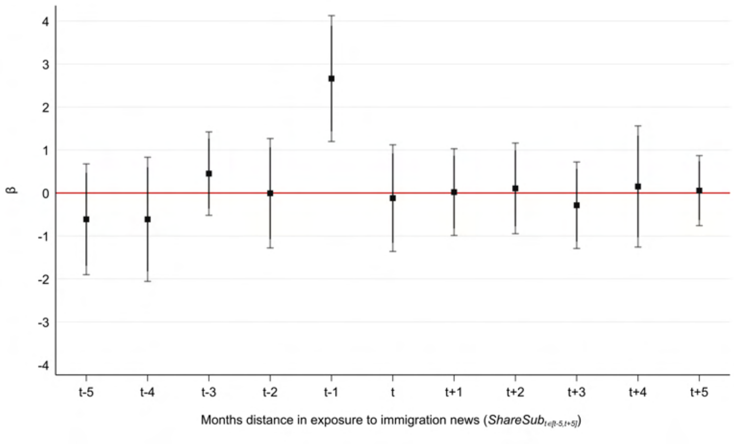
Overall, we find that an increase in the coverage of immigration has no effect on average attitudes toward immigration but that this null effect masks a shift in the distribution of attitudes toward both extremes, as individuals with initially moderate attitudes become more likely to report extremely positive and negative attitudes. This asymmetric change results from the heterogeneity in initial beliefs; those who were initially moderately positive become extremely positive, while those who were initially moderately negative become more concerned about immigration. As news coverage of immigration increases, attitudes become more polarized.

B Identification

As discussed in Section IIB, a legitimate concern in our analysis is that our previous results capture the perfect adjustment of channels to the attitude of their audience (Gentzkow and Shapiro, 2010). Indeed, individual fixed effects absorb the impact of any time-invariant individual characteristics on immigration views but not the effects of shocks correlated with these characteristics, and a channel covering of an immigration-related event could be based on how interested its viewers are likely to be in this event. Despite the lack of an experimental setting, we provide below several additional tests that mitigate these concerns, in addition to the use of coverage variations in the month preceding the measured attitudes. In Appendix C11, we also report additional 2SLS estimates that rely on news pressure to predict exogenous coverage of immigration, following Eisensee and Strömberg (2007); Durante and Zhuravskaya (2018); Djourelova and Durante (2022). The estimated 2SLS coefficients concur with our benchmark results, despite having lower precision than the OLS estimates.

Timing falsification. To mitigate potential confounding factors stemming from channels anticipating attitudinal changes among their viewers and strategically adjusting their immigration coverage accordingly, we regress our dependent variable of polarization on leads and lags of media coverage of immigration in Figure 4. To account for serial correlation in immigration coverage, we estimate all leads and lags within a single equation. Reassuringly, the non-significance of the lead variables shows that future coverage of immigration at time $t+1$ does not predict contemporaneous views on immigration at time t.[26] This test also allows us to assess the persistence of our estimated effect, revealing that it is only influenced by coverage from the previous month, as previous lags have no impact. This is consistent with recent findings by Angelucci and Prat (2023), which show that individual knowledge of news significantly declines over time. Note that this short-term effect does not diminish the significance of the findings. Migration is a heavily covered topic in France during election season, and given that the effect on attitudes toward migration can also translate into political attitudes (see Section IIIC), it has the potential to influence election results and thus the migration policy that newly elected officials will implement.

Figure 4: Leads and Lags of the Coverage of Immigration



Notes: The figure shows the marginal effects of $ShareSub_{ct-1}$ as well as its lagged and leading values on Pol estimated in a single regression. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Individual-channel fixed effects. Individuals' preferred channels for political

[26]Lead estimates are also non-significant when using *Anti-pol* or *Pro-pol* as dependent variables, as reported in Appendix C8.

information have previously been treated as time-invariant in our main specification, even though those who joined the panel in 2013 may have updated their channel preference by 2016. To address the concern that increased immigration coverage may be the result of channel switching triggered by attitude changes, we extend our benchmark specification with individual-by-channel fixed effects. The identifying variability with this new fixed effects structure is solely based on the correlation between monthly fluctuations in immigration coverage on a specific French television channel and the attitudes toward immigration of a given individual watching this channel. We report the result of our three benchmark tables presented in Section III in Appendix C9, which show that all of our conclusions remain unchanged under this alternative specification. This is not surprising given the strong loyalty that viewers show to their preferred news channels over the four years covered by our analysis, as discussed in Section IA.

Placebo estimates on non-TV viewers. In the presence of reverse causality bias, non-TV viewers should be also affected by the treatment assuming a parallel evolution in their attitudes to that witnessed among TV viewers. Thus, in Appendix Appendix C13, a television channel is assigned to individuals who do not list TV as one of their primary sources of political information, either randomly or by matching them with a TV viewer based on a broad set of observable characteristics. Placebo estimates on non-TV viewers are reported in Table C16. The main coefficient of interest remains non-significant and lower than the benchmark coefficient. This provides further evidence that the results truly capture the direct impact of television on attitudes and that the effect we identify is solely driven by channel-specific changes in migration news broadcasting.

Placebo estimates on concerns about alternative topics. To rule out the possibility that any other changes at the channel level confounded the estimates, we conduct additional placebo regressions that either replace the dependent variable with concerns about non-immigration topics in Tables C17 and C18 or the independent variable with news coverage on the same non-immigration topics in Table C19.[27] Reassuringly, the results report no significant effects for gender inequality, homosexuality, or environmental issues.[28] This test also speaks against reverse causality if individuals' attitudes on different dimensions co-evolved and channels adjusted their coverage on these dimensions.

[27] Despite the low frequency of non-immigration-related questions in our data, we report a significant benchmark coefficient on immigration concerns across all reduced samples, as shown at the bottom of Tables C17 and C18.

[28] This holds even though we find that gender and environmental news may affect general attitudes toward homosexuality and climate change in additional results available upon request.

Oster's methodology and ideological controls. The issue of selection on time-varying unobservables can also be addressed using a control variables approach. Table C15 provides evidence that self-selection is unlikely to drive our results to the extent that selection on unobservables is sufficiently correlated with selection on observables. We follow the methodology proposed by Oster (2019) and compute δ, the degree of selection on unobservables relative to observables required to make the coefficient of interest equal zero. As reported by Oster (2019), concerns about self-selection on unobservables can be ruled out as long as $\delta > 1$. In our benchmark specification, $\delta = 2.06$. This means that the selection on unobservables would have to be two times greater than the selection on observables to change the nature of the findings.

Following Facchini et al. (2017), we also provide evidence in Appendix C10 that the main results are robust to including time-varying ideological controls such as political interest, a 10-point left-right self-reported scale on political orientation, and TV viewing time, measured as the number of days per week that an individual watches television.[29] Nevertheless, these results must be interpreted with caution because these variables are jointly determined with political attitudes toward immigration and could thus be considered "bad controls" (Angrist and Pischke, 2008).

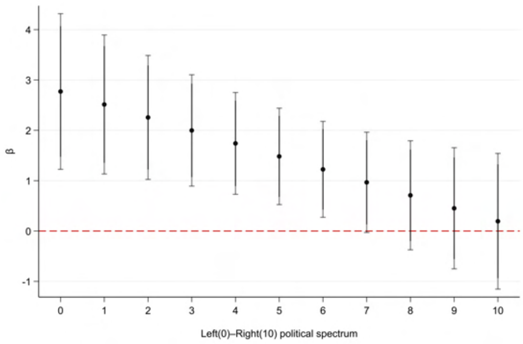
C Political Affiliation

This section investigates how the polarization in attitudes from increased immigration coverage interacts with individuals' political affiliations. We conduct this analysis using additional questions from the ELIPSS survey on political affiliation. First, we employ a self-assessed measure of individuals' political positions on a continuous 10-point scale ranging from zero (for respondents endorsing far-left ideologies) to ten (for respondents endorsing far-right ideologies). Figures 5a and 5b report the marginal impact of increased immigration coverage on the likelihood of left or right polarization, conditional on different levels of political affiliation, and thus mirror previous estimates presented in equation (3).[30] The closer individuals are to the left (right), the greater the magnitude and significance of pro-immigration polarization (anti-immigration polarization). For instance, individuals who do not have a strong initial position either on the right or left of the political spectrum (score of 5) have a 1.6 pp. lower probability

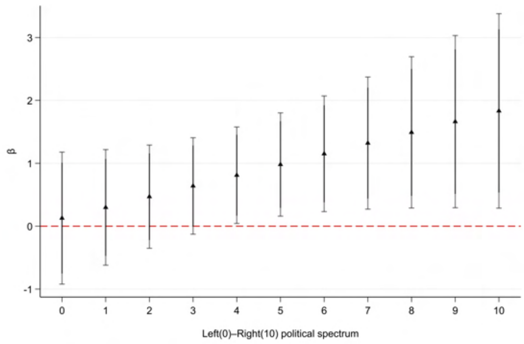
[29] Facchini et al. (2017) rely on a similar source of variation with cross-sectional data in the United States and find that Fox News viewers are more likely to report negative attitudes toward illegal immigrants than CBS viewers.

[30] The same figure for overall polarization is reported in Figure D3.

Figure 5: Coverage of Immigration Interacted with Political Affiliation



(a) *Pro-Pol* as Dependent Variable



(b) *Anti-Pol* as Dependent Variable

Notes: The figures report the marginal impact of an increase in the coverage of immigration, conditional on levels of political affiliation, on *Pol*, *Pro-pol*, and *Anti-pol*. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

of polarizing toward extreme attitudes than individuals with a strong political leaning (score of zero in Figure 5a and ten in Figure 5b, respectively). This confirms that the direction of polarization for moderates strongly aligns with initial beliefs and political leaning.

Second, we extend the analysis by focusing on party affiliations. Although the ELIPSS survey does not ask about voting intentions or preferred party, it does record respondents' likelihood of voting for each French political party on a 10-point scale.[31] Based on their position on the political spectrum, political parties are classified into the following political groups: far-right, right, center, left, and far-left as reported in Figure D1. Respondents who report a high likelihood of voting for far-right parties are more likely to be anti-immigration, whereas those who report a high likelihood of voting for the left are more likely to be pro-immigration.[32] Anti-immigration moderates are more likely to be aligned with the right, whereas pro-immigration moderates are more likely to be aligned with the center.[33] Figure D2 investigates whether there is a polarization to more

[31]Due to a reorganization of the French political landscape near the end of the survey, questions were not asked for all parties in every survey wave. As a result, the analysis is restricted to major historical political parties with a sufficient number of observations over time (at least six waves).

[32]The left is composed of the socialist and green parties, the two parties with the highest correlation with pro-immigration attitudes in Figure D1.

[33]According to Table D1, an increase in immigration coverage does not significantly increase the average likelihood of voting for a particular party or voting more to the left or right, although the coefficients on each political group suggest a clear pattern toward more right-leaning and less left-leaning positions after an increase in immigration coverage.

extreme political groups employing the same estimation strategy as previously described. A rise in immigration coverage significantly increases the likelihood of individuals with a high probability of voting for the right in the last wave voting for far-right parties (Figure D2b). At the other end of the political spectrum, such a rise increases the likelihood that individuals who previously expressed a high probability of voting for the center to vote for the left (Figure D2d).[34]

Media coverage of immigration can thus polarize not only attitudes toward immigration but also electoral preferences toward parties that hold more radical stances on immigration. These findings resonate with those of Colussi et al. (2021), who show that an increase in the salience of immigration has an asymmetric impact on voters' electoral preferences in the German context. Using our individual panel data matched to our television data, we can provide evidence on the specific role of the media in increasing the salience of a contentious topic and identify the switchers driving the effect.

D Framing of Immigration News

This section explores which types of framing within immigration news contribute to polarization. To this end, we break down our measure of coverage of immigration in equations (2) and (3) into tones and topics.[35]

Topic analysis. We apply an unsupervised Latent Dirichlet Allocation algorithm (LDA) to the complete corpus of immigration news to identify topics within our period of analysis. The LDA generative process aims to discover uncorrelated topics in migration subjects and assign each migration subject to a mutually exclusive category.[36] We uncover nine distinct subject clusters related to migration during the analysis period, namely migration burden (17.3%), French politics (13.1%), refugee camps in France (12.7%), the Syrian conflict (11.7%),

[34] The fact that polarization is primarily driven by individuals affiliated with political parties in the center and center-right (moderates) aligns with the standard prediction of probabilistic voting models, such as the median voter theorem (Downs, 1957). Extreme voters may have limited voting mobility because they are already on the policy spectrum's edges. Even if their party moves closer to the median voter, they may not be able to find significantly better parties. Center-aligned voters, on the other hand, have greater mobility by influencing parties to align more closely with their positions. However, probabilistic voting models emphasize political parties' adaptation to voter preferences rather than genuine shifts in voters attitudes, which we find in our analysis.

[35] For immigration coverage in Germany, Gehring et al. (2022) shows that average changes in sentiment are primarily attributed to changes in topics rather than changes in sentiment within topics.

[36] Given that we restrict the topic analysis to immigration-related subjects, we opt for an unsupervised LDA that uncovers topics rather than a semisupervised LDA that requires topics to be specified ex-ante using a seed word dictionary and that generates a residual category.

terrorism and attacks (10.8%), the refugee crisis in the Mediterranean (9.9%), the United States (8.9%), the European Union (8.3%), and Germany (7.3%).[37] Information is then aggregated at the channel-month level, and Appendix E provides descriptive statistics on the evolution of topics across channels and over time.

To mitigate the issue of low variability in the topic data that may impede the precise estimation of these patterns, topics are classified into three broader, more consistent groups: i) subjects pertaining to immigrant integration and associated costs in France – "migration burden", "French politics", or "refugee camps in France"–, ii) subjects concerning immigration in foreign host countries –"Germany", "European Union", or "United-States"–, and iii) other subjects related to sudden shocks – "Syrian conflict", "terrorism and attacks", or "Refugee crisis in the Mediterranean".[38] The results are depicted in Figure 6a. Subjects addressing immigration in France exhibit a polarization effect, whereas subjects addressing immigration in other contexts outside the national territory tend to foster pro-immigrant attitudes. This suggests that concerns among natives about immigration are notably shaped by economic and psychological costs linked to hosting immigrants, with the latter arising only when welcoming them into one's own country.[39] Figure E4 confirms that these heterogeneous reactions depend on initial attitudes. Respondents with initially moderate views tend to become more negative as media coverage of immigration in France increases, whereas those with initially positive views are more likely to report highly positive attitudes. The coverage of immigration in France thus widens the gap between those with differing initial attitudes. When it comes to immigration in foreign countries, we find that pro-immigration viewers drive the empathy effect the most. Finally, while other subjects seem to be associated with an increase in anti-immigrant sentiments, additional robustness checks reveal that it is entirely driven by the coverage of terrorist attacks in France during the period of analysis.

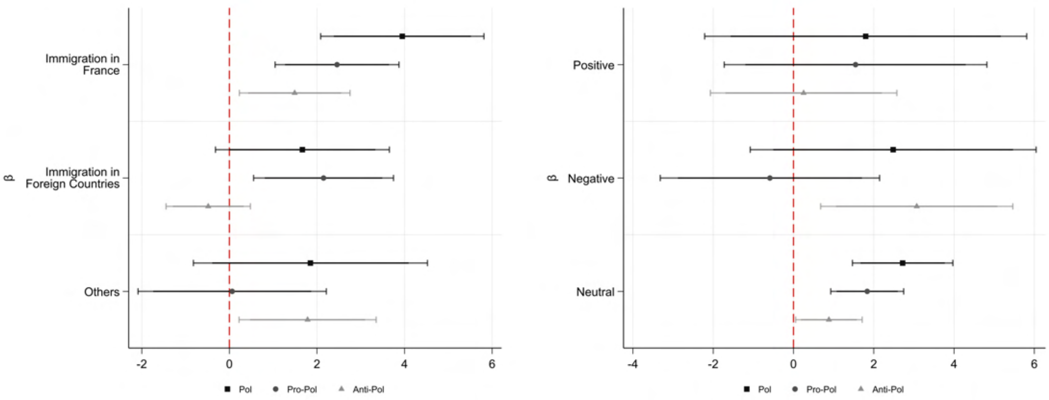
Sentiment analysis. To capture the tone expressed in migration subjects, we run a sentiment analysis on the complete corpus of migration subjects. This exercise proves particularly challenging within our context. First, the regula-

[37]We adopt the methodology proposed by Deveaud et al. (2014) to determine the optimal number of LDA topics. The nine topics are labeled based on their top words, which are detailed in Table E1. The cross-correlation between topics is low, as illustrated in Figure E1, which rules out concerns of collinearity.

[38]This grouping results not only from thematic similarities, but also from the fact that when isolating topics one by one in Figure E5, their estimates point in the same direction.

[39]This echoes findings by Bordalo et al. (2020), who show that the end of the Cold War increased the salience of domestic issues, translating into higher perceived polarization and partisanship.

Figure 6: Topic and Sentiment Analysis



(a) Topics

(b) Sentiments

Notes: The figures show the marginal effect of $ShareSubj_{ct-1}$ on *Pol*, *Pro-pol*, and *Anti-pol* for specific topics and sentiments. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

tory authority for audiovisual and digital communication in France (ARCOM, formerly CSA) aims to maintain channels' neutrality (Philippe and Ouss, 2018), which may limit variations over time and across channels compared to the US media market (DellaVigna and Kaplan, 2007), for instance. However, some recent studies have shown that French TV channels' neutrality is not completely absolute (Cagé et al., 2022). Second, unlike existing studies that predominantly focus on press articles, the lack of written transcripts of the broadcasted content means that our analysis relies on descriptions provided either directly by INA employees or by the Kantar society, which are fundamentally shorter and more neutral than the original content. Third, some negative terms, such as "shipwreck," may be perceived as ambiguous in the context of migration and may elicit diverging reactions from the population. With these limitations in mind, we rely on the French Expanded Emotion Lexicon (Abdaoui et al., 2017), which is, to our knowledge, the lexicon of reference for sentiment analysis in French, to identify positive and negative words in each subject. We first compute the share of positive (negative) words in the total number of words for each subject.[40] Then, we classify a subject as positive or negative if its share of positive or negative words exceeds the 75th percentile of the subject distribution. Of the migration subjects, 11.41% and 16.47% are classified as positive, or negative,

[40] We remove from the sentiment analysis words that have already been used in the migration lexicon.

respectively. All other subjects are classified as neutral (72.13%).[41] The information is again aggregated by computing the share of positive, negative, and neutral immigration subjects at the channel-month level. Appendix F provides descriptive statistics on the evolution of sentiment across channels and over time. Interestingly, sentiments and topics do not overlap, as shown in Figure F2, with the two highest correlations being between terrorism and the share of negative subjects at 0.30 and between French politics and the share of positive subjects at 0.26.

The results are reported in Figure 6b. Polarization at both ends of the distribution is primarily driven by subjects who are neither extremely positive nor extremely negative. Instead, neutral subjects increase the likelihood of polarization toward both pro- and anti-migration sentiments. Figure F6c confirms that an increase in immigration coverage with a neutral framing increases both the likelihood of pro-immigration moderates reporting extremely positive attitudes and anti-immigration moderates reporting extremely negative attitudes. Two additional patterns emerge for viewers whose initial attitudes are pro- or anti-migration. On the one hand, Figure 6b indicates that negative framing may increase the likelihood of polarization toward extremely negative attitudes, and F6b shows that it is driven by pro-immigration individuals who can reverse their attitudes when they are exposed to extremely negative events, such as terrorist attacks.[42] On the other hand, F6a demonstrates that a positive framing that contradicts their initial beliefs can cause anti-immigration viewers to hold their negative attitudes even more strongly.

IV Mechanisms

This section investigates three possible mechanisms by which individuals with moderate attitudes toward immigration are more likely to report extreme attitudes in a direction that depends on initial perceptions as media coverage of

[41]Figure F1 depicts the most frequent positive and negative French words in the most positive and negative subjects, respectively. A small number of emotionally charged immigration subjects (1.5%) were initially classified as both positive and negative. To ensure that our classification is exclusive, we reclassify subjects as positive if the number of positive words within the subject is greater than the number of negative words and vice versa. The results remain robust when excluding these subjects from the analysis or not reclassifying them. Our conclusions remain unchanged when using the 50th percentile as a threshold, but it reduces the number of neutral subjects to 33.32%, as reported in Figure F5.

[42]This effect echoes the positive coefficient for the topic "Other" in Figure E4. When removing terrorism from the "Other" topic, the coefficient becomes non-significant and close to zero. Shifts from pro- to anti-immigration are thus only driven by the coverage of terrorist attacks in France during our analysis period.

immigration increases, namely motivated reasoning and backlash, persuasion, and salience.[43]

A Motivated thinking and backlash

Polarization from moderate to extreme attitudes could be attributed to motivated reasoning if TV viewers selectively seek and accept information that aligns with their preexisting beliefs while discounting or dismissing conflicting information (Taber and Lodge, 2006; Bénabou and Tirole, 2016). Experimental research has also shown that exposing individuals to information contradicting their initial beliefs may trigger a backlash, reinforcing their initial attitudes toward immigration, even if overall the evidence is scarce (Nyhan and Reifler, 2010; Wood and Porter, 2019; Guess and Coppock, 2020). Our results provide little support for these explanations.

First, if backlash were the main explanation for our results, we would expect viewers to react to news coverage framed in the opposite direction of their initial attitudes, thereby reinforcing their initial attitudes. Figure F6a shows a nearly significant backlash response of anti-immigration viewers to positive immigration coverage, which contradicts their initial beliefs, toward holding more strongly negative attitudes. Other than this effect, we do not find supporting evidence of a backlash effect on other types of viewers. Anti-immigration moderates do not adopt more negative attitudes when exposed to positive news, and pro-immigration viewers, whether moderate or not, do not adopt more positive attitudes when exposed to negatively framed immigration news.

Second, if motivated reasoning were the main explanation for our results, we would expect viewers to respond to information framing that confirms their initial beliefs but not to information that contradicts them. However, Figures F6a and F6b reveal null coefficients for pro-immigration moderates exposed to positive coverage and for anti-immigration moderates exposed to negative coverage. Although Figure F6a indicates that pro-immigration individuals are more likely to maintain extremely favorable attitudes when exposed to positive information, Figure F6b shows that pro-immigration individuals still do not dismiss negative information about migration and that such negative information may cause a shift in their attitudes toward the opposite ends of the distribution, driven here by migration topics related to terrorism.

[43] As ELIPSS is an anonymous self-administered questionnaire that uses a touch-screen tablet instead of face-to-face interviews, it is unlikely that our results reflect an increase in the likelihood of reporting extreme attitudes due to greater social acceptance of extreme positions.

Finally, the overall lack of changes in the attitudes of anti-immigration individuals following an increase in the coverage of immigration in our baseline results also suggests that motivated reasoning is unlikely to explain all of our results. In contrast, it is consistent with a salience mechanism if immigration is always salient for individuals with strong anti-immigration priors but not for others, as suggested in the literature (Dennison and Geddes, 2019; Kustov, 2023). We provide strong support for a salience mechanism in the following section.

B Persuasion vs. Salience

In a world with Bayesian learning, the preferences of TV viewers may be updated based on the types of news they see. Polarization could occur as a result of TV viewers self-selecting into different channels based on their initial beliefs and thus being exposed to different biased information sets, leading them to update their attitudes in different directions. If this is the case, pro(anti)-immigration moderates will shift to extremely positive (negative) attitudes as their exposure to positive (negative) immigration news increases. This interpretation of the results would echo the literature on the persuasive power of the media (DellaVigna and Gentzkow, 2010), but several findings contradict such an interpretation of our results. Instead, a more plausible interpretation of the results is that increased immigration coverage increases the prominence of this subject in the minds of TV viewers, causing them to place greater emphasis on the immigration topic when forming their opinion, thereby amplifying their initial position on the distribution of attitudes from moderate to extreme. This salience interpretation aligns with findings by Alesina et al. (2022) and Colussi et al. (2021), among others.

First, we examine how the effect varies based on the bias in immigration news coverage. According to previous results in Figure 6, a rise in exposure to migration news about the same topic (e.g., immigration in France) or with a neutral framing leads pro-immigration moderates to have an increased likelihood of reporting extremely positive attitudes, while anti-immigration moderates have an increased likelihood of reporting extremely negative attitudes. Contrary reactions to an increase in immigration coverage by pro- and anti-moderates, despite being exposed to news with the same or no bias, provide preliminary evidence against interpreting this result solely through the lens of persuasion.

Second, Bayesian updating theory suggests that extreme viewers should be less likely to update their beliefs due to their existing polarized opinions. However, comparing pro- and anti-immigration viewers at the extremes, we find that an increase in the coverage of immigration significantly affects pro-immigration respondents with no symmetric effect for anti-immigration respondents. This asymmetric impact is consistent with a salience interpretation, as several studies show that anti-immigration respondents regard immigration as a salient topic regardless of media coverage, whereas pro-immigration respondents may only perceive its importance as media coverage increases (Dennison and Geddes, 2019; Kustov, 2023).

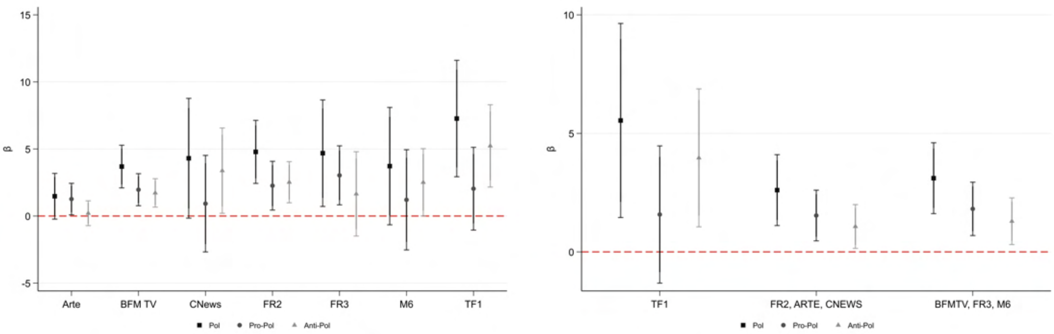
Third, as shown in Figure 4, the polarization effect of immigration coverage has a short-term impact, typically within a month. This also aligns with the reactivation of preexisting prejudices in the context of limited attention, rather than a long-lasting persuasion toward extreme positions.

Finally, we implement a more direct test focusing on within-channel polarization. If the only plausible interpretations of the results were Bayesian updating and persuasion, we would not expect any opposite shifts in attitudes among viewers of the same channel. Instead, viewers' attitudes should converge in the same direction as a result of exposure to the same biased content. To test this hypothesis, we interact exposure to immigration with individuals' preferred TV channel, using the same estimation strategy we followed in equations (3) and (4) for the interaction with preexisting attitudes. Figure 7a shows positive point estimates for both *Anti-* and *Pro-pol* for all channels, suggesting that increased immigration coverage amplifies the attitudes of viewers of the same channel in the direction of their initial bias. Polarization is only significant for four of the seven channels studied. However, there are positive and significant coefficients for both *Anti-* and *Pro-pol* for BFM TV and France 2, which are the channels with a sufficient number of individual observations (26.50% and 22.70% of the overall sample, respectively) as well as a sufficient mix of viewers with different initial attitudes.[44] Thus, consistent with a salience interpretation, we see that individuals exposed to the same information react differently. To enhance the precision of our estimates, we group channels in Figure 7b, based on the overall attitudes of their viewers (TF1 attracts anti-immigrant viewers, France2, Arte, and CNews attract pro-immigrant viewers, and the other three channels have mixed viewership, as reported in Table A3.). These new estimates confirm that viewers exposed to the same coverage can polarize in opposite directions, par-

[44] Table A2 shows the number of observations per channel. Figure A6 shows the distributions of attitudes within channels. Because TF1 has a disproportionate number of anti-immigration viewers, it only reports a significant and positive coefficient for anti-immigration polarization. Arte, on the other hand, has a disproportionate number of pro-immigration viewers and thus has only a significant and positive coefficient for pro-immigration polarization.

ticularly for channels that attract both positive and mixed viewers. However, the effect on pro-immigration polarization remains non-significant for TF1. This is most likely because the distribution of TF1's viewers, which includes a disproportionate number of anti-immigration moderates, does not provide enough statistical power to produce a significant coefficient on polarization toward extremely positive attitudes.

Figure 7: Coverage of Immigration and Attitudes by Channel



(a) Channels Separately

(b) Grouped Channels

Notes: The figures show the marginal effect of $ShareSubj_{ct-1}$ on *Pol*, *Pro-pol*, and *Anti-pol* conditional on the preferred channel to get political information. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

To conclude, the findings in this section suggest that motivated reasoning and backlash can be at work for viewers who already have extremely positive or negative attitudes, as these strategic adjustments require strong initial attitudes (Swire et al., 2017). For viewers with moderate attitudes, however, the effect appears to be driven by a salience mechanism and the reactivation of latent prejudices. Because polarization is mainly driven by these viewers moving toward the extreme, salience plays an important role in explaining the polarization effect observed following an increase in media coverage.

V Conclusions

This paper investigates how increased media coverage of immigration affects natives' attitudes toward immigration. It combines INA data on French television news programs with ELIPSS monthly individual panel data on attitudes from 2013 to 2017. Connecting all respondents to immigration coverage on their preferred channel for political information, we find that increases in the coverage of immigration shift moderate individuals' attitudes toward both extremes of the distribution in the short run. In particular, natives with moderately positive attitudes adopt highly positive attitudes, whereas those with moderately negative attitudes become very concerned about immigration. Interestingly, this main result is at odds with most of the literature on the impact of media on attitudes toward immigration, which usually finds that priming immigration mainly drives natives' attitudes in a specific direction. This paper therefore highlights the importance of looking beyond average effects when studying how exposure to the same information affects attitudes and beliefs. Additional results in the paper point to a salience mechanism driving the effect, *i.e.* increased exposure to immigration raises the topic's prominence in viewers' minds, leading to a disproportionate influence of the latter on subsequent decisions.

These findings highlight the role of the media, particularly television in our context, in polarizing attitudes. They have important implications for how the media covers issues such as immigration because they imply that, regardless of how the topic is framed, the mere mention of immigration can change the preferences of moderate individuals. Finally, the results also show that priming immigration influences not only attitudes but also voting decisions, which is especially important when considering media coverage during election seasons. All of these observations call for future research on media regulation policies to mitigate potential adverse effects, such as the possible manipulation of the political agenda by political leaders of extreme parties.

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Media Coverage, Salience of Immigration and the Polarization of Attitudes.

Online Appendix.

Appendix A Additional Descriptive Statistics for the ELIPSS

Table A1: Individual Characteristics and Natives' Attitudes Toward Immigration
Difference in Means

	Pro-immig.	Pro-immig. moderates	Anti-immig. moderates	Anti-immig.	Mean (All)
Age	-0.579***	-0.005	0.372***	0.063	5.583
High education	0.138***	0.071***	-0.053***	-0.197***	0.653
Employed	0.057***	0.025**	-0.050***	-0.031**	0.671
Marital status	-0.021	-0.016	0.039***	-0.007	0.664
Nb. Child	-0.003	0.004	0.065**	-0.103***	0.788
Nb. Household member	-0.015	-0.000	0.006	0.007	2.476
Blue collar	-0.064***	-0.037***	0.031***	0.088***	0.212
Income category	0.204***	0.171***	-0.027	-0.491***	3.091

Notes: This table reports the difference between the mean of each group and the mean for the full sample used in the empirical analysis. We also report whether the difference is significant with a two-sample t-test. The "Age" variable is composed of 11 categories from less than 24 years old to more than 70 years old. The "High education" variable equals one if the individual has a diploma equivalent to the French baccalaureate and 0 otherwise. The "Employed" variable equals one if the individual is employed and 0 otherwise. The variable "Marital status" equals one if the individual is in a couple and 0 otherwise. The variable "Nb. Child" ranges from 0 for no children to 3 for more than 3 children. The variable "Nb. Household Member" ranges from 1 for one individual to 6 for more than 6 individuals in the household. The variable "Blue collar" equals one if the individual is a blue-collar worker and 0 otherwise. The "Income category." variable is composed of 7 categories from 0 monthly income to more than 6000 €monthly income.
Sources: Authors' elaboration on ELIPSS data.

Table A2: Respondents by Preferred TV Channel

Channel	2013		2016		Overall Nb. of Obs.	
TF1	149	32.11	291	27.25	2,023	29.77
France 2	120	25.86	298	27.97	1,801	26.50
BFM TV	108	23.28	228	21.35	1,543	22.70
M6	43	9.27	110	10.30	652	9.59
France 3	21	4.53	60	5.62	353	5.19
CNews	13	2.80	48	4.49	236	3.47
Arte	10	2.16	33	3.09	188	2.77
Indiv.	464		1,068		6,796	

Notes: This table reports the breakdown of respondents across French TV channels used as primary sources for political information in 2013 and 2016.
Sources: Authors' elaboration on ELIPSS data.

Figure A1 depicts how we selected the analysis sample from the initial ELIPSS surveys. For the initial 2013 sample and the panel refreshment in 2016, as described in the paper's data description, we begin with a sample of French citizens and retain only those individuals who use TV as their primary source of political information (69%). Other individuals are kept for further placebo estimations (31%). Then, we exclude individuals for whom the channel watched for political information is of marginal significance or is not recorded (5 and 1%, respectively), as their inclusion would result in a too small sample size for our analysis. The figure further presents the number of individuals and the number of survey waves in which they are present. 62% of individuals have zero missing waves.

Figure A1: Sample of Analysis

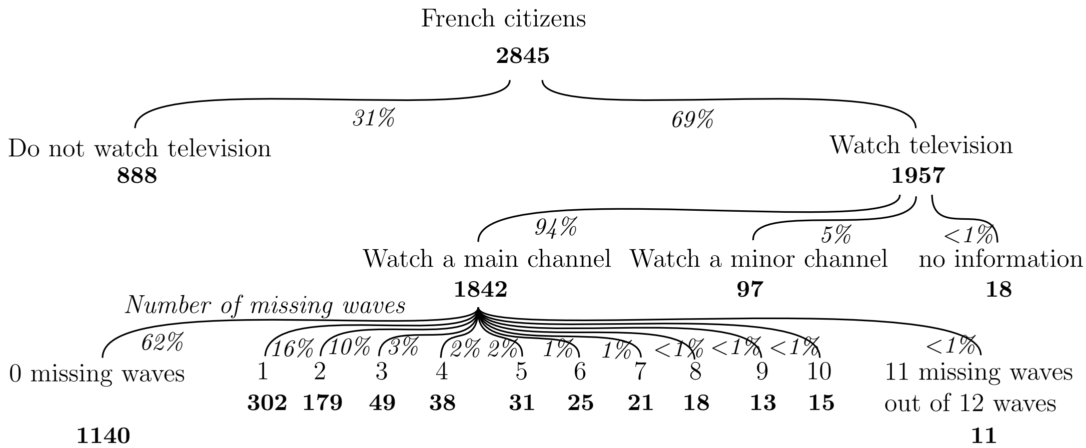


Figure A2: Sample of analysis – 2013 sample

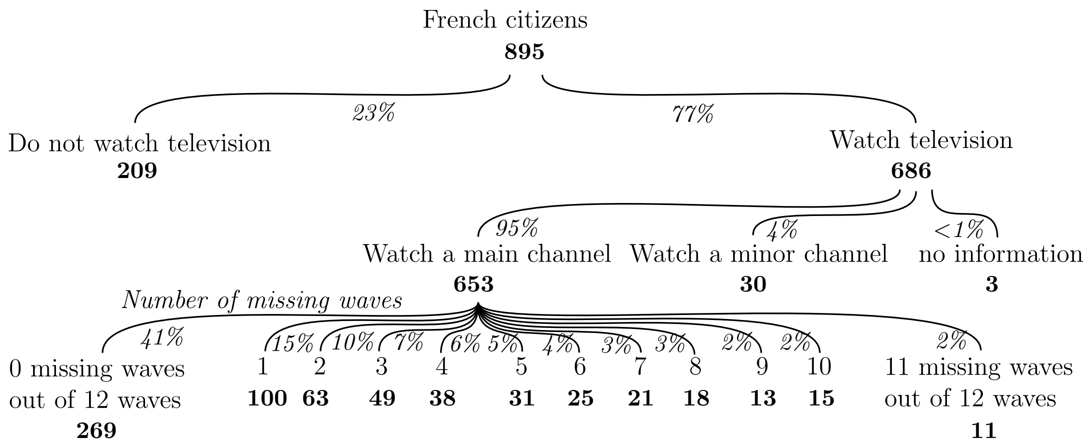
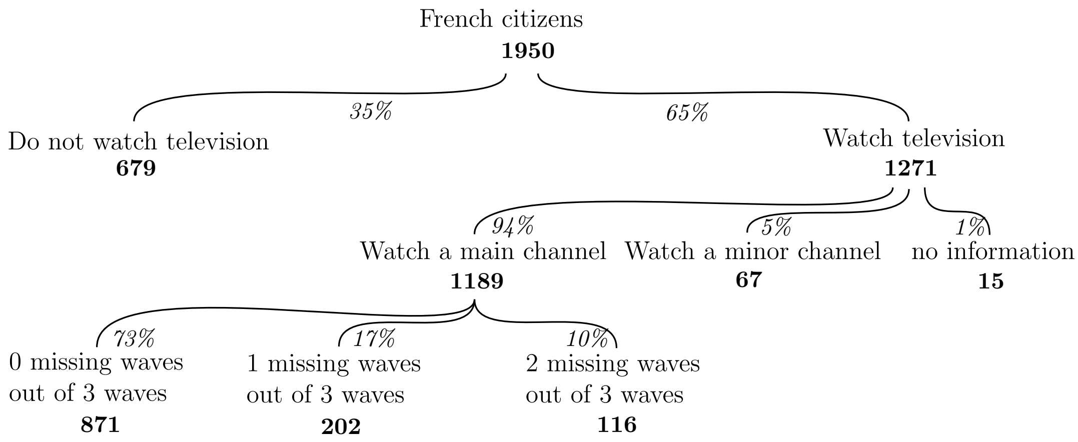


Figure A3: Sample of analysis – 2016 sample



Source: Author's elaboration on ELIPSS data.

Appendix A1 Selection into Channels and Individual Characteristics

This appendix investigates the selection of individuals across channels based on their attitudes toward immigration and individual characteristics.

Overall, Table A3 reports that individuals opposed to immigration tend to favor TF1 for political information, while immigration supporters are more likely to choose Arte, France 2, or CNews. CNews's alignment with more positive immigration attitudes may come as a surprise, but it is important to note that this channel shifted its political stance after Vincent Bolloré's takeover in July 2015, which affects only the last four waves of our sample (Cagé et al., 2022).

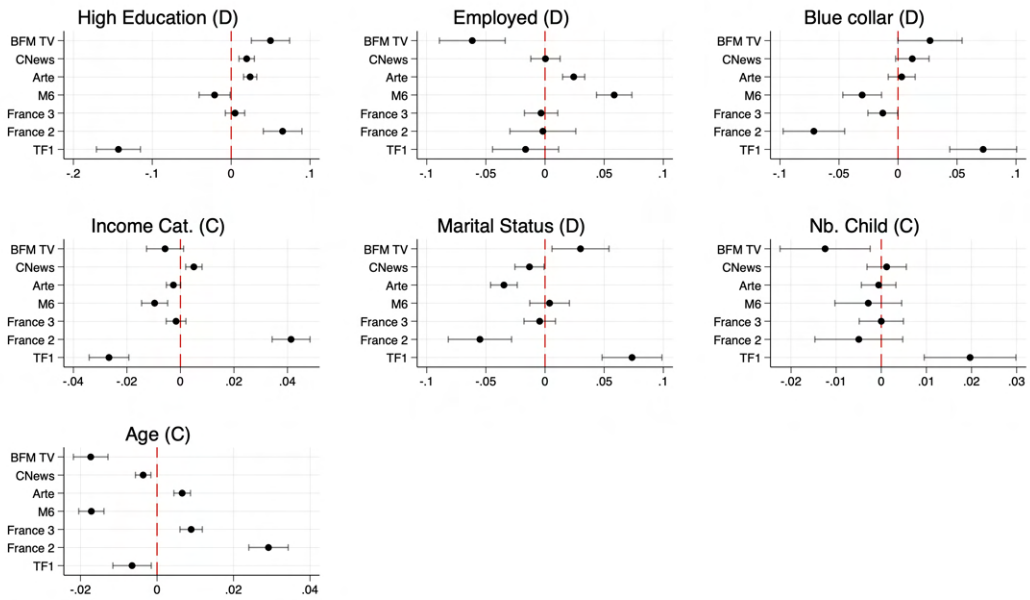
Table A3 also reports strong selection across channels based on individuals' characteristics. This selection leads to varying distributions of attitudes for each channel, as shown in Figure A6. Nonetheless, the majority of channels attract a diverse set of respondents with mixed attitudes toward immigration. Since there could be high correlations across individual characteristics, we study the selection into channels based on observable characteristics using multinomial logit regressions presented in Figure A4. Regarding the two main television channels in France, TF1 (where individuals are more against immigration) and France 2 (where individuals are more in favor of immigration, according to Figure A5), we find that, *ceteris paribus*, being less educated, a blue-collar worker or having less income or more children for instance increases the likelihood of choosing TF1 as the main source of political information, while it decreases the probability of watching France 2. We provide evidence in Figure A5 that average attitudes toward immigration still differ across French television channels after partialling out individuals' characteristics.

Table A3: Preferred Television Channel and Natives' Attitudes Toward Immigration
Difference in Means

	TF1	France 2	France 3	M6	Arte	CNews	BFM TV	Mean (All)
$Attitudes_{it}$	0.296***	-0.222***	0.017	-0.003	-0.605***	-0.383***	0.001	2.483
Age	0.134**	0.655***	1.202***	-1.522***	0.720***	-0.888***	-0.523***	5.583
High education	-0.150***	0.074***	-0.039	0.057***	0.134***	0.173***	0.053***	0.653
Employed	-0.044***	-0.035***	-0.141***	0.197***	0.079**	0.122***	0.018	0.671
Marital status	0.017	0.019	-0.041	-0.027	-0.345***	-0.003	0.019	0.664
Nb. Child	0.070**	0.079***	0.139**	-0.216***	-0.038	-0.067	-0.110***	0.788
Nb. Household member	0.083**	-0.075**	-0.422***	0.087	-1.045***	0.270***	0.124***	2.476
Blue collar	0.085***	-0.073***	-0.042*	-0.037**	-0.037	-0.013	0.006	0.212
Income category	-0.357***	0.523***	-0.113	-0.232***	-0.516***	0.460***	-0.026	3.091

Notes: This table reports the difference between the mean of each group and the mean for the full sample used in the empirical analysis. We also report whether the difference is significant with a two-sample t-test. The "Age" variable is composed of 11 categories from less than 24 years old to more than 70 years old. The "High education" variable equals one if the individual has a diploma equivalent to the French baccalaureate and 0 otherwise. The "Employed" variable equals one if the individual is employed and 0 otherwise. The variable "Marital status" equals one if the individual is in a couple and 0 otherwise. The variable "Nb. Child" ranges from 0 for no children to 3 for more than 3 children. The variable "Nb. Household Member" ranges from 1 for one individual to 6 for more than 6 individuals in the household. The variable "Blue collar" equals one if the individual is a blue-collar worker and 0 otherwise. The "Income category." variable is composed of 7 categories from 0 monthly income to more than 6000 €monthly income.
Sources: Authors' elaboration on ELIPSS data.

Figure A4: Multinomial Logit Regressions
Probabilities of Choosing a Given Channel

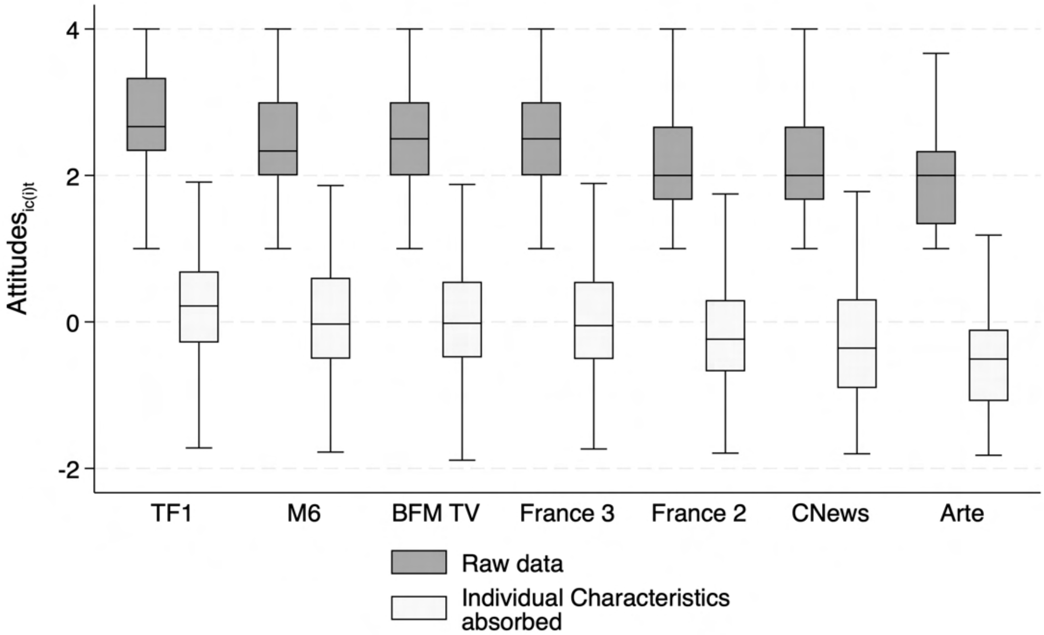


Notes: Coefficients are obtained from predictive margins for continuous (C) and dummy variables (D) after a multinomial logit with alternative channels as dependent variables and age, education, employment status, marital status, number of children, and income as predictors. For graphical representation, income, age, and the number of children are considered continuous variables in the specific regression. Using categorical variables does not affect the interpretation of the results and these estimates are available upon request. Confidence intervals are presented at the 95% level.

Interpretation: The probability of choosing TF1, ceteris paribus, is on average 1.41 percentage points lower for high-skilled compared to low-skilled viewers.

Sources: Authors' elaboration on ELIPSS data.

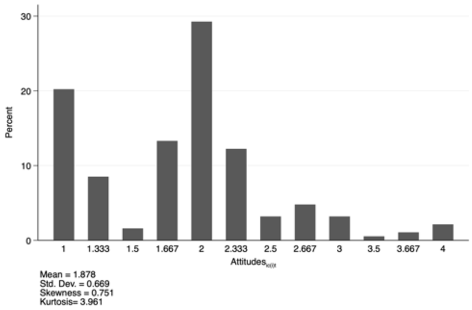
Figure A5: Attitudes by Preferred TV Channel, 2013-2017
Individual characteristics partialled-out



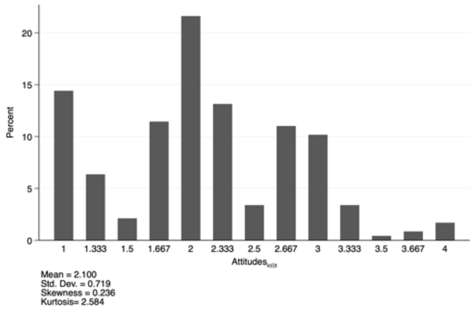
Notes: Individual attitudes by preferred TV channel for political information after absorbing variations from differences in observable characteristics. $Attitudes_{it}$ is the average attitude of individual i in year-month t on the dimensions namely, the number of immigrants in the resident population, the cultural enrichment resulting from immigration, and the extent to which Muslims are just like any other citizens. The higher $Attitudes_{it}$ is, the more the individual is against immigration. Controls include age, education, employment status, marital status, number of children, household size, a dummy for blue-collar, and income categories.
Sources: Authors' elaboration on ELIPSS data (2013-2017).

Figure A6: Individuals' Attitudes Toward Immigration by Channel

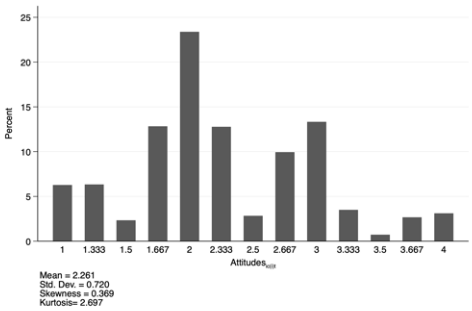
(a) Arte



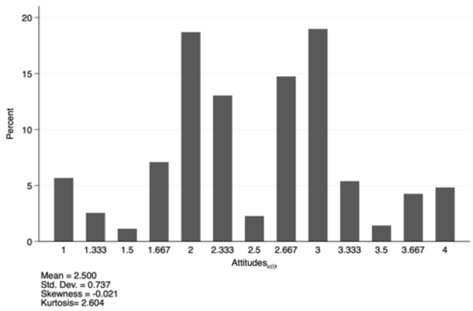
(b) CNews



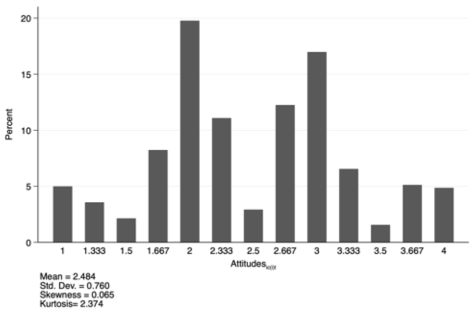
(c) France 2



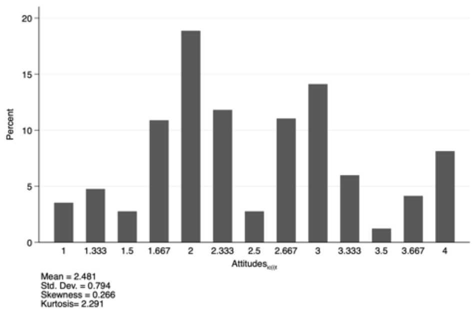
(d) France 3



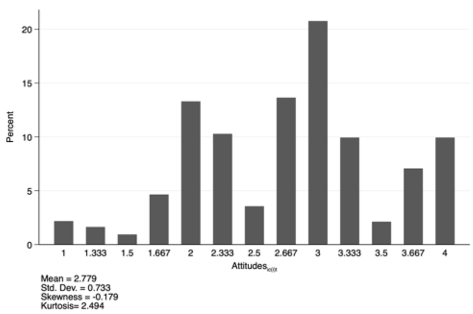
(e) BFM TV



(f) M6



(g) TF1



Note: Distribution of individuals' attitudes toward immigration by preferred channel.
Sources: Authors' elaboration on ELIPSS data.

Appendix B Additional Descriptive Statistics for the INA

Appendix B1 Identifying Migration Subjects

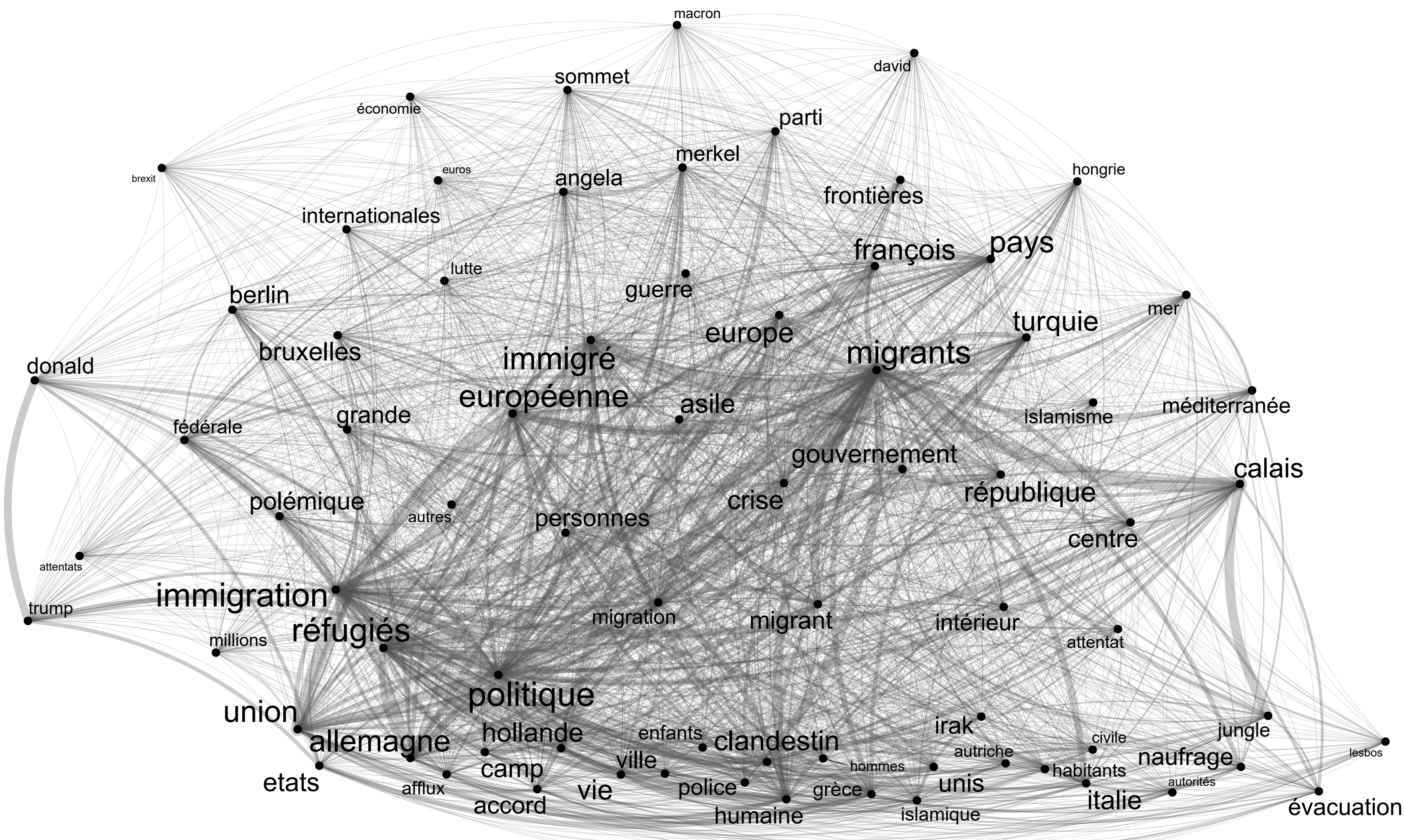
Lexicon

The lexicon includes the following list of French words: migration, migrations, immigration, immigrations, immigré, immigrés, immigrée, immigrées, immigre, immigres, immigree, immigrees, réfugié, réfugiés, réfugiée, réfugiées, réfugie, réfugies, réfugiee, réfugiees, refugié, refugiés, refugiée, refugiées, refugie, refugies, refugiee, refugiees, migrant, migrants, immigrant, immigrants, migrante, migrantes, immigrante, immigrantes, sans-papier, sans-papiers, mineur non accompagné, mineurs non accompagnés, mineur isolé étranger, mineurs isolés étranger, clandestin, clandestins, asile, asiles, demandeur d'asile, demandeurs d'asile, demandeuse d'asile, demandeuses d'asile, demandeur d asile, demandeurs d asile, demandeuse d asile, demandeuses d asile, demande d'asile, demandes d'asile, demande d asile, demandes d asile, étranger, etranger, étrangers, etrangers, étrangère, etrangere, étrangere, etrangère, étrangères, etrangeres, étrangeres, etrangères.

Aside from the words denoting the act of migrating ("migration"), the other words are all the ones used to denominate migrants according to the French Museum of the History of Immigration.[1] A cleaning process is therefore performed to remove identification of subjects: i) where the word "réfugié" (refugee) picks up the action verb to take refuge in a specific place (usually in the context of attacks where victims or military take refugee in a building), ii) where the word "étranger" (foreign) or "clandestin" (clandestine) applies to entities or objects and does not denote immigration-related individuals (for instance, we remove references to foreign firms or clandestine hospital), iii) where the word "asile" (asylum) denotes psychiatric asylum, and iv) where the word "migration" (migration) denotes the migration of birds and other animals. Our main conclusions remain valid even when we remove these additional exclusion rules. The lexicon approach is further validated by the co-occurrence network of words in migration subjects depicted in Figure B1. It illustrates the approach's efficacy in identifying migration-related topics within the French context, as there are no irrelevant themes or words associated with the migration subject.

[1] See https://www.histoire-immigration.fr/les-mots, last accessed on April 3rd, 2023.

Figure B1: Network of Co-occurrences of Words in Migration Subjects

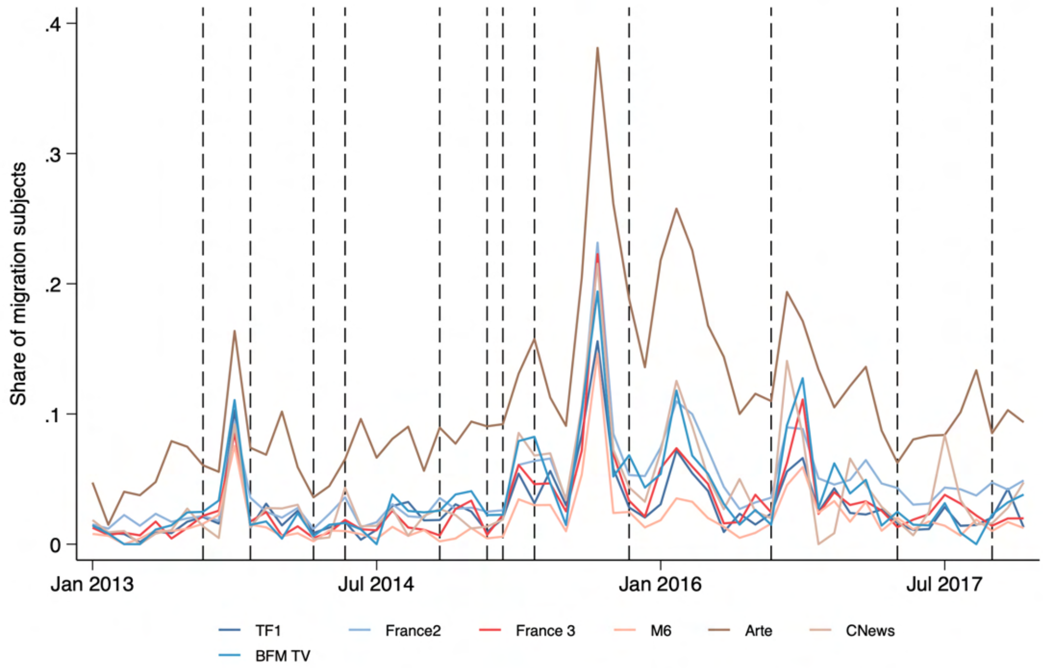


Notes: Co-occurrence networks are the collective interconnection of terms based on their paired presence within a subject. This plots the co-occurrences of the top 75 words in migration subjects where the edges show the co-occurrences of words.

Sources: Authors' elaboration on INA data.

Appendix B2 Coverage of Immigration Between 2013 and 2017

Figure B2: Media Coverage and the 2015 Refugee Crisis by Channel



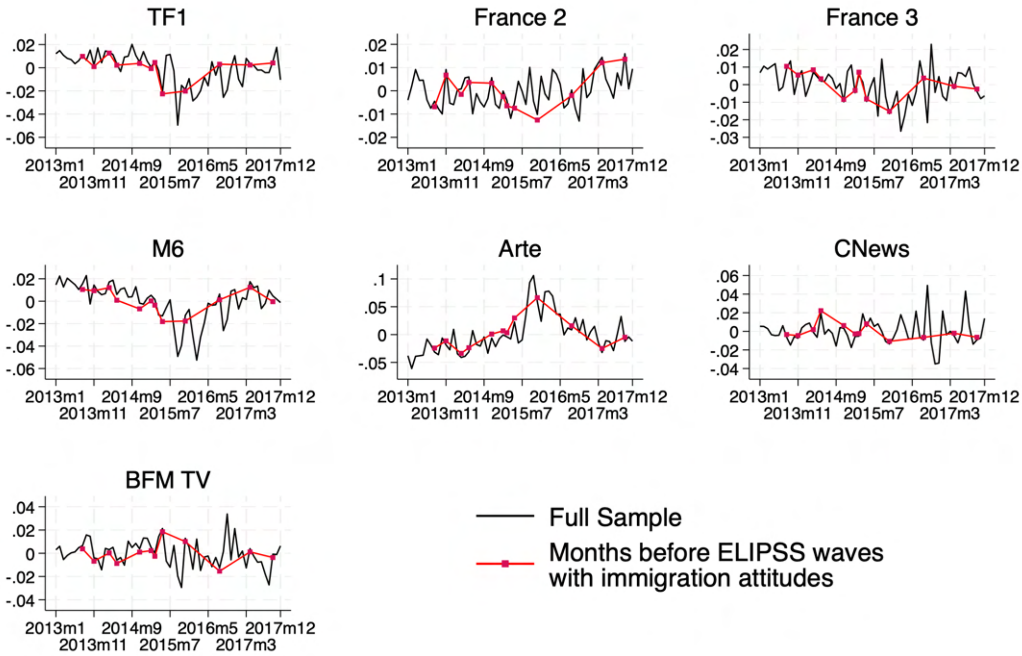
Notes: This graph depicts the average aggregated share of subjects devoted to immigration-related topics on French TV evening news programs for each channel. Horizontal lines display months preceding ELIPPS waves that include questions on attitudes toward immigrants.
Sources: Authors' elaboration on INA data.

Table B1: Average Share of Migration Subjects on Evening Television Programs
Full INA Sample

	Before the refugee crisis (09.2015)				***After the refugee crisis (09.2015)***				***All***			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
TF1	0.025	0.022	0.002	0.103	0.035	0.030	0.009	0.156	0.029	0.026	0.002	0.156
France 2	0.031	0.022	0.012	0.097	0.061	0.040	0.027	0.232	0.045	0.035	0.012	0.232
France 3	0.022	0.020	0.004	0.085	0.043	0.042	0.013	0.223	0.032	0.033	0.004	0.223
M6	0.014	0.016	0.000	0.076	0.025	0.027	0.005	0.146	0.019	0.022	0.000	0.146
Arte	0.081	0.040	0.015	0.205	0.146	0.071	0.062	0.381	0.111	0.065	0.015	0.381
CNews	0.028	0.027	0.000	0.105	0.053	0.047	0.000	0.215	0.039	0.039	0.000	0.215
BFM TV	0.029	0.028	0.000	0.111	0.048	0.042	0.000	0.194	0.038	0.036	0.000	0.194
Total	0.033	0.033	0.000	0.205	0.059	0.058	0.000	0.381	0.045	0.048	0.000	0.381

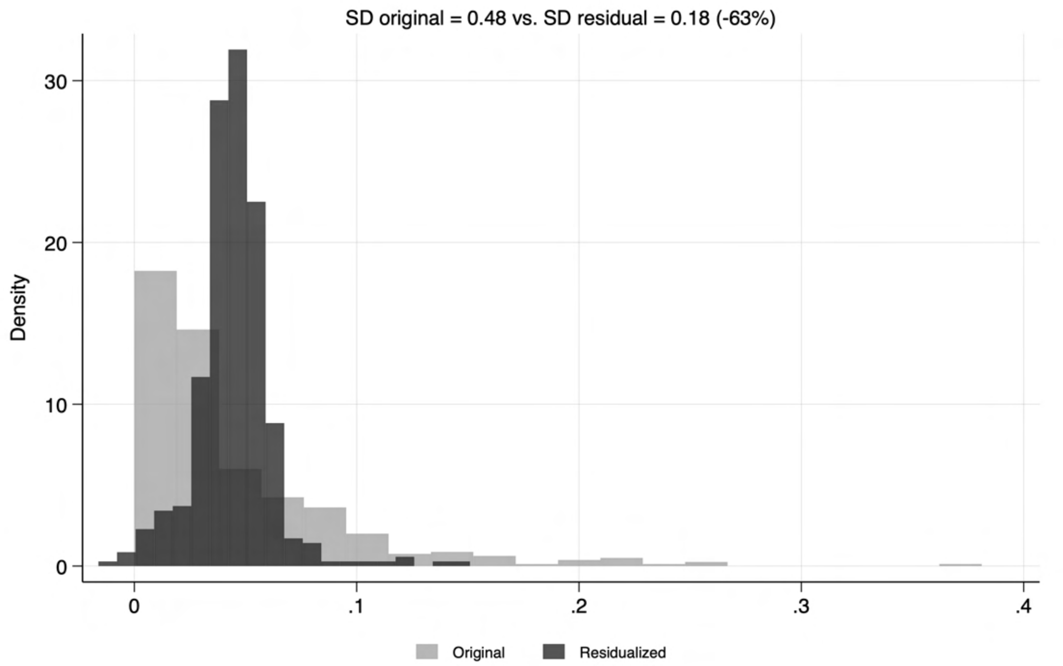
Notes: This table reports the average monthly share of migration subjects on evening TV programs from 2013 to 2017. The date of the refugee crisis in our context is September 2015.
Sources: Authors' elaboration on INA data.

Figure B3: Media Coverage of Immigration
Year-month and Channel Fixed Effects Partialled Out



Notes: This figure plots the coverage of immigration on French evening news programs at the channel level. Channel fixed effects, as well as wave fixed effects, are partialled out.
Sources: Authors' elaboration on INA data.

Figure B4: Media Coverage of Immigration
Distribution Before and After Year-month and Channel Fixed Effects
are Partialled Out



Notes: This figure plots the distribution of the coverage of immigration on French evening news programs between 2013 and 2017, before and after channel fixed effects, as well as wave fixed effects, are partialled out.
Sources: Authors' elaboration on INA data.

Appendix B3 Coverage of Immigration in Months Preceding the ELIPSS Waves

As reported in Table B1, the average share of immigration-related news stands at 4.50% between 2013 and 2017, with a standard deviation of 4.80% and a maximum of 38,10% (Arte in September 2015). This corresponds to an average number of immigration-related subjects of 17.50 and to an average duration of immigration-related topics for the months of analysis of approximately 31.38 minutes per month, while the duration share stands at 4.95%. Unfortunately, our analysis does not allow us to track individual attitudes every month because we can only do so for a subsample of 12 ELIPSS waves, as described in Table 1. This subsample consisting of only media data for the months preceding each wave of the ELIPSS survey is, however, representative of the variation recorded in the full INA database. First, Figure B2 shows that the different waves of surveys are well distributed over the analysis period, both before and after the refugee crisis. Second, Table B2 reports descriptive statistics for the average share of migration subjects on evening news programs for the 12 preceding months of the ELIPSS waves that are used for the empirical analysis. The average share of immigration-related news stands at 3.33% between 2013 and 2017, with a standard deviation of 3.32% and a maximum of 18,80% (Arte in November 2015). As long as September 2015 is excluded from the full INA sample, we do not find statistically significant mean differences in coverage between the full INA sample and the 12 waves from ELIPSS.

Table B2: Average Share of Migration Subjects on Evening Television Programs
Months Preceding ELIPSS Waves Only

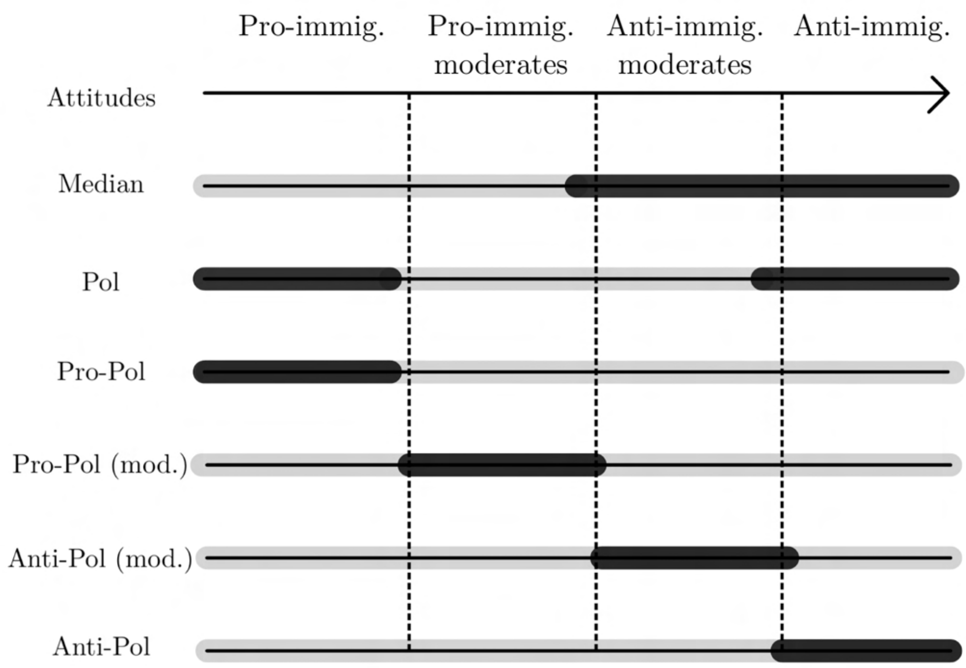
	Before the refugee crisis (09.2015)				***After the refugee crisis (09.2015)***				***All***			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
TF1	0.017	0.007	0.009	0.031	0.022	0.005	0.016	0.028	0.019	0.007	0.009	0.031
France 2	0.032	0.015	0.012	0.064	0.045	0.007	0.036	0.053	0.036	0.014	0.012	0.064
France 3	0.018	0.013	0.005	0.046	0.021	0.010	0.013	0.033	0.019	0.012	0.005	0.046
M6	0.011	0.009	0.002	0.030	0.018	0.006	0.010	0.025	0.013	0.009	0.002	0.030
Arte	0.083	0.036	0.036	0.158	0.111	0.055	0.062	0.188	0.093	0.043	0.036	0.188
CNews	0.025	0.021	0.004	0.068	0.024	0.013	0.016	0.044	0.025	0.018	0.004	0.068
BFM TV	0.027	0.023	0.006	0.082	0.033	0.024	0.015	0.068	0.029	0.023	0.006	0.082
Total	0.030	0.030	0.002	0.158	0.039	0.038	0.010	0.188	0.033	0.032	0.002	0.188

Notes: This table reports the average monthly share of migration subjects on evening TV programs for months preceding the 12 waves in the ELIPSS sample. The date of the refugee crisis in our context is September 2015.
Sources: Authors' elaboration on INA data.

Appendix C Additional Estimates and Robustness Checks

Appendix C1 Descriptives

Figure C1: Dependent Variables



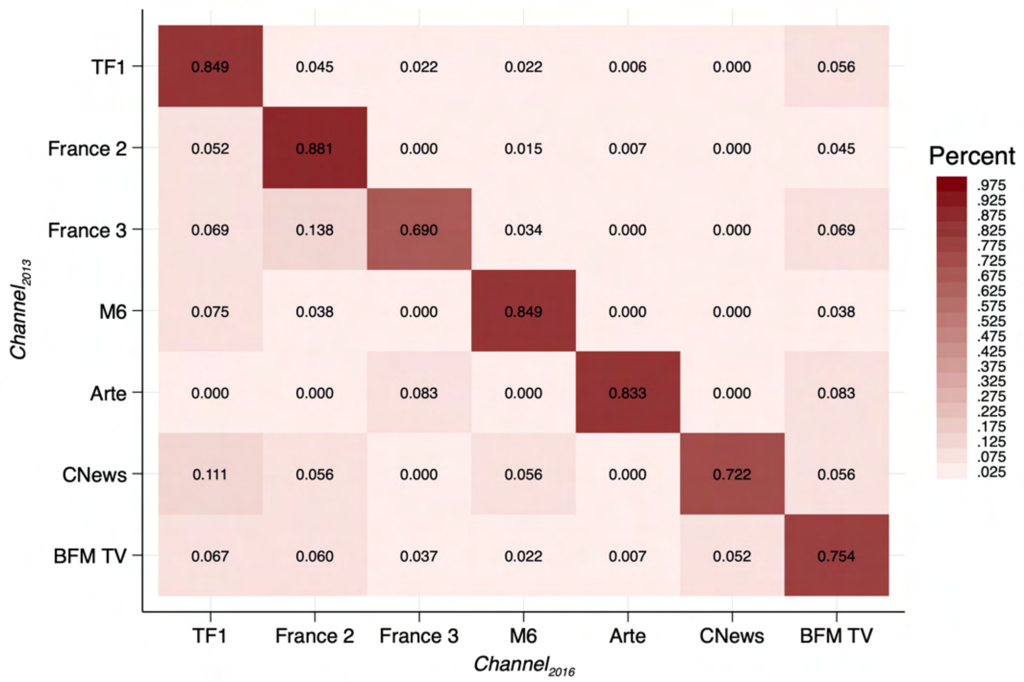
Notes: This figure depicts the definition of the main dependent variables. Grey zones are coded as zero while dark zones are coded as one. *Attitudes* is the continuous average attitude of individual i in year-month t toward immigration. $Median$ is a dummy variable equal to one for respondents with attitudes above the median and zero otherwise. *Pol* is a dummy variable that takes the value of one for individuals with extreme attitudes (pro-and anti-immigration) and zero otherwise (moderates). *Pro-pol* is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration and moderates). *Pro-pol (mod.)* is a dummy equal to one for pro-immigration moderates and zero otherwise (anti-immigration, anti-immigration moderates, and pro-immigration). *Anti-pol (mod.)* is a dummy equal to one for anti-immigration moderates and zero otherwise (anti-immigration, pro-immigration moderates, and pro-immigration). *Anti-pol* is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration and moderates).
Sources: Authors' elaboration on INA and ELIPSS data.

Table C1: Summary Statistics

	Mean	Std. Dev.	Min.	Max.	Type
$Attitudes_{it}$	2.483	0.776	1	4	Categorical
Median	0.466	0.499	0	1	Dummy
Pol.	0.382	0.486	0	1	Dummy
Pro-Pol	0.198	0.399	0	1	Dummy
Pro-Pol moderates	0.336	0.472	0	1	Dummy
Anti-Pol moderates	0.282	0.450	0	1	Dummy
Anti-Pol	0.184	0.388	0	1	Dummy
$ln(Dur_{ct-1})$	3.632	0.865	0.421	5.249	Continous
$ShareDur_{ct-1}$	0.031	0.021	0.001	0.198	Continous
$ln(Sub_{ct-1})$	3.010	0.778	0.881	4.625	Continous
$ShareSubj_{ct-1}$	0.027	0.019	0.002	0.188	Continous
$Days_{ct-1}$	9.009	4.876	1	26	Continous
Age, 5-year cat.	5.583	2.648	0	10	Categorical
High education	0.654	0.476	0	1	Dummy
Employed	0.671	0.470	0	1	Dummy
Marital Status	0.664	0.472	0	1	Dummy
Nb. Child	0.788	1.077	0	3	Categorical
Blue collar	0.212	0.409	0	1	Dummy
Income category	3.091	1.824	0	6	Categorical
Nb. Household member	2.476	1.299	1	6	Categorical
Nb. observations		6,796			

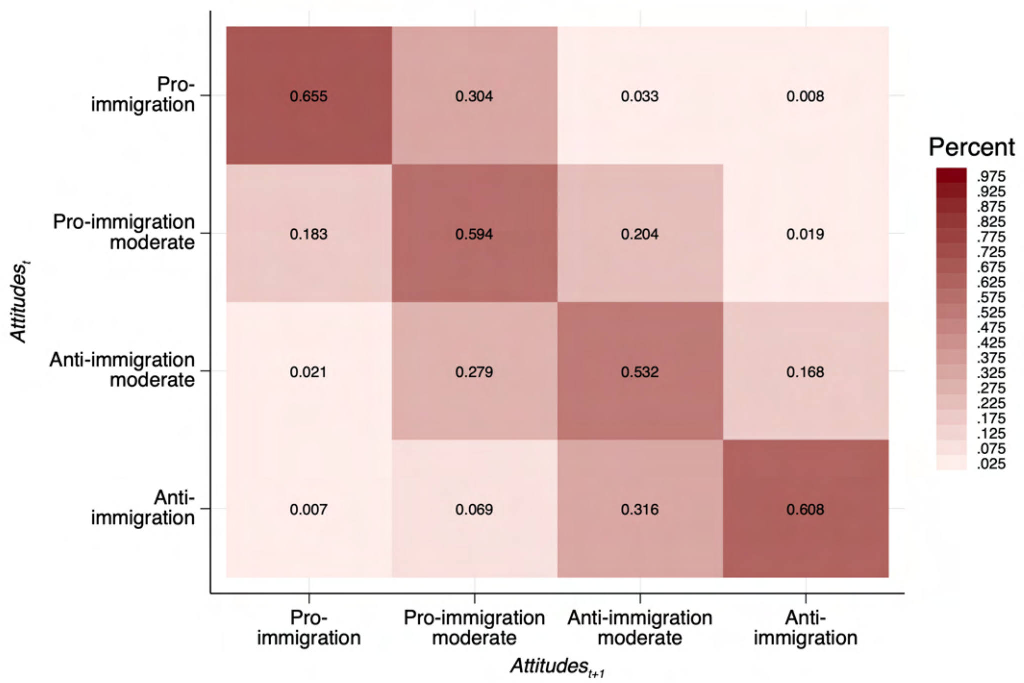
Notes: $Attitudes_{it}$ is the continuous average attitude of individual i in year-month t toward immigration. $Median$ is a dummy variable equal to one for respondents with attitudes above the median and zero otherwise. Pol is a dummy variable that takes the value of one for individuals with extreme attitudes (pro-and anti-immigration) and zero otherwise (moderates). *Anti-pol* is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration and moderates). *Pro-pol* is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration and moderates). *Pro-pol (mod.)* is a dummy equal to one for pro-immigration moderates and zero otherwise (anti-immigration, anti-immigration moderates, and pro-immigration). *Anti-pol (mod.)* is a dummy equal to one for anti-immigration moderates and zero otherwise (anti-immigration, pro-immigration moderates, and pro-immigration). $ShareSubj_{ct}$ is the share of subjects devoted to the topic of migration in year-month t on the evening news program of channel c. $ln(Subj_{sct})$ is the log total number of subjects related to immigration in year-month t during the evening news program of channel c. $ln(Dur_{ct})$ is the log total number of minutes in year-month t devoted to immigration during the evening news program of channel c. $ShareDur_{ct}$ is the share of the time devoted to immigration out of the total broadcasting time. The "Age" variable is composed of 11 categories ranging from less than 24 years old to more than 70 years old. The "High education" variable equals one if the individual has a diploma equivalent to the French baccalaureate and 0 otherwise. The "Employed" variable equals one if the individual is employed and 0 otherwise. The variable "Marital Status" equals one if the individual is in a couple and 0 otherwise. The variable "Nb. Child" ranges from 0 for no children to 3 for more than 3 children. The variable "Nb. Household member" ranges from 1 for one individual to 6 for more than 6 individuals in the household. The variable "Blue collar" equals one if the individual is a blue-collar worker and 0 otherwise. The "Income category" variable is composed of 7 categories ranging from 0 monthly revenue to more than 6000€monthly revenues (Less than 1200, [1200;2000[, [2000;2500[, [2500;3000[, [3000;4000[, [4000;6000[, more than 6000.). Sources: Authors' elaboration on INA and ELIPSS data.

Figure C2: Transition Matrix of Preferred Channel



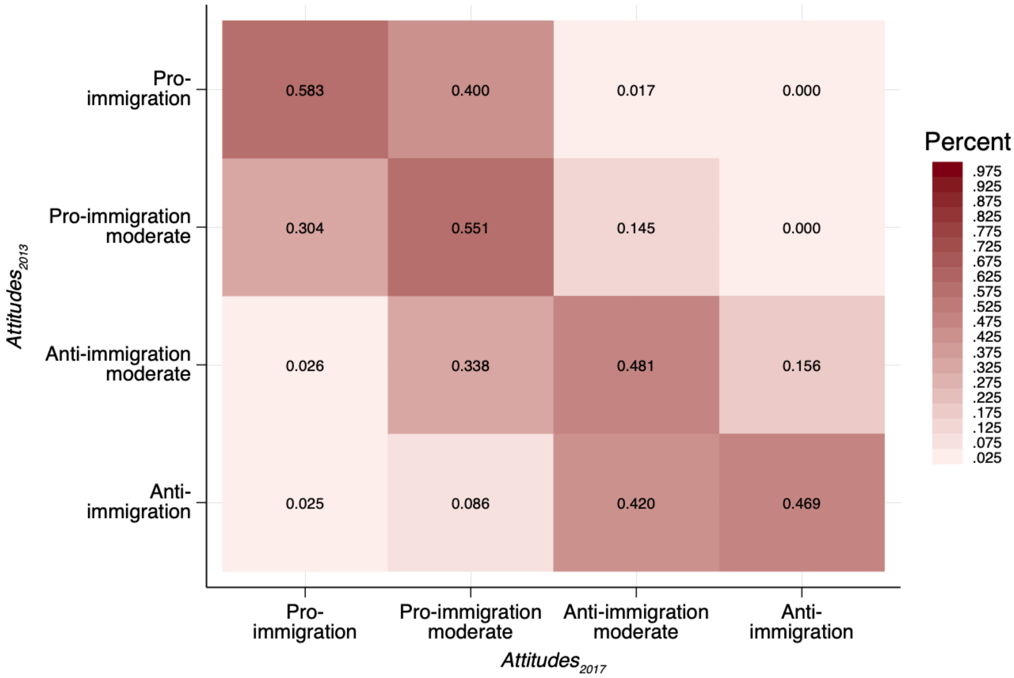
Notes: This figure depicts the transition matrix of TV viewers from their declared channel in 2013 to their declared channel in 2016.
Sources: Authors' elaboration on ELIPSS data.

Figure C3: Transition Matrix of Attitudes



Notes: This figure depicts the transition matrix of respondents from their declared attitudes toward immigration in wave t to their declared attitudes toward immigration in wave $t+1$.
Sources: Authors' elaboration on INA and ELIPSS data.

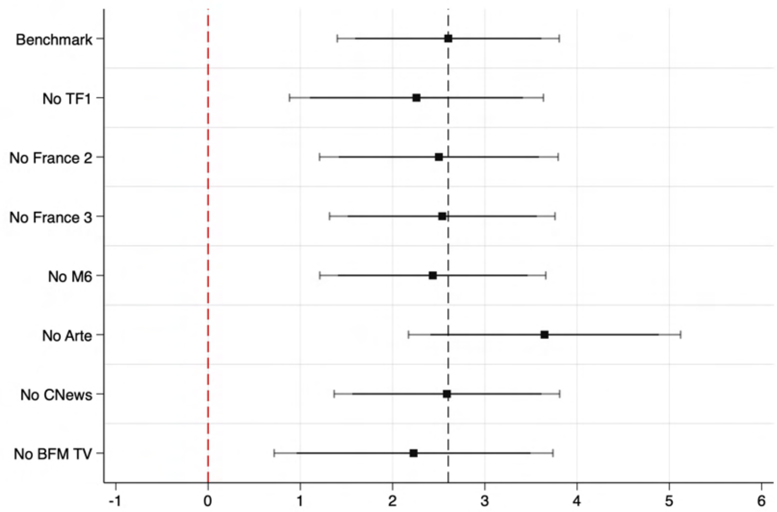
Figure C4: Transition Matrix of Attitudes



Notes: This figure depicts the transition matrix of respondents from their declared attitudes toward immigration in the first wave of 2013 to their declared attitudes toward immigration in the last wave of 2017.
Sources: Authors' elaboration on INA and ELIPSS data.

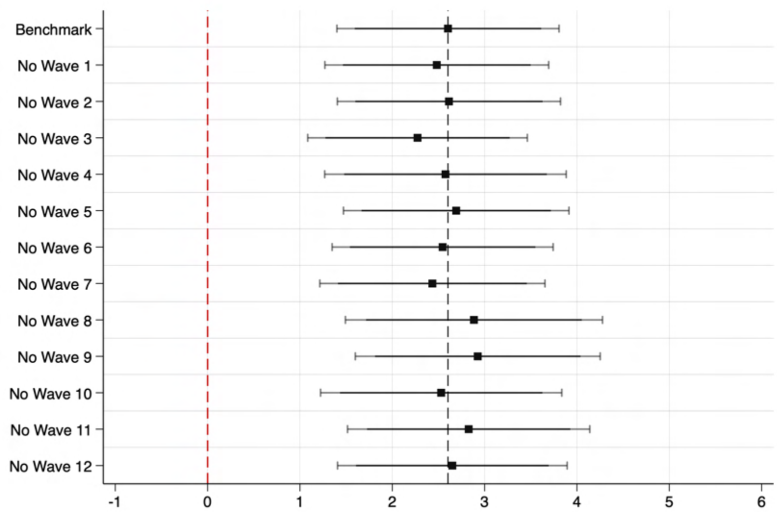
Appendix C2 Robustness to Sub-Sample

Figure C5: Removing Channels One by One



Notes: These coefficients are obtained estimating Equation 2 and removing all channels one after the other. The dependent variable is polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Figure C6: Removing Waves One by One



Notes: These coefficients are obtained estimating Equation 2 and removing each wave one after the other. The dependent variable is polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix C3 Alternative Dependent Variable

This appendix assesses the robustness of our main results, derived from estimating Equation 2, to alternative dependent variables.

We measure attitudes towards immigration in France by considering responses to three questions, namely (1) *There are too many immigrants in France*, (2) *France's cultural life is enriched by immigrants* and (3) *French Muslims are French citizens same as any others*. We argue that these three statements effectively capture attitudes towards immigration in France, even the third question. This is justified by the fact that Muslims constitute 43% of the immigrant population in France, blurring the distinction between these two groups within the native population (Simon and Tiberj, 2016).[2] Our main variable, $Attitudes_{it}$, represents the average attitude of individual i in year-month t across these three dimensions.

Table C2: Coverage of Immigration in the News and Average Attitudes Toward Immigration

	(1) Mean	(2) Mean	(3) Mean	(4) Mean	(5) Median	(6) Median	(7) Median	(8) Median
$ShareSubj_{ct-1}$	-6.635***	-1.532***	0.307	0.336	-3.713***	-0.883***	0.119	0.061
	(0.798)	(0.336)	(0.490)	(0.536)	(0.417)	(0.286)	(0.435)	(0.484)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Wave FE	No	No	Yes	Yes	No	No	Yes	Yes
Channel FE	No	No	No	Yes	No	No	No	Yes
Nb. Observations	6,796	6,796	6,796	6,796	6,796	6,796	6,796	6,796
Adjusted R^2	0.109	0.766	0.786	0.786	0.089	0.633	0.659	0.659
Std. coefficient	-0.127	-0.029	0.006	0.006	-0.071	-0.017	0.002	0.001
Bootstrap t-stat	-4.164	-3.833	0.382	0.398	-4.062	-2.697	0.240	0.112
Bootstrap p-value	0.027	0.113	0.668	0.736	0.034	0.089	0.849	0.925

Notes: The dependent variable from Columns (1) to (4) is continuous and represents the average attitudes of individual i toward immigration. The dependent variable from Columns (5) to (8) is the median split of average attitudes. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient). Bootstrap t-stats and p-values clustered at the channel level are also reported in the table footer (Bootstrap t-stat and Bootstrap p-value).
Sources: Authors' elaboration on INA and ELIPSS data.

In Table C2, we explore the relationship between immigration coverage and average native attitudes toward immigration. In Columns (1) to (4), we employ a continuous variable ($Attitudes_{ic_{(i)}t}$) as the dependent variable. Subsequently,

[2]Table C4 reports the outcomes of an increase in the coverage of news related to Muslims in France using a lexicon that only encompasses Muslim-specific vocabulary. Although the coefficients are not statistically significant, they closely match those of our benchmark specification.

in Columns (5) to (9), we re-estimate the model using a dummy variable equal to one for individuals with positive attitudes and zero otherwise (*Median*). In both cases, the most comprehensive specification confirms the absence of a significant association between immigration coverage and native attitudes toward immigration. This underlines that null effects on the average or median may conceal underlying polarization within the distribution of attitudes.

Table C3 reports the impact of focusing on or removing each of the three dimensions of $Attitudes_{it}$ separately. Note that the average $Attitudes_{it}$ is only calculated based on the available questions, as not all three questions are asked in every survey wave, as shown in Table 1. Excluding dimensions reduces therefore the number of observations in our analysis. Columns (1) to (3) demonstrate that our main conclusion regarding the polarizing effect of increased immigration coverage remains consistent when each dimension is excluded one after the other. In Columns (4) to (6), we find that when focusing on one dimension at a time, the coefficient of interest becomes insignificant for two out of three questions. However, we provide evidence that our primary conclusions remain unaffected when employing a principal component analysis (PCA) that captures the shared component of all three dimensions in Column (7).[3]

Table C3: Alternative Dependent Variable

	Excluding:			Focusing on:			
	Muslims=citizens	Immigration=Culture	Too much immigrants	Too much immigrants	Immigration=Culture	Muslims=Citizens	PCA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ShareSubj_{ct-1}$	2.233***	2.680***	2.128***	0.677	1.080*	0.254	1.077**
	(0.549)	(0.594)	(0.585)	(0.547)	(0.558)	(0.568)	(0.495)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	4,874	5,054	5,218	5,867	5,946	5,948	5,007
Adjusted R^2	0.601	0.514	0.510	0.495	0.445	0.493	0.470
Bootstrap t-stat	5.130	5.217	3.157	1.938	1.049	0.879	2.378
Bootstrap p-value	0.026	0.032	0.021	0.080	0.440	0.451	0.034

Notes: The dependent variable is Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

[3]Taking the average of the three dimensions still appears to be a superior option because the PCA ignores observations when information on at least one of the three dimensions is missing, either because one of the three questions is not asked on a specific year or due to individual non-response (less than 1% for all questions separately).

Table C4: Exposure to Immigration-Related News Concerning Muslims

	(1) Pol.	(2) Pro-Pol	(3) Pro-Pol (mod.)	(4) Anti-Pol (mod.)	(5) Anti-Pol
$ShareSubj_{ct-1}$	2.654*	1.992	-1.194	-1.461	0.663
	(1.572)	(1.310)	(1.749)	(1.202)	(0.797)
Nb. Observations	6,796	6,796	6,796	6,796	6,796
Adjusted R^2	0.448	0.584	0.369	0.350	0.556

Notes: The dependent variable in Column (1) is Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in Column (2) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). The dependent variable in Column (3) is a dummy equal to one for individuals with pro-immigration moderate attitudes and zero otherwise (pro-immigration, anti-immigration moderates, and anti-immigration). The dependent variable in Column (4) is a dummy equal to one for individuals with anti-immigration moderate attitudes and zero otherwise (pro-immigration, pro-immigration moderates, and anti-immigration). The dependent variable in Column (5) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix C4 Alternative Independent Variable

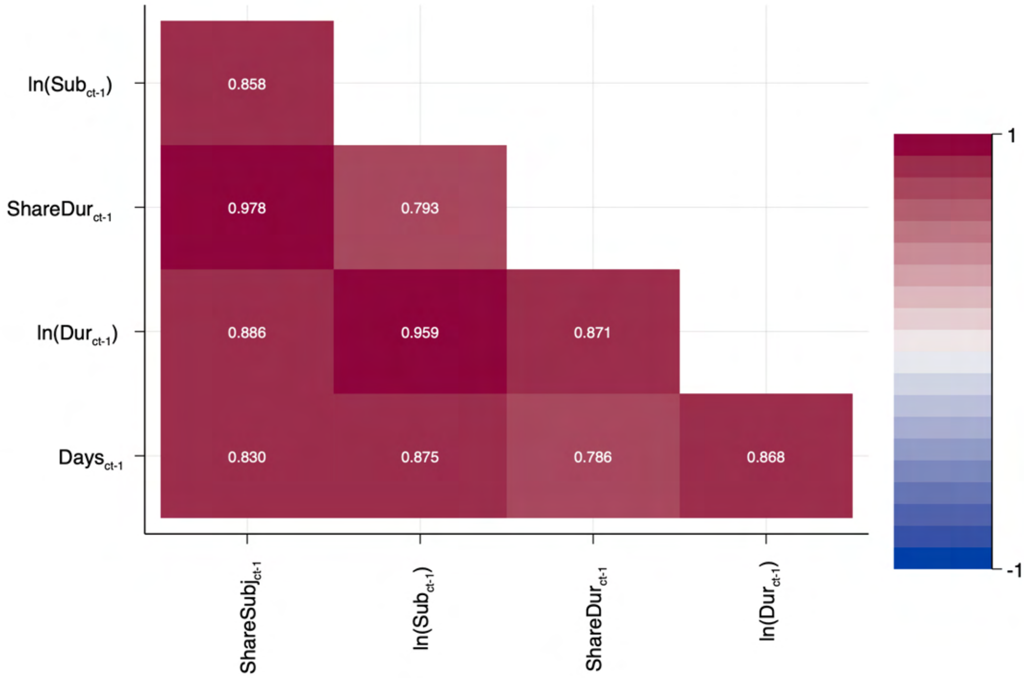
This appendix tests the robustness of the result using alternative measures of the salience of the migration topic.

We define Dur_{ct} as the total number of minutes in year-month t devoted to immigration during the evening news program of channel c. Then, we define $ShareDur_{ct}$ as the share of time devoted to immigration from the total broadcasting time on French TV channels. In contrast, to Dur_{ct}, $ShareDur_{ct}$ does not denote a stock but rather accounts for the prevalence of immigration within the overall broadcasting time devoted to political information on French television channels. To capture whether the distribution of the coverage of immigration in the month matters, we also use $Days_{ct}$, which is the number of days in the month that migration has been discussed on the TV channel, as a dependent variable.[4] We also report the results of the benchmark specification with $ShareSubj_{ct}$ (our benchmark independent variable of interest) and $Subj_{ct}$, the share and the total number of subjects related to immigration, respectively. All variables are

[4]Note that Dur_{ct} and Sub_{ct} are monotonically rescaled using the inverse hyperbolic sine. The inverse hyperbolic sine is defined as $(log(x_i + \sqrt{x_1^2 + 1})$. Unlike the log transformation, the inverse hyperbolic sine transformation is defined at zero (if the channel coverage of immigration in a given month is null), while the interpretation of the coefficients is identical. All the conclusions remain unchanged when using the log transformation of Dur_{ct} and Sub_{ct}, and the results are available upon request to the authors.

standardized to ease comparison across estimates.

Figure C7: Cross-Correlations Between Measures of Salience



Notes: This graph depicts the Pearson's correlations between various measures of salience.
Sources: Authors' elaboration on INA data.

Table C5 reports the results of the benchmark specification using the aforementioned alternative independent variables. Irrespective of the measure, we always find a positive effect of an increase in the coverage of immigration on the likelihood of polarization. Our effect is always highly significant for polarization toward positive attitudes (column 2) and for three out of five variables for polarization toward negative attitudes (Column 5). This is not surprising as Figure C7 reports strong correlations between all variables.

Table C5: Alternative Independent Variables
Standardized coefficients

	(1) Pol.	(2) Pro-Pol	(3) Pro-Pol (mod.)	(4) Anti-Pol (mod.)	(5) Anti-Pol
$ShareSubj_{ct-1}$	0.050***	0.032***	-0.033**	-0.017	0.018**
	(0.012)	(0.008)	(0.013)	(0.011)	(0.008)
$ln(Sub_{ct-1})$	0.045***	0.024**	-0.028*	-0.016	0.020**
	(0.014)	(0.011)	(0.015)	(0.014)	(0.010)
$ShareDur_{ct-1}$	0.038***	0.024***	-0.025**	-0.012	0.014**
	(0.010)	(0.007)	(0.011)	(0.010)	(0.006)
$ln(Dur_{ct-1})$	0.026**	0.016**	-0.018	-0.008	0.010
	(0.011)	(0.008)	(0.012)	(0.011)	(0.008)
$Days_{ct-1}$	0.041***	0.032***	-0.039***	-0.002	0.009
	(0.014)	(0.010)	(0.014)	(0.013)	(0.009)
Nb. Observations	6,796	6,796	6,796	6,796	6,796
Adjusted R^2	0.450	0.585	0.370	0.350	0.557

Notes: The dependent variable in Column (1) is Polarization, which takes value one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in Column (2) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). The dependent variable in Column (3) is a dummy equal to one for individuals with pro-immigration moderate attitudes and zero otherwise (pro-immigration, anti-immigration moderates, and anti-immigration). The dependent variable in Column (4) is a dummy equal to one for individuals with anti-immigration moderate attitudes and zero otherwise (pro-immigration, pro-immigration moderates, and anti-immigration). The dependent variable in Column (5) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). This table reports standardized coefficients for comparison between estimates. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix C5 Heterogeneity Analysis

To investigate whether the polarization effect of an increase in the coverage of immigration on natives' attitudes toward immigration is heterogeneous across individual characteristics and sources of political information, we augment Equation (2) using an interaction term between the treatment variable and various characteristics set at the beginning of the period, to be considered as exogenous as possible. We consider several individual dimensions that may drive a heterogeneous effect, including gender, age, education, employment status, income and political interest. For all variables, we chose the splitting value for the dummy to be as close as possible to the median value of the variable. For age, we compare individuals who are below and above 50 years old. For education, we compare people with and without a tertiary diploma. For employment, we compare employed individuals with their unemployed and out-of-labor-market counterparts. For income, we compare individuals who have an income below and above 2500€ per month. The benchmark equation is modified as follows:

$$\begin{aligned} Pol_{ic_{(i)}t} = \beta_1 ShareSubj_{ct-1} + \beta_3 ShareSubj_{ct-1} \times Characteristic_{ic_{(i)}} \\ + \boldsymbol{\beta' X_{it}} + \gamma_i + \gamma_c + \gamma_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where $Characteristic_{ic_{(i)}}$ is an indicator equal to one for each aforementioned individual characteristic and zero otherwise. Being, time-invariant, the direct effect of these characteristics is absorbed by the individual fixed effects such that β_1 and β_3 can be directly interpreted as the marginal impact of an increase in the coverage of immigration when $Characteristic_{ic_{(i)}} = 0$ and $Characteristic_{ic_{(i)}} = 1$, respectively. We plot β_1 and β_3, the total effects of exposure to immigration news by categories of interest in Figure C8.

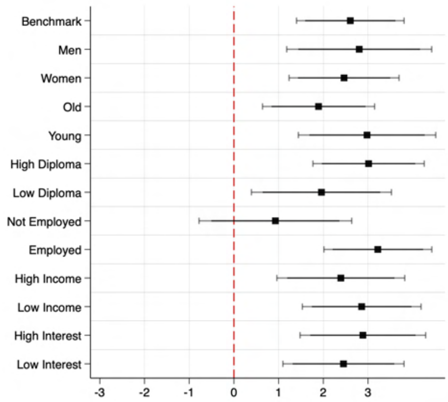
Figure C8a reports that polarization is significant for most of the individuals in the population except for unemployed respondents. Further investigations on $Anti-pol$ and $Pro-Pol$ highlight few differences in the magnitude of the effect along all individual characteristics.

Figure C8b shows that the priming effect toward pro-immigration attitudes is slightly lower for individuals with low education and unemployed individuals.

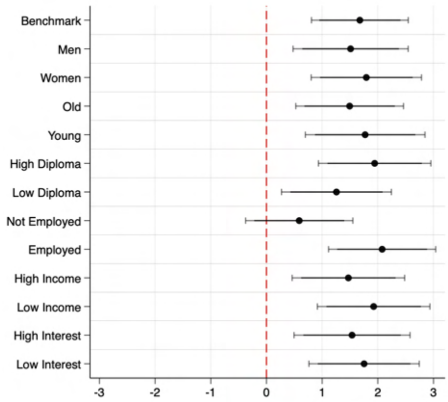
In the same way, Figure C8c, which focuses on polarization toward extremely negative attitudes also reports a lower probability of switching toward extremely negative attitudes for women, low-skilled, and unemployed individuals. The interpretation of these results is that individuals who are unemployed and less educated are less likely than others to change their attitudes and remain entrenched on their positions. In addition, we find that younger respondents are more likely to endorse anti-immigration attitudes than older respondents when the salience of immigration increases.

We further investigate whether the main effect of polarization is heterogeneous over individuals' second source of political information. Indeed, the data record not only whether respondents use TV as a first or second source of political information but also whether they rely on radio, the internet, or printed news. These results are reported in Figure C9 in the Appendix. We find that polarization is stronger among people who declare that they also listen to the radio on top of watching their preferred channel, while we still find a significant polarization effect when viewers also obtain political information from the internet or traditional press. Several patterns could explain the greater effect

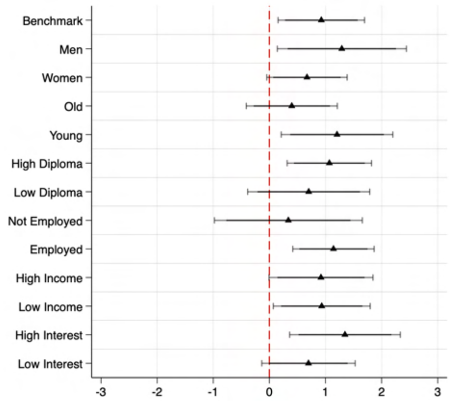
Figure C8: Heterogeneity Analysis by Individual Characteristics



(a) *Pol* as Dependent Variable



(b) *Pro-Pol* as Dependent Variable

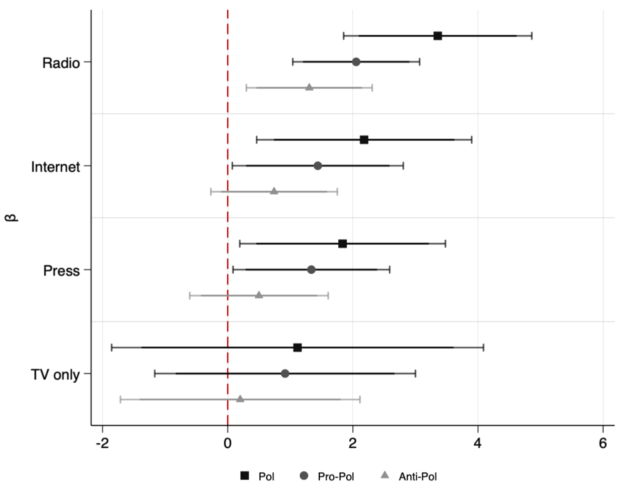


(c) *Anti-Pol* as Dependent Variable

Notes: The figure shows the marginal effect of $ShareSub_{ct-1}$ on polarization, *Anti-pol*, and *Pro-pol*, respectively, conditional on individuals' characteristics, and estimated in Equation (3). All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

of the radio: i) TV coverage may correlate more strongly with radio coverage than other forms of media, ii) there could be a greater likelihood of joint media consumption of TV and radio, or iii) individuals watching TV may have similar characteristics as those who listen to the radio.

Figure C9: Heterogeneity Analysis by Alternative Sources of Information



Notes: The figure shows the marginal effect of $ShareSub_{ct-1}$ on polarization, *Anti-pol*, and *Pro-pol*, respectively, conditional on individuals' second source of information, and estimated in Equation (3). For instance, the first group "radio" is composed of individuals who mentioned using the radio as a second source of political information. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

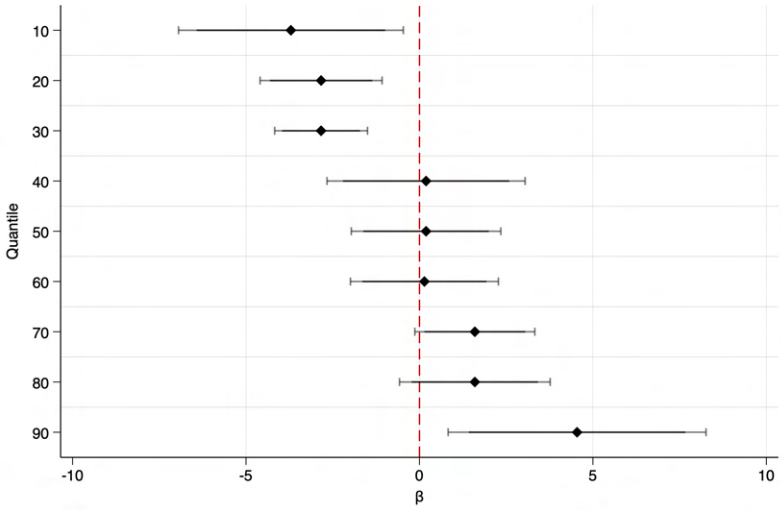
Appendix C6 Quantile Estimates

This appendix tests the robustness of our main specification using quantile estimates. This allows us to exploit the full spectrum of information within our measure of attitudes towards immigrants, without the need to construct separate dummies, such as pro- or anti-polarization indicators. Still, it is worth noting that quantile estimates are primarily designed for continuous variables, while our measure of attitudes towards immigrants is an aggregation of three discrete variables and, by design, is not perfectly continuous.

With this caveat in mind, we run quantile estimates using our measure of average attitudes toward immigrants, which can take 13 distinct values. Specifically, we perform unconditional quantile estimates, as conditional quantile results cannot be generalized to the overall population (Firpo et al., 2009). To do so, we rely on the `rifhdreg` STATA command, which runs recentered influence function regressions, following the methodology developed by (Firpo et al., 2009).

Our findings are depicted in Figure C10. The estimated coefficients support previous results that increased immigration coverage impacts the likelihood of displaying extreme attitudes on both ends of the distribution. It is associated with both an increase in the likelihood of having more positive attitudes toward

Figure C10: Unconditional Quantile Regressions (Firpo et al., 2009)



Notes: These coefficients are obtained estimating unconditional quantile regressions (Firpo, Fortin, and Lemieux 2009) with the `rifhdreg` in STATA 18. The dependent variable is continuous and represents the average attitudes of individual i toward immigration. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Bootstrapped standard errors with 100 replications. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

immigrants at the left-hand side of the distribution (quantiles 10 to 30) and a significant increase in the likelihood of having more negative attitudes toward immigrants at the right-hand side of the distribution (quantiles 70 to 90). Overall, these new estimates confirm that an increase in the coverage of immigration is associated with polarization at both sides of the distribution and in opposite directions.

Appendix C7 Clustering at the Channel Level and Bootstrapping

Table C6: Coverage of Immigration in the News and the Polarization of Attitudes Toward Immigration
Clustering at the Channel Level

	(1)	(2)	(3)	(4)
$ShareSubj_{ct-1}$	1.640***	1.747***	2.171***	2.603**
	(0.245)	(0.220)	(0.546)	(0.893)
Controls	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes
Wave FE	No	No	Yes	Yes
Channel FE	No	No	No	Yes
Nb. Observations	6,796	6,796	6,796	6,796
Adjusted R^2	0.018	0.431	0.449	0.450
Std. coefficient	0.031	0.033	0.042	0.050
Bootstrap t-stat	6.699	7.959	3.977	3.461
Bootstrap p-value	0.007	0.002	0.007	0.013

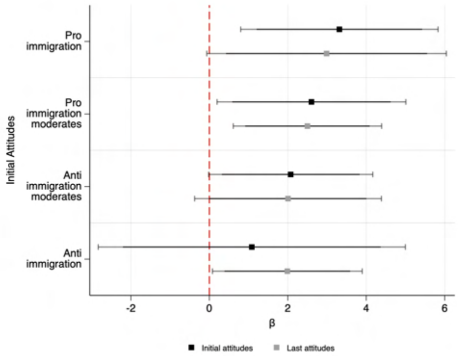
Notes: The dependent variable is Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the channel level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient). Bootstrap t-stats and p-values clustered at the channel level are also reported in the table footer (Bootstrap t-stat and Bootstrap p-value).
Sources: Authors' elaboration on INA and ELIPSS data.

Table C7: Direction of the Polarization
Clustering at the Channel Level

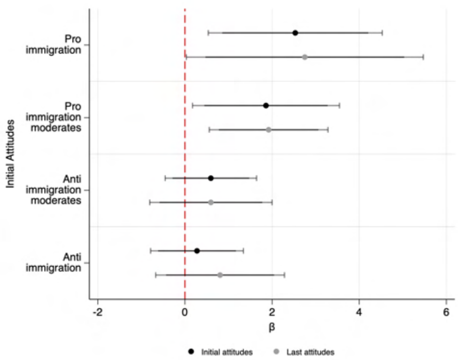
	(1) Pol.	(2) Pro-Pol	(3) Pro-Pol (mod.)	(4) Anti-Pol (mod.)	(5) Anti-Pol
$ShareSubj_{ct-1}$	2.603**	1.677***	-1.739	-0.865**	0.926
	(0.893)	(0.391)	(0.912)	(0.277)	(0.630)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,796	6,796	6,796	6,796	6,796
Adjusted R^2	0.450	0.585	0.370	0.350	0.557
Std. coefficient	0.050	0.032	-0.033	-0.017	0.018
Bootstrap t-stat	2.912	4.287	-1.906	-3.123	1.468
Bootstrap p-value	0.005	0.023	0.108	0.020	0.238

Notes: The dependent variable in Column (1) is Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in Column (2) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). The dependent variable in Column (3) is a dummy equal to one for individuals with pro-immigration moderate attitudes and zero otherwise (pro-immigration, anti-immigration moderates, and anti-immigration). The dependent variable in Column (4) is a dummy equal to one for individuals with anti-immigration moderate attitudes and zero otherwise (pro-immigration, pro-immigration moderates, and anti-immigration). The dependent variable in Column (5) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the channel level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient). Bootstrap t-stats and p-values clustered at the channel level are also reported in the table footer (Bootstrap t-stat and Bootstrap p-value).
Sources: Authors' elaboration on INA and ELIPSS data.

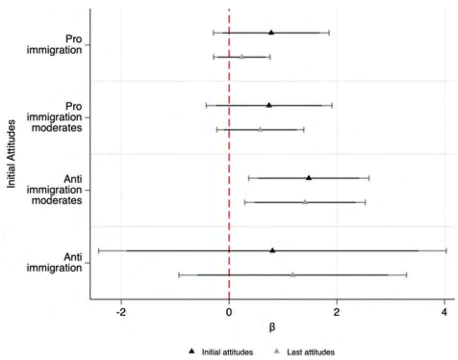
Figure C11: Coverage of Immigration Interacted with Preexisting Attitudes Clustering at the Channel Level



(a) *Pol* as Dependent Variable



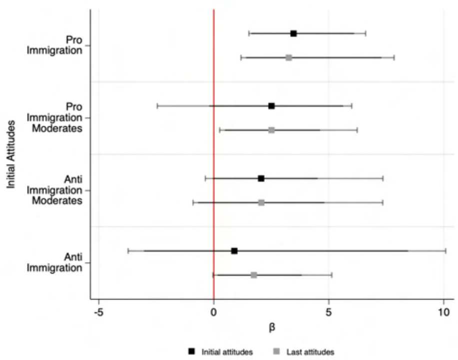
(b) *Pro-Pol* as Dependent Variable



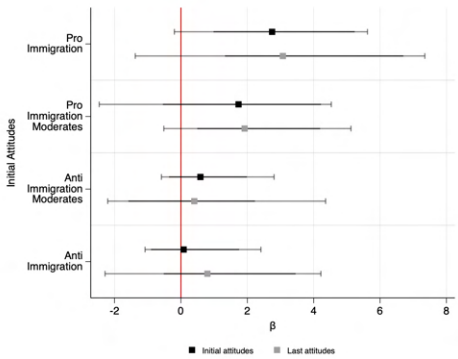
(c) *Anti-Pol* as Dependent Variable

Notes: The figure shows the marginal effect of $ShareSubj_{ct-1}$ on polarization, *Anti-pol* and *Pro-pol* respectively, estimated separately from Equation (3). Each coefficient represents the marginal effect of the variable for different preexisting attitudes. All estimates include wave, channel, and individual fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the channel level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

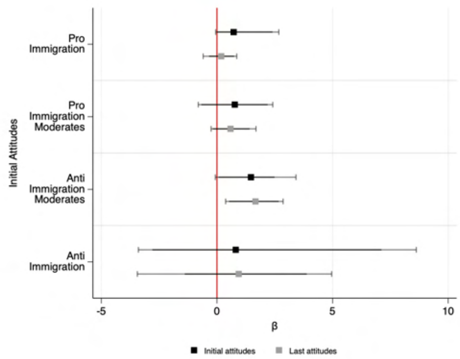
Figure C12: Coverage of Immigration Interacted with Preexisting Attitudes
Bootstrapped Standard Errors at the Channel Level



(a) *Pol* as Dependent Variable



(b) *Pro-Pol* as Dependent Variable

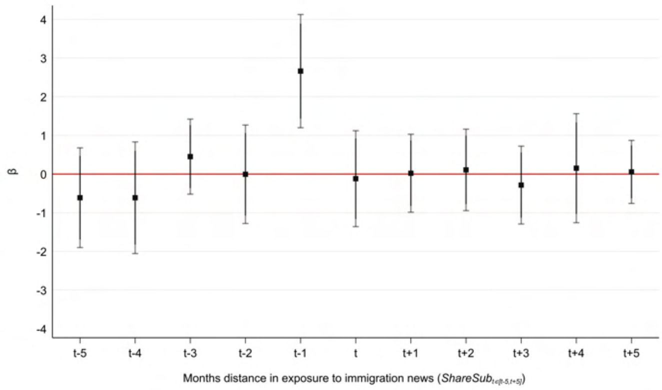


(c) *Anti-Pol* as Dependent Variable

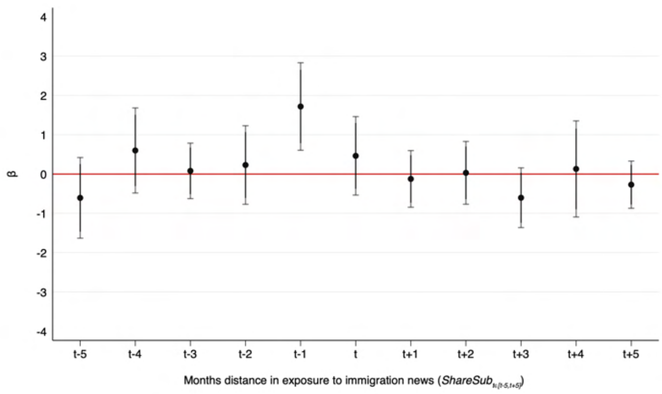
Notes: The figure shows the marginal effect of $ShareSubj_{ct-1}$ on polarization, *Anti-pol* and *Pro-pol* respectively, estimated separately from Equation (3). Each coefficient represents the marginal effect of the variable for different preexisting attitudes. All estimates include wave, channel, and individual fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Bootstrapped confidence intervals are presented at the 95% and 90% levels. Wild cluster bootstrap with 999 replications and Webb weights.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix C8 Distributed Leads and Lags Model

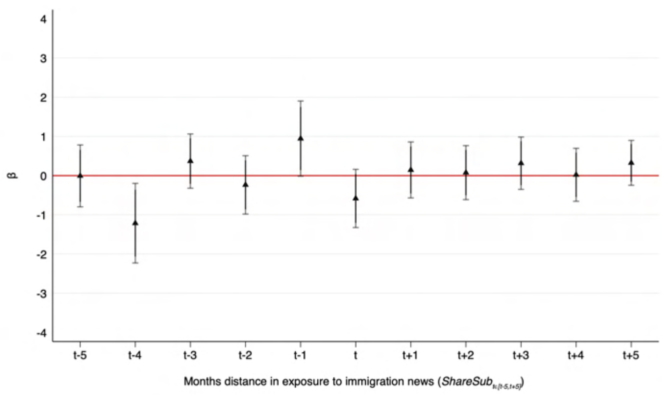
Figure C13: Leads and Lags of the Coverage of Immigration



(a) *Pol* as Dependent Variable



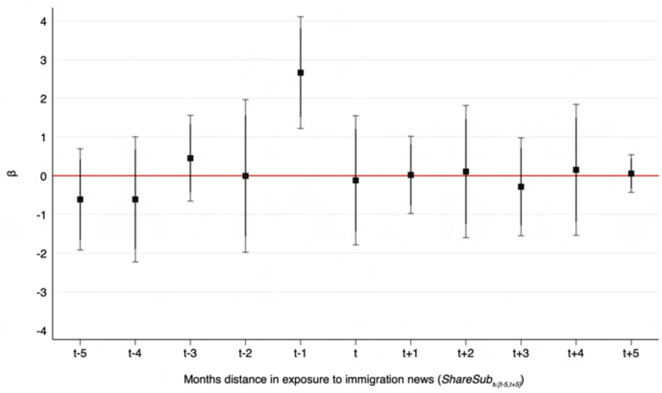
(b) *Pro-Pol* as Dependent Variable



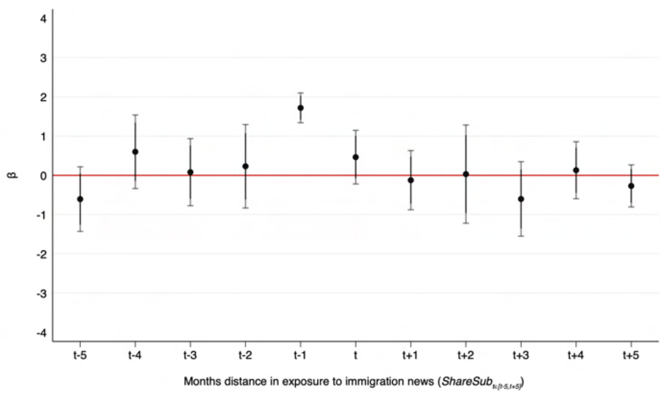
(c) *Anti-Pol* as Dependent Variable

Notes: The figure shows the marginal effect of $ShareSub_{ct-1}$ as well as its lagged and leading values on *Pol* estimated in one single regression. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

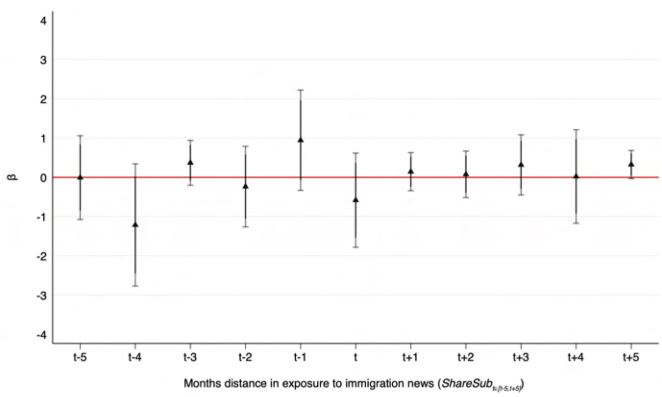
Figure C14: Leads and Lags of the Coverage of Immigration
Clustering at the Channel Level



(a) *Pol* as Dependent Variable



(b) *Pro-Pol* as Dependent Variable



(c) *Anti-Pol* as Dependent Variable

Notes: The figure shows the marginal effect of $ShareSub_{ct-1}$ as well as its lagged and leading values on Pol estimated in one single regression. Robust standard errors clustered at the channel level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix C9 Robustness to Individual-Channel Fixed Effects

Table C8: Coverage of Immigration in the News and the Polarization of Attitudes Toward Immigration
Robustness to Individual-Channel Fixed Effects

	(1)	(2)	(3)	(4)	(5)
$ShareSubj_{ct-1}$	1.640***	1.747***	2.171***	2.603***	2.621***
	(0.459)	(0.361)	(0.554)	(0.613)	(0.620)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes	No
Wave FE	No	No	Yes	Yes	Yes
Channel FE	No	No	No	Yes	No
Indiv. × Channel FEs	No	No	No	No	Yes
Nb. Observations	6,796	6,796	6,796	6,796	6,776
Adjusted R^2	0.018	0.431	0.449	0.450	0.453
Std. coefficient	0.031	0.033	0.042	0.050	0.050

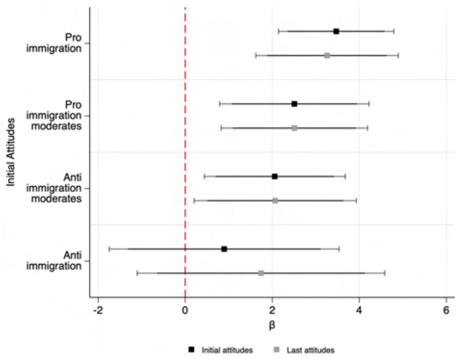
Notes: The dependent variable is Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient).
Sources: Authors' elaboration on INA and ELIPSS data.

Table C9: Direction of the Polarization
Robustness to Individual-Channel Fixed Effects

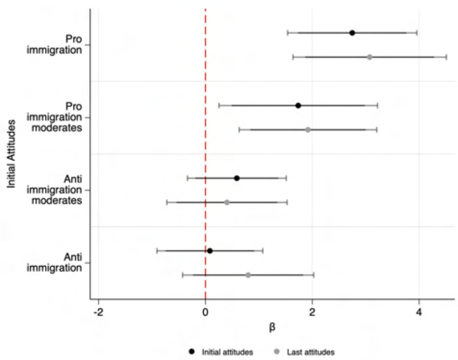
	(1) Pol.	(2) Pro-Pol	(3) Pro-Pol (mod.)	(4) Anti-Pol (mod.)	(5) Anti-Pol
$ShareSubj_{ct-1}$	2.621***	1.716***	-1.827***	-0.794	0.905**
	(0.620)	(0.447)	(0.683)	(0.579)	(0.395)
Controls	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes
Indiv. × Channel FEs	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,776	6,776	6,776	6,776	6,776
Adjusted R^2	0.453	0.586	0.370	0.354	0.559
Std. coefficient	0.050	0.033	-0.035	-0.015	0.017

Notes: The dependent variable in Column (1) is Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in Column (2) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). The dependent variable in Column (3) is a dummy equal to one for individuals with pro-immigration moderate attitudes and zero otherwise (pro-immigration, anti-immigration moderates, and anti-immigration). The dependent variable in Column (4) is a dummy equal to one for individuals with anti-immigration moderate attitudes and zero otherwise (pro-immigration, pro-immigration moderates, and anti-immigration). The dependent variable in Column (5) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient).
Sources: Authors' elaboration on INA and ELIPSS data.

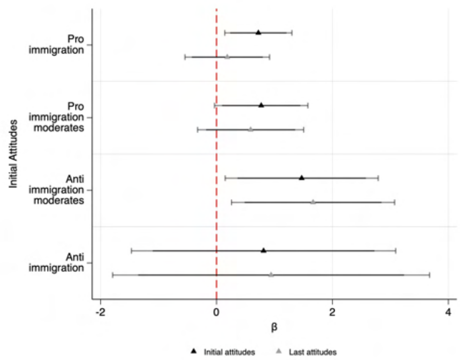
Figure C15: Coverage of Immigration Interacted with Preexisting Attitudes
Robustness to Individual-Channel Fixed Effects



(a) *Pol* as Dependent Variable



(b) *Pro-Pol* as Dependent Variable



(c) *Anti-Pol* as Dependent Variable

Notes: The figure shows the marginal effect of $ShareSubj_{ct-1}$ on polarization, *Anti-pol* and *Pro-pol* respectively, estimated separately from Equation (3). Each coefficient represents the marginal effect of the variable for different preexisting attitudes. All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix C10 Robustness to Ideological Controls

Table C10: Coverage of immigration in the news and the polarization of attitudes toward immigration.
Robustness to ideological controls

	(1)	(2)	(3)	(4)
$ShareSubj_{ct-1}$	1.726***	2.099***	2.010***	2.450***
	(0.500)	(0.424)	(0.602)	(0.673)
Left(0)-Right(10) scale	-0.010**	0.010**	0.008*	0.008*
	(0.005)	(0.005)	(0.005)	(0.005)
Interest in politics	-0.051***	-0.042***	-0.027**	-0.026**
	(0.014)	(0.013)	(0.013)	(0.013)
TV frequency	0.006	0.005	0.008	0.006
	(0.006)	(0.011)	(0.010)	(0.011)
Controls	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes
Wave FE	No	No	Yes	Yes
Channel FE	No	No	No	Yes
Nb. Observations	6,457	6,443	6,443	6,443
Adjusted R^2	0.028	0.427	0.444	0.446
Std. coefficient	0.033	0.040	0.039	0.047

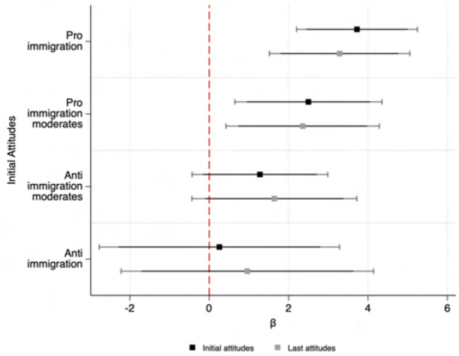
Notes: The dependent variable is Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient).
Sources: Authors' elaboration on INA and ELIPSS data.

Table C11: Direction of the polarization
Robustness to Ideological Controls

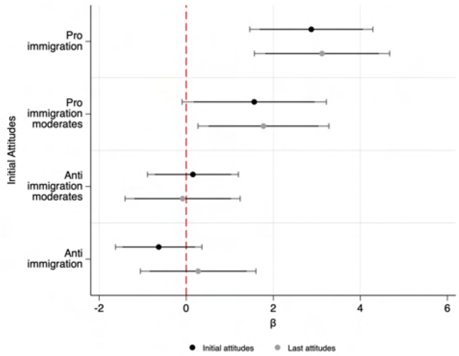
	(1) Pol.	(2) Pro-Pol	(3) Pro-Pol (mod.)	(4) Anti-Pol (mod.)	(5) Anti-Pol
$ShareSubj_{ct-1}$	2.450***	1.494***	-1.428*	-1.022*	0.956**
	(0.673)	(0.496)	(0.764)	(0.612)	(0.425)
Left(0)-Right(10) scale	0.008*	-0.002	-0.002	-0.006	0.010***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
Interest in politics	-0.026**	-0.023**	0.032**	-0.006	-0.003
	(0.013)	(0.010)	(0.014)	(0.013)	(0.009)
TV frequency	0.006	0.004	-0.011	0.004	0.003
	(0.011)	(0.006)	(0.010)	(0.010)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,443	6,443	6,443	6,443	6,443
Adjusted R^2	0.446	0.586	0.368	0.350	0.545
Std. coefficient	0.047	0.029	-0.027	-0.020	0.018

Notes: The dependent variable is Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient).
Sources: Authors' elaboration on INA and ELIPSS data.

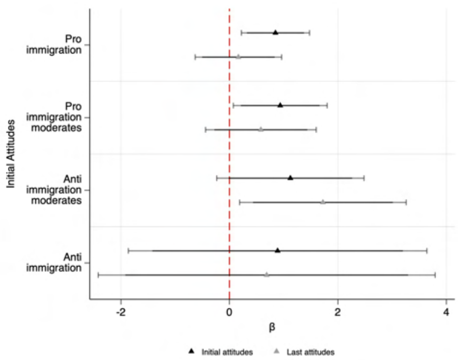
Figure C16: Coverage of Immigration Interacted with Preexisting Attitudes
Robustness to Ideological Controls



(a) *Pol* as Dependent Variable



(b) *Pro-Pol* as Dependent Variable



(c) *Anti-Pol* as Dependent Variable

Notes: The figure shows the marginal effect of $ShareSubj_{ct-1}$ on polarization, *Anti-pol* and *Pro-pol* respectively, estimated separately from Equation (3). Each coefficient represents the marginal effect of the variable for different preexisting attitudes. All estimates include wave, channel, and individual fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix C11 2SLS Estimates

Recent advances in the media literature have relied on an identification strategy that uses news pressure to predict exogenous coverage of specific topics (Eisensee and Strömberg, 2007; Durante and Zhuravskaya, 2018; Djourelova and Durante, 2022). This approach assumes that the presence of significant stories may displace news attention, consequently limiting the time available for covering other subjects. We adapt this strategy at the monthly level by leveraging an additional source of data from INA, which records the relative coverage allocated to 15 different topics across channels during our period of analysis. We use these measures as an instrument for the coverage of immigration.[5] The topic classification of the INA does not cover CNews and BFM TV, which reduces our sample of analysis by 26%.

The strength of our instruments relies on the assumption that certain channels may specialize in particular events, such as sports, and that in certain periods, like during the soccer World Cup, the available time to discuss immigration is therefore constrained. Thus, we only report 2SLS estimates that i) fulfill the instrument needs to be sufficiently strong (Kleibergen-Paap test exceeding 20) and ii) for which the first-stage coefficient is negative, indicating that higher coverage of a specific topic is associated with less coverage of immigration.[6] Four topics satisfy these conditions, namely, justice, disasters, sports, and sciences. Note that this identification strategy relies on additional assumptions that cannot be empirically tested, and which explains why it cannot be used as our primary identification strategy. Specifically, it assumes that the coverage of other topics is uncorrelated with attitudes toward immigration, which can be viewed as a heroic assumption of exogeneity.[7]

Our results are reported in Table C12, C13 and C14 for Pol, $Pro-pol$ and $Anti-pol$ as dependent variables, respectively. Overall, the estimated 2SLS coefficients concur with our benchmark results, despite having lower precision than the OLS estimates. On the one hand, almost all 2LS coefficients are positive as in our benchmark specification. On the other hand, the estimated coefficients

[5] All cited papers have in common the use of daily media reporting data. This prevents us from using the exact same strategy due to the monthly-level nature of the ELIPSS data. Indeed, unexpected major news stories that could reduce the available time for covering migration topics would be diluted when information is averaged at the monthly level.

[6] For instance, the "international" topic is one where the first-stage result is strong but positive, indicating that this topic may overlap with the coverage of immigration in French TV news.

[7] Even topics like sports may be related to immigration. In France, for instance, debates about the origins of national soccer team players, often driven by far-right parties, are quite salient, especially during election periods.

Table C12: 2SLS estimates. Dependent is Pol

	(1) Disasters	(2) Justice	(3) Sciences	(4) Sport
$ShareSubj_{ct-1}$	5.961**	0.353	2.472	4.784**
	(2.582)	(3.494)	(2.443)	(2.143)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes
Nb. Observations	5,010	5,010	5,010	5,010
First stage	-0.204	-0.243	-0.369	-0.111
KP-F test	239.606	85.591	387.115	172.671

Notes: The dependent variable is *Pol*. All estimates include wave, channel, and individual fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

are less precise than those in the OLS estimates (standard deviations are multiplied by more than 4). As a result, they lack significance for polarization toward extremely positive attitudes but do show significance for $Anti - Pol$ and Pol when using Disasters and Sports as instruments.

Table C13: 2SLS estimates. Dependent is Pro-Pol

	(1) Disasters	(2) Justice	(3) Sciences	(4) Sport
$ShareSubj_{ct-1}$	2.110	-0.523	1.482	2.350
	(1.891)	(2.837)	(1.844)	(1.626)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes
Nb. Observations	5,010	5,010	5,010	5,010
First stage	-0.204	-0.243	-0.369	-0.111
KP-F test	239.606	85.591	387.115	172.671

Notes: The dependent variable is *Pro-Pol*. All estimates include wave, channel, and individual fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

Table C14: 2SLS estimates. Dependent is Anti-Pol

	(1) Disasters	(2) Justice	(3) Sciences	(4) Sport
$ShareSubj_{ct-1}$	3.851**	0.876	0.991	2.435*
	(1.735)	(2.139)	(1.688)	(1.378)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes
Nb. Observations	5,010	5,010	5,010	5,010
First stage	-0.204	-0.243	-0.369	-0.111
KP-F test	239.606	85.591	387.115	172.671

Notes: The dependent variable is *Anti-Pol*. All estimates include wave, channel, and individual fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix C12 Oster's Methodology: Accounting for Selection in Unobservables

This section tests the robustness of our main results regarding selection on unobservables using the approach developed by Oster (2019). To the extent that selection on unobservables is sufficiently correlated with selection on observables, this methodology measures the degree of selection on unobservables in the estimates. Indeed, Oster (2019) demonstrates that changes in the coefficient and R-squared following the introduction of observables allow estimating the likelihood that the coefficient of interest is entirely driven by unobservables. The results are reported in Table C15.

We compute δ, the degree of selection on unobservables relative to observables that would be necessary to make the coefficient of interest equal to zero in various specifications. As reported by Oster (2019), concerns regarding self-selection on unobservables are ruled out as long as $\delta > 1$. Computing δ requires choosing a value for the R-squared of the hypothetical regression of Pol on $ShareSubj_{ct-1}$, while controlling for both observables and unobservables (R_{max}). Without further insights into how to choose an appropriate value for the bound on R_{max} in our setting, we follow the advice provided by Oster (2019) and set $R_{max} = 1.3\tilde{R}$, with $\tilde{R}$ being the R-squared of the benchmark specification with full controls and fixed effects. Interestingly, it is very close to the benchmark R-squared reported in the seminal paper by DellaVigna and Kaplan (2007).

Overall, we find that selection on unobservables would have to be 2.06 times higher than the selection on observables to change the nature of the findings. In the most comprehensive specification estimated in column (5), the bounding values of the coefficient of interest after correcting for the selection on unobservables are [1.18,110.84]. Thus, the identification set excludes zero and is of the same sign as the coefficient of interest.

Table C15: Accounting for Selection in Unobservables
$R^2_{max} = 1.3 \times R^2$

	(1) Pol.	(2) Pol.	(3) Pol.	(4) Pol.	(5) Pol.
$ShareSubj_{ct-1}$	1.792***	1.747*	2.171***	2.603***	2.621***
	(0.628)	(0.797)	(0.554)	(0.613)	(0.620)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes	No
Wave FE	Yes	No	Yes	Yes	Yes
Channel FE	No	No	No	Yes	No
Indiv. $\times$ Channel FEs	No	No	No	No	Yes
Nb. Observations	6,796	6,796	6,796	6,796	6,776
R^2	0.039	0.543	0.558	0.560	0.569
Adjusted R^2	0.033	0.431	0.449	0.450	0.453
Lower CI	1.195	1.195	1.195	1.195	1.195
Upper CI	349.482	2.430	104.973	132.476	110.840
δ for $R^2_{max} = 0.73$	4.186	6.025	1.775	1.898	2.063

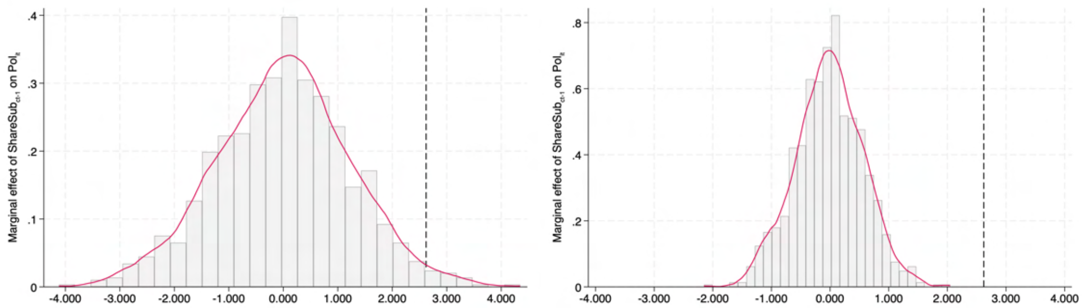
Notes: The dependent variable is Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the individual level. The set of control variables includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. δ is the level of selection on unobservables compared to observables which produces $\beta = 0$ given the value of R_{max}. The identified set (lower and upper CI) is bounded by $\hat{\beta}$ when $\delta = 0$ (no bias-adjustment) and $\tilde{\beta}$ when $\delta = 1$ (observables as important as unobservables).
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix C13 Placebo Estimates

In the presence of reverse causality bias, non-TV viewers should be also affected by the treatment assuming a parallel evolution in their attitudes to that witnessed among TV viewers. We thus perform placebo estimations on individuals who do not report TV as one of their top sources of political information. Indeed, a significant coefficient for non-TV viewers would suggest that the previous estimates plausibly captured a spurious correlation between media and attitudes e.g., if a particular event increased the salience of immigration in a specific TV channel but also separately increased the negative attitudes of viewers of this channel through direct exposure or through external factors such as social networks for instance. We first run 1,000 replications of the benchmark specification where non-TV viewers are randomly assigned to a specific TV channel. We constrain the random allocation to perfectly match the distribution of channels across individuals in the benchmark sample. The results of these placebo estimations are shown in Figure C17 (a). One can see that the coefficient of interest follows a standard normal distribution centered at zero.[8] Then, we perform an additional exercise where individuals are assigned to channels based on their individual characteristics instead of randomly. Indeed, using a Mahalanobis distance, each non-TV viewer is matched to the coverage of immigration on the preferred channel of the closest TV viewer who shares the same characteristics. The list of characteristics encompasses control variables such as age, education, employment status, marital status, number of children, household size, worker category (blue vs. white collar), and income, as well as political attitudes and interest. Again, considering individuals who never declared watching TV in our sample, the main coefficient of interest remains non-significant, as reported in Table C16. This tackles the issue that channels could decide how much coverage to give to newsworthy events based on how interested their viewers are likely to be in the event.

Figure C17: Placebo Estimates

(a) Non-Television Viewers (b) Television Viewers



Notes: These graphs depict the distribution of the estimates of the effect of an increase in salience on the polarization of attitudes for 1,000 different regressions where we randomly assign a channel to each respondent.
Sources: Authors' elaboration on INA and ELIPSS data.

[8] We replicate the exercise by randomly allocating channels to all TV- viewers. After 1,000 additional replications, we also obtain a point estimate that is centered at zero and is below the benchmark coefficient reported in Table 2. This finding supports that the results truly capture the direct influence of TV on attitudes and that the effect we identify is solely driven by channel-specific changes in migration news broadcasting.

Table C16: Placebo Estimates on Non-TV Viewers

	(1) Pol.	(2) Pro-Pol	(3) Pro-Pol (mod.)	(4) Anti-Pol (mod.)	(5) Anti-Pol
$ShareSubj_{ct-1}$	0.800	1.136	-1.246	0.446	-0.336
	(1.253)	(1.121)	(1.250)	(0.817)	(0.612)
Nb. Observations	2,080	2,080	2,080	2,080	2,080
Adjusted R^2	0.505	0.643	0.383	0.403	0.587
Std. coefficient	0.016	0.023	-0.025	0.009	-0.007

Notes: The dependent variable in Column (1) is Polarization, which takes value one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in Column (2) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). The dependent variable in Column (3) is a dummy equal to one for individuals with pro-immigration moderate attitudes and zero otherwise (pro-immigration, anti-immigration moderates, and anti-immigration). The dependent variable in Column (4) is a dummy equal to one for individuals with anti-immigration moderate attitudes and zero otherwise (pro-immigration, pro-immigration moderates, and anti-immigration). The dependent variable in Column (5) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Standardized coefficients for the coverage of immigration, with a mean of 0 and a standard deviation of 1, are also reported in the table footer (Std. coefficient). Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

Table C17: Placebo - Attitudes Towards Alternative Topics - Gender & LGBT

	(1) Women Abortion	(2) Women Children	(3) Women Intolerance	(4) Homosexuality Adoption	(5) Homosexuality Acceptable	(6) Homosexuality Intolerance
$ShareSubj_{ct-1}$	0.307	-0.033	0.150	-0.027	0.037	0.262
	(0.377)	(0.382)	(0.647)	(0.757)	(0.476)	(0.735)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	3,174	3,174	3,176	3,152	3,159	3,170
Adjusted R^2	0.449	0.456	0.487	0.448	0.525	0.451
Benchmark coefficient	2.713	2.712	2.710	2.746	2.733	2.678
Benchmark P-value	0.001	0.001	0.001	0.001	0.001	0.001

Notes: The dependent variable refers to a measure of the likelihood that a respondent holds extreme positions on various dimensions, with extreme views being defined as those falling outside of the middle 50% of the distribution of answers. Women intolerance in (3) is an index combined of attitudes against women's ability to abort in (1) and views that women are made to make and raise children in (2). Homosexuality intolerance in (6) is an index combined of attitudes against homosexuals' ability in (4) and views that homosexuality is not acceptable in (5). All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

Table C18: Placebo - Attitudes Towards Alternative Topics - Environment

	(1) Climate Change Human-caused	(2) Slow Growth Environment	(3) Nuclear Energy	(4) Environment Intolerance
$ShareSubj_{ct-1}$	-0.807	0.225	-0.268	0.582
	(0.788)	(0.601)	(0.622)	(0.716)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes
Nb. Observations	3,129	3,999	3,567	4,006
Adjusted R^2	0.531	0.294	0.475	0.309
Benchmark coefficient	2.050	2.324	2.507	2.254
Benchmark P-value	0.023	0.001	0.002	0.001

Notes: The dependent variable refers to a measure of the likelihood that a respondent holds extreme positions on various dimensions, with extreme views being defined as those falling outside of the middle 50% of the distribution of answers. Environment intolerance in (4) is an index combined of views that climate change is not caused by humans in (1), that growth should not be slowed for the environment in (2), and the support for the use of nuclear energy for energy production in (3). All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

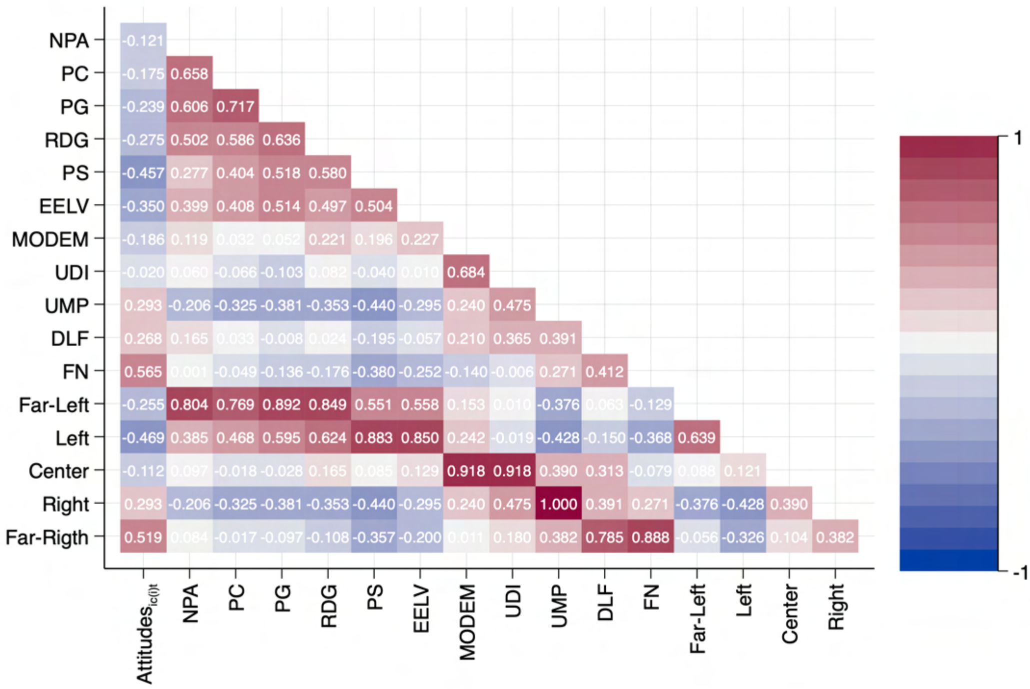
Table C19: Placebo Estimates with Share of Subjects of Alternative Topics

	(1) Benchmark Migration	(2) Crime	(3) Employement	(4) Terrorism	(5) Aid	(6) Gender	(7) Environment
$ShareSubj_{ct-1}$	2.603***	-0.220	0.164	0.103	0.187	0.826	-0.105
	(0.613)	(0.205)	(0.313)	(0.279)	(0.301)	(0.705)	(0.549)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,796	6,796	6,796	6,796	6,796	6,796	5,010
Adjusted R^2	0.450	0.448	0.448	0.448	0.448	0.448	0.450
Mean $ShareSubj_{ct-1}$	0.027	0.237	0.100	0.103	0.100	0.016	0.045

Notes: The dependent variable is Polarization, which takes a value of one for individuals with extreme attitudes toward immigration (deeply concerned or not concerned at all) and zero otherwise. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix D Additional Results for the Political Analysis

Figure D1: French Political Parties and Attitudes Toward Immigration
Cross-Correlations



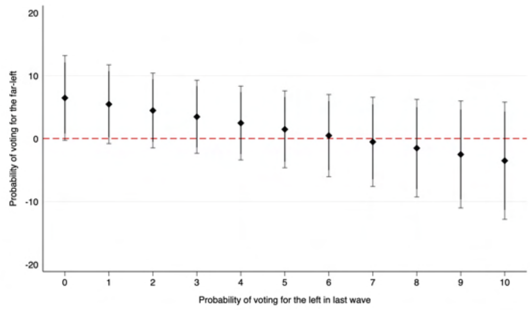
Notes: Political variables report the self-declared probabilities (0 to 10) that respondents vote for a party. "NPA" refers to the "Nouveau Parti Anticapitaliste" party; "PG refers to the "Parti de Gauche"; "RDG" refers to the "Radicaux de Gauche" party; "PS" refers to the "Parti Socialiste" party. "EELV" refers to the party "Europe Ecologie/Les Verts" party; "ModeM" refers to the "Mouvement Démocrate" party; "UDI" refers to the "Union des Démocrates et Indépendants" parti; "UMP" refers to the "Union pour un Mouvement Populaire" party and later called "Les Républicains"; "DLF" refers to the "Debout la France" party"; "FN" refers to the "Front National" party and later called "Rassemblement National"; "FG" refers to the "Front de Gauche" party. $Attitudes_{it}$ is a continuous variable and represents the average attitudes of individual i toward immigration. Sources: Authors' elaboration on ELIPSS data.

Table D1: Probability of Voting for a Given Political Party

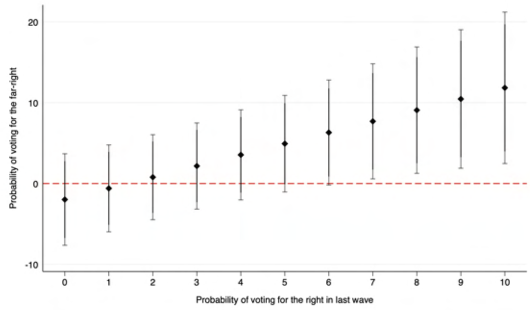
	(1) Left-Right scale	(2) Far-Left	(3) Left	(4) Center	(5) Right	(6) Far-Right
		PG NPA RDG PC	PS EELV	UDI MODEM	UMP	FN DLF
$ShareSubj_{ct-1}$	-0.096	-2.571	-1.123	-0.873	1.151	0.325
	(1.695)	(2.435)	(1.882)	(2.648)	(2.218)	(2.152)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,443	5,862	6,327	6,271	6,300	6,330
Adjusted R^2	0.744	0.645	0.763	0.648	0.774	0.763

Notes: The dependent variable in column (1) is a continuous 10-point scale that ranges from zero (for respondents endorsing far-left ideologies) to 10 (for respondents close to far-right ideologies). Other columns use the average self-declared probabilities (0 to 10) that respondents vote for a group of political parties as the dependent variable. "NPA" refers to the "Nouveau Parti Anticapitaliste" party; "PC" refers to the "Parti Communiste" party; "RDG" refers to the "Radicaux de Gauche" party; "PS" refers to the "Parti Socialiste" party; "EELV" refers to the party "Europe Ecologie/Les Verts" party; "Modem" refers to the "Mouvement Démocrate" party; "UDI" refers to the "Union des Démocrates et Indépendants" parti; "UMP" refers to the "Union pour un Mouvement Populaire" party and later called "Les Républicains"; "DLF" refers to the "Debout la France" party"; "FN" refers to the "Front National" party and later called "Rassemblement National". The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' elaboration on INA and ELIPSS data.

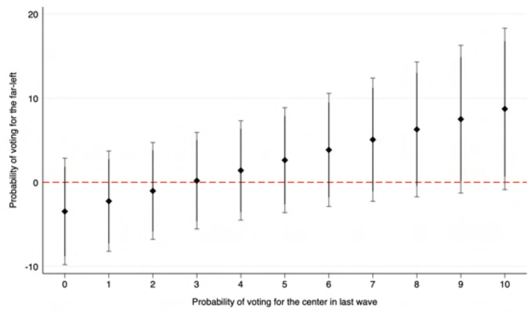
Figure D2: Switching Parties from Left, Right and Center



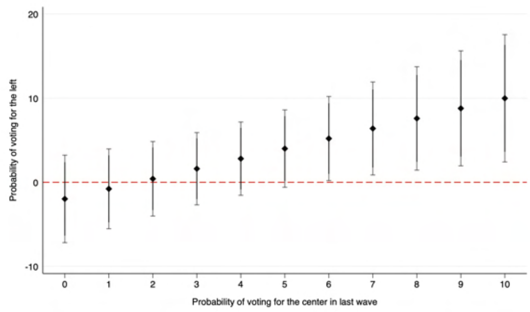
(a) Left to Far-Left



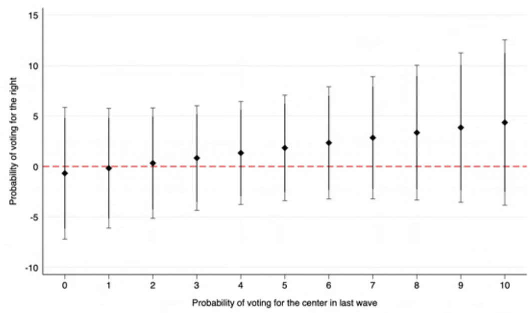
(b) Right to Far-Right



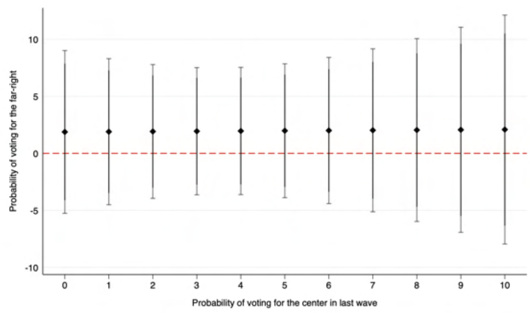
(c) Center to Far-Left



(d) Center to Left



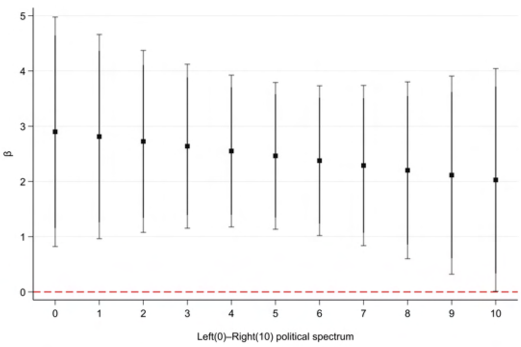
(e) Center to Right



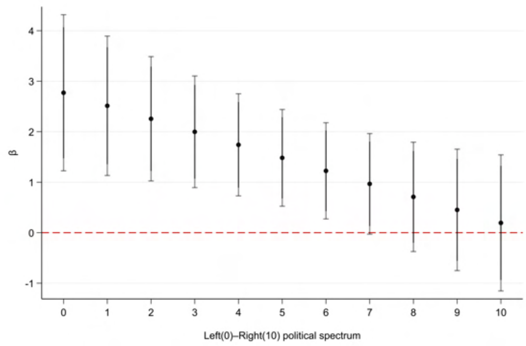
(f) Center to Far-Right

Notes: The figure shows the marginal effect of an increase in the coverage of immigration on an individual's probability of voting for a party conditional on his or her initial political preferences. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

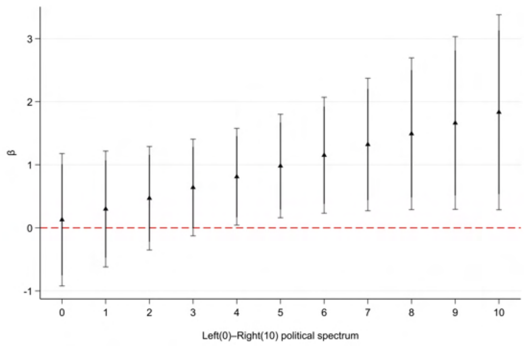
Figure D3: Coverage of Immigration Interacted with Political Affiliation



(a) *Pol* as Dependent Variable



(b) *Pro-Pol* as Dependent Variable



(c) *Anti-Pol* as Dependent Variable

Notes: The figures report the marginal impact of an increase in the coverage of immigration, conditional on levels of political affiliation, on *Pol*, *Pro-pol*, and *Anti-pol*, respectively. All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix E Additional Results for the Topic Analysis

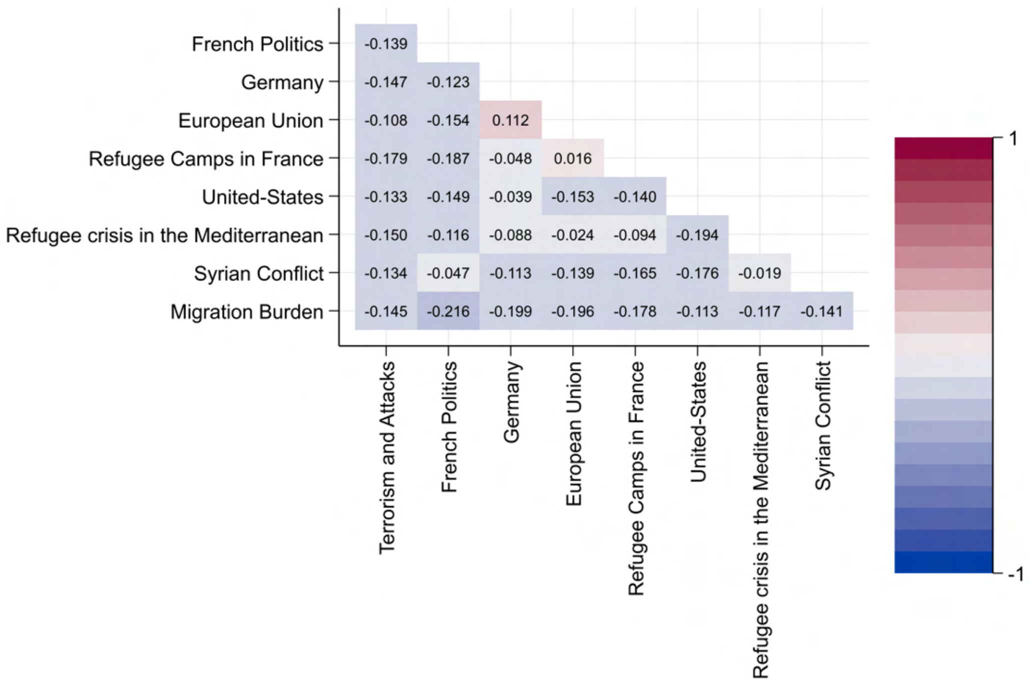
Appendix E1 Detection of Topics

Table E1: Top 15 Words in Topics

United-States	Terrorism and Attacks	Syrian Conflict	European Union	Refugee Crisis in the Mediterranean	French Politics	Migration Burden	Refugee Camps in France	Germany
Unis	Attack	Syria	Europe	Italy	François	Foreigners	Calais	Germany
States	Police	Conflict	Turkey	Shipwreck	Hollande	French	Jungle	Federal
Trump	Terrorism	Irak	Greece	Mediterranean	Minister	Economics	Paris	Republic
Donald	Terrorist	War	Crisis	Sea	Asylum	Work	Center	Merkel
President	Paris	State	Hungaria	Libya	Valls	Foreigner	Life	Angela
United-States	Victim	Syrians	Agreement	Offshore	Rights	Paris	Camp	Party
London	Fundamentalism	Islamic	Brussels	Rescue	President	Tourism	Camps	Right
Decree	Attacks	Army	Summit	Victims	Controversy	Economy	Evacuation	Berlin
American	Man	Aid	Borders	Drowning	Statement	Movie	Conditions	Election
Kingdom	Islamism	Camp	European	Lampedusa	Expulsion	Tourists	Large	Extremes
Russia	March	Syrian	Relations	People	Pope	Firm	Bernard	Pen
Relations	Berlin	Humanitarian	Inflow	Disaster	Macron	World	Association	Campaign
United	Foreigners	Situation	Conference	Boat	Manuel	Euros	Mayor	Marine
Brexit	Attacked	UN	Monitoring	Island	Prime	Jobs	Police	German
David	Christmas	Civilians	Austria	Sicilia	Visit	Life	Cazeneuve	Strikes

Notes: Topics were identified using an unsupervised latent Dirichlet allocation algorithm on the corpus of migration subjects. The names of the topics were chosen by the authors for their interpretability. Words have been translated from French to English by the authors.
Sources: Authors' elaboration on INA data

Figure E1: Cross Correlations Across Subjects in Immigration news



Notes: Topics were identified using an unsupervised latent Dirichlet allocation algorithm on the corpus of migration subjects. The names of the topics were chosen by the authors for their interpretability, and the top words identified in each topic are displayed in Table E1.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix E2 Descriptive Statistics

This appendix provides additional descriptive statistics on the topics detected by the Latent Dirichlet Algorithm in immigration subjects between 2013 and 2017. As reported in Table E2, one can observe a decrease in immigration-related news before and after the 2015 refugee crisis, for topics such as "French politics", "migration burden", "Syrian conflict", and the "refugee crisis in the Mediterranean". In contrast, there is an increase in news related to "Refugee camps in France", and immigration in foreign contexts, specifically "Germany", "United States", and the "European Union". These variations are depicted at the monthly level in Figure E2(b). It reveals that the evolution of broadcasted topics over time is mainly influenced by world events. For instance, one can observe a peak following the major terrorist attacks in France or during the period of the Syrian conflict in 2014 and the refugee crisis in Europe and Germany in late 2015.

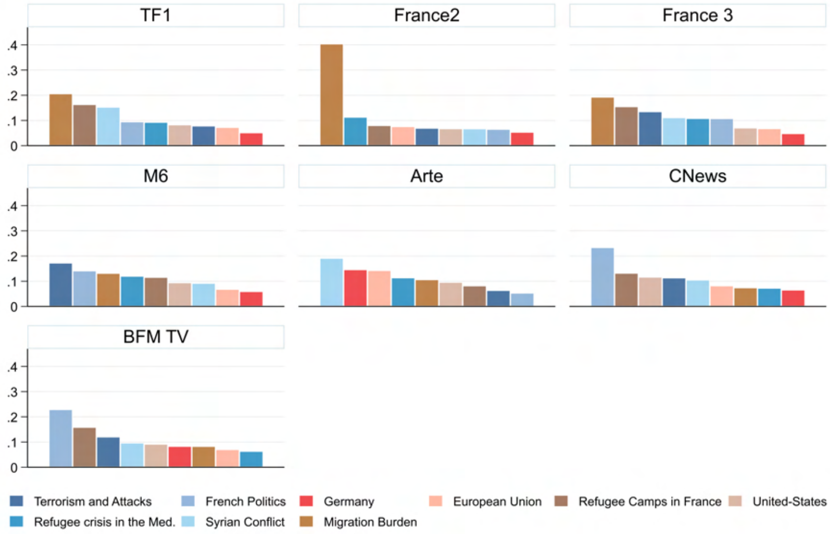
Table E2: Share of Topics in Immigration News

	All	All before Sep. 2015	All after Sep. 2015	TF1	France 2	France 3	M6	Arte	CNews	BFM TV
Terrorism and Attacks	0.108	0.107	0.109	0.079	0.070	0.136	0.173	0.064	0.114	0.121
French Politics	0.131	0.149	0.112	0.095	0.066	0.108	0.142	0.054	0.234	0.230
Germany	0.073	0.043	0.106	0.052	0.054	0.048	0.060	0.147	0.066	0.084
European Union	0.083	0.052	0.119	0.073	0.076	0.068	0.069	0.143	0.083	0.071
Refugee Camps in France	0.127	0.098	0.160	0.164	0.081	0.155	0.116	0.082	0.133	0.159
United-States	0.089	0.077	0.102	0.083	0.068	0.071	0.095	0.097	0.117	0.092
Refugee crisis in the Mediterranean	0.099	0.119	0.076	0.093	0.114	0.109	0.121	0.114	0.073	0.064
Syrian Conflict	0.117	0.153	0.077	0.154	0.068	0.112	0.093	0.192	0.106	0.097
Migration Burden	0.173	0.203	0.139	0.207	0.405	0.193	0.132	0.107	0.075	0.083

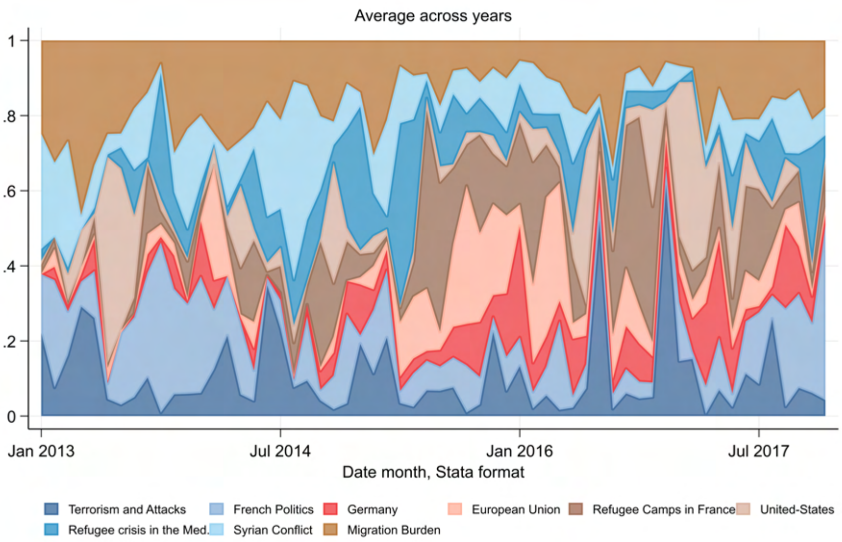
Notes: This table reports the average share of topics among all migration news in evening television programs of Arte, BFM-TV, CNews, TF1, France 2, France 3, and M6. The date of the refugee crisis in our context is September 2015. Topics were identified using an unsupervised latent Dirichlet allocation algorithm on the corpus of migration subjects. The names of the topics were chosen by the authors for their interpretability, and the top words identified in each topic are displayed in Table E1.
Sources: Authors' elaboration on INA and ELIPSS data.

As far as heterogeneity between channels is concerned, Figure E2(a) reveals that, on average, channels allocate different broadcasting time to various immigration-related topics. For instance, the two main national TV evening programs of TF1 and France 2 are relatively more likely than other channels to associate immigration with its economic cost ("migration burden). Similarly, 24-hour news channels are more likely to cover immigration news in the context of "French politics", and Arte, a European public service channel with programming provided by its French and German subsidiaries, is relatively more likely to cover immigration news in "Germany" and the "European Union". Combining average differences across channels and the evolution of world events, Figure E3 depicts the evolution of topics within channels and over time. It reports substantial variability and supports the use off within-channel variations over time

Figure E2: Topic Frequency in Immigration News



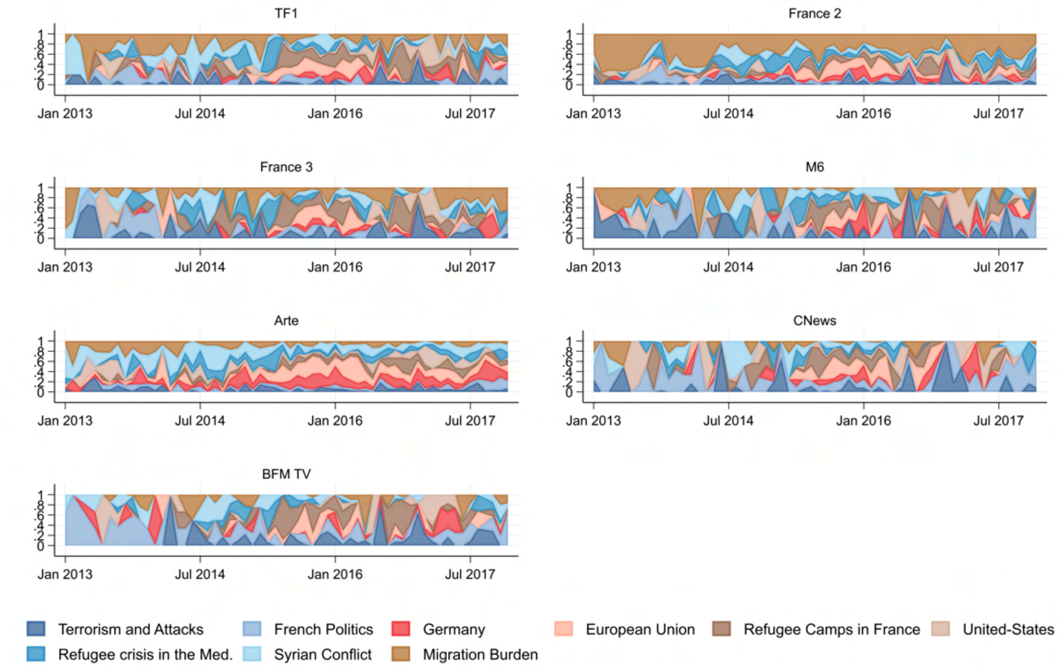
(a) Average across channels



(b) Average Across Years

Notes: This figure plots the share of topics among migration news in evening television programs of Arte, BFM-TV, CNews, TF1, France 2, France 3, and M6. Topics were identified using an unsupervised latent Dirichlet allocation algorithm on the corpus of migration subjects. The names of the topics were chosen by the authors for their interpretability, and the top words identified in each topic are displayed in Table E1.
Sources: Authors' elaboration on INA data

Figure E3: Topic Frequency in Immigration News
By channel



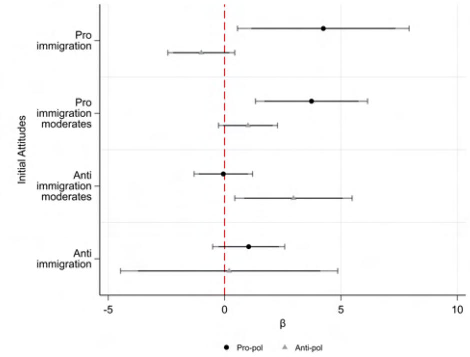
Notes: This figure plots the share of topics among migration news in evening television programs of Arte, BFM-TV, CNews, TF1, France 2, France 3, and M6. Topics were identified using an unsupervised latent Dirichlet allocation algorithm on the corpus of migration subjects. The names of the topics were chosen by the authors for their interpretability, and the top words identified in each topic are displayed in Table E1.
Sources: Authors' elaboration on INA data

in our topic analysis.

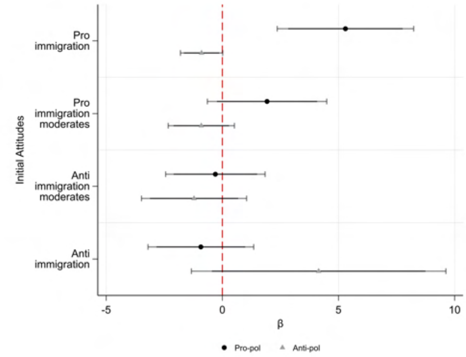
Appendix E3 Additional Results on Topic Analysis

Figure E5 reveals distinct patterns in the association between different topics and the polarization of attitudes toward immigration. Topics related to the integration of immigrants into French national territory ("migration burden" and "refugee camps in France" for instance), which can be viewed as a threat or an opportunity by French residents, show a positive association with increased polarization on both ends of the distribution. In contrast, coefficients associated with immigration outside of France (the "European Union" or the "United-States" for instance), although not always significant, indicate that an increase in immigration news coverage focusing on foreign countries tends to reduce the likelihood of anti-polarization while increasing pro-polarization. Finally, "terrorism" or the "Syrian Conflict" are found to be associated with highly negative attitudes toward immigrants, leading to polarization toward only the right-hand side of the distribution.

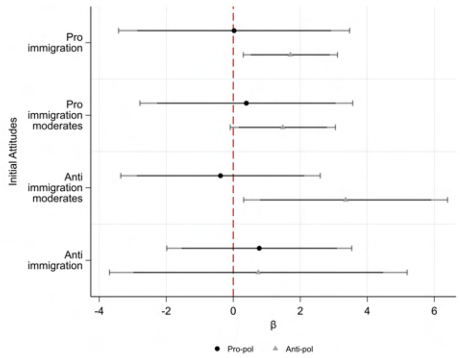
Figure E4: Coverage of Immigration Interacted with Preexisting Attitudes
Topic analysis



(a) Immigration in France



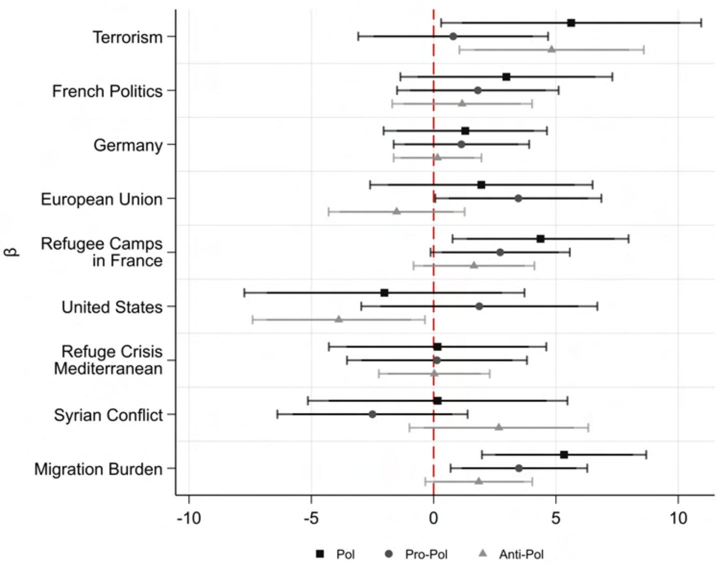
(b) Immigration in Foreign Countries



(c) Others

Notes: The figure shows the marginal effect of $ShareSubj_{ct-1}$ on *Pro-pol* and *Anti-pol* respectively. Each coefficient represents the marginal effect of the variable for different preexisting attitudes. All estimates include wave, channel and individual fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Figure E5: Topic Analysis



Notes: The dependent variables are alternatively Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise, a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates), and a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave, individual and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Appendix F Additional Results for the Sentiment Analysis

Appendix F1 Detection of Sentiments

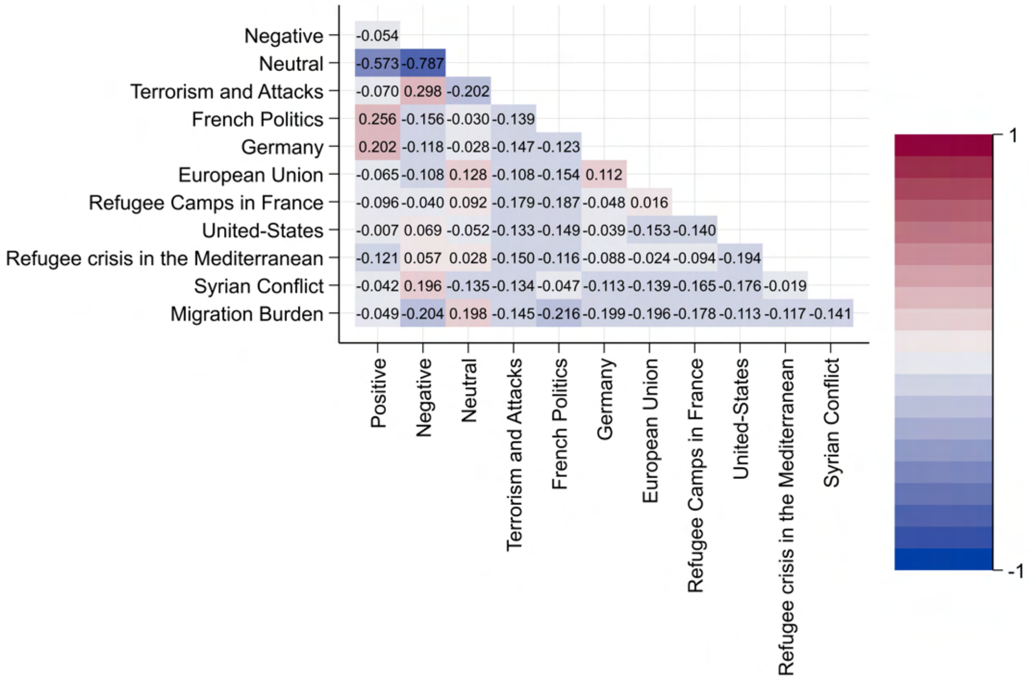
Figure F1: Most Frequent Words in the Sentiment Analysis of Migration Subjects

(a) Positive Subjects

(b) Negative Subjects

Notes: Figure F1a represents the most frequent positive tokens from the FEEL lexicon in positive migration subjects. Figure F1b represents the most frequent negative tokens from the FEEL lexicon in negative migration subjects. A subject as positive or negative if its share of positive or negative words exceeds the 75th percentile of the subject distribution. All other subjects are classified as neutral.
Sources: Authors' elaboration on INA data.

Figure F2: Cross Correlations Across Subjects and Sentiments in Immigration news



Notes: Topics were identified using an unsupervised latent Dirichlet allocation algorithm on the corpus of migration subjects. The names of the topics were chosen by the authors for their interpretability, and the top words identified in each topic are displayed in Table E1.
Sources: Authors' elaboration on INA data.

Appendix F2 Descriptive Statistics

This appendix provides additional descriptive statistics on the sentiments detected in immigration subjects between 2013 and 2017. As reported in Table F1, there is an overall increase in the neutrality of subjects at the expense of a decrease in extremely positive and negative subjects. This increase is mainly due to the relative decrease in the share of negative subjects (-25%), while the share of positive subjects is little affected. These variations are depicted at the monthly level in Figure F3(b). As far as heterogeneity between channels is concerned, Figure F3(b) reveals that, on average, channels mainly use neutral subjects to talk about immigration. France 2 is the channel that uses the most neutral framing (86.5% of subjects), whereas M6 tends to frame its coverage of immigration more negatively.[9] Combining average differences across channels and the overall evolution of world events, Figure F4 depicts the evolution of sentiment within channels and over time. It provides support for enough variability to use within-channel variations on sentiment over time in our empirical analysis. Interestingly, channels that attract the most positive viewers toward immigration (such as France 2 and Arte) exhibit the most stable sentiment over time, indicating that they are less inclined to alter the framing of the immigration topic over time. Conversely, entertainment channels like M6 or 24-hour news channels (CNews or BFM TV) display significantly more variability in their framing, which may suggest a more sensationalized treatment of immigration over time.

Table F1: Sentiments in Immigration News

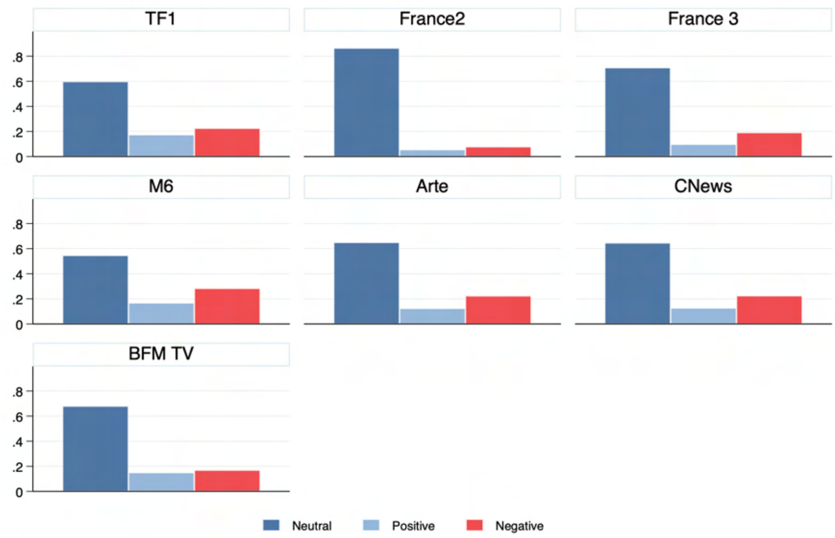
	All Channels	All channels before the refugee crisis (09.2015)	All channels after the refugee crisis (09.2015)	TF1	France 2	France 3	M6	Arte	CNews	BFM TV
Neutral	0.671	0.638	0.710	0.599	0.865	0.710	0.547	0.651	0.647	0.680
Positive	0.128	0.135	0.121	0.175	0.056	0.099	0.169	0.125	0.128	0.150
Negative	0.200	0.227	0.170	0.226	0.079	0.192	0.284	0.224	0.226	0.170

Notes: This table reports the average share of sentiments among all migration news in evening television programs of Arte, BFM-TV, CNews, TF1, France 2, France 3, and M6. The date of the refugee crisis in our context is September 2015.
Sources: Authors' elaboration on INA and ELIPSS data.

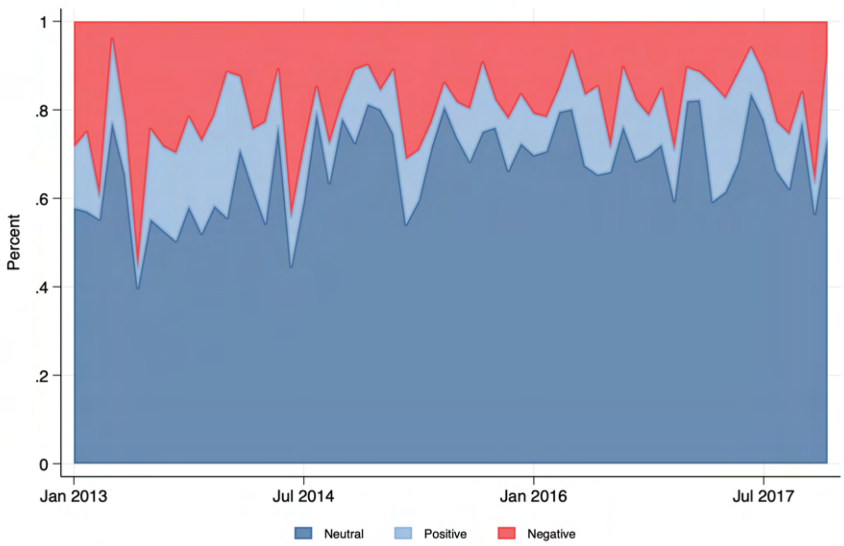
Appendix F3 Additional Results on Sentiment Analysis

[9] Interestingly, we find a slight change in the framing of immigration news in CNews toward more negative content, compared to other channels at the end of our period of analyses. This echoes previous findings in Cagé et al. (2022) who report that the timeshare of radical-right guests in CNews has gradually increased from 8 to 15 percentage points after Bolloré's takeover.

Figure F3: Sentiments in Immigration News



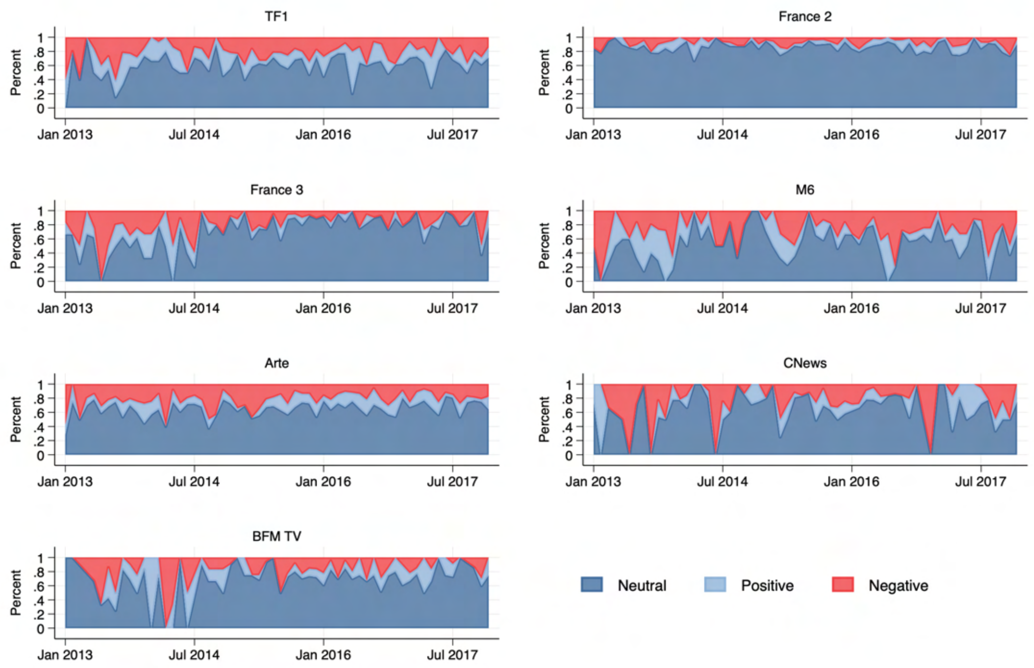
(a) Average Across Channels



(b) Average Across Years

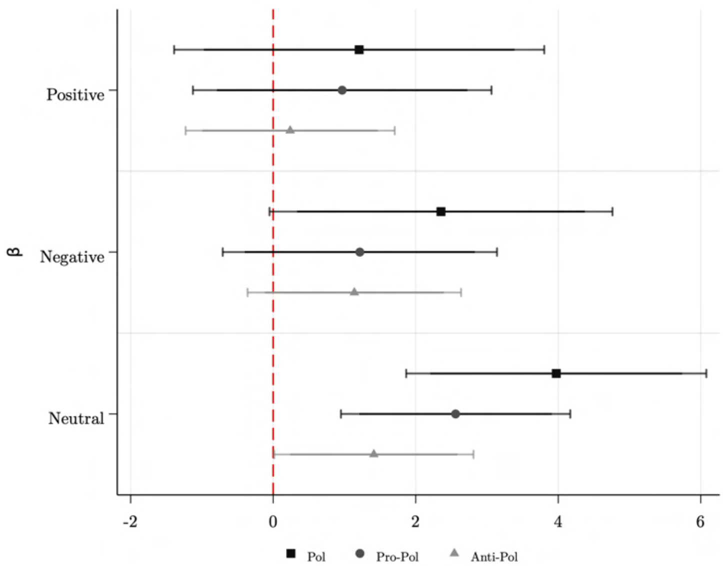
Notes: This figure plots sentiments among migration news in evening television programs of Arte, BFM-TV, CNews, TF1, France 2, France 3, and M6.
Sources: Authors' elaboration on INA data

Figure F4: Sentiments in Immigration News
By Channel



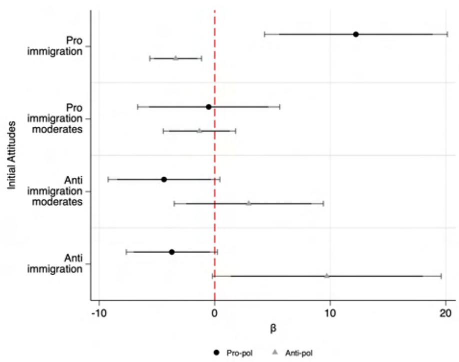
Notes: This figure plots sentiments among migration news in evening television programs of Arte, BFM-TV, CNews, TF1, France 2, France 3, and M6.
Sources: Authors' elaboration on INA data

Figure F5: Sentiment Analysis with a 50% Threshold Classification

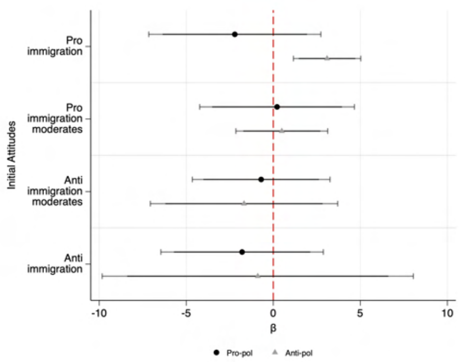


Notes: The dependent variables are alternatively Polarization, which takes a value of one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise, a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates), and a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave, individual, and channel fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

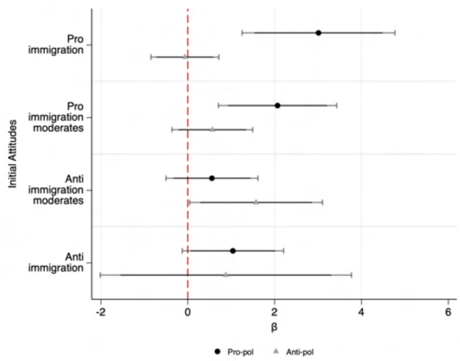
Figure F6: Coverage of Immigration Interacted with Preexisting Attitudes
Sentiment Analysis



(a) Positive



(b) Negative



(c) Neutral

Notes: The figure shows the marginal effect of $ShareSubj_{ct-1}$ on *Pro-pol* and *Anti-pol* respectively. Each coefficient represents the marginal effect of the variable for different preexisting attitudes. All estimates include wave, channel and individual fixed effects. The vector of time-varying controls includes age, education, employment status, marital status, number of children, household size, a dummy for blue-collar and income categories. Robust standard errors clustered at the individual level. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

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