Impact of real and perceived insecurity on conditional cooperation in a good game public

Sylvain Estebe
M.Sc. Cognitive Science, Aarhus University

December 22, 2024

Abstract

This study examines how real and perceived insecurity affects conditional cooperation in a public goods game. It examines whether there is a correlation between an index and the overall outcome for the group of the game, and whether individual decisions differ by applying a decision model to explain the effects in terms of social decision dynamics. The study uses an existing dataset of groups playing a public goods game in thirteen economically diverse societies. Although for various reasons the result must be taken with caution, the results suggest that the experience of insecurity does not affect contribution, but people in nations with higher levels of perceived insecurity contribute less. Furthermore, the study shows that a higher worry index is associated with lower initial optimism regarding others' contributions at the beginning of the game and increased sensitivity to others contributions, which accelerates the decay of cooperation (research question 2).

Keywords – Cooperation, Public Goods Game, Insecurity, Worry

GitHub: https://github.com/SylvainEstebe/decision_making_project

Contents

1 Introduction

In the future, diverse nations will likely need to work together more than ever to meet new challenges. For example, climate change is one of the most pressing global issues we face today, and addressing it will require extensive cooperation. For example, reducing CO2 emissions can be viewed as a public goods game, in which individual countries contribute to a certain level of reductions with the explicit or implicit understanding that others will do the same. Many factors influence a country's willingness to match other countries announced reductions. One factor that has been somewhat overlooked in the discussion of global cooperation on climate change is the different levels of security of the countries involved. Security refers to both the objective safety issues of a country, such as access to food and water, low violent crime rates, minimal deaths from natural disasters, good mental health, absence of war, and road safety, as well as the subjective perception of security with respect to these different components. Therefore, security can be divided into two parts: the perception of being in a secure environment and the reality of the security of this environment. Research has demonstrated that an increase in perceived security can lead to prosocial tendencies and behaviour towards others (Gillath et al., 2016). Conversely, perceived insecurity has been found to have a negative impact on cooperation, while still positively influencing trust and altruism (Vélez et al., 2016). In addition, humans appear to possess a security motivation system that can be triggered by specific information and deactivated by more abstract and distant information (Woody & Szechtman, 2013).

This paper investigates the impact of a country's security on cooperation at the individual level. The objective of this investigation is to determine whether a nation's security, both perceived and actual, affects the conditional cooperation decision making of individuals from various countries in a public goods game.

1.1 Real and perceived insecurity

On one hand, we have the experience of insecurity. We can distinguish the fear of insecurity, which is related to emotion, and insecurity, which is connected to risk theories and cognitive processes (Valera & Guàrdia, 2014). By risk, for example, we have environmental risk (e.g., climate change, production shocks, technological change, floods, earthquakes), which is an exogenous stochastic process that generates adverse events that negatively affect individuals' payoff (Bilancini et al., 2024). It can be shown that risk perception and experience influence individual decision-making processes, especially in terms of preparedness and recovery from disasters (Kieu & Senanayake, 2023). When people experience severe environmental conditions, a process of adaptation could occur. Then, people who live in violent circumstances could develop strategies to reduce its impact (Wills-Herrera, 2014). We can ask if these adaptations have an effect on individual decision-making. Different experimental research investigating the relationship between the experience of insecurity and cooperation has been done. For example, in real-world settings, it has been shown that individuals from communities subjected to violent conflict tend to contribute more to public goods and exhibit more trust compared to those from peaceful communities (Gilligan et al., 2014). However, individuals from households that have been victimized, despite showing more altruism, do not demonstrate a higher likelihood to contribute to public goods or show more trust compared to those from non-victimized households (Gilligan et al., 2014).

On the other hand, we have a perception of insecurity, which can be defined as risk perception to evaluate potential threats (Kieu & Senanayake, 2023). In real-world settings, it has been shown that with risk perception, citizens engage in behavior that will increase their safety and feelings of security (Reid et al., 2020). In experimental settings, a team developed a cognitive-affective measure of subjective insecurity to capture individual perceptions of insecurity for personal, family, and community dimensions of 80 farmers for each game. The farmers were drawn from different rural districts in Colombian villages exposed to varying levels of violence. The team conducted a public good game with 15 rounds. According to Vélez et al. (2016), subjective insecurity negatively affects cooperation in public good games, but has a positive influence on trust and altruism, and no effect on reciprocity. The authors also note that research on the relationship between perceived insecurity and cooperation is underdeveloped.

1.2 Public good games

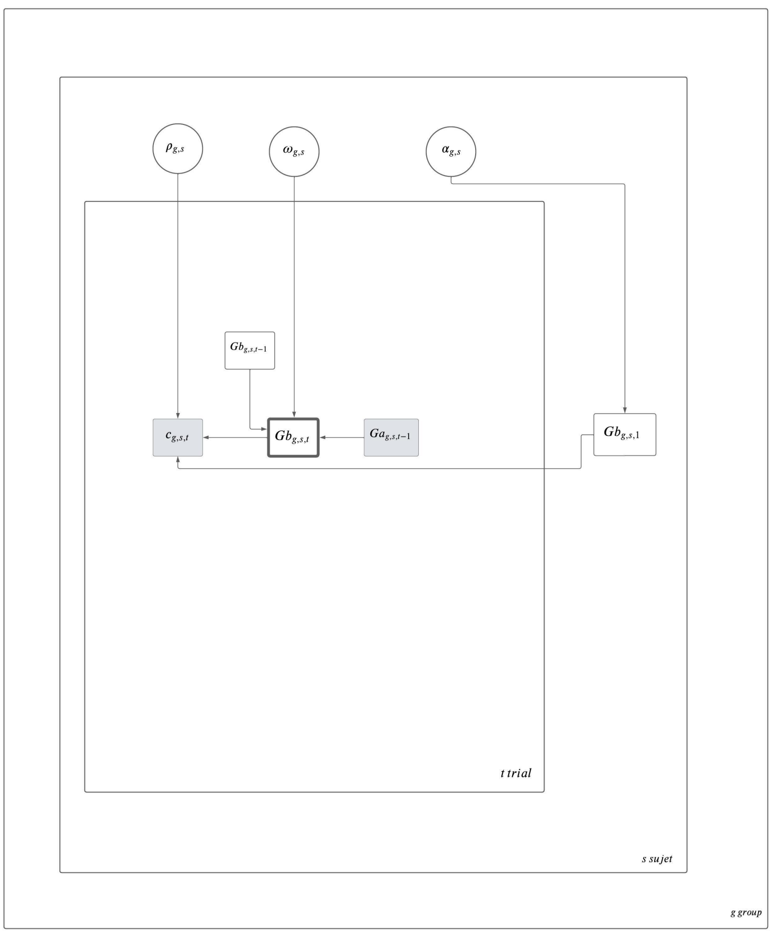
Public good games (PGG) are a well-known group known to study situations that require people to cooperate to achieve a goal that is considered beneficial to all (Tomassini & Antonioni, 2020). In this game, each player determines the amount of resources (tokens) they want to contribute to a shared pot. The tokens in the pot are then multiplied by a specific factor, and the resulting "public good" payoff is split equally among all the players, regardless of their contributions. Each participant also gets to keep the tokens they choose not to contribute. The best outcome is achieved when everyone contributes all their tokens to the pot, and the resulting payoff indicates the player's level of cooperation in their group. It has been shown that the proportion of conditional co-operators explains why contributions stay relatively high but go down over time

([Villeval](#), [2012](#)). Many factors could affect the size of the contribution: the repetition of the game, experience and learning, communication, marginal payoff, size of the group, and others (Reiss, 2021).

1.3 Cognitive Model of Conditional Cooperation in Public Good Games

In this work, I use a model of conditional cooperation that combines two different models of cognitive mechanisms to explain conditional cooperation. One comes from the reinforcement learning literature, that is, how humans and machine animals act on feedback to maximize a reward. In the public good game, individuals update their preference to contribute based on feedback from other contributions (Camerer & Hua Ho, 1999)(Erev & Roth, 1998). On the other hand, Fischbacher & Gächter in 2010 showed that human behavior in PGG can be better described by a combination of self- and other-regarding preferences. The study suggests that most people are imperfect conditional cooperators who only partially match the contributions of others. This behavior suggests that voluntary cooperation in Public Goods Games is inherently fragile. To investigate the relationship between real and perceived insecurity in participants' home country and their decision-making in the game, the same formal implementation of the conditional cooperation schema used in this study was employed : Fischbacher & Gächter (2010) and Skewes & Nockur (2023).

1.3.1 Formalisation of the model



$$c_{g,s,t} \sim Poisson(P_{g,s,t})$$
$$P_{g,s,t} = p_{g,s} \cdot Gb_{g,s,t}$$
$$Gb_{g,s,t} = (1 - \omega_{g,s}) \cdot Gb_{g,s,t-1} + \omega_{g,s} \cdot Ga_{g,s,t-1}$$
$$Gb_{g,s,1} \sim Poisson(\alpha_{g,s})$$

$\alpha_{g,s}$ Initial Belief

$\omega_{g,s}$ Sensitivity of other contribution

$\rho_{g,s}$ Tendance to cooperate

Figure 1: The figure shows the tile notation of the Conditional Cooperation Model. Here is the legend for: Square - discrete, circle - continuous Thick line - deterministic, thin line - stochastic Shaded - data, unshaded - latent

Figure 1 shows the plate notation[1] of the conditional cooperation model used in this paper.

[1] In Bayesian inference, plate notation is a method of representing variables that repeat in a graphical model. Instead of drawing each repeated variable individually, a plate or rectangle is used to group variables into a subgraph that repeat

First, the participant s in group g on trial 1 will contribute a quantity of token $c_{g,s,1}$. This is affected by two way: First, the initial belief about how others will contribute which follow a Poisson distribution with parameter $\alpha_{g,s} \in [0; 20]$

$$Gb_{g,s,1} \sim Poisson(\alpha_{g,s}) \tag{1}$$

Optimistic participants believe that others will contribute the maximum token possible $\alpha_{g,s} = 20$, while pessimistic participants believe that others will contribute none of their tokens in the first round $\alpha_{g,s} = 0$. The initial belief about how much others will contribute in the first round is modeled.

After that, the individual has a preference to cooperate or not, $\rho_{g,s}$ represents the individual's preferences for conditional cooperation with $\rho_{g,s} \in [0; 1]$

This product gives us the unobservable or hidden tendency of the individual to have a preference for contributing on the first trial. Then, the contribution is drawn by the Poisson distribution with $P_{g,s,t}$ in the parameter.

$$P_{g,s,1} = \rho_{g,s} \cdot Gb_{g,s,1} \tag{2}$$

$$c_{g,s,1} \sim Poisson(P_{g,s,1}) \tag{3}$$

After the first trial, the three remaining participants made their contributions. For the remaining nine trials, their beliefs about how others will contribute are updated using the following equation:

$$Gb_{g,s,t} = (1 - \omega_{g,s}) \cdot Gb_{g,s,t-1} + \omega_{g,s} \cdot Ga_{g,s,t-1} \tag{4}$$

$1 - \omega_{g,s}$ represents the weight that an individual has in his previous belief about group contribution, then $Gb_{g,s,t-1}$ denotes the individual's belief about the group's contribution on the previous trial $Ga_{g,s,t-1}$ represents the average contribution observed on the last trial, and $\omega_{s,g}$ is a weighting for the influence of the observed contribution, relative to the individual's prior beliefs. So, someone sensitive to other's contributions will quickly update their belief according to the observation about what the group has contributed in the last round and according to less importance to his old belief on the previous trial. If someone is less sensitive, it should be the inverse, which is observed. The $Ga_{g,s,t-1}$ is observed, it is included in the model as data.

The parameter $\omega_{g,s}$ must be inferred and is assumed to be between 0 and 1. If $\omega_{g,s}$ is presumed to be equal to 0, then the individual is entirely insensitive to the group's behavior and will never update their beliefs about what the group will contribute. They will fix a belief at the beginning of the game, and it will not change. If $\omega_{g,s}$ is inferred to be equal to 1, then the individual is maximally sensitive to the group's behavior, and their beliefs about contributions on the subsequent trial will always reflect what they observed on the last trial. Values in between represent more or less sensitivity to others, defined as more or less rapid belief updating.

After updating $Gb_{g,s,t}$ the scaling with the individual preference for conditional cooperation $\rho_{g,s}$ is made and give $P_{g,s,t}$ as parameter for the Poisson distribution.

$$P_{g,s,t} = \rho_{g,s} \cdot Gb_{g,s,t} \tag{5}$$

$$c_{g,s,t} \sim Poisson(P_{g,s,t}) \tag{6}$$

To summarise the model, has three decision parameters we need to estimate:

- $\rho_{g,s} \in [0; 1]$ which represents the **individual's preference for conditional cooperation** (Fischbacher & Gächter, 2010)
- $\omega_{g,s} \in [0; 1]$ which represents the **individual's sensitivity to information about the rest of the group's contributions in updating their beliefs** (Masel, 2007)
- $\alpha_{g,s} \in [0; 20]$ which represents the **individual's optimism about how much the rest of the group will contribute to the first trial**

1.4 Research question 1

To address our first research question, I reanalyzed open data from an experimental implementation of the public goods game played by groups from various nations (Herrmann et al., 2008). The game winnings[2] of each group were correlated with two indexes: the experience of insecurity and the perceived security. These indexes represent the experience and worry levels for the country from which the experimental participants were sampled.

together, and a number is drawn on the plate to represent the number of repetitions of the subgraph in the plate source

[2]The general gain of the group will depend on the members' ability to cooperate by contributing equitably to the public good. The higher the level of cooperation, the more significant the group's general gain will be, demonstrating the importance of cooperation in achieving a collective benefit.

Both indexes are from The Lloyd's Register Foundation 2021 World Risk Poll dataset, a global survey on individual's risk perception experience across various potential threats[3]
The dataset's availability, which only covers 2021. Although a dataset for 2019 exists, it does not include data on food insecurity, water insecurity, violent crime, severe weather events, and mental health issues. As outlined in our limitations section, the results must be interpreted with caution. The worry index measures an individual's risk perception across various categories, while the experience index evaluates an individual's experience of harm across theses categories[4].

Our focus is on the experience and worry index score. The indexes range from 0 to 1, with 0 indicating the lowest level of concern or harm and 1 indicating a higher level of concern or harm.[5]. If the experience (or worry) index reduces cooperation in the experimental public goods game, we should observe a negative correlation between the experience index coefficient and the winnings made in the game when played in different countries.

1.5 Research question 2

The second research question investigates how insecurity and perceived insecurity can decrease cooperation. The cognitive model of conditional cooperation is used to analyze the effect of national insecurity (real and perceived) on economic cooperation and individual decision-making. Groups may exhibit distinct variations in the parameters of the decision model based on the level of insecurity in their country, if national insecurity consistently affects economic cooperation and individual decision-making.

1.6 Research Questions Summary

To recap, the present study addresses two questions these are:

- RQ1) What is the relationship between the national experience of insecurity and contributions in an experimental public goods game? What is the relationship between national perceived insecurity and contributions in an experimental public goods game?
- RQ2) What are the decision-making mechanisms involved?

2 Method

2.1 Datasets

The data used to address research questions RQ1 and RQ2 were gathered in 2008 by Herrmann et al.. As of 2017, the researchers have made this data publicly available. During the experiment, participants engaged in a ten-round public goods game in groups of four. Each round presented the choice of keeping 20 tokens or contributing them to the public good. The tokens contributed to the public good were multiplied by a factor of 1.6, and the new total was then redistributed to all group members, regardless of their contributions. The experiment included two versions of the game, played in a counterbalanced order. The first version was the standard game, while the second allowed group members to punish each other. However, we only focus on data from the standard game, as most participants completed this version first. The experiment involved 1120 participants, grouped into 280 groups from 15 different nations, including Australia, Belarus, China, Denmark, Germany, Greece, South Korea, Oman, Russia, Saudi Arabia, Switzerland, Turkey, the UK, Ukraine, and the USA. Notably, excluding participants who experienced the punishment version first kept the findings of any analyses the same.

Experience of insecurity (Experience index) and Feeling of security (Worry index) coefficients for the years 2002-2006 were retrieved from the **The Lloyd's Register Foundation World Risk Poll** for as many participating countries as possible. The data was collected in 2021, after the pandemic. The index includes five risk domains: Health (including harm from eating food and drinking water), Personal (mental health), Violence (violent crime), Work (workplace injuries), and Environment (severe weather). Questionnaires use item response theory (IRT) and the Rasch model, an IRT psychometric model for analyzing categorical data, which provides tools for assessing the suitability of risk perception items for constructing a measurement scale. The IRT tools indicated that the risk perception items met appropriate validity and reliability criteria for measure development (Lloyd's Foundation, 2021).

Worry and Experience index coefficients were unavailable for Oman, and Saudi Arabia, so data collected from participants in these nations were not included in the analysis. Data from the other 13 countries were included. For this reason, 25 groups were excluded from the analysis (cf the list of dataset used Appendix A)

[3] https://wrp.lrfoundation.org.uk/lrf_wrp_2021_full_methods.pdf

[4] the food you eat, the water you drink, violent crime, severe weather events such as floods or violent storms, mental health issues, and the work you do, please refer to the Lloyd's Register Foundation (2022) 2021 World Risk Poll Data set available at https://wrp.lrfoundation.org.uk/data-resources

[5] https://wrp.lrfoundation.org.uk/2021-risk-indexes/

The experimental data included in the analysis are from 10 groups from Australia, 17 groups from Belarus, 24 groups from China, 17 groups from Denmark, 15 groups from Germany, 11 groups from Greece, 21 groups from Korea, 38 groups from Russia, 47 groups from Switzerland, 16 groups from Turkey, 14 groups from the UK, 11 groups from Ukraine, and 14 groups from the USA.

2.2 Hierarchical model structure

The parameters for the conditional cooperation model were estimated using, Bayesian hierarchical modeling [6] (Gelman et al., 2020)(Lee & Wagenmakers, 2014). Hierarchical modeling is appropriate when accounting for repeated measures across analysis levels or for the effects of other kinds of random effects in the data. Additionally, it has been shown to improve parameter estimation at the individual level (Katahira, 2016).

The cognitive model consists of four levels: trial, participant, group, and national. The trial level includes data on token contributions. At the participant level, three parameters are present: α, ρ, and ω. The group level involves analyzing the overall group contribution in the laboratory, while at the national level, the social context is considered through worry and experience indexes. Group dynamics are represented as shared variance, enabling inferences about the national context by modeling the effects of national-level measures on cognitive model parameters. (Lee & Wagenmakers, 2014).

2.3 Statistical analyses

For the first model related to research question 1, I used a default Bayesian hierarchical correlation model to represent this question (Skewes & Nockur, 2023) (Wetzels & Wagenmakers, 2012). Data for this model was the overall contribution Y of each group g. This was calculated by adding all contributions on a trial and then adding across all trials. The equation of this statistical model can be found in Appendix B.

For the second model related to research question 2, I used a default correlation model (Wetzels & Wagenmakers, 2012) to model the relationship between the national worry experience index and worry index and national level estimates for each of the parameters in the decision model. I used the same fully hierarchical model to infer decision parameters simultaneously for all participants, in all groups, and within each nation. Then, I predicted the inferred national-level estimates for the decision model parameters from the worry and experience index. At the prior individual level, our three parameters are the following: Because ρ and ω are $\in [0;1]$, a beta distribution is used. For α which $\in [0;20]$ a gamma distribution is used. The description for national level shape parameters and re-parameterization can be found in Appendix C.

$$\rho_{g,s} \sim Beta(\beta shape1^{\rho}_{nation}, \beta shape2^{\rho}_{nation}) \tag{7}$$

$$\omega_{g,s} \sim Beta(\beta shape1^{\rho}_{nation}, \beta shape2^{\rho}_{nation}) \tag{8}$$

$$\alpha_{g,s} \sim Gamma(\gamma shape^{\alpha}_{nation}, \gamma rate^{\alpha}_{nation}) \tag{9}$$

2.3.1 Convergence Diagnostics

Convergence to target distributions was checked by trace plot inspection, as well as numerically with scale reduction factors $\hat{R}$ for each estimate tracked in the model. for each parameter (Vehtari et al., 2019). $\hat{R}$ suggest having values below 0.01 for all parameters. For the experience index, they were between 1.494 and 1.101, which is poor and will be taken into account when interpreting the result. For the worry index, they were between 1.023 and 1.069. We take this into account when interpreting the results. The result can be found in Appendix E.

2.3.2 Specification

The analysis was performed using R (R Core Team, 2022) in RStudio (RStudio Team, 2020), employing the following packages. All inference was done using Markov Chain Monte Carlo (MCMC) sampling implemented in JAGS software (Plummer, 2023) via the R2jahs R package (Su & Yajima, 2021). For all models, I used four chains of 15000 samples, with 5000 samples discarded as burn-in. I report posterior distributions and Bayesian credible intervals for parameters of interest in all models, and these can be interpreted as national-level regression coefficients. The data handling and analysis were run on the MacBookPro Apple M3 Max with Sonoma 14.2.1 (23C71) version..

[6] a model written in hierarchical form that is estimated using Bayesian methods (Allenby et al., 2005)

2.4 Parameter recovery

Parameter recovery was used to evaluate the model's ability to recover actual parameter values (α, ρ, ω). I simulated synthetic contribution data for 280 groups and ten trials for the true parameter, which was sampled from a uniform distribution bounded between. $\alpha \in [0;20]$ $\rho \in [0;1]$ $\omega \in [0;1]$ The model was then fit to the simulated data, and JAGS was used to estimate the sampled parameter by running an MCMC simulation. JAGS outputs a posterior density for each parameter and compares the maximum point of each distribution to the sampled (true) parameter. I simulated data for (4*280) participants across four chains, with 15000 iterations and a burn-in of 5000.

The maximum of the posterior density of the recovered parameter is taken, and both the 'true' and 'inferred' (estimated) parameters are plotted.

On the individual level, the parameters were not well-recovered. This should be taken into account when using my model for analysis, as it may distort the results. The recovered values of α were, in general, underestimated, with a tendency to have lower recover values. While the recovered values of ω a are overestimated. The recover parameters for ρ were the better, even thought for higher value of true ρ, the parameter is overestimated and tend to give one a each recover 2

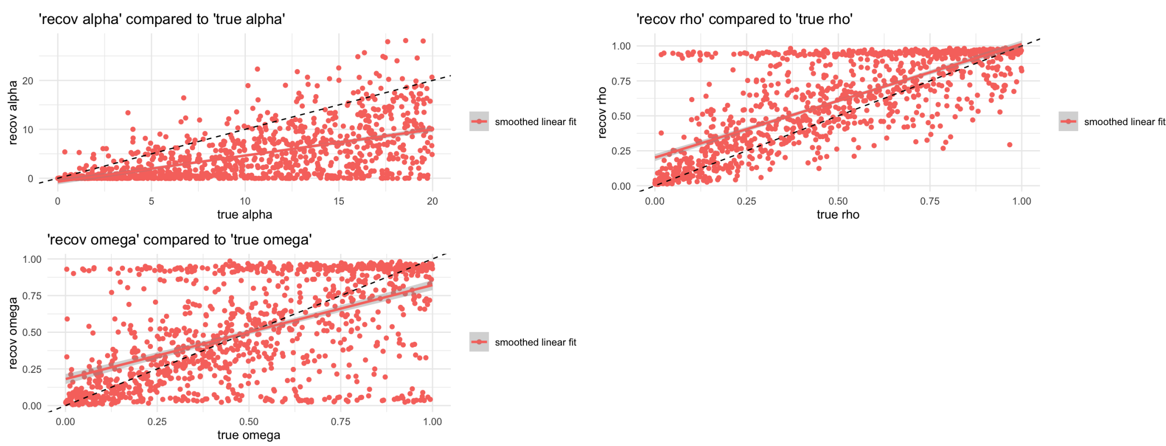


Figure 2: Parameter recovery results conditional cooperation model Comparison of recover and true α, ρ and ω

3 Result

3.1 RQ1

Here are the results relevant to the RQ1. Figure 3 presents the empirical relationship between the national index of experience in security and winning in the public good game. Drawing conclusive evidence about the existence of a relationship between the two variables based on the visual representation is difficult. Figure 3 presents the full posterior for the model of this relationship – the coefficient for the default Bayesian correlation model (Wetzels & Wagenmakers, 2012). The panel shows that the mean of the posterior distribution is negative, indicating a negative effect of the experience index or a negative relationship between the experience index and winning in the group. The 95% Bayesian Credible Intervals include zero, which is significant that I cannot discern whether the slope of the correlation is zero or different from zero.

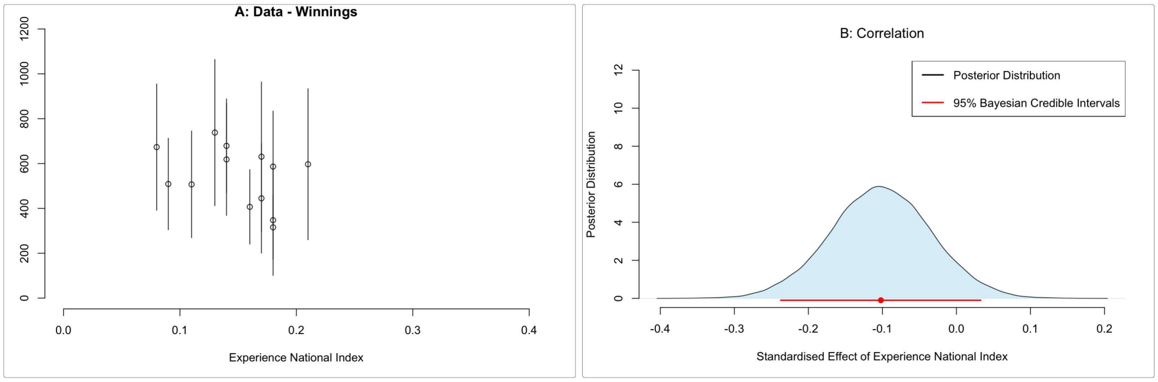


Figure 3: **Panel A**: Empirical relationship between group winning and experience index. The point represent the mean for the data collected within each nation, and the error bars represent standard deviations between groups recruited at the different national sites of the experiment. **Panel B:** Posterior distribution for the standardized effect of experience index coefficient on group winning, as inferred using the default hierarchical correlation model. The point represents the mean of the posterior distribution of the effect of experience index on winning amount, and the error bar represents the Bayesian Credible Interval

Figure 4 presents results relevant to our RQ1, presenting the empirical relationship between the national worry index and the winning in the public good game. The plot suggests that in countries with higher worry index, groups winning is less on average in the experimental game. Figure 4 presents the full posterior for the model of this relationship – the coefficient for the default Bayesian correlation model (Wetzels & Wagenmakers, 2012), which supports this inference. The panel shows that the mean of the posterior distribution is negative, indicating a negative effect of the experience index or a negative relationship between the worry index and winning in the group. The 95% Bayesian Credible Intervals do not include zero. This indicates that a negative relation exists between the winning and the worry index.

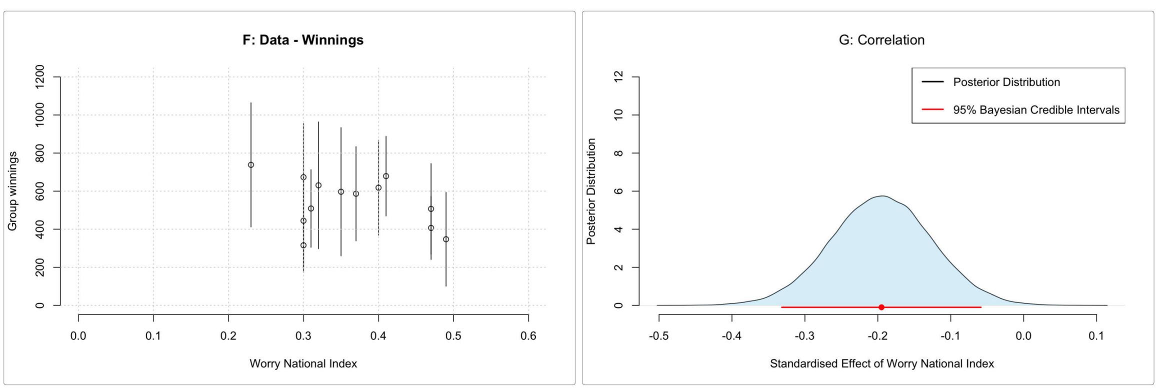


Figure 4: Panel F: Empirical relationship between group winning and worry index. The point represent the mean for the data collected within each nation, and the error bars represent standard deviations between groups recruited at the different national sites of the experiment/ Panel G: Posterior distribution for the standardized effect of worry index coefficient on group winning, as inferred using the default hierarchical correlation model. The point represents the mean of the posterior distribution of the effect of experience index on winning amount, and the error bar represents the Bayesian Credible Interval

3.2 RQ2

Figure 5 presents the results relevant to the RQ2. These are the relationships between the national experience of the insecurity index and national-level estimates for the (hierarchical) cognitive model parameters.

This indicates that it is unlikely that the national insecurity index is associated with an increase in initial belief or that more data would be required to demonstrate an association between the national experience insecurity index and initial belief. Figure 5 presents the posterior distribution for the effect of the experience of insecurity on the belief learning weight parameter in the model. For the belief learning, it indicates that the national experience of insecurity index is unlikely to be associated with an increase in belief learning weight or that more data would be required to demonstrate an association between the national experience insecurity index and belief learning weight. Figure 5 presents the posterior distribution for the effect of the experience of insecurity on the conditional preferences parameter in the model. The panel shows that the mean of the posterior is negative; the 95% Bayesian credible intervals do not include zero. This indicates that the experience of the national insecurity index is associated with a decrease in conditional preference.

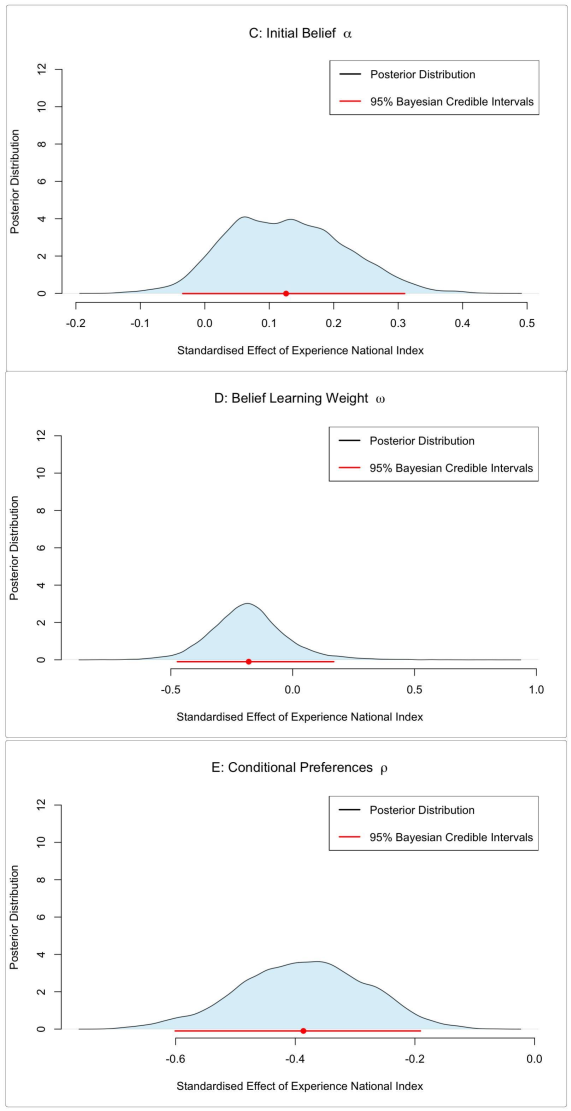


Figure 5: Panel C: Posterior distributions for the standardized effects of national experience index on decision model parameters α. The points represent the means of the posterior distributions, and the error bar represents the Bayesian Credible Intervals.Panel D: Posterior distributions for the standardized effects of national experience index on decision model parameters ω The points represent the means of the posterior distributions, and the error bar represents the Bayesian Credible Intervals.Panel E: Posterior distributions for the standardized effects of national experience index on decision model parameters ρ. The points represent the means of the posterior distributions, and the error bar represents the Bayesian Credible Intervals

Figure 6 This indicates that the worry index is associated with a decrease in initial belief. Figure 6 presents the posterior distribution for the effect of the perceived insecurity index on the belief learning weight parameter in the mode. The panel shows that the mean of the posterior is positive, and the 95% Bayesian credible intervals do not include zero. This indicates that the perceived insecurity index is associated with an increase in belief learning weight. Figure 6 presents the posterior distribution for the effect of the perceived insecurity index on conditional preference. The panel shows that the mean of the posterior is positive, and the 95% Bayesian credible intervals do not include zero. This indicates that the perceived insecurity index is associated with an increase in conditional preference.

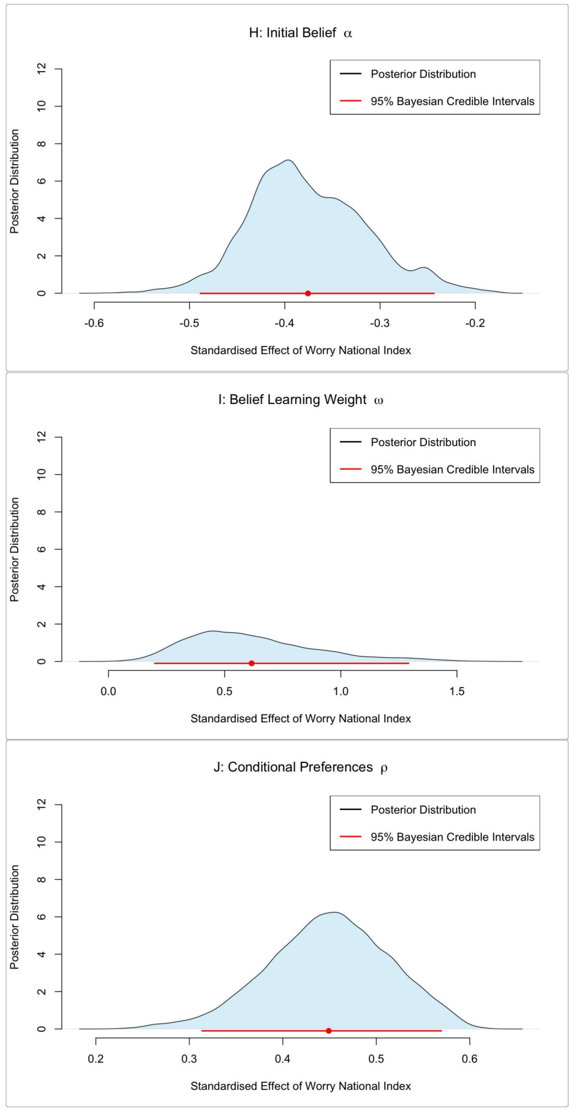


Figure 6: Panel H: Posterior distributions for the standardized effects of national worry index on decision model parameters α. The points represent the means of the posterior distributions, and the error bar represents the Bayesian Credible Intervals. Panel I: Posterior distributions for the standardized effects of national worry index on decision model parameters ω The points represent the means of the posterior distributions, and the error bar represents the Bayesian Credible Intervals. Panel J: Posterior distributions for the standardized effects of national worry index on decision model parameters ρ. The points represent the means of the posterior distributions, and the error bar represents the Bayesian Credible Intervals

4 Discussion

Firstly, it is essential to approach these interpretations objectively, as the data was not collected during the same period, the parameters were not all accurately recovered, and the convergence test was not optimal.

These results provide answers to the research questions. Regarding RQ1, the 'national experience of insecurity' index is not clearly associated with reduced cooperation in the public good game, as measured by overall reduced winning. These results are consistent with the study by found the same result in a one-shot or repeated public good game (Théroude & Zylbersztejn, 2020) that found that environmental risk does not affect the patterns of cooperation either in the one-shot or in the finitely repeated version of public good game.

However, perceived insecurity appears to have a negative impact on cooperation in the public goods game, resulting in an overall decrease in winning. Previous studies have shown that subjective insecurity has a negative effect on cooperation in public good games (Vélez et al., 2016).

Regarding RQ2, the results for the experience of insecurity are challenging to interpret due to the model's inadequate convergence. Nevertheless, the findings suggest that the experience of insecurity is not associated with initial optimism or sensitivity toward others. However, it does seem to be correlated with a proclivity for conditional cooperation.

The model suggests which individual-level decision processes might be responsible for reducing group contributions in countries where perceived uncertainty is more important. Specifically, the model shows that a higher national worry index is associated with lower initial optimism about what others will contribute. This means that even individuals with a higher level of perceived insecurity (as measured by the worry index) tend to have a preference for conditional cooperation. There is a negative correlation between the level of perceived insecurity and individuals' optimism about the size of the initial contribution of other participants. This pessimism may lead to less contribution on their part, which could be perceived by others as a lack of cooperation. As a result, the level of cooperation may decrease over the course of the experiment. Individuals with higher levels of worry tend to update their beliefs more quickly. If other participants contribute less in subsequent rounds, individuals with a high worry index may also participate less. This could lead to a further decrease in cooperation over time.

4.1 Limitations

It is important to note that there are limitations to these interpretations. The worry index and experience index data are from 2021, while the public good game dataset is from 2006-2008. Therefore, different events could have impacted both indexes during those years. The safety perception index is divided into several subcomponents, including Health (Food, Drink), Mental health, Violent Crime, Workplace injury, and Severe weather. To gain a better understanding of the potential evolution of these seven domains, I consulted graphs on Our World in Data for certain variables (see Appendix D).

The second limitation is the challenge of finding a consensus and developing a representative index due to the numerous definitions of perceived insecurity in the literature. Reporting both real and perceived security through polls could be biased and may not accurately reflect the perceived and absolute security. Research has shown that various factors, including fear of crime, perceived risk, and restricted behaviors, have complex relationships (Valera & Guàrdia, 2014). Although this study did not examine the subcomponents of a model that explains perceived insecurity, it is possible to break it down into different parts as shown 7 (Carro et al., 2010). Furthermore, Kieu & Senanayake notes that comparing subjective risk metrics across different global contexts requires careful interpretation due to the influence of various contextual factors on risk perceptions and experiences.

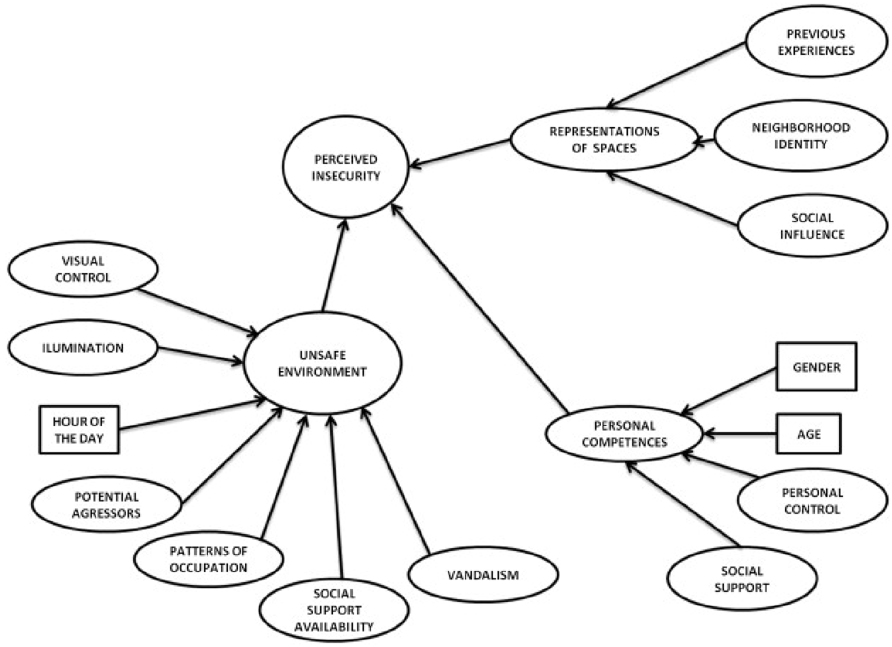


Figure 7: Graphic representation of the theoretical model on perceived insecurity (Carro et al., 2010)

4.2 Further perspective

The present work explores how conditional cooperation on public goods can be influenced by two factors of insecurity: real and perceived. To address the limitation, future research should aim to find public good game data or index in alignment with the temporal investigated. Additionally, a more nuanced index that takes into consideration the subcomponents of perceived insecurity could be taken and could enhance our understanding of which part of perceived insecurity influences conditional cooperation. Moreover, efforts to develop a standardized and comprehensive index for perceived insecurity would contribute to a more robust foundation for the next studies.

References

Bilancini, E., Boncinelli, L., Nardi, C., & Pizziol, V. (2024, February). Cooperation is unaffected by the threat of severe adverse events in public goods games. *Journal of Behavioral and Experimental Economics*, *108*, 102145. Retrieved 2024-01-06, from https://www.sciencedirect.com/science/article/pii/S2214804323001714 doi: 10.1016/j.socec.2023.102145

Camerer, C., & Hua Ho, T. (1999, July). Experience-weighted Attraction Learning in Normal Form Games. *Econometrica*, *67*(4), 827–874. Retrieved 2024-01-07, from http://doi.wiley.com/10.1111/1468-0262.00054 doi: 10.1111/1468-0262.00054

Carro, D., Valera, S., & Vidal, T. (2010, February). Perceived insecurity in the public space: personal, social and environmental variables. *Quality & Quantity*, *44*(2), 303–314. Retrieved 2024-01-10, from https://doi.org/10.1007/s11135-008-9200-0 doi: 10.1007/s11135-008-9200-0

Erev, I., & Roth, A. E. (1998). Predicting How People Play Games: Reinforcement Learning in Experimental Games with Unique, Mixed Strategy Equilibria. *The American Economic Review*, *88*(4), 848–881. Retrieved 2024-01-07, from https://www.jstor.org/stable/117009

Fischbacher, U., & Gächter, S. (2010). Social Preferences, Beliefs, and the Dynamics of Free Riding in Public Goods Experiments. *The American Economic Review*, *100*(1), 541–556. Retrieved 2024-01-06, from https://www.jstor.org/stable/27804940

Gelman, A., Hill, J., & Vehtari, A. (2020). *Regression and Other Stories* (1st ed.). Cambridge University Press. Retrieved 2024-01-06, from https://www.cambridge.org/highereducation/product/9781139161879/book doi: 10.1017/9781139161879

Gillath, O., Karantzas, G. C., & Fraley, R. C. (2016). What Is the Attachment Behavioral System? And, How Is It Linked to Other Behavioral Systems? In *Adult Attachment* (pp. 169–192). Elsevier. Retrieved 2023-12-03, from https://linkinghub.elsevier.com/retrieve/pii/B9780124200203000086 doi: 10.1016/B978-0-12-420020-3.00008-6

Gilligan, M. J., Pasquale, B. J., & Samii, C. (2014, July). Civil War and Social Cohesion: Lab-in-the-Field Evidence from Nepal. *American Journal of Political Science*, *58*(3), 604–619. Retrieved 2024-01-10, from https://onlinelibrary.wiley.com/doi/10.1111/ajps.12067 doi: 10.1111/ajps.12067

Herrmann, B., Thoni, C., & Gachter, S. (2008, March). Antisocial Punishment Across Societies. *Science*, *319*(5868), 1362–1367. Retrieved 2023-12-25, from https://www.science.org/doi/10.1126/science.1153808 doi: 10.1126/science.1153808

Katahira, K. (2016, August). How hierarchical models improve point estimates of model parameters at the individual level. *Journal of Mathematical Psychology*, *73*, 37–58. Retrieved 2024-01-07, from https://www.sciencedirect.com/science/article/pii/S0022249616300025 doi: 10.1016/j.jmp.2016.03.007

Kieu, M., & Senanayake, G. (2023, November). Perception, experience and resilience to risks: a global analysis. *Scientific Reports*, *13*(1), 19356. Retrieved 2024-01-06, from https://www.nature.com/articles/s41598-023-46680-1 doi: 10.1038/s41598-023-46680-1

Lee, M. D., & Wagenmakers, E.-J. (2014). *Bayesian Cognitive Modeling: A Practical Course*. Cambridge University Press. (Google-Books-ID: Gq6kAgAAQBAJ)

Masel, J. (2007, October). A Bayesian model of quasi-magical thinking can explain observed cooperation in the public good game. *Journal of Economic Behavior & Organization*, *64*(2), 216–231. Retrieved 2024-01-06, from https://www.sciencedirect.com/science/article/pii/S0167268106000977 doi: 10.1016/j.jebo.2005.07.003

Reid, I. D., Appleby-Arnold, S., Brockdorff, N., Jakovljev, I., & Zdravković, S. (2020, July). Developing a model of perceptions of security and insecurity in the context of crime. *Psychiatry, Psychology and Law*, *27*(4), 620–636. Retrieved 2024-01-09, from https://www.tandfonline.com/doi/full/10.1080/13218719.2020.1742235 doi: 10.1080/13218719.2020.1742235

Reiss, J. (2021). Public Goods. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy* (Fall 2021 ed.). Metaphysics Research Lab, Stanford University. Retrieved 2024-01-07, from https://plato.stanford.edu/archives/fall2021/entries/public-goods/

Sheehy-Skeffington, J. (2019). Inequality from the Bottom Up: Toward a "Psychological Shift" Model of Decision-Making Under Socioeconomic Threat. In J. Jetten & K. Peters (Eds.), *The Social Psychology of Inequality* (pp. 213–231). Cham: Springer International Publishing. Retrieved 2023-12-07, from https://doi.org/10.1007/978-3-030-28856-3_14 doi: 10.1007/978-3-030-28856-3_14

Skewes, J. C., & Nockur, L. (2023, January). National inequality, social capital, and public goods decision-making. *Current Research in Ecological and Social Psychology*, *4*, 100112. Retrieved 2024-01-10, from https://www.sciencedirect.com/science/article/pii/S2666622723000254 doi: 10.1016/j.cresp.2023.100112

Su, Y.-S., & Yajima, M. (2021, August). *R2jags: Using R to Run 'JAGS'.* Retrieved 2024-01-09, from https://cran.r-project.org/web/packages/R2jags/index.html

Théroude, V., & Zylbersztejn, A. (2020, April). Cooperation in a risky world. *Journal of Public Economic Theory*, *22*(2), 388–407. Retrieved 2024-01-06, from https://onlinelibrary.wiley.com/doi/10.1111/jpet.12366 doi: 10.1111/jpet.12366

Tomassini, M., & Antonioni, A. (2020). Public Goods Games on Coevolving Social Network Models. *Frontiers in Physics*, *8*. Retrieved 2024-01-06, from https://www.frontiersin.org/articles/10.3389/fphy.2020.00058

Valera, S., & Guàrdia, J. (2014, June). Perceived insecurity and fear of crime in a city with low-crime rates. *Journal of Environmental Psychology*, *38*, 195–205. Retrieved 2024-01-10, from https://www.sciencedirect.com/science/article/pii/S0272494414000140 doi: 10.1016/j.jenvp.2014.02.002

Vehtari, A., Gelman, A., Simpson, D., Carpenter, B., & Bürkner, P.-C. (2019, March). *Rank-normalization, folding, and localization: An improved \$\widehat{R}\$ for assessing convergence of MCMC.* Retrieved 2024-01-09, from https://arxiv.org/abs/1903.08008v5 doi: 10.1214/20-BA1221

Villeval, M. C. (2012, May). Contribution aux biens publics et préférences sociales: Apports récents de l'économie comportementale. *Revue économique*, *Vol. 63*(3), 389–420. Retrieved 2024-01-10, from https://www.cairn.info/revue-economique-2012-3-page-389.htm?ref=doi doi: 10.3917/reco.633.0389

Vélez, M. A., Trujillo, C. A., Moros, L., & Forero, C. (2016, July). Prosocial Behavior and Subjective Insecurity in Violent Contexts: Field Experiments. *PLoS ONE*, *11*(7), e0158878. Retrieved 2023-12-08, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4966936/ doi: 10.1371/journal.pone.0158878

Wetzels, R., & Wagenmakers, E.-J. (2012, December). A default Bayesian hypothesis test for correlations and partial correlations. *Psychonomic Bulletin & Review*, *19*(6), 1057–1064. Retrieved 2023-12-25, from https://doi.org/10.3758/s13423-012-0295-x doi: 10.3758/s13423-012-0295-x

Wills-Herrera, E. (2014). Feeling Safe. In A. C. Michalos (Ed.), *Encyclopedia of Quality of Life and Well-Being Research* (pp. 2233–2235). Dordrecht: Springer Netherlands. Retrieved 2024-01-06, from https://doi.org/10.1007/978-94-007-0753-5_1027 doi: 10.1007/978-94-007-0753-5_1027

Woody, E., & Szechtman, H. (2013). A biological security motivation system for potential threats: are there implications for policy-making? *Frontiers in Human Neuroscience*, *7*. Retrieved 2023-12-03, from https://www.frontiersin.org/articles/10.3389/fnhum.2013.00556

5 Appendix

A Data

Country	Worry Index - 2021	Experience Index - 2021
Denmark	0.23	0.13
Australia	0.3	0.18
United Kingdom	0.3	0.17
Switzerland	0.32	0.17
United States	0.35	0.21
Germany	0.37	0.18
Belarus	0.3	0.08
China	0.31	0.09

Table 1: Worry and Experience index: source

B Bayesian hierarchical correlation winning and index model

The statistic model come from Sheehy-Skeffington (2019) and Skewes & Nockur (2023) paper and is adapted for our two index.

The prior for contribution Y_g was assumed to be:

$$Y_g \sim Normal(\mu_{nation}, \tau) \tag{10}$$

Here μ_{nation} represents the expected average contribution for groups in a nation, and τ is the national level precision (inverse of the variance). An uninformative Gamma distribution was used as a prior for τ

$$\tau \sim Gamma(0.01, 0.01) \tag{11}$$

The relation between insecurity (the national Gini coefficient) and the national level estimate of group contribution μ_{nation} was modelled as a linear relationship:

$$\mu_{nation} = \beta_0 + \beta_{Worry} * Worry_{nation} \tag{12}$$

$$\mu_{nation} = \beta_0 + \beta_{Experience} * Experience_{nation} \tag{13}$$

Because both index was standardized before entry into the model, a standard normal distribution was used as the prior for the model intercept β_0. For the model slope, the Jeffreys–Zellner–Siow (JZS) prior was used. The general form of this is:

$$\beta \sim Normal(0, (g/\varphi)(X^T * X)^{-1}) \tag{14}$$

where φ is assigned the prior

$$\varphi \sim Gamma(0.01, 0.01) \tag{15}$$

g is assigned the prior

$$g = \frac{(n/(2^{1/2}))}{(Gamma\frac{1}{2})} \cdot g^{\frac{-3}{2}} \cdot e^{\frac{-n}{2g}} \tag{16}$$

and n is the number of groups. The parameter of interest for this model is the effect of inequality β_{Worry} and β_{EXP}

C Correlation model of relationship between the index and national level estimates for each of the parameters in the decision mode

The statistic model come from (Skewes & Nockur, 2023) paper and is adapted for our two index.

$$\rho_{g,s} \sim Beta(\beta shape1^{\rho}_{nation}, \beta shape2^{\rho}_{nation}) \tag{17}$$

$$\beta shape1^{\rho}_{nation} \tag{18}$$

and

$$\beta shape2^{\rho}_{nation} \tag{19}$$

were re-parameterized in terms of national level mean μ^{p}_{nation} and concentration (or precision) σ^{p}_{nation}

$$\beta shape1^{\rho}_{nation} = \mu^{\rho}_{nation} \cdot \sigma^{\rho}_{nation} \tag{20}$$

$$\beta shape2^{\rho}_{nation} = (1 - \mu^{\rho}_{nation}) \cdot \sigma^{\rho}_{nation} \tag{21}$$

The concentration parameter was assigned a uniform prior

$$\sigma^{\rho}_{nation} \sim Uniform(1, 100) \tag{22}$$

and the relationship between the Probit transformed national level estimate and worry and experience index was assumed to follow the group level linear model.

$$Probit(\mu^{\rho}_{nation}) = \beta_0 + \beta_{Worry} \cdot Worry_{nation} \tag{23}$$

$$Probit(\mu^{\rho}_{nation}) = \beta_0 + \beta_{Experience} \cdot Experience_{nation} \tag{24}$$

Because the worry and experience variable was standardized, the prior for the model intercept β_0 was assumed to be a standard normal distribution. The prior for the regressor β_{Worry} and $\beta_{Experience}$ was the same JZS prior that was applied in the contributions model.

The relation between Gini and Learning rate $\omega_{g,s}$ was modelled in the same way as contribution preferences $\rho_{g,s}$ and so the specification is the same.

The optimism or initial beliefs parameter $\alpha_{g,s}$ can range continuously from 0 to 20. The subject level prior for this parameter was therefore assumed to follow a Gamma distribution

$$\alpha_{g,s} \sim Gamma(\gamma shape^{\alpha}_{nation}, \gamma rate^{\alpha}_{nation}) \tag{25}$$

Which was re-parameterised in terms of the mode and standard deviation

$$\gamma shape^{\alpha}_{nation} = 1 + \mu^{\alpha}_{nation} \cdot \gamma rate^{\alpha}_{nation} \tag{26}$$

$$\gamma rate^{\alpha}_{nation} = \mu^{\alpha}_{nation} + \frac{\sqrt{(\mu^{\alpha}_{nation})^2 + 4 \cdot (\sigma^{\alpha}_{nation})^2}}{2 \cdot (\sigma^{\alpha}_{nation})^2} \tag{27}$$

The standard deviation was transformed to precision and assigned an uninformative Gamma prior

$$\sigma^{\alpha}_{nation} = \frac{1}{\sqrt{\tau^{\alpha}_{nation}}} \tag{28}$$

$$\tau^{\alpha}_{nation} \sim Gamma(0.01, 0.01) \tag{29}$$

and the log transformed national level estimate was assumed to have a linear relationship with national worry and experience index:

$$log(\mu^{\alpha}_{nation}) = \beta_0 + \beta_{Worry} \cdot Worry_{nation} \tag{30}$$

$$log(\mu^{\alpha}_{nation}) = \beta_0 + \beta_{Experience} \cdot Experience_{nation} \tag{31}$$

The prior for the model intercept β_0 was assumed to be a standard normal distribution. The prior for the regressor β_{Worry} and $\beta_{Experience}$was the same JZS parameter that I applied in the contributions model.

D Evolution of different sub components of the index

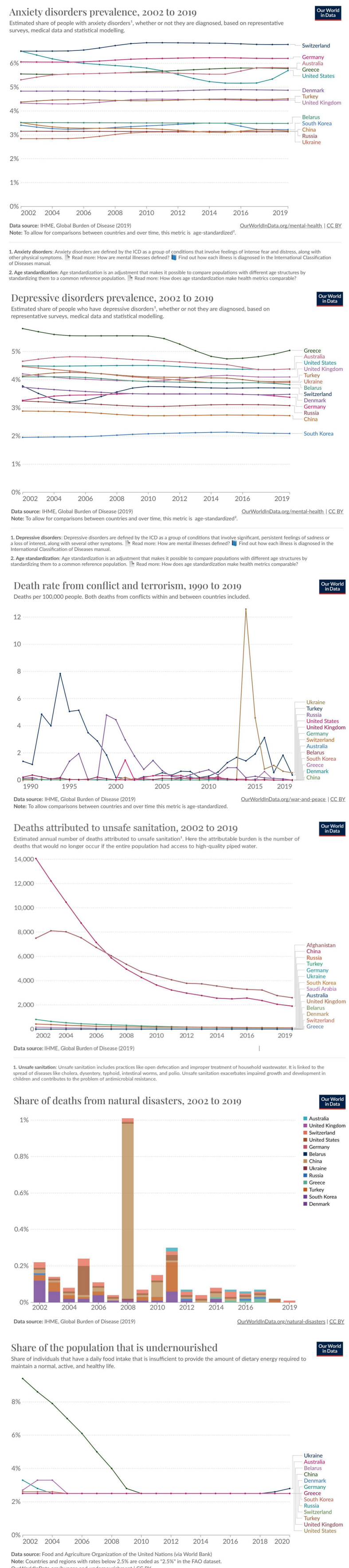


Figure 8: The figure displays the evolution of differents threat between 2002 and 2019

E Convergence

```
Inference for Bugs model at "~/Code/decision_project/decision_making_project/analysis/CC_corr.txt", fit using jags,
 4 chains, each with 15000 iterations (first 5000 discarded)
 n.sims = 40000 iterations saved
             mu.vect sd.vect       2.5%       25%       50%       75%     97.5%  Rhat
beta0_alpha     2.800   0.062     2.675     2.760     2.802     2.843     2.909 1.037
beta0_omega    -2.095   0.381    -3.060    -2.308    -2.005    -1.811    -1.576 1.028
beta0_rho      -0.087   0.050    -0.177    -0.122    -0.089    -0.055     0.018 1.023
betaX_alpha    -0.377   0.060    -0.488    -0.418    -0.382    -0.336    -0.249 1.069
betaX_omega     0.590   0.275     0.186     0.388     0.542     0.745     1.266 1.034
betaX_rho       0.446   0.062     0.322     0.404     0.447     0.489     0.565 1.037
deviance    70791.065  83.148 70628.268 70735.272 70791.396 70846.590 70952.425 1.002
            n.eff
beta0_alpha    95
beta0_omega   160
beta0_rho     160
betaX_alpha    42
betaX_omega   110
betaX_rho      94
deviance     2900

For each parameter, n.eff is a crude measure of effective sample size,
and Rhat is the potential scale reduction factor (at convergence, Rhat=1).

DIC info (using the rule, pD = var(deviance)/2)
pD = 3453.5 and DIC = 74244.5
DIC is an estimate of expected predictive error (lower deviance is better).
>
```

Figure 9: The figure displays the estimated parameter values with worry index for conditional cooperation model

```
Inference for Bugs model at "~/Code/decision_project/decision_making_project/analysis/CC_corr.txt", fit using jags,
 3 chains, each with 15000 iterations (first 5000 discarded)
 n.sims = 30000 iterations saved
             mu.vect sd.vect      2.5%       25%       50%       75%     97.5%  Rhat n.eff
beta0_alpha     2.572   0.089     2.408     2.518     2.563     2.630     2.754 1.509     8
beta0_omega    -1.576   0.145    -1.915    -1.653    -1.559    -1.479    -1.338 1.184    17
beta0_rho       0.074   0.081    -0.097     0.027     0.086     0.131     0.213 1.593     7
betaX_alpha     0.126   0.091    -0.034     0.058     0.122     0.189     0.310 1.512     8
betaX_omega    -0.180   0.157    -0.473    -0.278    -0.186    -0.095     0.168 1.095    27
betaX_rho      -0.386   0.105    -0.601    -0.459    -0.385    -0.312    -0.191 1.461     8
deviance    70642.037  86.216 70473.799 70583.904 70641.723 70700.424 70810.369 1.118    22

For each parameter, n.eff is a crude measure of effective sample size,
and Rhat is the potential scale reduction factor (at convergence, Rhat=1).

DIC info (using the rule, pD = var(deviance)/2)
pD = 3361.1 and DIC = 74003.2
DIC is an estimate of expected predictive error (lower deviance is better).
```

Figure 10: The figure displays the estimated parameter values with experience index for conditional cooperation model

F Code Source

The code used for data pre-processing and analysis is freely available at the github repository: Github