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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 towards 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.

Keywords: meta-analysis; attitudes toward immigration; public opinion; migration; intergroup relations
JEL Classification: F22, J15

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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. Commission, 2019*a*,*b*). Public attitudes toward immigration are becoming part of a new political cleavage (Kriesi et al., 2012; Hobolt, 2016), 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 individual 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 towards 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 systematise 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 to 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 towards 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); Hainmueller and Hopkins (2014); Dražanová (2022)) rather than understudied factors such as, for example, disgust sensitivity (Aarøe, Bang 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 connection to social class but also represents a value-based cleavage. On the other hand, age is negatively associated with negative 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 lead to significantly more positive attitudes to immigration. Living in urban areas positively correlates with pro-immigration attitudes since urban residents have more contact and may also self-select into cities. Researchers should thus be careful in using and interpreting this variable in their statistical analyses due to its potential endogeneity. Furthermore, based on Bayesian model averaging (BMA), we show 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.

Finally, our results reveal that immigration policy attitudes and attitudes towards 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 article's next section (2) presents the theoretical framework most of the literature uses to explain how and why different individual-level characteristics may affect attitudes to immigration. In section 3, we then describe our research strategy and the sample of quantitative studies used in the meta-analysis. In the subsequent section (4), we systematically describe and analyse the individual factors most frequently used in these quantitative analyses to explain attitudes to immigration. Technical issues such as publication bias, study heterogeneity and quality of the estimates are addressed as well. We conclude the paper in section (5) 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 the 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 paper 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 sociotropic economic evaluation of the effect of migration on the host country as a whole.

Labour market competition hypothesis suggests 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). At the same time, unemployed individuals may perceive that the presence of such immigrants makes their job search more difficult.

According to the labour market competition hypothesis, highly skilled and rich natives are expected to prefer low-skilled immigrants, but empirical literature documents the odds. Still, recent studies (Pardos-Prado and Xena, 2019; Dancygier and Donnelly, 2013) underline that the labour market threat plays a role in many contexts.[2]

Another relevant economic channel for opposition to immigration is 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). This concern should be more pronounced among low earners if additional benefits make adjustments necessary that result in lower transfers to natives. 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 towards immigration (Gerber et al., 2017; Hainmueller and Hopkins, 2014).[3]

[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]Dancygier and Donnelly (2013) find that individuals employed in growing sectors, where the creation of new jobs is likely, are more likely to support immigration than those employed in shrinking sectors. Pardos-Prado and Xena (2019) develop a new version of the labour market competition hypothesis that emphasises the importance of skill transferability in theories about economic competition. The theory accounts for whether natives risk losing their jobs due to labour demand being limited in their industry and whether they would struggle to find a new job because their skills are highly industry-specific. Their results indicate that skill specificity is indeed a strong driver of negative attitudes towards immigration, regardless of natives' skill levels as measured by education.

[3]Most of these studies are based on the assumption that immigrants receive more welfare benefits than natives, despite a lack of evidence for this in many countries. Scholars studying the impact of immigration on the state budget often find immigrants' welfare utilisation below natives' (Huber and Oberdabernig, 2016; Barrett and Maître, 2013). As a consequence, it is not entirely clear whether it is the perception of the effects of immigration on natives' welfare benefits or rather the actual situation regarding immigrants' receipt of welfare benefits driving the result (Card, Dustmann and Preston, 2012; Scheve and Slaughter, 2001; Gang, Rivera-Batiz and Yun, 2013). Other characteristics partly drive this perception. For example, more educated

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 (Helbling and Kriesi, 2014; Naumann, Stoetzer and Pietrantuono, 2018; Gerber et al., 2017; Hainmueller and Hiscox, 2007, 2010; Hainmueller, Hiscox and Margalit, 2015; Hainmueller and Hopkins, 2015). The authors reckon that natives prefer the arrival of high-skilled immigrants because they perceive them as contributing to the economy as a whole, i.e. as complements instead of substitutes to the existing labour force, as well as creating additional jobs. Citizens tend to exhibit a negative attitude toward immigrants who could potentially affect welfare services, either through a reduction in natives' welfare benefits or an increased tax burden if fiscal exposure to migration is high. 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 (Sniderman, Hagendoorn and Prior, 2004; Fetzer, 2000). Admitting immigrants familiar with national traditions and identity would be therefore preferred as they are perceived as more likely to culturally assimilate within the nation rather than taint the national culture and the homogeneous composition of the population (Gorodzeisky and Semyonov, 2019).

Intergroup social contact is another cultural driver of positive attitudes toward immigration, which does not originate from the "competitive threat" theoretical model and fear of competition (Pettigrew and Tropp, 2006). Intergroup contact under appropriate conditions (intimate personal experience, deeper knowledge, affective ties, and in-group reappraisal) can effectively reduce prejudice between majority and minority group members. In contrast, lack of contact is likely to preserve prejudice and negative attitudes toward out-groups (Allport, 1979). However, it is worth emphasising that people are shown to have a general tendency to interact with others similar to them rather than with more socially distant individuals (Bogardus, 1959). Attitudes toward immigrants thus vary across groups, being more negative toward ethnic and religious minorities (Ben-Nun Bloom, Arikan and Lahav, 2015; Gorodzeisky and Semyonov, 2009; Hellwig and Sinno, 2017), such as Muslims and Roma in the European context (Gorodzeisky and Semyonov, 2019) as contacts are less frequent with this group. Nevertheless, although telling causes from consequences can be tricky, and the causal relations between contact and attitudes are not fully established, a large body of research lends firm support to the hypothesis that contact is likely to decrease negative attitudes and reduce hostility toward outsiders (Pettigrew and Tropp, 2006).

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 towards immigration are stable

respondents tend to exhibit more optimism toward the economic impacts of immigration (Hainmueller and Hiscox, 2007), further strengthening the positive relationship between attitudes and education. Moreover, the extent to which immigrants depend on benefits is not only influenced by their income but is also the product of several institutional factors. These depend on entitlements and rules on eligibility for welfare benefits.

over adulthood (Kustov, Laaker and Reller, 2021; Hooghe and Wilkenfeld, 2008) 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. Such cohort effects are a prime example of why it can be complicated to analyse the causal mechanisms behind 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 assumed to be 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 towards 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. Education playing a role in cultural theories increases the expected positive correlation between education and immigration attitudes. 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.

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 towards 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).

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 (Hainmueller and Hopkins, 2015; Margalit, 2019; Card, Dustmann and Preston, 2012) 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 data used in the meta-analysis below were collected as part of a project that seeks to systematise recent empirical findings on public attitudes towards immigrants (Dražanová et al., 2022). 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[4] 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 21 in 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 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. We rely on three further selection criteria to include analyses from relevant papers. 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

[4]Google Scholar only provides a top-20 ranking per discipline.

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 not have to be attitudes to immigration.

The dependent variables matter for which analyses are included. We select analyses whose (8) 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 (9) measure attitudes to immigration directly and express positive or negative opinions (as opposed to neutral statements towards immigrants or neutral policy preferences). To account for dependent variables that were created through dimension-reduction techniques, e.g., additive indices, (10) the analysis is included only if the dependent variable includes all or a majority of attitudinal indicators directly related to immigration as defined in the previous item.[5] Finally, the dependent variable must (11) be directly interpretable as a measure of attitudes, e.g., not a party vote, even if it is an anti-immigrant party.

Our initial eleven 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 the following ten higher-ordered groups of dependent variables based on the dependent variable they use:

- Attitudes and policy preferences on integration issues (rights and opportunities)
- Attitudes and policy preferences on cultural issues
- Concerns and feelings towards immigrants
- Contribution and consequences of immigration (e.g., economic, cultural, social, political)
- Attitudes and policy preferences on refugees/asylum seekers management issues (e.g., border management, support, management of flows)
- Attitudes and policy preferences on immigration flows and level
- Individual behaviour towards immigrants (e.g., financial support, social distance, assisting in arresting immigrants)
- A mix of attitudes to immigrants (indistinct)
- Prejudice and trust towards immigrants

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

[5] For example, a dependent variable that is an index composed of three questions (attitudes towards immigrants, religious minorities, and ethnic minorities would hence be excluded.

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.[6] 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 (12) do not impose any demographic, geographic, ethnic, or other restrictions based on respondents' characteristics, e.g., their religious background or minority status. Yet, we (13) 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. Dražanová (2022); Ceobanu and Escandell (2010)) 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. Table 5 lists all the independent variables included in our meta-analysis.

Based on the above, every study included in the analysis is a unique combination of the dependent variable (capturing the type of attitudes towards immigration), independent variable (capturing a specific individual factor), and sample (a given population group). For each of these studies, we choose to include a unique estimate, i.e coefficients drawn from a single model. We do so to avoid 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.[7] As a result, each effect size contained in the dataset represents the estimated partial correlation between a type of attitude towards immigration and a specific individual factor for a given population group. 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 6 provides a list of all eighth individual factors covered frequently enough, along with the corresponding number of effect sizes.

The full protocol and justification used to generate the universe of relevant studies and estimates as well as the complete bibliography of the studies is described in the Appendix.

Figures 1 - 18 present a series of visualizations of the information contained in articles regarding public opinion towards migration, which underlie our meta-analysis. The figures provide insights in terms of data, study design, and research methods used.

The quantitative study of attitudes to immigration relies on public opinion surveys. Figure 1

[6]A detailed list of attitudes included under these two categories is available in Table 22

[7]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.

shows each discipline's data source usage in attitudes to immigration research. We classified data sources as either commonly and/or publicly available datasets (such as the European Social Survey, World Value Survey, and the like), data with partial data development and as original data developed by the respective author(s). We counted the author(s)' efforts as partial data development if they modified or extended, in either substantive, temporal, or geographic terms, at least one variable contained in a publicly available dataset (but not if they only recoded or aggregated existing measures). New data means introducing entirely original measures, such as a completely new dataset or new and original data generated for at least one variable. As is apparent from Figure 1 while sociology, economics, and migration/ethnic/demographic studies rely mostly on publicly and/or commonly available datasets in their study of public attitudes to immigration, political scientists and especially psychologists mostly rely on original data developed by the respective authors.

On the one hand, political scientists and psychologists invest in developing original data, sociologists, economists, and migration/ethnic/demography scholars appear to accept the constraints imposed by data availability. On the other hand, original data development leads to fewer opportunities for the reproducibility of empirical results. It is worth mentioning that the replication crisis is highly salient, particularly in psychology. Nevertheless, our intent here is diagnostic rather than normative. We wish to empirically establish some structural features of research conducted on attitudes to immigration across disciplines rather than normatively evaluating data usage. Evaluating whether original or common/publicly available (and thus, somehow limited in country coverage based on their availability) data usage across disciplines leads to more or fewer novel findings would require a prior examination of their quality. Such an evaluative assessment lies beyond the scope of this article.

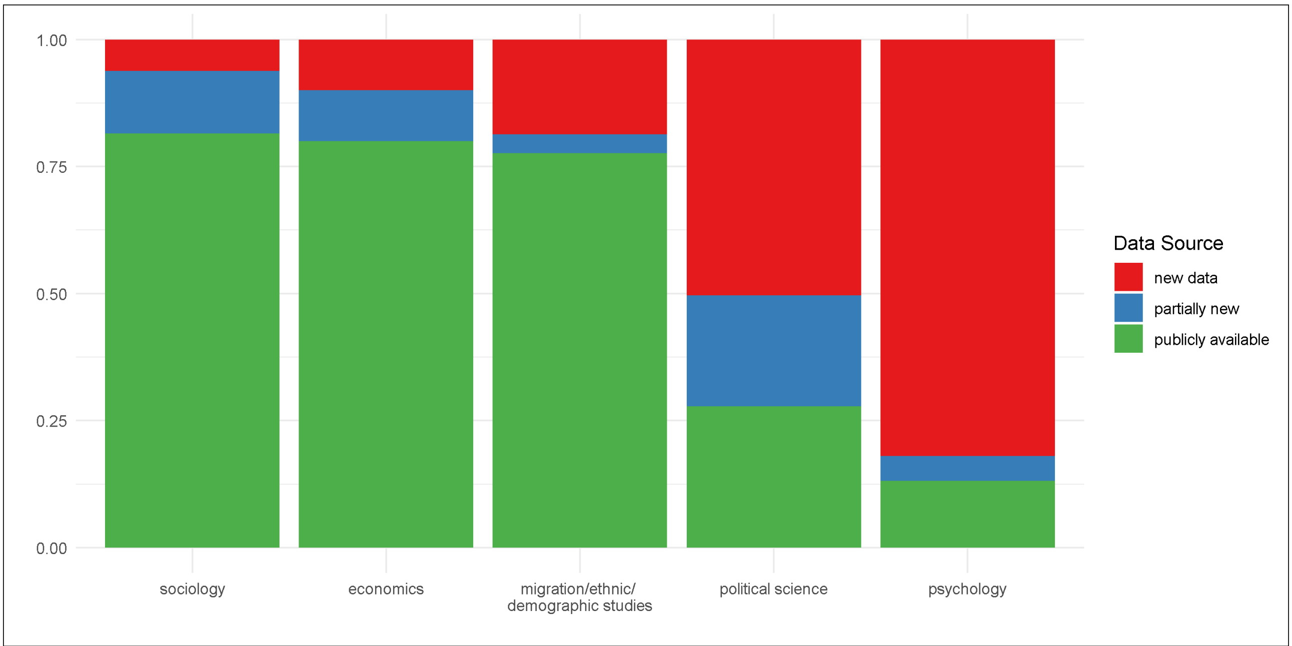

Figure 1: Data source according to discipline

We also looked at what method was used to generate the new data.[8] Figure 2 shows the distribution of research designs across disciplines. It shows that in all disciplines, data generation

[8]If more than one method is used, we selected multiple values.

mostly relies on surveys. While survey experiments also have a large share as data sources in political science (above one-fourth), other fields use them less. Economics, for example, appears to rely frequently on laboratory experiments as well as quasi-experiments when studying attitudes to immigration. Interviews are a widespread data collection method in sociology. All research designs seem to require similar levels of measurement innovation. [9] ,[10]

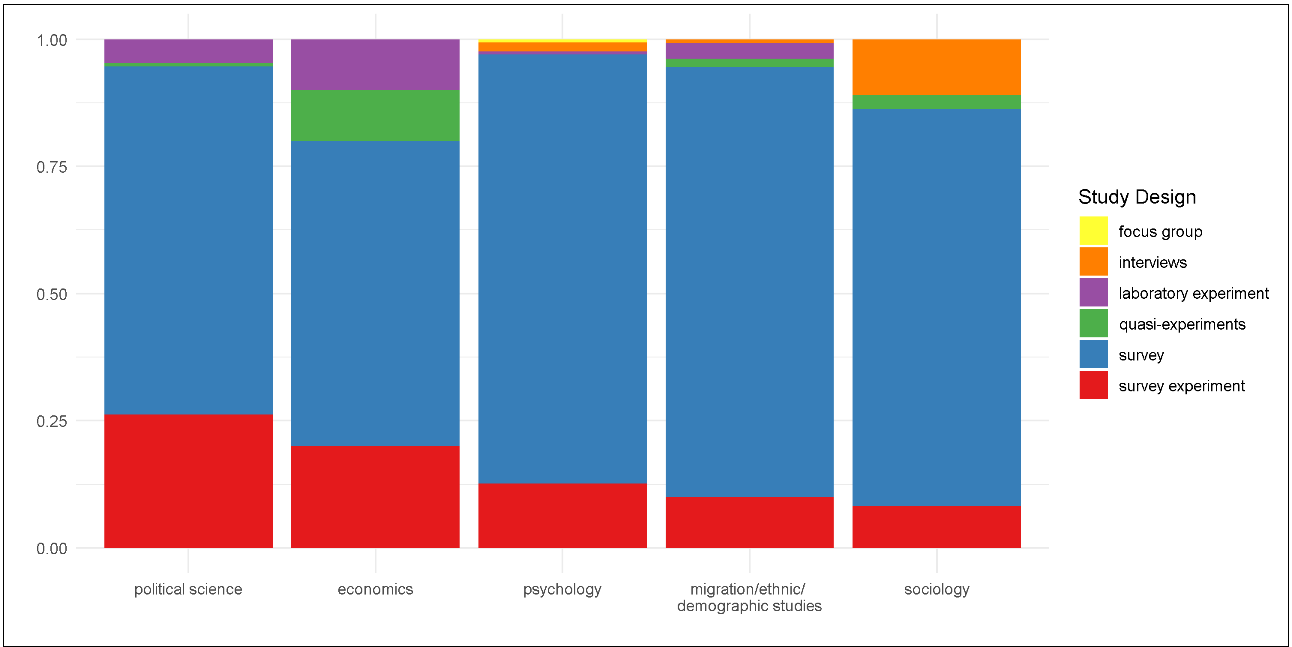

Figure 2: Study design according to discipline
Note: The study design refers to how original data was generated.

The map in Figure 3 displays the number of studies that study specific countries as a heatmap overlay. We can read this as a rough measurement that answers the question about which countries the scholars in our dataset write about the most. It is immediately noticeable that the United States is the country which is mentioned by far the most, followed by European countries such as Spain, Germany and the Netherlands. Figure 3 shows that our dataset's sample of countries studied is skewed towards the countries in the Global North, particularly the Western hemisphere. This might lead to gaps in the knowledge of whether theories confirmed in the West work the same way also in countries with other political, cultural, and socio-demographic backgrounds.

[9]Figure 18 in the Appendix shows when causality in relation to attitudes to immigration is explicitly discussed in our sample studies across disciplines. Generally, the explicit discussion of causality is rather seldom across all disciplines. Future research on factors affecting attitudes to immigration shall discuss causality explicitly.

[10]We refer readers interested in more visualisations of the dataset of articles about public opinion towards migration, which underlies the meta-analysis to look at Dražanová et al. (2022).

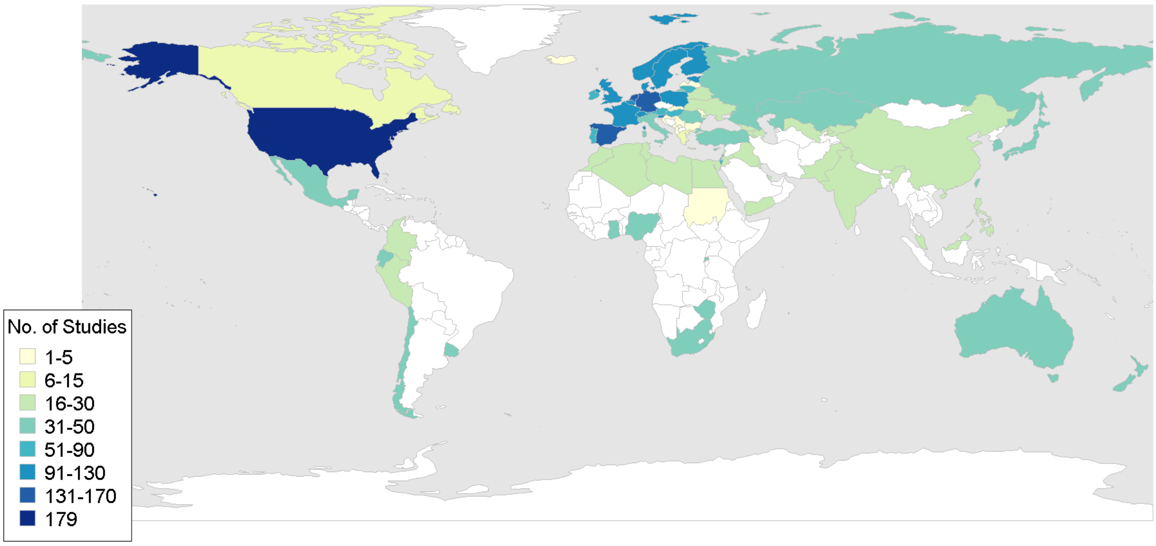

Figure 3: Map of countries studied

Note: If countries worldwide were studied, we included the list of countries from the World Value Survey 2010-2014 wave. If countries Europe-wide were studied, we included the list of countries from the European Social Survey 2012-2014 wave.

3.2 The Meta-Analytical methodology

Because this meta-analysis aims to estimate the relationship between individual socio-economic characteristics - which cannot be subjected to experimental conditions - and attitudes towards immigration, the studies in our dataset are non-experimental. Incidentally, how individual characteristics are measured varies across studies, which use different empirical methods and therefore report different 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. Finally, 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 through 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 characteristic and attitudes towards immigration. It captures the correlation between an individual factor and positive attitudes towards 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 association, respectively. For every individual factor, PCCs and their standard errors are plotted in section B of the Appendix.

To analyse the data, we use a meta-analytical multilevel random effects model. Like the fixed effects approach, the random effect model weighs the partial correlation coefficients by the inverse of their estimated variance and therefore considers the estimate's precision. Additionally, it accounts for between-study heterogeneity, as different studies will apply different methods to estimate the coefficient we use in our meta-analysis.

Moreover, in our application, the conventional assumption of meta-analytical studies that estimates are from independent samples is likely to be violated. As illustrated in Table 7, many estimates derive from the same or partly overlapping samples, such as the European Social Survey, the European Value Study, or the World Value Survey, creating dependencies between them. Following Dinesen, Schaeffer and Sønderskov (2020), we address the issue of partly overlapping samples by adding random effects for the study dataset to our econometric model.

Further details about the meta-analytical procedure and how we investigate the impact of publication bias and study characteristics (e.g., type of attitudes to immigration (DV), number and type of controls, type of data used) on our results can be found in the Appendix in subsection A.3.

4 Results

4.1 Main results

Figure 4 shows 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 4 is the partial correlation between education and pro-immigration attitudes. Having a high-skill occupation[11], as the second strongest positive association, has a substantially smaller positive PCC and other economic factors such as income and unemployment have even 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 4 shows that the higher an individual's income, the more pro-immigration their attitude. Unemployment is, on average,

[11]This captures the skill level of an individual's job.

associated with more anti-immigration attitudes, but this effect is marginally insignificant at the 95% confidence level.

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, but the coefficient does not significantly differ from zero at the 95 % confidence level suggesting that this is not always the case and may thus depend on the context in our PCC analysis. That fits the expected ambiguity of the relationship where cultural factors may lead to more openness and economic factors lead to less openness of minorities towards 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). On the other hand, when immigrants perceive scarcity (of resources such as jobs or welfare) or competition from other immigrant groups, they may start to police national boundaries (Just and Anderson, 2015). Our data suggest that on average across studies, neither effect dominates.

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.

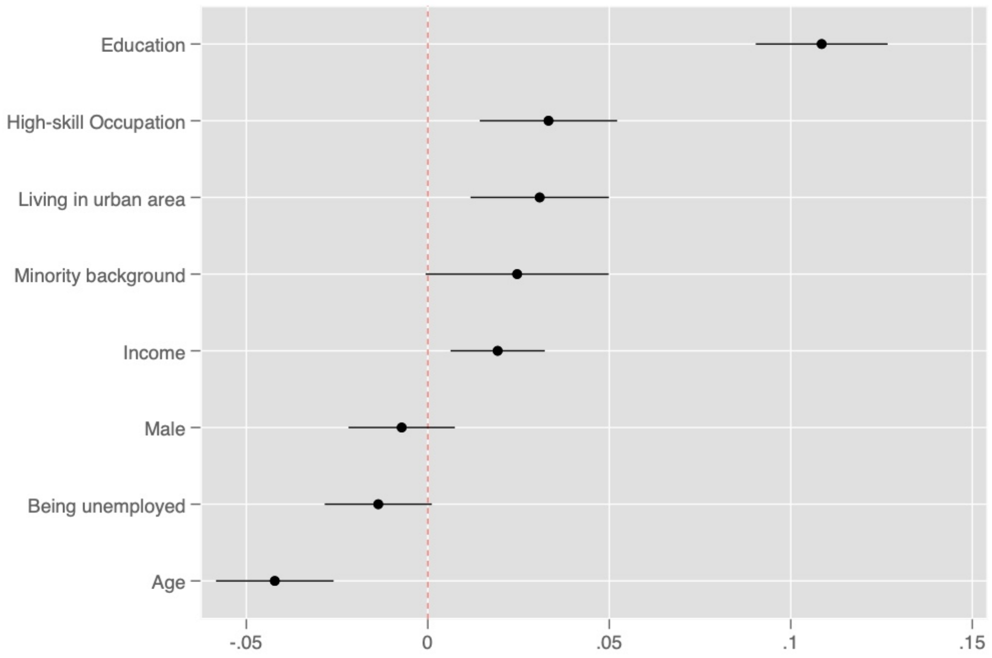

Figure 4: Partial correlation between individual characteristics and positive attitudes to immigration

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

4.2 Heterogeneity analysis

We next divide the dataset into two subsets, distinguishing between equations estimating the relationship between individual drivers and (1) public opinion towards migration policy and (2) individuals' assessment of migrants' contribution to their destination country. When looking at the results shown in Figures 5 and 6 it becomes evident why it is important to look also at the two sets of dependent variables separately. Figure 5 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 towards the effect of immigration. Being male and unemployed have no significant association. On the other hand, Figure 6 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 address 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.

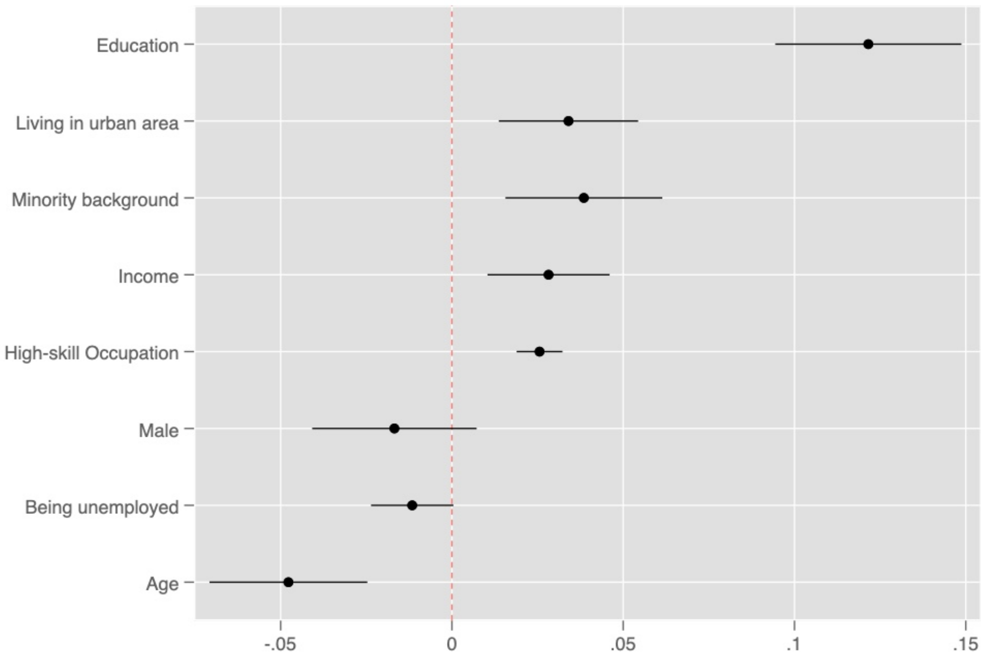

Figure 5: Partial correlation between individual characteristics and positive attitudes to immigrants' contribution

Note: The figure visualises the partial correlations between the individual characteristics of interest and positive attitudes to immigrants' contribution.

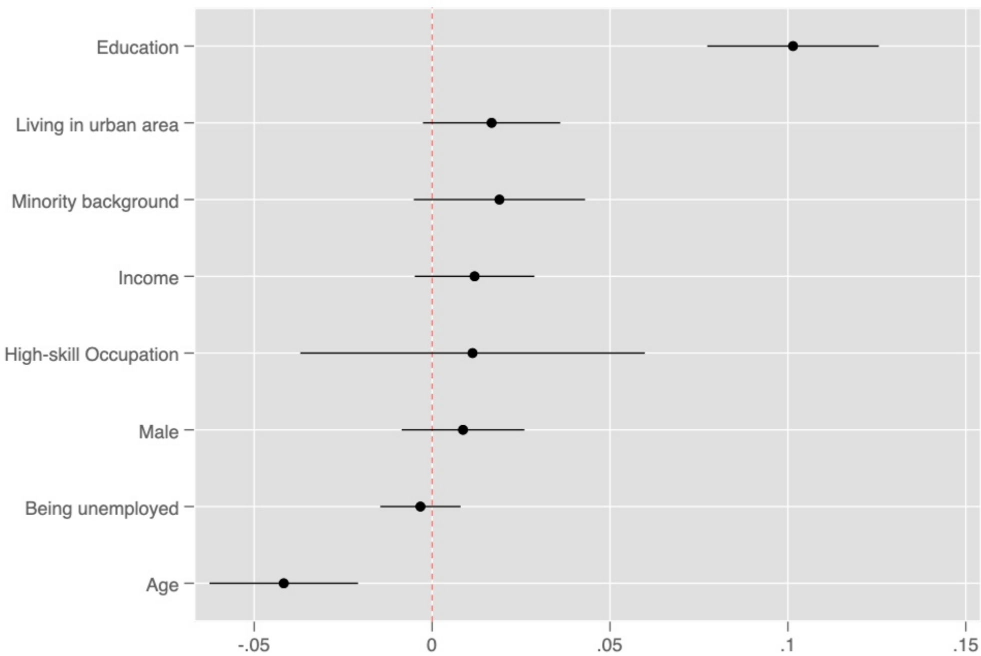

Figure 6: Partial correlation between individual characteristics and positive attitudes to open immigration policies

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

4.3 Publication bias

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 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. In what follows, we first perform a publication bias test and explore how study characteristics influence the results.

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 1 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 1 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 towards 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 1 suggest that economic factors are robust predictors of attitudes to immigration. On the other hand, Table 1 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.

[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.

Table 1: Publication bias

Indiv. factor	Age Model 1	Age Model 2	Education Model 1	Education Model 2	Male Model 1	Male Model 2	HS Occ. Model 1	HS Occ. Model 2
Intercept	-0.0129***	-0.00647	0.0795***	0.0795***	0.00689***	0.00689***	0.0231***	0.0231***
	(-5.21)	(-1.83)	(10.54)	(10.58)	(3.61)	(3.63)	(5.32)	(5.39)
Standard Error	-1.330***	-1.686**	1.365	1.365	-0.715*	-0.715*	0.168	0.168
	(-3.62)	(-3.27)	(1.13)	(1.13)	(-2.17)	(-2.18)	(0.27)	(0.27)
Observations	220	220	248	248	177	177	83	83
Indiv. factor	Income Model 1	Income Model 2	Minority Model 1	Minority Model 2	Unemployed Model 1	Unemployed Model 2	Urban res. Model 1	Urban res. Model 2
Intercept	0.0394***	0.0374***	-0.00350	-0.00350	-0.00804***	-0.00819***	0.0188***	0.0206***
	(12.83)	(11.25)	(-1.31)	(-1.32)	(-5.36)	(-4.70)	(6.87)	(6.65)
Standard Error	-0.885*	-0.775*	1.779***	1.779***	-0.106	-0.0799	-0.112	-0.174
	(-2.50)	(-2.06)	(3.73)	(3.75)	(-0.45)	(-0.31)	(-0.27)	(-0.37)
Observations	112	112	147	147	98	98	100	100

Note: Standard errors in parentheses. Notes: * $p < .10$, ** $p < .05$, *** $p < .01$
The table presents the estimates of the publication bias for the different independent variables. Model 1 fits a weighted least square model. Model 2 fits a weighted multilevel model with random effects clustering that accounts for dependencies between studies relying on the same samples.

4.4 Study heterogeneity

As already outlined in section 3.2, 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, definition of the dependent variable, choice of empirical models, nature of population studied, etc.).

One such dimension of heterogeneity that is 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. 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. To assess the role of systematic heterogeneity in the inclusion of individual factors among studies on the estimated relationship between each individual factor and positive attitudes towards immigration, we fit the same multilevel weighted least square model with random effects for the study population as in Section 4.3 -, and extend the list of independent variables in the regression beyond the estimate's standard error to variables that capture features in which the studies in our dataset vary.

Besides the eight individual factors that we investigate in this paper, we also include as a precaution the choice of the dependent variable used to measure attitudes to immigration,[13] the number of control variables and whether the data used in the study was original or not. Including these study characteristics allows extracting other potential sources of heterogeneity from the data at our disposal. It also helps to make sure that we correctly assess whether the inclusion of other correlated variables might significantly impact the estimated effect of some individual characteristics on attitudes to immigration. 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. Tables 8 to 15 in section

[13] As in section 4.2 we distinguish between studies investigating the relationship between individual drivers affecting public opinion towards migration policy and those regarding individuals' assessment of migrants' contribution to their destination country

A.5.1 of the Appendix present descriptive statistics of the explanatory variables included in the regression for each individual factor.

With twelve potential explanatory variables, many correlated with each other. The results of a simple linear regression may suffer from over-specification bias due to model uncertainty. While the effect of each individual factor taken separately has been extensively discussed in the literature (see section 2), there is little theoretical framework that could help us decide which variables among them influence their partial correlation with attitudes to immigration. To address the resulting regression model uncertainty, we apply Bayesian model averaging (BMA; Raftery, Madigan and Hoeting (1997); Hoeting et al. (1999)). This method is frequently used in meta-analyses, for example by Cazachevici, Havranek and Horvath (2020) and Havranek and Sokolova (2020). BMA runs numerous different regressions with different subsets of the explanatory variables. Each of these models is then assigned the posterior model probability (PMP), measuring how well the model fits the data conditional on the model's size (this measure is equivalent to R^2). The final result is computed by the average model coefficients weighted by their PMP. Analogous to statistical significance in regression models, the posterior inclusion probability (PIP) is composed of the sum of the PMPs for all the models, including the variable. We use the bms R package developed by Zeugner and Feldkircher (2015) to estimate the BMA for the relationship between the different explanatory variables and attitudes toward immigrants. We visualise the graphical results of the BMA for education in Figure 7.

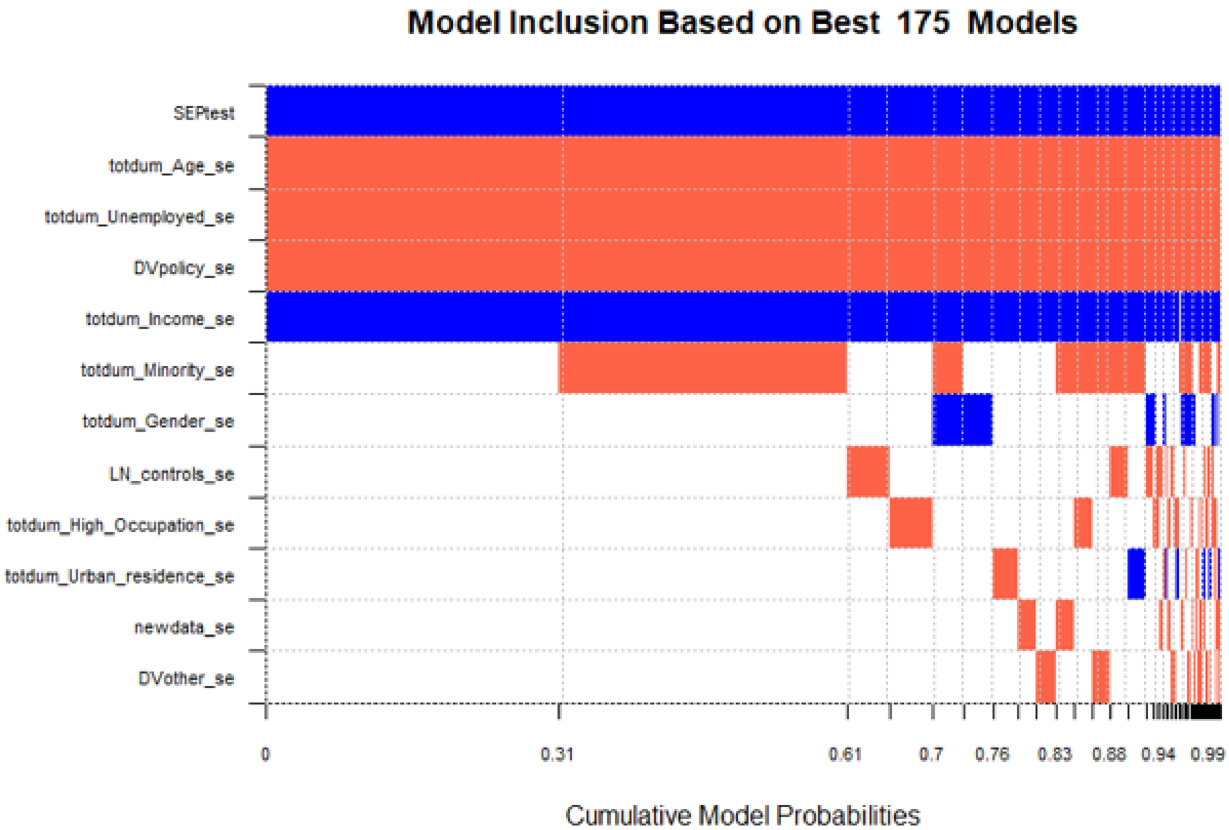

Figure 7: Model inclusion in Bayesian model averaging.

Note: The response variable is the effect of education on attitudes towards immigrants (partial correlation coefficient). A blue cell indicates a positive effect and a red cell indicates that the estimated coefficient of a variable is negative

The different explanatory variables are displayed on the vertical axis, sorted in descending order according to their PIPs. The horizontal axis represents the individual regression models sorted in descending order according to their inclusion probability. The colour of the individual cell visualises the sign of the regression coefficient. A blue cell indicates a positive effect, i.e., the variable causes the estimated effect of education on attitudes toward immigrants to be larger. By contrast, a red cell indicates that the estimated coefficient of a variable is negative. An empty cell indicates that the variable is not included in the model. Table 2 presents the posterior mean, the standard deviation, and the PIP for each explanatory variable.

Table 2: Numerical results of BMA for the education variable

	Posterior Mean	Posterior SD	PIP
SEPtest	0.190	0.018	1.000
LN_control	-0.001	0.005	0.093
newdata	-0.001	0.012	0.061
DVpolicy	-0.053	0.009	1.000
DVother	-0.001	0.018	0.060
Age	-0.078	0.011	1.000
Gender	0.003	0.011	0.098
High-skill_Occupation	-0.001	0.006	0.091
Income	0.044	0.011	0.996
Minority	-0.010	0.012	0.461
Unemployed	-0.061	0.009	1.000
Urban_residence	0.000	0.003	0.067
(Intercept)	0.873	NA	1.000

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.

Kass and Raftery (1995) provide a rule of thumb for the interpretation of the PIPs. PIPs with values below 0.5 denote a negligible effect, and PIPs above 0.99 indicate a decisive effect. For the variables in question – namely income, occupation, and unemployment – the PIPs suggest a decisive impact of income and employment status, while the occupation is negligible. The results from Figure 7 indicate that controlling for income strengthens the effect of education on attitudes towards immigrants. These results are expected because income and education capture partly overlapping concepts in the analysis. Without controlling for unemployment, the effect of education would be overestimated. Higher education commonly goes along with a lower possibility of being unemployed. Therefore, if an analysis lacks the unemployment variable, part of this effect is wrongly attributed to education. The same holds true for the age variable.

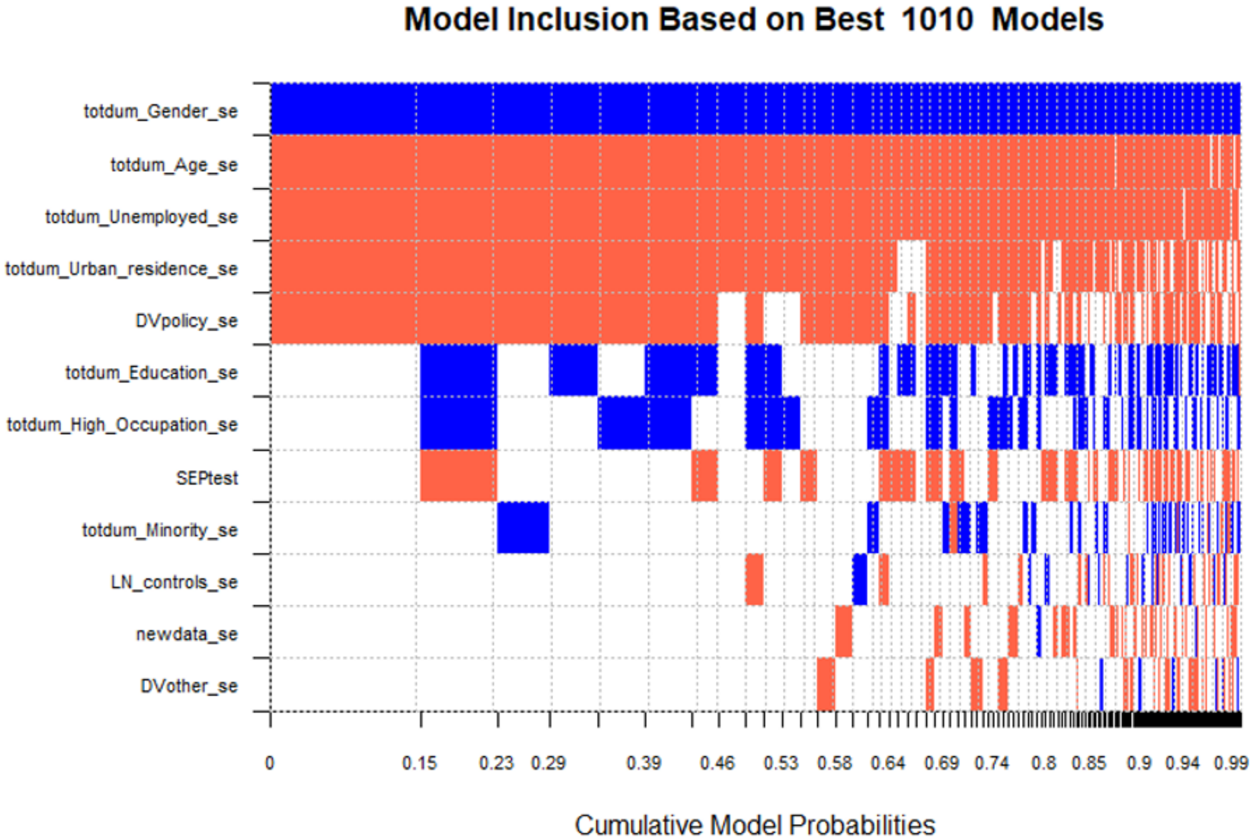

Figure 8: Model inclusion in Bayesian model averaging.
Note: The response variable is the effect of income on attitudes towards immigrants (partial correlation coefficient). A blue cell indicates a positive effect and a red cell indicates that the estimated coefficient of a variable is negative

Table 3: Numerical results of BMA for the income variable

	Posterior Mean	Posterior SD	PIP
SEPtest	-0.010	0.018	0.340
LN_control	0.000	0.004	0.126
newdata	-0.001	0.006	0.116
DVpolicy	-0.009	0.006	0.792
DVother	-0.001	0.005	0.097
Age	-0.032	0.009	0.993
Education	0.011	0.015	0.441
Gender	0.076	0.013	1.000
High-skill_Occupation	0.007	0.010	0.394
Minority	0.001	0.004	0.175
Unemployed	-0.022	0.006	0.991
Urban_residence	-0.020	0.010	0.906
(Intercept)	0.090	NA	1.000

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.

Equivalently to the education variable, are the results regarding the income variable. Age and unemployment both have a strong and negative effect on the estimation of income on attitudes towards immigration (Figure 8 and Table 3). Similarly, we find a strong negative effect of (urban) residence on the estimation. Without controlling for these variables, the effect of income becomes overestimated. Without controlling for gender the effect becomes decisively underestimated due to males earning more than females on average.

The results of the BMA for age are shown in Figure 9 and Table 4.

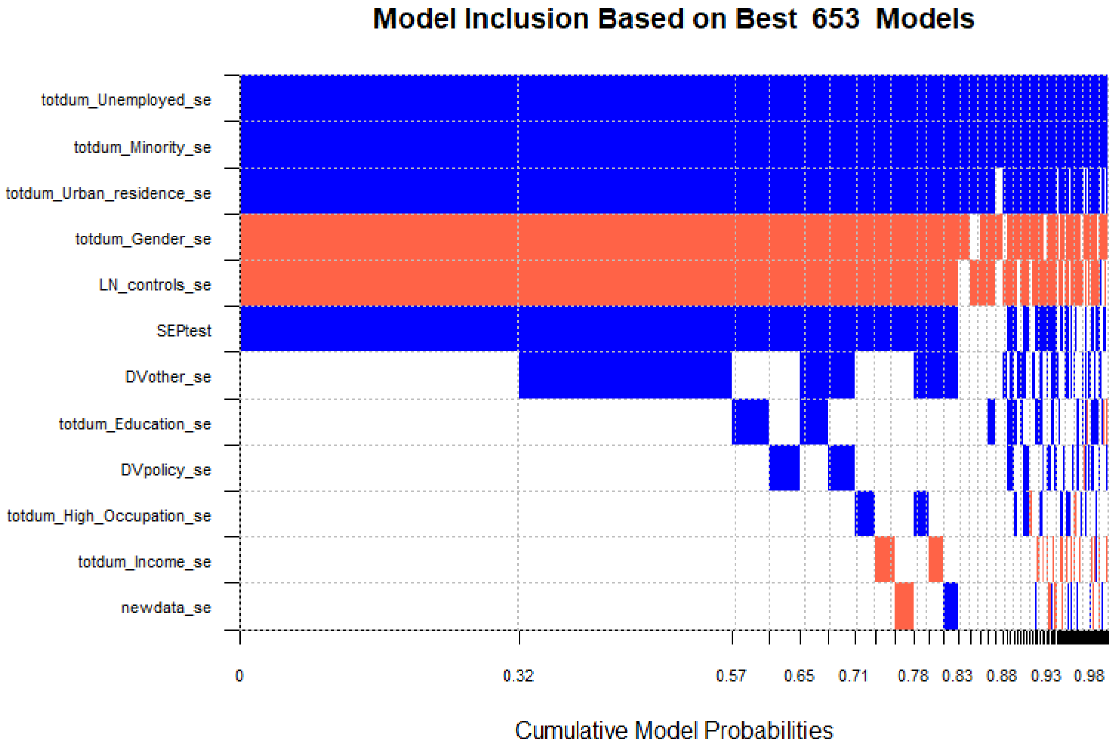

Figure 9: Model inclusion in Bayesian model averaging.

Note: The response variable is the effect of age on attitudes towards immigrants (partial correlation coefficient). A blue cell indicates a positive effect and a red cell indicates that the estimated coefficient of a variable is negative

Table 4: Numerical results of BMA for the age variable

	Posterior Mean	Posterior SD	PIP
SEPtest	0.056	0.026	0.892
LN_control	-0.032	0.011	0.951
newdata	0.000	0.004	0.065
DVpolicy	0.000	0.002	0.105
DVother	0.042	0.059	0.416
Education	0.002	0.007	0.128
Gender	-0.040	0.013	0.968
High-skill_Occupation	0.000	0.003	0.077
Income	0.000	0.001	0.067
Minority	0.026	0.005	1.000
Unemployed	0.025	0.005	1.000
Urban_residence	0.038	0.011	0.981
(Intercept)	-1.593	NA	1.000

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.

Four variables have a strong or decisive effect on the estimation of age on attitudes toward immigrants. [14]

First, without accounting for the minority status of the respondent, the effect of age on attitudes towards immigrants would be underestimated. Immigration attitudes of younger and older minority respondents differ less than 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, this bias will not exist.

Second, including a measure for unemployment in the regression boosts the effect of age in the regression. The same holds for the urban residence variable. These effects 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 unemployment-prone or rural locations, respectively. Thus, these two variables would pick up part of the age differences and bias the age coefficient toward zero.

Third, without controlling for gender, the effect of age on attitudes towards immigrants becomes overestimated.[15] 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.

[14] The results for the BMA of the other variables provide little insight and can be found in Appendix A.6

[15] 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.

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 to migration and what (negative or positive) effects they have.

The scholarly literature on factors affecting attitudes to immigration often provides conflicting findings from individual studies. Therefore, to analyse the effect sizes of factors affecting attitudes to 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). This quantitative summary of empirical results from studies addressing a common research question shall lead to a less biased interpretation of each factor's effect. By conducting a meta-analysis, we can provide more reliable answers to what individual-level factors are consistently associated with attitudes to immigration compared to single studies, especially if those studies have small sample sizes. Finally, it should be highlighted that a quality of a meta-analysis is determined by the quality of the studies it analyses. Based on our choice to include only studies published in top journals of each social science discipline, we tried to create only such quality samples.

Empirical results across multiple studies highlight that educational attainment is one of the key factors affecting individual's attitude toward immigration, with the higher-educated holding more liberal views. Studies analysing individual-level factors affecting attitudes to immigration that cannot control the educational effect should be approached with caution. From the results of our meta-analysis, which shows that its effect remains even after controlling for economic factors, it can be concluded that education may be understood not only as a proxy for skill level and social class but also as a source of a value-based cleavage. Notably, education is also a stronger predictor of attitudes to immigration than economic variables such as income. Positive attitudes to immigration are also correlated with the economic standing of an individual – the higher his skill, occupation, and income, the more significantly positive attitudes to 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 is positively associated 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.

We show that immigration policy attitudes and attitudes towards 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.

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. 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.

The present meta-analysis can inform future research on which factors to consider in the empirical analysis of factors affecting attitudes to immigration and where to be cautious when planning the set of explanatory variables 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.

Each individual lives their life in a specific environment and period characterised by historical, economic, and political circumstances that 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 affecting attitudes to immigration under different societal contexts of the country and region where individuals live. For instance, economic theories would predict that skilled individuals should 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 convert these caveats on country-level factors affecting individual factors' relationship with attitudes to immigration into firmly based explanations. Including additional evidence to better understand the sources of country-level variation in attitudes to immigration and how macro-level factors mediate individual-level relationships remains in the purview of future research.

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A Supplementary Material

A.1 Tables

Table 5: List of independent variables

Independent variables	**Definition**
Age	Age measured in years or in decades; cohorts
Education	Years spent in education; highest degree obtained
Gender	Gender of the respondent (being male is the reference)
High-skill occupation	Based on the skill intensity of an individual's job
High Income	High income measured as annual/monthly personal/household income
Minority status	Measured as a self-reported ethnic minority, or migration background
Unemployed	Being unemployed
Urban residence	Rural or urban area of residence

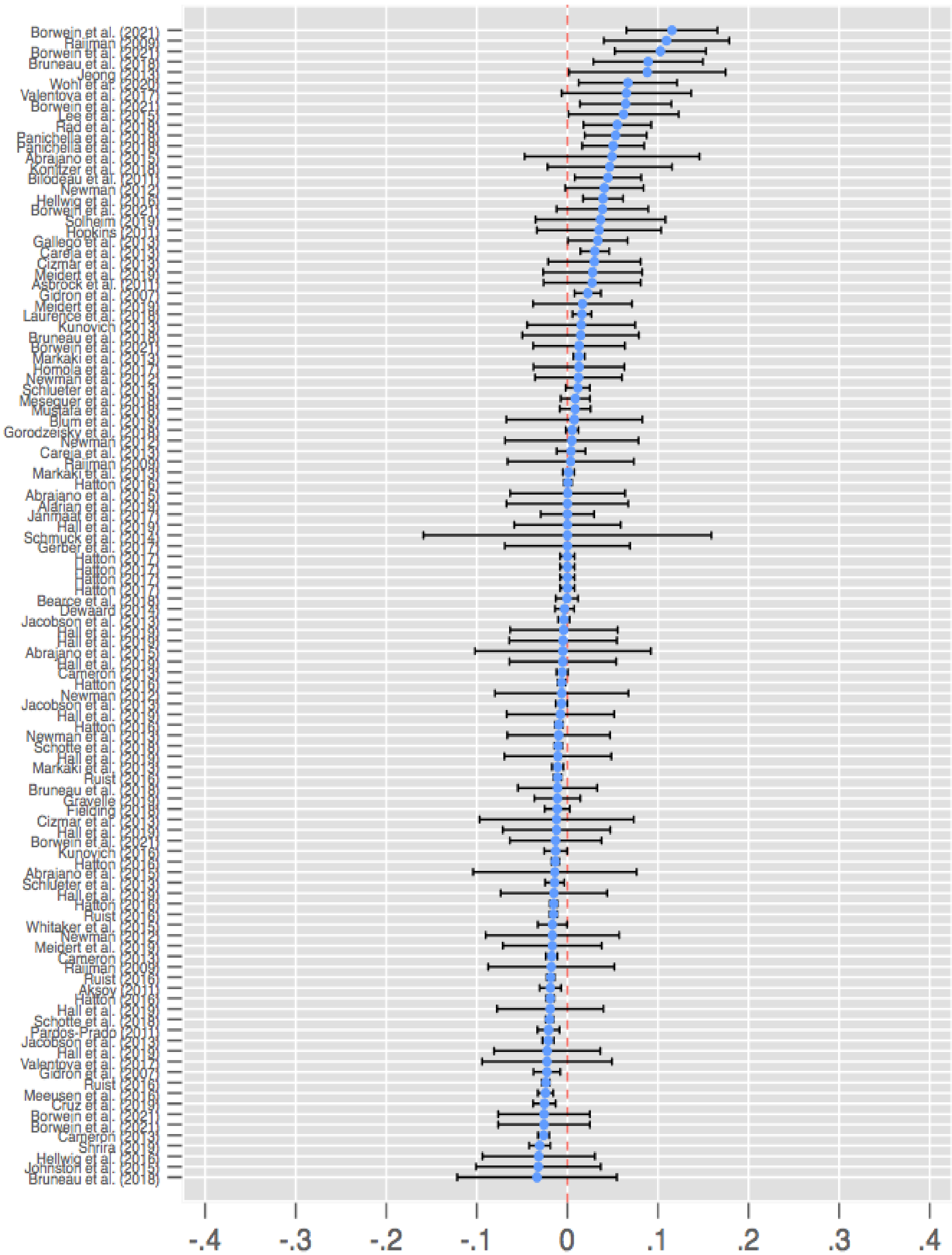
Table 6: Number of effect sizes

Individual factor	**Number of estimates**
Age	220
Education	248
Male	177
High-skill occupation	83
High Income	112
Minority status	147
Unemployed	98
Urban residence	100
Total	1185

A.2 Figures

The following are forest plots of estimates of the relationship between each individual factor and positive attitudes towards immigration. They represent partial correlation coefficients with associated 95% confidence intervals.

Figure 10: Figure 1.1: Age



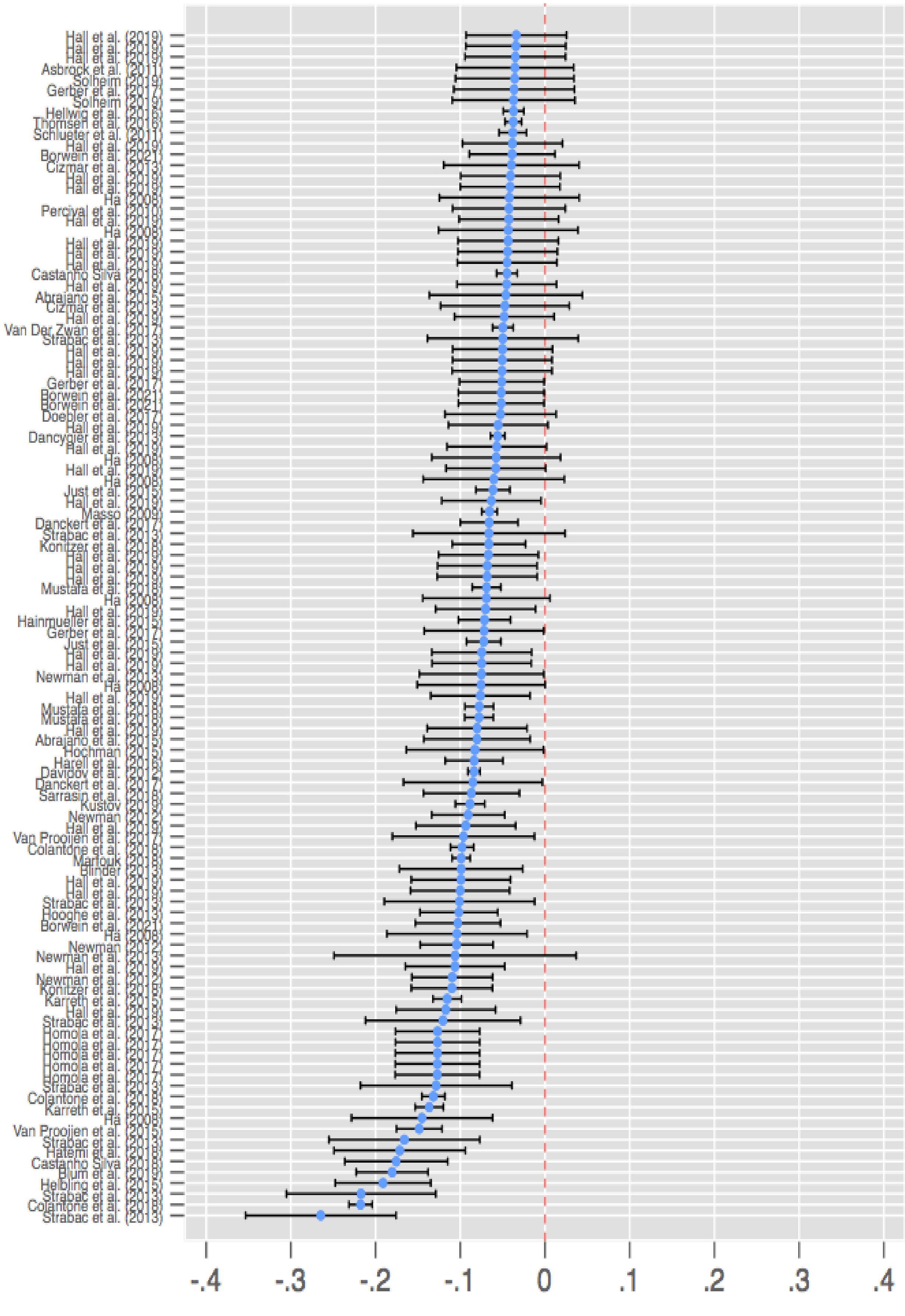

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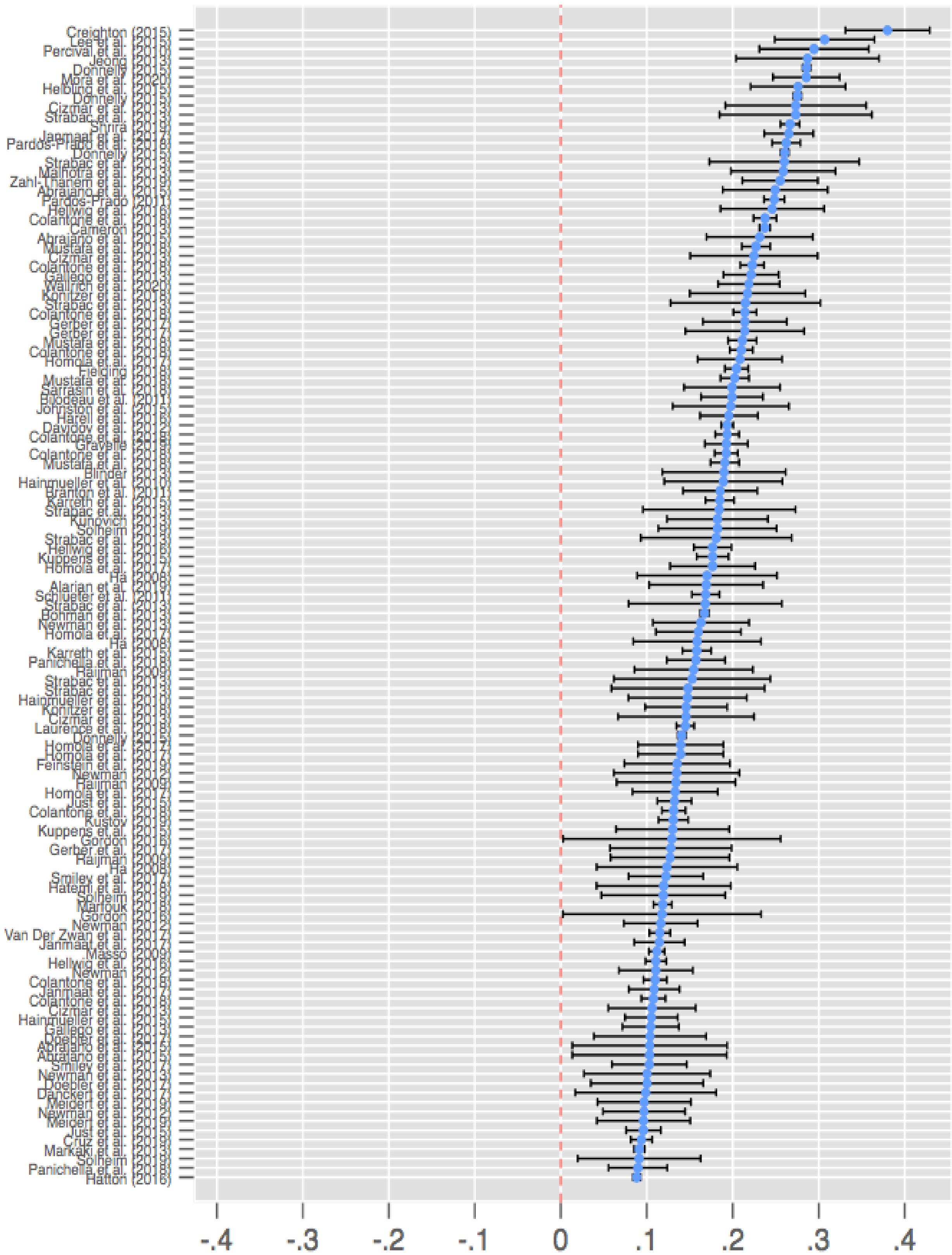
Figure 11: Figure 1.2: Education



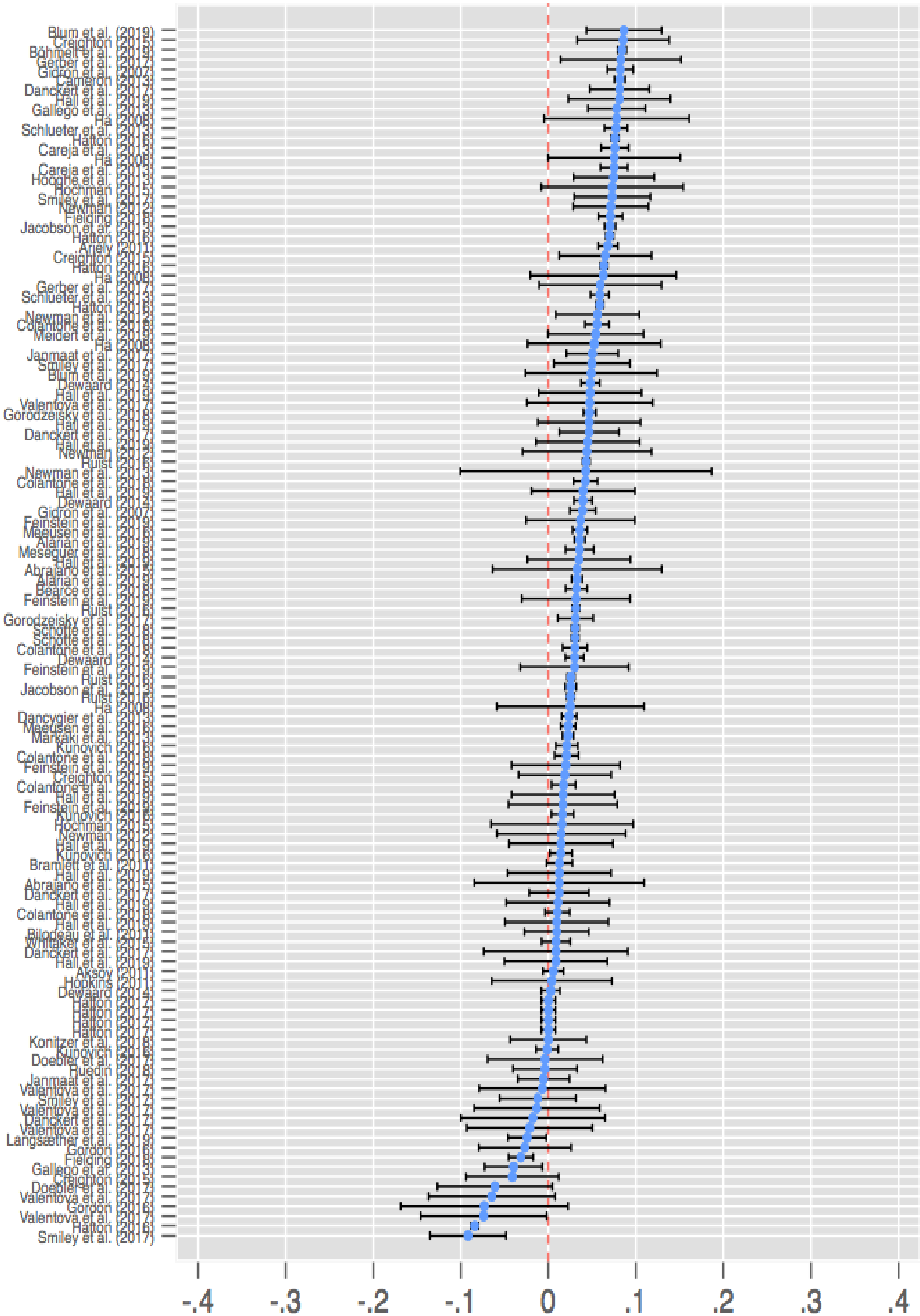
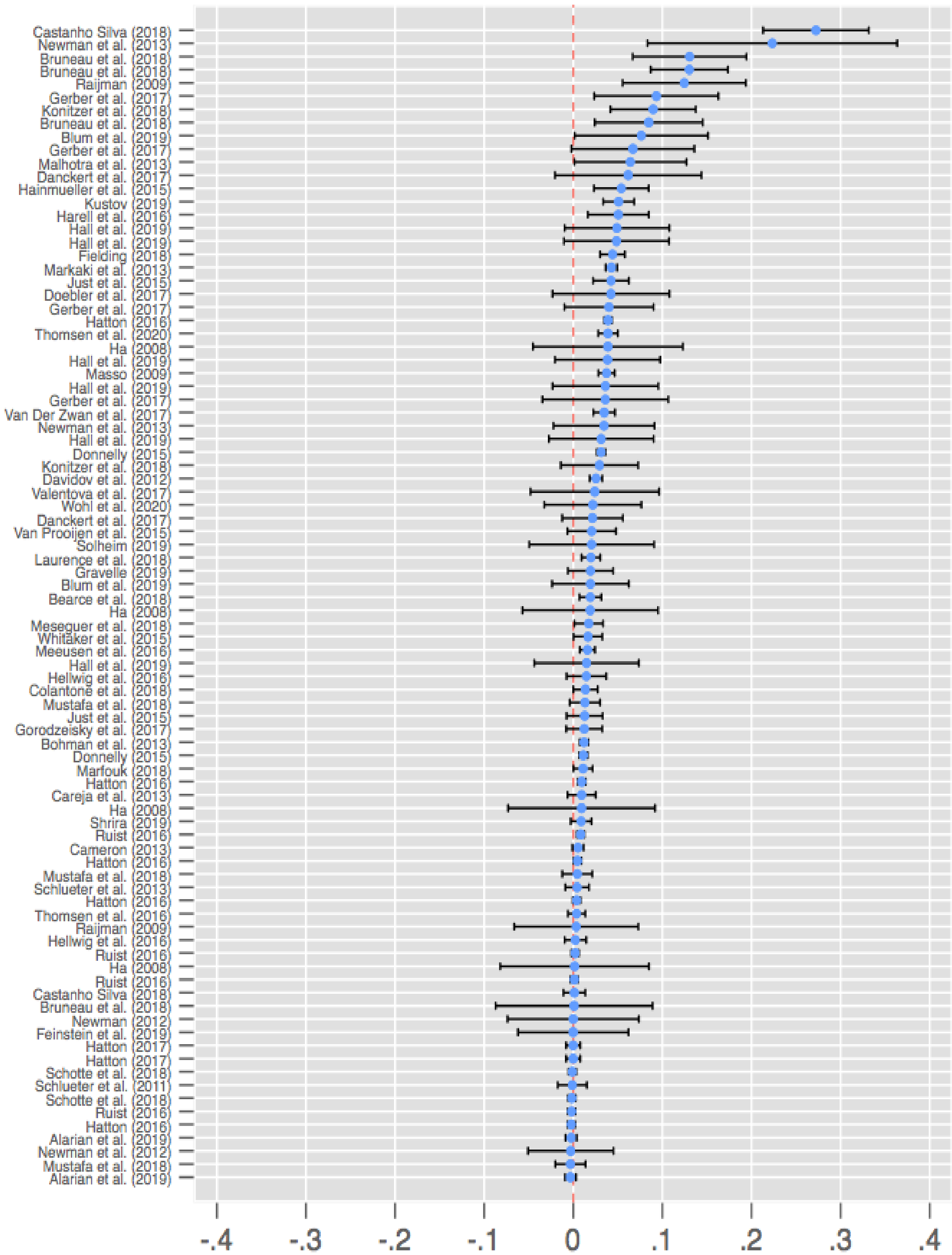


Figure 12: Figure 1.3: Male



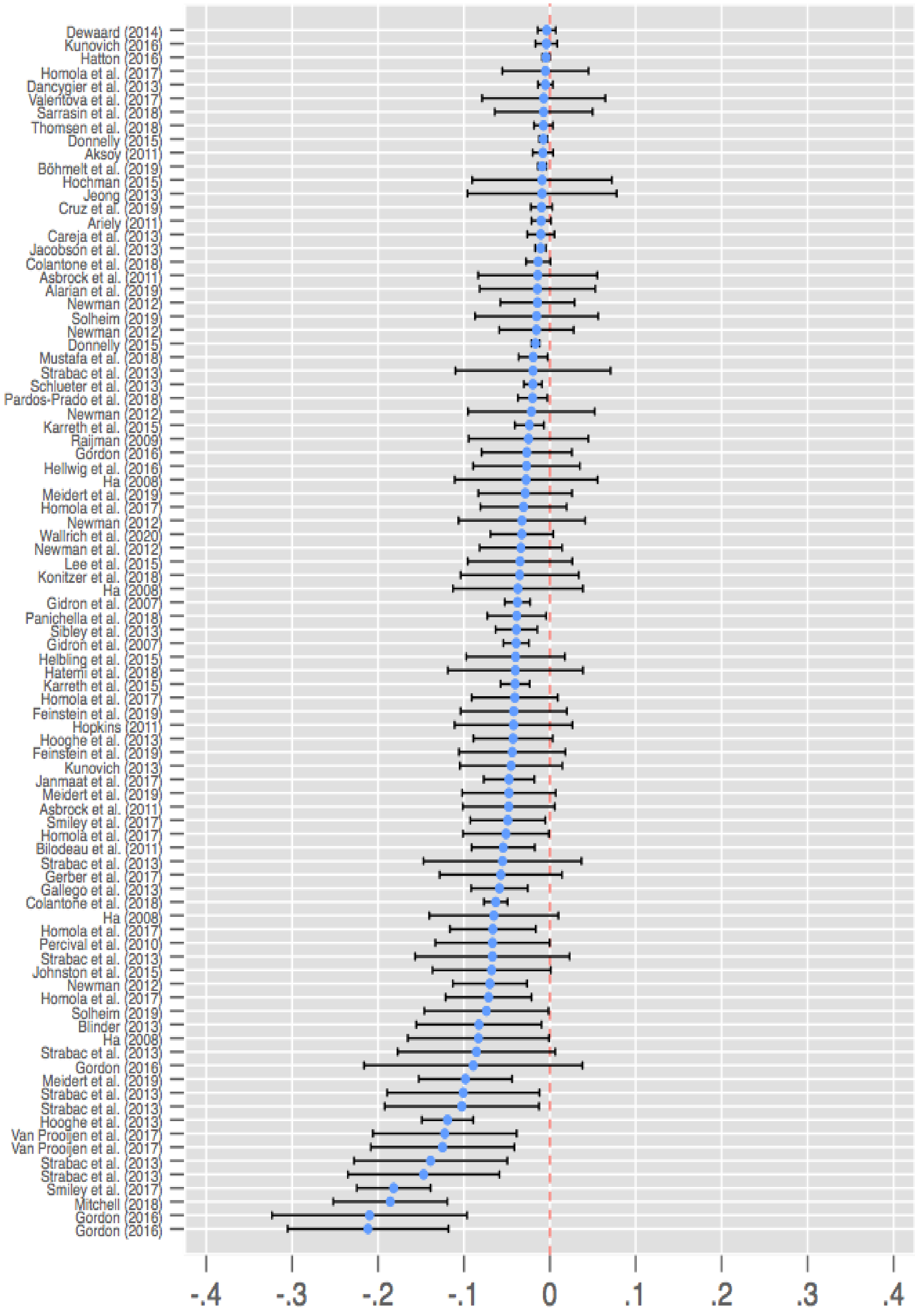

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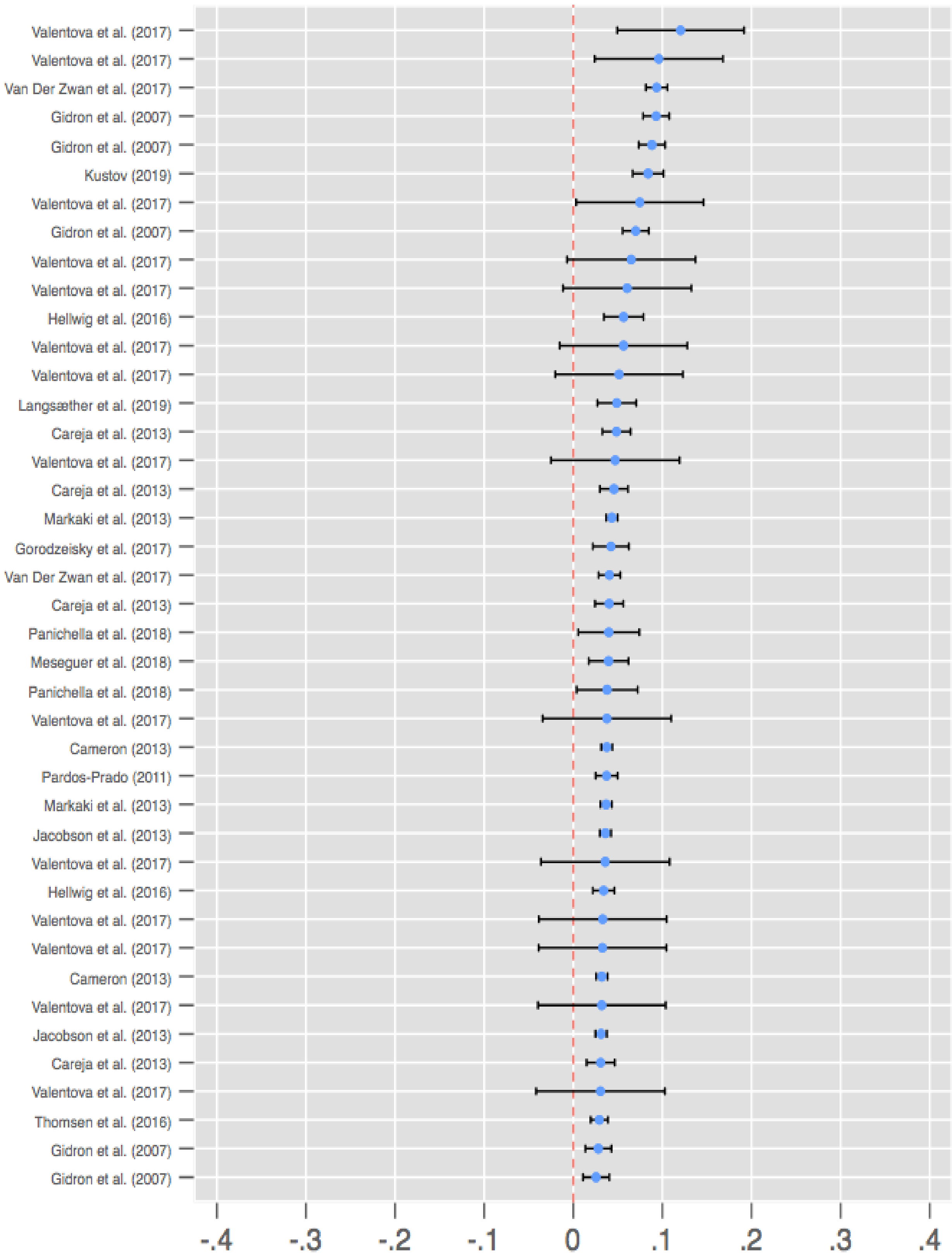
Figure 13: Figure 1.4: High-skilled occupation



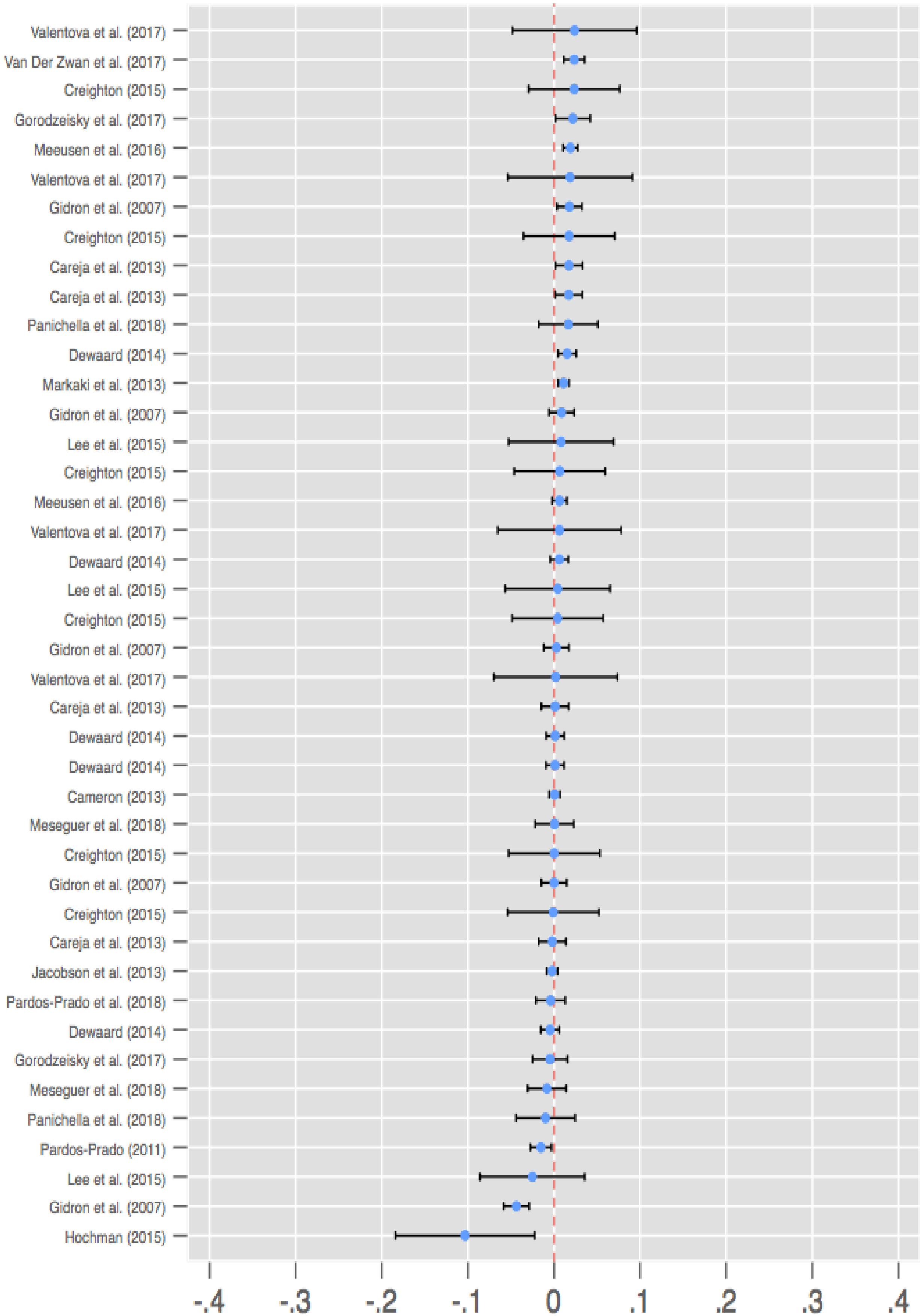

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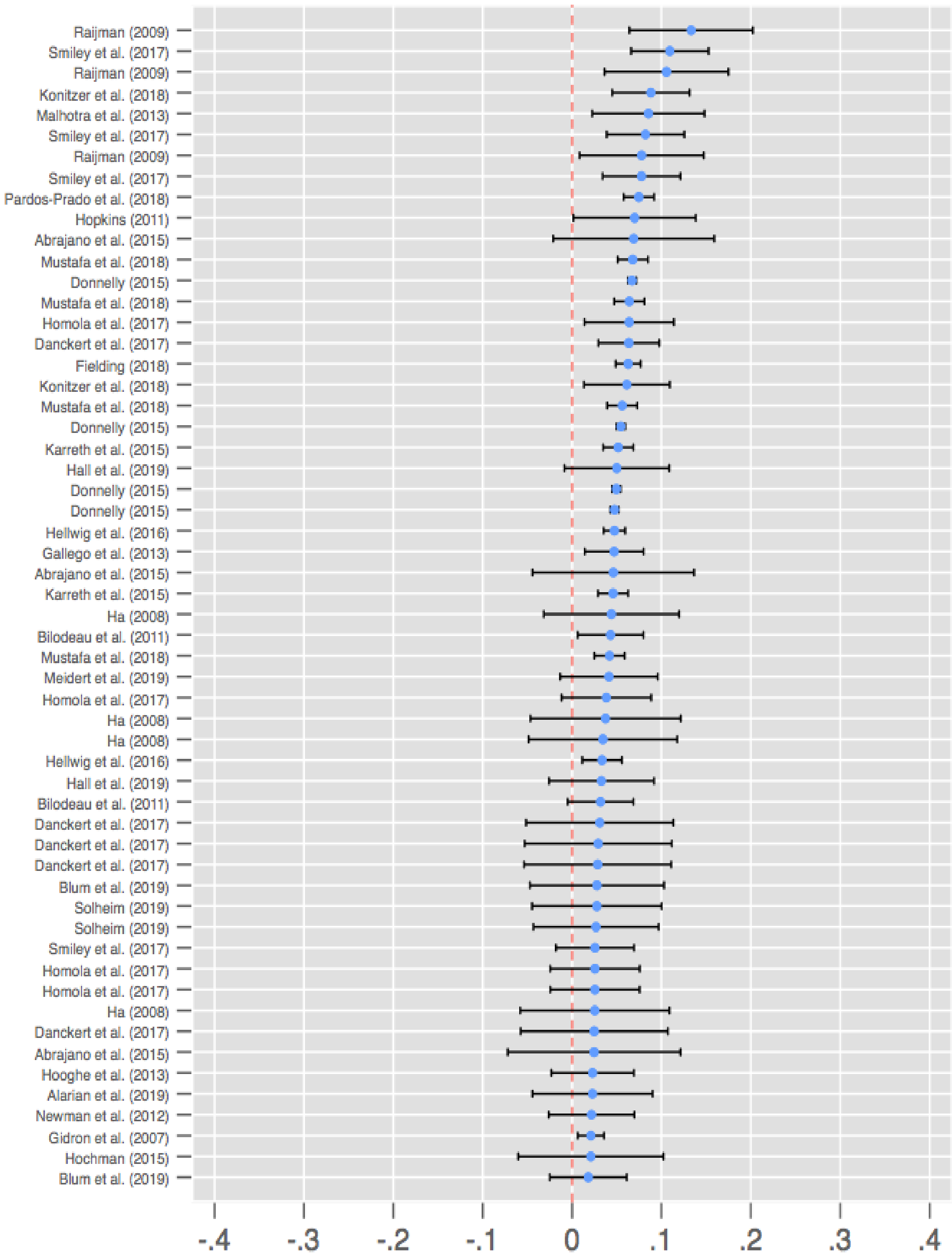
Figure 14: Figure 1.5: High income



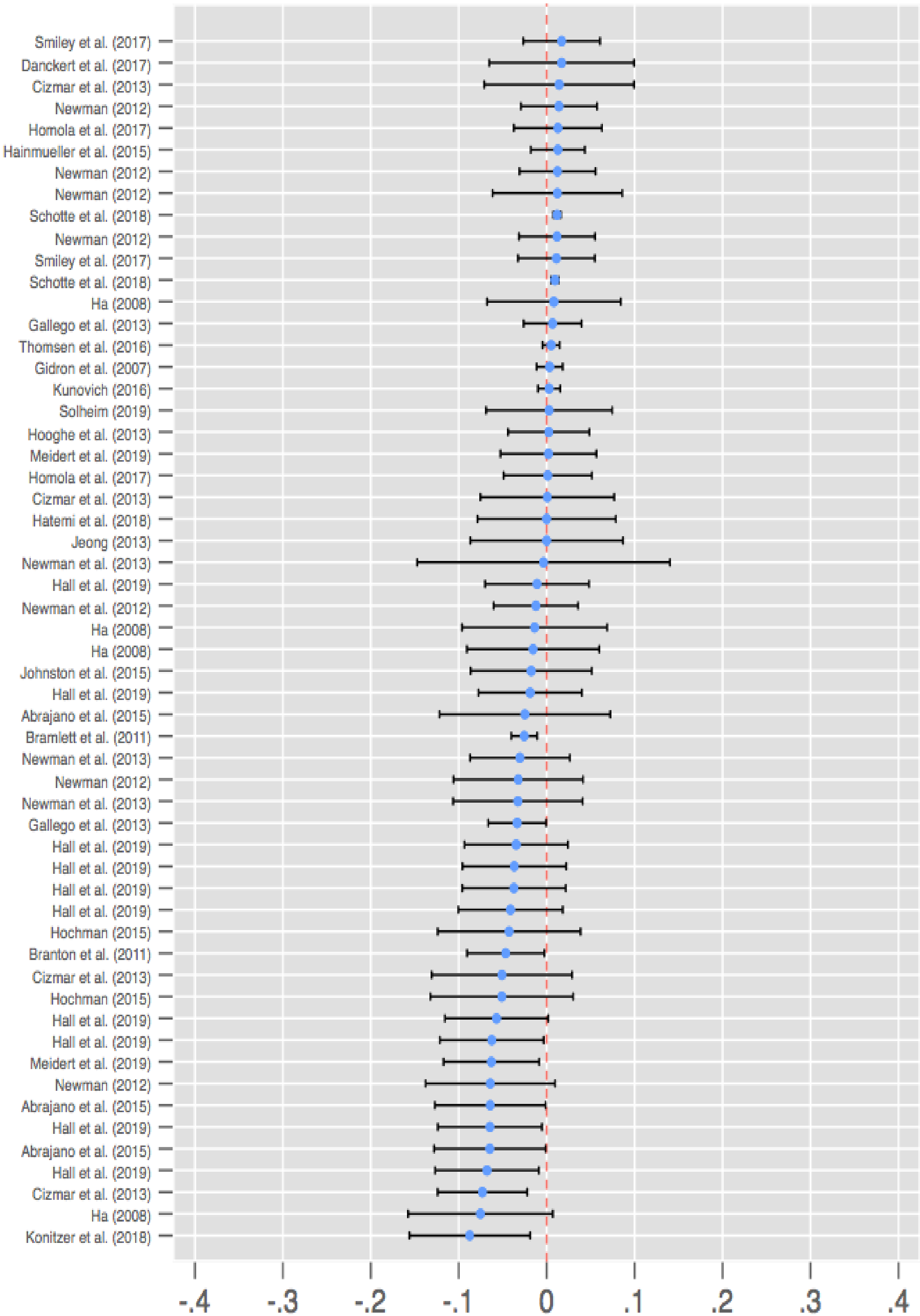

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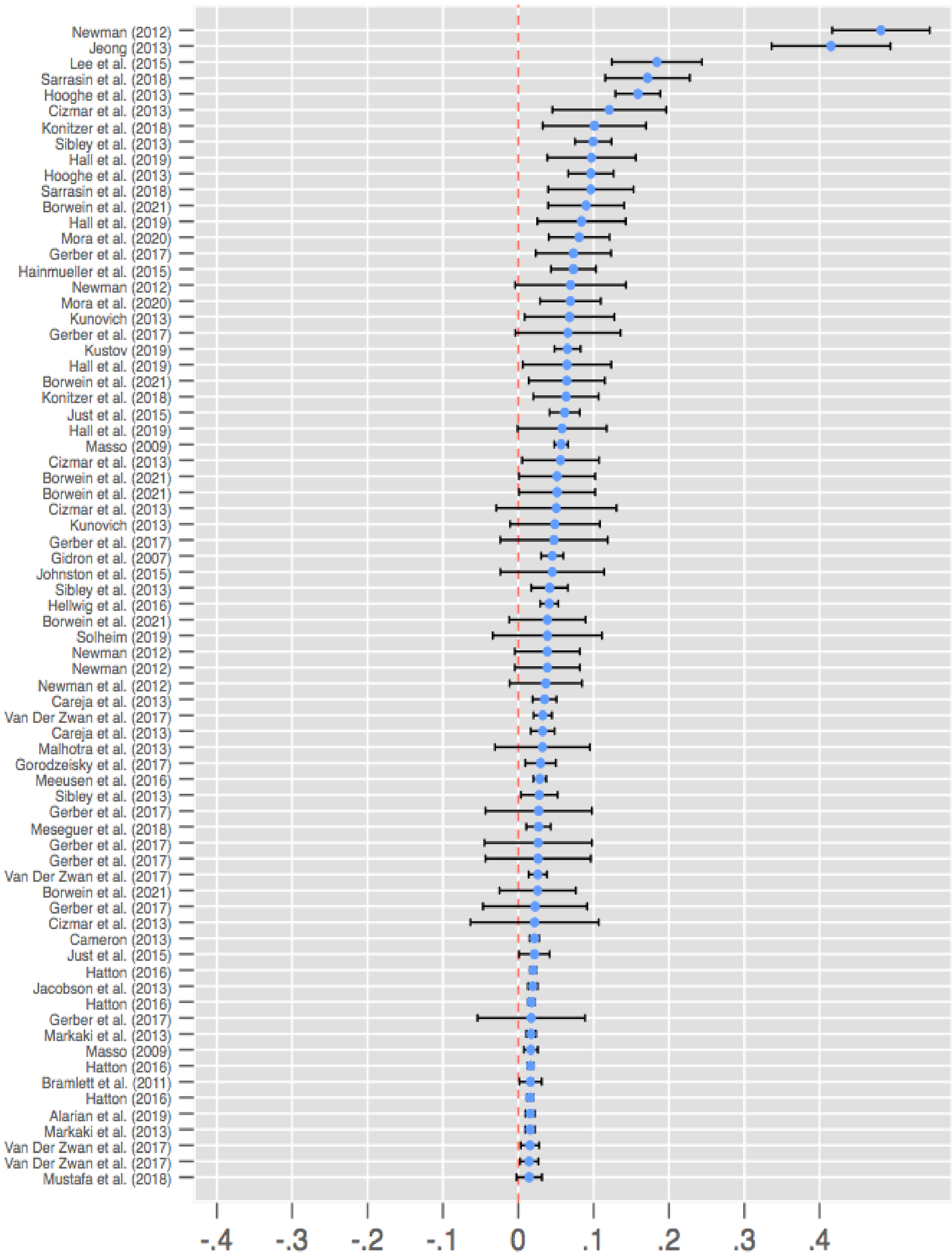
Figure 15: Figure 1.6: Minority status



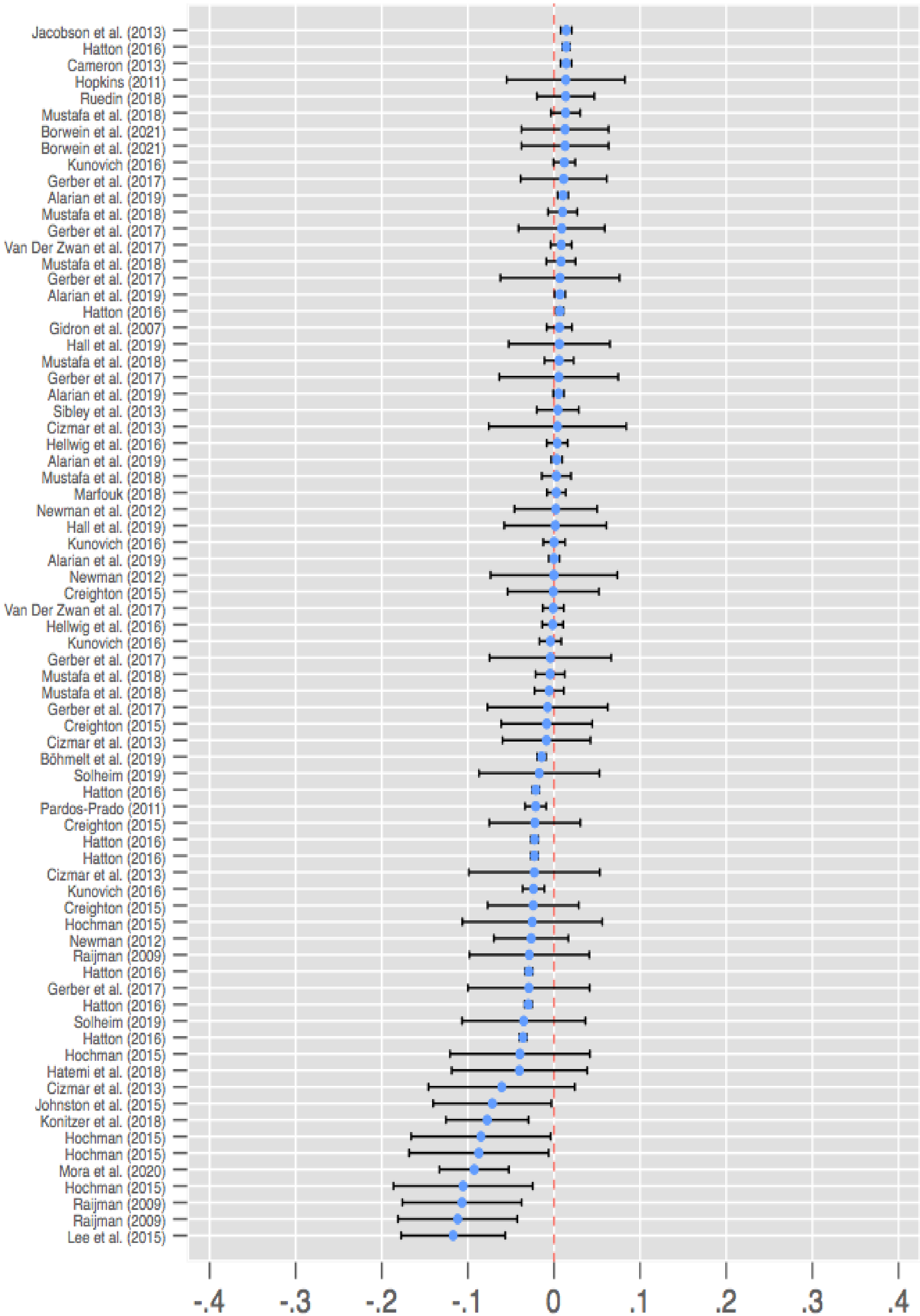

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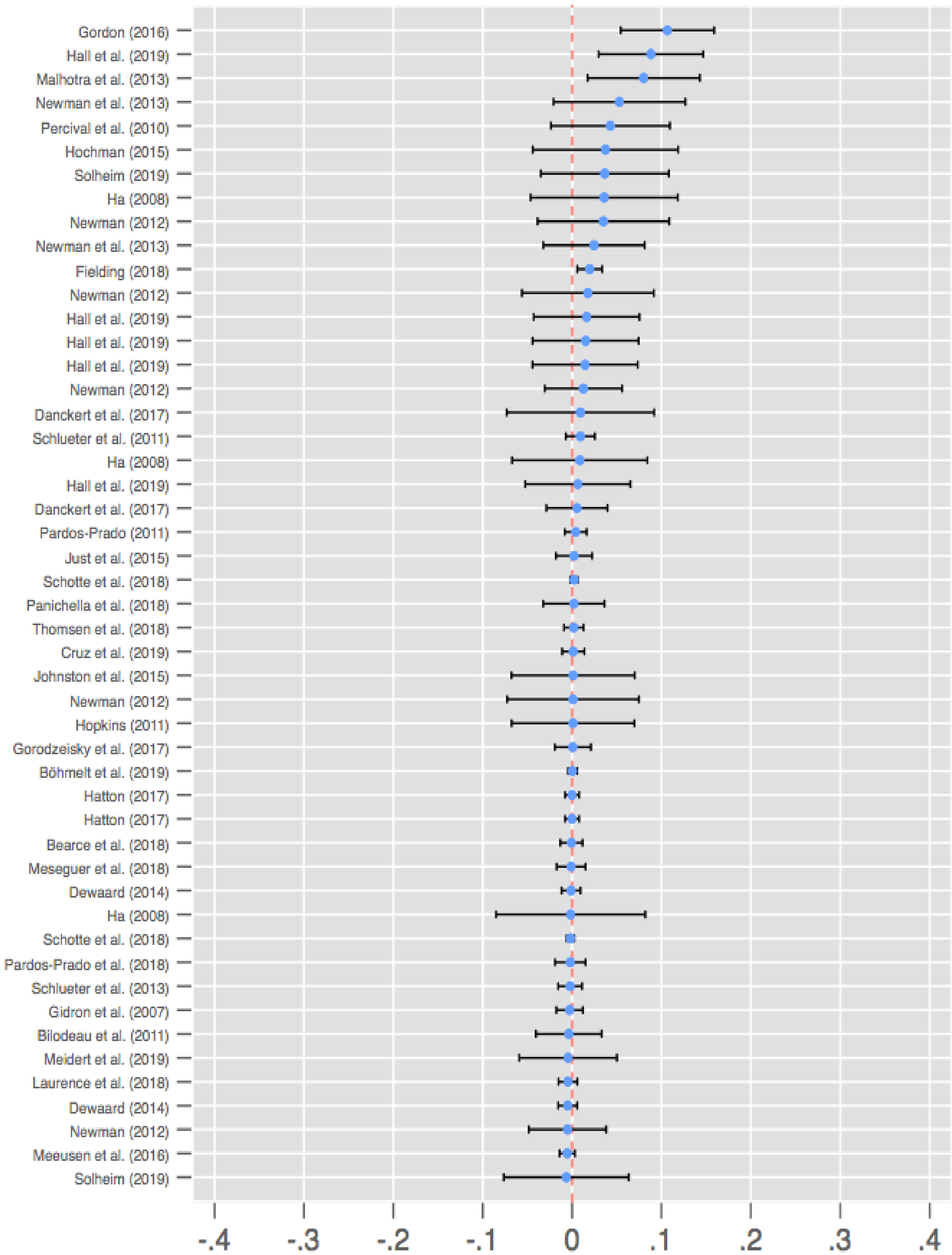
Figure 16: Figure 1.7: Unemployed



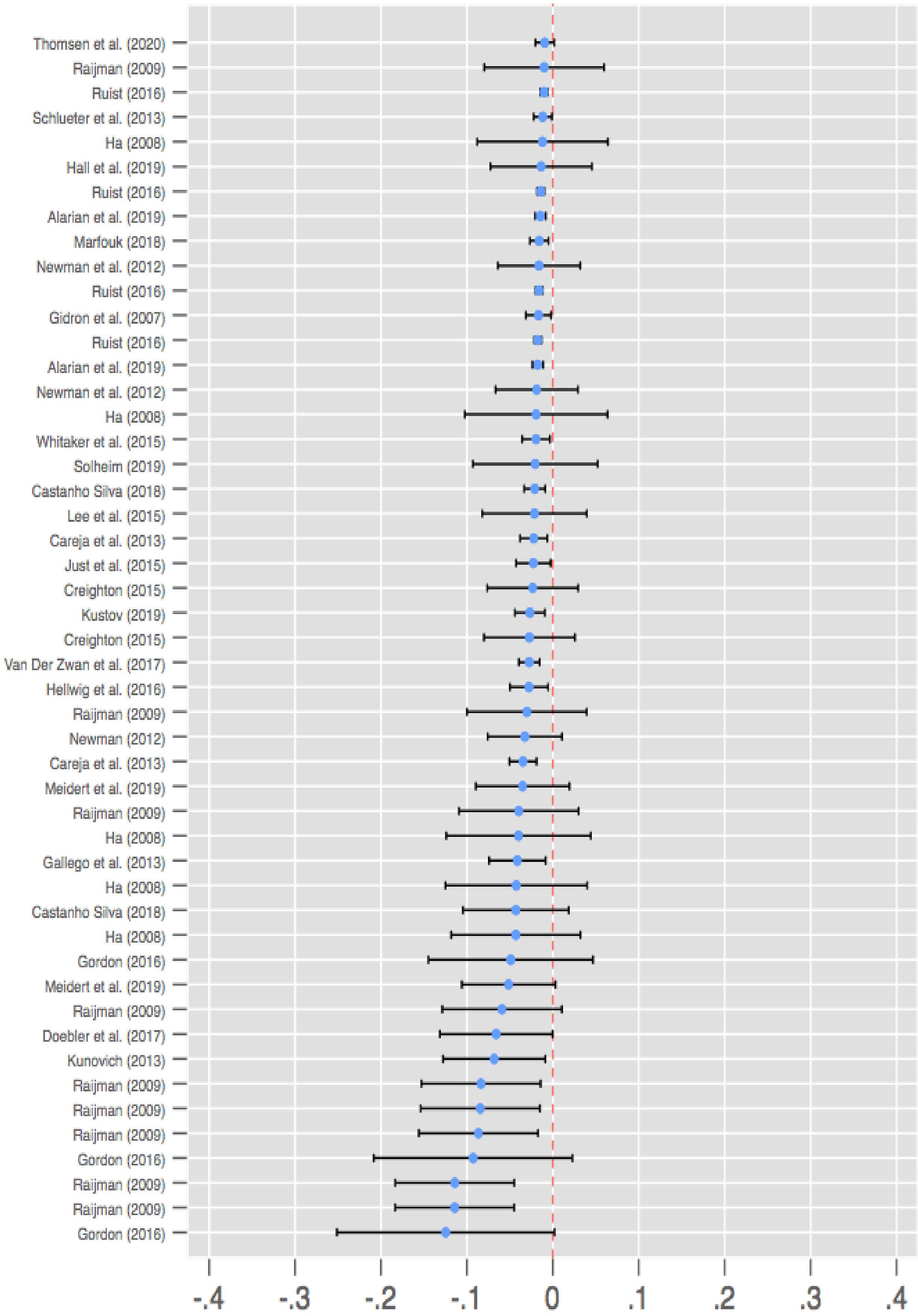


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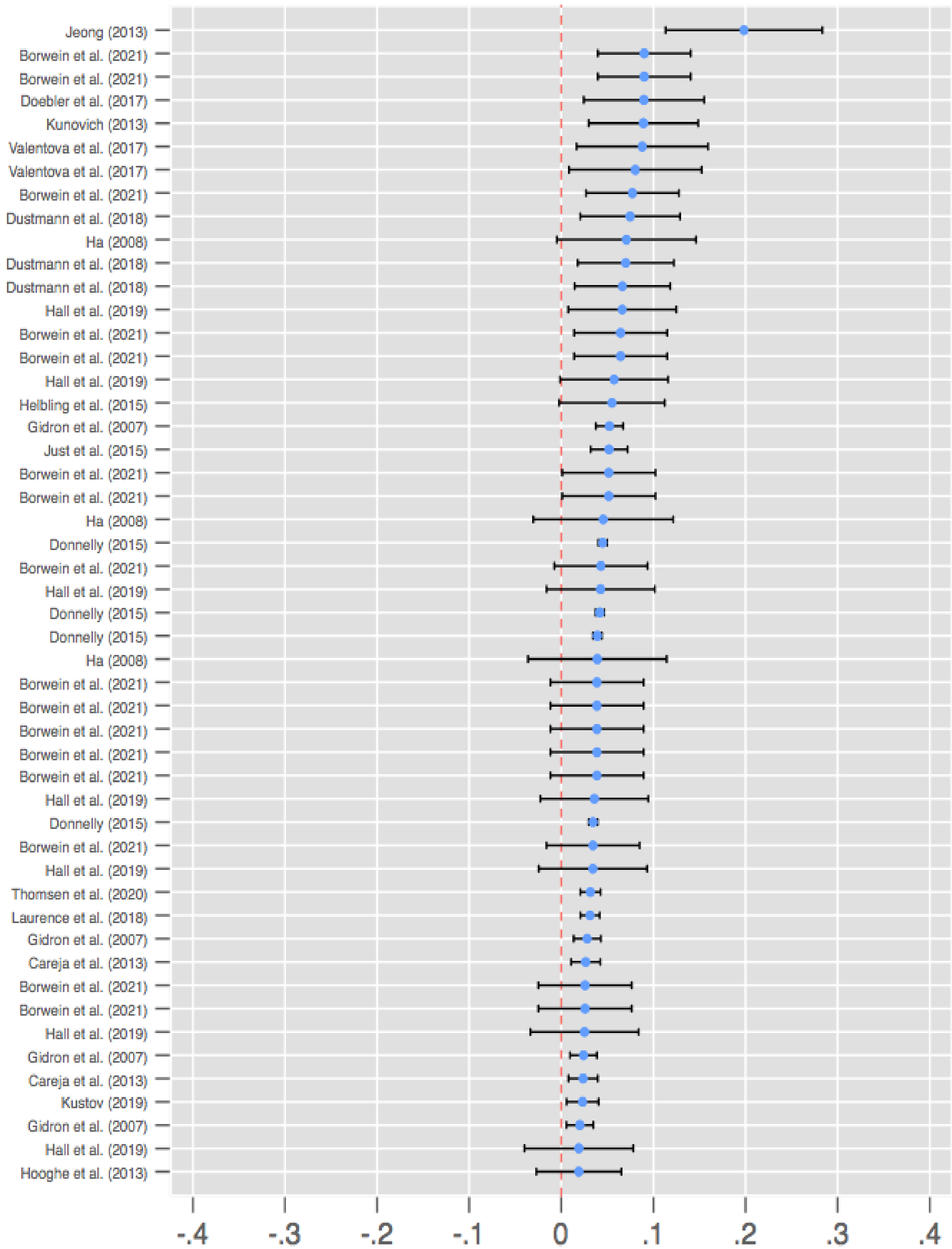
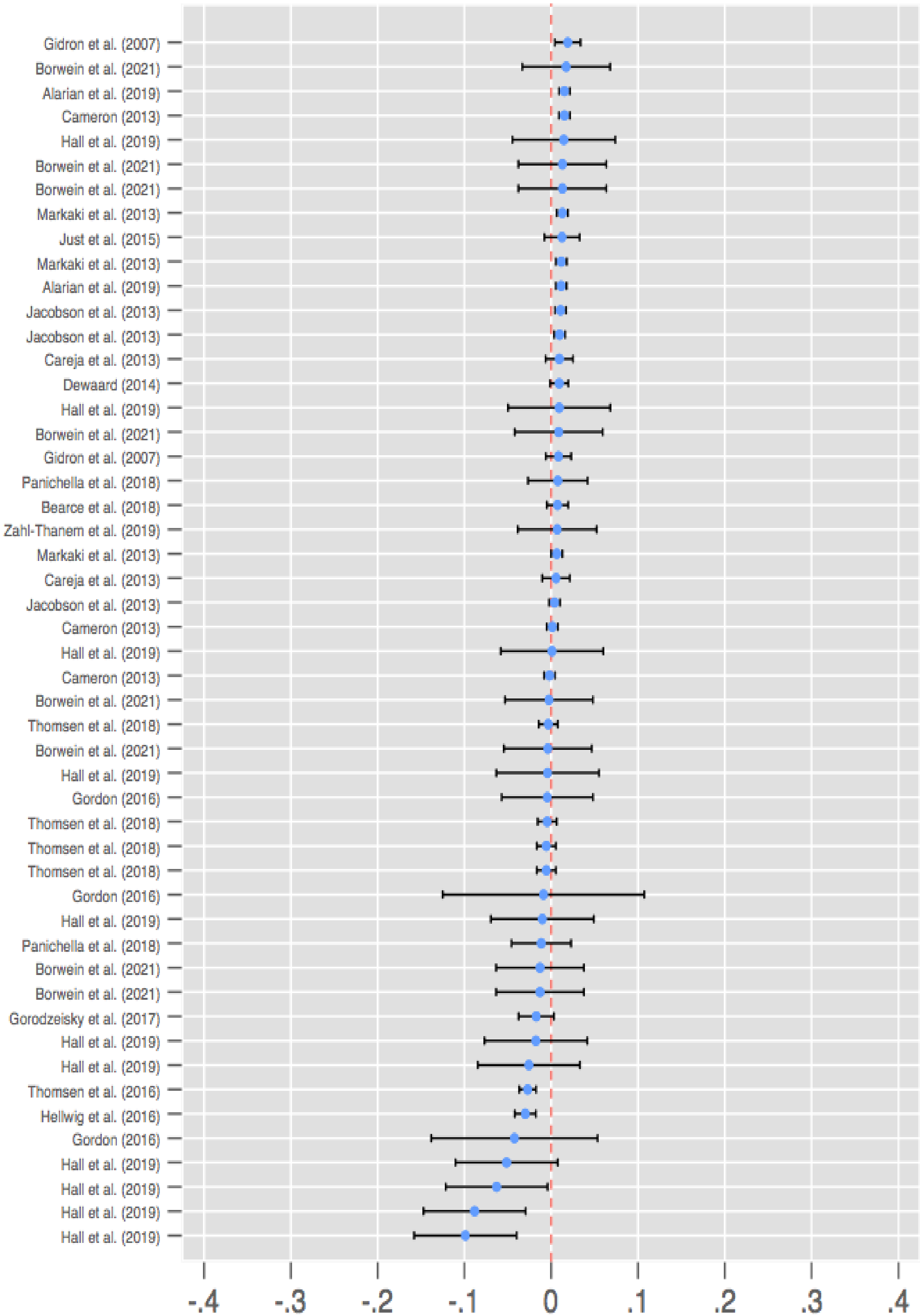
Figure 17: Figure 1.8: Urban residence

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A.3 Meta-analytical approach

This section gives a more detailed description of the meta-analytical technique used in the paper.

To analyze our metadata, we use meta-analytical multilevel random effects models. 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. A specific issue with our dataset is that dependencies between estimates may arise from the fact that most studies analyze widely-used survey data such as the European Social Survey, the European Value Study, or the World Value Survey. or the World Values. To analyze our metadata, we use the method developed by (Bagos, 2015) using the gllam package in Stata, where estimates from each study are grouped - or nested - based on the data used.

It is worth stressing that despite the inclusion of random effects for the sample used, 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. The corresponding samples are therefore partly overlapping in a way that is impossible to identify without access to the actual data. We therefore follow Dinesen, Schaeffer and Sønderskov (2020) and add random effects for the data used but ignore specific years of survey waves.

Table 7 below shows how many estimates are drawn from partly or completely overlapping samples.

Table 7: Datasets

Dataset	Number of estimates
European Social Survey	352
Own dataset	315
Citizenship, involvement, democracy (CID)	54
American National Election Studies	46
Pew Research Center surveys	36
International Social Survey Programme	35
European Value Study	30
British Election Study (BES)	28
Attitudes toward minority workers survey (Eurobarometer)	24
The American Panel Survey	24
Social Capital Community Benchmark Survey	20
General Social Survey (GSS)	26
CEO	18
German General Social Survey (ALLBUS)	17
South African Social Attitudes Survey (SASAS)	17
HAS	15
Copenhagen Area Surveys	14
Canadian Election Studies	11
AES	10
Longitudinal Internet Studies for the Social sciences	10
The Latin American Public Opinion Project (LAPOP)	8
Northern Ireland Life and Times Survey	8
BSA	7
CIS	7
World Value Survey	7
Danish National Election Studies (DNES)	6
Eurobarometer	6
SCIF	6
MOSAiCH Survey (Switzerland)	5
ASEP	4
SCDS (State Convention Delegate Study)	4
Swiss Electoral Studies (SELECTS)	4
Belgian Political Panel Survey	3
CMS	3
NAES	3
USS	1
Youth and society dataset	1

A.4 Discussion of causality according to discipline

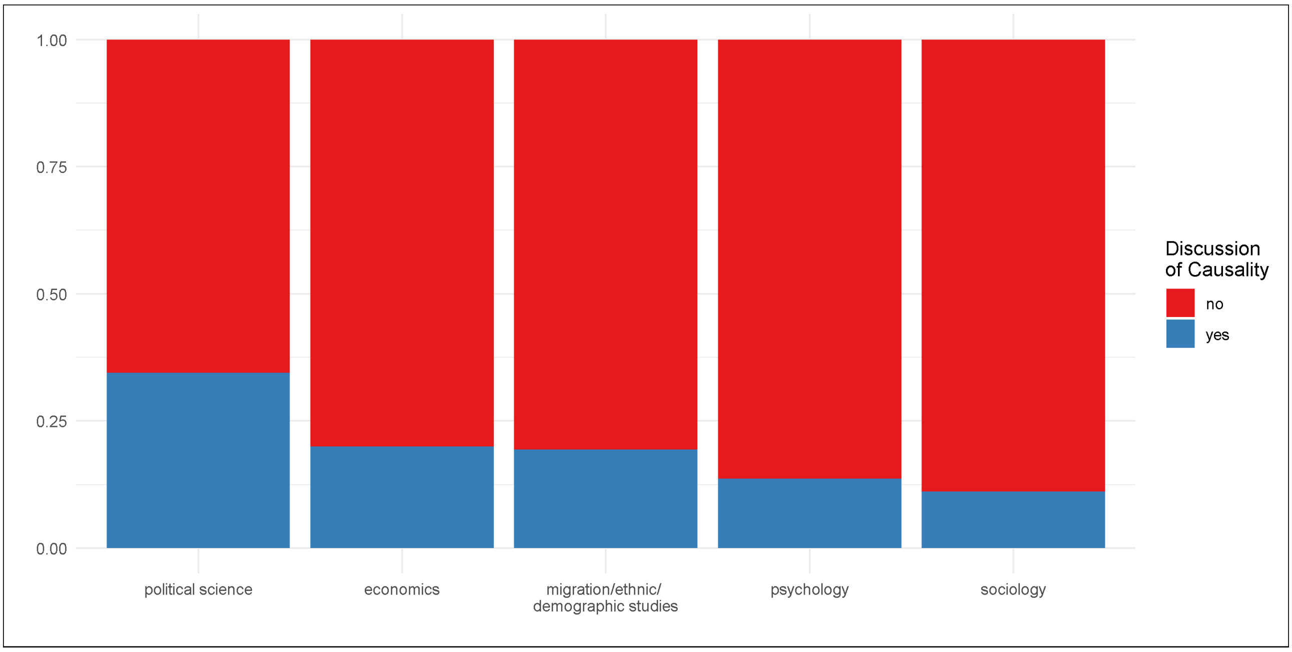

Figure 18: Discussion of causality according to discipline

A.5 Study heterogeneity

A.5.1 Tables

Table 8: AGE - Description and summary statistics of explanatory variables

Variable	**Definition**	**Mean**	**St. Dev.**
TSTAT	Estimated t-statistic of the effect size	-2,55	4,46
PCC	Partial correlation coefficient	-0,04	0,06
Precision	Precision of the estimated partial correlation coefficient (the inverse of the standard error)	94,35	114,84
Number of variables	Logarithmm of number of explanatory variables	2,24	0,54
Original data	Dummy, 1 if original data used, 0 otherwise	0,41	0,49
Measure of attitudes			
Migration policy	Dummy, 1 if attitudes towards the number of immigrants are used, 0 otherwise	0,55	0,50
Mixed attitudes	Dummy, 1 if attitudes towards both the number and contribution of immigrants are used, 0 otherwise	0,01	0,10
Contribution of immigrants (base cat.)	Dummy, 1 if attitudes towards the contribution of immigrants are used, 0 otherwise	0,44	0,50
Control variables - factors			
Age	Dummy, 1 if age is included, 0 otherwise	1,00	0,00
Education	Dummy, 1 if education is included, 0 otherwise	0,86	0,34
Gender	Dummy, 1 if gender is included, 0 otherwise	0,85	0,35
High-skill occupation	Dummy, 1 if occupation is included, 0 otherwise	0,12	0,33
Income	Dummy, 1 if income is included, 0 otherwise	0,52	0,50
Minority status	Dummy, 1 if minority status is included, 0 otherwise	0,55	0,50
Unemployed	Dummy, 1 if employment status is included, 0 otherwise	0,51	0,50
Urban residence	Dummy, 1 if a measure of whether individuals lives in an urban or rural area is included, 0 otherwise	0,40	0,49

Table 9: EDUCATION - Description and summary statistics of explanatory variables

Variable	Definition	Mean	St. Dev.
TSTAT	Estimated t-statistic of the effect size	9,96	16,92
PCC	Partial correlation coefficient	0,10	0,09
Precision	Precision of the estimated partial correlation coefficient (the inverse of the standard error)	108,14	118,76
Number of variables	Logarithmm of number of explanatory variables	2,18	0,49
Original data	Dummy, 1 if original data used, 0 otherwise	0,21	0,40
Measure of attitudes			
Migration policy	Dummy, 1 if attitudes towards the number of immigrants are used, 0 otherwise	0,46	0,50
Mixed attitudes	Dummy, 1 if attitudes towards both the number and contribution of immigrants are used, 0 otherwise	0,02	0,15
Contribution of immigrants (base cat.)	Dummy, 1 if attitudes towards the contribution of immigrants are used, 0 otherwise	0,52	0,50
Control variables - factors			
Age	Dummy, 1 if age is included, 0 otherwise	0,79	0,41
Education	Dummy, 1 if education is included, 0 otherwise	1,00	0,00
Gender	Dummy, 1 if gender is included, 0 otherwise	0,87	0,34
High-skill occupation	Dummy, 1 if occupation is included, 0 otherwise	0,17	0,37
Income	Dummy, 1 if income is included, 0 otherwise	0,45	0,50
Minority status	Dummy, 1 if minority status is included, 0 otherwise	0,38	0,49
Unemployed	Dummy, 1 if employment status is included, 0 otherwise	0,46	0,50
Urban residence	Dummy, 1 if a measure of whether individuals lives in an urban or rural area is included, 0 otherwise	0,25	0,43

Table 10: GENDER - Description and summary statistics of explanatory variables

Variable	Definition	Mean	St. Dev.
TSTAT	Estimated t-statistic of the effect size	0,07	3,40
PCC	Partial correlation coefficient	-0,01	0,06
Precision	Precision of the estimated partial correlation coefficient (the inverse of the standard error)	114,49	129,98
Number of variables	Logarithmm of number of explanatory variables	2,07	0,48
Original data	Dummy, 1 if original data used, 0 otherwise	0,26	0,44
Measure of attitudes			
Migration policy	Dummy, 1 if attitudes towards the number of immigrants are used, 0 otherwise	0,47	0,50
Mixed attitudes	Dummy, 1 if attitudes towards both the number and contribution of immigrants are used, 0 otherwise	0,01	0,11
Contribution of immigrants (base cat.)	Dummy, 1 if attitudes towards the contribution of immigrants are used, 0 otherwise	0,52	0,50
Control variables - factors			
Age	Dummy, 1 if age is included, 0 otherwise	0,80	0,40
Education	Dummy, 1 if education is included, 0 otherwise	0,88	0,32
Gender	Dummy, 1 if gender is included, 0 otherwise	1,00	0,00
High-skill occupation	Dummy, 1 if occupation is included, 0 otherwise	0,12	0,32
Income	Dummy, 1 if income is included, 0 otherwise	0,42	0,50
Minority status	Dummy, 1 if minority status is included, 0 otherwise	0,40	0,49
Unemployed	Dummy, 1 if employment status is included, 0 otherwise	0,47	0,50
Urban residence	Dummy, 1 if a measure of whether individuals lives in an urban or rural area is included, 0 otherwise	0,25	0,43

Table 11: HIGH-SKILL OCCUPATION - Description and summary statistics of explanatory variables

Variable	Definition	Mean	St. Dev.
TSTAT	Estimated t-statistic of the effect size	2,87	4,02
PCC	Partial correlation coefficient	0,03	0,03
Precision	Precision of the estimated partial correlation coefficient (the inverse of the standard error)	116,90	88,58
Number of variables	Logarithmm of number of explanatory variables	2,64	0,36
Original data	Dummy, 1 if original data used, 0 otherwise	0,06	0,24
Measure of attitudes			
Migration policy	Dummy, 1 if attitudes towards the number of immigrants are used, 0 otherwise	0,07	0,26
Mixed attitudes	Dummy, 1 if attitudes towards both the number and contribution of immigrants are used, 0 otherwise	0,00	0,00
Contribution of immigrants (base cat.)	Dummy, 1 if attitudes towards the contribution of immigrants are used, 0 otherwise	0,93	0,26
Control variables - factors			
Age	Dummy, 1 if age is included, 0 otherwise	0,72	0,45
Education	Dummy, 1 if education is included, 0 otherwise	0,95	0,22
Gender	Dummy, 1 if gender is included, 0 otherwise	0,86	0,35
High-skill occupation	Dummy, 1 if occupation is included, 0 otherwise	1,00	0,00
Income	Dummy, 1 if income is included, 0 otherwise	0,18	0,39
Minority status	Dummy, 1 if minority status is included, 0 otherwise	0,59	0,49
Unemployed	Dummy, 1 if employment status is included, 0 otherwise	0,60	0,49
Urban residence	Dummy, 1 if a measure of whether individuals lives in an urban or rural area is included, 0 otherwise	0,72	0,45

Table 12: INCOME - Description and summary statistics of explanatory variables

Variable	Definition	Mean	St. Dev.
TSTAT	Estimated t-statistic of the effect size	1,79	4,74
PCC	Partial correlation coefficient	0,01	0,04
Precision	Precision of the estimated partial correlation coefficient (the inverse of the standard error)	67,93	93,15
Number of variables	Logarithmm of number of explanatory variables	2,28	0,48
Original data	Dummy, 1 if original data used, 0 otherwise	0,21	0,41
Measure of attitudes			
Migration policy	Dummy, 1 if attitudes towards the number of immigrants are used, 0 otherwise	0,62	0,49
Mixed attitudes	Dummy, 1 if attitudes towards both the number and contribution of immigrants are used, 0 otherwise	0,04	0,21
Contribution of immigrants (base cat.)	Dummy, 1 if attitudes towards the contribution of immigrants are used, 0 otherwise	0,34	0,48
Control variables - factors			
Age	Dummy, 1 if age is included, 0 otherwise	0,84	0,37
Education	Dummy, 1 if education is included, 0 otherwise	0,96	0,21
Gender	Dummy, 1 if gender is included, 0 otherwise	0,85	0,36
High-skill occupation	Dummy, 1 if occupation is included, 0 otherwise	0,08	0,27
Income	Dummy, 1 if income is included, 0 otherwise	1,00	0,00
Minority status	Dummy, 1 if minority status is included, 0 otherwise	0,45	0,50
Unemployed	Dummy, 1 if employment status is included, 0 otherwise	0,54	0,50
Urban residence	Dummy, 1 if a measure of whether individuals lives in an urban or rural area is included, 0 otherwise	0,23	0,42

Table 13: MINORITY STATUS - Description and summary statistics of explanatory variables

Variable	Definition	Mean	St. Dev.
TSTAT	Estimated t-statistic of the effect size	1,35	4,25
PCC	Partial correlation coefficient	0,02	0,07
Precision	Precision of the estimated partial correlation coefficient (the inverse of the standard error)	121,55	131,26
Number of variables	Logarithmm of number of explanatory variables	2,30	0,40
Original data	Dummy, 1 if original data used, 0 otherwise	0,30	0,46
Measure of attitudes			
Migration policy	Dummy, 1 if attitudes towards the number of immigrants are used, 0 otherwise	0,55	0,50
Mixed attitudes	Dummy, 1 if attitudes towards both the number and contribution of immigrants are used, 0 otherwise	0,00	0,00
Contribution of immigrants (base cat.)	Dummy, 1 if attitudes towards the contribution of immigrants are used, 0 otherwise	0,45	0,50
Control variables - factors			
Age	Dummy, 1 if age is included, 0 otherwise	0,81	0,39
Education	Dummy, 1 if education is included, 0 otherwise	0,89	0,31
Gender	Dummy, 1 if gender is included, 0 otherwise	0,82	0,39
High-skill occupation	Dummy, 1 if occupation is included, 0 otherwise	0,23	0,42
Income	Dummy, 1 if income is included, 0 otherwise	0,41	0,49
Minority status	Dummy, 1 if minority status is included, 0 otherwise	1,00	0,00
Unemployed	Dummy, 1 if employment status is included, 0 otherwise	0,42	0,50
Urban residence	Dummy, 1 if a measure of whether individuals lives in an urban or rural area is included, 0 otherwise	0,27	0,45

Table 14: EMPLOYMENT STATUS - Description and summary statistics of explanatory variables

Variable	Definition	Mean	St. Dev.
TSTAT	Estimated t-statistic of the effect size	-0,95	1,99
PCC	Partial correlation coefficient	-0,01	0,04
Precision	Precision of the estimated partial correlation coefficient (the inverse of the standard error)	104,46	118,58
Number of variables	Logarithmm of number of explanatory variables	2,26	0,40
Original data	Dummy, 1 if original data used, 0 otherwise	0,10	0,30
Measure of attitudes			
Migration policy	Dummy, 1 if attitudes towards the number of immigrants are used, 0 otherwise	0,38	0,49
Mixed attitudes	Dummy, 1 if attitudes towards both the number and contribution of immigrants are used, 0 otherwise	0,02	0,14
Contribution of immigrants (base cat.)	Dummy, 1 if attitudes towards the contribution of immigrants are used, 0 otherwise	0,60	0,49
Control variables - factors			
Age	Dummy, 1 if age is included, 0 otherwise	0,82	0,39
Education	Dummy, 1 if education is included, 0 otherwise	0,92	0,28
Gender	Dummy, 1 if gender is included, 0 otherwise	0,92	0,28
High-skill occupation	Dummy, 1 if occupation is included, 0 otherwise	0,18	0,39
Income	Dummy, 1 if income is included, 0 otherwise	0,52	0,50
Minority status	Dummy, 1 if minority status is included, 0 otherwise	0,51	0,50
Unemployed	Dummy, 1 if employment status is included, 0 otherwise	1,00	0,00
Urban residence	Dummy, 1 if a measure of whether individuals lives in an urban or rural area is included, 0 otherwise	0,32	0,47

Table 15: URBAN / RURAL RESIDENCE - Description and summary statistics of explanatory variables

Variable	Definition	Mean	St. Dev.
TSTAT	Estimated t-statistic of the effect size	1,91	3,65
PCC	Partial correlation coefficient	0,02	0,04
Precision	Precision of the estimated partial correlation coefficient (the inverse of the standard error)	107,40	110,49
Number of variables	Logarithmm of number of explanatory variables	2,52	0,44
Original data	Dummy, 1 if original data used, 0 otherwise	0,44	0,50
Measure of attitudes			
Migration policy	Dummy, 1 if attitudes towards the number of immigrants are used, 0 otherwise	0,38	0,49
Mixed attitudes	Dummy, 1 if attitudes towards both the number and contribution of immigrants are used, 0 otherwise	0,00	0,00
Contribution of immigrants (base cat.)	Dummy, 1 if attitudes towards the contribution of immigrants are used, 0 otherwise	0,62	0,49
Control variables - factors			
Age	Dummy, 1 if age is included, 0 otherwise	0,80	0,40
Education	Dummy, 1 if education is included, 0 otherwise	0,67	0,47
Gender	Dummy, 1 if gender is included, 0 otherwise	0,72	0,45
High-skill occupation	Dummy, 1 if occupation is included, 0 otherwise	0,28	0,45
Income	Dummy, 1 if income is included, 0 otherwise	0,35	0,48
Minority status	Dummy, 1 if minority status is included, 0 otherwise	0,70	0,46
Unemployed	Dummy, 1 if employment status is included, 0 otherwise	0,52	0,50
Urban residence	Dummy, 1 if a measure of whether individuals lives in an urban or rural area is included, 0 otherwise	1,00	0,00

A.6 BMA

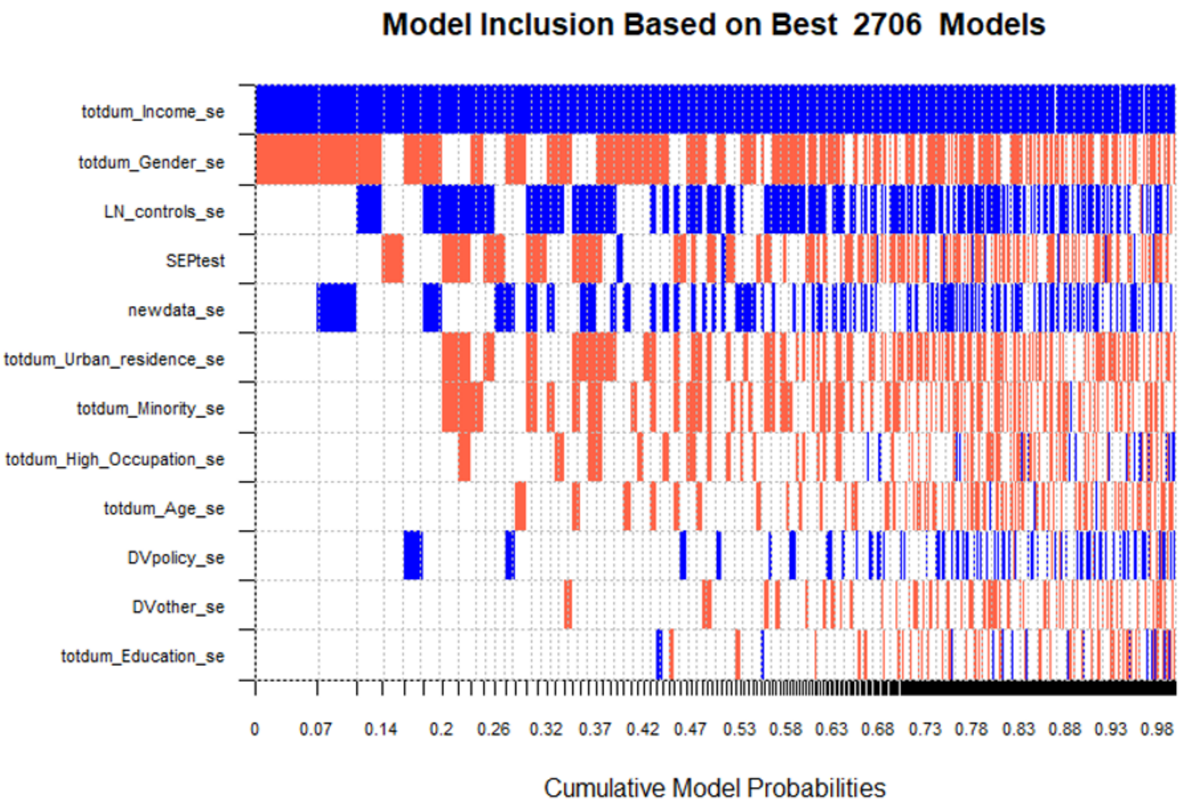

Figure 19: Model inclusion in Bayesian model averaging.

Note: The response variable is the effect of unemployment on attitudes towards immigrants (partial correlation coefficient). A blue cell indicates a positive effect and a red cell indicates that the estimated coefficient of a variable is negative

Table 16: Numerical results of BMA for unemployment

	Posterior Mean	Posterior SD	PIP
SEPtest	-0.009	0.015	0.416
LN_control	0.006	0.007	0.554
newdata	0.010	0.015	0.397
DVpolicy	0.000	0.001	0.175
DVother	-0.003	0.010	0.141
Age	-0.001	0.002	0.185
Education	0.000	0.002	0.126
Gender	-0.009	0.009	0.652
High-skill_Occupation	-0.001	0.003	0.210
Income	0.009	0.003	0.987
Minority	-0.002	0.004	0.351
Urban_residence	-0.003	0.005	0.357
(Intercept)	-0.349	NA	1.000

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.

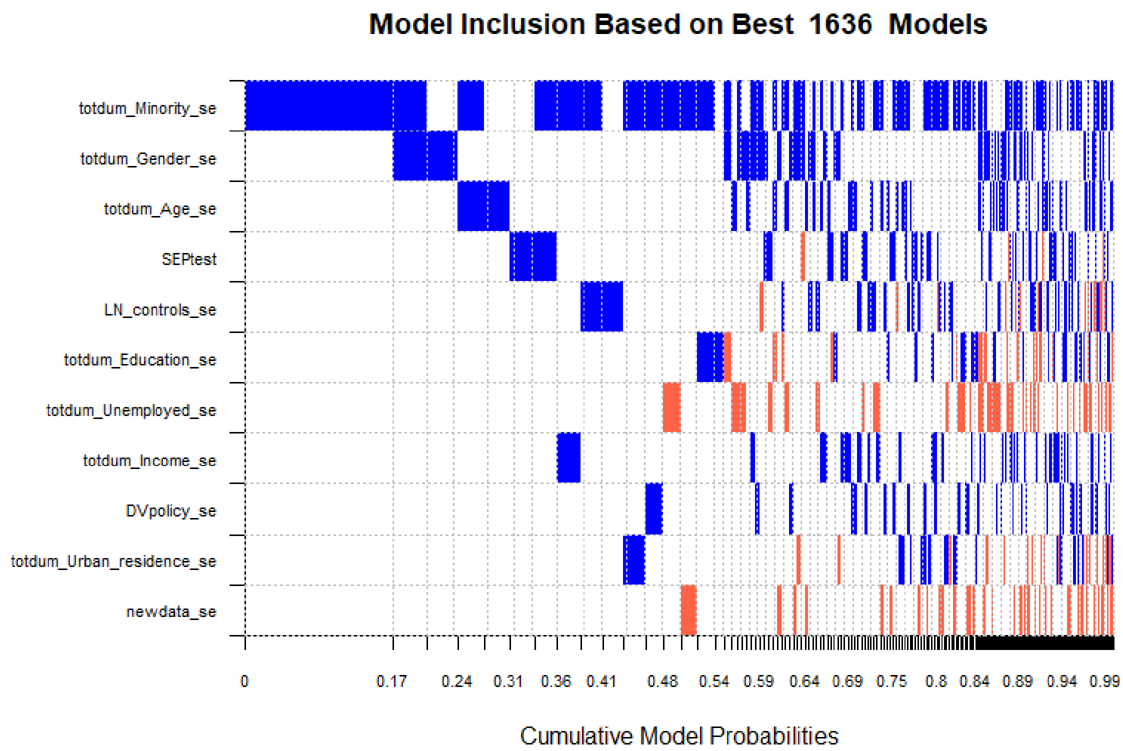

Figure 20: Model inclusion in Bayesian model averaging.

Note: The response variable is the effect of (high-skill) occupation on attitudes towards immigrants (partial correlation coefficient). A blue cell indicates a positive effect and a red cell indicates that the estimated coefficient of a variable is negative

Table 17: Numerical results of BMA for (high-skill) occupation

	Posterior Mean	Posterior SD	PIP
SEPtest	0.002	0.008	0.171
LN_control	0.001	0.003	0.163
newdata	-0.001	0.011	0.106
DVpolicy	0.001	0.007	0.111
Age	0.002	0.007	0.189
Education	0.000	0.006	0.137
Gender	0.003	0.008	0.227
High_Occupation	0.001	0.003	0.125
Income	0.012	0.010	0.665
Minority	-0.001	0.003	0.131
Unemployed	0.000	0.003	0.111
(Intercept)	0.802	NA	1.000

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.

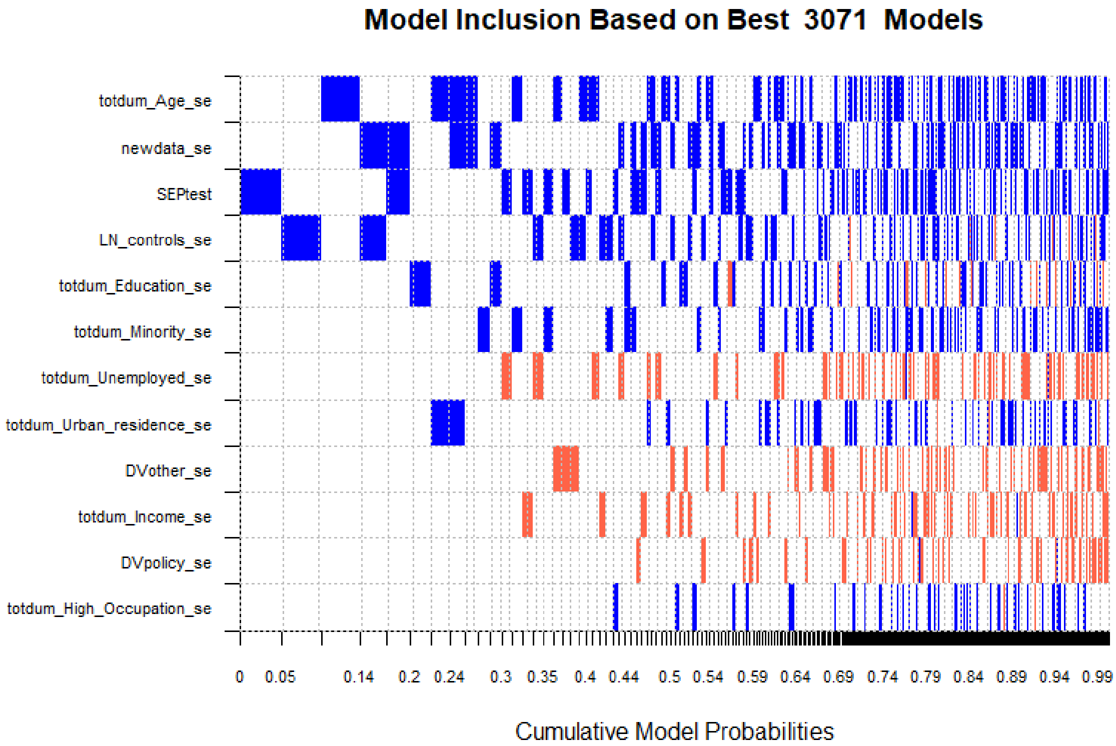

Figure 21: Model inclusion in Bayesian model averaging.

Note: The response variable is the effect of gender on attitudes towards immigrants (partial correlation coefficient). A blue cell indicates a positive effect and a red cell indicates that the estimated coefficient of a variable is negative

Table 18: Numerical results of BMA for gender

	Posterior Mean	Posterior SD	PIP
SEPtest	0.003	0.004	0.333
LN_control	0.001	0.002	0.283
newdata	0.011	0.018	0.345
DVpolicy	0.000	0.001	0.111
DVother	-0.009	0.026	0.158
Age	0.002	0.004	0.356
Education	0.001	0.003	0.187
High-skill_Occupation	0.000	0.002	0.102
Income	-0.001	0.002	0.148
Minority	0.001	0.002	0.185
Unemployed	-0.001	0.002	0.176
Urban_residence	0.001	0.003	0.174
(Intercept)	-0.791	NA	1.000

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.

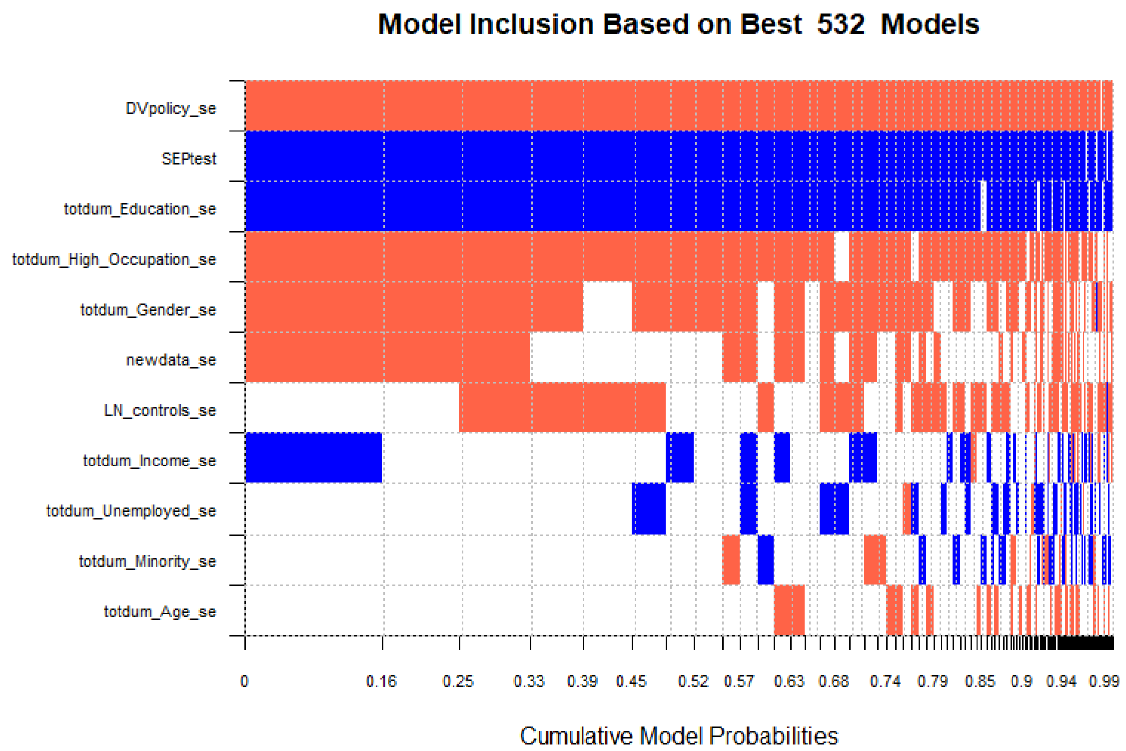

Figure 22: Model inclusion in Bayesian model averaging.

Note: The response variable is the effect of uban residence on attitudes towards immigrants (partial correlation coefficient). A blue cell indicates a positive effect and a red cell indicates that the estimated coefficient of a variable is negative

Table 19: Numerical results of BMA for (urban) residence

	Posterior Mean	Posterior SD	PIP
SEPtest	0.062	0.022	0.995
LN_control	-0.007	0.009	0.478
newdata	-0.017	0.019	0.544
DVpolicy	-0.019	0.004	0.999
Age	-0.001	0.003	0.139
Education	0.023	0.006	0.983
Gender	-0.034	0.022	0.807
High-skill_Occupation	-0.025	0.009	0.945
Income	0.002	0.004	0.344
Minority	0.000	0.004	0.159
Unemployed	0.001	0.003	0.200
(Intercept)	0.438	NA	1.000

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.

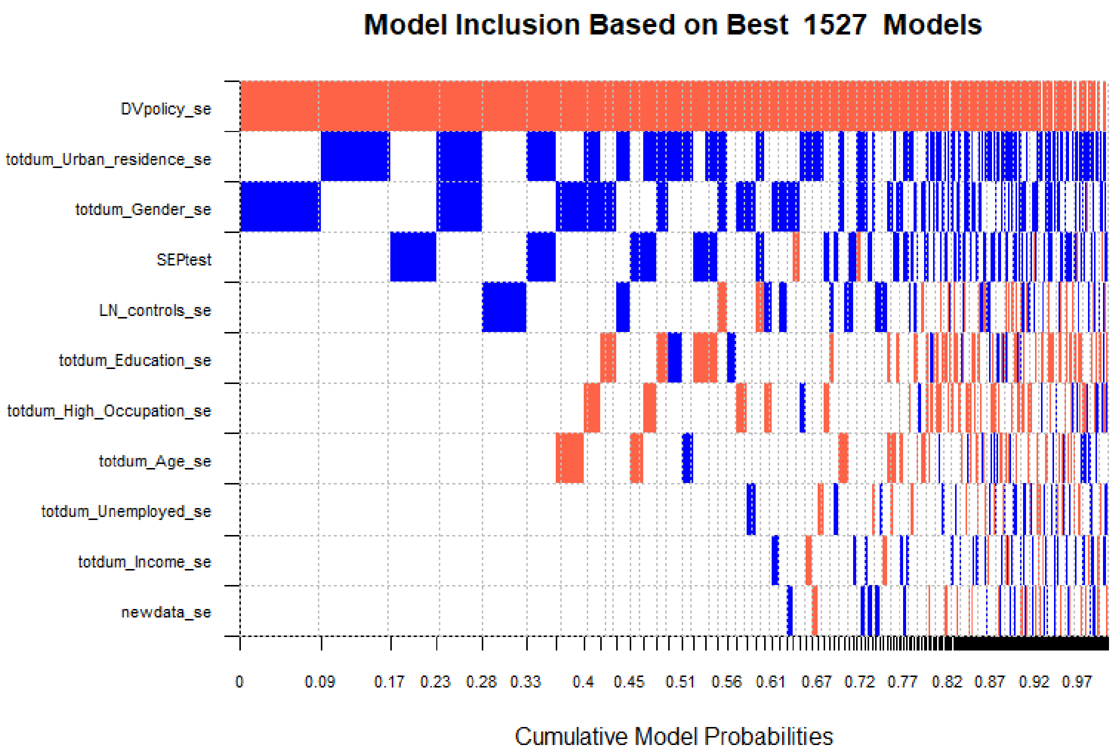

Figure 23: Model inclusion in Bayesian model averaging.
Note: The response variable is the effect of minority background on attitudes towards immigrants (partial correlation coefficient). A blue cell indicates a positive effect and a red cell indicates that the estimated coefficient of a variable is negative

Table 20: Numerical results of BMA for minority status

	Posterior Mean	Posterior SD	PIP
SEPtest	0.007	0.015	0.299
LN_control	0.000	0.004	0.213
newdata	0.000	0.006	0.083
DVpolicy	-0.019	0.007	0.982
Age	-0.001	0.003	0.155
Education	-0.003	0.012	0.198
Gender	0.008	0.012	0.428
High-skill_Occupation	-0.001	0.005	0.156
Income	0.000	0.002	0.084
Unemployed	0.000	0.002	0.088
Urban_residence	0.005	0.007	0.474
(Intercept)	1.289	NA	1.000

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.

A.7 List of journals

Table 21: List of top-ranked journals included in the meta-analysis for each discipline

Political Science
African Affairs
American Journal of Political Science
American Political Science Review
Annual Review of Political Science
British Journal of Political Science
Comparative Political Studies
Democratization
Electoral Studies
European Journal of Political Research
Governance
International Organization
JCMS: Journal of Common Market Studies
Journal of Conflict Resolution
Journal of Democracy
Journal of European Public Policy
Party Politics
Perspectives on Politics
Political Analysis
Political Behavior
Political Psychology
Political Research Quarterly
Political Studies
Public Administration
Public Opinion Quarterly
Regulation and Governance
Review of International Political Economy
Socio-economic Review
The Journal of Politics
West European Politics
World Politics
Sociology
American Sociological Review
Sociology of Education
Annual Review of Sociology
American Journal of Sociology
New Media and Society
Socio-Economic Review
European Sociological Review
Work and Occupations
Gender and Society
Theory and Research in Social Education
Sociological Theory

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Table 21 – *Continued from previous page*

Work, Employment and Society
Social Forces
Sociological Methods and Research
Sociology
Theory, Culture and Society
International Political Sociology
Sociological Review
Social Problems
Sociologia Ruralis
British Journal of Sociology
American Journal of Cultural Sociology
British Journal of Sociology of Education
Social networks
Journal of Consumer Culture
European Journal of Social Theory
Social Science Research
Chinese Sociological Review
Journal of Marriage and Family
Sociological Forum
Psychology
Cyberpsychology Behavior and Social Networking
Personality and Social Psychology Bulletin
Journal of research in personality
Journal of experimental social psychology
Personality and Individual differences
Social Psychological and Personality Science
Social and Personality Psychology Compass
European Journal of Social Psychology
British Journal of Social Psychology
Group Processes
Intergroup Relations
Psychology of Popular Media Culture
Personality and Social psychology review
Social Issues and Policy Review
Journal of Personality and social psychology
European Journal of personality
Journal of Personality
Journal of Social and Personal Relationships
Social Behavior and Personality: An International Journal
Self and Identity
Annual Review of Organizational Psychology and Organizational Behavior
Nature Human Behaviour
Organizational Psychology Review
Research in Organizational Behavior
Journal of Research in Crime and Delinquency
European Review of Social Psychology

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Table 21 – *Continued from previous page*

The Journal of Social Psychology
Journal of Social and Political Psychology
International Review of Social Psychology
Media Psychology
Journal of Counseling Psychology
Economy
American Economic Review
Econometrica
Journal of Political Economy
Quarterly Journal of Economics
Review of Economic Studies
American Economic Journal: Macroeconomics
American Economic Journal: Economic Policy
Journal of labour Economics
American Economic Journal: Applied Economics
Journal of Human Resources
Journal of Monetary Economics
Review of Economics and Statistics
Journal of the European Economic Association
Theoretical Economics
Journal of Economic Growth
Journal of Econometrics
Economic Journal
American Economic Journal: Microeconomics
Quantitative Economics
Journal of International Economics
Journal of Applied Econometrics
Review of Economic Dynamics
Journal of Economic Theory
Journal of Business and Economic Statistics
RAND Journal of Economics (formerly: Bell Journal of Economics)
Economic Policy (formerly: Economic Policy: A European Forum)
Journal of Public Economics
IMF Economic Review (formerly: IMF Staff Papers International Monetary Fund Staff Papers)
International Economic Review
Journal of Development Economics
Human Migration/Ethnic Studies
Journal of Ethnic and Migration Studies
Ethnic and Racial Studies
Journal of Refugee Studies
Journal of Immigrant
Refugee Studies
Identities
Ethnicities
Ethnicity
Health

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Table 21 – *Continued from previous page*

Mobilities
International Migration Review
Global Networks
International Migration
Citizenship Studies
Comparative Migration Studies
Journal of International Migration and Integration
Migration Studies
IZA Journal of Migration
Journal of Intercultural Studies
Refugee Survey Quarterly
Migration Letters
International Journal of Refugee Law
Demography
Demography
Journal of Population Economics
Population and Development Review
Studies in Family Planning
Population, Space and Place
Perspectives on Sexual and Reproductive Health
European Journal of Population
Population and Environment
Demographic Research
Population Studies

A.8 List of measures of attitudes to immigration

Table 22: List of attitudes included in the meta-analysis

Contribution and consequences of immigration
Benefits of immigrants for the country
Benefits of immigrants from Ethiopia for country
Benefits of immigrants from FSU (former Soviet Union) for country
Benefits of immigrants from Western countries for country
Economic competition with immigrants
Benefits of immigrants for the country
Benefits of refugees for the country
Immigrants steal jobs
Immigrants are a strain on the welfare system
Immigrants are a problem for the community
Immigrants enrich culture
Immigrants are good for the economy
Immigrants make country a better place
Immigrants are a problem for security
Immigrants are a problem for security in the community
Immigrants are a problem for security/Afraid of immigrants
Mix of attitudes to benefits of Muslim immigrants for the country
Mix of attitudes to benefits of high skill immigration for the country
Mix of attitudes to benefits of immigrants for the country
Mix of attitudes to benefits of low skill immigration
Mix of attitudes to benefits of refugees/asylum seekers
Threat from asylum seekers
Threat from immigrants from Ethiopia
Threat from immigrants from FSU (former Soviet Union)
Threat from immigrants from Western countries
Threat from immigrants to the economic welfare of the country
Threat from immigrants to the economic welfare of the household
Threat from immigrants to the economic welfare system of the country
Threat from immigrants to national identity
Refugees' contribution to the country
Refugees are a problem for security
Attitudes and policy preferences on immigration flows and level
Allow refugees to bring family
Ban on Muslim immigrants
Government judgement of refugee applications
Government should accept refugees
Mix of attitudes to immigration policy
Mix of attitudes to refugees/asylum seekers policy
Mix of attitudes to selective admission of immigrants
More/less Arab immigrants
More/less asylum seekers
More/less immigrants from a different ethnic group

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Table 22 – *Continued from previous page*

More/less immigrants from poor countries
More/less immigrants from poor European countries
More/less immigrants from the same ethnic group
More/less immigrants
More/less Jewish immigrants from poor countries
More/less labour immigrants
More/less Muslim immigrants
More/less Muslim immigrants from poor countries
More/less refugees
More/less refugees/Mix of attitudes to refugees
More/less refugees from countries with terrorists
More/less Roma immigrants from poor countries
More/less same ethnic group
More/less skilled immigrants
More/less unskilled immigrants