Supplementary Materials: Does a Pandemic Increase Religiosity in a Secular Nation? A Longitudinal Examination

Anne Lundahl Mauritsen[1], Theiss Bendixen[1,*], Henrik Reintoft Christensen[1]

[a] *Department of the Study of Religion, Aarhus University, DK*

Overview

The Supplementary document is organized as follows. We discuss the promises and pitfalls of causal inference in a longitudinal design with missing data (Section S1), outline our statistical approach in more detail (Section S2), including the structure of our fully adjusted main model (Section S2.1), simple prior and posterior predictive checks of all models (Section S2.2), details on poststratification (Section S2.3) and imputation (Section S2.4). We then present supplementary results (Section S3) as well as a list of `R` packages, their dependencies, and version number used for the project (Section S4).

S1. Missingness assumptions

Missing data threaten the inferences that can be drawn from any analysis that aims to assess causal effects in observational data. Indeed, handling missing data is sometimes regarded as a special type of causal inference problem—and vice versa (e.g., Ding and Li, 2018; Mohan et al., 2013). For instance, in the context of the present longitudinal survey study, participants might drop out or choose not to respond to certain items non-randomly. A common approach for handling missing values is to retain only those cases for which a complete set of variables are available. Such complete-case analysis is justified under special circumstances, such as when the tendency for a variable to be missing is assumed to be unrelated with either relevant covariates (observed or unobserved) or the outcome. That is, when values are "missing completely at random" (MCAR; cf., Rubin, 1976; Little and Rubin, 2019). Although the validity of such an assumption ultimately depends on knowledge exogenous to the data at hand, scenarios where complete-case analysis yield unbiased estimates are generally considered rare. More realistic scenarios are where missingness are driven by either one or more covariates or the outome or both. Translated into the context of the present study, these scenarios would respectively entail: That one or more covariates cause missingness such that, for instance, participants' health, age, income, or education level influences their likelihood of completing a survey and/or that an individual's level of religiosity causes (non-)response. Beyond MCAR, a scenario in which only observed predictors cause missingness is the most benign case, and it is the one that we assume in our analysis (i.e., values are "missing at random", MAR). That is, we deem it unlikely that religiosity *per se* influences response rates (i.e., values would be "missing not at random", MNAR). Figure S1 illustrates this assumption by adding

[*]Corresponding author for the supplements: `tb@cas.au.dk` (Theiss Bendixen)

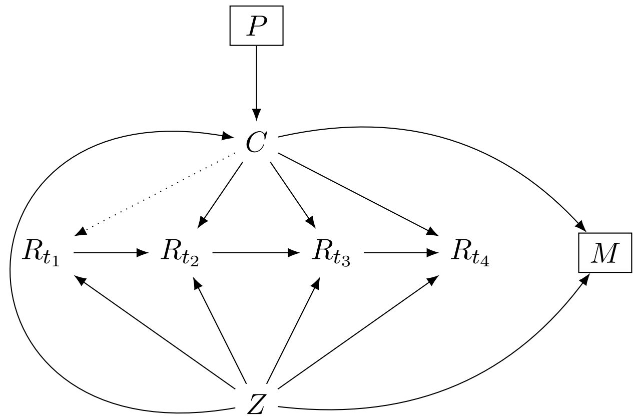

Figure S1: Directed acyclic graph (DAG) of the assumed causal structure of the data-generating process including a missingness indicator, M.

a missingness indicator M to the causal diagram of the main manuscript[1]. Here, missingness is caused by both the time-varying C and time-invariant Z covariates but not the outcome R. The missingness indicator M is boxed to illustrate that the data is conditional on the missing data (see Schuessler and Selb, 2019). Under this causal structure, M is a "collider" that when conditioned on will open non-causal paths to R through C and Z, which in turn induce bias in the estimate of R. In the main manuscript we discuss in detail how we address the challenges of missingness and causal inference in the present study, namely by fitting models that include versus exclude covariates, employing full Bayesian imputation of missing covariates, and poststratification. We now turn to a walk-through of our main statistical model.

S2. Statistical analysis

S2.1. Model structure

To assess the change in religiosity across time points and covariates, we apply a series of Bayesian multilevel models of varying complexity. Here, we provide details on our fully adjusted model (model `m1`) as all other main models are variants thereof.

In a multilevel model, the estimate of each cluster (in our case, individual participants j) is informed by all other clusters, known as "partial pooling". This is essential in settings where each cluster have few data points, such as the present study where data were collected in four waves yielding a maximum of just four sets of data points per individual. All models further take the form of an ordinal regression as our outcome variable was measured using a $1-4$ response scale

[1]Our DAGs could be expanded in a number of ways. First, both sets of covariates could be split up into its constituent parts. Second, the time-varying covariates C could further be split up into nodes denoting each covariate at T_{1-4}, as with the religion R nodes. Third, the missingness indicator M specifically represents missingness due to non-response, but could be split up into additional nodes denoting missingness processes at various stages of the study, including the "coverage stage" (e.g., who are available for sampling?) and the "sampling stage" (e.g., who are actually sampled?) (see Schuessler and Selb, 2019). Finally, unobserved confounders could be added to a practically endless level of detail. However, we leave out these complications for ease of visualization.

(Bürkner and Vuorre, 2019; Liddell and Kruschke, 2018). In notational form, our fully adjusted main model thus takes the following structure for each individual observation, i:

$$\text{Religiosity}_i \sim \text{Ordered-logit}(\phi_i, \kappa)$$

where ϕ is a linear model of predictors and κ is a vector of random thresholds (also known as cut-points) with length three, the number of outcome response options minus 1. The multilevel linear model is given by:

$$\phi_i = \beta_{W_{j[i]}} W_i + \beta_E E_i + \beta_H H_i + \beta_S S_i + \beta_A A_i + \beta_G G_i + \beta_{WH} W_i \times H_i + \beta_{WS} W_i \times S_i$$

where the subscript $j[i]$ denotes the j^{th} unique participant for the i^{th} observation, allowing participants to have varying intercepts and slopes across time, W. We treat the time-invariant covariates (age A, gender G, education E) as fixed effects and each of the time-varying covariates (household income H, subjective health S) as interacting (denoted by $\times$) with the time variable W[2], while also including their simple main effects. We model ordinal covariates (education, household income, subjective health) and time (due to uneven lengths of time between measurement points) as monotonic (Liddell and Kruschke, 2018), such that a covariate's β coefficient represents the expected average difference between two adjacent categories (Bürkner and Charpentier, 2020). We assume equal variances throughout[3]. Age was sample-mean centered. For ordinal covariates, the reference category was set at their middle response value and for gender, woman was the reference category.

We define our priors, which we checked through iterative cycles of prior predictive simulation (see Section S2.2), as follows. The thresholds κ are modeled with Normal$(0, 10)$, all β coefficients with Normal$(0, 0.5)$, and all monotonic covariates with a Dirichlet distribution with α denoting a series of 2's equaling the number of response options minus 1 (e.g., for education there are six levels, so $\alpha = \{2, 2, 2, 2, 2\}$). The Dirichlet prior encodes the expectation that any of the response options could be more or less likely than the others (McElreath, 2020, p. 392-394). Overall, the specified set of priors is weakly regularizing.

S2.2. Prior and posterior predictive simulation

A prior predictive check is a way to assess the predictions of the model before having fit the model to data. Here, we employ weakly regularizing priors that allow for a broad range of parameter values while being skeptical toward very strong relationships. Posterior predictive checks, on the other hand, are evaluations of the fit between the model and (some aspects of) the data after model fitting. Figure S2 contrasts a prior predictive check (top) to a posterior predictive check (bottom) of `m0`. The blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted proportions of each outcome response option grouped by wave. Horizontal lines are 95% credible intervals. The changes in point estimates and intervals from the prior to the posterior predictions are an indication of the extent to which

[2]For a general discussion on how to model time-varying covariates in longitudinal designs, see Singer and Willett (2003). For a Bayesian implementation of Singer and Willett (2003), see Kurz (2021).

[3]Allowing unequal variances tended to make the models less stable in terms of sampling efficiency and chain convergence but yielded qualitatively similar inferences.

the model has learned from the data. Since the posterior predictive intervals mostly include the observed proportions, we regard the fit as reasonable[4].

In the following Figures S3 – S7, we present similar prior and posterior check plots for all main model specifications (cf., Table 2 in main manuscript).

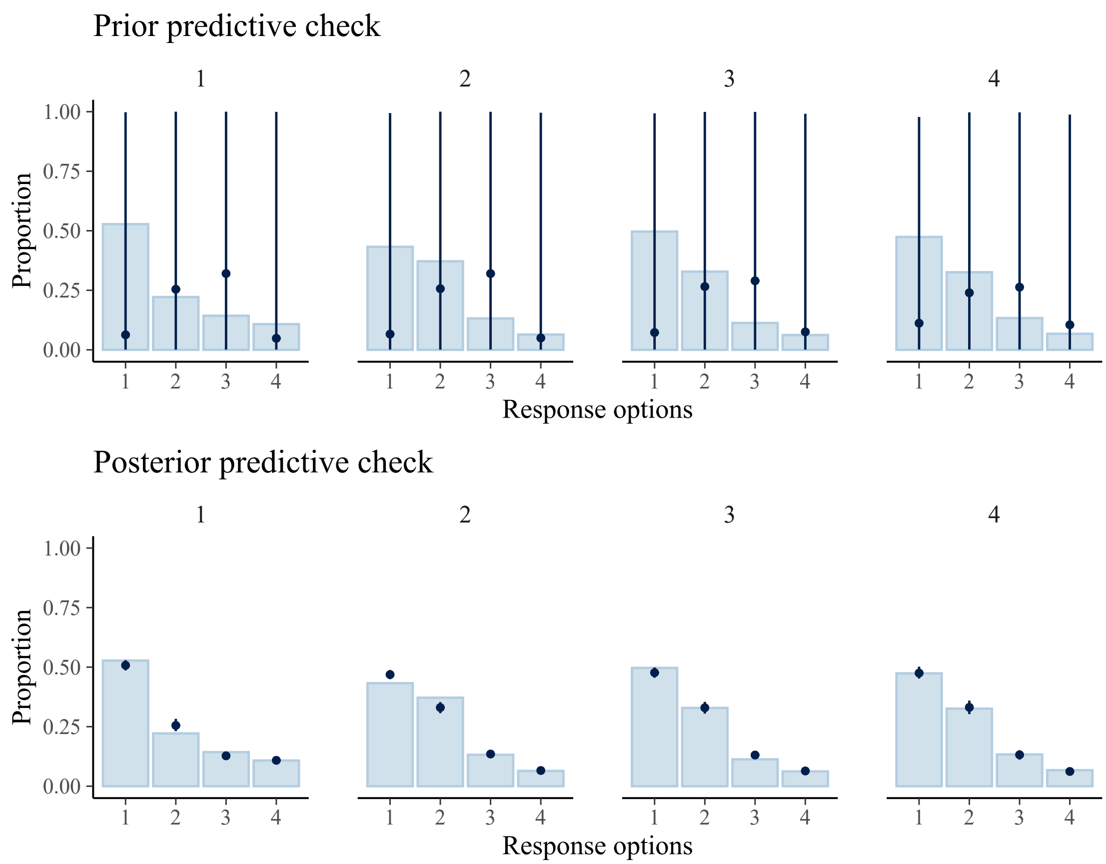

Figure S2: **Model `m0`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted proportions of each outcome response option grouped by wave. Lines are 95% credible intervals.

[4]In Bayesian statistics, intervals such as the 95% "credible intervals" used throughout have an intuitive interpretation; that is, X% of the data (or parameter estimates) are within the X% interval. Whether the resulting intervals are, in fact, "credible" is not directly verifiable but depends on the model, data, and exogenous information. Others prefer the term "compatibility intervals" on the grounds that it more precisely captures the inferential allowances. That is, the intervals represent a range of values that are compatible with the data and model (McElreath, 2020). Here, however, we follow convention and refer to intervals as "credible intervals".

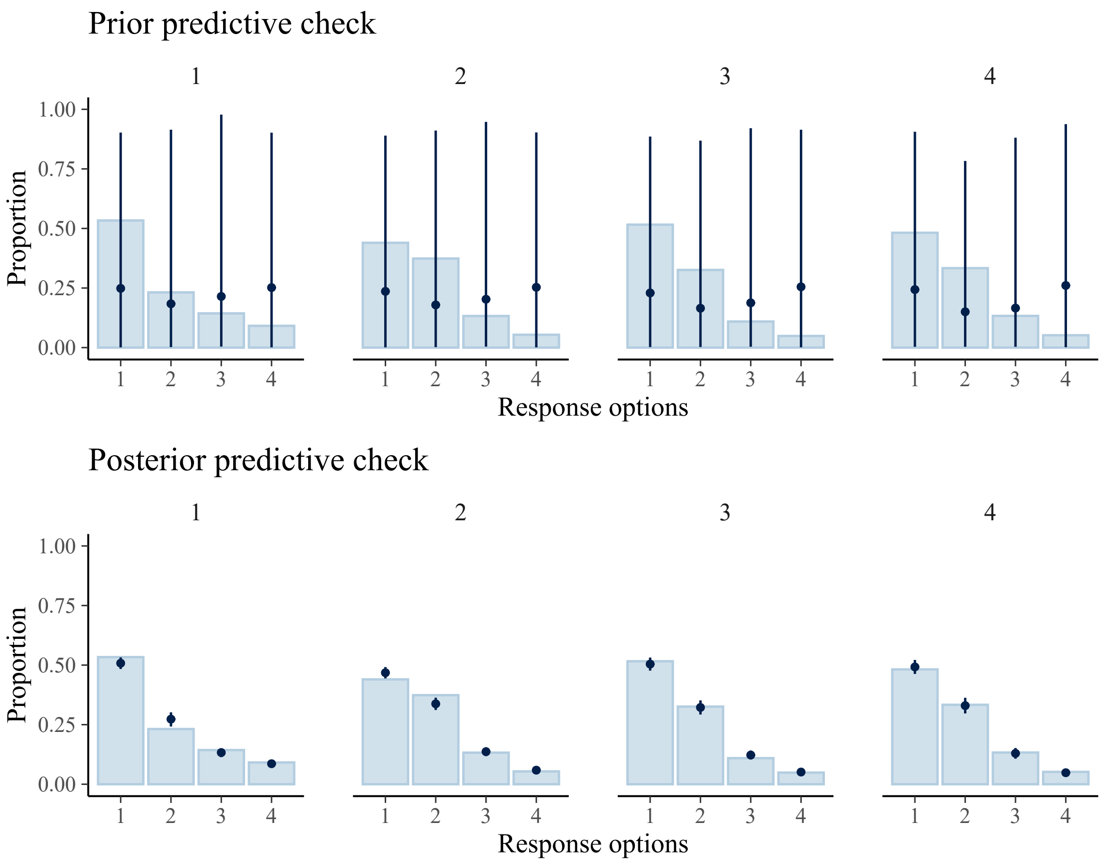

Figure S3: **Model `m1`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is “not at all important”) to 4 (religion is “very important”). Points are prior (top panel) and posterior (bottom panel) means of the predicted proportions of each outcome response option grouped by wave. Lines are 95% credible intervals.

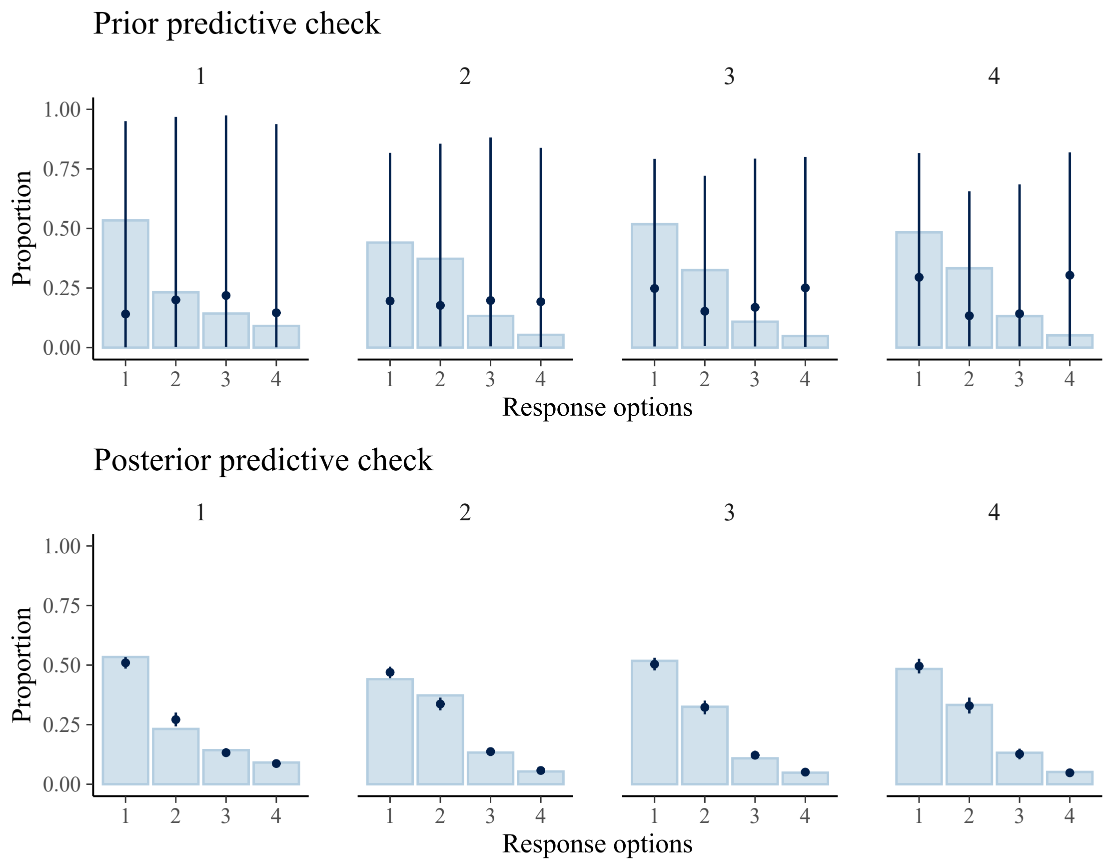

Figure S4: **Model `m_hinc`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted proportions of each outcome response option grouped by wave. Lines are 95% credible intervals.

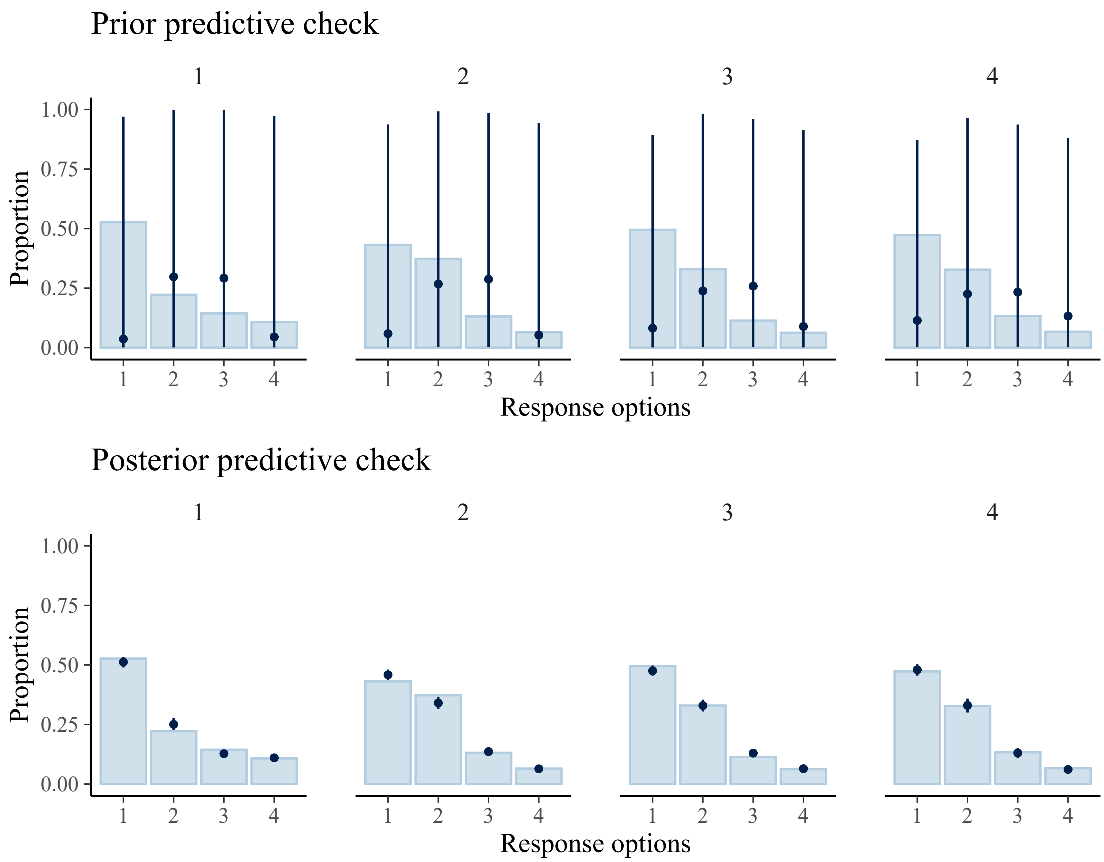

Figure S5: **Model `m_health`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted proportions of each outcome response option grouped by wave. Lines are 95% credible intervals.

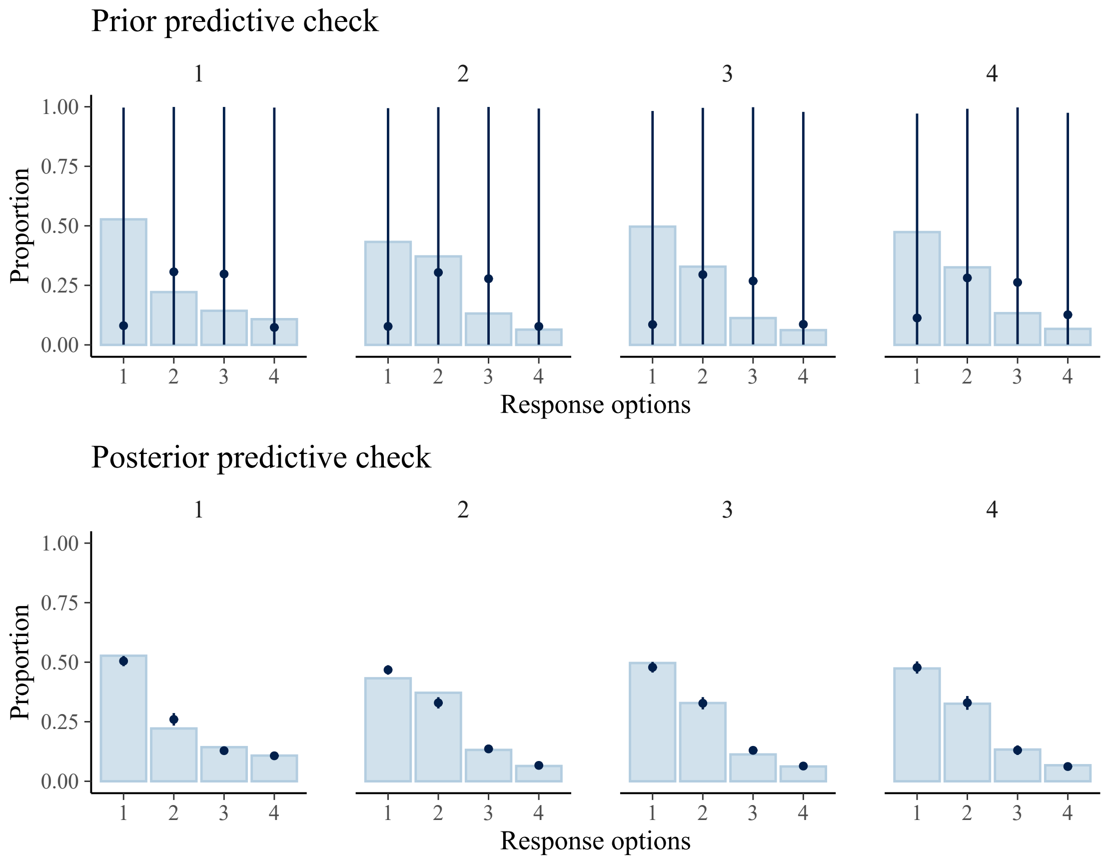

Figure S6: **Model `m_mrp`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted proportions of each outcome response option grouped by wave. Lines are 95% credible intervals.

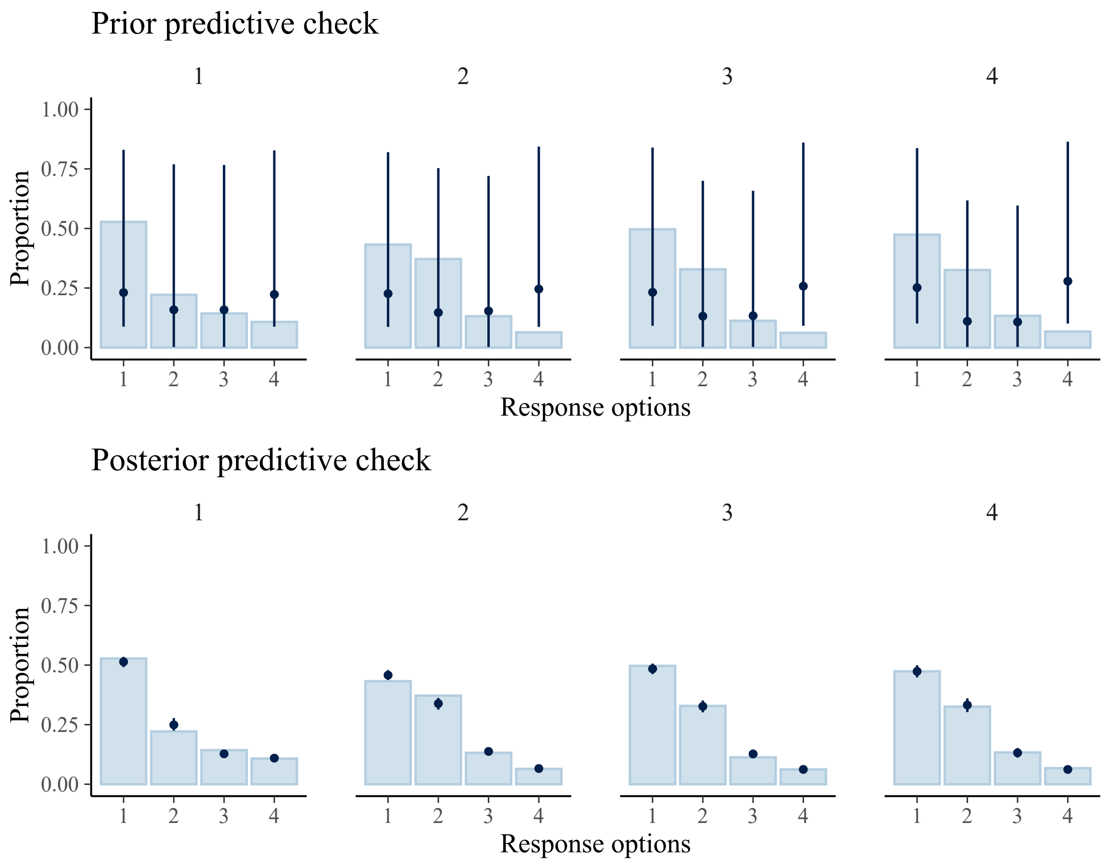

Figure S7: **Model `m1_imp`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted proportions of each outcome response option grouped by wave. Lines are 95% credible intervals.

S2.3. Poststratification

Poststratification is a statistical adjustment technique that aims to generalize estimates from a non-representative sample to a population of interest (Kennedy and Gelman, 2021; Little, 1993). This is done by fitting a multilevel model on the sample including variables for which external, representative data can be accessed (e.g., census data). These external data are then used to re-weigh the fitted model's posterior predictions. Here, we obtained external data on educational levels by age and gender for the greater Danish population through Eurostat[5]. These external data are binned in age groups that do not completely overlap with the age range of our sample. To achieve maximal coverage of age groups while retaining reasonable (i.e., not too large, not too small) bin sizes with externally available age ranges, we chose data for age groups 15-24, 25-49, and 50-74 years. Further, we binned educational levels of our sample to be consistent with the external data, which follows the International Standard Classification of Education (ISCED11): Less than primary, primary and lower secondary education (levels 0-2), upper secondary and post-

[5] https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=lfsa_pgaed

secondary non-tertiary education (levels 3 and 4), and tertiary education (levels 5-8). Available gender categories are female and male. All data are from 2021. Table S1 presents the obtained poststratification table in its entirety.

We fit a multilevel model with varying intercepts for these binned variables along with varying effects of individuals across measurement waves. We specify varying intercepts for the demographic variables to make use of partial pooling of information across categories, which improves estimates of cells (i.e., combination of covariates) with low sample sizes. We then use the externally obtained proportion of individuals in each cell to poststratify the model's posterior predictions with 300 draws for each cell and wave[6]. As such, the resulting poststratified posterior predictions are adjusted to the greater Danish population for the included variables.

Figure S8 compares model predictions from poststratification model `m_mrp` against the unadjusted model `m0`. Results are qualitatively similar, likely due to the fact that the demographic variables had little association with religiosity in the present data.

Gender	**Age**	**Education**	***N***
Female	From 15 to 24 years	Levels 0-2	188300
Female	From 15 to 24 years	Levels 3-4	138300
Female	From 15 to 24 years	Levels 5-8	17200
Female	From 25 to 49 years	Levels 0-2	117400
Female	From 25 to 49 years	Levels 3-4	288400
Female	From 25 to 49 years	Levels 5-8	498600
Female	From 50 to 74 years	Levels 0-2	221500
Female	From 50 to 74 years	Levels 3-4	370200
Female	From 50 to 74 years	Levels 5-8	308000
Male	From 15 to 24 years	Levels 0-2	217200
Male	From 15 to 24 years	Levels 3-4	125200
Male	From 15 to 24 years	Levels 5-8	14700
Male	From 25 to 49 years	Levels 0-2	160900
Male	From 25 to 49 years	Levels 3-4	387500
Male	From 25 to 49 years	Levels 5-8	370700
Male	From 50 to 74 years	Levels 0-2	211700
Male	From 50 to 74 years	Levels 3-4	426000
Male	From 50 to 74 years	Levels 5-8	245200

Table S1: **Poststratification table**. N is the (estimated) number of individuals with the given combination of gender, age, and education in the general Danish population obtained via `https://ec.europa.eu/eurostat`.

[6] One way to improve our poststratification procedure would be to assign or obtain uncertainty for the external data, which are themselves statistical estimates of the greater population.

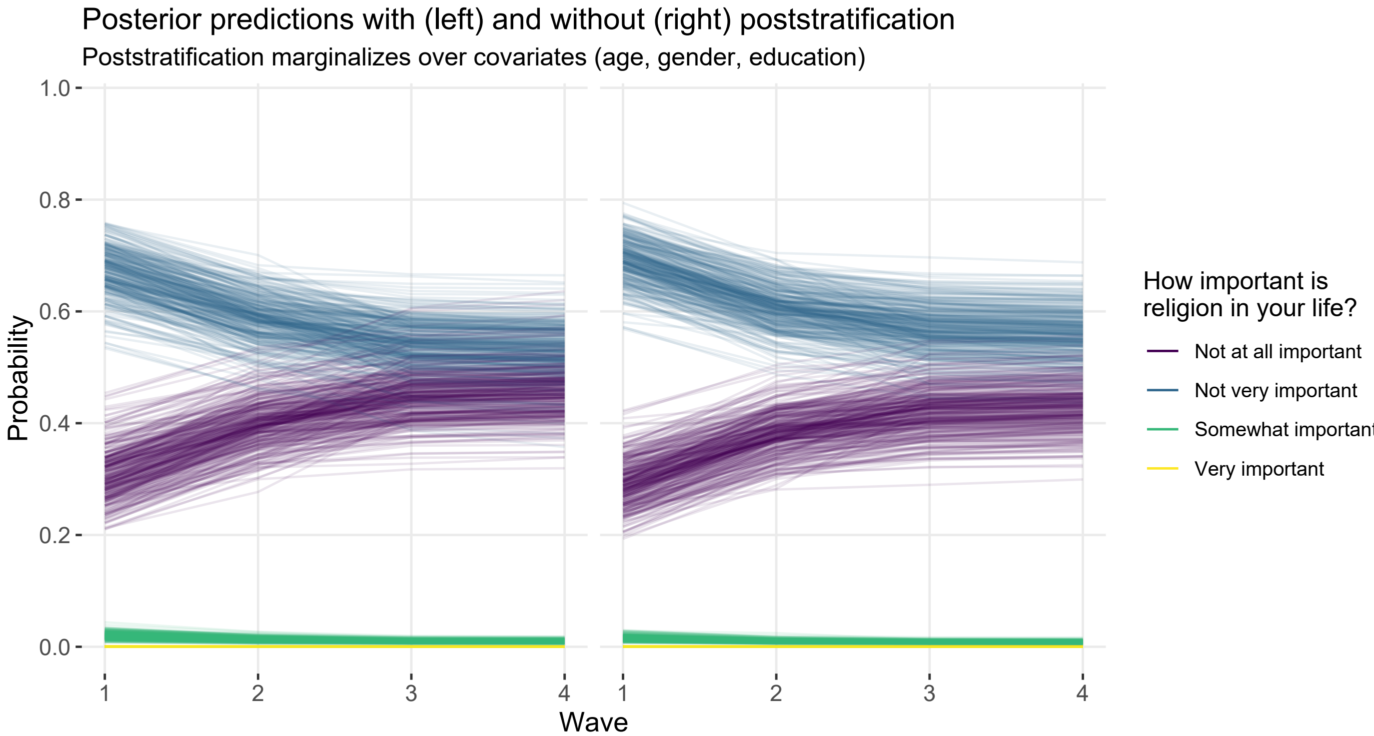

Figure S8: **Poststratification: Predicted probabilities across measurement waves for each response option**. Poststratification model `m_mrp` (left) vs. the unadjusted model `m0`. Lines are posterior predictive draws.

S2.4. Imputation of missing values

Full Bayesian imputation is arguably the most principled approach to handling missing values (e.g., Erler et al., 2016, 2019a; McElreath, 2020, ch. 15). However, with `Stan` (and therefore `brms`) it is not (yet) possible to straightforwardly impute categorical variables. Therefore, in the imputation model `m1_imp`, we model categorical covariates as metric. We specify a joint distribution of observed and missing data, based on the assumed data-generating process (cf., Figure 1 in main manuscript), ensuring that missing values are informed by relevant covariates, and we constrain the imputed values to be within realistic ranges. The imputation model otherwise takes the same form as model `m1`.

Figure S9 shows the cumulative probabilities across measurement waves for each response option for men (left) and women (right) as predicted by the imputation model with covariates at their observed/imputed values. In cases of missing data, we get predictions at the mean of the imputed values. While not identical, results are similar to other adjusted model specifications.

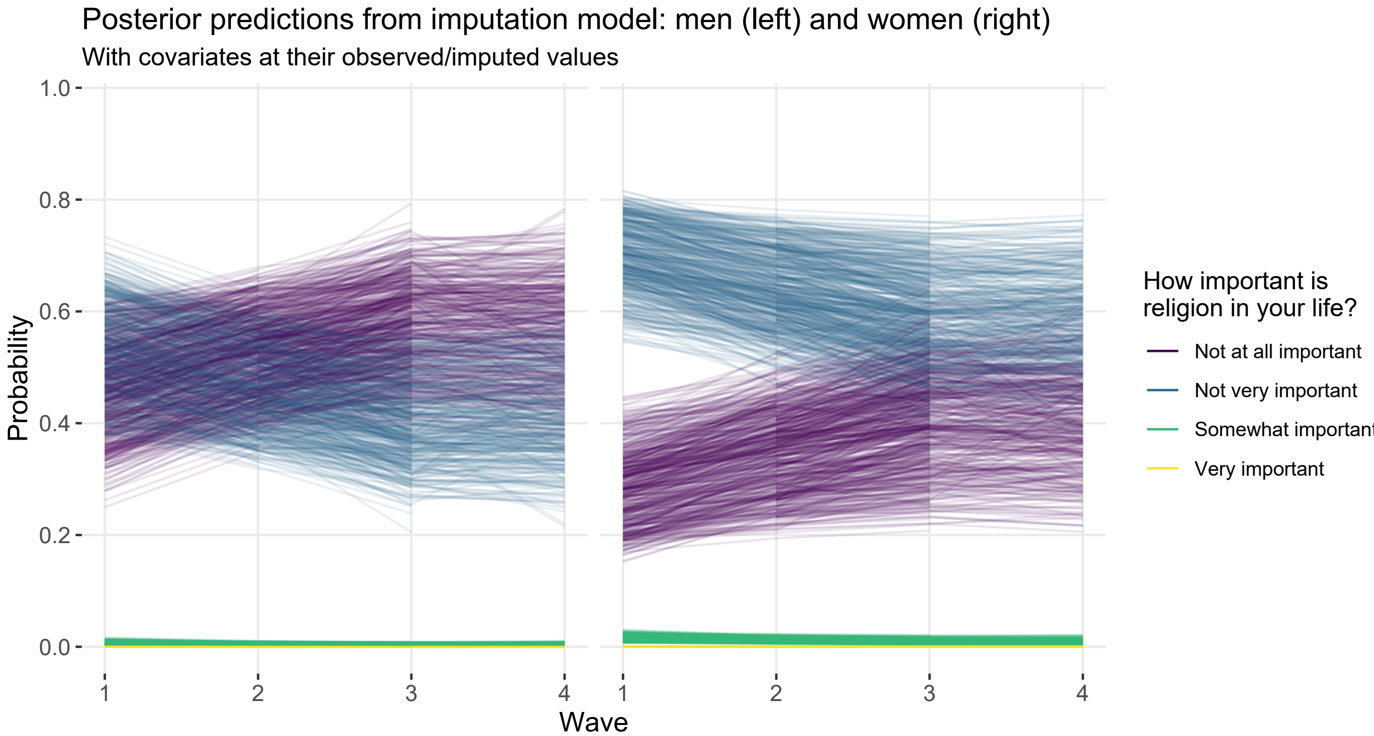

Figure S9: **Imputation model `m1_imp`: Predicted probabilities across measurement waves for each response option**. For men (left) and women (right) with covariates at their observed/imputed values. Lines are posterior predictive draws. Random effects not included in predictions.

S3. Supplementary results and plots

Here, we report supplementary plots.

In the main manuscript, we plot predictions from model `m1` with categorical covariates set at their reference values and age set at 0 (as it is mean-centered). Figure S10 is an alternative to this figure, in that we instead simulate predictions for the observed values

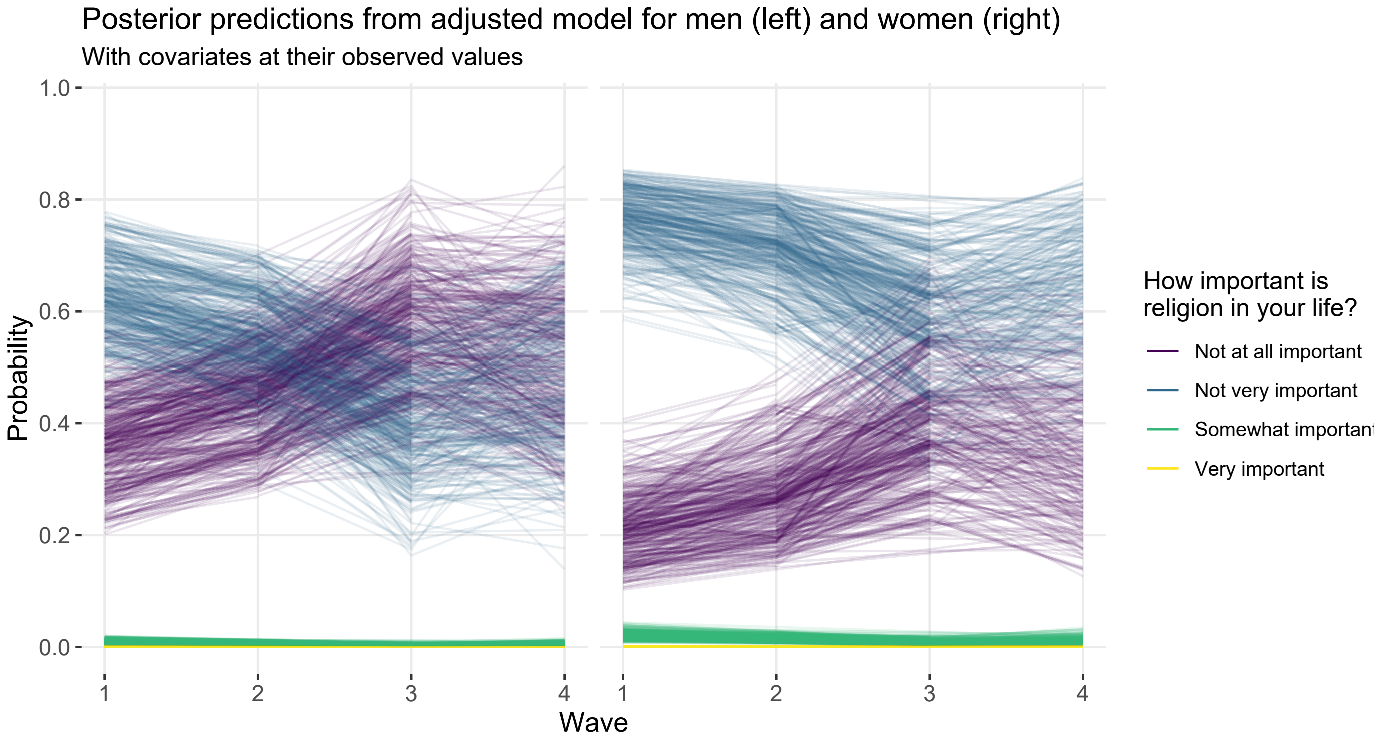

Figure S10: **`m1` at observed covariate values: Predicted probabilities across measurement waves for each response option**. For men (left) and women (right) with categorical covariates set at their observed values. Lines are posterior predictive draws. Random effects not included in predictions.

Figure S11 compares predictions from the two unadjusted models: listwise deletion model `m0` and complete-cases model (`m0_complete`). Figure S12 shows predictions from the complete-cases model `m1_complete`. Although model predictions differ in their "effect sizes" – i.e., how much/little religiosity changes over time – they all tell the same story (cf., the main manuscript): the lowest response option (i.e., purple lines; religion is "not at all important") becomes more probable and the second-lowest response option (i.e., blue lines; religion is "not very important") becomes less probable, while the probability of the higher response options remain low and relatively unchanged.

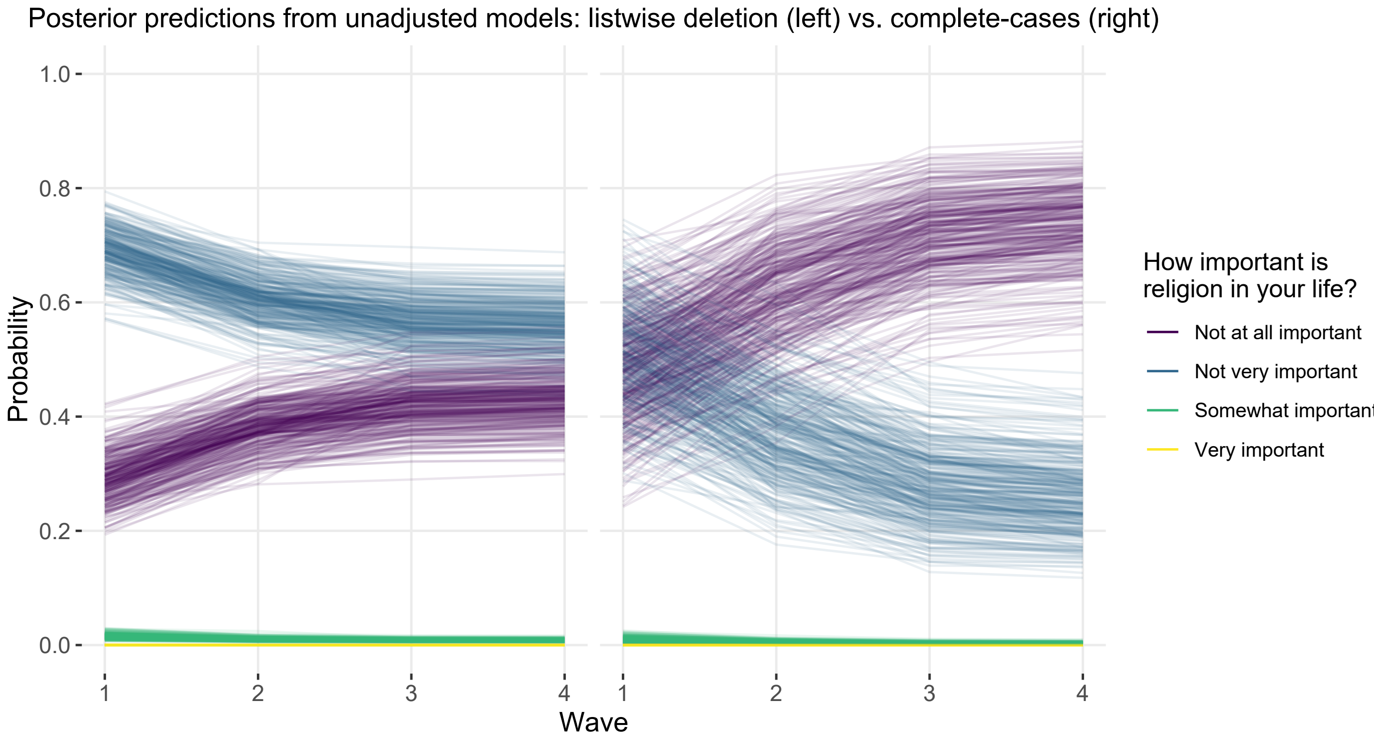

Figure S11: **Unadjusted models: Predicted probabilities across measurement waves for each response option**. For listwise deletion model `m0` vs. complete-cases model (`m0_complete`). Lines are posterior predictive draws. Random effects not included in predictions.

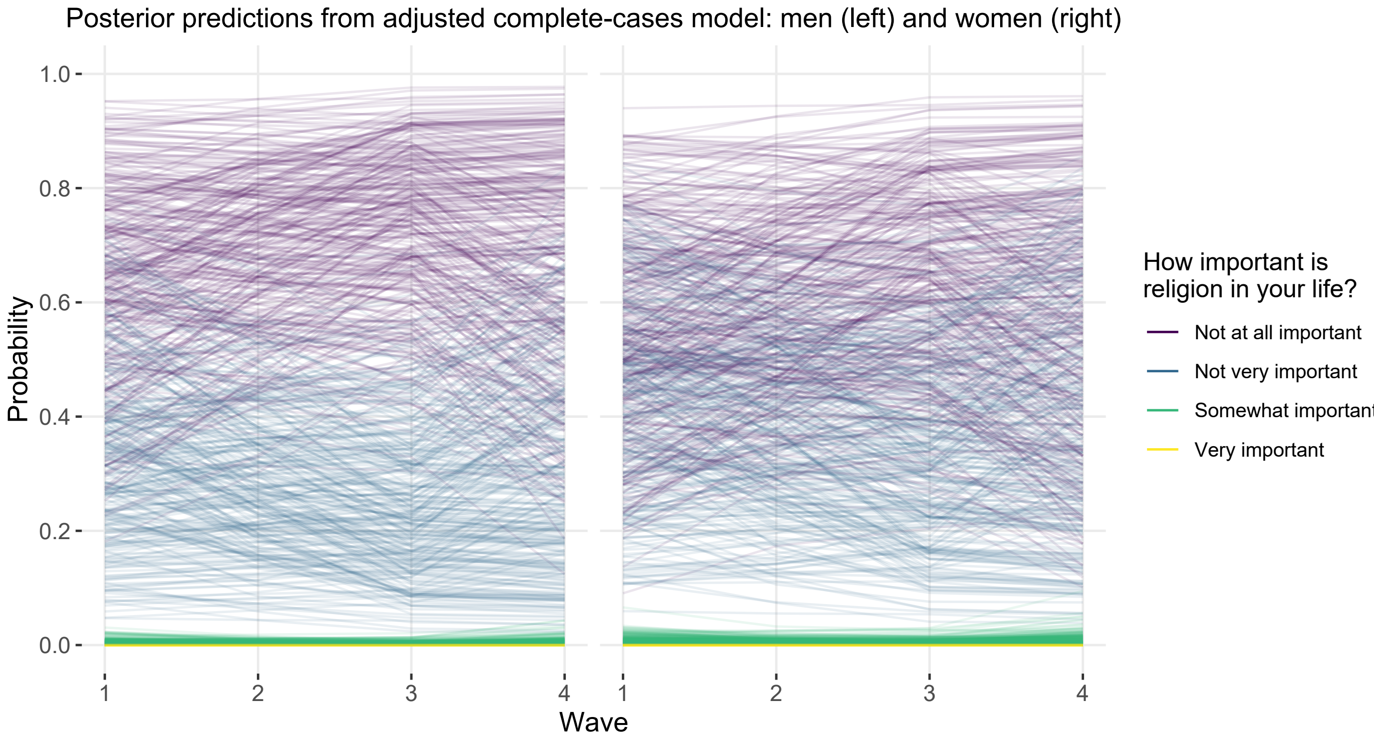

Figure S12: **Complete-cases model `m1_complete`: Predicted probabilities across measurement waves for each response option**. For men (left) and women (right) with categorical covariates set at their reference values and age set at 0 (as it is mean-centered). Lines are posterior predictive draws. Random effects not included in predictions.

Figure S13 shows predictions from `m_hinc`, where we interacted household income with time but included no other covariates. Thick lines are posterior medians and bands are 95% credible intervals. There's little to no interaction effect, according to this plot (consistent with our inspection of raw coefficients; see Table 3 in main manuscript). Likewise, Figure S14 shows predictions from `m_health`, where we interacted self-reported health with time but included no other covariates. There's a hint of an interaction effect according to this plot, which is again consistent with our inspection of raw coefficients; see Table 3 in main manuscript.

Finally, Figures S13 – S18 show interaction plots of our alternative operationalization of pandemic exposure. Each of these models interact a measure of pandemic exposure (self, household, family, and relations, respectively) with time but include no other covariates. Again, there's little evidence for a pronounced interaction effect. Note the very wide uncertainty intervals; this is due to the fact that very few people in our sample reported being "very ill" or "hospitalized" with the virus.

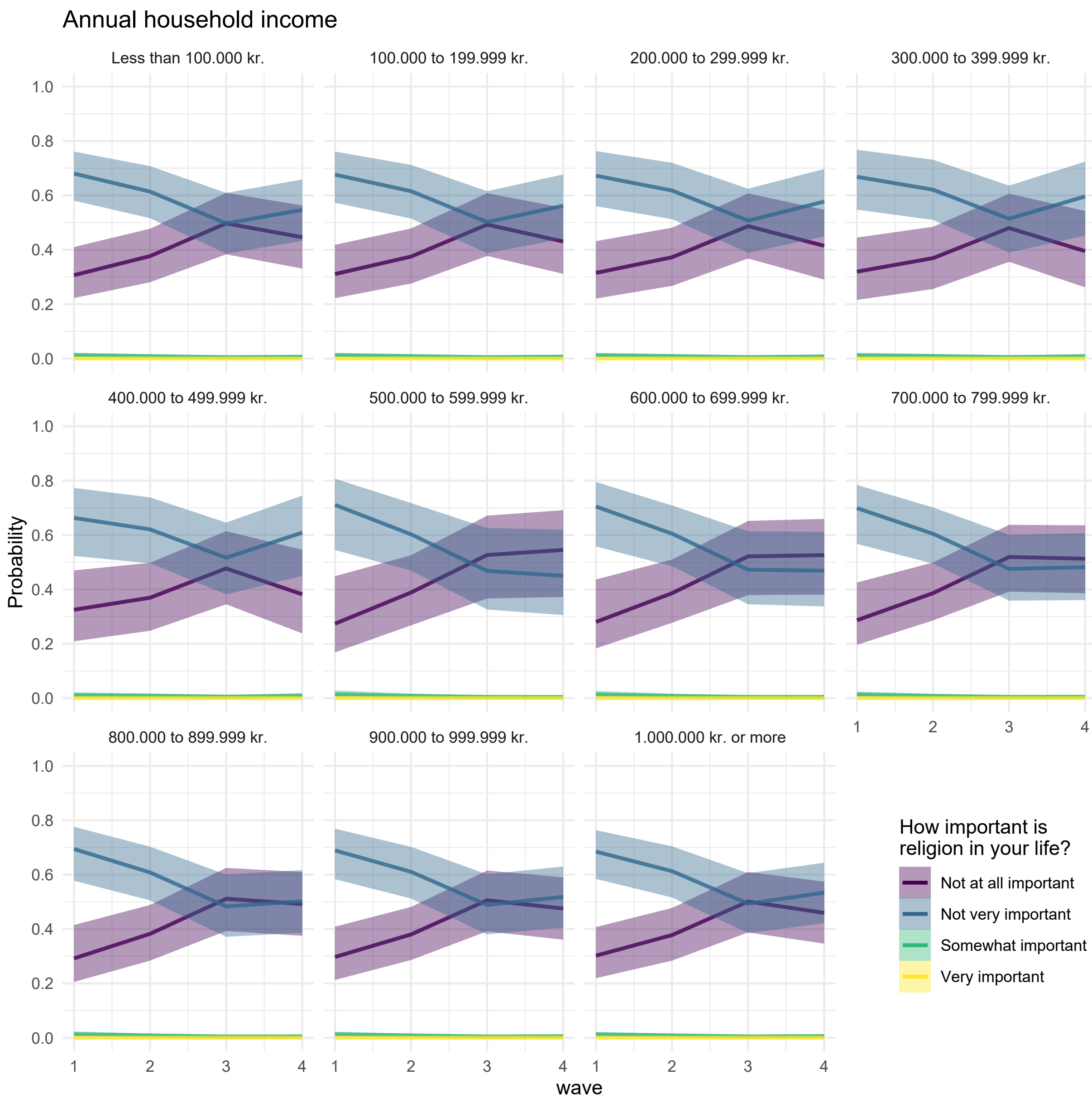

Figure S13: **Interaction plot** `m_hinc`: Predicted probabilities for each response option across measurement waves and income levels. Thick lines are posterior medians and bands are 95% credible intervals.

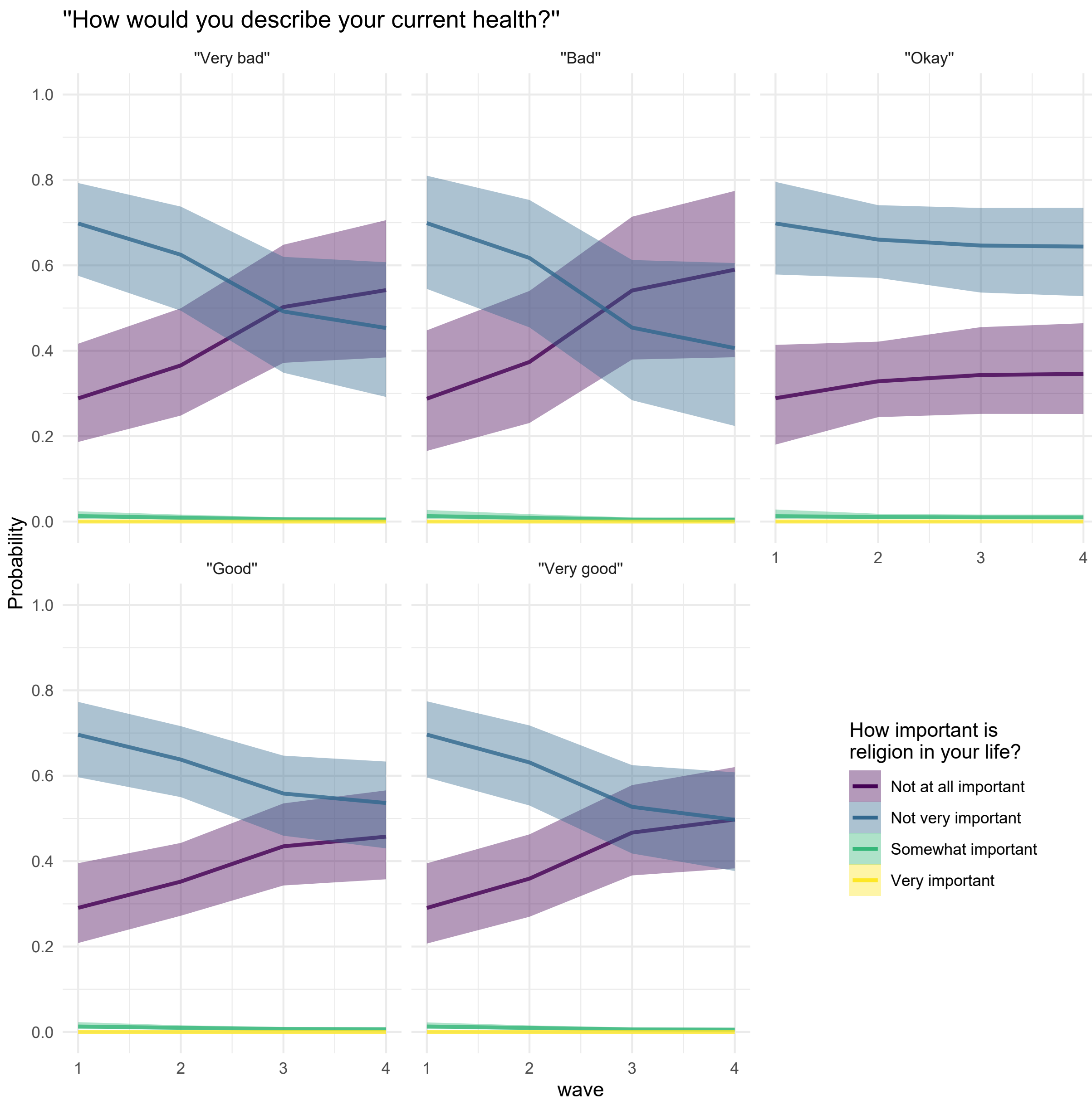

Figure S14: **Interaction plot `m_health`**: Predicted probabilities for each response option across measurement waves and self-reported health. Thick lines are posterior medians and bands are 95% credible intervals.

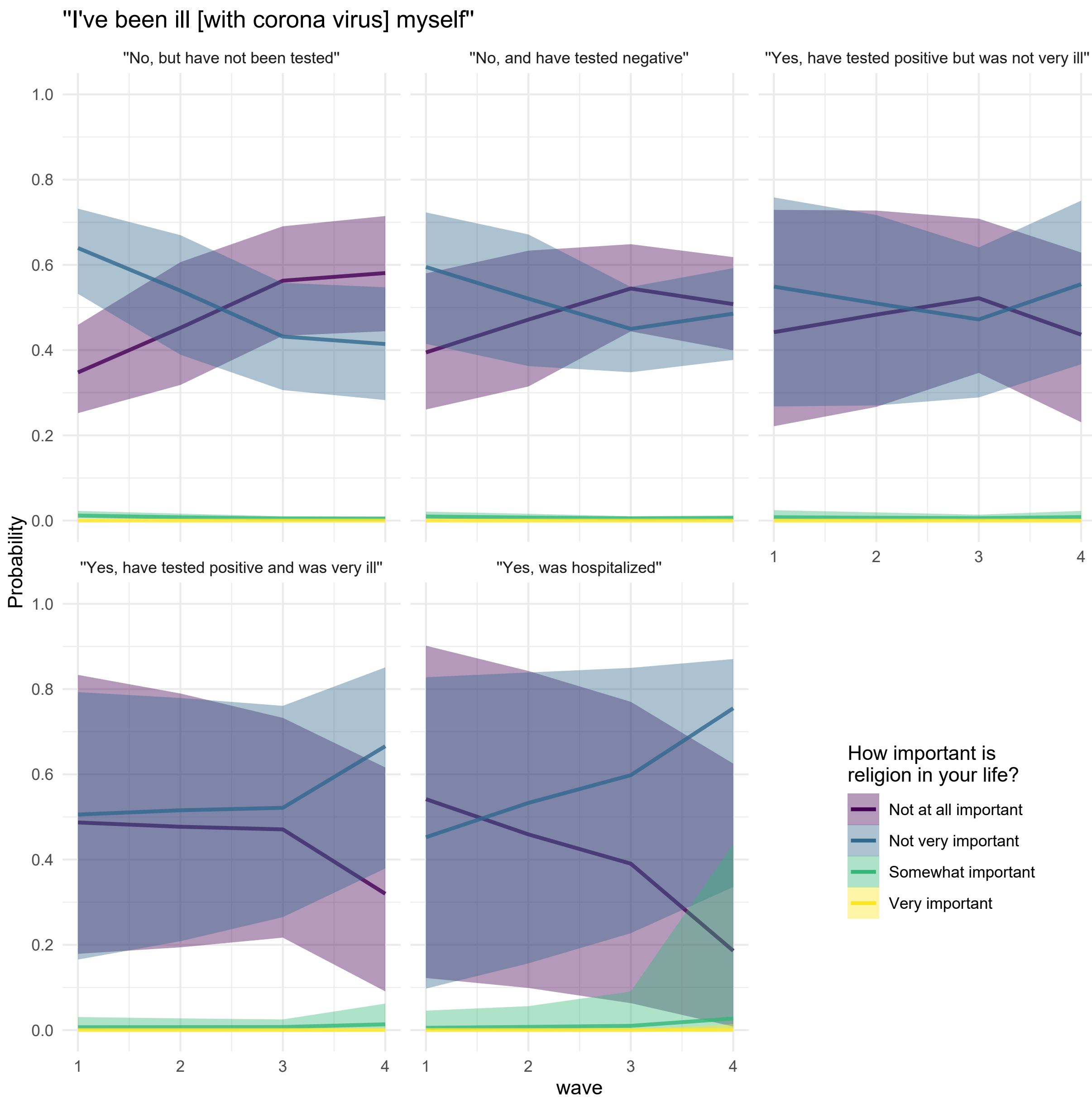

Figure S15: **Interaction plot `m_self`**: Predicted probabilities for each response option across measurement waves and self-reported exposure to corona virus. Thick lines are posterior medians and bands are 95% credible intervals.

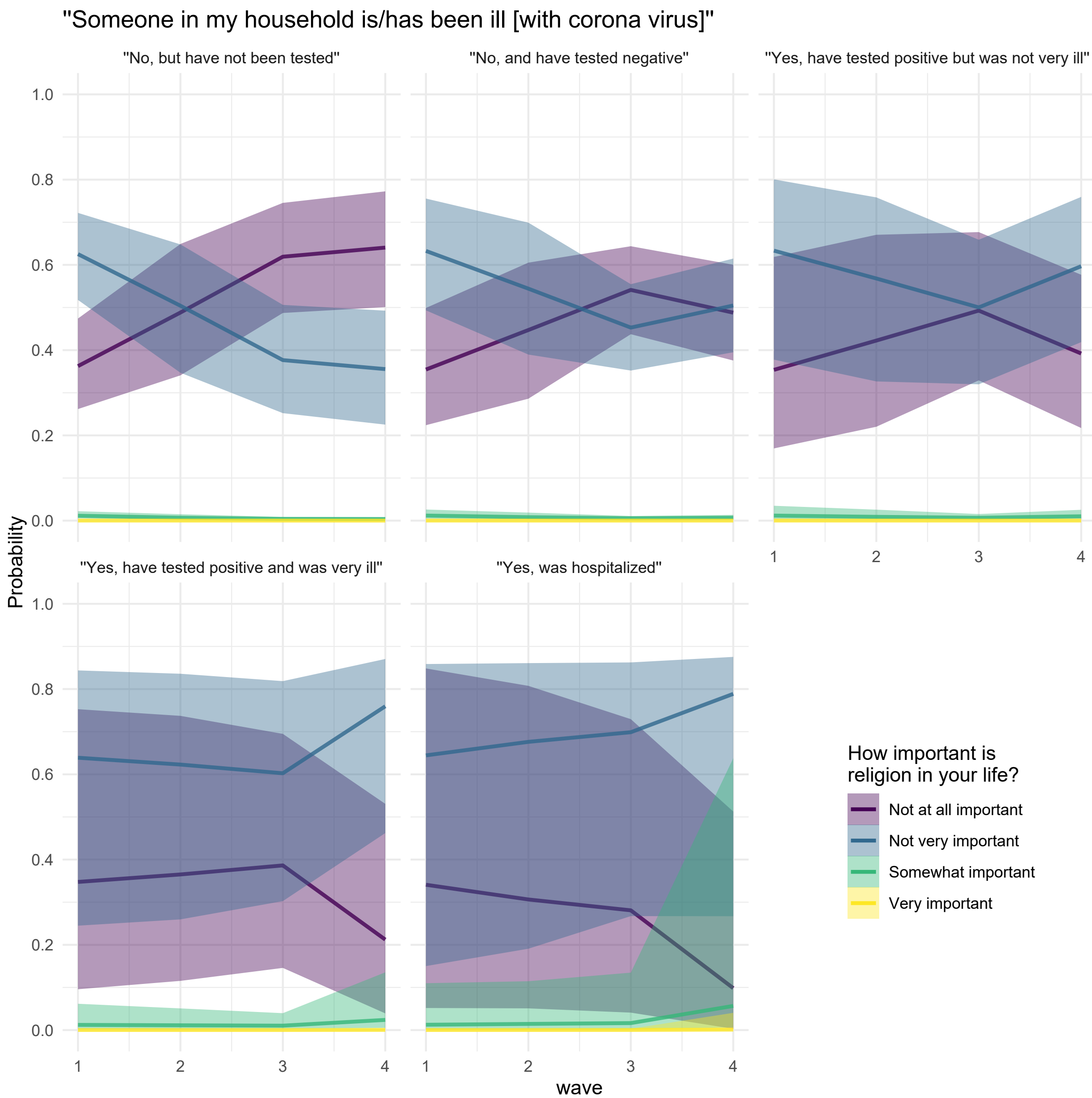

Figure S16: **Interaction plot `m_household`**: Predicted probabilities for each response option across measurement waves and self-reported exposure to corona virus. Thick lines are posterior medians and bands are 95% credible intervals.

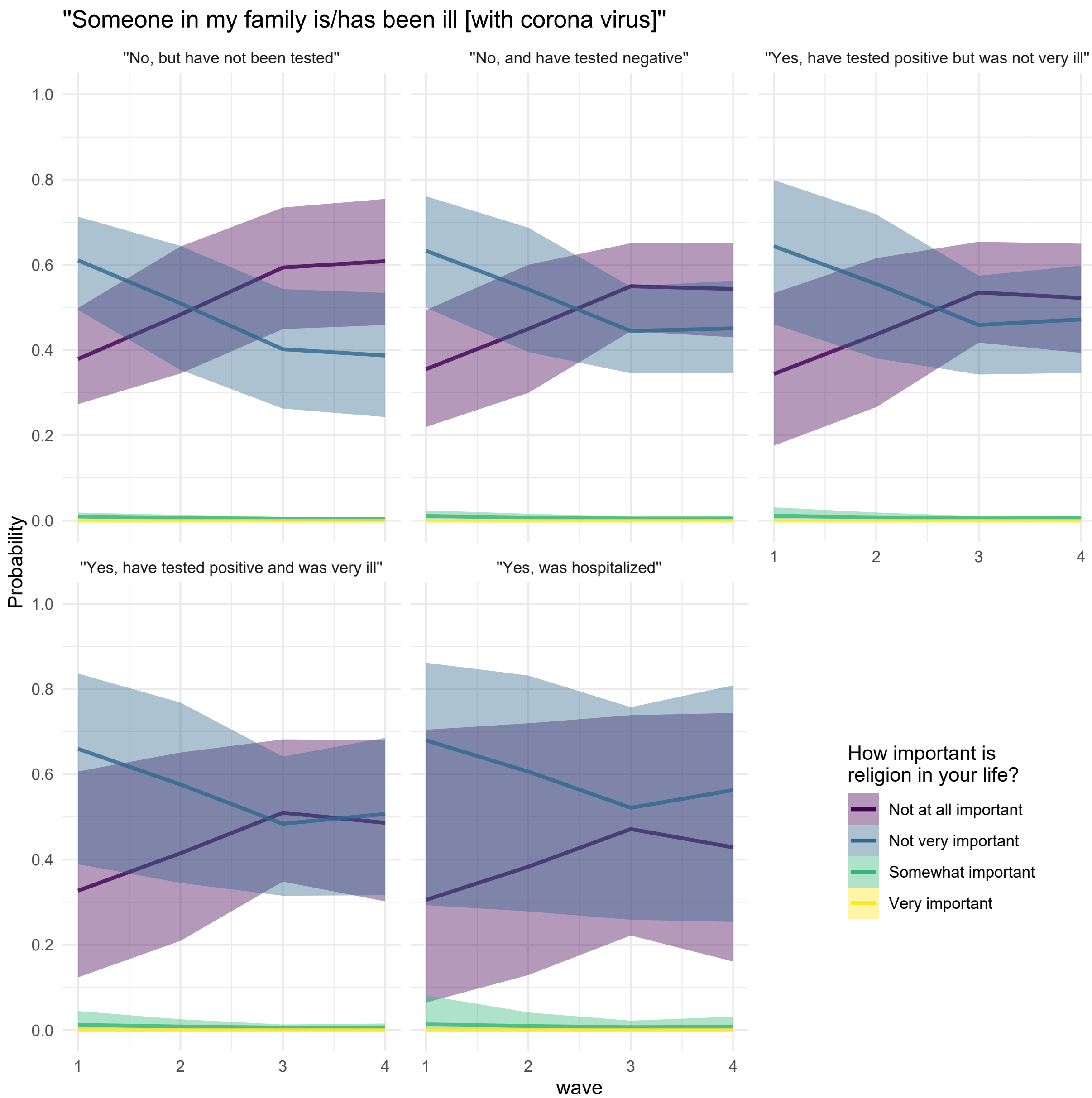

Figure S17: **Interaction plot `m_family`**: Predicted probabilities for each response option across measurement waves and self-reported exposure to corona virus. Thick lines are posterior medians and bands are 95% credible intervals.

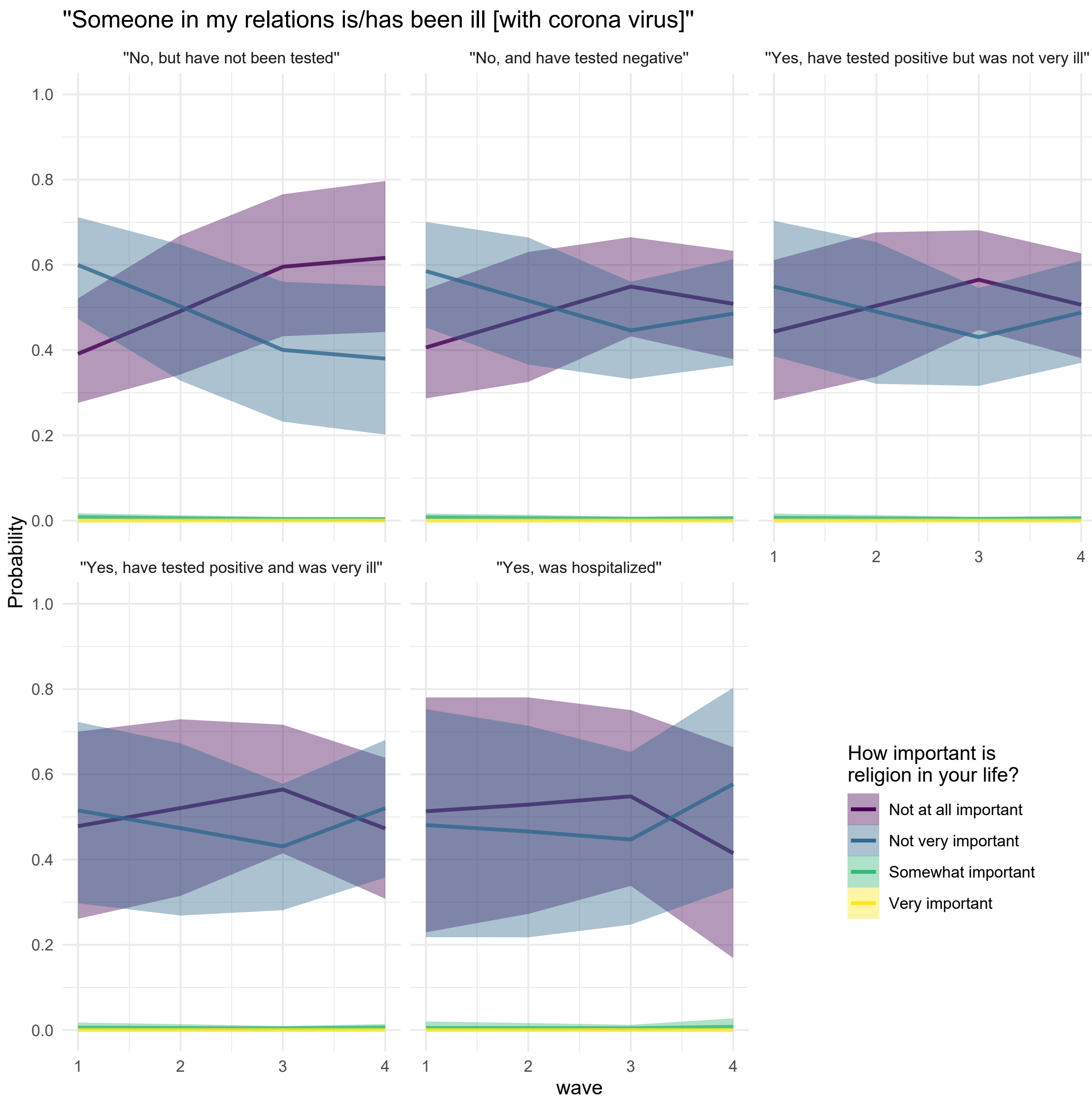

Figure S18: **Interaction plot `m_relations`**: Predicted probabilities for each response option across measurement waves and self-reported exposure to corona virus. Thick lines are posterior medians and bands are 95% credible intervals.

S4. R package environment

We used R version 4.1.2 (R Core Team, 2021) and the following R packages: abind v. 1.4.5 (Plate and Heiberger, 2016), arrayhelpers v. 1.1.0 (Beleites, 2020), askpass v. 1.1 (Ooms, 2019), assertthat v. 0.2.1 (Wickham, 2019a), backports v. 1.4.1 (Lang and R Core Team, 2021), base64enc v. 0.1.3 (Urbanek, 2015), bayesplot v. 1.8.1 (Gabry et al., 2019; Gabry and Mahr, 2021), Bayesrel v. 0.7.1 (Pfadt et al., 2021), BH v. 1.75.0.0 (Eddelbuettel et al., 2021), bit v. 4.0.4 (Oehlschlägel and Ripley, 2020), bit64 v. 4.0.5 (Oehlschlägel and Silvestri, 2020), blob v. 1.2.2 (Wickham, 2021a), bridgesampling v. 1.1.2 (Gronau et al., 2020), brio v. 1.1.2 (Hester, 2021), brms v. 2.16.3 (Bürkner, 2017, 2018, 2021), Brobdingnag v. 1.2.6 (Hankin, 2007), bslib v. 0.3.1 (Sievert and Cheng, 2021a), cachem v. 1.0.6 (Chang, 2021a), Cairo v. 1.5.12.2 (Urbanek and Horner, 2020), callr v. 3.7.0 (Csárdi and Chang, 2021a), car v. 3.0.12 (Fox and Weisberg, 2019), carData v. 3.0.4 (Fox et al., 2020), cellranger v. 1.1.0 (Bryan, 2016), checkmate v. 2.0.0 (Lang, 2017), clipr v. 0.7.1 (Lincoln, 2020), coda v. 0.19.4 (Plummer et al., 2006), colorspace v. 2.0.2 (Zeileis et al., 2009; Stauffer et al., 2009; Zeileis et al., 2020), colourpicker v. 1.1.1 (Attali, 2021a), commonmark v. 1.7 (Ooms, 2018), corrplot v. 0.90 (Wei and Simko, 2021), cowplot v. 1.1.1 (Wilke, 2020), cpp11 v. 0.4.2 (Hester and François, 2021), crosstalk v. 1.2.0 (Cheng and Sievert, 2021), curl v. 4.3.2 (Ooms, 2021a), data.table v. 1.14.2 (Dowle and Srinivasan, 2021), DBI v. 1.1.2 (R Special Interest Group on Databases (R-SIG-DB) et al., 2021), desc v. 1.4.0 (Csárdi et al., 2021), diffobj v. 0.3.5 (Gaslam, 2021), digest v. 0.6.29 (with contributions by Antoine Lucas et al., 2021), distributional v. 0.3.0 (O'Hara-Wild et al., 2022), DT v. 0.20 (Xie et al., 2021), dygraphs v. 1.1.1.6 (Vanderkam et al., 2018), ellipse v. 0.4.2 (Murdoch and Chow, 2020), ellipsis v. 0.3.2 (Wickham, 2021b), evaluate v. 0.14 (Wickham and Xie, 2019), fansi v. 1.0.2 (Gaslam, 2022), farver v. 2.1.0 (Pedersen et al., 2021), fastmap v. 1.1.0 (Chang, 2021b), fftwtools v. 0.9.11 (Rahim, 2021), fontawesome v. 0.2.2 (Iannone, 2021), foreach v. 1.5.1 (Microsoft and Weston, 2020), fs v. 1.5.2 (Hester et al., 2021c), future v. 1.23.0 (Bengtsson, 2021c), gargle v. 1.2.0 (Bryan et al., 2021), generics v. 0.1.2 (Wickham et al., 2022), ggdist v. 3.0.1 (Kay, 2021), ggpubr v. 0.4.0 (Kassambara, 2020), ggrepel v. 0.9.1 (Slowikowski, 2021), ggridges v. 0.5.3 (Wilke, 2021), ggsci v. 2.9 (Xiao, 2018), ggsignif v. 0.6.3 (Constantin and Patil, 2021), globals v. 0.14.0 (Bengtsson, 2020), glue v. 1.6.1 (Hester and Bryan, 2022), grateful v. 0.1.11 (Rodríguez-Sánchez et al., 2022), gridExtra v. 2.3 (Auguie, 2017), gtable v. 0.3.0 (Wickham and Pedersen, 2019), gtools v. 3.9.2 (Warnes et al., 2021), HDInterval v. 0.2.2 (Meredith and Kruschke, 2020), highr v. 0.9 (Xie and Qiu, 2021), htmltools v. 0.5.2 (Cheng et al., 2021b), htmlwidgets v. 1.5.4 (Vaidyanathan et al., 2021), httpuv v. 1.6.5 (Cheng and Chang, 2022), ids v. 1.0.1 (FitzJohn, 2017), igraph v. 1.2.11 (Csardi and Nepusz, 2006), inline v. 0.3.19 (Sklyar et al., 2021), insight v. 0.14.5 (Lüdecke et al., 2019), installr v. 0.23.2 (Galili, 2021), isoband v. 0.2.5 (Wilke and Pedersen, 2021), iterators v. 1.0.13 (Analytics and Weston, 2020), job v. 0.3.0 (Lindeløv, 2021), JointAI v. 1.0.3 (Erler et al., 2019b), jquerylib v. 0.1.4 (Sievert and Cheng, 2021b), knitr v. 1.37 (Xie, 2014, 2015, 2021a), labeling v. 0.4.2 (Talbot, 2020), LaplacesDemon v. 16.1.6 (Statisticat and LLC., 2021b,a,c,d), later v. 1.3.0 (Chang and Cheng, 2021), lavaan v. 0.6.9 (Rosseel, 2012), lazyeval v. 0.2.2 (Wickham, 2019b), lifecycle v. 1.0.1 (Henry and Wickham, 2021a), listenv v. 0.8.0 (Bengtsson, 2019), lme4 v. 1.1.27.1 (Bates et al., 2015), loo v. 2.4.1 (Vehtari et al., 2017; Yao et al., 2017; Vehtari et al., 2020), maptools v. 1.1.2 (Bivand and Lewin-Koh, 2021), markdown v. 1.1 (Allaire et al., 2019), mathjaxr v. 1.4.0 (Viechtbauer, 2021), MatrixModels v. 0.5.0 (Bates and Maechler, 2021), matrixStats v. 0.61.0 (Bengtsson, 2021a), mcmcse v. 1.5.0 (Flegal et al., 2021), mime v. 0.12 (Xie, 2021b), miniUI v. 0.1.1.1 (Cheng, 2018), minqa v. 1.2.4 (Bates et al., 2014), mnormt v. 2.0.2 (Azzalini and Genz, 2020), munsell v. 0.5.0

(Wickham, 2018), mvtnorm v. 1.1.3 (Genz and Bretz, 2009; Genz et al., 2021), nleqslv v. 3.3.2 (Hasselman, 2018), nloptr v. 1.2.2.2 (Johnson), numDeriv v. 2016.8.1.1 (Gilbert and Varadhan, 2019), openssl v. 1.4.5 (Ooms, 2021b), packrat v. 0.7.0 (Ushey et al., 2021), parallelly v. 1.29.0 (Bengtsson, 2021b), patchwork v. 1.1.1 (Pedersen, 2020), pbivnorm v. 0.6.0 (code by Alan Genz. R code by Brenton Kenkel and based on Adelchi Azzalini's 'mnormt' package., 2015), pbkrtest v. 0.5.1 (Halekoh and Højsgaard, 2014), pkgbuild v. 1.3.1 (Wickham et al., 2021c), pkgconfig v. 2.0.3 (Csárdi, 2019), pkgload v. 1.2.4 (Wickham et al., 2021a), plyr v. 1.8.6 (Wickham, 2011a), polynom v. 1.4.0 (Venables et al., 2019), posterior v. 1.2.0 (Vehtari et al., 2021; Bürkner et al., 2022), praise v. 1.0.0 (Csardi and Sorhus, 2015), prettyunits v. 1.1.1 (Csardi, 2020), processx v. 3.5.2 (Csárdi and Chang, 2021b), progress v. 1.2.2 (Csárdi and FitzJohn, 2019), promises v. 1.2.0.1 (Cheng, 2021), ps v. 1.6.0 (Loden et al., 2021), quantreg v. 5.86 (Koenker, 2021a), R6 v. 2.5.1 (Chang, 2021c), rappdirs v. 0.3.3 (Ratnakumar et al., 2021), rbibutils v. 2.2.4 (Boshnakov and Putman, 2021), RColorBrewer v. 1.1.2 (Neuwirth, 2014), Rcpp v. 1.0.8 (Eddelbuettel and François, 2011; Eddelbuettel, 2013; Eddelbuettel and Balamuta, 2018), RcppArmadillo v. 0.10.7.5.0 (Eddelbuettel and Sanderson, 2014), RcppEigen v. 0.3.3.9.1 (Bates and Eddelbuettel, 2013), RcppParallel v. 5.1.5 (Allaire et al., 2022), Rdpack v. 2.1.2 (Boshnakov, 2021), rematch v. 1.0.1 (Csardi, 2016), rematch2 v. 2.1.2 (Csárdi, 2020), renv v. 0.15.2 (Ushey, 2022), reshape2 v. 1.4.4 (Wickham, 2007), rjags v. 4.12 (Plummer, 2021), rmarkdown v. 2.11 (Xie et al., 2018, 2020; Allaire et al., 2021), rprojroot v. 2.0.2 (Müller, 2020), rsconnect v. 0.8.25 (Atkins et al., 2021), rstan v. 2.21.3 (Stan Development Team, 2021), rstantools v. 2.1.1 (Gabry et al., 2020), rstatix v. 0.7.0 (Kassambara, 2021), sass v. 0.4.0 (Cheng et al., 2021a), scales v. 1.1.1 (Wickham and Seidel, 2020), selectr v. 0.4.2 (Potter, 2012), shiny v. 1.7.1 (Chang et al., 2021), shinyjs v. 2.1.0 (Attali, 2021b), shinystan v. 2.5.0 (Gabry, 2018), shinythemes v. 1.2.0 (Chang, 2021d), sjlabelled v. 1.1.8 (Lüdecke, 2021), sourcetools v. 0.1.7 (Ushey, 2018), sp v. 1.4.5 (Pebesma and Bivand, 2005; Bivand et al., 2013), SparseM v. 1.81 (Koenker, 2021b), StanHeaders v. 2.21.0.7 (Stan Development Team, 2020), stringi v. 1.7.6 (Gagolewski, 2021a,b), svUnit v. 1.0.6 (Grosjean, 2021), sys v. 3.4 (Ooms, 2020), tensorA v. 0.36.2 (van den Boogaart, 2020), testthat v. 3.1.2 (Wickham, 2011b), threejs v. 0.3.3 (Lewis, 2020), tidybayes v. 3.0.2 (Kay, 2020), tidyselect v. 1.1.1 (Henry and Wickham, 2021b), tidyverse v. 1.3.1 (Wickham et al., 2019), tinytex v. 0.36 (Xie, 2019, 2021c), tmvnsim v. 1.0.2 (Bhattacjarjee, 2016), tzdb v. 0.2.0 (Vaughan, 2021), utf8 v. 1.2.2 (Perry, 2021), uuid v. 1.0.3 (Urbanek and Ts'o, 2021), vctrs v. 0.3.8 (Wickham et al., 2021b), viridis v. 0.6.2 (Garnier et al., 2021a), viridisLite v. 0.4.0 (Garnier et al., 2021b), vroom v. 1.5.7 (Hester et al., 2021b), waldo v. 0.3.1 (Wickham, 2021c), withr v. 2.4.3 (Hester et al., 2021a), xfun v. 0.29 (Xie, 2021d), xtable v. 1.8.4 (Dahl et al., 2019), xts v. 0.12.1 (Ryan and Ulrich, 2020), yaml v. 2.2.2 (Stephens et al., 2022), zoo v. 1.8.9 (Zeileis and Grothendieck, 2005).

References

Allaire, J., Francois, R., Ushey, K., Vandenbrouck, G., Geelnard, M., and Intel (2022). *RcppParallel: Parallel Programming Tools for 'Rcpp'*. R package version 5.1.5.

Allaire, J., Horner, J., Xie, Y., Marti, V., and Porte, N. (2019). *markdown: Render Markdown with the C Library 'Sundown'*. R package version 1.1.

Allaire, J., Xie, Y., McPherson, J., Luraschi, J., Ushey, K., Atkins, A., Wickham, H., Cheng, J., Chang, W., and Iannone, R. (2021). *rmarkdown: Dynamic Documents for R*. R package version 2.11.

Analytics, R. and Weston, S. (2020). *iterators: Provides Iterator Construct*. R package version 1.0.13.

Atkins, A., McPherson, J., and Allaire, J. (2021). *rsconnect: Deployment Interface for R Markdown Documents and Shiny Applications*. R package version 0.8.25.

Attali, D. (2021a). *colourpicker: A Colour Picker Tool for Shiny and for Selecting Colours in Plots*. R package version 1.1.1.

Attali, D. (2021b). *shinyjs: Easily Improve the User Experience of Your Shiny Apps in Seconds*. R package version 2.1.0.

Auguie, B. (2017). *gridExtra: Miscellaneous Functions for "Grid" Graphics*. R package version 2.3.

Azzalini, A. and Genz, A. (2020). *The R package `mnormt`: The multivariate normal and t distributions (version 2.0.2).*

Bates, D. and Eddelbuettel, D. (2013). Fast and elegant numerical linear algebra using the RcppEigen package. *Journal of Statistical Software*, 52(5):1–24.

Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1):1–48.

Bates, D. and Maechler, M. (2021). *MatrixModels: Modelling with Sparse and Dense Matrices*. R package version 0.5-0.

Bates, D., Mullen, K. M., Nash, J. C., and Varadhan, R. (2014). *minqa: Derivative-free optimization algorithms by quadratic approximation*. R package version 1.2.4.

Beleites, C. (2020). *arrayhelpers: Convenience Functions for Arrays*. R package version 1.1-0.

Bengtsson, H. (2019). *listenv: Environments Behaving (Almost) as Lists*. R package version 0.8.0.

Bengtsson, H. (2020). *globals: Identify Global Objects in R Expressions*. R package version 0.14.0.

Bengtsson, H. (2021a). *matrixStats: Functions that Apply to Rows and Columns of Matrices (and to Vectors)*. R package version 0.61.0.

Bengtsson, H. (2021b). *parallelly: Enhancing the 'parallel' Package*. R package version 1.29.0.

Bengtsson, H. (2021c). A unifying framework for parallel and distributed processing in r using futures. 10.32614/RJ-2021-048.

Bhattacjarjee, S. (2016). *tmvnsim: Truncated Multivariate Normal Simulation*. R package version 1.0-2.

Bivand, R. and Lewin-Koh, N. (2021). *maptools: Tools for Handling Spatial Objects*. R package version 1.1-2.

Bivand, R. S., Pebesma, E., and Gomez-Rubio, V. (2013). *Applied spatial data analysis with R, Second edition*. Springer, NY.

Boshnakov, G. N. (2021). Rdpack: Update and manipulate rd documentation objects. R package version 2.1.2.

Boshnakov, G. N. and Putman, C. (2021). *rbibutils: Read 'Bibtex' Files and Convert Between Bibliography Formats*. R package version 2.2.4.

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, 80(1):1–28.

Bürkner, P.-C. (2018). Advanced Bayesian multilevel modeling with the R package brms. *The R Journal*, 10(1):395–411.

Bürkner, P.-C. (2021). Bayesian item response modeling in R with brms and Stan. *Journal of Statistical Software*, 100(5):1–54.

Bürkner, P.-C. and Charpentier, E. (2020). Modelling monotonic effects of ordinal predictors in Bayesian regression models. *British Journal of Mathematical and Statistical Psychology*, 73(3):420–451.

Bürkner, P.-C., Gabry, J., Kay, M., and Vehtari, A. (2022). posterior: Tools for working with posterior distributions. R package version 1.2.0.

Bürkner, P.-C. and Vuorre, M. (2019). Ordinal regression models in psychology: A tutorial. *Advances in Methods and Practices in Psychological Science*, 2(1):77–101.

Bryan, J. (2016). *cellranger: Translate Spreadsheet Cell Ranges to Rows and Columns*. R package version 1.1.0.

Bryan, J., Citro, C., and Wickham, H. (2021). *gargle: Utilities for Working with Google APIs*. R package version 1.2.0.

Chang, W. (2021a). *cachem: Cache R Objects with Automatic Pruning*. R package version 1.0.6.

Chang, W. (2021b). *fastmap: Fast Data Structures*. R package version 1.1.0.

Chang, W. (2021c). *R6: Encapsulated Classes with Reference Semantics*. R package version 2.5.1.

Chang, W. (2021d). *shinythemes: Themes for Shiny*. R package version 1.2.0.

Chang, W. and Cheng, J. (2021). *later: Utilities for Scheduling Functions to Execute Later with Event Loops*. R package version 1.3.0.

Chang, W., Cheng, J., Allaire, J., Sievert, C., Schloerke, B., Xie, Y., Allen, J., McPherson, J., Dipert, A., and Borges, B. (2021). *shiny: Web Application Framework for R*. R package version 1.7.1.

Cheng, J. (2018). *miniUI: Shiny UI Widgets for Small Screens*. R package version 0.1.1.1.

Cheng, J. (2021). *promises: Abstractions for Promise-Based Asynchronous Programming*. R package version 1.2.0.1.

Cheng, J. and Chang, W. (2022). *httpuv: HTTP and WebSocket Server Library*. R package version 1.6.5.

Cheng, J., Mastny, T., Iannone, R., Schloerke, B., and Sievert, C. (2021a). *sass: Syntactically Awesome Style Sheets ('Sass')*. R package version 0.4.0.

Cheng, J. and Sievert, C. (2021). *crosstalk: Inter-Widget Interactivity for HTML Widgets*. R package version 1.2.0.

Cheng, J., Sievert, C., Schloerke, B., Chang, W., Xie, Y., and Allen, J. (2021b). *htmltools: Tools for HTML*. R package version 0.5.2.

code by Alan Genz. R code by Brenton Kenkel, F. and based on Adelchi Azzalini's 'mnormt' package. (2015). *pbivnorm: Vectorized Bivariate Normal CDF*. R package version 0.6.0.

Constantin, A.-E. and Patil, I. (2021). ggsignif: R package for displaying significance brackets for 'ggplot2'. *PsyArxiv*.

Csardi, G. (2016). *rematch: Match Regular Expressions with a Nicer 'API'*. R package version 1.0.1.

Csardi, G. (2020). *prettyunits: Pretty, Human Readable Formatting of Quantities*. R package version 1.1.1.

Csardi, G. and Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal*, Complex Systems:1695.

Csardi, G. and Sorhus, S. (2015). *praise: Praise Users*. R package version 1.0.0.

Csárdi, G. (2019). *pkgconfig: Private Configuration for 'R' Packages*. R package version 2.0.3.

Csárdi, G. (2020). *rematch2: Tidy Output from Regular Expression Matching*. R package version 2.1.2.

Csárdi, G. and Chang, W. (2021a). *callr: Call R from R*. R package version 3.7.0.

Csárdi, G. and Chang, W. (2021b). *processx: Execute and Control System Processes*. R package version 3.5.2.

Csárdi, G. and FitzJohn, R. (2019). *progress: Terminal Progress Bars*. R package version 1.2.2.

Csárdi, G., Müller, K., and Hester, J. (2021). *desc: Manipulate DESCRIPTION Files*. R package version 1.4.0.

Dahl, D. B., Scott, D., Roosen, C., Magnusson, A., and Swinton, J. (2019). *xtable: Export Tables to LaTeX or HTML*. R package version 1.8-4.

Ding, P. and Li, F. (2018). Causal Inference: A Missing Data Perspective. *Statistical Science*, 33(2):214 – 237.

Dowle, M. and Srinivasan, A. (2021). *data.table: Extension of 'data.frame'*. R package version 1.14.2.

Eddelbuettel, D. (2013). *Seamless R and C++ Integration with Rcpp*. Springer, New York. ISBN 978-1-4614-6867-7.

Eddelbuettel, D. and Balamuta, J. J. (2018). Extending extitR with extitC++: A Brief Introduction to extitRcpp. *The American Statistician*, 72(1):28–36.

Eddelbuettel, D., Emerson, J. W., and Kane, M. J. (2021). *BH: Boost C++ Header Files*. R package version 1.75.0-0.

Eddelbuettel, D. and François, R. (2011). Rcpp: Seamless R and C++ integration. *Journal of Statistical Software*, 40(8):1–18.

Eddelbuettel, D. and Sanderson, C. (2014). Rcpparmadillo: Accelerating r with high-performance c++ linear algebra. *Computational Statistics and Data Analysis*, 71:1054–1063.

Erler, N. S., Rizopoulos, D., Jaddoe, V. W., Franco, O. H., and Lesaffre, E. M. (2019a). Bayesian imputation of time-varying covariates in linear mixed models. *Statistical Methods in Medical Research*, 28(2):555–568.

Erler, N. S., Rizopoulos, D., and Lesaffre, E. M. (2019b). JointAI: Joint analysis and imputation of incomplete data in r. *arXiv e-prints*, page arXiv:1907.10867.

Erler, N. S., Rizopoulos, D., Rosmalen, J. v., Jaddoe, V. W. V., Franco, O. H., and Lesaffre, E. M. E. H. (2016). Dealing with missing covariates in epidemiologic studies: a comparison between multiple imputation and a full Bayesian approach. *Statistics in Medicine*, 35(17):2955–2974.

FitzJohn, R. (2017). *ids: Generate Random Identifiers*. R package version 1.0.1.

Flegal, J. M., Hughes, J., Vats, D., Dai, N., Gupta, K., and Maji, U. (2021). *mcmcse: Monte Carlo Standard Errors for MCMC*. Riverside, CA, and Kanpur, India. R package version 1.5-0.

Fox, J. and Weisberg, S. (2019). *An R Companion to Applied Regression*. Sage, Thousand Oaks CA, third edition.

Fox, J., Weisberg, S., and Price, B. (2020). *carData: Companion to Applied Regression Data Sets*. R package version 3.0-4.

Gabry, J. (2018). *shinystan: Interactive Visual and Numerical Diagnostics and Posterior Analysis for Bayesian Models*. R package version 2.5.0.

Gabry, J., Goodrich, B., and Lysy, M. (2020). *rstantools: Tools for Developing R Packages Interfacing with 'Stan'*. R package version 2.1.1.

Gabry, J. and Mahr, T. (2021). bayesplot: Plotting for bayesian models. R package version 1.8.1.

Gabry, J., Simpson, D., Vehtari, A., Betancourt, M., and Gelman, A. (2019). Visualization in bayesian workflow. *J. R. Stat. Soc. A*, 182:389–402.

Gagolewski, M. (2021a). stringi: Fast and portable character string processing in r. *Journal of Statistical Software*. to appear.

Gagolewski, M. (2021b). *stringi: Fast and portable character string processing in R*. R package version 1.7.6.

Galili, T. (2021). *installr: Using R to Install Stuff on Windows OS (Such As: R, 'Rtools', 'RStudio', 'Git', and More!)*. R package version 0.23.2.

Garnier, Simon, Ross, Noam, Rudis, Robert, Camargo, Pedro, A., Sciaini, Marco, Scherer, and Cédric (2021a). *viridis - Colorblind-Friendly Color Maps for R*. R package version 0.6.2.

Garnier, Simon, Ross, Noam, Rudis, Robert, Camargo, Pedro, A., Sciaini, Marco, Scherer, and Cédric (2021b). *viridis - Colorblind-Friendly Color Maps for R*. R package version 0.4.0.

Gaslam, B. (2021). *diffobj: Diffs for R Objects*. R package version 0.3.5.

Gaslam, B. (2022). *fansi: ANSI Control Sequence Aware String Functions*. R package version 1.0.2.

Genz, A. and Bretz, F. (2009). *Computation of Multivariate Normal and t Probabilities*. Lecture Notes in Statistics. Springer-Verlag, Heidelberg.

Genz, A., Bretz, F., Miwa, T., Mi, X., Leisch, F., Scheipl, F., and Hothorn, T. (2021). *mvtnorm: Multivariate Normal and t Distributions*. R package version 1.1-3.

Gilbert, P. and Varadhan, R. (2019). *numDeriv: Accurate Numerical Derivatives*. R package version 2016.8-1.1.

Gronau, Q. F., Singmann, H., and Wagenmakers, E.-J. (2020). bridgesampling: An R package for estimating normalizing constants. *Journal of Statistical Software*, 92(10):1–29.

Grosjean, P. (2021). *SciViews-R*. UMONS, MONS, Belgium.

Halekoh, U. and Højsgaard, S. (2014). A kenward-roger approximation and parametric bootstrap methods for tests in linear mixed models – the R package pbkrtest. *Journal of Statistical Software*, 59(9):1–30.

Hankin, R. K. S. (2007). Very large numbers in r: Introducing package brobdingnag. *R News*, 7.

Hasselman, B. (2018). *nleqslv: Solve Systems of Nonlinear Equations*. R package version 3.3.2.

Henry, L. and Wickham, H. (2021a). *lifecycle: Manage the Life Cycle of your Package Functions*. R package version 1.0.1.

Henry, L. and Wickham, H. (2021b). *tidyselect: Select from a Set of Strings.* R package version 1.1.1.

Hester, J. (2021). *brio: Basic R Input Output.* R package version 1.1.2.

Hester, J. and Bryan, J. (2022). *glue: Interpreted String Literals.* R package version 1.6.1.

Hester, J. and François, R. (2021). *cpp11: A C++11 Interface for R's C Interface.* R package version 0.4.2.

Hester, J., Henry, L., Müller, K., Ushey, K., Wickham, H., and Chang, W. (2021a). *withr: Run Code 'With' Temporarily Modified Global State.* R package version 2.4.3.

Hester, J., Wickham, H., and Bryan, J. (2021b). *vroom: Read and Write Rectangular Text Data Quickly.* R package version 1.5.7.

Hester, J., Wickham, H., and Csárdi, G. (2021c). *fs: Cross-Platform File System Operations Based on 'libuv'.* R package version 1.5.2.

Iannone, R. (2021). *fontawesome: Easily Work with 'Font Awesome' Icons.* R package version 0.2.2.

Johnson, S. G. (?). The nlopt nonlinear-optimization package. *?*, ?(?):?

Kassambara, A. (2020). *ggpubr: 'ggplot2' Based Publication Ready Plots.* R package version 0.4.0.

Kassambara, A. (2021). *rstatix: Pipe-Friendly Framework for Basic Statistical Tests.* R package version 0.7.0.

Kay, M. (2020). *tidybayes: Tidy Data and Geoms for Bayesian Models.* R package version 2.3.0.

Kay, M. (2021). *ggdist: Visualizations of Distributions and Uncertainty.* R package version 3.0.1.

Kennedy, L. and Gelman, A. (2021). Know your population and know your model: Using model-based regression and poststratification to generalize findings beyond the observed sample. *Psychological Methods.*

Koenker, R. (2021a). *quantreg: Quantile Regression.* R package version 5.86.

Koenker, R. (2021b). *SparseM: Sparse Linear Algebra.* R package version 1.81.

Kurz, A. S. (2021). *Applied longitudinal data analysis in brms and the tidyverse.* version 0.0.2 edition.

Lang, M. (2017). checkmate: Fast argument checks for defensive r programming. *The R Journal*, 9(1):437–445.

Lang, M. and R Core Team (2021). *backports: Reimplementations of Functions Introduced Since R-3.0.0.* R package version 1.4.1.

Lüdecke, D. (2021). *sjlabelled: Labelled Data Utility Functions (Version 1.1.8).*

Lüdecke, D., Waggoner, P., and Makowski, D. (2019). insight: A unified interface to access information from model objects in R. *Journal of Open Source Software*, 4(38):1412.

Lewis, B. W. (2020). *threejs: Interactive 3D Scatter Plots, Networks and Globes.* R package version 0.3.3.

Liddell, T. M. and Kruschke, J. K. (2018). Analyzing ordinal data with metric models: What could possibly go wrong? *Journal of Experimental Social Psychology*, 79:328–348.

Lincoln, M. (2020). *clipr: Read and Write from the System Clipboard.* R package version 0.7.1.

Lindeløv, J. K. (2021). *job: Run Code as an RStudio Job - Free Your Console.* R package version 0.3.0.

Little, R. J. and Rubin, D. B. (2019). *Statistical analysis with missing data.* John Wiley & Sons, 2nd edition.

Little, R. J. A. (1993). Post-stratification: A modeler's perspective. *Journal of the American Statistical Association*, 88(423):1001–1012.

Loden, J., Daeschler, D., Rodola', G., and Csárdi, G. (2021). *ps: List, Query, Manipulate System Processes.* R package version 1.6.0.

McElreath, R. (2020). *Statistical Rethinking: A Bayesian course with examples in R and Stan.* CRC Press, second edition.

Meredith, M. and Kruschke, J. (2020). *HDInterval: Highest (Posterior) Density Intervals.* R package version 0.2.2.

Microsoft and Weston, S. (2020). *foreach: Provides Foreach Looping Construct.* R package version 1.5.1.

Müller, K. (2020). *rprojroot: Finding Files in Project Subdirectories.* R package version 2.0.2.

Mohan, K. and Pearl, J. (2021). Graphical models for processing missing data. *Journal of the American Statistical Association*, 116(534):1023–1037.

Mohan, K., Pearl, J., and Tian, J. (2013). Missing data as a causal inference problem. Technical report.

Murdoch, D. and Chow, E. D. (2020). *ellipse: Functions for Drawing Ellipses and Ellipse-Like Confidence Regions.* R package version 0.4.2.

Neuwirth, E. (2014). *RColorBrewer: ColorBrewer Palettes.* R package version 1.1-2.

Oehlschlägel, J. and Ripley, B. (2020). *bit: Classes and Methods for Fast Memory-Efficient Boolean Selections.* R package version 4.0.4.

Oehlschlägel, J. and Silvestri, L. (2020). *bit64: A S3 Class for Vectors of 64bit Integers.* R package version 4.0.5.

O'Hara-Wild, M., Kay, M., and Hayes, A. (2022). *distributional: Vectorised Probability Distributions*. R package version 0.3.0.

Ooms, J. (2018). *commonmark: High Performance CommonMark and Github Markdown Rendering in R*. R package version 1.7.

Ooms, J. (2019). *askpass: Safe Password Entry for R, Git, and SSH*. R package version 1.1.

Ooms, J. (2020). *sys: Powerful and Reliable Tools for Running System Commands in R*. R package version 3.4.

Ooms, J. (2021a). *curl: A Modern and Flexible Web Client for R*. R package version 4.3.2.

Ooms, J. (2021b). *openssl: Toolkit for Encryption, Signatures and Certificates Based on OpenSSL*. R package version 1.4.5.

Pebesma, E. J. and Bivand, R. S. (2005). Classes and methods for spatial data in R. *R News*, 5(2):9–13.

Pedersen, T. L. (2020). *patchwork: The Composer of Plots*. R package version 1.1.1.

Pedersen, T. L., Nicolae, B., and François, R. (2021). *farver: High Performance Colour Space Manipulation*. R package version 2.1.0.

Perry, P. O. (2021). *utf8: Unicode Text Processing*. R package version 1.2.2.

Pfadt, J. M., van den Bergh, D., and Goosen, J. (2021). *Bayesrel: Bayesian Reliability Estimation*. R package version 0.7.1.

Plate, T. and Heiberger, R. (2016). *abind: Combine Multidimensional Arrays*. R package version 1.4-5.

Plummer, M. (2021). *rjags: Bayesian Graphical Models using MCMC*. R package version 4-12.

Plummer, M., Best, N., Cowles, K., and Vines, K. (2006). Coda: Convergence diagnosis and output analysis for mcmc. *R News*, 6(1):7–11.

Potter, S. (2012). Introducing the selectr package. Technical report, The University of Auckland, Auckland, New Zealand.

R Core Team (2021). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

R Special Interest Group on Databases (R-SIG-DB), Wickham, H., and Müller, K. (2021). *DBI: R Database Interface*. R package version 1.1.2.

Rahim, K. (2021). *fftwtools: Wrapper for 'FFTW3' Includes: One-Dimensional, Two-Dimensional, Three-Dimensional, and Multivariate Transforms*. R package version 0.9-11.

Ratnakumar, S., Mick, T., and Davis, T. (2021). *rappdirs: Application Directories: Determine Where to Save Data, Caches, and Logs*. R package version 0.3.3.

Rodríguez-Sánchez, F., Jackson, C. P., and Hutchins, S. D. (2022). *grateful: Facilitate citation of R packages*. R package version 0.1.5.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, 48(2):1–36.

Rubin, D. B. (1976). Inference and missing data. *Biometrika*, 63(3):581–592.

Ryan, J. A. and Ulrich, J. M. (2020). *xts: eXtensible Time Series*. R package version 0.12.1.

Schuessler, J. and Selb, P. (2019). Graphical causal models for survey inference. osf.io/preprints/-socarxiv/hbg3m.

Sievert, C. and Cheng, J. (2021a). *bslib: Custom 'Bootstrap' 'Sass' Themes for 'shiny' and 'rmarkdown'*. R package version 0.3.1.

Sievert, C. and Cheng, J. (2021b). *jquerylib: Obtain 'jQuery' as an HTML Dependency Object*. R package version 0.1.4.

Singer, J. D. and Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. Oxford University Press.

Sklyar, O., Murdoch, D., Smith, M., Eddelbuettel, D., Francois, R., Soetaert, K., and Ranke, J. (2021). *inline: Functions to Inline C, C++, Fortran Function Calls from R*. R package version 0.3.19.

Slowikowski, K. (2021). *ggrepel: Automatically Position Non-Overlapping Text Labels with 'ggplot2'*. R package version 0.9.1.

Stan Development Team (2020). StanHeaders: Headers for the R interface to Stan. R package version 2.21.0-6.

Stan Development Team (2021). RStan: the R interface to Stan. R package version 2.21.3.

Statisticat and LLC. (2021a). *Bayesian Inference*. R package version 16.1.6.

Statisticat and LLC. (2021b). *LaplacesDemon: Complete Environment for Bayesian Inference*. R package version 16.1.6.

Statisticat and LLC. (2021c). *LaplacesDemon Examples*. R package version 16.1.6.

Statisticat and LLC. (2021d). *LaplacesDemon Tutorial*. R package version 16.1.6.

Stauffer, R., Mayr, G. J., Dabernig, M., and Zeileis, A. (2009). Somewhere over the rainbow: How to make effective use of colors in meteorological visualizations. *Bulletin of the American Meteorological Society*, 96(2):203–216.

Stephens, J., Simonov, K., Xie, Y., Dong, Z., Wickham, H., Horner, J., reikoch, Beasley, W., O'Connor, B., Warnes, G. R., Quinn, M., and Kamvar, Z. N. (2022). *yaml: Methods to Convert R Data to YAML and Back*. R package version 2.2.2.

Talbot, J. (2020). *labeling: Axis Labeling*. R package version 0.4.2.

Urbanek, S. (2015). *base64enc: Tools for base64 encoding*. R package version 0.1-3.

Urbanek, S. and Horner, J. (2020). *Cairo: R Graphics Device using Cairo Graphics Library for Creating High-Quality Bitmap (PNG, JPEG, TIFF), Vector (PDF, SVG, PostScript) and Display (X11 and Win32) Output*. R package version 1.5-12.2.

Urbanek, S. and Ts'o, T. (2021). *uuid: Tools for Generating and Handling of UUIDs*. R package version 1.0-3.

Ushey, K. (2018). *sourcetools: Tools for Reading, Tokenizing and Parsing R Code*. R package version 0.1.7.

Ushey, K. (2022). *renv: Project Environments*. R package version 0.15.2.

Ushey, K., McPherson, J., Cheng, J., Atkins, A., and Allaire, J. (2021). *packrat: A Dependency Management System for Projects and their R Package Dependencies*. R package version 0.7.0.

Vaidyanathan, R., Xie, Y., Allaire, J., Cheng, J., Sievert, C., and Russell, K. (2021). *htmlwidgets: HTML Widgets for R*. R package version 1.5.4.

van den Boogaart, K. G. (2020). *tensorA: Advanced Tensor Arithmetic with Named Indices*. R package version 0.36.2.

Vanderkam, D., Allaire, J., Owen, J., Gromer, D., and Thieurmel, B. (2018). *dygraphs: Interface to 'Dygraphs' Interactive Time Series Charting Library*. R package version 1.1.1.6.

Vaughan, D. (2021). *tzdb: Time Zone Database Information*. R package version 0.2.0.

Vehtari, A., Gabry, J., Magnusson, M., Yao, Y., Bürkner, P.-C., Paananen, T., and Gelman, A. (2020). loo: Efficient leave-one-out cross-validation and waic for bayesian models. R package version 2.4.1.

Vehtari, A., Gelman, A., and Gabry, J. (2017). Practical bayesian model evaluation using leave-one-out cross-validation and waic. *Statistics and Computing*, 27:1413–1432.

Vehtari, A., Gelman, A., Simpson, D., Carpenter, B., and Bürkner, P.-C. (2021). Rank-normalization, folding, and localization: An improved rhat for assessing convergence of mcmc (with discussion). *Bayesian Analysis*.

Venables, B., Hornik, K., and Maechler, M. (2019). *polynom: A Collection of Functions to Implement a Class for Univariate Polynomial Manipulations*. R package version 1.4-0. S original by Bill Venables, packages for R by Kurt Hornik and Martin Maechler.

Viechtbauer, W. (2021). *mathjaxr: Using 'Mathjax' in Rd Files*. R package version 1.4-0.

Warnes, G. R., Bolker, B., and Lumley, T. (2021). *gtools: Various R Programming Tools*. R package version 3.9.2.

Wei, T. and Simko, V. (2021). *R package 'corrplot': Visualization of a Correlation Matrix*. (Version 0.90).

Wickham, C. (2018). *munsell: Utilities for Using Munsell Colours*. R package version 0.5.0.

Wickham, H. (2007). Reshaping data with the reshape package. *Journal of Statistical Software*, 21(12):1–20.

Wickham, H. (2011a). The split-apply-combine strategy for data analysis. *Journal of Statistical Software*, 40(1):1–29.

Wickham, H. (2011b). testthat: Get started with testing. *The R Journal*, 3:5–10.

Wickham, H. (2019a). *assertthat: Easy Pre and Post Assertions*. R package version 0.2.1.

Wickham, H. (2019b). *lazyeval: Lazy (Non-Standard) Evaluation*. R package version 0.2.2.

Wickham, H. (2021a). *blob: A Simple S3 Class for Representing Vectors of Binary Data ('BLOBS')*. R package version 1.2.2.

Wickham, H. (2021b). *ellipsis: Tools for Working with ...* R package version 0.3.2.

Wickham, H. (2021c). *waldo: Find Differences Between R Objects*. R package version 0.3.1.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., and Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43):1686.

Wickham, H., Chang, W., Hester, J., and Henry, L. (2021a). *pkgload: Simulate Package Installation and Attach*. R package version 1.2.4.

Wickham, H., Henry, L., and Vaughan, D. (2021b). *vctrs: Vector Helpers*. R package version 0.3.8.

Wickham, H., Hester, J., and Csárdi, G. (2021c). *pkgbuild: Find Tools Needed to Build R Packages*. R package version 1.3.1.

Wickham, H., Kuhn, M., and Vaughan, D. (2022). *generics: Common S3 Generics not Provided by Base R Methods Related to Model Fitting*. R package version 0.1.2.

Wickham, H. and Pedersen, T. L. (2019). *gtable: Arrange 'Grobs' in Tables*. R package version 0.3.0.

Wickham, H. and Seidel, D. (2020). *scales: Scale Functions for Visualization*. R package version 1.1.1.

Wickham, H. and Xie, Y. (2019). *evaluate: Parsing and Evaluation Tools that Provide More Details than the Default*. R package version 0.14.

Wilke, C. O. (2020). *cowplot: Streamlined Plot Theme and Plot Annotations for 'ggplot2'*. R package version 1.1.1.

Wilke, C. O. (2021). *ggridges: Ridgeline Plots in 'ggplot2'*. R package version 0.5.3.

Wilke, C. O. and Pedersen, T. L. (2021). *isoband: Generate Isolines and Isobands from Regularly Spaced Elevation Grids*. R package version 0.2.5.

with contributions by Antoine Lucas, D. E., Tuszynski, J., Bengtsson, H., Urbanek, S., Frasca, M., Lewis, B., Stokely, M., Muehleisen, H., Murdoch, D., Hester, J., Wu, W., Kou, Q., Onkelinx, T., Lang, M., Simko, V., Hornik, K., Neal, R., Bell, K., de Queljoe, M., Suruceanu, I., Denney, B., Schumacher, D., , and Chang., W. (2021). *digest: Create Compact Hash Digests of R Objects*. R package version 0.6.29.

Xiao, N. (2018). *ggsci: Scientific Journal and Sci-Fi Themed Color Palettes for 'ggplot2'*. R package version 2.9.

Xie, Y. (2014). knitr: A comprehensive tool for reproducible research in R. In Stodden, V., Leisch, F., and Peng, R. D., editors, *Implementing Reproducible Computational Research*. Chapman and Hall/CRC. ISBN 978-1466561595.

Xie, Y. (2015). *Dynamic Documents with R and knitr*. Chapman and Hall/CRC, Boca Raton, Florida, 2nd edition. ISBN 978-1498716963.

Xie, Y. (2019). Tinytex: A lightweight, cross-platform, and easy-to-maintain latex distribution based on tex live. *TUGboat*, (1):30–32.

Xie, Y. (2021a). *knitr: A General-Purpose Package for Dynamic Report Generation in R*. R package version 1.37.

Xie, Y. (2021b). *mime: Map Filenames to MIME Types*. R package version 0.12.

Xie, Y. (2021c). *tinytex: Helper Functions to Install and Maintain TeX Live, and Compile LaTeX Documents*. R package version 0.36.

Xie, Y. (2021d). *xfun: Supporting Functions for Packages Maintained by 'Yihui Xie'*. R package version 0.29.

Xie, Y., Allaire, J., and Grolemund, G. (2018). *R Markdown: The Definitive Guide*. Chapman and Hall/CRC, Boca Raton, Florida. ISBN 9781138359338.

Xie, Y., Cheng, J., and Tan, X. (2021). *DT: A Wrapper of the JavaScript Library 'DataTables'*. R package version 0.20.

Xie, Y., Dervieux, C., and Riederer, E. (2020). *R Markdown Cookbook*. Chapman and Hall/CRC, Boca Raton, Florida. ISBN 9780367563837.

Xie, Y. and Qiu, Y. (2021). *highr: Syntax Highlighting for R Source Code*. R package version 0.9.

Yao, Y., Vehtari, A., Simpson, D., and Gelman, A. (2017). Using stacking to average bayesian predictive distributions. *Bayesian Analysis*.

Zeileis, A., Fisher, J. C., Hornik, K., Ihaka, R., McWhite, C. D., Murrell, P., Stauffer, R., and Wilke, C. O. (2020). colorspace: A toolbox for manipulating and assessing colors and palettes. *Journal of Statistical Software*, 96(1):1–49.

Zeileis, A. and Grothendieck, G. (2005). zoo: S3 infrastructure for regular and irregular time series. *Journal of Statistical Software*, 14(6):1–27.

Zeileis, A., Hornik, K., and Murrell, P. (2009). Escaping RGBland: Selecting colors for statistical graphics. *Computational Statistics & Data Analysis*, 53(9):3259–3270.