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An Agent-Based Model of Prosocial Equilibrium: The Role of Religiously Motivated Behaviour in the Formation and Maintenance of Large-Scale Societies



Ivan Puga-Gonzalez , F. LeRon Shults , Ross Gore ,
and Konrad Talmont-Kaminski

Abstract This paper outlines a new agent-based model that represents the dynamics by which a society achieves and maintains prosocial equilibrium. The latter is understood as a social balance involving the interplay of prosocial behavior, anxiety, environmental threats, and religiosity in the population. Experiments showed that the model was able to simulate the emergence of relatively large societies under the sorts of conditions that would be expected based on the theoretical literature and other empirical findings in the relevant fields. We conclude by describing the main insights of the simulation experiments and pointing toward future work currently being planned by the research team.

Keywords Agent-based model · Religiosity · Prosocial behavior

1 Introduction

1.1 Theory on Prosocial Behavior and Intro to the Model

The study of the behavior of humans and other animals in the last few decades has spent considerable efforts looking at explanations of altruistic behavior. Kin selection and reciprocal altruism have helped to understand cooperation among other animals

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[1, 2] and in small-scale human societies, without reference to previously popular but largely discredited group selection explanations [3]. These results have, however, thrown into sharp contrast the situation with large-scale human societies. The issue is that in large-scale societies, where most interactions are one-off with unrelated individuals, the logic behind the theories used to explain animal cooperation breaks down and the strategy of becoming a free rider appears to be much more attractive [4]. Many solutions were suggested for this problem, but most of these were largely concerned with altruistic punishment [5], which was odd because on the whole this was still a form of altruistic behavior that was costly to the individual [6].

The lack of a generally accepted explanation for cooperation in large-scale human societies motivated some researchers to look to religion for an explanation. The idea that religion could play the role of motivating social cohesion and cooperation is one that has a long history, with numerous scholars having argued for it [7, 8]. In recent years, scholars working within cognitive science of religion have proposed several mechanisms by which religious beliefs and practices could help to motivate costly pro-social behavior [9, 10] as well as seeking to connect the historical appearance of large-scale societies with changes in religious traditions that could have played a role in making those societies possible [8, 11]. At the same time, a range of studies also going back close to a hundred years has provided evidence for the claim that increased levels of anxiety lead—in the short-term as well as well in the long-term—to increased espousal of religious claims and engagement in religious practices [12–14].

When taken together, the connection between religion and cooperation as well as the connection between anxiety and religion potentially form two parts of a negative feedback mechanism that could underpin a prosocial equilibrium, the connection between cooperation and anxiety forming the final element [15, 16]. The picture is that of environmental threats leading to increased anxiety and thereby to increased religiosity. However, an increase in religiosity drives increased cooperation, which helps the society deal with the threats and thereby lower anxiety. In effect, a relatively high level of religiosity and cooperation is maintained, allowing large-scale societies to thrive.

To test the plausibility of such a prosocial equilibrium we decided to construct an agent-based model in which altruistic, prosocial behavior that was not motivated by reciprocal arrangements or genetic connections would have the opportunity to allow the growth of societies with many hundreds or even thousands of members. A key assumption of the model was that religiosity is primarily determined by observing/participating in religious practices during the period of socialization. The practices focused upon in the model are forms of religiously-motivated pro-social behavior such as participation in work for the community, tithing and other forms of religious charity, as well as those forms of sacrifice in which the offering is made use of by the community—which are considered to play a large role in motivating religiosity.

2 Methods

2.1 The Model

The model was written in AnyLogic v.8.7.9. Here we present a brief description of the model. A full ODD + D protocol description can be found at the github repository: URL <https://github.com/ivanpugagonzalez/Prosociality-ABM-Model>

Model overview and agents. The artificial society represented in the model is inhabited by individual human agents who have eight different variables: age, gender, marital status, religiosity, wellbeing, insecurity, sensitivity, and anxiety. On initialization, 1000 adult agents are created, the age distribution follows a typical pyramid shape (0–100 years). The initial values of religiosity, and sensitivity are drawn from a normal distribution $N(\mu = 0.5, \sigma = 0.1)$ and that of insecurity is set to 0. Every year all agents experience a given number of environmental threats of different intensity. The number and intensity of threats are controlled by a Poisson and exponential distribution (13–14 in Table 1). Threats increase the insecurity of agents and in turn insecurity increases anxiety. Anxiety and religiosity may then trigger a prosocial behavior. Prosocial behaviors increase the religiosity and decrease the insecurity of the performing agents and that of close by neighbors (7–10 in Table 1). Prosocial behaviors are costly and reduce the wellbeing of performing agents (11 in Table 1). Agents also increase/decrease their wellbeing according to their current age and insecurity values (15–21 in Table 1). Agents reproduce if they are married, female, and within the age of reproduction. Agents that are 25 y.o. or younger, reduce a percentage of their religiosity every year (24 in Table 1). Agents die with a probability given by their wellbeing value. Figure 1 shows a summary of the model cycle and order of processes during the simulation.

Wellbeing processes. Wellbeing (WB) determines the probability of an agent surviving every year. A survival probability curve was mimic using data from 1950's in Norway. This choice was arbitrary, but it doesn't have a major effect on the model's behavior. Both the reference model and the one with prosocial behavior (see Sects. 2.2 and 2.3) use the same survival probability curve, and because we compare one against the other the effect of the survival probability curve becomes irrelevant.

Wellbeing and age. At initialization, wellbeing is determined by a polynomial function of the agents' age. This equation mimics the survival probability of both sexes according to age during 1950's in Norway. Then, after initialization, WB of agents increases and decrease every year according to its age. The gain or loss of WB is determined by two equations.

The gain of WB is given by equation 1:

$$Gain = -4C * \left(\frac{Age - WB_Age_Threshold}{100 - WB_Age_Threshold} \right)^{Exp1} + C \quad (1)$$

Table 1 Model parameters

Parameter	Value	Description	Process
1. Rep Cost	OP	% of WB taken from each parent	Rep
2. Rep mid threshold	OP	Reproduction probability is 0.5	
3. Rep Curve Shape	OP	Parameters determining the shape of probability of reproduction curve	
4. Importance Insec	SA		
5. Importance WB	1		
6. PB threshold	SA	Threshold value to trigger PB	PB
7. PB inc rel self	SA	Increase in agent’s and neighbors’ religiosity after a PB	
8. PB inc rel neigh	SA		
9. PB dec insec self	SA	Decrease in agent’s and neighbors’ insecurity after a PB	
10. PB dec insec neigh	SA		
11. PB wellbeing cost	SA	Decrease in agent’s WB after a PB	
12. Neigh Benefited	SA	# of nearby neighbors benefited	
13. Threats Rate	SA	Shape of the Poisson distribution	Threats
14. Threats Intensity	SA	Shape of the exponential distribution	
15. WB Age Threshold	OP	Parameters determining the increase/decrease of WB according to agents’ age	WB-Age
16. WB Intercept C	OP		
17. WB Exp Gain eq	OP		
18. WB Exp Loss eq	OP		
19. WB Insec Threshold	0.1	Parameters determining the increase/decrease of WB according to agents’ insecurity	WB-Insecurity
20. WB Max Inc	OP		
21. WB Max Dec	0.25		
22. Marriage Age Diff	OP	Max age difference between partners	Others
23. Radius Local Area	50	Radius of area of nearby neighbors	
24. Rel Dec Perc	SA	% of religiosity decrease every year	

WB wellbeing, *PB* prosocial behavior, *Insec* insecurity, *Rep* reproduction, *inc* increase, *dec* decrease, *rel* religiosity, *OP* optimized parameter, *SA* sensitivity analysis

The loss in WB is then given by equation 2:

$$Loss = -4C * \left(\frac{Age - WB_Age_Threshold}{100 - WB_Age_Threshold} \right)^{Exp2} + C \quad (2)$$

where WB Age Threshold (15 in Table 1) is the age at which the gain/loss in WB is given by equation 2 instead of equation 1; C (16 in Table 1) is the equation intercept, and *Exp1* and *Exp2* (17–18 in Table 1) determine the shape of the curve.

Wellbeing and insecurity. In addition to being affected by age, WB is also affected by the agents' insecurity. Depending on the insecurity value and the value of *WB Insec Threshold* (19 in Table 1), wellbeing may increase or decrease every year according to equations 3 and 4 respectively.

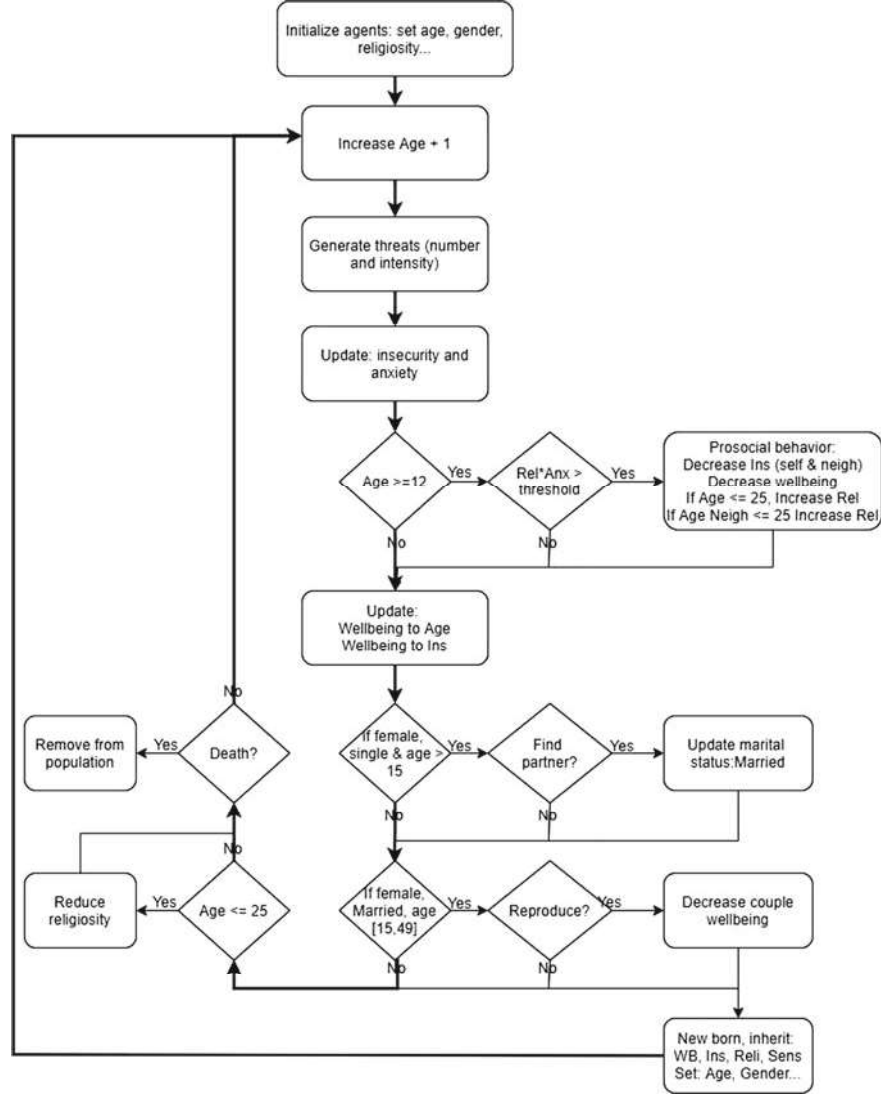


Fig. 1 Model cycle and order of processes

If insecurity \leq WB Insec Threshold:

$$Gain = WB.Max.Inc + \left(Ins * \frac{WB.Max.Inc}{WB.Insec.Th} \right) \quad (3)$$

The left-hand side term corresponds to the intercept and the fraction on the right-hand side to the slope. *Ins* is the current insecurity of the agent; *WB.Max.Inc* represents the maximum gain in WB when insecurity equals 0; and *WB.Ins.Th* is the insecurity value at which there is neither gain nor loss in WB (19–20 in Table 1).

If insecurity > *WB Insec Threshold*:

$$Loss = \frac{-WB.Max.Dec}{(1 - WB.Insec.Th)} * WB.Insec.Th + \left(Ins * \frac{WB.Max.Dec}{(1 - WB.Insec.Th)} \right) \quad (4)$$

The left-hand side term corresponds to the intercept and the fraction on the right-hand side to the slope. *Ins* is the current insecurity of the agent; *WB.Max.Dec* represents the maximum loss in WB when insecurity equals 1; and *WB.Ins.Th* is the insecurity value at which there is neither gain nor loss in WB (19–20 in Table 1).

Mortality process. As previously mentioned, WB determines the probability of agents dying and mimics the probability of dying reported in census data during 1950's in Norway. According to this data, the probability of dying for both sexes increase with age (Fig. 2a). To mimic this probability, we fitted a polynomial curve across the census data and input wellbeing instead of age. This resulted in the probability of dying curve shown in Fig. 2b.

Marriage and Reproduction process. To marry, agents had to meet several conditions: not being married, being over 15 y.o., and that the age difference between potential partners is not higher than *Marriage Age Diff* (22 in Table 1). If these conditions were met, agents were set to a married marital status.

Once married, female agents in the age of reproduction have the chance to reproduce every year. The probability of reproduction depends on the WB and insecurity of the married agents, it is given by equation 5:

$$Prob.Rep = \frac{1}{1 + e^{(-b*(x-a))}} \quad (5)$$

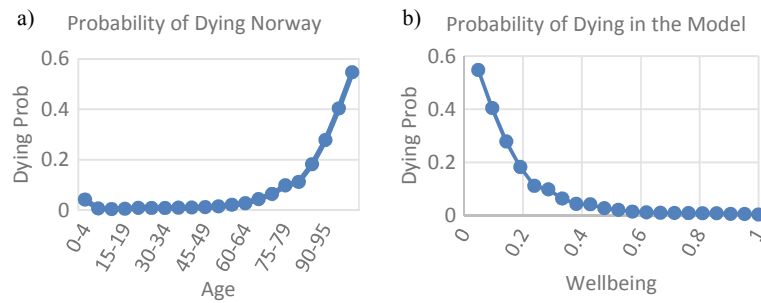


Fig. 2 Probability of dying according to **a** census data and **b** wellbeing

where b is the parameter *Rep curve shape* (3 in Table 1) determining the shape of the sigmoidal curve. x is a weighted average equal to:

$$\frac{(Average.WB.Partners) * Importance.WB + (Average.Ins.Partners) * Importance.Ins}{Importance.WB + Importance.Ins}$$

and represents the importance of WB and insecurity in the reproduction decision (4–5 in Table 1), and a is the WB threshold at which reproduction probability is equal to 0.5 (2 in Table 1).

If agents reproduce, then their WB is decreased by a percentage given by Rep Cost (1 in Table 1). The loss in WB from both partners is then passed into the offspring, and this value becomes the initial WB value of the offspring. Further, offspring inherit the religiosity, insecurity, and sensitivity values from one of their parents (this parent is selected at random).

Threats process. Every year a certain number of threats are generated. The number and intensity of threats is determined by drawing numbers from a Poisson distribution and an exponential distribution, respectively (13–14 in Table 1). Each year, the intensity value of all threats is added to the current insecurity of agents (if after this addition insecurity is > 1 , insecurity is set to 1).

Prosocial behavior process. Every year, agents aged 12 y.o. or older are allowed to perform a prosocial behavior. Prosocial behavior is triggered when the product of the agents' religiosity times anxiety goes above the *PB threshold* (8 in Table 1). Anxiety is the product of their insecurity times their sensitivity. Prosocial behaviors increase the religiosity and decrease the insecurity of the performing agents and that of close by neighbors (7–10 in Table 1). Neighbors are considered those agents within a certain radius of distance from the performing agent (24 in Table 1). If the number of close by agents exceed the number of benefited neighbors (23 in Table 1); then, benefited neighbors are selected randomly from all close by ones. Prosocial behaviors are costly and performing agents reduce their wellbeing every time they perform a prosocial behavior (11 in Table 1).

2.2 Optimization Experiments and Reference Models

We created a reference model (RM) against which we could compare the effects of environmental threats and prosocial behavior on the growth rate of the society. The RM was needed because otherwise we would not know if societies were not successful because rate of threats and their intensity did not trigger the appropriate amount of prosocial behavior or because the parameters determining the mortality, reproduction and marriage processes were not tuned accurately and thus made societies go extinct. To create a RM, we turned off the environmental threats and prosocial

behaviors, and searched for optimal parameter values (related to wellbeing, mortality, marriage, and reproduction; OP parameters in Table 1) that allowed a society to keep its population size constant over time.

We used the optimization engine of AnyLogic, which allows the user to obtain a combination of parameter values that increases or decreases a specific output value obtained from an input function. In our case, the input function calculated the residual sum of squares (RSS) between the observed yearly growth rate (i.e., $\text{pop_size}_{y+1}/\text{pop_size}_y$) and the expected growth rate if the population size remained constant over time (i.e., 1). The optimization experiments found the combination of parameter values that minimize the output value. We ran 20 different optimization experiments from which we obtained 20 different combinations of parameters. Each simulation lasted for 500 years. We chose the two best simulations as RM (see ODD + D protocol for further details on the RMs).

2.3 Sensitivity Analysis: The Role of Threats and Prosocial Behavior

To explore the effect of threats and threats' intensity on prosocial behavior, religiosity, and the growth rate of societies, we did a sensitivity analysis by varying the values of 11 parameters related to prosociality, religiosity, reproduction, and threats (SA parameters in Table 1). During the sensitivity analysis we kept fixed the optimized parameters found for the two best simulations during the optimization experiments.

We used latinhypercube sampling to sample the parameter space 20,000 times per RM. For each combination of parameter values we ran one simulation. Each simulation was run for 500 years and every 25 years we collected the population size and average religiosity of the population. We classify as successful societies those that at the end of the simulation (500 years), had population size greater than 2000 individuals. We choose this value because it is a value greater than the median and the third interquartile range of population sizes of the RMs.

3 Results

3.1 Successful Societies

The percentage of simulations with successful societies (i.e., with a population size > 2000) for RM 1 and 2 were 0.44% ($n = 88$) and 2.15% ($n = 431$) respectively. We used the verification and validation (V&V) calculator tool (available at <https://vmasc.shinyapps.io/VandVCalculator/>), whose use is illustrated in [17–19], in order to explore the conditions leading to successful societies in our model. The Sensitivity Assessor identified four conditions that were observed much more frequently in the

successful societies than in all the parameter sampling. These conditions were related to specific parameters' values being below or above a certain threshold (Table 2). For instance, the PB threshold below 0.2 (or 0.3) was observed in 100% of the successful runs in RM1 (or 97% in RM2); whereas this condition was observed only in 39% of cases in the whole parameter sampling for RM1 (or 59% for RM2; Table 2). Similarly, the four conditions identified by the Sensitivity Assessor were observed over 90% of the time in successful simulations, a percentage well above the value expected from their appearance in the parameter sampling (Table 2). This suggested that societies may be successful if the values of PB threshold, PB wellbeing cost and the importance of insecurity in reproduction were kept below these thresholds and the number of neighbors benefited were above or equal to 2. Note that although these thresholds were somewhat different depending on the RM, the same parameters were identified in both models (Table 2).

Additionally, the Sensitivity Assessor identified other conditions concerning the value of the PB threshold and the WB cost of PB in relation to the value of other parameters (Table 3). More specifically, it seemed like successful societies were those where the values of both the PB threshold and WB cost of PB were lower than the decrease of insecurity (in self and neighbors) and the increase in religiosity (in self and neighbors) after a PB (Table 3).

To corroborate that these conditions were necessary for societies to be successful, we resampled the parameter. We first resampled (20,000 times per reference model) the parameter space by keeping the values of the parameters in Table 2 within the range identified by the Sensitivity Assessor. This indeed increased the percentage of successful societies: 12.59% ($n = 2517$) and 28.27% ($n = 5655$) for RM 1 and 2, respectively. This was a significant increase; however, the percentage of successful societies was far from being a majority, i.e., $> 50\%$. Therefore, we decided to resample

Table 2 Conditions observed in successful societies

Condition	# of times observed in:		% Obs	% Exp	Obs-Exp
	Successful runs	All sampling			
Reference model 1					
PB threshold < 0.2	88	7755	100	39	61
PB wellbeing cost < 0.12	84	11,960	95	60	36
Importance Insec < 0.8	86	2500	98	13	85
# Neigh benefited > = 2	88	2500	100	88	13
Reference model 2					
PB threshold < 0.3	417	11,836	97	59	38
PB wellbeing cost < 0.14	395	13,969	92	70	22
Importance Insec < 1.0	429	3333	100	17	83
# Neigh benefited > = 2	416	2500	97	88	09

Table 3 Extra conditions observed in successful societies

Condition	# of times observed in:		% Obs	% Exp	Obs-Exp
	Successful runs	All sampling			
Reference model 1					
PB th < PB dec ins neigh	85	10,046	0.97	0.50	0.47
PB th < PB dec ins self	83	9999	0.94	0.50	0.44
PB th < PB inc rel self	85	10,025	0.97	0.50	0.47
PB th < PB inc rel neigh	77	10,065	0.88	0.50	0.38
PB WB cost < PB dec ins neigh	82	10,014	0.93	0.50	0.43
PB WB cost < PB dec ins self	74	10,001	0.84	0.50	0.34
PB WB cost < PB inc rel self	81	10,000	0.92	0.50	0.42
PB WB cost < PB inc rel neigh	72	10,007	0.82	0.50	0.32
Reference model 2					
PB th < PB dec ins neigh	330	10,014	0.77	0.50	0.27
PB th < PB dec ins self	346	9964	0.80	0.50	0.30
PB th < PB inc rel self	354	10,027	0.82	0.50	0.32
PB th < PB inc rel neigh	334	10,081	0.77	0.50	0.27
PB WB cost < PB dec ins neigh	316	10,010	0.73	0.50	0.23
PB WB cost < PB dec ins self	329	10,004	0.76	0.50	0.26
PB WB cost < PB inc rel self	329	10,005	0.76	0.50	0.26
PB WB cost < PB inc rel neigh	301	9973	0.70	0.50	0.20

the parameter space by not only maintaining the conditions in Table 2 but also those in Table 3. This resulted in the largest number of successful societies: 63.4% ($n = 12,680$) and 71.81% ($n = 14,361$) for RM 1 and 2 respectively.

3.2 The Effect of Threats' Rate and Intensity

Surprisingly, the conditions identified by the Sensitivity Assessor (Tables 2 and 3) did not include the rate and intensity of threats. However, we know that the rate and intensity of threat must play a role, otherwise societies would not be different from the RMs (i.e., without any threats). To explore this, we generated a heat map illustrating the difference in frequency of occurrence of successful societies within

that specific parameter range (# successful societies within parameter range/ total # of successful societies) and the frequency expected given the number of simulations run within that given parameter space (# simulations run within parameter range/total # of simulations run). Every tile in Fig. 3 represents simulations within a specific parameter space range. These ranges comprise steps of 0.5 and 1 for *lambda threat rate* and *lambda rate intensity* respectively (12–13 in Table 1 and Fig. 3). The color code shows the difference between observed and expected. The yellow-white areas show that the condition was more frequent and orange-red areas that it was much less frequent in successful societies than in the whole parameter sampling. Hence, societies thrive in the white-yellow zone, when the rate of threats is low-medium (i.e., 0.5–7) and the intensity of threats is low (i.e., 30–50, the higher the value of lambda intensity, the lower the intensity of threats) (Fig. 3).

Finally, using the same parameter ranges as in Fig. 3, we generated a heatmap plotting the average religiosity of the successful societies falling within that specific parameter range (Fig. 4). The average religiosity of the society increases the higher the rate (high values x-axis) and intensity (low values y-axis) of threats (Fig. 4).

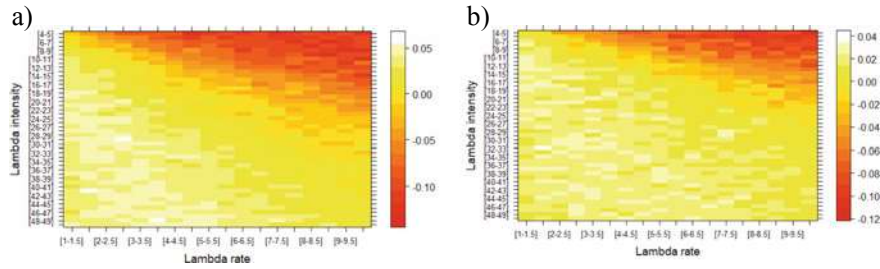


Fig. 3 Heat map of the differences between the percentage of successful societies observed and the percentage expected given the number of simulations run within that specific parameter range for RM **a** 1 and **b** 2. Color scale are the difference between % observed–% expected

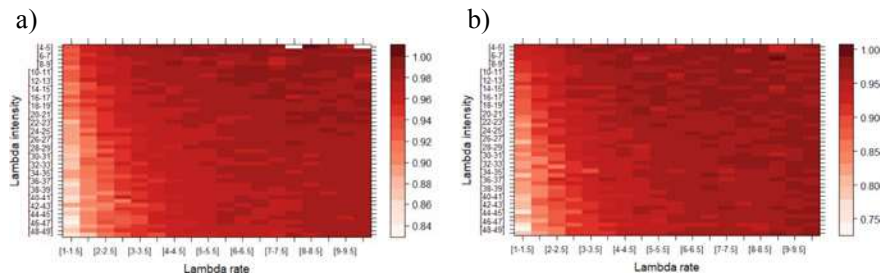


Fig. 4 Heat map of average religiosity of successful societies falling within a specific parameter range for **a** RM 1 and **b** RM 2. Color scale are values of average religiosity

4 Discussion

The simulation results presented above have shown the plausibility of the central idea underlying the model—that large scale societies may have been made possible by religiously-motivated pro-social behavior. In the model, societies in which the agents readily performed pro-social behavior were able not just to survive when facing environmental threats but even to grow many times beyond their initial size. The relative harshness of the environments faced by the societies can be understood when we consider that in the initial sensitivity analysis only a very small minority of societies was successful.

The conditions that were identified as overwhelmingly present among successful societies across the two reference models give us a lot of additional insight. In particular, it is clear that it is important that agents be readily willing to engage in pro-social behavior, that the behavior not be particularly costly, that it benefits a larger number of individuals, and that insecurity plays a smaller role in whether people have children than their wellbeing. Most significantly, it was shown that: (1) pro-social behavior had to be efficient, i.e., its cost had to be smaller than its effect on security and religiosity; and (2) the less effective the pro-social behavior, the more readily the agents must be willing to engage in it. While these results are not fundamentally surprising, they do show that the modelled societies are behaving in ways that appear to capture important aspects of reality.

The key results for the plausibility of the model, however, were those showing the relationship between threat levels, on the one hand, and the religiosity and success of societies, on the other. Firstly, it was clear that the most religious societies were those facing the most severe and most frequent threats—as has been seen in many historical real-life cases. Interestingly, the rate of threats appears to be more significant—showing that infrequent but large threats are not enough to maintain very high religiosity in a society.

Secondly, the relationship between threat levels and success was more involved. When it came to success, the pattern is similar in that the greatest number of successful societies is to be met where neither the rate nor the severity of threats is too great. However, an interesting difference is that very low threat rates do not lead to the highest rates of success but, instead, seem to be connected with somewhat decreased success. This is most probably because in the intermediate conditions, religiously-motivated pro-social behaviors could counteract the insecurity while also maintaining high levels of religiosity. In environments where the threats were more intense or more frequent, even high levels of religiosity and resulting pro-social behavior were not enough to keep insecurity low and allow the societies to succeed. Unlike religiosity, success appears to be more connected to the average size of the threats—showing that less infrequent but large threats can overwhelm a society that has not maintained sufficiently high levels of cooperation. This is also likely to be connected to the fact that societies facing the lowest frequency of threats were not particularly successful even if those threats were not particularly large.

In future work, we plan to extend the architecture of this Prosocial Equilibrium model in order to address other research questions such as: What is the role of non-religious central institutions (of the sort common in secular societies) in promoting prosociality, lowering anxiety and enhancing wellbeing? These further developments will contribute to major debates in the scientific study of religion and secularization.

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