Supplemental Information for *'Navigating the COVID-19 Infodemic: The Influence of Metacognitive Efficiency on Health Behaviors and Policy Attitudes'*

Matteo Lisi[*,†,‡,§]

Contents

[*]Department of Psychology, University of Essex
[†]Department of Psychology, Royal Holloway, University of London
[‡]matteo.lisi@rhul.ac.uk
[§]m.lisi@essex.ac.uk

1 Supplemental Material

1.1 Statements about COVID-19 and rationale for their classification as true or false

1. **More than 70% of people infected with COVID-19 display no symptoms at all (FALSE).** Although some early reports provided very high estimates of the rate of asymptomatic infections, these have since been revised downward, and already at the time of the survey it was safe to conclude that the true proportion of asymptomatic is substantially less than 70%: A systematic meta-analysis[1] had concluded that (excluding pre-symptomatic cases) the proportion of asymptomatic cases was about 17%. Taking together pre-symptomatic and asymptomatic cases, the percentage could go up to about 40% - 50% of total cases: for instance, 51% of Diamond Princess passengers were asymptomatic at the time of testing[2]; and a more recent systematic review and meta-analysis found that about 40.5% of the population with confirmed COVID-19 had no symptoms at the time of testing[3].

2. **Wearing a face mask for a long time can cause intoxication from re-breathing exhaled breath (FALSE).** Claims that masks can cause hypoxia or intoxications have been debunked in several studies[4–6].

3. **COVID-19 is a bio-weapon intentionally spread by the Chinese state to weaken Western economies (FALSE).** While the origins of Sars-CoV-2 virus remain unclear, the claim that it would be a bioweapon has no factual basis and more recently has been declared 'scientifically invalid' in a declassified report from US intelligence agencies (Office of the Director of National Intelligence[7].

4. **Some COVID-19 vaccines use a new technology that could alter people's genetic code (their DNA) (FALSE).** COVID-19 vaccines do not directly alter or interact with DNA in any way: this misconception about mRNA vaccines has been debunked by many authoritative sources[8].

5. **There is a small chance of catching COVID-19 from the vaccine (FALSE).** None of the vaccines authorized for use in the UK (Moderna, Oxford/AstraZeneca, Pfizer/BioNTech) contain live Sars-CoV-2 virus, therefore they cannot cause COVID-19.

6. **Some COVID-19 vaccines contain small particles that can affect fertility (FALSE).** This is another misconceptions that circulated on social media but lacked any scientific basis. Prior to our survey the Royal College of Midwives and the Royal College of Obstetricians and Gynaecologists (RCOG) issued a joint statement indicating clearly that there was no evidence to suggest that COVID-19 vaccines would affect fertility[9]. More recently, a prospective cohort study reported that COVID-19 vaccination was not associated with any impairment in fertility[10].

7. **COVID-19 can be transmitted by houseflies and/or mosquito bites (FALSE).** The World Health Organization myth-buster page, already at the time of the survey, stated clearly that Sars-CoV-2 cannot be transmitted by mosquito[11]. This was corroborated by an empirical study that showed how Sars-CoV-2 would be unable to replicate in common species of mosquitoes[12]. A later study on houseflies showed that although these can under some conditions acquire the virus, they did not transmit detectable infectious virus[13].

8. **COVID-19 can be spread by those who display no symptoms at all (TRUE).** Although the transmission potential of asymptomatic cases is likely lower than that of symptomatic cases, several lines of evidence converged in indicating that asymptomatic cases

play an substantial role in the transmission and spread of COVID-19[14–17].

9. **You can catch COVID-19 more than once (TRUE).** Repeated COVID-19 infection is clearly possible and was already well documented at the time of the survey[18].

10. **COVID-19 is over 10 times deadlier than the seasonal flu (TRUE).** One simple way to characterize the risk of death from a disease is the case-fatality ratio (CFR, that is the ratio between confirmed deaths and confirmed cases). At the time of our survey (April 2021) in the UK the CFR was $\approx 2.9\%$[19]. In comparison, the case fatality ratio of seasonal flu is estimated to be $<0.1\%$[20]. This indicates that at the time of the survey a confirmed COVID-19 case was up to ≈ 29 times deadlier than a case of seasonal flu. (The CFR has since then decreased due to vaccination of the population and emergence of new variants).

11. **The vast majority of people who test positively for COVID-19 with a swab test truly have the disease (TRUE).** The specificity of PCR tests is likely to be very high: data from a study that tested nearly all eligible population in Wuhan after the lockdown[21] found only 300 positive cases out of nearly 10 million people tested. If all people tested were false positive (which is unlikely, given also that the majority of people who tested positive also had positive IgG antibody tests) then the specificity would be 99.997%. Data from the ONS[22] also indicates that it is likely higher than 99.92%. The sensitivity of the tests is considered to be within 85% and 98%[22]. Data from the Coronavirus Infection Survey indicates that in the period prior to our survey about 1 in 340 people in England had COVID-19[23]. Taken together, these estimates suggests that even under conservative assumptions (85% sensitivity and 99.92% specificity) at the time of the survey more than 75% of the people who tested positive had COVID-19.

12. **In 2020 the total number of deaths in the UK was much higher than average (over 75,000) compared to the 5 years before (TRUE).** Estimates from the ONS[24] indicate that the number of deaths up to 1 January 2021 in England and Wales was 75013 more than the 5-year average. Northern Ireland and Scotland also recorded excess deaths above the 5-year average for 2020[25,26].

13. **You can still get infected with COVID-19 after getting the second dose of the vaccine (TRUE).** Vaccine trials showed that the effectiveness against infection, albeit high, is less than 100%. This information was publicly available from the beginning of the vaccine rollout, thus well before our survey.

14. **The average period between infection with COVID-19 and the onset of symptoms is 5 days (TRUE).** Reliable estimates of the incubation period of COVID-19 were available already in the early phase of the pandemic[27].

1.2 Statements about general physical and biological sciences

Note: '*' denotes statements that were taken or adapted from the factual knowledge question of the National Science Foundation[28].

1. **Antibiotics can kill viruses as well as bacteria* (FALSE).**
2. **All radioactivity is man-made* (FALSE).**
3. **Lasers work by focusing sound waves* (FALSE).**
4. **Humans only use 10% of their brain (FALSE).**
5. **The sun makes up of approximately 85% of matter in our solar system (FALSE).** (Note: the sun contains over 99% of the matter in the solar system.)
6. **The earliest humans lived at the same time as the dinosaurs (FALSE).**
7. **Humans have about 60% of their genetic code (DNA) in common with cows (FALSE).** Note: cows share about 80% of their genes with humans.)
8. **Human beings, as we know them today, developed from an earlier species of animal* (TRUE).**
9. **The father's genes determine whether the baby is a boy or a girl* (TRUE).**
10. **The centre of the Earth is very hot* (TRUE).**
11. **The continents on which we live have been moving their location for millions of years, and will continue to move in the future* (TRUE).**
12. **One cubic centimetre of water has a mass of 1 gram (TRUE).**
13. **Electrons are smaller than atoms* (TRUE).**
14. **There are some mammals that reproduce by laying eggs (TRUE).** (Note: one example is the Platypus, *Ornithorhynchus anatinus*)

1.3 Questions on attitudes and behaviours during lockdown.

After judging the statements reported in the previous two sections (randomly interleaved), respondents were asked the following questions.

Q1. *Considering all health, economic, and social factors, how justified or unjustified do you think the following measures implemented by the UK Government were during the most recent lockdown (starting 6th January 2021)?*
a) Closing of bars, pubs and restaurants
b) Closing of schools
c) Restrictions on meeting with others outside your household or support bubble

Response options:
<1> Very justified
<2> Somewhat justified
<3> Neither justified or unjustified
<3> Somewhat unjustified
<4> Very unjustified
<5> Don't know

Q2. *Since the start of the most recent national lockdown (starting 6th January 2021), how many different times, if at all, have you met to socialise with family, friends, or others outside of your household or support bubble?*

Response options:
<1> None
<2> Less than 5
<3> Between 5 and 10 times
<4> More than 10 times
<5> Don't know

Q3. *Since the start of the most recent national lockdown (starting 6th January 2021), how often, if at all, have you worn a mask to cover your mouth and nose when you...*
a) ... Visited a supermarket or grocery store?
b) ... Used a public transport?

Response options:
<1> Always
<2> Most of the time
<3> Sometimes
<4> Rarely
<5> Never
<6> Not applicable- I do not wear a mask for medical reasons
<7> Not applicable – I have not done this

Q4. *Do you personally know anybody, including yourself, whose health has been badly affected from having COVID-19?*

Response options:
<1> Yes, I do
<2> No, I do not
<3> Don't know
<4> Prefer not to say

Q5. *If a vaccine against COVID-19 was available to you, how likely would you be to get vaccinated?*

Response options:
<1> Very likely
<2> Fairly likely
<3> Fairly unlikely
<4> Very unlikely
<5> Don't know
<6> Not applicable – I am medically exempt
<7> Not applicable – I have already received at least one dose of the COVID-19 vaccine

2 Supplemental Tables

2.1 Re-coding of education levels

For the purpose of modelling, the information about education levels of respondents were recoded in a smaller number of categories according to the following table.

Original category	**Recoded category**
No formal qualifications	Level-0
Youth training certificate/skillseekers	Professional
Recognised trade apprenticeship completed	Professional
Clerical and commercial	Professional
City & Guilds certificate	Professional
City & Guilds certificate - advanced	Professional
CSE grades 2-5	Level-1
CSE grade 1, GCE O level, GCSE, School Certificate	Level-1
Scottish Ordinary/ Lower Certificate	Level-1
ONCLevel-2	Level-2
GCE A level or Higher Certificate	Level-2
Scottish Higher Certificate	Level-2
Nursing qualification (e.g. SEN, SRN, SCM, RGN)	Level-3
Teaching qualification (not degree)	Level-3
University diploma	Level-3
University or CNAA first degree (e.g. BA, B.Sc, B.Ed)	Level-3
University or CNAA higher degree (e.g. M.Sc, Ph.D)	Level-4
Other technical, professional or higher qualification	Other
Don't know	Other
Prefer not to say	Other

2.2 Comparison of sample to GB population

Table 2: Demographic characteristics of the sample, and comparison with quotas of Great Britain population (provided by YouGov and based on census data).

Characteristic	Group	N	percent (sample)	percent (GB population)
Age	[18,25]	144	8.5	11.6
	(25,50]	691	40.9	42.2
	(50,65]	432	25.6	24.0
	(65,100]	422	25.0	22.2
Gender	male	744	44.0	48.6
	female	945	56.0	51.4
Education	Level-0	93	5.5	5.3
	Professional	172	10.2	10.1
	Level-1	274	16.2	16.6
	Level-2	265	15.7	17.1
	Level-3	459	27.2	27.0
	Level-4	150	8.9	8.2
	Other	276	16.3	15.7
CIE social grade	A	237	14.0	12.5
	B	304	18.0	15.5
	C1	470	27.8	29.0
	C2	263	15.6	21.0
	D	192	11.4	10.5
	E	223	13.2	11.5
Region	North East	60	3.6	4.0
	North West	187	11.1	10.6
	Yorkshire and the Humber	158	9.4	9.5
	East Midlands	143	8.5	8.2
	West Midlands	152	9.0	8.4
	East of England	171	10.1	9.2
	London	156	9.2	12.0
	South East	269	15.9	14.8
	South West	162	9.6	9.6
	Wales	90	5.3	5.1
	Scotland	141	8.3	8.6
Vote EU referendum	I voted to Remain	680	40.3	37.1
	I voted to Leave	686	40.6	39.6
	I did not vote	292	17.3	21.1

3 Supplemental Methods

3.1 Ordered logistic regression

3.1.1 Model details

Responses to the additional questions about attitudes and behaviours (see 1.1) are defined on an ordinal scale, therefore we analysed rhwm using a Bayesian ordered logistic regression model (also know as proportional odds model). One way to think about this model is by assuming the existence of a continuous latent quantity, call it y, specified by a logistic probability density function. The latent distribution is partitioned into a series of k intervals, where k is the number of ordered choice options available to respondents, using $k+1$ latent cut-points, $c_1, \ldots, c_{k+1}$. By integrating the latent density function within each interval we obtain the ordinal response probabilities $p_1, \ldots, p_k$. Other choices are possible (e.g. assuming a normally distributed latent variable would yield an ordered *probit* model). Beyond mathematical convenience, one advantage of the ordered logit is that coefficient can be interpreted as ordered log-odds, implementing the proportional odds assumption[29].

Formally, the model can be notated as

$$\begin{aligned} p_k &= p\left(c_{k-1} < y \leq c_k \mid \mu\right) \\ &= \operatorname{logit}^{-1}\left(c_k - \mu\right) - \operatorname{logit}^{-1}\left(c_{k-1} - \mu\right) \end{aligned}$$

where

$$\operatorname{logit}^{-1}(\alpha) = \frac{1}{1+e^{-\alpha}}$$

is the cumulative function of the logistic distribution (also known as inverse-logit), and

$$\mu = \mathbf{x}\beta + z_{\text{edu}} + z_{\text{income}} + z_{\text{region}} + z_{\text{cie}} + z_{\text{voteEU}} + z_{\text{vote2019}} + z_{\text{marsta}}$$

is the linear part of the model. The vector $\mathbf{x}$ is composed by the individual-level predictors, that is age, gender (coded as male minus female), d' (that is, the ability to discriminate true vs false COVID-19 statements) and $\log$ M-ratio (metacognitive efficiency). We include also age squared as predictor, to accomodate possible non-linearities in the age effect. As indicated also in the main text, continuous predictors (age, d', and $\log$ M-ratio) were centred and scaled by 2 standard deviations to put them approximately on the same scale as the other dichotomous dummy variables[30]. The u indicate the 'random' group-specific intercepts.

For all models the priors were

$$\begin{aligned} \beta &\sim \mathcal{N}(0,1) \\ z_j &\sim \mathcal{N}(0,\sigma_j) \\ \sigma_j &\sim \text{HalfCauchy}(0,1). \end{aligned}$$

For the latent cut-points, we used a push-forward Dirichlet prior as described by Betancourt[31]. This involves a uniform Dirichlet prior (all concentration parameters set to 1) on the response frequencies to indirectly induce (making the necessary Jacobian adjustment) a probability density function on the ordered cut points and thus regularize their locations on the latent space.

4 Supplemental Results

4.1 Multilevel Meta-d' model

4.1.1 Parameters estimation

Metacognitive efficiency was estimated using a hierarchical Bayesian approach, as described by Fleming[32]. The original JAGS code was modified to account for a within-subject design with 2 conditions. We run 3 chains for 30'000 samples, after 5'000 burn-in samples, with thinning of 9, yielding 9999 total posterior samples. The figure shows trace plots of Markov chains for the population means of the metacognitive efficiencies general science (`mu_logMratio_1`) and COVID-19 (`mu_logMratio_2`) as well as for the standard deviations of individual random effects (`sigma_logMratio_1` and `sigma_logMratio_2` for general science and COVID-19, respectively). All R-hat values[33] were less than 1.01.

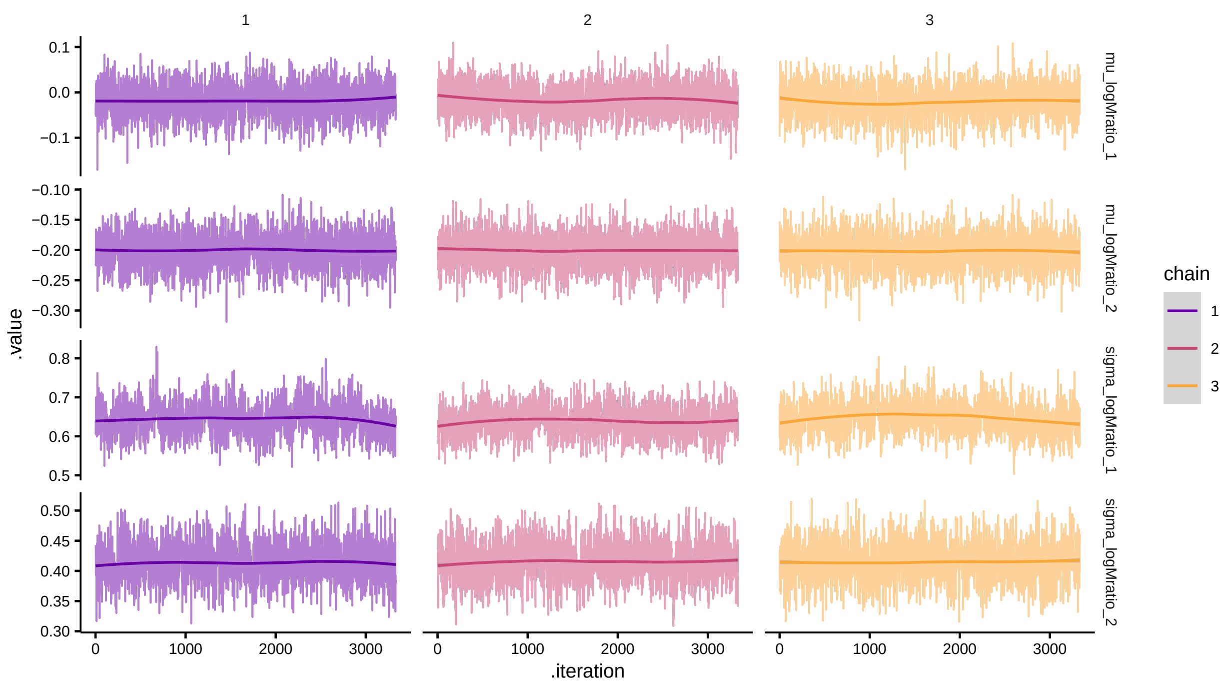


Figure 1: Trace plots of Markov chains of population parameters

4.1.2 Prior choice and calculation of Bayes factor

In order to compute a sensible estimate of the Bayes factor for the difference across conditions, we used an informative prior on the population-level metacognitive efficiency parameter. More specifically, for both general science and COVID-19 we assumed that $\log \text{M-ratio} \sim \mathcal{N}(-0.3, 0.3)$, which amounts to assigning 95% prior probability to the possibility that the population-level M-ratio lies in $(0.41, 1.33)$. As the prior was identical for the metacognitive efficiencies of general science and COVID-19, this corresponds to assuming the following prior for their difference (here notated with Δ):

$$\Delta_{\log \text{M-ratio}} \sim \mathcal{N}\left(0, \sqrt{0.3^2 + 0.3^2} \approx 0.42\right)$$

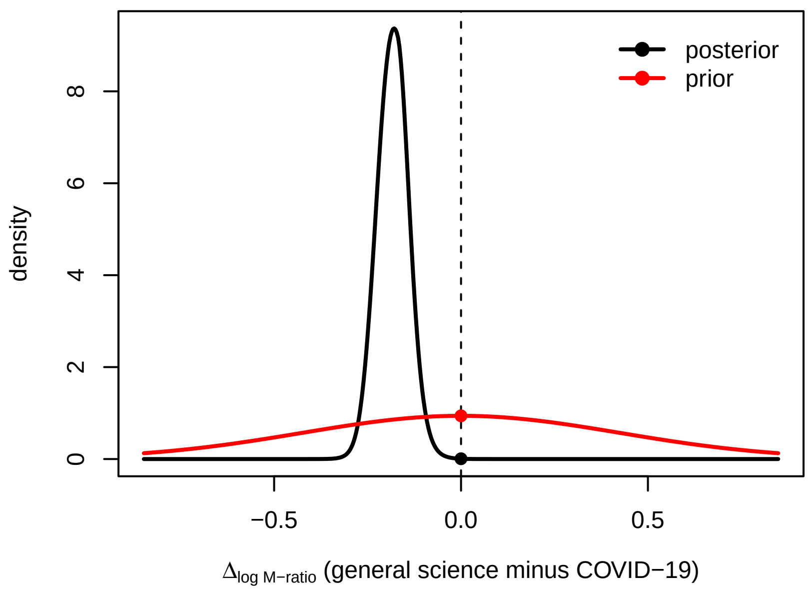


Figure 2: Prior and posterior density of the difference in metacognitive efficiency.

We used this to calculate, using the Savage-Dickey density ratio method[34], a Bayes factor for the difference in metacognitive efficiency. The estimated Bayes factor indicate that the data was approximately 147.05 times more likely under the alternative hypothesis.

4.2 Metacognitive efficiency estimates and conspiracy theories

In order to assess whether the difference in metacognitive efficiency (M-ratio) was mainly driven by a minority of participants that held extreme views and/or explicitly subscribed to conspiracy theories, we re-run the main analysis after removing the subset of participants who judged the statement *"COVID-19 is a bio-weapon intentionally spread by the Chinese state to weaken Western economies"* as true (18.77 % of total participants).

Table 3: Group level estimates of metacognitive efficiency after removing a subset of participants who believed in the COVID-19 bio-weapon conspiracy theory

parameter	posterior mean	.lower	.upper
M-ratio (general science)	1.030	0.961	1.099
M-ratio (COVID-19)	0.813	0.768	0.860
difference	-0.237	-0.319	-0.152

The results are shown in the table. This analysis suggests that the difference in metacognitive efficiency that we have observed are likely not uniquely due to a minority of respondents who believe in extreme conspiracy theories and have a disproportionate influence on population-level estimates, but rather are better explained as due to influences on metacognition that are more subtle and pervasive (see Discussion in the main text).

4.3 Comparing the degree of confidence in judgments about science and COVID-19

We sought to assess whether respondents expressed on average higher confidence when judging the truth of COVID-19 or general science statements. To do so, we considered the degree of confidence, thus expressed on a 3-point scale (1, *'not at all confident'*; 2, *'fairly confident'*;3, '*extremely confident'*), independently from the choice about the statement (true or false). We used a multilevel Bayesian ordinal regression model that can accommodate both the ordinal nature of the dependent variable as well as the repeated-measures structure of the dataset. We included also the accuracy of responses as a predictor, since this differed across COVID-19 and general science, and it is well known that people tend to report higher confidence in correct responses[36].

Formally, the model can be notated as

$$\begin{aligned} p_k &= \text{logit}^{-1}\left(c_k - \mu\right) - \text{logit}^{-1}\left(c_{k-1} - \mu\right) \\ \mu &= \left(\beta_1 + z_1\right) x_{\text{covid}} + \left(\beta_2 + z_2\right) x_{\text{correct}} \end{aligned}$$

where x_{covid} and x_{correct} are dummy variables that indicate whether a rating was about a COVID-19 statement and wheter it was correct, respectively. β_1, β_2 are fixed-effects parameters, and were given zero-centred Gaussian priors, $\beta \sim \mathcal{N}(0, 1)$. z_1, z_2 are the random (respondent-specific) effects, which were defined according to:

$$\begin{aligned} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} &\sim \mathcal{N}(0, \Omega) \\ \Omega &= \begin{bmatrix} \sigma_1 \\ \sigma_2 \end{bmatrix} I \ \mathbf{R} \begin{bmatrix} \sigma_1 \\ \sigma_2 \end{bmatrix} I \\ \sigma_j &\sim \text{HalfCauchy}(0, 1) \\ \mathbf{R} &\sim \text{LKJcorr}\,(2) \end{aligned}$$

where I is the identity matrix, $\mathbf{R}$ is a correlation matrix, and LKJcorr(2) indicate a regularizing prior for correlation matrices[37]. For the latent cutpoints, we used the same pushforward Dirichlet prior described above[31]. The model was fit in Stan using 4 chains of 1000 samples each (plus 1000 warm-up).

Table 4: Posterior means and percentile intervals

	mean	sd	2.5%	97.5%	n_eff	Rhat
beta[1]	0.052	0.026	0.002	0.102	3002.182	1.001
beta[2]	1.310	0.035	1.242	1.379	1507.205	1.003

As shown above, this analysis revealed a tendency for respondents to report higher confidence levels in COVID-19 items than general science ones, since β_1 (`beta[1]`) was greater than zero. More precisely, the fixed-effects estimate of the odds-ratio in the model is given by e^{β_1}; thus respondents were approximately 1.053, 95% HDI interval [1.002, 1.107] times more likely to report a higher confidence rating for COVID-19 statements relative than for general science statements.

4.4 Metacognitive efficiency in general science does not predict protective attitudes and behaviours

We examined whether the association that we have measured between metacognitive efficiency are specific for metacognition around COVID-19 knowledge, or whether also metacognitive efficiency around general science knowledge was also associated with health protective behaviours and attitudes. In order to do so, we repeated the ordinal regression analyses (model described in section 3.1.1) including as predictors not only the metacognitive efficiency around COVID-19 ($\log M\text{-ratio}_{\text{covid-19}}$) but also the metacognitive efficiency around general science knowledge ($\log M\text{-ratio}_{\text{science}}$).

The results are summarized in the figure below: as it can be seen, for all models only metacognive insight about COVID-19 knowledge was predictive of behaviours, attitudes and vaccination intention (all odds-ratio greater than 1), whereas metacognitive insight around general science did not systematically provide information for predicting responses (the 95% credible interval around the odds ration include 1 in all models).

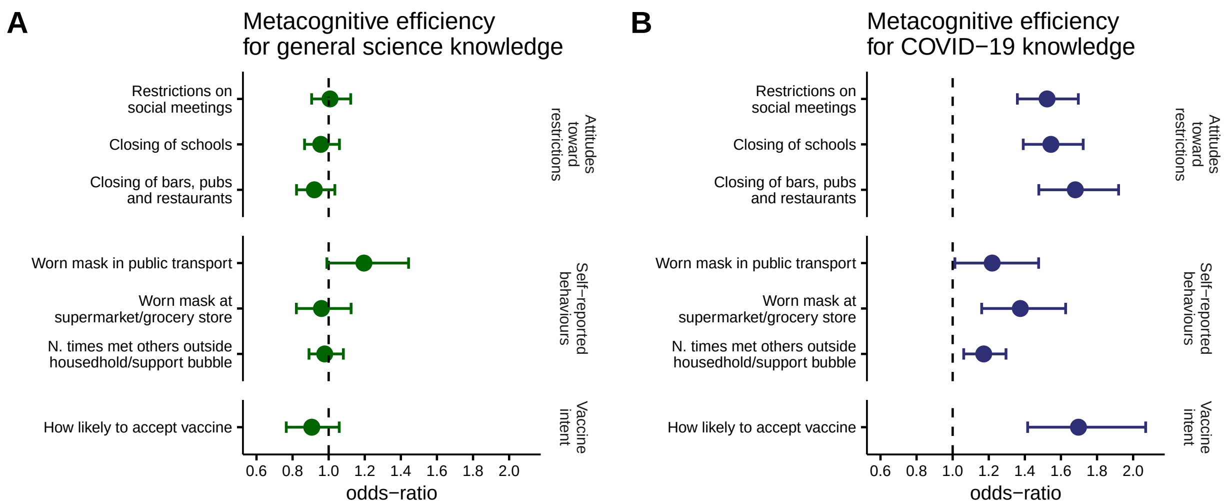


Figure 3: Effects of metacognitive efficiency about general science (A) and COVID-19 (B). The effects are expressed as odds-ratio, defined as the multiplicative change in the odds of respondents indicating more compliant/health-protective attitudes and behaviours associated with an increase of 1 standard deviation in metacognitive efficiency

4.5 Experience of COVID-19

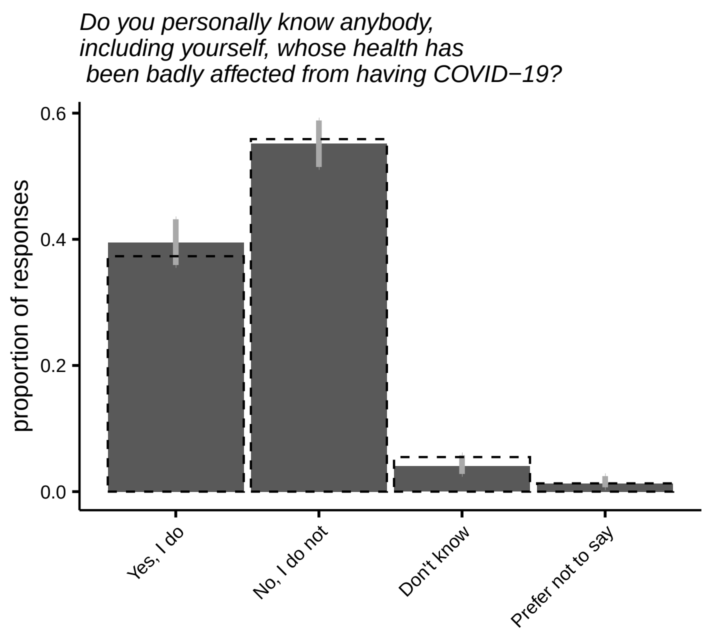


Figure 4: Proportion of responses to the question about experience of COVID-19 impact on health. Error bars are multinomial 95% confidence intervals; lines shows proportions weighted to be representative of GB adults.

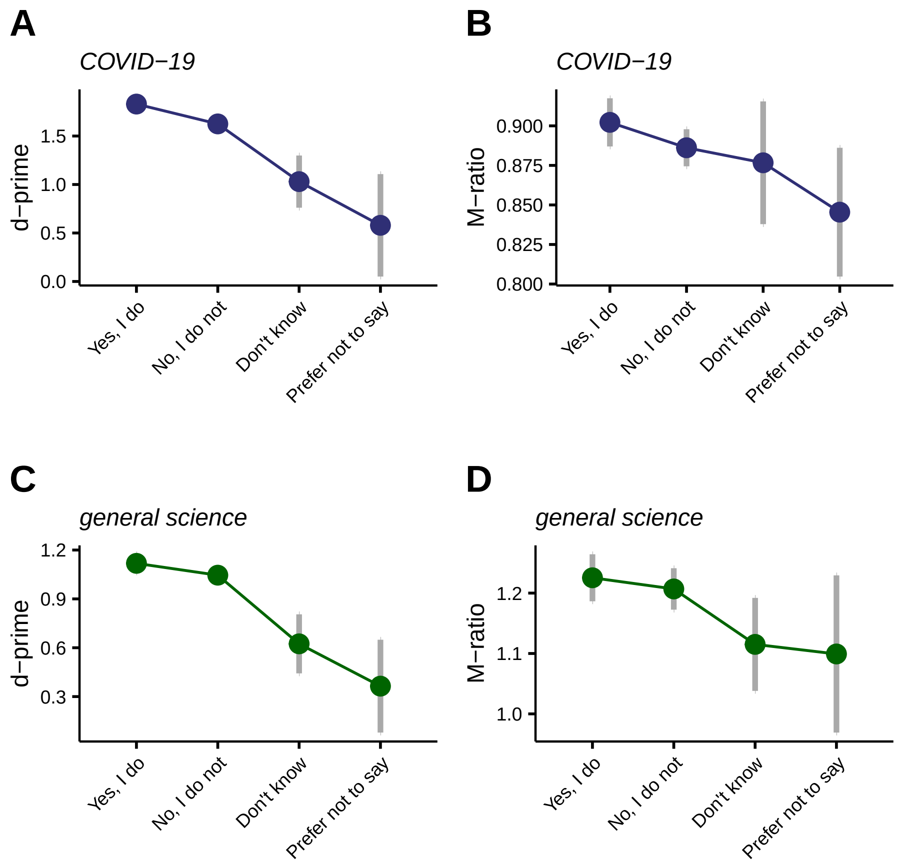
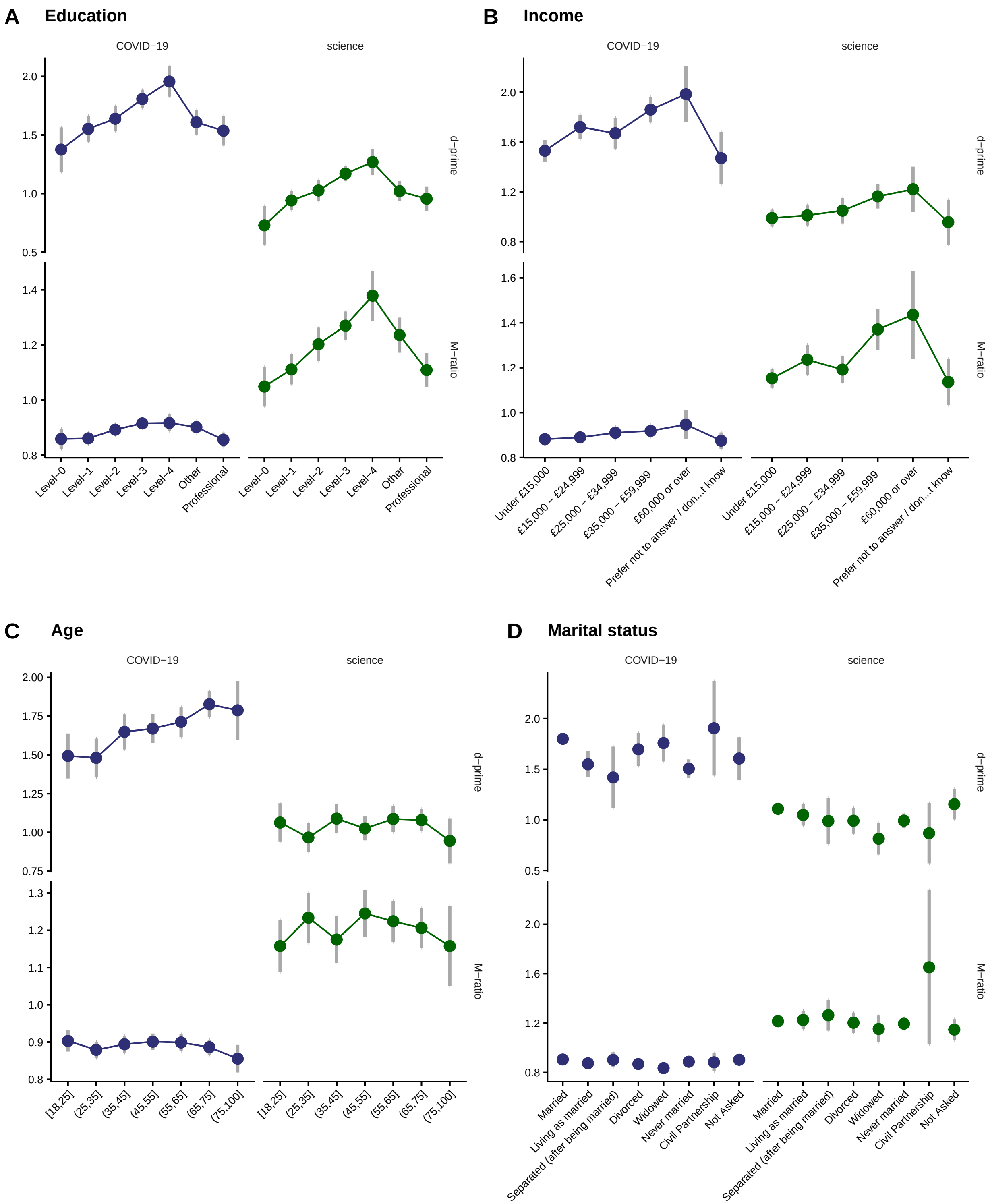


Figure 5: Estimated signal-detection theoretic parameters split according to the response to the question about experiences of COVID-19 (mean and 95% confidence intervals). Note that panels A and B suggest better knowledge and metacognitive insight in people who experienced more directly the impact of COVID-19 on health. While this may hint at an effect of COVID-19 experience on d-prime and M-ratio, a similar trend can be seen in parameters estimated from general science statements (panel C and D). This suggests that these trends may be due to other factors or socio-demographics characteristics that correlates with both knowledge accuracy and metacognitive sensiticity across domains as well as the likelihood of residing in an area with a high spread of COVID-19.

4.6 Signal-detection theory estimates across socio-demographic variables



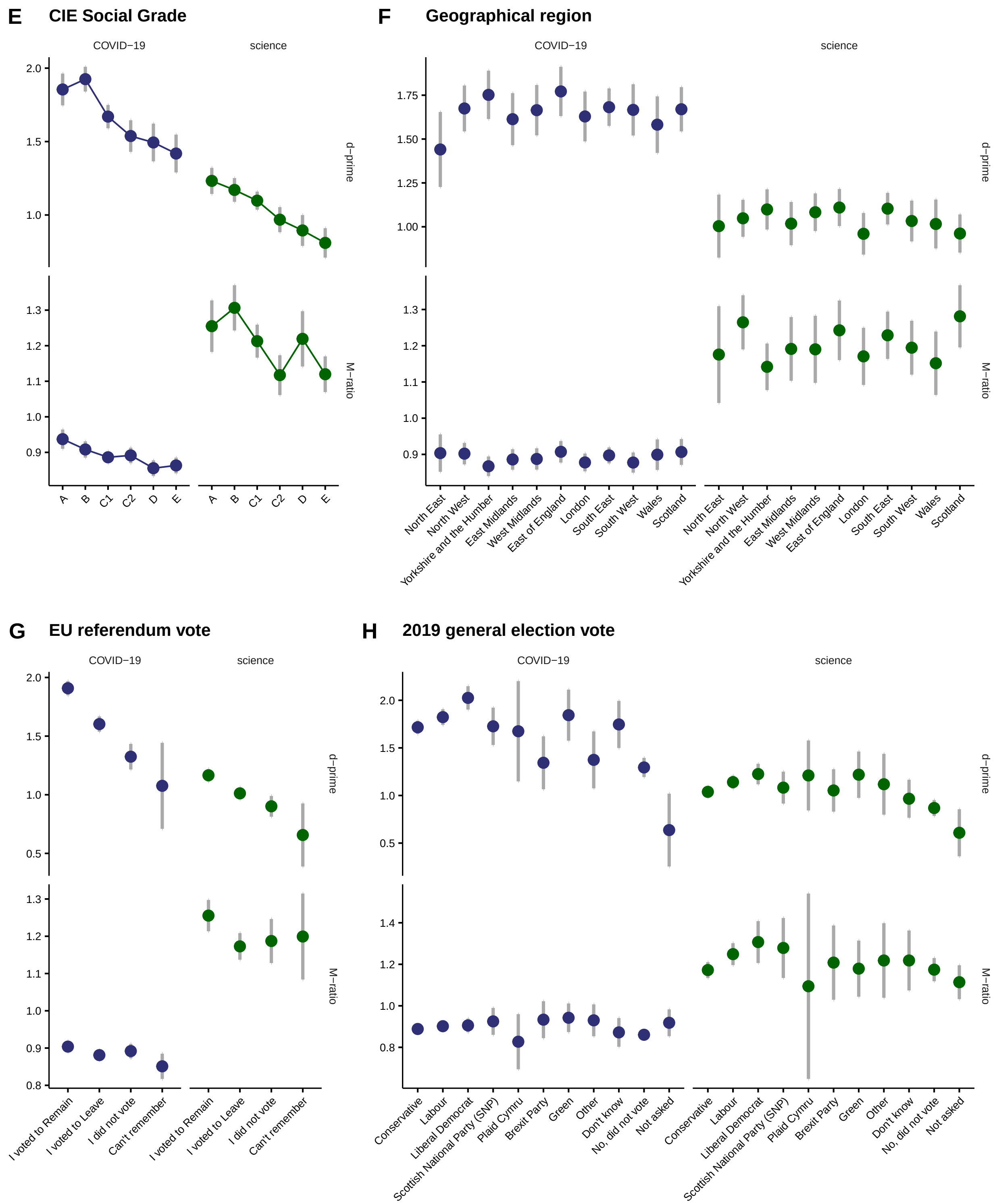


Figure 6: Mean values of signal detection theory indexes (d-prime and M-ratio, first and second row of each plot, respectively) across different groups. Each bar represents a specific demographic or political preference category, error bars are 95% confidence intervals. (Continued from previous page)

4.7 Partial correlations between individual answers to knowledge questions and self-reported behaviours and attitudes

In this section, additional analyses were conducted to examine correlations between answers to COVID-19 knowledge questions and self-reported behaviors and attitudes. These analyses aimed to provide further insight into how the content of the beliefs relates to the self-report questions. Given the content of the COVID-19 statements, certain associations with attitudes, self-reported behaviors, and vaccination intentions can be anticipated. For example, the belief that COVID-19 vaccines may alter DNA (Question 4) can be expected to be associated with low vaccination intentions, but not necessarily with negative attitudes toward restrictions or social-distancing measures.

For this analysis, answers to COVID-19 questions were transformed as belief in the correct answer. The partial correlation matrix was computed after taking into account the effect of knowledge accuracy (the d' sensitivity index) and some demographic variables that were also included in the ordinal regression (age, gender, having had experience of COVID-19, income, education and CIE social grade). Since several of these variables are defined only on an ordinal scale, I used the package `polycor` in R[38] to compute polychoric and polyserial correlations. The partial correlation matrix was computed using the Schur complement method, taking into account the effect of the covariates. To estimate the statistical significance of partial correlation coefficients, I used a permutation test (1000 iteration).

The results are presented in the figure below. In addition to the expected correlations based on the content of the statements, evidence of unexpected correlations was found. For instance, respondents who confidently rejected the notion of COVID-19 as a bio-weapon (Question 3) showed greater support for restrictive measures and had higher vaccination intentions. These attitudes do not directly follow from the content of the statement itself, as the belief in COVID-19 as a bio-weapon does not inherently warrant or oppose vaccination and restrictions. Similarly, respondents who expressed confidence in the inaccurate statement that more than 70% of people with COVID-19 display no symptoms (Question 1) reported higher support for restrictions and vaccination intentions. These findings support the view that the content of beliefs interacts with individuals' broader belief system and cognitive and meta-cognitive factors, shaping behaviors and attitudes.

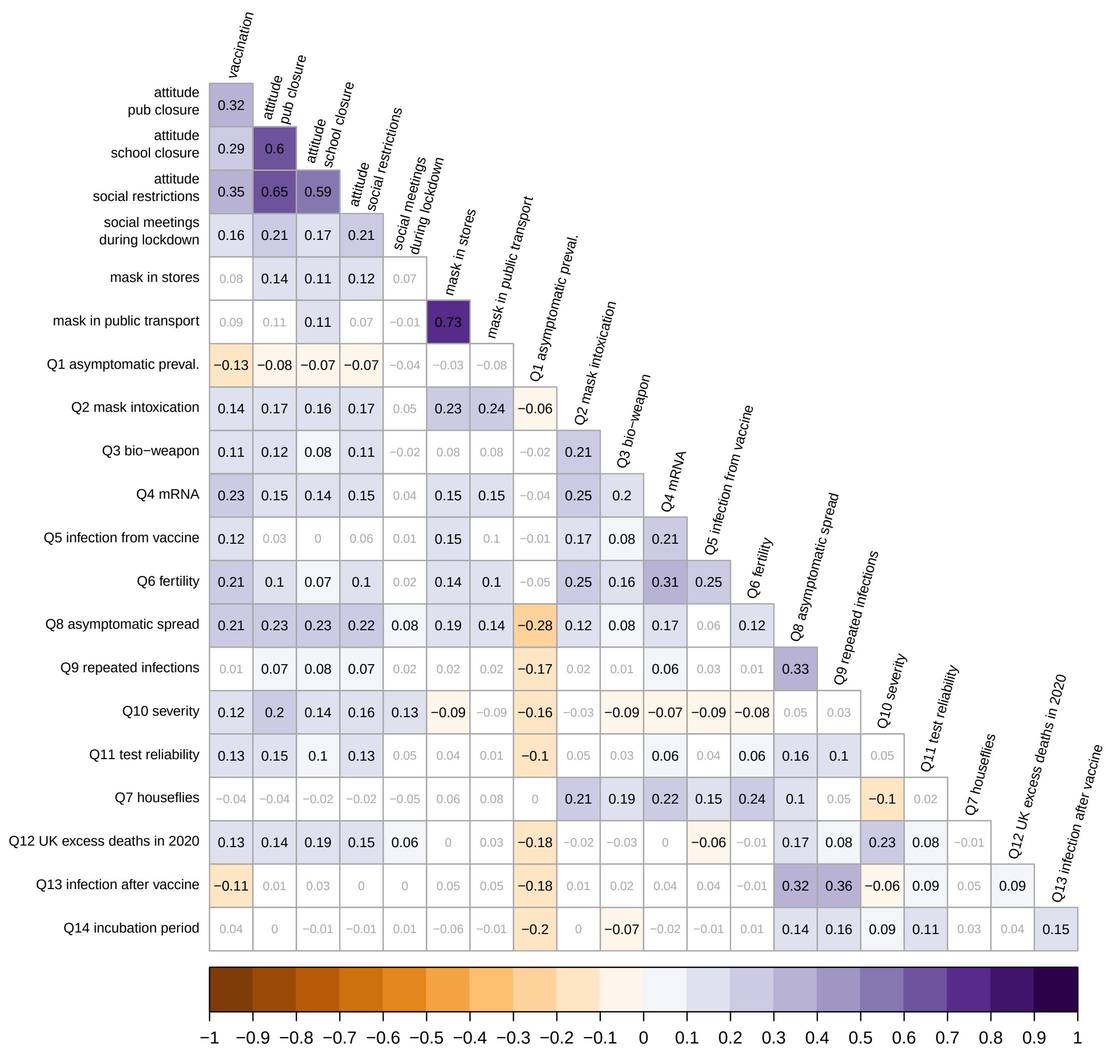


Figure 7: Partial correlation matrix. Statistically significant (alpha=0.05) correlation coefficients are shown in black font (with the square colored according to correlation value). Grey font and whote squares indicate correlations that did not reach statistical significance.

5 Supplemental Figures

5.1 Distribution of confidence ratings

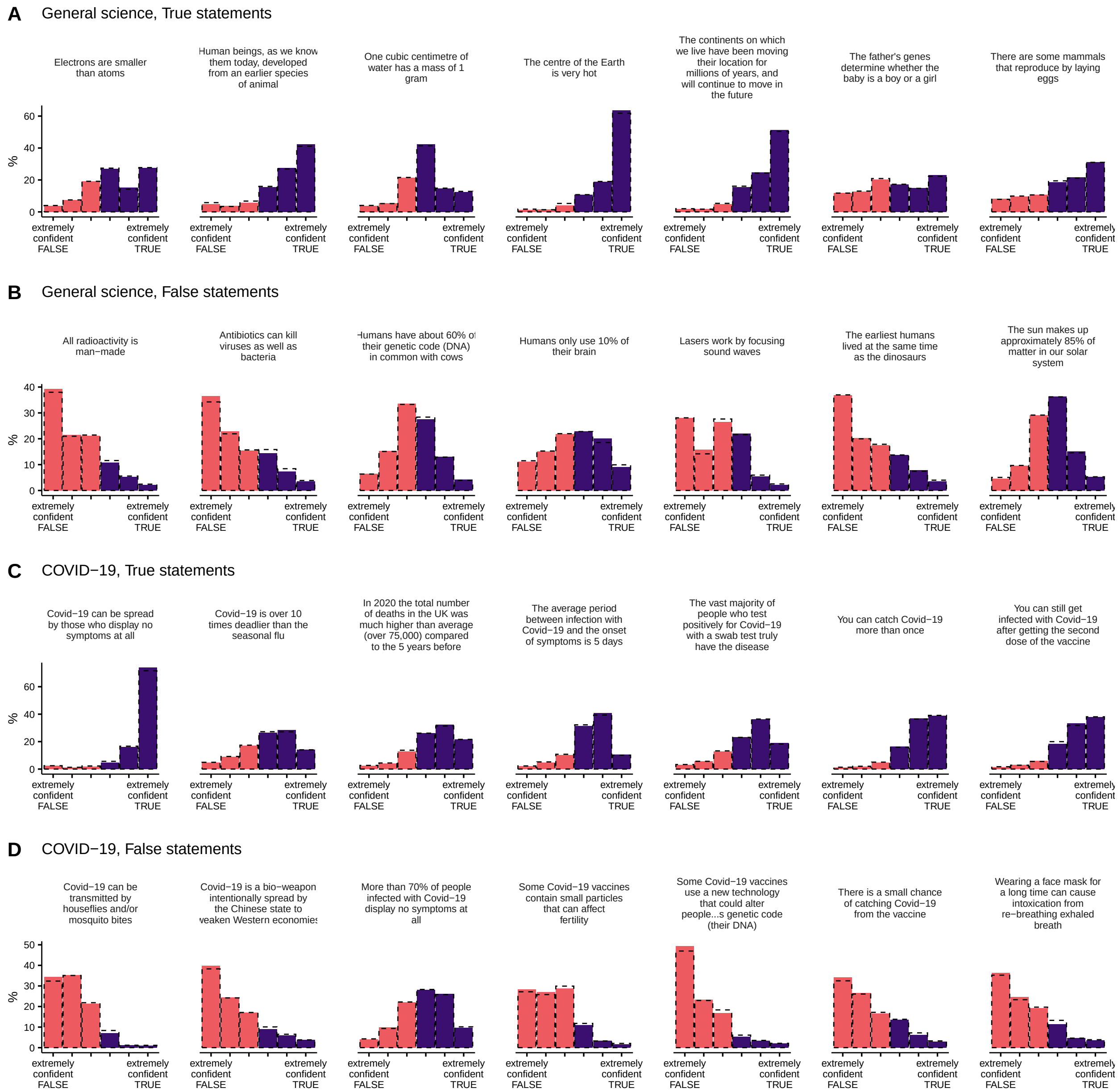


Figure 8: Distributions of confidence ratings for each question. Blue and red bars indicate true and false responses, respectively. Coloured columns are calculated from the un-weighted sample, whereas dashed lines shows percentages weighted to be representative of GB adults.

5.2 Ordered logistic regressions

5.2.1 Figure conventions

The next sections provide plots of model fit and posterior distribution of all parameters of the ordinal regression models of all questions. The error bars at the bottom of the kernel density plots represents 95% and 50% Bayesian highest posterior density intervals (HPDI). Note that in all cases negative values of the coefficients (either the slopes β or the group-specific effects u "move" the probability mass toward response options that are shown to the left side of the histogram; in all cases these indicate health-protective behaviours and attitudes). The slope for gender represents the difference males minus females.

Error bars on the histograms of responses are multinomial 95% confidence intervals calculated on the pooled data. Also, the black line shown alongside the histogram represents the model fit to the data.

5.2.2 Figures for: Q1. *Closing of bars, pubs and restaurants*

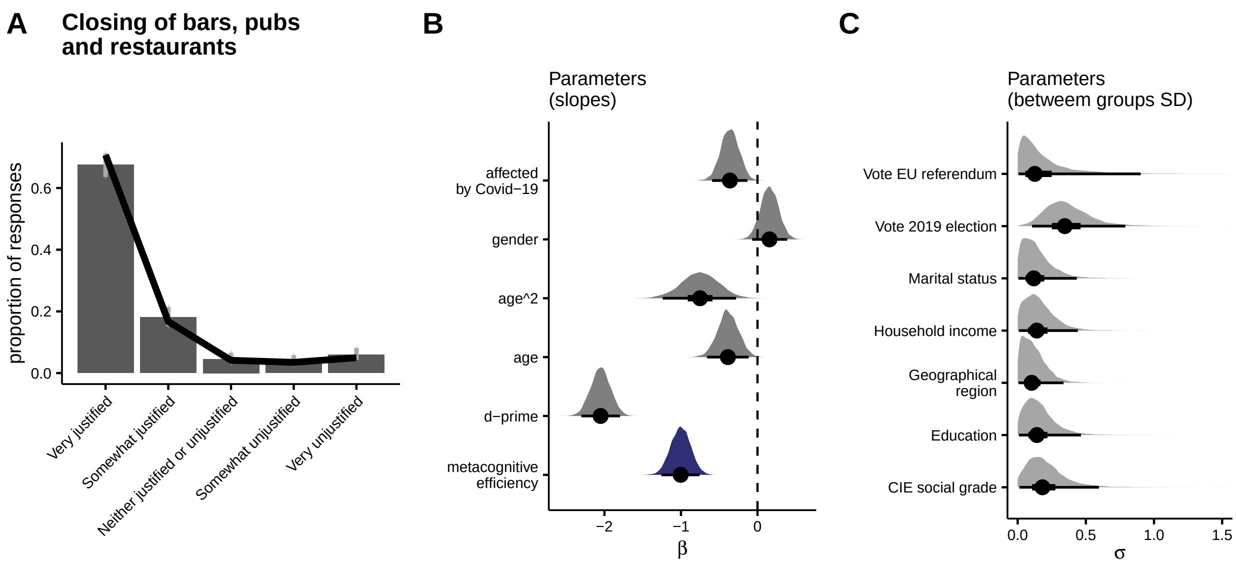


Figure 9: Q1, Closing of bars, pubs and restaurants.

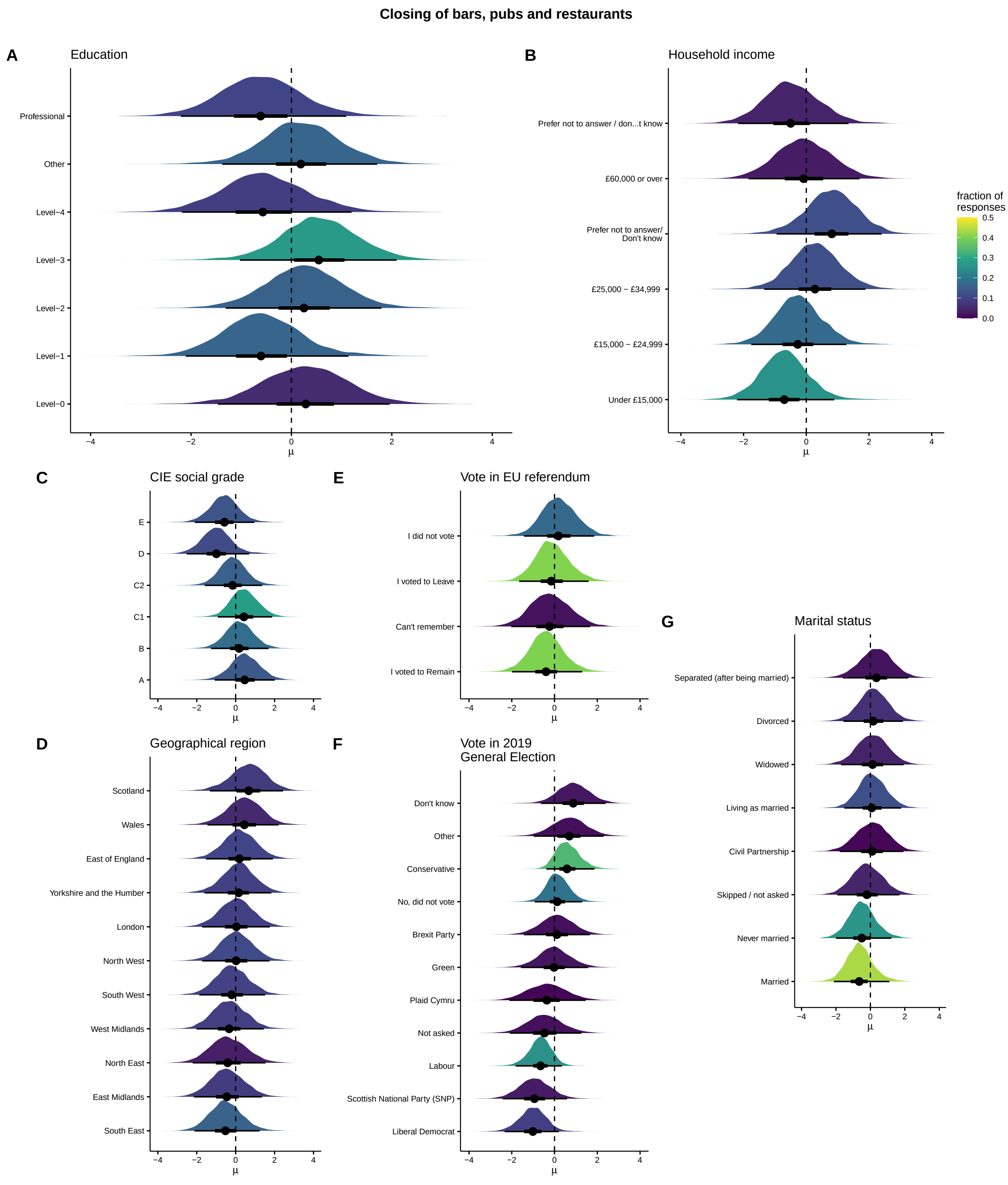


Figure 10: Q1, Closing of bars, pubs and restaurants; Group-specific intercepts.

5.2.3 Figures for: Q1. *Closing of schools*

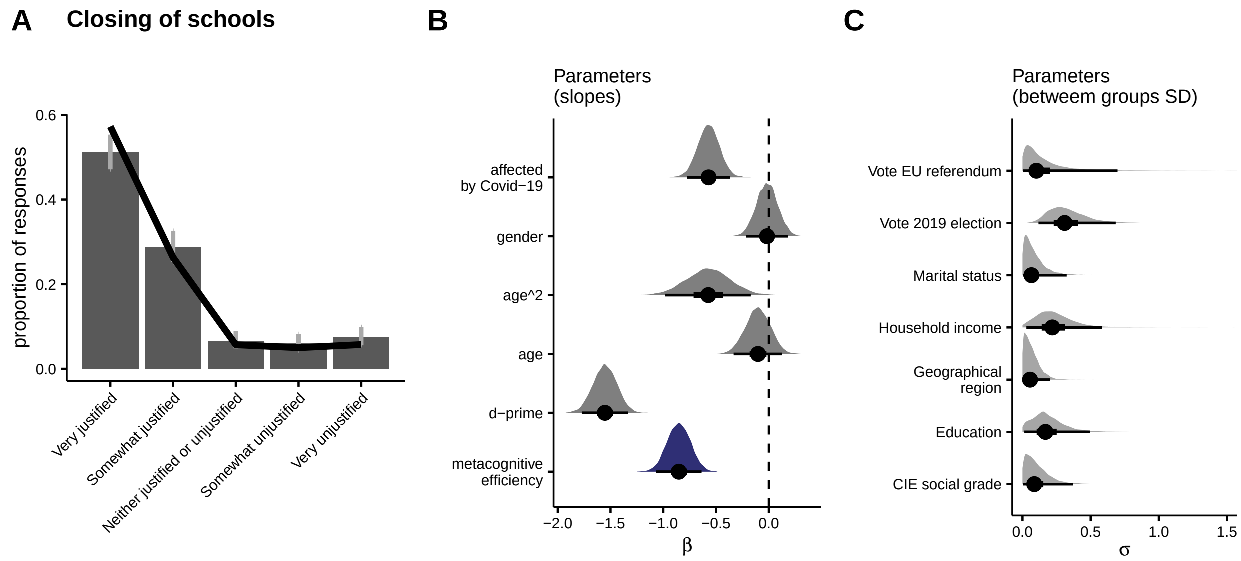


Figure 11: Q1, Closing of schools.

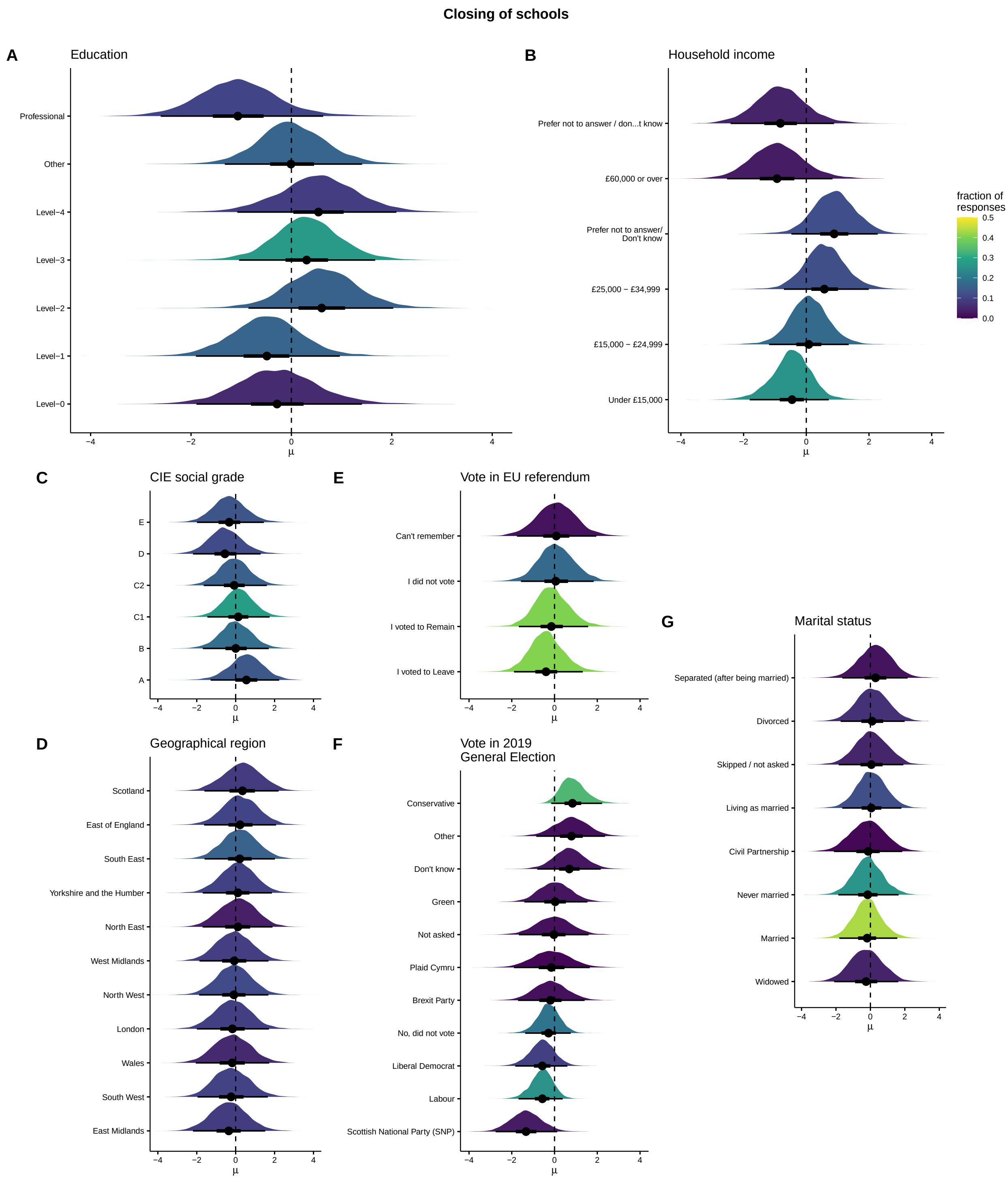


Figure 12: Q1, Closing of schools; Group-specific intercepts.

5.2.4 Figures for: Q1. *Restrictions on social meetings*

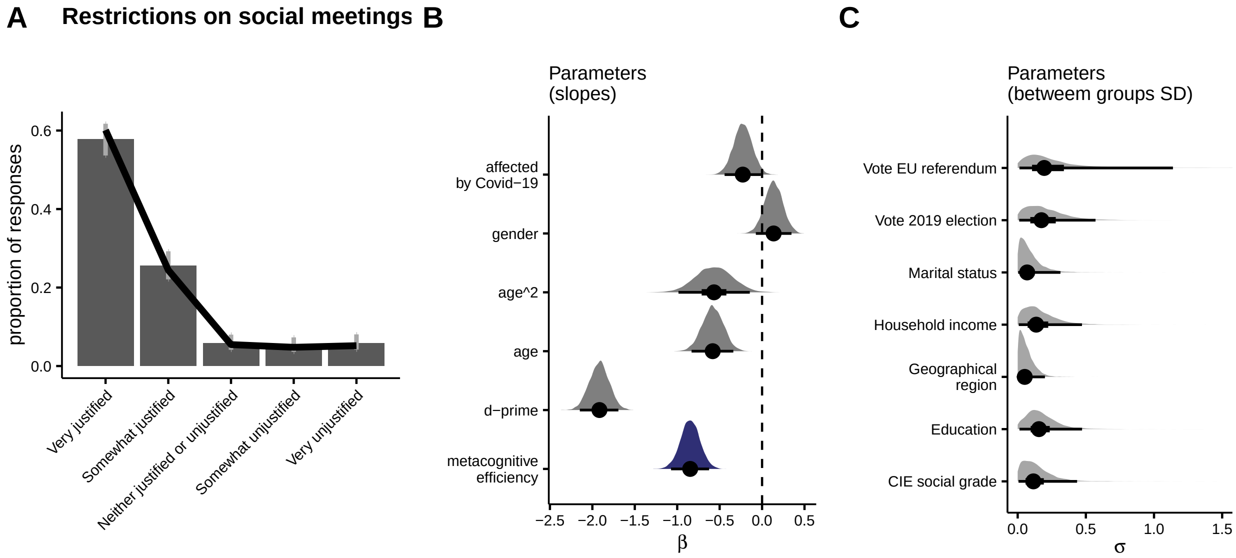


Figure 13: Q1, Restrictions on social meetings.

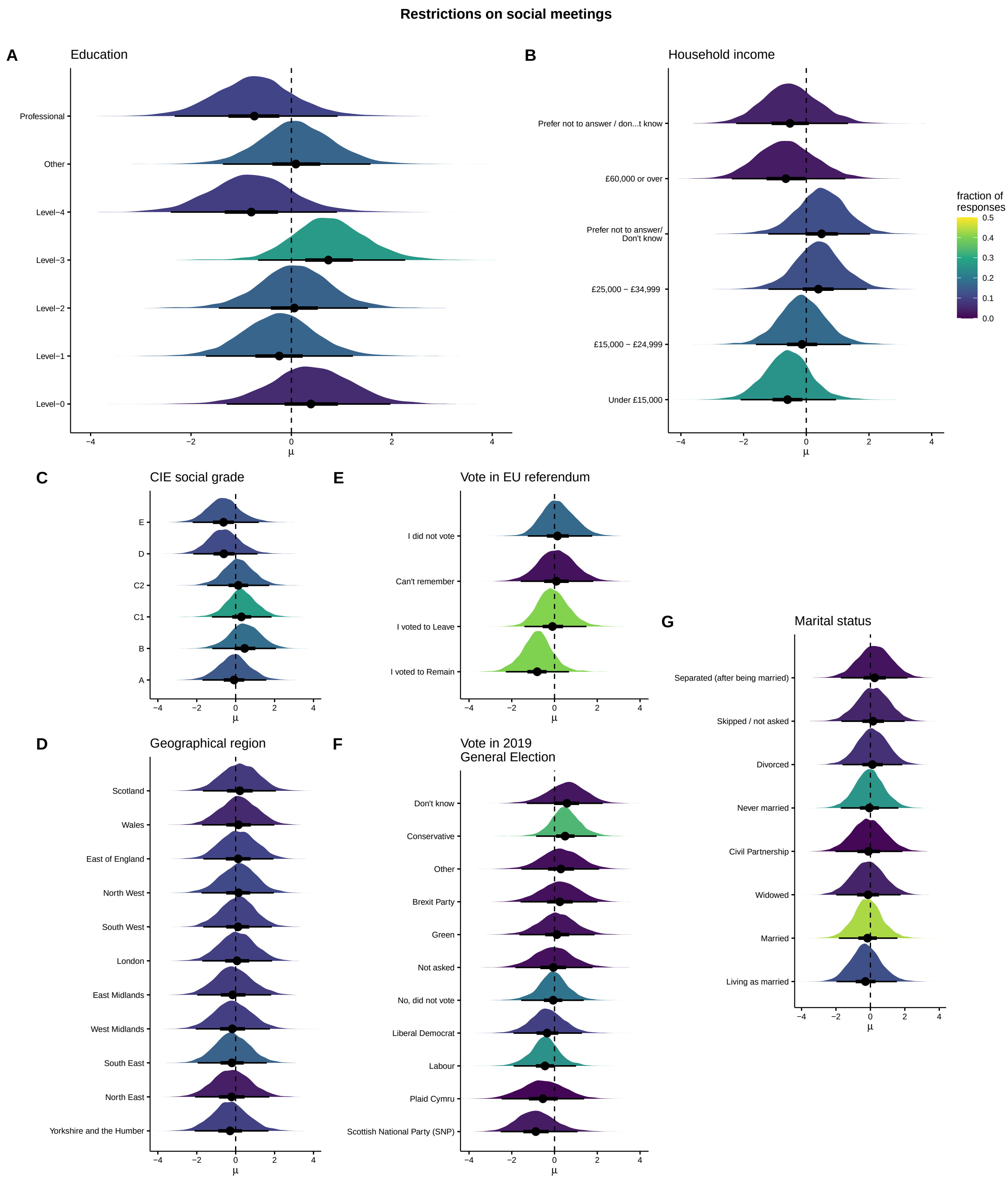


Figure 14: Q1, Restrictions on social meetings, group-specific intercepts.

5.2.5 Figures for: Q2. *Self-reported social meetings with others*

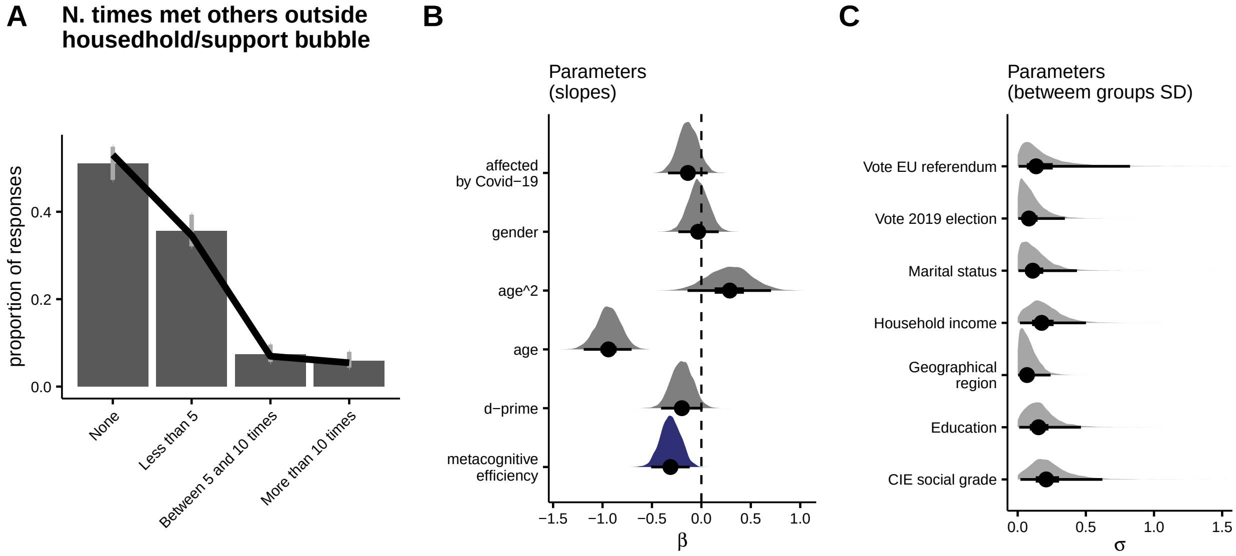


Figure 15: Q2, Self-reported social meetings with others.

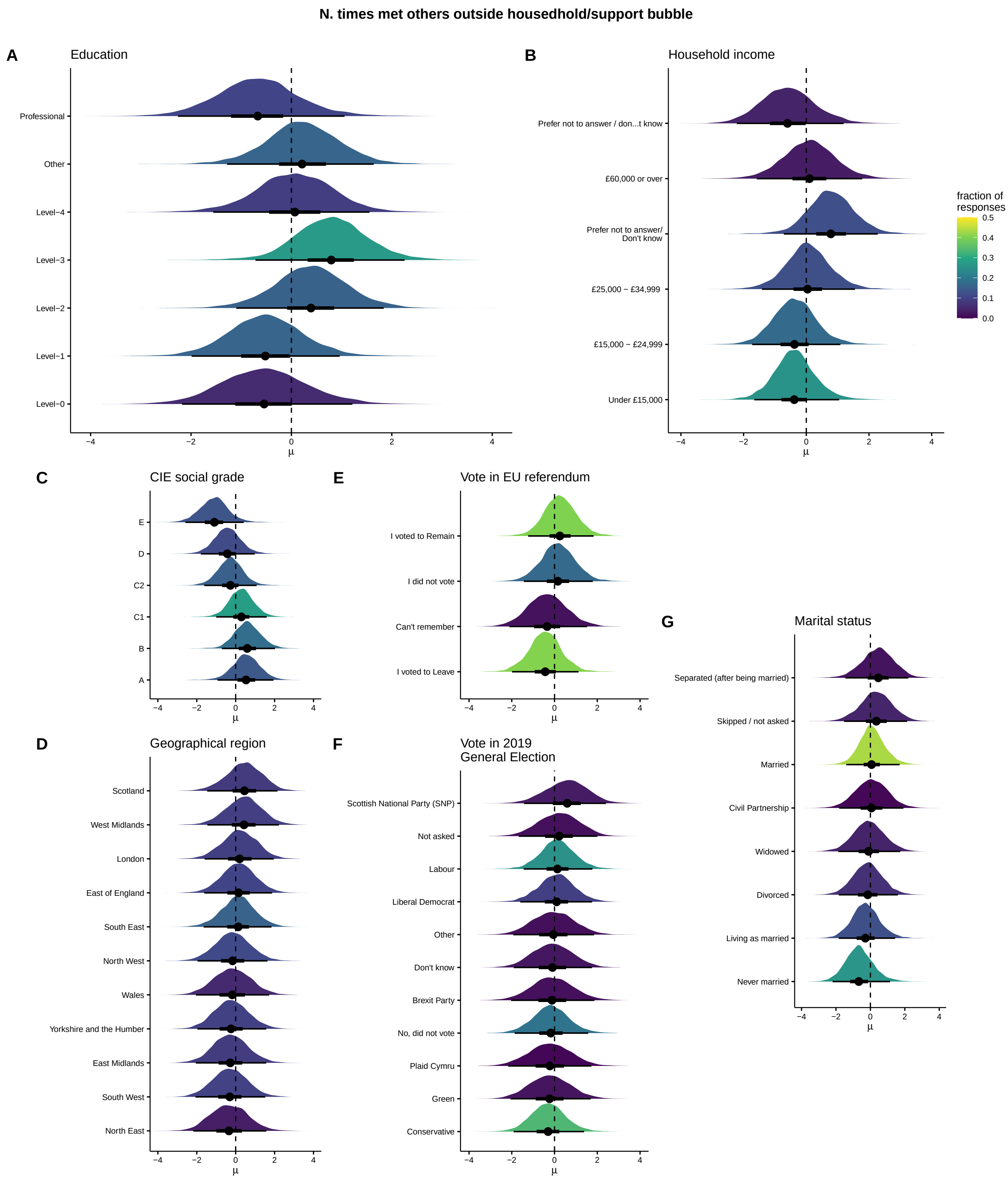


Figure 16: Q2, Self-reported social meetings with others, group-specific intercepts.

5.2.6 Figures for: Q3. *Mask wearing in supermarket or grocery store*

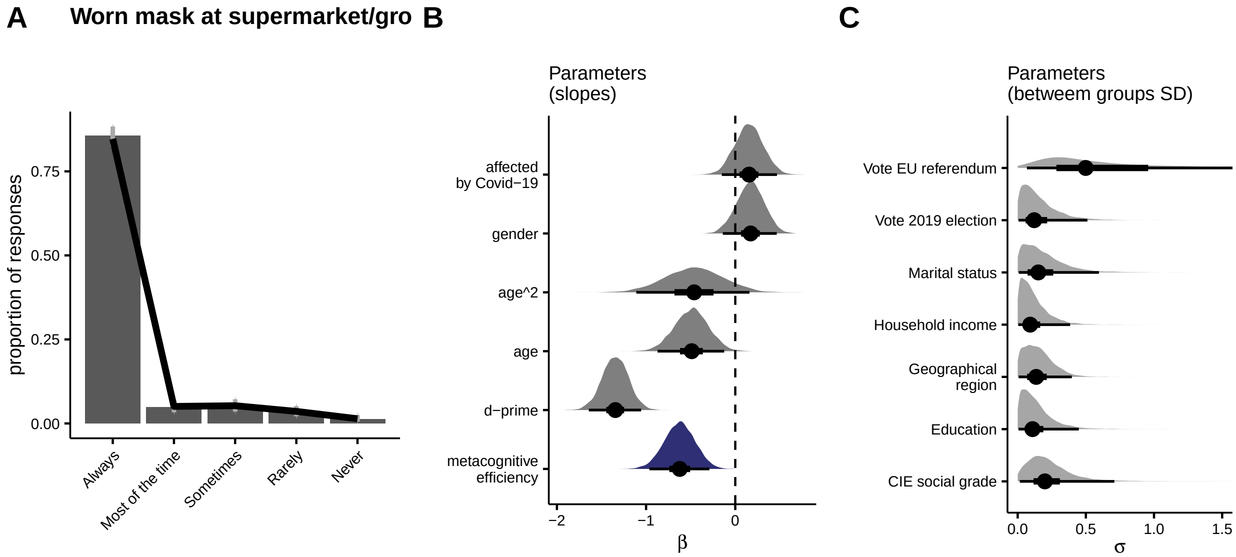


Figure 17: Q3, Mask wearing in supermarket or grocery store.

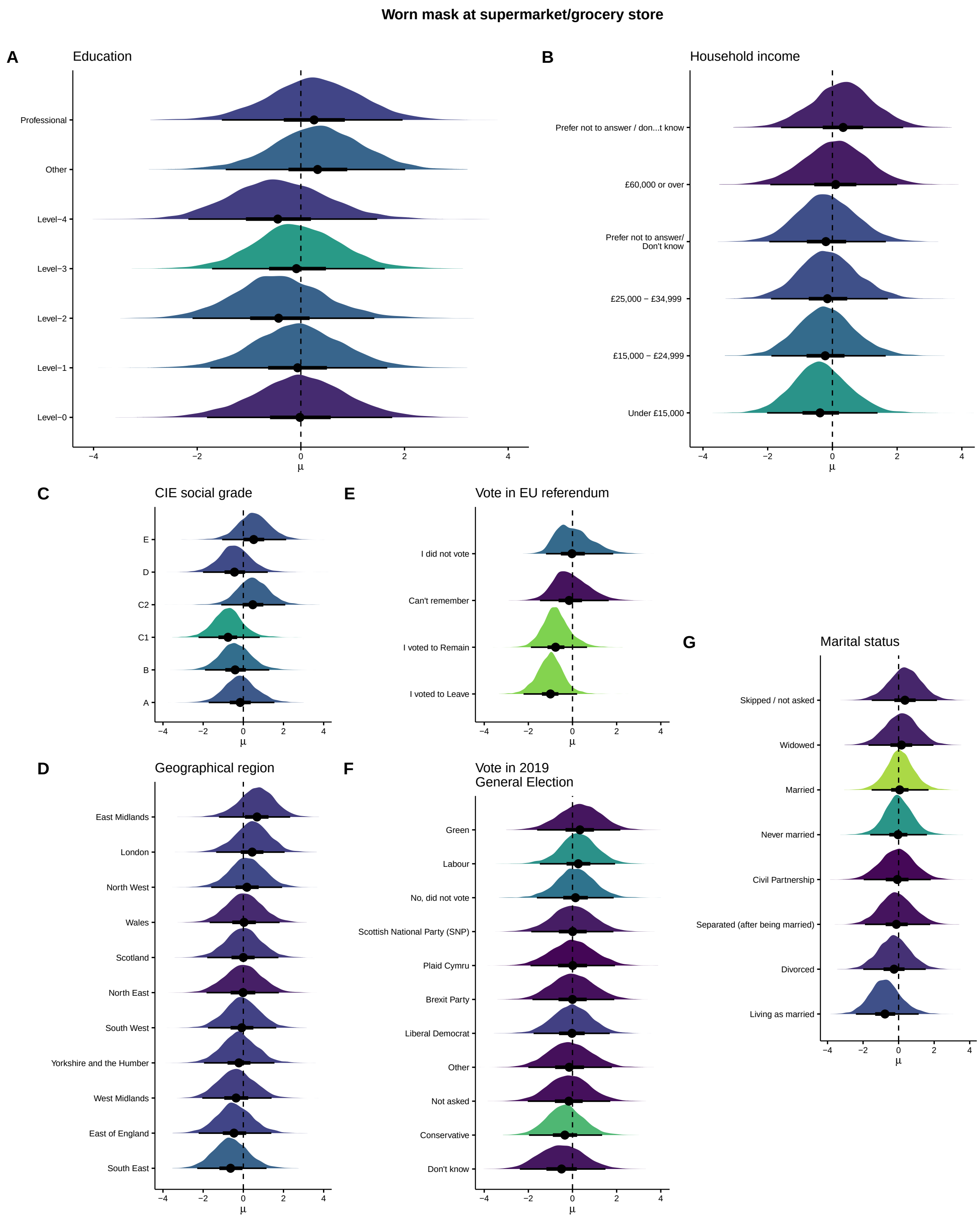


Figure 18: Q3, Mask wearing in supermarket or grocery store, group-specific intercepts.

5.2.7 Figures for: Q3. *Mask wearing in public transport*

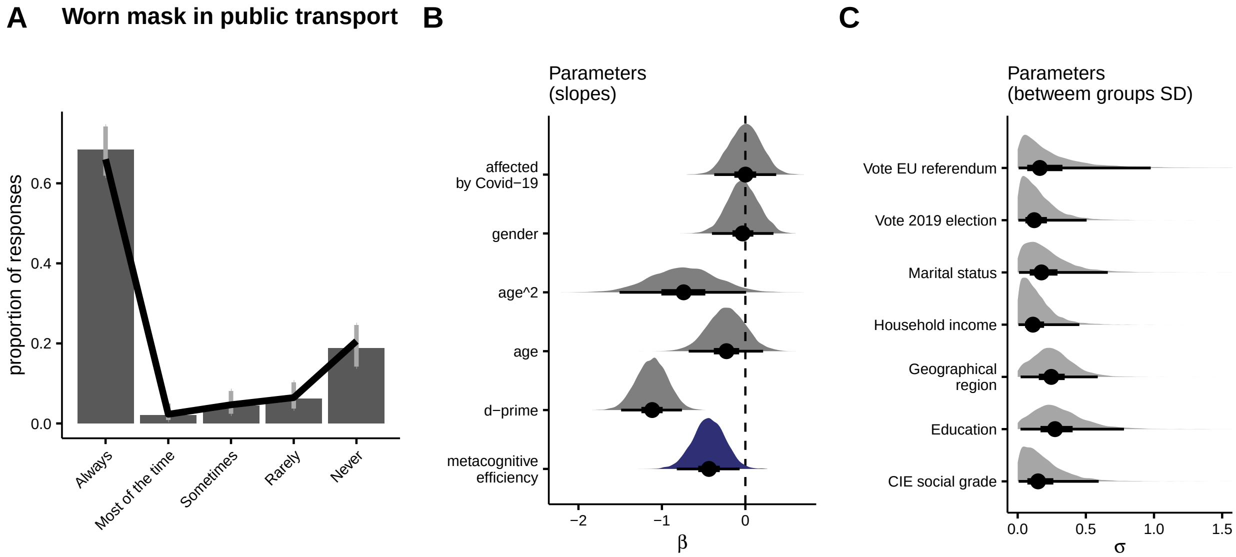


Figure 19: Q3, Mask wearing in public transport. Note that respondents had the option to indicate they never used a public transport during lockdown (in this case their responses were not included in this model).

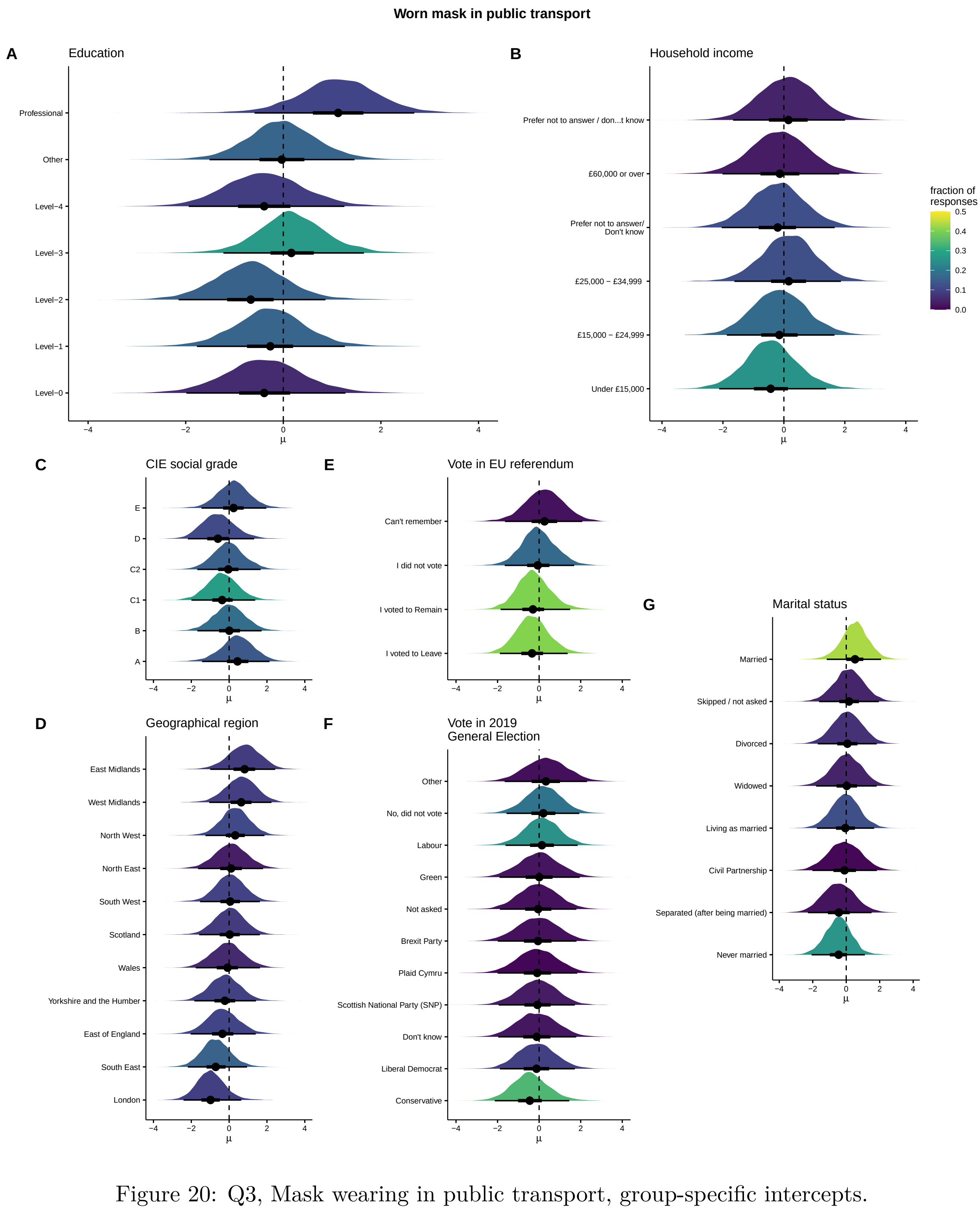


Figure 20: Q3, Mask wearing in public transport, group-specific intercepts.

5.2.8 Figures for: Q5. *Vaccine intentions*

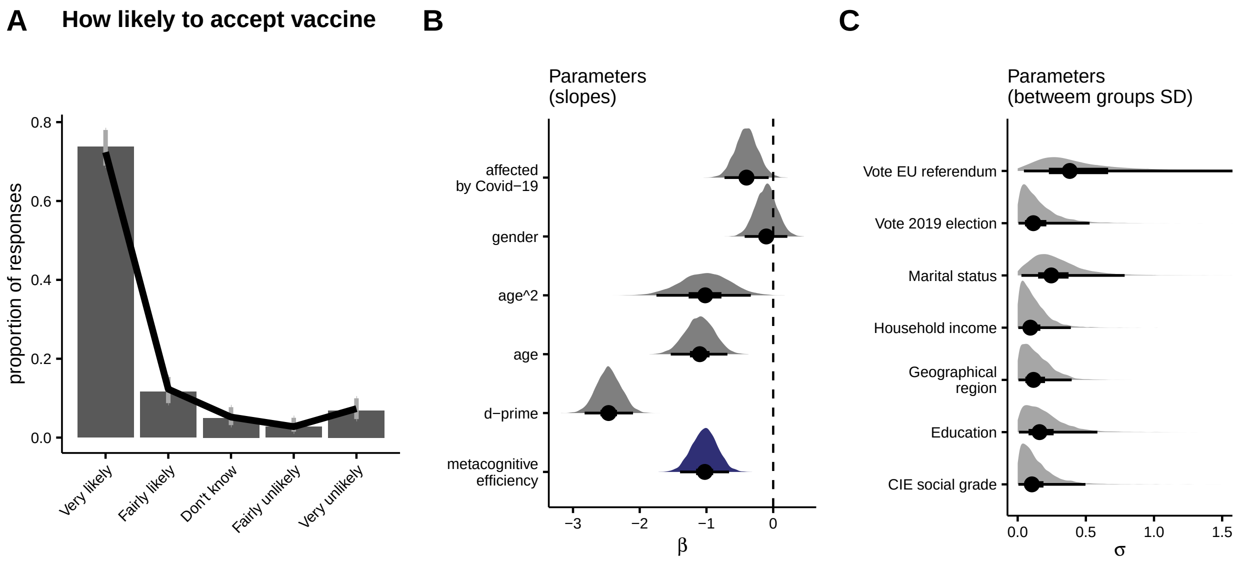


Figure 21: Q5, Vaccine intentions (respondents who had already one or more doses of the vaccine were excluded).

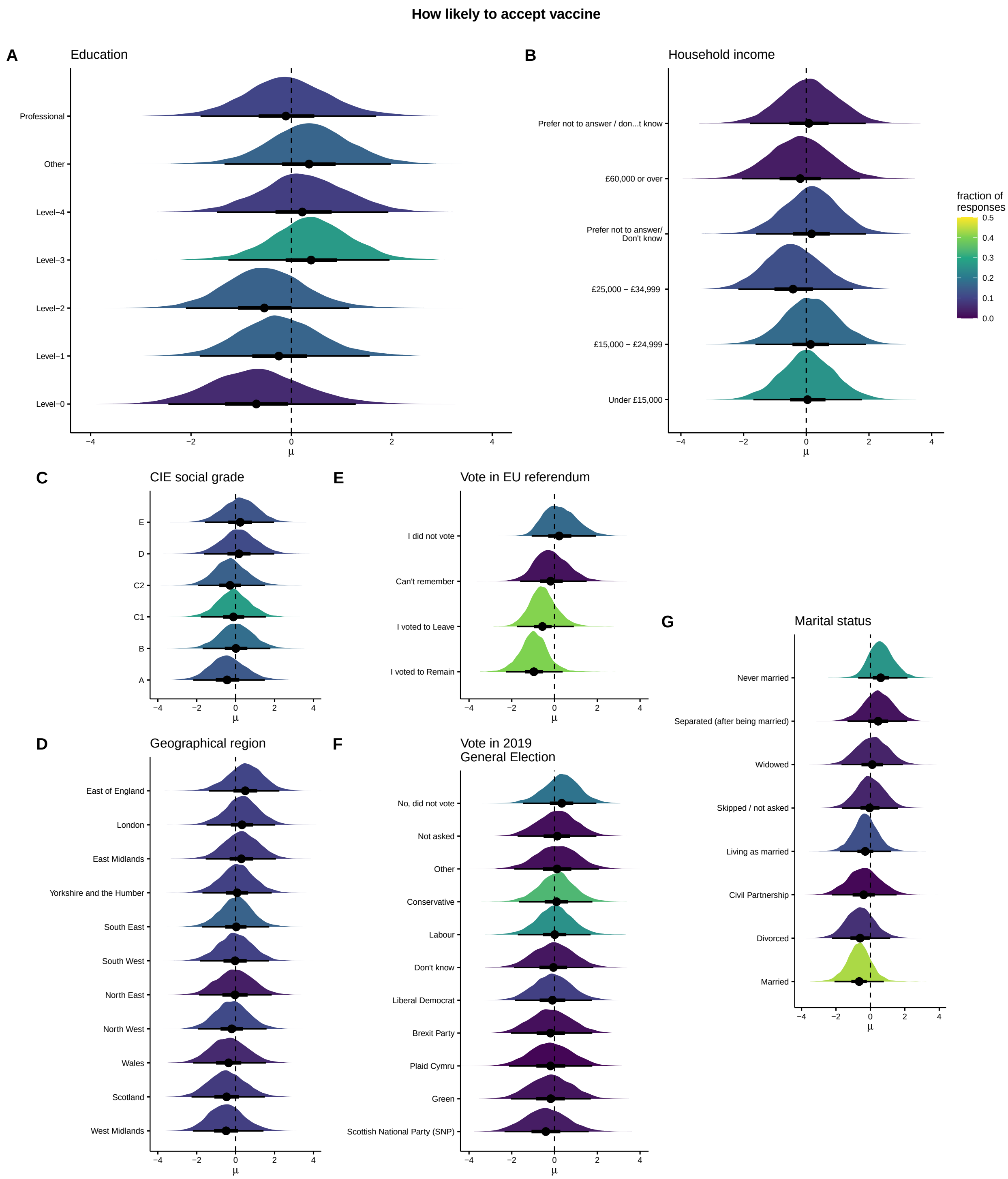


Figure 22: Q5, Vaccine intentions, group-specific intercepts.

6 Computing environment

```
sessionInfo()
R version 4.3.0 (2023-04-21)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 20.04.6 LTS

Matrix products: default
BLAS:   /usr/lib/x86_64-linux-gnu/blas/libblas.so.3.9.0
LAPACK: /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.9.0

locale:
 [1] LC_CTYPE=en_GB.UTF-8       LC_NUMERIC=C
 [3] LC_TIME=en_GB.UTF-8        LC_COLLATE=en_GB.UTF-8
 [5] LC_MONETARY=en_GB.UTF-8    LC_MESSAGES=en_GB.UTF-8
 [7] LC_PAPER=en_GB.UTF-8       LC_NAME=C
 [9] LC_ADDRESS=C               LC_TELEPHONE=C
[11] LC_MEASUREMENT=en_GB.UTF-8 LC_IDENTIFICATION=C

time zone: Europe/London
tzcode source: system (glibc)

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] ggtext_0.1.2         polspline_1.1.22     corrplot_0.92
 [4] ggpubr_0.6.0         kableExtra_1.3.4     rstan_2.21.8
 [7] StanHeaders_2.21.0-7 tidybayes_3.0.4      lubridate_1.9.2
[10] forcats_1.0.0        stringr_1.5.0        dplyr_1.1.2
[13] purrr_1.0.1          readr_2.1.4          tidyr_1.3.0
[16] tibble_3.2.1         ggplot2_3.4.2        tidyverse_2.0.0
[19] rjags_4-14           coda_0.19-4          knitr_1.42

loaded via a namespace (and not attached):
  [1] gridExtra_2.3        gld_2.6.6            inline_0.3.19
  [4] readxl_1.4.2         rlang_1.1.0          magrittr_2.0.3
  [7] matrixStats_0.63.0   e1071_1.7-13         compiler_4.3.0
 [10] mgcv_1.8-42          loo_2.6.0            systemfonts_1.0.4
 [13] callr_3.7.3          vctrs_0.6.2          rvest_1.0.3
 [16] pkgconfig_2.0.3      arrayhelpers_1.1-0   crayon_1.5.2
 [19] fastmap_1.1.1        backports_1.4.1      labeling_0.4.2
 [22] utf8_1.2.3           mlisi_1.0.0.1        rmarkdown_2.21
 [25] tzdb_0.3.0           ps_1.7.5             ragg_1.2.5
 [28] bit_4.0.5            xfun_0.39            HDInterval_0.2.4
 [31] broom_1.0.4          parallel_4.3.0       prettyunits_1.1.1
 [34] DescTools_0.99.48    R6_2.5.1             stringi_1.7.12
 [37] car_3.1-2            boot_1.3-28          cellranger_1.1.0
```

```
 [40] Rcpp_1.0.10           Matrix_1.5-4.1      splines_4.3.0
 [43] timechange_0.2.0      tidyselect_1.2.0    rstudioapi_0.14
 [46] abind_1.4-5           yaml_2.3.7          codetools_0.2-19
 [49] processx_3.8.1        pkgbuild_1.4.0      lattice_0.21-8
 [52] withr_2.5.0           posterior_1.4.1     evaluate_0.20
 [55] proxy_0.4-27          RcppParallel_5.1.7  ggdist_3.2.1
 [58] xml2_1.3.3            pillar_1.9.0        carData_3.0-5
 [61] tensorA_0.36.2        checkmate_2.2.0     stats4_4.3.0
 [64] distributional_0.3.2 generics_0.1.3      vroom_1.6.1
 [67] hms_1.1.3             rootSolve_1.8.2.3   munsell_0.5.0
 [70] scales_1.2.1          class_7.3-21        glue_1.6.2
 [73] lmom_2.9              tools_4.3.0         data.table_1.14.8
 [76] webshot_0.5.4         ggsignif_0.6.4      Exact_3.2
 [79] mvtnorm_1.1-3         cowplot_1.1.1       grid_4.3.0
 [82] colorspace_2.1-0      nlme_3.1-162        cli_3.6.1
 [85] textshaping_0.3.6     expm_0.999-7        fansi_1.0.4
 [88] svUnit_1.0.6          viridisLite_0.4.1   svglite_2.1.1
 [91] gtable_0.3.3          rstatix_0.7.2       digest_0.6.31
 [94] farver_2.1.1          htmltools_0.5.5     lifecycle_1.0.3
 [97] httr_1.4.5            gridtext_0.1.5      MASS_7.3-59
[100] bit64_4.0.5
```

```
writeLines(readLines(file.path(Sys.getenv("HOME"), ".R/Makevars")))
```

```
CXX14FLAGS=-O3 -march=native -mtune=native -fPIC
CXX14=g++
```

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