Media Coverage of Immigration and the Polarization of Attitudes.*

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Abstract

This paper investigates the causal impact of media on attitudes toward immigration. We combine data on French television news programs with monthly individual panel data on attitudes from 2013 to 2017. Information on respondents' preferred television channel allows us to exploit within-individual-channel variations over time that tackles usual concerns on ideological self-selection into channels. We find that increasing the salience of immigration does not necessarily worsen natives' attitudes toward immigration, but rather increases polarization by pushing moderates to the two extremes of the distribution, depending on their initial attitudes. We show that these results are robust to controlling for differences in the framing of immigration-related subjects across television channels. Framing is found to drive attitudes in specific directions depending on its nature.

JEL classification codes: F22, L82

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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.

1 Introduction

In 2016, an opinion poll found that only 16% of the French public viewed immigration positively, while 56% believed it had a negative overall influence on society.[1] This survey was conducted in a very specific context, shortly after the start of Europe's 2015 refugee crisis, which received widespread coverage in the media, and plausibly shaped attitudes toward immigration at this time.[2] As conceptualized in accessibility-based models based on media theories, such as agenda-setting or priming, it is likely that the increase in media reporting on the refugee crisis disproportionately increased viewers' attention toward immigration and reactivated existing prejudices regarding immigrants, thus modifying natives' attitudes along the aforementioned dimension.[3] In fact, 30% of respondents who declared that they had helped refugees over the past 12 months reported that they had done so after being exposed to immigration-related press articles or television shows.

This paper investigates the extent to which media coverage of immigration impacts natives' attitudes toward the latter. It focuses specifically on the media's role in priming immigration in the news, which disproportionately increases the salience of this specific topic in viewers' minds. Salience is defined as the psychological process by which an individual's attention is increasingly drawn to a particular topic, resulting in the topic being overweighted in subsequent decisions made by the individual (Kahneman, 2011; Bordalo et al., 2013). In addition to priming, this paper also aims to study the impact of media framing on immigration attitudes, i.e how immigration is framed in the news by journalists who may manipulate the tone and the subjects associated with the immigration topic.

To perform this analysis, we rely on data from the French National Audiovisual Institute (INA), which records a complete description of all topics covered by French television channels over time. We use this information to assess the overall monthly prominence of immigration in evening television programs defined as the share of immigration-related subjects in total broadcasting. Natural language processing techniques such as sentiment analysis and the Latent Dirichlet Algorithm (LDA)

[1]IFOP (2016). French perceptions on immigration, refugees and identity. Source: https://www.ifop.com/wp-content/uploads/2018/03/3814-1-study_file.pdf (Accessed on July, 2021).

[2]See Eisensee and Strömberg (2007) or Snyder Jr and Strömberg (2010) among others for examples on the salient role of the press.

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

applied to the INA's detailed subject descriptions allow us to characterize the tone of immigration-related news as well as the subjects associated with this topic. This data is combined with individual panel data from the ELIPSS survey (Longitudinal Internet Studies for Social Sciences) that allows us to track individuals' attitudes toward immigration between January 2013 and December 2017. Unlike most papers that use variations in local media coverage or treatment, the ELIPSS data enables us to connect each respondent to his or her time-varying preferred television channel for political information. Controlling for individual-channel fixed effects in our empirical specification, we adress therefore the common endogeneity concern of self-selection that occurs when individuals watch television channels that align with their ideology. As a result of this rich structure of fixed effects, the identifying variability stems solely from the correlation between monthly variation in the salience of immigration in a specific French television channel and the attitudes toward immigration of a given individual watching this channel.

The results show that an increase in the salience of immigration has an asymmetric impact on natives' attitudes. Depending on their initial beliefs, respondents develop more radical attitudes toward immigration as coverage of immigration grows. In particular, natives with moderate positive attitudes move to extremely positive attitudes, whereas their counterparts with initially moderate negative attitudes become very concerned about immigration. Thus, priming immigration is found to reactivate pre-existing prejudices in the population, driving polarization at the aggregated level. Regarding the magnitude of the effect, we find that a one-standard-deviation increase (1.6%) in the share of immigration-related subjects in overall broadcasting is associated with a 3.5 percentage point increase in the likelihood that individuals with moderate attitudes develop extreme attitudes. A heterogeneity analysis also reveals that polarization toward extremely negative attitudes is magnified for young and individuals close to right-wing ideologies, while polarization toward extremely negative attitudes is higher for high-skilled, employed and, individuals closer to left-wing ideologies.[4] These results also translate to the political level, with the polarization of voters toward candidates of the extremes. Respondents initially affiliated with political parties in the center of the political spectrum (which also have the lowest correlation with attitudes toward immigration) become

[4]We also find that the initial distribution of attitudes predicts the direction of polarization within channels. For instance, an increase in the salience of immigration on TF1, the channel with the most initially anti-immigrant viewers, mainly results in increased immigration concerns. On the contrary, the same increase in salience for a channel with historically pro-immigrant audiences, such as Arte, only increases viewers' likelihood of reporting extremely positive attitudes toward immigration. Between these two extremes, channels with less skewed distributions of attitudes, such as BFM TV or France 2, see their existing moderate viewers shifting toward extreme attitudes on both sides of the distribution.

more likely to vote both for far-right and left-wing parties in response to an increase in the salience of immigration in the media. Interestingly, the results also indicate that individuals with already anti-immigration attitudes are unlikely to change their beliefs or votes compared to those with moderate or pro-immigration attitudes. This implies that changing the attitudes of those with strong exclusionary attitudes may be more difficult, as suggested by Kalla and Broockman (2021).

Regarding the framing of immigration news, the results show that while discussing immigration in foreign host countries (such as Germany or the United States) increases French natives' support for immigration, discussions about immigrants' integration in France are consistently associated with an increase in polarization. This suggests that the economic or psychological costs associated with hosting migrants in France partly determine the native-born population's response. The results also provide suggestive evidence that more negative contents are associated with an increase in anti-immigrant sentiment. Thus, unlike the salience of immigration, framing can drive attitudinal changes in very specific directions. Finally, we show that the impact of an increase of the salience of immigration on polarization is robust to controlling for the framing of immigration topics.

This paper has several contributions. First, it contributes to the fast-growing literature on the impact of salience on natives' political attitudes.[5] In the context of immigration, some papers in the literature manipulate the salience of this topic using self-reported measures of salience (Dennison and Geddes, 2019) or experimental settings (Barrera et al., 2020). For instance, Alesina et al. (2022) randomize the order in which respondents receive questions about immigration and redistribution in an online survey experiment conducted in six countries; they find that priming immigration without any additional information deteriorates natives' attitudes toward immigration and reduces support for redistribution. Few other papers exploit quasi-natural experiments to capture meaningful variations in the salience of the migration topic. Gagliarducci and Tabellini (2021) find that catholic churches' construction in the United States between 1890 and 1920 increased the salience of the Italian community and resulted in the resurgence of negative stereotypes about this group in the local press. Similarly, Giavazzi et al. (2020) demonstrate that the increase in the salience of immigration in German social networks between 2013 and 2017 in response to criminal events or terrorist attacks is associated with an increase

[5]While related to our paper, we do not review the growing literature on the impact of direct exposure to immigration on natives' attitudes and votes. See Alesina and Tabellini (2020) for an extended review on this specific question. Other papers in the literature also investigate the impact of salience on individuals' decisions and beliefs on various topics such as consumption, investment, the judicial and tax systems (See Barber and Odean, 2007; Chetty et al., 2009; Finkelstein, 2009; Bordalo et al., 2013, 2015; Ochsner and Roesel, 2019, among others)

in votes for far-right parties. Overall, all these papers find that priming immigration tends to sway natives' attitudes in a particular direction, increasing anti-immigration attitudes. A notable exception in this literature 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 in German municipalities with mosques. Compared to Colussi et al. (2021), we systematically associate individuals with their exposure to immigration over time through television news. Similarly, we show that short-term variations in the salience of immigration are a strong driver of political polarization.

Second, this paper adds to the literature on the role of media in shaping political attitudes, in which most papers use exogenous variation in broadcasting or penetration to infer causality.[6] This paper specifically 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; Djourelova, 2020; Keita et al., 2021) and does not rely on a natural experiment to compare attitudes before and after a given treatment. Instead, it uses systematic within-channel variation in the coverage of immigration to investigate the effect of differential monthly exposure to immigration through television. Thus, the panel dimension of this analysis allows focusing on intra-individual variability rather than on local average effects. In comparison with existing works, the identification strategy relies on individual-channel fixed effects that definitely address the issue of ideological self-selection into channels and the nonrandom matching between television channels and viewers.[7] To the best of our knowledge, only Facchini et al. (2017) rely on a similar source of variation at the individual-channel level in the United States immigration context. While they find that Fox News viewers are more likely to report negative attitudes toward illegal immigrants than CBS viewers, they only address ideological self-selection into television channels with ideological controls, such as party identification, which all can be considered "bad controls" (Angrist and Pischke, 2008).

Third, this paper and its results echo the emerging literature on the cultural and political polarization in modern societies (DiMaggio et al., 1996; Fiorina and

[6]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.

[7]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. Our paper also extensively documents the ideological self-selection of individuals into television channels.

Abrams, 2008; Desmet et al., 2017; Martin and Yurukoglu, 2017; Gentzkow et al., 2019; Alesina et al., 2020). Conversely, to most of these papers that focus on the United States, it provides evidence for a similar polarization effect in a European country. In addition, while existing works suggest that social media could drive polarization by creating echo chambers that exacerbate political divisions (Bail et al., 2018; Levy, 2020; Allcott et al., 2020; Cinelli et al., 2021),[8] this paper demonstrates that traditional media such as television can also be a driver of the polarization of attitudes. This is an important result given that television news are less targeted to users' ideological views and more commonly fact-checked than information spread on social media.

Finally, a fourth contribution of this paper lies in our ability to provide suggestive evidence that beyond the salience of immigration, traditional media may also affect natives' attitudes toward immigration by framing the content of their programs. Indeed, even within a constant broadcasting time, the literature suggests that portraying immigrants negatively or positively can produce asymmetric changes in immigration attitudes (Brader et al., 2008; Alesina et al., 2022; Cattaneo et al., 2020). While Alesina et al. (2022) raise the issue of the difficulty of estimating these two channels separately, given that exposing individuals' to different narratives is already itself a priming of the immigration topic, our data allows us to include both effects separately in the same estimation. In line with their results, the polarization effect of priming immigration is not affected by controlling for the framing as measured through a sentiment. Our findings, also demonstrate that a more negative tone in immigration-related news increases anti-immigrant attitudes and particularly among positive individuals. Again, individuals with already anti-immigration beliefs are not affected by a change in the narrative.

The remainder of the paper is organized as follows. Section 2 describes the data on individuals' attitudes toward immigration and media reporting on immigration. Section 3 describes the empirical and identification strategy. Section 4 reports the main results on the effect of the salience of immigration on attitudes and the proposed interpretation. Section 5 presents some heterogeneity analysis, and Section 6 provides suggestive evidence on the role of framing immigration news. Section 7 concludes the paper.

[8]See Zhuravskaya et al. (2020) for a review of the literature, which concludes that while social media increases exposure to content ideologically similar to users' own beliefs, there is still no robust evidence that the latter is a driver of political polarization.

2 Data

This section describes the main dataset that we use in this paper and provides some descriptive statistics. First, it describes attitudes toward immigration from the ELIPSS panel survey and documents the extent to which viewers self-select into TV channels. Then, it shows descriptive evidence on the coverage of the immigration topic on French television between January 2013 and December 2017 using data from the French National Audiovisual Institute (INA).

2.1 Individual attitudes toward immigration and self-selection into TV channels

Attitudes toward immigration are measured with the ELIPSS survey, a representative panel study on attitudes and digital practices. Every month, respondents complete a 30-minute self-administered questionnaire using a touchscreen tablet and a 4G Internet subscription. The 2013 pilot study included 1,039 individuals, and 80% remained in the 2016 sample when 2,514 new individuals joined the panel.

This paper employs specific waves of the ELIPSS panel (Dynamob), which simultaneously measure individual attitudes toward immigration and media consumption. 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 who watch news programs at least one day per week.[9] The sample of analysis is described in Figure A1 in the Appendix. In the sample, 69% of respondents reported television as a source of political information, well ahead of radio (44%), internet (42%), or newspapers (26%). Among them, 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.[10] In addition, individuals in the ELIPSS survey are asked to provide their "usual preferred channel to watch political news programs". This allows us to link each respondent to the content they have been exposed to during the period of analysis.[11] One constraint

[9]We find no effect of media priming on attitudes when restricting the analysis to non-citizen respondents, as reported in Table C8 in the Appendix. This result has to be interpreted with caution because the number of non-citizens in the ELIPSS survey is very small and does not allow to draw any strong conclusion.

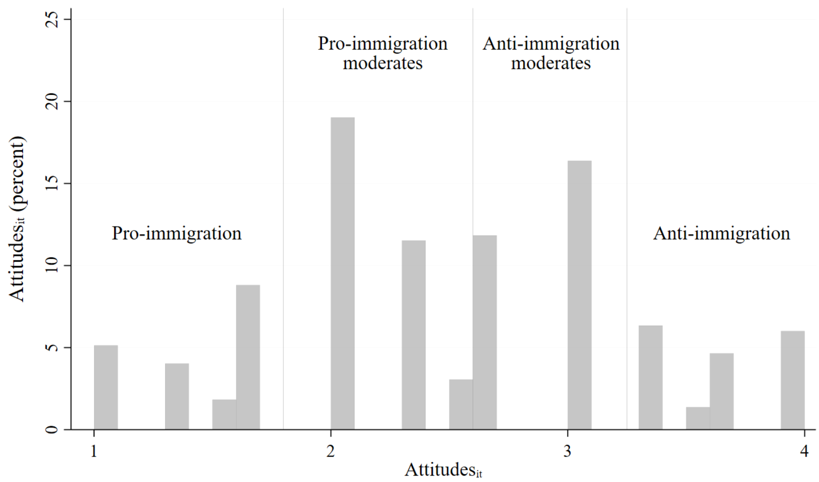
[10]In the same way, the 2021 Reuters Institute Digital News Report shows that TV remained the first source of information for news in France between 2013 and 2021 despite a slight decline over the period in favor of online information.

[11]Unfortunately, data on media consumption for political information are only available in two waves of the ELIPSS panel in September 2013 and 2016. We assume in the analysis that individuals' preferences on media are constant between 2013 and 2016, as well as after 2016. Information in

of this analysis is that individuals are only asked to specify one preferred channel. Still, while this information can be considered as restrictive regarding the overall television consumption of an individual, it is worth noting that this analysis only focuses on political information of evening news programs. The assumption that individuals cannot watch simultaneously multiple evening news programs broadcasted on different channels at the same time seems reasonable.

For our purposes, twelve-monthly waves of the ELIPSS survey are of particular interest because they include additional questions on attitudes toward immigrants in France.[12] Specifically, respondents are asked to answer to what extent they agree or disagree with the following statements (1) *There are too many immigrants in France*, (2) *France's cultural life is enriched by immigrants* and (3) *French Muslims are French citizens like any others*. Respondents specify their level of agreement with a 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

Figure 1: Individuals' attitudes toward immigration, 2013-2017.



Notes: $Attitudes_{it}$ is the average attitude of individual i in year-month t on three dimensions namely, the extent to which he or she believes that there are too many immigrants, the level of cultural enrichment he or she believes results from immigration and the extent to which Muslims are just like any others citizens. Higher values for $Attitudes_{it}$ reflect stronger opposition to immigration. *Pro-immigration moderates* corresponds to $Attitudes_{it} \in [2; 2.5]$. *Anti-immigration moderates* corresponds to $Attitudes_{it} \in]2.5; 3]$. *Pro-immigration* corresponds to $Attitudes_{it} \in [1; 2[$. *Anti-immigration* corresponds to $Attitudes_{it} \in]3; 4]$.
Source: Authors' elaboration on ELIPSS data.

the period between 2013 and 2017 may thus only be updated in September 2016, as described in Table A1 in the Appendix. Note that 33% of those who reported their preferred TV channel for political information in both 2013 and 2016 changed their preferred TV channel between the two periods.

[12]Wave dates are reported in Table A2 in the Appendix.

the average attitude of individual i in year-month t on the three aforementioned dimensions.[13]

Figure 1 depicts the distribution of individual attitudes toward immigration in our sample. Attitudes follow a normal distribution with most of the respondents reporting moderate attitudes toward immigration. We classify respondents into four categories based on their attitudes toward immigration. Bins are constructed following Fisher (1958) by minimizing the sum of squared deviations from the group mean. Between 2013 and 2017, 33.60% of the respondents are considered as *pro-immigration moderates* with $Attitudes_{it} \in [2; 2.5]$ and 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 have very positive attitudes toward immigration with $Attitudes_{it} \in [1; 2[$), while 18.37% of them present strong negative attitudes with $Attitudes_{it} \in]3; 4]$). Individuals with extreme political attitudes are respectively called *pro-immigration* and *anti-immigration* respondents in the rest of the

Table 1: Individual characteristics and natives' attitudes toward immigration. Difference in means.

	Pro-immig.	Pro-immig. moderates	Anti-immig. moderates	Anti-immig.	Mean (All)
Age	-0.585**	0.000	0.368***	0.067	5.584
High education	0.139***	0.070***	-0.053***	-0.197***	0.654
Employed	0.059***	0.024**	-0.049***	-0.031**	0.671
Marital Status	-0.020	-0.017	0.039***	-0.007	0.664
Nb. Child	-0.005	0.005	0.063**	-0.102***	0.789
Nb. Household Memb.	-0.016	-0.001	0.007	0.009	2.476
Blue collar	-0.063***	-0.037***	0.031***	0.089***	0.213
Income Cat.	0.205***	0.171***	-0.030	-0.487***	3.092

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 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 Members" 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 "Revenues" variable is composed of 7 categories ranging from 0 monthly revenue to more than 6000€monthly revenues.
Source: Authors' elaboration on ELIPSS data.

[13] Note that all three questions are not asked in each survey wave, as reported in Table A2 in the Appendix. Thus, the average is always computed on the available questions. We present robustness tests on the dimensions used for the index in Section 4.4. Specifically, we show that the main conclusions are not affected by removing any of the three dimensions from the analysis or by using a composite index computed using a Principal Component Analysis (PCA). Note that no additional questions in the survey can be interpreted as directly related to immigration.

empirical analysis. Not surprisingly, individual characteristics strongly differ across the four groups of immigration attitudes. Table 1 reports that on average respondents with more (less) positive attitudes toward immigration are significantly more (less) likely to be young, highly educated, employed, and have higher incomes. The characteristics of pro-immigration moderates follow the same patterns as those of pro-immigration individuals, and similarly, the characteristics of anti-immigration moderates are close to those of anti-immigration individuals.

Regarding self-selection into channels, both theoretical and empirical papers in the literature provide 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).[14] Our data strongly support this evidence as depicted in Table 2. Individuals who are more against immigration are more likely to watch TF1 for political information, while those who are more in favor of immigration are more likely to watch Arte or France 2 for instance. This echoes traditional views that the main evening news programs on TF1 share more conservative and traditional values than France 2 or Arte news programs.[15,16] As expected, self-selection patterns also strongly correlate with individual observable

Table 2: Preferred television channel and natives' attitudes toward immigration. Difference in means.

	TF1	France 2	France 3	M6	Arte	CNews	BFM TV	Mean
$Attitudes_{it}$	0.297***	-0.223***	-0.015	-0.001	-0.604***	-0.383***	-0.001	2.482
Age	0.137**	0.653***	1.202***	-1.525***	0.700***	-0.886***	-0.524***	5.584
High Education	-0.151***	0.075***	-0.041	0.057***	0.138***	0.174***	0.054***	0.654
Employed	-0.044***	-0.035***	-0.141***	0.197***	0.083***	0.122***	0.018	0.671
Marital Status	0.018	0.019	-0.043*	-0.029	-0.348***	-0.004	0.019	0.664
Nb. Child	0.070**	0.079***	0.137**	-0.215***	-0.045	-0.065	-0.110***	0.789
Household Nb.	0.084**	-0.049**	-0.428***	0.084	-1.048***	0.265***	0.125***	2.476
Blue Collar	0.085***	-0.073***	-0.042*	-0.037**	-0.036	-0.010	0.005	0.213
Income Cat.	-0.354***	0.523***	-0.120	-0.237***	-0.525***	0.451***	-0.022	3.092

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 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 Memb." 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 Cat." variable is composed of 7 categories from 0 monthly income to more than 6000 €monthly income. Source: Authors' elaboration on INA and ELIPSS data.

[14] We provide descriptive evidence in Appendix Table A1 of the breakdown of respondents across channels in 2013 and 2016.

[15] This selection into channels can also be observed in the distribution of individuals' attitudes by channel presented in Figure B2 in the Appendix.

[16] One could be surprised that CNews is associated with relatively positive attitudes toward immigration in this analysis. Nevertheless, it is worth keeping in mind that CNews only started to change its political leanings after the takeover by Vincent Bolloré in 2016 (Cagé et al., 2021) in the end of the period of analyis.

characteristics.[17] Thus, we provide evidence in Figure B3 in the appendix that average attitudes toward immigration still differ across French television channels after partialling out individuals' characteristics. All of this descriptive evidence indicates that self-selection of individuals across television channels should be carefully considered in the empirical analysis and strongly supports the inclusion of individual-channel fixed effects in the benchmark equation.

2.2 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 with various details on each broadcasted subject (Philippe and Ouss, 2018; Cagé et al., 2019). The analysis is restricted to all the news covered by evening news programs between 6:45 p.m. and 9:30 p.m. from 2011 to 2017 in TF1, France 2, France 3, Arte, M6, BFM TV and CNews (I-Tele before February, 2017).[18]

To identify whether subject s on channel c in year-month t is related to the immigration topic ($Immigration_{sct} = 1$), we built a lexicon that includes keywords associated with immigration and their variations in spelling.[19] Using a bag-of-words model, we count the number of words from the lexicon appearing in the title and in the full description of each subject content.[20] 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 of September 16, 2015, is classified as immigration-related since it includes keywords 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

[17] 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 B1. 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 B3), we find that, *ceteris paribus*, being older, less educated, a blue-collar worker or having less income or more children increases the likelihood of choosing TF1 as the main source of political information while it decreases the probability of watching France 2.

[18] The analysis is restricted only to these seven channels due to the limited sample size of the individual survey measuring natives' attitudes. 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 aforementioned survey. Figure A1 shows that 94% of the respondents watched one of the seven channels included in the sample as a source of political information.

[19] The full description of the lexicon is available in Appendix D.

[20] We make use of INA's account of news and descriptors. This is the most comprehensive information available on each subject, as there is no transcription of all television programs.

increased following the pictures of ***migrants*** *in Hungary or Germany. 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.*

On average, the description of each subject in the sample contains 59 words and the average number of immigration words detected in immigration-related subjects stands at 2.32, with a standard deviation of 1.34. Figure E1 in the Appendix plots the network of co-occurrences of words in migration subjects to assess whether the subjects we identify using the lexicon approach adequately capture immigration-related subjects. It shows no themes or words that could be completely unrelated to the immigration topic in the French context. This indicates that the lexicon approach performs well in identifying migration-related subjects. We identify that on average, 3.2% of subjects on televised evening news programs between 2011 and 2017 covered immigration, with a standard deviation of 3.4% and a maximum of 36.6% (on Arte in September 2015), as reported in the Appendix in Table A3. We observe a systematic increase in the coverage of immigration after the 2015 refugee crisis, with the average number of immigration-related subjects before September 2015 being 2.4% and 4.4% thereafter. The channels that have greater coverage of migration in the sample are, in descending order, Arte, BMF TV, CNews, TF1, France 2, France 3, and M6.

The empirical analysis exploits this unique framework to compute a measure of the salience of immigration on French TV news channels. We define $ShareSubj_{ct}$ as the share of subjects devoted to the migration topic in year-month t on the evening news program of channel c such as:

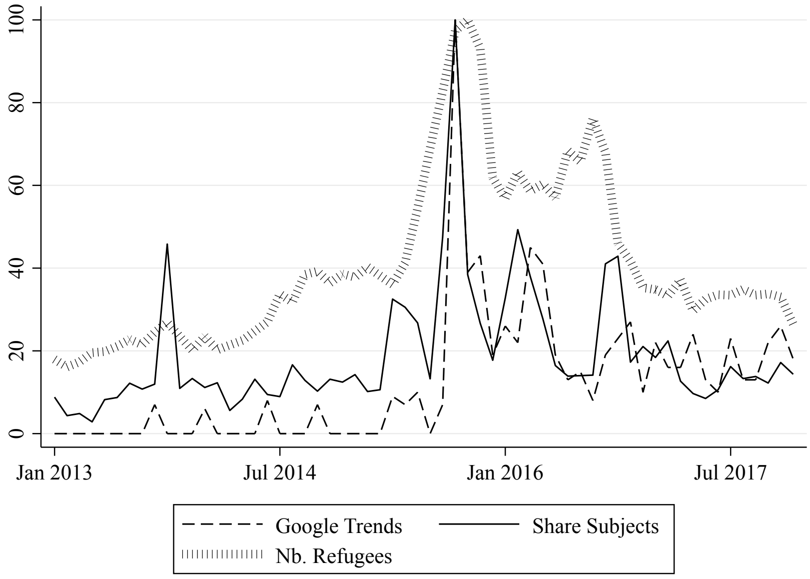
$$ShareSubj_{ct} = \frac{\sum_s (Subj_{sct} | Immigration_{sct} = 1)}{\sum_s Subj_{sct}} \tag{1}$$

where $Subj_{sct}$ is the total number of subjects related to immigration in year-month t during the evening news program of channel c. This variable captures the prevalence of this topic within the overall broadcasting devoted to political information on French television channels.[21] Regarding the benchmark sample,[22] Table A3 identifies

[21]In Section 4, we test the robustness of the result using alternative measures of the salience of the migration topic, for instance using the total time devoted to migration-related subjects or the number of days in the month that migration has been discussed on a given TV channel. The results remain virtually unchanged using these variables instead of $ShareSubj_{ct}$.

[22]This sample corresponds to the one that we use in the empirical analysis after the media data are merged with individual attitudes from the ELIPSS. It includes 12 months between 2013 and 2017, as described in Table A2 in the Appendix. Regardless of the measure of salience used, it is worth noting that we find no significant mean salience differences between the full INA and the restricted ELIPSS samples.

Figure 2: Media coverage of immigration and the 2015 refugee crisis



Notes: "Share Subjects" is the average aggregated share of subjects devoted to immigration-related topics on French TV evening news programs. Google trends data shows how often a given term related to the refugee crisis was entered into the Google search engine for a given month. Nb. Asylum Applicants corresponds to the total number of asylum applicants in Europe provided on a monthly basis by Eurostat. Asylum applicant refers to a person who submitted an application for international protection or has been included in such an application as a family member. All time series are scaled such that the highest peak is set at 100.
Source: Authors' elaboration on INA, Google trends and Eurostat data.

2.6% of all evening news programs being related to immigration, with a standard deviation of 2.3% and a maximum of 16.6% for Arte in November 2015. The average duration of immigration-related topics for the months of analysis is approximately 19 minutes per month with a standard deviation of 15 minutes.[23]

As reported in Figure 2, the recent surge in overall immigration coverage overlaps with a dramatic increase in the total number of asylum seekers arriving in Europe in 2015. We plot additional data from Google Trends on the refugee crisis category in this figure to illustrate how natives' attention to immigration shifted in response to the increased salience of immigration. Google trends data indicate – with the deviation from the highest observed peak – how often a refugee-related term is entered into the Google search engine. It confirms that variations in the treatment of immigration in the media are systematically associated with variations in public interest in immigration in subsequent months. This relationship appears to be particularly strong after the 2015 refugee crisis. The empirical analysis exploits deviations from the average coverage over time for each channel. Thus, in

[23]The corresponding figures for the full sample of months between 2011 and 2017 are 24 and 23 minutes, respectively.

Figure A5 in the Appendix, we provide descriptive evidence that the data capture meaningful and sufficient variation at the channel level for the available waves of the ELIPSS survey. Even after absorbing common shocks at the monthly level, as well as specific time-invariant characteristics of the channels, appreciable variation over time remains in the coverage of immigration topics across the various French evening news programs. Indeed, channel and year-month fixed effects account for only 75% to 80% of the variance across the different salience variables that we use.

3 Empirical Strategy

The benchmark empirical model features the average attitude toward immigration of individual i watching evening news programs on his/her preferred channel c to obtain political information in year-month t as the dependent variable. We estimate the following specification:

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

where $ShareSubj_{ct-1}$ is the aforementioned measure of the salience of immigration on channel c during the month preceding the month of the interview.[24] The coefficient of interest β_1 captures the effect of an increase in the salience of immigration on natives' attitudes toward immigration. γ_t stands for year-month fixed effects that absorb time-varying shocks that are common to all individuals, such as the impact of the 2015 refugee crisis in Europe that unambiguously affected natives' attitudes toward immigration (Hangartner et al., 2019; Steinmayr, 2020; Schneider-Strawczynski, 2020).

The main concern associated with this framework is that individuals self-select into television channels that fit their attitudes toward immigration. First, this benchmark model includes a vector $\boldsymbol{X_{it}}$ of time-varying covariates with age, marital status, education, household size, number of children, employment status, occupation, and income categories that reduces such concerns.[25] Second, following Facchini et al. (2017), we provide evidence 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

[24] Unfortunately, because ELIPSS data only include the month of the interview and not the day, we cannot link each respondent to a more fine-grained measure of the immigration topic's salience. Still, the within-channel variability, when media data is aggregated at the month level, corresponds to 75% of the within variability when information is considered at the day level. Additionally, focusing on monthly variations allows us to capture the effect of repeated exposure to immigration-related topics.

[25] A detailed description of the control variables is available in the Appendix Table A4.

of days per week that an individual watches television. Nevertheless, note that such variables should be considered "bad controls" because they are very likely to be jointly determined with the choice of the television channel (Angrist and Pischke, 2008). Third, we exploit the panel dimension of the analysis to augment the specification with individual-channel fixed effects (γ_{ic}). This not only addresses the issue of time-invariant unobservables at the individual level but also the crucial issue of ideological self-selection across channels. This entails that the identifying variability comes only from the correlation between monthly variation in the salience of immigration on a specific French TV channel and the attitudes toward immigration of a given individual watching this channel for a given year. Note that the inclusion of these fixed effects makes the estimation of the equation quite demanding.[26] Finally, to the extent that selection on unobservables is sufficiently correlated with selection on observables, we also provide evidence, following the methodology proposed by Oster (2019), that self-selection is unlikely to drive the results.

We alternatively use five different dependent variables for the analysis of attitudes toward immigration. First, $Attitudes_{ic_{(i)}t}$ that is the continuous average attitude toward immigration of individual i exposed to channel c in year-month t. Second, $Median$ is a dummy variable equal to one for respondents with attitudes above the median and zero otherwise. Third, *Pol* is a dummy variable taking the value one for individuals with extreme attitudes (pro- and anti-immigration) and zero otherwise (moderates). The latter tests whether any polarization is at play with moderates shifting toward extreme views. Finally, we compute *Anti-pol*, a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration individuals and moderates), and symmetrically *Pro-pol*, a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration individuals and moderates). This allows us to check whether any polarization is occurring on one or both sides of the distribution of attitudes.[27]

Given that the sampling process is not clustered, we follow Abadie et al. (2017) and report standard errors clustered at the individual level to account for potential correlations in individuals over time. We extend the discussion on clustering in Section 4.4 and provide robustness checks that the estimates are not affected by clustering standard errors at the channel or channel-month levels.

[26] Individual fixed effects also control for whether the individual is part of the 2013 and/or 2016 samples. Note further that the main results remain unchanged when restricting the empirical analysis to the 2013 sample.

[27] In Table A4 in the Appendix, we describe all the variables we construct for the main analysis and provide a graphical representation of the coding of the different dependent variables in Figure A4.

4 Main Results

In this section, we present the main results on the polarization of immigration attitudes in Subsections 4.1 and 4.2, with an interpretation of the results in Subsection 4.3. Then, we provide a summary of the robustness checks we performed in Subsection 4.4.

4.1 Baseline estimates

Table 3 reports the results of the benchmark specification. Overall, it shows that priming immigration does not push attitudes in a specific direction but rather increases the polarization of attitudes toward the extremes. In column (1), we first use a continuous variable measuring natives' attitudes toward immigration as a dependent variable ($Attitudes_{ic_{(i)}t}$), and then, in column (2), we re-estimate the specification using a dummy variable equal to one for respondents with positive attitudes and zero otherwise ($Median$). In both cases, we find no significant association between the salience of immigration and natives' attitudes toward immigration. However, column (3) reports a positive and highly significant effect of an increase in the salience of immigration on the polarization of attitudes.[28]

Regarding the magnitude of the effect, the estimates suggest that a one-percent increase in the share of immigration subjects ($ShareSubj_{ct-1}$) is associated with a 2.19 percentage point increase in the likelihood that individuals with moderate attitudes fall into extreme attitudes. Expressed in terms of standard deviations, we find that a one-standard-deviation increase (0.016) in the share of subjects devoted to immigration (over the total number of subjects) is associated with a $0.016 \times 2.194 = 3.51$ percentage point increase in the likelihood of polarization. Columns (4) and (5) provide evidence that pro- and anti-moderates react in opposite ways to an increase in the salience of immigration. We first replace the dependent variable in column (4) with *Anti-pol*, a dummy variable equal to one for individuals with anti-immigration attitudes as described in Figure 1 and zero otherwise (pro-immigration, pro- and anti-immigration moderates). While less precisely estimated, the coefficient of interest is positive, which suggests that an increase in immigration coverage re-activates preexisting negative prejudices for anti-immigration moderates, increasing their concerns about immigration. We perform the symmetric exercise in column (5) with *Pro-pol* that is equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-moderates). The coefficient of interest is

[28]These results are also robust to excluding all channels one by one, as reported in Figure C1 in the Appendix, or to applying survey weights as well as weights based on the channels' popularity (results available upon request).

Table 3: Priming immigration in the news and attitudes toward immigration

	(1) $Attitudes_{ic_{(i)}t}$	(2) Median	(3) *Pol*	(4) Anti-pol	(5) Pro-pol	(6) Placebo
$ShareSubj_{ct-1}$	0.420	0.010	2.194***	0.792*	1.402***	-0.621
	(0.573)	(0.514)	(0.661)	(0.423)	(0.479)	(0.743)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. × Channel FE	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,776	6,776	6,776	6,776	6,776	6,776
Adjusted R^2	0.787	0.660	0.452	0.559	0.585	0.241

Notes: The dependent variable in column (1) is continuous and represents the average attitudes of individual i toward immigration. The dependent variable in column (2) is the median split of average attitudes. The dependent variable in column (3) is Polarization, which takes a value one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in column (4) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). The dependent variable in column (5) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). Column (6) estimates a placebo regression with anti-immigration natives and pro-immigration moderates (0) against anti-immigration moderates and pro-immigration natives (1). 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.
Sources: Authors' elaboration on INA and ELIPSS data.

also positive and significant at conventional levels. Again, this suggests that priming immigration re-activates preexisting positive preconceptions for pro-immigration moderates, amplifying their initial positive attitudes toward immigration. Column (6) estimates a placebo regression with anti-immigration and pro-immigration moderates (0) vs. anti-immigration moderates and pro-immigration individuals (1) as described in Figure A4 in the Appendix. Reassuringly, the coefficient of interest is not significant.

To provide additional evidence that the effect captures the shift of individuals with moderate attitudes toward extreme views, we interact the treatment variable with preexisting attitudes. Preexisting attitudes are defined as the attitude of individual i in the previous survey wave. Thus, the benchmark specification becomes:

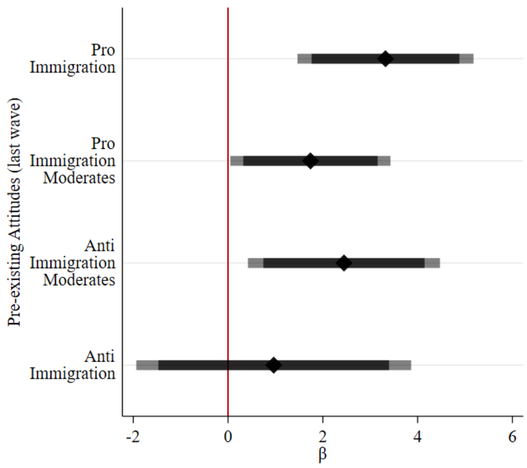
$$\begin{aligned} Pol_{ic_{(i)}t} &= \beta_1 ShareSubj_{ct-1} + \beta_2 PreAttitudes_{it} \\ &\quad + \beta_3 ShareSubj_{ct-1} \times PreAttitudes_{it} + \boldsymbol{\beta' X_{it}} + \gamma_{ic} + \gamma_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where $PreAttitudes_{it}$ is a categorical variable classifying whether individual i was *"Pro-immigration"*, a *"Pro-immigration moderate"*, an *"Anti-immigration moderate"*, or *"Anti-immigration"* in the previous wave. Results are reported in Figure 3.

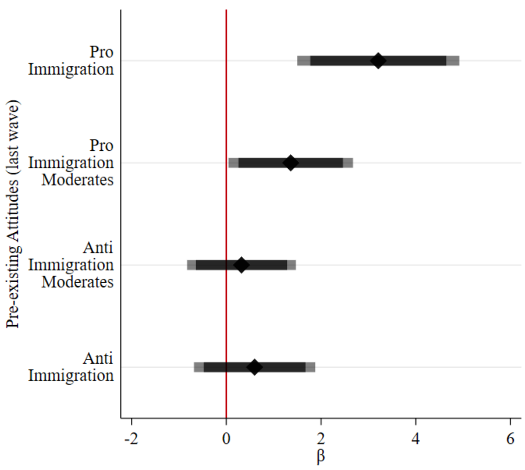
Two main figures emerge from the estimated coefficients and corroborate the previous findings. On the one hand, when the salience of immigration on TV increases, anti-immigration moderates are those more likely to become anti-immigration, while pro-immigration moderates are more likely to become pro-immigration. It is mainly this change in two opposite directions that pulls the polarization at the aggregate level. On the other hand, at the two extremes of the distribution of attitudes, only pro-immigration individuals seem to be affected by news content. Indeed, a rise in the salience of immigration increases the probability that pro-immigration respondents will remain on the left-hand side of the distribution, while anti-immigration individuals are not affected by the salience of immigration. This suggests that anti-

Figure 3: Priming effect interacted with preexisting attitudes

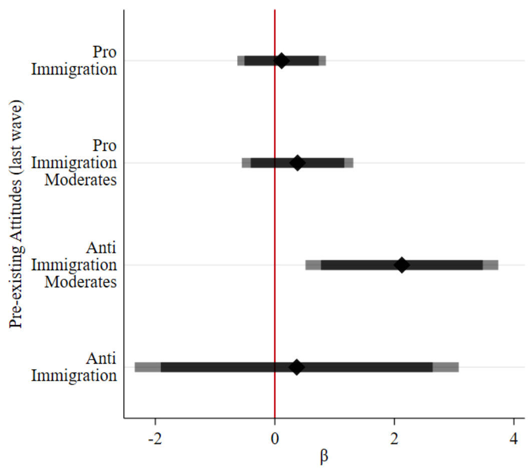
(a) *Pol* as dependent variable



(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 Eq. (3). Each coefficient represents the marginal effect of the variable for different preexisiting attitudes. Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

immigration individuals are unlikely to change their interpersonal attitudes toward immigration over time, irrespective of the salience of the latter.

4.2 Additional results

This subsection summarizes additional results on the polarization effect of priming immigration in the news.

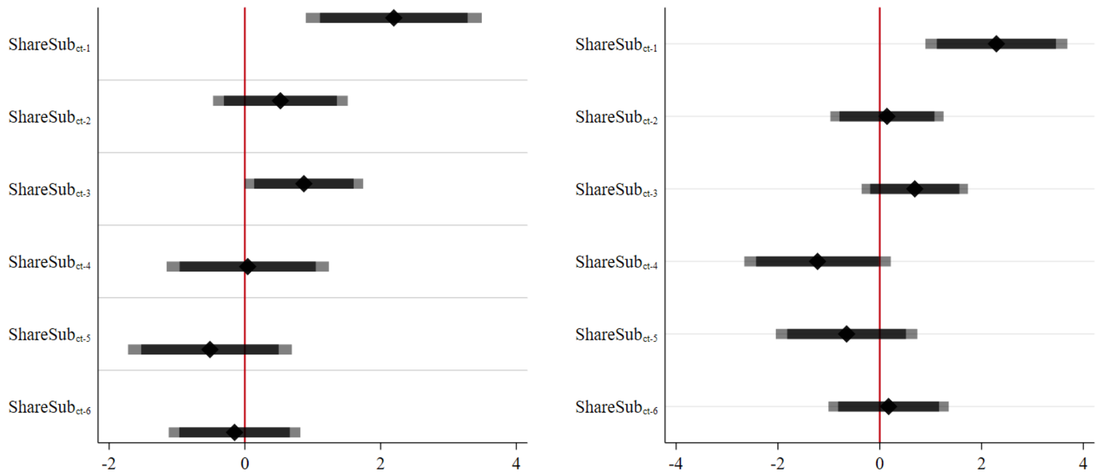
Political analysis and electoral outcomes. We provide an extended analysis in Appendix E on how an increase in the salience of immigration affects an individual's probability of voting for a party conditional on his or her initial political preferences. This analysis uses additional information provided in the ELIPSS surveys on the individual's likelihood of voting for a given party on a 10-point scale.[29] Due to a reorganization of the French political offer, near the end of the survey, such questions are not asked for all parties in all survey waves. The analysis is thus restricted to historical political parties for which a sufficient number of observations are available over time. Political parties are classified as far-right, right, left, and far-left according to their position on the political spectrum and their correlation with the variable of attitude toward immigration as reported in Table F1. As expected, respondents affiliated with far-right parties are less likely to support immigration, while individuals closer to the left and green parties are less likely to report anti-immigration attitudes. The analysis examines switches away from the center (MODEM and UDI) and toward the left (PS), far-left (PG and NPA), right (UMP), and far-right (FN and DLF) parties in response to an increase in the salience of immigration. The analysis is then replicated for individuals switching from left and right to far-left and far-right parties, respectively. Finally, a closer examination of the Green party (EELV) is presented, as it has a strong correlation with individual favorable attitudes toward immigration, as reported in Table F1. For all estimates, we report in Figures F1 to F6 the probability that a respondent will vote for a more extreme party when the salience of immigration increases, conditional on his or her political affiliation with each party in the last wave. Overall, a rise in the salience of immigration significantly increases the likelihood of an individual initially affiliated with the right and/or the center to vote for far-right parties. At the other end of the political spectrum, priming immigration increases the likelihood that individuals initially closer to the center will vote for the left or green party, the two parties with the highest correlation with pro-immigration attitudes. Overall, these results corroborate the previous findings that an increase in the salience of immigration

[29] While these variables do not reflect an individual's actual vote for a particular party, they remain good proxies of an individual's ideological proximity to each party.

increases the polarization of society and induces political reshaping.[30] These findings are also in line with those of Colussi et al. (2021), who demonstrate the impact of an increase in the salience of immigration on voters' electoral preferences in the German context.

Persistence of the effect. To evaluate the persistence of the salience effect on attitudes toward immigration, Figure 4 reports the effect of a change in salience from one to six months prior to the survey. It shows that the results are driven by information from the previous month, while prior lags, estimated separately or in a distributed lags model, have no effect. This is consistent with recent findings by Angelucci and Prat (2020), which show that individual knowledge of news decreases significantly over time.

Figure 4: Lags of salience on the polarization



(a) Simple lags

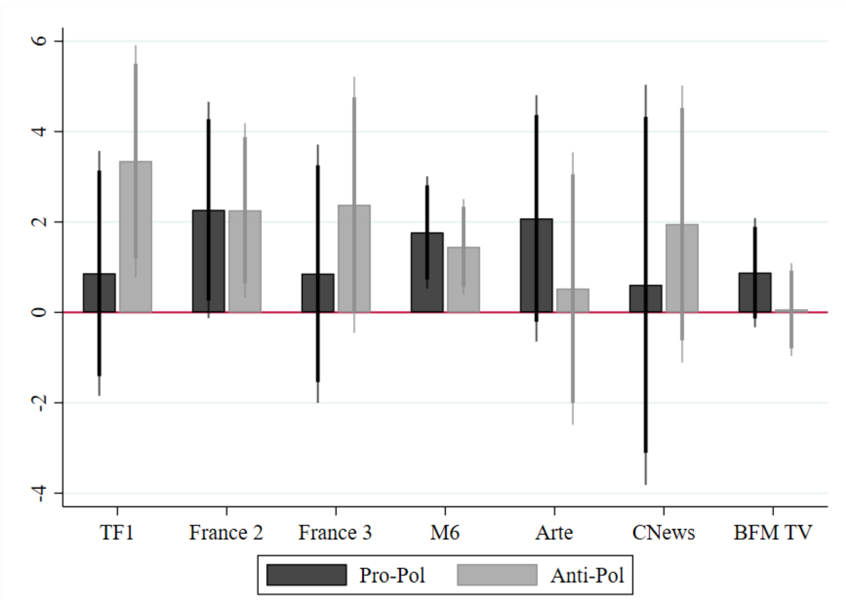
(b) Distributed lag model

Notes: The figure (a) shows the marginal effect of $ShareSub_{ct-1}$ as well as its lagged values on Pol, estimated separately from Eq. 6. The figure (b) shows the marginal effect of $ShareSub_{ct-1}$ as well as its lagged values on Pol, estimated simultaneously in Eq. 6. Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

Within-channel polarization. While an increase in the salience of immigration makes moderate individuals more likely to fall into extreme attitudes, with the direction of this shift related to initial attitudes, one can infer from Figures B3 and B2 in the Appendix that the distribution of attitudes varies across French TV channels. For instance, TF1 is more likely to be watched by individuals who have negative attitudes toward immigration, and thus the distribution of this channel's viewers' attitudes toward immigration is skewed to the left. Arte, on the other hand, is more

[30] Additional results in Table F2 report that an increase in the salience of immigration does not increase the likelihood to vote for a given party on average.

Figure 5: Heterogeneity analysis: priming effect by channels



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 a given channel in the population as defined in Eq. (7). The vertical lines are 90% and 95% confidence intervals. Source: Authors' elaboration on INA and ELIPSS data.

likely to be watched by individuals with positive attitudes, and its distribution of attitudes is therefore skewed to the right. These observations call for a heterogeneity analysis at the channel level, even if the interaction between the treatment variable and the preferred TV channel requires a large number of observations and variability in the data that the sample may not offer.[31] The results in Figure 5 provide suggestive evidence that an increase in the salience of the immigration topic amplifies attitudes toward preexisting bias in channels with extreme anti- or pro-immigration attitudes, such as in TF1 or Arte. In contrast, channels with a less skewed distribution of attitudes, such as M6 and France 2, seem to be those in which the within-channel polarization toward both extreme attitudes occurs, as suggested by the positive and significant signs for both the *Anti-* and *Pro-pol* variables.[32]

4.3 Interpretation of the results

This first set of results demonstrates that an increase in the salience of immigration in the media drives moderate television viewers to two extremes of the distribution

[31]In this way, we mostly draw the conclusions in this subsection from the size of the estimated coefficients rather than the precision of the estimates.

[32]As reported in Section 6, an increase in the salience of immigration in the media may be systematically associated with a channel-specific frame. However, controlling for the tone used in the different channels when discussing immigration-related news does not affect the results depicted in Figure 5. These results are available upon request.

of attitudes. This finding can be interpreted through the length of two distinct theoretical frameworks.

On the one hand, the interaction between ideologically biased news and the sorting of individuals among channels may generate polarization. In a world with Bayesian learning, TV viewers update their initial preferences along with the types of news they are exposed to. If this is the case, pro(anti)-immigration moderates shift to extremely positive (negative) attitudes in response to an increase in their exposure to positive (negative) news about immigration. Polarization occurs as a result of different TV viewers being exposed to differing information sets and updating their attitudes in different directions based on their initial beliefs. This interpretation of the result echoes the literature on the persuasion impact of the media (DellaVigna and Gentzkow, 2010).

On the other hand, the estimated effect could be seen as a pure priming effect. Individuals' limited attention is disproportionately drawn to immigration when the salience of this topic increases in the news. This results in an overweighting of the topic when television viewers are required to express their views on immigration or to vote for specific candidates. In other words, inducing people to think about immigration reactivates their pre-existing attitudes, pushing them from moderate to extreme positions on the same side. Thus, an increase in the salience of immigration generates a polarization of the society by giving disproportionate importance to the immigration phenomenon in viewers' minds. This interpretation of the findings is consistent with that of Alesina et al. (2022) and Colussi et al. (2021), among others.

Several results reported throughout the paper support this second interpretation. First, the within-channel polarization presented in Figure 5 is consistent with a priming interpretation of the results. There is a shift at the two extremes of the attitudes distribution for channels with both types of moderate viewers. However, we should not expect any polarization with Bayesian updating because different viewers' attitudes should rather converge as a result of exposure to similar types of biased information.

Second, comparing pro- and anti-immigration viewers at the distribution's two extremes in Figure 3 lends support to the priming theory. Indeed, the Bayesian updating theory predicts that these two populations are less likely to update their beliefs because they already share the polarized opinions they are exposed to through their preferred channels. However, the results show that priming pro-immigration individuals increases their likelihood of preserving extremely positive attitudes, whereas there is no symmetric effect for anti-immigration respondents. This is consistent with the fact that for anti-immigration viewers, immigration is always a salient topic, whereas priming immigration for pro-immigration viewers serves to remind them of the topic's political importance.

Third, as demonstrated previously in Figure 4, the salience effect is primarily a short-term impact that materializes only within a month. This is consistent with a reactivation of pre-existing prejudices in the context of limited attention, rather than with persistent persuasion toward extreme positions.

Finally, there is still a positive and significant impact of an increase in the salience of the immigration topics on polarization after controlling for the framing of the news in Section 6. This also strongly reduces support for the Bayesian updating model, which generates polarization via the presence of biased information across channels. Overall, all this evidence points toward the fact that the estimated effects can be viewed as pure priming effects.

4.4 Robustness checks

This subsection summarizes additional robustness checks that corroborate the main findings on the polarization effect of priming immigration in the news.

Alternative specifications. We report the results of alternative specifications in Table C1 in the Appendix. Column (1) does not include either individual controls or fixed effects. This simple correlation already captures the main association between priming immigration and polarization. The effect is robust to the inclusion of individual and wave fixed effects in column (2), as well as exploiting the panel dimension of the data by controlling for individual fixed effects interacted with channel fixed effects in column (3). In our preferred specification in column (4), we also show that the main conclusions remain unchanged when controlling for individual time-varying controls.[33] Finally, and following Facchini et al. (2017), we provide evidence in column (5) that the results are robust to controlling for ideological controls, such as political interest, political orientation, and news program viewing time. Nevertheless, these results must be taken with caution, since these variables could be considered "bad controls" (Angrist and Pischke, 2008), being jointly determined with political attitudes toward immigration.

Alternative dependent variable. The measures of attitudes toward immigration are constructed using answers to three types of questions: (1) *There are too many immigrants in France*, (2) *France's cultural life is enriched by immigrants* and (3) *French Muslims are French citizens like any others*. We assume that these three

[33]Interestingly, we do not find any nonlinearities in the benchmark specification when using quadratic measures of the salience of immigration.

questions are good proxies for attitudes toward immigration in France, even question (3), as Muslims account for 43 percent of the immigrant population in France, which results in a blurred distinction between the two groups among the native population (Simon and Tiberj, 2016). However, one could be concerned that the effects are driven by only one of these three dimensions. As a robustness check, we provide additional estimates when sequentially excluding each of the three dimensions in the empirical analysis. Table C2 in the Appendix shows that, while excluding some dimensions reduces data variability and the number of observations, the main conclusion about the polarizing effect of increased immigration salience remains unchanged. Additional estimates in Table C3 report that when focusing on one dimension at a time, the coefficient of interest becomes insignificant, again reflecting a lack of variability in the data.[34] Finally, we provide evidence that the main conclusions remain unchanged when using a principal component analysis (PCA) that extracts the shared component of all three dimensions.[35]

Alternative measures of salience. Table C4 in the Appendix reports the results of the benchmark specification using alternative dependent variables. 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:

$$Dur_{ct} = \sum_{s} (Duration_{sct} | Immigration_{sct} = 1) \tag{4}$$

Then, we define $ShareDur_{ct}$ as the share of time devoted to immigration out of the total broadcasting time on French TV channels:

$$ShareDur_{ct} = \frac{\sum_{s} (Duration_{sct} | Immigration_{sct} = 1)}{\sum_{s} Duration_{sct}} \tag{5}$$

In contrast, to the Dur_{ct} salience measure, $ShareDur_{ct}$ does not denote for a stock but rather accounts for the prevalence of immigration within the overall broadcasting time devoted to political information on French television channels. We also report the results of the benchmark specification with $ShareSubj_{ct}$ and $Subj_{ct}$,

[34] We also provide evidence in Table C7 in the Appendix that the results are not driven solely by an increase in the salience of the Muslim community during the 2015 refugee crisis. Using a new lexicon that only captures words related to Muslims in France, we find no systematic association between the different variables of interest and attitudes toward immigration.

[35] 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). It is worth noting that the benchmark results are also robust to restricting the analysis to the set of respondents who have non-missing answers on all the questions in the index.

the share and the total number of subjects related to immigration, respectively. To capture whether the distribution of the salience of immigration in the month matters, we also use $Days_{ct}$, the number of days in the month that migration has been discussed on the TV channel, as a dependent variable. Note that both Dur_{ct} and Sub_{ct} are monotonically rescaled using the inverse hyperbolic sine.[36] Irrespective of the measure of salience, we always find a positive effect of an increase in the salience of immigration on the likelihood of polarization. As far as the magnitude of the effect is concerned, these estimates suggest that a one-percent increase in the duration of immigration subjects (Dur_{ct-1}) is associated with a 0.03 percentage point increase in the likelihood that individuals with moderate attitudes fall into extreme attitudes. Similarly, using $ShareDur_{ct-1}$ as a variable of interest, we find that a one-standard-deviation increase (0.019) in the share of broadcasting time devoted to immigration (relative to the total number of subjects) is associated with a 2.75 percentage point increase in the likelihood of polarization.

Alternative clustering. Given the sampling design and following Abadie et al. (2017), we cluster the standard errors at the individual level to account for potential correlations in individuals over time. We next provide evidence for the robustness of the results to alternative clustering at the TV channel level in Table C5 in the Appendix. Given that there are few channel clusters (7), we perform a wild cluster bootstrap (999,999 replications) with Webb weights (Cameron and Miller, 2015; MacKinnon and Webb, 2017; MacKinnon et al., 2019).[37] Again, the estimates are not affected by this change. Finally, it is worth noting that the main conclusions remain unchanged when clustering at the channel-month level. Still, MacKinnon et al. (2019) underline that when working with panel data,"it is never to cluster below the cross-section level".[38]

Self-selection concerns. Table C6 in the Appendix provides additional evidence, if needed, that the results are not driven by self-selection. We follow the methodology developed by Oster (2019) to measure the degree of selection on unobservables in the estimates, assuming that selection on observables is informative about selection on unobservables. From columns (1) to (3), we report the results of the baseline estimate with and without control variables and fixed effects. Indeed, Oster (2019) demonstrates that the changes in the coefficient and R-squared following the intro-

[36]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 salience of immigration in a given month-channel is zero) 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.

[37]We use the Stata `boottest` package to perform the wild cluster bootstrap with Webb weights.

[38]These additional results are available upon request.

duction of observables allow estimating the likelihood that the coefficient of interest is entirely driven by unobservables. This 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 on 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). We first compute δ, the degree of selection on unobservables relative to observables that would be necessary to make the coefficient of interest equal to zero. As reported by Oster (2019), concerns regarding self-selection on unobservables are ruled out as long as $\delta > 1$. Focusing on column (4), we find that selection on unobservables would have to be 1.8 times higher than selection on observables to change the nature of the findings. Second, we compute in column (5) the bounding values of the coefficient of interest after correcting for selection on unobservables. The identification set excludes zero and is of the same sign as the coefficient of interest. Overall, this new set of results supports that the main effect is unlikely to be driven by self-selection on unobservables.

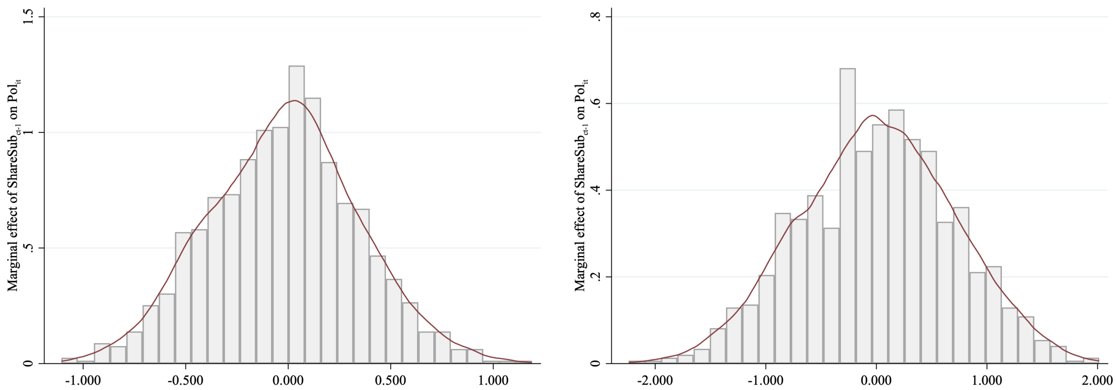
Placebo estimates. We perform placebo estimations to show that the results are not driven by idiosyncratic changes in immigration news broadcasted by different channels. To do so, we run 1,000 replications of the benchmark specification where individuals are randomly assigned to a different TV channel. We constraint 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 6a. One can see that the coefficient of interest follows a standard normal distribution centered at zero. In addition, all estimations always report a coefficient that is significantly lower than the main estimates reported in Table 3. This absence of any effect when randomly assigning channels to respondents demonstrate that the effect we identify is solely driven by channel-specific changes in migration news broadcasting.[39] Second, we replicate the exercise by randomly allocating channels to individuals who do not report TV as one of their top sources of political information. Indeed, a significant coefficient for non-television 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

[39] It is worth noting that wave fixed effects already ruled out that the results capture a general increase in the salience of immigration in the media that would lead people to look for, or pay more attention to, information on immigration in social media, driving users toward extreme attitudes (Zhuravskaya et al., 2020).

TV channel but also separately increased the negative attitudes of viewers of this channel through external factors such as social networks for instance. Again, Figure 6b shows that, after 1,000 replications, we obtain a point estimate that is centered at zero and is below the benchmark coefficient. This supports that the results truly capture the direct influence of TV on attitudes.

Figure 6: Placebo estimates of the priming effect

(a) Television viewers (b) Non-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 regression where we randomly assign a channel to each respondent.
Source: Authors' elaboration on INA and ELIPSS data.

5 Heterogeneity Analysis

This section investigates whether the polarization effect of an increase in the salience 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 as follows:

$$Pol_{ic_{(i)}t} = \beta_1 Salience_{ct-1} + \beta_2 Salience_{ct-1} \times Z_{it_0} + \boldsymbol{\beta' X_{it}} + \gamma_{ic} + \gamma_t + \varepsilon_{it} \qquad (6)$$

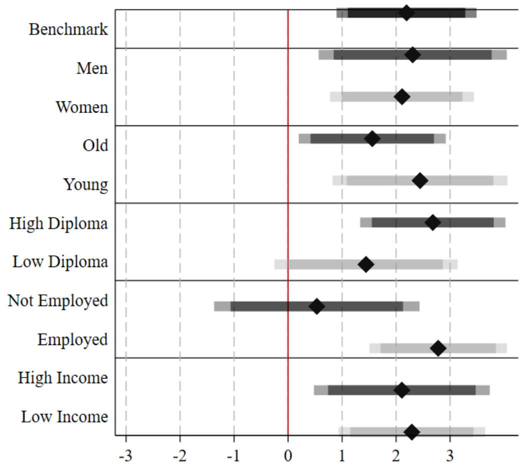
where Z_{it_0} is a dummy variable denoting the beginning of the period t_0 over which we perform the heterogeneity analysis. To recover the total effect from the interaction in Equation (6), we recalculate the effect for each of the two categories of the dummy using:

$$\frac{\partial Pol_{ic_{(i)}t}}{\partial Salience_{ct-1}} = \beta_1 + \beta_2 Z_{it_0} \qquad (7)$$

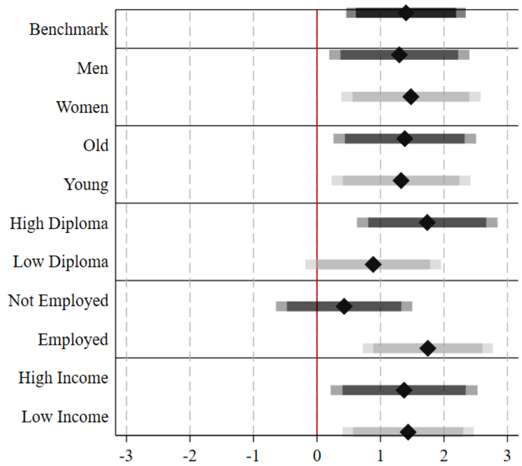
where the effect for the reference category ($Z_{it_0} = 0$) equals β_1, and the effect for the other ($Z_{it_0} = 1$) is the linear combination of $\beta_1 + \beta_2$ (Brambor et al., 2006).

Figure 7: Heterogeneity analysis: priming effect by characteristics

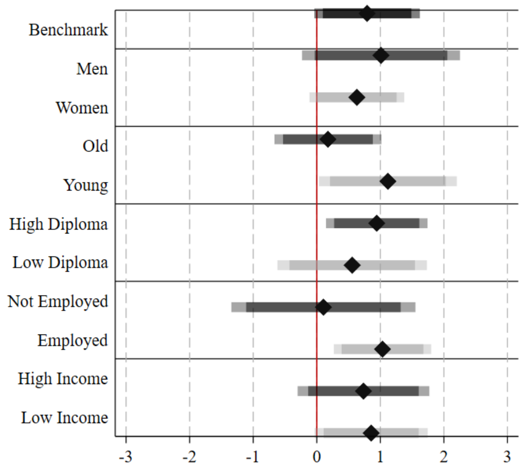
(a) *Pol* as dependent variable



(b) *Pro-Pol* as dependent variable



(c) *Anti-Pol* as dependent variable

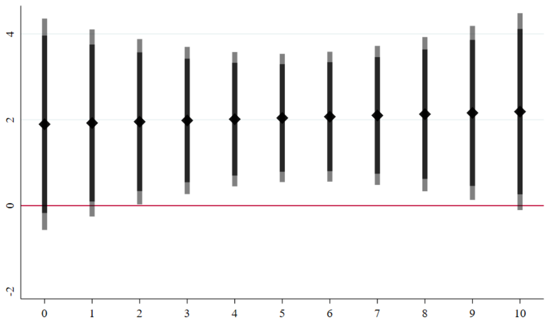


Notes: The figure shows the marginal effect of $ShareSub_{ct-1}$ on Polarization, Anti-pol, and Pro-pol estimated separately from Eq. 6. Each coefficient represents the marginal effect of the variable for a sub-group in the population as defined in Eq. 7. Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

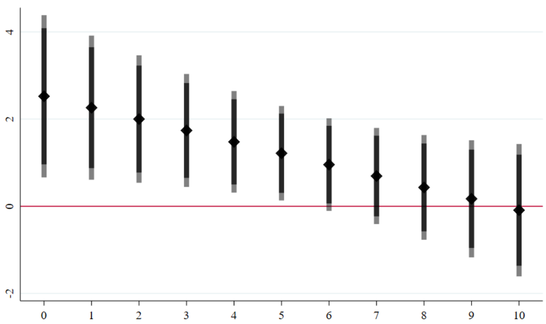
Individuals' characteristics. First, we consider several individual dimensions that may drive a heterogeneous effect, including gender, age, education, employment status, and income. To be considered as exogenous as possible, we fix individual characteristics in the different sets of interactions at the first non-missing observation for each individual. 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 the age, we compare individuals that 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 and those who have an income above. Using Equation (7), we plot the total effect of exposure to immigration news by the categories of interest in Figure 7. Figure 7a reports that polarization is significant for most of the individuals in the population. However, we highlight substantial differences in the magnitude of the effect along with age, education, and employment variables. Figure 7b shows that the priming effect toward pro-immigration attitudes is magnified for individuals highly educated and employed. Figure 7c depicts similar results for employed and highly educated viewers becoming more anti-immigration following an increase in the salience of immigration. In addition, we find that younger respondents are more likely to endorse anti-immigration attitudes than older respondents when the salience of immigration increases. The interpretation of the results is that individuals who are young, employed, and highly educated are more likely to update their beliefs rather

Figure 8: Priming effect interacted with political affiliation

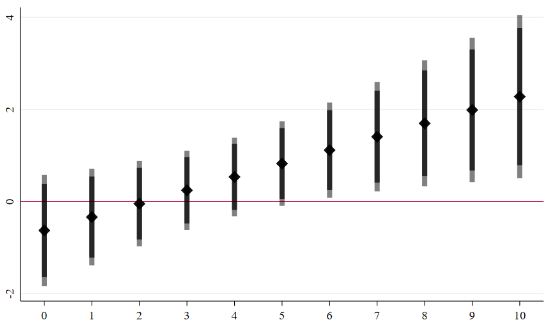
(a) *Pol* as dependent variable



(b) *Pro-Pol* as dependent variable



(c) *Anti-Pol* as dependent variable



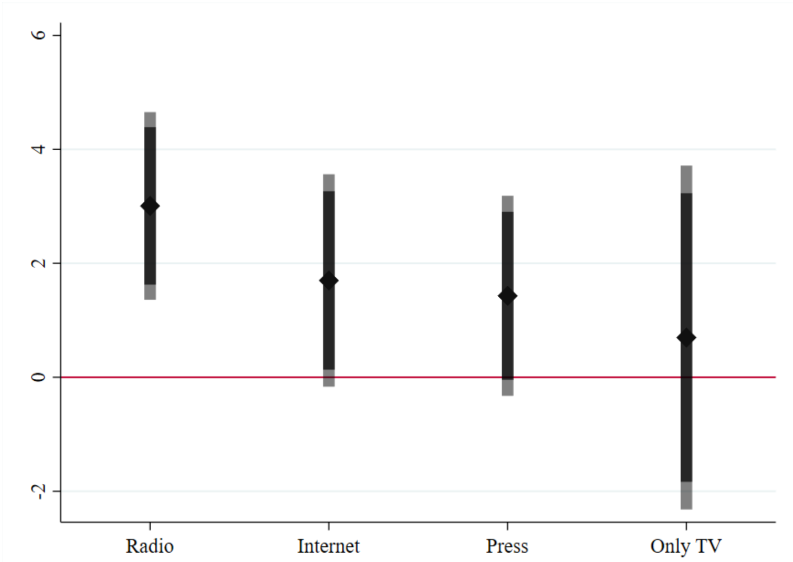
Notes: The figure shows the marginal effect of the independent variables on Polarization, Anti-pol and Pro-pol. Each coefficient represents the marginal effect of the variable for a given level on the political scale as defined in Eq. 7. Confidence intervals are presented at the 95% and 90% levels. Source: Authors' elaboration on INA and ELIPSS data.

than remain entrenched in their position, and thus to change their interpersonal attitudes.

Political affiliation Second, we investigate how polarization interplays with individuals' political affiliation. We employ a 10-point self-assessment scale that classifies individuals across the entire political spectrum. In contrast to previous estimates, we treat political affiliation as a continuous variable ranging from zero, for respondents endorsing far-left ideologies to 10 for respondents close to far-right ideologies. As expected, Figure 8 suggests that the polarization effect mainly comes from individuals at the center of the political spectrum, who are more likely to shift toward extreme immigration attitudes. Further investigations reported in Figures 8b and 8c reveal that the likelihood of left polarization (right polarization) increases as individuals become closer to the left (right). As a result, those becoming pro-immigration (anti-immigration) include only individuals who initially self-identify as left-wing (right-wing).

Alternative source of information. Third, we investigate whether the main effect is heterogenous 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

Figure 9: Priming effect interacted with the alternative sources of information



Notes: The figure shows the marginal effect of $ShareSub_{ct-1}$ on Polarization, estimated separately from Eq. 6. Each coefficient represents the marginal effect of the variable for a sub-group in the population as defined in Eq. 7, where a group is composed according to the second source of information. For instance, the first group "radio" is composed of individuals who mentioned using the radio as a second source of political information. Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

news. These results are reported in Figure 9. We find that the polarization occurs mainly among people who declare that they also listen to the radio on top of watching their preferred channel, and we only find a weakly significant polarization effect when viewers also get political information from the internet or traditional press. Several patterns could explain the greater effect of the radio: i) TV coverage could correlate more strongly with radio coverage than other forms of media, ii) there could be a greater likelihood of a joint media consumption of TV and radio, or iii) individuals watching TV could have similar characteristics as those who listen to the radio. Interestingly, this confirms that the results are not driven by the alternative story that an increase in the salience of one channel leads to increased internet searches, and thus to more polarized attitudes because of echo chambers. Again, this supports that the results do not capture the polarization impact of social media but the direct impact of TV on attitudes.

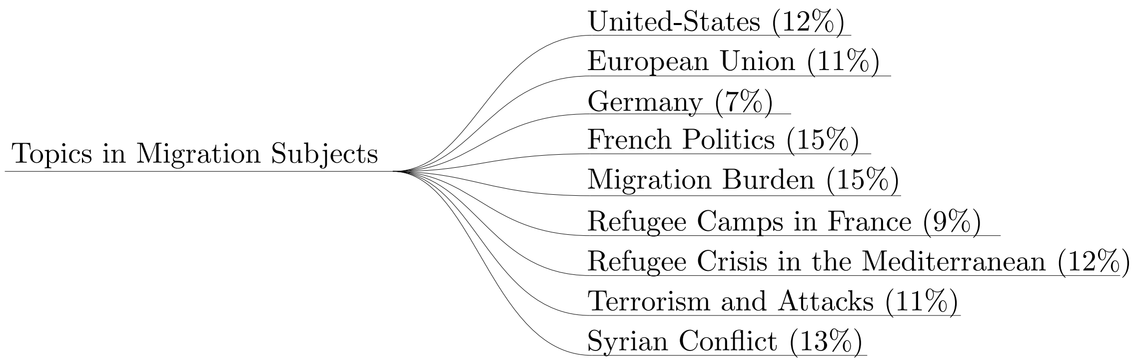
6 From Priming to Framing

To some extent, the previous results may capture differences in the treatment of the same subject across various TV channels. This section provides therefore evidence that the priming effect of immigration is robust to controlling for the framing of immigration-related subjects in evening news programs.

To characterize the framing of migration subjects on evening news programs, we first identify the topics associated with migration using an unsupervised latent Dirichlet allocation algorithm (LDA) on the corpus of migration subjects. The goal of the LDA generative process is to discover uncorrelated topics from the collection of migration subjects and to assign each subject to a mutually exclusive category. In the sample, the LDA algorithm detects nine different topics associated with migration subjects in the period of analysis, all depicted in Figure 10.[40] Table E2 in the Appendix reports the share of each topic on TV news programs before and after the refugee crisis. As expected, one can see a shift in the main topics before and after the 2015 refugee crisis, from "Migration Burden", "French Politics", and "Syrian Conflict" before the refugee crisis, to "Refugee Camps in France", "Migration Burden", and "Terrorism and Attacks" after. Investigating channel heterogeneity in Figure E2 in the Appendix, we see that TF1 or M6 are more likely than Arte or France 2, for instance, to associate immigration with "Migration Burden" or "Terrorism", which again underlines differences in framing across channels. This, again,

[40] In Table E1 in the Appendix, we describe the top words associated with each topic found by the LDA algorithm.

Figure 10: Main topics associated with migration subjects (LDA algorithm)



Source: Authors' elaboration on a LDA algorithm applied to INA data.

also highlights the need to account for the non-random matching between viewers and TV channels, as we do in the empirical analysis.

Second, we perform a sentiment analysis to characterize the tone employed in migration subjects. To do so, we use the French Expanded Emotion Lexicon (Abdaoui et al., 2017), which is, to the best of our knowledge, the lexicon of reference for sentiment analysis in French.[41] This allows us to obtain measures of positivity and negativity for each immigration-related subject.[42] To do so, we compute the number of positive (negative) words relative to the total number of words in the subject. Since some subjects may be particularly emotionally charged, we also retain a third measure that takes the difference between the number of positive and negative words over the total number of words in the subject. Table E5 in the Appendix reports the share of positive and negative attitudes among migration subjects and across channels. Interestingly, while Philippe and Ouss (2018) underline that the relative neutrality of the different French TV channels is enforced by the Superior Council of Audiovisual Media, we find substantial variability across channels and months. The tone of migration subjects became more positive after the refugee crisis and, on average, the most positive channels were Arte and France 2, while the most negative ones were BFM TV and CNews during the period of analysis.

6.1 Topic analysis

In this section, we disaggregate the measures of salience into the nine main topics identified by the LDA algorithm. Indeed, it is desirable to determine whether the

[41]We removed from the sentiment analysis words that were already used in the lexicon on immigration.

[42]Figure E3 in the Appendix depicts the most frequent positive and negative French words in the most positive and negative subjects, respectively.

polarization effect of salience that we uncovered averages heterogeneous reactions to various topics. We estimate the following model:

$$\begin{aligned} Pol_{ic_{(i)}t} =& \beta_1 ShareSubj[Terrorism\ and\ Attacks]_{ct-1} + ... + \\ & \beta_9 ShareSubj[Migration\ Burden]_{ct-1} + \boldsymbol{\beta' X_{it}} + \gamma_{ic} + \gamma_t + \varepsilon_{it} \end{aligned} \tag{8}$$

where, for instance, $ShareSubj[Terrorism\ and\ Attacks]_{ct-1}$ is the share of subjects devoted to the topic of immigration and talking specifically about "Terrorism and Attacks", in all broadcasted subjects in year-month t during the evening news program of channel c. As topics are mutually exclusive and TV channels have a finite amount of broadcasting time, the salience of one topic may be correlated with the salience of other topics, thus reflecting only editorial choices. To account for the possibility that one topic is the omitted variable of another, we include all the topics in the same regression despite potential collinearity.

Table E3 in the Appendix displays the raw results. The main topics for which we consistently detect a polarization effect are "Migration Burden", "Refugee Camps

Table 4: Topic analysis – $ShareSubj_{ct-1}$

Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
France	Refugee Camps in France	5.572***	2.824***	2.749***
	French Politics	(1.128)	(0.794)	(0.818)
	Migration Burden			
Foreign	European Union	0.443	-1.264**	1.707**
	Germany	(1.082)	(0.595)	(0.859)
	United-States			
Other	Refugee Crisis Med.	0.849	1.111	-0.263
	Terrorism	(1.232)	(0.712)	(1.000)
	Syrian			
Controls		Yes	Yes	Yes
Wave FE		Yes	Yes	Yes
Indiv.×Channel FE		Yes	Yes	Yes
Nb. Observations		6,776	6,776	6,776
Adjusted R^2		0.454	0.560	0.586

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 anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). The dependent variable in column (3) is 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 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.
Source: Authors' elaboration on INA and ELIPSS data.

in France" and "French Politics". The low significance of the other coefficients suggests that we may not be able to capture any additional patterns due to the low variability in the data when focusing on specific topics. Thus, we group the main topics into three larger consistent categories, namely i) subjects related to France and the integration of immigrants in the national territory, ii) subjects related to immigration in foreign host countries, and iii) subjects related to the refugee crisis, terrorism and the Syrian conflict. These results are reported in Table 4. On the one hand, subjects priming immigration in France produce a polarization effect, whereas those priming immigration in other contexts outside of the national territory (such as in Germany or the United States) increase pro-immigrant attitudes. Thus, the issue of integration and the potential costs associated with immigration at home appears to push attitudes on immigration in both directions depending on initial attitudes. On the other hand, priming immigration in foreign host countries may increase natives' empathy for immigrants. Interestingly, we do not detect any effect of immigration subjects specifically depicting terrorism or the refugee crisis.[43] Alternative groupings of topics do not change the conclusions and are available upon request. Specifically, the results on the polarization effect of French stories still hold when excluding "Migration Burden " from the France category, as reported in the Appendix.

6.2 Sentiment analysis

Regardless of the topic associated with immigration-related subjects, journalists, as well as editorial boards, may frame the essence of the same story in very different ways (Moy et al., 2016). In addition, negatively framed immigration news could receive more attention in the media than positive news because the media may be more interested in spreading disruptive news.[44] Overall, an increase in the salience of immigration in the media may be systematically associated with channel-specific frames driving attitudes in opposite directions. Thus, we augment the benchmark specification previously described in Equation (2) with measures of sentiment to check whether the polarization effect of priming migration is affected by controlling for the framing of the content and the tone employed by each channel when discussing migration.[45]

[43] In the same spirit, Table C7 in the Appendix shows that we do not detect an effect on attitudes of the salience of Muslim immigration news using a lexicon for Muslim-related keywords.

[44] In a related context, Vosoughi et al. (2018) observe that false news may spread faster among Twitter users due to its degree of novelty and emotionally charged content.

[45] Another natural specification would have been to include an interaction term between priming and framing in the benchmark specification to check whether the two mechanisms play simultaneously on natives' attitudes toward immigration and reinforce each other. We find no significant

Table 5: Sentiment analysis

	(1) *Pol*	(2) Anti-pol	(3) Pro-pol	(4) *Pol*	(5) Anti-pol	(6) Pro-pol	(7) *Pol*	(8) Anti-pol	(9) Pro-pol
$ShareSubj_{ct-1}$	2.033***	0.737*	1.296***	2.008***	0.779*	1.229**	2.177***	0.782*	1.395***
	(0.663)	(0.424)	(0.481)	(0.663)	(0.425)	(0.482)	(0.662)	(0.424)	(0.480)
Sent. Score	0.213**	0.072	0.141*						
	(0.098)	(0.066)	(0.074)						
Share of negative				-0.268*	-0.019	-0.249**			
				(0.155)	(0.102)	(0.121)			
Share of positive							0.270*	0.150	0.119
							(0.162)	(0.112)	(0.119)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. × Channel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,776	6,776	6,776	6,776	6,776	6,776	6,776	6,776	6,776
Adjusted R^2	0.452	0.560	0.586	0.452	0.559	0.586	0.452	0.560	0.585

Notes: The dependent variable in columns (1), (4), and (7) is Polarization, which takes a value one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in columns (2), (5), (8) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). The dependent variable in columns (3), (6), (9) is 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 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.
Source: Authors' elaboration on INA and ELIPSS data.

Controlling for the framing of immigration-related news content in Table 5, the polarization effect of an increase in the salience of immigration always remains positive and highly significant. This supports that the previous results did not capture differences in the tone employed across the different French TV channels.[46] Regarding the framing of immigration-related news, the first measure, which takes the difference between the number of positive and negative words over the total number of words in the subject, shows that increasing (decreasing) the share of negative (positive) content is associated with a decrease in polarization (column 1) that occurs mainly on the left side of the distribution of attitudes. Indeed, the comparison between columns (2) and (3) reveals that having more negative content is associated with less positive attitudes toward immigration (column 3), but without any significant changes on the right side of the distribution of attitudes (column 2). Consistent patterns are found from columns (4) to (6) when focusing only on the share of negative content in immigration news programs. Indeed, column (6) shows that an increase in the share of negative content is associated with more negative attitudes toward immigration. Again, this result is driven by the shift of individu-

effect for this interaction, which suggests that priming and framing act independently. These additional results are available in Table E6 in the Appendix.

[46]Note that controlling for the framing of the content also does not affect the results regarding the within-channel effect of priming immigration.

als from pro-immigration to pro-immigration moderates attitudes, which results in a less polarized distribution (column 4). We still do not find any significant association between the framing and natives' attitudes toward immigration on the right-hand side of the distribution (column 5). Finally, in line with the literature on sentiment analysis, we find no clear association between the share of positive content only and attitudes toward immigration from columns (7) to (9).[47] Overall, the results of this analysis confirm that an increase in the salience of migration topics has a polarization effect and is robust to controlling for the framing of immigration-related news. These findings also suggest that in contrast to priming, a change in the framing mostly drives viewers' attitudes in specific directions.

7 Conclusions

This paper investigates the extent to which the media, in particular television, influence attitudes toward immigration by modifying the salience of this topic on the political agenda. Combining monthly data on the TV coverage of the immigration topic with individual panel data on natives' attitudes toward immigration, we find that priming immigration in the news results in more polarized attitudes. In particular, natives with moderately positive attitudes shift to extremely positive attitudes, while their counterparts with moderately negative initial attitudes become very concerned about immigration. The empirical strategy relies on natives' differential exposure to immigration through their preferred television channel. Together with the panel dimension of the data, this allows us to control for individual-channel fixed effects, which strongly reduce concerns about ideological self-selection into channels. Interestingly, the main result is at odds with most of the existing literature on the impact of media on attitudes toward immigration, which usually finds that priming immigration mainly drives natives' attitudes in a specific direction. Investigating the content of immigration-related topics, we find that immigration news relating to France polarizes immigration attitudes, whereas immigration news relating to other host countries, such as Germany or the United States, increases pro-immigration attitudes. In addition, we find no evidence that the polarization effect of priming immigration reflects differences in the treatment of the immigration topic across French TV channels. Indeed, if changes in the tone used in migration subjects

[47] These average effects may also conceal substantial heterogeneity if individuals with specific initial attitudes react differently to the same framing. As a result, Figure E4 in the appendix investigates the heterogeneous response to a change in the tone of migration content on viewers' attitudes by channel. It shows that having more negative content tends to increase anti-immigration attitudes, with effects that seem to be relatively homogeneous across channels.

can drive viewers' attitudes in a specific direction, the main polarization effect of salience remains significant when we control for framing effects. The results also show that priming immigration has an effect on voter decisions, which is especially relevant when considering media coverage during election seasons. Overall, this new evidence calls for additional research on the priming and framing role of the media in reactivating and exacerbating preexisting prejudices in the native population. It also highlights the role of the media, particularly television, in polarizing natives' attitudes in society.

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

Online Appendix.

Appendix A: Additional Descriptive Statistics

Table A1: Respondents by preferred TV channel

Channel	2013		2016		Overall Nb. of Obs.	
TF1	149	32.11	289	27.97	2,020	29.81
France 2	120	25.86	294	27.97	1,796	26.51
BFM TV	108	23.28	226	21.50	1,540	22.73
M6	43	9.27	108	10.28	650	9.59
France 3	21	4.53	58	5.52	351	5.18
CNews	13	2.80	44	4.19	232	3.42
Arte	10	2.16	32	3.04	187	2.76
Indiv.	464		1,051		6,776	

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

Table A2: Number of individual observations per wave

Wave	Year	Month	Obsv.	%	Too Much Migrants	Immigration = Culture	Muslims= Citizens
1	2013	September	464	6.85	√	√	√
2	2013	December	447	6.60		√	√
3	2014	April	405	5.98	√		
4	2014	June	406	5.99	√	√	√
5	2014	December	411	6.07	√		√
6	2015	March	382	5.64	√	√	√
7	2015	April	417	6.15		√	
8	2015	June	393	5.80	√	√	√
9	2015	December	392	5.79	√	√	√
10	2016	September	1,051	15.51	√	√	√
11	2017	May	982	14.49	√	√	√
12	2017	November	1,026	15.14	√	√	√
Total:			6,776	100			

Notes: This Table reports the number of individual observations per wave in the benchmark sample.
Source: Authors' elaboration on INA and ELIPSS data.

Figure A1: Sample of analysis

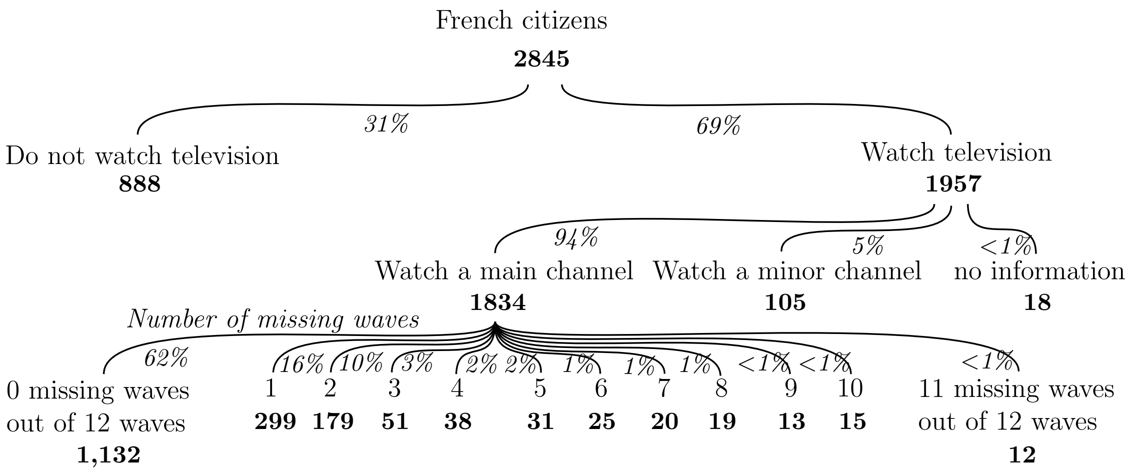


Figure A2: Sample of analysis – 2013 sample

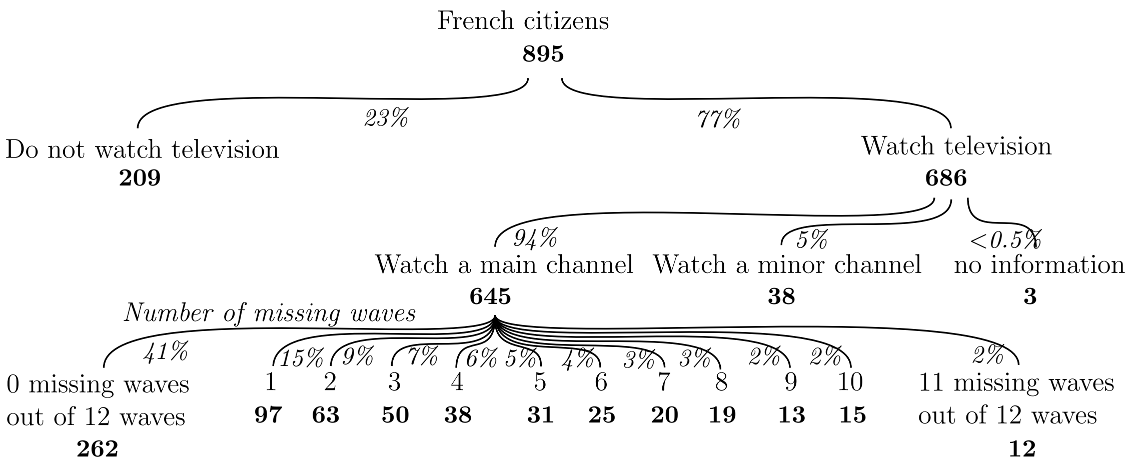
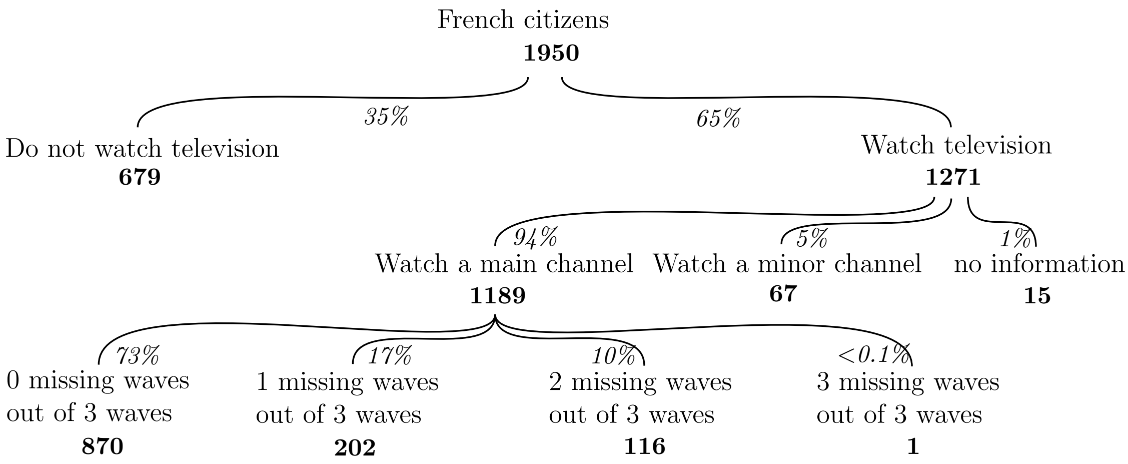


Figure A3: Sample of analysis – 2016 sample



Source: Author's elaboration on ELIPSS data.

Table A3: Share of migration subjects on evening television programs

January 2011 to December 2018	Mean	Std. Dev.	Min.	Max.
All channels:	0.032	0.034	0.000	0.366
-Before the refugee crisis (09.2015)	0.024	0.022	0.000	0.201
-After the refugee crisis (09.2015)	0.044	0.046	0.000	0.366
TF1	0.027	0.022	0.003	0.163
France 2	0.025	0.025	0.001	0.189
France 3	0.024	0.025	0.002	0.193
Arte	0.081	0.059	0.007	0.366
M6	0.018	0.018	0.002	0.146
BFM TV	0.036	0.033	0.000	0.194
CNews - Itele	0.032	0.033	0.000	0.215
Nb. observations:	314,739			

12 ELIPSS months	Mean	Std. Dev.	Min.	Max.
All channels :	0.026	0.023	0.001	0.166
-Before the refugee crisis (09.2015)	0.024	0.021	0.001	0.154
-After the refugee crisis (09.2015)	0.030	0.027	0.004	0.166
TF1	0.022	0.007	0.011	0.035
France 2	0.019	0.011	0.001	0.046
France 3	0.015	0.009	0.002	0.034
Arte	0.078	0.040	0.034	0.166
M6	0.015	0.008	0.002	0.030
BFM TV	0.030	0.021	0.012	0.082
CNews - Itele	0.025	0.018	0.004	0.068
Nb. observations:	38,079			

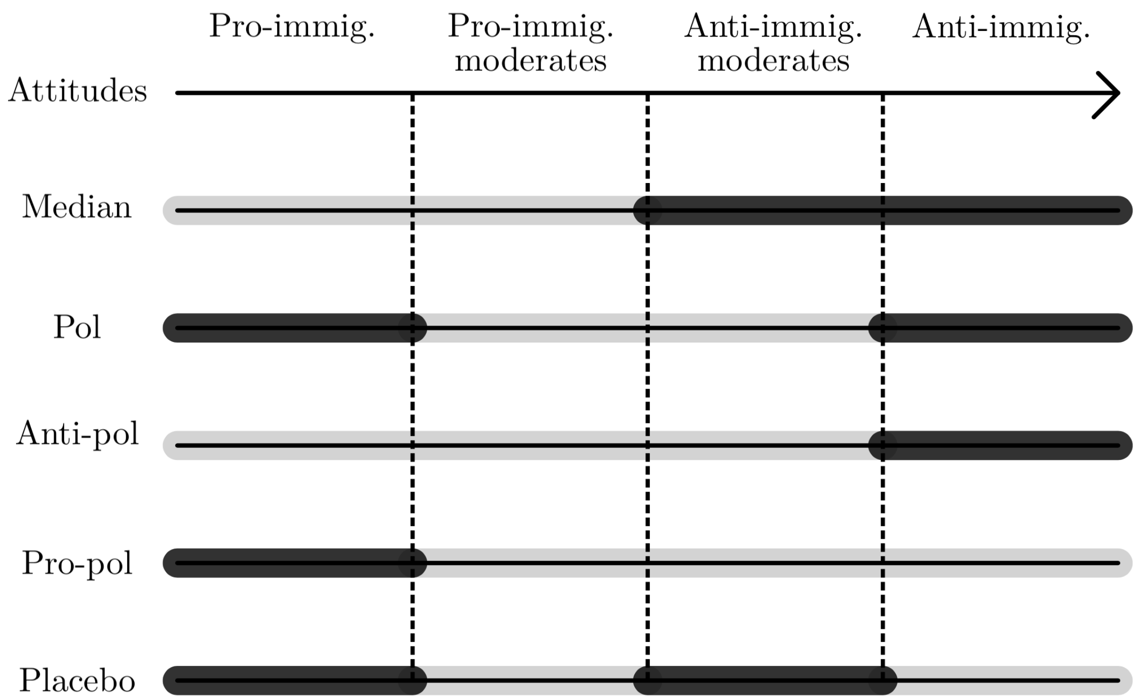
Notes: This Table computes the average share of migration subjects among all subjects on evening television programs of Arte, BFM-TV, CNews, TF1, France 2, France 3, and M6.
Source: Authors' elaboration on INA data.

Table A4: Summary statistics

	Mean	Std. Dev.	Min.	Max.	Type
$Attitudes_{it}$	2.482	0.775	1.000	4.000	Categorical
Median	0.466	0.499	0.000	1.000	Dummy
Pol	0.382	0.486	0.000	1.000	Dummy
Anti-pol	0.184	0.387	0.000	1.000	Dummy
Pro-pol	0.802	0.399	0.000	1.000	Dummy
$ShareSubj_{ct-1}$	0.023	0.016	0.001	0.166	Continuous
$ln(Subj_{ct-1})$	2.856	0.678	0.881	4.500	Continuous
$ln(Dur_{ct-1})$	3.500	0.730	0.421	5.144	Continuous
$ShareDur_{ct-1}$	0.027	0.019	0.001	0.178	Continuous
Age, 5-year categories	5.584	2.647	0.000	10.000	Categorical
High Education	0.654	0.476	0.000	1.000	Dummy
Employment Status	0.671	0.470	0.000	1.000	Dummy
Marital Status	0.664	0.472	0.000	1.000	Dummy
Nb. of child	0.789	1.077	0.000	3.000	Categorical
Household number	2.476	1.300	1.000	6.000	Categorical
Blue Collar	0.213	0.409	0.000	1.000	Dummy
Income categories	3.092	1.823	0.000	6.000	Categorical
Nb. observations:	6,776				

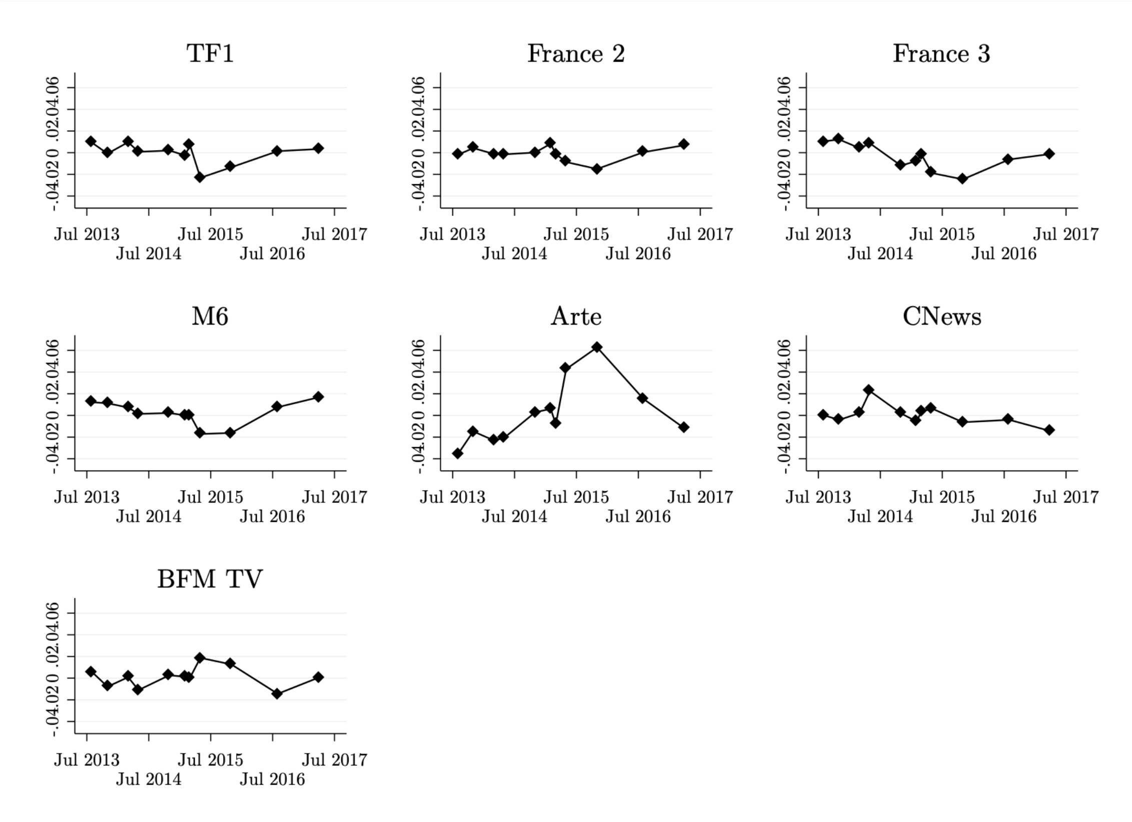
Notes: $Attitudes_{it}$ is the continuous average attitude of individual i in year-month t toward immigration. $Median$ is a dummy variable equal to one for respondents with attitudes above the median and zero otherwise. *Pol* is a dummy variable which takes the value of one for individuals with extreme 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). $ShareSubj_{ct}$ 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 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 Members” 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 “Revenues” 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.).
Source: Authors’ elaboration on INA and ELIPSS data.

Figure A4: Alternative 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 which 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). $Placebos$ is a dummy variable equal to one for individuals with pro-immigration or anti-immigration moderates attitudes and zero otherwise.
Source: Authors' elaboration on INA and ELIPSS data.

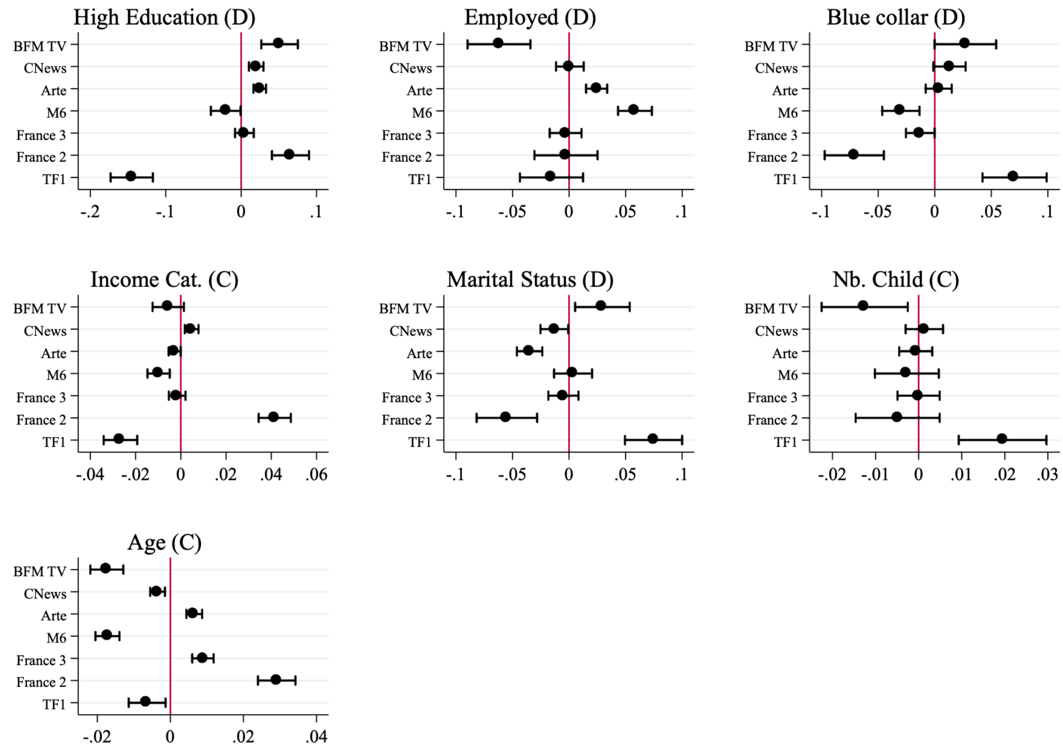
Figure A5: Media coverage of immigration
Year-month and channel fixed effects partialled out



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

Appendix B: Self-selection into Channels

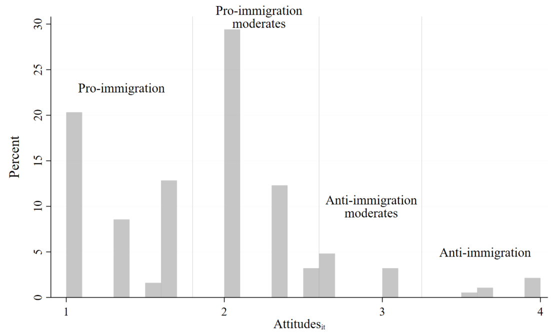
Figure B1: Multinomial logit regressions
Probabilities of choosing a given channel



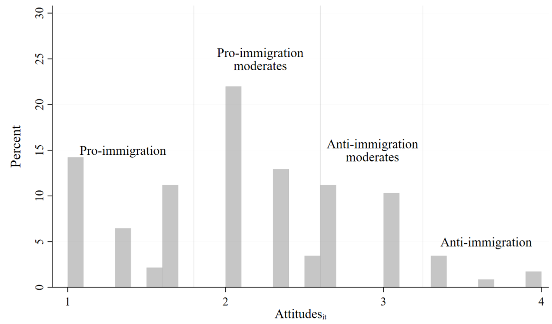
Interpretation: The probability of choosing TF1, ceteris paribus, is on average 1.41 percentage points lower for High-skilled compare to Low-skilled viewers.
Notes: Coefficients are obtained from predictive margins for continuous (C) and dummy variables (D) after a multinomial logit with alternative channels as dependent variable and age, education, employment status, marital status, number of children and income as predictors. For graphical representation, income, age and 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.
Source: Authors' elaboration on ELIPSS data.

Figure B2: Individuals' attitudes toward immigration by channel

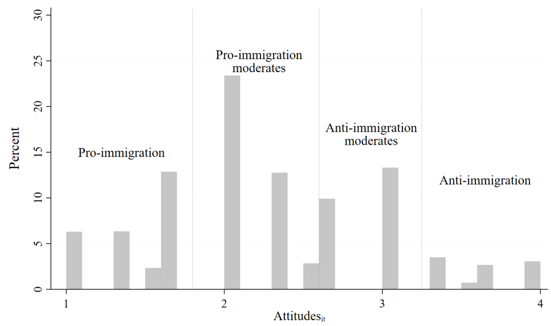
(a) Arte (skewness=0.744, kurtosis=3.938)



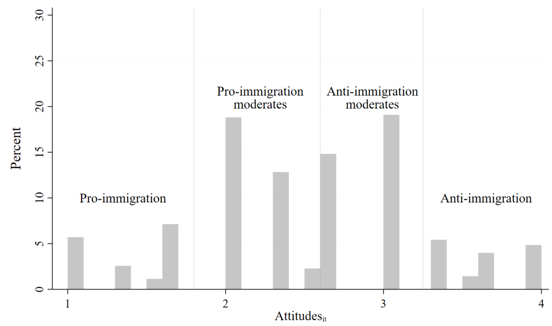
(b) CNews (skewness=0.230, kurtosis= 2.600)



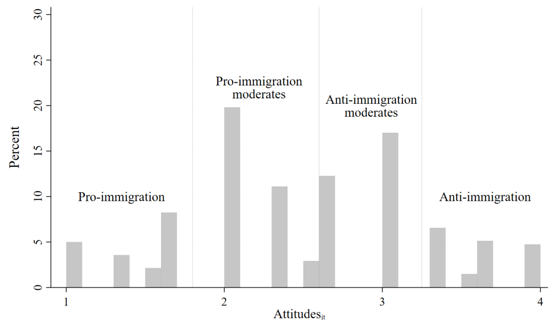
(c) France 2 (skewness=0.368, kurtosis=2.694)



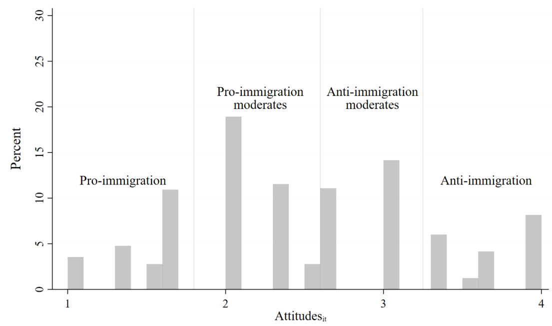
(d) France 3 (skewness=-0.020, kurtosis=2.609)



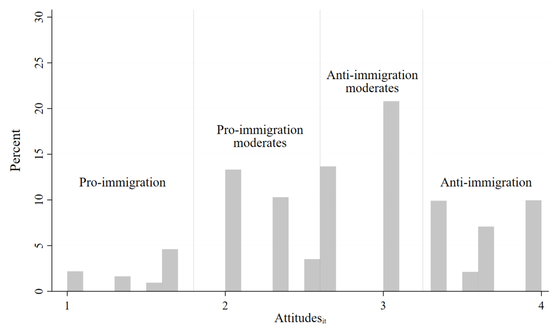
(e) BFM TV (skewness=0.064, kurtosis=2.378)



(f) M6 (skewness=0.264, kurtosis=2.284)

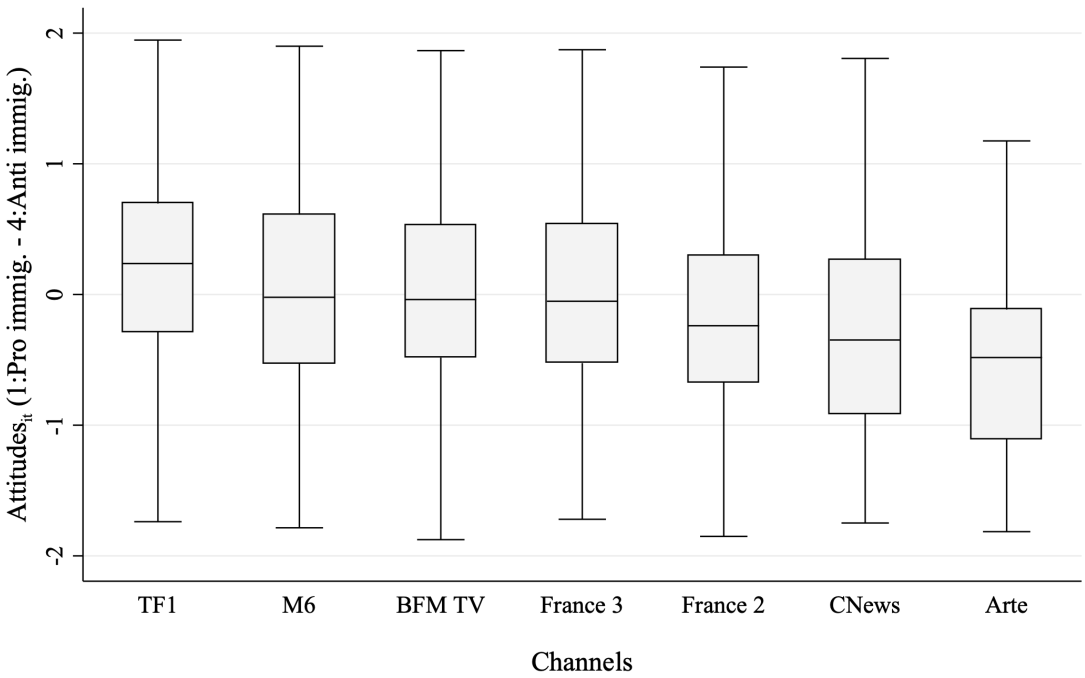


(g) TF1 (skewness=-0.179, kurtosis=2.494)



Note: Distribution of individuals' attitudes with respect to immigration by channels.
Source: Authors' elaboration on ELIPSS data.

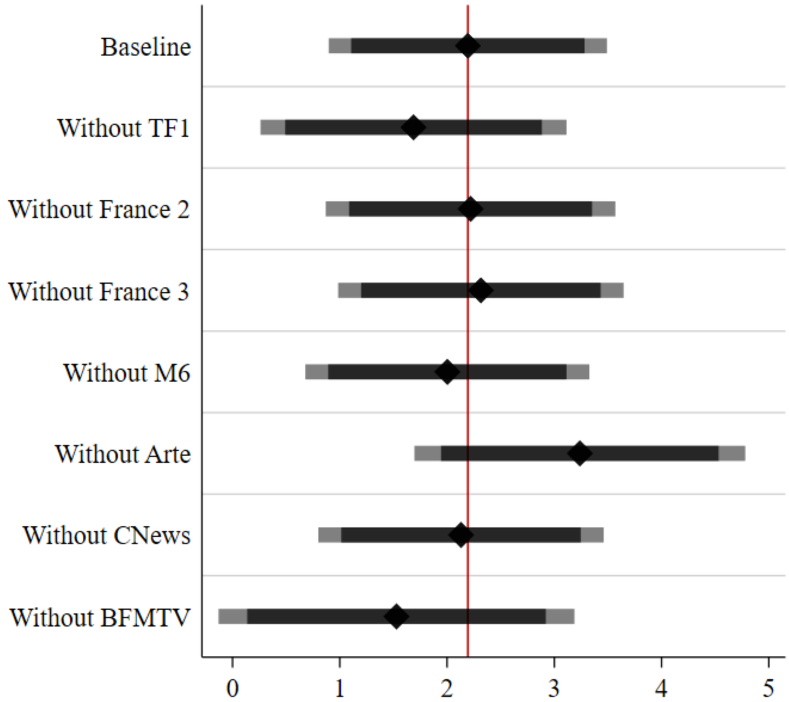
Figure B3: Attitudes by preferred TV channel, 2013-2017.
Individual characteristics partialled-out.



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, income categories and a dummy for new individuals in the 2016 sample.
Source: Authors' elaboration on ELIPSS data.

Appendix C: Additional Robustness Checks

Figure C1: Priming effect removing channels one by one



These coefficients are obtained estimating Eq. 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. Confidence intervals are presented at the 95% and 90% levels.
Sources: Authors' elaboration on INA and ELIPSS data.

Table C1: Alternative Specifications

	(1) *Pol*	(2) *Pol*	(3) *Pol*	(4) *Pol*	(5) *Pol*
$ShareSubj_{ct-1}$	1.493***	2.293***	2.225***	2.194***	2.030***
	(0.527)	(0.641)	(0.652)	(0.661)	(0.759)
Controls	No	No	No	Yes	Yes
Ideological Controls	No	No	No	No	Yes
Indiv. FE	No	Yes	No	No	No
Wave FE	No	Yes	Yes	Yes	Yes
Indiv. $\times$ Channel FE	No	No	Yes	Yes	Yes
Nb. Observations	6,776	6,776	6,776	6,776	6;422
Adjusted R^2	0.002	0.448	0.452	0.452	0.449

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 control includes age, education, employment status, marital status, number of children, household size, a dummy for blue collar and income categories. Ideological control include political interest, political orientation and viewing time. 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 C2: Alternative dependent variable

Dependent var. : *Pol*	(1)	(2)	(3)
First dimension $\rightarrow$	Too Much Migrants	Too Much Migrants	Immigration = Culture
Second dimension $\rightarrow$	Immigration = Culture	Muslims = Citizens	Muslims = Citizens
$ShareSubj_{ct-1}$	1.884***	2.420***	1.791***
	(0.552)	(0.644)	(0.632)
Controls	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Indiv. $\times$ Channel FE	Yes	Yes	Yes
Nb. Observations	4,843	5,023	5,189
Adjusted R^2	0.603	0.518	0.510

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.
Source: Authors' elaboration on INA and ELIPSS data.

Table C3: Alternative dependent variables (cont'd)

	(1) Too Much Migrants	(2) Immigration= Culture	(3) Muslims= Citizens	(4) PCA
$ShareSubj_{ct-1}$	0.718	0.752	0.138	1.049**
	(0.554)	(0.594)	(0.584)	(0.493)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Indiv. × Channel FE	Yes	Yes	Yes	Yes
Nb. Observations	5,844	5,926	5,929	4,985
Adjusted R^2	0.503	0.449	0.498	0.472

Notes: All the dependent variable take the 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, income categories. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration on INA and ELIPSS data.

Table C4: Priming effect with alternative independent variables

	(1) $Attitudes_{ic_{(i)}t}$	(2) Median	(3) Pol	(4) Anti-pol	(5) Pro-pol	(6) Placebo
			Table C4 (a)			
$ShareSubj_{ct-1}$	0.420	0.010	2.194***	0.792*	1.402***	-0.621
	(0.573)	(0.514)	(0.661)	(0.423)	(0.479)	(0.743)
			Table C4 (b)			
$ln(Subj_{ct-1})$	0.035**	0.009	0.042***	0.018*	0.024**	-0.015
	(0.017)	(0.013)	(0.015)	(0.010)	(0.012)	(0.019)
			Table C4 (c)			
$ShareDur_{ct-1}$	0.237	0.083	1.445***	0.554*	0.891**	-0.421
	(0.430)	(0.392)	(0.471)	(0.302)	(0.356)	(0.560)
			Table C4 (d)			
$ln(Dur_{ct-1})$	0.019	0.008	0.032***	0.014*	0.018*	-0.012
	(0.013)	(0.010)	(0.012)	(0.008)	(0.009)	(0.014)
			Table C4 (e)			
$Days_{ct-1}$	0.005*	0.001	0.007**	0.003	0.005**	-0.003
	(0.002)	(0.02)	(0.003)	(0.002)	(0.002)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. × Channel FE	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,776	6,776	6,776	6,776	6,776	6,776
Adjusted R^2	0.787	0.660	0.452	0.559	0.585	0.241

Notes: The dependent variable in column (1) is continuous and represents the average attitudes of individual i toward immigration. The dependent variable in column (2) is the median split of average attitudes. The dependent variable in column (3) is Polarization, which takes a value one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in column (4) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). The dependent variable in column (5) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). Column (6) estimates a placebo regression with anti-immigration natives and pro-immigration moderates (0) against anti-immigration moderates and pro-immigration natives (1). 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.
Sources: Authors' elaboration on INA and ELIPSS data.

Table C5: Std. errors clustered at the channel level

	(1) *Pol*	(2) *Pol*	(3) *Pol*	(4) *Pol*	(5) *Pol*	(6) *Pol*	(7) *Pol*	(8) *Pol*
$ln(Dur_{ct-1})$	0.032**	0.030**						
	(4.687)	(3.411)						
$ShareDur_{ct-1}$			1.445***	1.234**				
			(3.159)	(3.112)				
$ln(Subj_{ct-1})$					0.042**	0.041**		
					(4.126)	(4.097)		
$ShareSubj_{ct-1}$							2.194**	2.030***
							(2.216)	(2.256)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ideological Controls	No	Yes	No	Yes	No	Yes	No	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. $\times$ Channel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,776	6,422	6,776	6,422	6,776	6,422	6,776	6,422
Adjusted R^2	0.452	0.449	0.452	0.449	0.452	0.449	0.452	0.449

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. Ideological control include political interest, political orientation and viewing time. Bootstrap t-stat clustered at the channel level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration on INA and ELIPSS data.

Table C6: Accounting for remaining selection in unobservables, Oster (2019)

Dependent var. : Pol	Estimates			$R_{max} = 1.3 \times R^2 = 0.72$	
	(1)	(2)	(3)	(4)	(5)
	No controls	FEs	FEs & Controls		
	$(s.d.)[R^2]$	$(s.d.)[R^2]$	$(s.d.)[R^2]$	δ for $\beta = 0$	*Id. set*
$ShareSubj_{ct-1}$	1.493***	2.225***	2.194***	1.794	[1.493,12.821]
	(0.527)[0.003]	(0.652)[0.566]	(0.661)[0.568]		

Notes: *** 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. Column (3) include wave fixed effects and individual-channel fixed effects. Columns (4) shows the value of δ which produces $\beta = 0$ given the value of R_{max}. The identified set in columns (5) is bounded by $\hat{\beta}$ when $\delta = 0$ (no bias-adjustment) and $\tilde{\beta}$ when $\delta = 1$ (observables as important as unobservables). The results from column (4) are related to the full model presented in column (3).
Source: Authors' elaboration on INA and ELIPSS data.

Table C7: Exposure to immigration-related news concerning Muslims.

	(1) $Attitudes_{ic_{(i)}t}$	(2) Median	(3) Pol	(4) Anti-pol	(5) Pro-pol	(6) Placebo
$ShareSubj_{ct-1}$	0.003	-0.007	0.002	0.002	0.000	0.008
	(0.008)	(0.007)	(0.008)	(0.006)	(0.006)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. × Channel FE	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,776	6,776	6,776	6,776	6,776	6,776
Adjusted R^2	0.787	0.660	0.451	0.559	0.585	0.241

Notes: The dependent variable in column (1) is continuous and represents the average attitudes of individual i toward immigration. The dependent variable in column (2) is the median split of average attitudes. The dependent variable in column (3) is Polarization, which takes a value one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in column (4) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). The dependent variable in column (5) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). Column (6) estimates a placebo regression with anti-immigration natives and pro-immigration moderates (0) against anti-immigration moderates and pro-immigration natives (1). 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.
Sources: Authors' elaboration on INA and ELIPSS data.

Table C8: Baseline estimates with only non-citizens respondents.

	(1) $Attitudes_{ic_{(i)}t}$	(2) Median	(3) Pol	(4) Anti-pol	(5) Pro-pol	(6) Placebo
$ShareSubj_{ct-1}$	-0.255	3.550	-1.642	-1.181	-0.461	-4.270
	(3.334)	(2.824)	(3.606)	(1.489)	(3.265)	(4.641)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. × Channel FE	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	314	314	314	314	314	314
Adjusted R^2	0.748	0.620	0.350	0.506	0.529	0.178

Notes: The dependent variable in column (1) is continuous and represents the average attitudes of individual i toward immigration. The dependent variable in column (2) is the median split of average attitudes. The dependent variable in column (3) 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 (4) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). The dependent variable in column (5) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). Column (6) estimates a placebo regression with anti-immigration natives and pro-immigration moderates (0) against anti-immigration moderates and pro-immigration natives (1). 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.
Sources: Authors' elaboration on INA and ELIPSS data.

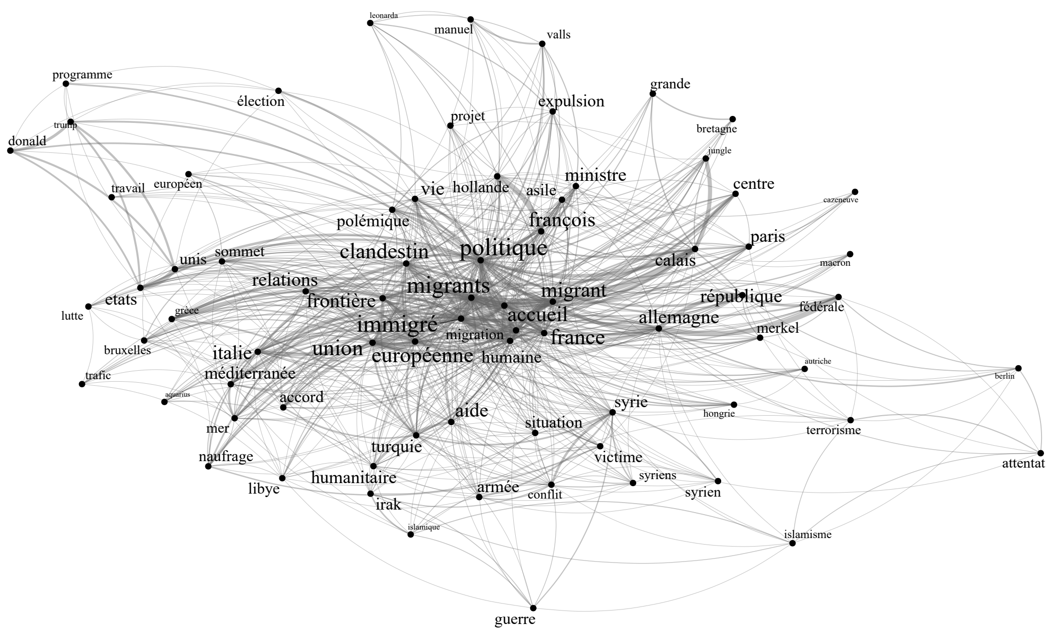
Appendix D: Text Analysis

Lexicon

Our lexicon includes the following list of French words:

immigré, immigrés, immigrée, immigrées, immigre, immigres, migration, migrations, immigration, immigrations, 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, clandestin, clandestins, clandestine, clandestines, 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, étrangers, etranger, etrangers, étrangère, étrangères, etrangère, etrangères, étrangere, étrangeres, etrangere, etrangeres.

Figure E1: Network of co-occurences 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.

Topics

Table E1: Top 15 words in topics

Terrorism and Attacks	French Politics	Germany	European Union	Refugee Camps in France	United-States	Refugee Crisis in the Mediterranean	Syrian Conflict	Migration Burden
police	French	Germany	Greece	Calais	United	Italy	Syria	foreigners
terrorism	Hollande	federal	Turkey	settlement	states	mediterranean	conflict	labor
investigation	minister	asylum	Europe	Paris	Trump	shipwreck	army	foreigner
attack	statement	law	crisis	jungle	Donald	sea	Iraq	more
Paris	Valls	demonstration	agreement	evacuation	relationships	relations	war	economic
victim	president	Merkel	summit	camp	diplomatic	boat	violence	French
terrorist	election	right wing	Hungary	papers	Mexico	international	camp	child
islamism	controversy	law	Brussels	center	pope	rescue	Syrians	social
fire	Sarkozy	extreme	conference	condition	aid	victim	state	children
fundamentalism	Macron	center	European	expulsion	Africa	trafficking	repression	employment
saint	Pen	project	quota	large	Russia	Lampedusa	aid	Kingdom
trial	presidential	Angela	international	Roma	internet	Libya	Syrian	tourism
market	Marine	controversy	countries	Bernard	US	Spain	civil	United-States
security	Manuel	Berlin	borders	Brittany	decree	aid	revolt	Paris
arrest	campaign	racism	surveillance	association	famine	disaster	humanitarian	country

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.

Source: Authors' elaboration on INA data

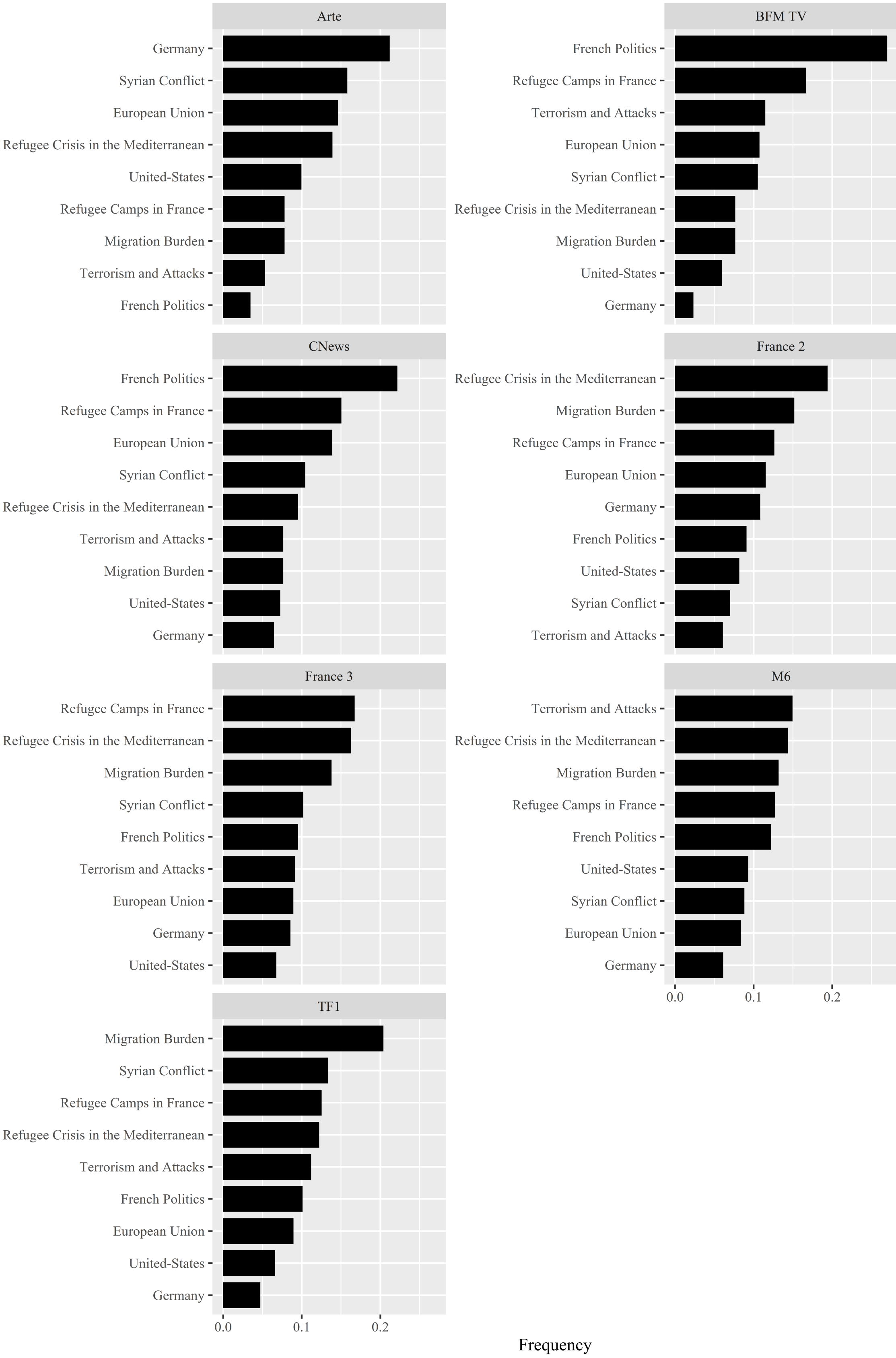
Table E2: Share of migration-related topics to all topics

	All channels	All channels before the refugee crisis	All channels after the refugee crisis	BFM TV	M6	TF1	CNews	France 3	France 2	Arte
Terrorism and Attacks	0.109	0.102	0.121	0.124	0.190	0.121	0.120	0.102	0.070	0.049
French Politics	0.152	0.183	0.105	0.365	0.139	0.106	0.285	0.087	0.108	0.038
Germany	0.072	0.043	0.116	0.024	0.049	0.049	0.067	0.067	0.078	0.189
European Union	0.062	0.032	0.106	0.045	0.046	0.065	0.063	0.043	0.067	0.103
Refugee Camps in France	0.112	0.089	0.147	0.123	0.096	0.104	0.110	0.162	0.111	0.072
United-States	0.092	0.083	0.105	0.071	0.090	0.080	0.090	0.086	0.099	0.112
Refugee Crisis in the Mediterranean	0.116	0.118	0.111	0.068	0.126	0.084	0.076	0.138	0.169	0.138
Syrian Conflict	0.131	0.182	0.053	0.103	0.106	0.155	0.116	0.110	0.080	0.209
Migration Burden	0.154	0.166	0.134	0.078	0.159	0.235	0.072	0.202	0.218	0.089

Notes: This table computes the average share of migration-related topics among all migration subjects 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, but the top words identified in each topic are displayed in Table E1.

Source: Authors' elaboration on INA data.

Figure E2: Topic frequency by channel



Notes: This figure plots the average share of topics among migration subjects 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 topics are displayed in Table E1.

Source: Authors' elaboration on INA data.

Table E3: Priming effect by topic

	(1) *Pol*	(2) Anti-pol	(3) Pro-pol
Terrorism and Attacks	1.241	1.955	0.810
	(2.243)	(1.451)	(1.776)
French Politics	4.594***	3.232***	-1.359
	(1.780)	(1.179)	(1.349)
Germany	-0.074	-1.137	-1.003
	(1.902)	(0.895)	(1.724)
European Union	1.927	-1.682	-3.662
	(3.048)	(1.507)	(2.490)
Refugee Camps in France	5.340***	2.729**	-2.570*
	(1.893)	(1.289)	(1.429)
United States	1.591	-1.393	-3.026
	(3.114)	(2.143)	(2.303)
Refuge Crisis in the Med.	0.739	0.186	-0.510
	(2.704)	(1.354)	(2.175)
Syrian Conflict	-0.304	1.182	1.449
	(2.861)	(1.606)	(2.268)
Migration Burden	7.245***	2.669**	-4.604***
	(1.965)	(1.306)	(1.505)
Controls	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Indiv. $\times$ Channel FE	Yes	Yes	Yes
Nb. Observations	6,776	6,776	6,776
Adjusted R^2	0.453	0.560	0.586

Notes: The dependent variable in column (1) is Polarization that takes the 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 anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). The dependent variable in column (3) is 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 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, income categories and a dummy for new individuals in the 2016 sample. Robust standard errors clustered at the individual level are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration on INA and ELIPSS data.

Table E4: Topic analysis with alternative grouping

Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
Migration Burden		7.122***	2.698**	-4.424***
		(1.869)	(1.263)	(1.408)
France	Refugee Camps in France	4.964***	2.873***	-2.091**
	French Politics	(1.242)	(0.901)	(0.876)
Foreign	European Union	0.741	-1.288**	-2.029**
	Germany	(1.122)	(0.610)	(0.904)
	United-States			
Other	Refugee Crisis Med.	0.834	1.112	0.279
	Terrorism	(1.231)	(0.712)	(1.000)
	Syrian Conflict			
Controls		Yes	Yes	Yes
Wave FE		Yes	Yes	Yes
Indiv.×Channel FE		Yes	Yes	Yes
Nb. Observations		6,776	6,776	6,776
Adjusted R^2		0.454	0.560	0.586

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 anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). The dependent variable in column (3) is 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 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.
Source: Authors' elaboration on INA and ELIPSS data.

Sentiment analysis

Figure E3: Most frequent words in the sentiment analysis of migration subjects

(a) Top 500 positive subjects (b) Top 500 negative subjects

Notes: Figure E3a represents the most frequent positive tokens from the FEEL lexicon in the top 500 of positive migration subject. Figure E3b represents the most frequent negative tokens from the FEEL lexicon in the top 500 of negative migration subjects.
Source: Authors' elaboration on INA data.

Table E5: Share of sentiments in migration subjects

	All Channels	All channels before the refugee crisis	All channels after the refugee crisis	BFM TV	M6	TF1	CNews	France 3	France 2	Arte
Sent. Score	0.111	0.097	0.122	0.096	0.098	0.100	0.097	0.109	0.136	0.115
Share of positive	0.175	0.167	0.181	0.141	0.151	0.150	0.147	0.178	0.209	0.197
Share of negative	0.064	0.070	0.059	0.044	0.053	0.050	0.051	0.069	0.072	0.082

Notes: This table computes the average share of sentiment among all migration subjects in evening television programs on Arte, BFM-TV, CNews, TF1, France 2, France 3, and M6. The date of the refugee crisis in our context is September 2015. Sentiment analysis was performed using the French Expanded Emotion Lexicon (FEEL). The most frequent negative and positive words from the FEEL lexicon identified in the migration subjects are displayed in Figure E3 in the main document. The first row is the average share of positive-negative words (computed within each subject) in migration subjects.
Source: Authors' elaboration on INA data.

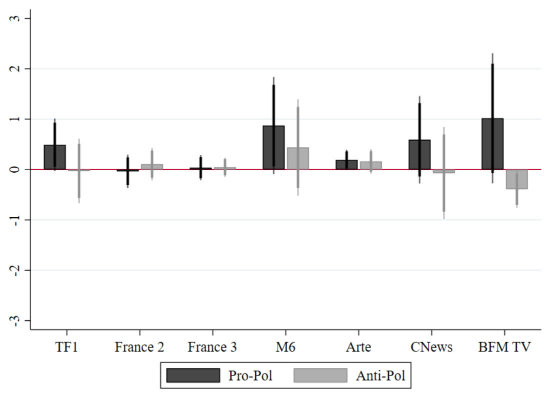
Table E6: Interaction between priming and framing

	(1) Pol_{ict}	(2) Pol_{ict}	(3) Pol_{ict}	(4) Pro-pol	(5) Pro-pol	(6) Pro-pol	(7) Anti-pol	(8) Anti-pol	(9) Anti-pol
$ShareSubj_{ct-1}$	1.087	2.972***	1.332	0.073	2.627***	0.294	1.014*	0.345	1.037
	(1.066)	(1.047)	(1.480)	(0.920)	(0.899)	(1.219)	(0.591)	(0.583)	(0.885)
Sent. Score	0.147			0.056			0.091		
	(0.115)			(0.089)			(0.076)		
$ShareSubj_{ct-1}$ × Sent. Score	7.699			9.954			-2.255		
	(7.038)			(6.297)			(3.197)		
Share of negative		-0.090			0.008			-0.099	
		(0.202)			(0.167)			(0.125)	
$ShareSubj_{ct-1}$ × Share of negative		-20.729			-30.059*			9.330	
		(17.795)			(16.093)			(9.219)	
Share of positive			0.219			0.054			0.166
			(0.183)			(0.136)			(0.126)
$ShareSubj_{ct-1}$ × Share of positive			4.997			6.503			-1.507
			(7.967)			(6.463)			(4.507)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. × Channel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6,776	6,776	6,776	6,776	6,776	6,776	6,776	6,776	6,776
Adjusted R^2	0.452	0.452	0.452	0.586	0.586	0.586	0.559	0.559	0.559

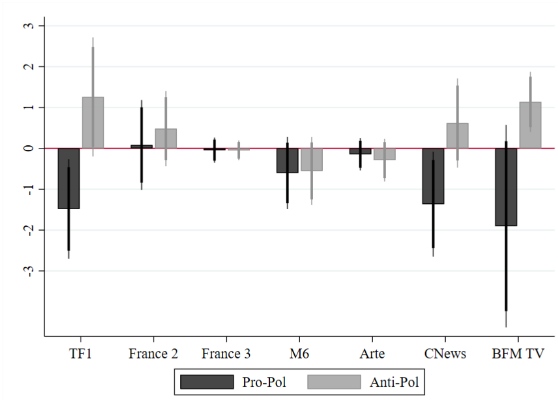
Notes: The dependent variable in columns (1), (2), and (3) is Polarization, which takes a value one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in columns (4), (5), (6) is a dummy equal to one for individuals with pro-immigration attitudes and zero otherwise (anti-immigration, pro- and anti-immigration moderates). The dependent variable in columns (7), (8), (9) 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.
Source: Authors' elaboration on INA and ELIPSS data.

Figure E4: Sentiment analysis by channels

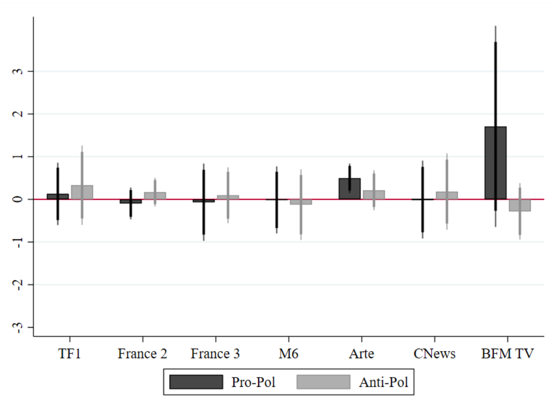
(a) Positive - Negative



(b) Negative



(c) Positive



Notes: The figure shows the marginal effect of the independent variables on Pro-pol and Anti-pol respectively. Each coefficient represents the marginal effect of $ShareSub_{ct-1}$ for a given channel in the population as defined in Eq. 7. The vertical lines are 90% and 95% confidence intervals.
Source: Authors' elaboration on INA and ELIPSS data.

Appendix E: Political Analysis

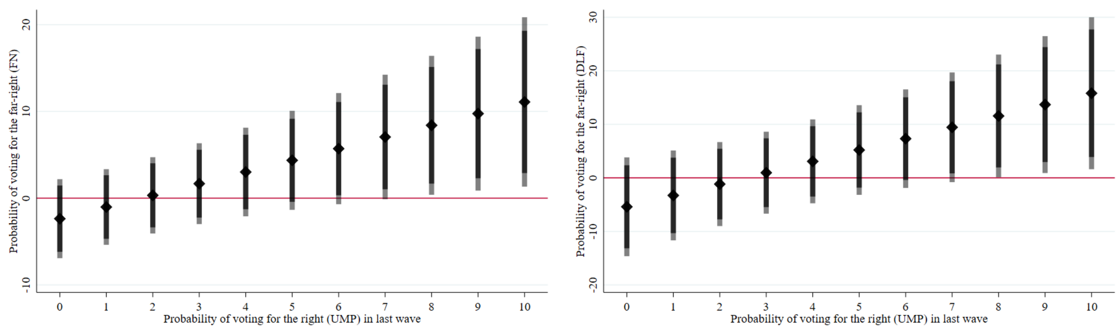
Table F1: French political parties and attitudes toward immigration
Cross-correlation

		Far-left		Left	Green Pol.	Center		Right	Far-right	
	$Attitudes_{it}$	NPA	PG	PS	EELV	MODEM	UDI	UMP	DLF	FN
$Attitudes_{it}$	1.000									
NPA	-0.121	1.000								
PG	-0.238	0.605	1.000							
PS	-0.428	0.275	0.522	1.000						
EELV	-0.358	0.390	0.513	0.517	1.000					
MODEM	-0.171	0.091	0.044	0.218	0.222	1.000				
UDI	-0.001	0.038	-0.107	-0.015	0.023	0.671	1.000			
UMP	0.235	-0.160	-0.383	-0.318	-0.227	0.298	0.568	1.000		
DLF	0.280	0.157	-0.016	-0.159	-0.046	0.184	0.348	0.403	1.000	
FN	0.576	0.007	-0.139	-0.350	-0.246	-0.145	0.003	0.212	0.433	1.000

Notes: 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"; "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.

Probability of switching from center or right to far-right

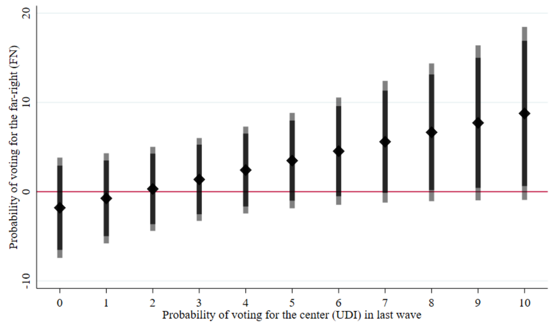
Figure F1: Switching parties from right to far-right



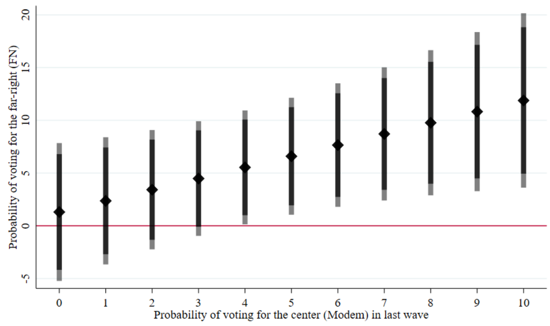
(a) UMP to FN (b) UMP to DLF

Notes: Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

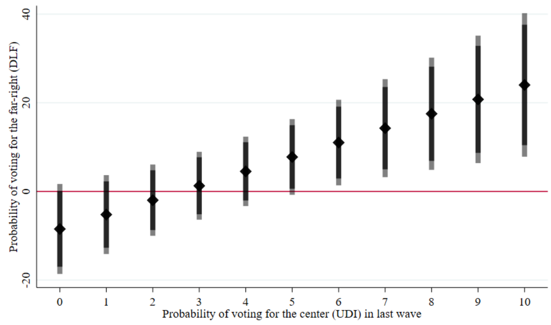
Figure F2: Switching parties from center to far-right



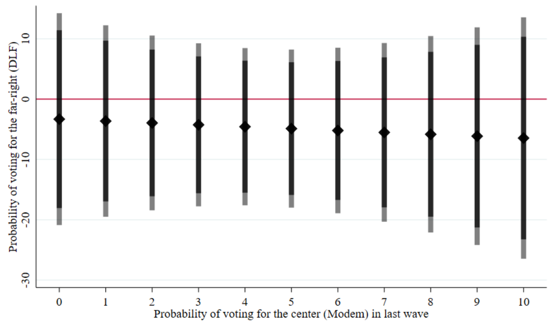
(a) UDI to FN



(b) MODEM to FN



(c) UDI to DLF

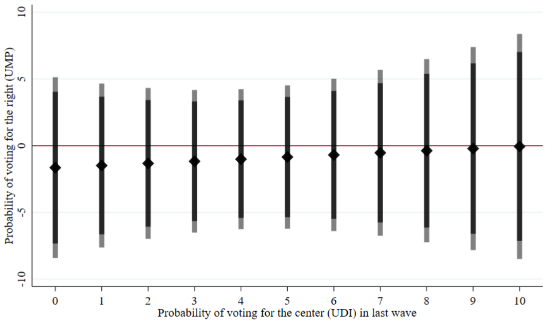


(d) MODEM to DLF

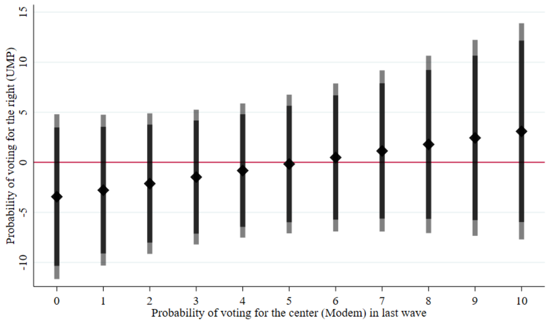
Notes: Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

Probability of switching from center to right

Figure F3: Switching parties from center to right



(a) UDI to UMP

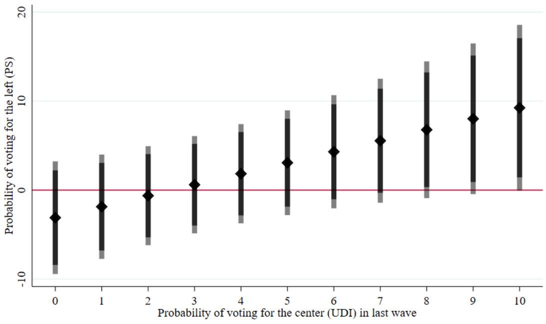


(b) MODEM to UMP

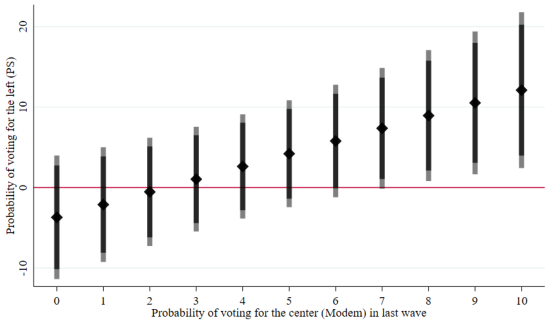
Notes: Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

Probability to switch from center to left and green politics

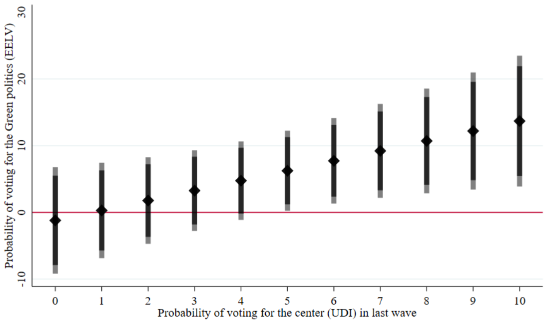
Figure F4: Switching parties from center to left



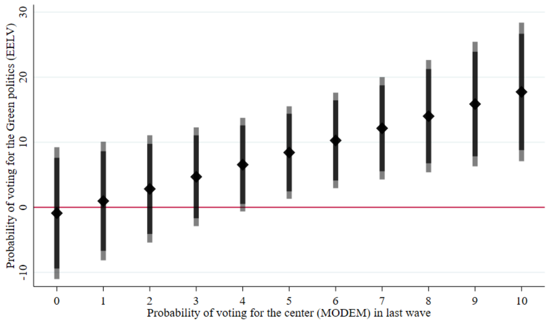
(a) Center (UDI) to left (PS)



(b) Center (MODEM) to left (PS)



(c) Center (UDI) to Green (EELV)

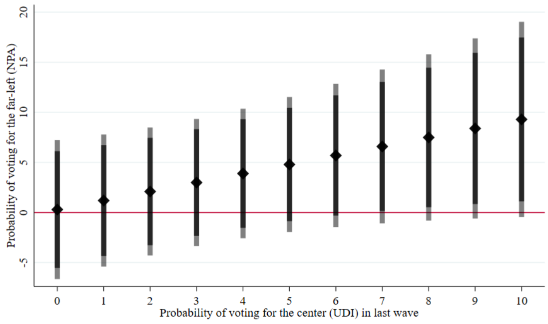


(d) Center (Modem) to Green (EELV)

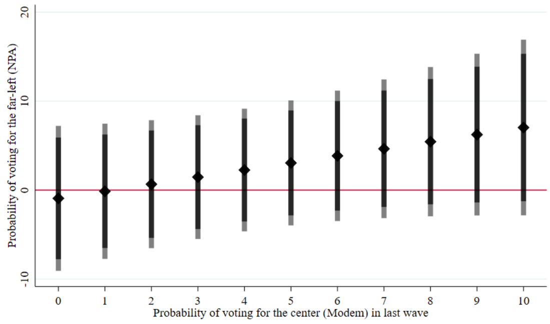
Notes: Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

Probability of switching from center and left to far-left

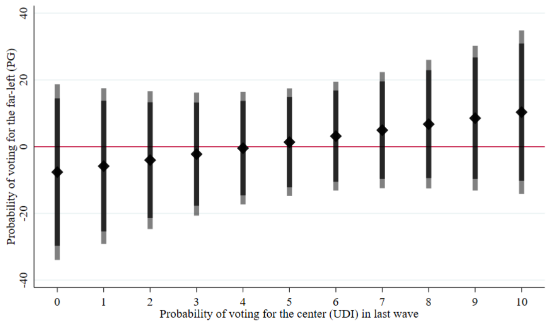
Figure F5: Switching parties from center to far-left



(a) UDI to NPA

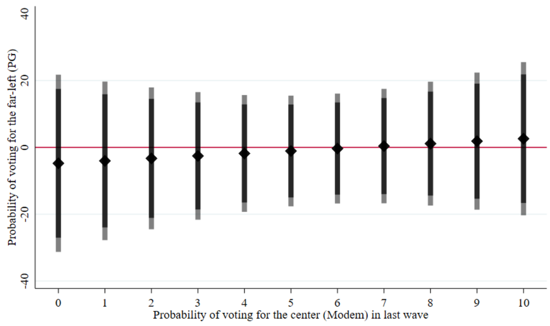


(b) MODEM to NPA



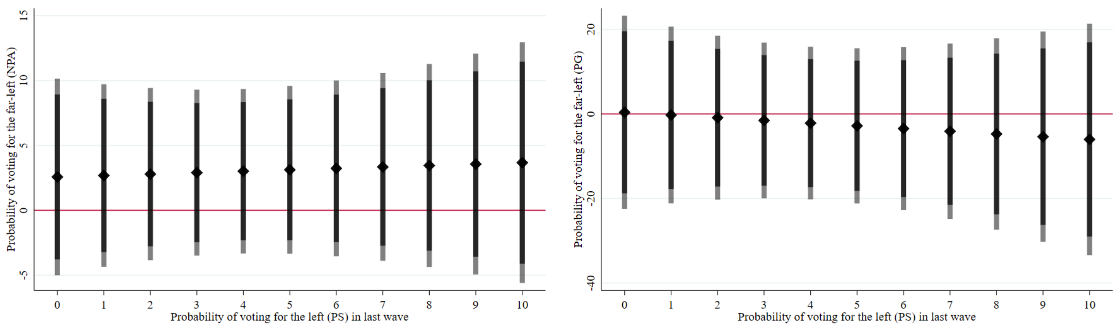
(c) UDI to PG

(d) MODEM to PG



Notes: Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F6: Switching parties from left to far-left



(a) PS to NPA (b) PS to PG

Notes: Confidence intervals are presented at the 95% and 90% levels.
Source: Authors' elaboration on INA and ELIPSS data.

Probability of voting for a given political party

Table F2: Probability of voting for a given political party

	(1) NPA	(2) PG	(3) PS	(4) EELV	(5) MoDem	(6) UDI	(7) UMP	(8) DLF	(9) FN
$ShareSubj_{ct-1}$	2.078	-6.219	-0.724	1.147	4.436	1.786	0.827	1.466	0.634
	(2.692)	(8.297)	(2.486)	(2.516)	(4.440)	(2.857)	(2.335)	(2.832)	(1.871)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. $\times$ Channel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	5,777	2,499	6,290	6,292	5,518	6,218	6,279	5,875	6,306
Adjusted R^2	0.625	0.674	0.761	0.715	0.643	0.632	0.778	0.572	0.834

Notes: Political variables from (1) to (9) are the self-declared probabilities (0 to 10) that respondents vote for a party. “NPA” refers to the “Nouveau Parti Anticapitaliste” party; “PC” refers to the “Parti Communiste” 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.