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

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

[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. Indeed, handling missing data is sometimes regarded as a special type of causal inference problem—and vice versa (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 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 depend on 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 are "missing not at random", MNAR). Figure S1 illustrates this assumption by adding a missingness indicator $M$

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

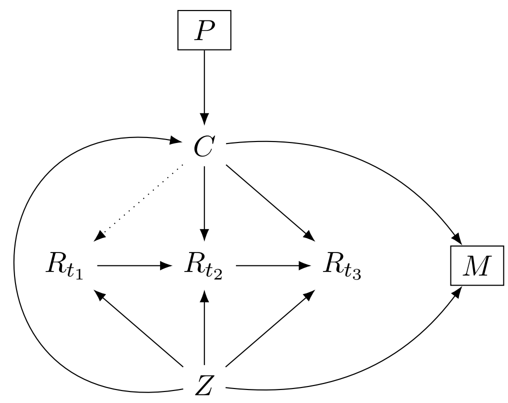


Figure S1: Directed acyclic graph (DAG) of the assumed causal structure of the data-generating process including a missingness indicator, $M$.

to the causal diagram of the main manuscript[1] (Mohan and Pearl, 2021). 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 (cf., 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 how we address the challenges of missingness and causal inference in the present study, including fitting models that include versus exclude covariates, full Bayesian imputation of missing covariates, and poststratification.

## 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, `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 three waves yielding a maximum of just three 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 (Bürkner and Vuorre, 2019; Liddell and Kruschke, 2018). In notational form, our fully adjusted

[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 $T_{1-3}$, 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?) (cf., 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.

main model thus takes the following structure for each individual observation, $i$:

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

where $\phi_i$ is a linear model of predictors and $\kappa$ is a vector of random cut-points. The linear model is given by:

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

where $i(j)$ gives the individual participant $j$ for each individual observation $i$, 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]. 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), so that a covariate's $\beta$ 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 $\kappa$ are modeled with Normal$(0, 10)$, all $\beta$ coefficients with Normal$(0, 0.5)$, and all monotonic covariates with a Dirichlet distribution with $\alpha$ 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 the model has learned from the data. Since the posterior predictive intervals mostly include the observed proportions, we regard the fit as reasonable[4].

[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.

[4] In Bayesian statistics, intervals such as the 50% and 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

In the following (Figures S2 – S7), we present similar prior and posterior check plots for all main model specifications (cf., Table 2 in main manuscript).

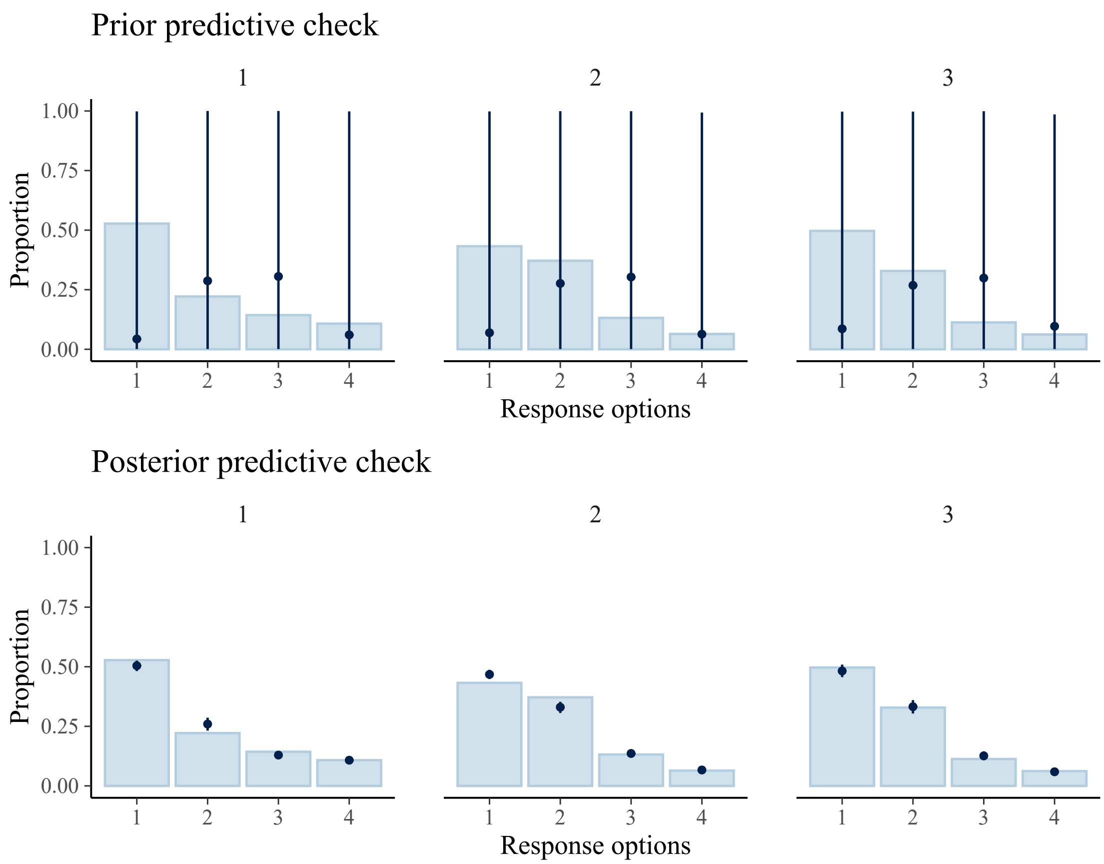


Figure S2: **Model `m0`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted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

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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".

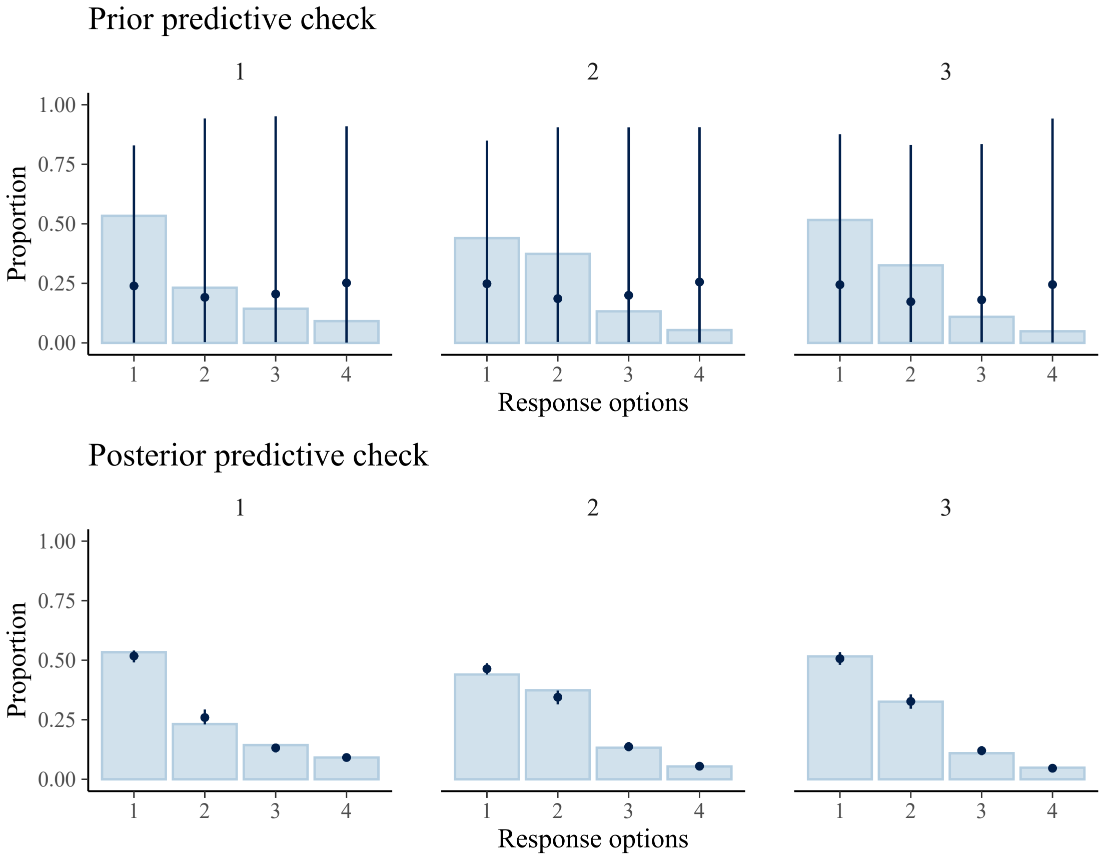


Figure S3: **Model `m1`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted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

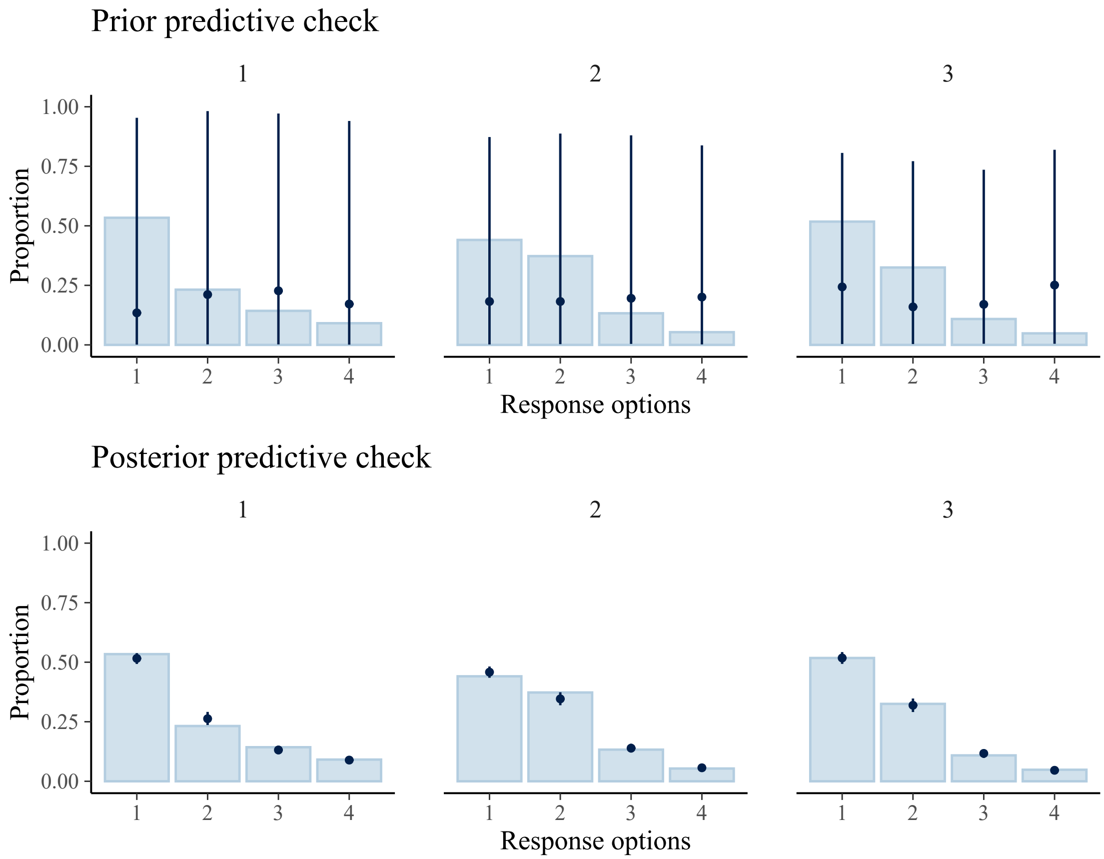


Figure S4: **Model `hinc_model`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the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

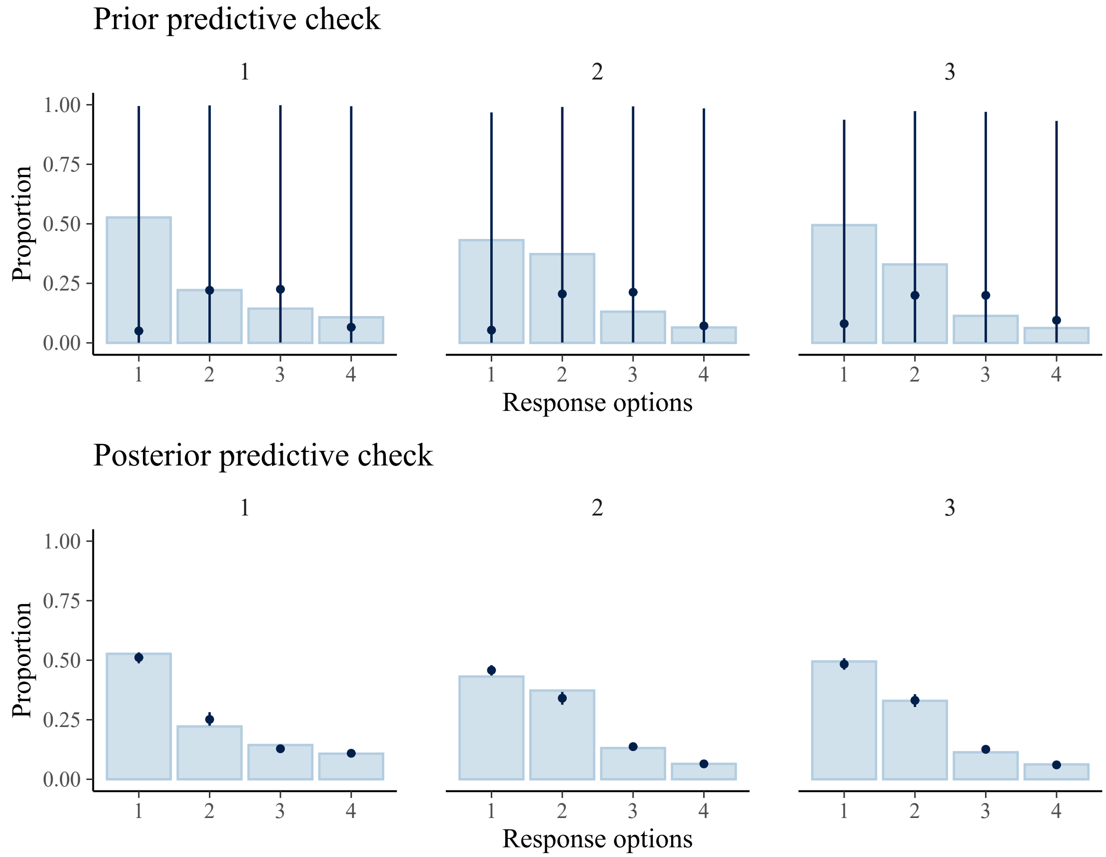


Figure S5: **Model `health_model`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the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

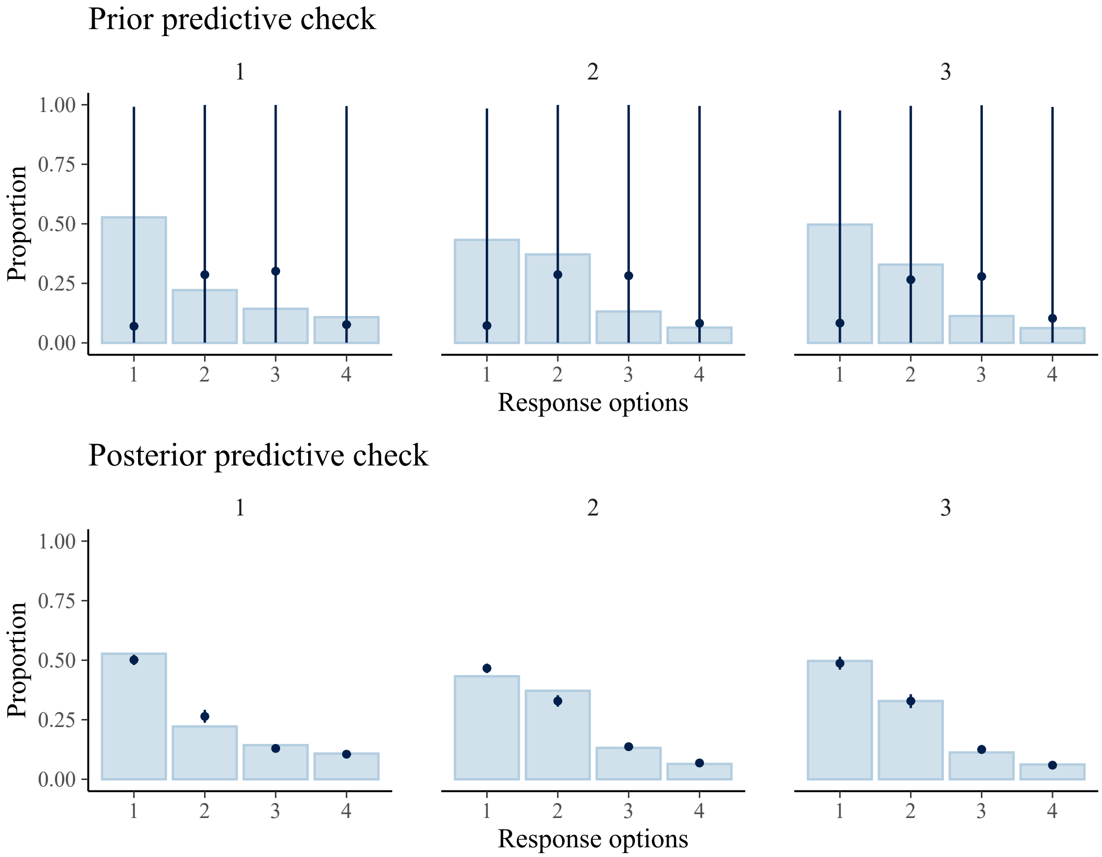


Figure S6: **Model `m_mrp`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted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

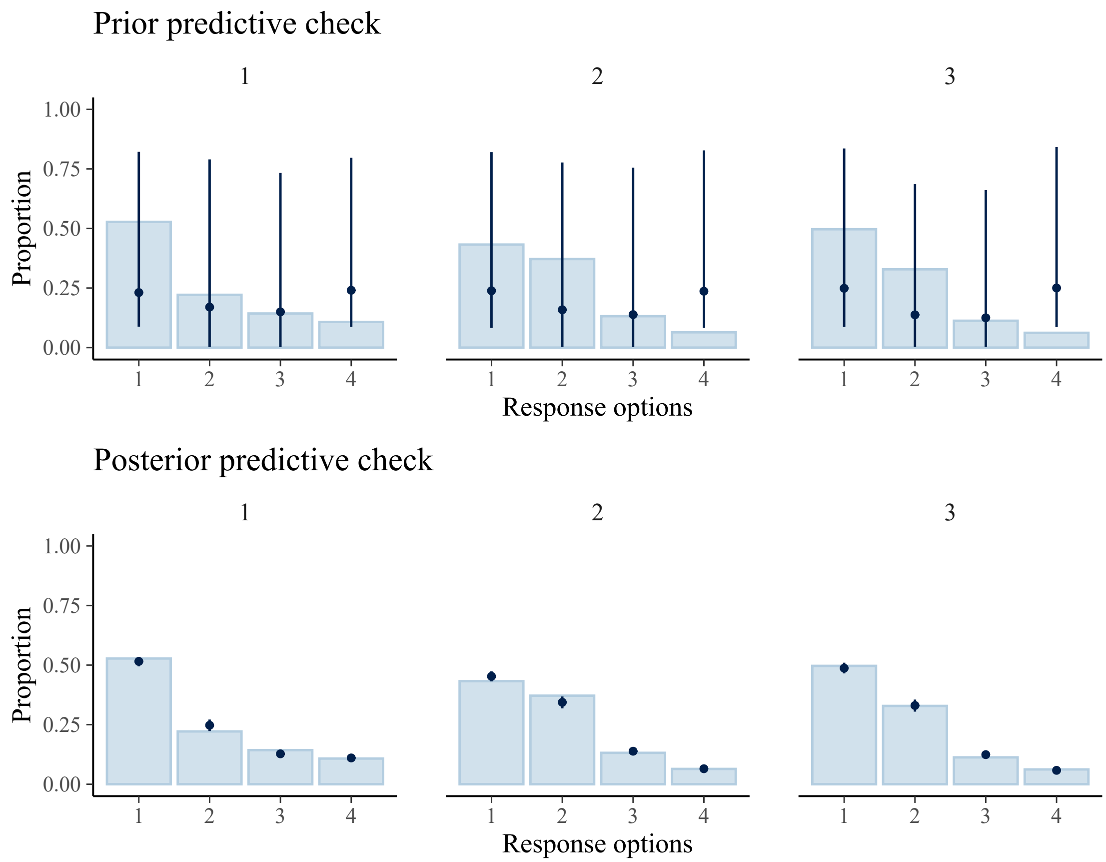


Figure S7: **Model `m1_imp`: Prior and posterior predictive checks**. Blue bars are observed proportions of each outcome response option, ranging from 1 (religion is "not at all important") to 4 (religion is "very important"). Points are prior (top panel) and posterior (bottom panel) means of the predicted 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). 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-secondary non-tertiary education

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

(levels 3 and 4), and tertiary education (levels 5-8). Available gender categories are female and male. All data are from 2020. 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 100 draws for each cell and wave, and then summarize these predictions by the median and the 2.5% and 97.5% quantiles[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 | Y15-24 | Levels 0-2 | 185100 |
| Female | Y15-24 | Levels 3-4 | 140100 |
| Female | Y15-24 | Levels 5-8 | 21100 |
| Female | Y25-49 | Levels 0-2 | 128100 |
| Female | Y25-49 | Levels 3-4 | 300700 |
| Female | Y25-49 | Levels 5-8 | 470100 |
| Female | Y50-74 | Levels 0-2 | 227600 |
| Female | Y50-74 | Levels 3-4 | 377600 |
| Female | Y50-74 | Levels 5-8 | 298000 |
| Male | Y15-24 | Levels 0-2 | 217400 |
| Male | Y15-24 | Levels 3-4 | 128600 |
| Male | Y15-24 | Levels 5-8 | 14300 |
| Male | Y25-49 | Levels 0-2 | 171200 |
| Male | Y25-49 | Levels 3-4 | 384500 |
| Male | Y25-49 | Levels 5-8 | 364500 |
| Male | Y50-74 | Levels 0-2 | 213900 |
| Male | Y50-74 | Levels 3-4 | 423600 |
| Male | Y50-74 | Levels 5-8 | 246200 |

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.

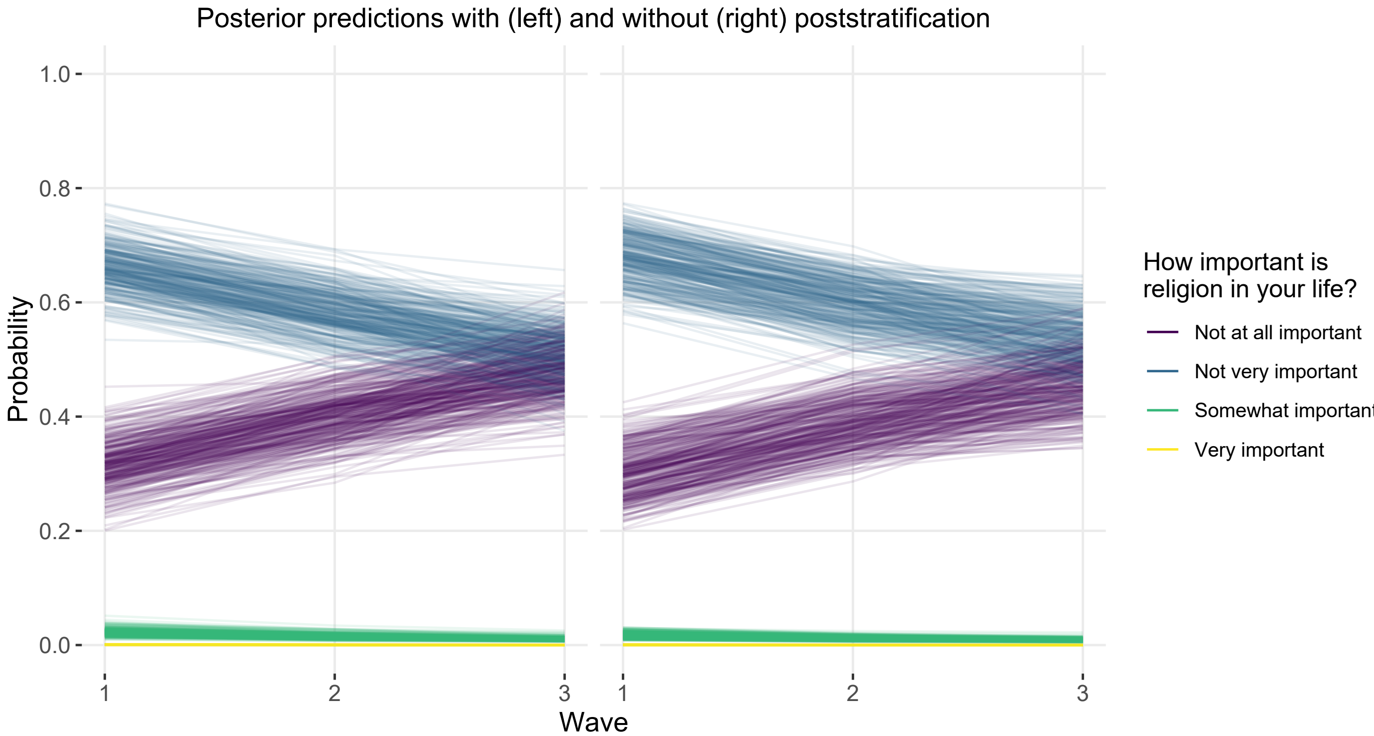


Figure S8: **Poststratification: Predicted cumulative probabilities across measurement waves for the response options**. Poststratification model `m_mrp` (left) vs. the unadjusted model `m0`. Lines are posterior predictive draws.

### *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 take 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. While not identical, results are similar to model `m1` (cf., Figure 3 in main manuscript).

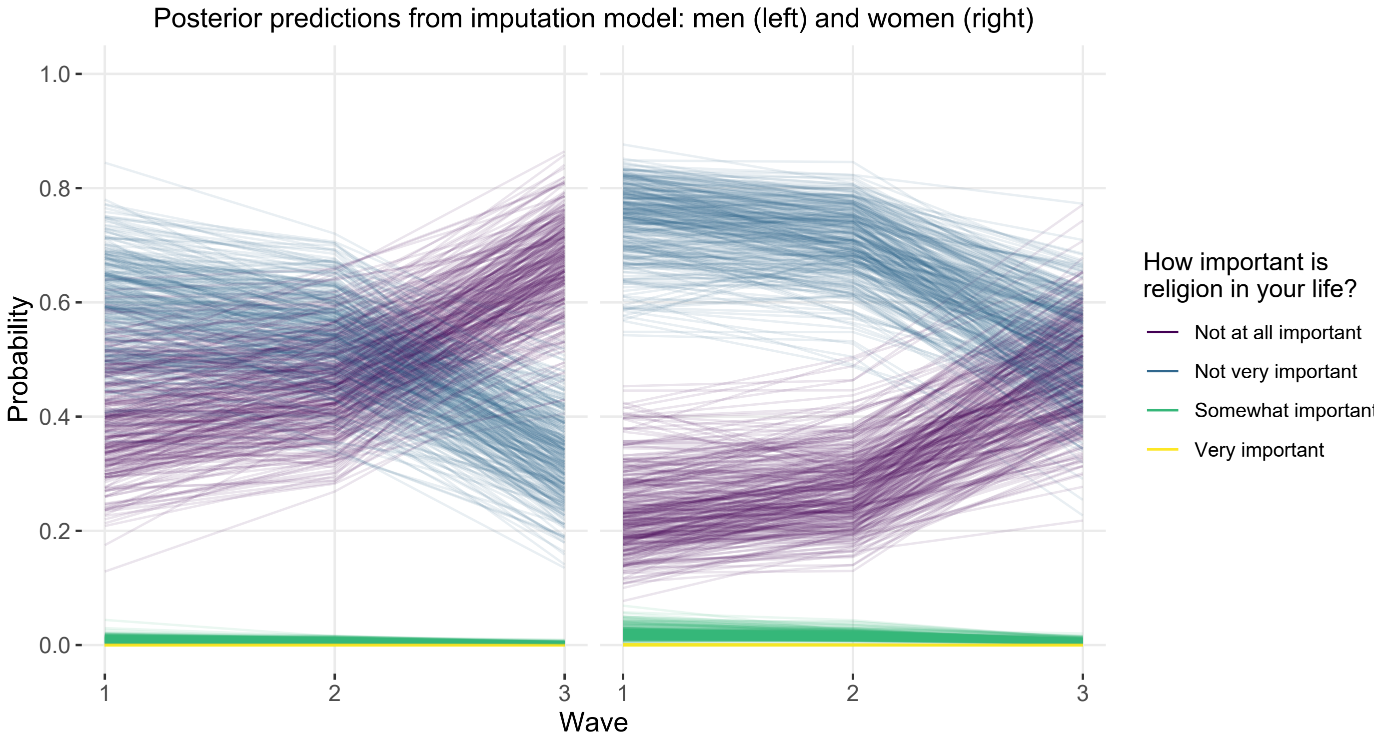


Figure S9: **Imputation model `m1_imp`: Predicted cumulative probabilities across measurement waves for the response options**. For men (left) and women (right) with categorical covariates set at their reference values and age set at 0 (as it is mean-centered). Lines are posterior predictive draws. Random effects not included in predictions.

## S3. Supplementary results and plots

Here, we report supplementary plots.

Figure S10 compares predictions from the two unadjusted models: listwise deletion model `m0` and complete-cases model (`m0_complete`). Figure S11 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.

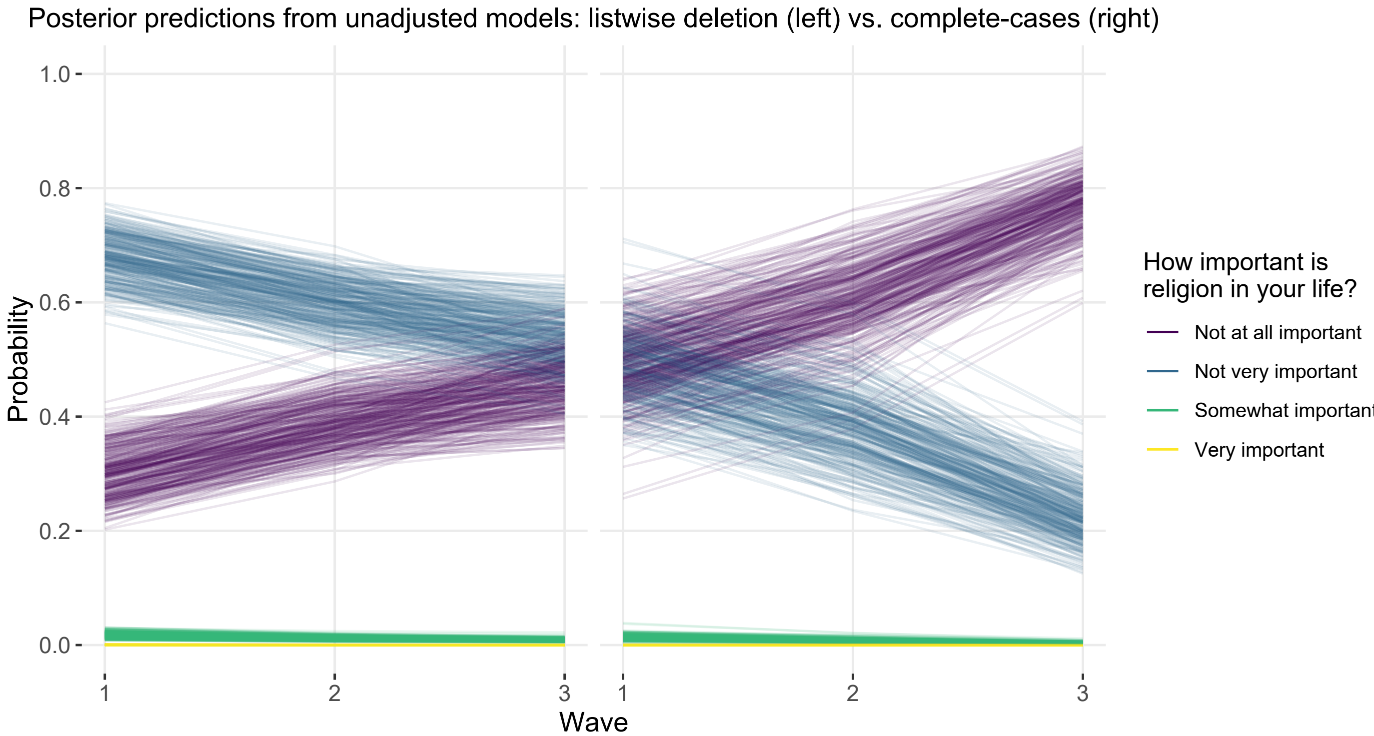


Figure S10: **Unadjusted models: Predicted cumulative probabilities across measurement waves for the response options**. For listwise deletion model `m0` vs. complete-cases model (`m0_complete`). Lines are posterior predictive draws. Random effects not included in predictions.

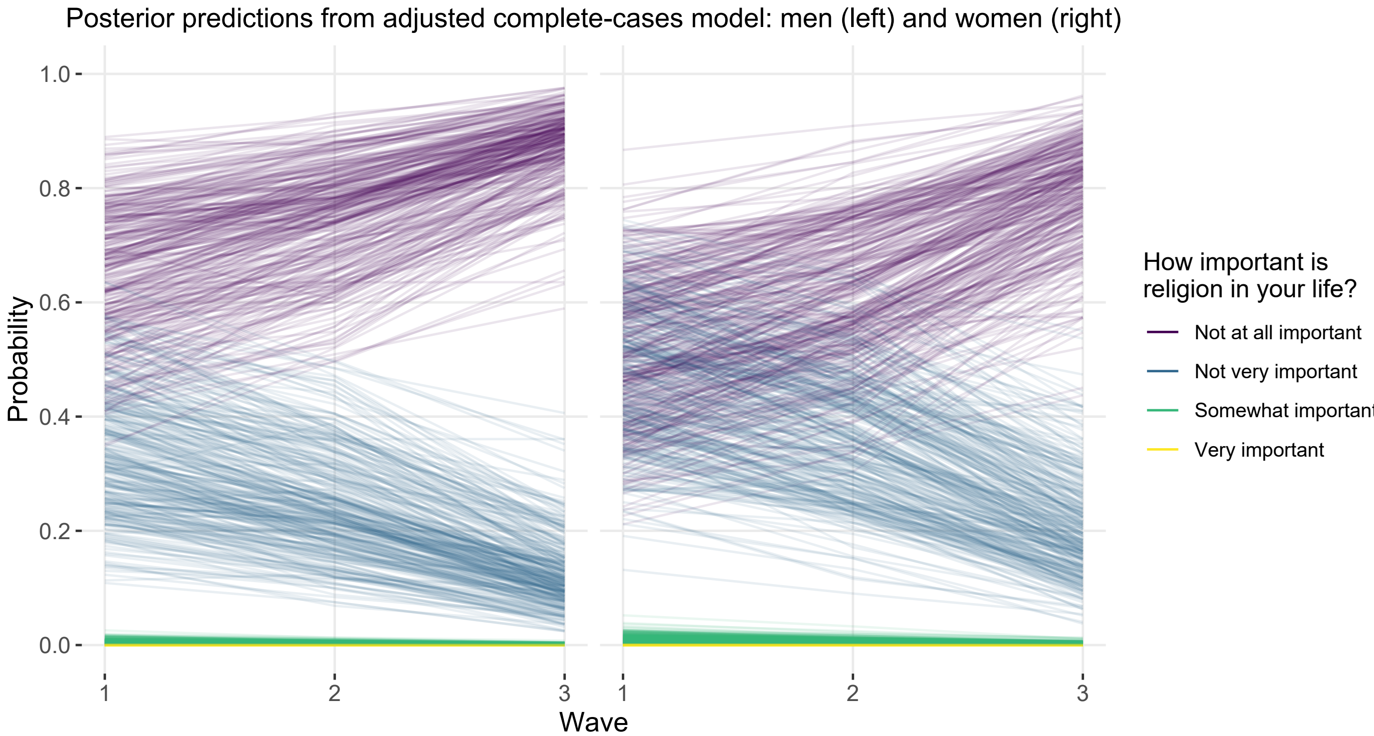


Figure S11: **Complete-cases model `m1_complete`: Predicted cumulative probabilities across measurement waves for the response options**. For listwise deletion model `m0` vs. complete-cases model (`m0_complete`). For men (left) and women (right) with categorical covariates set at their reference values and age set at 0 (as it is mean-centered). Lines are posterior predictive draws. Random effects not included in predictions.

Figure S12 shows predictions from `hinc_model`, 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 S13 shows predictions from `health_model`, 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 S12 – S17 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.

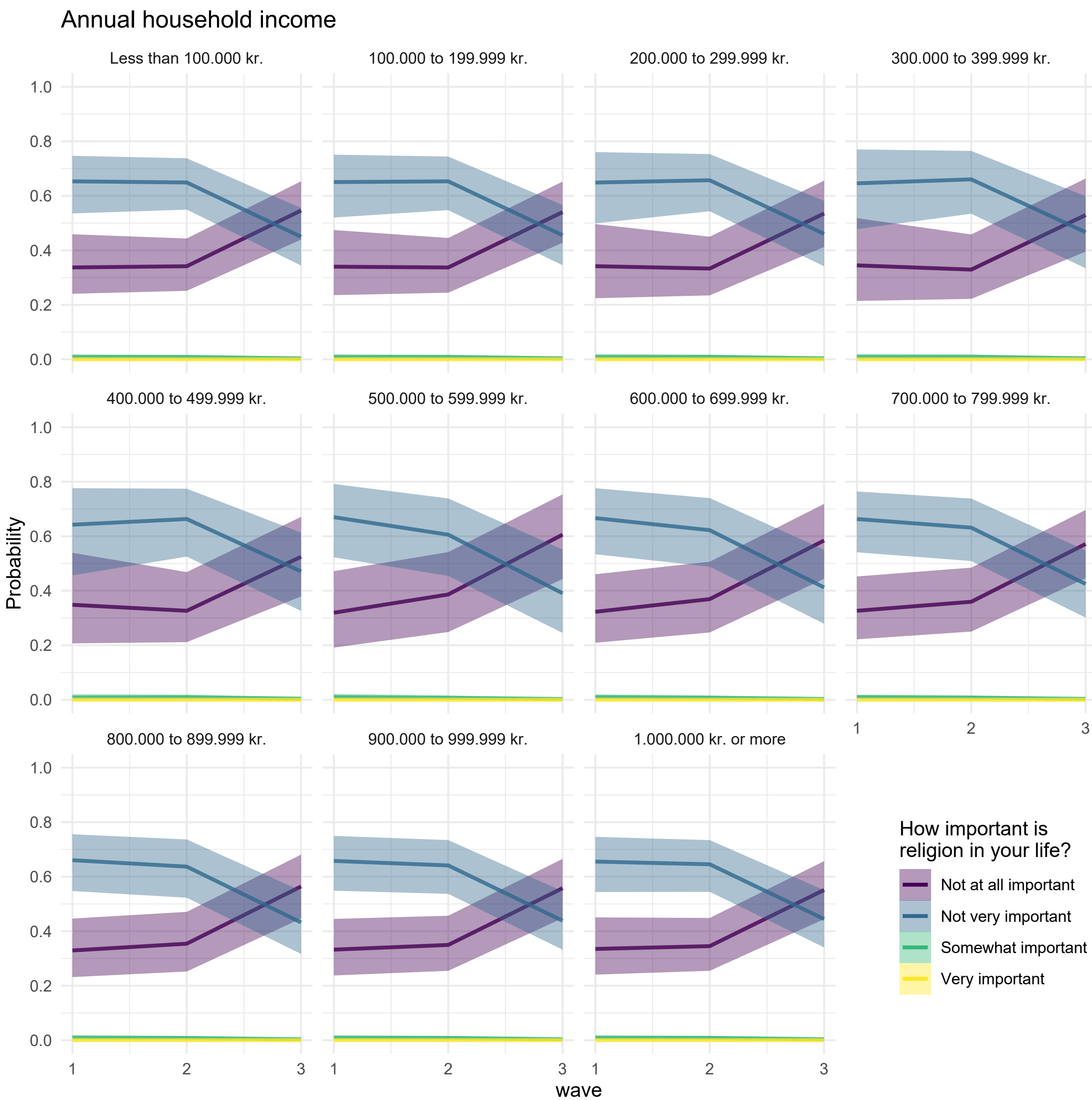


Figure S12: **Interaction plot** `hinc_model`: Predicted cumulative probabilities of response options across measurement waves and income levels. Thick lines are posterior medians and bands are 95% credible intervals.

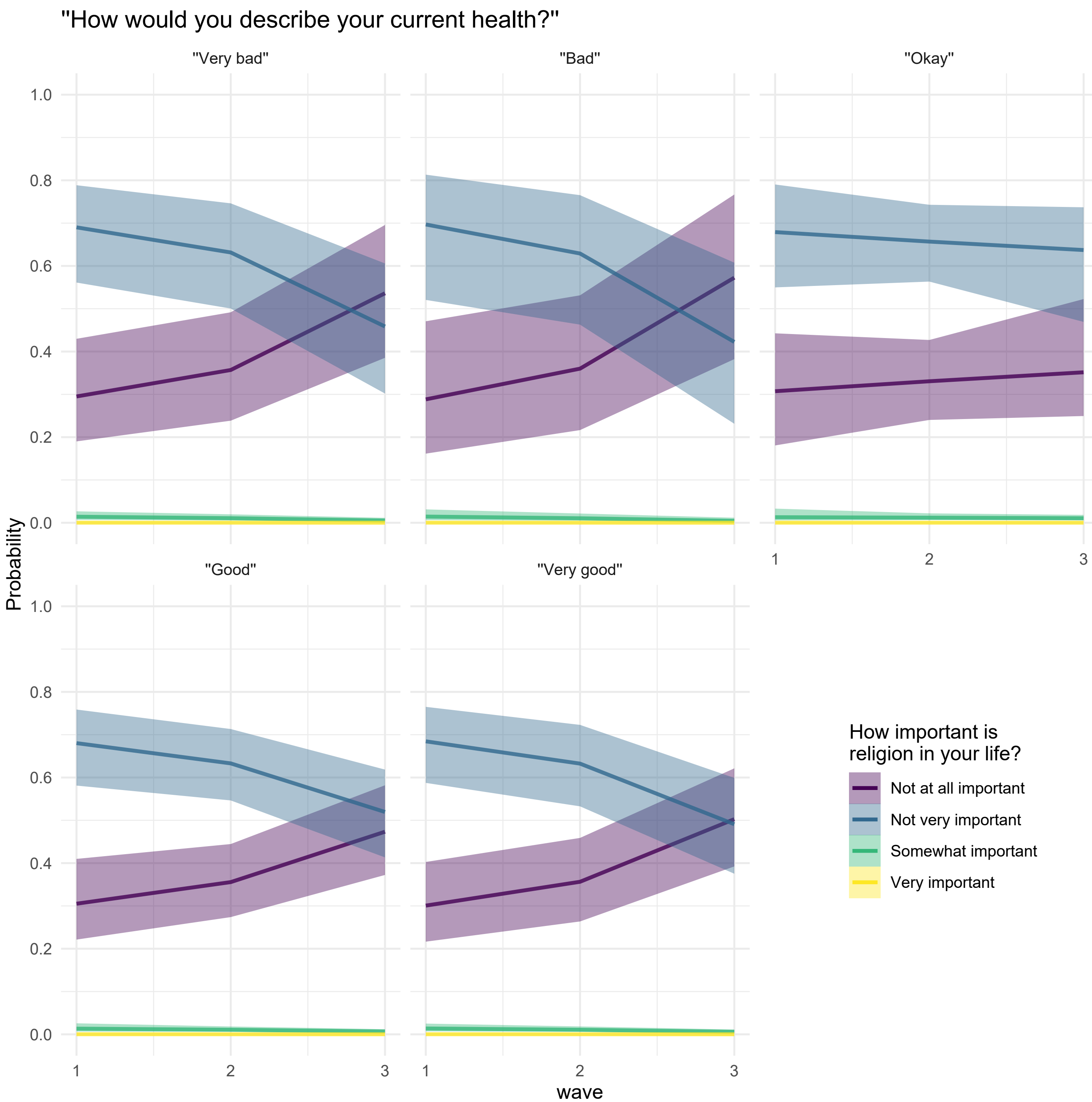


Figure S13: **Interaction plot `health_model`**: Predicted cumulative probabilities of response options across measurement waves and self-reported health. Thick lines are posterior medians and bands are 95% credible intervals.

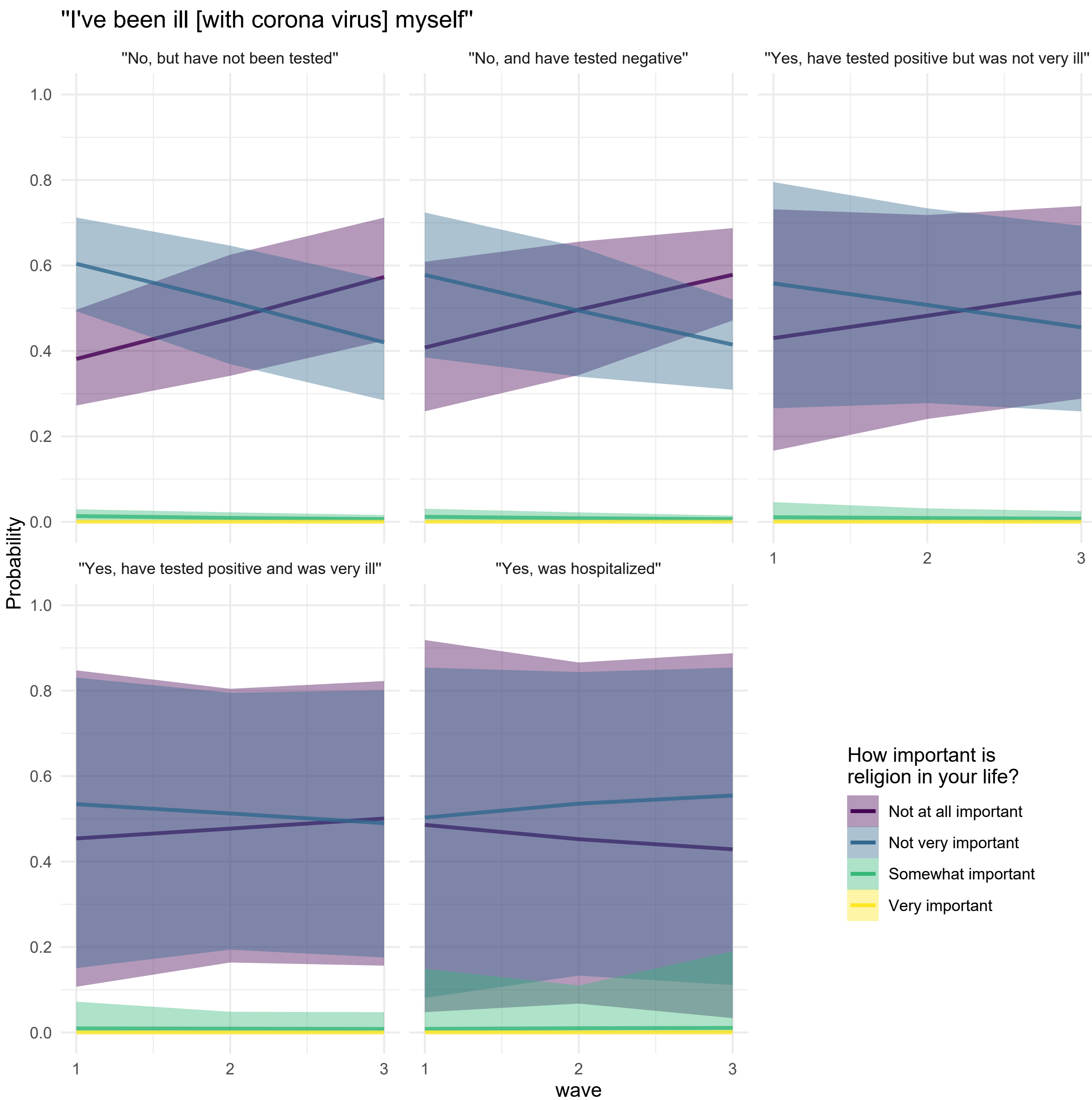


Figure S14: **Interaction plot `m_self`**: Predicted cumulative probabilities of response options across measurement waves and self-reported exposure to corona virus. Thick lines are posterior medians and bands are 95% credible intervals.

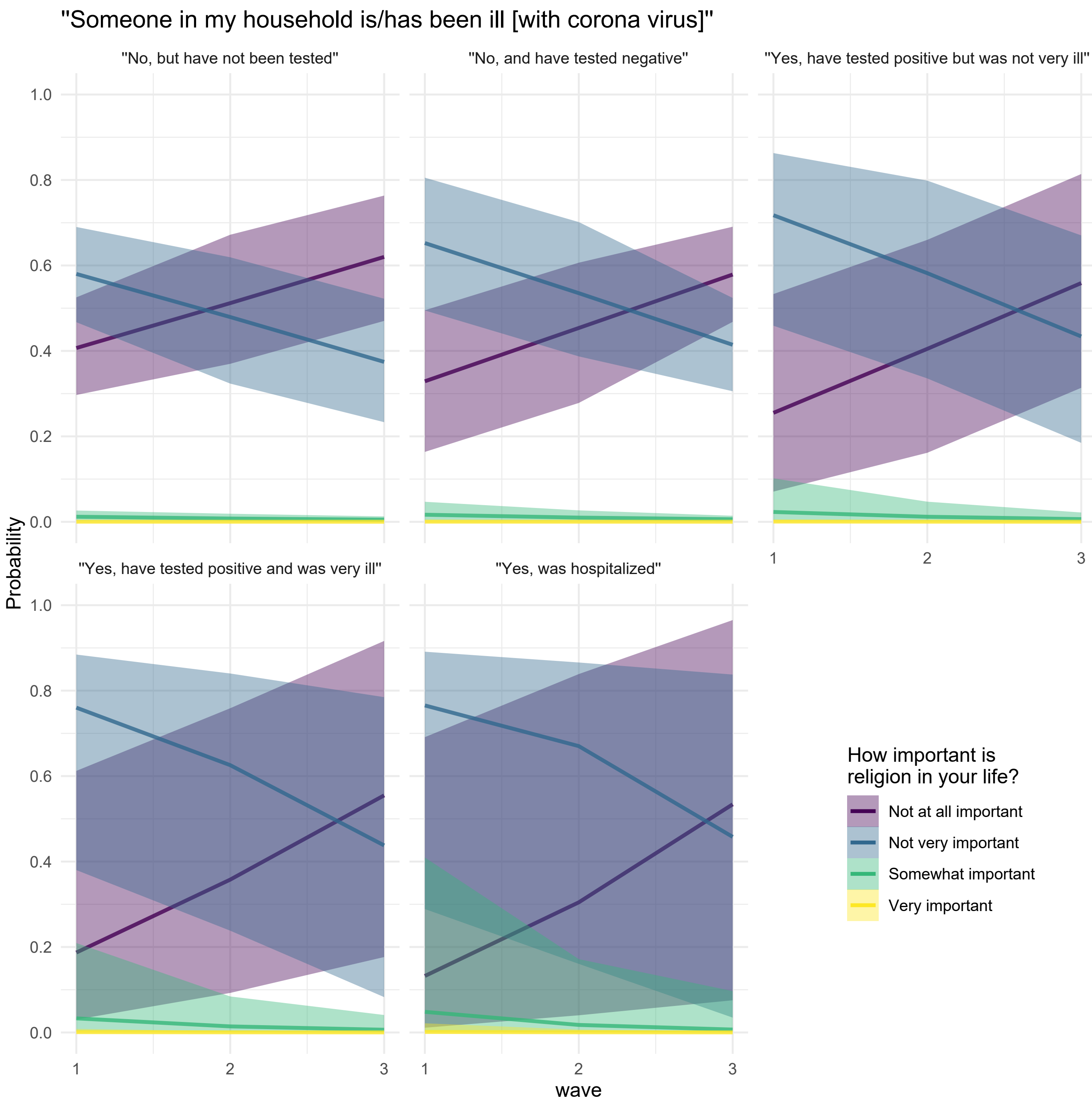


Figure S15: **Interaction plot `m_household`**: Predicted cumulative probabilities of response options across measurement waves and self-reported exposure to corona virus. Thick lines are posterior medians and bands are 95% credible intervals.

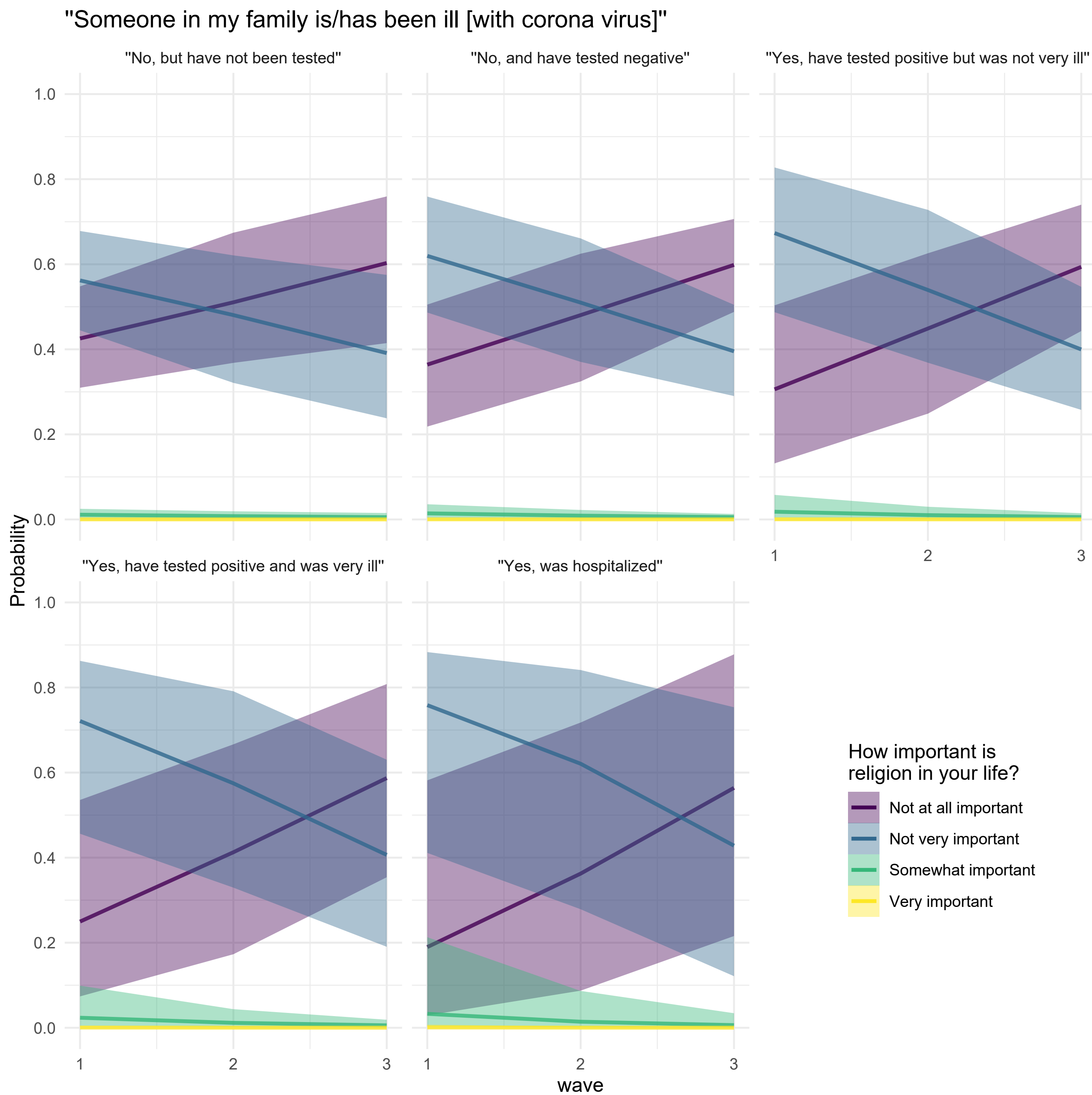


Figure S16: **Interaction plot `m_family`**: Predicted cumulative probabilities of response options across measurement waves and self-reported exposure to corona virus. Thick lines are posterior medians and bands are 95% credible intervals.

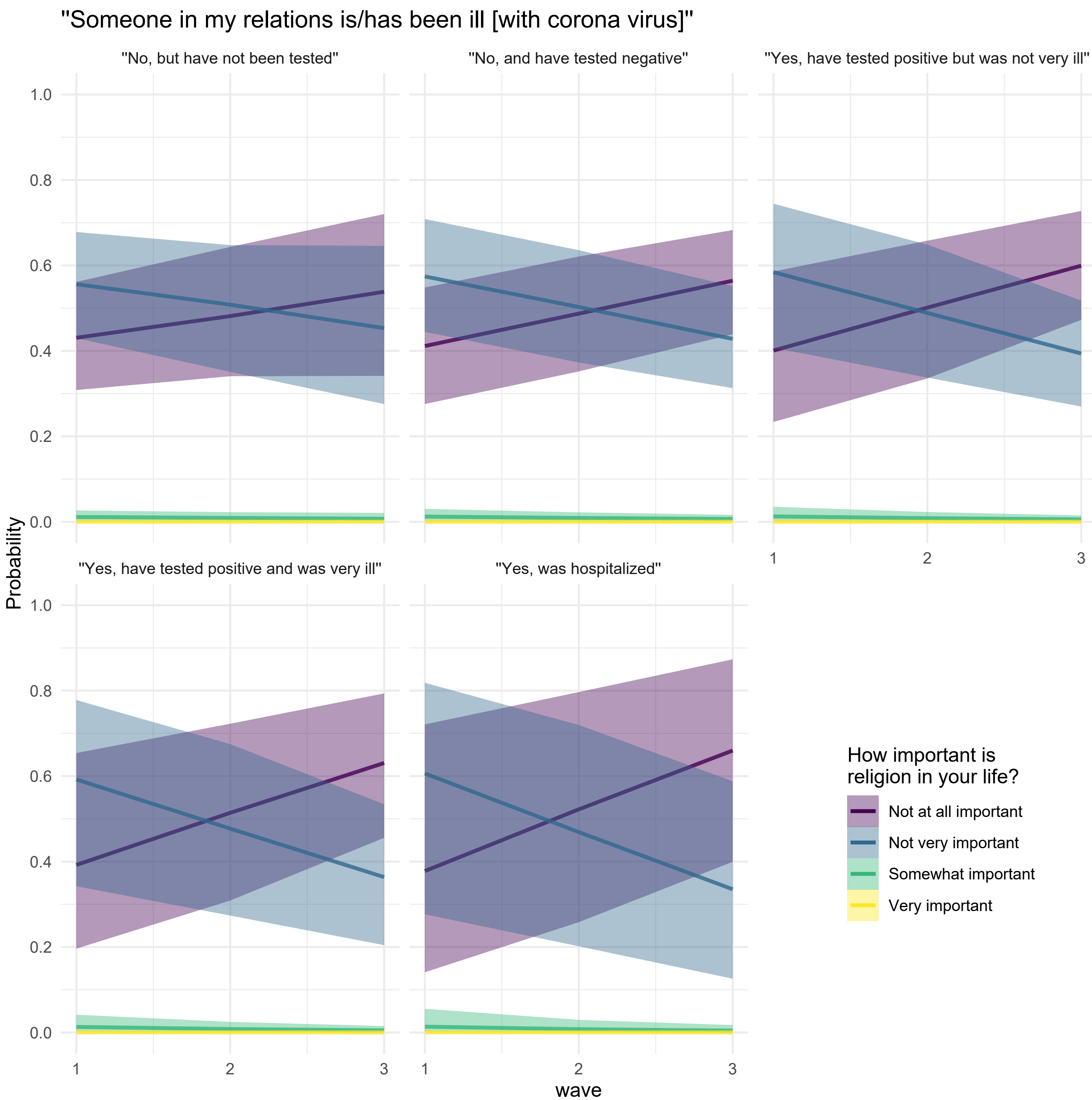


Figure S17: **Interaction plot `m_relations`**: Predicted cumulative probabilities of response options across measurement waves and self-reported exposure to corona virus. Thick lines are posterior medians and bands are 95% credible intervals.

## 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).

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