Media Coverage of Immigration and the Polarization of Attitudes [*]

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Abstract

This paper investigates the extent to which media impact immigration attitudes by modifying the salience of this topic. We measure the salience of immigration using original data including all the news covered on the main French national television evening news programs between 2013 and 2017. We combine this information with individual panel data that enable us to link each respondent to his/her preferred TV channel for political information. This allows us to address ideological self-selection into channels with individual-channel fixed effects. In contrast to prior evidence in the literature, we do not find that an increase in the salience of immigration necessarily drives natives' attitudes in a specific direction. Instead, our results suggest that it increases the polarization of natives by pushing individuals with moderate beliefs toward the two extremes of the distribution of attitudes. We show that these results are robust to controlling for differences in the framing of immigration-related subjects across TV channels. Conversely to priming, framing is found to drive natives' attitudes in very specific directions.

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"The news media isnt just an actor in politics. Its arguably the most powerful actor in politics".

Klein (2020), *Why We're Polarized*, pp 240.

I. Introduction

A 2016 survey reported that only 16% of the French population saw immigration as a positive phenomenon while 56% thought that immigration had a negative overall impact on society.[1] This survey took place in a very specific context, after the start of the 2015 refugee crisis in Europe. A legitimate concern would be that these figures did not capture natives' deep preferences on immigration but rather a transitory change in attitudes when the salience of immigration reached a historical high. Indeed, the salience of a particular topic is largely driven by the coverage of the latter in traditional media,[2] such as television. Regarding immigration, news coverage increased dramatically with the 2015 refugee crisis.[3] 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 reactivated existing prejudices regarding immigrants and foreigners, thus modifying natives' attitudes along the aforementioned dimensions.[4] In fact, 30% of respondents who declared that they had helped refugees over the past 12 months reported that they had done so after having been exposed to press articles or TV programs focusing on immigration issues.

This paper investigates the extent to which media reporting on immigration impacts natives' attitudes toward the latter. Using original data provided by the French National Audiovisual Institute (INA), that record the full universe of topics covered by French TV channels between January 2013 and December 2017, we measure the overall salience of the immigration topic on evening news programs at the monthly level. We define four measures of salience that capture, in terms of both levels and shares, the number of minutes and the number of subjects devoted to immigration on evening news programs. We combine this information with individual panel data from the ELIPSS survey (Longitudinal Internet Studies for Social Sciences), which includes attitudes along several dimen-

[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] For examples on the salient role of the press, see Eisensee and Strömberg (2007) or Snyder Jr and Strömberg (2010).

[3] See additional descriptive statistics on this in Section II.

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

sions such as the number of immigrants in the country or the cultural enrichment caused by immigration. Unlike most papers using variations in media coverage or treatment at the local level, we link each respondent to his/her time-varying self-declared preferred TV channel for political information. Together with the panel dimension of the data, this allows us to control for individual-channel fixed effects that address the usual concerns regarding self-selection into channels.[5] 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 on a specific French TV channel and the attitudes toward immigration of a given individual watching this channel. Our analysis documents and benefits from the 2015 refugee crisis in Europe, which dramatically increased the coverage of immigration-related news in the media with substantial variation across TV channels and months, allowing us to recover individual variation in exposure to immigration for natives watching different programs.

The contributions of this paper are manyfold. First, this paper adds to the literature on the role of media in shaping political attitudes in which most of the papers make causal inference using exogenous variation in broadcasting or penetration (see, among others, 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).[6] In contrast, our paper does not rely on a natural experiment to compare attitudes before and after a given treatment, but instead uses 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 our analysis allows us to focus on intra-individual variability rather than on local average effects. Within this broad literature, we specifically focus 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., 2019; Djourelova, 2020; Keita et al., 2021). 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 US immigration context. While they find that Fox News viewers are more likely to report negative attitudes toward

[5] In addition, we report additional estimates *à la* Oster (2019) to confirm that our results are unlikely to be driven by self-selection. We also provide robustness checks that our results are not affected by adding time-varying ideological controls to our specification.

[6] See DellaVigna et al. (2014); DellaVigna and La Ferrara (2015); Enikolopov and Petrova (2015) for extended reviews of the literature on the impact of media on political outcomes.

illegal immigrants than CBS viewers, they only address ideological self-selection into TV channels with ideological controls, such as party identification, which all can be considered "bad controls" (Angrist and Pischke, 2008). In comparison with existing works, our identification strategy relies on individual-channel fixed effects that definitely address the issue of ideological self-selection into channels and the nonrandom matching between TV channels and viewers.[7] This paper also relates to the growing literature investigating whether priming immigration affects natives' attitudes on the topic. These papers either manipulate the salience of immigration using experimental settings (Alesina et al., 2018; Barrera et al., 2020) or employ self-reported measures of salience (Dennison and Geddes, 2019). Overall, they find that an increase in the salience of immigration deteriorates natives' attitudes toward immigration and reduces support for redistribution. We contribute to this emerging literature by highlighting the media's specific role in driving the relative salience of the immigration topic.

Our results suggest that an increase in the salience of immigration has an asymmetric impact on natives' attitudes toward immigration, depending on initial attitudes. We find that, on average, respondents with moderate views switch toward extreme attitudes when the coverage of immigration increases. Specifically, natives with moderate positive attitudes switch to extremely positive attitudes while their counterparts with initially moderate negative attitudes become very concerned about immigration. This result is at odds with existing papers in the literature finding that, on average, priming immigration mostly drives natives' attitudes in a specific direction. Regarding the magnitude of the effect, we find that a one-standard-deviation increase (2%) in the share of subjects related to immigration in total broadcasting is associated with a 2.75 percentage point increase in the likelihood that individuals with moderate attitudes fall into extreme attitudes. Thus, our results indicate that increasing the salience of a first-order issue such as immigration may translate into a more polarized society at the aggregate level by reactivating preexisting mixed prejudices in the population. We confirm this result with a heterogeneity analysis at the channel level showing that the initial distribution of attitudes matters and predicts the direction of the polarization. For instance, an increase in the salience of immigration on TF1, the channel with the most initially anti-immigrant viewers mainly results in more

[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 TV channels.

concerns about immigration. However, the same variation for channels with initially pro-immigration attitudes, such as Arte, only makes viewers more likely to report extremely positive attitudes toward immigration. Between those two extremes, channels with less skewed distributions of attitudes, such as BFM TV or France 2, see their moderate viewers switching toward extreme attitudes on both sides of the distribution.

Our main results therefore suggest that a third contribution of this paper relates to the emerging literature on the cultural and political polarization in modern societies (DiMaggio et al., 1996; Fiorina and Abrams, 2008; Desmet et al., 2017; Martin and Yurukoglu, 2017; Gentzkow et al., 2019; Alesina et al., 2020). In contrast to most of these papers that focus on the US, this paper provides evidence for a similar polarization effect in a European country. In addition, while existing works suggest that social media could be a driver of polarization by creating echo chambers that exacerbate political divisions (Bail et al., 2018; Levy, 2020; Allcott et al., 2020; Cinelli et al., 2021),[8] our paper demonstrates that traditional media can also be a source of the polarization of attitudes, which is an important result given that news on television may be less targeted to users' ideological views and more fact-checked than information spread on social media.

Finally, the 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.[9] We exploit the detailed descriptions that are provided by the INA for each subject to analyze both the semantics and the topics associated with immigration subjects. Using text analysis and natural language processing tools, we find that topics associated with immigration in foreign host countries (such as Germany or the US) increases French natives' support for immigration. On the other hand, discussions around the integration of immigrants in France are systematically associated with an increase in polarization. Moreover, 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., 2018; Cattaneo et al., 2020). Our sentiment analysis on immigration-related subjects confirms these findings. After controlling for the salience of

[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, there is still no robust evidence that the latter is a driver of political polarization.

[9]In line with Alesina et al. (2018) our main result on the polarization effect of priming (an increase in the salience) is not affected by controlling for framing effects and the tone of subjects.

immigration, the presence of more negative contents is associated with an increase in anti-immigration attitudes, while having more positive content tends to boost pro-immigration attitudes. Thus, unlike the salience of immigration, this analysis suggests that framing mostly drives attitudes in very specific directions.

The remainder of the paper is organized as follows. Section II describes our data on individuals' attitudes toward immigration and media reporting on immigration. Section III describes our empirical strategy and how we address the identification challenges associated with it. Section IV reports our main results on the effect of the salience of immigration on television on immigration attitudes. Section V presents some heterogeneity analysis, and Section VI provides suggestive evidence on the role of framing immigration news. Section VII concludes the paper.

II. Data

This section describes the data that we use and provides some descriptive statistics. First, we describe attitudes toward immigration from the ELIPSS panel survey and document the extent to which viewers self-select into television channels. Then, we provide descriptive evidence on the coverage of the immigration topic on French television between January 2013 and December 2017 using data from the French INA.

Individual attitudes toward immigration and self-selection into television channels

We measure attitudes toward immigration through 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 an additional 2,514 new individuals joined the ELIPSS panel.

This paper employs specific waves of the ELIPSS panel (Dynamob) that measure attitudes toward immigration and include information on media consumption. Our analysis focuses on French citizens aged 18 to 79 years reporting television as one their two main sources of political information and watching news programs at least one day per week.[10][11][12] In 2016, 45% of all ELIPSS respondents reported television as a source of political information, well ahead of radio (21%), internet (18%) or newspapers (9%).[13] Among them, 75% declared watching the television at least five days a week. In addition, individuals are asked to provide their "usual preferred channel to watch political news programs". 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.

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.[14] 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 the average attitude of individual i in year-month t on the three aforementioned dimensions.[15]

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. Between 2013 and 2017, 33.60% of the respondents are *pro-immigration moderates* with $Attitudes_{it} \in [2;2.5]$ and 28.22% of

[10] Our sample of analysis is described in Figure A1 in the Appendix. In our sample, 69% of respondents reported television as a source of political information.

[11] Unfortunately, data on media consumption for political information are only available in two waves of the ELIPSS panel in Septembers 2013 and 2016. We assume in our analysis that individuals' preferences on media are constant between 2013 and 2016 as well as after 2016. Information in the period between 2013 and 2017 may thus only be updated in September 2016 as described in Table A1 in the Appendix.

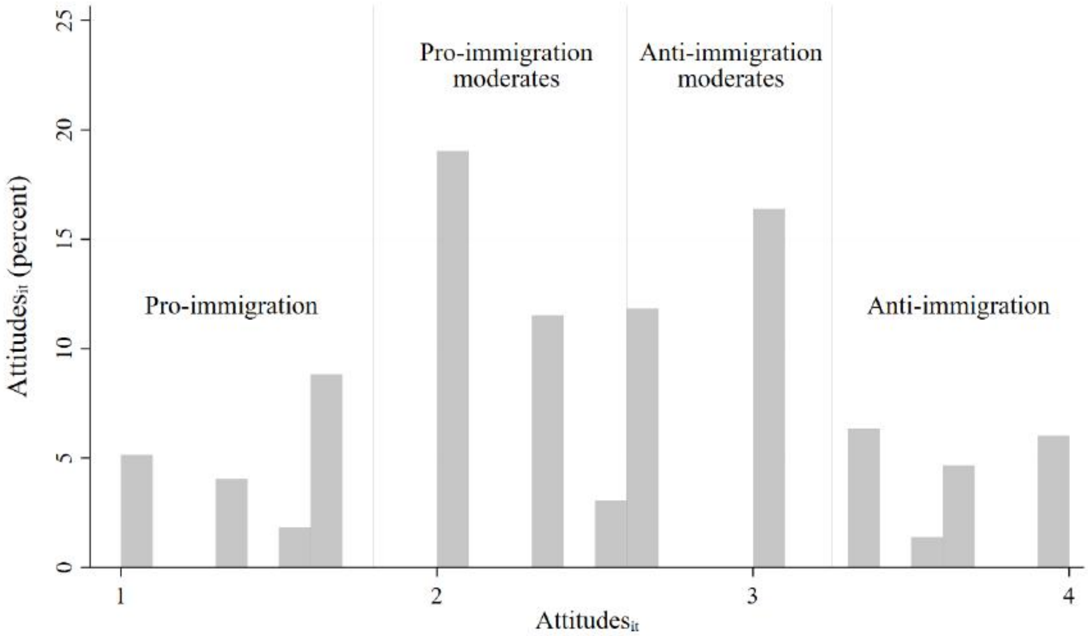
[12] We find no effect of media on attitudes when restricting our analysis to non-citizen respondents as reported in Table C7 in the Appendix. This result has to be interpreted with caution because the number of non-citizens in the ELIPSS survey is very small and does not allow us to draw any strong conclusion.

[13] 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. 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.

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

[15] We present robustness tests on the dimensions used for our index in Section IV.3. Specifically, we show that our main conclusions are not affected by removing any of the three dimensions from the analysis. Note that no additional questions in the survey can be interpreted as directly related to immigration.

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 they are too many immigrants, the cultural enrichment resulting from immigration and the extent to which Muslims are citizens like any others. 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.

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 our empirical analysis.

Not surprisingly, individual characteristics strongly differ across the four groups of immigration attitudes. Table 1 reports that on average respondents with more positive attitudes toward immigration are significantly more 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 similar 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 that conform to their

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 our 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 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 from 0 monthly revenue to more than 6000monthly revenues.
Source: Authors' elaboration on INA and ELIPSS data.

ideology (see Mullainathan and Shleifer, 2005; Gentzkow, 2006; Durante and Knight, 2012, among others). Our data strongly support this evidence as depicted in Figure 2.[16] One can see that average attitudes toward immigration differ across French television channels even after we partial out individuals' characteristics. TF1 is more likely to be watched by individuals with negative attitudes while respondents watching France 2 or Arte are more likely to have positive attitudes toward immigration. This echoes traditional views that the main evening news program on TF1 shares more conservative and traditional values than France 2 or Arte news programs.[17] Table B1 in the Appendix also confirms that 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.[18] As expected, self-selection patterns strongly correlate with individual observable characteristics.[19] Thus, all this descriptive evidence calls for a careful treatment

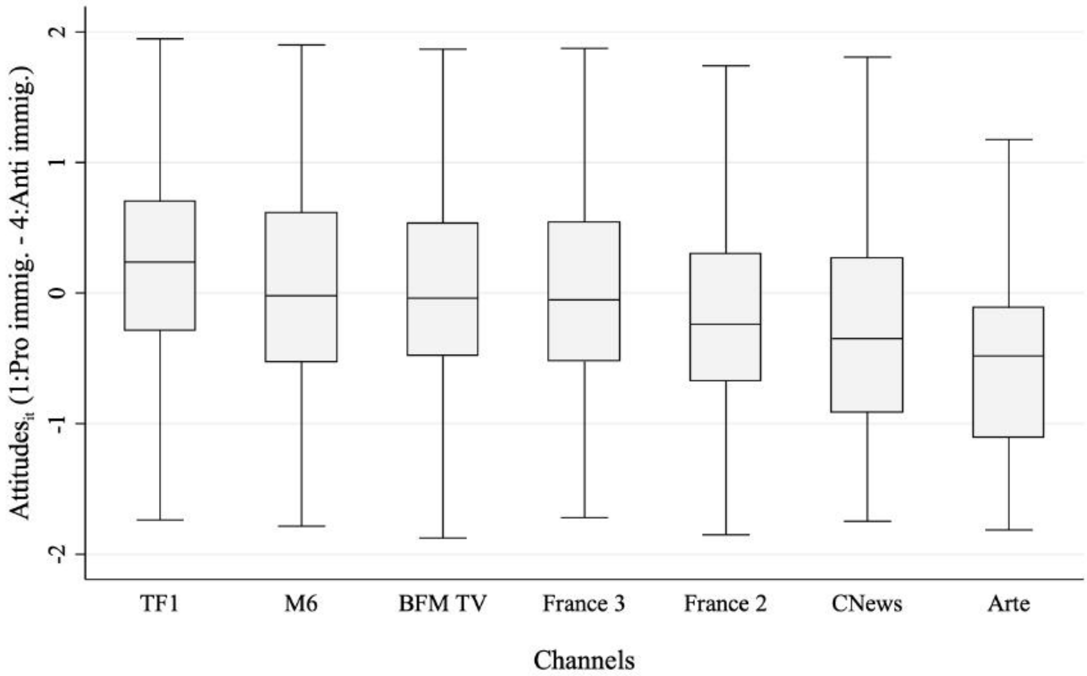
[16] We provide descriptive evidence in Appendix Table A1 of the breakdown of respondents across channels in 2013 and 2016.

[17] One could be surprised that CNews is associated with relatively positive attitudes toward immigration in our analysis. Nevertheless, note that CNews only started to change its political leanings after the takeover by Vincent Bolloré in 2017 (Cagé et al., 2021).

[18] This selection into channels can also be observed in the distribution of individuals' attitudes by channel presented in Figure B1 in the Appendix.

[19] Since there could be high correlations across individual characteristics, we study the selection into

Figure 2: Attitudes by preferred TV channel, 2013-2017.
Individual characteristics partialled-out.



Notes: Individual attitudes by preferred TV channel for political information after we absorbed 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 citizens like ay others. The higher $Attitudes_{it}$ the more the individual is against immigration. Controls includes the 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.

of the self-selection of individuals across television channels in our empirical analysis and strongly supports the inclusion of individual-channel fixed effects in our benchmark equation.

Immigration in the media and the 2015 refugee crisis

Our paper employs media data provided by the INA. These data include all the news covered by the main French national television evening news programs between 6:45 p.m. and 9:30 p.m. from 2011 to 2017 with various details on each subject. The channel list includes TF1, France 2, France 3, Arte, M6, BFM TV and CNews (I-Tele before

channels based on observable characteristics using multinomial logit regressions presented in Figure B2. 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 2, 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 a main source of political information while it decreases the probability of watching France 2.

February, 2017).[20]

To identify whether a subject s on channel c in year-month t is related to the immigration topic ($Immigration_{sct} = 1$), we built our own lexicon that includes keywords associated with immigration and their variations in spelling.[21] Using a bag-of-words model, we count the number of words from the lexicon appearing in the title and in the short description that is provided by the INA for each subject. A subject is classified as immigration-related if it includes at least one word from the lexicon. For instance, the following subject 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 increased following the pictures of ***migrants*** *in Hungary or Germany. European leaders are in panic. The reversal of opinion was predictable. The question of border control arises outside Schengen. Syrian* ***refugees*** *are not so interested in France.*

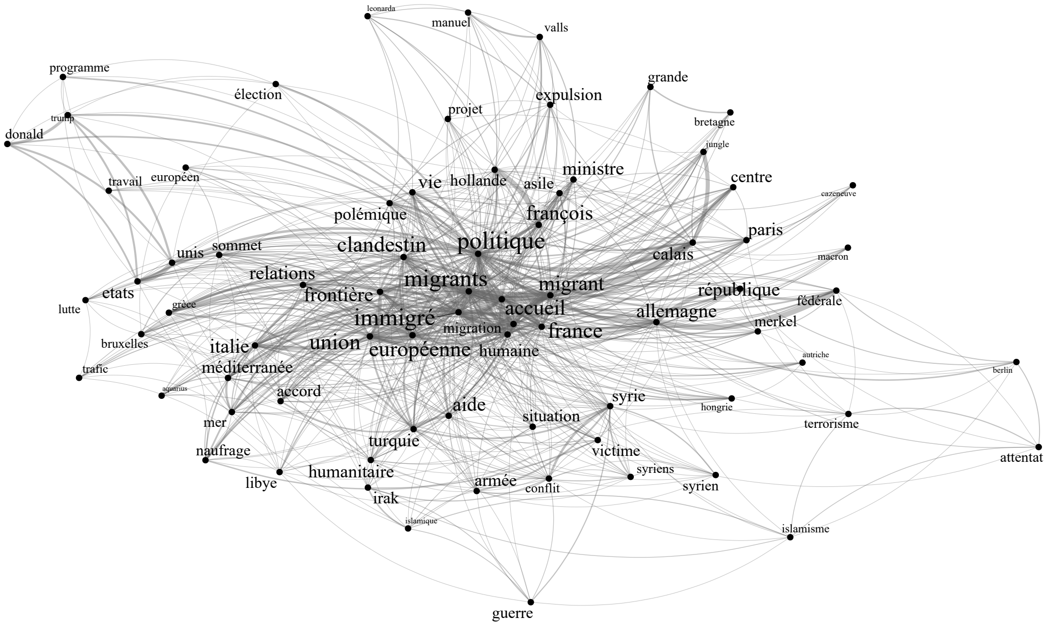
On average, subjects in our sample contain 59 words with a standard deviation of 45. The average number of immigration words detected in immigration-related subjects stands at 2.32 with a standard deviation of 1.34. In Figure 3, we graphically assess whether the subjects we identify with our lexicon approach capture well subjects that discuss immigration by plotting the network of co-occurrences of words in migration subjects. Figure 3 shows no themes or words that could be completely unrelated to the immigration topic in the French context. This indicates that our lexicon approach performs well in identifying migration-related subjects.

We identify that on average 3.2% of subjects on television evening programs covered immigration between 2011 and 2017 with a standard deviation of 3.4% and a maximum of 36.6% for 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, as the

[20] Our analysis is restricted to only seven channels due to the limited sample size of the individual survey that measures natives' attitudes. Specifically, we exclude channels such as Canal+, France 5, LCP or LCI for which we have fewer than 150 observations over time or 35 distinct respondents in the aformentionned survey. Figure A1 shows that 94% of the respondents watched one of the seven channels included in our sample as a source of political information.

[21] The full description of the lexicon is available in Appendix E.

Figure 3: 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 edges show co-occurrences of words.
Sources: Authors' elaboration on INA data.

average number of immigration-related subjects before September 2015 was 2.4% and 4.4% thereafter. The channels that have greater coverage of migration in our sample in descending order are Arte, BMF TV, CNews, TF1, France 2, France 3, and M6.

Our empirical analysis exploits this unique framework to compute four measures of the salience of immigration on French TV channels. First, 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:

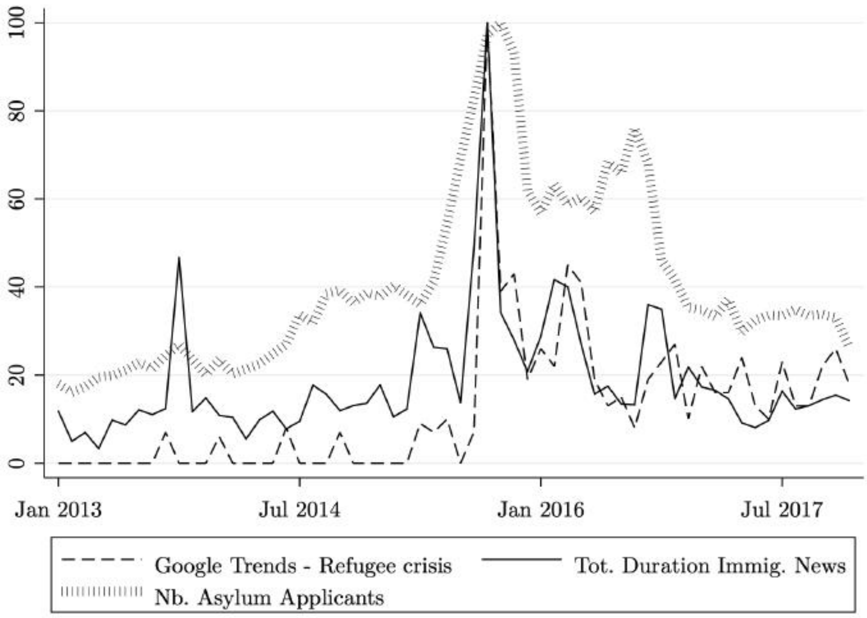
$$Dur_{ct} = \sum_{s} (Duration_{sct} | Immigration_{sct} = 1) \tag{1}$$

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

$$ShareDur_{ct} = \frac{\sum_s (Duration_{sct} | Immigration_{sct} = 1)}{\sum_s Duration_{sct}} \tag{2}$$

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. Using the same methodology, we compute Sub_{ct} and $ShareSub_{ct}$ as the total number of subjects and the share of subjects related to immigration, respectively. Note that both Dur_{ct} and Sub_{ct} are monotonically rescaled using the inverse hyperbolic sine.[22] Regarding our benchmark sample,[23] Table A3 identifies 2.6% of news evening programs as 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 our months of analysis is approximately 19 minutes per month with a standard deviation of 15 minutes.[24]

Figure 4: Media coverage of immigration and the 2015 refugee crisis



Notes: "Tot. Duration Immigration News" is the average aggregated number of minutes 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 applicants 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.

[22] The inverse hyperbolic sine is defined as $(log(x_i + \sqrt{x_1^2+1})$. All our conclusions remain unchanged when using the log transformation of Dur_{ct} and Sub_{ct}, and the results are available upon request. While Dur_{ct} and Sub_{ct} never takes a zero value, the hyperbolic sine transformation is useful when we investigate the impact of specific immigration-related topics on attitudes in Section VI for which the monthly channel broadcasting could be zero. Indeed, unlike the log transformation, the inverse hyperbolic sine transformation is defined at zero, while the interpretation of the coefficients is identical.

[23] This sample corresponds to the one that we use in our 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.

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

As reported in Figure 4, the recent surge in overall immigration coverage is largely driven by the dramatic increase in the total number of asylum seekers who arrived in Europe in 2015. As descriptive evidence that natives' attention to immigration did respond to this increase in the salience of immigration, we plot in this graph additional data from Google trends on the refugee crisis category. Google trends data indicates (with the deviation from the highest observed peak) how often a refugee-related term has been entered into the Google search engine. It confirms that variations in the treatment of immigration in the media are systematically associated with the variation in the public interest in immigration in subsequent months. This relationship appears to be particularly strong after the 2015 refugee crisis. Our empirical analysis exploits deviations from the average coverage over time for each channel. Thus, in Figure A5 in the Appendix, we provide descriptive evidence that our 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 reamains in the coverage of immigration topics across the various French evening news programs. Indeed, channel and year-month fixed effects only account for between 75% and 80% of the variance across the different salience variables.

III. Empirical Strategy

Our benchmark empirical model features the average attitude toward immigration of individual i watching the evening news programs on channel c for political information in year-month t as the dependent variable. We estimate the following specification:

$$Attitudes_{ict} = \beta_1 Salience_{ct-1} + \beta' X_{it} + \gamma_{ic} + \gamma_t + \varepsilon_{ict} \tag{3}$$

where $Salience_{c,t-1}$ is one of the four aforementioned measures of the salience of immigration on channel c during the month preceding the month of the interview.[25] β_1 is our coefficient of interest. It captures the effect of an increase in the salience of immigration on natives' attitudes toward immigration. γ_t stands for year-month fixed effects

[25] Unfortunately, ELIPSS data only provide access to the month of the interview, but the day is not available. Additional robustness checks in Appendix C show that our results are driven by information on the last month while no effect is found for prior lags, either estimated separately (Figure C2) or in a distributed lags model (Figure C3). This is consistent with recent findings by Angelucci and Prat (2020) who provide evidence that individual knowledge of the news significantly decreases over time.

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).

We alternatively use five different variables for the analysis of attitudes toward immigration. First, $Attitudes_{ict}$ is the continuous average attitude of individual i in year-month t toward immigration. Second, $Median$ is a dummy variable equal to one for respondents with attitudes above the median and zero otherwise. Third, Pol_{ict} is a dummy variable taking value one for individuals with extreme attitudes (pro- and anti-immigration) and zero otherwise (moderates). The latter tests whether any polarization is at play in our framework, with individuals with moderate attitudes 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 *Pro-pol*, a dummy equal to zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration individuals and moderates). This allows us to test whether any polarization is occurring at one, or both sides of the distribution of attitudes.[26]

The main concern associated with our framework is that individuals self-select into television channels that fit their attitudes toward immigration. First, our benchmark model includes a vector 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.[27] Second, following Facchini et al. (2017), we provide evidence that our main results are robust to including time-varying ideological controls such as political interest, a 10 point left-right self-reported scale on political orientation and TV viewing time, measured as the number of days per week that an individual watches television. 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). Thus, third, we exploit the panel dimension of our analysis to augment our 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 only comes from the correlation between monthly variation in the salience

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

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

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.[28] 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 our results.

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 IV.3 and provide a robustness check that our estimates are not affected by clustering standard errors at the channel level.

IV. Main Results

In this section, we present our main results on the polarization of immigration attitudes in Subsection IV.1. Then, we run a heterogeneity analysis at the channel level in Subsection IV.2. Finally, we provide a summary of the robustness checks we performed in Subsection IV.3.

IV.1. Baseline estimates

Table 2 reports the results of our benchmark specification using alternative dependent variables. 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 ($Attitudes_{ict}$), and then, in column (2), we re-estimate our specification using a dummy variable equal to one for respondents with positive attitudes and zero otherwise ($Median$). The retained threshold is the median value of $Attitudes_{ict}$ for positive and negative attitudes. In both cases, we find no significant association between the salience of immigration and natives' attitudes toward immigration. However, column (3)

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

Table 2: Baseline Estimates

	(1) $Attitudes_{ict}$	(2) Median	(3) Pol_{ict}	(4) Anti-Pol	(5) Pro-Pol	(6) Placebo
			Table 2 (a)			
$ln(Dur_{ct-1})$	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 2 (b)			
$ShareDur_{ct-1}$	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 2 (c)			
$ln(Sub_{ct-1})$	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 2 (d)			
$ShareSubj_{ct-1}$	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. $\times$ 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

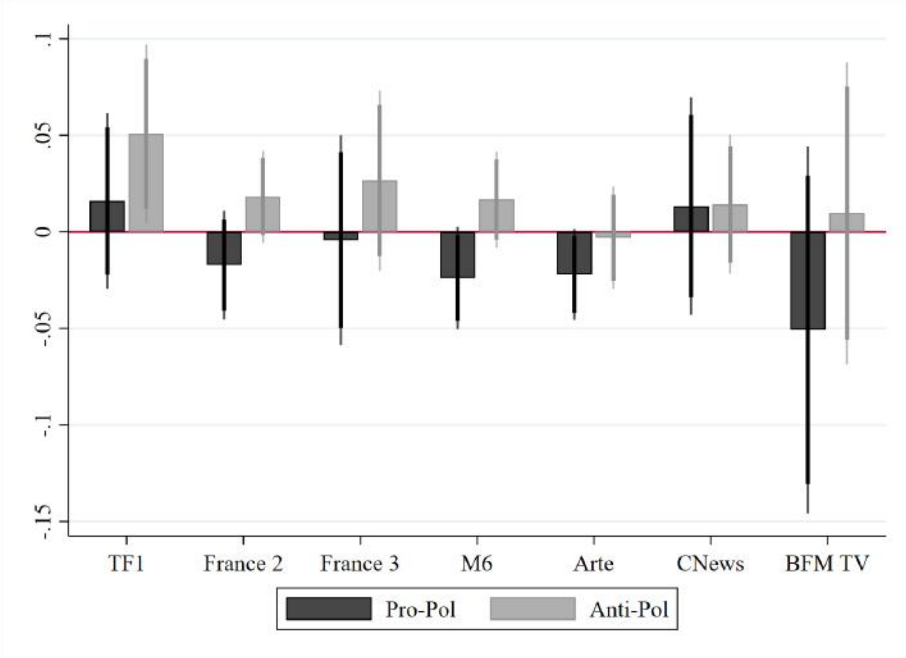
Notes: The dependent variable in column (1) is continuous and represents the average attitudes of individual i toward immigration. The dependent variable in column (2) is the median split of average attitudes. The dependent variable in column (3) is Polarization which takes the value one for individuals 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 zero for individuals with pro-immigration attitudes and one 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 the 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.

reports that irrespective of the measure of salience that we use, we always find a positive and highly significant effect of an increase in the salience of immigration on the polarization of attitudes. Regarding the magnitude of the effect, 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 (over the total number of subjects) is associated with a 2.75 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 our dependent variable in column (4) with *Anti-polarization*, 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, our coefficient of interest is always 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-polarization* that is equal to zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-moderates). Our coefficient of interest becomes negative and remains 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, our coefficient of interest is never significant irrespective of the salience measure.

IV.2. Heterogeneity analysis at the channel level

The previous subsection has shown that, on average, 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. However, one can infer from Figures 2 and B1 in the Appendix that the distribution of attitudes strongly differs across French TV channels. For instance, on the one hand, TF1 is more likely to be watched by individuals with negative attitudes toward immigration, and the distribution of viewers' attitudes toward immigration is therefore skewed to the left. Arte, on the other hand, is more 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 our treatment variable and the preferred TV channel requires a substantial amount of observations and variability in the data that our

Figure 5: Heterogeneity analysis: salience effect by channels



Notes: The figure shows the marginal effect of $ln(Dur_{ct-1})$ 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. (6). The vertical lines are 90% and 95% confidence intervals.
Source: Authors' elaboration on INA and ELIPSS data.

sample may not offer.[29] Our results are reported in Figure 5 for $ln(Dur_{ct-1})$, while the results for other variables of interest are reported in Figure C1 in the Appendix. As expected, we find 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 for instance. In contrast, channels with less skewed distribution of attitudes, such as BFM-TV, M6 or France 2, seem to be those in which we observe polarization toward both extreme attitudes as suggested by the opposite signs for the *Anti-* and *Pro-polarization* variables.[30]

IV.3. Robustness checks

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

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

[30] As reported in Section VI, an increase in the salience of immigration in the media may be systematically associated with a channel-specific frame. However, note that 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.

Alternative specifications. We first report the results of alternative specifications in Table C1 in the Appendix. Column (1) does not include either individual controls or fixed effects. One can see that this simple correlation already captures our main association between priming immigration and polarization. This effect is robust to the inclusion of individual and wave fixed effects in column (2), as well as exploiting the panel dimension of our 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 our main conclusions remain unchanged when controlling for individual time-varying controls. Regardless of the measure of salience we use, we always find that increasing the coverage of the immigration topic pushes natives' attitudes toward extreme attitudes.[31] Finally, and following Facchini et al. (2017), we provide evidence in column (5) that our 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.

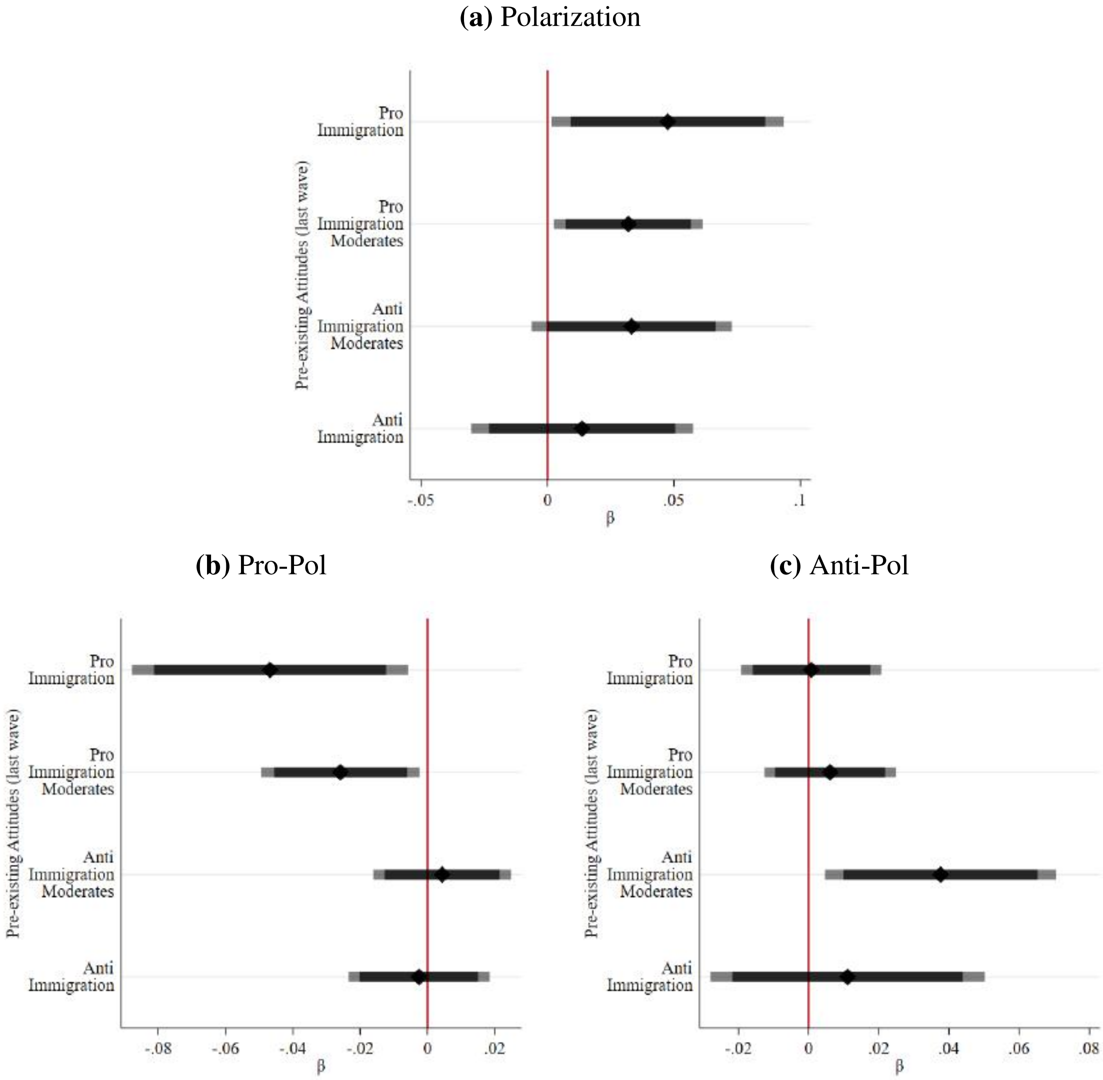
Preexisting attitudes. To provide additional evidence that our effect captures the shift of individuals with moderate attitudes toward extreme views, we interact our treatment variable with preexisting attitudes. Preexisting attitudes are defined as the attitude of individual i in the previous survey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

$$\begin{aligned} Pol_{ict} = {} & \beta_1 Salience_{ct-1} + \beta_2 PreAttitudes_{it} \\ & + \beta_3 Salience_{ct-1} \times PreAttitudes_{it} + \beta' X_{it} + \gamma_{ic} + \gamma_t + \varepsilon_{ict} \end{aligned} \tag{4}$$

where $PreAttitudes_{it}$ is a categorical variable classifying whether individual i is *"Pro-immigration"*, *"Pro-immigration moderate"*, *"Anti-immigration moderate"*, or *"Anti-immigration"* in the previous wave. Our results are reported in Figure 6 for $ln(Dur_{ct-1})$ and in Figures C4, C5 and C6 in the Appendix for other variables of interest. Two main figures emerge from the estimated coefficients and validate our previous findings. On the one hand, anti-immigration moderates are those more likely to polarize and become anti-immigration while pro-immigration moderates are more likely to become pro-immigration when the salience of immigration on TV increases. On the other hand, at the

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

Figure 6: Interaction with preexisting attitudes, $ln(Dur_{ct-1})$



Notes: The figure shows the marginal effect of $ln(Duration_{ct-1})$ on Polarization, Anti-Pol and Pro-Pol respectively, estimated separately from Eq. (4). Each coefficient represents the marginal effect of the variable for different preexisiting attitudes. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

two extremes of the distribution of attitudes, only pro-immigration individuals seem to be affected by news content. Indeed, an increase in the salience of immigration increases the probability for pro-immigration respondents to remain at the right-hand side of the distribution, while anti-immigration individuals are not affected by the salience of immigration. This suggests that anti-immigration individuals are very unlikely to change their interpersonal attitudes toward immigration over time, irrespective of the salience of the latter.

Placebo estimates. We perform placebo estimations to show that our results are not driven by idiosyncratic changes in immigration news broadcasted by different channels.

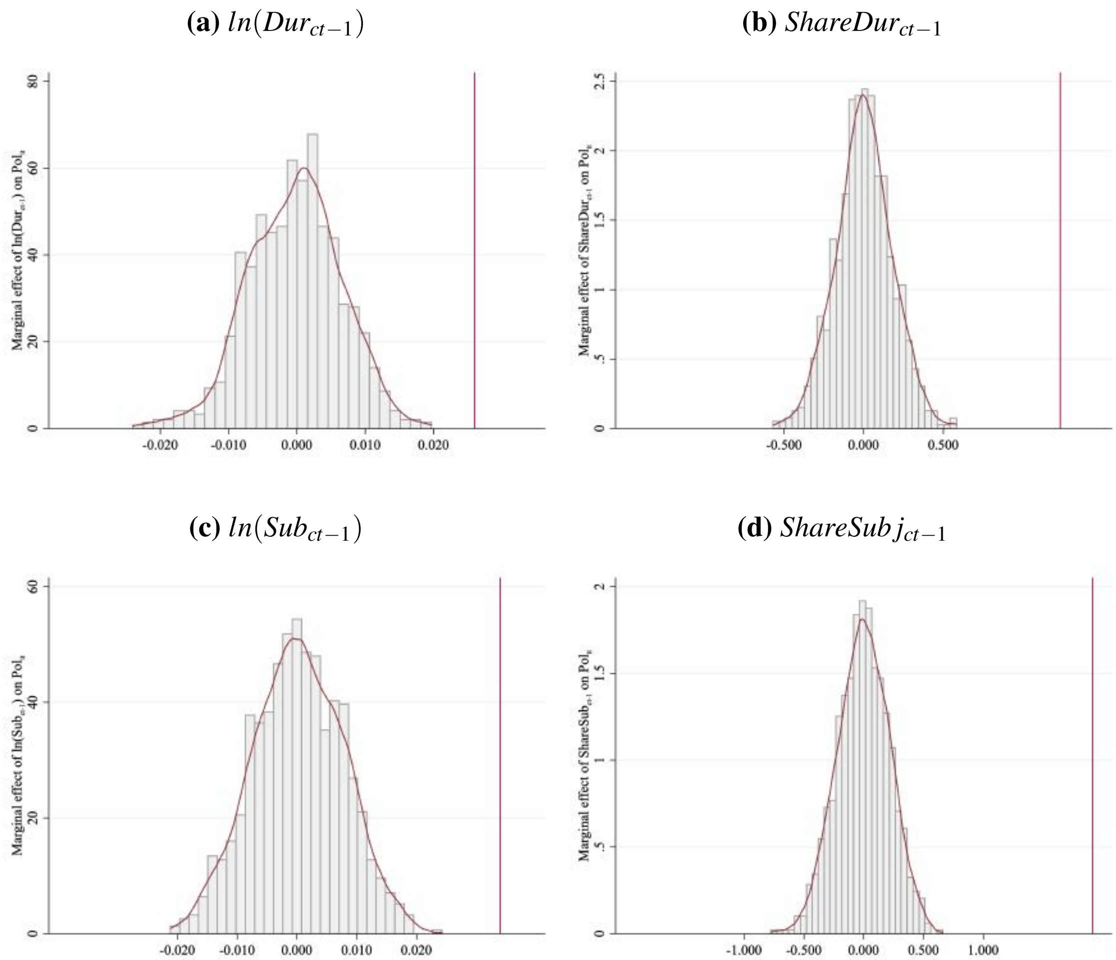
To do so, we run 1,000 replications of our benchmark specification for each variable of interest where individuals are randomly assigned to a different TV channel. The results of these placebo estimations are shown in Figure 7. One can see that our coefficient of interest follows a standard normal distribution centered at zero. In addition, all estimations always report a coefficient that is significantly lower than our main estimates. This absence of any effect when randomly assigning channels to respondents suggests that our findings are not driven by idiosyncratic changes in immigration news broadcasted by different channels or a general increase in the salience of immigration in the media following a migration-related event. In other words, it demonstrates that our effect is solely driven by channel-specific changes in migration news broadcasting.[32]

Alternative dependent variable. Our measures of attitudes toward immigration are constructed in our analysis 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 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 our 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 our empirical analysis. Table C2 in the Appendix shows that while excluding some dimensions reduces data variability and the number of observations, our main conclusion about the polarization effect of an increase in the salience of immigration remains unchanged. Additional estimates in Table C3 report that when we focus on one dimension at a time, our coefficient of interest becomes insignificant, again reflecting a lack of variability in the data.[33] Finally, we provide evidence that our main conclusions remain unchanged when using a principal component analysis

[32] It also rules out that our results capture a general increase in the salience of immigration in the media that would lead people to look for, or pay more attention, information on immigration in social media, driving users toward extreme attitudes. If this were true, our main effect would also be larger for individuals reporting the internet as their second main source of political information, which is not the case, as depicted in Figure D4 in the Appendix.

[33] We also provide evidence in Table C6 in the Appendix that our 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 our different variables of interest and attitudes toward immigration.

Figure 7: Placebo estimates



Notes: These graphs depicts the distribution of the estimates of the effect of an increase in salience on the polarization of attitudes for 1,000 different regression were we randomly assign a channel to each respondents. The red vertical line represents our benchmark coefficients with the preferred TV channel of the respondents estimated in column (3) in Table 2.
Source: Authors' elaboration on INA and ELIPSS data.

(PCA) that extracts the shared component of all three dimensions.[34]

Alternative clustering. Given our sampling design and following Abadie et al. (2017), we cluster our standard errors at the individual level to account for potential correlations in individuals over time. We nxt provide evidence for the robustness of our results to alternative clustering at the TV channel level in Table C4 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).[35] Again, our estimates are not affected by this change.

[34]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.

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

Self-selection concerns. Table C5 in the Appendix provides additional evidence, if needed, that our results are not driven by self-selection. We follow the methodology developed by Oster (2019) that allows us to measure the degree of selection on unobservables in our estimates, assuming that selection on observables is informative about selection on unobservables. From columns (1) to (3), we report the results of our baseline estimate with and without control variables and fixed effects. Indeed, Oster (2019) demonstrates that coefficient and R-squared changes following the introduction of observables allow estimating the likelihood that the coefficient of interest is entirely driven by unobservables. This requires us to choose a value for the R-squared of the hypothetical regression of Pol_{ict} on $Salience_{ct-1}$ 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 our benchmark specification with full controls and fixed effects. We first compute δ, the degree of selection on unobservables relative to observables that would be necessary to make our coefficient of interest equal to zero. As reported by Oster (2019), concerns regarding self-selection on unobservables are ruled out as long as $\delta > 1$. Irrespective of our variable of interest, and focusing on column (4), we find that selection on unobservables would have to be on average 1.8 times higher than selection on observables to change the nature of our findings. Second, we compute in column (5) the bounding values of our coefficient of interest after correcting for selection on unobservables. In all cases, the identification sets exclude zero and are of the same sign as our coefficient of interest. Overall, this new set of results is reassuring that our main effect is unlikely to be driven by a self-selection on unobservables.

V. Heterogeneity Analysis

This section investigates whether the polarization effect of an increase in the salience of immigration on natives' attitudes toward immigration is heterogenous across individual characteristics. We augment Equation (3) using an interaction term between the treatment variable and various individual characteristics as follows:

$$Pol_{ict} = \beta_1 Salience_{ct-1} + \beta_2 Salience_{ct-1} \times Z_{it_0} + \beta' X_{it} + \gamma_{ic} + \gamma_t + \varepsilon_{it} \qquad (5)$$

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 (5), we recalculate the effect for each of the two categories of the dummy using:

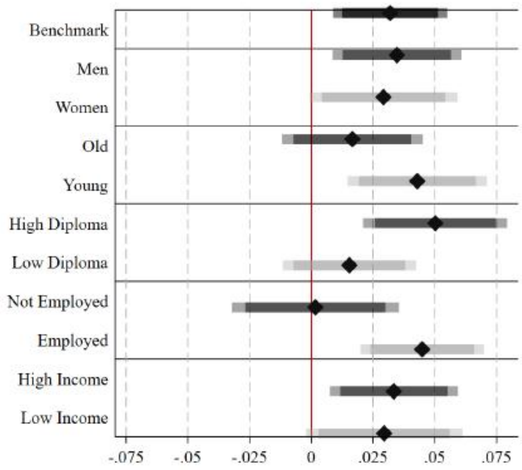
$$\frac{\partial Pol_{ict}}{\partial Salience_{ct-1}} = \beta_1 + \beta_2 Z_{it_0} \tag{6}$$

where the effect for the reference category ($Z_{it_0} = 0$) equals β_1 and the effect for other ($Z_{it_0} = 1$) is the linear combination of $\beta_1 + \beta_2$ (Brambor et al., 2006). Our results from the heterogeneity analysis are reported only for a single measure of salience, namely $ln(Dur_{ct-1})$. The results for the other variables of interest are reported in Appendix D, and lead to the same conclusions.

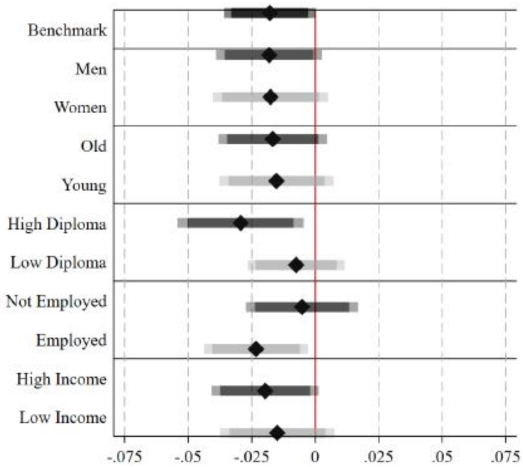
We consider several dimensions that may drive a heterogeneous effect, including gender, age, education, employment status, and income. To be considered as exogenous as possible, we fix individual characteristics in the different sets of interactions at the first nonmissing observation for each individual. 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 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 a revenue below and above 2500 per month. Using Equation (6), we plot the total effect of exposure to immigration news by the categories of interest in Figure 8.

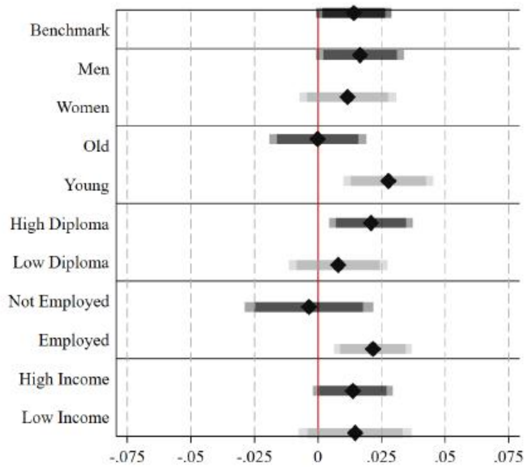
Figure 8a reports that our polarization effect is significant for most of the individuals in the population. However, we highlight substantial differences in the magnitude of the effect along with the age, education, and employment variables. Figure 8b shows that those who become pro-immigration following an increase in exposure to immigration news are more likely to be highly educated, and employed. We find no significant differences regarding sex, age or income. Figure 8c 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. Our interpretation of the results is that young, employed, and highly educated individuals are the most likely to update their beliefs rather than remain entrenched in

Figure 8: Heterogeneity Analysis, $ln(Dur_{ct-1})$



(a) Polarization





(b) Pro-Pol

(c) Anti-Pol

Notes: The figure shows the marginal effect of $ln(Duration_{ct-1})$ on Polarization, Anti-Pol and Pro-Pol respectively, estimated separately from Eq. (5). Each coefficient represents the marginal effect of the variable for a sub-group in the population as defined in Eq. (6). Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

their position and thus to change their interpersonal attitudes.

Finally, 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 D5 in the Appendix suggests that our 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 D6 and D7 reveal that the likelihood of left polarization (right polarization) increases as individuals become closer to the left (right). As a result, individuals becoming pro-immigration (anti-immigration) are only individuals who identify themselves as left-wing (right-wing) members.[36]

VI. From Priming to Framing

One could be concerned that our previous results mainly captured differences in the treatment of the same subject across various TV channels. Thus, this section provides evidence that the priming effect of immigration on polarization does not only capture how TV channels frame immigration-related subjects in their news programs.

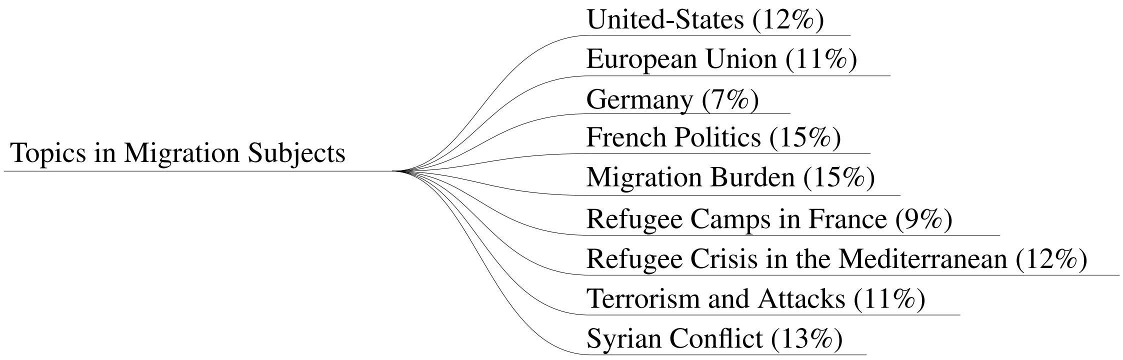
To characterize the framing of migration subjects on evening news programs, we first identify the topics associated with migration using an unsupervised latent Dirichlet allocation algorithm (LDA) on the corpus of migration subjects. The goal of the LDA generative process is to discover uncorrelated topics from the collection of migration subjects and to assign each subject to a mutually exclusive category. In our sample, the LDA algorithm detects nine different topics associated with migration subjects in our period of analysis, all depicted in Figure 9.[37]

Table E2 in the Appendix reports the share of each topic before and after the refugee crisis on TV news programs. 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 E1 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

[36] Note that the same interactions with the likelihood to vote for a given party (on a 10 point scale) are all not significant, irrespective of the party at hand and these results are available upon request. Nevertheless, we provide an extended analysis in Appendix F on how an increase in the salience of immigration affects an individual’s probability to vote for a party conditional on his/her initial political preferences. Overall, we find that a rise in the salience of immigration significantly increases the likelihood of an individual affiliated with right and/or the center to vote for far-right parties. At the other end of the political spectrum, we find evidence that priming immigration increases the likelihood of individuals close to the center to vote for the left or green party, the two parties with the highest correlation with pro-immigration attitudes.

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

Figure 9: Main topics associated with migration subjects (LDA algorithm)



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

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

Second, we perform a sentiment analysis to characterize the tone of 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.[38] This allows us to obtain measures of positivity and negativity for each immigration-related subject. Figure E2 in the Appendix depicts the most frequent French words identified as positive or negative in the most positive and negative subjects respectively. To assess the degree of positivity (negativity) of a subject we compute the number of positive (negative) words over 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 E12 in the Appendix reports the share of positive and negative sentiments among migration subjects and across channels. It shows that the tone of migration subjects became more positive after the refugee crisis and that, on average, the most positive channels were Arte and France 2, while the most negative ones were BFM TV and CNews during our period of analysis.

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

VI.1. Topic analysis

In this section, we disaggregate our measures of salience into the nine main topics identified by the LDA algorithm. Indeed, it would be desirable o determine whether the polarization effect of salience that we uncovered averages heterogeneous reactions to various topics. We estimate the following model:

$$
\begin{aligned}
Pol_{ict} = \beta_1 Salience[Terrorism\ and\ Attacks]_{ct-1} + \beta_2 Salience[French\ Politics]_{ct-1} \\
+ \ldots + \beta_9 Salience[Migration\ Burden]_{ct-1} + \beta' X_{it} + \gamma_{ic} + \gamma_t + \varepsilon_{ict} \quad (7)
\end{aligned}
$$

where, for instance, $Salience[Terrorism\ and\ Attacks]_{ct-1}$ is the salience of the topic "Terrorism and Attacks". 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 our results. The main topic for which we consistently detect an effect is "Migration Burden", which polarizes attitudes as its prominence in evening news programs increases. 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 our data when focusing on specific topics. Thus, we group our 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 3. On the one hand, topics associated with immigration in France produce a polarization effect, whereas those discussing immigration in the media in other contexts outside of the national territory (such as in Germany or the US) 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 depicting terrorism or the refugee crisis in particular.[39] Alternative groupings of topics do not change our conclusions and are available upon request. Particularly, our results on the polarization effect of French stories still hold when excluding "Migration Burden " from the France category as reported in Appendix E.

Table 3: Topic analysis, $ln(Dur_{ct-1})$

Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
France	Refugee Camps in France	0.021***	0.011***	-0.010***
	French Politics	(0.005)	(0.003)	(0.003)
	Migration Burden			
Foreign	European Union	0.001	-0.007*	-0.007*
	Germany	(0.005)	(0.004)	(0.004)
	United-States			
Other	Refugee Crisis Med.	0.003	0.003	0.001
	Terrorism	(0.004)	(0.003)	(0.003)
	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		0.453	0.561	0.586

Notes: The dependent variable in column (1) is Polarization which takes the value one for individuals with extreme attitudes (deeply concerned or not concerned at all) and zero otherwise. The dependent variable in column (2) is a dummy equal to one for individuals with anti-immigration attitudes and zero otherwise (pro-immigration, pro- and anti-immigration moderates). The dependent variable in column (3) is a dummy equal to zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti- immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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.

VI.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

[39] Similar results are obtained with alternative variables of interest as reported in Appendix E. Table C6 also shows that we do not detect an effect on attitudes of the salience of Muslim-related immigration news.

spreading disruptive news.[40] Overall, an increase in the salience of immigration in the media may be systematically associated with channel-specific frames and different framings may be expected to drive attitudes in opposite directions. Thus, we augment our benchmark specification previously described in Equation (3) 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 about migration.

Table 4: Sentiment Analysis

	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol	(4) Pol_{ict}	(5) Anti-Pol	(6) Pro-Pol	(7) Pol_{ict}	(8) Anti-Pol	(9) Pro-Pol
$ln(Dur_{ct-1})$	0.031***	0.014*	-0.017*	0.028**	0.014*	-0.014	0.034***	0.015**	-0.019**
	(0.012)	(0.008)	(0.009)	(0.012)	(0.008)	(0.009)	(0.012)	(0.007)	(0.009)
Sent. Score	0.254**	0.085	-0.168**						
	(0.099)	(0.067)	(0.074)						
Share of negative				-0.316*	-0.028	0.288**			
				(0.161)	(0.105)	(0.125)			
Share of positive							0.337**	0.179	-0.157
							(0.162)	(0.111)	(0.120)
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 the 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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.

When we control for the framing of the content of immigration news in Table 4, the polarization effect of an increase in the salience of immigration always remains positive and highly significant. This is reassuring that our previous results were not capturing differences in the tone employed across the different French TV channels.[41] Regarding the framing of immigration-related news, our first measure, which takes the difference between the number of positive and negative words over the total number of words in

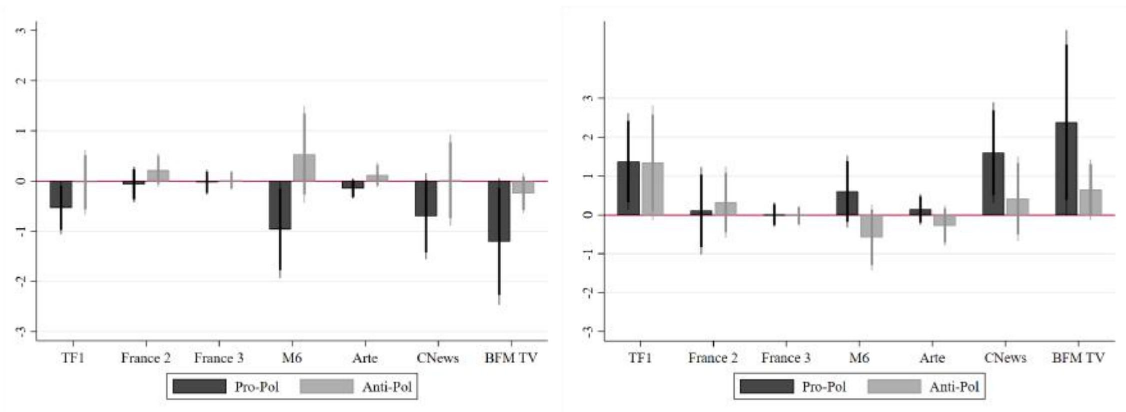
[40] In a related context, Vosoughi et al. (2018) observe that false news may spread faster among Twitter users due to its degree of novelty and emotionally charged content.

[41] Note that controlling for the framing of the content also does not affect the results presented in Subsection IV.2 regarding the effect of priming immigration by TV channel.

the subject, shows that increasing the share of positive content (or reducing negative content) is associated with polarization that occurs mainly on the left side of the distribution of attitudes. Indeed, the comparison between columns (2) and (3) reveals that having a more positive content is associated with more positive attitudes toward immigration (column 3) but without any significant changes on the right side of the distribution of attitudes (column 2). Thus, the shift of individuals from pro-immigration moderates to pro-immigration attitudes results in a more polarized distribution as reported in column (1). Similar patterns are found from columns (5) to (6) when focusing only on the share of negative content in immigration news programs. Indeed, one can see in column (6) that an increase in the share of negative content is associated with more negative attitudes toward immigration. However, we find no significant association between the framing and natives' attitudes toward immigration on the right side of the distribution (column 5). In this case, the shift of individuals from pro-immigration moderates to pro-immigration attitudes results in a less polarized distribution (column 4). 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).

Figure 10: Sentiment Analysis, $ln(Dur_{ct-1})$

(a) Positive - Negative **(b)** Negative



Notes: The figure shows the marginal effect of our sentiment variables on Pro-Pol and Anti-Pol respectively,. Each coefficient represents the marginal effect of the variable for a channel in the population as defined in Eq. (6). The vertical lines are 90% and 95% confidence intervals.
Source: Authors' elaboration on INA and ELIPSS data.

Again, these average effects may conceal substantial heterogeneity if individuals with specific initial attitudes react differently to the same framing. As a result, Figure 10 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, whereas having more positive content tends to raise pro-immigration attitudes on average, with effects that seem to be relatively homogeneous across channels. For instance, an increase in positive content on TF1 where viewers are mostly anti-immigrant significantly reduces concerns about immigration. However, having more negative content on the same channel indeed generates anti-immigration reactions on both sides of the distribution of attitudes. Similar patterns are found for other channels on average, while the precision of the estimates is strongly affected by the number of observations available for each channel.[42] Overall, the results of this exploratory analysis confirm that an increase in the salience of migration topics has a polarization effect even when we control for framing. These findings also suggest that in contrast to priming, a change in the framing mostly drives viewers' attitudes in specific directions.

VII. 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 an increase in immigration coverage 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. Our empirical strategy relies on natives' differential exposure to immigration through their preferred television channel. Together with the panel dimension of our data, this allows us to control for individual-channel fixed effects, which strongly reduce concerns about ideological self-selection into channels. Interestingly, our main result is at odds with the existing literature on the impact of media on attitudes toward immigration, which 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 US, increases pro-immigration attitudes. In addition, we find no evidence that the polarization effect of priming immigration reflects differences

[42] Graphical representations for other independent variables are available in Appendix E and lead to the same conclusions.

in the treatment of the immigration topic across French TV channels. Indeed, if changes in the tone used in migration subjects can drive viewers' attitudes in a specific direction, our main polarization effect of salience remains significant when we control for framing effects. Overall, this new evidence calls for additional research into 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.

Appendix

A. Additional Descriptive Statistics

Table A1: 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	

Source: Authors' elaboration on ELIPSS data.

Table A2: Number of individual observations per wave

Wave	Year	Month	Obsv.	%
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 our benchmark sample. Source: Authors' elaboration on INA and ELIPSS data.

Figure A1: Sample of analysis

French citizens
2845

31% Do not watch television **888**

69% Watch television **1957**

94% Watch a main channel **1834**

5% Watch a minor channel **105**

<1% no information **18**

Number of missing waves

62%	*16%*	*10%*	*3%*	*2%*	*2%*	*1%*	*1%*	*1%*	*<1%*	*<1%*	*<1%*
0 missing waves out of 12 waves	1	2	3	4	5	6	7	8	9	10	11 missing waves out of 12 waves
1,132	**299**	**179**	**51**	**38**	**31**	**25**	**20**	**19**	**13**	**15**	**12**

Figure A2: Sample of analysis – 2013 sample

French citizens
895

23% Do not watch television **209**

77% Watch television **686**

94% Watch a main channel **645**

5% Watch a minor channel **38**

<0.5% no information **3**

Number of missing waves

41%	*15%*	*9%*	*7%*	*6%*	*5%*	*4%*	*3%*	*3%*	*2%*	*2%*	*2%*
0 missing waves out of 12 waves	1	2	3	4	5	6	7	8	9	10	11 missing waves out of 12 waves
262	**97**	**63**	**50**	**38**	**31**	**25**	**20**	**19**	**13**	**15**	**12**

Figure A3: Sample of analysis – 2016 sample

French citizens
1950

35% Do not watch television **679**

65% Watch television **1271**

94% Watch a main channel **1189**

5% Watch a minor channel **67**

1% no information **15**

73%	*17%*	*10%*	*<0.1%*
0 missing waves out of 3 waves	1 missing waves out of 3 waves	2 missing waves out of 3 waves	3 missing waves out of 3 waves
870	**202**	**116**	**1**

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			

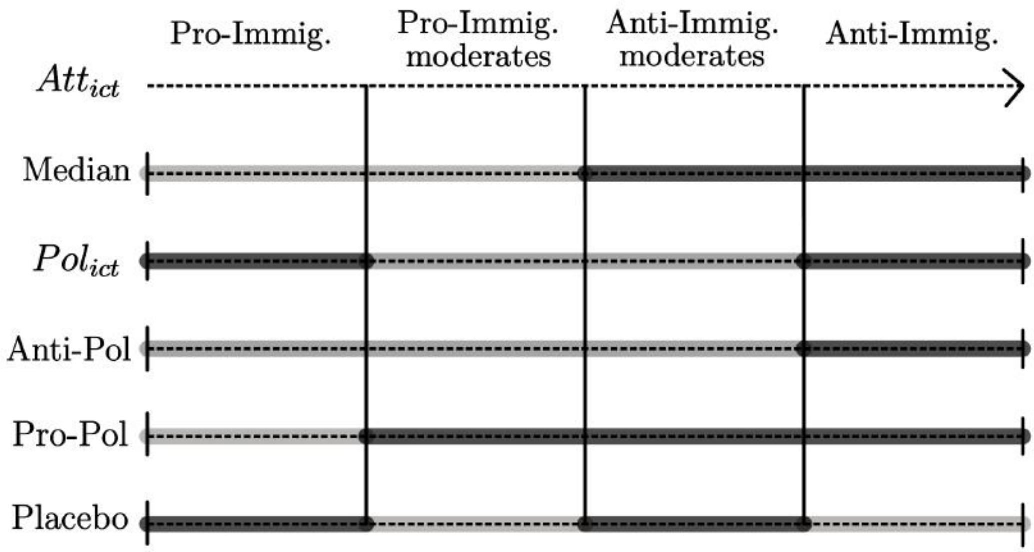
Source: Authors' elaboration on INA data.

Table A4: Summary statistics

	Mean	Std. Dev.	Min.	Max.	Type
$Attitudes_{ict}$	2.482	0.775	1.000	4.000	Categorical
Median	0.466	0.499	0.000	1.000	Dummy
Pol_{ict}	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
$ln(Dur_{ct-1})$	3.500	0.730	0.421	5.144	Continous
$ShareDur_{ct-1}$	0.027	0.019	0.001	0.178	Continous
$ln(Sub_{ct-1})$	2.856	0.678	0.881	4.500	Continous
$ShareSubj_{ct-1}$	0.023	0.016	0.001	0.166	Continous
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 Nb.	2.476	1.300	1.000	6.000	Categorical
Blue Collar	0.213	0.409	0.000	1.000	Dummy
Income Cat.	3.092	1.823	0.000	6.000	Categorical
Nb. observations:	6,776				

Source: Authors' elaboration on INA and ELIPSS data.

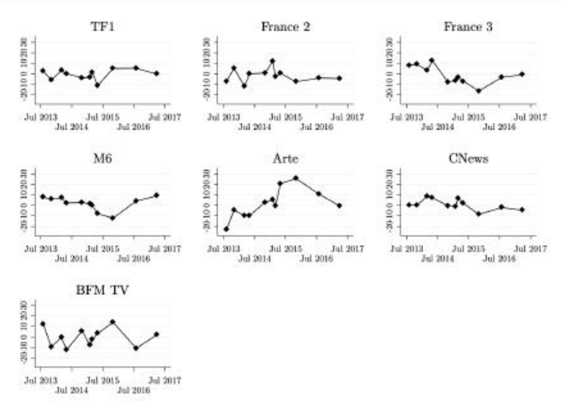
Figure A4: Alternative dependent variables



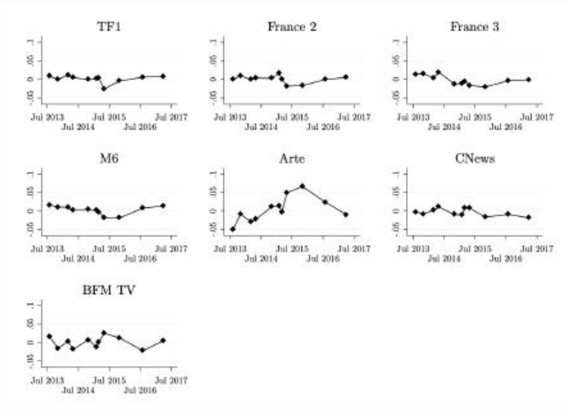
Notes: This figure depicts the definition of the main dependent variables. Grey zones are coded as zero while dark zones are coded as one. *$Attitudes_{ict}$* is the continuous average attitude of individual *i* in year-month *t* toward immigration. *Median* is a dummy variable equal to one for respondents with attitudes above the median and zero otherwise. *Pol_{ict}* 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 zero for individuals with pro-immigration attitudes and one 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

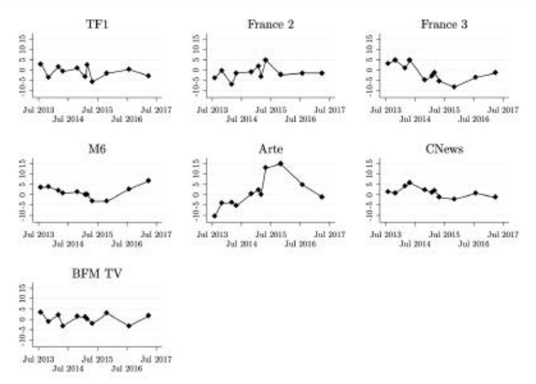
(a) $ln(Duration_{ct-1})$



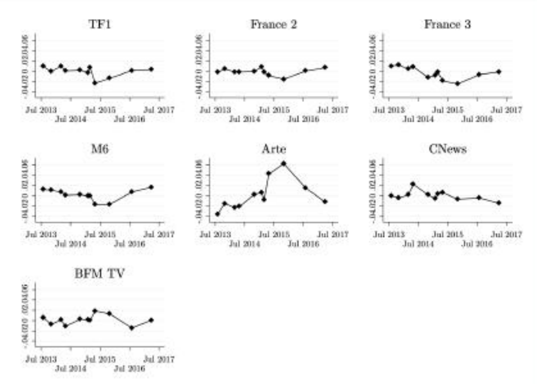
(b) $ShareDur_{ct-1}$



(c) Sub_{ct-1}



(d) $ShareSubj_{ct-1}$



Notes: This figure plots the coverage of immigration topics on the 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.

B. Self-selection into Channels

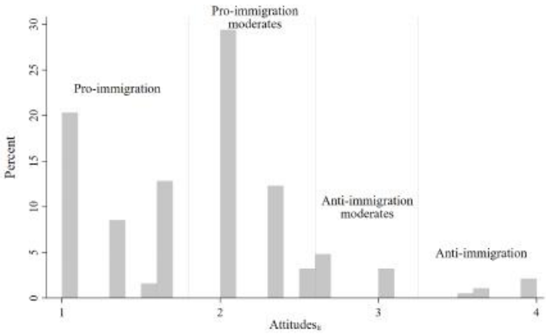
Table B1: Preferred TV channel and natives' attitudes toward immigration. Difference in means.

	TF1	France 2	France 3	M6	Arte	CNews	BFM TV	Mean
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
$Attitudes_{ict}$	0.297***	-0.223***	-0.015	-0.001	-0.604***	-0.383***	-0.001	2.482

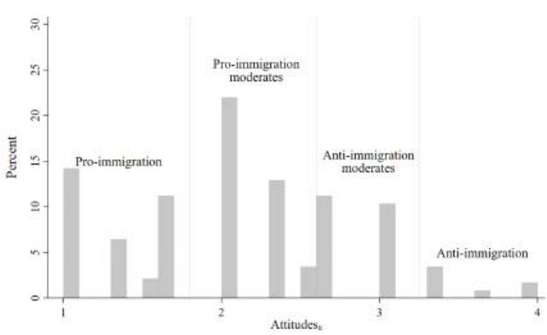
Notes: This table reports the difference between the mean of each group and the mean for the full sample used in our empirical analysis. We also report whether the difference is significant with a two-sample t-test. The "Age" variable is composed of 11 categories from less than 24 years-old to more than 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.

Figure B1: Individuals attitudes toward immigration by channel

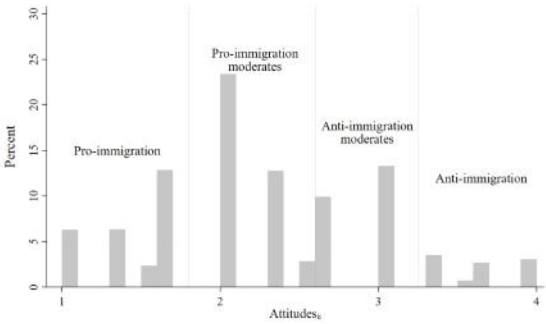
(a) Arte (skewness=0.744, kurtosis=3.938)



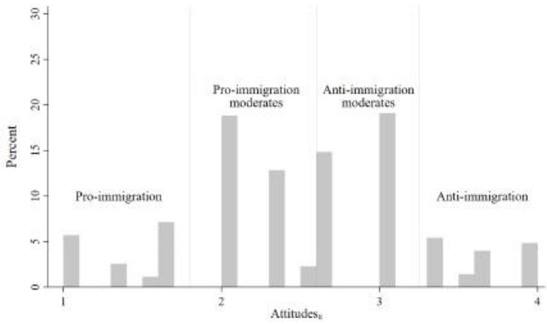
(b) CNews (skewness=0.230, kurtosis= 2.600)



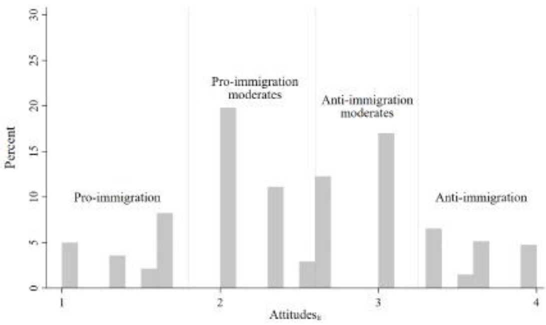
(c) France 2 (skewness=0.368, kurtosis=2.694)



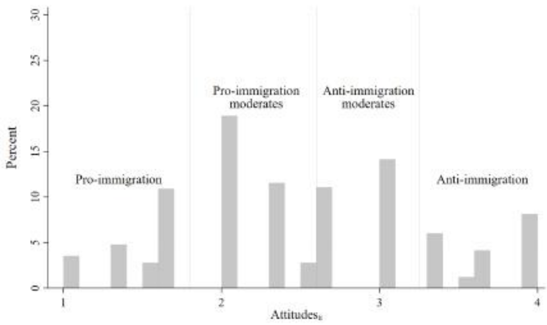
(d) France 3 (skewness=-0.020, kurtosis=2.609)



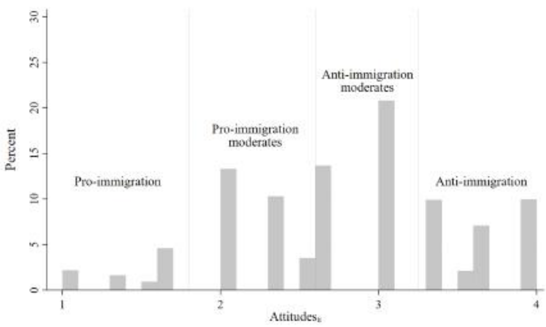
(e) BFM TV (skewness=0.064, kurtosis=2.378)



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

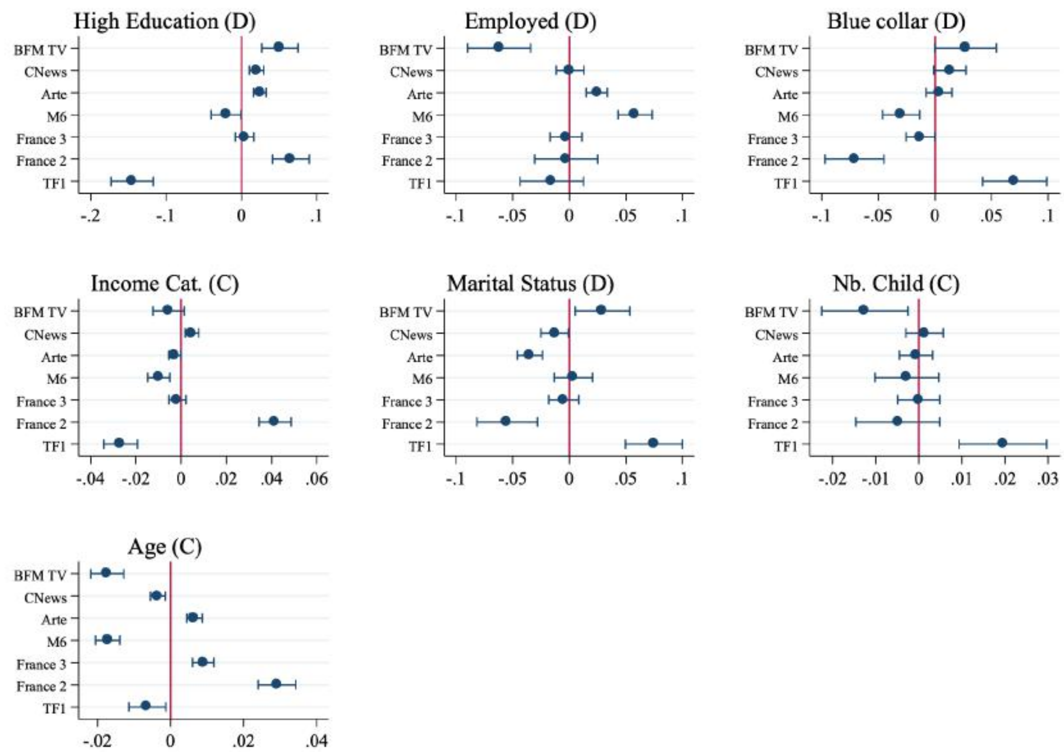


(g) TF1 (skewness=-0.179, kurtosis=2.494)



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

Figure B2: Multinomial logit regressions
Probabilities of choosing a given channel

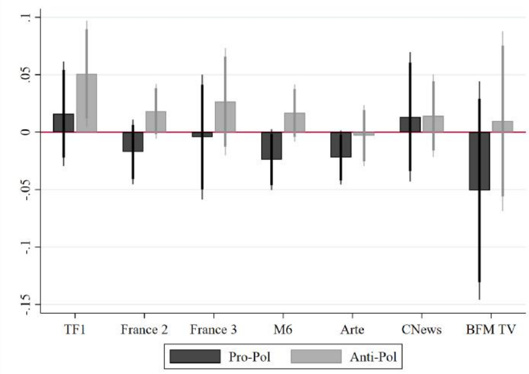


Interpretation: The probability of choosing TF1, ceteris paribus, is on average 1.41 percentage points lower for High-skilled compare to Low-skilled viewers.
Notes: Coefficients are obtained from predictive margins for continuous (C) and dummy variables (D) after a multinomial logit with alternative 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 in the specific regression as continuous variables. Using categorical variables does not affect the interpretation of our results and these estimates are available upon request.
Source: Authors' elaboration on ELIPSS data.

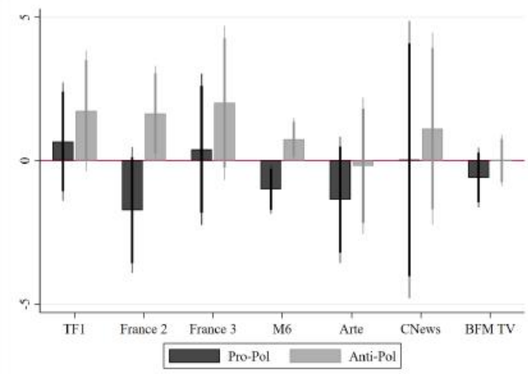
C. Additional Robustness Checks

Figure C1: Heterogeneity analysis: salience effect by channel

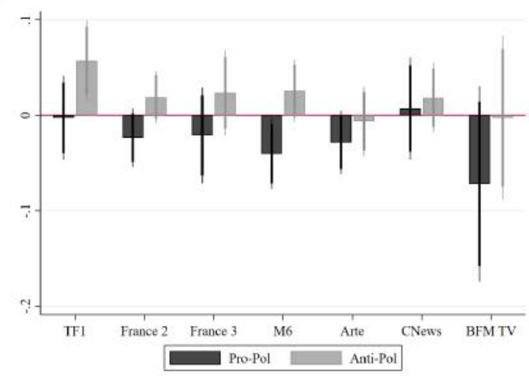
(a) $ln(Dur_{ct-1})$



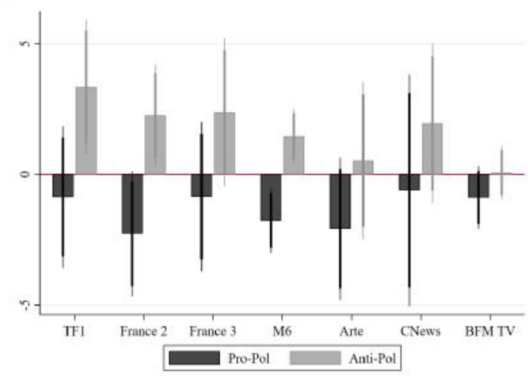
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



(d) $ShareSubj_{ct-1}$



Notes: The figure shows the marginal effect of our independent variables 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. 6. The vertical lines are 90% and 95% confidence intervals.
Source: Authors' elaboration on INA and ELIPSS data.

Table C1: Alternative Specifications

	(1)	(2)	(3)	(4)	(5)
	Pol_{ict}	Pol_{ict}	Pol_{ict}	Pol_{ict}	Pol_{ict}
			Table C1 (a)		
$ln(Dur_{ct-1})$	0.028***	0.032***	0.032***	0.032***	0.030**
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
			Table C1 (b)		
$ShareDur_{ct-1}$	0.951**	1.567***	1.447***	1.445***	1.234**
	(0.461)	(0.463)	(0.465)	(0.471)	(0.542)
			Table C1 (c)		
$ln(Sub_{ct-1})$	0.042***	0.039***	0.043***	0.042***	0.041**
	(0.011)	(0.015)	(0.015)	(0.015)	(0.016)
			Table C1 (d)		
$ShareSubj_{ct-1}$	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 the 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: Baseline results. Alternative dependent variable

Dependent var. : Pol_{it} First dimension → Second dimension →	(1) Too Much Migrants Immigration = Culture	(2) Too Much Migrants Muslims = Citizens	(3) Immigration = Culture Muslims = Citizens
		Table C2 (a)	
$ln(Dur_{ct-1})$	0.007 (0.013)	0.036*** (0.014)	0.019 (0.015)
		Table C2 (b)	
$ShareDur_{ct-1}$	1.028** (0.429)	1.564*** (0.478)	1.066** (0.467)
		Table C2 (c)	
$ln(Sub_{ct-1})$	0.017 (0.016)	0.052*** (0.019)	0.033* (0.020)
		Table C2 (d)	
$ShareSubj_{ct-1}$	1.884*** (0.552)	2.420*** (0.644)	1.791*** (0.632)
Controls	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Indiv. × 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 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 the 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: Baseline results. Alternative dependent variables (cont'd)

	(1) Too Much Migrants	(2) Immigration= Culture	(3) Muslims= Citizens	(4) PCA
$ln(Dur_{ct-1})$	-0.009	0.011	-0.009	0.016
	(0.012)	(0.013)	(0.013)	(0.011)
$ShareDur_{ct-1}$	0.221	0.434	0.125	0.725**
	(0.410)	(0.441)	(0.436)	(0.359)
$ln(Sub_{ct-1})$	-0.005	0.022	-0.020	0.022
	(0.015)	(0.016)	(0.018)	(0.015)
$ShareSubj_{ct-1}$	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. $\times$ 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 the 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: Baseline results. std. errors clustered at the channel level

	(1) Pol_{ict}	(2) Pol_{ict}	(3) Pol_{ict}	(4) Pol_{ict}	(5) Pol_{ict}	(6) Pol_{ict}	(7) Pol_{ict}	(8) Pol_{ict}
$ln(Dur_{ct-1})$	0.032**	0.030**						
	(4.687)	(3.411)						
$ShareDur_{ct-1}$			1.445***	1.234**				
			(3.159)	(3.112)				
$ln(Sub_{ct-1})$					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. × 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 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 the 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.

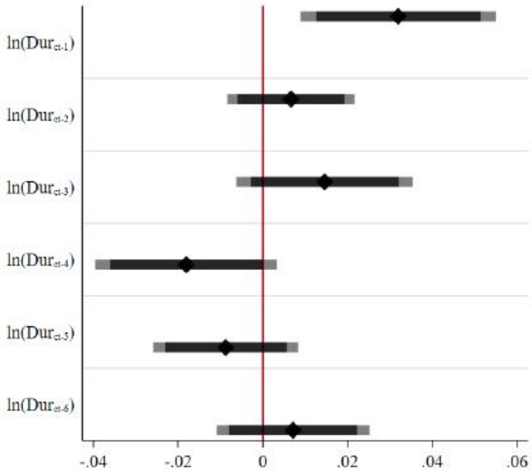
Table C5: Accounting for selection in unobservables, Oster (2019)

Dependent var. : Pol_{it}	Estimates			$R_{max} = 1.3 \times R^2 = 0.72$	
	(1) No controls $(s.d.)[R^2]$	(2) FEs $(s.d.)[R^2]$	(3) FEs & Controls $(s.d.)[R^2]$	(4) δ for $\beta = 0$	(5) *Id. set*
$ln(Dur_{ct-1})$	0.028***	0.032***	0.032***	1.738	[0.028,0.043]
	(0.011)[0.002]	(0.012)[0.565]	(0.012)[0.567]		
$ShareDur_{ct-1}$	0.951**	1.447***	1.445***	2.551	[0.951,3.218]
	(0.461)[0.001]	(0.465)[0.565]	(0.471)[0.568]		
$ln(Sub_{ct-1})$	0.042***	0.043***	0.042***	1.016	[0.019,0.042]
	(0.011)[0.004]	(0.015)[0.565]	(0.015)[0.567]		
$ShareSubj_{ct-1}$	1.493***	2.225***	2.194***	1.794	[1.493,12.821]
	(0.527)[0.003]	(0.652)[0.566]	(0.661)[0.568]		

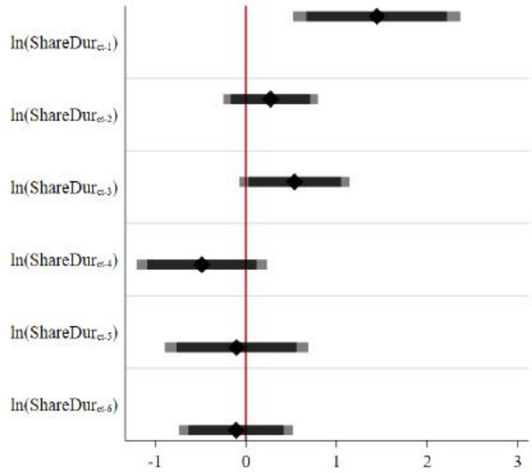
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the individual level. The set of control variables includes age, education, employment status, marital status, number of children, household size, a dummy for blue collar and income categories. Column (3) include wave 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) is related to the full model presented in column (3).
Source: Authors' elaboration on INA and ELIPSS data.

Figure C2: Lags

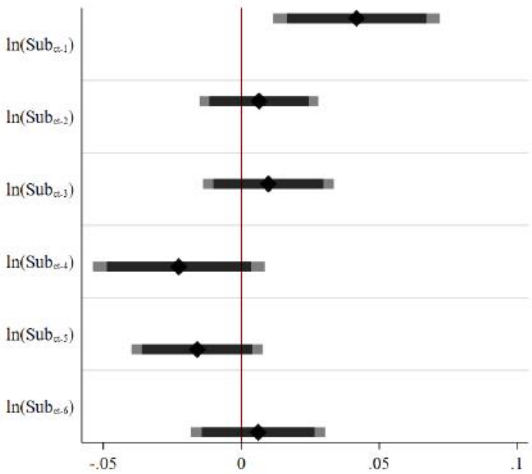
(a) $ln(Dur_{ct-1})$



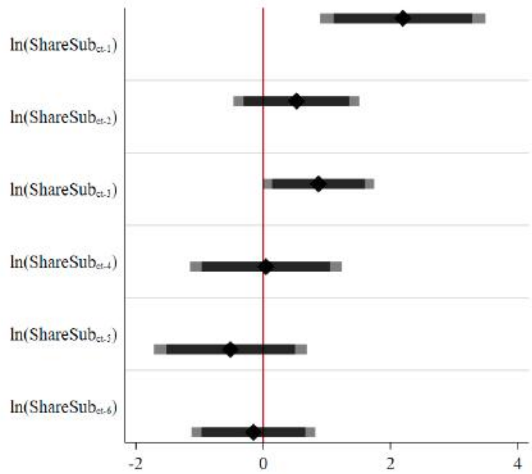
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



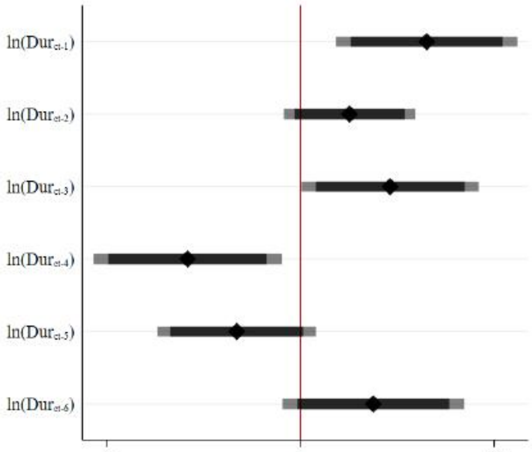
(d) $ShareSub_{ct-1}$



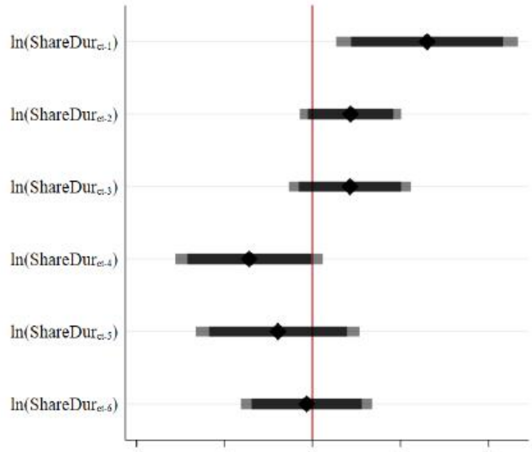
Notes: The figure shows the marginal effect of $ln(Duration_{ct-1})$, $ShareDur_{ct-1}$, $ln(Sub_{ct-1})$ and $ShareSub_{ct-1}$ as well as their lagged values on Pol_{it}, estimated separately from Eq. 5. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure C3: Distributed lag model

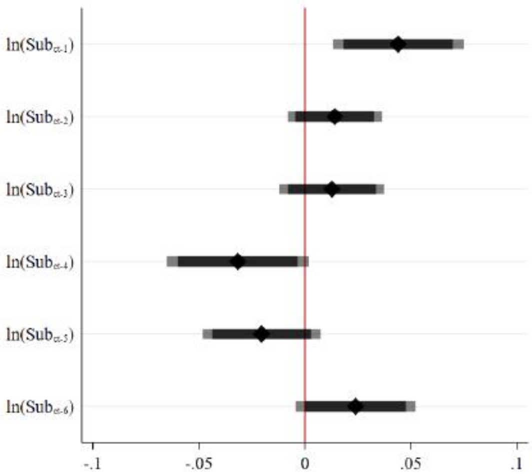
(a) $ln(Dur_{ct-1})$



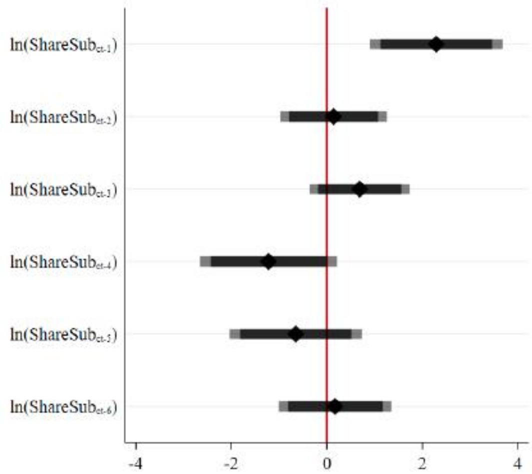
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



(d) $ShareSub_{ct-1}$

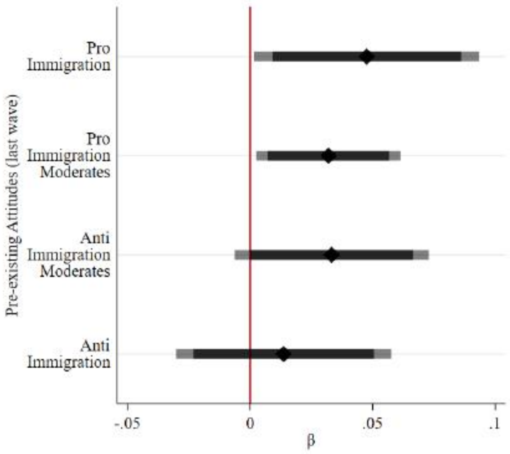


Notes: The figure shows the marginal effect of $ln(Duration_{ct-1})$, $ShareDur_{ct-1}$, $ln(Sub_{ct-1})$ and $ShareSub_{ct-1}$ as well as their lagged values on Pol_{it}, estimated simultaneously in Eq. 5. Confidence intervals are presented at the 95% and 90% level.

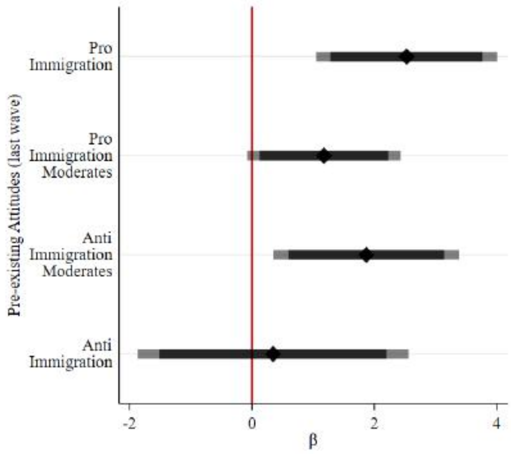
Source: Authors' elaboration on INA and ELIPSS data.

Figure C4: Interaction with preexisting attitudes, Dependent variable is Pol_{it}

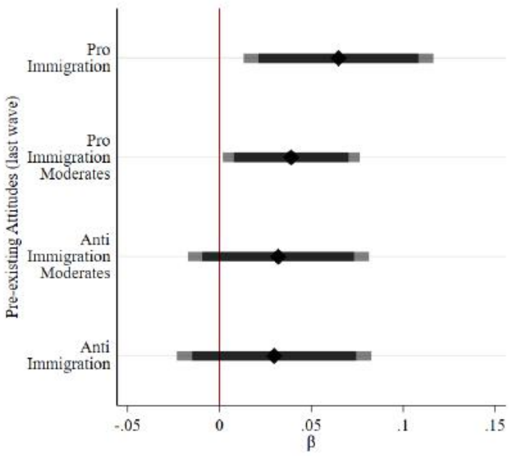
(a) $ln(Dur_{ct-1})$



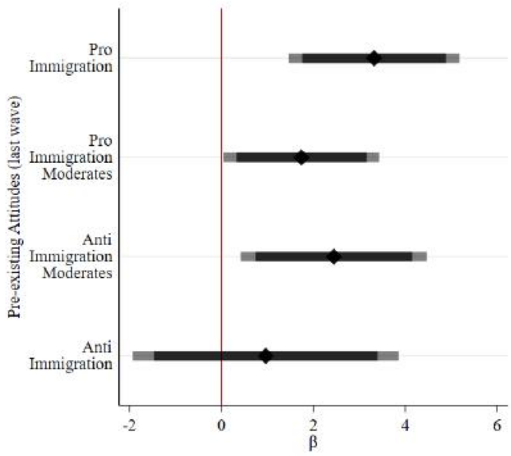
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



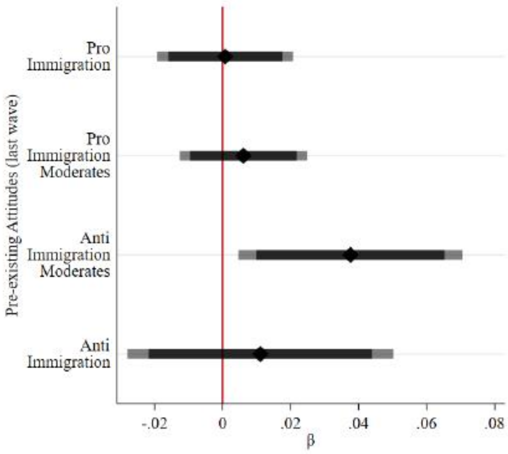
(d) $ShareSubj_{ct-1}$



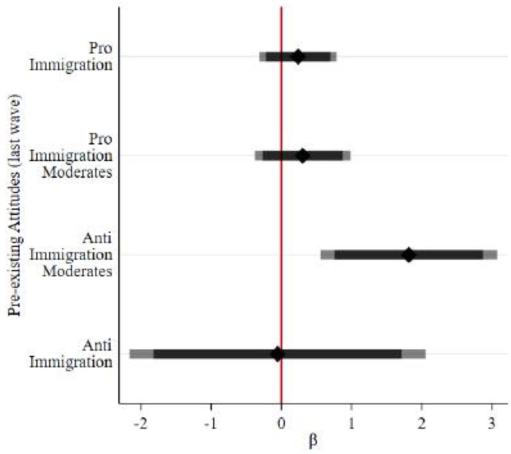
Notes: The figure shows the marginal effect of our independent variables on Pol_{it} conditional on individuals' attitudes in the last wave. Preexisting attitudes stands for whether individual i is classified as *"Pro-immigration"*, *"Pro-immigration moderate"*, *"Anti-immigration moderate"* or *"Anti-immigration"* in the previous wave. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure C5: Interaction with preexisting attitudes, Dependent variable is Anti-Pol

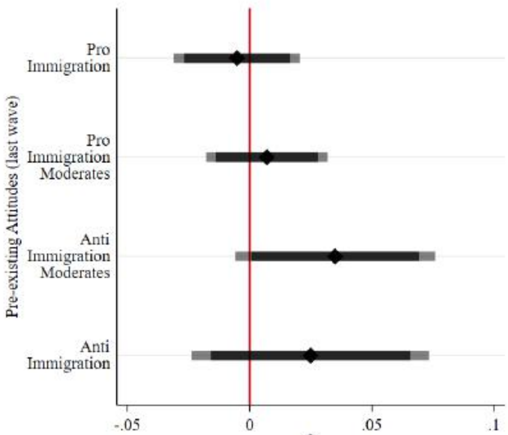
(a) $ln(Dur_{ct-1})$



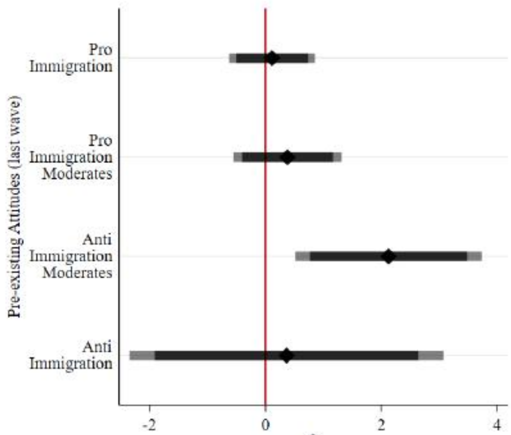
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



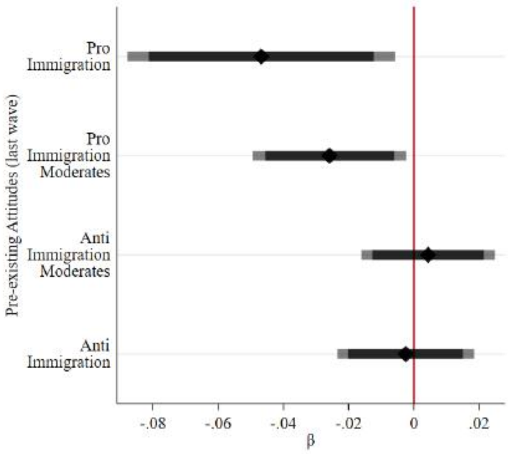
(d) $ShareSubj_{ct-1}$



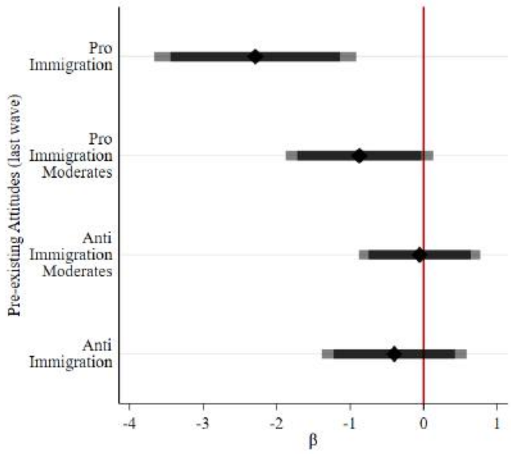
Notes: The figure shows the marginal effect of our independent variables on Anti-Pol conditional on individuals' attitudes in the last wave. Preexisting attitudes stands for whether individual i is classified as *"Pro-immigration"*, *"Pro-immigration moderate"*, *"Anti-immigration moderate"* or *"Anti-immigration"* in the previous wave. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure C6: Interaction with preexisting attitudes, Dependent variable is Pro-Pol

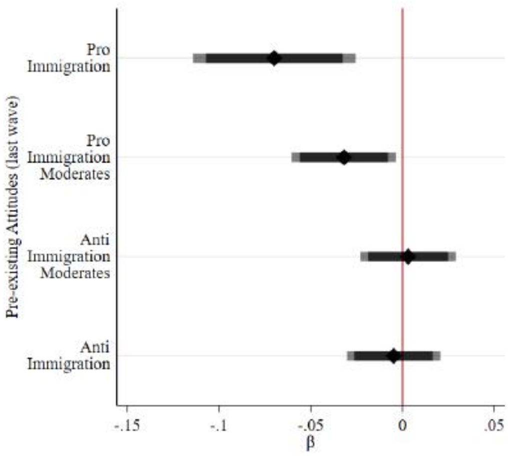
(a) $ln(Dur_{ct-1})$



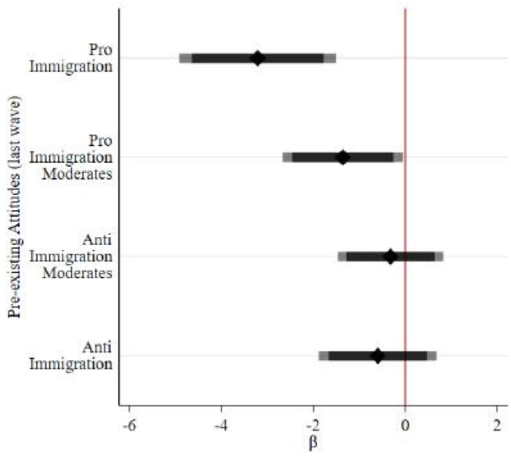
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



(d) $ShareSubj_{ct-1}$



Notes: The figure shows the marginal effect of our independent variables on Pro-Pol conditional on individuals' attitudes in the last wave. Preexisting attitudes stands for whether individual i is classified as *"Pro-immigration"*, *"Pro-immigration moderate"*, *"Anti-immigration moderate"* or *"Anti-immigration"* in the previous wave. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Table C6: Exposure to news related to muslims in immigration news.

	(1) $Attitudes_{ict}$	(2) Median	(3) Pol_{ict}	(4) Anti-Pol	(5) Pro-Pol	(6) Placebo
	Table C6 (a)					
$ln(Dur_{ct-1})$	-0.002	-0.005	0.001	-0.001	-0.002	0.003
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)
	Table C6 (b)					
$ShareDur_{ct-1}$	-0.740	-0.831	0.531	-0.242	-0.773	-0.184
	(0.881)	(0.763)	(0.952)	(0.572)	(0.747)	(1.112)
	Table C6 (c)					
$ln(Sub_{ct-1})$	-0.852	-1.569	0.388	-0.237	-0.626	0.706
	(1.369)	(1.180)	(1.487)	(0.845)	(1.209)	(1.719)
	Table C6 (d)					
$ShareSubj_{ct-1}$	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. $\times$ 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 the 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 zero for individuals with pro-immigration attitudes and one 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 the 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 C7: Baseline Estimates with only non citizens respondents.

	(1) $Attitudes_{ict}$	(2) Median	(3) Pol_{ict}	(4) Anti-Pol	(5) Pro-Pol	(6) Placebo
	Table C7 (a)					
$ln(Dur_{ct-1})$	-0.078	0.012	-0.018	-0.032	-0.014	-0.059
	(0.066)	(0.054)	(0.059)	(0.034)	(0.042)	(0.067)
	Table C7 (b)					
$ShareDur_{ct-1}$	0.537	3.518*	-1.290	-0.511	0.779	-3.251
	(2.179)	(1.969)	(2.176)	(0.765)	(2.019)	(3.026)
	Table C7 (c)					
$ln(Sub_{ct-1})$	-0.128	-0.025	-0.021	-0.048	-0.027	-0.051
	(0.078)	(0.071)	(0.076)	(0.044)	(0.049)	(0.088)
	Table C7 (d)					
$ShareSubj_{ct-1}$	-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

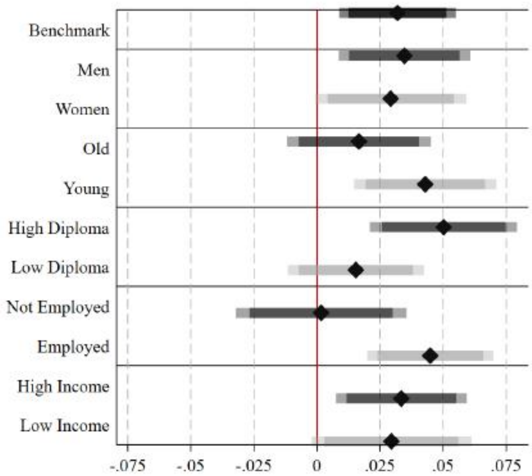
Notes: The dependent variable in column (1) is continuous and represents the average attitudes of individual i toward immigration. The dependent variable in column (2) is the median split of average attitudes. The dependent variable in column (3) is Polarization which takes the value of one for individuals 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 zero for individuals with pro-immigration attitudes and one 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 the 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.

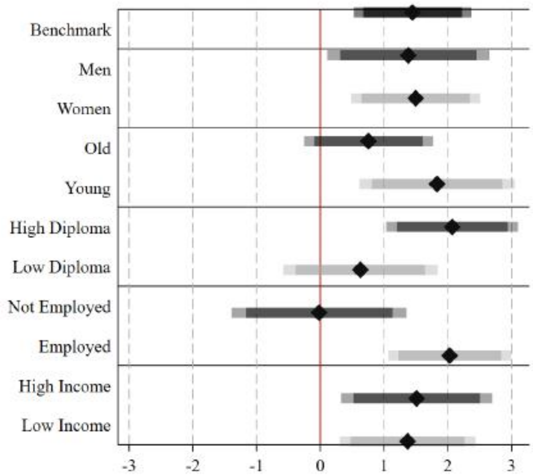
D. Heterogeneity Analysis

Figure D1: Heterogeneity Analysis, Polarization

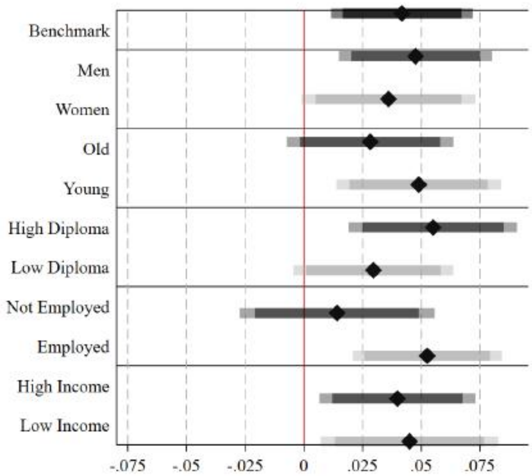
(a) $ln(Dur_{ct-1})$



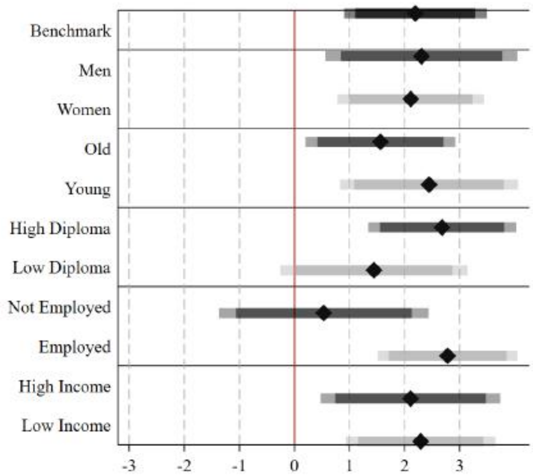
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



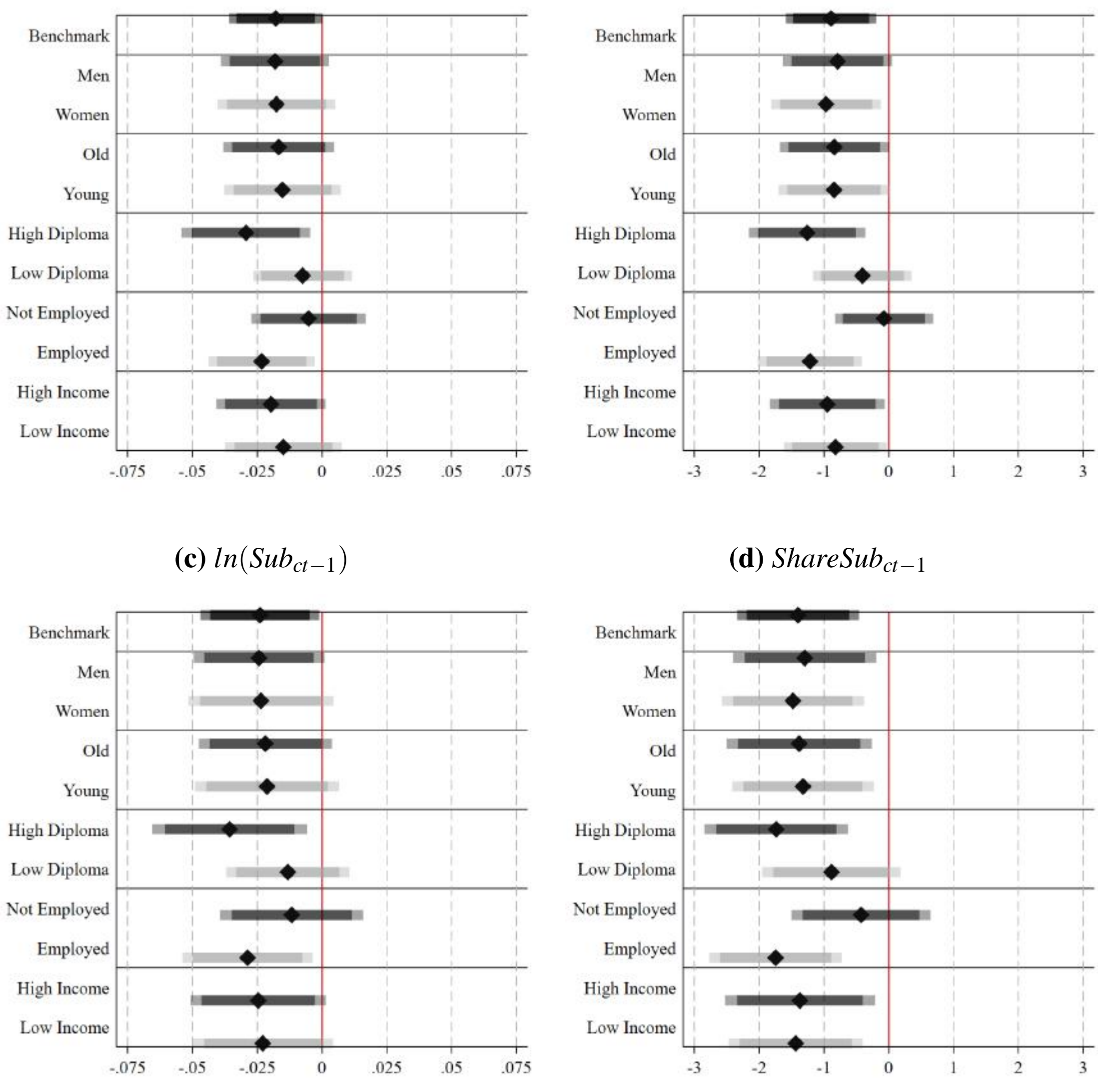
(d) $ShareSub_{ct-1}$



Notes: The figure shows the marginal effect of $ln(Duration_{ct-1})$, $ShareDur_{ct-1}$, $ln(Sub_{ct-1})$ and $ShareSub_{ct-1}$ on Polarization, estimated separately from Eq. 5. Each coefficient represents the marginal effect of the variable for a sub-group in the population as defined in Eq. 6. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure D2: Heterogeneity Analysis, Pro Polarization

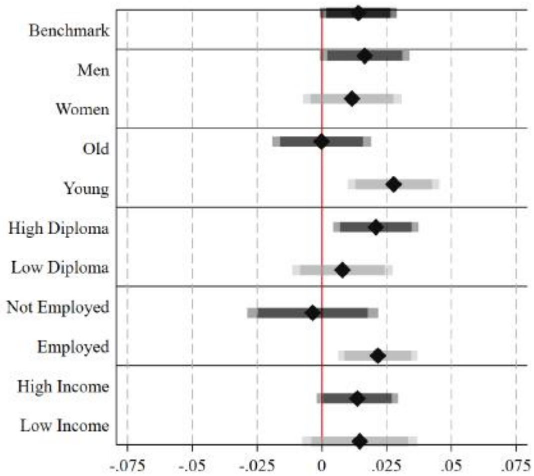
(a) $ln(Dur_{ct-1})$ **(b)** $ShareDur_{ct-1}$ **(c)** $ln(Sub_{ct-1})$ **(d)** $ShareSub_{ct-1}$



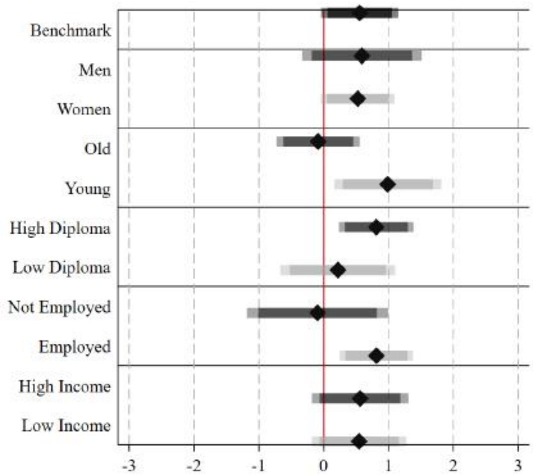
Notes: The figure shows the marginal effect of $ln(Duration_{ct-1})$, $ShareDur_{ct-1}$, $ln(Sub_{ct-1})$ and $ShareSub_{ct-1}$ on Pro Polarization, estimated separately from Eq. 5. Each coefficient represents the marginal effect of the variable for a sub-group in the population as defined in Eq. 6. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure D3: Heterogeneity Analysis, Anti Polarization

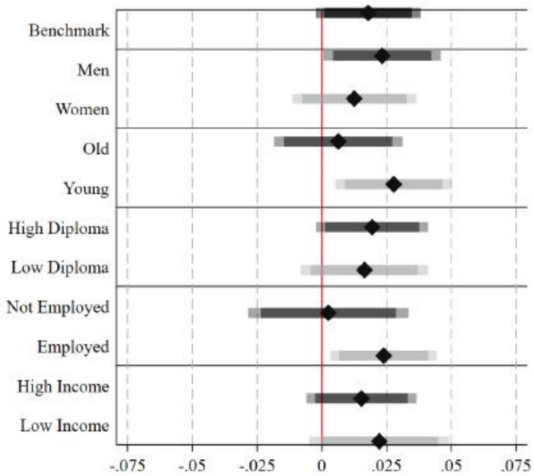
(a) $ln(Dur_{ct-1})$



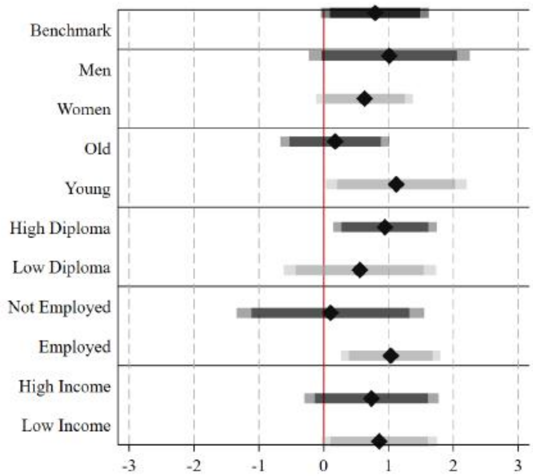
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



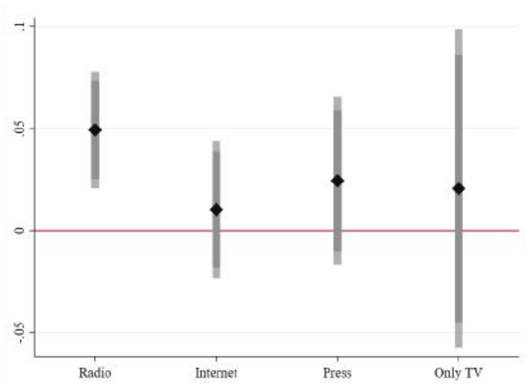
(d) $ShareSub_{ct-1}$



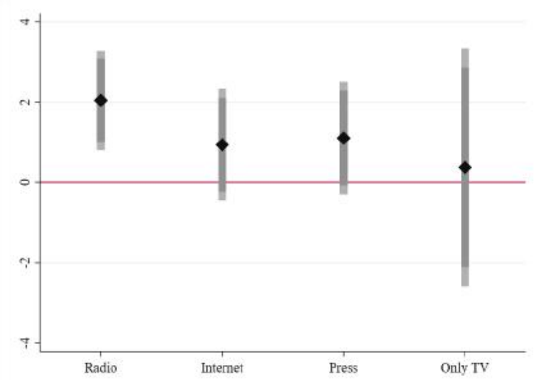
Notes: The figure shows the marginal effect of $ln(Duration_{ct-1})$, $ShareDur_{ct-1}$, $ln(Sub_{ct-1})$ and $ShareSub_{ct-1}$ on Anti Polarization, estimated separately from Eq. 5. Each coefficient represents the marginal effect of the variable for a sub-group in the population as defined in Eq. 6. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure D4: Alternative sources of information

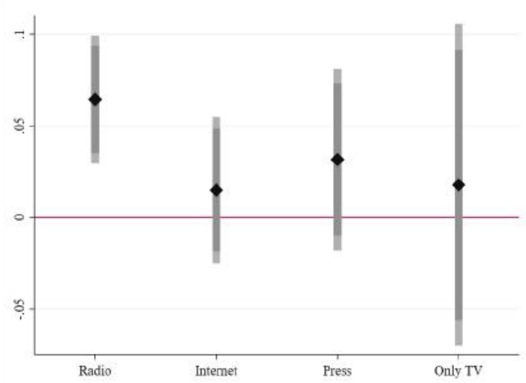
(a) $ln(Dur_{ct-1})$



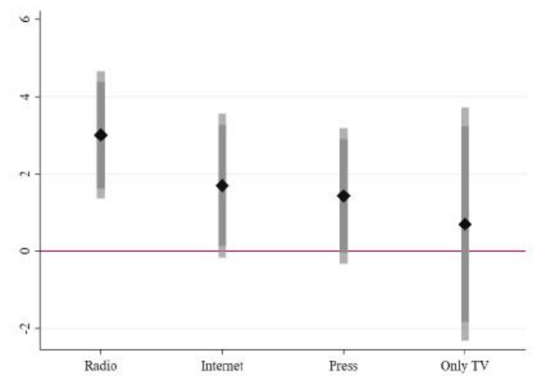
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



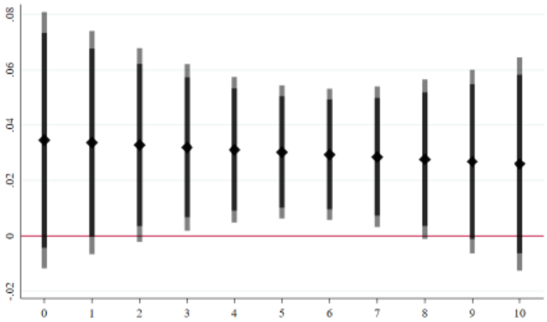
(d) $ShareSubj_{ct-1}$



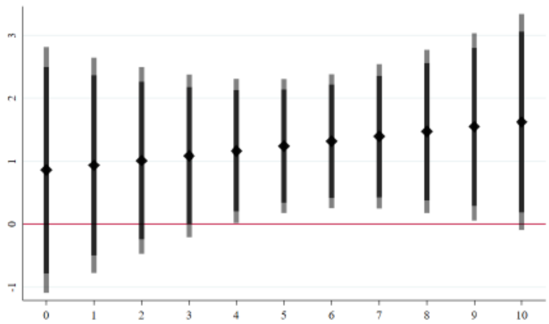
Notes: The figure shows the marginal effect of $ln(Duration_{ct-1})$, $ShareDur_{ct-1}$, $ln(Sub_{ct-1})$ and $ShareSub_{ct-1}$ on Polarization, estimated separately from Eq. 5. Each coefficient represents the marginal effect of the variable for a sub-group in the population as defined in Eq. 6, where 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% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure D5: Interaction with political affiliation, Dependent variable is Pol_{it}

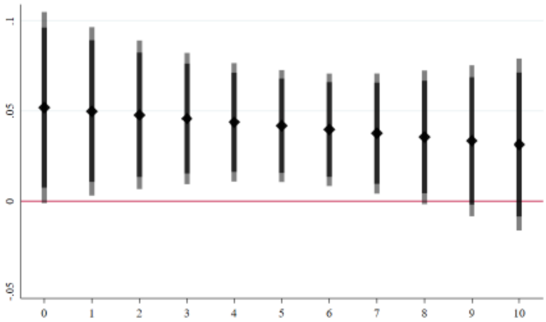
(a) $ln(Dur_{ct-1})$



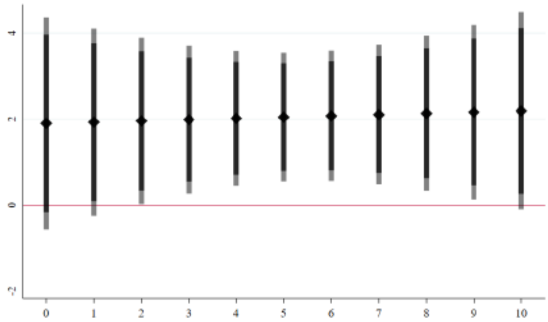
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$

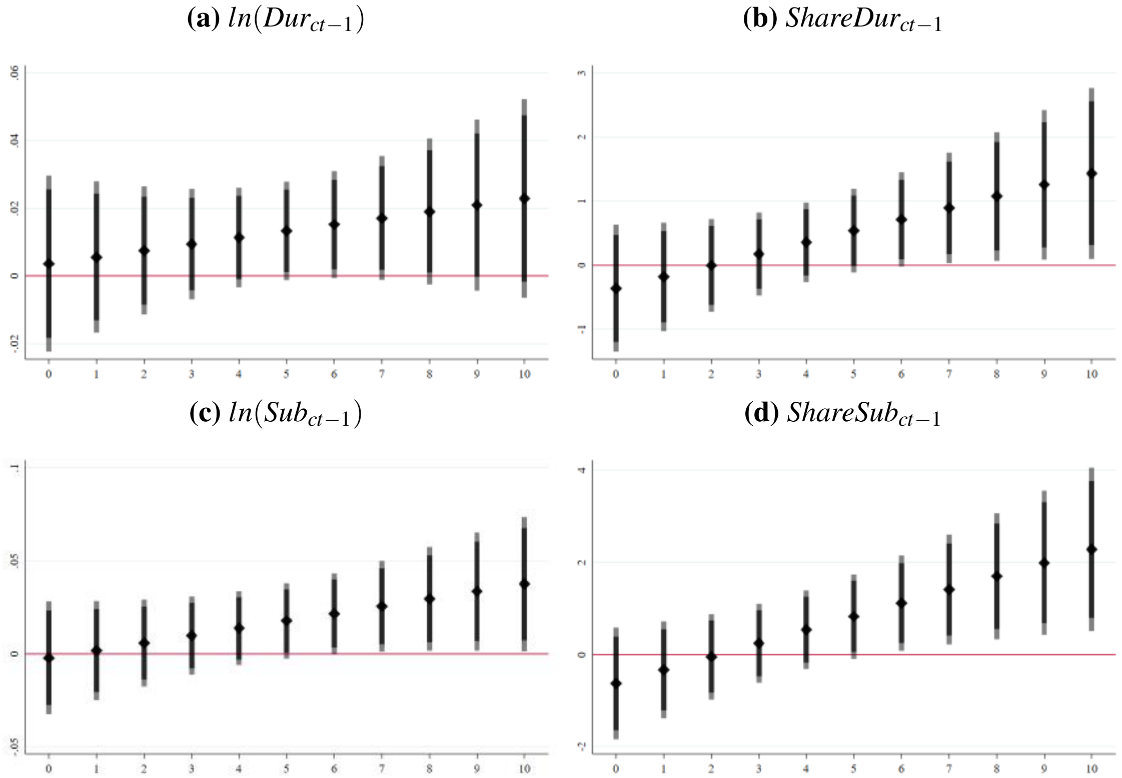


(d) $ShareSub_{ct-1}$



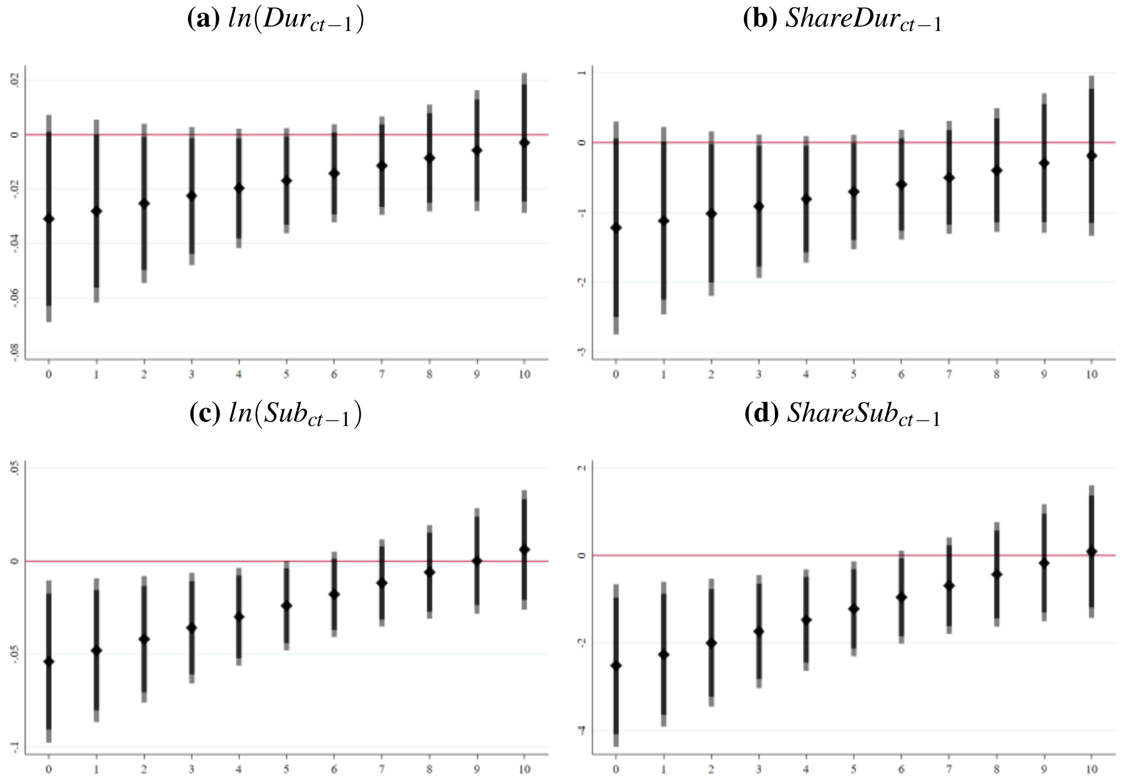
Notes: The figure shows the marginal effect of our independent variables on Polarization. Each coefficient represents the marginal effect of the variable for a given level on the political scale as defined in Eq. 6. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure D6: Interaction with political affiliation, Dependent variable is Anti-Pol



Notes: The figure shows the marginal effect of our independent variables on Anti-Pol. Each coefficient represents the marginal effect of the variable for a given level on the political scale as defined in Eq. 6. Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure D7: Interaction with political affiliation, Dependent variable is Pro-Pol



Notes: The figure shows the marginal effect of our independent variables on Pro-Pol. Each coefficient represents the marginal effect of the variable for a given level on the political scale as defined in Eq. 6. Confidence intervals are presented at the 95% and 90% level.

Source: Authors' elaboration on INA and ELIPSS data.

E. 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.

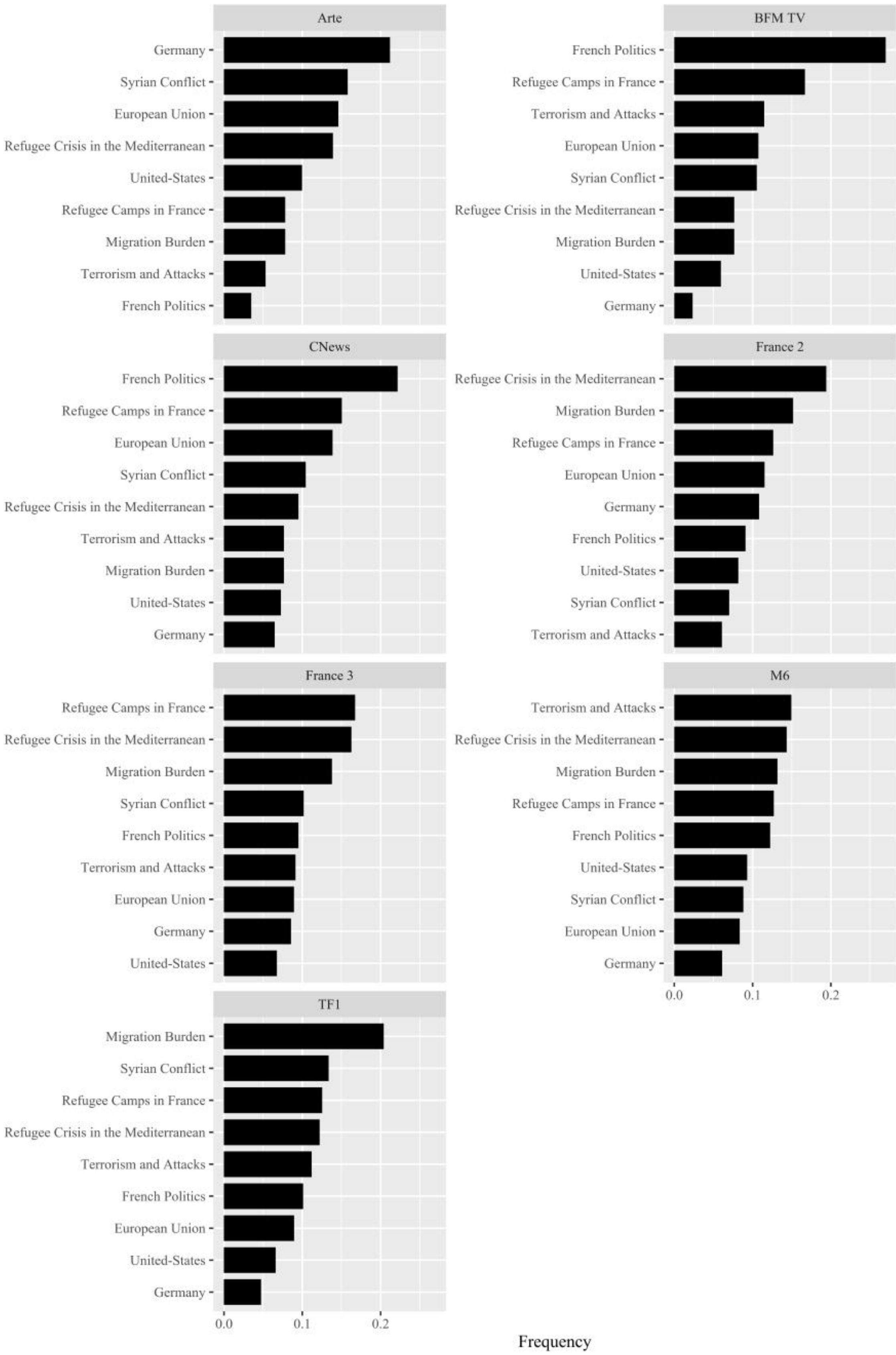
Topics

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 name of topics were chosen by the authors for interpretability.
Source: Authors' elaboration on INA data

Figure E1: Topics' frequency by channels



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 name of topics were chosen by the authors for interpretability, but the top words identified in each topics are displayed in Table E1.
Source: Authors' elaboration on INA data.

Table E2: Share of topics 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
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 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 name of topics were chosen by the authors for interpretability, but the top words identified in each topics are displayed in Table E1.
Source: Authors' elaboration on INA data.

Table E3: Salience effect by topics

Migration Salience	$ln(Dur_{ct-1})$			$ShareDur_{ct-1}$			$ln(Sub_{ct-1})$			$ShareSubj_{ct-1}$		
	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol	(4) Pol_{ict}	(5) Anti-Pol	(6) Pro-Pol	(7) Pol_{ict}	(8) Anti-Pol	(9) Pro-Pol	(10) Pol_{ict}	(11) Anti-Pol	(12) Pro-Pol
Terrorism and Attacks	-0.001	0.001	0.002	0.094	0.518	0.427	-0.001	0.007	0.008	1.241	1.955	0.810
	(0.008)	(0.006)	(0.006)	(1.798)	(1.039)	(1.452)	(0.010)	(0.007)	(0.007)	(2.243)	(1.451)	(1.776)
French Politics	0.024***	0.015***	-0.009	0.931	1.214*	0.343	0.037***	0.017**	-0.020**	4.594***	3.232***	-1.359
	(0.008)	(0.006)	(0.005)	(0.947)	(0.627)	(0.733)	(0.012)	(0.008)	(0.009)	(1.780)	(1.179)	(1.349)
Germany	-0.008	-0.006	0.003	-0.609	-1.995**	-1.363	-0.022*	-0.012	0.011	-0.074	-1.137	-1.003
	(0.009)	(0.006)	(0.007)	(1.786)	(0.919)	(1.495)	(0.013)	(0.008)	(0.010)	(1.902)	(0.895)	(1.724)
European Union	0.021*	0.008	-0.012	5.784**	2.029	-3.769*	0.012	-0.000	-0.012	1.927	-1.682	-3.662
	(0.011)	(0.007)	(0.009)	(2.621)	(1.518)	(2.047)	(0.014)	(0.009)	(0.011)	(3.048)	(1.507)	(2.490)
Refugee Camps in France	0.010	0.006	-0.005	2.046	0.990	-1.063	0.025**	0.018**	-0.006	5.340***	2.729**	-2.570*
	(0.008)	(0.005)	(0.006)	(1.526)	(1.018)	(1.153)	(0.012)	(0.009)	(0.009)	(1.893)	(1.289)	(1.429)
United States	0.008	-0.007	-0.015**	1.260	-0.955	-2.231	0.005	-0.010	-0.015	1.591	-1.393	-3.026
	(0.009)	(0.006)	(0.006)	(2.283)	(1.615)	(1.622)	(0.013)	(0.009)	(0.009)	(3.114)	(2.143)	(2.303)
Refuge Crisis in the Med.	0.008	0.011**	0.004	0.696	0.991	0.355	0.004	0.010	0.007	0.739	0.186	-0.510
	(0.008)	(0.005)	(0.006)	(1.961)	(1.039)	(1.638)	(0.012)	(0.008)	(0.009)	(2.704)	(1.354)	(2.175)
Syrian Conflict	-0.013	-0.009	0.004	-2.520	-1.702	0.694	-0.004	0.001	0.005	-0.304	1.182	1.449
	(0.010)	(0.006)	(0.008)	(2.304)	(1.482)	(1.750)	(0.013)	(0.008)	(0.010)	(2.861)	(1.606)	(2.268)
Migration Burden	0.030***	0.009*	-0.021***	5.034***	2.052**	-2.989***	0.039***	0.009	-0.030***	7.245***	2.669**	-4.604***
	(0.008)	(0.005)	(0.006)	(1.351)	(0.879)	(1.044)	(0.010)	(0.007)	(0.008)	(1.965)	(1.306)	(1.505)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indiv. × Channel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb. Observations	6776	6776	6776	6776	6776	6776	6776	6776	6776	6776	6776	6776
Adjusted R^2	0.453	0.561	0.586	0.453	0.560	0.586	0.453	0.560	0.586	0.453	0.560	0.586

Notes: The dependent variable in columns (1), (4), (7), and (10) 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 columns (2), (5), (8), and (11) 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), and (12) is a dummy equal to zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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, $ln(Dur_{ct-1})$

Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
France	Refugee Camps in France	0.021***	0.011***	-0.010***
	French Politics	(0.005)	(0.003)	(0.003)
	Migration Burden			
Foreign	European Union	0.001	-0.007*	-0.007*
	Germany	(0.005)	(0.004)	(0.004)
	United-States			
Other	Refugee Crisis Med.	0.003	0.003	0.001
	Terrorism	(0.004)	(0.003)	(0.003)
	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		0.453	0.561	0.586

Notes: The dependent variable in column (1) is Polarization which 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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 E5: Topic analysis, $ShareDur_{ct-1}$

Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
France	Refugee Camps in France	2.591***	1.597***	-0.994**
	French Politics	(0.639)	(0.451)	(0.459)
	Migration Burden			
Foreign	European Union	0.513	-1.075*	-1.589*
	Germany	(1.074)	(0.632)	(0.849)
	United-States			
Other	Refugee Crisis Med.	0.360	0.466	0.106
	Terrorism	(0.977)	(0.539)	(0.818)
	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		0.453	0.560	0.586

Notes: The dependent variable in column (1) is Polarization which 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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 E6: Topic analysis, $ln(Sub_{ct-1})$

Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
France	Refugee Camps in France French Politics Migration Burden	0.033*** (0.007)	0.015*** (0.005)	-0.017*** (0.006)
Foreign	European Union Germany United-States	-0.002 (0.007)	-0.008* (0.004)	-0.006 (0.005)
Other	Refugee Crisis Med. Terrorism Syrian	0.002 (0.005)	0.005 (0.004)	0.003 (0.004)
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		0.452	0.560	0.586

Notes: The dependent variable in column (1) is Polarization which 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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 E7: 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 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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 E8: Topic analysis, alternative grouping, $ln(Dur_{ct-1})$

Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
Migration Burden		0.025***	0.007	-0.018***
		(0.007)	(0.005)	(0.006)
France	Refugee Camps in France	0.020***	0.013***	-0.007**
	French Politics	(0.005)	(0.004)	(0.004)
Foreign	European Union	0.001	-0.007**	-0.008**
	Germany	(0.006)	(0.004)	(0.004)
	United-States			
Other	Refugee Crisis Med.	0.002	0.004	0.002
	Terrorism	(0.004)	(0.003)	(0.003)
	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		0.453	0.561	0.586

Notes: The dependent variable in column (1) is Polarization which 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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 E9: Topic analysis, alternative grouping, $ShareDur_{ct-1}$

Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
Migration Burden		4.978***	2.027**	-2.951***
		(1.302)	(0.855)	(1.006)
France	Refugee Camps in France	1.735**	1.443***	-0.292
	French Politics	(0.712)	(0.498)	(0.514)
Foreign	European Union	1.285	-0.936	-2.222**
	Germany	(1.144)	(0.660)	(0.921)
	United-States			
Other	Refugee Crisis Med.	-0.006	0.400	0.406
	Terrorism	(0.975)	(0.541)	(0.817)
	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		0.453	0.560	0.586

Notes: The dependent variable in column (1) is Polarization which 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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 E10: Topic analysis, alternative grouping, $ln(Subj_{ct-1})$

Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
Migration Burden		0.033***	0.008	-0.024***
		(0.010)	(0.006)	(0.007)
France	Refugee Camps in France	0.033***	0.018***	-0.014***
	French Politics	(0.008)	(0.006)	(0.005)
Foreign	European Union	-0.002	-0.009**	-0.007
	Germany	(0.007)	(0.004)	(0.005)
	United-States			
Other	Refugee Crisis Med.	0.002	0.006	0.004
	Terrorism	(0.006)	(0.004)	(0.004)
	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		0.453	0.561	0.586

Notes: The dependent variable in column (1) is Polarization which 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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 E11: Topic analysis, alternative grouping, $ShareSubj_{ct-1}$

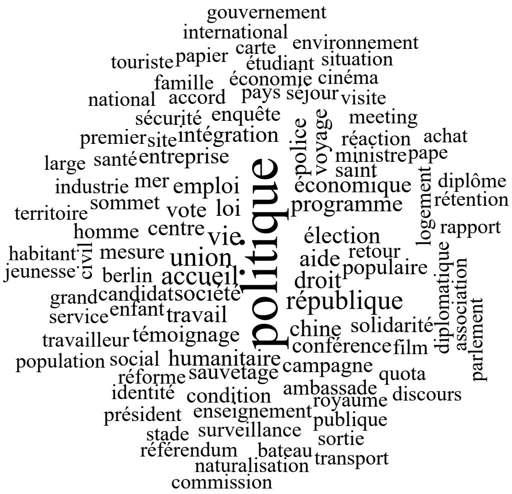
Categories	Topics	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol
Migration Burden		7.122***	2.698**	-4.424***
		(1.869)	(1.263)	(1.408)
France	Refugee Camps in France	4.964***	2.873***	-2.091**
	French Politics	(1.242)	(0.901)	(0.876)
Foreign	European Union	0.741	-1.288**	-2.029**
	Germany	(1.122)	(0.610)	(0.904)
	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 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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.

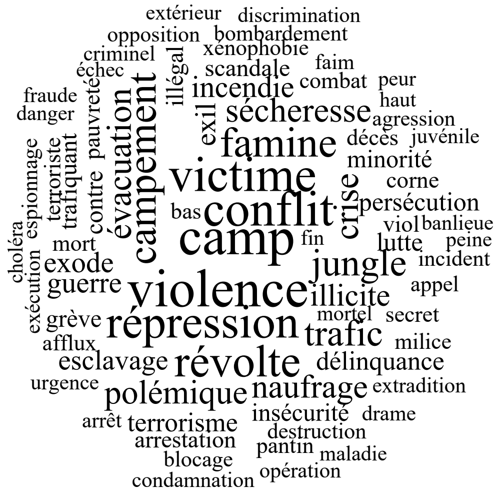
Sentiment analysis

Figure E2: Most frequent words in the sentiment analysis of migration subjects

(a) In the top 500 of positive subjects



(b) In the top 500 of negative subjects



Notes: Figure E2a represents the most frequent positive tokens from the FEEL lexicon in the top 500 of positive migration subject. Figure E2b 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 E12: 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
Positive-Negative	0.111	0.097	0.122	0.096	0.098	0.100	0.097	0.109	0.136	0.115
Positive	0.175	0.167	0.181	0.141	0.151	0.150	0.147	0.178	0.209	0.197
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 of 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 E2 in the main document. A positive sentiment is computed at the number of positive words identified over the total number of words in the migration subject. Other variables are computed similarly. The first row is the average share of Postive-Negative words (computed within each subject) in migration subjects.
Source: Authors' elaboration on INA data.

Table E13: Sentiment Analysis

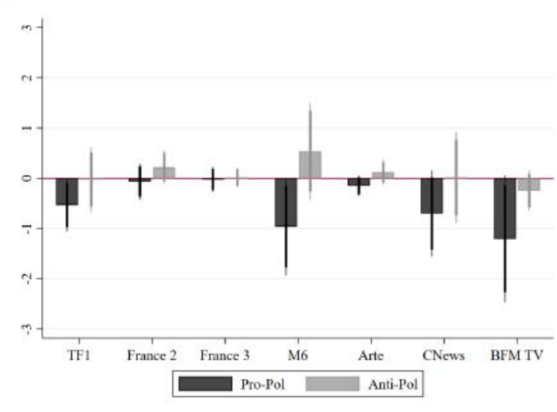
	(1) Pol_{ict}	(2) Anti-Pol	(3) Pro-Pol	(4) Pol_{ict}	(5) Anti-Pol	(6) Pro-Pol	(7) Pol_{ict}	(8) Anti-Pol	(9) Pro-Pol
$ln(Dur_{ct-1})$	0.031***	0.014*	-0.017*	0.034***	0.015**	-0.019**	0.028**	0.014*	-0.014
	(0.012)	(0.008)	(0.009)	(0.012)	(0.007)	(0.009)	(0.012)	(0.008)	(0.009)
Sent. Score	0.254**	0.085	-0.168**						
	(0.099)	(0.067)	(0.074)						
Share of positive				0.337**	0.179	-0.157			
				(0.162)	(0.111)	(0.120)			
Share of negative							-0.316*	-0.028	0.288**
							(0.161)	(0.105)	(0.125)
$ShareDur_{ct-1}$	1.350***	0.522*	-0.828**	1.461***	0.562*	-0.899**	1.305***	0.540*	-0.765**
	(0.470)	(0.301)	(0.356)	(0.472)	(0.303)	(0.356)	(0.471)	(0.302)	(0.357)
Sent. Score	0.235**	0.079	-0.156**						
	(0.097)	(0.066)	(0.074)						
Share of positive				0.293*	0.159	-0.134			
				(0.162)	(0.112)	(0.119)			
Share of negative							-0.305**	-0.030	0.274**
							(0.155)	(0.102)	(0.121)
$ln(Sub_{ct-1})$	0.040***	0.017*	-0.023**	0.046***	0.020*	-0.026**	0.037**	0.017*	-0.019
	(0.015)	(0.010)	(0.012)	(0.015)	(0.010)	(0.012)	(0.016)	(0.011)	(0.012)
Sent. Score	0.255**	0.086	-0.169**						
	(0.099)	(0.067)	(0.074)						
Share of positive				0.359**	0.188*	-0.171			
				(0.162)	(0.110)	(0.121)			
Share of negative							-0.300*	-0.022	0.278**
							(0.162)	(0.106)	(0.125)
$ShareSubj_{ct-1}$	2.033***	0.737*	-1.296***	2.177***	0.782*	-1.395***	2.008***	0.779*	-1.229**
	(0.663)	(0.424)	(0.481)	(0.662)	(0.424)	(0.480)	(0.663)	(0.425)	(0.482)
Sent. Score	0.213**	0.072	-0.141*						
	(0.098)	(0.066)	(0.074)						
Share of positive				0.270*	0.150	-0.119			
				(0.162)	(0.112)	(0.119)			
Share of negative							-0.268*	-0.019	0.249**
							(0.155)	(0.102)	(0.121)
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	0.45	0.56	0.59	0.45	0.56	0.60	0.45	0.56	0.59

Notes: The dependent variable in columns (1), (4), and (7) is Polarization which takes the value of 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 zero for individuals with pro-immigration attitudes and one otherwise (anti-immigration, pro- and anti-immigration moderates). All estimates include wave and individual-channel fixed effects. The vector of time-varying controls includes the 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.

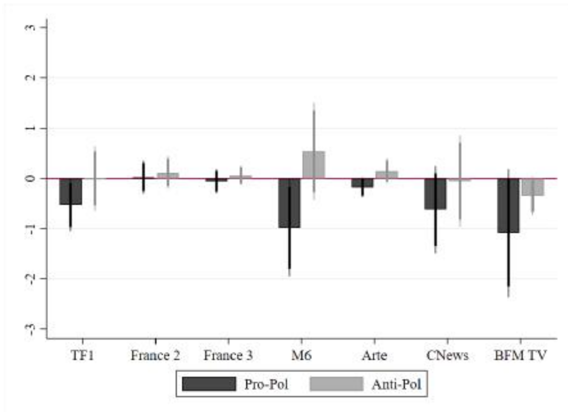
Source: Authors elaboration on INA and ELIPSS data.

Figure E3: Sentiment Analysis, Positive - Negative

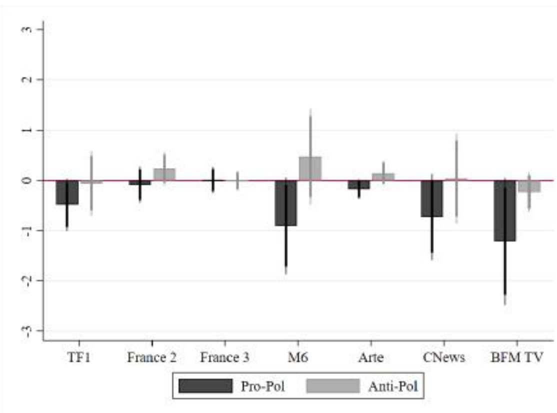
(a) $ln(Dur_{ct-1})$



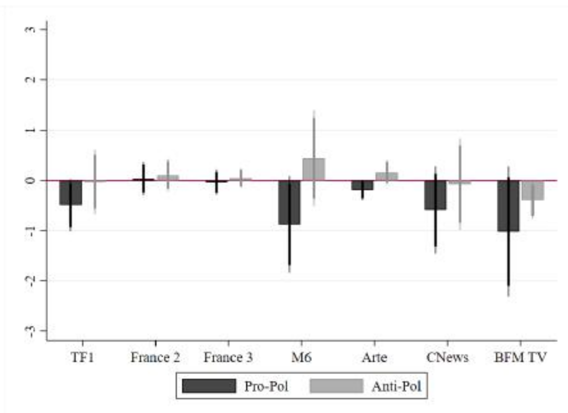
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



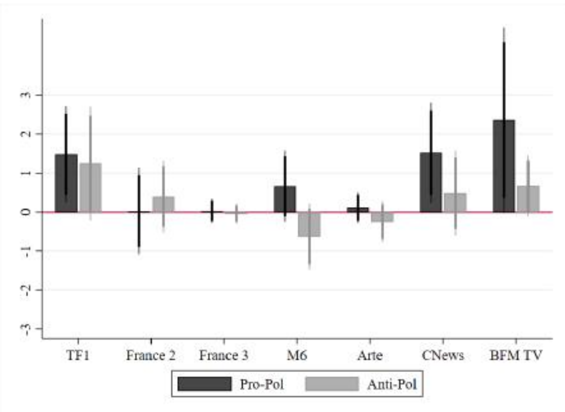
(d) $ShareSub_{ct-1}$



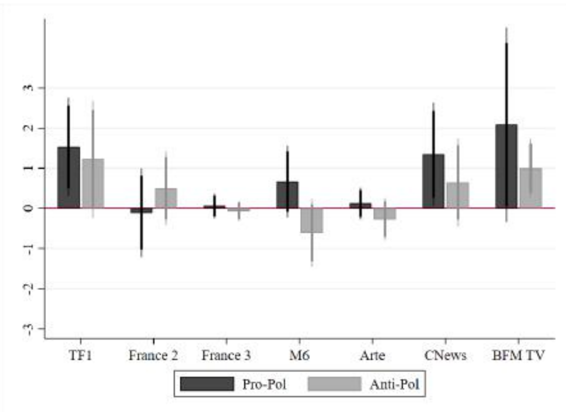
Notes: The figure shows the marginal effect of our independent variables on Pro-Pol and Anti-Pol respectively. Each coefficient represents the marginal effect of the variable for a given channel in the population as defined in Eq. 6. The vertical lines are 90% and 95% confidence intervals.
Source: Authors' elaboration on INA and ELIPSS data.

Figure E4: Sentiment Analysis, Negative

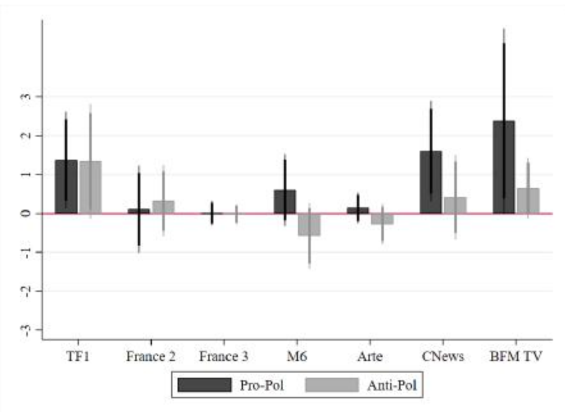
(a) $ln(Dur_{ct-1})$



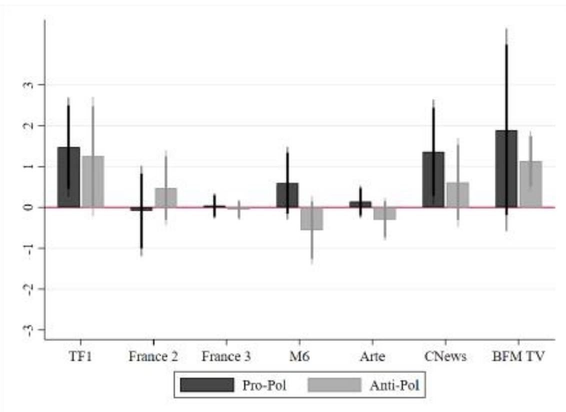
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



(d) $ShareSub_{ct-1}$

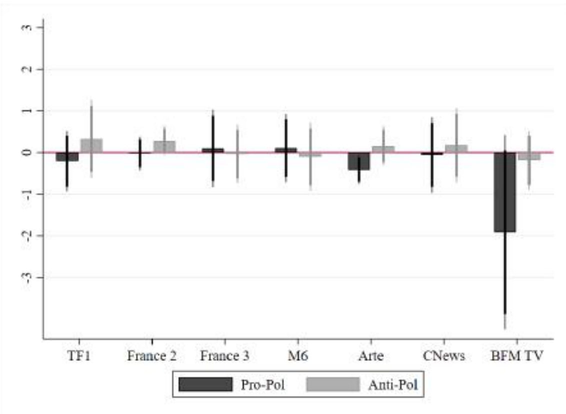


Notes: The figure shows the marginal effect of our independent variables on Pro-Pol and Anti-Pol respectively. Each coefficient represents the marginal effect of the variable for a given channel in the population as defined in Eq. 6. The vertical lines are 90% and 95% confidence intervals.

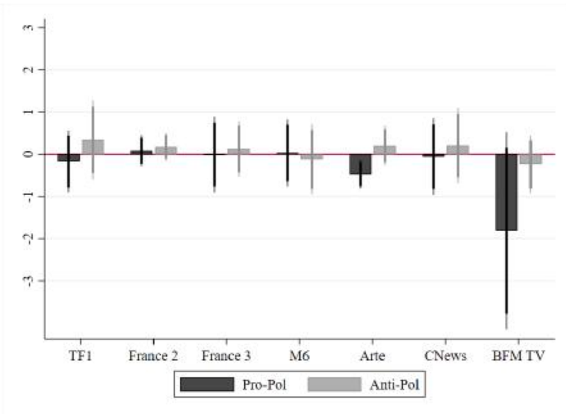
Source: Authors' elaboration on INA and ELIPSS data.

Figure E5: Sentiment Analysis, Positive

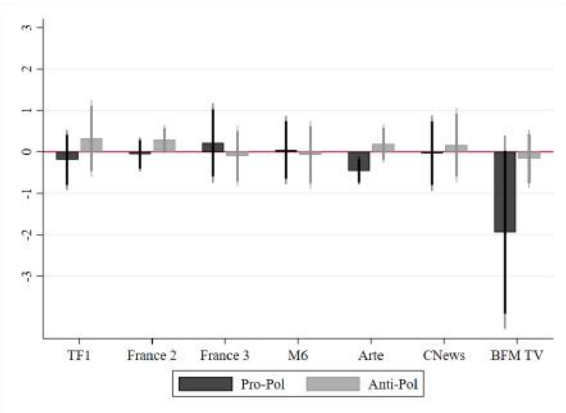
(a) $ln(Dur_{ct-1})$



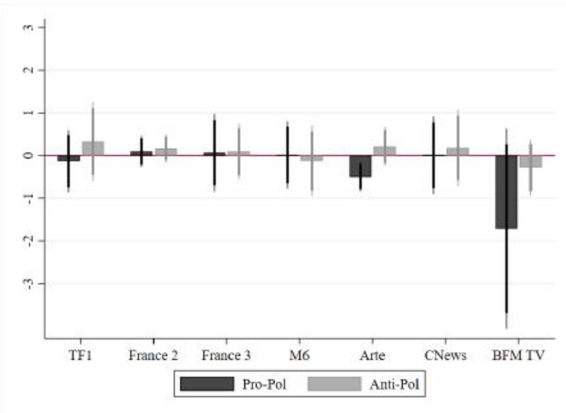
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



(d) $ShareSub_{ct-1}$



Notes: The figure shows the marginal effect of our independent variables 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. 6. The vertical lines are 90% and 95% confidence intervals.
Source: Authors' elaboration on INA and ELIPSS data.

F. Political Analysis

We extend our analysis to check whether an increase in the salience of immigration affects individuals' probability to vote for a given party. Indeed, while we have already seen that polarization is conditional on individuals' self-declared political affiliation (on 10-point left-right scale), we wish to check whether priming migration in the media also makes individuals at the center of the political spectrum more likely to vote for extreme parties.

We employ additional information provided in the ELIPSS surveys on the individual likelihood to vote for a given party on a 10-point scale.[43] Unfortunately, such questions are not asked for all the parties in all waves due to a recomposition of the political offerings in France in the end of our period of analysis. Thus, we concentrate our analysis on historical political parties for which we have a sufficient number of observations. Political parties are classified between far-right, right, left and far-left according to their positioning on the political spectrum as well as their correlation with our variable of attitudes 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.

In the rest of the analysis, we attempt to identify switches from the center (MODEM and UDI) to left (PS), far-left (PG and NPA), right (UMP) and far-right (FN and DLF) parties when the salience of immigration increases, which would corroborate our previous findings. Then, we replicate the analysis for switching from left and right to far-left and far-right parties respectively. Finally, we more closely examine the Green party (EELV) that presents strong correlations with individual attitudes toward immigration as reported in Table F1. For all estimates, we report from Figures F1 to F18 the probability that a respondent will vote for a more extreme party when the salience of immigration increases, conditional on his/her political affiliation with each party in the last wave.

Our results report that a rise in the salience of immigration significantly increases the likelihood of an individual affiliated with right and/or the center to vote for far-right parties. This echoes our main results that individuals with moderate attitudes tend to switch to extreme attitudes when immigration is primed. The picture is less clear at the other

[43] Note that these variables do not capture the real vote of an individual for a given party but represent good proxies for individuals' ideological proximity to each party.

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

		Far-left		Left	Green Pol.	Center		Right	Far-right	
	$Attitudes_{ict}$	NPA	PG	PS	EELV	MODEM	UDI	UMP	DLF	FN
$Attitudes_{ict}$	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. $Attitudes_{ict}$ is a continuous variable and represents the average attitudes of individual i toward immigration.
Sources: Authors elaboration on ELIPSS data.

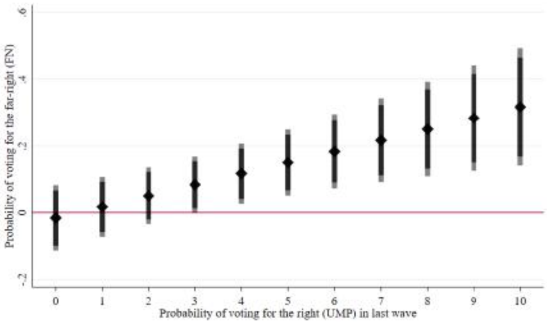
end of the political spectrum. On the one hand, we do not find significant relationships between center and left affiliations and the likelihood to vote for the far-left when the salience of immigration increases. However, this is consistent with the observation that these parties do not present high correlations with individuals’ attitudes toward immigration in Table F1. On the other hand, we find evidence that priming immigration increases the likelihood of individuals close to the center to vote for the left or green parties, the two parties with the highest correlation with pro-immigration attitudes.[44] Overall, these results corroborate our previous findings that an increase in the salience of immigration increases the polarization of society and induces political reshaping: those parties for which the correlation with attitudes toward immigration is the strongest benefit the most from these shifts.

[44] 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.

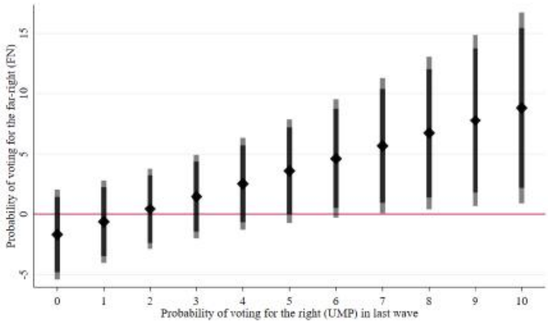
Probability to switch from center and right or far-right

Figure F1: Switching parties from right (UMP) to far-right (FN)

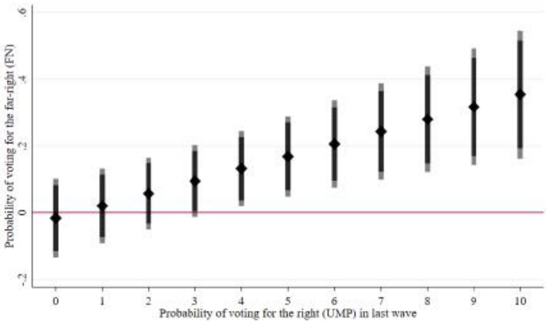
(a) $ln(Dur_{ct-1})$



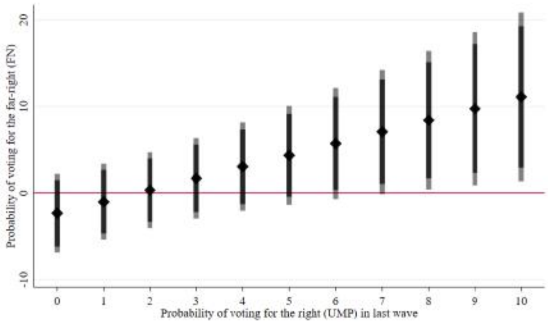
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



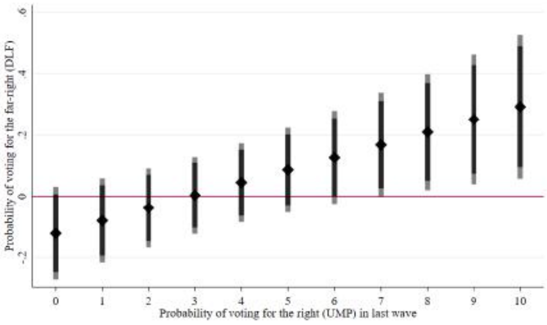
(d) $ShareSub_{ct-1}$



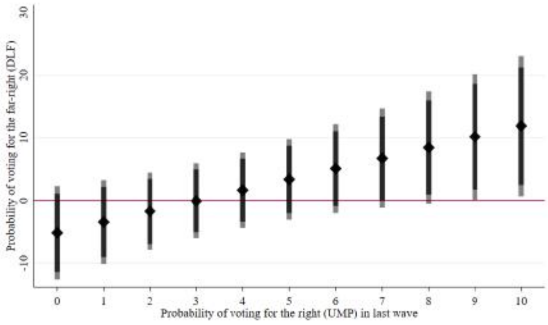
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F2: Switching parties from right (UMP) to far-right (DLF)

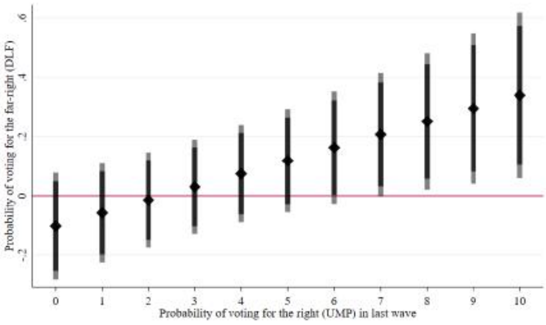
(a) $ln(Dur_{ct-1})$



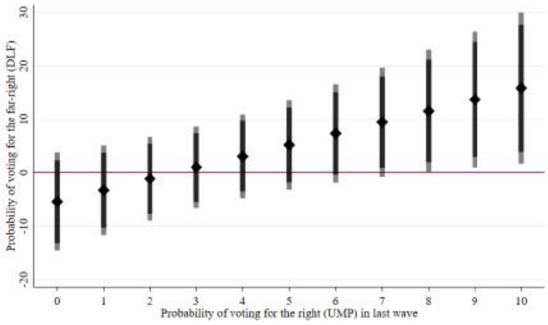
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



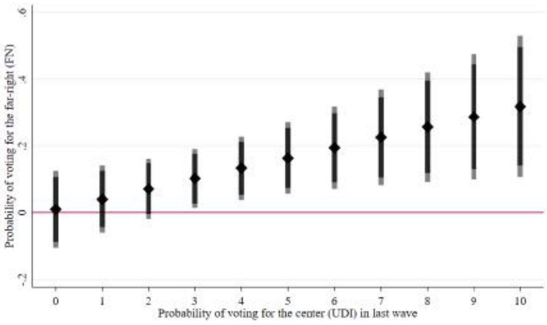
(d) $ShareSub_{ct-1}$



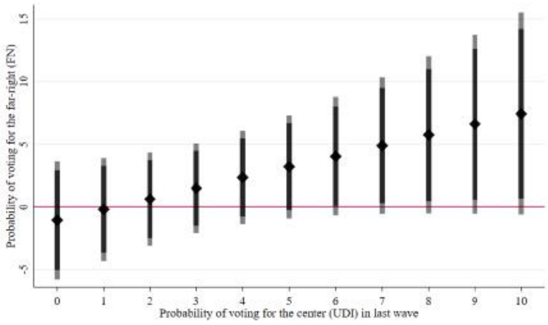
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F3: Switching parties from right (UDI) to far-right (FN)

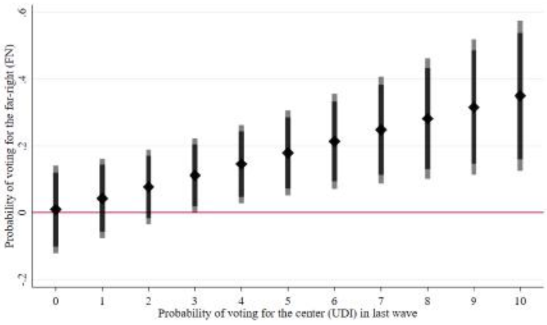
(a) $ln(Dur_{ct-1})$



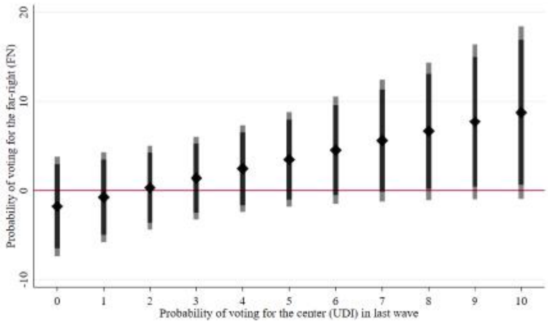
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



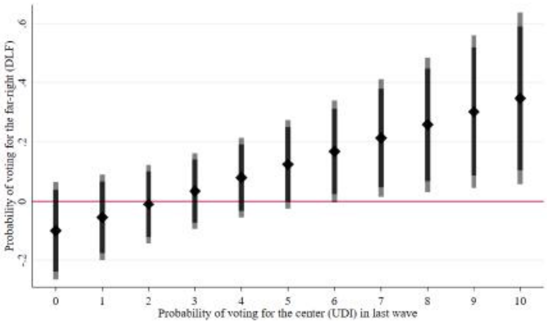
(d) $ShareSub_{ct-1}$



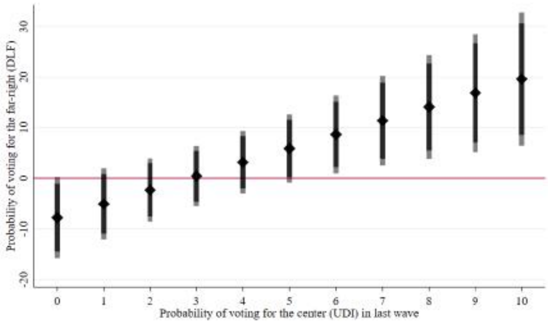
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F4: Switching parties from right (UDI) to far-right (DLF)

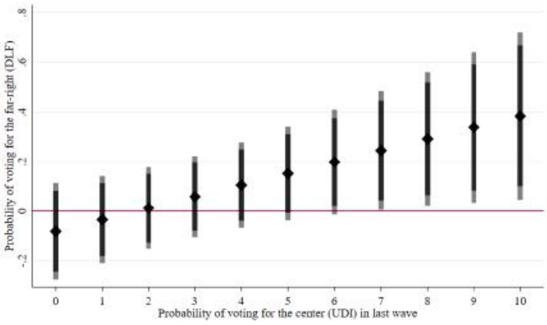
(a) $ln(Dur_{ct-1})$



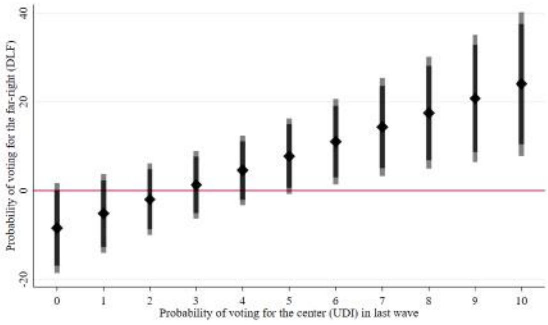
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



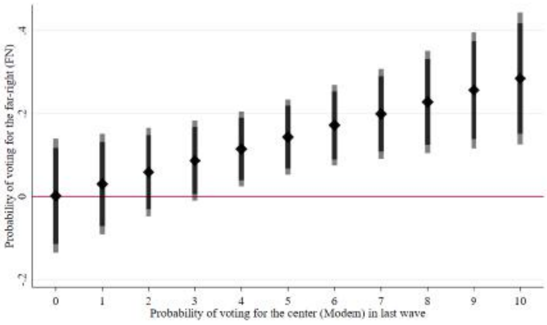
(d) $ShareSub_{ct-1}$



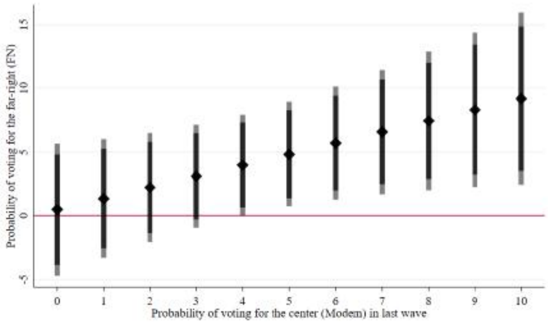
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F5: Switching parties from right (MODEM) to far-right (FN)

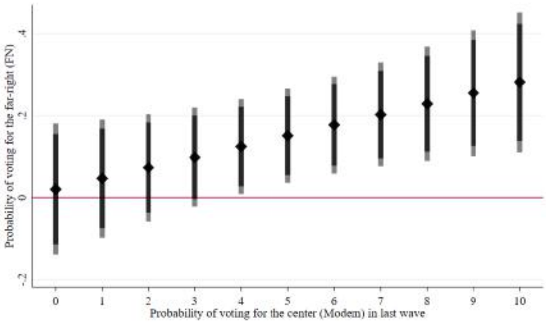
(a) $ln(Dur_{ct-1})$



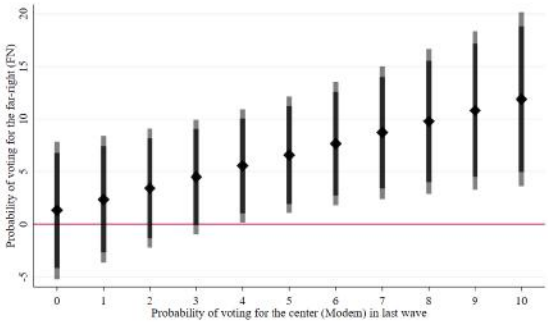
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$

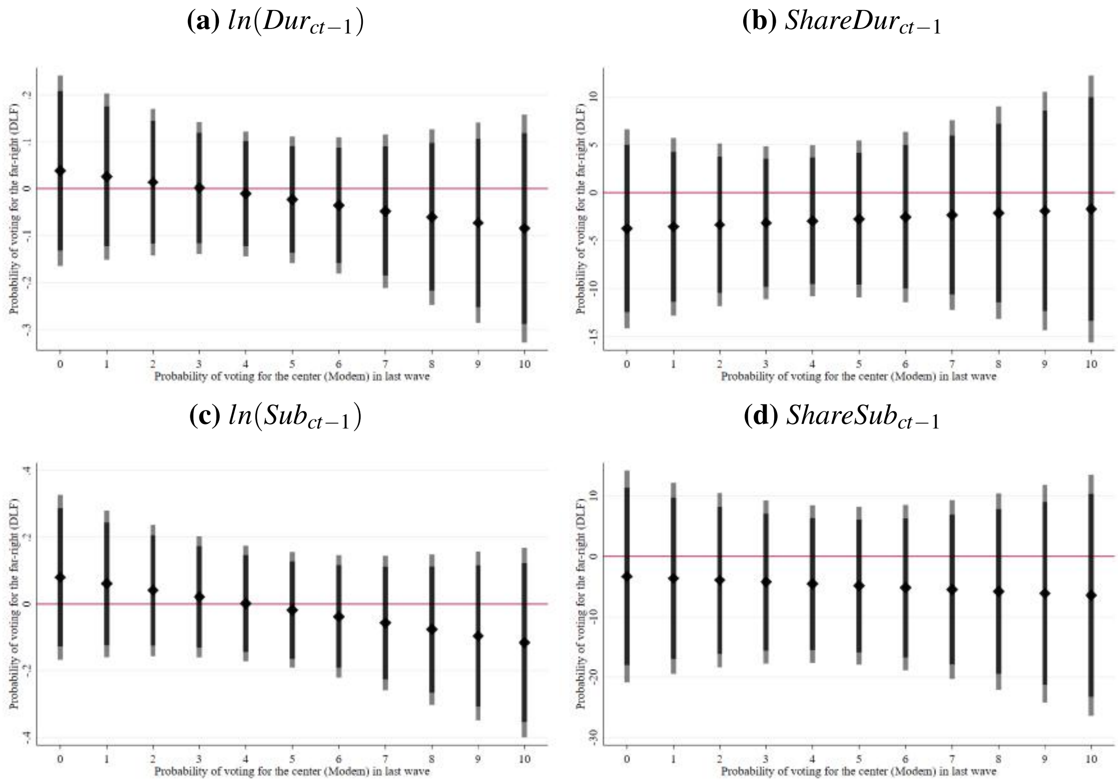


(d) $ShareSub_{ct-1}$



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

Figure F6: Switching parties from right (MODEM) to far-right (DLF)

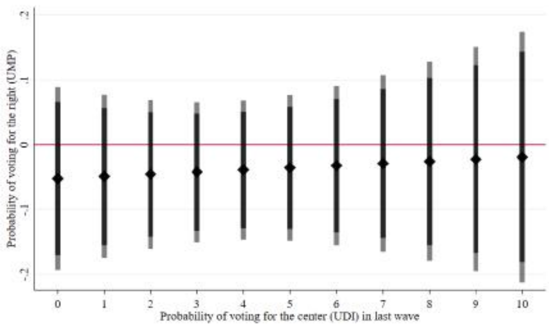


Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

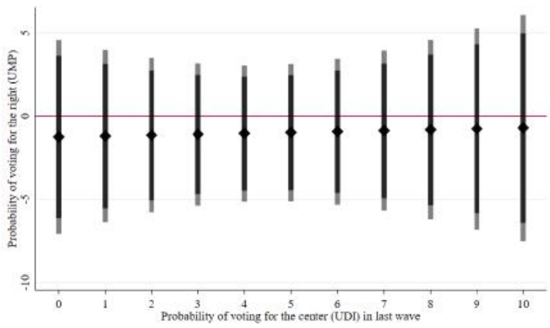
Probability to switch from center to right

Figure F7: Switching parties from right (UDI) to right (UMP)

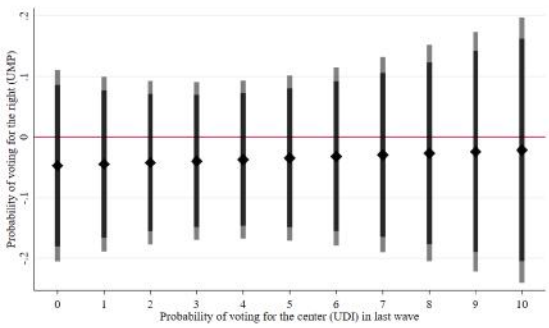
(a) $ln(Dur_{ct-1})$



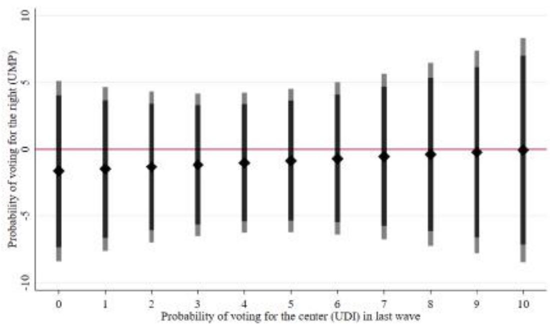
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$

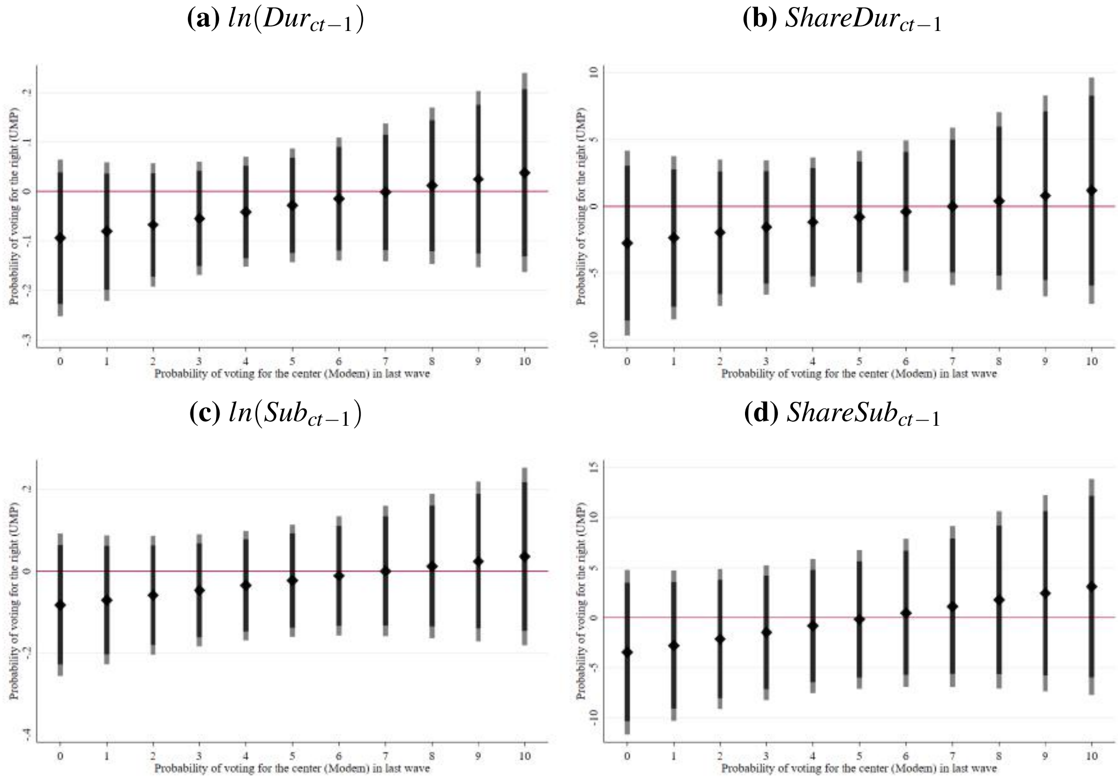


(d) $ShareSub_{ct-1}$



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

Figure F8: Switching parties from right (MODEM) to right (UMP)

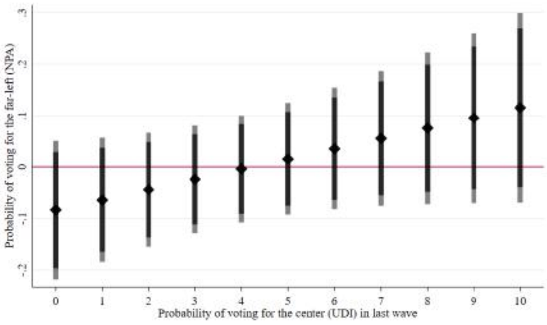


Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

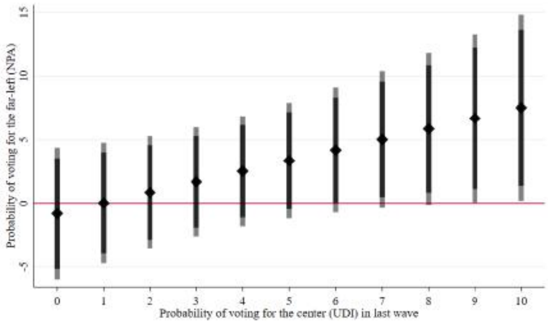
Probability to switch from center or left to far-left

Figure F9: Switching parties from right (UDI) to far-left (NPA)

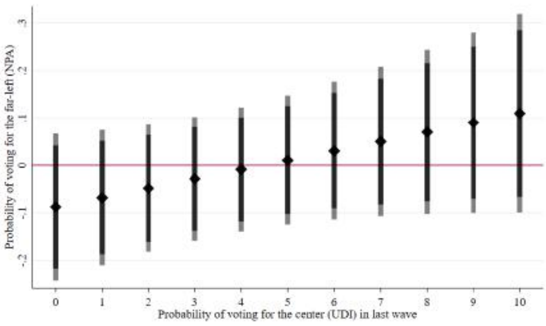
(a) $ln(Dur_{ct-1})$



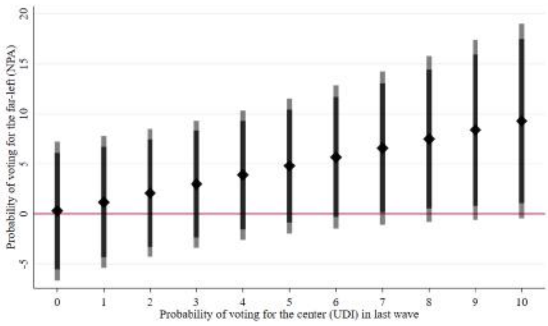
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



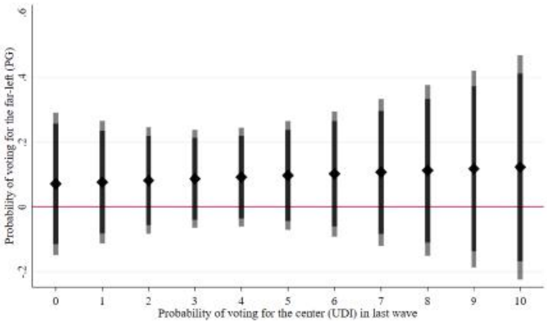
(d) $ShareSub_{ct-1}$



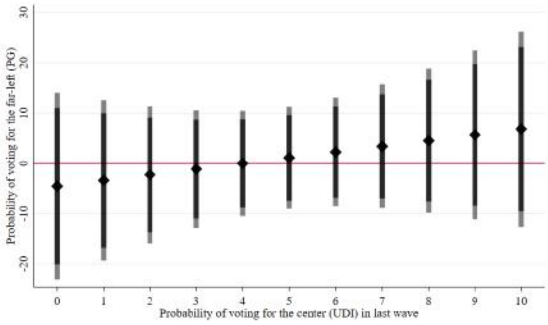
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F10: Switching parties from right (UDI) to far-left (PG)

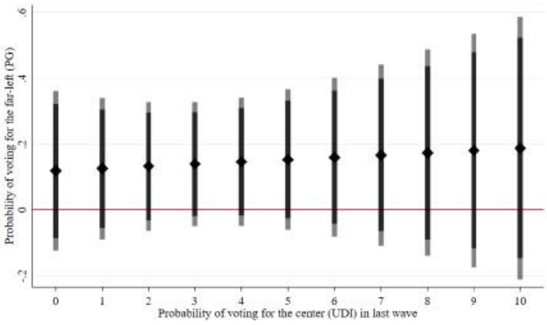
(a) $ln(Dur_{ct-1})$



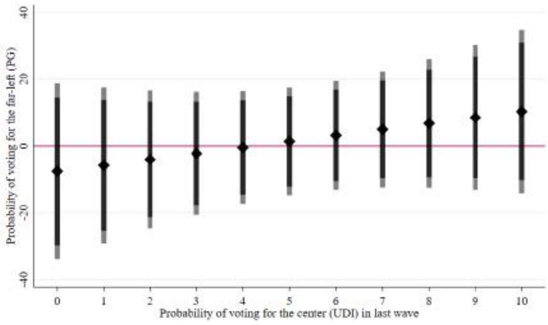
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



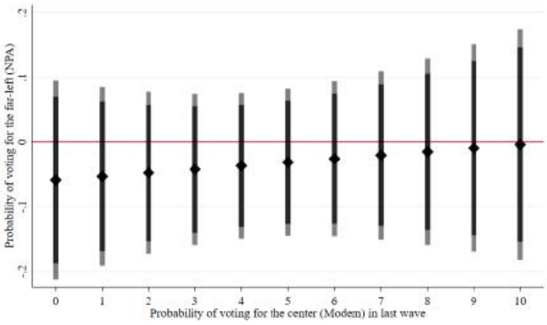
(d) $ShareSub_{ct-1}$



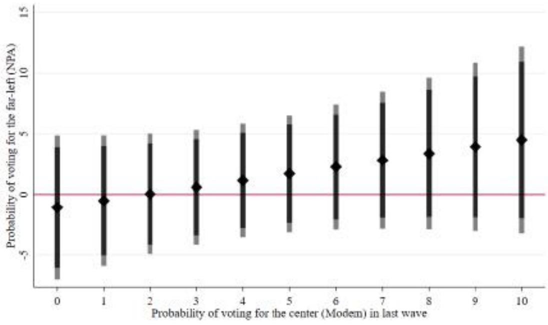
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F11: Switching parties from right (MODEM) to far-left (NPA)

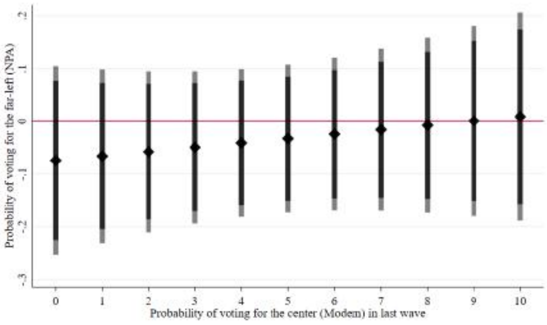
(a) $ln(Dur_{ct-1})$



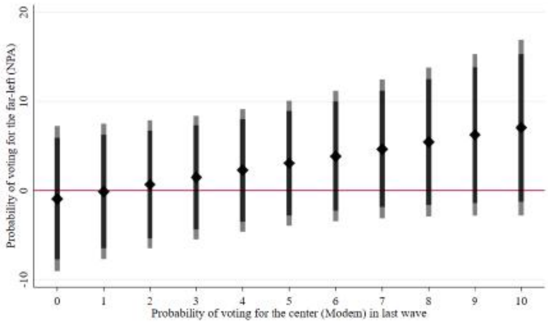
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



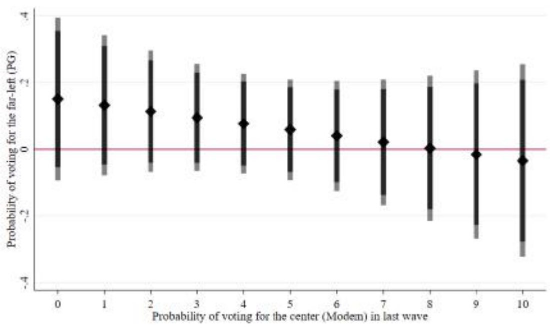
(d) $ShareSub_{ct-1}$



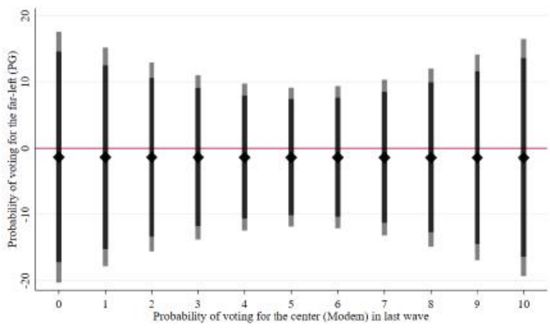
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F12: Switching parties from right (MODEM) to far-left (PG)

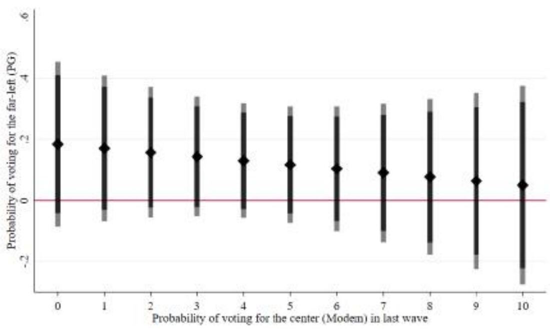
(a) $ln(Dur_{ct-1})$



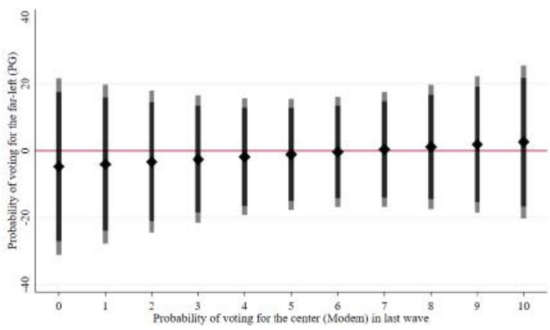
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



(d) $ShareSub_{ct-1}$



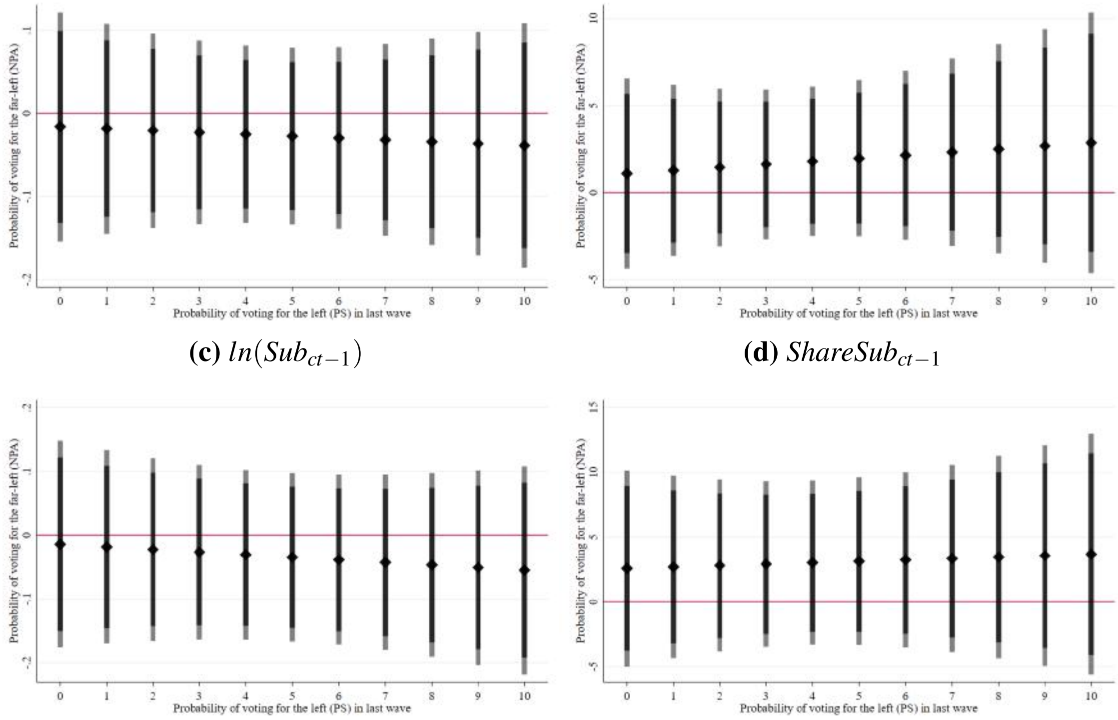
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Probability to switch from left to far-left

Figure F13: Switching parties from left (PS) to far-left (NPA)

(a) $ln(Dur_{ct-1})$ **(b)** $ShareDur_{ct-1}$

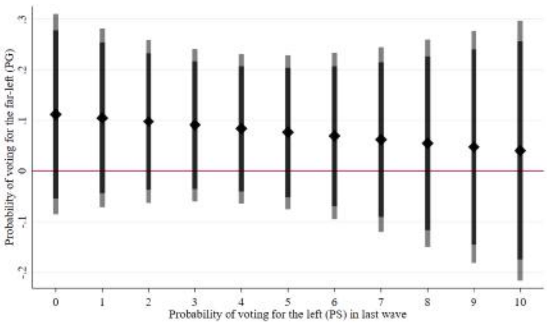
(c) $ln(Sub_{ct-1})$ **(d)** $ShareSub_{ct-1}$



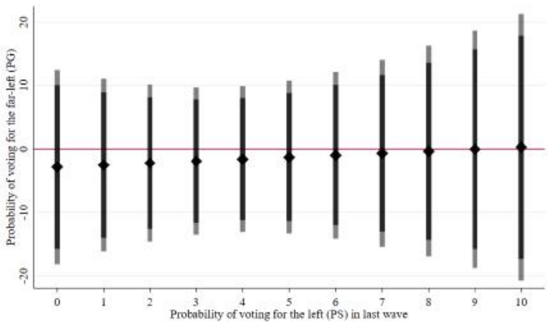
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F14: Switching parties from left (PS) to far-left (PG)

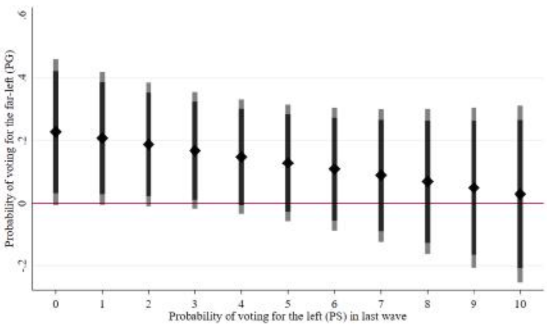
(a) $ln(Dur_{ct-1})$



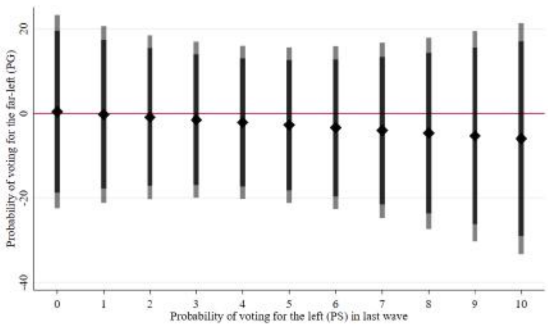
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



(d) $ShareSub_{ct-1}$

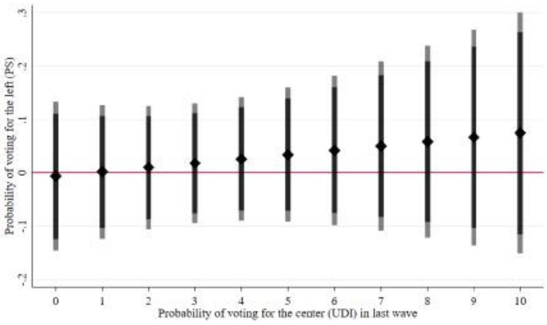


Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

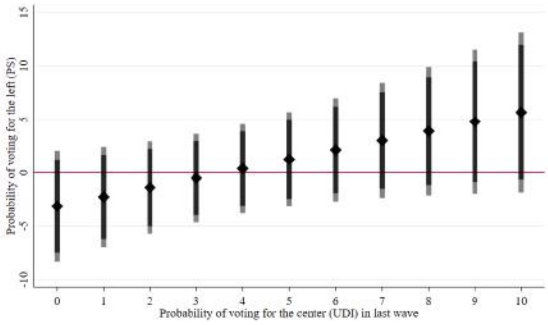
Probability to switch from center to Left and Green politics

Figure F15: Switching parties from right (UDI) to left (PS)

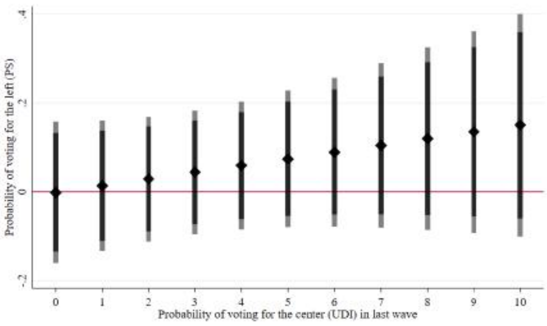
(a) $ln(Dur_{ct-1})$



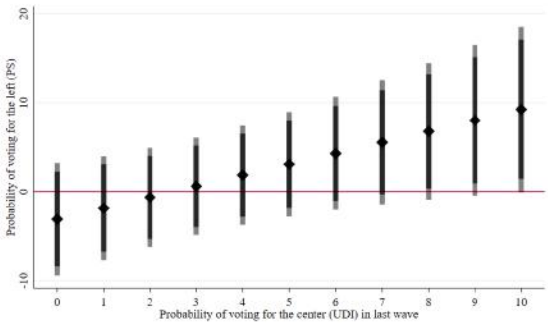
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



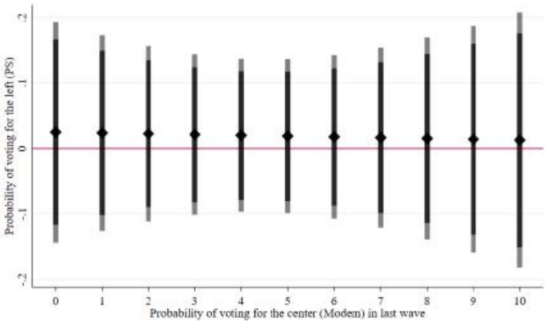
(d) $ShareSub_{ct-1}$



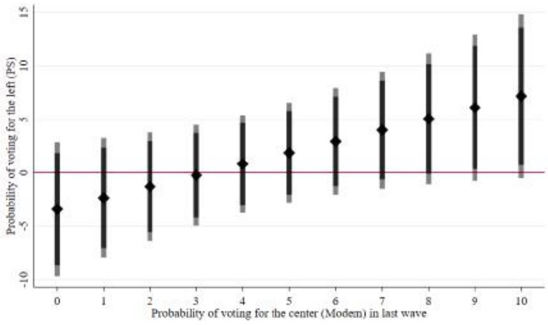
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F16: Switching parties from right (MODEM) to left (PS)

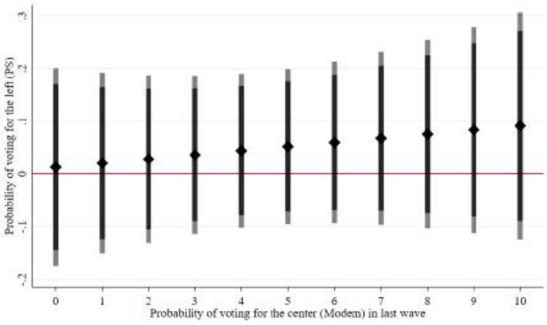
(a) $ln(Dur_{ct-1})$



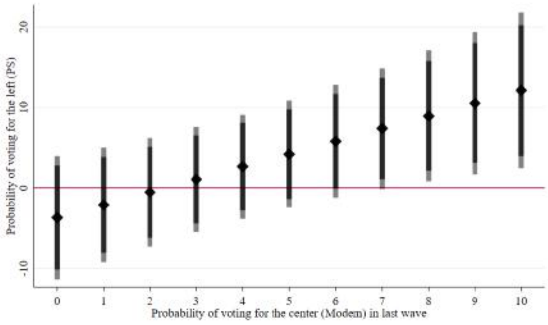
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



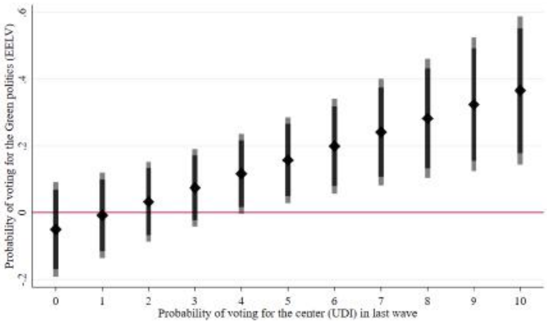
(d) $ShareSub_{ct-1}$



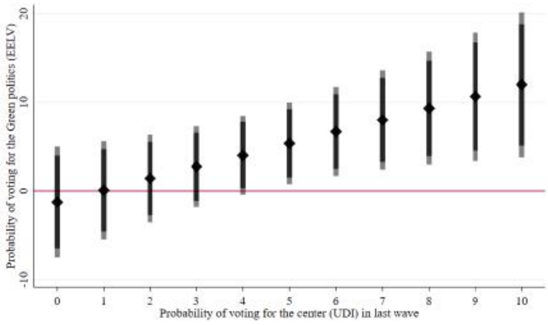
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F17: Switching parties from center (UDI) to Green (EELV)

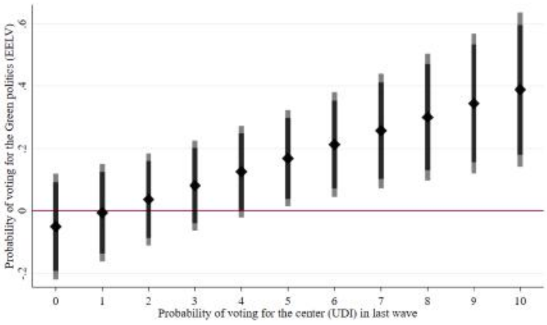
(a) $ln(Dur_{ct-1})$



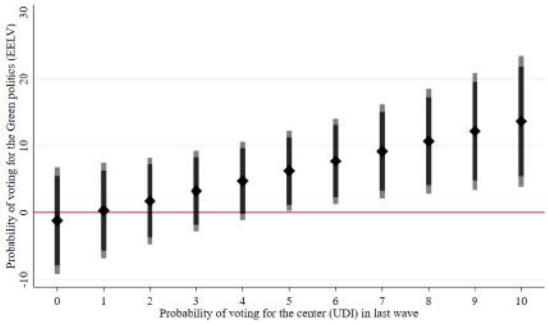
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



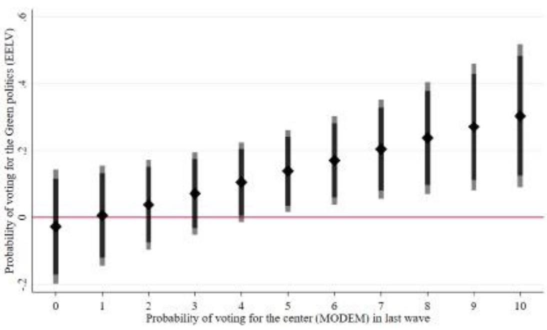
(d) $ShareSub_{ct-1}$



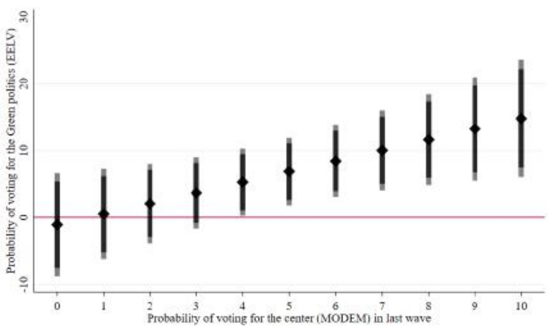
Notes: Confidence intervals are presented at the 95% and 90% level.
Source: Authors' elaboration on INA and ELIPSS data.

Figure F18: Switching parties from center (Modem) to Green (EELV)

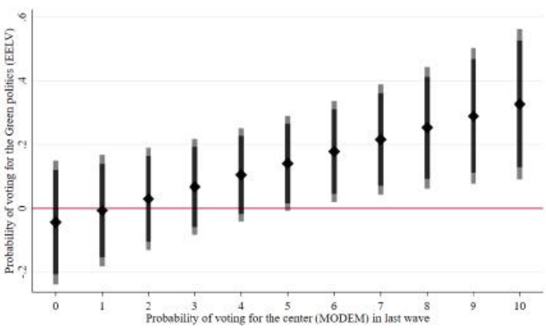
(a) $ln(Dur_{ct-1})$



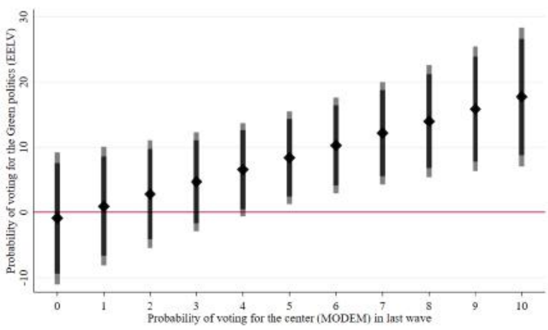
(b) $ShareDur_{ct-1}$



(c) $ln(Sub_{ct-1})$



(d) $ShareSub_{ct-1}$



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

Table F2: Probability to vote for political parties

	(1) NPA	(2) PG	(3) PS	(4) EELV	(5) MoDem	(6) UDI	(7) UMP	(8) DLF	(9) FN
					Table F2 (a)				
$ln(Dur_{ct-1})$	-0.016	0.065	0.029	0.037	0.043	0.082	-0.028	0.025	0.057
	(0.045)	(0.070)	(0.052)	(0.052)	(0.052)	(0.055)	(0.049)	(0.054)	(0.039)
					Table F2 (b)				
$ShareDur_{ct-1}$	1.510	-2.157	-0.890	1.456	2.162	2.165	-0.238	0.919	1.126
	(1.894)	(5.135)	(1.965)	(2.004)	(2.895)	(2.223)	(1.866)	(2.141)	(1.457)
					Table F2 (c)				
$ln(Sub_{ct-1})$	-0.015	0.096	0.036	0.038	0.058	0.090	0.000	0.051	0.055
	(0.055)	(0.087)	(0.064)	(0.062)	(0.063)	(0.068)	(0.057)	(0.067)	(0.047)
					Table F2 (d)				
$ShareSubj_{ct-1}$	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. × 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 the 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.

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