Pupillary correlates of computations underlying human responder behaviour in the Ultimatum Game

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Abstract

Negotiating with others about how finite resources (e.g. achievement-based rewards) should be distributed is an important aspect of human social life. However, little is known about the mechanisms underlying value computations during goal-driven social interactions. Here, we report pupillary correlates of computations underlying human responder behaviour in a novel Ultimatum Game (UG) task, in which the opponent's facial emotions and offer amounts were drawn probabilistically based on the participant's (acting as the responder) decisions, creating a gradually evolving social interactive decision-making environment. Our model-free results confirm the prediction that both the opponent's facial emotions and the offer amount significantly influence participant choice behaviour. These main effects clearly demonstrate that human behaviour violates the assumptions of the Rational Actor model (the optimal decision strategy for the UG) which posits that in order to maximise the reward rate all offers should be accepted irrespective of the offer size and the opponent's facial emotions. Model-based results extend these findings and demonstrate that participants use an inequality aversion model while computing decision values in the UG. We show that the opponent's facial responses to participant decisions influence how people perceive inequality, relaxing its otherwise negative influence on decision values. This cognitive model underlies how offers initially rejected can gradually become more acceptable under affective load. Our pupillary results highlight that negative affective reactions from the proposer, in response to participant decisions, lead to significant pupil dilation. We further demonstrate that a model-based surprise response is encoded in pupil size and also influence participants' acceptance probability negatively. Our results highlight that surprising offers which violate participant's expectations, for better or for worse, are less likely to be accepted.

Keywords: Ultimatum game, computational modelling, emotional processing, social decision-making, pupillometry

Introduction

Negotiating with other people for one's own share of finite resources is an important part of human social-economic life. Recent historic events (e.g. "trade wars" between the United States and China, Brexit negotiations between the European Union and the United Kingdom[1,2]) further highlight this importance, wherein the outcome of negotiations between only a handful of people will directly affect the lives of many others. The Ultimatum Game (UG) is a common behavioural economic measure which is used as an experimental probe of such social interactive decision-making processes. Rejecting an unfair proposal in the UG is regarded as a form of altruistic punishment [3-5], as a responder rejecting an offer sacrifices the amount of money offered to them at the expense of conveying an implicit message to the proposer that the amount offered had been *unfair*. This is because both the proposer and the responder receive nothing when an offer is rejected in the UG. Consequently, the responder's rejections in the UG violate the assumptions of the Rational Actor Model, which posits that any monetary gain is better than no gain[6] and all offers should be accepted. In a recent study, we showed evidence to suggest that *proposers* use a risky decision-making model to navigate around violating responders' fairness threshold, and try maximise their gains by choosing between Ultimatums based on their expected values[7]. Despite a breadth of studies describing decision-making processes in the UG[8-11], the value computations underlying human responder behaviour are elusive and summary statistics describing average acceptance probabilities at different offer amounts remains as the only the primary outcome measure commonly reported in the literature.

A key factor which can also influence one's negotiation strategy in social interactive decision-making relates to negative or positive biases that distort the way people perceive others' emotions (e.g. thinking that the other person displayed a negative facial emotion when in fact s/he was neutral). During goal-driven social interactions (e.g. in various negotiation situations), others' facial emotions can provide us a window into how they perceive our requests, helping us to decipher their otherwise hidden valuation processes. Although humans are known to detect subtle changes in others' facial emotions, the existing literature also suggests that people are prone to affective biases in facial emotion recognition[12-14]. Few decision-making studies have investigated the effect of proposers' facial emotions on human responder behaviour in the UG. A previous study showed that responders are consistently more likely to accept offers coming from attractive faces of the opposite sex irrespective of the offer amount [15], while a large-scale online study suggested that offers coming from proposers with smiling faces are more likely to be accepted relative to those coming from angry faces[16]. However, a key limitation of the previous studies is the experimental approach: pairing affective faces *randomly* with different monetary offer amounts. By this methodology, on

each trial, participants are asked to respond to a stimulus which is intended to be completely *independent* of what they were presented with in the preceding trial(s). Considering that in daily social interactions people's facial emotions do not jump randomly from one affective state to another, the previous experimental approaches would have limited ecological validity in terms of capturing real-world human social interactive decision-making processes. In order to improve on this key limitation, we designed a novel UG task in which opponents' facial emotions and offer amounts were generated from two sliding windows with transition probabilities based on participant responses in the preceding trials (Figure 1). We had previously argued that this approach would break the trial-wise independence of experimental stimuli, allowing participants to experience a gradually changing social interactive decision-making environment based on their responses in the previous trials[17]. These modifications to the UG allowed us to model key influences on participant choice behaviour during social interactive decision-making: the magnitude of social rewards and the opponent's affective states. Our *a priori* hypothesis was that the proposers' facial emotions, the offer amounts and an interaction between these domains should influence participant's decisions to accept/reject offers. In the following sections, by mathematical modelling of participant choice behaviour, we describe how the opponent's facial expressions, which are perceived nonlinearly, influence human responders' value computations by acting selectively on perceived self—other inequality in the UG.

Figure 1. Experimental timeline of the novel Ultimatum Game task. On each trial the participant is presented with an affective face of the opponent/confederate (i.e. the red arrow) followed by the offer. In response to participant's decision (i.e. accept versus reject), the opponent's facial emotion may stay the same or change to a neighbouring stimuli based on predefined transition probabilities associated with each response type (e.g. the proposer is more likely to be happier if the offer is accepted). Similarly, based on other predefined transition probabilities, the offer on trial (t+1) may stay the same or may be revised to one of neighbouring offer amounts based on participant response (e.g. 200 offer as shown in the example above for trial (t) may increase and become 250 on trial (t+1), after participant rejected the 200 offer on trial (t)). The predefined transition probabilities for facial emotions and offer amounts for the novel UG task are available in Supplementary Materials.

Previous studies highlighted a role for the pupil-linked central arousal systems in human reinforcement-learning (RL) and value-based decision-making, particularly those performed in dynamically changing environments [18-20]. Recent neurophysiology studies demonstrated that changes in pupil size reflects the firing rate of the central norepinepheric neurons in the locus coeruleus[21,22] (LC). These studies provide a quantitative support for a number of converging theoretical [23] and experimental accounts of human behaviour [18-20,24], all implicating a role for the central norepinephrine (NE) system in guiding behavioural adaptations in response to environmental change, as assessed by measuring pupil size. Nevertheless, the role of pupil-linked central arousal systems during social interactive decision-making remains unknown. Considering that our experimental task was specifically tailored to allow participants to experience an evolving interpersonal negotiation environment, we asked healthy volunteers (N=44) to perform the novel UG task while undergoing pupillometry and investigated the role of pupil-linked central arousal systems in social interactive decision-making. Informed by previous studies, we expected pupil size to encode a surprise response (e.g. offers and/or opponent's affective reactions), as well as showing

sensitivity to the opponent's affective states. In line with these predictions, we present results highlighting the role of central arousal systems during social interactive decision-making, by showing that pupil size encodes the opponent's facial emotional reactions and a surprise response associated with offers which violate the participant's expectations from the proposer.

Results.

Participant Demographics. Forty four participants recruited from the general public completed the UG experiment with pupillometry. The demographic details of this cohort are summarised in Table 1.

Table 1. Demographic details of participants

Measure	Mean (SD)
Age	33.7 (11.30)
Gender	68.18% Female
QIDS-16	8.11 (7.60)
Trait-STAI	42.77 (13.52)
State-STAI	33.43 (12.21)

QIDS-16; Quick Inventory of Depressive Symptoms, 16 item self-report version. Trait/State-STAI; Speilberger State-Trait Anxiety Inventory. Note that scores of 6 or above on the QIDS-16 indicate the presence of mild depressive symptoms. The Trait/State-STAI has no standard cut-off scores.

Rating tasks. Participants initially rated 100 different Ultimatum offers presented in randomised order, on a 1-9 Likert scale indicating how much they would like the proposed offer (all offers between £0.50 and £9.50 expressed in pence). These ratings allowed us to develop liking-based decision models for the main social interactive experiment. The liking ratings monotonically increased from 50p to 500p (i.e. 50/50 split between proposer and responder) where they peaked. The liking ratings were lower for offers advantageous for the participant (>500p) relative to the 50/50 split, indicating inequality aversion (Supplementary Figure 1).

After rating the Ultimatum offers, participants rated their opponent's facial emotions, again on a 1-9 Likert scale (i.e. from negative to positive). Overall participants' Likert ratings correlated highly significantly with the emotional intensity of the opponents' facial expressions (average correlation coefficient $r = .869$, $p<.001$). However, participants were significantly better at accurately rating opponent's faces displaying positive emotions relative to negative emotions (average r values .821 versus .539, respectively; $t(86)=-4.55$, $p<.001$). This indicated that participants' affective biases were more prominent for negative emotions (i.e. a larger deviation from the dashed diagonal line in Figure 2A). In order to capture participants' social affective biases, which we thought should influence value computations in the UG, we further analysed these ratings by exploiting the properties of a 2-parameter exponential-logarithmic function (see Materials and Methods, Eq.1).

This analysis suggested that participants perceived their opponent's affective states nonlinearly, albeit with some individual variability (Figure 2A). We further investigated whether the parameter estimates from this model were influenced by participants' own mood states (i.e. factors such symptoms of depression and anxiety). This analysis suggested that none of the continuous or categorical variables that we considered in the regression model significantly influenced estimates of the model parameters (Figure 2B). Factors such as opponent type (i.e. confederate versus computerised) or opponent sex did not influence the parameter estimates either, indicating that the nonlinearity captured in participants ratings was not a direct result of the potential nonlinearity in the way opponents might have expressed their emotions while their pictures were taken initially.

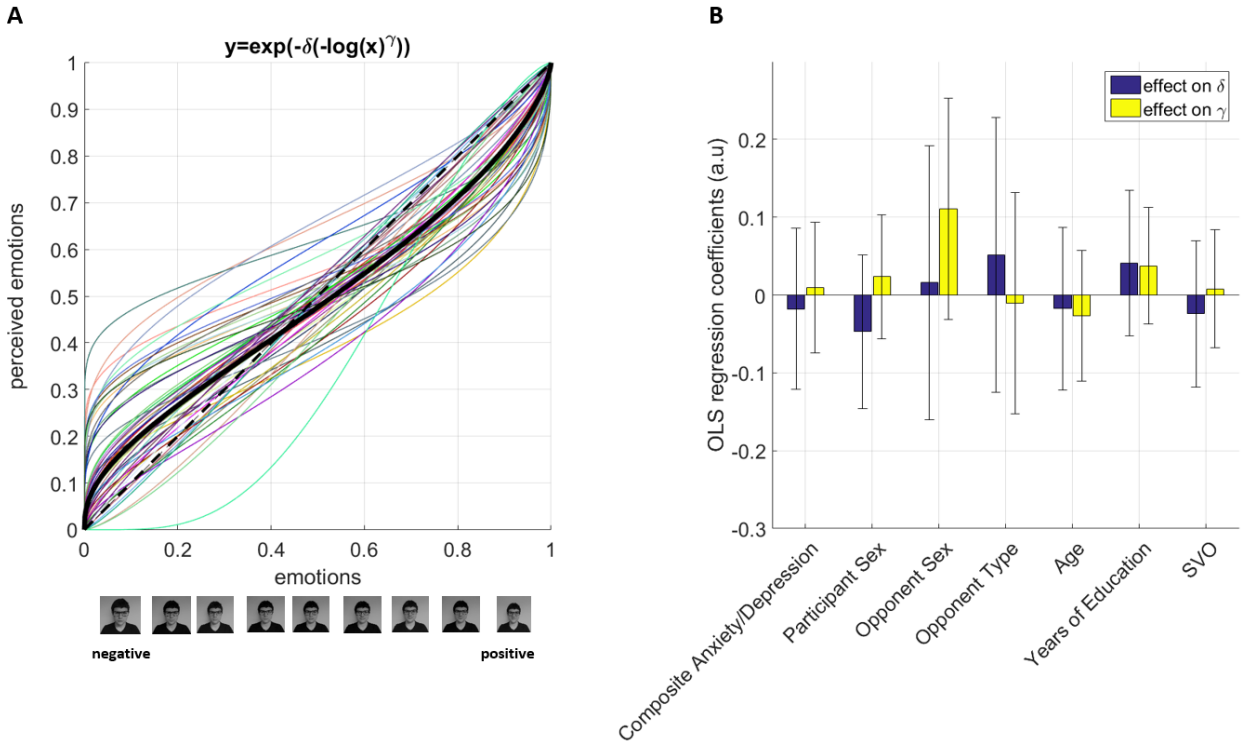

Figure 2. Results of the facial emotion rating task. (A). Participants perceived their opponent's facial emotions nonlinearly. The x-axis shows the opponent faces assembled from negative to neutral to positive (i.e. same as in Fig.1), and y-axis represents participants perceived emotions according to the best fitting nonlinear weighting model. Thick black line designates the population mean. **(B)** The model parameters [δ, γ, also see Eq.1] were not influenced by factors such as symptoms of depression and anxiety or participant and opponent sex. Composite depression and anxiety scores were established for each participant by linearly transforming (i.e. summing up scores from each domain within-subjects) the z-scores of depression, and state and trait anxiety measures to avoid collinearity in the model, as these measures were highly correlated with each other in this cohort of non-clinical volunteers (all $r(42)>.69$, all $p<.001$). Opponent type designates whether participants were told they would be playing against a human confederate or a computerised opponent. SVO: Social Value Orientation, which is a continuous measure defining one's degree of prosociality. Error bars denote 95% CI.

Model-free analysis of participant choice behaviour. We first concatenated all participant data and binned average acceptance probabilities for all combinations of proposer's facial emotions and offer amounts (Figure 3A) and analysed this data with an ordinary least squares (OLS) regression model.

This analysis suggested a main effect of facial emotion (based on t-tests on OLS coefficient estimates, t (43) =8.43), a main effect of offer amount (t (43) =8.85) and a significant facial emotion x offer amount interaction term (t (43) =3.70) influencing participants' probability of accepting an offer (all p<.001, Figure 3B). This means that people were more likely to accept unfair offers if the proposer's facial emotion was more positive. For completeness, the average number of trials participants spent in each state-space during the UG experiment (facial emotion x offer amount) is shown in Supplementary Figure 2.

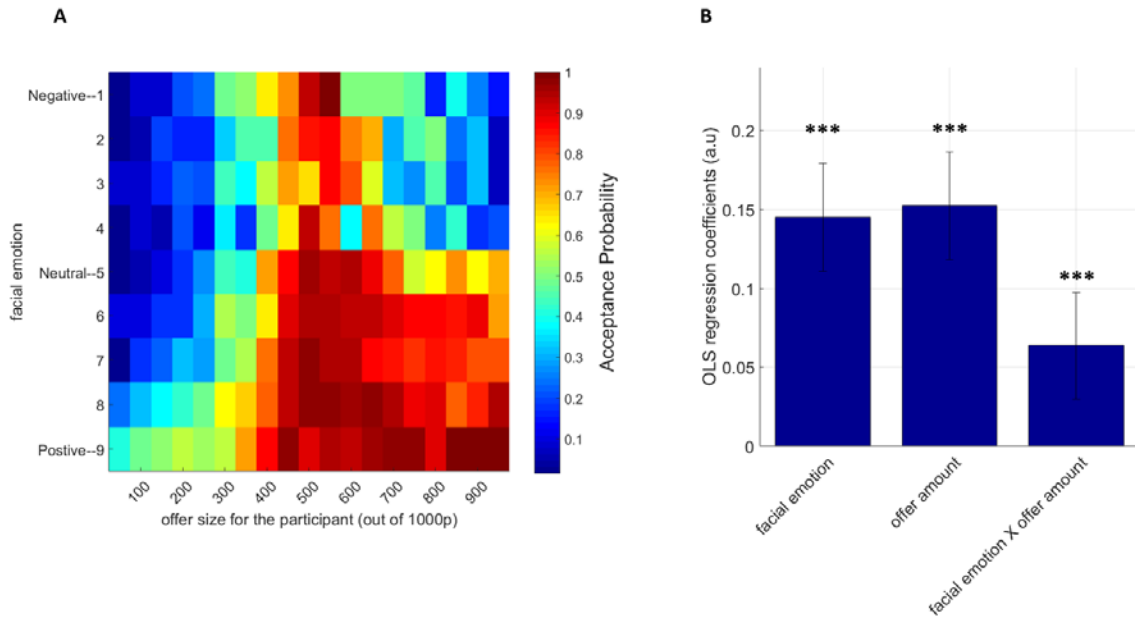

Figure 3. Behavioural results from the Ultimatum Game. (A). Participants' average acceptance probabilities across all possible combinations of opponent's facial emotion (y-axis) and offer amounts (x-axis) represented as a heat map. Colour bar shows the probability of accepting an offer. Changes in the colour gradient in the heat map suggests that unfair offers coming from positive faces were more likely to be accepted relative to offers associated with negative facial emotions, even if the offer amount is advantageous to the participant. **(B)** An OLS regression analysis conducted on the acceptance probabilities indicated a significant main effect of facial emotion, a main effect of offer amount and a significant facial emotion by offer amount interaction term influencing participants' probability of accepting an offer (***p<.001).

Logistic regression analysis of participant choice behaviour. One of the main features of our experimental design was that participants responded to offers generated based on their responses in preceding trials. We used this approach to break the trialwise independence of stimuli present in other methodologies. Consequently, we investigated how stimuli shown in preceding trials (i.e. n-1th to n-3th) as well as participants' previous decisions, influenced their choice behaviour on the current trial (i.e. the nth trial) using a logistic regression model. There were four regressors in this model: opponent's facial emotion, the offer amount, a facial emotion x offer amount interaction term and the participant choice. This analysis suggested all regressors from the n-1th trial significantly influenced participant choice behaviour on the current trial (all |t (43)| >2.84, p<.01), with offer

amount on the previous trial being the most significant influence (t (43) =9.56, p<.001; Figure 4). The influence of these variables on participant choice behaviour decayed further down the trials. These results are also in line with the general notion that human choice behaviour in social interactive decision-making games can be defined in terms of n-1 (i.e. memory-1) conditional-probabilistic strategies[25].

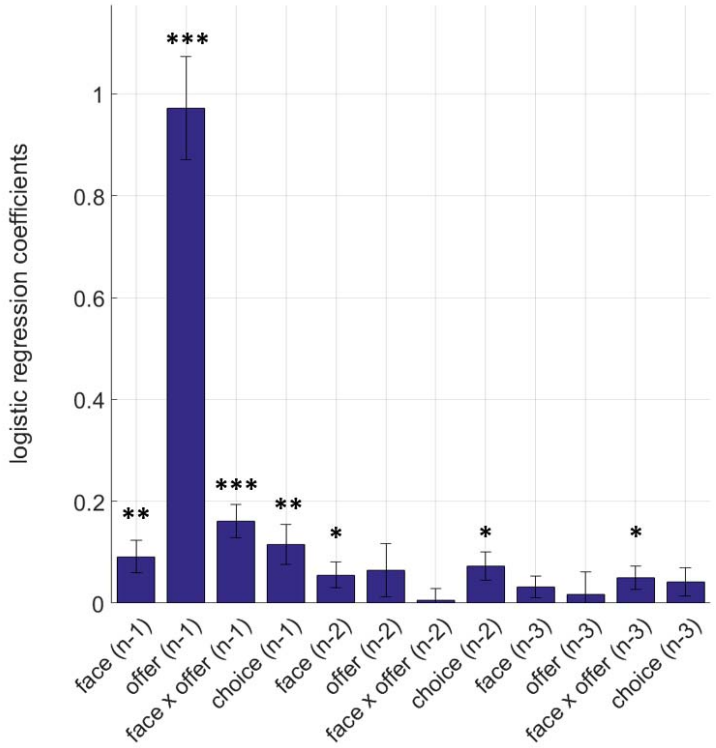

Figure 4. Logistic regression analysis of participant choice behaviour. Coefficient estimates from the logistic regression model fitted to participant choices on the current (n^{th}) trial indicates that all regressors from the n-1th trial significantly influence participant choice behaviour (***p<.001, **p<.01). Absolute values of the coefficient estimates are shown for plotting purposes. The coefficient estimates for the influence of previous choices were all negative, indicating that offers on the current trial is more likely to be accepted if the offers on previous trials were rejected. The influence of these variables decayed down the trials. Error bars denote ±1SEM.

Computational model-based analysis of participant choice behaviour. We fitted a number of computational models which we thought plausible to describe participant choice behaviour in the UG task (see Methods and Materials for model descriptions). The best-fitting model (Model 7), was able to predict participant choices in 83.3% of the trials, assumed that social affective biases which modulate how the proposer's facial emotions are perceived (as shown in Figure 2A), act on participants' perception of inequality[26] in the UG, and relaxes the negative valuations associated with it (Eqs. 1 and 9). In descriptive terms, this would mean that if the proposer insists on the same offer amount that is rejected iteratively by the participant, and continues to respond to the participant's rejections by displaying increasingly negative emotions, at some point the opponent

238 can overcome the participant's negative valuation associated with perceived inequality. This model
239 can also flexibly adapt to other situations which occur during the game. For example, in situations
240 where the proposer's facial expressions are neutral, the affective influence part of the model would
241 diminish (Eq. 9), allowing participants to hold on to their perceived inequality. In situations in which
242 the proposer displays increasingly positive emotions in each iteration, the model then reduces the
243 overall influence of perceived inequality on decision-values, accounting for compromises (e.g. "the
244 offer is unfair, but if I accept it, at least it makes the other side happier"). Bayesian model selection
245 metrics[27] supported these assertions, showing that the model in which facial emotion recognition
246 biases selectively act on the inequality term (Model 7), but not on the self-reward amounts (Model
247 8), or both the self-reward and the inequality term independently (Model 9, Supplementary Figure
248 3) fits better to explain participant choice behaviour. The parabolic (Model 7), rather than an
249 exponential (Model 6, Supplementary Figure 3), shape of this affective influence indicates that
250 proposer's increasing negative or positive facial emotions act on the inequality term in a similar
251 manner, while neutral facial emotions would not influence participant's perception of inequality.
252 Further analysis of trials mispredicted by the best-fitting model did not show any significant main
253 effect of the opponent's facial emotions or offer amounts (Supplementary Figure 4), indicating that
254 the model does not fail systematically in converting these input stimuli into decision-values.
255 However, there was a significant facial emotion x offer amount interaction in the mispredicted trials
256 ($t(43)=-3.2452$, $p<.01$). Negative regression coefficients on this interaction term indicate that the
257 model struggled more in predicting participant decisions at the extremes (e.g. unfair offers coupled
258 with very positive faces).

259 Similar to the OLS analysis that we reported for social affective bias parameters (Figure 2B), we
260 analysed which variables influence the parameter estimates of the best-fitting choice model in the
261 UG. This analysis suggested that a significant relationship between participants' social value
262 orientation (SVO, as measured by the SVO Slider Measure[28]) and parameter estimates for the
263 inequality term, meaning that people with higher SVO scores (i.e. people with more altruistic
264 tendencies) perceive self—other inequality more negatively ($t(43)= -2.166$, $p=0.036$, Figure 5).

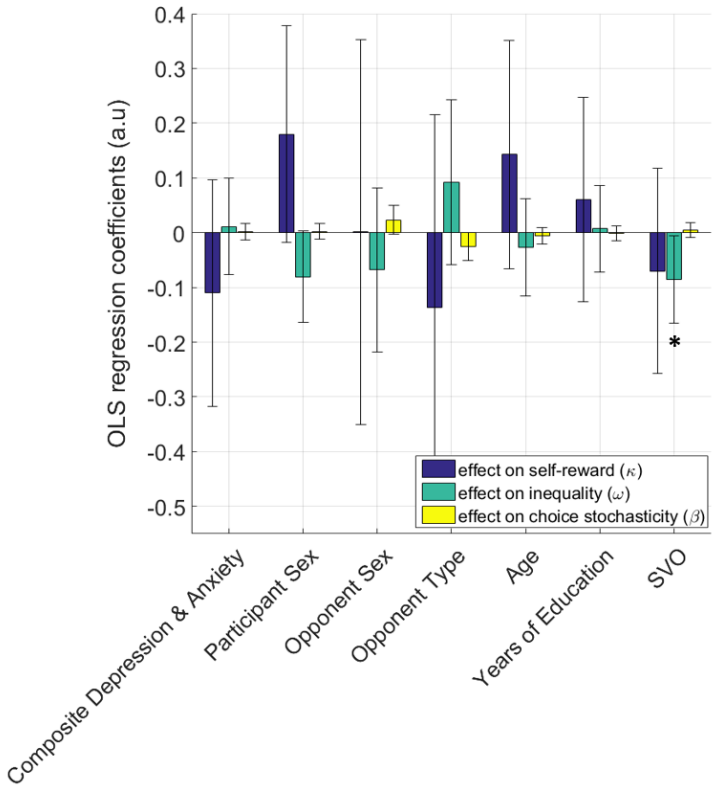

Figure 5. Prosocial individuals perceive self-other inequality more negatively in the UG. Coefficient estimates from an OLS regression model fitted to parameter estimates of the best-fitting computational choice model (i.e. Model 7) suggested that people with higher social value orientation will perceive self-other inequality more negatively (*p<.05). A generate-recover simulation analysis (50 iterations) based on stochastic choices generated by this model demonstrate the stability of the estimated parameters (Supplementary Figure 5). Error bars denote 95% CI.

Pupillometry Results. We analysed participants' pupil response during the decision stage of the UG task (i.e. the window from the presentation of the offer until the end of outcome presentation). A simple model-free analysis of pupil response by binning average pupil size for all combinations of opponent's facial emotions and offer amounts (Supplementary Figure 6A), followed by an OLS regression analysis (i.e. comparable to model-free behavioural analysis reported in Figure 3B) suggested a significant main effect of the proposer's facial emotions on pupil size (t (42) =-2.22, p=0.028), pupil dilating more when the opponent is displaying negative facial emotions (Supplementary Figure 6B).

We further analysed the pupillary data with a complementary OLS model to investigate the degree to which regressors generated under the best-fitting computational model correlated with pupil size during the UG experiment (see Materials and Methods for the details of the pupillary regression model, Eq. 11). One caveat that we evaluated quantitatively before fitting the pupillary regression model is the correlation between proposers' perceived facial emotions and the offer amounts given

285 to the participant. Normally, one would try to decorrelate these regressors as much as possible to
286 evaluate their unique pupillary or neural signatures. However, in the case of our task, the
287 computerised strategy was designed to display positive faces with higher probability if the offers
288 were accepted (as logically should happen in interpersonal exchanges in real life). In the extreme
289 case of a proposer's facial emotions and offers being completely decorrelated, the computerised
290 opponent would no longer feel like a human opponent (e.g. proposer reacting to participant's
291 decisions by showing random emotions or offers). The histograms of correlation coefficients
292 between social affective biases (i.e. proposer's facial emotions modulated by the nonlinear
293 weighting model, Eq.1) and decision-values generated under the best-fitting model for each
294 participant is shown in Supplementary Figure 7A (correlation coefficient *r* (mean±SD) =.058±.26). In a
295 similar manner to our previous study[7], we also asked our participants a number of questions related
296 to how they felt about their opponents to make sure that the computerised strategy was perceived
297 as "human-enough" (full set of questions given in Supplementary Figure 7B legends). On average,
298 participants were able to identify more than one person from their social circles who would make
299 offers and display affective reactions in a similar manner to the computerised opponent (response to
300 Q3; mean (±SD) =3.82(±.40); t (43) =7.12, p<.001), reassuring that our experimental manipulation
301 was successful in terms of the computerised opponent adequately mimicking human behaviour
302 while keeping the correlations between perceived faces and offer amounts within an acceptable
303 range.

304 Two key regressors that we were interested in were the decision-values generated by the best-
305 fitting model and opponents' facial emotions modulated by the nonlinear weighting function. Time
306 evolution of estimated coefficients for these two regressors are reported in Figure 6. Subsequent
307 analysis (i.e. average regression coefficients binned at each second after offer presentation, analysed
308 by 1-sample t-tests from baseline) indicated that pupils dilate more in reaction to opponent's faces
309 perceived as displaying negative emotions (peak response between 1000-2000 ms, t (42)=-3.638,
310 p=.001, Figure 6B). This result is in agreement with the model-free pupil results reported in the
311 preceding section.

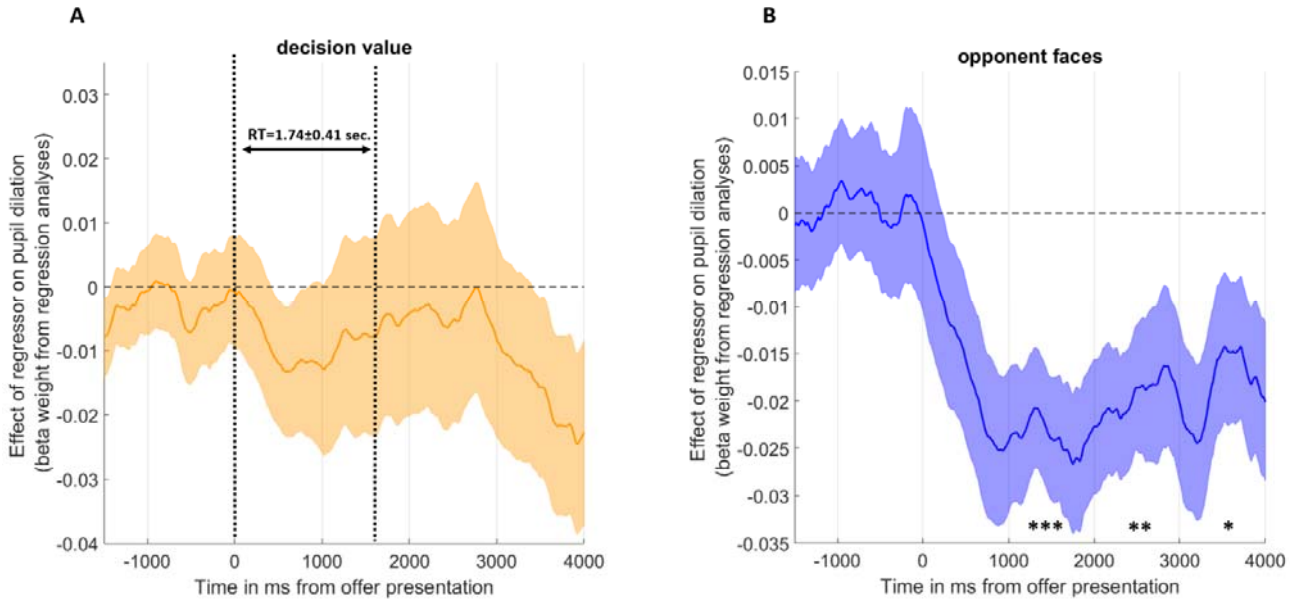

Figure 6. Pupillary signal of decision-values and social affective biases. (A) Coefficient estimates from the pupillary OLS regression model correlating with decision-values (i.e. the orange line and shading ±1SEM) from the best-fitting behavioural model. Although time evolution of regression coefficients dip during offer presentation (the window marked with dashed lines designating the decision reaction time (RT)) and post-decision interval, indicating that pupil dilate more to lower value offers, this signal was not statistically significant. **(B)** The proposer's faces perceived as negative will lead to pupil dilation (i.e. the blue line and shading ±1SEM). The signal is statistically significant and remains significant from ~1 second after outcome presentation (***p<.001, **p<.01,*p<.05). Error shading denotes ±1SEM.

The other regressors that we were interested in while constructing the pupil model were those quantitatively defining how the social interactive decision-making environment changed (i.e. environmental volatility and environmental noise[29]), as well as participants' response to those changes (i.e. surprise). These were estimated from the raw stimuli (i.e. the offer amounts and facial emotion valence on each trial) by a recursive Bayesian filter[29] that can estimate the generative statistics of the stimuli uniquely for each participant, and helps with objectively quantifying how the social interaction environments changed, as these changes also depended on participant choice behaviour, meaning that each participant experienced a unique sequence of stimuli. The analyses of these regressors indicated that pupils dilate more in response to surprising offers ($t(42) = 2.166$, $p = .036$, Figure 7A). Regressors defining environmental volatility and noise did not lead to any statistically significant pupil response, suggesting that pupil size does not encode higher order statistics of the social interactive decision-making environment.

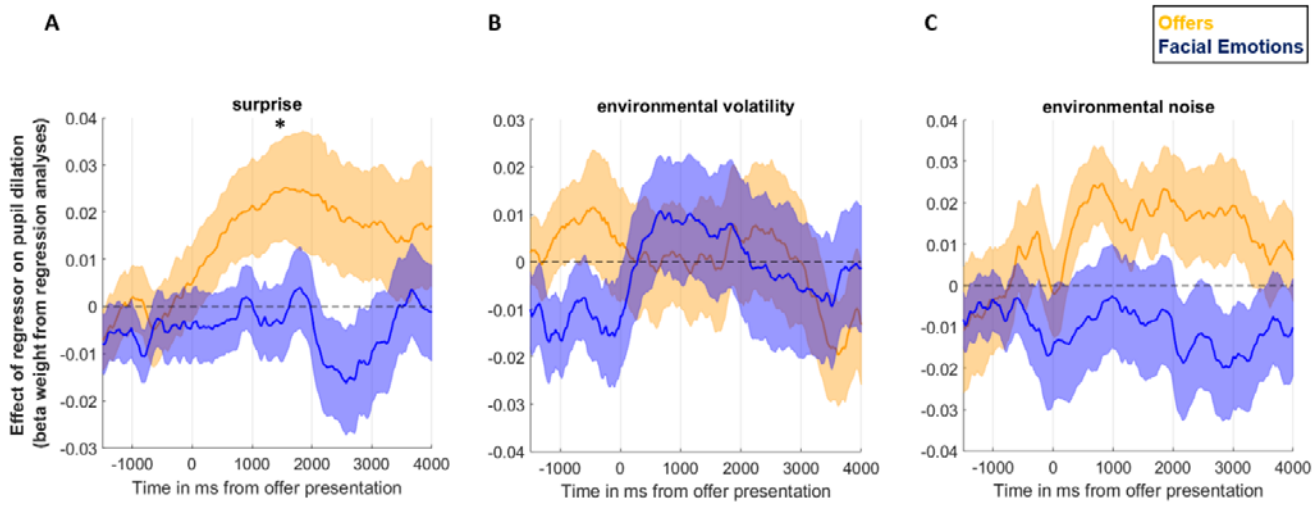

Figure 7. Pupillary signal correlating with regressors extracted by the Bayesian filter. (A) Time evolution of coefficient estimates from the pupillary OLS regression model correlating with surprise associated with offer amounts and proposer's facial emotions. The surprise signal peaked around decision RT (*p<.05). **(B-C)** Time evolution of regression coefficients from the pupillary regression model for regressors describing environmental change. Pupil response was not statistically significant for any of these regressors. Error shading denotes ±1SEM.

Surprise is the common variable influencing both pupil size and choice behaviour

At the last step we investigated the degree to which regressors describing the changes in the social interactive decision-making environment which were computed by the recursive Bayesian filter also influenced participant choice behaviour. We fitted a logistic regression model to participant choices in which surprise, volatility and noise regressors were predictive variables (for both the proposer's facial emotions and the offers). We further included the factors which we had already established to influence choice behaviour (i.e. facial emotions, offer amount and their interaction as reported in Figure 3B) and the trial number (i.e. 1 to 240, total number of trials) as regressors of no interest. After excluding six extreme outliers, this analysis indicated that surprising offers were less likely to be accepted (all t(37)=-2.469, all p=.018), whereas noisy fluctuations in the opponent's facial emotions increased participant's probability of accepting an offer (t(37)=2.024, p=.05, Figure 8). Taken together, surprise response to offer amounts seems to be the overarching process which correlate with pupil size (Figure 7A) and influence participant choice behaviour. A final control analysis investigating the correlation between the surprise regressor generated uniquely for each participant and the offer amounts observed by the participant suggested a marginally positive correlation in this cohort (correlation coefficient r(238) = .17±.09 (i.e. mean±SD), Supplementary Figure 8). This indicates that offers which violated the expectations of the participant, but not necessarily the lower offers, were less likely to be accepted.

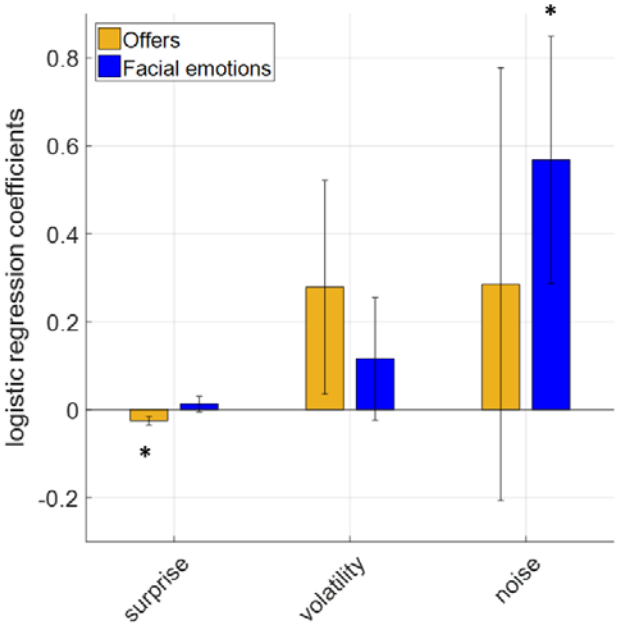

Figure 8. Influence of regressors extracted by the Bayesian filter on participant choice behaviour. Significantly negative correlation coefficients were observed only for the way offer amounts changed during social interactive decision-making. The results suggest that offers associated with greater surprise, environmental volatility and noise are less likely to be accepted (***p<.001, **p<.01). Error bars denote ±1SEM.

Discussion

In the present work we describe value computations underlying human responder behaviour in a novel UG task which also involved participants observing the proposers' affective reactions. The results that we present here indicate that human participants exhibit perceptual social affective biases which are represented nonlinearly (Fig. 2A). We show that proposers' facial emotions significantly influence participant choice behaviour in social interactive decision-making (Fig. 3A-B). The influence of the proposer's facial emotions on participant choice behaviour is also shown in results from different methods of analysing the behavioural data (i.e. both logistic regression and computational model-based). Reassuringly, we show that parameter estimates for the inequality term from the best-fitting computational model were significantly negatively correlated with participants' SVO, indicating that people with higher prosocial tendencies perceived self-other inequality more negatively, and were less likely to accept unfair offers (Fig. 5). Computational modelling of participant choices further reveal that social affective biases act on participants' perception of inequality, relaxing its negative influence in a parabolic shape (i.e. Model 7). This meant that participants were more likely to accept unfair offers, irrespective of whether they were advantageous or disadvantageous, when their rejections are persistently confronted with an affective response (i.e. emotional faces apart from a neutral facial expression) coming from the proposer (also partially illustrated in the model-free faces x offer amount interaction effect, Figure 3). The pupillary regression analysis shows that proposers' affective responses are represented by corresponding changes in participants' pupil size (Fig. 6B), while a surprise response estimated by a recursive Bayesian filter in response to offers given by the proposer led to pupil dilation (Fig. 7A), which indicates that pupil size encodes violations of participants' expectations. Subsequent analysis suggests that this surprise response is the overarching variable which is encoded by the changes in pupil size and also influence participant choice behaviour (Fig. 8). Thus, our data suggests that surprising or unexpected offers lead to pupil dilation and are less likely to be accepted. To the best of our knowledge, these results constitute the first line of evidence quantifying the role of pupil-linked central arousal systems in human social interactive decision-making.

Among behavioural economic games, the UG is one of the most commonly used zero-sum game, meaning that gains are mutually exclusive between the proposer and the responder. The linear payoff structure and sequential decision-making nature of the UG makes it relatively easier to model computationally compared to other nonzero-sum games like the Prisoner's Dilemma (PD). The UG is known to have a strong non-monotonicity, which indicates that people's acceptance probability does not increase monotonically with increasing self-reward magnitudes[30]. We demonstrated that our participants also behaved in this manner, as indicated by results from the

411 analysis of choice behaviour (Figure 3A), and liking ratings (Supplementary Figure 1). This non-
412 linearity in acceptance probabilities is more likely to be driven by inequality aversion (Eq. 6, ω
413 parameter). Human rejection behaviour of unfair offers driven by perceived inequality contradicts
414 the Rational Actor Model, which is regarded as the optimal decision-making policy in the UG from an
415 economic point of view, and dictates that accepting all offers, irrespective of inequality, maximises
416 the reward rate. Within this framework, and by using a confederate design, we demonstrate that a
417 modified UG task can adequately mimic social interactive decision-making in an ecologically valid
418 manner, as supported by responses from participants on the behaviour of the computerised
419 opponent (Supplementary Figure 7B). Our results demonstrate that the affective content of the
420 proposers' facial expressions serve as another source of suboptimality in social interactive decision-
421 making. This finding which we demonstrate both in our model-free (Figure 3) and model-based
422 analyses, contradicts with the predictions of the Rational Actor model, which would also posit that a
423 strategy ignoring all affective information would be optimal.

424 The present results complement the findings of a recent work in which we described a
425 computational model accounting for human *proposer* behaviour in the UG[7]. In these two studies,
426 focussing on value computations underlying the proposer's and the responder's behaviour
427 separately allow us to restrict the vast model space and identify suitable models accounting for
428 human social interactive decision-making. It would be very important for future studies to go one
429 step further than these preliminary reference points that we identified in the UG decision model
430 space, and independently validate risky decision-making models accounting for proposer behaviour
431 versus inequality aversion models accounting for responder behaviour in a two-person interactive
432 experimental design. The extent of the decision model space has been one of the key challenges
433 which limited the number studies reporting computational models of choice behaviour in social
434 interactive games[31-33], as the difficulty associated with modelling recursive ToM processes is making
435 social interactive decision-making a topic "too hot to handle". Although a recent neurophysiology
436 study in monkeys has shown that it is possible by-pass some of these difficulties by modelling the
437 opponent's future decisions in a binary format (i.e. cooperate versus defect in PD) to illustrate
438 underlying neural correlates of ToM processes[34], these novel approaches require neural data with
439 very high temporal precision and has not yet been implemented in human participants. As a result,
440 and despite the fact that humans are social animals, our understanding of social interactive decision-
441 making processes in healthy and patient groups are lagging far behind other well-defined cognitive
442 processes such as reinforcement learning (RL)[19,20,35,36].

443 A number of previous studies reporting computational mechanisms underlying learning and
444 decision-making in dynamically changing environments interpreted phasic changes in pupil size as an

445 index for the firing of the central NE neurons[18-21]. In the current work, we showed that pupil dilation
446 correlates significantly (i) positively with surprise associated with offers (Fig. 7A), and (ii) negatively
447 with opponents' perceived facial emotions (Fig. 6B). Although previous work suggested that
448 norepinephrine reuptake inhibitors (SNRIs) module neural responses to facial emotions[37], indicating
449 a role for the central norepinephrine system in facial emotion recognition, it is important to
450 acknowledge that pupil dilation in response to task components may also be under the influence of
451 cholinergic activity in the brain (see a more detailed discussion in Faber, 2017[38] and Muller et al.,
452 2019[24]). Another key neurotransmitter which is involved in social decision-making[4,11,39] and facial
453 emotion recognition[14,40-42] is serotonin (5-HT), and previous work also suggested that
454 pharmacological agents acting on the 5-HT system modulates pupil dilation[43,44]. Teasing out the
455 influence of these neurotransmitters on pupil dilation during social interactive decision-making
456 ideally requires experimental pharmacology methods and should be tested in future studies to
457 further understand mechanisms of causality. The current experimental approach could also be
458 useful in teasing apart neural responses associated with information processing during social
459 interactive decision-making, considering existing literature clearly demonstrates that facial emotion
460 recognition and social decision-making activate fronto-striatal and limbic regions[5,8,33,39,45-47]. The
461 main strength of the current experimental design is that it probes facial emotion processing and
462 social decision-making domains simultaneously with a relatively fine gradient (by generating stimuli
463 probabilistically from two sliding windows, 9 different facial emotions x 19 different offer amounts,
464 in total 171 unique stimulus combinations, Fig. 2A), therefore it can be used as an experimental
465 probe for addressing these mechanistic questions about information processing during social
466 decision-making.

467 One of the key rating tasks which also informed our modelling of participant choice
468 behaviour in the UG evaluated participants' social affective biases to opponents' facial emotions. We
469 modelled participants' ratings on a Likert scale by exploiting the properties of a 2-parameter
470 weighting function. Although our modelling approach revealed individual variability in these
471 perceptual biases, the parameters of this model did not correlate significantly with symptoms of
472 depression (QIDS range: 0-27) and anxiety in this non-clinical cohort (Figure 2). These results are not
473 in line with predictions based on some of the previous studies in depressed groups which used the
474 FERT[12,13]. Consequently, it may be worthwhile to highlight some of the experimental differences
475 between the traditional FERT and the facial emotion rating task that we used in the current study. In
476 the traditional FERT, participants are presented with affective faces for a very brief period,
477 approximately for 800 milliseconds; and they are asked to label faces into one of seven different
478 emotional categories: sad, angry, happy, surprise, fear, disgust and neutral. Brief stimulus

479 presentation duration does not allow too much time for participants to decode the individual parts
480 of the face while forming a judgment about its affective content. The faces are presented in an oval
481 frame cutting out some of the facial features such as hair and ears (approximate size 56.25 cm^2). It is
482 possible that these aspects of the FERT create ambiguity and an information gap which probes
483 affective biases more strongly in clinical groups relative to non-clinical volunteers. On the other
484 hand, our rating task was self-paced (i.e. ratings were made while viewing the faces, RT (mean ± SD)
485 = 2.90 ± 1.04 seconds). It is possible that accurately rating affective faces on a scale may be more
486 challenging than categorising them into predetermined labels (e.g. happy, sad, fear etc.). In the
487 rating task, the faces were presented in rectangular frame similar to a passport picture occupying
488 102.7 cm^2 area. These modifications allow participants to gather more information about the
489 affective content of the faces, reducing ambiguity and increasing ecological validity of the stimuli
490 and the ratings (e.g. the fact that in real life social interactions people have reasonably long time to
491 observe others' facial emotions, see Sonkusare, Breakspear and Guo (2019) for a critical appraisal of
492 existing task designs in cognitive neuroscience[48]). Therefore, in future studies, it would be very
493 important to gather large-scale data to validate the affective content of the facial expressions used
494 in the current study, which can help understanding how symptoms of depression and anxiety
495 influence facial emotion recognition in the wider population. While our current modelling results
496 suggest that facial emotion processing (i.e. evaluating intensity and valence) and social interactive
497 decision-making processes are not systematically impaired by increasing symptoms of depression
498 and anxiety in a group of *non-clinical* volunteers, it would be very informative to implement the
499 current experimental design in clinical groups, such as patients with major depression, in which
500 facial emotion recognition and social decision-making processes were shown to be affected in
501 previous studies [9,17,49,50].

502 Taken together, our key results demonstrate that, under affective load, inequality aversion
503 in human participants is a malleable cognitive process. We show that central arousal systems (i.e.
504 pupil size) track the valence of the opponent's affective responses to participant decisions during
505 social interactive decision-making. These findings may have important implications for
506 understanding the cognitive processes that underlies suboptimal outcomes (e.g. settling down for an
507 unfair split in interpersonal negotiations) in social interactive decision-making.

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510

511 **Methods and Materials.**

512 **Participants.** Forty four participants were recruited from the local community via advertisements.
513 Potential participants who had a history of neurological disorders or who were currently on a
514 psychotropic medication were excluded from the study. In order to increase the overall
515 generalisability of study results, eleven confederates were recruited from the staff of University of
516 Oxford Department of Psychiatry. The confederates attended to two testing sessions. In their first
517 visit, they were instructed to display different emotions (i.e. 9 different from negative to neutral to
518 positive) while the pictures of their faces were taken. These pictures were later used in the facial
519 emotion rating task and the Ultimatum Game (UG, Fig. 1).

520 **Procedures.** Before the experimental tasks, participants completed the Spielberger State-Trait
521 Anxiety Inventory, Quick Inventory of Depressive Symptoms and Social Value Orientation (SVO)
522 Slider Measure [28] in a pen and paper questionnaire format. After these, participants completed two
523 rating tasks in which they were asked to rate various (i.e. in total 100 unfair, fair and advantageous
524 offers) Ultimatum offers coming from an anonymous proposer on a 1-9 Likert scale (dislike vs liking).
525 All offers involved splitting £10 between the proposer and the participant, and the offer amounts
526 were presented in pence unit. After that participants rated their opponents' (i.e. the confederate's)
527 pictures displaying different facial emotions, on a 1-9 Likert scale (i.e. from negative to neutral to
528 positive, 9 different emotions in 6 randomised iterations, a total of 54 ratings). These rating tasks
529 were administered to establish participants' baseline preferences independently, and the ratings
530 were later used to construct computational models accounting for decision-making processes in the
531 UG.

532 After the rating tasks, participants completed the UG while undergoing pupillometry recording
533 (n=44). The task consisted of 6 blocks of 40 trials each. Where available, each participant was paired
534 with one of 11 different confederates. The participants were told that they would be playing an
535 interpersonal negotiation game against another participant recruited from general public, and in the
536 game they would be interacting with the other person through internet connection to an online
537 server. To strengthen the confederate manipulation, the participants were told that their opponents
538 attended on 2 occasions, and in their first visit they also respond to the same questionnaires as the
539 participant did, and their pictures were taken while displaying different emotions, later to be used in
540 the negotiation game. For some participants (47.7%) it was not possible to arrange a confederate
541 due to feasibility issues (e.g. a mismatch between the participant, testing room and confederate
542 availability). Those individuals were explicitly told that they would be playing against a computerised
543 strategy which was developed based on the behaviour of a previous participant. We used this

544 manipulation in our previous work to investigate proposer behaviour in the UG[51]. In fact, all
545 participants played against the same computerised strategy which was developed to sample offers
546 and facial emotions probabilistically from two independent sliding windows.

547 In descriptive terms, the opponent strategy was designed to test the participants' acceptance
548 threshold by sampling offers probabilistically around the threshold (e.g. previously rejected offers
549 can stay the same mimicking an insisting behaviour, improve or even get lower), and displays
550 negative facial emotions with relatively higher probability when the offers are rejected or displays
551 positive facial emotions with relatively higher probability when the offers are accepted (details of
552 the computer strategy is available in Supplementary Materials.). A full debriefing letter summarising
553 the aims and objectives of the study along with reasons for deception was provided at the end of the
554 study.

555 At the beginning of the UG experiment, the participants were explicitly told that their opponents
556 would be selecting one offer out of a window of different offers to make a proposal. Participants
557 were told that this is to make sure that their opponents could not consistently make unfair or fair
558 (i.e. 50/50 split) offers in which case the negotiation would get stuck in a limited range of offers. This
559 measure was taken to make sure that the decision-making process was confined to responding to
560 combinations of faces/offers in a gradually evolving task environment, and the influence of higher
561 order cognitive processes (e.g. Theory of Mind tracking[32], learning about the proposer's strategy) is
562 limited and/or becomes redundant. We think that UG is a particularly suitable task for this purpose
563 as it allows reducing model complexity (e.g. eliminating recursive models), relative to other tasks
564 such as the Stag Hunt[33], the Trust[52] or the Inspection games[31]. This is because the Rational Actor
565 model[6], which posits that any gain is better than no gain and all offers should be accepted, describes
566 the optimal strategy for maximising rewards. Secondly, recursive ToM models with which
567 participants can try to influence the opponent behaviour would only work effectively if the
568 opponent's subsequent offer is more than twice as good as the offer rejected on the current trial, as
569 otherwise the reward rate per trial cannot exceed the reward rate per trial if all offers are accepted.
570 However, we minimised this possibility in our task design (~9% of trials, offer amount (mean±SD):
571 132.6 ± 38), as offers were drawn from a sliding window and did not increase in a multiplicative
572 manner.

573 Just like in any traditional UG experiment, participants were told that their task is to accept or reject
574 these offers coming from the proposer. The participants were told that the accepted offers will be
575 distributed as proposed, but if they reject an offer both sides would get nothing for that trial. The
576 participants were told that after their decision, the proposer would see 9 faces displaying different

emotions (i.e. the same 9 faces the participant rated previously) and would select one to communicate how s/he feels in response to the participant's response and in the next trial the proposer would see another set of options, also giving him/her an opportunity to revise his/her offer. The participants were told that each block would start with a neutral face and a fair offer (i.e. 50/50 split) and can go any direction from that point onwards based on their negotiation ability. The participants were instructed that at the end of the game a computer algorithm would randomly select 20 trials and the outcome of those trials would be paid to each side. At this point we told participants that they may be inclined to accept all offers (i.e. the optimal decision-making according to Rational Actor model which posits that any gain is better than zero) so that those randomly selected 20 trials would always have a monetary outcome for the participant, but in that case, we told them, that their opponent may detect this tendency and try to make offers as low as possible. We then told participants to use the accept/reject responses strategically to negotiate better terms for themselves.

During pupillometry recording, participants' heads were stabilised using a head-and-chin rest placed 70 cm from the screen on which an eye tracking system was mounted (Eyelink 1000 Plus; SR Research). The eye tracking device was configured to record the coordinates of both of the eyes and pupil area at a rate of 500 Hz. The pupillometry data collection lasted approximately 70 min per participant.

Modelling affective biases in facial emotion recognition. We modelled participant rating responses to affective faces (on a 1-9 Likert scale from negative to positive) by exploiting the properties of the 2-parameter probability weighting function[53]:

$$\varepsilon = \exp(-\delta(-\log(\varphi))^{\gamma}) \tag{1}$$

where φ is the true emotional state of the proposer's face as displayed, and can take values from 1 to 9. The parameters [δ , γ] determine the curvature of the weighting function and where it crossed the $\varepsilon = \varphi$ diagonal line (Figure 2A). We implemented the probability weighting function like a nonlinear regression model that minimises the difference between model estimates and participant's actual ratings (after performing a simple linear transformation by dividing these Likert ratings by 10, such that both the ratings and the estimates are bounded by 0 and 1).

Modelling liking ratings for Ultimatum Offers. In line with previous literature[45], we modelled participants liking ratings (χ) for each Ultimatum Offer (again, based on participant ratings on a 1-9 Likert scale) with a multiple linear regression model.

608 $$\chi = \phi_0 + \phi_1 R_S + \phi_2 |R_S - R_O| \quad (2)$$

609 where R_S is the self-reward and R_O is the reward amount to the proposer, and absolute value
610 difference accounts for how much the participant cares for inequality. Here, it is important to clarify
611 that because all offers involve splitting £10, R_O is not entered to this regression model as an
612 independent regressor as all monetary information is conveyed by the self-reward amount and the
613 inequality term.

614 **Modelling participant choice behaviour in the Ultimatum Game.** The model-free analyses of
615 participant choice behaviour indicated that both offer amount and the proposer's facial emotions
616 should influence how people generate decision-values in the UG. Here, we formally describe all the
617 models that we considered, to identify the cognitive model which accounts for participant choice
618 behaviour the best.

619 The first model that we considered assumes that participants construct the decision-value ($\tilde{v}$) of
620 each offer utilising a Constant Elasticity of Substitution (CES) function, commonly used to account for
621 consumer behaviour [54,55]. According to the CES function, the decision-value is computed as:

622 $$\tilde{v} = (\alpha R_S^{\rho} + (1-\alpha)|R_S - R_O|^{\rho})^{1/\rho} \quad (3)$$

623 where ρ is a nonlinear power utility parameter determining the concavity of preferences and α
624 determines how much weight is assigned for the self-reward magnitude or the absolute value
625 difference between the self and the other's reward magnitude (i.e. the inequality term).

626 We considered another model in which the decision-value is generated by comparing the inequality
627 term relative to one's fairness threshold:

628 $$\tilde{v} = \lambda - |R_S - R_O| \quad (4)$$

629 where λ is the fairness threshold parameter freely estimated between 50 and 950 (i.e. bounded by
630 the minimum and maximum offer amount), defining the participant's subjective threshold in term of
631 what they regard as acceptable.

632 The next model assumed that participants accept or reject offers based on their liking ratings, as
633 established by the independent rating task participants completed prior to the social interactive
634 decision-making task. In this model, participant's liking of offers during the UG is estimated by

feeding each participant's estimated coefficients from the linear regression model back to Eq.2. Here, the decision-value is equal to:

$$\tilde{v} = \chi \tag{5}$$

We also considered another model with a similar structure in which the decision-values are generated online during the social decision-making task, instead of depending on participant's previous liking ratings. This model addresses the prediction that there will be a dissociation between how much people like offers when these ratings do not have any financial consequence and how they value them in a social interactive context with monetary consequences (i.e. the fact that participants would be paid the outcome of 20 randomly selected trials). Here, the decision-value is computed as

$$\tilde{v} = \kappa R_S - \omega |R_S - R_O| \tag{6}$$

For model simplicity we used a single inequality aversion parameter, instead modelling advantageous and disadvantageous inequality separately. All models assume that conditions with relatively higher subjective value should be more likely to be accepted and participants' acceptance probability is generated by a sigmoid function:

$$q_A = 1/(1+\exp(-\beta(\tilde{v})) \tag{7}$$

where β is the inverse temperature term which modulates the stochasticity of participant choices.

We first chose between these models which define participants' likelihood of accepting an offer solely based on the numerical components of the offer amount. We implemented this reduction in model space based on our model-free analysis which suggested that offer amount has a greater influence on acceptance probabilities than the proposer's facial emotions. Group-wise sum of Bayesian Information Criterion (BIC) scores indicated that the model described by Eqs. 6 and 7 was the best fitting model to account for how offer amounts were translated to decision-values.

We then used this best fitting model from the first stage as a template to further evaluate how facial emotions of the proposers may influence the way decision-values are computed in the social decision-making task. Based-on previous literature, we considered a model in which the effect of proposer's facial emotion depends on the participants' individual variability in how malleable they are to external emotional influence [56]:

$$\tilde{v} = \kappa^{(\varepsilon-\mu)} R_S - (\omega^{(\varepsilon-\mu)} |R_S - R_O|) \tag{8}$$

where parameters κ and ω are estimated between 0 and 10 and determines the degree to which the modulations of self-reward and the inequality term are subjected to emotional influence. In this model, social affective biases (Eq.1) act like an exponential function modulating this influence parameter [6] and μ is the mean value where perceptual biases crossover the diagonal line (Figure 2A, μ=0.4). We considered 3 variants of this model where opponent's facial emotions influence the self-reward amount (R_S) or the inequality term ($|R_S - R_O|$), or both independently.

We also investigated whether the proposer's facial emotions influence the inequality term in a parabolic, rather than an exponential functional form:

$$\tilde{v} = \kappa R_S + (\omega + (\varepsilon - \mu)^2) \, | R_S - R_O | \tag{9}$$

For any given offer amount, this formulation relaxes the negative modulation of inequality as the opponent's facial emotions are gradually getting negative or positive, while assuming that neutral faces do not influence the inequality term.

Finally, we considered a competing model which assumes that the proposer's facial emotions influence the value of offers through a weighted integration.

$$\tilde{v} = w\tilde{v} + (1 - w)(\varepsilon - \mu) \tag{10}$$

Here, *w* is a free parameter estimated between 0 and 1, and determines the degree to which the participant assigns credit to subjective value of the offers and/or to the proposer's facial emotions which are nonlinearly modulated by affective biases. The additive integration means that other's facial emotions should have an intrinsic value, an assumption that is in line with existing literature [57].

All model parameters were estimated by a Bayesian model fitting procedure, by calculating the full joint posterior distribution of the parameters over the whole parameter space, and deriving exact parameter values by integrating these probabilities with their corresponding discrete parameter values.

Pupillometry data preprocessing. Eye blinks were identified using the built in filter of the Eyelink system and were then removed from the data. A linear interpolation was implemented for all missing data points (including blinks). The resulting trace was subjected to a low pass Butterworth filter (cut-off of 3.75 Hz) and then z transformed across the session (Browning et al., 2015; Nassar et al., 2012). The pupil response was extracted from each trial, using a time window based on the presentation of the offer amount. This included a 7.5 second baseline period before the

presentation of the outcome (including the period at the beginning of a trial marked by a fixation cross and presentation of the opponent faces alone, Figure 1), and a 4.5 second period following offer presentation. Baseline correction was performed by subtracting the mean pupil size during the 7.5 seconds baseline period prior to the presentation of each offer, from each time point in the decision and outcome period. Individual trials were excluded from the pupillometry analysis if more than 50% of the data from the outcome period had been interpolated (mean =10.9% of trials) (Browning et al., 2015). The preprocessing resulted in a single sets of pupil timeseries per participant containing pupil dilation data for each of the included trials.

Regression analysis of pupillometry data. We implemented an OLS model in a similar manner to a functional neuroimaging (fMRI) analysis, by fitting the regression model to the pre-processed pupillary data at every 2-millisecond time point. The pupil model had 10 regressors as defined by the following linear regression equation:

$$\begin{aligned} pupil(2\pi r) &= \gamma_0 + \gamma_1 i + \gamma_2 \tilde{v}^i_{Model7} + \gamma_3 \varepsilon^i + \gamma_4 surprise^i_{offer} + \gamma_5 surprise^i_{faces} + \\ &\gamma_6 vol^i_{offer} + \gamma_7 vol^i_{faces} + \gamma_8 noise^i_{offer} + \gamma_9 noise^i_{faces} \end{aligned} \quad (11)$$

Here we provide brief descriptions for each regressor in the model. The regressor for the constant term (γ_0) captures the variance in pupil size across all trials in the task. The regressor (γ_1) accounts for the effect of trial numbers, as a proxy for accumulated fatigue (*i*: taking values from 1 to 240). We entered one regressor (γ_2) which represents the subjective value of each offer under the best-fitting behavioural model. The regressor (γ_3) encodes the perceived facial emotions modulated by 2 weighting parameters (Eq.1). The rest of the regressors were defined by a recursive Bayesian filter that we recently reported[27] which can optimally track the hidden structures (i.e. environmental volatility (i.e. vol in the above formula) and noisy fluctuations (i.e. noise) in the environment) of dynamically changing environments. The surprise regressor was congruent –log probability of an offer coming from a distribution with mean and standard deviation (SD) estimated by the Bayesian filter. This would mean that stimuli which violate the expectations of the observer should lead to a greater pupillary surprise signal. This regressor was calculated for both the offers and the proposer's facial emotions.

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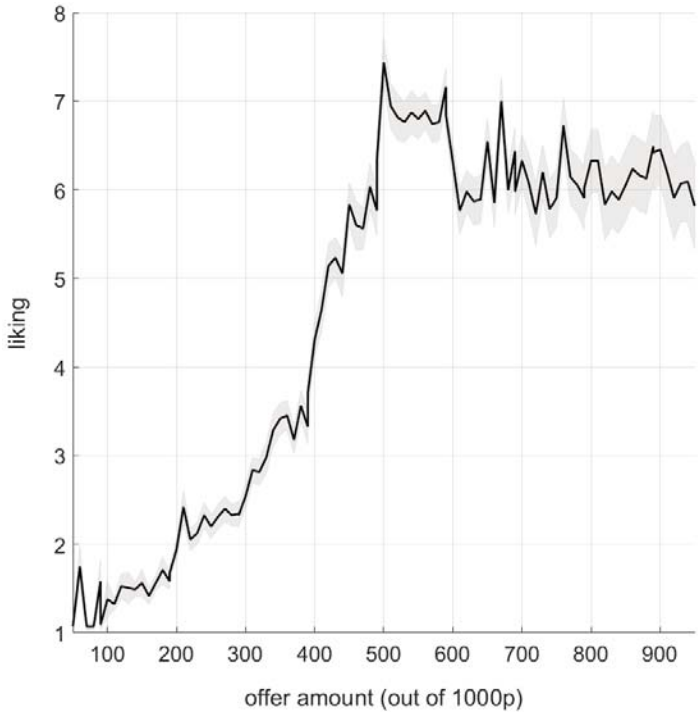
894 **Supplementary Figures**



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896 **Supplementary Figure 1.** Participants' liking ratings monotonically increase from 50p to 500p, which was the point of
897 50/50 split in the current experimental design. Relatively lower ratings for advantageous offers (>500p) indicate inequality
898 aversion in this cohort. Wider SEM shading around the ratings of advantageous offers indicate a greater individual
899 variability in terms of self-other inequality relative to how unfair offers were rated.

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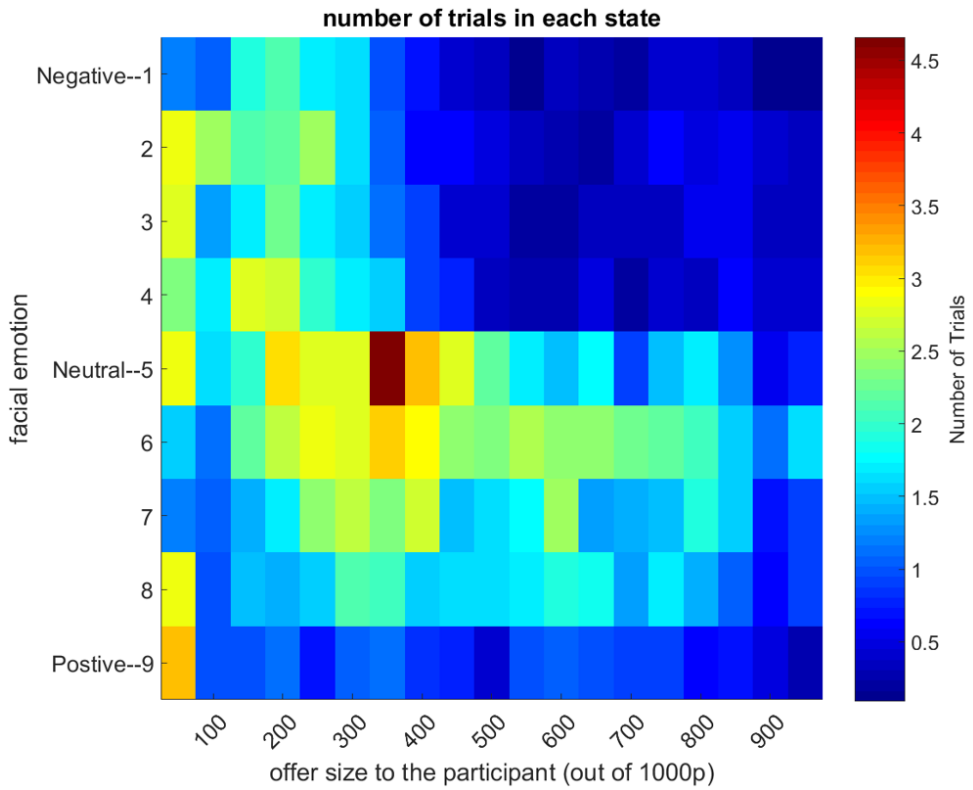
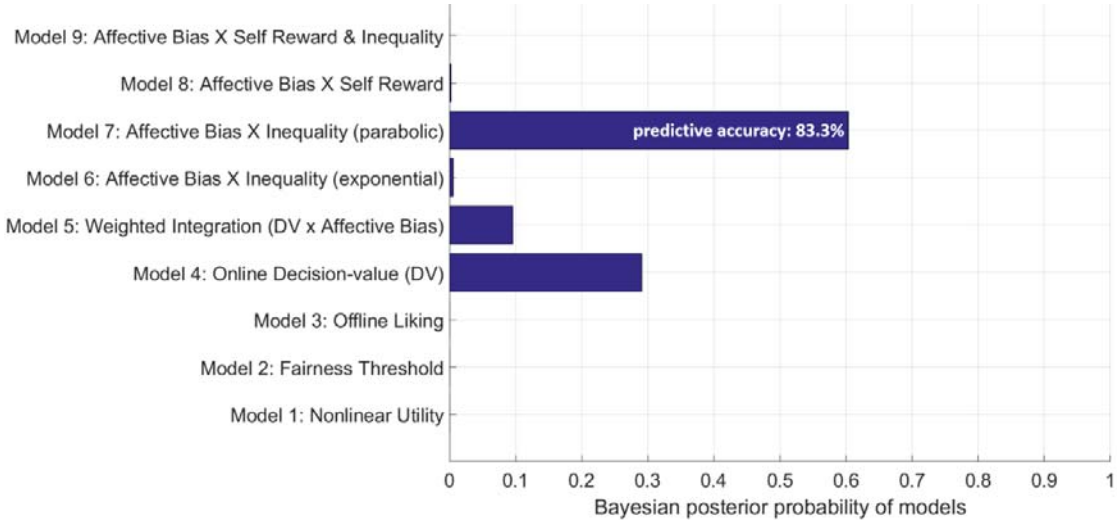
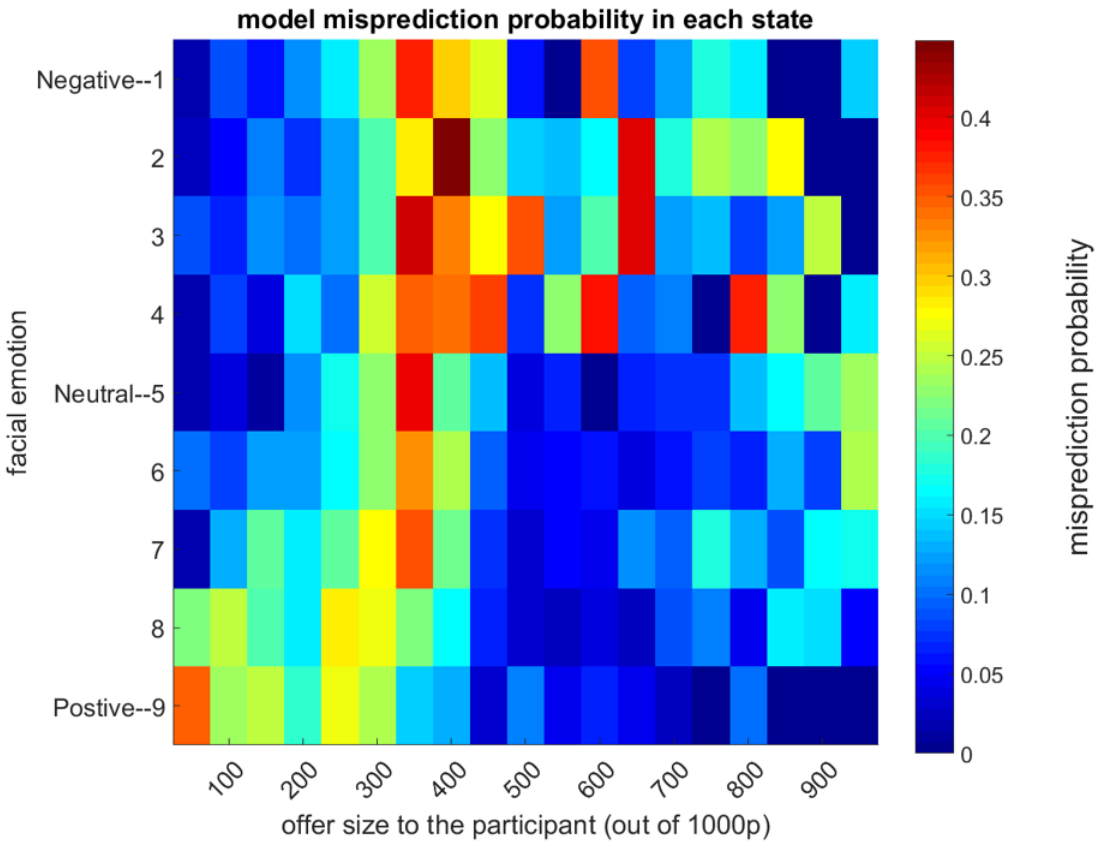


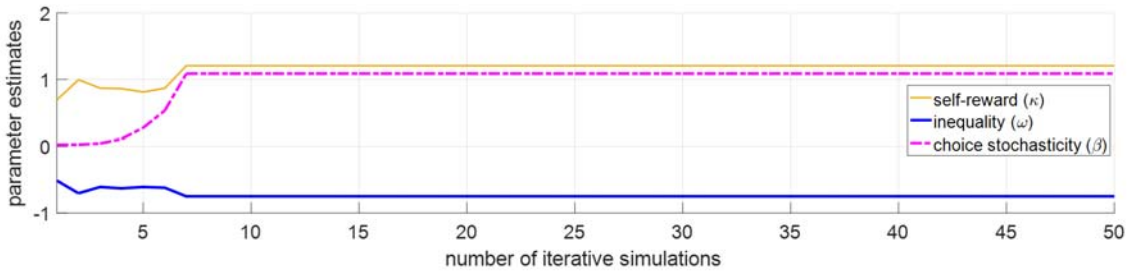
Supplementary Figure 2. Out of 240 trials, average number of trials participants spent in each state-space (i.e. combinations of opponent's facial emotion (y-axis) and offer amounts (x-axis)) represented as a heat map. Colour bar shows the number of trials. On average participants had 12.6±15.9 (mean±SD) trials in the upper right hand quarter (i.e. advantageous offers while the opponent is displaying a negative facial expression).



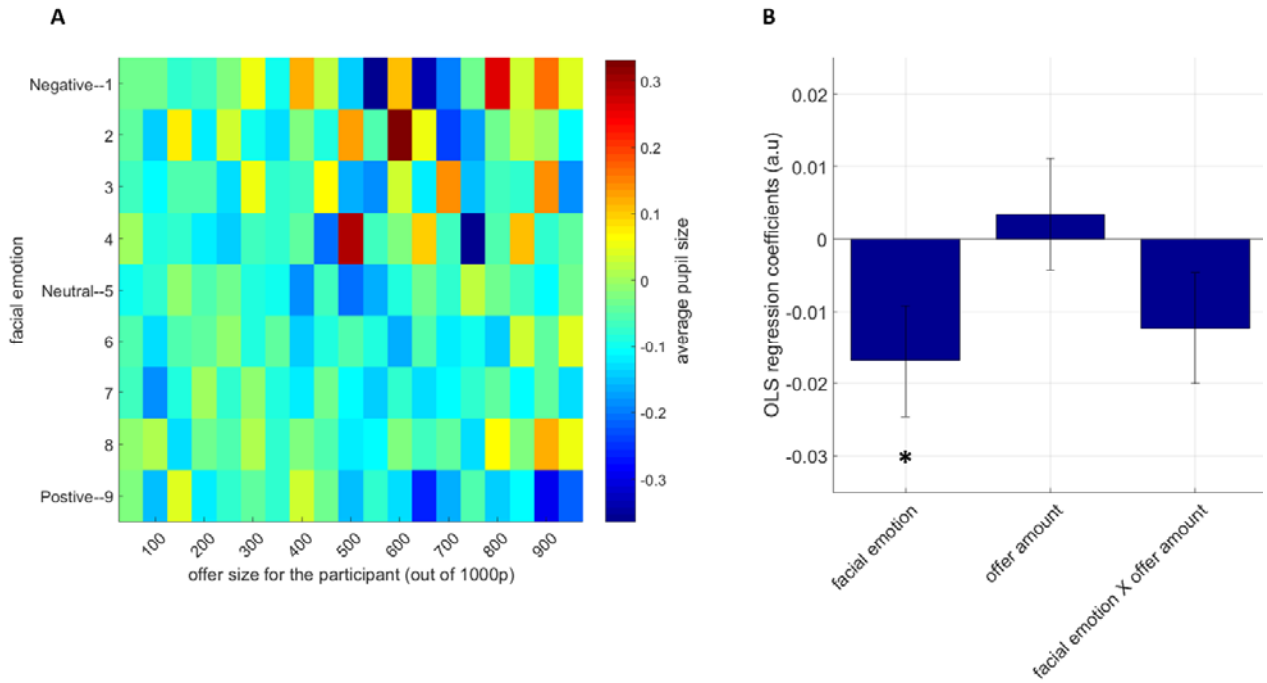
Supplementary Figure 3. Model selection implemented by feeding each model's log-likelihood values in a matrix format (number of participants x number of models) to spm_BMS.m (i.e. the Bayesian Model Selection from SPM12 library), suggests that Model 7 is most likely to be the generative model for the observed data (based on model exceedance probabilities). This model suggests that social affective biases selectively act on the inequality term in a parabolic form.



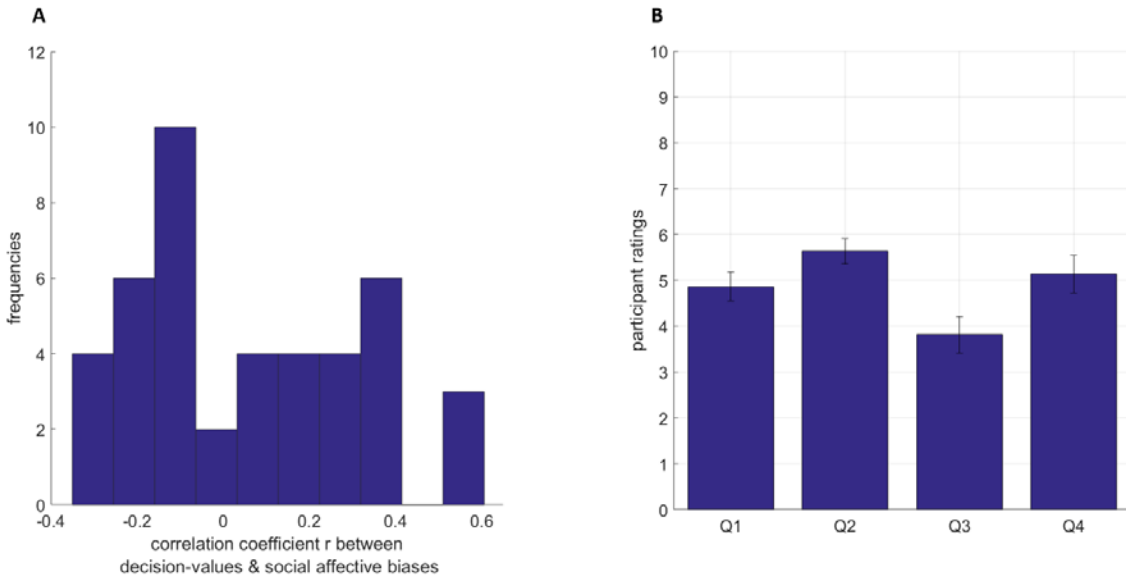
Supplementary Figure 4. Misprediction probabilities of the best-fitting model over the stimuli space. A regression analysis of the trials mispredicted by the best-fitting model did not show a significant main effect of opponent's facial emotions or the offer amount, indicating that the model does not miss the behavioural effect of faces and the offer amount (Figure 3) in a systematic manner.



Supplementary Figure 5. Stability of parameter estimates in generate-recover simulations. Iterative simulations of the best-fitting model based on the population average of the parameters on a task environment experienced by a representative subject demonstrate that model parameters quickly stabilise. In these simulations choices were generated stochastically by a sigmoid function and the parameters were re-estimated based on the choices from the previous simulation.



Supplementary Figure 6. Average pupil size in the Ultimatum Game. (A). Participants' average pupil size across all possible combinations of opponent's facial emotion (y-axis) and offer amounts (x-axis) represented as a heat map. Colour bar shows the average pupil size after presentation of the offer. **(B)** An OLS regression analysis conducted on the pupil size suggested only a significant main effect of opponent's facial emotion (*p<.05).



Supplementary Figure 7. Relationship between social affective biases and decision-values. (A) The distribution of correlation coefficients *r* between social affective biases and decision-values entered in to the pupillary model. Frequencies on the y-axis indicate the number of participants.

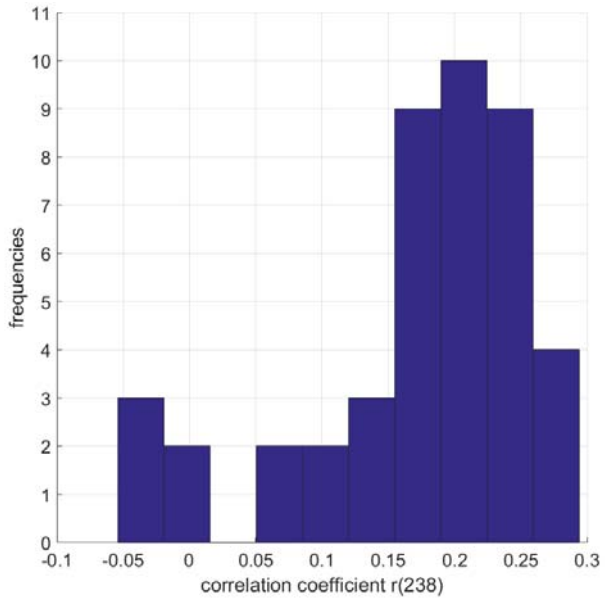
(B) Participants rated the proposer on 4 questions from 0 to 10.

Q1. How much do you think this person cares about rewards to others? (0: does not care at all, 10: cares very much)

Q2. How much would you like this person if you spent 1 hour with him/her in real-life? (0: strong dislike, 10: very likeable)

Q3. How many people do you know in real life who resembles this person (not physical appearance)? (number 0-10)

Q4. How socially close do you feel towards those people that you know? (0: not close at all, 10: very close).



Supplementary Figure 8. Relationship between surprise associated with offers and the actual offer amount. Distribution of correlation coefficients between the surprise regressor generated by the Bayesian filter uniquely for each participant and the vector of offer amounts observed by the participant throughout the task. Frequencies on the y-axis indicate the number of participants.