Supporting material for "Value of freedom to choose encoded by the human brain" by Juri Fujiwara, Nobuo Usui, Soyoung Q Park, Tony Williams, Toshio Iijima, Masato Taira, Ken-Ichiro Tsutsui and Philippe N. Tobler

Illustration of individual difference assessment by simulation

In the main part of the paper, we used several different methods to quantify individual differences in the valuation of choice (Fig. 3). One method entailed using the slope in indifference values (converted to ratings) and comparing it to the slope in the maximum possible pre-ratings (both slopes were computed as a function of the number of choice alternatives). This measure thus captured how much additional value can maximally arise from having more items to choose from for a given choice in the different conditions. In order to determine the amount of additional value, we used all the pre-ratings and sampled 2, 4, or 8 ratings 500,000 times. Each time, we noted the maximum rating and determined the means and standard deviations of these maximum ratings for each condition. These two values then allowed us to plot Gumbel distributions for each condition separately (Fig. S1, top). To compute the slope, we took the mode of each distribution as a function of the number of choice alternatives. In Fig. 3c, we then compared these slopes to the slopes that were entailed in the indifference values, based on Gaussian distributions as plotted with the mean and standard deviations in indifference values (Fig. S1, bottom).

Additional regression analysis on overvaluation based on expected utility

In addition to the regression analyses shown in Tab. 1, we ran regression analyses on all the mistakes (i.e. when the lower utility option was chosen) and on all choices. In both of these analyses we used our definition of choice as captured by the number of choice items. We also considered an alternative, binary, definition of choice, according to which choice does not depend on the number of items (1 item vs. 2, 4 and 8 items). Throughout, we controlled for differences in expected utility. First, we regressed the subject's choice – equal to 0 (1) when the money (choice) option was selected – against the number of choice items. Thus, we used only trials in which a subject made a mistake, meaning that the subject selected the option with lower expected utility. In line with Fig. 3f, this showed a significant effect of the variable "number of items", indicating that participants chose the choice option increasingly often when the opportunity to choose increased (Tab. S1). The alternative, binary choice variable independent variable – equal to 0 (1) when the choice size contained 1 (2,4, or 8) items – was not significant. Second,

we repeated this analysis using all trials and not only those in which a subject made a mistake (Tab. S2). With increasing opportunity to choose in Choice 2, participants chose the choice option more often in Choice 1, even though we controlled for the difference in expected utility between the various options. In this more sensitive analysis, also the binary independent variable for choice was significant. Thus, irrespective of how choice is defined, participants on average overvalue it. In these analyses, the significant variable “Constant” (choice from 1 item) can be interpreted as risk aversion: participants tend to prefer the safe monetary amount when they have no opportunity to choose. By contrast, they become increasingly risk seeking the more items they are offered to choose from in Choice 2, in violation of rational choice models (which do allow for increasing tolerance for risk but do not allow individuals to change from being risk-averse to risk-seeking).

Psychophysiological interactions (PPIs)

In the main part of the paper, we tested for activations that specifically coded the value of choice over and above the value of items and vice versa and found limited activations at an exploratory threshold (a temporal region coded the value of items more strongly than the value of choice and a region in anterior cingulate cortex (ACC) showed preferential activation for value of choice over the value of items). In order to further assess aspects specific to value type with respect to the common value-processing striatal regions identified in Fig. 4e, we performed a whole-brain PPI analysis to determine whether there was value-specific connectivity with the common striatum region.

PPI methods

First, we sorted the trials into 8 classes on the basis of value of item and value of choice (2 value-of-item levels [high, low] × 4 value-of-choice levels [1, 2, 4, 8]). We extracted the entire time series of each subject in the bilateral striatum cluster. Since the time series were highly correlated ($r=0.7$; $p<0.01$), we collapsed them over the two hemispheres. Without combination, we found somewhat weaker but qualitatively similar results from each hemisphere separately. PPI regressors were created by multiplying the normalized (z-transformed) time series with condition vectors that contained ones for 6 TRs after each trial belonging to the respective class and zeros otherwise. Z transformation was used to prevent the results from reflecting differences in means between conditions. The time window of 6 TRs was selected to capture the entire

positive part of the hemodynamic response function (HRF; cf. Kahnt et al., 2009; Park et al., 2010). Here, we relied on correlations in the observed BOLD time-series data and made no assumptions about the nature of the neural event contributing to the BOLD signal.

The PPI general linear model included the following regressors: 1) 8 psychological regressors convolved with an HRF (4 onset regressors for the value-of-choice levels at a low value-of-item level and 4 regressors for the value-of-choice levels at a high value-of-item level), 2) 1 physiological regressor (the entire time series from the striatum), and finally 3) 8 PPI regressors. The value-of-item contrast was computed by contrasting the high versus low value-of-item PPI regressors, whereas the value of choice was computed by contrasting 1 and 2 vs. 4 and 8 choice alternative PPI regressors.

PPI results

The PPI analysis revealed that value of items significantly modulated striatal connectivity with the insula (-32/8/12; Fig. S2a; Tab. S3). This coupling was stronger when the value of items was high as compared to low (Fig. S2b), suggesting more intimate cross-talk between these two regions during high than low item value trials. In contrast, striatal connectivity with ACC was significantly modulated by the opportunity to choose (18/50/18; Fig. S2c). Specifically, this coupling was negative, indicating that the connectivity between striatum and ACC was higher when there were fewer choice alternatives (Fig. S2d). This suggests that cingulate regions primarily synchronize with the striatum when fewer choices are available.

The dorsal ACC has been shown to be more strongly activated by cues predicting that an opportunity to choose will certainly or possibly arise than by cues predicting that there will be no opportunity to choose (Leotti & Delgado, 2011). Our exploratory analyses support these findings and raise the possibility that the ACC may be particularly susceptible to value-related striatal input when making a choice is relatively easy (due to there being fewer choice alternatives). Further research is necessary to test whether the ACC is more in tune with the more frontal and cortical regions, such as dorsolateral prefrontal cortex (DLPFC) or ventromedial prefrontal cortex (VMPFC), when making a choice is more difficult due to there being more choice alternatives with many different attributes. Interestingly, the difficulty of integrating the value of attributes has been associated with the DLPFC whereas the value of multiple

attributes appears to be integrated in VMPFC (Kahnt et al., 2011).

References

Leotti LA, Delgado MR (2011) The inherent reward of choice. *Psychol Sci* 22:1310-1318.

Kahnt T, Park SQ, Cohen MX, Beck A, Heinz A, Wrase J (2009) Dorsal striatal-midbrain connectivity in humans predicts how reinforcements are used to guide decisions. J Cogn Neurosci 21:1332-1345.

Kahnt T, Heinzle J, Park SQ, Haynes JD (2011) Decoding different roles for vmPFC and dlPFC in multi-attribute decision making. Neuroimage 56:709-715.

Park SQ, Kahnt T, Beck A, Cohen MX, Dolan RJ, Wrase J, Heinz A (2010) Prefrontal cortex fails to learn from reward prediction errors in alcohol dependence. *J Neurosci* 30:7749-7753.

EU Difference	-0.013	-0.013	-0.013
	(7.90)**	(8.16)**	(8.43)**
Choice (binary)		0.130	
		(1.72)	
Number of items			*0.021*
			*(2.62)**
Constant	0.554	0.438	0.470
	(13.36)**	(5.71)**	(9.38)**
R^2	0.52	0.52	0.53
N	668	668	668

* $p<0.05$; ** $p<0.01$

Table S1.Choice Overvaluation: linear probability model
This analysis uses only trials where the lower-valued option was selected (mistakes). Dependent variable is option selected, equal to 0 (1) when money (choice) option is selected. The independent variable "Choice (binary)" is equal to 0 (1) when choice option contains 1 (2, 4, or 8) item(s). We also subtract 1 to construct "Number of items" so that the estimate can be interpreted directly as the effect for no choice (1 item). Robust standard errors clustered by subject. t-statistic reported in parentheses.

Logit regressions

EU Difference	0.052	0.052	0.053
	(7.62)**	(7.35)**	(7.11)**
Choice (binary)	–	0.589	–
	–	(2.08)*	–
Number of items	–	–	*0.134*
	–	–	(2.33)*
Constant	-0.030	-0.475	-0.391
	(0.11)	(4.04)**	(2.45)*
N	4,235	4,235	4,235

* $p<0.05$; ** $p<0.01$. Robust standard errors clustered by subject. t-statistic reported in parentheses.

Linear probability model

EU Difference	0.006	0.006	0.006
	(12.99)**	(13.18)**	(13.26)**
Choice (binary)	–	0.069	–
	–	(2.42)*	–
Number of items	–	–	*0.015*
	–	–	(2.40)*
Constant	0.482	0.429	0.439
	(13.10)**	(20.45)**	(17.33)**
R^2	0.43	0.44	0.44
N	4,235	4,235	4,235

* $p<0.05$; ** $p<0.01$. Robust standard errors clustered by subject. t-statistic reported in parentheses. Constant not significantly different from 0.5 (random choice) in baseline regression.

Probit regressions

EU Difference	0.028	0.028	0.028
	(7.64)**	(7.42)**	(7.26)**
Choice (binary)	–	0.335	–
	–	(2.16)*	–
Number of items	–	–	*0.066*
	–	–	(2.17)*
Constant	-0.049	-0.310	-0.244
	(0.32)	(4.24)**	(2.56)*
N	4,235	4,235	4,235

* $p<0.05$; ** $p<0.01$. Robust standard errors clustered by subject. t-statistic reported in parentheses.

Table S2.Choice Overvaluation: This analysis uses all trials. Dependent variable is option selected, equal to 0 (1) when money (choice) option is selected. The independent variable "Choice (binary)" is equal to 0 (1) when choice option contains 1 (2, 4, or 8) item(s). We also subtract 1 to construct "Number of items" so that the estimate can be interpreted directly as the effect for no choice (1 item).

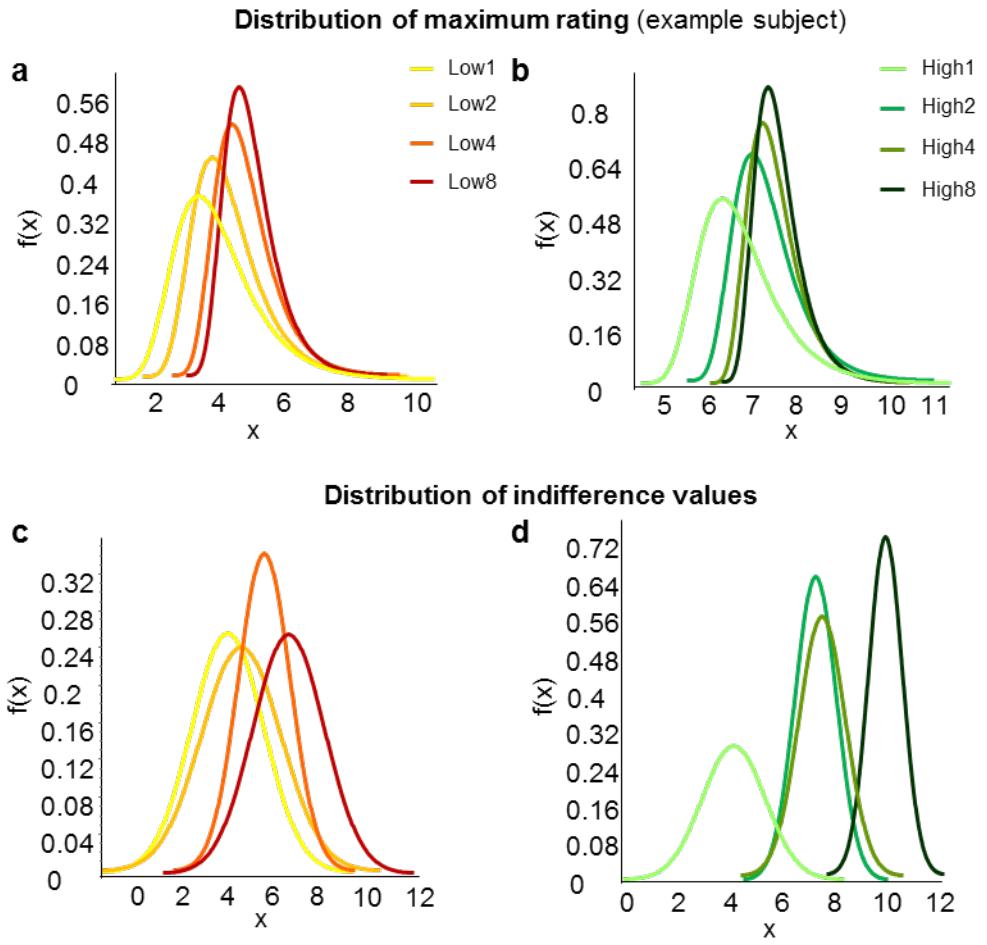

Figure S1. Example subject. (a, b) Gumbel distributions of maximum rating in (a) low-value and (b) high-value conditions. (c, d) Gumbel distributions of indifference values (converted to rating equivalents). The modes in (c and d) were slightly more spread out than those in (a and b), resulting in slight overvaluation in the slope plot of Figure 3c.

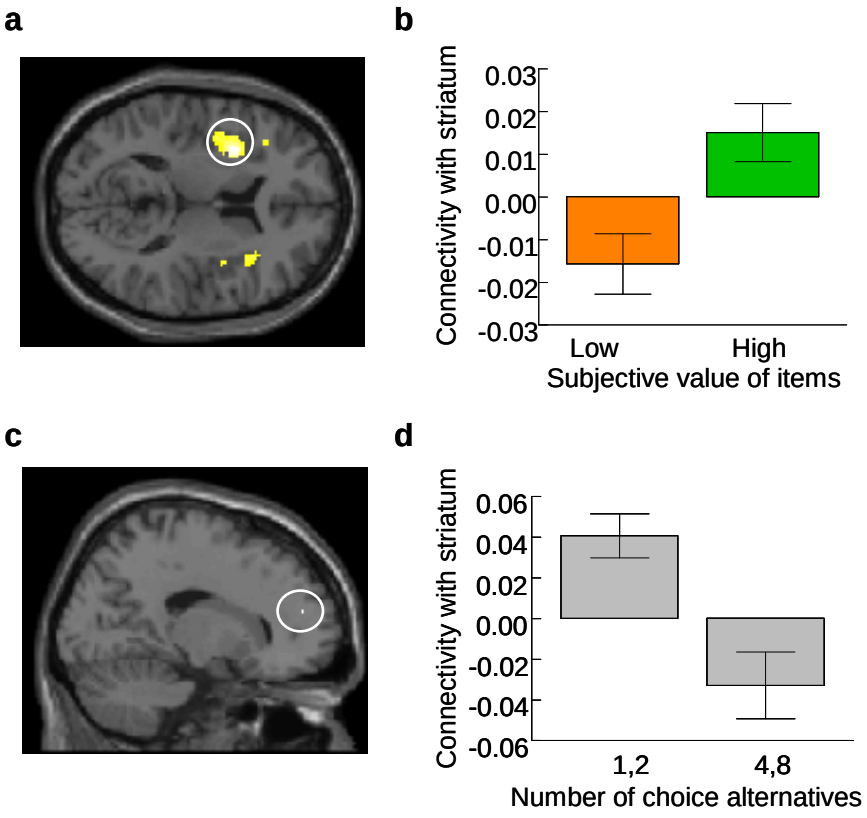

Figure S2. Connectivity results. (a) Location in insula showing positive coupling with item value (x/y/z: -32/8/12). (b) Illustration of effect shown in (a). (c) Location in anterior cingulate cortex showing negative coupling with opportunity to choose (x/y/z: 18/50/18). (d) Illustration of effect shown in (c). Analysis was based on common value cluster in striatum. For (c,d), low (1, 2) and high (4, 8) degrees of freedom were collapsed. Error bars indicate standard error of the mean.

		x	y	z	z score	Voxels
Insula	L	-34	8	12	3.75	257
	R	36	-2	18	3.18	42
Caudate	L	-16	22	14	2.79	12
	R	22	22	16	3.67	127
Medial temporal lobe	L	-28	-48	18	3.22	30
	R	32	-44	16	2.93	7

P<0.005, uncorrected, >5 voxels

Table S3. Additional PPI results for the value of the item. Regions more strongly coupled with striatum in trials in which item value was high as compared to low.

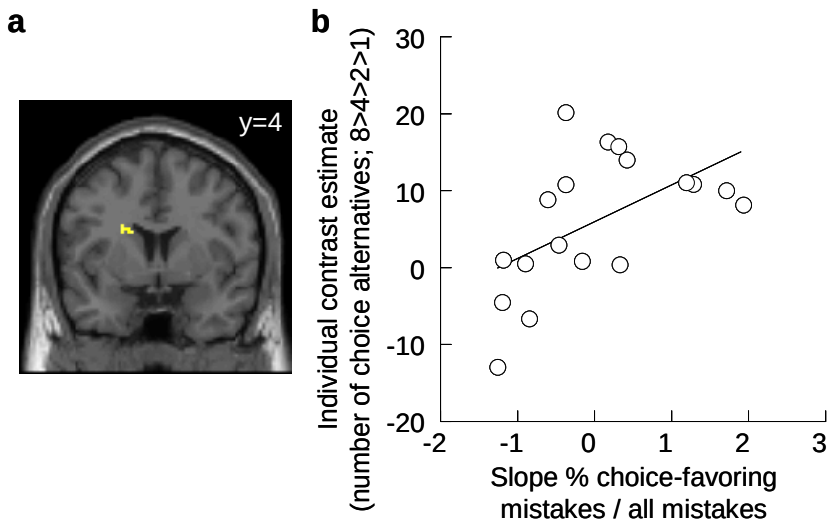

Figure S3. Additional analyses related to choice overvaluation. (a) Location in dorsolateral striatum showing correlation between utility-based choice overvaluation and activation increases to higher number of choice alternatives. In this analysis, we assessed the correlation between the tendency to mistakenly choose the choice option as the number of choice alternatives increased with brain activation to these conditions (8>4>2>1). (b) Illustration of effect in (a).