ARTICLES
DOI: 10.1038/s41562-017-0207-1
nature human behaviour

Brain response patterns to economic inequity predict present and future depression indices

Toshiko Tanaka[1,2], Takao Yamamoto[3] and Masahiko Haruno[1,2*]

Widening economic inequity has been suggested to associate with depression. However, little is known about the underlying neural mechanisms of this link. Here, we demonstrate that functional magnetic resonance imaging activity patterns in the amygdala and hippocampus induced by the inequity between the self and other rewards during an economic game can predict participants' present and future (measured one year later) depression indices. Such predictions were not possible using participant's behavioural and socio-economic status measures. These findings suggest that sensitivity to economic inequity has a critical effect on human mood states, and the amygdala and hippocampus play a key role in individual differences in the effect.

Widening economic inequity has become an increasing concern for society[1] and has been implicated as a source of several psychiatric diseases including depression[2,3]. Previous large-scale cohort-based studies (for example, the Whitehall Study[4]) have indicated a link between economic gaps and major depression[5–7], where economic and material disadvantage are crucial in explaining depressive symptoms. Despite this importance, little is known about the neural mechanism that underlies the link between economic inequity and mood change. The revelation of such a mechanism would provide deeper understanding of depression and contribute to the development of preventative measures[8].

Social value orientation describes the different attitudes towards economic inequity among people[9,10]. Prosocials choose to allocate resources in a way that minimizes the inequity between themselves and others, simultaneously maximizing the sum of the two parties. By contrast, individualists prioritize the maximization of self-income regardless of the other's gain. A third and small category of people, termed competitors, like to maximize their superiority over others. Social value orientation is determined using a forced three-choice task of money division dubbed the triple-dominance measure task[10] (see also Supplementary Methods). Several functional magnetic resonance imaging (fMRI) studies have reported that activity in the amygdala in correlation with the absolute value of reward difference between the self and other was larger in prosocials than in individualists. Furthermore, this amygdala activity in prosocials was correlated with how much each prosocial dislikes inequity[11–13].

The amygdala, along with the hippocampus, has been identified as a key brain structure in major depression. The functional activity of the amygdala and hippocampus in response to emotional stimuli differs between depression patients and normal controls[14,15], as does the anatomical volume of these two structures[16–18]. These functional and anatomical changes in patients with depression have been linked partly with the increased level of cortisol produced by the hypothalamic–pituitary–adrenal (HPA) axis, which releases a cascade of hormones including the primary stress hormone cortisol, under the influences of excitation input from the amygdala and inhibition feedback from the hippocampus[19].

Based on the critical and complementary contributions of the amygdala and hippocampus to depression and stress processing in general, together with previous literature proposing that people who worry about others' perspectives are more prone to depression[20,21], we hypothesized that the response pattern of the amygdala and hippocampus to economic inequity may relate to the depressive mental state and therefore examined whether brain response patterns to economic inequity during an ultimatum game[22,23] could predict present and future (measured one year later) depressive indices (the Beck Depression Inventory-II (BDI; ref. [24]) in a non-clinical population.

Results

Depression index distribution. To examine differences in attitudes towards economic inequity, we first measured the social value orientation[10] of 343 participants using the 8 (trials) triple-dominance measure task (see Supplementary Methods). Next, we quantified the depression tendency of the participants identified as prosocial or individualist using the BDI questionnaire[24]. Figure 1a shows the distribution of the depression index for prosocials (defined as those who dislike economic inequity and maximize joint outcome) and individualists (defined as those who prioritize self-reward regardless of the other). This was significantly different between the two groups (bootstrap Kolmogorov–Smirnov test, $P=0.0045$), with middle-to-high scores more frequent in prosocials. Differences in the scores for each question are shown in Fig. 1b, in which 'guilty feelings' is higher for prosocials (Wilcoxon rank sum test, $P=0.022$). Such a distributional difference was not seen in terms of gender (male versus female, bootstrap Kolmogorov–Smirnov test, $P=0.80$).

Differential neural activity between prosocials and individualists. To identify the neural substrates underlying the differences between prosocials and individualists with respect to inequity, of the original 343 participants, 59 prosocials and 35 individualists underwent fMRI while playing an ultimatum game[22] (see Methods). In this game, proposers made a series of offers about money sharing to a responder who then decided whether to accept or reject each offer. If the responder accepted an offer, money was distributed as proposed; otherwise, neither side received any money. In our experiments, participants were asked to take the role of responder (Fig. 1c). Consistent with the definition of prosocials as people who like to minimize reward difference, prosocials exhibited a higher rejection rate of unfair offers in comparison with individualists (Fig. 1d, Kolmogorov–Smirnov test, $P=0.034$) and the rejection

[1]Center for Information and Neural Networks, National Institute of Information and Communications Technology, Osaka 565-0871, Japan. [2]Brain Science Institute, Tamagawa University, Tokyo 194-8610, Japan. [3]NHK (Japan Broadcasting Corporation), Tokyo 150-8001, Japan. *e-mail: mharuno@nict.go.jp

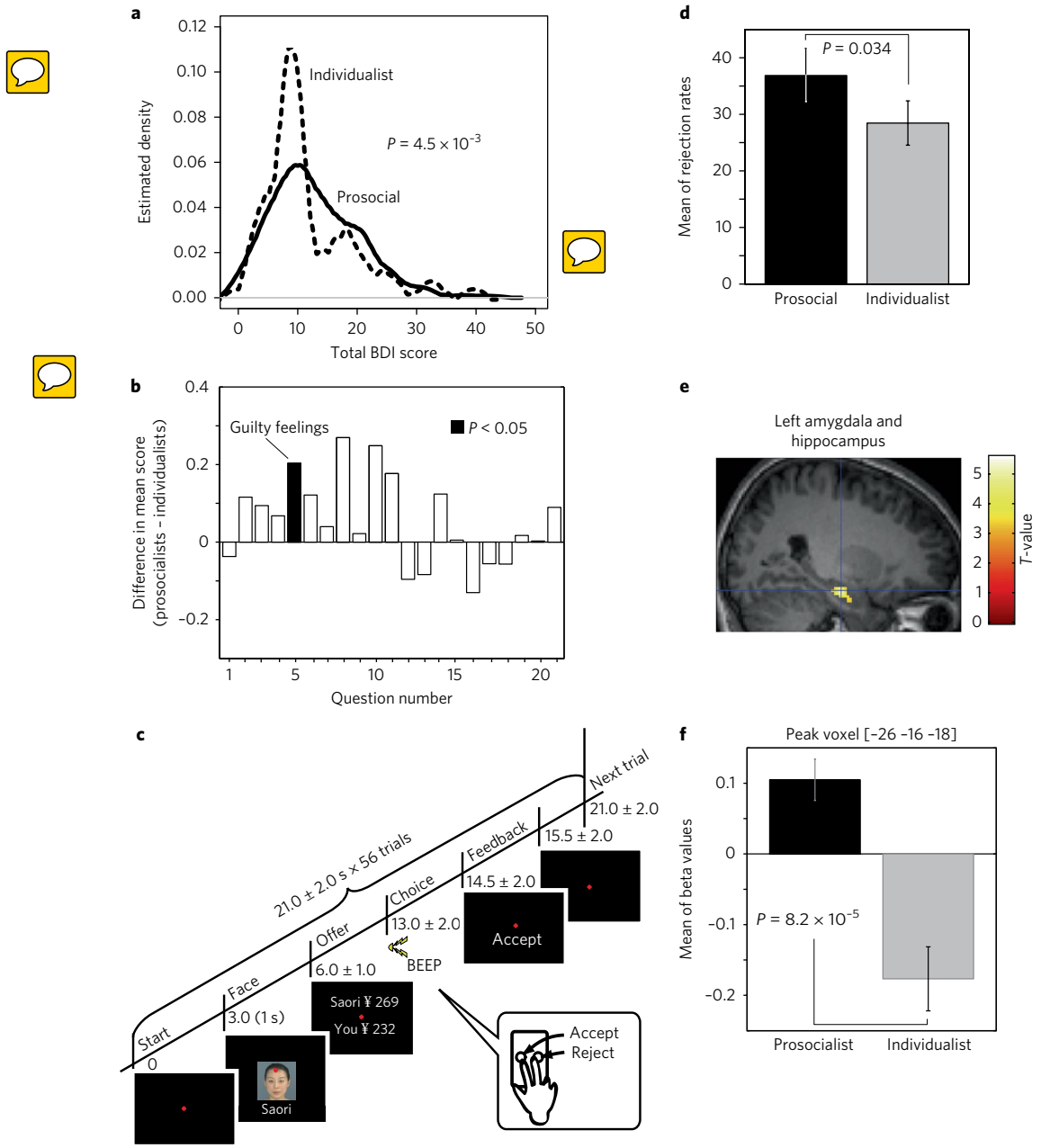

Fig. 1 | Tasks and responses. a, Probability density plots of BDI scores were different between prosocials (solid line, $n = 174$) and individualists (dashed line, $n = 59$) ($P = 0.0045$, bootstrap Kolmogorov–Smirnov test; number of bootstrap sampling = 100,000). The proportion of low BDI scores was higher in individualists, while prosocials exhibited a higher proportion in the middle-to-high score population range. **b**, Differences in scores for each BDI question between prosocials ($n = 174$) and individualists ($n = 59$). Scores of the question on guilty feelings (question 5) were significantly different ($P = 0.022$, Wilcoxon rank sum test). **c**, Task design of the ultimatum game. Each participant took the role of responder. **d**, Mean rejection rates to unfair offers were significantly different ($P = 0.034$, Kolmogorov–Smirnov test) between prosocials (black, $n = 59$) and individualists (grey, $n = 35$). The error bars represent standard errors. **e**, We identified a significant difference in amygdala and hippocampus activation between prosocials ($n = 59$) and individualists ($n = 35$) in correlation with disadvantageous inequity (multiple regression, $P < 0.05$ small volume corrected). The Montreal Neurological Institute (MNI) coordinates of the peak position were −26, −16, −18 (peak positions are also presented in Table 1). **f**, The beta values (representing the strength of correlation with inequity) at the peak position in the left amygdala and hippocampus (**e**) were positive in prosocials (black) and negative in individualists (grey) and the difference was significant ($P = 8.2 \times 10^{-5}$, Kolmogorov–Smirnov test). The error bars represent standard errors.

rate for fair offers was comparable between prosocials and individualists (Kolmogorov–Smirnov test, $P = 0.94$).

We conducted a general linear model analysis of the fMRI data using SPM12 (http://www.fil.ion.ucl.ac.uk/spm). In the first each subject-level analysis, we separated offer events intro thee types—unfair (disadvantageous), fair and unfair (advantageous)—and included disadvantageous inequity (hereafter referred to as 'inequity' and defined as the difference between the self and other reward when the reward for the other was larger, otherwise 0; see also Methods) as a regressor associated with offer presentation events. In the second across-subject analysis, we contrasted prosocials and individualists in terms of inequity using multiple

Table 1 | Whole-brain activity differences between prosocials and individualists induced by disadvantageous inequity

Region	*k*	Peak position			*T*-score	*Z*-score	P_{uncorr} (whole)	P_{FWE} (SVC)
		x	*y*	*z*				
Social value orientation								
Amy/hippo (L)	184	−26	−16	−18	5.54	5.11	1.6×10^{-7}	1.5×10^{-4} ($P=0.015$ (whole brain FWE_corr))
Amy (R)	35	20	−4	−22	4.27	4.06	2.4×10^{-5}	6.6×10^{-3}
Insula (R)	60	32	26	−2	4.45	4.21	1.3×10^{-5}	2.7×10^{-3}
Socioeconomic status								
Caudate (L)	62	16	16	14	4.70	4.43	4.8×10^{-6}	2.6×10^{-4}
Caudate (R)	36	−16	30	10	4.44	4.20	1.3×10^{-5}	7.6×10^{-3}

Amy, amygdala; hippo, hippocampus; L, left; R, right; SVC, small volume correction. MNI coordinates are shown. SVC used the anatomical region that contained the peak voxel of the cluster. *P* values at the peak positions are shown. *P* values are cluster-level corrected. The statistical thresholds were $P<0.05$ for corrected activity and $P<0.001$ for uncorrected activity. Activity in amy/hippo (L) was also significant for $P<0.05$, FWE corrected for the whole brain.

regression, which incorporated social value orientation (prosocial or individualist), gender (male or female), age, income level (discretionary money per month) and socioeconomic status (social hierarchy) obtained through a post-experimental questionnaire (see also Supplementary Methods).

We found that activity in the amygdala and hippocampus correlating with inequity was higher in prosocials than individualists ($P<0.05$ small volume corrected; Table 1 and Fig. 1e; this key activity was also significant with $P<0.05$ family-wise error (FWE) corrected for the whole brain), consistent with previous reports[11–13]. At the peak voxel of this inequity-correlated amygdala and hippocampus response, prosocials exhibited positive correlation, while individualists exhibited negative correlation (Fig. 1f, Kolmogorov–Smirnov test, $P=8.2\times10^{-5}$). This differential activity remained the same even when we equalized the number of prosocial and individualist participants (that is, the first 35 prosocials and 35 individualists; supplementary Fig. 1; see also Methods). However, we did not find any inequity-correlated activity common to prosocials and individualists, nor was a correlation revealed by the opposite contrast of individualists minus prosocials. In addition, other than social value orientation, socioeconomic status produced significant inequity-correlated activity in the caudate nucleus ($P<0.05$ small volume corrected; Table 1), consistent with a previous study[25] reporting the involvement of the striatum in inequity processing in terms of the relative status of people. We did not find any other significant activity for any event that correlated with gender, age or income level (even at a very weak threshold $P<0.005$ uncorrected). Based on these analyses, we were able to exclude gender, age, income level and socioeconomic status from the potential confounders of the differential activity of the amygdala and hippocampus.

We contrasted unfair and fair offers and obtained stronger activity in the insula and anterior cingulate cortices for unfair (disadvantageous) offers than fair offers (Fig. 2 and Table 2, $P<0.05$ FWE corrected), which is highly consistent with previous reports[11,23]. However, the other contrast—unfair (advantageous) minus fair offers—did not yield a significant result. In addition, we contrasted rejected and accepted offers using a separate general linear model in which all other contrasts were kept the same. Again consistent with previous reports[23], we found higher activity in the anterior insula for rejected offers than accepted offers (Supplementary Fig. 2 and Supplementary Table 1 (activity differences between rejected and accepted trials induced by offer presentations)).

Correlations with BDI score. To investigate whether behavioural indices of the participants could predict their BDI index, we plotted the total BDI score of each participant against their number of prosocial choices in the 8 triple-dominance measure task, which was used to determine social value orientation (Supplementary Fig. 3a,b), and the rejection ratio in the ultimatum game (Supplementary Figs. 3c and 4d). We found that these basic behavioural indices could not predict the BDI score. In addition, neither income level (discretionary money per month) nor socioeconomic status (social hierarchy) was correlated with the BDI score (Supplementary Table 2). There was no significant gender difference in terms of the BDI score either (Kolmogorov–Smirnov test, $P=0.72$).

Next, we evaluated the Pearson correlation coefficients between the total BDI scores of the participants and their beta values in each voxel in correlation with inequity. We found negative correlations in the hippocampus (Fig. 2b) and positive correlations in the amygdala (Fig. 2c), but no significant difference between the correlation coefficients of prosocials and individualists (analysis of covariance, $P=0.73$, Supplementary Fig. 4). Based on these voxel-level correlational observations, we further hypothesized that the amygdala and hippocampus response patterns to inequity might predict present and future depression indices.

Predicting present BDI scores from brain response patterns. We then examined whether the amygdala and hippocampus response patterns to inequity could predict total BDI scores. To analyse multi-voxel activity patterns, we developed a model-based multi-voxel pattern analysis method (Fig. 3a), which focused on the voxel response pattern specific to the inequity when conducting a prediction. This method was based on the sparse Bayesian kernel-based leaning algorithm and had two remarkable characteristics. The first was the model-based feature: the input to the prediction system was the beta values (that is, linear coefficients) of brain activity in correlation with inequity. This property allowed us to focus on amplitudes of inequity-correlated brain activity for prediction and not only on a simple increase or decrease in activity. The second was the sparseness achieved by sparse Bayesian methods. This property allowed us to automatically select a limited number of participants who were informative for prediction and was particularly useful for high-dimensional noisy data such as fMRI signals (see also Supplementary Methods). We defined functional regions of interest (ROI) as the clusters shown in Table 1.

We compared actual and predicted (by the leave-one-out method) total BDI scores for each participant. The total BDI score predicted by the response pattern to inequity in the left amygdala and hippocampus ROI had a positive correlation with the actual BDI (Fig. 3b, slope = 0.24, $R=0.48$, $P=1.5\times10^{-5}$), demonstrating predictability of the present depression index. A similar prediction was also possible by the response pattern to inequity in the right amygdala (Fig. 3c, slope = 0.15, $R=0.36$, $P=1.6\times10^{-3}$). Importantly, this prediction was also possible even if we split the left amygdala and hippocampus ROI into separate amygdala and hippocampus measures (amygdala: slope = 0.20, $R=0.42$, $P=2.2\times10^{-3}$;

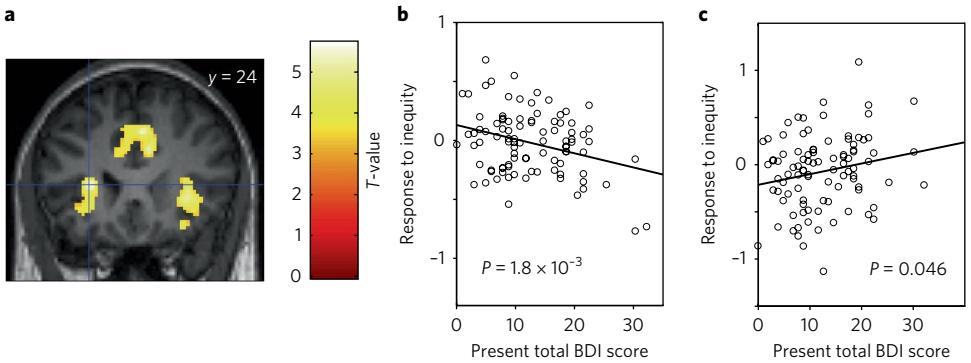

Fig. 2 | Basic brain activity during the ultimatum game. a, Brain responses to unfair (disadvantageous) offers were compared with fair offers in all participants ($n=94$). Peak positions are presented in Table 2 (two sample *t*-test, $P<0.05$, FWE corrected). For display purposes, an image with $P<0.001$, uncorrected, is shown. The MNI coordinates of the peak position were −28, 24, 8. $P_{FWE}=5.0\times10^{-3}$. **b**,**c**, Correlations between the present BDI scores and beta values of each single voxel in the amygdala and hippocampus clusters were computed and the maximally negative and positive correlations were identified in the hippocampus (**b**) (MNI coordinates −30, −16, −18; $P=1.8\times10^{-3}$, $R=0.32$) and amygdala (**c**) (MNI coordinates 12, −8, −16; $P=0.046$, $R=0.21$).

Table 2 | Whole-brain activity differences between unfair (disadvantageous) and fair conditions induced by offer presentations

Region	*k*	Peak position			*T*-score	*Z*-score	P_{FWE}
		x	*y*	*z*			
Insula (L)	18	−28	24	8	5.74	5.29	5.0×10^{-3}
		−28	16	14	5.17	4.83	0.040
	25	−34	16	−6	5.68	5.24	6.2×10^{-3}
Insula (R)	3	32	22	4	5.26	4.91	0.039
ACC (R)	8	6	22	42	5.45	5.06	0.015
ACC (L)	1	−6	18	42	5.18	4.84	0.029

ACC, anterior cingulate cortex; L, left; R, right. MNI coordinates and *P* values at the peak positions are shown.

hippocampus: slope = 0.19, R = 0.47, $P=2.8\times10^{-5}$). We also found that the response pattern in the caudate nucleus to inequity (detected by the socioeconomic status) could weakly predict the present BDI scores (Supplementary Fig. 5, slope = 0.14, $R=0.31$, $P=7.5\times10^{-3}$). However, such a prediction was not possible for the other region in Table 1 (that is, the insula, Fig. 3d, slope = 0.010, $R=0.081$, $P=0.50$).

Prediction from the response pattern induced by the proposer's face presentation (slope $=1.4\times10^{-5}$, $R=1.1\times10^{-4}$, $P=0.99$) or offer presentation (slope $=8.8\times10^{-3}$, $R=0.075$, $P=0.53$) was impossible (Supplementary Fig. 6, see also Methods). Indeed, we found that the slopes of the regression lines were different between the inequity condition (Fig. 3b) and the face or offer presentation condition (Supplementary Fig. 6, analysis of covariance; interaction of linear regression, inequity versus face, $P\approx0$ and inequity versus offer, $P\approx0$). Finally, we also tried to predict the BDI score from brain activity patterns in the insula and anterior cingulate cortex identified by the (unfair (disadvantageous) – fair) contrast (Fig. 2a) and found that prediction was not possible (insula: slope $=4.4\times10^{-3}$, $R=0.053$, $P=0.66$; anterior cingulate cortex: slope = −0.011, $R=0.011$, $P=0.34$).

Predicting long-term changes in BDI scores from brain response patterns. We next considered whether the amygdala and hippocampus response pattern to inequity could also predict the future depression index. We addressed this issue by testing whether the inequity response pattern could predict a one-year change in the total BDI score after the same group of participants ($n=73$) underwent BDI one year later (see also Supplementary Methods). The distributions of the second total BDI were different between prosocials and individualists (Fig. 3e, bootstrap Kolmogorov–Smirnov test, $P=0.017$), consistent with the results from one year before. However, the distribution of the change in total BDI score was not different between the two groups. This finding indicates that distinctions in prosocials and individualists cannot predict BDI changes (Supplementary Fig. 7, bootstrap Kolmogorov–Smirnov test, $P=0.79$). In addition, there was no single question in the BDI questionnaire that showed a significant increase or decrease after one year. There were no significant differences in the first and second fMRI participants in income level, socioeconomic status or BDI score (Table 3). Importantly, there was no correlation between income level and socioeconomic status and BDI score one year later (Supplementary Table 3) or the change in BDI scores (Supplementary Table 4). All these results indicate the difficulty in predicting BDI changes behaviourally.

Prediction of the one-year change in BDI score was conducted using the same sparse Bayesian kernel-based multi-voxel pattern analysis method used for the present case. Figure 3f,g shows plots of the observed (*x* axis) and predicted (*y* axis, by the leave-one-out method) changes of the total BDI score for each participant (from the left amygdala and hippocampus and the right amygdala, respectively). These results show that the predicted change had a positive correlation with the observed change (slope = 0.23, $R=0.36$, $P=1.9\times10^{-3}$ and slope = 0.11, $R=0.30$, $P=9.5\times10^{-4}$, respectively). However, the prediction was not possible for other areas in Table 1; for instance, the insula and caudate nucleus (insula: slope = 0.047, $R=0.051$, $P=0.67$; caudate nucleus: slope = −0.014, $R=0.44$, $P=8.7\times10^{-5}$). Again, it was difficult to predict changes in the BDI score from the response pattern induced by the proposer's face presentation (slope = 0.054, $R=0.16$, $P=0.19$) or offer presentation (slope = 0.067, $R=0.25$, $P=0.035$, Supplementary Fig. 8) and the slopes of the regression lines were significantly different (interaction of linear regression, inequity versus face, $P=0.032$; inequity versus offer, $P=0.035$). Thus, the amygdala and hippocampus response pattern to inequity was found to predict not only the present but also the future depression index.

Differences between prosocials and individualists. We have so far focused on (disadvantageous) inequity in our analysis. However, the definitions of prosocials and individualists (prosocials dislike bidirectional (disadvantageous + advantageous) inequity; individualists prioritize self-reward) made us hypothesize that bidirectional inequity might have different effects on the two groups. Therefore, we examined whether bidirectional inequity (hereafter referred to

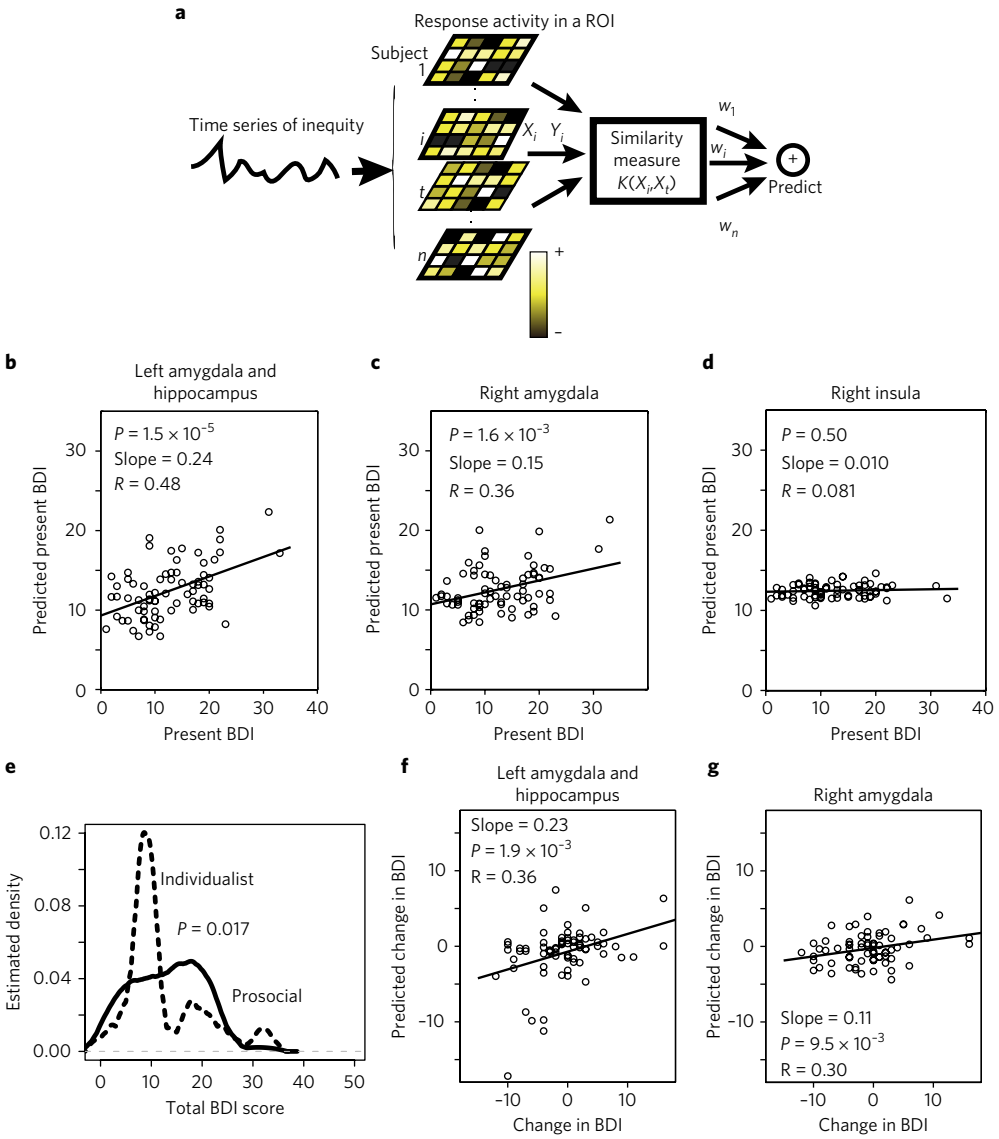

Fig. 3 | Prediction of the present and one-year change in BDI scores. a, Conceptual scheme of the prediction method of BDI scores using multi-voxel pattern analysis. For each participant '*i*', beta values for inequity were computed for all voxels in the ROI and principal component scores were used as input, X_i, to the kernel function, which quantifies the similarity of X_i with new data, X_t. Y_i is a target value representing a present or future BDI score. Y_t is predicted as the weighted sum of $w_i \times K(X_i, X_t)$. The optimization of w_i was conducted using SparseBayes version 2 software (http://www.miketipping.com), where the majority of w_i is estimated to be 0, which allows us to select participants important for the prediction. **b**–**d**, Prediction of present BDI scores from brain response patterns induced by inequity. The present BDI scores were predicted using the inequity-correlated beta values in **b** (left amygdala and hippocampus, **c** (right amygdala) and **d** (right insula and caudate) and plotted against actual BDI scores. Generalization was evaluated by the leave-one-out cross-validation procedure ($n = 73$) and linear regression indicated that prediction of the present total BDI scores was possible in the amygdala and hippocampus regions, but difficult in the insula region. **e**–**g**, Prediction of one-year change in BDI scores from brain response patterns induced by inequity. **e**, The distributions of present (first) BDI scores for prosocials ($n = 47$, solid line) and individualists ($n = 26$, dashed line) were different (bootstrap Kolmogorov–Smirnov test, $P = 0.017$). BDI score changes were predicted from the left amygdala and hippocampus (**f**) and the right amygdala (**g**) ROIs and plotted against the observed changes in BDI scores. Generalization was evaluated by the leave-one-out cross-validation procedure ($n = 73$) and linear regression indicated that prediction of the present BDI scores was possible.

as 'absolute-value inequity' and defined as the absolute value of the difference between the self and other rewards) and disadvantageous inequity result in different predictions of the depression index.

Consistent with disadvantageous inequity (Fig. 1e), the same general linear model analysis showed that amygdala and hippocampus activity correlated with absolute-value inequity more in prosocials than in individualists (Fig. 4a and Table 4). We then compared the predictions of the present BDI score based on disadvantageous and absolute-value inequity. Predictions of the present BDI score based on disadvantageous inequity (using the same ROI as in Fig. 3b) are separately displayed for prosocials and individualists (Fig. 4b). The estimated slopes were positive for both groups and no significant differences were seen (interaction in linear regression, $P = 0.36$), indicating that the sensitivity to disadvantageous inequity in the amygdala and hippocampus is important for the prediction in prosocials and individualists. In contrast, the same analysis based on absolute-value inequity revealed that prediction of the depression index was possible in prosocials, but not in individualists (Fig. 4c,d). The difference in the slopes of these two regression lines was significant (interaction of linear regression, $P = 0.019$). These

Table 3 | Comparisons of income, socioeconomic status and BDI score measurements one year apart

		First measurements	Second measurements		*P* value
Income					
All	Range	1–4 ($n=94$)	1–4 ($n=73$)		
	Mean ± s.e.	2.71 ± 0.11	2.66 ± 0.13		0.81
Prosocial	Range	1–4 ($n=59$)	1–4 ($n=47$)		
	Mean ± s.e.	2.53 ± 0.15	2.61 ± 0.17		0.71
Individualist	Range	1–4 ($n=35$)	1–4 ($n=26$)		
	Mean ± s.e.	3.00 ± 0.17	2.76 ± 0.22		0.40
Male	Range	1–4 ($n=56$)	1–4 ($n=47$)		
	Mean ± s.e.	2.89 ± 0.14	2.56 ± 0.16		0.14
Female	Range	1–4 ($n=38$)	1–4 ($n=26$)		
	Mean ± s.e.	2.44 ± 0.18	2.85 ± 0.22		0.14
Socioeconomic status					
All	Range	2–9 ($n=94$)	2–9 ($n=73$)		
	Mean ± s.e.	5.91 ± 0.15	5.70 ± 0.20		0.79
Prosocial	Range	2–8 ($n=59$)	2–8 ($n=47$)		
	Mean ± s.e.	5.93 ± 0.18	5.72 ± 0.25		0.72
Individualist	Range	3–9 ($n=35$)	3–9 ($n=26$)		
	Mean ± s.e.	5.88 ± 0.18	5.84 ± 0.28		0.81
Male	Range	2–8 ($n=56$)	2–8 ($n=47$)		
	Mean ± s.e.	5.76 ± 0.19	5.59 ± 0.25		1
Female	Range	2–9 ($n=38$)	3–9 ($n=26$)		
	Mean ± s.e.	6.12 ± 0.23	5.88 ± 0.33		0.97
BDI score		First	First	Second	
All	Range	0–33 ($n=94$)	1–33 ($n=73$)	2–28	
	Mean ± s.e.	12.80 ± 0.73	12.60 ± 0.79	11.92 ± 0.72	0.89
Prosocial	Range	1–31 ($n=59$)	1–23 ($n=47$)	2–28	
	Mean ± s.e.	13.15 ± 0.89	12.64 ± 0.91	11.60 ± 0.86	0.73
Individualist	Range	0–33 ($n=35$)	3–33 ($n=26$)	2–24	
	Mean ± s.e.	12.22 ± 1.28	12.53 ± 1.47	12.46 ± 1.28	0.85
Male	Range	0–33 ($n=56$)	1–33 ($n=47$)	2–28	
	Mean ± s.e.	12.89 ± 0.98	12.83 ± 0.95	12.19 ± 0.86	0.91
Female	Range	2–23 ($n=38$)	1–23 ($n=26$)	2–24	
	Mean ± s.e.	12.68 ± 1.17	12.19 ± 1.37	11.42 ± 1.29	0.73

Kolmogorov–Smirnov test.

results indicate that advantageous inequity (when reward for the self is larger than reward for the other) has effects only on prosocials.

Discussion

We have discussed in this paper the relationship between brain response patterns induced by inequity and the depression index in a non-clinical population. We first showed that the distribution of the depression index (that is, the BDI score) was different between prosocials and individualists, who also showed different responses to BDI questions, such as guilty feelings, and differential inequity-correlated fMRI activity in the amygdala and hippocampus during an ultimatum game. We found voxel-level positive and negative correlations between BDI scores and inequity-correlated activity in the amygdala and hippocampus, respectively (Fig. 2b,c). We further showed that the response pattern in the amygdala and hippocampus induced by the inequity could predict not only the present but also the future depression index using a model-based multi-voxel pattern analysis method (Fig. 3). Separate analyses based on disadvantageous and absolute-value inequity revealed that the response to inequity was capable of predicting responses by both prosocials and individualists, but the prediction in response to absolute-value inequity was only effective in prosocials (Fig. 4).

The amygdala and hippocampus have been consistently identified as key brain structures in terms of major depression. Functional activity in the amygdala and hippocampus is different for emotional stimuli[14,15] in depression patients compared with normal controls, as is the anatomical volume of the two structures[16–18,26]. Guilty feelings and self-criticalness, which are often observed in patients with depression have been associated with changes in amygdala and hippocampus activity[27,28]. These functional and anatomical changes in patients with depression have been partly linked with the increased cortisol levels produced by the HPA axis. The HPA axis produces a cascade of hormones including the primary stress hormone cortisol under the influences of excitation input from the amygdala and feedback inhibition from the hippocampus[19]. Several recent fMRI studies have reported that activity in the amygdala is correlated with the way in which prosocial people dislike inequity[11–13]. These results may suggest that in the present study, amygdala activity represents

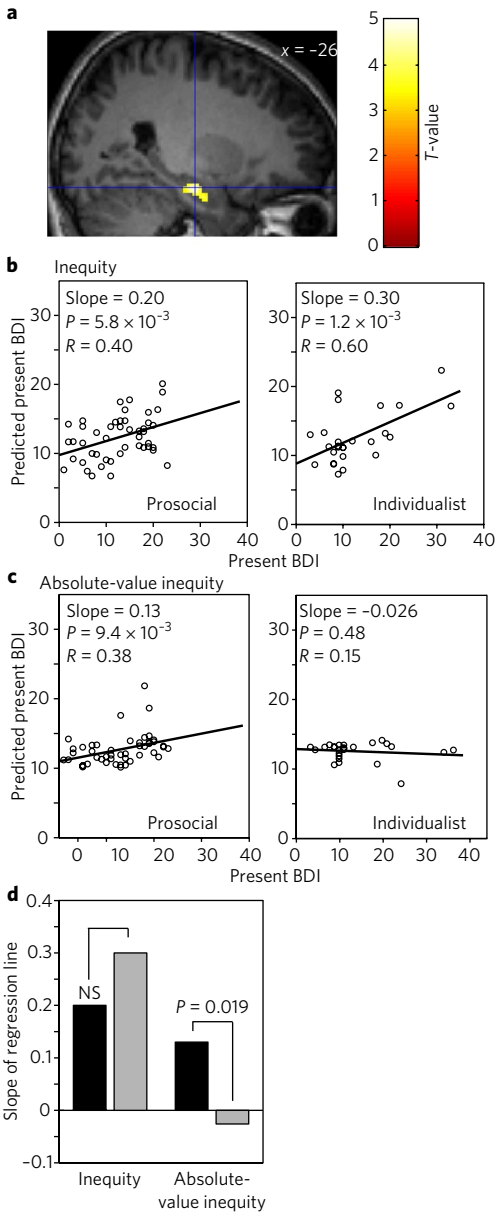

Fig. 4 | Prediction of the present BDI scores from absolute-value inequity responses. a, Whole-brain general linear model analysis conducted in correlation with the absolute value of the difference between self and other rewards. We identified a significant difference in amygdala and hippocampus activation between prosocials ($n=59$) and individualists ($n=35$) in correlation with absolute-value inequity (multiple regression, $P<0.05$ small volume corrected). The MNI coordinates of the cluster peak were −26, −16, −18. $P_{svc}=1.2\times10^{-3}$ (see also Table 4). The displayed peak cluster was used as the ROI for prediction. **b**, Prediction of the present BDI scores based on (disadvantageous) inequity was separately conducted in prosocials (left, $n=47$) and individualists (right, $n=26$) and linear regression showed that both predictions were possible. **c**, Present BDI scores were predicted based on absolute-value inequity responses. The prediction was possible in prosocials (left), but not in individualists (right). **d**, The difference in the slopes of the regression lines between prosocials and individualists was significant for absolute-value inequity (linear regression, $P=0.019$), but not for (disadvantageous) inequity (linear regression, $P=0.36$). NS, not significant.

the stress-induced response induced by economic inequity and hippocampus activity represents the feedback inhibition response. This view is consistent with the voxel-level positive and negative correlations of the amygdala and hippocampus with BDI scores. Other than the amygdala and hippocampus, the inequity response pattern in the caudate nucleus, which was also implicated in inequity processing[13,25], could predict the present BDI but not the one-year change in the BDI. Recent studies have started to show that experiences affect mood and mood in turn affects subsequent decision-making and experiences[29–31]. The amygdala and hippocampus, together with the caudate nucleus, may well be involved in such a two-way interaction mechanism that connects mood and decision-making and can therefore be used to predict the dynamics of an individual's mood.

Accurate prediction of the present and future depression index was not possible using only basic behaviours and the status of the participants, such as the number of prosocial choices in the 8 triple-dominance task and the rejection rate in an ultimatum game, gender income level and socioeconomic status. It might be puzzling at a glance that although prosocials exhibited a higher proportion of middle-to-high BDI scores at the population level, individual BDI scores could not be predicted using the prosocial versus individualist distinction. As an explanation, we propose that the amygdala response to inequity lies at the core of both the BDI dynamics and social value orientation, but the behavioural link between BDI dynamics and social value orientation is weaker than the multidimensional neural link between BDI dynamics and the amygdala response to inequity.

We also showed that amygdala and hippocampus activity patterns for face presentation and offer presentation could not predict present or future BDI scores (Supplementary Figs. 6 and 8). Although these data suggest that brain response patterns in the amygdala and hippocampus to inequity measured by fMRI may be a better predictor of the depression index than behavioural and status information, this does not necessarily mean that inequity-driven brain activity is the only information in the brain that can be used to predict BDI scores. For instance, brain response patterns to other emotional stimuli, such as fearful faces, may also predict the future depression index. Identifying which kind of brain response is most effective for predicting the future change in the depression index is crucial for basic understanding of human social stress and the development of clinical methodologies.

Finally, we demonstrated that the amygdala and hippocampus response pattern induced by absolute-valued inequity could predict the depression index in prosocials but not in individualists (Fig. 4c). This result marks a sharp contrast with disadvantageous inequity, which was predictive of the depression index for both groups (Fig. 4b). This difference coincides well with the definitions of the two groups, as prosocials prioritize equity and thus minimize differences in the self and other interests, while individualists prioritize self-interest. Related to this distinction, previous clinical studies have proposed that people who worry about others' perspectives are more prone to depression[20,21] and this is consistent with our observation that prosocials showed a higher proportion of middle-to-high BDI scores at the population level even though the prosocial versus individualist distinction did not predict individual-level BDI scores. In addition, a recent resting-state fMRI study reported that a neural network that includes the amygdala and hippocampus defines a subcategory of depression patients. Thus, the amygdala and hippocampus response pattern described in the present study may be useful for understanding premorbid personalities and different types of depression[32].

In summary, this study revealed that amygdala and hippocampus response patterns to inequity can predict both the present and future depression index for a non-clinical population, providing behavioural and neural evidence of a biological link between economic inequity and the depression index. In the future, not only large-scale but also long-term clinical (and cross-cultural) studies with higher temporal and spatial resolutions are needed to clarify

Table 4 | Whole-brain activity differences between prosocials and individualists induced by absolute-value inequity

Region	*k*	Peak position			*T*-score	*Z*-score	P_{uncorr} (whole)	P_{FWE} (SVC)
		x	*y*	*z*				
Amy/hippo (L)	231	−26	−16	−18	4.97	4.65	1.6×10^{-6}	1.2×10^{-3}
Amy (R)	52	20	−2	−22	4.67	4.40	5.3×10^{-6}	1.8×10^{-3}
Hippo (R)	37	28	−18	−18	4.48	4.24	1.1×10^{-5}	3.7×10^{-3}
Insula (R)	60	34	26	−2	4.71	4.44	4.6×10^{-6}	1.1×10^{-3}

Amy, amygdala; hippo, hippocampus; L, left; R, right; SVC, small volume correction. SVC used the anatomical region that contained the peak voxel of the cluster. MNI coordinates and *P* values at the peak positions are shown.

how interactions between the amygdala and hippocampus lead to depression symptoms under economic inequity and which response patterns can be recognized as warning signals of depression.

Methods

Ultimatum game. We used the ultimatum game[22] to examine brain responses to inequity. As shown in Fig. 1c, after the name and face of a proposer were displayed for 1 s, the participant was asked to decide whether to accept or reject the offered division of ¥500 (equivalent to US $5) and respond by a button press within 1 s after a beep (otherwise, the reward for the trial became ¥0). Base offers were one of ¥350–150, ¥300–200, ¥250–250, ¥200–300, ¥150–350, ¥100–400 or ¥50–450 for the participant and proposer (each base offer appeared eight times in one session in random order). Therefore, one session comprised 56 trials. We did not include ¥400–100 or ¥450–50 splits, not only because we confirmed that very few participants rejected them in our pilot experiment but also because we wished for the scan time to remain short for participants' concentration. In our version of the ultimatum game, the base offers were fluctuated in each trial by adding a uniform random number ranging from ¥−25 to ¥25. This modification was introduced to maximize the participants' involvement in the task. The 'unfair (disadvantageous)' condition was defined as trials in which the reward for other was larger than the reward for self (that is, ¥200–300, ¥150–350, ¥100–400 and ¥50–450 base offer trials). The disadvantageous inequity was the amount of the reward for the other minus the reward for self when positive, otherwise it took a value of 0. On the other hand, when we considered absolute-value inequity, we used the absolute difference between the self and other rewards in all trials. Participants were instructed that their task performances determined the amount of reward. In addition, the name and face were utilized once for each individual proposer and the task was a sequential one-shot ultimatum game. One-fourth of the distributed money plus a basic honorarium (¥3,000) were provided to the participants. All faces were taken from the Advanced Telecommunication Rearch Institute facial expression database[33] and had neutral facial expressions. Participants were informed that the proposers were students of other universities nearby and their rewards were determined by the participants' choices in the scanner. No participants raised questions about this experimental setting in the post-experimental interview. One trial lasted 21 ± 2 s, and the total time of a session was 1,176 s.

Prediction of the BDI score. For participant '*i*', beta values in correlation with (disadvantageous or absolute-value) inequity extracted from all voxels in the ROI were processed by principal component analysis (X_i). The actual BDI score (or its change) for participant '*i*' is denoted as Y_i. The *i*-th input to the prediction system of *n* participants was X_i and Y_i. The task of the system was to make a prediction ($\hat{Y}_t$) for the target participant '*t*' that minimized the expectation of error ($Y_t - \hat{Y}_t$), which we achieved using the sparse Bayesian methodology[34]; that is, maximization of the posterior probability of parameters and hyper-parameters given the data. In the present study, we used a kernel-based model[35]. When we conducted the predictions based on a proposer's face presentation and offer presentation, we used beta values in correlation with the face presentation and offer presentation regressors, respectively.

Bayesian kernel method. In the Bayesian kernel method[36], the prediction $\hat{Y}_t$ of Y_t was modelled by a weighted sum of $(n-1)$ kernel functions:

$$\hat{Y}_t = \sum_i w_i K(X_i, X_t)$$

Here, kernel function $K(X_i, X_t)$ measures the similarity between the *i*-th participant's brain activity pattern, X_i, and target brain activity pattern, X_t. Weights, w_i, are adjustable parameters and estimated so as to minimize the expectation of error ($Y_t - \hat{Y}_t$) in a Bayesian manner. This model is linear in its parameters, which allows for efficient computation. At the same time, the kernel function can be non-linear and represent complex functions. We subtracted baseline symptom by including a constant in the regression model.

The key to the sparse Bayesian methodology is the definition of a hyper-parameterized prior over the model parameters *w* (set of w_i) of the form:

$$p(w|\alpha) \propto \prod_{i=1}^{n} \alpha_i^{\frac{1}{2}} exp\left(-\frac{\alpha_i}{2} w_i^2\right)$$

This type of prior favours models that fit the data well and are also sparse. In other words, the prior locates most of its probability mass at $w_i = 0$, which means in the present study that only a small number of participants take a non-zero value of w_i and are used for the prediction. The sparse Bayesian method computes the posterior distribution over the hyper-parameters α_i given the data and returns their most probable values by maximizing the marginal likelihood function, which results in a posterior distribution over the parameters w_i, many of which are set to 0. In the current implementation, optimization was conducted using SparseBayes software version 2.0 (http://www.miketipping.com/sparsebayes.htm) on MATLAB and we computed *K* based on the linear spline kernel $K(X_i, X_t)$ proposed by Vapnik et al.[37] for X_i and X_t. Hyper-parameters of the kernel were determined by the tenfold cross-validation procedure so that the mean squared errors between the observed and predicted changes in the BDI score were minimized (Supplementary Fig. 9). The goodness of the generalization in prediction (that is, Fig. 3) was evaluated by the leave-one-out cross validation procedure[34].

Participants. The ethical committees of the National Institute of Information and Communications Technology and Tamagawa University approved this study. Informed consent for the behavioural and fMRI experiments was obtained from all participants before the experiments started.

Code availability. The MATLAB codes that support the findings of this study are available from the corresponding author upon request.

Data availability. The preprocessed fMRI and BDI data that support the findings of this study are available from the corresponding author upon request.

Received: 13 December 2016; Accepted: 21 August 2017;
Published online: 2 October 2017

References

1. Piketty, T. *Capital in the Twenty-first Century* (Belknap Press, Cambridge, MA, 2014).
2. Kawachi, I. & Kennedy, B. P. *The Health of Nation: Why Inequity is Harmful to Your Health* (The New Press, New York, NY, 2002).
3. Wilkinson, R. G. & Pickett, K. E. Income inequality and population health: a review and explanation of the evidence. *Soc. Sci. Med.* **62**, 1768–1784 (2006).
4. Marmot, M. G. et al. Health inequalities among British civil servants: the Whitehall II study. *The Lancet* **337**, 1387–1393 (1991).
5. Hamad, R., Fernald, L. C., Karlan, D. S. & Zinman, J. Social and economic correlates of depressive symptoms and perceived stress in South African adults. *J. Epidemiol. Community Health* **62**, 538–544 (2008).
6. Stansfeld, S. A., Head, J., Fuhrer, R., Wardle, J. & Cattell, V. Social inequalities in depressive symptoms and physical functioning in the Whitehall II study: exploring a common cause explanation. *J. Epidemiol. Community Health* **57**, 361–367 (2003).
7. Turner, R. J., Lloyd, D. A. & Roszell, P. Personal resources and the social distribution of depression. *Am. J. Community Psychol.* **27**, 643–672 (1999).
8. Jang, K. L. *The Behavioral Genetics of Psychopathology: A Clinical Guide* (Lawrence Erlbaum Association, Mahwah, NJ, 2008).
9. Messick, D. M. & McClintock, C. G. Motivational bases of choice in experimental games. *J. Exp. Soc. Psychol.* **4**, 1–25 (1968).
10. Van Lange, P. A. M. The pursuit of joint outcomes and equality in outcomes: an integrative model of social value orientation. *J. Pers. Soc. Psychol.* **77**, 337–349 (1999).

11. Gospic, K. et al. Limbic justice—amygdala involvement in immediate rejection in the Ultimatum Game. *PLoS Biol.* **9**, e1001054 (2011).
12. Haruno, M. & Frith, C. D. Activity in the amygdala elicited by unfair divisions predicts social value orientation. *Nat. Neurosci.* **13**, 160–161 (2010).
13. Haruno, M., Kimura, M. & Frith, C. D. Activity in the nucleus accumbens and amygdala underlies individual differences in prosocial and individualistic economic choices. *J. Cog. Neurosci.* **26**, 1861–1870 (2014).
14. Groenewold, N. A., Opmeer, E. M., de Jonge, P., Aleman, A. & Costafreda, S. G. Emotional valence modulates brain functional abnormalities in depression: evidence from a meta-analysis of fMRI studies. *Neurosci. Biobehav. Rev.* **37**, 152–163 (2013).
15. Matthews, S. C., Strigo, I. A., Simmons, A. N., Yang, T. T. & Paulus, M. P. Decreased functional coupling of the amygdala and supragenual cingulate is related to increased depression in unmedicated individuals with current major depressive disorder. *J. Affect. Disord.* **111**, 13–20 (2008).
16. Bremner, J. D. et al. Hippocampal volume reduction in major depression. *Am. J. Psychiatry* **157**, 115–118 (2000).
17. Lorenzetti, V., Allen, N. B., Fornito, A. & Yücel, M. Structural brain abnormalities in major depressive disorder: a selective review of recent MRI studies. *J. Affect. Disord.* **117**, 1–17 (2009).
18. Sheline, Y. I., Wang, P. W., Gado, M. H., Csernansky, J. G. & Vannier, M. W. Hippocampal atrophy in recurrent major depression. *Proc. Natl Acad. Sci. USA* **93**, 3908–3913 (1996).
19. Nestler, E. J., Hyman, S. E. & Malenka, R. J. *Molecular Neuro-pharmacology. A Foundation for Clinical Neuroscience* 2nd edn (McGraw-Hill, New York, NY, 2009).
20. Akiskal, H. S., Hirschfeld, R. M. & Yerevanian, B. I. The relationship of personality to affective disorders. *Arc. Gen. Psychiatry* **40**, 801–810 (1983).
21. Von Zerssen, D., Tauscher, R. & Possl, J. The relationship of premorbid personality to subtypes of an affective illness. A replication study by means of an operationalized procedure for the diagnosis of personality structures. *J. Affect. Disord.* **32**, 61–72 (1994).
22. Güth, W., Schmittberger, R. & Schwarze, B. An experimental analysis of ultimatum bargaining. *J. Econ. Behav. Organ.* **3**, 367–388 (1982).
23. Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E. & Cohen, J. D. The neural basis of economic decision-making in the ultimatum game. *Science* **300**, 1755–1758 (2003).
24. Beck, A. T., Steer, R. A., Ball, R. & Ranieri, W. Comparison of Beck Depression Inventories -IA and -II in psychiatric outpatients. *J. Pers. Assess.* **67**, 588–597 (1996).
25. Tricomi, E., Rangel, A., Camerer, C. & O'Doherty, J. Neural evidence for inequality averse social preferences. *Nature* **463**, 1089–1091 (2011).
26. Schmaal, L. et al. Subcortical brain alterations in major depressive disorder: findings from the ENIGMA Major Depressive Disorder working group. *Mol. Psychiatry* **21**, 806–812 (2016).
27. Michl, P. et al. Neurobiological underpinnings of shame and guilt: a pilot fMRI study. *Soc. Cogn. Affect. Neurosci.* **9**, 150–157 (2014).
28. Doerig, N. et al. Neural representation and clinically relevant moderators of individualised self-criticism in healthy subjects. *Soc. Cogn. Affect. Neurosci.* **9**, 1333–1340 (2014).
29. Eldar, E. & Niv, Y. Interaction between emotional state and learning underlies mood instability. *Nat. Commun.* **6**, 6149 (2015).
30. Eldar, E., Rutledge, R. B., Dolan, R. J. & Niv, Y. Mood as representation of momentum. *Trends Cogn. Sci.* **20**, 15–24 (2016).
31. Headey, B. & Veenhoven, R. in *How Harmful is Hapiness? Consequences of Enjoying Life or Not* (ed. Veenhoven, R.) 106–127 (Universitaire Pers, Rotterdam, 1989).
32. Drysdale, A. T. et al. Resting-state connectivity biomarkers define neurophysiological subtypes of depression. *Nat. Med.* **23**, 28–38 (2017).
33. Ogawa, T. & Oda, M. *Construction and Evaluation of the Facial Expression Database* ATR Technical Report TR-H-244 (1998).
34. Bishop, C. M. *Pattern Recognition and Machine Learning* (Springer, New York, NY, 2006).
35. Shawe-Taylor, J. & Cristianini, N. *Kernel Methods for Pattern Analysis* (University Press, Cambridge, 2004).
36. Tipping, M. E. Sparse bayesian learning and the relevance vector machine. *J. Mach. Learn. Res.* **1**, 211–244 (2001).
37. Vapnik, V., Golowich, S. E. & Smola, A. Support vector method for function approximation, regression estimation, and signal processing. In *Proc. 9th International Conference on Neural Information Processing Systems* 281–287 (MIT Press, Cambridge, MA, 1996).

Acknowledgements

This work was supported by Core Research for Evolutional Science and Technology (CREST), Japan Science and Technology Agency (JST), the Center of Innovation at Osaka University and Grant-in-Aid for Scientific Research (KAKENNHI) (17H06314 and 26242087). We are grateful to S. Tada and T. Haji for technical assistance and P. Karagiannis for editing an early version of the manuscript. The funders had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript.

Author contributions

M.H. and T.Y. designed the study. T.T. conducted the experiment. T.T. and M.H. analysed the data. T.T. and M.H. wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at doi:10.1038/s41562-017-0207-1.

Reprints and permissions information is available at www.nature.com/reprints.

Correspondence and requests for materials should be addressed to M.H.

Publisher's note: Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

nature research

Corresponding author(s): Masahiko Haruno

☐ Initial submission ☐ Revised version ☒ Final submission

Life Sciences Reporting Summary

Nature Research wishes to improve the reproducibility of the work that we publish. This form is intended for publication with all accepted life science papers and provides structure for consistency and transparency in reporting. Every life science submission will use this form; some list items might not apply to an individual manuscript, but all fields must be completed for clarity.

For further information on the points included in this form, see Reporting Life Sciences Research. For further information on Nature Research policies, including our data availability policy, see Authors & Referees and the Editorial Policy Checklist.

Experimental design

1. Sample size

Describe how sample size was determined.

The total sample size of fMRI measurement was determined based on our previous study.

2. Data exclusions

Describe any data exclusions.

We only considered prosocial and individualistic participants determined by the Triple-Dominance task.

3. Replication

Describe whether the experimental findings were reliably reproduced.

Prosocial's Inequity-correlated activity in the amygdala has been reproduced in our and other group's studies. We confirmed the replication of depression index prediction results by sampling subpopulations.

4. Randomization

Describe how samples/organisms/participants were allocated into experimental groups.

Training and test participants were allocated by the leave-one-out cross validation.

5. Blinding

Describe whether the investigators were blinded to group allocation during data collection and/or analysis.

We were blind to Training and test participants separation since it was randomly and systematically determined by the cross validation.

Note: all studies involving animals and/or human research participants must disclose whether blinding and randomization were used.

6. Statistical parameters

For all figures and tables that use statistical methods, confirm that the following items are present in relevant figure legends (or in the Methods section if additional space is needed).

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement (animals, litters, cultures, etc.)
☐	☒	A description of how samples were collected, noting whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☒	☐	A statement indicating how many times each experiment was replicated
☐	☒	The statistical test(s) used and whether they are one- or two-sided (note: only common tests should be described solely by name; more complex techniques should be described in the Methods section)
☐	☒	A description of any assumptions or corrections, such as an adjustment for multiple comparisons
☐	☒	The test results (e.g. *P* values) given as exact values whenever possible and with confidence intervals noted
☐	☒	A clear description of statistics including central tendency (e.g. median, mean) and variation (e.g. standard deviation, interquartile range)
☐	☒	Clearly defined error bars

See the web collection on statistics for biologists for further resources and guidance.

Software

Policy information about availability of computer code

7. Software

Describe the software used to analyze the data in this study.	R and matlab.

For manuscripts utilizing custom algorithms or software that are central to the paper but not yet described in the published literature, software must be made available to editors and reviewers upon request. We strongly encourage code deposition in a community repository (e.g. GitHub). *Nature Methods* guidance for providing algorithms and software for publication provides further information on this topic.

Materials and reagents

Policy information about availability of materials

8. Materials availability

Indicate whether there are restrictions on availability of unique materials or if these materials are only available for distribution by a for-profit company.	All materials were available from us or companies.

9. Antibodies

Describe the antibodies used and how they were validated for use in the system under study (i.e. assay and species).	NA.

10. Eukaryotic cell lines

a. State the source of each eukaryotic cell line used.	NA.
b. Describe the method of cell line authentication used.	NA.
c. Report whether the cell lines were tested for mycoplasma contamination.	NA.
d. If any of the cell lines used are listed in the database of commonly misidentified cell lines maintained by ICLAC, provide a scientific rationale for their use.	NA.

Animals and human research participants

Policy information about studies involving animals; when reporting animal research, follow the ARRIVE guidelines

11. Description of research animals

Provide details on animals and/or animal-derived materials used in the study.	We used human participants.

Policy information about studies involving human research participants

12. Description of human research participants

Describe the covariate-relevant population characteristics of the human research participants.	Three hundred and forty three Japanese students (181 males, age = 19.0±0.096, and 162 females, age = 19.2±0.11) who did not declare any history of neurological or psychiatric disorders participated in the behavioral experiment using the Triple-Dominance measure task and BDI-II (BDI, hereafter) questionnaire. We identified 174 prosocials (88 males and 86 females) and 59 individualists (40 males and 19 females). We invited all these prosocials and individualists to the fMRI experiments. As a result of matching their availability and scanning slots, 94 participants (56 males: age = 19.4±0.17, 32 prosocials and 24 individualists; and 38 females: age = 19.5±0.24, 27 prosocials and 11 individualists.

nature research

Corresponding Author: Masahiko Haruno

Date: 5th August 2017

Reporting Summary for MRI studies

Form fields will expand as needed. Please do not leave fields blank.

Experimental design

1. Describe the experimental design.	Event-related.
2. Specify the number of blocks, trials or experimental units per session and/or subject, and specify the length of each trial or block (if trials are blocked) and interval between trials.	56 trials, 21±2 sec/trial, interval between trials = 9±2 sec.
3. Describe how behavioral performance was measured.	Button press & response time were recorded. Button press during a short time window (1.5s) for economic choices

Acquisition

4. Imaging	
a. Specify the type(s) of imaging.	Functional imaging.
b. Specify the field strength (in Tesla).	3 Tesla.
c. Provide the essential sequence imaging parameters.	Gradient echo, EPI, field of view =192mm, matrix size = 64 x 64, slice thickness = 3mm, TE = 2.5msec, TR =2sec, flip angle =90.
d. For diffusion MRI, provide full detail on imaging parameters.	NA.
5. State area of acquisition	Whole brain scan.

Preprocessing

6. Describe the software used for preprocessing.	spm12 for realignment, co-registration to Ta&T2 structural images, segmentation, normalization and smoothing.
7. Normalization	
a. If data were normalized/standardized, describe the approach(es).	non-linear
b. Describe the template used for normalization/transformation.	ICBM152
8. Describe your procedure for artifact and structured noise removal.	6-dimensional motion parameters
9. Define your software and/or method and criteria for volume censoring and state the extent of such censoring.	spm12. We also censored volumes during scanning.

Statistical modeling & inference

10. Define your model type and settings.	type:GLM and multivariate pattern analysis setting: SPM12 and Sparse Bayese Toolbox ver 2.0

11. Specify the precise effect tested.	the effects of social value orientation and socio-economic status on the activity induced by reward differences were tested. The factorial design was used. We measure prediction goodness of BDI scores based on the multi-variate pattern analysis of beta values obtained by the SPM GLM analysis. Evaluation was done based on the one-leave-out cross validation procedure.
12. Analysis	
a. Specify whether analysis is whole brain or ROI-based.	whole brain analysis (for key results) and ROI based small volume correction.
b. If ROI-based, describe how anatomical locations were determined.	We used the ROIs defined by Shen et al, (2013).
13. State the statistic type for inference. (See Eklund et al. 2016.)	voxel wise statistics and the one-leave-out cross validation procedure.
14. Describe the type of correction and how it is obtained for multiple comparisons.	FWE, Bonferroni method was used for multi-clusters in small volume corrected and whole-rain corrected results.
15. Connectivity	
a. For functional and/or effective connectivity, report the measures of dependence used and the model details.	NA.
b. For graph analysis, report the dependent variable and functional connectivity measure.	NA.
16. For multivariate modeling and predictive analysis, specify independent variables, features extraction and dimension reduction, model, training and evaluation metrics.	Prediction was done for each participant's depression index (BDI). Features are a vector of beta values which were obtained through a standard SPM GLM analysis. For dimension reduction, we applied PCA, and evaluation was done based on the one-leave-out cross validation procedure.