The role of “morality” in moralistic supernatural punishment: Pre-registering an analysis across 15 field sites

Theiss Bendixen[a,*], Aaron D. Lightner[a], Coren Apicella[b], Quentin Atkinson[c,d], Alexander Bolyanatz[e], Emma Cohen[f], Carla Handley[g], Joseph Henrich[h], Eva Kundtová Klocová[i], Carolyn Lesorogol[j], Sarah Mathew[g], Rita A. McNamara[k], Cristina Moya[l], Ara Norenzayan[m], Caitlyn Placek[n], Montserrat Soler[o], Tom Vardy[p], Jonathan Weigel[q], Aiyana K. Willard[r], Dimitris Xygalatas[s,t], Martin Lang[i], Benjamin Grant Purzycki[a,*]

[a] *Aarhus University, DK*
[b] *Department of Psychology, University of Pennsylvania, USA*
[c] *Department of Psychology, University of Auckland, NZ*
[d] *Max Planck Institute for the Science of Human History, DE*
[e] *College of DuPage, USA*
[f] *Wadham College, University of Oxford, UK*
[g] *Arizona State University, USA*
[h] *Harvard University, USA*
[i] *LEVYNA, Masaryk University, CZ*
[j] *Washington University in St. Louis, USA*
[k] *School of Psychology, Victoria University of Wellington, NZ*
[l] *Department of Anthropology, University of California Davis, USA*
[m] *University of British Columbia, CA*
[n] *Department of Anthropology, Ball State University, USA*
[o] *Ob/Gyn and Women's Health Institute Cleveland Clinic, USA*
[p] *Department of International Development, London School of Economics, UK*
[q] *Business and Public Policy Group, Haas School of Business, University of California Berkeley, USA*
[r] *Brunel University, UK*
[s] *Department of Anthropology, University of Connecticut, USA*
[t] *Department of Psychological Sciences, University of Connecticut, USA*

[*] Corresponding authors

Email addresses: `tb@cas.au.dk` (Theiss Bendixen), `bgpurzycki@cas.au.dk` (Benjamin Grant Purzycki)

Preprint submitted to ... *October 31, 2022*

Abstract

Recent cultural evolutionary accounts propose that beliefs about punitive and monitoring gods, spirits, and forces concerned with inter-personal behavior facilitate expansions of cooperation. However, the role of a deity's *explicit* moral concerns—above and beyond any tendency to punish and monitor human behavior more broadly—on the workings of moralistic supernatural punishment beliefs and their behavioral consequences remains unclear. Here, we pre-register an analysis plan to assess whether *free-listing* a locally relevant deity as moralistic predicts fair play in two permutations of two economic games using data from up to 15 diverse field sites. Free-listing might be a more appropriate measure of supernatural moral salience than pre-fabricated item scales used in previous studies. The study therefore contributes substantially to the current literature by a) testing a central hypothesis in the evolutionary and cognitive science of religion using b) a large and culturally diverse data set with c) measures that are behavioral (i.e., economic games) and ethnographically rich (i.e., free-listing).

Keywords

behavioral economics, cognitive anthropology, cultural evolutionary psychology, evolutionary and cognitive science of religion, free-list

1. Introduction

Religion is a human universal (Brown, 1991) and to account for its ubiquity, scholars of religion have long contemplated the role of religious appeals, beliefs, and rituals in human morality and cooperation (e.g., Durkheim, 2001 [1912]; Ellwood, 1918; Evans-Pritchard, 1965; Lang, 1909; Malinowski, 1936; Rappaport, 1968; Wallace, 1966; for recent reviews, see Bendixen et al., forthcomingb; McKay and Whitehouse, 2014; Purzycki and McKay, 2023). While a common view holds that traditional religions of small-scale societies are mostly uncoupled from moral matters (e.g., Boyer, 2021; Tylor, 1920), recent cultural evolutionary accounts propose that beliefs about moralizing deities—that is, punitive and monitoring gods and spirits that are thought of as concerned with inter-personal behavior (see Purzycki and McNamara, 2016)—foster cooperative relationships (Johnson and Bering, 2006; Purzycki and Sosis, 2022; Rossano, 2007) and help societies increase in size and complexity (Atran and Henrich, 2010; Henrich and Muthukrishna, 2021; Norenzayan et al., 2016; Schloss and Murray, 2011; Shariff and Norenzayan, 2007).

Society-level analyses based on data coded from ethnographic material suggest that notions of moralizing supernatural punishment is positively associated with a society's size and political stratification (Roes and Raymond, 2003; Swanson, 1960; Watts et al., 2015) as well as environmental stressors (Botero et al., 2014; Skoggard et al., 2020; Snarey, 1996). These empirical links are based on the general assumption that moralizing deities can help solve collective action problems, particularly in response to social conflict (Caluori et al., 2020; Skali, 2017) and ecological threats (Hayden, 1987; Jackson et al., 2021).

However, database studies of coded ethnographic sources potentially suffer from a variety of biases, including non-representative sampling of cultural groups, systematic missingness in focal variables, and debatable data coding schemes (e.g., whether a moralizing god is also by necessity a *high god*, that is a creator deity; Lightner et al., 2022; Purzycki and McKay, 2023; Purzycki and Watts, 2018; Purzycki et al., 2022a; Watts et al., 2015, 2022). Further, cursory surveys of the ethnographic record (Beheim et al., 2021; Boehm, 2008; Bendixen and Purzycki, 2020, forthcoming; Evans-Pritchard, 1965; Purzycki and McNamara, 2016;

Purzycki and Sosis, 2022) as well as recent individual-level ethnographic inquiries (Bendixen et al., forthcominga; Purzycki, 2011, 2013, 2016; Purzycki et al., 2022d; Shaver et al., 2017; Singh et al., 2021; Townsend et al., 2020) strongly indicate that notions of supernatural punishment of inter-personal behavior are ubiquitous even in smaller-scale societies, calling into question the reliability of databases that suggest otherwise (Lightner et al., 2022).

Studies using individual-level data have found mixed evidence of a causal relationship between notions of monitoring and punitive deities and increased prosociality. For instance, Ge et al. (2019) failed to find a clear association between belief in supernatural punishment and charitable donations in cross-community economic games with a culturally diverse sample. Conversely, Townsend et al. (2020) found that among the Ik of Uganda reminding participants about the possibility of supernatural punishment made them allocate more money to a needy and anonymous co-community member compared to a control condition. Survey (e.g., Atkinson and Bourrat, 2011; McCleary and Barro, 2006; White et al., 2019) and experimental (e.g., Shariff and Norenzayan, 2011; Shariff et al., 2016; Yilmaz and Bahçekapili, 2016) studies conducted primarily in industrialized societies likewise tend to find positive relationships between beliefs in supernatural punishment and/or reward and various indices of cooperation, although the general literature on religion and prosociality is contested (see e.g., Bloom, 2012; Galen, 2012).

In what is arguably the largest and most ethnographically rich project on the topic to date, Lang et al. (2019) found a small but robust association between ratings of deities as punitive and monitoring and non-selfish coin allocations in two anonymous economic games played across 15 field sites, supporting the notion that moralizing religions can indeed facilitate an expansion of cooperative circles. However, critically, in Lang et al. (2019) ratings of deities as morally concerned—specifically, a three-item "moral interest scale" on the extent to which a deity cares for punishing theft, lying, and murder—did *not* consistently predict coin allocations.

To date, then, individual-level studies are inconclusive with regards to establishing a link between moralistic supernatural punishment and prosociality (Bendixen et al., forthcomingb). More particularly, the role of a deity's *explicit* moral concerns—as opposed to any *broad* tendency to punish and monitor human behavior—on the workings of moralistic supernatural punishment beliefs and their behavioral consequences remains unclear. That is, to what extent does the explicit *content* of gods' punitive concerns (Bendixen et al., forthcominga) matter for facilitating cooperation above and beyond a god's perceived capabilities for punishment and monitoring more broadly?

Aside from Lang et al. (2019) and Purzycki et al. (2016b), few studies have attempted to address this question. It's an important question, however, because while deities of non-world religions are often perceived as having a relatively narrower scope for monitoring and punishment, many deities are nonetheless attributed with concerns that seem to directly correspond to locally pressing problems with coordination and cooperation, such as territoriality, ecological management, resource distribution and, crucially, breaches of moral norms (Bendixen and Purzycki, 2020, forthcoming; Bendixen et al., forthcominga; McNamara and Purzycki, 2020; Purzycki and McNamara, 2016; Purzycki et al., 2022d). As such, determining whether these explicit concerns impact individuals' behavior would help clarify the role that supernatural appeals and beliefs might have played in human societies, past and present (Bendixen et al., forthcomingb).

1.1. The present study

Here, building on the dataset from Lang et al. (2019), we pre-register an analysis plan to assess the importance of moral content in moralistic supernatural punishment beliefs and their behavioral consequences. Specifically, we test whether *free-listing* a locally relevant deity as angered by breaches of "morality" (for details, see Section 3.3) predicts fair play in two permutations of each of two economic games.

Free-listing involves simply asking people to list their associations on some topic, in this case what angers a locally relevant moralistic deity. The earlier an item is listed the more likely that item is also to figure in the lists of participants drawn from the same cultural milieu (Bendixen et al., forthcominga; Purzycki, 2011, 2013, 2016; Willard et al., 2020). Therefore, free-listing unequivocally reflects cognitive and cultural models of the target topic, given that this topic is relevant in the local context (Quinlan, 2017). Free-listing might therefore be a more appropriate measure of supernatural moral salience than pre-fabricated item scales used in previous studies. In fact, a recent cross-cultural methodological analysis (Bendixen and Purzycki, n.d.) failed to find clear evidence of within-subject agreement between the three-item "moral interest scale" from Lang et al. (2019) and Purzycki et al. (2016b) and a corollary free-list task, hinting at a dissociation between these two instruments. While free-lists are more often used for descriptive or exploratory purposes (e.g., informing item scale construction), here then we leverage free-list data as a predictor variable in a series of multilevel regression models. This arguably allows for a higher-resolution and more ethnographically rich assessment of peoples' cultural beliefs and their behavioral implications, compared to forced item responses.

In addition, studies reviewed above suggest that we should distinguish between a deity's tendency to punish and monitor inter-human behavior more broadly from a deity's *explicit* moral concerns. Here, we want to investigate whether attributing both explicit moral concern *and* broad capabilities for punishment and monitoring to a deity (i.e., interaction effects) facilitates prosociality in economic game play to a greater extent compared to these attributes in isolation (i.e., additive effects). That is, does the perceived scope of a deity's capabilities for monitoring and punitiveness moderate the impact on behavior of explicit moral concerns attributed to a supernatural agent?

In our analysis, we hold relevant covariates constant (Section 2). We operationalize *punitive* and *monitoring/omniscient* according to two item scales (Section 3.2). Prosociality is measured as coin allocations across two different economic games and two permutations of each game (Section 3.1). We operationalize *moralistic* according to a pre-specified list of relevant human behaviors and attributes as they appear in our coded free-list data (Sections 3.3). Our key hypotheses are as follows:

H_1: Free-listing a locally relevant deity as moralistic predicts increased probability of non-selfish coin allocations.

H_2: Free-listing a locally relevant deity as moralistic *while also* rating that same deity as punitive *and* omniscient (i.e., a three-way interaction) predict increased probability of non-selfish coin allocations.

In this pre-registration, we first lay out our causal model (Section 2) and then our methods and data sources (Section 3). Next, we detail our statistical approach (Section 4) and, to give a sense of how we might present results, we report analyses on simulated data (Section 5). The synthetic data analyses also ensure parameter recovery under ideal conditions (e.g., no model misspecification). Finally, we discuss some supplementary analyses that we plan to undertake (Section 6).

2. Causal model

To guide model-building and inference and based on the above review of previous literature, Figure 1 illustrates our assumed causal structure of the data-generating process in the form of a *directed acyclic graph* (DAG; see Pearl et al., 2016).

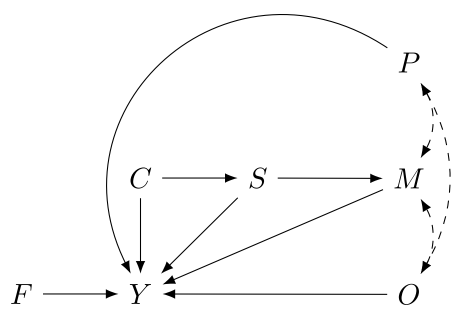

Figure 1: Directed acyclic graph (DAG) of the assumed causal structure of the data-generating process. C = number of children; S = food insecurity; P = punitive tendency of deity; O = knowledge breadth of deity; M = moral salience of deity; Y = prosociality; F = Structural features of the game set-up. Dashed double-headed arrows refer to bidirectional causal relationships.

Here, Y denotes prosociality, M, P and O denote respectively the moral concern, punitive tendency, and knowledge breadth of a deity (between which we assume bidirectional causal relationships represented by dashed double-headed arrows), S denotes food (in)security, C denotes number of children, and F denotes a set of structural features of the game set-up (game order, game check, and game type; see Sections 3.1 and 3.2). These assumed relationships derive from previous empirical studies and evidence syntheses[1] (Lang et al., 2019; Purzycki et al., 2016b, 2018a,b,c, 2022c). Our target relationship, or *estimand*, then, is the direct effect $M \rightarrow Y$, where M is measured using free-lists and Y is operationalized as economic game play.

According to this causal model and assuming no relevant unobserved confounding, to block all back-door paths from M to Y, we need only condition on—or "control for"—P, O, and S. The path from C to M through S is blocked when we condition on S; conditioning on C is therefore not strictly necessary. However, including C can reduce variation in Y, thereby increasing the precision of the target relationship (see e.g., Cinelli et al., 2021, and references therein), and we therefore include both C and S in our conditioning set[2]. For the same reason, we include the structural features of the game set-up, F. The only colliders in this graph are the main predictor variables M, P and O, and the outcome variable, Y, and so, under this model, conditioning on covariates does not induce spurious associations in our estimand. Moreover, while we assume no systematic missingness pattern, our statistical models employ full Bayesian imputation of missing covariates (McElreath, 2020) in an attempt to address bias that might arise from non-balanced response patterns[3]

[1]Note that our adjustment set is rather minimal. We justify this on the grounds that previous analyses (in particular, see Lang et al., 2019) did not find consistent relationships between common control variables (sex, education, etc.) and coin allocation to the DISTANT cup across a wide range of model specifications.

[2]Two additional variables could be included on these grounds, namely measures of emotional closeness to the LOCAL/DISTANT players using pictorial "fusion" scales. While previous research found small effects of these variables on prosocial coin allocations, a concern was raised that rather than being measures of "fusion" *per se*, these instruments might measure prosocial tendencies in general (cf., Purzycki and Lang, 2019). Given ambiguities around validity, we refrain from including these variables here.

[3]We could expand our causal model to explicitly include potential sources of bias arising from various sampling strategies and missing data (see e.g., Deffner et al., 2021; Schuessler and Selb,

(see Section 4).

In the next section (Section 3), we map these abstract relationships to available variables in our dataset.

3. Data & Methods

The data come from the Evolution of Religion and Morality Project (Lang et al., 2019; Purzycki et al., 2016a, 2018a, 2022c). The full data set consists of two waves of data collection across a total of 15 field sites (Table 1). As such, the data are already collected, assembled, and partly analyzed – for site-specific and omnibus reports, see: Tanna, Vanuatu (Atkinson, 2018; Vardy and Atkinson, 2022), Lovu, Fiji (Willard, 2018), Mauritius (Klocová et al., 2022; Xygalatas et al., 2018), Pesqueiro, Brazil (Cohen et al., 2018), Tyva Republic (Purzycki and Kulundary, 2018), Yasawa, Fiji (McNamara and Henrich, 2018; McNamara et al., 2021), Hadza, Tanzania (Apicella, 2018; Stagnaro et al., 2022), Sursurunga, Papua New Guinea (Bolyanatz, 2022), Mysore, India (Placek and Lightner, 2022), Cachoeira, Brazil (Soler et al., 2022), Kananga, D. R. Congo (Kapepula et al., 2022), omnibus (Baimel et al., 2022; Bendixen et al., forthcominga; Lang et al., 2019; Purzycki and Lang, 2019; Purzycki et al., 2016b, 2018b, 2022d; Vardy et al., 2022).

2019). However, while sampling strategies differed across sites (see Lang et al., 2019), we have no *a priori* reason to suspect more or less site-specific representativeness for the graphed variables.

Table 1: Selected moralistic deities, primary economy, and cultural group of the anonymous DISTANT recipient in the two economic games for each field site.

Site	Economy	Moralistic deity	DISTANT recipient
Cachoeira, Brazil	Wage labor	Christian God	Candomble
Coastal Tanna	Hort./Hunting	Christian God	Christian
Hadza	Hunting	*Haine*	Hadza
Huatasani, Peru	Agro-pastoralism	Christian God	Catholic
Inland Tanna	Hort./hunting	*Kalpapen*	Kastom
Kananga, DRC	Wage labor	Christian God	Non-Luluwa Christ.
Lovu, Fiji	Wage labor	Shiva	Hindu
Marajó, Brazil	Wage labor	Christian God	Christian
Mauritius	Wage labor	Shiva	Hindu
Mysore, India	Wage labor/farming	Shiva	Hindu
Samburu, Kenya	Herding/wage labor	Christ./Trad. (*Nkai*)	Christ. Samburu
Sursurunga, Papua New Guinea	Horticulture	Christian God (*Káláu*)	Christ. Sursurunga
Turkana, Kenya	Pastoralism	Christ. God (*Akuj*)	Christ. Turkana
Tyva Republic	Wage labor/herding	*Buddha-Burgan*	Buddhist
Yasawa, Fiji	Fishing/farming	Christian God	Hindu

However, while the first 8-site wave of free-list data (see Bendixen et al., forthcominga) has been thematically coded by a pair of independent coders (see Section 3.3) and cleaned (see Section 3.3.1), the remaining free-list data (wave two) are coded but are yet to be systematically assessed, checked, cleaned, and analyzed. Therefore, we consider it timely to now transparently document and pre-register our planned workflow before moving to the next stage of data preparation and analysis.

3.1. Economic games

Our focal outcome measure of wider prosociality is behavioral response in two economic games, the Random Allocation Game and the Dictator Game. The participants played each game in two conditions: SELF vs. DISTANT (i.e., coins are either allocated to the participant themselves or an anonymous, geographically distant co-religionist) and LOCAL vs.

DISTANT (i.e., coins are either allocated to a local co-religioinst or a distant co-religionist)[4]. The combined total stakes across games and conditions were set at the local daily wage with a show-up fee of ≈25% of the local daily wage.

The Random Allocation Game (RAG) is a simple economic game experiment designed to measure impartial rule-following (Hruschka et al., 2014; Jiang, 2013; McNamara et al., 2016). In our RAG, participants were endowed with 30 coins, a die with two outcomes (e.g., black and white), and two cups each designated as the cup of two different recipients, a cup for SELF/LOCAL and another cup for DISTANT depending on condition (see just above). For each coin, participants were asked to think of the recipient to whom they wish to allocate the coin and then roll the die. If the die lands with a particular outcome (e.g., black), then the participant can allocate the coin to the wished-for recipient; otherwise, the coin goes in the opposite cup. However, since the intended recipient is never revealed, participants are in a position to place the coins in whichever cup they want. Since we expect the coin allocations to be binomially distributed with a fair die, systematic deviances from this assumption are interpreted as increased (or decreased) rule-breaking in favor of self/in-group.

In the Dictator Game (DG), participants are endowed with a stack of coins (10 in this case) and are simply asked to split this in two (SELF vs. DISTANT or LOCAL vs. DISTANT, depending on game condition) however they like. As with the RAG, the DG is a measure of self/in-group favoritism. Playing two different games with the same sample ensures that any result is not isolated to a particular game set-up.

[4]Two further conditions were employed in the full protocol: SELF vs. OUTGROUP (i.e., coins are either allocated to the participant themselves or an outgroup member), and DISTANT vs. OUTGROUP (i.e., coins are either allocated to a distant co-religionist or an outgroup member). For the present study, we focus exclusively on the SELF vs. DISTANT and LOCAL vs. DISTANT conditions, since the OUTGROUP conditions entail distinct theoretical predictions (cf., Lang et al., 2019) that are outside the scope of our current aims.

3.2. Covariates

A comprehensive overview of variables, sampling procedures, and field sites characteristics employed in the Evolution of Religion and Morality Project can be found in Purzycki et al. (2016a) and Lang et al. (2019). Here, we describe the operationalization of covariates relevant for the present study. In addition to the conditioning set identified in Section 2, we include three variables (game order, game check and game type; see explication below) related to the structural features of the game set-up (see Purzycki et al., 2018b).

Children: the self-reported number of children that a participant has fathered or given birth to.

Food insecurity: participant's self-reported food (in)security measured with a dichotomous (yes/no) item: "Do you worry that in the next month your household will have a time when it is not able to buy or produce enough food to eat?".

Punitiveness: The mean of two dichotomous (yes/no) items: "Does [moralistic deity] ever punish people for their behavior?" and "Can [moralistic deity] influence what happens to people after they die?".

Knowledge breadth: The mean of two dichotomous (yes/no) items: "Can [moralistic deity] see into people's hearts or know their thoughts and feelings?" and "Can [moralistic deity] see what people are doing if they are far away in [a distant town or city familiar to locals]?"

Game order: An indicator denoting which game participants played first. 0 = SELF Game first, 1 = LOCAL Game first.

Game check: An indicator denoting whether, when asked what they thought the games were about during debriefing, a participant's response included (= 1) "honesty," "fairness," and/or "cheating".

Game type: An indicator for game type. SELF Game = 1.

3.3. Free-listing

As part of the main study protocol, participants were asked to freely list the kinds of things that angers a locally important "moralistic deity" (i.e., a deity perceived as concerned with inter-personal behavior)[5] (Bendixen et al., forthcominga). The free-list data were subsequently thematically coded by two pairs of independent coders, one pair for each wave, according to both a top-down, twelve-category coding rubric (our "general codes") drawn from Purzycki and McNamara (2016), and a bottom-up rubric subjective to each coder (our "specific codes"). According to the general coding rubric, "Morality" was coded as *generalized behaviors that have a benefit or cost to other people (e.g., hurting, being generous, sharing, etc.)* (Purzycki and McNamara, 2016).

In our analysis, we will use free-list responses to predict game behavior in a series of multilevel regression models. As we are interested in measuring the extent to which individuals ascribe moral concern to their deities, we will use the *proportion of moral items* in each participant's lists as our focal predictor. Free-list data processing will be carried out with the `AnthroTools` package (Jamieson-Lane and Purzycki, 2016; Purzycki and Jamieson-Lane, 2016) for `R` (R Core Team, 2021).

3.3.1. Free-list data cleaning

Following the workflow of Bendixen et al. (forthcominga), the data entries for the general codes will be cleaned and systematized (e.g., in terms of spelling, typos, and blank spaces) to avoid that the same codes will be treated as separate by the parsing in `R` and `AnthroTools`. Then, in cases of disagreement between coders, we will select for final analysis the best fitting of the two codes according to the general coding scheme (see Purzycki and McNamara, 2016). A column designating these (dis)agreements will be added to the spreadsheet, and the selected code will be stored in a separate column for full transparency.

[5]In the full protocol, participants were also asked to list the kinds of things that please the target deity. Participants were also prompted to list what angers and pleases a "local deity" (i.e., a deity that is locally relevant but less moralistic, punitive, and knowledgeable) and the police (see Bendixen et al., forthcominga, for an empirical report of the wave 1 free-list data). Both kinds of deities were selected for each site on the basis of preliminary ethnographic interviews. For the present study, we focus on what *angers* the "moralistic deities", since for each field site the frame of the experimental game was explicitly about the religious traditions of those deities.

4. Statistical models

In this section, we lay out our statistical approach and detail the main models in formal notation. The models are extensions of the main model from Purzycki et al. (2018b). We analyze the RAG with a binomial model (Section 4.1) and the DG with an ordered categorical model (Section 4.2). Both sets of models include varying effects to manage repeated observations on individuals and groups. We calibrated and verified the models on simplified simulated data to ensure that the models in fact recover key parameters in an ideal scenario under the assumed data-generating process (see Figure 1).

For H_1 the key parameter is that of free-listed morality β^{M} on coin allocation y. To assess H_2 for each of the two outcomes we fit two different models: (1) The theoretically informed "interaction model" including three two-way interaction terms, one for punitiveness and free-listed morality β^{MP}, another for knowledge breadth and free-listed morality β^{MO}, a third for punitiveness and knowledge breadth β^{PO} (not directly relevant to H_2 but a sub-component of the three-way interaction), and one three-way interaction term β^{MPO}, as well as main effects of morality β^{M}, punitiveness β^{P} and knowledge breadth β^{O}; and (2) an "additive model", which excludes all interaction terms but retains the main effects, and serves then as a "null model" in contrast to the theoretically informed interaction model.

We will then 1) inspect the interaction terms to evaluate whether their coefficients (e.g., posterior means or medians) and corresponding intervals have the bulk of their mass above a log odds of 0 (i.e., "no effect"), 2) assess the posterior predictions of the interaction terms on their natural scales (e.g., posterior predicted probabilities; see Section 5), and 3) compare the two model pairs with approximate leave-one-out cross-validation (LOO-CV; Vehtari et al., 2017), a convenient model comparison tool that computes metrics of out-of-sample predictive accuracy while penalizing model complexity[6]. Model code and data are prepared with the

[6] More specifically, LOO-CV approximates the focal models' relative accuracy in predicting a new observation in one of the observed groups. An alternative approach is leave-one-group out cross-validation (LOGO-CV) which assesses models' relative accuracy in predicting a new observation in a new (unobserved) group. This procedure is much more computationally intensive, because it

`rethinking` package (McElreath, 2020) for `R` and fit with `RStan` (Carpenter et al., 2017; Stan Development Team, 2021).

Below, we explain the full interaction models for each game in pieces.

4.1. RAG model

To model the coin allocations to the distant cup y out of a total of 30 coins in the RAG, we use Bayesian multilevel binomial regression:

$$
\begin{aligned}
y_i &\sim \text{Binomial}(30, p_i) && (1)\\
\text{logit}(p_i) &= \alpha + \sigma_{\text{id}} z_{\text{id}i]} + a_{\text{group}[i]} && (2)\\
&\quad + \beta^{\text{M}}_{\text{group}[i]} M_i + \beta^{\text{P}}_{\text{group}[i]} P_i + \beta^{\text{O}}_{\text{group}[i]} O_i && (3)\\
&\quad + \beta^{\text{MP}}_{\text{group}[i]} M_i P_i + \beta^{\text{MO}}_{\text{group}[i]} M_i O_i + \beta^{\text{PO}}_{\text{group}[i]} P_i O_i && (4)\\
&\quad + \beta^{\text{MPO}}_{\text{group}[i]} M_i P_i O_i && (5)\\
&\quad + \beta^{\text{children}} c_i + \beta^{\text{food}} s_i && (6)\\
&\quad + \beta^{\text{order}} r_i + \beta^{\text{check}} \chi_i + \beta^{\text{game}} g_i && (7)
\end{aligned}
$$

The linear model $\text{logit}(p_i)$ (line 2) includes an average intercept α and varying intercepts for individual and group (i.e., field site). The next lines (3-5) captures the three cultural variables of interest: free-listed moral code M, gods' punishment P, and knowledge breadth (i.e., omniscience) O and their respective interactions. For these parameters, each group has its own varying slope. The last two lines contain simple (i.e., fixed) individual-level effects for the remaining conditioning set: number of children, food insecurity, game order, game check, and game type (SELF game = 1), respectively.

All simple effects above are assigned weakly-regularizing priors, $\text{Normal}(0, 1)$. These guard against finding strong effects in small samples or those that vary considerably in responses, but are easily overwhelmed in large or consistent samples. The varying intercepts

---

involves refitting the model k times, where k equals the number of observed groups. For this reason, and because we're here mostly interested in global, cross-cultural – in contrast to site-specific – inferences, we'll likely refrain from pursuing LOGO-CV in the present analysis.

for individuals are given a prior scale of $\sigma_{\text{id}} \sim \text{Exponential}(1)$. This is likewise weakly regularizing. The varying effects for group are bound together in a common variance-covariance matrix:

$$\begin{bmatrix} a_{\text{group}} \\ \beta^{\text{M}}_{\text{group}} \\ \beta^{\text{P}}_{\text{group}} \\ \beta^{\text{O}}_{\text{group}} \\ \beta^{\text{MP}}_{\text{group}} \\ \beta^{\text{MO}}_{\text{group}} \\ \beta^{\text{PO}}_{\text{group}} \\ \beta^{\text{MPO}}_{\text{group}} \end{bmatrix} \sim \text{MVNormal}\left(\begin{bmatrix} 0 \\ \beta^{\text{M}} \\ \beta^{\text{P}} \\ \beta^{\text{O}} \\ \beta^{\text{MP}} \\ \beta^{\text{MO}} \\ \beta^{\text{PO}} \\ \beta^{\text{MPO}} \end{bmatrix}, \mathbf{SRS} \right)$$

where $\mathbf{S}$ is a diagonal matrix of standard deviations of the intercept and the main and interaction terms for the three cultural variables of interest:

$$\mathbf{S} = \begin{bmatrix} \sigma_a & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\beta^{\text{M}}} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{\beta^{\text{P}}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\beta^{\text{O}}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{\beta^{\text{MP}}} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{\beta^{\text{MO}}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\beta^{\text{PO}}} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\beta^{\text{MPO}}} \end{bmatrix}$$

and $\mathbf{R}$ is a full rank correlation matrix of the same variables. Each standard deviation is assigned an independent Exponential(1) prior as before, and $\mathbf{R}$ is given a weakly regularizing prior from the LKJ family (Lewandowski et al., 2009), a common choice of prior distribution for covariance matrices:

$$\mathbf{R} \sim \text{LKJCorr}(4)$$

4.1.1. Imputation models

Our three key predictor variables above have missing values: free-listed morality, punishment, and knowledge breadth. We build an imputation model for each of these variables so that the imputed values are informed by their field site. For example, the morality free-list imputation model looks as follows:

$$
\begin{aligned}
M_i &\sim \text{Normal}(\mu_i^{\text{m}}, \sigma^{\text{m}}) \\
\mu_i^{\text{m}} &= M_{\text{group}[i]} \\
\sigma^{\text{m}} &\sim \text{Exp}(1) \\
M_{\text{group}} &\sim \text{Normal}(\mu^{\text{M}}, \sigma^{\text{M}}) \\
\mu^{\text{M}} &\sim \text{Normal}(0.5, 2) \\
\sigma^{\text{M}} &\sim \text{Exp}(1)
\end{aligned}
$$

where the imputed values M range between 0 and 1 and are drawn from a normal distribution with mean μ^{m} and standard deviation σ^{m} that are informed by the individual's field site's estimated mean proportion of free-listed moral items M_{group}. This value is in turn drawn from a normal distribution with a mean and standard deviation that are assigned weakly regularizing priors themselves. The prior for μ^{M}, the mean proportion of free-listed moral items for a given group, is centered on 0.5 as it is the mid-point of the variable, which ranges between 0 and 1; however, with a standard deviation of 2 this estimate is allowed to take on a wide range of values, although we constrain it via `Stan` at 0 and 1. The imputation models for punishment and knowledge breadth are similar, although those two variables are each means of two binary items and can therefore take on values 0, 1, and 2[7].

Similarly, following the same structure, we impute missing values in number of children so that the imputations are informed by the respective site-specific mean number of children

[7] In the accompanying `R` scripts, we show how to plot the distribution of observed values against the imputed data.

(truncated at zero).

$$\begin{aligned}
\text{children}_i &\sim \text{Normal}(\text{children}_i^{\mu}, \text{children}_{\sigma}) \\
\text{children}_i^{\mu} &= \text{Children}_{\text{group}[i]} \\
\text{children}_{\sigma} &\sim \text{Exp}(10) \\
\text{Children}_{\text{group}} &\sim \text{Normal}(\mu^{\text{Children}}, \sigma^{\text{Children}}) \\
\mu^{\text{Children}} &\sim \text{Normal}(1, 2) \\
\sigma^{\text{Children}} &\sim \text{Exp}(1)
\end{aligned}$$

We relied on the following prior distributions for the remaining parameters (including missing data imputation) as well as constrain each parameter to be within realistic ranges:

$$\begin{aligned}
\text{food} &\sim \text{Bernoulli}(\phi_{\text{food}}) \\
\phi_{\text{food}} &\sim \text{Beta}(1, 1) \\
\text{order} &\sim \text{Bernoulli}(0.5) \\
\text{check} &\sim \text{Bernoulli}(\phi_{\text{check}}) \\
\phi_{\text{check}} &\sim \text{Beta}(1, 1) \\
\text{game} &\sim \text{Bernoulli}(\phi_{\text{game}}) \\
\phi_{\text{game}} &\sim \text{Beta}(1, 1)
\end{aligned}$$

4.2. DG model

To model coin allocations to the distant cup y out of a total of 10 coins in the DG, we use an ordered categorical likelihood model, where we regard each coin as a discrete ordered response

$$y_i \sim \text{Ordered Categorical}(\eta_i, K)$$

The cumulative property of the ordered categorical neatly captures the cumulative aspect of coin allocations in the DG game. However, since zero is not a valid value for the ordered categorical model but was an option in the game (i.e., no coins allocated to the distant cup) and falls naturally on the ordering of the response (i.e., zero coins is less than one, less than two, etc.), we add a "dummy coin" to the response variable, such that the response value ranks from one to 11, where one means zero coins, two means one coin, etc. This yields a vector of $11 - 1 = 10$ random cut-points K, on which we put a prior of $\text{Normal}(0, 2)$ to be estimated along with a linear model η_i that is otherwise similar to the RAG model.

5. Synthetic data analysis

In order to give a basic sense of how we will report results from the planned analyses, here we present results from analyses on simplified simulated data. Across analyses, we are interested in *the contrast in posterior predicted probability of putting a coin in the DISTANT cup between free-listing "Morality" vs. not free-listing "Morality"*, all the while marginalizing over covariates. This is to assess H_1. Once the models are fitted, these contrasts are obtained as follows[8]:

1. Duplicate original dataset and set M to 0 (i.e., no moral items in an individual's free-list) for all rows, retaining covariates as observed.
2. Duplicate original dataset and set M to 1 (i.e., only moral items in an individual's free-list) for all rows, retaining covariates as observed.
3. For each draw of the posterior distribution, use the fitted model to get expected values for each of these counter-factual datasets.
4. For each individual and draw of the posterior distribution, compute contrast between focal conditions (i.e., not listing vs. listing only "Morality").
5. Compute and plot distributions and summary statistics (e.g., mean probabilities of coin allocations).

[8]Also referred to as *g-computation* or *standardisation* (Morris et al., 2022), we aim for a target quantity akin to a (marginal) "average treatment effect" using an "observed-value" approach (e.g., Hanmer and Ozan Kalkan, 2013). For individuals with missing covariates, we get predictions at the posterior mean of the imputed values.

This is also how we can assess the interaction terms for H_2, namely by "turning on/off" P and O while holding all other covariates as observed (not pursued further here). We start with the RAG analysis.

5.1. RAG synthetic data analysis

First, we run a posterior predictive check. That is, how well does the model capture (some relevant features of) the original data? Figure 2 (panel A) represents a convenient option. Each bar is the observed marginal proportion of each coin allocation to the DISTANT cup. The points are posterior predictive medians and vertical lines are 90% intervals. Since the predictive point ranges mostly include the observed proportions, the model does a fair job at retrodicting the sample on this particular dimension.

Figure 2 (panel C and E) plots the posterior distributions for focal raw parameter estimates for the RAG interaction model and RAG additive model, respectively. For context, we simulated the hypothetical coefficients in log odds such that the "true" effects of food security β^{S} and number of children β^{C} is -0.3 each, the "true" effects of morality β^{M}, knowledge breadth, β^{O}, and punishment β^{P}, their interactions (β^{MP} and β^{MO}) 0.3 each, and zero for the three-way interaction β^{MPO}. For β^{S}, β^{C}, and β^{MPO} the two models recover the simulated coefficients quite precisely. For the remaining parameters, the two models differ in their precision. While the interaction model generally recovers the simulated estimates, the intervals are very wide and are often compatible with an effect of the opposite direction of the simulated "true" effect. This is likely due to low statistical power in the context of the interaction terms (note, however, that the posterior point estimates largely recover the simulated true effects). On the other hand, the additive model over-shoots the "true" effects due to unmodeled interaction effects. This exercise underscores the value of fitting both the interaction model and the additive model.

However, ultimately we're less interested in the raw coefficients. Rather, as laid out above, we aim to compute the contrast in posterior predicted probabilities between a focal predictor on the outcome. Figure 3 plots such result for the RAG. The posterior predicted contrast is between not free-listing "Morality" (i.e., $M = 0$) vs. free-listing only "Morality"

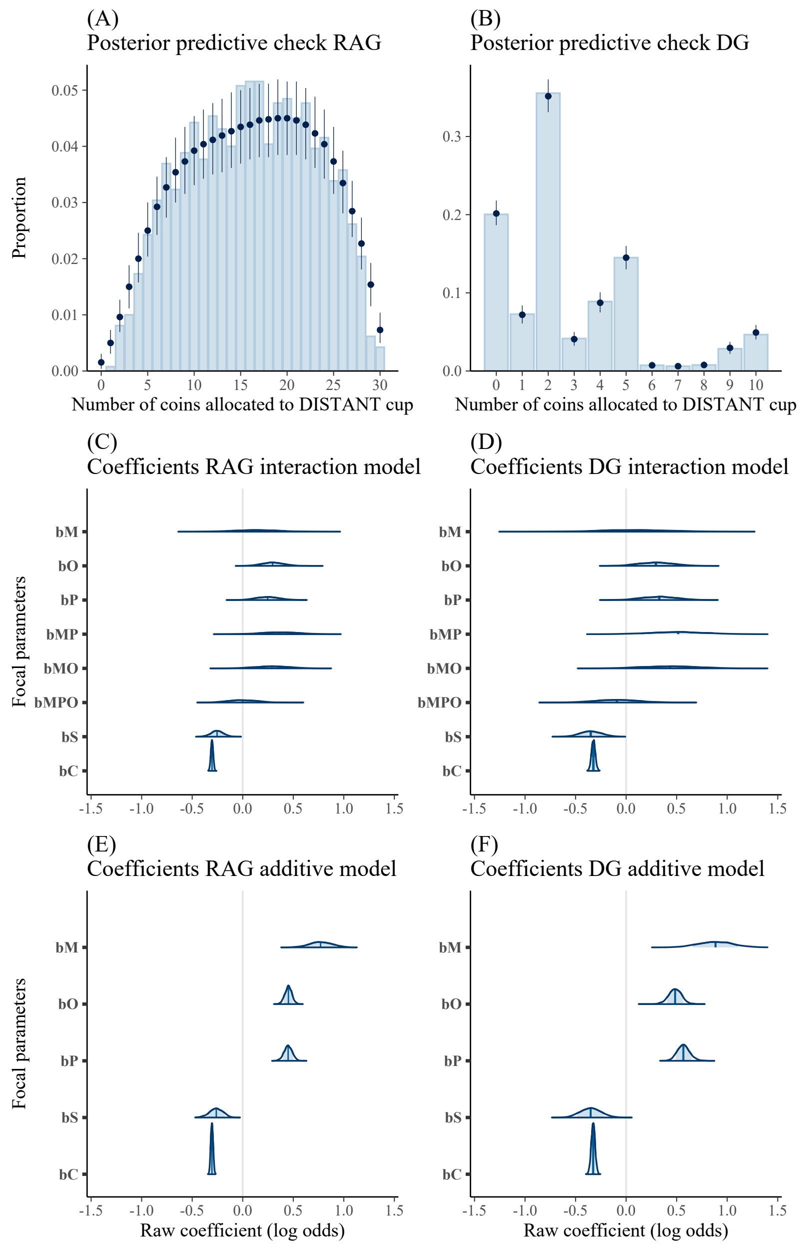

Figure 2: **Posterior predictive checks and coefficients for RAG and DG models**. Posterior predictive checks for RAG interaction model (A) and DG interaction model (B). (C) to (F) plot the posterior distribution of coefficients for focal parameters for the interaction and additive models.

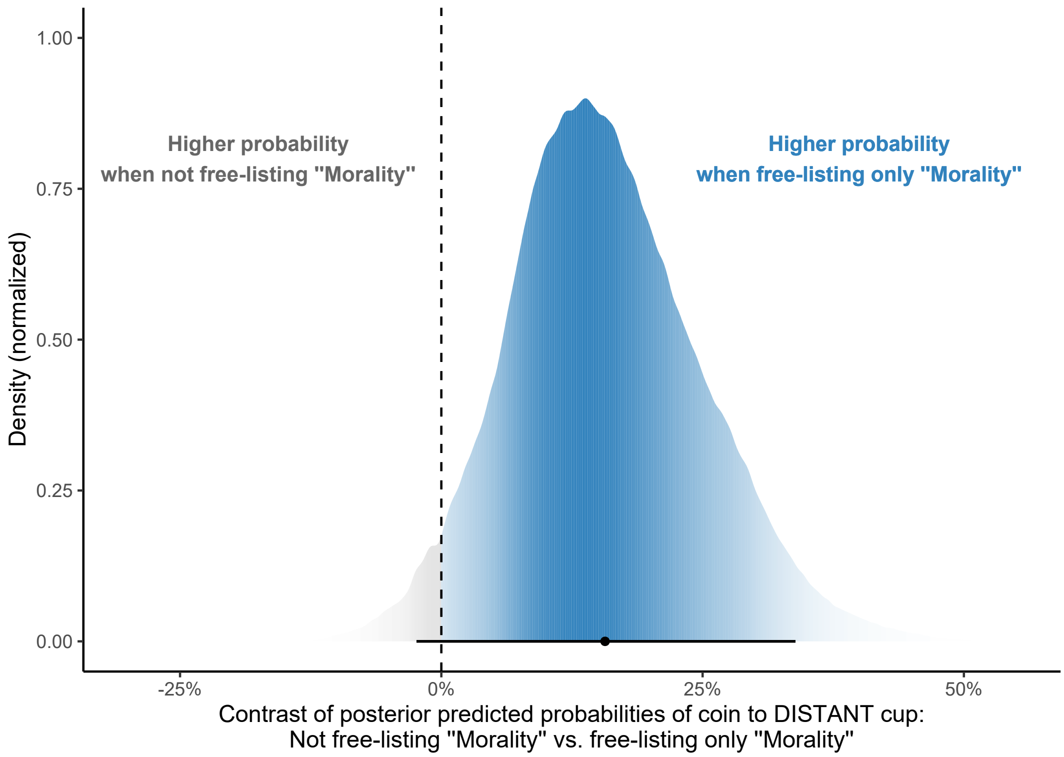

Figure 3: **Contrast plot of RAG model**. Contrast of posterior predicted probabilities of allocating a coin to the DISTANT cup (in percentage points) between not listing and listing only "Morality". 0% means no difference between the two conditions. Color gradient reflects posterior mass. Mean and 95% highest posterior density interval in black. Distribution is normalized.

(i.e., $M = 1$) while holding all other covariates as observed. In this simulation, free-listing only "Morality" (i.e., $M = 1$) is associated with around 15% expected higher chance of allocating a coin to the DISTANT cup, when marginalizing over covariates.

5.2. DG synthetic data analysis

We now turn to the DG analysis. Again, we run a posterior predictive check (Figure 2, panel B). Again, each bar is the observed marginal proportion of a coin allocation to the DISTANT cup. The points are posterior predictive medians and vertical lines are 90% intervals. Since the predictive point ranges mostly include the observed proportions, the model does a reasonable job at retrodicting the sample on this particular dimension.

As above, Figure 2 (panel D and F) plots the posterior distributions for focal raw parameter estimates for the DG interaction model and DG additive model, respectively. The simulated coefficients are identical to the RAG model and we see generally the same patterns of divergence between the additive and interaction model as in the RAG analysis.

From the analysis of the DG, we can get the posterior predicted probability for each coin allocation to the DISTANT cup. Similar to the RAG, we can represent the predicted contrast for each coin allocation as a ridge plot (Figure 4). Again, our focal contrast is between not free-listing "Morality" (i.e., $M = 0$) vs. free-listing only "Morality" (i.e., $M = 1$). As for interpreting this plot, we see that free-listing "Morality" is generally associated with higher probability of putting more coins in the DISTANT cup. For instance, free-listing only "Morality" is associated with $\sim 3\%$ higher expected probability of allocating all ten coins to the DISTANT cup, whereas not free-listing "Morality" is associated with $\sim 11\%$ higher expected probability of allocating zero coins to the DISTANT cup.

Recall that our model include site-specific random offsets and so for the actual analysis we'll panel each of these plots (for both the RAG and the DG) on the site level to inspect between-site variation.

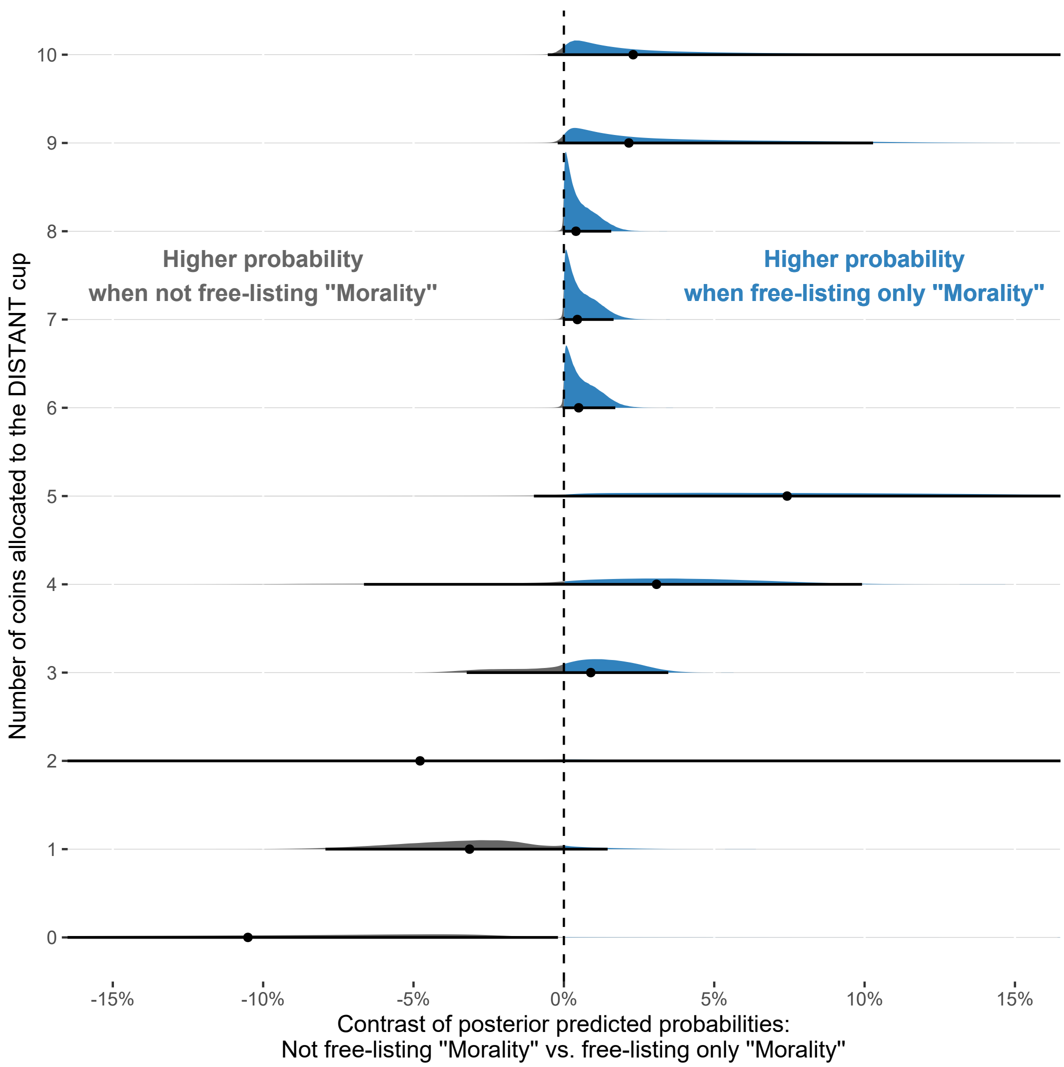

Figure 4: **Ridge plot of DG model**. Contrasts of posterior predicted probabilities of allocating a coin to the DISTANT cup (in percentage points). 0% means no difference between the two conditions. Medians and 95% highest posterior density intervals in black. Distributions are normalized.

6. Supplementary analyses

6.1. Moral rating scale

As noted in Section 1, previous studies failed to find a statistical association between coin allocation and a three-item rating scale on the extent to which a deity cares for punishing theft, lying, and murder (Lang et al., 2019; Purzycki et al., 2016b). These previous analyses, however, did not assess the presence of an interaction term between this moral rating scale and a deity's punitive tendencies and/or knowledge breadth. We'll address this here by re-scaling the three-item moral scale on to a 0-1 variable and then substitute that variable for proportion of free-listed moral items. The remaining modeling features and workflow are otherwise identical.

6.2. Alternative likelihood model for the DG

For the main analysis of the DG, we commit to an ordered categorical likelihood model for reasons spelled out in Section 4.2. However, we recognize that this is a somewhat unconventional choice; a more common choice is a Tobit model (Engel, 2011). However, a recently proposed likelihood distribution, the "ordered beta" (Kubinec, 2020), was specifically designed for continuous data with lower and upper bounds, making it a promising model for DG coin allocations, if scaled to proportions of the full endowment. We will re-analyze the DG models with the ordered beta. This re-analysis serves the dual-purpose of a robustness check (i.e., are our results sensitive to an alternative likelihood specification?) and a methodological assessment of a novel alternative to common practice in DG data analysis.

6.3. Alternative free-list code: "Resource/social exchange"

Since the general free-list code "Morality" captures responses that might not directly translate to the economic game contexts (e.g., "murder", "violence", etc.), we're also going to code for a more narrow set of free-list responses with a higher face validity for the present study having to do specifically with resource and social exchange (e.g., dishonesty, insincerity, not trustworthy, unfairness, lies, stealing, deception, greed, no sharing, selfishness; along with their synonyms and derivations). The rationale for this approach is to explore whether beliefs about supernatural punishment that are more relevant to the game context, compared to moral items in general, more clearly predict game behavior. This analysis partly follows from recent theoretical developments that emphasize the socioecological contexts in which appeals to and beliefs about the supernatural play out (e.g., Bendixen et al., forthcominga; McNamara and Purzycki, 2020; Purzycki and Sosis, 2022; Purzycki et al., 2022b). However, we do not claim that we're conducting a direct test of these hypotheses; it's unclear to what extent the behavioral economic games reflect genuine, supernaturally-sanctioned socioecological dilemmas in our ethnographic contexts and, therefore, whether we'd expect appeals to or beliefs about the supernatural to be implicated in behavior.

There are practical issues, however, that complicate this analytic route. First, we have little in the way of either well-formulated theory to base this analysis on or external validation of selected target free-list responses, complicating the interpretation of any result. Second and relatedly, it creates further issues to be resolved in the data preparation and analysis stages, including how to ultimately select the game-relevant items to code for in the free-list data. For instance, what to do about responses with ambiguous meanings, such as "cheating" (e.g., playing unfairly, adultery, etc.) (see Purzycki et al., 2018b), or vague and abstract responses, such as "bad behaviour"? For these reasons, we restrict it to a exploratory set of analyses and, erring on the side of keeping the analysis thematically focused, settle on *excluding* ambiguous and vague responses. As in the main analysis, we'll model the *proportion* of the target codes in participants' free-list; a participant gets a "hit", if a target code appears in at least one of the two coders' specific code column for what angers the relevant moralistic deity.

Data Availability

All data is available at: http://github.blah.blah.com.

Acknowledgments

TB, ADL, and BGP thank Aarhus University Research Foundation for financial support and Cecilie Sandfeld and Andreas Damgaard for coding the second wave of free-list data.

References

Apicella, C.L., 2018. High levels of rule-bending in a minimally religious and largely egalitarian forager population. Religion, Brain & Behavior 8, 133–148.

Atkinson, Q.D., 2018. Religion and expanding the cooperative sphere in kastom and christian villages on Tanna, Vanuatu. Religion, Brain & Behavior 8, 149–167.

Atkinson, Q.D., Bourrat, P., 2011. Beliefs about God, the afterlife and morality support the role of supernatural policing in human cooperation. Evolution and Human Behavior 32, 41–49.

Atran, S., Henrich, J., 2010. The Evolution of Religion: How Cognitive By-Products, Adaptive Learning Heuristics, Ritual Displays, and Group Competition Generate Deep Commitments to Prosocial Religions. Biological Theory 5, 18–30.

Baimel, A., Apicella, C., Atkinson, Q., Bolyanatz, A., Cohen, E., Handley, C., Henrich, J., Klocová, E.K., Lang, M., Lesogorol, C., Mathew, S., McNamara, R., Moya, C., Norenzayan, A., Placek, C.D., Soler, M., Vardy, T., Weigel, J., Willard, A., Xygalatas, D., Purzycki, B., 2022. Material insecurity predicts greater commitment to moralistic and less commitment to local deities: a cross-cultural investigation. Religion, Brain & Behavior 12, 4–17. doi:10.1080/2153599X.2021.2006287.

Beheim, B., Atkinson, Q.D., Bulbulia, J., Gervais, W., Gray, R.D., Henrich, J., Lang, M., Monroe, M.W., Muthukrishna, M., Norenzayan, A., Purzycki, B.G., Shariff, A., Slingerland, E., Spicer, R., Willard, A.K., 2021. Treatment of missing data determined conclusions regarding moralizing gods. Nature 595, E29–E34. doi:10.1038/s41586-021-03655-4.

Bendixen, T., Apicella, C., Atkinson, Q., Cohen, E., Henrich, J., McNamara, R.A., Norenzayan, A., Willard, A.K., Xygalatas, D., Purzycki, B.G., forthcominga. Appealing to the minds of gods: Religious beliefs and appeals correspond to features of local social ecologies. Religion, Brain & Behavior doi:10.31234/osf.io/tjn3e.

Bendixen, T., Lightner, A.D., Purzycki, B.G., forthcomingb. The cultural evolution of religion and cooperation, in: Kendal, R., Tehrani, J., Kendal, J. (Eds.), Oxford Handbook of Cultural Evolution. Oxford University Press. doi:10.31234/osf.io/fhscv.

Bendixen, T., Purzycki, B.G., 2020. Peering into the minds of gods: What cross-cultural variation in gods' concerns can tell us about the evolution of religion. Journal for the Cognitive Science of Religion 5, 142–165. doi:10.1558/jcsr.40951.

Bendixen, T., Purzycki, B.G., forthcoming. Accounting for cross-cultural variation in the minds of gods, in: Purzycki, B.G., Bendixen, T. (Eds.), The Minds of Gods: New Horizons in the Naturalistic Study of Religion. Bloomsbury Publishing.

Bendixen, T., Purzycki, B.G., n.d. Cognitive and cultural models in psychological science: A tutorial on modeling free-list data as a dependent variable in Bayesian regression URL: psyarxiv.com/4n2jm.

Bloom, P., 2012. Religion, Morality, Evolution. Annual Review of Psychology 63, 179–199. doi:10.1146/annurev-psych-120710-100334.

Boehm, C., 2008. A biocultural evolutionary exploration of supernatural sanctioning, in: Bulbulia, J., Sosis, R., Harris, Erica, Genet, R, Wyman, K. (Eds.), Evolution of Religion:

Studies, Theories, and Critiques. Collins Foundation Press, Santa Margarita, CA, pp. 143–152.

Bolyanatz, A.H., 2022. When god is watching: dictator game results from the sursurunga of new ireland, papua new guinea. Religion, Brain & Behavior 12, 61–78. doi:10.1080/2153599X.2021.2006284.

Botero, C.A., Gardner, B., Kirby, K.R., Bulbulia, J., Gavin, M.C., Gray, R.D., 2014. The ecology of religious beliefs. Proceedings of the National Academy of Sciences 111, 16784–16789. doi:10.1073/pnas.1408701111.

Boyer, P., 2021. Deriving features of religions in the wild. Human Nature 32, 557–581.

Brown, D.E., 1991. Human Universals. McGraw-Hill.

Caluori, N., Jackson, J.C., Gray, K., Gelfand, M., 2020. Conflict Changes How People View God. Psychological Science 31, 280–292. doi:10.1177/0956797619895286.

Carpenter, B., Gelman, A., Hoffman, M., Lee, D., Goodrich, B., Betancourt, M., Brubaker, M., Guo, J., Li, P., Riddell, A., 2017. Stan: A probabilistic programming language. Journal of Statistical Software 76.

Cinelli, C., Forney, A., Pearl, J., 2021. A crash course in good and bad controls. Available at SSRN 3689437 .

Cohen, E., Baimel, A., Purzycki, B.G., 2018. Religiosity and resource allocation in Marajó, Brazil. Religion, Brain Behavior 8, 168–184. doi:10.1080/2153599X.2016.1267029.

Deffner, D., Rohrer, J.M., McElreath, R., 2021. A causal framework for cross-cultural generalizability. URL: psyarxiv.com/fqukp, doi:10.31234/osf.io/fqukp.

Durkheim, E., 2001 [1912]. The elementary forms of religious life / Emile Durkheim; translated by Carol Cosman. Oxford world's classics, Oxford University Press, New York.

Ellwood, C.A., 1918. Religion and social control. The Scientific Monthly 7, 335–348.

Engel, C., 2011. Dictator games: A meta study. Experimental economics 14, 583–610.

Evans-Pritchard, E.E., 1965. Theories of primitive religion. Oxford University Press, Oxford.

Galen, L.W., 2012. Does religious belief promote prosociality? A critical examination. Psychological Bulletin 138, 876–906. doi:10.1037/a0028251. place: US Publisher: American Psychological Association.

Ge, E., Chen, Y., Wu, J., Mace, R., 2019. Large-scale cooperation driven by reputation, not fear of divine punishment. Royal Society Open Science 6, 190991. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6731744/, doi:10.1098/rsos.190991.

Hanmer, M.J., Ozan Kalkan, K., 2013. Behind the curve: Clarifying the best approach to calculating predicted probabilities and marginal effects from limited dependent variable models. American Journal of Political Science 57, 263–277. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-5907.2012.00602.x, doi:https://doi.org/10.1111/j.1540-5907.2012.00602.x, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-5907.2012.00602.x.

Hayden, B., 1987. Alliances and ritual ecstasy: Human responses to resource stress. Journal for the Scientific Study of Religion , 81–91.

Henrich, J., Muthukrishna, M., 2021. The Origins and Psychology of Human Cooperation. Annual Review of Psychology 72, 207–240. doi:10.1146/annurev-psych-081920-042106.

Hruschka, D., Efferson, C., Jiang, T., Falletta-Cowden, A., Sigurdsson, S., McNamara, R., Sands, M., Munira, S., Slingerland, E., Henrich, J., 2014. Impartial Institutions, Pathogen Stress and the Expanding Social Network. Human Nature 25, 567–579. URL: https://doi.org/10.1007/s12110-014-9217-0, doi:10.1007/s12110-014-9217-0.

Jackson, J.C., Caluori, N., Abrams, S., Beckman, E., Gelfand, M., Gray, K., 2021. Tight cultures and vengeful gods: How culture shapes religious belief. Journal of Experimental Psychology: General , No Pagination Specified–No Pagination Specified-doi:10.1037/xge0001033.

Jamieson-Lane, A., Purzycki, B.G., 2016. AnthroTools: Some custom tools for anthropology. R package version 0.8.

Jiang, T., 2013. Cheating in mind games: The subtlety of rules matters. Journal of Economic Behavior & Organization 93, 328–336. doi:10.1016/j.jebo.2013.04.003. place: Netherlands Publisher: Elsevier Science.

Johnson, D., Bering, J., 2006. Hand of god, mind of man: Punishment and cognition in the evolution of cooperation. Evolutionary psychology 4, 147470490600400119.

Kapepula, G.T., Konshi, M.M., Weigel, J.L., 2022. Prosociality and pentecostalism in the d.r. congo. Religion, Brain & Behavior 12, 150–170. doi:10.1080/2153599X.2021.2006289.

Klocová, E.K., Lang, M., Maňo, P., Kundt, R., Xygalatas, D., 2022. Cigarettes for the dead: effects of sorcery beliefs on parochial prosociality in mauritius. Religion, Brain & Behavior 12, 116–131. doi:10.1080/2153599X.2021.2006286.

Kubinec, R., 2020. Ordered beta regression: A parsimonious, well-fitting model for survey sliders and visual analog scales. URL: osf.io/preprints/socarxiv/2sx6y, doi:10.31235/osf.io/2sx6y.

Lang, A., 1909. The making of religion. Longmans, London.

Lang, M., Purzycki, B.G., Apicella, C.L., Atkinson, Q.D., Bolyanatz, A., Cohen, E., Handley, C., Kundtová Klocová, E., Lesorogol, C., Mathew, S., et al., 2019. Moralizing gods, impartiality and religious parochialism across 15 societies. Proceedings of the Royal Society B 286, 20190202.

Lewandowski, D., Kurowicka, D., Joe, H., 2009. Generating random correlation matrices based on vines and extended onion method. Journal of multivariate analysis 100, 1989–2001.

Lightner, A., Bendixen, T., Purzycki, B.G., 2022. Moralistic supernatural punishment is probably not associated with social complexity. URL: osf.io/preprints/socarxiv/29at3, doi:10.31235/osf.io/29at3.

Malinowski, B., 1936. The Foundations of Faith and Morals. London: Oxford University Press UK.

McCleary, R.M., Barro, R.J., 2006. Religion and economy. Journal of Economic perspectives 20, 49–72.

McElreath, R., 2020. Statistical Rethinking: A Bayesian course with examples in R and Stan. Second ed., CRC Press.

McKay, R., Whitehouse, H., 2014. Religion and Morality. Psychological Bulletin doi:10.1037/a0038455.

McNamara, R.A., Henrich, J., 2018. Jesus vs. the ancestors: how specific religious beliefs shape prosociality on Yasawa Island, Fiji. Religion, Brain & Behavior 8, 185–204.

McNamara, R.A., Norenzayan, A., Henrich, J., 2016. Supernatural punishment, in-group biases, and material insecurity: experiments and ethnography from Yasawa, Fiji. Religion, Brain & Behavior 6, 34–55. doi:10.1080/2153599X.2014.921235.

McNamara, R.A., Purzycki, B.G., 2020. Minds of gods and human cognitive constraints: socio-ecological context shapes belief. Religion, Brain & Behavior 10, 223–238. doi:10.1080/2153599X.2019.1678510.

McNamara, R.A., Senanayake, R., Willard, A.K., Henrich, J., 2021. God's mind on morality. Evolutionary Human Sciences 3, E6. doi:10.1017/ehs.2021.1.

Morris, T.P., Walker, A.S., Williamson, E.J., White, I.R., 2022. Planning a method for covariate adjustment in individually randomised trials: a practical guide. Trials 23, 1–17.

Norenzayan, A., Shariff, A.F., Gervais, W.M., Willard, A.K., McNamara, R.A., Slingerland, E., Henrich, J., 2016. The cultural evolution of prosocial religions. Behavioral and brain sciences 39.

Pearl, J., Glymour, M., Jewell, N.P., 2016. Causal inference in statistics: A primer. John Wiley & Sons.

Placek, C., Lightner, A., 2022. Moralizing gods, local gods, and complexity in hindu god concepts: evidence from south india. Religion, Brain & Behavior 12, 97–115. doi:10.1080/2153599X.2021.2006282.

Purzycki, B.G., 2011. Tyvan *cher eezi* and the socioecological constraints of supernatural agents' minds. Religion, Brain & Behavior 1, 31–45.

Purzycki, B.G., 2013. The minds of gods: A comparative study of supernatural agency. Cognition 129, 163 – 179. doi:http://dx.doi.org/10.1016/j.cognition.2013.06.010.

Purzycki, B.G., 2016. The evolution of gods' minds in the Tyva Republic. Current Anthropology 57, S88–S104. doi:10.1086/685729.

Purzycki, B.G., Apicella, C., Atkinson, Q.D., Cohen, E., McNamara, R.A., Willard, A.K., Xygalatas, D., Norenzayan, A., Henrich, J., 2016a. Cross-cultural dataset for the evolution of religion and morality project. Scientific Data 3, 160099. doi:10.1038/sdata.2016.99.

Purzycki, B.G., Apicella, C., Atkinson, Q.D., Cohen, E., McNamara, R.A., Willard, A.K., Xygalatas, D., Norenzayan, A., Henrich, J., 2016b. Moralistic gods, supernatural punishment and the expansion of human sociality. Nature 530, 327–330. doi:10.1038/nature16980.

Purzycki, B.G., Bendixen, T., Lightner, A., 2022a. Coding, causality, and statistical craft: The emergence and evolutionary drivers of moralistic supernatural punishment remain unresolved. Technical Report. SocArXiv. URL: https://osf.io/preprints/socarxiv/qvjfp/, doi:10.31235/osf.io/qvjfp. type: article.

Purzycki, B.G., Bendixen, T., Lightner, A.D., Sosis, R., 2022b. Gods, games, and the socioecological landscape. Current Research in Ecological and Social Psychology 3, 100057.

Purzycki, B.G., Henrich, J., Apicella, C., Atkinson, Q.D., Baimel, A., Cohen, E., McNamara, R.A., Willard, A.K., Xygalatas, D., Norenzayan, A., 2018a. The evolution of religion and morality: a synthesis of ethnographic and experimental evidence from eight societies. Religion, Brain & Behavior 8, 101–132.

Purzycki, B.G., Jamieson-Lane, A., 2016. Anthrotools: An R package for cross-cultural ethnographic data analysis. Cross-Cultural Research 51, 51–74.

Purzycki, B.G., Kulundary, V., 2018. Buddhism, identity, and class: fairness and favoritism in the tyva republic. Religion, Brain & Behavior 8, 205–226.

Purzycki, B.G., Lang, M., 2019. Identity fusion, outgroup relations, and sacrifice: A cross-cultural test. Cognition 186, 1–6. doi:https://doi.org/10.1016/j.cognition.2019.01.015.

Purzycki, B.G., Lang, M., Henrich, J., Norenzayan, A., 2022c. The evolution of religion and morality: Reflections and looking ahead. Religion, Brain & Behavior X.

Purzycki, B.G., McKay, R., 2023. Moralistic gods and social complexity: A brief history of the problem, in: Purzycki, B.G., Bendixen, T. (Eds.), The Minds of Gods: New Horizons in the Naturalistic Study of Religion. Bloomsbury Publishing, London, pp. 121–132.

Purzycki, B.G., McNamara, R.A., 2016. An ecological theory of gods' minds, in: De Cruz, H., Nichols, R. (Eds.), Cognitive Science of Religion and Its Philosophical Implications. Continuum, New York, pp. 143–167.

Purzycki, B.G., Pisor, A., Apicella, C., Atkinson, Q.D., Cohen, E., Henrich, J., McElreath, R., McNamara, R.A., Norenzayan, A., Willard, A.K., Xygalatas, D., 2018b. The cognitive and cultural foundations of moral behavior. Evolution and Human Behavior 39, 490–501.

Purzycki, B.G., Ross, C.T., Apicella, C., Atkinson, Q.D., Cohen, E., McNamara, R.A., Willard, A.K., Xygalatas, D., Norenzayan, A., Henrich, J., 2018c. Material security, life history, and moralistic religions: A cross-cultural examination. PloS one 13, e0193856.

Purzycki, B.G., Sosis, R., 2022. Religion Evolving: The Dynamics of Culture, Cognition and Ecology. Equinox.

Purzycki, B.G., Watts, J., 2018. Reinvigorating the comparative, cooperative ethnographic sciences of religion. Free Inquiry 38, 26–29.

Purzycki, B.G., Willard, A.K., Klocová, E.K., Apicella, C., Atkinson, Q., Bolyanatz, A., Cohen, E., Handley, C., Henrich, J., Lang, M., Lesorogol, C., Mathew, S., McNamara, R.A., Moya, C., Norenzayan, A., Placek, C., Soler, M., Weigel, J., Xygalatas, D., Ross, C.T., 2022d. The Moralization Bias of Gods' Minds: A Cross-Cultural Test. Religion, Brain and Behavior 12, 38–60.

Quinlan, M.B., 2017. The freelisting method. Handbook of research methods in health social sciences. Singapore: Springer , 1–16.

R Core Team, 2021. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. Vienna, Austria. URL: https://www.R-project.org/.

Rappaport, R.A., 1968. Pigs for the Ancestors: Ritual in the Ecology of a New Guinea People. Yale University Press.

Roes, F.L., Raymond, M., 2003. Belief in moralizing gods. Evolution and Human Behavior 24, 126–135. doi:10.1016/S1090-5138(02)00134-4.

Rossano, M.J., 2007. Supernaturalizing Social Life: Religion and the Evolution of Human Cooperation. Human Nature 18, 272–294. doi:10.1007/s12110-007-9002-4.

Schloss, J.P., Murray, M.J., 2011. Evolutionary accounts of belief in supernatural punishment: a critical review. Religion, Brain & Behavior 1, 46–99.

Schuessler, J., Selb, P., 2019. Graphical causal models for survey inference. URL: osf.io/preprints/socarxiv/hbg3m, doi:10.31235/osf.io/hbg3m. osf.io/preprints/socarxiv/hbg3m.

Shariff, A.F., Norenzayan, A., 2007. God is watching you: Priming god concepts increases prosocial behavior in an anonymous economic game. Psychological science 18, 803–809.

Shariff, A.F., Norenzayan, A., 2011. Mean gods make good people: Different views of god predict cheating behavior. The International Journal for the Psychology of Religion 21, 85–96.

Shariff, A.F., Willard, A.K., Andersen, T., Norenzayan, A., 2016. Religious Priming: A Meta-Analysis With a Focus on Prosociality. Personality and Social Psychology Review: An Official Journal of the Society for Personality and Social Psychology, Inc 20, 27–48. doi:10.1177/1088868314568811.

Shaver, J.H., Fraser, G., Bulbulia, J., 2017. Charismatic signaling: How religion stabilizes cooperation and entrenches inequality. The Oxford Handbook of Evolutionary Psychology and Religion .

Singh, M., Kaptchuk, T.J., Henrich, J., 2021. Small gods, rituals, and cooperation: The Mentawai water spirit Sikameinan. Evolution and Human Behavior 42, 61–72.

Skali, A., 2017. Moralizing gods and armed conflict. Journal of Economic Psychology 63, 184–198. doi:10.1016/j.joep.2017.01.009.

Skoggard, I., Ember, C.R., Pitek, E., Jackson, J.C., Carolus, C., 2020. Resource Stress Predicts Changes in Religious Belief and Increases in Sharing Behavior. Human Nature 31, 249–271. doi:10.1007/s12110-020-09371-8.

Snarey, J., 1996. The natural environment's impact upon religious ethics: A cross-cultural study. Journal for the Scientific Study of Religion , 85–96.

Soler, M., Purzycki, B.G., Lang, M., 2022. Perceptions of moralizing agents and cooperative behavior in northeastern brazil. Religion, Brain & Behavior 12, 132–149. doi:10.1080/2153599X.2021.2006285.

Stagnaro, M.N., Stibbard-Hawkes, D.N.E., Apicella, C.L., 2022. Do religious and market-based institutions promote cooperation in hadza hunter-gatherers? Religion, Brain & Behavior 12, 171–189. doi:10.1080/2153599X.2021.2006293.

Stan Development Team, 2021. RStan: the R interface to Stan. URL: https://mc-stan.org/. r package version 2.21.3.

Swanson, G.E., 1960. The birth of the gods: The origin of primitive beliefs. University of Michigan Press.

Townsend, C., Aktipis, A., Balliet, D., Cronk, L., 2020. Generosity among the Ik of Uganda. Evolutionary Human Sciences 2. URL: https://www.cambridge.org/core/journals/evolutionary-human-sciences/article/generosity-among-the-ik-of-uganda/06953719700BD212126D5480C6E56216, doi:10.1017/ehs.2020.22.

Tylor, E.B., 1920. Primitive culture: Researches into the development of mythology, philosophy, religion, language, art, and custom. London: Murray.

Vardy, T., Atkinson, Q.D., 2022. Moralistic and local god beliefs and the extent of prosocial preferences on tanna island, vanuatu. Religion, Brain & Behavior 12, 79–96. doi:10.1080/2153599X.2021.2006290.

Vardy, T., Moya, C., Placek, C.D., Apicella, C.L., Bolyanatz, A., Cohen, E., Handley, C., Klocová, E.K., Lesorogol, C., Mathew, S., McNamara, S.A., Purzycki, B.G., Soler, M., Weigel, J.L., Willard, A.K., Xygalatas, D., Norenzayan, A., Henrich, J., Lang, M., Atkinson, Q.D., 2022. The religiosity gender gap in 14 diverse societies. Religion, Brain & Behavior 12, 18–37. doi:10.1080/2153599X.2021.2006292.

Vehtari, A., Gelman, A., Gabry, J., 2017. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Statistics and Computing 27, 1413–1432. doi:10.1007/s11222-016-9696-4.

Wallace, A., 1966. Religion: An anthropological view. Random House.

Watts, J., Greenhill, S.J., Atkinson, Q.D., Currie, T.E., Bulbulia, J., Gray, R.D., 2015. Broad supernatural punishment but not moralizing high gods precede the evolution of political complexity in Austronesia. Proceedings of the Royal Society of London B: Biological Sciences 282, 20142556. doi:10.1098/rspb.2014.2556.

Watts, J., Jackson, J.C., Arnison, C., Hamerslag, E., Shaver, J.H., Purzycki, B.G., 2022. Building quantitative cross-cultural databases from ethnographic records: Promises, problems and principles. Cross-Cultural Research 56, 62–94. doi:10.1177/10693971211065720.

White, C.J., Kelly, J.M., Shariff, A.F., Norenzayan, A., 2019. Supernatural norm enforcement: Thinking about karma and god reduces selfishness among believers. Journal of Experimental Social Psychology 84, 103797.

Willard, A.K., 2018. Religion and prosocial behavior among the indo-fijians. Religion, Brain & Behavior 8, 227–242. URL: https://doi.org/10.1080/2153599X.2016.1267032, doi:10.1080/2153599X.2016.1267032.

Willard, A.K., Baimel, A., Turpin, H., Jong, J., Whitehouse, H., 2020. Rewarding the good and punishing the bad: The role of karma and afterlife beliefs in shaping moral norms. Evolution and Human Behavior 41, 385–396. doi:10.1016/j.evolhumbehav.2020.07.001.

Xygalatas, D., Kotherová, S., Maňo, P., Kundt, R., Cigán, J., Klocová, E.K., Lang, M., 2018. Big gods in small places: The random allocation game in mauritius. Religion, Brain & Behavior 8, 243–261. doi:10.1080/2153599X.2016.1267033.

Yilmaz, O., Bahçekapili, H.G., 2016. Supernatural and secular monitors promote human cooperation only if they remind of punishment. Evolution and Human Behavior 37, 79–84.