

Is possessing general political knowledge diagnostic of holding issue-specific knowledge? Stress-testing the generalist assumption

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Abstract

The practice of using general political knowledge questions to explain variation in policy-specific outcomes invokes a potentially strong generalist assumption: possessing general knowledge is diagnostic of holding issue-specific knowledge. Is this warranted? Using convergent evidence drawn from best-available US and European surveys, we argue it is. First, factor analysis applied to 2018 European data that, unusually, include questions about general politics and the specific issue of EU immigration reveals how combining the questions produces a plausibly unidimensional set. Second, knowledge scales built using Item Response Theory (IRT) modeling of responses to each set of questions display similar associations with known correlates of political knowledge—gender, age, education—including by country and with well-established ANES, CES, and BES knowledge measures. Finally, these patterns remain after extending our analysis to surveys that test knowledge about public health (specifically COVID-19) and climate change. We propose steps for conducting similar stress-tests on unidimensionality assumptions.

Keywords: political knowledge; immigration; public health; climate change

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1 Introduction

Political knowledge has been called a “workhorse variable” (Kleinberg 2022) owing to its usefulness as a proxy for other concepts including political sophistication and competence (Delli Carpini and Keeter 1996). However, survey-based practice has operationalized this variable in different ways, which potentially threatens conclusions about both its determinants and consequences. In their overview of 335 knowledge questions fielded between 2007-10, Barabas et al. (2014) identify two dimensions that characterize these questions: a temporal dimension capturing how recently the factual information emerged; and a topical dimension capturing whether the factual information refers to general institutions or actors, or specific public policy issues. In particular, they focus on the *temporal* dimension of their typology to examine the mechanisms by which voters acquire knowledge.

By contrast, our interest lies in the *topical* dimension of political knowledge questions—specifically in assessing how general and policy-specific knowledge relate, and what this implies for researchers’ necessarily constrained efforts to effectively and efficiently measure voters’ levels of knowledge. Such an assessment matters because, as survey researchers try to explain variation in policy-specific attitudes or behaviors using knowledge items intended to distinguish between more- and less-informed respondents, they invoke a potentially strong assumption: possessing general political knowledge is diagnostic of holding issue-specific knowledge (and vice versa). We call this the *generalist assumption*.

In various forms, the idea that people who are knowledgeable in one area of politics will be knowledgeable in others as well has underpinned much of the key work in public opinion (e.g. Zaller 1986 and 1992; Delli Carpini and Keeter 1996). Methodologically, this is attractive because it implies that researchers can use a general knowledge scale to measure the extent to which people are politically informed across specific domains, even in the absence of items directly concerned with the particular topics represented within those domains. Yet despite its methodological centrality, this assumption has remained largely untested, partly due to the lack of available survey instruments which contain both general and issue-specific factual items.

In response, we present convergent evidence that stress-tests the generalist assumption by applying a variety of methods to a range of the best-available survey evidence spanning country contexts (the US and seven European countries), topics (immigration, public health, and climate change), and respondent panel type (established omnibus and bespoke online panels). Among other steps, we leverage cross-national European survey data that, unusually, contains questions about both general politics and a specific issue, namely European Union immigration (Meltzer et al. 2019). By assessing the dimensionality and construct validity of the range of knowledge questions contained within our assembled surveys, and by comparing these features to widely-used instruments (the American National Elections Studies, the Cooperative Election Study, and the British

Election Study), we conclude that the generalist assumption holds up to scrutiny. Besides contributing empirical evidence for this common methodological practice, we offer practical advice for researchers who either want to conduct similar stress-tests of their own topic- and context-specific survey data on grounds of unidimensionality assumptions, or are considering which types of knowledge questions to include in future studies while acknowledging concerns about resources, time, and survey attentiveness.

2 The Generalist Assumption about Political Knowledge

The generalist assumption can be traced back at least to John Zaller’s analysis of information items in the 1985 National Election Study Pilot, where he argued that “political information is a relatively general trait that can be effectively measured with a general-purpose information scale” (Zaller 1986, 2). This conclusion subsequently informed his landmark study on public opinion, where he noted that he was “assuming that persons who are knowledgeable about politics in general are habitually attentive to communications on most particular issues as well” (Zaller 1992, 43). That same assumption is investigated and defended by Delli Carpini and Keeter (1996), and relied upon in both Bartels’s (1996) and Althaus’s (2003) highly influential work on information effects, measuring differences between actual preference reports and modeled estimates of the preferences reports respondents likely would have given, had they been fully informed.

More specifically, in operationalizing the relevant notion of informedness, Bartels relies upon interviewer ratings of respondents’ “general level of information about politics and public affairs” (1996, 203) while Althaus uses the type of general scales developed by Delli Carpini and Keeter. Subsequent work across a variety of geographical contexts including the US (Ahlstrom-Vij 2021), Denmark (Bhatti 2010; Hansen 2009), Sweden (Oscarsson 2007) and Canada (Blais et al. 2009) follows the norms set by these early studies by using either a variety of general knowledge items or a scale of both general and specific campaign items alongside interviewer ratings of the respondent’s knowledge. As such, the generalist assumption has come to carry an increasingly heavy burden: not only is the catalogue of geographical contexts in which researchers investigate the impacts of knowledge on political attitudes and choice expanding, but so also is the list of the specific political and policy issues that feature either directly or indirectly in models of voter attitude and choice in a range of political circumstances.

In parallel, there has been a growth in experimental work on the role of knowledge and information on specific policy matters, one such area being immigration. For example, providing corrective information about the levels and impacts of immigration appears to reduce misconceptions and change attitudes (Grigorieff, Roth, and Ubfal 2020), as well as

policy preferences in some circumstances (Blinder and Schaffner 2019; Facchini, Margalit, and Nakata 2022), although the presence and direction of these effects is not consistent (Jørgensen and Osmundsen 2020). Clearly, further work is needed, but due to resource constraints, much of that research will need to be observational rather than experimental, in which case researchers will in many cases need to rely on available general knowledge items even when concerned with specific policies issues. This puts further pressure on the generalist assumption.

So, does that assumption hold? That is the question we set out to answer below, using immigration knowledge and general political knowledge as our test case, before moving on to a wider set of issue-specific knowledge scales. If the assumption holds, we expect that different methods of analysis (which we describe later) will converge to support its core expectations: that (1) relevant pattern of observed variables can plausibly be represented by a single latent trait (factor) in factor analysis; (2) regressing the knowledge scales on demographic variables will produce the associations that one would expect from prior work into the determinants of political knowledge, and the estimated marginal mean level of measured knowledge by education, gender, and age should both hold cross-nationally and also exhibit similar patterns to those found in established measures of political knowledge from BES, ANES, and CCES; and (3) those same marginal means should also coincide with the patterns found in relation to independent scales measuring knowledge on other, issue-specific matters, namely: public health and climate change.

3 Methods and Data

3.1 Dataset

We use a subset of online survey data collected as part of the REMINDER (Role of European Mobility and Its Impacts in Narratives, Debates and EU Reforms) project (Meltzer et al. 2019).¹ Unlike many existing data sets, the survey component of the REMINDER project is both cross-national and includes general political knowledge questions as well as immigration-specific ones. Therefore, the data set is uniquely suitable for testing the generalist assumption as it is implicitly invoked in information effects research, as per the previous section. Moreover, as the project covers seven European countries, the data also allow us to examine any geographic variation – between Germany, Hungary, Poland, Romania, Spain, Sweden, and the UK – thereby testing if previous results on unidimensionality are possibly artifacts of particular national profiles, e.g. the US, where early studies on the unidimensionality of political knowledge took place.

The original REMINDER study used a panel design comprising three waves across

¹Full details about the data set, including its documentation and questionnaire design, are available at <https://doi.org/10.11587/LBSMPQ>.

Table 1: Demographic details of the sample

Nationality	Germany	Hungary	Poland	Romania	Spain	Sweden	UK
Mean age	54	46	48	44	48	52	54
Male	914	747	788	703	872	731	800
Female	841	712	717	662	756	689	817
ISCED 0	2	6	2	1	3	3	24
ISCED 1	2	4	6	12	34	37	14
ISCED 2	424	216	22	35	72	164	420
ISCED 3	561	467	535	374	96	476	582
ISCED 4	205	170	168	118	480	180	48
ISCED 5	128	121	4	52	270	239	73
ISCED 6	192	274	177	518	473	205	313
ISCED 7	227	180	562	241	164	95	128
ISCED 8	14	21	29	14	36	21	15
N	1755	1459	1505	1365	1628	1420	1617

2017-18, whose sampling procedures used quotas by age, gender, and region (at NUTS2 level) to approximate representativeness for each country’s adult population. We use data from the second wave (collected between June 6-July 16, 2018) because our items of interest were only asked in that wave alongside the two sets of knowledge questions. Our sample covers 10,749 respondents, with a breakdown of demographic details appearing in Table 1.

3.2 General and Specific Knowledge

To measure general political knowledge, we identify correct responses to the following statements:

- (G1) “Switzerland is a member of the EU” (False);
- (G2) “Every country in the EU elects the same number of representatives to the European Parliament” (False); and
- (G3) “[NAME OF THE HEAD OF GOVERNMENT] belongs to the [NAME OF CORRECT PARTY]”, depending on the survey country.

Then, to measure specific migration knowledge, we identify correct responses to the following statements:

- (I1) “The free movement of persons is a fundamental right guaranteed by the EU to its citizens” (True);
- (I2) “Greece is part of the Schengen Area” (True);
- (I3) “In 2015, Afghans have been the largest group of people that applied for

asylum in the EU” (False); and
(I4) “In 2015, asylum in the EU was more frequently granted to Syrians than any other nationality” (True).

3.3 Methods

In evaluating the generalist assumption, we apply a three-step approach that expands on that taken by Delli Carpini and Keeter (1996) in their early work on knowledge scales, and is in our case also line with recent interest in open science by making available all code used for the analyses. First, we use a combination of exploratory and confirmatory factor analysis to investigate the dimensionality of the political knowledge response data. Second, we use regression analysis to investigate construct validity, i.e. whether any latent traits identified exhibit the type of correlations with demographic traits that you would expect if they corresponded to political knowledge. To do this, we use Item Response Theory (IRT) to create and validate general and immigration-specific knowledge scales based on the batteries of questions available in the data set (de Ayala 2009; DeMars 2010). We also use three additional reference datasets from BES (Wave 17), ANES (2019 Pilot study), and CCES (2020 study) in order to calculate estimated marginal mean level of general political knowledge by education, gender, and age, and investigate whether these exhibit the same patterns as the two scales above, and moreover hold even if we break down the data by nationality. Third, in order to rule out that our results are an artifact of immigration knowledge being uniquely related to general political knowledge, we also compare the patterns on our general and immigration knowledge scales with two, independent scales measuring knowledge on other, issue-specific matters, namely: public health and climate change.

4 Empirical Analysis

4.1 Step 1: Factor analysis

First, we combine all six items from both knowledge batteries, and run a parallel analysis to get an initial estimate of the likely number of factors involved. Such a parallel analysis suggests four factors in our case. We then apply exploratory factor analysis (EFA) set to four factors. As can be seen from Table 2, three of the immigration items (I1, I2, and I4) load well onto one factor (Factor 2) while two of the general items (G1 and G2) load well onto another (Factor 4). A further parallel analysis of the three general items (G1-3) suggests one factor, while a parallel analysis for the three immigration items does the same, if excluding I3. This offers some initial evidence of two separate factors,

Table 2: EFA of General (G) and Immigration (I) Knowledge Questions

Item	Factor 1	Factor 2	Factor 3	Factor 4
G1	0.121	0.139	0.21	0.529
G2	0.13	0.207		0.456
G3			1	
I1		0.708		
I2		0.632		
I3	1.002			
I4	0.385	0.378	0.161	-0.237

Table 3: CFA fit measures of General (G) and Immigration (I) Knowledge Questions for unidimensional (1D) and two-dimensional (2D) models

Measure	1D, 6 items	1D, 5 items	2D, 6 items	2D, 5 items
RMSEA	0.046	0.046	0.031	0.011
CFI	0.975	0.982	0.990	0.999
TLI	0.958	0.964	0.981	0.998
AGFI	0.970	0.964	0.985	0.996

corresponding to general knowledge and immigration knowledge, respectively.²

Taking inspiration from Delli Carpini and Keeter (1996), we then probe further by using confirmatory factor analysis (CFA) to compare the fit of four models: two unidimensional ones and two two-dimensional ones, with the first one in each pair containing all six items and the second one excluding one of these (G3, i.e., the one that failed to load well onto Factor 4 in the above EFA). As shown in Table 3, the model with the best fit is two-dimensional (2D) and with five items, but the unidimensional models (1D) also show very good fit. For context, Root Mean Square Error of Approximation (RMSEA) values of less than 0.05 and 0.01 usually are taken to indicate good and very good fit, respectively (Andrews 2021). A Comparative Fit Index (CFI) or Tucker-Lewis Index (TLI) greater than 0.95 (Dima 2018), and an Adjusted Goodness-of-fit Index (AGFI) greater than 0.9, are typically taken to suggest good fit (Baumgartner and Hombur 1996).

Reading across these two sets of analyses, the EFA results suggest that the knowledge questions are potentially tapping into distinctive dimensions – which is not surprising, given that they were intended to measure different types of knowledge. At the same time, while the CFA results indicate that the two-dimensional models display superior fits, the fact that the unidimensional models also exhibit very good fit suggests that the generalist assumption is not obviously misguided at least at this stage.

²We do not look at scale reliability as measured by, e.g., Chronbach’s alpha, since such reliability can be high even given multidimensionality (Fabrigar and Wegener 2012).

4.2 Step 2: Construct validation

Factor analysis enables us to investigate the extent to which patterns in correlations between items can be plausibly explained with reference to a certain number of factors, or underlying traits. However, such analysis does not speak to what those traits are, i.e. to the matter of *construct validity*. For this reason, we now examine the extent to which the correlations between each of the two knowledge scales and a variety of demographic variables appear the way we would expect if these scales were measuring forms of knowledge – and, moreover, whether the correlations exhibited by the two scales are similar, as they should be, if the generalist assumption holds.

To that end, we first create two knowledge scales using IRT modelling (de Ayala 2009; DeMars 2010). IRT models are used to measure latent traits assumed to fall on a continuous scale. Values on that scale are usually referred to by way of the Greek letter θ (theta), and taken to range from $-\infty$ to $+\infty$, with a mean of 0 and standard deviation of 1. This means that, while the individual θ value ascribed to any particular respondent has no intrinsic meaning, it can nevertheless be interpreted relative to an estimated population mean. Full details on the IRT models used in this section as well as those used subsequently can be found in the separate Supporting Information document.

Having made sure that the two sets of items satisfy standard assumptions for an IRT model (unidimensionality, local independence, and acceptable model fit), we then regress these scales on gender, age, and education, across the entire data set (i.e., not segmenting by nationality). The first two variables are self-explanatory. In the data set, the education variable takes on a value from 0 to 8, corresponding to the nine International Standard Classification of Education (ISCED) levels of education, from early childhood education (0) to doctorate (8). Details about the resulting models can be found in Table 4.

Table 4: Regression models (OLS)

	General knowledge	Immigration knowledge
(Intercept)	−0.842 (0.030)***	−0.836 (0.028)***
Male	0.230 (0.014)***	0.239 (0.013)***
Age	0.009 (0.000)***	0.008 (0.000)***
Education	0.058 (0.004)***	0.072 (0.004)***
R ²	0.084	0.095
Adj. R ²	0.083	0.095
Num. obs.	10749	10749

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

As can be seen from Table 4, the coefficient values in both cases cohere with what we know about the relationship between political knowledge and demographics: men tend to have more political knowledge than women (vanHeerde-Hudson 2020; Plutzer 2020),

and the educated more political knowledge than the uneducated (Hebbelstrup and Rasmussen 2016). It also seems reasonable to assume that political knowledge increases with age, as indeed is the case on both models. Moreover, as can also be seen from the table, the associations are very similar between the two scales, which speaks in favour of unidimensionality, in that it is consistent with both scales measuring the same fundamental, underlying trait.

In a further test of construct validation, we also compare the two scales developed here, with established measures of political knowledge from the BES, ANES, and CCES, respectively. In the case of BES, we use Wave 17 of the 2014-2023 British Election Study Internet Panel (Fieldhouse et al. 2020) ($N = 34,366$). That data set contains the following knowledge items, which together form a scale satisfying standard assumptions for an IRT model (as above):

- (BES1) No-one may stand for parliament unless they pay a deposit (True)
- (BES2) The Liberal Democrats favour a system of proportional representation (True)
- (BES3) MPs from different parties are on parliamentary committees (True)
- (BES4) The number of members of parliament is about 100 (False)

The ANES data set used is the 2019 Pilot Study (ANES 2019) ($N = 3,000$), which contains the following knowledge items:

- (ANES1) What job or political office is now held by John Roberts? (Correct: Chief Justice of the US Supreme Court)
- (ANES2) What job or political office is now held by Angela Merkel? (Correct: Chancellor of Germany [in 2019])
- (ANES3) For how many years is a United States Senator elected – that is, how many years are there in one full term of office for a U.S. Senator? (Correct: 6 years)

These items, too, form a scale satisfying standard assumptions for an IRT model.

The CCES data set used is the 2020 Cooperative Election Study (Ansolabehere et al. 2021) ($N = 61,000$), which contains the following knowledge items, which together satisfy standard IRT assumptions:

Please indicate whether you’ve heard of this person and if so which party he or she is affiliated with (response options: Never heard of person; Republican; Democrat; Other Party/Independent; Not sure):

- (CCES1) *Name of Governor of respondent’s state.*
- (CCES2) *Name of first US Senator of respondent’s state.*
- (CCES3) *Name of second US Senator of respondent’s state.*

(CCES4) *Name of one member of the US House of Representatives of respondent's state.*

As the education variables differ between the REMINDER data set used above, and the BES, ANES, and CCES data sets (the latter three use standard UK/US education categories rather than ISCED), we consider the best way to compare the associations across these data sets being to plot and compare patterns of estimated marginal means, which we do in Figures 1 and 2.

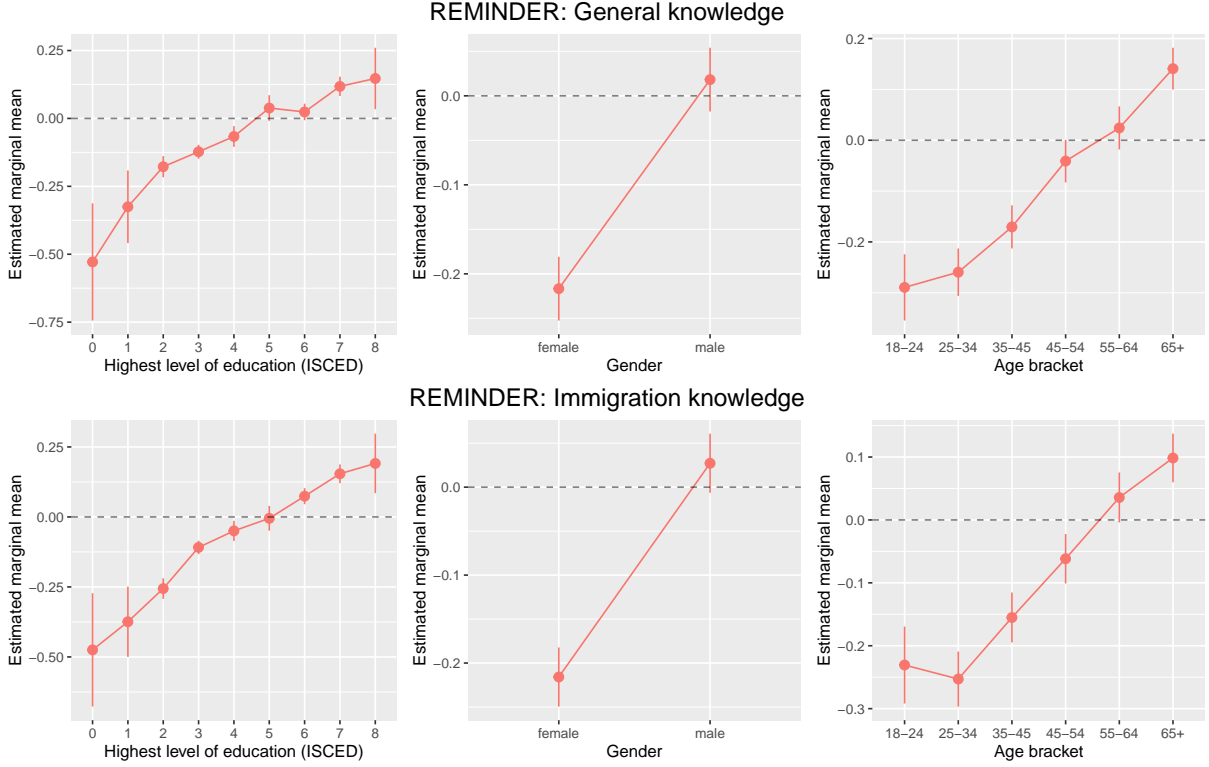


Figure 1: Estimated marginal means for REMINDER knowledge scales

Looking at Figure 1 first, we can see that the estimated marginal means for each of the three demographic variables are very similar across the general and immigration specific knowledge scales. This is consistent with the evidence from previous sections for the generalist assumption – if both scales tap into the same underlying trait, then we should expect the marginal means to exhibit similar patterns across these variables, as indeed they do. Turning then to Figure 2, the fact that the two scales from the previous figure moreover exhibit similar patterns in their marginal means to the tree established scales from BES, ANES, and CCES offers further evidence for both the generalist assumption, and for construct validity, i.e., for the scales tapping into a form of knowledge in particular.

Breaking down the estimated means from the REMINDER scales by the seven nationalities in the data set in Figures 3 and 4, we also see that, while the smaller sample sizes render the results somewhat more noisy, the observations made in relation to the aggregated data generally hold also in the case of the individual countries as well. This

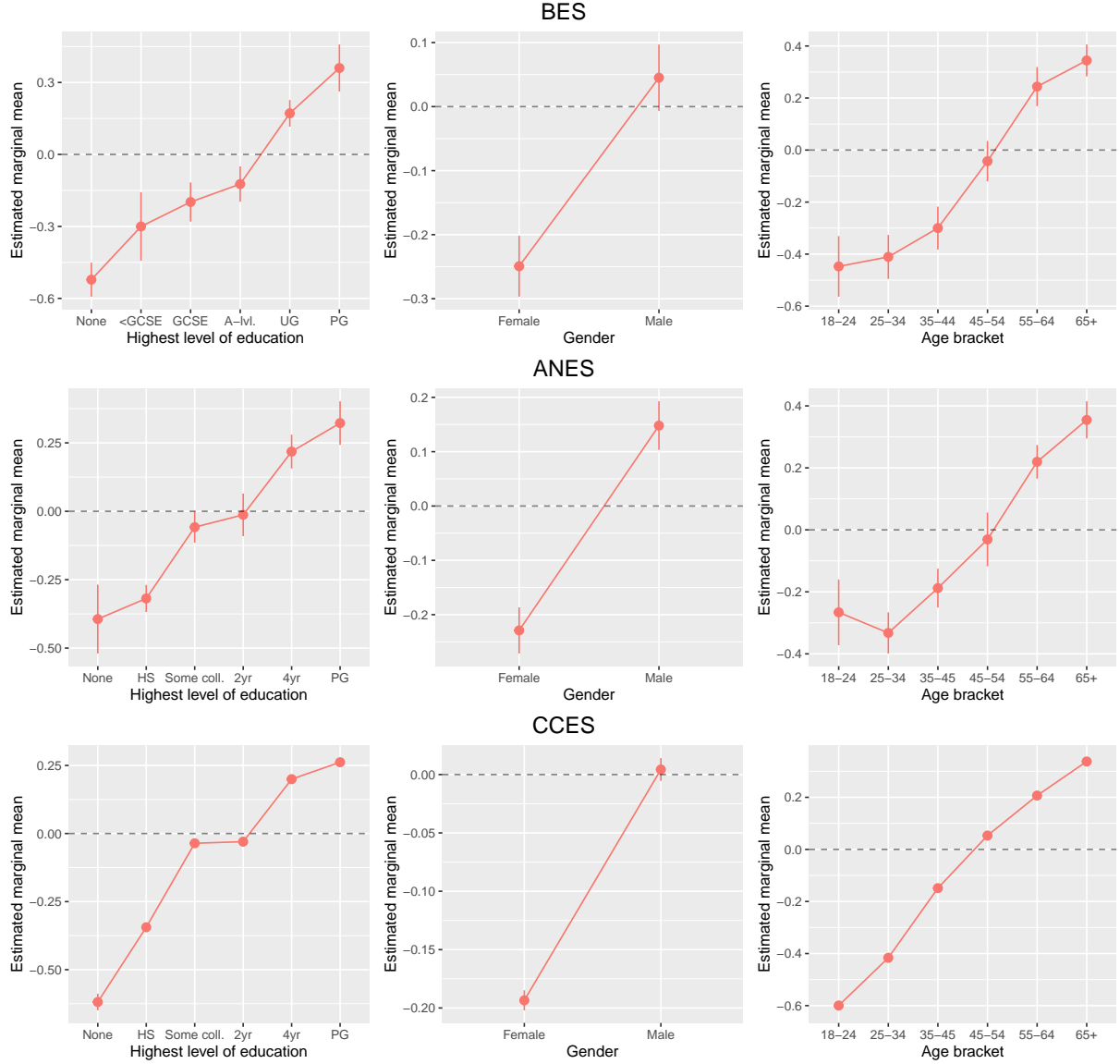


Figure 2: Estimated marginal means for BES and ANES knowledge scales

offers some evidence that the generalist assumption is robust in the face of geographical segmentation as well.

4.3 Step 3: Stress-testing the generality of the generalist assumption

So far, we have seen evidence for the generalist assumption in the context of general political knowledge versus immigration specific knowledge. This evidence does not rule out that there is something unique about immigration specific knowledge in particular, and that the generalist assumption as such would not generalize to other, issue-specific areas. For this reason, in our third and final step, we compare the marginal means of our two scales to that of two, separate issue-specific scales: one relating to public health, and

to knowledge about COVID in particular; and one relating to knowledge about climate change.

Our COVID data set comes from a pre-registered survey experiment ($N = 2,917$ UK citizens) fielded in the UK through the wake of its first wave in July 2020 (Allen and Ahlstrom-Vij, under review). The survey contains the following knowledge items, which together form a scale satisfying standard assumptions for IRT:

- (COV1) COVID-19 can be transmitted in areas with hot and humid climate (True)
- (COV2) There is currently no vaccine to protect against COVID-19 (True [in July 2020])
- (COV3) Most people who get COVID-19 recover from it (True)

The climate change data set is from the European Perceptions of Climate Change survey (Pidgeon 2016). The survey was not designed to measure knowledge about climate change in particular, but it contains the following three items which reasonably can be taken to tap into such knowledge, and moreover also form a scale satisfying standard assumptions for IRT:

- (CC1) As far as you know, do you think the world’s climate is changing or not? (Correct: The climate is changing)
- (CC2) Thinking about the causes of climate change, which, if any, of the following best describes your opinion? (Correct: Climate change is partly, mainly, or completely caused by human activity)
- (CC3) To the best of your knowledge, what proportion of scientists agree that climate change is happening and that humans are largely causing it? (Correct: The vast majority of scientists agree, at 80% or more)

Figure 5 plots the estimated marginal means for the same demographic variables as in the previous section for the above COVID and Climate Change knowledge scales.

For both scales, the marginal means by education shows the same, monotonic trend that we saw in both Figure 1 and 2. In the case of both scales, men also generally have more knowledge than women, which again is in line with what we found in regards to the scales in the previous section. In the case of age, we see a much more pronounced drop from the first to the second bracket than what we saw for our previous four scales. Additionally, the climate change scale in particular exhibits a less straightforward relationship than the other scales, in having substantially higher levels of knowledge in the first bracket, and also a dip in the case of the final bracket (65+). It is worth reflecting on whether knowledge about climate change can be expected to have a non-standard distribution, especially given the potential for higher levels of awareness among younger compared to older people, in light of how the former have a greater number of years of exposure to the effects of climate change ahead of them.

5 Practical guidance for researchers

We mentioned at the outset that one ambition with revisiting the dimensionality of knowledge was to outline a series of steps that can be taken by others in need of evaluating the dimensionality of their knowledge scales(s). Specifically, we imagine it might be helpful for other researchers to replicate our analyses for their own purposes, for example in so far as they have data sets with different knowledge items and want to evaluate for dimensionality in order to decide on what scale to use, or are collecting data and want to run a pilot with different items, and then potentially save funds and time (and respond to quality concerns relating to survey attentiveness) on only collecting on the items that a dimensionality analysis suggests that they need.

In light of that, and the steps taken as part of our analysis above, we recommend the following:

1. Start by conducting a parallel analysis on the total set of knowledge items, and then investigate the loadings from an exploratory factor analysis (EFA) on those same items.
2. Let your EFA inform a confirmatory factor analysis (CFA) that compares a uni-dimensional model to one or several multi-dimensional models, depending on the number of factors suggested by the EFA, and in order to see whether the former exhibits a good enough fit to compete with the multi-dimensional model(s). If it can, this would count towards unidimensionality.
3. Construct two or more knowledge scales, depending on the dimensionality under investigation, and then use each scale as an outcome in a regression model, with gender, education, and age as predictors. See if there any similarities in coefficients between the two. High similarity across all predictors would count towards unidimensionality.
4. Estimate marginal mean levels of knowledge by gender, education, and age, respectively for each of your scales, and compare the patterns in these levels to those exhibited in Figures 1, 2 and 5. Similarity with the patterns found there would count towards both construct validity and unidimensionality.

For any given project, all or only some of these steps will be appropriate or possible. However, it is our hope that the above steps will nonetheless offer helpful guidance for researchers concerned with questions about knowledge scale dimensionality. To facilitate replication, and in line with Open Science principles, we also publicly offer the code underlying the present investigation as a template for others to use in a public GitHub repository.

6 Discussion

As research into the consequences of political knowledge demonstrates, being more informed potentially matters not only for how people vote but also what they think about specific issues. Whether on principled grounds or simply for reasons of being limited to general knowledge items in available data sets, however, the majority of existing work is based on observational survey data and typically invokes what we have called a generalist assumption: that knowing a great deal about general political topics is indicative of having greater knowledge about specific issues as well. Yet testing whether this is the case – and in which contexts – is difficult owing to the lack of cross-national survey instruments that combine both general and issue-specific knowledge questions.

In response, we have exploited a recent large-scale survey that, unusually, contains both types of items in one instrument across seven European countries. Combining several analytical approaches, we conclude that the preponderance of evidence points to the generalist assumption being defensible. First, exploratory and confirmatory factor analyses applied to various combinations of the knowledge items revealed how the collection of questions performed well when treated unidimensionally. Second, in terms of construct validity, key demographic features that prior theory leads us to expect are relevant to political knowledge exhibit very similar associations between our political and immigration knowledge scales. Moreover, both scales exhibit similar patterns in estimated marginal mean level of knowledge to established knowledge scales from the BES, ANES, and CCES, both in the aggregate and when broken down by nationality. Third, the same marginal means patterns arise also in the case of other issue-specific knowledge scale, in relation to public health (COVID) and climate change in particular, which offers some reason to believe that the generalist assumption is robust across individual issues, as opposed to holding for immigration knowledge only.

Our study has implications for the ways that researchers use political knowledge questions as they study domain-specific attitudes and preferences. Although we argue the generalist assumption is defensible, at least in the particular domains that we have been concerned with in this paper (i.e., immigration, public health, and climate change), we also emphasize that it should not be deployed uncritically. Rather, we advise that researcher should stress-test it as far as the available data allow, notably by including knowledge items from different domains, and by using a combination of methods to evaluate its plausibility in specific contexts. To that end, and in the spirit of Open Science, we have also offered practical steps for researchers to take in evaluating dimensionality assumptions in relation to their own data sets, as well as made our approach (its code and method) available in a public GitHub repository to facilitate replication.

7 References

References forthcoming...

Acknowledgements

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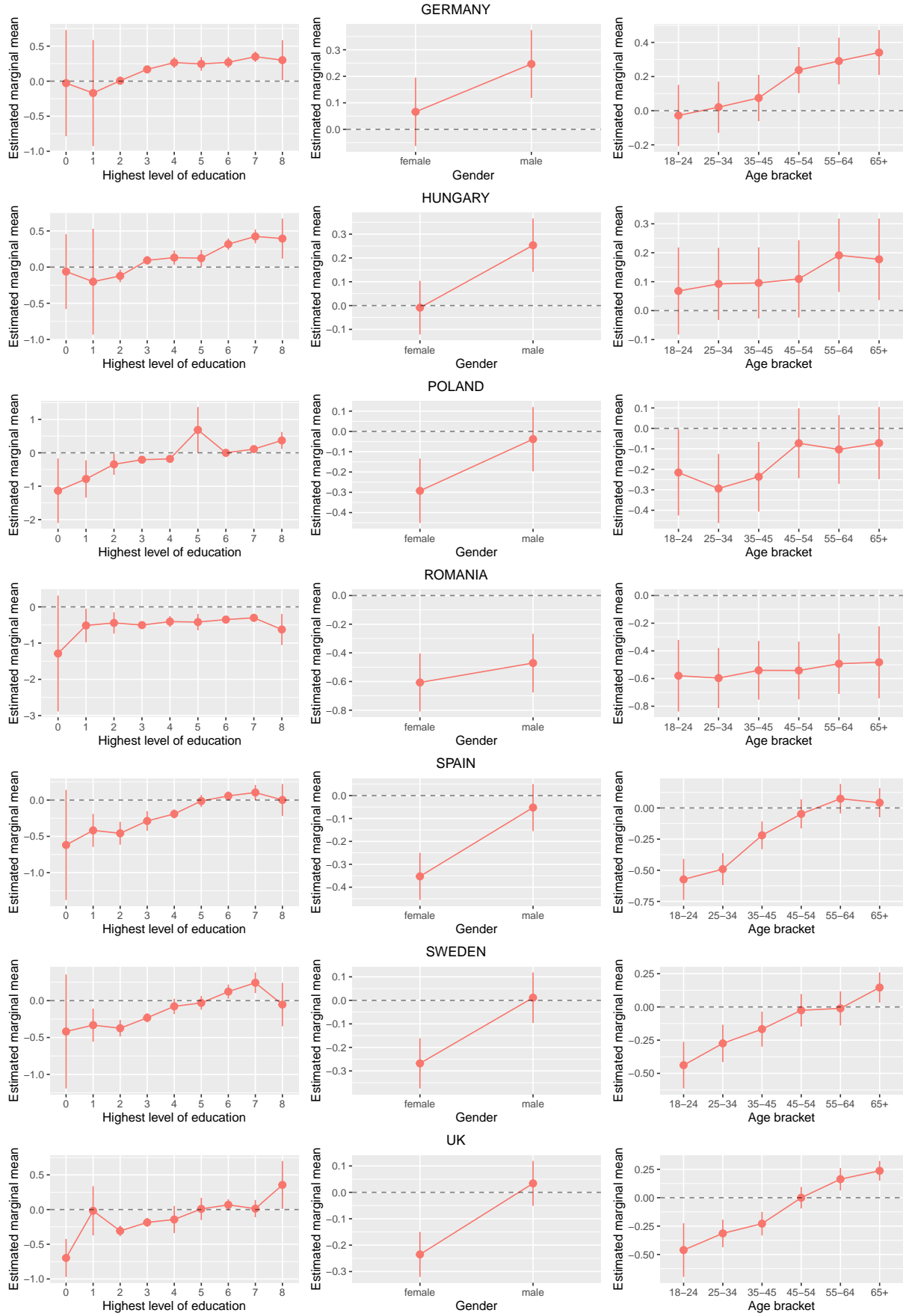


Figure 3: Estimated marginal means for general knowledge scale by country

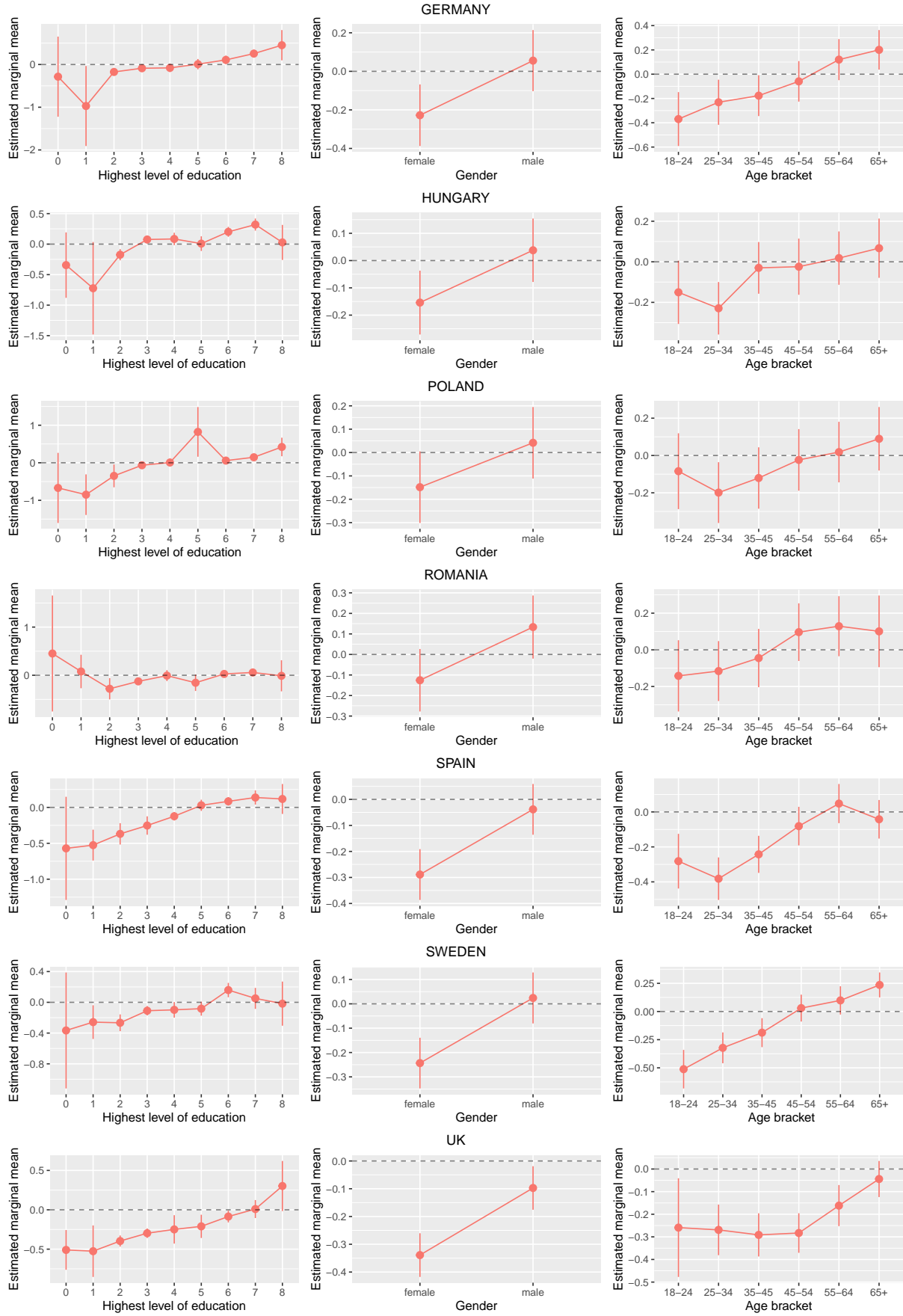


Figure 4: Estimated marginal means for immigration knowledge scale by country

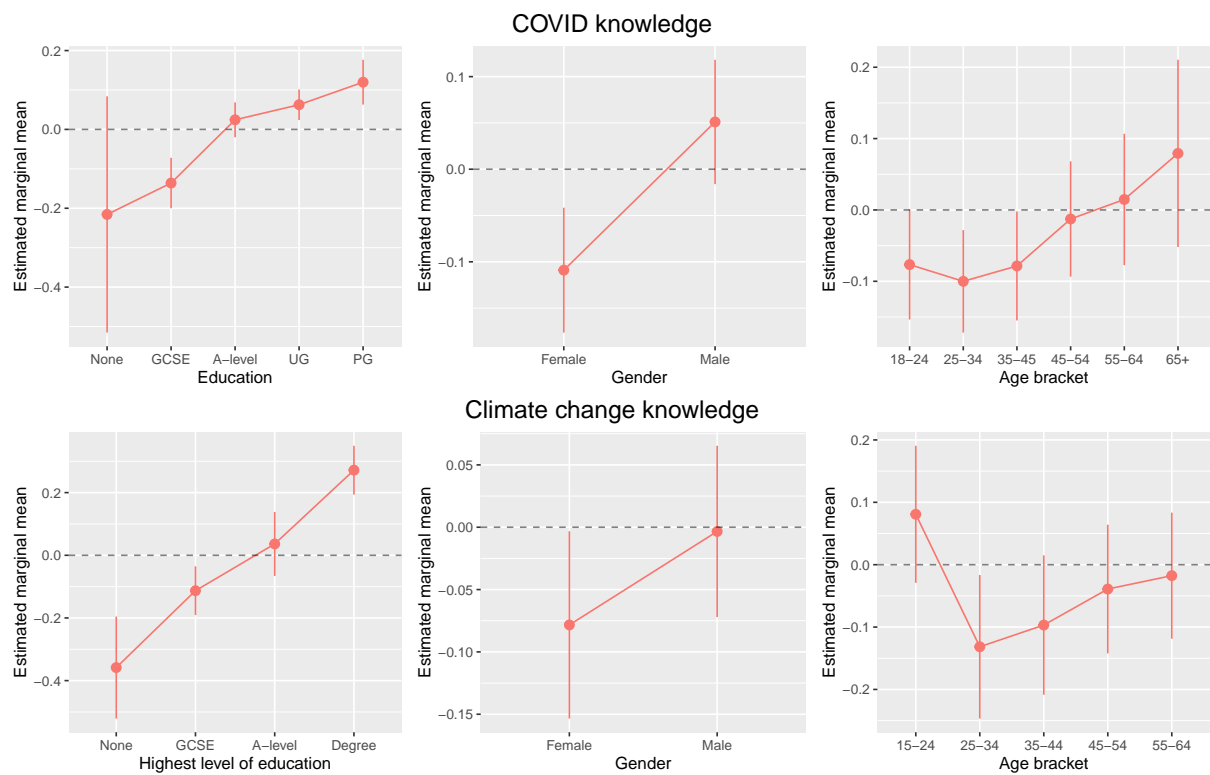


Figure 5: Estimated marginal means for COVID and Climate Change knowledge scales