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Poverty and Threat Reactivity

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Abstract

Poverty is associated with a cluster of psychological traits such as high time-discounting and impulsivity. These traits are sometimes assumed to stem from an evolutionarily stable strategy that is adaptive in harsh environments. Error management theory predicts that humans are more likely to over-detect than to under-detect threats, and recent work in behavioral ecology suggests that this bias may be even more acute in harsh environments. This observational study tests whether a socio-economic gradient exists on the negativity bias – defined here as threat reactivity. Our design is a discrimination task with two hardly distinguishable but asymmetrically-rewarded stimuli. We use signal detection theory to evaluate participants' response bias, which we take as a proxy for threat reactivity. We predict that poverty is associated with higher threat reactivity.

Introduction

Multiple studies have demonstrated that both humans and non-human animals are more likely to over-detect than to under-detect threats (Rozin & Royzman, 2001). Error management theory suggests that this bias may be an adaptation to the asymmetrical costs associated by Type I and Type II errors when facing potential threats. Humans are more wary of false positives than false negatives because false positives are potentially deadly while false negatives usually yield a negligible cost (Haselton & Buss, 2000). In line with this idea, surveys consistently show that people overperceive all kinds of threats, such as crime rates, terrorism or unemployment risk (Gilbert et al., 2016; Lieder et al., 2016).

The present study tests the association between threat reactivity and poverty. A low threshold for reacting to threats is adaptive for all humans but, we argue, especially so for individuals living in harsh environments. Threat over-detection should be more prevalent for individuals with little or no buffer to compensate for potential mistakes (Nettle & Bateson, 2012). False positives may prove even more unforgiving for individuals living in poverty. Thus, we predict that the amplitude of the threat reactivity is negatively correlated with socioeconomic status .

We use signal detection theory to measure response bias for each participant, which we interpret as a proxy for threat reactivity. The theoretical power of signal detection theory is that it allows us to analyze discrimination tasks as resulting from two distinct and orthogonal cognitive mechanisms. Accuracy – or discriminability (d') – refers to the participants' ability to accurately discriminate stimuli from noise. Bias (b) describes

how participants' biases or strategies affect their decisions. To do so, SDT categorizes decisions in 4 possible cases: hits, misses, false alarms and correct rejections (see table below).

Signal was... Response was...	Present	Absent
Present	Hit	Miss
Absent	False alarm	Correct rejection

Figure 1: A representation of all 4 possible decision outcomes in a signal detection paradigm.

While standard accuracy measures only compare correct and wrong answers, signal detection analyses account for the specific kinds of correct answers (hits or correct rejections) and wrong answers (misses or false alarms) participants give. In theory, individuals with the same discrimination abilities (d' held constant) may have different biases.

Our main prediction is that socioeconomic status is negatively correlated to the response bias in a signal detection task. As in our task, a high response bias corresponds to a lower threshold for reacting to threats, we take response bias as a proxy for threat reactivity. To be more precise, we predict that threat reactivity will be significantly higher in participants from lower socioeconomic backgrounds.

To test our hypotheses, we designed a signal detection task with asymmetric financial threats.

Methods

Ethics Statement. Our study was approved by the local Ethical Committee (CERES n°201659). Each participant received a description of the study and provided their informed consent before starting the experiment. This study was pre-registered on OSF. All scripts and raw data are available in the OSF project (<https://osf.io/tyb84>).

Participants. 361 participants were recruited on Prolific Academic. 27 participants were excluded for not having completed the study, leaving 334 participants. Due to an error in the pre-screening criteria, some participants were not British residents as intended. Localization data on our participants allowed us to retrieve the country in which they conducted the experiment, which we assumed to be their country of residence. We excluded 222 participants who were not in the United Kingdom during the experiment, leaving a sample of 112 participants. 23 participants were removed for reporting a monthly income of 0£ or above 12,500£. 3 were excluded for having an accuracy rate above or below two standard deviations of the mean. All observations with a response time above 2500ms or below 150ms were excluded and so were 4 participants for having more than 40% of observations in these extreme segments. Our inclusion criteria thus leave us with a final sample of 82 participants (36 males, 45 females, 1 NA. Mean monthly income = 1558.028£. Age ranged between 22 and 69 with a mean of 40). All levels of the income distribution were represented. 33 participants declared a monthly income that categorized them in the first quartile of the British income

distribution, 18 in the second, 23 in the third, and 8 in the fourth. The experiment was conducted on January 15th, 2020 between 4 P.M and 7 P.M, on January 17th, 2020 between 5 P.M and 7 P.M, on January 20th between 2 P.M and 5 P.M, on January 27th between 4 P.M and 7 P.M and finally on January 28th between 11 A.M and 3 P.M.

Materials. The task was presented using Qualtrics. Monetary punishments were presented using text (“- 5 pennies”), which represented the true amount that was subtracted from participants’ total bonus payment at the end of the experiment. The punishments were provided in response to incorrect identifications of a line appearing in the center of a circle as being short (11.5mm) or long (13mm). Following the experimental task, participants completed questionnaires including standard socio-demographic questions (age, income, education, postal code of residence) as well as their perceived sensitivity to diseases.

Design and Procedure. The experiment was conducted online and lasted approximately 25 minutes. Participants were told that their task was to classify a line as either short or long by pressing the corresponding key and that feedback for incorrect responses would occur some of the time. The training phase consisted of 22 practice trials during which the difficulty of the task was progressively raised until real-game conditions were reached.

The experiment consisted of 300 trials separated in three 100-trial blocks. Each trial began with the presentation of a fixation cross (300ms), followed by an empty circle (300ms). The short or the long line was then flashed within the circle (40ms) then disappeared to show a plain black screen during which participants could submit their responses (Figure 2). An equal number of short and long lines were presented within

each block. Short and long lines were presented in a random order. Although they received the instruction to answer as fast as they can, participants were given an infinite amount of time to indicate their response using 'e' or 'p' on the keyboard. Based on the reinforcing schedule, incorrect responses were followed by a 800ms negative feedback screen in 75% or 25% of the cases, depending on the stimulus type (see below). In the remaining cases, the next trial was immediately presented after participants gave their responses.

An asymmetrical reinforcement ratio was introduced such that one type of line (i.e. short or long) was punished more often. The line type that was punished more frequently is referred to as the "harsh stimulus" (or "harsh line") and the line type that was punished less frequently is referred to as the "lenient stimulus" (or "lenient line"). Misidentifying the harsh line (i.e., if the harsh line is short, a misidentification is to respond "long") was followed by a negative feedback with a probability of 75%. Misidentifying the lenient line (i.e., if the lenient line is long, a misidentification is to respond "short") was followed by a negative feedback with a probability of 25%. Analyses from our data prove that the actual distribution of negative feedbacks corresponds to the anticipated asymmetric ratio design: on average, 76.1% of errors on the Harsh line and 29.4% of errors on the Lenient line were followed by a negative feedback (-5 pennies). These results are consistent across conditions and blocks. 74% of errors on harsh lines and 28% of errors on lenient lines were punished in Block 1; 74% and 30% in Block 2; and 74% and 21% in Block 3.

The long line was randomly assigned to being the harsh or the lenient stimulus for each participant.

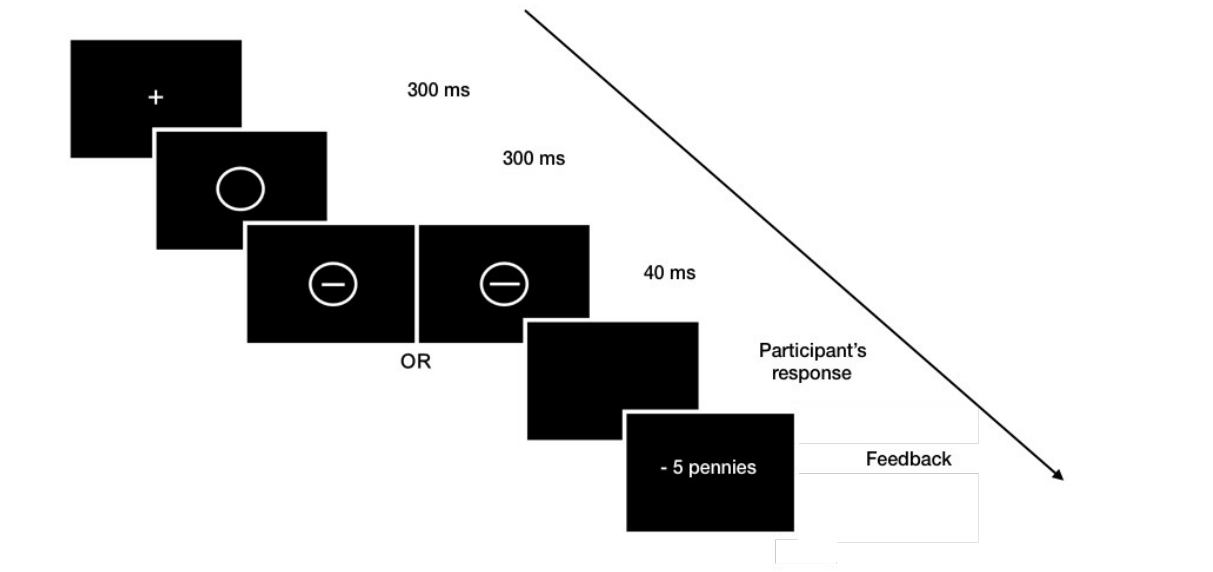


Figure 2. Schematic representation of the tasks A fixation cross appears for 300ms, followed by an empty circle. A short or a long line is then flashed inside the circle for 40ms. Participants have an infinite amount of time to respond before they receive a punishment for some of their incorrect responses.

Threat reactivity. Threat reactivity was conceptualized as participants' bias to avoid punishment. In our task this meant over-detecting the line for which misidentification was associated with more frequent punishment (i.e., the harsh line). Response bias towards the harsh line was computed using the standard signal detection measure:

$$\log(b) = \frac{1}{2} \times \log\left(\frac{Harsh_{correct} * Lenient_{incorrect}}{Harsh_{incorrect} * Lenient_{correct}}\right)$$

with $Harsh_{correct}$ and $Lenient_{correct}$ correspond to the proportion of correct identifications (hits and correct rejections) to the total number of harsh and lenient trials respectively,

and $Harsh_{incorrect}$ and $Lenient_{incorrect}$ correspond to the proportion of false identifications (misses and incorrect rejections) to the total number of harsh and lenient trials respectively. When accuracy was equal to 1 or 0, we followed the log linear correction procedure described by Hautus (1995).

Following proposed by Pizzagalli et al. (2005) and Chevallier et al. (2016), threat reactivity was computed by measuring the change in bias towards the harsh line between the first block (in which the participant is naive about the value of the two lines) and the last block (in which the participant has experienced that the misidentification of one line is more frequently associated with punishments).

Socio-demographic information. A questionnaire was included at the end of the experiment, in which participants provided information about their monthly income, age, gender and level of education. The questionnaire also included a Mac Arthur scale and three Likert-scale (from 1 to 7) questions about their perceived financial deprivation adapted from Griskevicius et al. (2009). We constructed an “Objective SES” index summing the z-scores of the monthly income and education level (ranging from 1 = No higher education degree to 6: Postgraduate degree) and a “Subjective SES” index summing the z-scores of the three financial deprivation questions and the Mac Arthur scale.

Analyses

The mean accuracy rate of participants was 80%. Importantly, the mean punishment responsiveness in our sample was 0.29, which we found to be statistically different from zero ($t = 3.23$; $df = 81$; $p = 0.002$). These results suggest that participants completed the experiment as expected and that, on average, they did learn from the negative feedback

they received and increasingly avoided the harsh line throughout blocks.

We performed Pearson's correlations to test the relationship between threat reactivity and objective or subjective socioeconomic status. We found no significant correlation between punishment responsiveness and objective socioeconomic status ($r = -.11$, $df = 80$, $p = .310$). Likewise, we found no significant correlation between punishment responsiveness and subjective socioeconomic status ($r = -.09$, $df = 80$, $p = .403$). Our data does not support our hypothesis.

In our dataset, the economic variable that most correlated - although not significantly - with punishment responsiveness was education ($r = -.17$, $df = 80$, $p = .118$).

As the effect we measure may be small, our study may have been underpowered. We performed a power calculation in R using the `pwr.r.test()` function in the *pwr* package. To observe a correlation of a similar size of $-.17$ with a significance level of $.05$ and a power of $.80$, we would need 269 participants instead of the 112 participants analyzed in the present study. Further studies could investigate the impact of education on negativity bias but with a larger sample size.

Bibliography

Chevallier, C., Tonge, N., Safra, L., Kahn, D., Kohls, G., Miller, J., & Schultz, R. T. (2016). Measuring Social Motivation Using Signal Detection and Reward Responsiveness. *PLOS ONE*, 11(12), e0167024. <https://doi.org/10.1371/journal.pone.0167024>

Gilbert, J., Uggla, C., & Mace, R. (2016). Knowing your neighbourhood: Local ecology and personal experience predict neighbourhood perceptions in Belfast, Northern Ireland. *Royal Society open science*, 3(12), 160468.

Haselton, M. G., & Buss, D. M. (2000). Error management theory: A new perspective on biases in cross-sex mind reading. *Journal of personality and social psychology*, 78(1), 81.

Hautus, M. J. (1995). Corrections for extreme proportions and their biasing effects on estimated values of d' . *Behavior Research Methods, Instruments, & Computers*, 27(1), 46-51. <https://doi.org/10.3758/BF03203619>

Lieder, F., Griffiths, T., & Hsu, M. (2016). Over-representation of extreme events in decision-making reflects rational use of cognitive resources. In OSF Preprints (kxxag; OSF Preprints). Center for Open Science. <https://ideas.repec.org/p/osf/osfxxx/kxxag.html>

Nettle, D., & Bateson, M. (2012). The evolutionary origins of mood and its disorders. *Current Biology*, 22(17), R712-R721.

Pizzagalli, D. A., Jahn, A. L., & O'Shea, J. P. (2005). Toward an objective characterization of an anhedonic phenotype: A signal-detection approach. *Biological Psychiatry*, 57(4), 319-327. <https://doi.org/10.1016/j.biopsych.2004.11.026>

Rozin, P., & Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. *Personality and social psychology review*, 5(4), 296-320.

