Supplemental Methods

Task Description

Each trial consisted of a choice between a smaller-sooner reward and a larger-later reward. The choice was presented serially, in three stages (see Fig. 1). This serial mode of presentation was a novel aspect of the study in relation to previous designs used in fMRI (e.g. McClure et al., 2004; Kable and Glimcher, 2007) where both options are presented together and the choice can be made from the onset of the presentation (i.e. a single stage). Our design was motivated to ensure we could separate the neural valuation signals for each option as well as separate valuation processes from the actual decision-making processes (thereby providing less ambiguous imaging data). Note that there may be additional processes occurring at the time of the second option, such as relative comparison and prediction error coding. However, the fMRI analysis is rationalised on the basis that the value should still be encoded at the time of the second stimulus, in addition to these other processes. (Note the presentation of sooner or later, and larger or smaller amounts, was randomized between option 1 and 2).

The first two stages consisted of presentation of the details of each option, *i.e.* the value of the reward in pounds and the delay to its receipt in units of weeks and months. After presentation of the options, a third screen prompted the subject to choose between 'option 1' (the option which was presented first) or 'option 2', by means of a button-box, using their right hand. A three-second delay ensued each of the three phases. The choice could only be made during the three seconds following presentation of the choice screen.

Once a choice had been made, the chosen option was highlighted in blue. Providing there was sufficient time, the subject could change his/her mind. There was a jittered delay of 1-4 secs following the choice phase, followed by presentation of a fixation cross for 1 sec.

The experiment consisted of a total of 200 trials. Option 1 was the smaller-sooner reward in 50% of trials. In addition we included a further 20 'catch' trials where one of the options was both greater in value and available sooner than the other one. These catch trials occurred approximately every tenth trial and enabled us to ascertain how well the subjects were concentrating on the task, under the assumption that the norm was to prefer the larger-sooner reward in these choices. Three arrays of choices were created with eight subjects assigned to each. The option values were created using randomly generated magnitudes varying from £1 to £100 in units of £1 and delays ranging from 1 week to 1 year in units of single weeks (but presented as a number of months and weeks), again with a random distribution. This random nature of values (and catch trials) helped in orthogonalising magnitude and delay. In order to create choices between smaller-sooner and larger-later rewards, we introduced the constraint that the option with greater magnitude should be delayed more than the smaller, and vice versa for the catch trials.

Finally, in order to impose ecological validity, we designed a payment system which ensured that all the choices would be made in a realistic manner, with realistic consequences. The thrust of this design was the random selection of two of the choices that were made during the experiment, with real payment of the option chosen during those two choices. This was achieved by way of two pre-paid credit cards which were loaded with the amounts won and activated at the time associated with the selected options. Each card required a PIN to be activated before any spending could be done with the card. This PIN was emailed to the subject at the specified time. The cards could be used in most retailers or over the internet.

Behavioural Analysis

Parameter estimation and model comparison

We utilised the softmax decision rule to assign a probability (P_{O1} for option 1) to each option of the choice given the value of the option (V_{O1} for option 1) whereby

$$P_{Oi} = \frac{e^{(V_{Oi}/\beta)}}{e^{(V_{O1}/\beta)} + e^{(V_{O2}/\beta)}} \qquad \text{(Eq. 1)}$$

V_{Oi} represents the value of an option (i.e. a delayed reward) according to a particular model of option valuation (see below). The β parameter represents the degree of stochasticity of the subject's behaviour (i.e., sensitivity to the value of each option).

We compared seven models of option valuation. The first model was the standard hyperbolic model (Mazur, 1987), which states that the subjective value (V) of a reward of magnitude (M) and with a delay (d) can be expressed as

$$V = D(d) \times U(M) = \frac{M}{(1+Kd)}$$

$$D = \frac{1}{(1+Kd)} \qquad \text{(Eq. 2)}$$

$$U = M$$

D can be thought of as the *discount factor* – the delay-dependent factor (between 0 and 1) by which the utility is discounted. The discount rate parameter K quantifies an individual's tendency to discount the future such that a person with a high K devalues rewards quickly as they become more distant.

The second model was our generalisation of the simple hyperbolic model where magnitude was replaced with undiscounted utility (U). Our utility function was an exponential function adapted from a function derived from data which accurately described choices of gambles (Holt and Laury, 2002). Utility is related to magnitude accordingly

$$U(M) = \frac{1 - e^{(-rM)}}{r} \qquad \text{(Eq. 3)}$$

where r is a free parameter governing the curvature of the relationship. The greater the value of r the more concave the utility function, and where r is negative, the utility function is convex. In both expected utility theory and prospect theory (von Neumann and Morgenstern, 1947; Kahneman and Tversky, 1979) r also determines an individual's risk aversion (in choices where risk is a factor such as gambles) such that increasing concavity of the utility function equates to greater risk aversion and increasing convexity to greater risk seeking. Therefore, we introduce a new model where V can be expressed as

$$V = D(d) \times U(M) = \frac{1 - e^{(-rM)}}{r(1 + Kd)} \qquad \text{(Eq. 4)}$$

Value (V) here represents discounted utility.

The third model was similar to the second model but incorporated an exponential temporal discounting function instead of a hyperbolic function. The exponential formula is a normative economic model and is deemed to be a 'rational' way to discount future rewards, unlike the hyperbolic model which is 'irrational' as it leads to preference reversals (Ainslie, 2001). Most behavioural literature indicates that humans and animals discount hyperbolically but there is on-going debate whether this is true, and if so under what conditions. Here V is expressed as

$$V = D(d) \times U(M) = e^{(-Kd)} \times \frac{1 - e^{(-rM)}}{r} \qquad \text{(Eq. 5)}$$
$$D = e^{(-Kd)}$$

The fourth model was similar to the third model in that it used an exponential discount function but here, undiscounted utility (*U*) was replaced with magnitude (*M*) (i.e. assuming a linear utility function) . In this model

$$V = D(d) \times U(M) = e^{(-Kd)} \times M \qquad \text{(Eq. 6)}$$
$$U = M$$

The fifth model was the quasi-hyperbolic beta-delta model (Phelps and Pollak, 1968). According to this model $D(d) = \beta\delta^{d}$; where δ represents the discount rate in the standard exponential formula and the β parameter (where $0 < \beta \leq 1$) represents a unique weighting placed on immediate rewards relative to rewards with more delayed receipt. This parameter therefore devalues future rewards relative to immediate rewards. This model was utilised (McClure et al., 2004) to express the concept of two decision making systems corresponding to the two parameters – one rational and one irrational. Again, using the utility function above, this can be reformulated as

$$V = D(d) \times U(M) = \beta e^{(-Kd)} \times \frac{1 - e^{(-rM)}}{r} \qquad \text{(Eq. 7)}$$
$$D = \beta e^{(-Kd)}$$

The sixth model was similar to the fifth model in implementing the beta delta function except undiscounted utility (*U*) was replaced with magnitude (*M*) (i.e. assuming a linear utility function). In this model

$$V = D(d) \times U(M) = \beta e^{(-Kd)} \times M$$
$$U = M \qquad \text{(Eq. 8)}$$

Finally, we also calculated an AIC score (Table 1) for the 'as soon as possible' model (ASAP) (Glimcher et al., 2007), earlier proposed by Green et al., (2005). In this model the delay common to both options is ignored, the sooner option is treated as an immediate one and the latter option is hyperbolically discounted.

To calculate the maximum likelihood parameters for each model as well as a measure of the fit, maximum likelihood estimation was used. For each subject, the probability was calculated for each of the 220 options chosen from the 220 choices (which included catch trials), using the softmax formula and implemented with optimisation functions in Matlab. The log-likelihood was calculated using the probability of the option chosen at trial t $P_{O(t)}$, from Eq.1 such that

$$\ln L = \sum_t \ln P_{O(t)} \qquad \text{(Eq. 9)}$$

To compare the second model (Eq.4) over the first (Eq.2), we performed a one-sample t-test comparing the estimated r values with zero. We expected that r should be greater than zero as most people have marginally decreasing (concave) utility functions (hence the 'law of diminishing marginal utility'). If there was no effect of diminishing marginal utility on choice behaviour, we would expect r to vary around zero. In addition we also performed a one-sample t-test comparing the k values against zero, to demonstrate an effect of temporal discounting.

To compare evidence in favour of each model we calculated the Akaike Information Criterion (AIC) for each subject, for each model. AIC is a popular 'information theoretic' approach to model comparison and selection (Burnham and Anderson, 2002; Wagenmakers and Farrell, 2004). It is known as information theoretic because it relates to the concept of 'information' as defined by Kullback and Leibler (1951; Burnham and Anderson, 2002). Kullback-Leibler information $I(f,g)$ is the information lost when model g is used to approximate f – full reality or truth. Stated more simply it is the distance between full reality and a model. Clearly the best model looses the least information relative to other models. Akaike (1973) found an estimator of relative, expected K-L information based on the maximized log-likelihood function. In model comparison, descriptive accuracy is not the only factor that should be considered – it is generally accepted that parsimony is preferred when selecting models. Under-fitted models can be biased whereas over-fitted models with many parameters may identify spurious effects, thus some balance is required (Burnham and Anderson, 2004). Akaike found that the bias in the maximised log-likelihood estimate is approximately equal to the number of free parameters (N) in the model (an asymptotic result) and so incorporated this as an asymptotic bias correction term (see Burnhan and Anderson, 2002; Burnham and Anderson, 2004). Equation 10 shows that the AIC rewards descriptive accuracy via the maximum likelihood and penalises lack of parsimony according to the number of free parameters :

$$AIC = -2\ln L + 2N \qquad \text{(Eq. 10)}$$

Thus, the smaller the AIC, the better/more likely the model – given the evidence. Using an information-theoretic approach, the AIC was summed over all subjects for each model separately and the absolute difference between the best model and each of the other models (ΔAIC) was calculated as

$$\Delta AIC = \Delta_i = AIC_i - \min AIC \qquad \text{(Eq. 11)}$$

This reflects our interest in the relative performance of the models as opposed to their absolute AIC values, by telling us how much information is lost by using a particular model relative to the best fitting model (Burnham and Anderson, 2002; Burnham and Anderson, 2004; Wagenmakers and Farrell, 2004). As a rule of thumb it has been suggested that a ΔAIC greater than 2 suggests evidence in favour of the better fitting model and a score of greater than 10 indicates that the worse model has essentially no support (Burnhan and Anderson, 2002; Burnham and Anderson, 2004). These guidelines have similar counterparts in the Bayesian literature (Kass and Raftery, 1995, where the AIC is treated as an asymptotic approximation to the log-evidence of marginal likelihood of a model).

Additionally, Akaike weights (W_i) were calculated for each model by normalizing the model likelihoods so that they sum to 1:

$$W_i = \frac{e^{(-\Delta_i .5)}}{\sum_{r=1}^{R} e^{(-\Delta_r .5)}} \qquad \text{(Eq. 12)}$$

Akaike weights provide another measure of the strength of evidence for each model, and represent the ratio of ΔAIC values for each model relative to the whole set of *R* candidate models (Burnham and Anderson, 2002; Burnham and Anderson, 2004; Wagenmakers and Farrell, 2004). Akaike weights indicate the probability that the model is the K-L best, among the set of candidate models (i.e. conditional on the data and set of candidate models). For example, an Akaike weight of 0.8 indicates that given the data, it has an 80% chance of being the best one among those considered. Evidence ratios (the weight of a better over a worse model) can also be calculated to see how much greater the likelihood of the better model is (see Burnham and Anderson, 2004; Wagenmakers and Farrell, 2004).

For the purposes of the imaging and reaction time analyses, a further estimation was performed whereby all the choices from each subject were grouped together (as if made by one subject) and modelled as a canonical subject, to estimate canonical parameter values (using the fitting procedure above, with the second model (Eq.4)). This was performed to reduce the noise associated with the fitting procedure at the single subject level and to make subjects (with greatly differing parameter estimates, over an order of magnitude (see supplemental Table 1) more comparable at the second level analyses.

Reaction time data

Reaction time data were analysed in an analogous manner to the imaging data on choice difficulty (see analysis 3 in methods). For each subject, three measures of difficulty were calculated for each of the 220 choices (using the canonical parameter estimates and model 2 (Eq.4)): namely, difference in value (V) (discounted utility), difference in discount factor (D) and difference in undiscounted utility (U) – of the two options. The canonical parameter estimates were the same as those calculated for the other analyses (see above) and were used for a number of reasons – to reduce noise associated with the fitting procedure at the subject level (i.e. of the individual parameter estimates), to make subjects with greatly differing parameter estimates comparable in the second level analyses, and to avoid building individual differences into the model, allowing for a neural analysis of inter-subject variability. These three vectors were then de-trended and orthogonalised with respect to each other, in the above order. This final step was taken to mimic the procedure used in SPM, which is to detrend and orthogonalise regressors by default. Although orthogonalisation can change regressors (the latter two columns in this case), we felt this was necessary in the RT/fMRI analyses as they were significantly correlated. A linear regression was then performed to model the relationship between the reaction time (RT) (i.e. decision latency) for each choice and the difficulty measure. The parameter estimates (betas) were then used as a summary statistic and a second level analysis was performed by means of a one-sample t-test comparing the betas against zero (again using the approach implemented by SPM for imaging analysis). This was performed for each difficulty measure - ΔV, ΔD and ΔU. The sign of the mean of the betas indicated the direction of the correlation (negative for ΔV and positive for ΔD). In summary, the imaging and RT analyses both used identical regressors to model the relationship between BOLD response/ decision latency and choice difficulty.

Supplemental results

Behavioural results and model comparison

As predicted, subjects responded to the 20 catch trials by choosing the larger-sooner reward (mean: 19.5), indicating that they were concentrating well on the task.

Results of the model comparisons (Table 1) indicate that model number 2 (Eq. 4), the hyperbolic discounting of utility, was the best fitting model. We also performed paired t-tests on the individual AIC scores for each model (against all other models) to complement our information-theoretic/Bayesian approaches and to ensure group measures were not driven by outliers (supplemental table 3).

Canonical parameter values used in the imaging analysis were r = .0089 and K = .0142. Note that this value of K is related to delay in units of weeks and would be equivalent to K = .002 for days. Individual parameter estimates for each subject under each model can be seen in supplemental Table 1. The range of estimated parameters was large, as can be seen from the table where, for example, under model 2the largest estimated K value was .161and the smallest was .0005. However these were outlying values at the extreme tails of the distribution. No significant correlation was found between K and r parameters.

Model	1	4	2	2	3	3	6	6	5	5	5
Parameter	*K*	*K*	*K*	*r*	*K*	*R*	*K*	Beta	*K*	*r*	Beta
Subject											
1	0.0954	0.0379	0.0571	0.0117	0.0322	0.0061	0.0379	0.0001	0.0322	0.0061	0.8182
2	0.0161	0.0122	0.0188	-0.0042	0.0139	-0.0047	0.0122	0.0001	0.0139	-0.0047	0.683
3	0.1358	0.0403	0.0295	0.0328	0.0163	0.0371	0.0403	0.0001	0.0163	0.0371	-0.2897
4	2.326	0.0905	0.161	0.0111	0.0644	0.0165	0.0905	0.0001	0.0644	0.0165	-0.2362
5	0.0233	0.0154	0.0275	-0.004	0.0163	-0.0021	0.0154	0.0001	0.0163	-0.0021	-0.3726
6	0.0232	0.0154	0.0115	0.0152	0.0087	0.0163	0.0154	0.0001	0.0087	0.0163	0.8094
7	0.0023	0.0021	0.0033	-0.0088	0.0031	-0.0088	0.0021	0.0001	0.0031	-0.0088	3.0044
8	0.0005	0.0005	0.0017	0.0097	0.0017	0.0003	0.0005	-7.5916	0.0017	0.0051	1.239
9	0.0124	0.0095	0.0145	-0.0038	0.0105	-0.0029	0.0095	0.0001	0.0105	-0.0029	0.8423
10	0.1946	0.0431	0.1324	0.0056	0.0412	0.0019	0.0431	0.0001	0.0412	0.0019	0.9714
11	0.0402	0.024	0.0256	0.0138	0.0182	0.0118	0.024	0	0.0182	0.0118	0.6969
12	0.0107	0.0082	0.0081	0.0064	0.0065	0.007	0.0082	0.0001	0.0065	0.007	0.8777
13	0.0003	0.0009	0.0012	0.0086	0.0008	0.0088	0.0014	0.0001	0.0002	0.0088	1.1168
14	0.033	0.0196	0.0359	-0.0023	0.0187	0.002	0.0196	0.0001	0.0187	0.002	0.599
15	0.045	0.0255	0.034	0.0102	0.02	0.0129	0.0255	0	0.02	0.0129	0.4518
16	0.0079	0.0064	0.0067	0.004	0.0054	0.0049	0.0064	0.0001	0.0054	0.0049	1.3679
17	0.0431	0.0231	0.0571	-0.0076	0.0233	-0.0004	0.0231	0.0001	0.0233	-0.0004	0.6367
18	0.0013	0.0013	0.001	0.0036	0.0009	0.0036	0.0013	0.0001	0.0009	0.0036	0.8621
19	0.0191	0.013	0.0118	0.0137	0.0087	0.0154	0.013	0.0001	0.0087	0.0154	0.993
20	0.0227	0.0153	0.0385	-0.0133	0.0228	-0.0136	0.0153	0.0001	0.0168	-0.0031	0
21	0.0229	0.0122	0.055	-0.0183	0.014	-0.0057	0.0122	0.0001	0.014	-0.0057	0.6247
22	0.0339	0.0193	0.0265	0.0065	0.0112	0.0211	0.0193	0.0001	0.0112	0.0211	0.3424
23	0.0335	0.0208	0.0328	0.0008	0.0212	-0.0009	0.0208	0.0001	0.0212	-0.0009	0.6767
24	0.0015	0.0015	0.0005	0.016	0.0005	0.0159	0.0015	0.0001	0.0005	0.0159	0.9371
Mean	0.131029	0.019083	0.033	0.004475	0.015854	0.005938	0.019104	-0.31623	0.015579	0.006575	0.7355

Supplemental Table 1. Parameter estimates. The table displays the best fitting parameter estimates for each subject under each model. (Note mean values do not correspond to canonical estimates used in fMRI analyses.)

Model (Eq.)	**2** (4)	**1** (2)	**4** (6)	**3** (5)	**6** (8)	**5** (7)
Subject						
1	96.62	99.58	95.42	95.81	96.92	97.81
2	104.11	103.52	103.52	105.03	105.52	107.03
3	154.74	166.50	167.14	155.22	176.64	157.22
4	186.24	189.76	195.41	199.67	202.41	201.67
5	103.70	105.09	107.59	109.49	109.59	111.49
6	58.11	63.84	65.84	59.52	67.84	61.52
7	45.81	46.52	40.49	45.79	38.49	47.79
8	8.02	10.35	10.35	8.02	12.35	11.06
9	138.25	137.54	136.78	139.96	138.78	141.96
10	94.61	93.98	94.98	96.85	96.98	98.85
11	215.69	215.77	213.55	214.75	212.55	216.75
12	89.97	91.59	91.93	93.17	93.93	95.17
13	69.05	68.68	68.68	69.00	70.68	71.00
14	252.35	250.48	251.69	255.71	253.69	257.71
15	276.14	277.18	272.58	276.48	269.58	278.48
16	133.82	132.57	134.17	135.07	136.17	137.07
17	229.87	228.91	228.07	242.80	230.07	244.80
18	90.03	88.35	88.36	90.03	90.36	92.03
19	231.80	233.64	235.16	233.01	237.16	235.01
20	192.97	197.52	201.10	197.79	203.10	199.79
21	241.90	243.99	246.46	250.98	248.46	252.98
22	238.53	237.55	241.34	242.58	243.34	244.58
23	240.66	238.67	238.71	240.70	240.71	242.70
24	102.36	108.25	108.11	102.36	110.21	104.36
Total	3595.34	3629.80	3637.43	3659.79	3685.53	3708.82

Supplemental Table 2. Individual AIC estimates. The table displays the AIC score for each subject under each model.

Model (Eq.)	**2** (4)	**1** (2)	**4** (6)	**3** (5)	**6** (8)	**5** (7)
2 (4)	…………	0.037	0.064	0.0032	0.0087	6.05E-06
1 (2)		…………	0.56	0.25	0.019	0.0045
4 (6)			…………	0.37	4.32E-04	0.007
3 (5)				…………	0.41	2.04E-24
6 (8)					…………	0.46
5 (7)						…………

Supplemental Table 3. Individual AIC comparisons. The table displays *p* values for t-test comparisons of the individual AIC scores under each model (supplemental Table 2). This traditional hypothesis testing of AIC scores was done to complement the Bayesian model comparison techniques.

fMRI data

Comprehensive imaging results for the three analyses are given in the tables below and are related in order, to the figures shown in the main text. Clusters which were corrected for multiple comparisons (family wise error corrected (FWE) $p<.05$) at the whole brain level, or with small volume corrections are indicated with an asterisk. Additionally we display high resolution figures of single subject SPMs as well as a further SPM relating to choice difficulty.

REGION	CLUSTER SIZE	MNI COORDINATES	*Z* VALUE
right occipital cortex / cerebellum	4057*†	[15 -78 -12]	5.55
right visual cortex		[12 -96 9]	5.53
left ventral striatum		[-18 9 -15]	5.46
right ventral striatum		[15 12 -3]	5.17
left ventral striatum		[-15 12 -3]	5.04
anterior cingulate cortex		[-6 30 30]	4.4
left putamen / caudate		[-15 9 6]	4.19
ventral tegmental area		[0 -18 -18]	3.91
left occipital cortex	349*	[-30 -96 -9]	5.51
right posterior insula / operculum	30	[30 -24 24]	4.79
left posterior insula / operculum	68	[-30 -30 21]	4.71
left cerebellum	156	[-42 -72 -30]	4.7
right inferior frontal gyrus	75	[45 6 24]	4.63
left postcentral gyrus	199	[-57 -24 48]	4.23
right superior temporal gyrus	41	[-63 -27 6]	4.13
right insula	18	[33 -9 12]	4.02

Supplemental Table 4. Regions correlating with undiscounted utility (*U*). These regions were parametrically modulated by the utility of each option. These activations correspond to Figure **2a** in the main text. († This large cluster incorporates all of the regions stated, until left occipital cortex.)

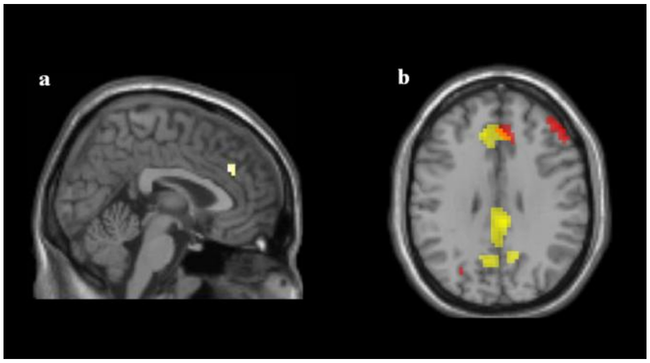
REGION	CLUSTER SIZE	MNI COORDINATES	*Z* VALUE
left inferior temporal cortex	35*	[-57 -51 -15]	5.12
left caudate nucleus	70	[-9 12 0]	4.47
right caudate nucleus	76	[12 12 0]	4.36
left angular gyrus	10	[-42 -60 42]	4.18
right anterior insula	23	[36 27 -3]	4.08
right cerebellum	8	[45 -57 -39]	3.85
right anterior cingulate cortex	22	[9 45 9]	3.85
left subgenual cingulate / medial orbitofrontal cortex	20	[-3 42 -12]	3.82
left inferior frontal gyrus orbital part	16	[-42 45 -6]	3.76
left inferior frontal gyrus	24	[-48 42 6]	3.76
left anterior insula	10	[-27 21 -3]	3.73
substantia nigra	9	[3 -18 -18]	3.73
posterior cingulate cortex	13	[-3 -27 33]	3.71
right inferior frontal gyrus	14	[54 24 0]	3.66
right inferior temporal gyrus / sulcus	9	[51 -21 -21]	3.62
right inferior frontal gyrus	21	[-57 21 -3]	3.58
left inferior temporal cortex	13	[-63 -24 -18]	3.52
left inferior frontal gyrus	8	[-51 12 15]	3.5
right laterat orbitofronal cortex	8	[36 36 -12]	3.49
left dorsolateral prefrontal cortex	15	[-54 27 27]	3.47
right dorsolateral prefrontal cortex	6	[54 18 33]	3.42
ventral tegmental area	11	[-6 -15 -3]	3.41

Supplemental Table 5. Regions correlating with the temporal discount factor (*D*).

These activations correspond to Figure **2b** in the main text.

REGION	CLUSTER SIZE	MNI COORDINATES	*Z* VALUE
left occipital cortex	42	[-21 -99 -9]	4.27
right occipital cortex	30	[15 -81 -9]	4.2
subgenual cingulate cortex	15	[9 45 12]	3.9
right superior temporal / angular gyrus	23	[60 -57 21]	3.58
right caudate nucleus	17	[15 1 15]	3.49
left angular/superior temporal	12	[-57 -54 33]	3.28
left ventral striatum	11	[-9 -3 0]	3.17

Supplemental Table 6. Regions correlating with discounted utility (*V*). These activations correspond to Figure **2c** in the main text.



Supplemental Figure 1. Regions correlating with choice difficulty. a Regions correlating with difference in discounted utility (ΔV) and in the discount factor (ΔD) of the two options. **b** Regions correlating with (ΔV) alone (in red) and (ΔD) alone (in yellow). Orange areas correlated with both.

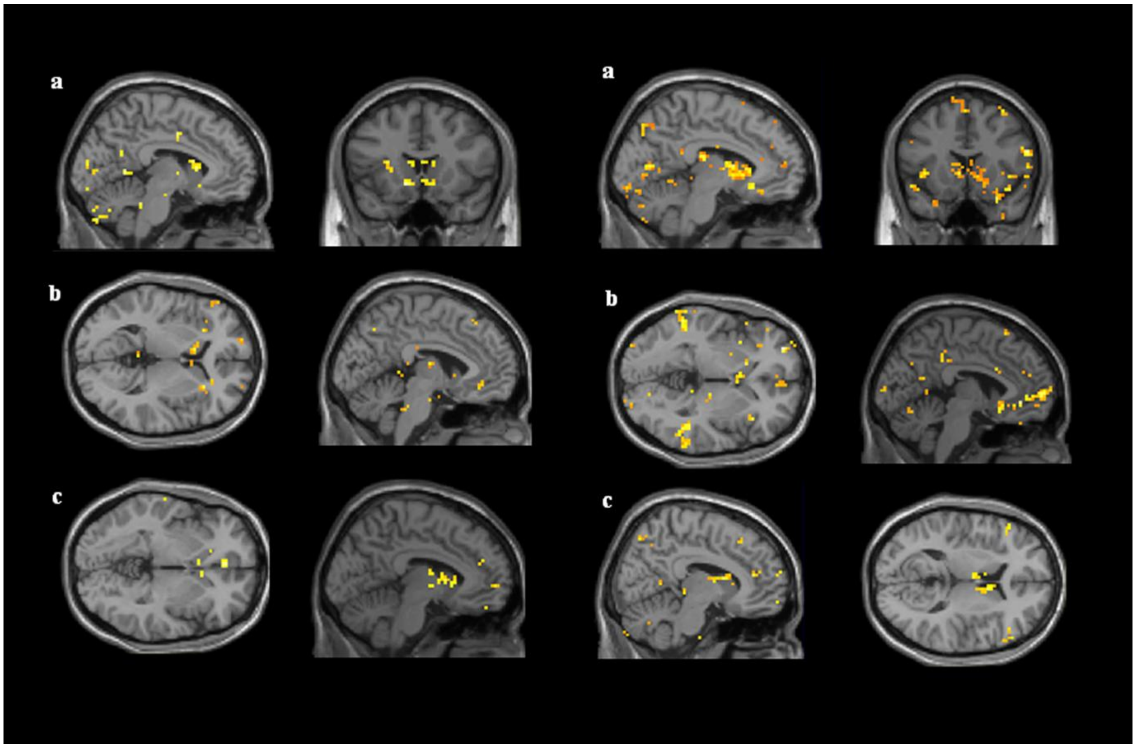
REGION	CLUSTER SIZE	MNI COORDINATES	*Z* VALUE
A			
motor / anterior cingulate cortex	108	[6 21 51]	4.88
right dorsolateral prefrontal cortex	101	[51 42 18]	4.86
right frontal pole	40	[30 60 9]	3.97
right anterior insula	34	[33 21 -9]	3.80
right anterior cingulate cortex	32	[6 36 27]	3.78
right supramarginal gyrus	7	[48 -36 45]	3.44
left anterior cingulate cortex	6	[-9 33 21]	3.44
B			
right dorsolateral prefrontal cortex	9	[54 15 12]	3.75
right anterior cingulate cortex	10	[12 39 33]	3.64
C			
posterior cingulate cortex	205	[0 -30 36]	5.07
anterior cingulate cortex	90	[-9 33 30]	4.4
left precuneus	31	[-6 -63 30]	4.15
left cerebellum	52	[-36 -69 -39]	4.09
right cerebellum	65	[39 -78 -36]	4.04
superior temporal gyrus	30	[-60 -27 -18]	3.93
right precuneus	17	[15 -60 30]	3.88
left anterior insula	21	[-39 18 -12]	3.79

right frontal pole	5	[33 57 -3]	3.49
right motor cingulated	13	[6 45 36]	3.39

Supplemental Table 7. Regions correlating with choice difficulty. a. Regions correlating with ΔV **b.** Regions correlating with ΔV which covaried with reaction time (decision latency) parameters. **c.** regions correlating with ΔD. These activations relate to the data presented in Figure 4 in the main text and supplemental Figure 1.

Regressor	**CLUSTER SIZE**	**MNI COORDINATES**	***Z* VALUE**
U	5	[18 20 14]	2.58
D	8	[15 24 3]	2.41
V	60	[15 0 15]	3.26

Supplemental Table 8. Striatal regions correlating with unique components of *U, D* and *V*. Striatal responses to the regressors in a more conservative regression model where the orthogonalisation step was removed, thus removing any shared variance components from the regressors. (Thresholded at $p<.01$ due to the strict nature of the model).



Supplemental Figure 2. Single subject SPMs of regions involved in option valuation and integration. High resolution (4mm smoothed) images of subjects 1 (on the left) and 12. **a.** Regions correlating with the undiscounted utility of each option (*U*) **b.** Regions correlating with the discount factor (*D*) of each option **c.** Regions correlating with the interaction of *U* and *D* – the discounted utility (*V*) or subjective value of each option.

Supplemental References

Ainslie G (2001) Breakdown of will. Cambridge, UK: Cambridge University Press.

Akaike H (1973) Information theory and an extension of the maximum likelihood principle. In: Proceedings of the second international symposium on information theory (Petrov BN, Caski F, eds), pp67-281. Budapest: Akademiai Kiado.

Burnham KP, Anderson DR (2002) Model selection and multimodal inference. 2nd Ed. New York, NY: Springer.

Burnham KP, Anderson DR (2004). Multimodal inference: Understanding AIC and BIC in model selection. Sociological Methods & Research 33:261-304.

Glimcher PW, Kable J, Louie K (2007) Neuroeconomic studies of impulsivity: Now or just as soon as possible. 97(2): 142-147.

Green L, Myerson J, Macaux EW (2005) Temporal discounting when the choice is between two delayed rewards. J Exp Psychol Learn Mem Cogn. 31(5):1121-33.

Holt CA, Laury SK (2002) Risk aversion and incentive effects. American Economic Review 92:1644-1655.

Kable JW, Glimcher PW (2007) The neural correlates of subjective value during intertemporal choice. Nat Neurosci 10:1625-1633.

Kahneman D, Tversky A (1979) Prospect theory: An analysis of decisions under risk. Econometrica 47:313-327.

Kass RE, Raftery AE (1995). Bayes factors. Journal of the American Statistical Association 90:773-795.

Kullback S, Leibler RA (1951) On information and sufficiency. Annals of Mathematical Statistics 22:79-86.

Mazur JE (1987) An adjusting procedure for studying delayed reinforcement. In: Quantitative analyses of behavior: V. The effect of delay and of intervening events on reinforcement value (Commons ML, Mazur JE, Nevin JA, Rachlin H, eds), pp 55-73. Hillsdale, NJ: Lawrence Erlbaum.

McClure SM, Laibson DI, Loewenstein G, Cohen JD (2004) Separate neural systems value immediate and delayed monetary rewards. Science 306(5695):503-7.

Phelps ES, Pollak RA (1968) On Second-Best National Saving and Game-Equilibrium Growth. Rev Econ Stud 35:185.

von Neumann J, Morgenstern O (1947) Theory of games and economic behaviour. Princeton, NJ: Princeton University Press.

Wagenmakers EJ, Farrell S (2004) AIC model selection using Akaike weights. Psychonomic Bulletin & Review 11:192-196.

<u>Appendix – Instruction sheet</u>

In this task, you have to make choices between two financial options. Each option consists of an amount of money between £1 and £100, available at some point in the future, between 1 week and 1 year. You have to choose the option you would prefer, and two of your choices will be selected randomly at the end of the experiment and paid to you in full, and at the specified time in the future

You will first see ‘option 1’ which will remain on the screen for 3 seconds, after which you will then see ‘option 2’, for a further 3 seconds. After option 2, you will be asked to choose which one you prefer, by selecting either one on the ‘choice’ screen, during which you have roughly 3 seconds to indicate your preference using a keypad. On the choice screen, the words ‘option 1’ will appear on the left and ‘option 2’ on the right. In the practice version that you will do in a minute, if you prefer option 1 press the left shift key, if you prefer option 2, press the right shift key. In the scanner, you will get a proper left-right keypad to make your choices. Remember, option 1 refers to the option that was presented first, not the option which is paid first. Once you have chosen one of the options, your choice will be highlighted. You can change your mind for as long as the choice screen is present, but please try to choose correctly first time since you don’t have too much time.

Please remember that when you come out of the scanner, 2 choices will be randomly selected – one from each session, and you will receive the option that you chose, for each of those 2 choices. It is therefore very important that you select the option which you really prefer. To do the random selection, you will then spin a genuine lottery machine, which contains numbered balls corresponding to each of the trials. The ball that comes out will be looked up from all the choices you made and it will be the choice you get (one for each session). We do it in this way so that you appreciate that it is a real gamble, and we will genuinely pay you the correct amount, so it is important you make your decisions understanding that they might be selected for real.

Of course, we have no control over the two options that are selected at the end, so there is quite a variation in the amount you could get, because some of the options are for small, and some large, amounts of money. In agreeing to take part in the experiment, you have to accept that this is a real gamble, and you might be unlucky and only get a few pounds, whereas other subjects might get lots. We cannot change the two selected options afterwards, and we are ethically obliged to give you no more or no less.

The way we pay you is with commercial pre-paid credit cards, which are activated at the time specified by the option. We arrange this after the experiment, and we have funded pot of money to cover the winnings for all our subjects. We will send you the cards (or you can pick it up if you prefer) after the experiment, and it will be activated automatically at the future date specified (we will keep all records here as well).

Please try and concentrate well for the whole experiment. You will do two sessions, each lasting 20mins. Please try to stay as still as possible throughout the task, and good luck!!!!