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Which individual-level factors explain public attitudes toward immigration? a meta-analysis

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ABSTRACT

Public attitudes toward immigration have attracted much scholarly interest and extensive empirical research in recent years. Despite a sizeable theoretical and empirical literature, no firm conclusions have been drawn regarding the factors affecting immigration opinion. We address this gap through a formal meta-analysis derived from the literature regarding immigration attitudes from the top journals of several social science disciplines in the years 2009–2019 and based on a population of 1185 estimates derived from 144 unique analyses on individual-level factors affecting attitudes to immigration. The meta-analytical findings show that two individual-level characteristics are most significantly associated with attitudes to immigration -- education (positively) and age (negatively). Our results further reveal that the same individual characteristics do not necessarily explain immigration policy attitudes and attitudes toward immigrants' contribution. The findings challenge several conventional micro-level theories of attitudes to immigration. The meta-analysis can inform future research when planning the set of explanatory variables to avoid omitting key determinants.

1. Introduction

Immigration is among voters' top concerns when asked about the main challenges for their country or other political entities such as the European Union (e.g. European Commission 2019a, 2019b). Public attitudes toward immigration are becoming part of a new political cleavage (Hobolt 2016; Kriesi et al. 2012), particularly in the aftermath of the so-called 'migration crisis'. Consequently, explaining the reasons for individual differences in attitudes to immigration has attracted increased scholarly interest. Various hypotheses regarding factors affecting attitudes to immigration have been proposed, resulting in often highly correlated determinants, making it difficult to assess which of these are truly relevant. In this article, we conduct a meta-study asking which demographic individual-level indicators are consistently found to influence attitudes to immigration within the

broad social science literature. Meta-analyses are essential for formally structuring and summarising the scholarly state-of-the-art on a topic. They also play a crucial role in explaining the origins of the heterogeneity of research results to academics who are non-experts in the field, policymakers, and practitioners. Our paper complements the influential review papers on attitudes toward migration (Ceobanu and Escandell 2010; Hainmueller and Hopkins 2014; Mayda 2006) by providing a quantitative meta-analytical overview. Moreover, it is also worth highlighting that these reviews were done several years ago and a lot of new insights have emerged from the literature since then.

We systematize the knowledge regarding attitudes to immigration across various social science fields and cover the thirty top-ranked journals for each discipline across economics, political science, sociology, psychology, and migration/ethnic/demographic studies published between 2009 and 2019. From these, we select all 350 articles that quantitatively analyse the determinants of attitudes toward immigration. After dropping all articles covering attitudes to immigration out of scope, we evaluate information from 140 academic articles and 1185 estimates in total. We thus provide an encompassing review of the research regarding attitudes to immigration published across different social science fields during the past decade.

Out of the 150 different types of attitudes to immigration that we have encountered in the literature, we focus on the two groups of dependent variables that are the most relevant and the two most commonly surveyed, which capture preferences toward migration policy (e.g. preferred levels of immigration) and views about immigrants' contribution to society. These two dependent variables complement each other as they measure two concepts — preferences regarding levels of immigration and opinions regarding the effect of immigration. We identify the relevant factors affecting attitudes to immigration based on statistically representative samples from all over the world.

Our approach focuses on eight individual-level indicators, namely age, gender, education, income, occupational and unemployment status, as well as respondents' minority background and the type of area (urban versus rural) they live in. When selecting individual independent variables, we followed other reviews of public opinion on migration and only focused on the widely used determinants (see Ceobanu and Escandell 2010; Dražanová 2022; Hainmueller and Hopkins 2014) rather than understudied factors such as, for example, disgust sensitivity (Aarøe, Petersen, and Arceneaux 2017). After this initial pre-selection, we further reduced the number of independent variables, as some (for example subjective economic well-being, political affiliation, etc.) had too few observations for a meta-analysis. Our study's main objective is to assess recent empirical evidence on which of these individual-level factors are consistently (positively or negatively) linked with attitudes to immigration.

A key result of our meta-analysis is that two individual-level characteristics are most significantly associated with attitudes to immigration – education (positively) and age (negatively). More educated individuals are consistently found to hold significantly more positive attitudes toward immigration. Further, we find that education's effect is not only due to its correlation to income, indicating that it also represents a value-based cleavage. On the other hand, age is negatively associated with attitudes toward immigration. Older respondents hold significantly more anti-immigration attitudes than younger respondents. Positive attitudes to immigration are also correlated with the economic standing of an individual – high-skill occupation, as well as higher

income, predict significantly more positive attitudes to immigration. Living in urban areas positively correlates with pro-immigration attitudes, likely partly due to urban residents having more contact and having self-selected into cities. Our meta-study highlights that if an analysis lacks certain variables, part of their effect might be wrongly attributed to other explanatory variables. For instance, we show that the effect of education, income and age are prone to vary based on whether other individual characteristics, such as minority background and gender, are accounted for. Researchers should thus tread carefully when selecting variables in their models and interpreting these variables. From a more methodological perspective, we also hope that our paper can inspire the use of BMA in future meta-analyses in the social sciences.

Finally, our results reveal that immigration policy attitudes and attitudes toward immigrants' contribution are not necessarily explained by the same individual characteristics. Thus, it appears that different factors should be tackled when addressing (or aiming at changing through informational campaigns) attitudes to immigration. These findings provide an original and insightful perspective on attitudes to immigration with implications for both researchers and policymakers.

The following section presents the theoretical framework most of the literature uses to explain how and why different individual-level characteristics may affect attitudes toward immigration. In the *Data and Methodology* section, we describe our research strategy and the sample of quantitative studies used in the meta-analysis. In *Results*, we systematically analyse the individual factors most frequently used in these quantitative analyses to explain attitudes toward immigration. Technical issues such as publication bias, study heterogeneity and quality of the estimates are addressed as well. We conclude the paper by summarising the lessons learned and discussing some opportunities for further research.

2. Theoretical arguments

Social scientists mostly agree that differences in attitudes to immigration are driven by two (sometimes overlapping) types of individual-level factors – economic and cultural. The theoretical framework most often used by social scientists in explaining opposition to immigration is the 'competitive threat' theoretical model. According to this model, anti-immigrant sentiment should be understood as a reaction to the threat of competition (whether real or perceived) with immigrants either in the economic sphere (labour market, welfare system) or in the cultural sphere (cultural homogeneity of society, social values). Each discipline among those we investigate in this article places more emphasis on studying one of the two groups. For instance, while economists usually focus on economic factors affecting attitudes to immigration, other disciplines, such as sociology or migration studies, predominantly study cultural factors. Within this framework, economic and cultural theories sometimes yield contradictory predictions. While economic theories suggest that natives should prefer immigrants who are different from themselves in terms of, for example, skills, cultural theories emphasise the importance of similarity.

Economic factors

Key theoretical arguments regarding economic concerns as drivers of anti-immigration attitudes extract two central motives: Firstly, the egocentric economic evaluation of

consequences for individuals' economic prospects due to migration. Secondly, the socio-tropic economic evaluation of the effect of migration on the host country as a whole.

Egocentric economic evaluations are often tight to the labour market competition hypothesis suggesting that the benefits and/or disadvantages of immigration are unevenly distributed within society. Natives who compete with immigrants in the labour market based on their income, employment status, and education or skill level[1] should perceive the newcomers more negatively than individuals who do not. Hence, according to the labour market competition theory, people who are in a weaker labour market situation (e.g. less education, lower wages, less job protection) are more likely to oppose low-skilled immigration because they may fear losing their jobs if immigrants can be hired at lower wages or worse working conditions (Gerber et al. 2017; Margalit 2019; Scheve and Slaughter 2001) while highly skilled and rich natives are expected to prefer low-skilled immigrants. At the same time, unemployed individuals may perceive that the presence of immigrants makes their job search more difficult. Recent studies (Dancygier and Donnelly 2013; Pardos-Prado and Xena 2019) underline that the labour market threat plays a role in many contexts.

Another relevant economic channel for opposition to immigration are sociotropic economic considerations about redistribution and the fiscal burden linked to the influx of immigrants. Immigration can be regarded as creating additional pressure on the national welfare system, with potential effects on the attitudes of both low- and high-skilled natives. On the one hand, native beneficiaries of a state's welfare system may fear an erosion of their welfare benefits if there is an increase in demand from immigrant recipients (Valentino et al. 2019). On the other hand, immigration may impose additional costs on tax-funded welfare systems, especially if most immigrants are low-skilled. If taxes are progressive, the brunt of these increased costs will be borne by higher-earning individuals, who could therefore develop opposing attitudes toward immigration (Gerber et al. 2017; Hainmueller and Hopkins 2014).

On aggregate, scholars find little evidence that personal economic circumstances influence immigration attitudes in a way that is consistent with predictions of the labour market theory (Hainmueller and Hopkins 2014). Rather, multiple studies show that in most countries highly skilled migrants are preferred over low-skilled migrants irrespective of natives' skill levels (Gerber et al. 2017; Hainmueller and Hiscox 2007, 2010; Hainmueller, Hiscox, and Margalit 2015; Hainmueller and Hopkins 2015; Helbling and Kriesi 2014; Naumann, Stoetzer, and Pietrantuono 2018).

Thus, economic self-interest does not seem to be the main driver of anti-immigration sentiments. In this regard, citizens' motivations are sociotropic rather than egocentric.

Cultural factors

Apart from the threat to economic interests, members of the majority population might feel threatened by the impact that immigrants exert on the national and cultural character of the society. Immigrants might therefore be perceived as a threat to cultural homogeneity, value system, national and cultural identity, purity of language, et cetera (Fetzer 2000; Sniderman, Hagendoorn, and Prior 2004).

An important factor that is driven primarily by culture is the far more negative views that older people have against migrants on average. These differences are not because

people become more anti-immigrant as they age. Several studies show that attitudes toward immigration are stable over adulthood (Hooghe and Wilkenfeld 2008; Kustov, Laaker, and Reller 2021) and remain remarkably persistent as the person grows older in a similar way to other political predispositions acquired in youth (Neundorf, Smets, and García-Albacete 2013; Vaisey and Kiley 2021). These values and attitudes are then expected to persist through the individuals' lifetime and rarely be subjected to change (Visser and Krosnick 1998). The correlation between age and anti-immigration views thus constitutes a cohort instead of a direct age effect (Jeannet and Dražanová 2019). Such cohort effects are a prime example of why it can be complicated to analyse the causal mechanisms behind individual-level factors' effect on migration attitudes.

This becomes even trickier, when self-selection is involved, i.e. when people's characteristics are not exogenous (like their age) but can be adjusted based on their preferences or be shaped by circumstance. For instance, people living in urban settings are often more likely to have positive attitudes to immigration. There exist three major explanations for why residents of more urban areas often hold more positive immigration attitudes. First, this is explained by their higher exposure to immigrants, which makes them more likely to form favourable attitudes toward them through interactions with them as equals in work or personal environments (McLaren 2003; Pettigrew and Tropp 2006; Stolle et al. 2013). Second, urban residency can also be linked to compositional effects leading to more positive attitudes to immigration (Maxwell 2019). This is, in part, based on self-selection. People more likely to hold positive attitudes to immigration are also more likely to self-select into large cities with their multicultural environments. Third, people in large cities are also more likely to be higher educated with higher-skill occupations and income, which, in turn, is associated with more positive attitudes to immigration.

Apart from being a skill proxy, education also plays a role in cultural theories. For example, more-educated respondents often have higher self-esteem and confidence and attach higher values to cultural diversity (Hainmueller and Hiscox 2007). The overall effect of education on attitudes is thus likely a combination of the labour market and cultural mechanisms. This increases the expected positive correlation between education and immigration attitudes.

Some factors cut across both theories, where the direction and predictions of their empirical relationship become ambiguous as mechanisms have different signs. Gender is a case in point. Studies generally assume men hold more anti-immigration attitudes due to their more authoritarian personalities (Adorno et al. 1950) and conservatism (Harteveld et al. 2015). However, with the recent politicisation of gender in immigration debates (Farris 2017), native women might view certain immigrants as a threat to gender equality (Ponce 2017). Another example of theoretical associations going both ways is minority status. Despite potentially being prejudiced toward other immigrants, members of minority groups can identify more strongly with other immigrants due to their migration history and their shared outgroup status (Becker 2019). On the other hand, members of minority groups already settled in a host country can perceive newcomers as a competitive threat. Our meta-study results partly agree with research showing that immigrants and ethnic and racial minorities are more favourable to immigration than native-born individuals (Just and Anderson 2015; Sedovic and Dražanová 2023).

In general, attitudes to immigration are thought to be shaped by the extent to which an individual feels threatened by different groups and ideas. These feelings of threat may be either economic or cultural or both. Many scholars (D. Card, Dustmann, and Preston 2012; Hainmueller and Hopkins 2015; Margalit 2019) argue that economic factors are consistently weaker predictors of attitudes to immigration than cultural concerns. Other studies (Mayda 2006; Scheve and Slaughter 2001), however, argue that economic concerns are of primary importance in explaining individual attitudes to immigration. Against this backdrop, the present meta-study may help to fill an important research gap by providing a systematic overview of the absolute and relative importance of different determinants of attitudes across studies and disciplines.

3. Data and methods

3.1. Study selection and data generation

The selection of studies can influence the results and conclusions of a meta-analysis (Smets and van Ham 2013), and statistically insignificant studies are less likely to be published - in both journals and pre-prints. Since the 'file drawer' problem also exists for pre-prints, we follow researchers treating studies' effect sizes and p-values as stemming from a censored distribution (Kasy 2021). We then focus on the studies that can be considered 'highest quality', i.e. those published in top-ranked journals which have gone through rigorous peer review.

As the best available yet imperfect measure of journal quality, we use different rankings, namely the Journal Impact Factor (JIF) by Clarivate, the SCImago Journal Ranking (SJR), and the Google Scholar ranking, which are those most often provided by academic publishers hosting these journals (see Appendix for details). To compile a joint list of journals that can serve as the sampling frame for the selection of studies, we use the top 30 journals from the JIF ranking and the top 20 journals from the Google Scholar ranking[2] for each discipline. We then exclude journals that are either assigned incorrectly to the field's journal rankings (e.g. finance journals in the economics ranking) or that only publish review, methodological or theoretical papers. The resulting lists are then filled up with journals from the list of the top journals of the SJR index. We use a similar approach for the smaller disciplines (ethnic studies/migration studies/demography, see Appendix for details). The full list of journals included for each discipline can be found in Table A1 in section A.1 of the Appendix.

To select papers for the meta-analysis, we follow the Cochrane protocol (Higgins et al. 2019) and especially Dinesen, Schaeffer, and Sønderskov (2020) in identifying the population of studies. To identify potential articles of interest, we applied the following three criteria; The study must be (1) published in one of the selected top 30 academic journals of the respective disciplines and has to be (2) in English. Since we want to provide a meta-analysis of the recent developments in the field, the study must (3) have been published between 2009 and 2019. We include (4) quantitative analyses only. Being interested in individual attitudes toward immigration, we (5) only include studies using individuals as the unit of observation. Finally, to be included, analyses (6) must measure how respondents' characteristics and circumstances affect their attitudes to immigration, i.e. not how immigrants' characteristics affect respondents' attitudes. The analyses included in the

meta-analysis (7) must contain information about factors affecting the variation in individual attitudes to immigration, but their principal focus does <u>not</u> have to be attitudes to immigration.

We then selected peer-reviewed articles using the keywords 'immigrant' or 'immigration' for the selected time frame (2009–2019). The identification process was carried out by two independent coders based on the additional criteria listed below. If both coders identified the same article, we included the article in our dataset. In case of a disagreement between the coders, a third coder made the decision.

When selecting analyses from articles to be included in the meta-analysis, one must bear in mind that an academic article may perform an analysis for different dependent variables. In this case, we include all these analyses separately. The dependent variables matter because they determine which analyses are included. We select analyses whose dependent variable refers to immigrants as a general category, illegal immigrants, refugees, asylum seekers, or migrants with specific ethnic, religious, and cultural backgrounds. The dependent variable must measure attitudes to immigration directly and express positive or negative opinions (as opposed to neutral statements toward immigrants or neutral policy preferences). To account for dependent variables that were created through dimension-reduction techniques, e.g. additive indices, the analysis is included only if the dependent variable includes all or a majority of attitudinal indicators directly related to immigration as defined previously.[3] Finally, the dependent variable must be directly interpretable as a measure of attitudes, e.g. not a party vote, even if it is an anti-immigrant party.

The complete bibliography of the studies is provided in Table A2 in section A.2 of the Appendix. Figures A1–A4 in the same section also present a series of visualisations of the information contained in articles regarding public opinion toward migration, which underlie our meta-analysis. The figures provide insights in terms of data, study design, and research methods used.

Our initial inclusion criteria result in around 150 different measures of attitudes to immigration that are used in the literature. For simplicity, we have grouped analyses into ten higher-ordered groups of dependent variables based on the dependent variable they use. The list of those higher-ordered groups can be found in section A.3 in the Appendix.

Many of the dependent variables covered above are not comparable to each other, and jointly considering them in a single analysis would not yield useful results. Instead, we focus on the two groups of dependent variables that are the most relevant and have the greatest number of analyses: 'contribution and consequences of immigration (e.g. economic, cultural, social, political)' and 'attitudes and policy preferences on immigration flows and level'. The former set of dependent variables includes mostly attitudes regarding the ex-post assessment of immigration's impact on society and whether immigration is beneficial to the community, e.g. in terms of economy or culture. The latter set includes attitudes such as allowing more or fewer immigrants of different types into the country (labour, refugees, unskilled, certain religions). This concept engages with policy debates about levels of immigration and entry criteria, such as debates about the introduction of points systems that privilege potential migrants with higher skills. Furthermore, these two types of dependent variables complement each other, with the former covering ex-post and current assessment and the latter preferences for the future. A

detailed list of attitudes included under these two categories is available in Table A3 in the Appendix. Our focus on these two groups of dependent variables leaves us with a total of 144 analyses. When considering the different samples that can be included, we do not impose any demographic, geographic, ethnic, or other restrictions based on respondents' characteristics, e.g. their religious background or minority status. Yet, we select samples based on their external validity, which we define as the extent to which attitudes of individuals in the sample are representative of a given population group and can serve as a meaningful basis for the analysis of attitudes toward immigration. Our meta-analysis thus covers both large and small-scale studies but excludes samples that lack information on representativeness. When an analysis consists of an experiment, we always use attitudes toward immigration from the pre-treatment period.

Based on previous studies (f.e. Ceobanu and Escandell 2010; Dražanová 2022) we initially pre-selected a sub-set of independent variables expected to affect attitudes to immigration and that appear in the literature frequently. Most independent variables offer little potential for our meta-analysis, as they occur in too few analyses to provide a large enough estimate sample. After the initial collection, we had to restrict the list of independent variables even further, as several originally included variables have not reached a critical number of estimates to be tested. The type of independent variables – continuous, categorical, binary – does not affect study inclusion as long as the corresponding coefficients can be exploited.

Within studies, estimates are drawn from a single model and are a unique combination of the dependent variable (capturing the type of attitudes toward immigration), independent variable (capturing a specific individual factor), and sample (a given population group). It should be however noted that some studies include more than one population sample. For instance, a study may conduct more than one analysis on surveys from different countries, in order to show the reliability of the results. In these cases, we choose to include a unique estimate, i.e. coefficients drawn from a single model. Hence, some studies are listed twice in the figures but always refer to two independent estimates. This is to limit within-study dependencies between estimates drawn from two or more models of the same study that differ only in the number of controls included in the regression, estimation techniques, or other minor features whose inclusion would yield little additional information.[4] We also exclude estimates for which neither the standard errors nor the p-value were reported and regressions with fewer than 30 degrees of freedom. Our final working dataset yields 1185 effect sizes across 110 studies. Table A4 and A5 in the Appendix list all the independent variables included in our meta-analysis along with the corresponding number of effect sizes.

3.2. The meta-analytical methodology

Because this meta-analysis aims to estimate the relationship between individual socio-economic characteristics – which cannot be changed experimentally – and attitudes toward immigration, the bulk of studies in our dataset are non-experimental. Studies furthermore vary in empirical methods and reported types of estimates (linear coefficients, odds ratio, probit, etc.). Moreover, because our meta-analysis contains data collected from different social sciences, each with specific guidelines for reporting estimation results, some studies present standard errors, others confidence intervals, and others

simply p-values. How most individual characteristics are measured is not constant across studies. For instance, while some studies capture age through the actual age of individuals, others use a categorical variable or cohort classification. Likewise, education can be measured through years of schooling, categories of highest degree obtained, or binary variables parting respondents between those with and without a post-secondary education.

As a result, we must transform the coefficients and the corresponding uncertainty estimates from each regression using a common metric. Following several existing meta-analyses (Cazachevici, Havranek, and Horvath 2020; Dinesen, Schaeffer, and Sønderskov 2020), we use the partial correlation coefficient (PCC) to standardise and compare these point estimates across studies. We first harmonise the direction of those estimates so that positive coefficients and t-statistics capture positive attitudes to immigration. We then derive the t-statistics and collect the sample size and the overall number of predictor variables contained in each regression. For each point estimate extracted from a regression, we then calculate the PCC as follows:

$$PCC = \frac{t}{t^2 + df}$$

where t denotes the corresponding t-statistic, and df corresponds to the number of degrees of freedom. We also calculate the standard error corresponding to the partial correlation coefficient using the following formula:

$$SE_{PCC} = \frac{PCC}{t}.$$

The partial correlation coefficient indicates the strength and direction of the relationship between a given individual characteristics and attitudes toward immigration. It captures the correlation between an individual factor and positive attitudes toward immigration, statistically adjusted for all other variables contained in the respective regression model. It can take values in the interval $[-1, 1]$, whose boundaries denote perfect negative and positive associations, respectively.

As seen in Section 3.1, every effect size behind a partial correlation coefficient is a unique combination of the dependent variable (capturing the type of attitudes toward immigration), independent variable (capturing a specific individual factor), and sample (a given population group). Although this methodology reduces the risk of within-study correlation between estimates, estimates may still be drawn from the same sample within a given study, which breaches the cardinal assumption of meta-analysis that coefficients derive from independent samples. Following N. A. Card (2015) and Dinesen, Schaeffer, and Sønderskov (2020), we, therefore, apply a two-step procedure in which we first meta-analyse the coefficients of each study. Because some studies run separate analyses using two or more independent datasets, we build study-dataset-specific estimates within each study, obtaining an overall meta-estimate per study-dataset pair that we call study-data pooled estimates.[5] These study-dataset pooled estimates allow us to get rid of within-study correlation issues that result from estimates being nested within studies. Following Stevens and Taylor (2009) and (Bagos 2015), we assume that within a single study, data that are independent and analysed separately will not lead to a dependence structure among their results.

In a second step, we then meta-analyse these study-data pooled estimates to obtain the overall meta-estimate of the relation between individual factors and attitudes to immigration. As stressed previously, a specific issue with our data is that dependencies between estimates may arise from the fact that a significant share of studies analyse widely-used survey data, such as the European Social Survey, the European Value Study, or the World Value Survey. In our application, while study-data pooled estimates make sure that the conventional assumption that samples are independent holds within a given study, this assumption is likely to be violated across studies covering the same or partly overlapping samples.[6]

We address the nesting of study-data pooled estimates within datasets with a meta-analytical multilevel random effects model. Stata contains several programs performing meta-analyses, such as the *metan* package, which can fit the random effects model. However, there is no dedicated module for performing meta-analysis with correlated estimates or, in our application, multilevel meta-analysis, where multiple estimates are 'nested' within samples. Instead, to analyse our metadata, we use the method developed by Bagos (2015) using the gllamm package in Stata, where estimates from each study are grouped – or nested – based on the data used.[7]

More specifically, we account for the clustering of study-data pooled estimates within datasets by fitting the following hierarchical model, which includes random effects for between-dataset variation and within-dataset variation:[8]

$$y_{ij} = \beta + b_i + b_{ij} + \varepsilon_{ij} \tag{1}$$

where y_{ij} represents study-data estimate j nested within dataset i and β the overall effect size that we estimate between individual characteristics and attitudes toward immigration. b_i is the random effect for between-dataset variation, which captures the variability in effect sizes between different datasets and follows a normal distribution with mean 0 and variance σ_d^2. b_{ij} is the random effect for within-dataset variation, which accounts for the variability in study-data estimates j nested within each dataset i. It follows a normal distribution with mean 0 and variance σ_s^2. Finally, the error term ε_{ij} represents the remaining variability or noise not accounted for by the random effects.[9]

It is worth stressing that it remains impossible to identify the dependencies between estimates perfectly. For instance, some regressions are performed on a single wave and a single country of the ESS, while others pool together several waves and/or countries. As a result, the corresponding samples partly overlap in a way that is impossible to identify without access to the actual data. Therefore, we follow Dinesen, Schaeffer, and Sønderskov (2020) and add random effects for the data used but ignore specific years of survey waves.
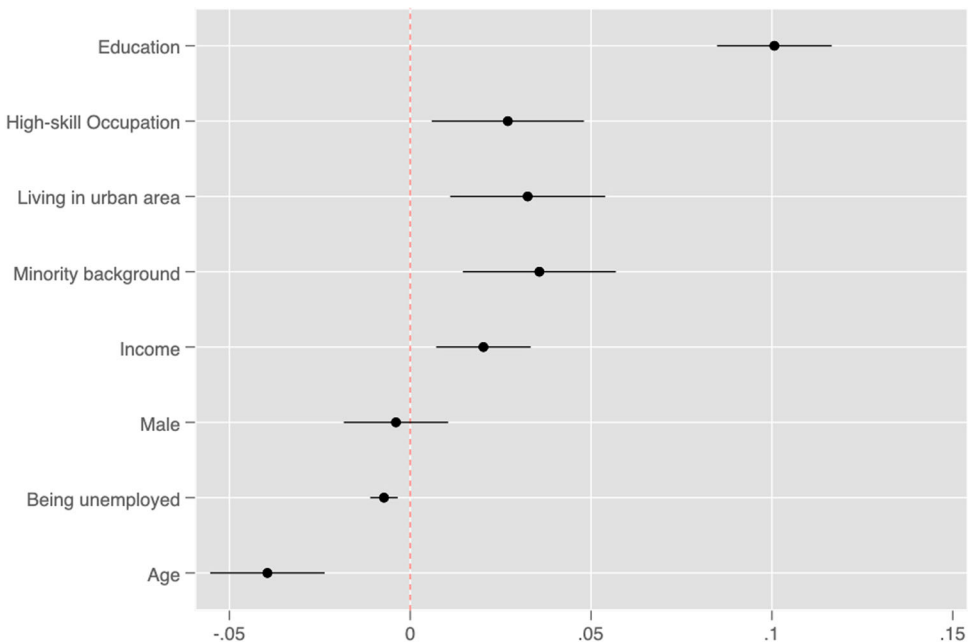
4. Results

4.1. Main results

Figure 1 and Table 1 present the results of model (1) capturing the partial correlations between the individual characteristics of interest and positive attitudes to immigration. We first examine the results of the partial correlation between individual factors and both attitudes to immigration as an overarching attitude.

The strongest positive association among all individual-level factors covered in Figure 1 is the partial correlation between education and pro-immigration attitudes. Having a high-skill occupation,[10] income and unemployment have substantially smaller associations. This fits the expectation that the effect of education is not necessarily about its correlation with higher social class, income or unemployment, but might also have a 'cultural effect' on its own and may be understood as a value-based cleavage that adds to its role in the economic mechanisms determining attitudes.

In line with the expectation and as mentioned earlier, the PCC in Figure 1 shows that the higher an individual's income, the more pro-immigration their attitude. Unemployment is, on average, associated with more anti-immigration attitudes.

As expected, living in an urban area is positively associated with pro-immigration attitudes. Since immigrants are over-represented in urban areas, this coefficient highlights the cultural component of living in cities. Urban residents have more contact and may also self-select into cities – urban residence is thus potentially endogenous. In the extreme, there could be a direct link between anti-immigration attitudes and not wanting to move to cities – a fact that should make researchers tread carefully when using and interpreting this variable in their statistical analyses.

Having a minority background is positively associated with attitudes to immigration. This fits the theory that cultural factors may lead to more openness of minorities toward migrants. For instance, immigrants and ethnic and racial minorities may be more favourable to immigration than native-born individuals because they can identify more strongly with other immigrants due to their migration history or similar outgroup status (Becker 2019).

Figure 1. Partial correlation between individual characteristics and positive attitudes to immigration.
Note: The figure visualises the partial correlations between the individual characteristics of interest and positive attitudes to immigration.

Table 1. Main results.

	(1) Age	(2) Education	(3) Male	(4) High Occupation	(5) Income	(6) Minority	(7) Unemployed	(8) Urban area
PCC	−0.039***	0.121***	−0.004	0.027**	0.020***	0.036***	−0.007***	0.032***
	[−0.055,−0.024]	[0.102,0.140]	[−0.018,0.010]	[0.006,0.048]	[0.007,0.033]	[0.015,0.057]	[−0.011,−0.003]	[0.011,0.054]
τ_s^2	.0016	.0055	.0007	.0002	.0005	.0021	.0001	.0004
τ_d^2	.0018	.0009	.0022	.0006	.0005	.0011	.0000	.0006
Samples	60	58	65	10	31	28	26	13
Study-data pooled est.	101	110	112	22	46	50	54	30
Single estimates	220	248	177	83	112	147	98	100

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. 95% confidence intervals in square brackets. The partial correlation coefficient are obtained using a multi-level model that accounts for the nesting of study-data pooled estimates within datasets and their respective random terms. τ_d^2 corresponds to the between-dataset variance, while τ_s^2 correspond to the variance between-study-data pair within a dataset.

Regarding gender differences, our data shows the expected empirical ambiguity. Men and women do not express significantly different attitudes to immigration in our PCC model, suggesting that gender differences are context-dependent and may furthermore depend on a study's specific framing.

Age plays a significant role across studies. Older respondents are significantly more likely to have anti-immigration views. As discussed in the theory section, the strong differences between older and younger people are not primarily because ageing makes them less tolerant of migrants but due to the different contexts in which people have been socialised.

For every individual factor, PCCs and their standard errors are plotted in Figures A5–A12 in section A.5 of the Appendix.[11] We also present the results of our baseline analysis for a selection of sub-samples from the main dataset: We run model (1) separately for each social science field surveyed in our analysis and on a subsample containing only non-experimental studies in our dataset. Results are presented in Appendix A.6. Although the meta-analysed PCCs vary slightly in statistical significance, we find that the direction of the association between individual factors and attitudes toward immigration remain unchanged across fields and type of studies.

4.2. Analysis by type of attitude

We next divide the dataset into two subsets, distinguishing between equations estimating the relationship between individual drivers and (1) public opinion toward migration policy and (2) individuals' assessment of migrants' contribution to their destination country. When looking at the results shown in Figures 2 and 3 and Tables 2 and 3 it becomes evident why it is important to look also at the two sets of dependent variables separately. Figure 2 shows that several individual-level characteristics (education, living in an urban area, having a minority background, having a high-skill occupation and high-income level) are significantly positively associated with attitudes to immigrants' contribution, while age is significantly negatively associated with attitudes toward the effect of immigration. Being male has no significant association. On the other hand, Figure 3 regarding support for more-/less-limiting immigration policies shows that only education (positively) and age (negatively) affect these attitudes. All other variables of interest appear not to be significantly associated with this type of attitude.

These results stress the importance of the analytical distinction between different types of attitudes to immigration in properly identifying the sources of public views toward immigration. Therefore, a comprehensive and effective approach to addressing negative attitudes toward immigration necessitates careful attention to the type of attitudes in question to understand and disentangle the different factors that influence individual preferences and public opinions toward immigration.

The perception that immigrants are a burden on society and challenge the status quo or, on the other hand, the unwillingness to allow an increase in arrivals of immigrants appears to be driven, apart from education and age, by different sources of opposition. Questions about 'immigrants' or 'immigration' are likely to be envisioned differently in the minds of different respondents.

It is important to emphasise that the numbers reported above may be biased. First, they do not account for the fact that estimates with different signs and statistical
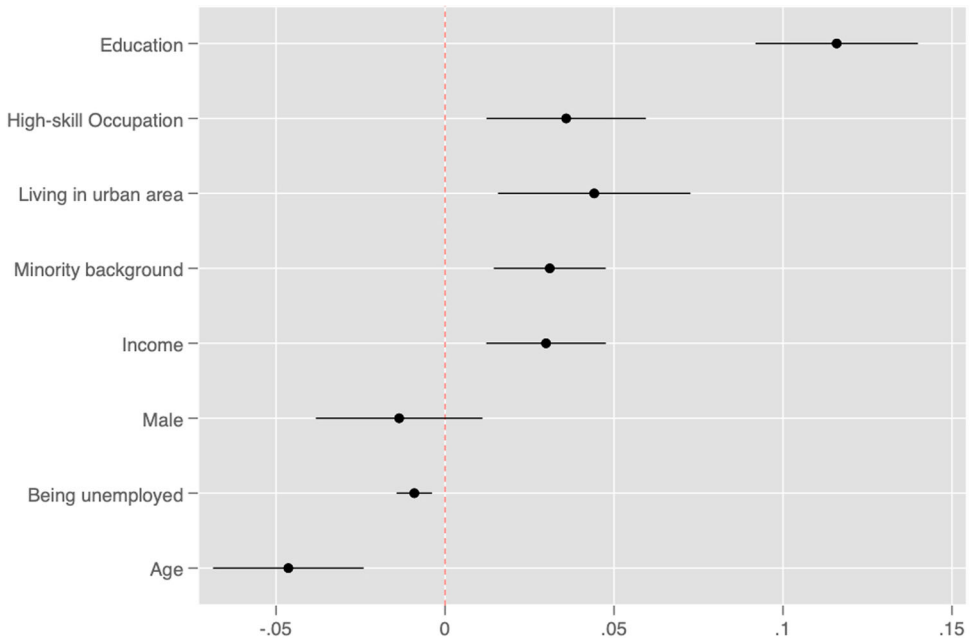
Figure 2. Partial correlation between individual characteristics and positive attitudes to immigrants' contribution.

Note: The figure visualises the partial correlations between the individual characteristics of interest and positive attitudes to immigrants' contribution.
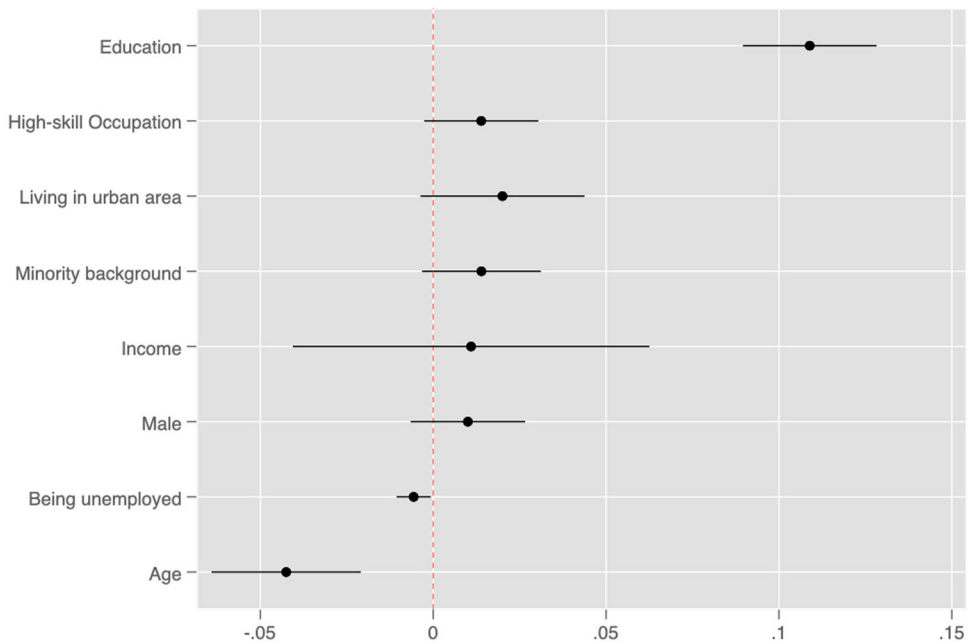
Figure 3. Partial correlation between individual characteristics and positive attitudes to open immigration policies.

Note: The figure visualises the partial correlations between the individual characteristics of interest and positive attitudes to open immigration policies.

Table 2. Contribution.

	(1) Age	(2) Education	(3) Male	(4) High Occupation	(5) Income	(6) Minority	(7) Unemployed	(8) Urban area
PCC	−0.046***	0.116***	−0.014	0.030***	0.031***	0.044***	−0.009***	0.036***
	[−0.069,−0.024]	[0.092,0.140]	[−0.038,0.011]	[0.012,0.048]	[0.014,0.048]	[0.016,0.073]	[−0.014,−0.004]	[0.012,0.059]
τ_s^2	.0011	.0057	.0004	.0002	.0006	.0041	.0001	.0004
τ_d^2	.0023	.0021	.0042	.0002	.0000	.0004	.0000	.0006
Samples	30	32	33	8	11	16	16	11
Study-data pooled est.	53	60	59	19	17	30	34	23
Single estimates	96	129	92	77	38	66	59	62

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. 95% confidence intervals in square brackets. The partial correlation coefficient is obtained using a multi-level model that accounts for the nesting of study-data pooled estimates within datasets and their respective random terms. τ_d^2 corresponds to the between-dataset variance, while τ_s^2 correspond to the variance between-study-data pair within a dataset.

Table 3. Policy.

	(1) Age	(2) Education	(3) Male	(4) High Occupation	(5) Income	(6) Minority	(7) Unemployed	(8) Urban area
PCC	−0.043***	0.109***	0.010	0.011	0.014	0.020*	−0.006**	0.014*
	[−0.064,−0.021]	[0.090,0.128]	[−0.007,0.027]	[−0.041,0.063]	[−0.003,0.031]	[−0.004,0.044]	[−0.011,−0.001]	[−0.003,0.030]
τ_s^2	.0014	.005	.0001	.0009	.0003	.0001	.0001	.0005
τ_d^2	.0027	.0000	.002	.0009	.0009	.0017	.0000	.0000
Samples	39	36	40	4	23	17	14	5
Study-data pooled est.	54	57	58	4	32	24	24	10
Single estimates	122	113	83	6	69	81	37	38

Note:*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. 95% confidence intervals in square brackets. The partial correlation coefficient is obtained using a multi-level model that accounts for the nesting of study-data pooled estimates within datasets and their respective random terms. τ_d^2 corresponds to the between-dataset variance, while τ_s^2 correspond to the variance between-study-data pair within a dataset.

significance may have a different probability of being reported, a problem usually referred to as publication bias.[12] Second, although our random effects model accounts for heterogeneity across studies, it assumes it to be random, which may not be true. We, therefore, perform a publication bias test and then explore how study characteristics influence the results.

4.3. Publication bias

Following Stanley and Doucouliagos (2015) and Cazachevici, Havranek, and Horvath (2020), we analyse publication bias using an estimate's standard error as a predictor in a regression weighted by the inverse of the variance of that estimate. The idea behind this test is that in the absence of publication bias, the estimated effect should be randomly distributed across studies, and the estimated effect size should not be correlated with its standard error. If the opposite is true and the standard error significantly predicts the size of the partial correlation, then estimates that suggest a particularly strong relationship between individual factors and attitudes to immigration would be systematically less precise. In that latter case, publication bias will have made results less robust and less likely to be replicable. Their internal and external validity would be lower and their results should thus be trusted less than in the absence of publication bias.

Table A7 in the Supplementary Material presents two models for each individual factor. The first one fits a weighted least square model as described above, while the second one is a weighted multilevel model with random effects clustering that accounts for dependencies between studies relying on the same samples. The only difference between the two models is that the second one takes the clustering of study populations into account. The interpretation of the results presented in Table A7 is relatively straightforward. Following Dinesen, Schaeffer, and Sønderskov (2020), we interpret the intercept as the expected value of the partial correlation between a given individual factor and positive attitudes toward immigration if the standard error were equal to zero. Therefore, an intercept significantly different from zero suggests an overall systematic association between individual factors and attitudes toward immigration despite publication bias. The results in Table A7 suggest that economic factors are robust predictors of attitudes to immigration. On the other hand, Table A7 also reveals that the effect of age should be interpreted with caution since once we account for sample dependency, the intercept becomes small and insignificant.

4.4. Study heterogeneity

As already outlined, the studies in our dataset differ in various respects, not least because they were collected from different social sciences, each with their own rules when it comes to quantitative analysis (methodology, the definition of the dependent variable, choice of empirical models, nature of population studied, etc.).

One such dimension of heterogeneity particularly relevant in our application is the correlation between our several variables of interest. Including specific independent variables like education and income might affect the magnitude of the coefficients of the other variables because different variables are partialled out. For example, higher education often goes along with higher income. As a result, including or omitting some

individual factors in a study is likely to influence the estimated effect of other individual characteristics. Besides individual factors, the choice of the dependent variable used to measure attitudes to immigration, the number of control variables, and whether the data used in the study was original or not can also affect the estimated coefficients. If we were to overlook these study characteristics, we could erroneously attribute the effect of the study's methodological features on our estimates to the inclusion of one or more correlated variables.

To investigate these aspects systematically, we use Bayesian Model Averaging. This approach allows us to account for model uncertainty by estimating the parameters for *all* possible models that could be based on a set of variables and then combining these results to obtain posterior probabilities that indicate how important including a specific variable in the model is for results.[13] We implement BMA using an R package by Zeugner and Feldkircher (2015), whose approach implements all possible linear regression models with intercept. Note that the BMA does estimate the exact equivalent of the meta-analytical regressions above but implements the approach described in detail in Cazachevici, Havranek, and Horvath (2020). Instead, it helps understand how estimated relationships depend on the inclusion of other variables in the model. It thus helps readers understand how their or other researchers' results might be affected if certain control variables are omitted and if studies do not have certain characteristics. When interpreting the results, it is important to keep in mind that BMA is not a causal technique.

We include a total of 17 indicators: Precision, the log number (+1) of controls, whether the study relies on new data, dummies for whether the outcome variable the attitude to policy (baseline: migrants' contribution) or a composite index, dummies for how specific the outcome variable is (e.g. attitudes toward rich non-EU migrants vs. migrants in general). To further assess studies' empirical rigor we include dummies for whether the study discusses causality or statistical identification, and is based on experiment or observational data. Furthermore, we include variables covering whether the study controls for the other individual-level explanatory variables that are the focus of our meta-study. We estimate the BMA using a uniform prior but results are robust to using alternative priors.

Section A.8 in the Appendix investigates the impact of study characteristics on our results and presents descriptive statistics of the explanatory variables included in the regression for each individual factor. The BMA results for age (Figure A24) are particularly interesting. Hence, we discuss these in some more detail. The BMA results for the other variables indicate, among other things, the known fact that urban residence is closely linked to education and occupation, so its coefficient in studies tends to vary strongly based on these other factors' inclusion. By contrast, gender's coefficient seems relatively unaffected by study design or inclusion of other individual-level variables according to our BMA.

Four variables and two study characteristics appear to have a strong effect on the estimation of age on attitudes toward immigrants (Table 4), as indicated by high posterior inclusion probabilities of above 95 percent: Unemployment, minority status, urban residence, and gender. When these variables get included in models, the estimated effect of age on attitude changes. Note that BMA is not a causal technique but rather helps spot dependency on the inclusion of different variables in the model. Kass and

Table 4. Numerical results of Bayesian Model Averaging for the age variable.

Variable	PIP	Posterior Mean	Posterior SD
Precision	0.620	0.052	0.045
Number of controls	1.000	−0.046	0.010
New data	0.065	0.000	0.004
DV: Policy	0.078	0.000	0.002
DV: other	0.634	0.073	0.066
DV is specific	0.187	−0.001	0.003
DV is a mix	0.102	−0.001	0.003
Causality discussed	0.991	−0.021	0.006
Any experiment	0.108	0.004	0.016
Any observational	0.424	0.031	0.041
Education	0.371	0.010	0.015
Gender	0.997	−0.043	0.011
High-Skill Occupation	0.116	0.001	0.005
Income	0.232	−0.002	0.005
Minority	0.999	0.024	0.005
Unemployed	1.000	0.031	0.005
Urban residence	1.000	0.049	0.009

Note: PIP = posterior inclusion probability. SD = standard deviation. The table shows unconditional moments from Bayesian model averaging. PIPs with values below 0.5 denote a negligible effect, and PIPs above 0.99 indicate a decisive effect.

Raftery (1995)'s rule of thumb for interpreting PIPs is that PIPs can indicate weak evidence of an effect (0.5-0.75), positive effects (0.75-0.95), strong effects (0.95-0.99), and decisive effects (0.99-1.00).

First, including a measure for unemployment in the regression tends to boost the effect of age in the regression. The same holds for the urban residence variable. These patterns emphasise that researchers should be cautious about self-selection patterns determining their sample composition. Both patterns could, for example, arise if older respondents are less mobile than younger respondents and therefore more likely to live in rural locations or unemployment-prone, respectively. Thus, these two variables could pick up part of the age differences and bias the age coefficient toward zero.

Second, without accounting for the minority status of the respondent, the effect of age on attitudes toward immigrants would likely be underestimated. Immigration attitudes of younger and older minority respondents typically differ less than those of younger and older majority respondents. For both younger and older minority members, socialisation will ensure more positive attitudes toward immigrants. For the majority members, this is not the case. The true age difference is thus likely underestimated if a sample contains both majority and minority respondents. If the sample only contains majority respondents, the risk of such a bias will be lower.

Third, without controlling for gender, the effect of age on attitudes toward immigrants tends to be higher, which indicates that it could be overestimated.[14] Therefore, beyond checking for sample composition, we recommend researchers test whether adding non-linear interactions between variables affects their main estimation results. Such robustness exercises are particularly important if variables partly overlap in the concepts they measure. But as highlighted by our analysis, such interactions can potentially also bias results for explanatory variables that are less closely related.

Finally, the log number of control variables and whether a study discusses causality also have decisive impacts. studies that discuss causality or identification, tend to show lower age coefficients, as do studies with more control variables. For the other variables

in the BMA there is only weak or no evidence of an impact on study estimates of age on attitudes.

5. Conclusion

Mass immigration is a global phenomenon affecting most countries. Public opinion on immigration has become a highly salient issue in many countries. Moreover, the debates surrounding migration are often highly polarised. Respondents' characteristics are found to play an important role in shaping their attitudes toward immigration. It is therefore crucial to understand what individual-level factors contribute to forming attitudes toward migration and what (negative or positive) effects they have.

The scholarly literature on factors affecting attitudes toward immigration often provides conflicting findings from individual studies. By conducting a meta-analysis, we can provide more reliable answers to which individual-level factors are consistently associated with attitudes toward immigration. Therefore, to analyse the effect sizes of factors affecting attitudes toward immigration, we synthesise recently published (between the years 2009-2019) individual studies from several social science disciplines (economics, political science, sociology, ethnic studies, demography and migration studies). When selecting studies for inclusion in the meta-study, we face the trade-off between quality and breadth. Including also poorly made studies maximises coverage of the meta-study but comes at the expense of results that are heavily affected by less credible evidence. To strike a balance and to be still able to cover the academically highest ranked and thus likely most influential works of the past decade, we include only studies in the top journals of each social science discipline. From these, we only select those meeting certain quality standards.

By analysing empirical results from studies and patterns related to study design and model selection, we hope to contribute to better-informed interpretations of the role played by each individual factor as a predictor of attitudes to immigration across the social sciences. Our meta-analysis can inform future research about which factors to include as explanatory variables in an empirical analysis to avoid omitting key determinants. For policymakers, we provide results with greater external validity than single studies by aggregating results from various disciplines and samples across the world, therefore making our findings on the relationship between individual characteristics and attitudes to immigration more generalisable.

Multiple studies across the social sciences highlight that higher-educated individuals hold more liberal views about immigration. Our meta-analysis shows that the effect of education is extremely significant and persists when controlling for economic characteristics. Studies analysing individual-level factors affecting attitudes to immigration without controlling for it should therefore be approached with caution. Positive attitudes to immigration are also correlated with the economic standing of an individual – the higher their skill, occupation, and income, the more significantly positive attitudes toward immigration the respondent holds. The respondent's age is also one of the most influential characteristics, with older respondents holding stronger views against immigration. Living in urban areas positively correlates with pro-immigration attitudes since urban residents have more contact and may self-select into cities. Researchers should thus be careful in using and interpreting this variable in their statistical analyses

due to its potential endogeneity. In contrast, gender does not seem to be decisive in predicting attitudes to immigration, as does not being part of a minority and being unemployed. Our meta-study also reveals that attitudes toward immigration policy and attitudes toward immigrants' contribution are not necessarily explained by the same individual characteristics. Even if the direction of the effect is the same, except for age and education, policy attitudes are less easily predicted by other individual characteristics used in the literature than attitudes toward immigrants' contribution. Further, the effects of education, income, and age are prone to vary based on whether other individual characteristics, such as minority background and gender are accounted for. Our BMA analysis thus indicates that researchers should test (1) for overlap between variables and (2) whether adding non-linear interactions between variables affects their main estimation results.

One aspect we do not cover in our meta-study is the moderating role of macro-level factors. Each individual lives their life in a specific environment and period characterised by historical, economic, and political circumstances, which may affect their attitudes toward and perception of minority groups. It is worth emphasising that our meta-analysis does not specifically focus on the differential effects of individual-level factors influencing attitudes to immigration under different societal contexts of the country and region where individuals live. For instance, some economic theories predict that skilled individuals favour immigration in countries where natives are more skilled than immigrants and oppose it otherwise. The literature has not extensively covered the role of macro-level institutional and sociopolitical forces in shaping public attitudes. For instance, when testing for the effect of concerns regarding immigrants' benefits reception on individual attitudes to immigration, the extent of immigrants' benefit dependence is not only influenced by their income but also institutional factors regarding entitlements and rules on eligibility for welfare benefits. Thus, individual concerns might be stronger or weaker depending on the country where the individual resides.

Future research is needed to improve our understanding of how context matters for attitudes to migration and how it affects individual factors' relationship with attitudes to immigration. First, new evidence should shed light on the sources of country-level variation in attitudes to immigration and how macro-level factors mediate individual-level relationships. Second, when critically assessing the migration literature, one should be aware that there is a stark geographical bias in the scholarly work on attitudes to immigration, with a heavy focus on developed countries and particularly the USA and Western Europe. This highlights a significant gap in the literature, which also has important implications for the evidence base to inform policymakers outside the Western industrialised countries (Gonnot, Dražanová, and Brunori 2020).

Notes

1. Empirically, skill is often approximated with formal education and the two terms are used interchangeably by many authors, although they are not the same. Trained crafts-persons may have scarcer and far better-remunerated skills than many college graduates.
2. Google Scholar only provides a top-20 ranking per discipline.
3. For example, a dependent variable that is an index composed of three questions (attitudes toward immigrants, religious minorities, and ethnic minorities) would hence be excluded.

4. In the literature, this issue is sometimes addressed using Card's two-step methodology (2015) by meta-analysing the coefficients of each study, thereby obtaining a study-specific meta-estimate called 'study-pooled estimate'. The overall meta-estimate is then obtained by meta-analysing the study-pooled estimates.

5. Unlike Dinesen, Schaeffer, and Sønderskov (2020), some studies in our dataset provide estimates that are drawn from separate analyses using two or more datasets. For instance, Because it is necessary to account for the nesting of studies within datasets, we choose to compute pooled estimates at the study-data level to be able to correctly account for dependencies between studies relying on the same samples.

6. Table A6 shows the number of estimates drawn from partly or completely overlapping samples.

7. The Stata code for replication is available in the RADAR repository.

8. In our equation, we follow Bagos (2015) and use the same notations.

9. A model featuring a single random effect capturing between-dataset variation is possible, all the more so as the within-dataset variance is found small in our study (see Tables 1, 2 and 3 in Appendix). However, we have preferred to opt for a more comprehensive assessment of the sources of variability in study-data effect sizes, both across and within different datasets. We thank an anonymous reviewer for suggesting that we clarify this point.

10. This captures the skill level of an individual's job.

11. Forest plots of the study-data pooled estimates are available from the authors upon request.

12. In this respect, because our estimates are most often collected from coefficients of variables used as controls in regressions, selective reporting is less likely to be an issue considering that the publication of the results is much less dependent on the significance and direction of these coefficients.

13. See Hinne et al. (2020) for an accessible introduction and Porwal and Raftery (2022) for a comparison to other methods that account for model uncertainty.

14. This could be due to several reasons, such as unbalanced samples by gender or non-linear age differences. For example, younger women might feel more threatened by immigrants than younger males, or women might be, on average, more tolerant than men. If the gender effect dissipates in older age groups, this could potentially bias the age effect.

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