

Supplemental Material: Facing the pandemic with trust in science

We present a Bayesian path analysis in Fig. 2 of the main text. The first aim of this supplementary material is to set out the reasons for the structure of this model, relative to the current research question (How does trust in science relate to individual approval and trust in science? Specifically, does trust in science affect compliance behaviour by changing minds?), and relative to factors known to be important in previous work.

The second aim is to briefly summarise the various robustness and sensitivity checks we carried out to ensure that our conclusions based on the path model in the main text did not depend on narrow assumptions. Detailed descriptions (along with full analysis scripts and model outputs) for all of these alternative analyses are all available in an Open Science Framework (OSF) repository at bit.ly/trust-in-science. For technical details not covered in this *brief* overview, please see the above OSF link.

1 Justifying the Bayesian model structure

Fig.S1 duplicates the structure of the path model in Fig. 2 of the main text, highlighting the paths specific to the current research question about trust in science in red, and showing other paths based on the existing literature in black. The red paths allow us to analyse whether trust in science has more of an effect on individual approval of the social distancing rules, or on adherence to those rules. Crucially, it also allows us to ask whether trust in science can improve behaviour because it changes minds (i.e., by improving approval of the rules).

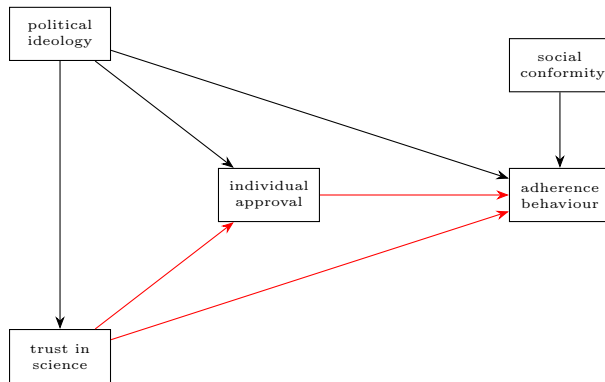

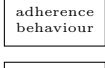
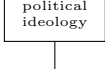
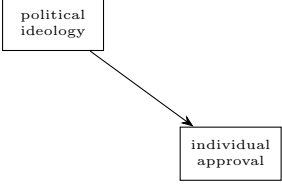
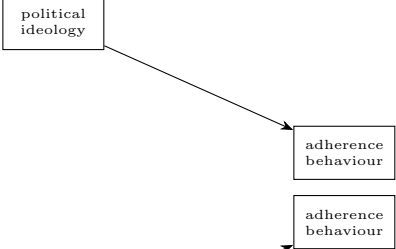

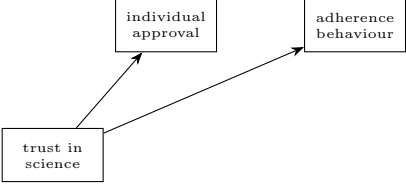
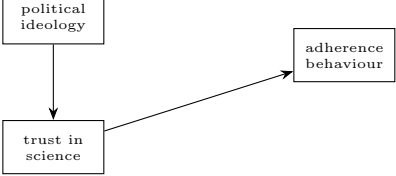


Fig. S1. The structure of the path model. Paths relevant to the current research question in red; relevant factors based on the literature in black.

However, we need to contextualise this analysis by including other factors known to be relevant (those shown in black in Fig.S1). Table S1 illustrates relationships between pairs of such factors, along with citations justifying the inclusion of those paths. The table also includes more complex paths, either making claims about mediation, or about multivariate outcomes. In this table, we reproduce the approximate orientations and layout of the individual paths from Fig. S1 in order to help the eye map the individual elements onto the larger structure.

Table S1. Evidence for pathways

Paths	Sources
 <pre> graph TD A[social conformity] --> B[adherence behaviour] </pre>	Bicchieri et al. (2021); Moehring et al. (2021)
 <pre> graph TD A[adherence behaviour] --> B[political ideology] </pre>	
 <pre> graph TD A[political ideology] --> B[trust in science] </pre>	Gauchat (2012); Rutjens, Sutton, and van der Lee (2018)
 <pre> graph TD A[political ideology] --> B[individual approval] </pre>	Collins, Mandel, and Schywiola (2021, their 'support for restrictions' variable)
 <pre> graph TD A[political ideology] --> B[adherence behaviour] </pre>	Pennycook, McPhetres, Bago, and Rand (2020)
 <pre> graph TD A[trust in science] --> B[adherence behaviour] </pre>	Pagliaro et al. (2021); Stosic, Helwig, and Ruben (2021)
 <pre> graph TD A[trust in science] --> B[individual approval] B --> C[adherence behaviour] </pre>	Dohle, Wingen, and Schreiber (2020)
 <pre> graph TD A[political ideology] --> B[trust in science] B --> C[adherence behaviour] </pre>	Plohl and Musil (2021)

Relative to these findings, then, our core innovation regarding this specific research question is in testing how the relationship between trust in science and adherence behaviour is affected by the inclusion of pathways from trust to approval, and from approval to adherence (Fig. S2) .

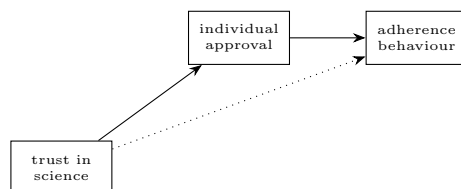


Fig. S2. The specific pathways that we are hypothesising: that any relationship between trust in science and adherence behaviour should be weakened (shown with a dotted line) when approval of the rules is included as an intervening variable.

2 Alternative structures

One question that is under-determined by previous work (Table S1) is how social conformity relates to our other predictors. In the path model reported in the main text, social conformity was treated as a covariate, but it could plausibly be related approval. To ensure that our conclusions do not depend on our decision to model it as an independent covariate, we tested three alternative structures: one where social conformity is a sister to approval (in being predicted by ideology and trust in science, and in turn predicting adherence), one with an additional path from social conformity to approval, and one that retains the path from social conformity to approval, but otherwise does not relate social conformity to ideology and trust in science. These model structures are illustrated below.

We stress that ‘social conformity’ here means something quite specific — the prevalence of social distancing among each participant’s social circle during early stages of the pandemic — not social conformity of behaviours or attitudes in general. Although it is plausible that there may be a social conformity effect on trust and ideology in some general sense, it is implausible that this specific sense of social conformity might affect trust in science or political ideology: after all, those factors pre-existed the pandemic. Thus, we do not consider alternative structures with paths from social conformity to trust or ideology.

Below, we show the schema for each alternative structure in turn, and we then compare the model path estimates with the original model reported in the main text. For all alternatives, we retain the weakly informative priors described in the main analysis, as well as the other modelling decisions (e.g., model family, random effects, and control variables).

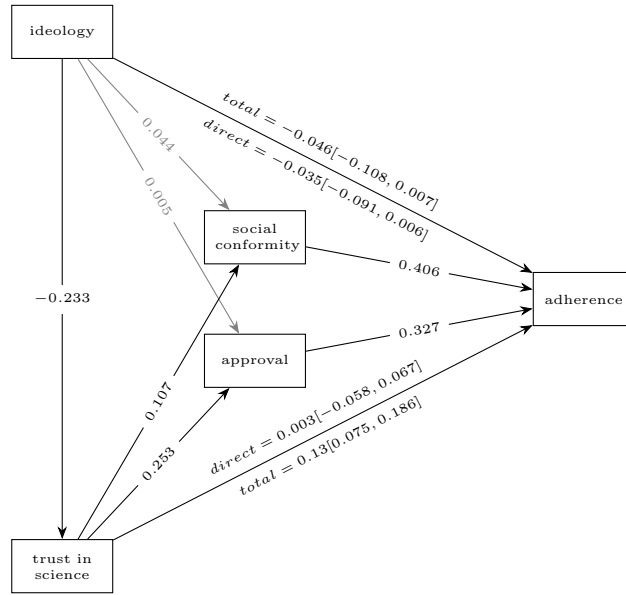


Fig. S3. The structure of alternative model 1: Social conformity as a sister node to approval (standardised coefficients, 95% CIs shown for the direct vs total effects of trust in science and ideology on adherence)

2.1 Alternative 1: social conformity as a sister to approval

This model adds pathways from trust and ideology to social conformity (Fig. S3), representing the possibility that people who trust in science might think that others do too (and thus similarly adhere to science-based policies), or that people’s political ideologies may have a similar effect. This possibility does not change much in terms of our claims about trust in science not having a direct effect on adherence, and about it predicting approval. If this structure is shown to be plausible in future work, it may be that trust in science has multiple indirect pathways to adherence (e.g., including via social conformity).

2.2 Alternative 2: Social conformity as a predictor of approval

This model differs from the previous one only in that it includes a pathway from conformity to approval (Fig. S4). Plausibly, a high prevalence of social distancing among one’s social circle might affect people’s attitudes to policies regarding such distancing.

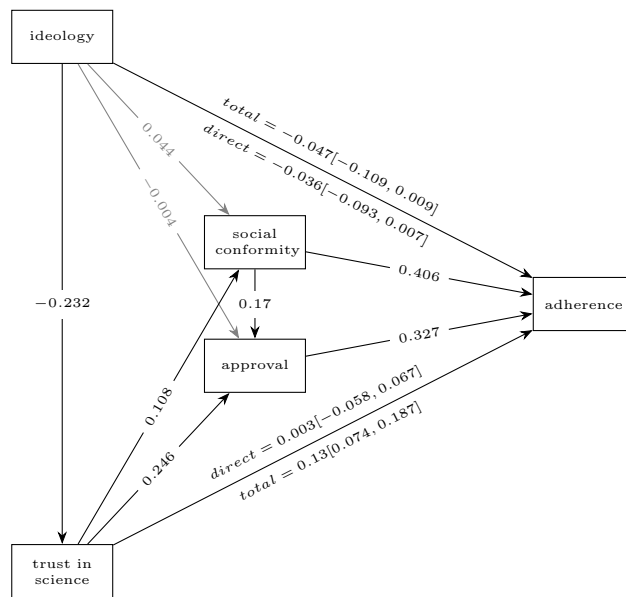


Fig. S4. The structure of alternative model 2: Social conformity as a predictor of approval (standardised coefficients, 95% CIs shown for the direct vs total effects of trust in science and ideology on adherence)

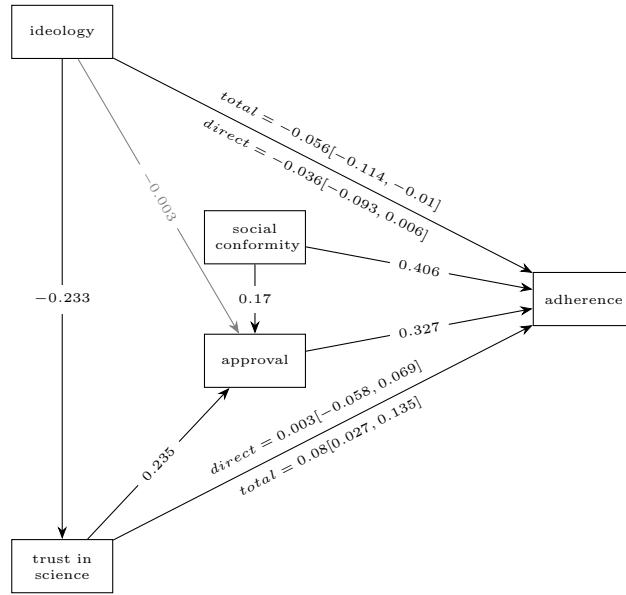


Fig. S5. The structure of alternative model 3: Social conformity as an independent predictor of approval (standardised coefficients, 95% CIs shown for the direct vs total effects of trust in science and ideology on adherence)

2.3 Alternative 3: Social conformity as an independent predictor of approval

This model (Fig. S5) differs from the previous one in dropping the pathways from ideology and trust in science to social conformity.

2.4 Consistency across alternatives

Our conclusions about the effects of trust in science are consistent across these various alternative model structures (Fig. S6).

3 Alternative regression families

We have reported Gaussian/linear regressions in the main text for reasons of parsimony and ease of interpretation, and Knief and Forstmeier (2021) argue that the dangers of using linear regressions that violate the normality assumption are often overstated. However, it is important to ensure that our decision to use linear regressions is not driving our conclusions, so we also model the data using a zero one inflated beta regression. Such a model is suitable for analysing slider data if the response values are divided by the maximum value of the slider

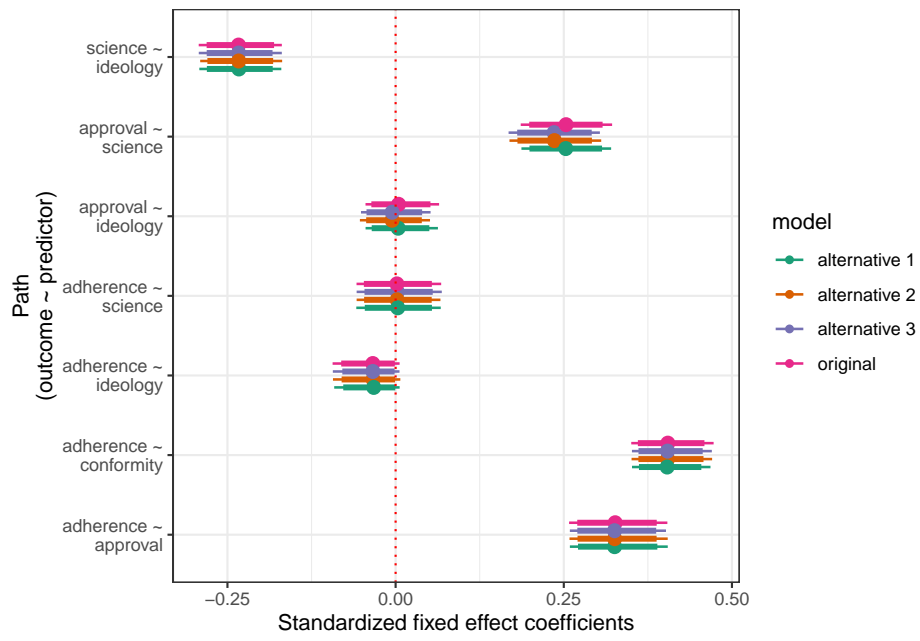


Fig. S6. A comparison of the models with alternative roles for social conformity, along with the original model reported in the main text (standardised coefficients with 89% and 95% CIs).

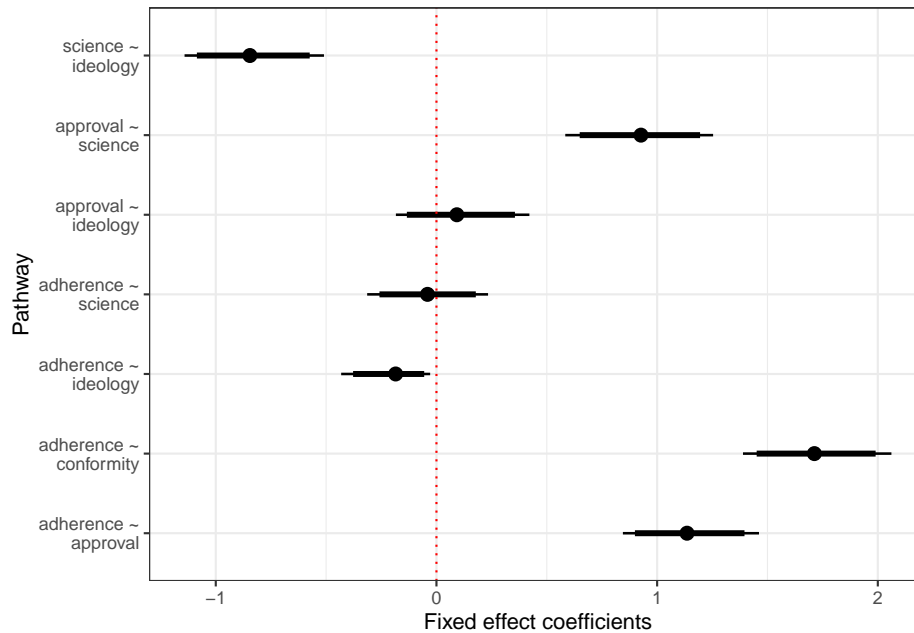


Fig. S7. A model with the same structure as the path model in the main text, except with the model family specified to be a zero one inflated beta regression (coefficients with 89% and 95% CIs).

(here, 100) to yield a response in the range $[0, 1]$, which is why we do not scale the predictors here (unlike in the main model).

To run such a model, we simply replace `family = gaussian` with `family = zero_one_inflated_beta()` in the model specification. The model (Fig. S7) does not substantially change our claims, except that there now appears to be a direct negative effect of ideology on adherence, such that conservatives were less likely to comply with distancing guidelines even after accounting for all the other factors.

4 Missing data

In the main text we described sources of missing data: participants who opted out of the question on political ideology, or participants who hadn't had a conversation with anybody in the preceding week. The analyses reported in the main text were for the complete dataset only. However, to examine whether excluding these data points would influence our conclusions, we additionally imputed missing data in two ways (once with an intercept-only model, and once with a model containing demographics — for full details of these models see the OSF link above). We then re-ran the path model described in the main text using both kinds of imputed data. Fig. S8 compares the coefficients for

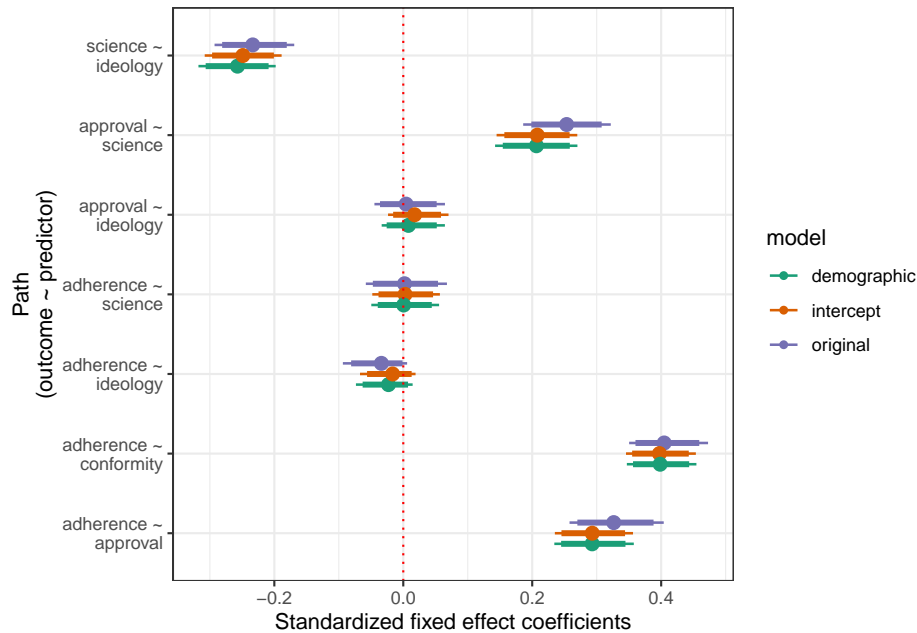


Fig. S8. A comparison of the coefficients from two models that had the same structure as the **original** path model in the main text, but that included imputation of missing data, using either an **intercept**-only imputation model or an imputation model that also included **demographics** (standardised coefficients with 89% and 95% CIs).

both imputation models with those from the original in the main text. Neither imputation method has affected our conclusions, though the estimates for some paths are slightly reduced.

5 National norms

Borgonovi and Pokropek (2020) report national trust norms based on data from an international survey (Wellcome Global Monitor, 2018), and Hale, Webster, Petherick, Phillips, and Kira (2020) provide indexes of the stringency of government responses to the pandemic, which we matched with our participants' reported countries of residence on the date of their participation in our survey.

We re-ran the path model in the main text including these national norms: Specifically, we added both of these norms as predictors of the outcome variables — science, approval and adherence. Fig. S9 shows that controlling for national levels of trust in science and stringency of pandemic prevention measures does not alter our conclusions about the role of trust in science.

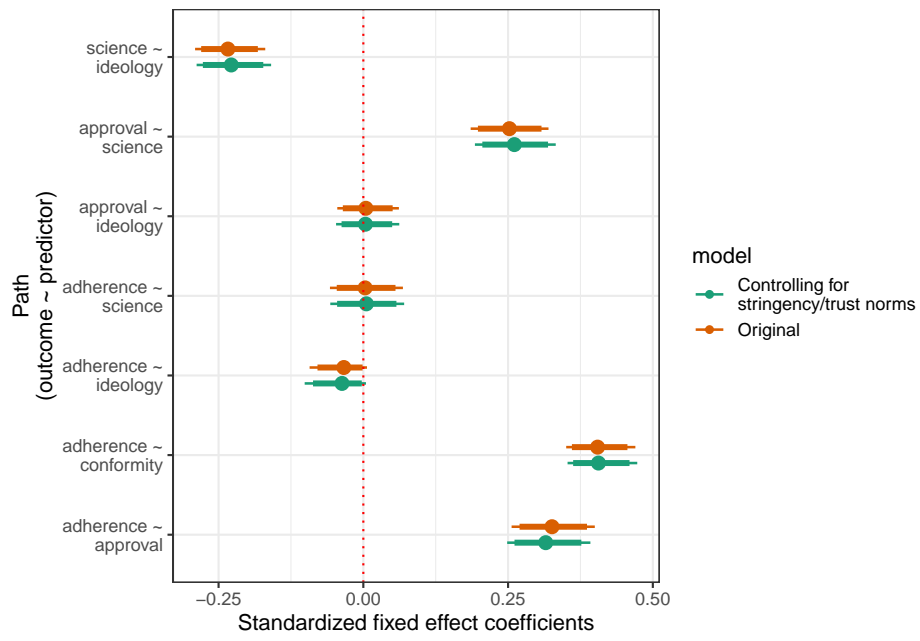


Fig. S9. A model including national trust in science norms as covariates, compared with coefficients from the original model reported in the main text (standardised coefficients with 89% and 95% CIs).

6 Unmeasured confound

We included a range of trust-relevant factors in our study, but in case some confound exists that we didn't measure, we wanted to check how strong that confound would have to be for our conclusions to alter (either for CIs that didn't overlap 0 in the main model to now overlap 0, or vice versa).

Full details of our procedure are available at the above OSF link, but briefly: We simulated a variable as defined in equation 1 below, where this simulated confound was related to the other variables in the model ($x_1 \dots x_n$) and where β is a parameter used to vary the strength of this relationship, and ϵ is random noise $\sim \text{Normal}(0,1)$.

$$\text{confound} = \beta * x_1 + \dots + \beta * x_n + \epsilon \tag{1}$$

We varied β in the range [0, 1]. For each level of the β parameter, we re-ran the path model including this confound variable (specifically, we included it as a predictor of each outcome variable: trust in science, approval, and adherence), where $\beta = 0$ corresponds to the original model, though with an additional source of random noise from ϵ in the above formula.

Fig. S10 shows how the model coefficients vary over a range of values of β , allowing us to see how strong the confound would have to be for our conclusions to alter. The full analysis at the OSF link above spells out in more detail how plausible the relevant (i.e., conclusion-altering) values of β are, but briefly, we do not consider them to be plausible (apart from the adherence \sim ideology pathway which has CIs excluding zero even for low values of β). For instance, the unmeasured confound would have to have a stronger relationship with trust in science than any other relationship trust has in our data, which seems unlikely.

7 Measurement error

These Bayesian models can account for measurement error by treating the *true* value of a variable as missing data, then imputing that value, and then using the imputed value in regressions where that variable is a predictor.

As we don't know how large the measurement error might be, we consider a range of values for the measurement error parameter (see the above OSF link for the implementation of this parameter). We starting by setting it to be the same size as the standard error of the predictors (which is 0.015 in our sample, as we scale all predictors to have the same SD). We then increase it by one order of magnitude (to 0.15), as well as considering an intermediate value (0.075). Fig. S11 shows how the measurement error parameters over this range result in slightly different coefficient sizes or CIs, but do not change any of our conclusions.

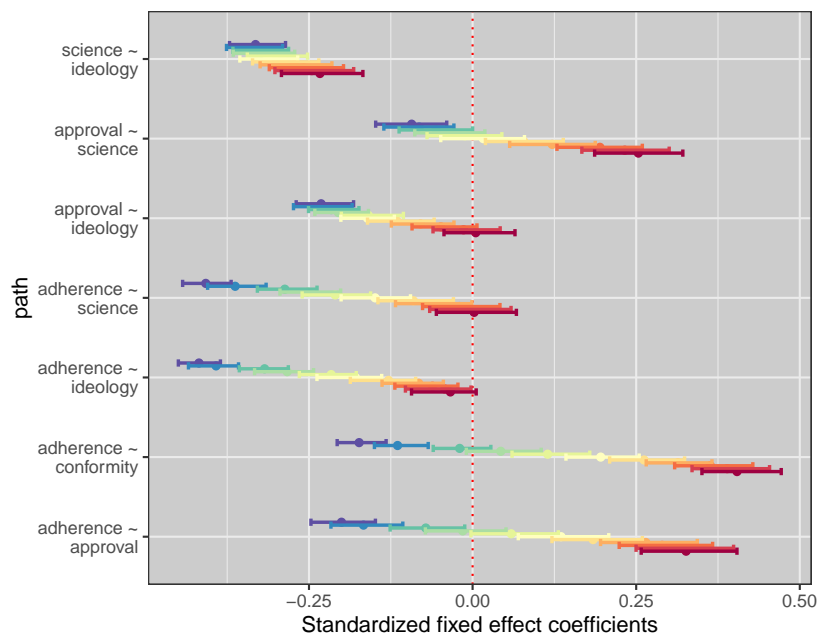


Fig. S10. The model coefficients varying according to the value of β , which we used to simulate an unmeasured confound of varying strength (standardised coefficients with 95% CIs).

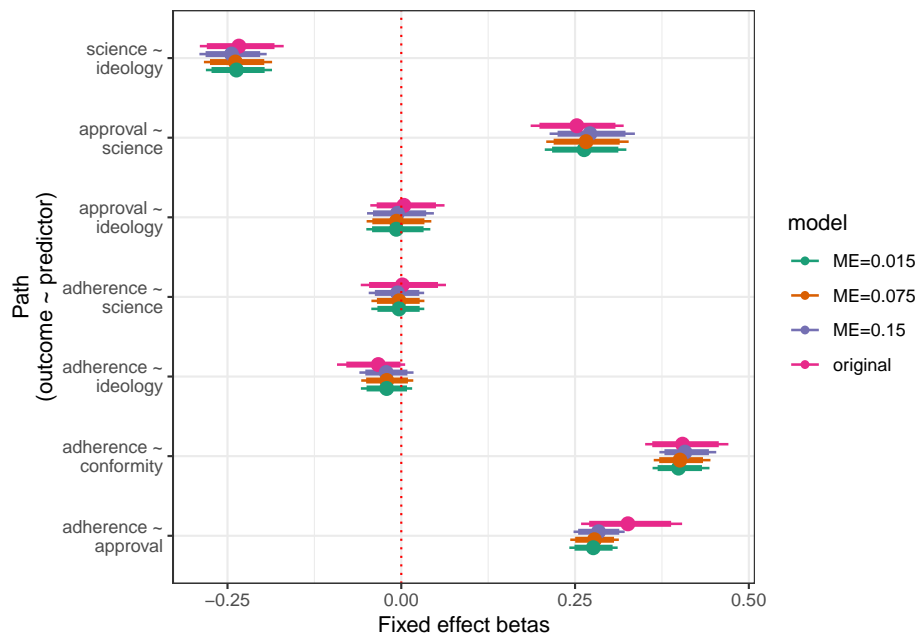


Fig. S11. The model fixed effects varying according to assumed level of measurement error (ME) ranging from ME=0.015 up to ME=0.15, as compared with the original model in the main text (standardised coefficients with 95% CIs).

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