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ABSTRACT

Do Anti-Immigration Attitudes Discourage Immigration? Evidence from a New Instrument*

We investigate the effect of anti-immigration attitudes on immigration plans to Europe. We propose a new instrument for attitudes toward immigration, namely, the number of country nationals killed in terrorist attacks taking place outside of Europe. Our first-stage results confirm that such terrorist attacks increase negative attitudes to immigration in the origin country of the victims. Our second-stage results then show that this higher hostility toward migrants decreases the attractiveness of the country for prospective immigrants.

JEL Classification: C1, F2, J1

Keywords: immigration, terrorism, anti-immigration attitudes, Europe

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1 Introduction

Over the last decades, the world has experienced a backlash against globalization (Norris and Inglehart, 2019), apparent for example from the increase in anti-immigration attitudes in many receiving countries. A large social sciences literature has focused on the economic and cultural determinants of anti-immigration attitudes.¹ In this paper, we ask whether a rise in anti-immigration attitudes in Europe affects the migration decisions and location choices of international migrants. We address a fundamental endogeneity issue pertaining to the fact that there are a host of factors that can jointly determine attitudes to immigration and immigration inflows. For example more generous welfare systems can both attract more migrants in case of welfare magnets and make natives more anti-immigration if immigrants are seen as net negative contributors. The bias could go in the other direction of course, for example in case of economic crises reducing the attractiveness of the country for prospective migrants while at the same time making native residents more anti-immigration.

We propose to identify the effect of anti-immigration attitudes on immigration using a new instrument: terrorist attacks. More precisely, we use the number of a country's nationals killed in terrorist attacks outside that country (actually, outside of Europe) to predict its anti-immigration attitudes. Unlike attacks taking place in the country itself, such events affect attitudes toward immigration without directly affecting the attractiveness of the country from the viewpoint of potential migrants. The first-stage results show that indeed, the number of a country's nationals killed in terrorist attacks taking place outside of Europe significantly increases negative attitudes toward immigration in that country. In turn, the second-stage results show that more negative attitudes of native residents decrease the attractiveness of the country for prospective migrants, more or less equally for all skill categories. More specifically, we find that a 1 percentage point (pp) increase in the proportion of individuals holding anti-immigration attitudes in a given country leads to a reduction of between 4% and 9% in the number of people willing to migrate to that country. In contrast, estimates from regressions that do not account for the endogeneity bias yield either insignificant or positive effects on anti-immigration attitudes. In other words, each additional national killed outside Europe in a terrorist incident results in a reduction of the intended immigration flows to that individual's home country by about 4% through the induced increase in the anti-immigration attitudes of the native population. To put this result further in perspective, we find that unemployment and attitudes have similar quantitative effects: a 1 pp increase in the country's unemployment rate and 1 pp increase in the number of people against immigration have a roughly similar effect on bilateral migration intentions.

The paper contributes to various strands of the literature. First and most obviously, we contribute to the literature looking at the impact of attitudes on immigration. While there is an extensive literature on the determinants of attitudes to immigration, there are only a few papers exploring their effects on immigration flows. At the cross-country level, Gorinas and Pytliková (2017) study the impact of anti-immigration attitudes on immigration inflows in 30 OECD countries over the 1980-2010 period using the Integrated Values Survey. They find a negative relationship between specific attitudes such as the propensity of natives to discriminate immigrants or their reluctance to have a foreign neighbor and inflows of immigrants. While they control for a large set of fixed effects, they do not account for the endogeneity of natives' attitudes. At the micro-level, Slotwinski

¹See, e.g., Facchini and Mayda (2012) or Card et al. (2012) and, for a recent survey, Alesina and Tabellini (2024).

and Stutzer (2019) study the effect of the vote against the construction of minarets in Switzer-land in 2009 and find that migrants (notably from neighboring European countries) are less likely to move to municipalities where the support for a ban on minarets construction was larger and deviated from past votes on similar issues. Finally, a recent literature investigating the effect of right-wing populist attitudes and policies on immigration flows found evidence of strong negative effects in contexts such as Italy at the municipality level (in case of election of a populist mayor (Bellodi et al. (2024)), the United States (on intentions to migrate of Mexicans during the first Trump presidency, Beine, Bierlaire, et al. (2025)) or in cross-country settings (Frederic Docquier and Vasilakis (2024)). Interestingly, the negative effect of populist attitudes and policies appears stronger for highly-skilled immigrants, resulting in adverse selection of immigrants and potentially generating a vicious circle between levels of right-wing populism and the skill-content of immigration (Frederic Docquier and Rapoport (2025)).

Our main contribution is to propose an identification strategy that captures the causal impact of natives' attitudes on the perceived attractiveness of their country for prospective migrants. To achieve this, we focus on migration intentions — specifically, the migration plans formed in origin countries. The use of intentions offers several advantages. First, unlike actual migration flows, intentions allow us to isolate the influence of attitudes as a self-selection factor of migration. In contrast, the impact of attitudes on actual immigration flows reflects a combination of self-selection and out-selection mechanisms. For example, in a country with strict immigration barriers, variations in immigration flows are likely driven by the number of immigrants permitted entry, rather than the number of people willing to migrate. Second, it has been shown that migration plans and intentions are good predictors of future moves (Frédéric Docquier et al., 2014; Clemens and Mendola, 2024).²

We also contribute to the literature on the relationship between terrorism and attitudes towards migrants. Our first-stage results corroborate those of several other papers showing that terrorism leads to more anti-immigration attitudes³. In particular, Cruz et al. (2020) find that terrorist incidents in a country lead to an increase in anti-immigration sentiment, especially towards out-group (i.e., culturally distant) migrants. Interestingly, there are instances of cross-border spillovers, as shown by Bove et al. (2021). Similarly, Legewie (2013) finds that terrorist attacks highly covered in the news may affect attitudes towards migrants even if they take place in a distant country. Finally, Jetter (2017) shows that increased media attention raises the likelihood of future terrorist events. We add to this literature by bringing a new dataset covering the number of European victims of terrorist attacks happening outside Europe, broken down by nationality. The data mostly come from news press agencies articles and are checked against the Global Terrorism Database, which is widely used in this literature.

The rest of the paper is organized as follows. Section 2 describes the empirical strategy; Section 3 details the various data sources used; Section 4 presents the results and Section 5 concludes.

 $^{^2}$ In addition, actual moves can be constrained by migration barriers, which might correlate with attitudes; this is less the case for migration plans.

³See Helbling and Meierrieks (2020) for a comprehensive review.

2 Estimating the impact of attitudes on migration aspirations

2.1 Empirical framework

To estimate the impact of anti-immigration attitudes on potential immigration, we use a traditional micro-founded gravity model.⁴ The structural equation of the model that we bring to the data takes the following form:

$$M_{ijt} = \exp(\gamma_{ij} + \gamma_{it} + \beta_1 Att_{j,t-1} + \mathbf{X_{jt}}' \lambda) \,\varepsilon_{ijt}$$
(1)

where M_{ijt} is the share of respondents from country i at time t that aspire to locate in country j among all respondents surveyed at time t. We measure M_{ijt} as:

$$M_{ijt} = \frac{Plan_{ijt}}{\sum_{j \neq i} Plan_{ijt}} \times \frac{Yes_{it}}{Resp_{it}}$$
 (2)

where $Plan_{ijt}$ is the number of respondents having a plan to migrate from country i to country j at time t. $\frac{Yes_{it}}{Resp_{it}}$ gives the proportion of respondents in wave t that state a willingness to leave their country.⁶

 Att_{jt} is a variable measuring the negative attitudes toward immigration of the natives of country j at time t. Attitudes are lagged to ensure that migration plans are formed after observing these attitudes. X_{jt} is a vector of control variables affecting the attractiveness of destination j.⁷ In this specification, we control through fixed effects γ_{ij} and γ_{it} for unobserved dyadic and time-varying origin country specific factors.

The estimation of equation (1) raises a number of questions. First, a large proportion of M_{ijt} is made of zeroes, reflecting that migration plans are concentrated on specific destinations.⁸ As identified by a couple of papers (Santos Silva and Tenreyro, 2006; Santos Silva and Tenreyro, 2011; Correia et al., 2020), such a high presence of zeroes leads to two specific issues, namely selection and bias in the estimation of the parameters of equation (1). To address these issues, we use an exponential form of the equation, which can be estimated by the Poisson Pseudo-Maximum Likelihood (PPML) estimator.

⁴See among others Beine, Bertoli, et al. (2016) and Head and Mayer (2014) for a detailed explanation on the use of gravity equation in the migration literature. This model might be derived from the equilibrium of a Random Utility Model (RUM). See Beine et al. (2011) or Grogger and Hanson (2011) as examples. We skip here this derivation to focus on the econometric specification.

 $^{^{5}}$ Note that j might equal to i to capture the impact on stayers. This is accounted for through the inclusion of origin-time fixed effects.

⁶Therefore, our dependent variable is the respondents having emigration plan to a specific destination as a share of total respondents, including the intended stayers.

 $^{{}^{7}\}mathbf{X_{jt}}'$ includes income per capita at destination, population size, and the number of victims of terrorism in the destination country j at year t.

⁸In our sample, we observe that about 90 percent of our observations are zeroes. This high concentration of choices on a limited set of destinations is a strong stylized fact on intention data (see Frédéric Docquier et al. (2014) on this) and more generally on dyadic international movements of individuals.

2.2 Endogeneity of attitudes

A more serious econometric problem is the endogeneity of anti-immigration attitudes in equation (1). Attitudes are indeed likely to be correlated with unobserved factors that can affect migration plans. For instance, a generous social security system at destination could at the same time encourage immigrants to come and increase anti-immigration attitudes if, say, natives consider that foreigners do not contribute enough to the system. Another example is provided by the massive arrivals of Syrian refugees in some countries in 2015. The liberal position of Angela Merkel in Germany induced a large inflow of more than one million Syrian refugees but at the same time also induced a rise in anti-immigration attitudes for a subset of the German population.

The endogenous nature of attitudes calls for a specific econometric treatment of equation (1). In this paper, we provide an instrumental variable solution to address this issue. In our context, an instrument should predict anti-immigration attitudes of natives without impacting directly migration plans. Unfortunately, instruments based on lagged values of attitudes are likely to be invalid since unobserved factors of attractiveness of the destination are likely to be persistent over time. This calls for the use of an external instrument. The main contribution of this paper is to propose such an instrument.

2.3 Victims of terrorist attacks outside Europe as an instrument

We rely on an instrument based on a specific measure of terrorist attacks, namely the number of nationals of country j killed in terrorist attacks outside Europe in a given period. The validity of the instrument rests on the fact that terrorist attacks making victims from j abroad do not target this destination country and generate a quasi-random distribution of victims by nationality. Take for example the case of the bombings of two nightclubs in Bali, Indonesia, in 2002 that killed 202 people. While the attacks explicitly targeted foreigners in Indonesia, the number of victims by nationality was unknown ex-ante to the perpetrators and includes therefore a strong random component.

Information, whether through traditional channels such as newspapers or through social media, is a key channel through which terrorist attacks will affect native's attitudes. We provide evidence that people living in the country of origin of these victims are likely to be informed about those attacks. Figures A5 and A6 in supplemental appendix A suggest that searches for "terrorism" or "terrorisme" have surged following the attacks in Tunisia and Morocco killing British and French citizens respectively. This could in turn affect attitudes towards immigration. To explore further this channel, we also use the fact that Eurobarometer waves are conducted over a few weeks, giving us the opportunity to compare the answers of individuals who were interviewed just before and just after an attack killed some of their fellow citizens abroad. Figure A4 shows that individuals interviewed the day following an attack, i.e. when this event is very likely to be reported in the media, are more prone to answer that immigration is one of the two main issues in their country.

Our successive estimations and the specific design of our instrument ensure that the exclusion restriction is validated. First, one could argue that terrorist attacks taking place abroad could predict the number of terrorist attacks on the destination's soil and in turn affect its attractiveness, violating the exclusion restriction. To address this important point, we do two separate things. First, we control explicitly for terrorists attacks taking place in country j. A recent literature (Fou-

bert and Ruyssen, 2024) has looked at the potential impact of such events on migration intentions. They find that terrorist attacks exert a negative impact on immigration flows and intentions.

Second, our instrument does not include nationals killed in terrorist attacks on the national territory. On top of that, we take a very conservative approach by excluding also terrorist attacks taking place not only in neighbouring countries but also in Europe as a whole. One could argue that through some contagion, terrorist attacks taking place, say, in Italy or Norway could raise the probability of future attacks in France, which would indirectly affect the attractiveness of the latter.

Third, we explore the correlation between the number of citizens of a specific country killed abroad and the number of victims of terrorism in that country (for instance French citizens killed abroad and the number of victims in attacks in France). We find a moderate positive correlation (0.13, p-value of 0.063), but it is almost entirely driven by the case of France in 2015. During this year, there were important attacks both in France and on French citizens abroad. Dropping this single observation removes completely the positive correlation (-0.02, p-value of 0.808).

Fourth, our instrument considers only the number of citizens killed in terrorist attacks abroad, excluding those who were injured. It also omits nationals killed in other contexts, such as sexual assaults or other violent incidents that may have specifically targeted certain individuals. Notably, even in terrorist attacks where foreigners appear to be deliberately targeted, the distribution of victims by nationality is often highly unpredictable—even for the perpetrators themselves. A Herfindahl index measuring the diversity of European victims by nationality (for attacks with more than two victims) confirms that victimization tends to be dispersed (HH = 0.6, showing there is a sixty percent chance that two randomly drawn European victims from terrorist attacks outside of Europe have different nationalities). Furthermore, data from attacks between 2009 and 2015 in which at least one European citizen was killed outside of Europe show that a significant proportion of the victims—41.8%—were either domestic nationals or foreigners from non-European countries. Finally, attacks resulting in only a single fatality are relatively rare (28.2%), and there are no recorded cases of multiple victims sharing all the same nationality. Taken together, this suggests that the distribution of victims by nationality in terrorist attacks contains a substantial random component.

Our instrument turns out to be a reasonably strong predictor of anti-immigration attitudes. The first-stage results are in line with a recent literature showing that terrorism increases anti-immigration attitudes (Legewie, 2013; Nussio et al., 2019; Ferrín et al., 2020), even when attacks happen abroad (Böhmelt et al., 2020). The channels of influence of such events on opinions are multiple but always involve the extent of the coverage by the national press (Jetter, 2017). The extent of press coverage is likely to be proportional to the severity of terrorist attacks which is best captured through the number casualties (rather than through a dummy for whether a terrorist attack took place).

We ensured that the timing of the attacks and of our measure of attitudes are consistent. Attitudes are measured from the Eurobarometer surveys (see section 3.2), which usually take place

⁹A relevant example is the terrorist attack at the Radisson Blu Hotel in Bamako. Although one might assume French nationals were the primary target, none were killed (though 12 were injured). Of the 20 fatalities, 6 were Malian, 6 Russian, and 2 Belgian.

over one or two weeks at different times of the year depending on the country surveyed. We therefore computed the number of victims of terrorism in the year preceding the Eurobarometer interview. This gives an individual measure that we then average over each country-wave.

2.4 Control Function Estimation

We use the control function approach, which can be seen as the counterpart of the IV estimation for non linear models (Wooldridge, 2014). It involves two steps. In the first step, we regress the endogenous variable on all the controls and the relevant fixed effects. In the second step, we estimate the structural equation (1) by PPML, adding the residuals of the first step regression. The underlying idea is that these residuals capture the role of unobserved factors of attractiveness and corrects the estimation for the endogenous nature of attitudes. The two equations take the following form:

$$Att_{jt} = \lambda_j + \lambda_t + \alpha_1 Terrorism_{jt} + \mathbf{X_{jt}}'\delta + \nu_{jt}$$
(3a)

$$M_{ijt} = \exp(\gamma_{ij} + \gamma_{it} + \beta_1 Att_{j,t-1} + \mathbf{X}_{jt}'\lambda + \beta_2 \nu_{jt-1}) + \varepsilon_{ijt}$$
(3b)

where equation (3a) is the first-stage regression and equation (3b) is the structural equation. To ensure the reliability of the standard errors in the second step, we use bootstrap on the full sample with replacement clustered by origin-destination dyad, with 1000 replications of the procedure. As emphasized by Wooldridge (2014), an attractive feature of the Control Function (CF) approach is that it provides a kind of Hausman test of the endogeneity of the variable of interest. A significance of the parameter β_2 would tend to suggest that the variable is endogenous in equation (1). Furthermore, the sign of $\hat{\beta}_2$ is indicative of endogeneity and of the direction of the estimation bias relative to equation (1).

3 Data

To estimate equations (3a) and (3b), we measure three main variables: bilateral migration plans, attitudes with respect to immigration and a measure of European victims by nationality killed in terrorist attacks by location. Our sample comprises 149 origin countries, 33 European destination countries, and goes from 2010 to 2015.

3.1 Migration plans

Individual migration plans are retrieved from the Gallup World Polls (GWP), an annual world-wide comprehensive survey that gathers data from a large number of respondents in a large set of countries. An attractive feature of the GWP is that they are harmonized across countries, which makes a cross-country investigation possible. Migration plans are aggregated from the individual data. Our unit of analysis involves a specific country of origin, a specific destination, and a specific year.

In order to measure migration plans, we rely on two questions that involve emigration plans and optimal destination choices. First, respondents are asked "Ideally, if you had the opportunity,

would you like to move permanently to another country, or would you prefer to continue living in this country?". The second question is asked only to those replying positively to the first one and is stated as: "To which country would you like to move?". The replies provide aspirations reflecting mobility preferences. Because they are unconstrained, scholars have used alternative measures of intentions. We therefore use a follow-up question about more tangible plans: "Are you planning to move permanently to another country in the next 12 months, or not?". While on average 22.3 % of the respondents would like to move permanently in an ideal world, only about between 2 and 3% of the respondents worldwide have plans to do so in the following year. Plans are used as measures of intentions rather than aspirations. Like for aspirations, we aggregate the individual data to compute bilateral intended migration flows. Figure A2 in the supplemental appendix shows the evolution in the share of respondents with an intention to emigrate, i.e. the proportion of those having plans to emigrate in the next 12 months. As already stated, migration plans and intentions have been shown to be very good predictors of future moves (Frédéric Docquier et al., 2014; Clemens and Mendola, 2024).

3.2 Attitudes towards immigration

Attitudes towards immigration in European countries are measured from the Eurobarometer, a survey conducted on a yearly basis.¹¹ We focus on native respondents only, and use the question "What do you think are the two most important issues facing [your country] at the moment?". Respondents are given a list of 14 issues including immigration. In line with the existing literature (see, e.g., Böhmelt et al., 2020; Hatton, 2021), we consider that people with anti-immigration attitudes are more likely to mention it. We use the share of individuals choosing immigration as our measure of anti-immigration attitudes.

In the Eurobaromater, attitudes are usually collected in May-June, with the precise dates varying from country to country. In contrast, the collection by Gallup of migration aspirations varies across countries. GWP surveys are conducted all year long. Therefore, we use lagged values of attitudes in equation (1) to avoid using migration plans measured before attitudes towards immigration.

3.3 Terrorism

Our instrument is the annual number of nationals of each destination country that were killed in terrorist attacks outside Europe. We use the online service Factiva and collect news coming from the main news agencies (Reuters, Associated Press, Agence France Presse). Specifically, we search for several keywords associations and manually reviewed the articles provided by Factiva to extract the number and nationality of victims of terrorism in the world. Since this information is very specific and articles all have different formats and wording, we cannot rely on an automated process. For English-speaking news agencies (Reuters and AP), we search for articles containing the word "citizen" and at least one of the following words: "killed", "assassinated", "beheaded",

 $^{^{10}}$ This question was only present in the Gallup interviews conducted between 2010 and 2015. Table A2 in the Appendix shows the coverage per country and per wave.

¹¹An alternative would be to use questions drawn from the European Social Surveys (ESS). Nevertheless, the bi-annual frequency as well as a significant share of missing data for specific countries would induce a much smaller and more selective sample of destination countries over our investigation period.

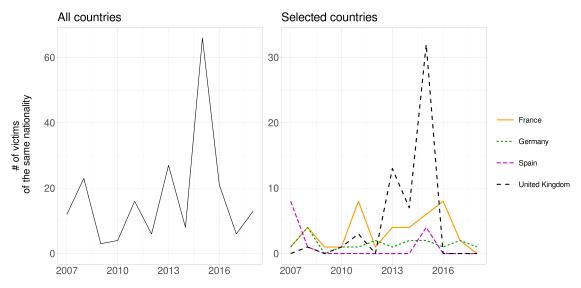


Figure 1: Total number of European victims of terrorist attacks outside Europe

and "shot". For Agence France Presse, we use the keywords "ressortissant tué" or "citoyen tué" (killed national or killed citizen).

One may be concerned that these three news agencies essentially focus on the United States and Western Europe, and are less likely to report attacks on citizens from Eastern European countries. To lower the risk of under-representation of Eastern European countries, we also search for articles coming from the Baltic News Network and Sofia Press Agency, two press agencies with international coverage implemented respectively in Austria and in Bulgaria. In total, we reviewed more than 5,000 articles over the period 2006-2019 to collect data on the number and nationalities of victims of terrorism abroad. In most cases, several articles from different news agencies reported the same information, which suggest a low risk of missing reported events or, on the contrary, of spurious cases. News agencies also quickly update their reports so that the number of victims is accurate. When possible, we also check the information from Wikipedia pages about these terrorist attacks, which were written afterwards and therefore contain richer information. We only keep attacks that were referenced in the Global Terrorism Database to ensure that the events are terrorist events.

Finally, since we consider terrorist attacks as predictors of attitudes, we have to ensure that those attacks happened before the surveys took place. The Eurobarometer is usually conducted over several weeks of May-June. Therefore, not all respondents were exposed to the same attacks. To address this, we first computed the number of attacks that happened in the past year relative to the interview date, hence obtaining a measure of exposure to terrorism at the individual level. We then averaged this result at the country-year level. Figure 1 shows the aggregate yearly number of victims between 2007 and 2018 (left panel) as well as for a selection of countries (right panel). It displays important variations between years and across countries, which is important to ensure the strength of our instrument.

3.4 Other data

We use several control variables in our main specification. We first capture variation that are destination specific and changing over time. We include the GDP per capita in the destination country, as it is an important pull factor. We also proxy the size of the destination country by its population size. GDP per capita and population size data come from the World Development Indicators (World Bank, n.d.). We also capture the role of policies at destination.

An important control is the number of terrorism victims of attacks taking place on the territory of the destination country. As explained before, this has been found in previous work to be a (negative) factor of attractiveness for potential migrants. It is also an important control shutting down one specific channel through which our instrument could be related directly to migration plans. This control is built using the Global Terrorism Database (GTD).

Finally, we saturate our specification with origin-time fixed effects to control for push factors in origin countries, such as political instability, conflicts or adverse climatic conditions, as well as origin-destination fixed effects to control for time-invariant characteristics of country pairs, such as the distance or existence of past colonial relationship.

4 Results

4.1 Baseline results

Table 1 reports the PPML estimations of equation (1) without instrumenting attitudes. We consider all types of respondents (column 1) as well as potential migrants with different levels of education (columns 2-5). Anti-immigration attitudes are found to increase or have no effect on the attractiveness of the destination. Such a counter-intuitive result confirms that estimation of equation (1) is subject to significant endogeneity issues. While the absence of an effect could be rationalized theoretically, the latter result suggests the existence of a positive selection bias in the estimation. One example of a specific pattern generating this bias is that (unobserved) factors raising the attractiveness of the country leads its natives to be relatively more against immigration.

Table 2 reports the results of the control function estimations¹². In Panel A, we report the first-stage results, i.e. the impact of victims of terrorist attacks outside Europe on anti-immigration attitudes. For all specifications, we show that attitudes of respondents towards immigrants become more negative when countrymen are killed in terrorist attacks. F-stat values suggest that the instrument is a strong predictor of these negative attitudes. Panel B reports the control-function estimation of equation (3b). In contrast to the OLS results presented in Table 1, we observe a negative and statistically significant effect of attitudes on the likelihood of potential immigrants choosing a particular destination. Across all specifications, this negative impact is consistent. Specifically, we find that an increase of 1 percentage point in the proportion of people holding anti-immigration attitudes is associated with a reduction between 4 and 9% in the intended immigration flows to that destination. To put further this result in perspective, we find in columns 3 and 4 that unemployment and attitudes have similar quantitative effects: a 1 pp increase in unemployment rate and a 1

 $^{^{12}}$ This uses standard errors clustered at origin-destination level. Very similar results with standard errors clustered at the destination level can be found in tables A8 and A9 in the Appendix.

Table 1: Impact of anti-immigration attitudes on migration plans: PPML

	(1)	(2)	(3)	(4)	(5)
	Mig	Mig (HSMS)	Mig (HS)	Mig (MS)	Mig (LS)
Eurobaro., lag	0.019**	0.017*	-0.001	0.026***	0.009
	(0.008)	(0.009)	(0.024)	(0.009)	(0.021)
GDP pc (log, lag)	2.018	2.800*	6.010	2.801	3.860
1 . 0 . 0,	(1.361)	(1.595)	(4.165)	(2.135)	(3.323)
Unemp. rate (lag)	-0.009	-0.010	-0.087	0.005	0.043
1 (0)	(0.028)	(0.038)	(0.083)	(0.046)	(0.075)
Terrorim at dest., lag	0.009***	0.004	-0.002	0.003	0.020***
	(0.003)	(0.006)	(0.011)	(0.007)	(0.004)
Pseudo-R2	0.376	0.408	0.419	0.400	0.324
Origin-Year FE	Yes	Yes	Yes	Yes	Yes
Origin-Destination FE	Yes	Yes	Yes	Yes	Yes
Observations	4651	4307	1851	3474	1234

 $^{^*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors clustered at the origin-destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. LS, MS, and HS correspond respectively to low-skilled (up to 8 years of education), middle-skilled (9-15 years of education), and high-skilled (4 years of education beyond high school). HSMS contains HS and MS individuals. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. Control variables are the log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year.

pp increase in the number of people against immigration have a roughly similar effect on bilateral migration intentions. Furthermore, the estimate of the first-stage residuals is significantly positive, confirming that naive regressions of equation (1) are subject to a significant bias. The inclusion of the first-stage residuals captures the impact of unobserved factors of attractiveness (such as the welfare magnet or quality institutions) and breaks down the correlation of these factors with the error term that generated the bias in estimations of Table 4.1. The reduced form estimate (col 5 in Panel B) suggests that each additional national killed outside Europe in a terrorist incident results in a reduction of the intended immigration flows by 4% through the induced increase in the anti-immigration attitudes of the native population.

4.2 Heterogeneity analysis

We explore the case for some heterogeneity in the impact of attitudes. We consider two main sources of heterogeneity.

4.2.1 Heterogeneity by education levels

An important source of heterogeneity of the impact of attitudes on attractiveness is the level of education of potential migrants. A higher sensitivity of highly skilled immigrants could give rise to a vicious circle. A higher proportion of low-skilled immigration could indeed fuel negative attitudes of natives, which is turn would deter more high-skilled immigrants to come, lowering the skill content of future flows. We use 3 standard education levels: primary (defined as low-skilled), secondary and non college higher education level (middle-skilled), and college-educated (high-skilled). Table A3 in the Appendix reports the results. We find compelling evidence that

¹³Evidence of such a vicious circle is provided by Beine, Bierlaire, et al. (2025) and Luca Bellodi et al. (2024).

Table 2: Anti-immigration attitudes and migration plans: First-stage and CF estimates

		Panel A: fir	st stage		
	(1)	(2)	(3)	(4)	
	Eurobaro.	Eurobaro.	Eurobaro.	Eurobaro.	
# terr. victims out Eur.	0.258***	0.239***	0.179***	0.189***	
	(0.016)	(0.016)	(0.016)	(0.016)	
GDP per cap. (log)		16.690***	-6.630***	-4.443***	
r (8)		(0.582)	(0.984)	(1.065)	
Unemp. rate			-0.602***	-0.562***	
1			(0.018)	(0.020)	
Terrorim at dest.				-0.015***	
				(0.001)	
Year FE	Yes	Yes	Yes	Yes	
Destination FE	Yes	Yes	Yes	Yes	
Observations	31,752	31,752	31,752	31,752	
KP F-statistic	256	234	124	141	
		Panel B: seco	nd stage		
	(1)	(2)	(3)	(4)	(5)
	Mig	Mig	Mig	Mig	Mig
Eurobaro., lag	-0.042***	-0.068***	-0.101***	-0.099***	
J	(0.009)	(0.009)	(0.010)	(0.010)	
1st stage resid. (lag)	0.071***	0.088***	0.120***	0.118***	
0 (0)	(0.005)	(0.005)	(0.005)	(0.005)	
GDP pc (log, lag)		4.320***	1.831	1.219	0.614
1 . 5 5.		(1.036)	(1.737)	(1.830)	(1.279)
Unemp. rate (lag)			-0.078**	-0.085**	-0.074***
			(0.036)	(0.037)	(0.025)
Terrorim at dest., lag				0.008	0.010***
<u> </u>				(0.005)	(0.003)
# terr. victims out Eur.					-0.039***
					(0.008)
Pseudo-R2	0.376	0.376	0.376	0.376	0.377
Origin-Year FE	Yes	Yes	Yes	Yes	Yes
Origin-Destination FE	Yes	Yes	Yes	Yes	Yes
Observations	4651	4651	4651	4651	4651

^{*}p < 0.10, ***p < 0.05, ***p < 0.01. Standard errors clustered at the origin-destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. # terr. victims out Eur. is the number of citizens of the destination country killed in terrorist attacks outside of Europe in the year before the Eurobarometer interview. Control variables are the first stage residuals, log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year. Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

negative attitudes affect the willingness to come for all types of migrants. This result is for instance in line with Beine, Bierlaire, et al. (2025). Second, we do not find evidence in favour of a vicious circle, i.e. higher sensitivity for high-skilled immigrants compared with low-skilled one. It should be nevertheless stressed that this last result is obtained from a sample with a lower number of observations.

4.2.2 Heterogeneity by country of origin

We also consider some heterogeneity by type of origin of the respondents. We first break down our investigation by level of development in the origin country. We use the World Bank classification of countries in terms of development. Table A4 in the Appendix reports the results. We find no evidence of heterogeneity in the effects of attitudes. Second, we look at whether European aspirational immigrants are more or less sensitive to anti-immigration attitudes. It could be argued that due to the higher proximity, respondents are better informed about these attitudes and take this more into account. Again, we do not find any evidence of a specific effect for respondents coming from another European country.

4.3 Robustness check: alternative measures of the instrument

The building of our instrument used so far aims at complying with the exclusion restriction of the control function procedure. The exclusion of victims in terrorist attacks not only on the territory of the destination but also in all other European countries rules out any confounding effect that could come from contagion effects in the perception by potential immigrants. Nevertheless, these contagion effects might be quite weak, which would justify a relaxation of the location constraint .

In Table 3, we assess whether our results are robust to some alternative definitions of the instrument. In column (1), we include, on top of victims killed outside Europe, nationals deceased in terrorist attacks located outside the territory and its neighbouring countries. In column (2), we include also in the instrument nationals killed in neighbouring European countries. Estimates from table 3 show that both first-stage and second-stage results are robust to these alternative definitions. Both alternative instruments are strong predictors of anti-immigration attitudes and estimates from the structural equation of attitudes are significantly negative, in line with findings from table 2.

4.3.1 Placebo: using future attitudes

Finally, we conduct a placebo analysis to assess further the robustness of our results. We look at the impact of future attitudes on migration plans. More specifically, we use attitudes collected in the Eurobarometer two years after the elicitation of location choices in the GWP.¹⁴ Table 4, reports these results, for all migrants altogether and distinguished by education levels. Results show that, unlike past anti-immigration attitudes, future attitudes by natives have no impact on the perceived attractiveness of potential immigrants.

 $^{^{14}}$ We use attitudes two years after rather than one year for two reasons. First, attitudes tend to be quite correlated over time. Second, because location intentions from the GWPS are measured at different moments across origin countries, using attitudes one year after would imply that, for some countries, attitudes in t+1 would be measured not long after the location choices.

Table 3: Impact of attitudes: alternative instruments

Pane	el A: first stage	
1 and	(1)	(2)
	Eurobaro.	Eurobaro.
# terr. victims out adj.	0.120***	Eurobaro.
# terr. victims out auj.	(0.015)	
	(0.010)	
# terr. victims abroad		0.120***
		(0.015)
CDP nor can (log)	-4.706***	-4.661***
GDP per cap. (log)		
	(1.063)	(1.064)
Unemp. rate	-0.569***	-0.569***
1	(0.020)	(0.020)
Terrorim at dest.	-0.015***	-0.015***
	(0.001)	(0.001)
Year FE	Yes	Yes
Destination FE	Yes	Yes
Observations	31,752	31,752
KP F-statistic	62	61
Panel	B: second stage	
	(1)	(2)
	Mig	Mig
Eurobaro., lag	-0.170***	-0.167***
	(0.010)	(0.010)
1	0.100***	0.10/***
1st stage resid. (lag)	0.189***	0.186***
	(0.005)	(0.005)
GDP pc (log, lag)	0.870	0.902
1 - (- 8, - 8,	(1.829)	(1.829)
	,	
Unemp. rate (lag)	-0.126***	-0.124***
	(0.037)	(0.037)
Terrorim at dest., lag	0.007	0.007
iciioiiii at acst., iag	(0.005)	(0.005)
	0.376	0.376
Pseudo-R2	U.5/h	
Pseudo-R2 Origin-Year FE		
Origin-Year FE	Yes	Yes

^{*}p < 0.10, **p < 0.05, ***p < 0.01. Standard errors clustered at the origin-destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. # terr. victims out adj. and # terr. victims abroad are respectively the number of citizens of the destination country killed in terrorist attacks outside of the country and its adjacent countries, and outside of the country only in the year before the Eurobarometer interview. Control variables are the first stage residuals, log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year. Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

Table 4: Placebo: impact of future attitudes on migration plans

	(1)	(2)	(3)	(4)	(5)
	Mig	Mig (HSMS)	Mig (HS)	Mig (MS)	Mig (LS)
Eurobaro., lead	-0.004	-0.012	0.028	-0.012	-0.001
	(0.009)	(0.011)	(0.028)	(0.014)	(0.019)
1st stage resid. (lead)	0.011	0.025*	-0.002	0.023	0.010
	(0.011)	(0.013)	(0.035)	(0.016)	(0.023)
GDP pc (log, lag)	1.793	2.413	4.706	2.429	3.931
	(1.849)	(2.027)	(5.699)	(2.662)	(4.652)
Lincone rate (las)	-0.032	-0.028	-0.102	-0.028	0.041
Unemp. rate (lag)			0		0.0
	(0.035)	(0.042)	(0.118)	(0.053)	(0.089)
Terrorim at dest., lag	0.009*	0.004	0.005	0.003	0.021
	(0.005)	(0.007)	(0.039)	(0.008)	(0.018)
Pseudo-R2	0.376	0.409	0.423	0.400	0.325
Origin-Year FE	Yes	Yes	Yes	Yes	Yes
Origin-Destination FE	Yes	Yes	Yes	Yes	Yes
Observations	4651	4307	1851	3474	1234

 $^*p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors clustered at the origin-destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. LS, MS, and HS correspond respectively to low-skilled (up to 8 years of education), middle-skilled (9-15 years of education), and high-skilled (4 years of education beyond high school). HSMS contains HS and MS individuals. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. The interest variable is measured using the Eurobarometer surveys conducted two years after the Gallup surveys (which are used to compute the dependent variable). Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

5 Conclusion

Using data on migration plans from the Gallup World Polls and anti-immigration attitudes from the Eurobarometer, we find that anti-immigration attitudes negatively impact immigration in the context of Europe. This is factually not surprising of course, however this could be due to a host of circumstances, including third factors that can jointly determine the pattern of immigration plans (on the side of prospective migrants) and attitudes toward immigration (on the side of host country residents). The main contribution of the paper, therefore, is to propose a novel identification strategy. More precisely, we instrument attitudes toward immigration in a given European country by the number of nationals of that country killed in terrorists attacks outside of Europe.

Our first-stage results indicate that terrorist attacks significantly increase negative attitudes toward immigration in the victims' country of origin. In the second stage, we find that these negative attitudes, in turn, reduce the attractiveness of the country as a destination for potential immigrants, regardless of their skill level. We emphasize the importance of addressing the endogeneity issue in this context, as failing to do so would produce misleading results suggesting that increased hostility in the destination country could attract more immigrants. Furthermore, we observe that the deterrent effect of anti-immigration attitudes is substantial: a 1 percentage point increase in the proportion of individuals holding anti-immigration views results approximately in a 9% reduction in migration intentions to that destination, an effect similar in magnitude to that of a 1 percentage point increase in the unemployment rate at destination.

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Supplemental Appendix

A Descriptive statistics

Table A1: Attractiveness of destinations Share of respondents (%) that have plans to migrate to [country]. If they don't have plans, then we consider 'Home' as their destination.

Home 93.886 93.615 94.916 93.264 93.228 92.635 Albania 0.004 0.004 0.007 0.015 0.004 0.015 Austria 0.087 0.122 0.146 0.257 0.180 0.266 Belgium 0.101 0.121 0.105 0.149 0.164 0.187 Bulgaria 0.007 0.009 0.029 0.010 0.008 0.011 0.008 0.011 0.008 0.012 0.008 0.011 0.008 0.012 0.003 0.016 0.018 0.012 0.023 0.023 0.031 0.041 0.025 0.031 0.041 0.025 0.031 0.041 0.025 0.032 0.028 0.022 0.020 0.020 0.020 0.020 0.020 0.020 0.020 0.020 0.020 0.021 0.025 0.032 0.026 0.031 0.015 0.025 0.026 0.024 0.020 0.020 0.020 0.020 0.020 0							
Albania 0.004 0.004 0.007 0.015 0.004 0.026 Austria 0.087 0.122 0.146 0.257 0.180 0.266 Belgium 0.101 0.121 0.105 0.149 0.164 0.187 Bulgaria 0.007 0.009 0.029 0.010 0.008 0.011 0.018 0.017 0.015 Croatia 0.010 0.008 0.011 0.018 0.012 0.023 Cyprus 0.032 0.039 0.016 0.018 0.012 0.023 Czechia 0.029 0.031 0.034 0.041 0.025 0.032 Denmark 0.064 0.061 0.040 0.081 0.065 0.137 Estonia 0.0024 0.070 0.065 0.069 0.080 0.082 France 1.235 1.518 0.979 0.999 1.121 1.168 Germany 0.903 0.882 0.948 1.416 1.562		2010	2011	2012	2013	2014	2015
Austria 0.087 0.122 0.146 0.257 0.180 0.264 Belgium 0.101 0.121 0.105 0.149 0.164 0.187 Bulgaria 0.007 0.009 0.029 0.010 0.008 0.011 0.018 0.011 0.018 0.011 0.018 0.011 0.018 0.011 0.018 0.012 0.023 Cyprus 0.032 0.039 0.016 0.018 0.012 0.023 Czechia 0.029 0.031 0.040 0.081 0.065 0.032 Denmark 0.064 0.061 0.040 0.081 0.065 0.137 Estonia 0.002 0.001 0.002 0.069 0.080 0.082 Finland 0.024 0.070 0.065 0.069 0.080 0.082 France 1.235 1.518 0.979 0.999 1.121 1.168 Germany 0.903 0.882 0.948 1.416 1.562	Home	93.886	93.615	94.916	93.264	93.228	92.635
Belgium 0.101 0.121 0.105 0.149 0.164 0.187 Bulgaria 0.007 0.009 0.029 0.010 0.008 0.011 0.018 0.017 0.015 Croatia 0.010 0.008 0.011 0.018 0.012 0.023 Czechia 0.029 0.031 0.034 0.041 0.025 0.032 Denmark 0.064 0.061 0.040 0.081 0.065 0.137 Estonia 0.002 0.001 0.002 0.006 0.001 0.005 Finland 0.024 0.070 0.065 0.069 0.080 0.082 France 1.235 1.518 0.979 0.999 1.121 1.168 Germany 0.903 0.882 0.948 1.416 1.562 1.756 Greece 0.097 0.062 0.047 0.091 0.051 0.084 Hungary 0.005 0.017 0.002 0.013 0.011	Albania	0.004	0.004	0.007	0.015	0.004	0.013
Bulgaria 0.007 0.009 0.029 0.010 0.008 0.011 0.018 0.017 0.015 Croatia 0.010 0.008 0.011 0.018 0.017 0.015 Cyprus 0.032 0.039 0.016 0.018 0.012 0.023 Czechia 0.029 0.031 0.044 0.041 0.025 0.032 Denmark 0.064 0.061 0.040 0.081 0.065 0.137 Estonia 0.002 0.001 0.002 0.066 0.001 0.005 Finland 0.024 0.070 0.065 0.069 0.080 0.082 France 1.235 1.518 0.979 0.999 1.121 1.168 Gereace 0.097 0.062 0.047 0.091 0.051 0.084 Hungary 0.005 0.017 0.002 0.013 0.011 0.007 Iceland 0.006 0.0071 0.036 0.048 0.050	Austria	0.087	0.122	0.146	0.257	0.180	0.266
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Denmark 0.064 0.061 0.040 0.081 0.065 0.137 Estonia 0.002 0.001 0.002 0.006 0.001 0.005 Finland 0.024 0.070 0.065 0.069 0.080 0.082 France 1.235 1.518 0.979 0.999 1.121 1.168 Germany 0.903 0.882 0.948 1.416 1.562 1.756 Greece 0.097 0.062 0.047 0.091 0.051 0.084 Hungary 0.005 0.017 0.002 0.013 0.011 0.007 Iceland 0.008 0.005 0.003 0.016 0.006 0.014 Ireland 0.060 0.071 0.036 0.048 0.050 0.062 Italy 0.593 0.607 0.495 0.658 0.626 0.592 Latvia 0.006 0.000 0.003 0.002 0.001 0.004 Luxembourg <t< td=""><td>Cyprus</td><td>0.032</td><td>0.039</td><td>0.016</td><td>0.018</td><td>0.012</td><td>0.023</td></t<>	Cyprus	0.032	0.039	0.016	0.018	0.012	0.023
Estonia 0.002 0.001 0.002 0.006 0.001 0.005 Finland 0.024 0.070 0.065 0.069 0.080 0.082 France 1.235 1.518 0.979 0.999 1.121 1.168 Germany 0.903 0.882 0.948 1.416 1.562 1.756 Greece 0.097 0.062 0.047 0.091 0.051 0.084 Hungary 0.005 0.017 0.002 0.013 0.011 0.007 Iceland 0.008 0.005 0.003 0.016 0.006 0.014 Ireland 0.060 0.071 0.036 0.048 0.050 0.062 Italy 0.593 0.607 0.495 0.658 0.626 0.592 Latvia 0.006 0.000 0.003 0.002 0.001 0.004 Lithuania 0.006 0.000 0.003 0.002 0.001 0.004 Luxembourg	Czechia	0.029	0.031	0.034	0.041	0.025	0.032
Finland 0.024 0.070 0.065 0.069 0.080 0.082 France 1.235 1.518 0.979 0.999 1.121 1.168 Germany 0.903 0.882 0.948 1.416 1.562 1.756 Greece 0.097 0.062 0.047 0.091 0.051 0.084 Hungary 0.005 0.017 0.002 0.013 0.011 0.007 Iceland 0.008 0.005 0.003 0.016 0.006 0.014 Ireland 0.060 0.071 0.036 0.048 0.050 0.062 Italy 0.593 0.607 0.495 0.658 0.626 0.592 Latvia 0.006 0.000 0.003 0.002 0.001 0.004 Latvia 0.006 0.000 0.003 0.002 0.001 0.002 0.001 0.002 0.001 0.002 0.001 0.002 0.001 0.002 0.001 0.002 <t< td=""><td>Denmark</td><td>0.064</td><td>0.061</td><td>0.040</td><td>0.081</td><td>0.065</td><td>0.137</td></t<>	Denmark	0.064	0.061	0.040	0.081	0.065	0.137
France 1.235 1.518 0.979 0.999 1.121 1.168 Germany 0.903 0.882 0.948 1.416 1.562 1.756 Greece 0.097 0.062 0.047 0.091 0.051 0.084 Hungary 0.005 0.017 0.002 0.013 0.011 0.007 Iceland 0.008 0.005 0.003 0.016 0.006 0.014 Ireland 0.060 0.071 0.036 0.048 0.050 0.062 Italy 0.593 0.607 0.495 0.658 0.626 0.592 Latvia 0.006 0.000 0.003 0.002 0.001 0.004 Lithuania 0.006 0.000 0.003 0.003 0.001 0.004 Luxembourg 0.037 0.019 0.006 0.021 0.012 0.024 Montenegro 0.002 0.003 0.001 0.000 0.000 0.000 Netherlands	Estonia	0.002	0.001	0.002	0.006	0.001	0.005
Germany 0.903 0.882 0.948 1.416 1.562 1.756 Greece 0.097 0.062 0.047 0.091 0.051 0.084 Hungary 0.005 0.017 0.002 0.013 0.011 0.007 Iceland 0.008 0.005 0.003 0.016 0.006 0.014 Ireland 0.060 0.071 0.036 0.048 0.050 0.062 Italy 0.593 0.607 0.495 0.658 0.626 0.592 Latvia 0.006 0.000 0.003 0.002 0.001 0.004 Lithuania 0.006 0.000 0.003 0.002 0.001 0.004 Luxembourg 0.037 0.019 0.006 0.021 0.012 0.024 Montenegro 0.002 0.003 0.001 0.000 0.003 0.001 0.000 0.003 Netherlands 0.167 0.146 0.159 0.177 0.179 0.220 <td>Finland</td> <td>0.024</td> <td>0.070</td> <td>0.065</td> <td>0.069</td> <td>0.080</td> <td>0.082</td>	Finland	0.024	0.070	0.065	0.069	0.080	0.082
Greece0.0970.0620.0470.0910.0510.084Hungary0.0050.0170.0020.0130.0110.007Iceland0.0080.0050.0030.0160.0060.014Ireland0.0600.0710.0360.0480.0500.062Italy0.5930.6070.4950.6580.6260.592Latvia0.0060.0000.0030.0020.0010.004Lithuania0.0060.0000.0030.0030.0010.006Luxembourg0.0370.0190.0060.0210.0120.024Montenegro0.0020.0030.0010.0000.0000.003Netherlands0.1670.1460.1590.1770.1790.220North Macedonia0.0030.0030.0000.0040.0000.000Poland0.0160.0240.0110.0400.0300.046Portugal0.0430.0420.0320.0580.0450.066Romania0.0090.0150.0080.0200.0110.018Serbia0.0010.0020.0000.0030.0040.006Slovakia0.0010.0020.0000.0030.0040.006Slovenia0.0070.0030.0180.0090.0110.016Spain1.1850.9440.6590.8930.7650.777Sweden0.2020.2540.202	France	1.235	1.518	0.979	0.999	1.121	1.168
Hungary0.0050.0170.0020.0130.0110.007Iceland0.0080.0050.0030.0160.0060.014Ireland0.0600.0710.0360.0480.0500.062Italy0.5930.6070.4950.6580.6260.592Latvia0.0060.0000.0030.0020.0010.004Lithuania0.0060.0000.0030.0030.0010.006Luxembourg0.0370.0190.0060.0210.0120.024Montenegro0.0020.0030.0010.0000.0000.003Netherlands0.1670.1460.1590.1770.1790.220North Macedonia0.0030.0030.0000.0040.0000.000Poland0.0160.0240.0110.0400.0300.046Portugal0.0430.0420.0320.0580.0450.066Romania0.0090.0150.0080.0200.0110.018Serbia0.0010.0020.0000.0030.0040.006Slovakia0.0070.0030.0180.0090.0110.016Spain1.1850.9440.6590.8930.7650.777Sweden0.2020.2540.2020.3420.2880.367Turkey0.0700.1460.1100.2420.2420.2420.261United Kingdom1.0951.15	Germany	0.903	0.882	0.948	1.416	1.562	1.756
Iceland0.0080.0050.0030.0160.0060.014Ireland0.0600.0710.0360.0480.0500.062Italy0.5930.6070.4950.6580.6260.592Latvia0.0060.0000.0030.0020.0010.004Lithuania0.0060.0000.0030.0030.0010.006Luxembourg0.0370.0190.0060.0210.0120.024Montenegro0.0020.0030.0010.0000.0000.003Netherlands0.1670.1460.1590.1770.1790.220North Macedonia0.0030.0030.0000.0040.0000.000Poland0.0160.0240.0110.0400.0300.046Portugal0.0430.0420.0320.0580.0450.066Romania0.0090.0150.0080.0200.0110.018Serbia0.0020.0010.0290.0310.0370.017Slovakia0.0010.0020.0000.0030.0040.006Slovenia0.0070.0030.0180.0090.0110.016Spain1.1850.9440.6590.8930.7650.777Sweden0.2020.2540.2020.3420.2880.367Turkey0.0700.1460.1100.2420.2420.2420.261United Kingdom1.0951.1	Greece	0.097	0.062	0.047	0.091	0.051	0.084
Ireland0.0600.0710.0360.0480.0500.062Italy0.5930.6070.4950.6580.6260.592Latvia0.0060.0000.0030.0020.0010.004Lithuania0.0060.0000.0030.0030.0010.006Luxembourg0.0370.0190.0060.0210.0120.024Montenegro0.0020.0030.0010.0000.0000.003Netherlands0.1670.1460.1590.1770.1790.220North Macedonia0.0030.0030.0000.0040.0000.000Poland0.0160.0240.0110.0400.0300.046Portugal0.0430.0420.0320.0580.0450.066Romania0.0090.0150.0080.0200.0110.018Serbia0.0020.0010.0290.0310.0370.017Slovakia0.0010.0020.0000.0030.0040.006Slovenia0.0070.0030.0180.0090.0110.016Spain1.1850.9440.6590.8930.7650.777Sweden0.2020.2540.2020.3420.2880.367Turkey0.0700.1460.1100.2420.2420.2420.261United Kingdom1.0951.1570.8770.9841.1641.074	Hungary	0.005	0.017	0.002	0.013	0.011	0.007
Italy0.5930.6070.4950.6580.6260.592Latvia0.0060.0000.0030.0020.0010.004Lithuania0.0060.0000.0030.0030.0010.006Luxembourg0.0370.0190.0060.0210.0120.024Montenegro0.0020.0030.0010.0000.0000.003Netherlands0.1670.1460.1590.1770.1790.220North Macedonia0.0030.0030.0000.0040.0000.000Poland0.0160.0240.0110.0400.0300.046Portugal0.0430.0420.0320.0580.0450.066Romania0.0090.0150.0080.0200.0110.018Serbia0.0020.0010.0290.0310.0370.017Slovakia0.0010.0020.0000.0030.0040.006Slovenia0.0070.0030.0180.0090.0110.016Spain1.1850.9440.6590.8930.7650.777Sweden0.2020.2540.2020.3420.2880.367Turkey0.0700.1460.1100.2420.2420.261United Kingdom1.0951.1570.8770.9841.1641.074	Iceland	0.008	0.005	0.003	0.016	0.006	0.014
Latvia0.0060.0000.0030.0020.0010.004Lithuania0.0060.0000.0030.0030.0010.006Luxembourg0.0370.0190.0060.0210.0120.024Montenegro0.0020.0030.0010.0000.0000.003Netherlands0.1670.1460.1590.1770.1790.220North Macedonia0.0030.0030.0000.0040.0000.000Poland0.0160.0240.0110.0400.0300.046Portugal0.0430.0420.0320.0580.0450.066Romania0.0090.0150.0080.0200.0110.018Serbia0.0020.0010.0290.0310.0370.017Slovakia0.0010.0020.0000.0030.0040.006Slovenia0.0070.0030.0180.0090.0110.016Spain1.1850.9440.6590.8930.7650.777Sweden0.2020.2540.2020.3420.2880.367Turkey0.0700.1460.1100.2420.2420.261United Kingdom1.0951.1570.8770.9841.1641.074	Ireland	0.060	0.071	0.036	0.048	0.050	0.062
Lithuania 0.006 0.000 0.003 0.003 0.001 0.006 Luxembourg 0.037 0.019 0.006 0.021 0.012 0.024 Montenegro 0.002 0.003 0.001 0.000 0.000 0.003 Netherlands 0.167 0.146 0.159 0.177 0.179 0.220 North Macedonia 0.003 0.003 0.000 0.004 0.000 0.000 Poland 0.016 0.024 0.011 0.040 0.030 0.046 Portugal 0.043 0.042 0.032 0.058 0.045 0.066 Romania 0.009 0.015 0.008 0.020 0.011 0.018 Serbia 0.001 0.002 0.001 0.029 0.031 0.037 0.017 Slovakia 0.001 0.002 0.000 0.003 0.004 0.006 Spain 1.185 0.944 0.659 0.893 0.765 0.777	Italy	0.593	0.607	0.495	0.658	0.626	0.592
Luxembourg0.0370.0190.0060.0210.0120.024Montenegro0.0020.0030.0010.0000.0000.003Netherlands0.1670.1460.1590.1770.1790.220North Macedonia0.0030.0030.0000.0040.0000.000Poland0.0160.0240.0110.0400.0300.046Portugal0.0430.0420.0320.0580.0450.066Romania0.0090.0150.0080.0200.0110.018Serbia0.0020.0010.0290.0310.0370.017Slovakia0.0010.0020.0000.0030.0040.006Slovenia0.0070.0030.0180.0090.0110.016Spain1.1850.9440.6590.8930.7650.777Sweden0.2020.2540.2020.3420.2880.367Turkey0.0700.1460.1100.2420.2420.261United Kingdom1.0951.1570.8770.9841.1641.074	Latvia	0.006	0.000	0.003	0.002	0.001	0.004
Montenegro 0.002 0.003 0.001 0.000 0.000 0.003 Netherlands 0.167 0.146 0.159 0.177 0.179 0.220 North Macedonia 0.003 0.003 0.000 0.004 0.000 0.000 Poland 0.016 0.024 0.011 0.040 0.030 0.046 Portugal 0.043 0.042 0.032 0.058 0.045 0.066 Romania 0.009 0.015 0.008 0.020 0.011 0.018 Serbia 0.002 0.001 0.029 0.031 0.037 0.017 Slovakia 0.001 0.002 0.000 0.003 0.004 0.006 Slovenia 0.007 0.003 0.018 0.009 0.011 0.016 Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey </td <td>Lithuania</td> <td>0.006</td> <td>0.000</td> <td>0.003</td> <td>0.003</td> <td>0.001</td> <td>0.006</td>	Lithuania	0.006	0.000	0.003	0.003	0.001	0.006
Netherlands 0.167 0.146 0.159 0.177 0.179 0.220 North Macedonia 0.003 0.003 0.000 0.004 0.000 0.000 Poland 0.016 0.024 0.011 0.040 0.030 0.046 Portugal 0.043 0.042 0.032 0.058 0.045 0.066 Romania 0.009 0.015 0.008 0.020 0.011 0.018 Serbia 0.002 0.001 0.029 0.031 0.037 0.017 Slovakia 0.001 0.002 0.000 0.003 0.004 0.006 Slovenia 0.007 0.003 0.018 0.009 0.011 0.016 Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.242 United Kingd	Luxembourg	0.037	0.019	0.006	0.021	0.012	0.024
North Macedonia 0.003 0.003 0.000 0.004 0.000 0.000 Poland 0.016 0.024 0.011 0.040 0.030 0.046 Portugal 0.043 0.042 0.032 0.058 0.045 0.066 Romania 0.009 0.015 0.008 0.020 0.011 0.018 Serbia 0.002 0.001 0.029 0.031 0.037 0.017 Slovakia 0.001 0.002 0.000 0.003 0.004 0.006 Slovenia 0.007 0.003 0.018 0.009 0.011 0.016 Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Montenegro	0.002	0.003	0.001	0.000	0.000	0.003
Poland 0.016 0.024 0.011 0.040 0.030 0.046 Portugal 0.043 0.042 0.032 0.058 0.045 0.066 Romania 0.009 0.015 0.008 0.020 0.011 0.018 Serbia 0.002 0.001 0.029 0.031 0.037 0.017 Slovakia 0.001 0.002 0.000 0.003 0.004 0.006 Slovenia 0.007 0.003 0.018 0.009 0.011 0.016 Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Netherlands	0.167	0.146	0.159	0.177	0.179	0.220
Portugal 0.043 0.042 0.032 0.058 0.045 0.066 Romania 0.009 0.015 0.008 0.020 0.011 0.018 Serbia 0.002 0.001 0.029 0.031 0.037 0.017 Slovakia 0.001 0.002 0.000 0.003 0.004 0.006 Slovenia 0.007 0.003 0.018 0.009 0.011 0.016 Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	North Macedonia	0.003	0.003	0.000	0.004	0.000	0.000
Romania 0.009 0.015 0.008 0.020 0.011 0.018 Serbia 0.002 0.001 0.029 0.031 0.037 0.017 Slovakia 0.001 0.002 0.000 0.003 0.004 0.006 Slovenia 0.007 0.003 0.018 0.009 0.011 0.016 Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Poland	0.016	0.024	0.011	0.040	0.030	0.046
Serbia 0.002 0.001 0.029 0.031 0.037 0.017 Slovakia 0.001 0.002 0.000 0.003 0.004 0.006 Slovenia 0.007 0.003 0.018 0.009 0.011 0.016 Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Portugal	0.043	0.042	0.032	0.058	0.045	0.066
Slovakia 0.001 0.002 0.000 0.003 0.004 0.006 Slovenia 0.007 0.003 0.018 0.009 0.011 0.016 Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Romania	0.009	0.015	0.008	0.020	0.011	0.018
Slovenia 0.007 0.003 0.018 0.009 0.011 0.016 Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Serbia	0.002	0.001	0.029	0.031	0.037	0.017
Spain 1.185 0.944 0.659 0.893 0.765 0.777 Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Slovakia	0.001	0.002	0.000	0.003	0.004	0.006
Sweden 0.202 0.254 0.202 0.342 0.288 0.367 Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Slovenia	0.007	0.003	0.018	0.009	0.011	0.016
Turkey 0.070 0.146 0.110 0.242 0.242 0.261 United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Spain	1.185	0.944	0.659	0.893	0.765	0.777
United Kingdom 1.095 1.157 0.877 0.984 1.164 1.074	Sweden	0.202	0.254	0.202	0.342	0.288	0.367
Č	Turkey	0.070	0.146	0.110	0.242	0.242	0.261
Total 100 100 100 100 100 100	United Kingdom	1.095	1.157	0.877	0.984	1.164	1.074
	Total	100	100	100	100	100	100

 $\label{eq:allower} \begin{tabular}{ll} Table A2: Gallup coverage \\ Country-year that received the question 'Are you planning to move in [country] in the next 12 months?' \\ \end{tabular}$

	2010	2011	2012	2013	2014	2015
AFG		<u> </u>				<u>∠</u>
	V		√	√	√	∨
AGO	•	\checkmark	√	√	√	✓
ALB ARE			√			
	√	√ √	√	√	✓ ✓	√
ARG	√		√	√		√
ARM	√	√	✓	√	\checkmark	√
AUS	√	√	•	√	•	√
AUT	√	√	•	√	✓	√
AZE	✓	√	✓	\checkmark		\checkmark
BDI		√	•	•	\checkmark	✓
BEL	\checkmark	√	•	✓	· ✓	
BEN	•	√	\checkmark	✓		√
BFA	\checkmark	\checkmark	•	\checkmark	\checkmark	\checkmark
BGD	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
BGR	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
BHR	\checkmark	\checkmark	\checkmark	\checkmark	✓	\checkmark
BIH		•	\checkmark	\checkmark	\checkmark	\checkmark
BLR	\checkmark	\checkmark	\checkmark	\checkmark	✓	\checkmark
BLZ			•		\checkmark	
BOL	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
BRA	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
BTN				\checkmark	\checkmark	\checkmark
BWA	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
CAF	\checkmark	\checkmark	•			
CAN	\checkmark	\checkmark	\checkmark	\checkmark		
CHE				•		\checkmark
CHL	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
CHN	\checkmark	\checkmark		\checkmark	\checkmark	\checkmark
CIV		•		\checkmark	\checkmark	✓ ✓ ✓
CMR	\checkmark	✓	\checkmark	\checkmark	\checkmark	\checkmark
COD		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
COG		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
COL	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
COM	\checkmark	\checkmark	\checkmark			
CRI		\checkmark	\checkmark	\checkmark	\checkmark	✓
CYP	✓ ✓	\checkmark		\checkmark		\checkmark
CZE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	√ √
DEU	\checkmark	\checkmark		✓		\checkmark
DJI	✓	\checkmark				
DNK	✓	✓ ✓		\checkmark		✓
DOM	· ✓	· ✓	\checkmark	\checkmark	✓	✓
DZA	✓	✓	✓		√	
ECU	✓	✓	\checkmark	\checkmark	✓ ✓	✓

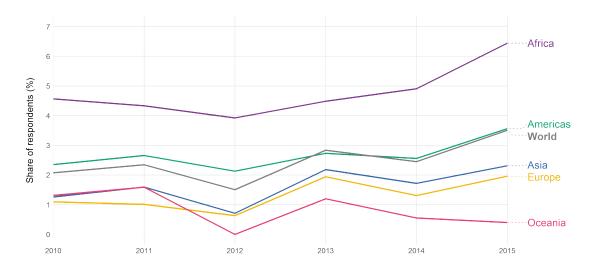
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EGY	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
ESP	\checkmark	✓ ✓	\checkmark			
EST		\checkmark	\checkmark	√ √	\checkmark	\checkmark
ETH				\checkmark	\checkmark	\checkmark
FIN	\checkmark			✓✓✓✓✓		\checkmark
FRA	\checkmark	\checkmark		\checkmark		\checkmark
GAB		\checkmark	\checkmark	\checkmark	✓	\checkmark
GBR	\checkmark	\checkmark		\checkmark		\checkmark
GEO	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
GHA	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
GIN		\checkmark		√ √	. ✓ ✓ ✓	\checkmark
GRC	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
GTM	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
HKG	\checkmark	\checkmark				
HND	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
HRV			\checkmark	\checkmark	\checkmark	\checkmark
HTI	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
HUN		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
IDN	√ √			✓✓✓✓		
IND	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
IRL	\checkmark	\checkmark				\checkmark
IRN		\checkmark	✓	✓✓✓✓✓	✓ ✓	\checkmark
IRQ	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
ISL				\checkmark		\checkmark
ISR	\checkmark	\checkmark	✓	\checkmark	\checkmark	\checkmark
ITA	\checkmark	\checkmark	\checkmark	\checkmark		\checkmark
JAM		\checkmark		\checkmark	✓ ✓	
JOR	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
JPN	\checkmark			√ √ √		
KAZ	✓ ✓ ✓	\checkmark	\checkmark	\checkmark	. ✓ ✓ ✓	\checkmark
KEN	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
KGZ	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
KHM	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
KOR	\checkmark	\checkmark	\checkmark	\checkmark		\checkmark
KWT	\checkmark	\checkmark	\checkmark	\checkmark		\checkmark
LAO		\checkmark				
LBN	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	✓
LBR	\checkmark			\checkmark	\checkmark	\checkmark
LBY			· ✓			✓
LKA	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
LSO		✓ ✓				
LTU	\checkmark	\checkmark	· ✓	\checkmark	\checkmark	✓
LUX	\checkmark	✓		\checkmark		\checkmark
LVA		\checkmark	✓ ✓	✓ ✓ ✓	\checkmark	\checkmark
MAR	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	√ √ √
MDA	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
MDG		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark

MEX	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
MKD			\checkmark	\checkmark	\checkmark	\checkmark
MLI	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
MLT	\checkmark	\checkmark		\checkmark		✓ ✓
MMR			\checkmark	\checkmark	\checkmark	\checkmark
MNE			\checkmark	\checkmark	\checkmark	\checkmark
MNG	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
MOZ		\checkmark				✓ ✓
MRT	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
MUS		\checkmark			✓ ✓	
MWI		\checkmark	\checkmark	\checkmark	\checkmark	✓
MYS	\checkmark	\checkmark	\checkmark	\checkmark		\checkmark
NAM					. ✓ ✓	
NER	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
NGA	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	✓ ✓
NIC	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	✓
NLD	\checkmark	\checkmark		√		√
NOR						✓ ✓ ✓
NPL	✓	✓	\checkmark	\checkmark	\checkmark	√
NZL	✓	√		\checkmark		✓
PAK	√	✓	\checkmark	✓	√	✓
PAN	√	✓	√	✓ ✓ ✓	√	✓ ✓
PER	· ✓	· ✓	· ✓	·	√	√
PHL	· ✓	· ✓	· ✓	✓	✓	·
POL	√	, ✓	√	, ✓	√	·
PRI	•	•	•	•	√	•
PRT	✓	✓	•	✓		✓
PRY	. ✓	· ./	✓	√	✓	./
PSE	√	√	√	√	,	√
QAT	√	•	√	•	•	
ROU	√		./			
RUS	./	./	✓ ✓	√	√	✓ ✓
RWA	•	•	√	v	√	√
SAU	✓	✓	√	√	√	∨
SDN	√	√	√	•	√	
SEN	√	∨ ✓	V		√	✓ ✓
SGP	∨ ✓	∨ ✓	✓	V	∨	v
SLE	∨ ✓	∨	V	✓	√	∨
SLV	∨	v	✓	∨ ✓	∨	v
SOM	V	V	V	V	∨ ✓	✓ ✓ ✓
SRB	•	•	✓	✓	∨ ✓	v
	•	•	V	V	∨ ✓	√
SSD	•	•	· ✓	•	v	
SUR			√ √	✓		· ✓
SVK	√ √	√ √	✓	√ √	✓	√
SVN			•		•	√
SWE	\checkmark	√	•	\checkmark	•	✓
SWZ	•	\checkmark	•	•	•	•

SYR	\checkmark	\checkmark	\checkmark	\checkmark		\checkmark
TCD	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
TGO	•	\checkmark			\checkmark	\checkmark
THA	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
TJK	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
TKM		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
TTO		\checkmark		\checkmark		
TUN	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
TUR	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
TWN	\checkmark	\checkmark		\checkmark		\checkmark
TZA	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
UGA	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
UKR	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
URY	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
USA	\checkmark	\checkmark	\checkmark	\checkmark		
UZB	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
VEN	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
VNM	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
YEM	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
ZAF	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
ZMB	•	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
ZWE	✓	✓	✓	✓	✓	✓

Figure A2: Share of respondents with a plan to migrate permanently in the 12 next months, by area of origin.



B Additional results and figures

Table A3: Impact of anti-immigration attitudes: heterogeneity by education level

	(1)	(2)	(3)	(4)
	Mig (HSMS)	Mig (HS)	Mig (MS)	Mig (LS)
Eurobaro., lag	-0.120***	-0.155***	-0.146***	-0.190***
	(0.011)	(0.030)	(0.013)	(0.026)
1st stage resid. (lag)	0.138***	0.157***	0.172***	0.199***
	(0.005)	(0.011)	(0.006)	(0.011)
CDD (1 1)	1.005	4.660	1 (15	2.022
GDP pc (log, lag)	1.805	4.669	1.615	2.823
	(2.002)	(5.877)	(2.546)	(4.591)
Unemp. rate (lag)	-0.101**	-0.193	-0.108**	-0.078
1 (0/	(0.043)	(0.118)	(0.053)	(0.098)
Terrorim at dest., lag	0.003	-0.003	0.001	0.017
	(0.007)	(0.044)	(0.008)	(0.018)
Pseudo-R2	0.409	0.420	0.401	0.325
Origin-Year FE	Yes	Yes	Yes	Yes
Origin-Destination FE	Yes	Yes	Yes	Yes
Observations	4307	1851	3474	1234

^{*}p < 0.10, **p < 0.05, ***p < 0.01. Standard errors clustered at the origin-destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. LS, MS, and HS correspond respectively to low-skilled (up to 8 years of education), middle-skilled (9-15 years of education), and high-skilled (4 years of education beyond high school). HSMS contains HS and MS individuals. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. The instrument used in the first stage is the number of citizens of the destination country killed in terrorist attacks outside of Europe in the year before the Eurobarometer interview. Control variables are the first stage residuals, log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year. Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

Table A4: Result with interaction on development level of origin

	(1)	(2)	(3)	(4)	(5)
	Mig	Mig (HSMS)	Mig (HS)	Mig (MS)	Mig (LS)
Eurobaro., lag	-0.117***	-0.125***	-0.146*	-0.149***	-0.184***
, 0	(0.017)	(0.022)	(0.083)	(0.028)	(0.038)
1st stage resid. (lag)	0.113***	0.129***	0.103***	0.167***	0.165***
13t stage resid. (lag)	(0.005)	(0.005)	(0.011)	(0.006)	(0.010)
CDD (I I)	4.40=	2.072	10	1.710	
GDP pc (log, lag)	1.485	2.073	5.742	1.749	3.306
	(1.797)	(2.001)	(5.970)	(2.538)	(4.618)
Unemp. rate (lag)	-0.077**	-0.091**	-0.139	-0.103*	-0.056
1 (0)	(0.037)	(0.044)	(0.120)	(0.054)	(0.099)
Terrorim at dest., lag	0.007	0.003	-0.003	0.001	0.017
rerreriin at acou, mg	(0.005)	(0.007)	(0.045)	(0.008)	(0.019)
Middle×Eurobaro., lag	0.037**	0.023	0.064	0.013	0.055
Middle × Eurobaro., lag	(0.019)	(0.023)	(0.084)	(0.029)	(0.041)
	, ,	, ,	, ,	,	,
High×Eurobaro., lag	0.004	0.008	0.049	0.005	-0.063
	(0.021)	(0.026)	(0.084)	(0.033)	(0.985)
Pseudo-R2	0.378	0.409	0.421	0.401	0.328
Origin-Year FE	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes
Observations	4600	4256	1837	3438	1234

*p < 0.10, ***p < 0.05, ****p < 0.01. Standard errors clustered at the origin-destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. LS, MS, and HS correspond respectively to low-skilled (up to 8 years of education), middle-skilled (9-15 years of education), and high-skilled (4 years of education beyond high school). HSMS contains HS and MS individuals. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. Control variables are the first stage residuals, log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year. The development level variable is taken from the World Bank classification, with lower-middle income and upper-middle income countries grouped as 'Middle'. The reference level for interactions with development level is 'Low'. Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

Table A5: Result with interaction on whether origin is in Europe

	(1)	(2)	(3)	(4)	(5)
	Mig	Mig (HSMS)	Mig (HS)	Mig (MS)	Mig (LS)
Eurobaro., lag	-0.100***	-0.125***	-0.156***	-0.153***	-0.161***
_	(0.012)	(0.013)	(0.040)	(0.016)	(0.027)
1st stage resid. (lag)	0.118***	0.137***	0.155***	0.172***	0.184***
0 (0)	(0.005)	(0.006)	(0.011)	(0.006)	(0.011)
GDP pc (log, lag)	1.206	1.744	4.675	1.519	2.996
r (8)	(1.835)	(2.029)	(5.900)	(2.583)	(4.555)
Unemp. rate (lag)	-0.085**	-0.102**	-0.192	-0.110**	-0.067
	(0.037)	(0.044)	(0.118)	(0.054)	(0.098)
Terrorim at dest., lag	0.008	0.003	-0.003	0.001	0.017
	(0.005)	(0.007)	(0.043)	(0.008)	(0.019)
In Europe=1×Eurobaro., lag	0.002	0.017	0.008	0.023	-0.040
in Europe Tive Europairon, ang	(0.016)	(0.016)	(0.043)	(0.019)	(0.047)
Pseudo-R2	0.376	0.409	0.420	0.401	0.325
Origin-Year FE	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes
Observations	4651	4307	1851	3474	1234

 $^{^*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors clustered at the origin-destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. LS, MS, and HS correspond respectively to low-skilled (up to 8 years of education), middle-skilled (9-15 years of education), and high-skilled (4 years of education beyond high school). HSMS contains HS and MS individuals. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. Control variables are the first stage residuals, log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year. Europe dummy is equal to 1 if the origin country is in Europe, and 0 otherwise. Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

Table A6: Result by skill using alternative instrument: victims outside adjacent countries

	(1)	(2)	(3)	(4)
	Mig (HSMS)	Mig (HS)	Mig (MS)	Mig (LS)
Eurobaro., lag	-0.198***	-0.216***	-0.246***	-0.339***
	(0.011)	(0.030)	(0.013)	(0.026)
1st stage resid. (lag)	0.216***	0.217***	0.272***	0.348***
	(0.006)	(0.011)	(0.006)	(0.011)
GDP pc (log, lag)	1.434	4.456	1.136	2.089
	(2.003)	(5.883)	(2.547)	(4.590)
Unamer water (last)	-0.146***	-0.226*	-0.165***	-0.165*
Unemp. rate (lag)				
	(0.043)	(0.118)	(0.053)	(0.098)
Terrorim at dest., lag	0.001	-0.004	-0.000	0.015
,	(0.007)	(0.044)	(0.008)	(0.018)
Pseudo-R2	0.409	0.420	0.401	0.325
Origin-Year FE	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes
Observations	4307	1851	3474	1234

^{*}p < 0.10, **p < 0.05, ***p < 0.01. Standard errors clustered at the origin-destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. LS, MS, and HS correspond respectively to low-skilled (up to 8 years of education), middle-skilled (9-15 years of education), and high-skilled (4 years of education beyond high school). HSMS contains HS and MS individuals. The instrument is the number of victims in terrorist attacks outside of the country and its adjacent countries. Control variables are the first stage residuals, log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year. Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

Table A7: Result by skill using alternative instrument: victims outside destination country

	(1)	(2)	(3)	(4)
	Mig (HSMS)	Mig (HS)	Mig (MS)	Mig (LS)
Eurobaro., lag	-0.197***	-0.199***	-0.244***	-0.321***
	(0.011)	(0.030)	(0.013)	(0.026)
1st stage resid. (lag)	0.215***	0.199***	0.270***	0.329***
	(0.006)	(0.011)	(0.006)	(0.011)
CDD (1 1)	1 455	4.500	1.174	0.010
GDP pc (log, lag)	1.455	4.599	1.164	2.213
	(2.003)	(5.883)	(2.547)	(4.590)
Unemp. rate (lag)	-0.145***	-0.215*	-0.164***	-0.154
1	(0.043)	(0.118)	(0.053)	(0.098)
m	0.001	0.004	0.001	0.017
Terrorim at dest., lag	0.001	-0.004	-0.001	0.016
	(0.007)	(0.044)	(0.008)	(0.018)
Pseudo-R2	0.409	0.420	0.401	0.325
Origin-Year FE	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes
Observations	4307	1851	3474	1234

^{*}p < 0.10, **p < 0.05, ***p < 0.01. Standard errors clustered at the origin-destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. LS, MS, and HS correspond respectively to low-skilled (up to 8 years of education), middle-skilled (9-15 years of education), and high-skilled (4 years of education beyond high school). HSMS contains HS and MS individuals. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. The instrument is the number of victims in terrorist attacks outside of the country. Control variables are the first stage residuals, log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year. Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

Table A8: Table 2 results, but with standard errors clustered at destination level

Panel A: first stage					
	(1)	(2)	(3)	(4)	
	Eurobaro.	Eurobaro.	Eurobaro.	Eurobaro.	
# terr. victims out Eur.	0.258***	0.239***	0.179***	0.189***	
	(0.016)	(0.016)	(0.016)	(0.016)	
GDP per cap. (log)		16.690***	-6.630***	-4.443***	
		(0.582)	(0.984)	(1.065)	
Unemp. rate			-0.602***	-0.562***	
Chemp. fate			(0.018)	(0.020)	
			(0.010)	,	
Terrorim at dest.				-0.015***	
				(0.001)	
Year FE	Yes	Yes	Yes	Yes	
Destination FE	Yes	Yes	Yes	Yes	
Observations	31,752	31,752	31,752	31,752	
KP F-statistic	256	234	124	141	
	Panel B	: second stage	2		
	(1)	(2)	(3)	(4)	
	Mig	Mig	Mig	Mig	
Eurobaro., lag	-0.042***	-0.068***	-0.101***	-0.099***	
	(0.015)	(0.016)	(0.017)	(0.017)	
1 at ata as world (las)	0.071***	0.088***	0.120***	0.118***	
1st stage resid. (lag)	(0.010)	(0.009)	(0.010)	(0.010)	
	(0.010)	(0.009)	(0.010)	(0.010)	
GDP pc (log, lag)		4.320***	1.831	1.219	
1 · (· · · · · · · · · · · · · · · · ·		(1.303)	(2.730)	(2.628)	
		, ,	,	, ,	
Unemp. rate (lag)			-0.078	-0.085	
			(0.060)	(0.060)	
Torrorim at doct lac				0.008	
Terrorim at dest., lag				(0.027)	
Pseudo-R2	0.376	0.376	0.376	0.376	
Origin-Year FE	Yes	Yes	Yes	Yes	
Origin-Destination FE	Yes	Yes	Yes	Yes	
Observations	4651	4651	4651	4651	
- CDSCI VALIOIIS	T001	TUJ1	TUU 1	1031	

^{*}p < 0.10, **p < 0.05, ***p < 0.01. Standard errors clustered at the destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. # terr. victims out Eur. is the number of citizens of the destination country killed in terrorist attacks outside of Europe in the year before the Eurobarometer interview. Control variables are the first stage residuals, log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year. Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

Table A9: Table 3 results, but with standard errors clustered at destination level

(1)	(2)	(3)	(4)
Mig (HSMS)	Mig (HS)	Mig (MS)	Mig (LS)
-0.120***	-0.155***	-0.146***	-0.190***
(0.021)	(0.048)	(0.026)	(0.035)
0.138***	0.157***	0.172***	0.199***
(0.013)	(0.020)	(0.014)	(0.021)
	4.669	1.615	2.823
(2.996)	(8.726)	(3.124)	(7.550)
-0.101	-0 193	-0.108	-0.078
			(0.168)
(0.003)	(0.134)	(0.073)	(0.100)
0.003	-0.003	0.001	0.017
(0.029)	(0.101)	(0.048)	(0.137)
0.409	0.420	0.401	0.325
Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes
4307	1851	3474	1234
	Mig (HSMS) -0.120*** (0.021) 0.138*** (0.013) 1.805 (2.996) -0.101 (0.063) 0.003 (0.029) 0.409 Yes Yes	Mig (HSMS) Mig (HS) -0.120*** -0.155*** (0.021) (0.048) 0.138*** 0.157*** (0.013) (0.020) 1.805 4.669 (2.996) (8.726) -0.101 -0.193 (0.063) (0.154) 0.003 -0.003 (0.029) (0.101) 0.409 0.420 Yes Yes Yes Yes Yes Yes	Mig (HSMS) Mig (HS) Mig (MS) -0.120*** -0.155*** -0.146*** (0.021) (0.048) (0.026) 0.138*** 0.157*** 0.172*** (0.013) (0.020) (0.014) 1.805 4.669 1.615 (2.996) (8.726) (3.124) -0.101 -0.193 -0.108 (0.063) (0.154) (0.073) 0.003 -0.003 0.001 (0.029) (0.101) (0.048) 0.409 0.420 0.401 Yes Yes Yes Yes Yes Yes

*p < 0.10, **p < 0.05, ***p < 0.01. Standard errors clustered at the destination country level in parenthesis. Variable Mig. is the ratio of movers from i to j over stayers derived from the standard RUM model. LS, MS, and HS correspond respectively to low-skilled (up to 8 years of education), middle-skilled (9-15 years of education), and high-skilled (4 years of education beyond high school). HSMS contains HS and MS individuals. Variable Eurobaro. is the share of individuals in the destination country that think immigration is one of the main two issues in their country. The instrument used in the first stage is the number of citizens of the destination country killed in terrorist attacks outside of Europe in the year before the Eurobarometer interview. Control variables are the first stage residuals, log of GDP per capita, the unemployment rate, and the number of victims of terrorist attacks in the destination country lagged by one year. Non-parametric bootstrap was applied on both steps of the control function, using the full sample with replacement (1000 replications).

Figure A3: Estimation results of equation (3b) when excluding one country of destination at a time. Each dot gives the estimated coefficient for the variable of anti-immigration attitudes, and the line shows the 95% confidence level. The country excluded from the estimation is reported on the X axis.

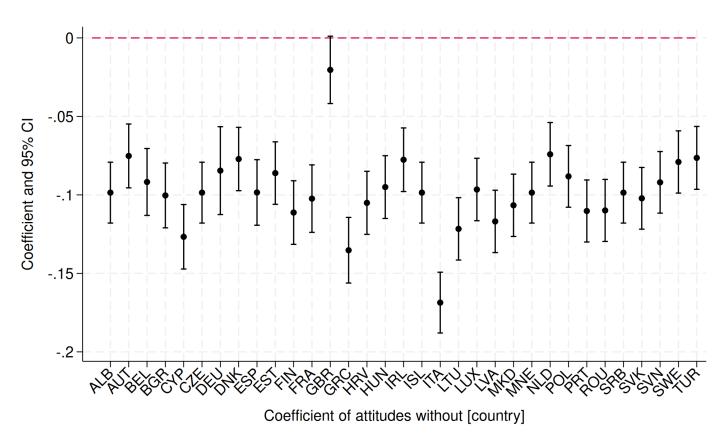
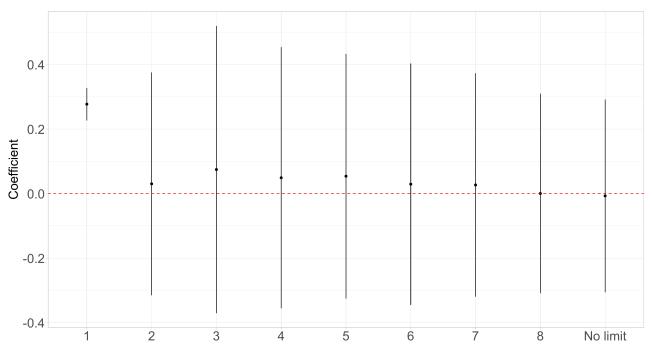


Figure A4: Effect of being interviewed after an attack happening during the Eurobarometer survey period on the likelihood of considering immigration as one of the two main issues in the country. Each point comes from a separate logit regression and corresponds to the coefficient of the variable 'Post', i.e. being interviewed after the attack outside Europe happens. The x-axis shows how many days around the attack are kept. For example, the value 1 means that we only focus on people who were interviewed one day before and one day after the attack. Standard errors are clustered at the country level.



Number of interview days kept before and after attack

Figure A5: Google trends for searches of the word 'terrorism' in Great Britain in 2015. This is a relative measure: the date with the most searches has the value 100. The dashed red line corresponds to the Sousse attack in Tunisia, which killed 30 British citizens (among other casualties).

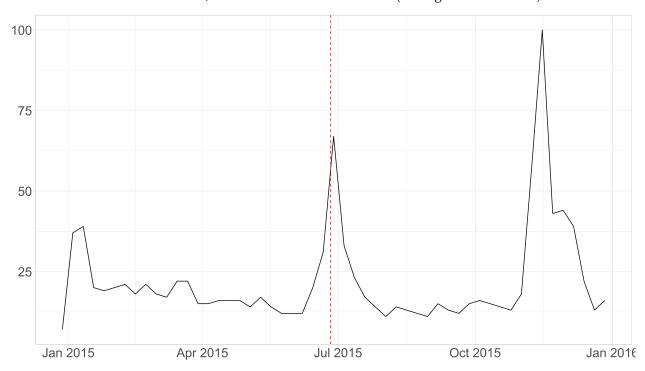


Figure A6: Google trends for searches of the word 'terrorisme' in France in 2011. This is a relative measure: the date with the most searches has the value 100. The dashed red line corresponds to the Marrakesh bombings, which killed 8 French people (among other casualties).

