Social Cognitive and Affective Neuroscience Advance Access published February 15, 2012

doi:10.1093/scan/nss002 SCAN (2012) 1 of 10

Emotion regulation reduces loss aversion and decreases amygdala responses to losses

Peter Sokol-Hessner,[1] Colin F. Camerer,[2] and Elizabeth A. Phelps[3]

[1]Division of the Humanities and Social Sciences (HSS), California Institute of Technology, [2]Division of the Humanities and Social Sciences (HSS) and Computational and Neural Systems (CNS), California Institute of Technology, 1200 E. California Blvd., Pasadena, CA 91125, USA, and [3]Department of Psychology, New York University, 6 Washington Place, New York, NY 10003, USA

Emotion regulation strategies can alter behavioral and physiological responses to emotional stimuli and the neural correlates of those responses in regions such as the amygdala or striatum. The current study investigates the brain systems engaged when using an emotion regulation technique during financial decisions. In decision making, regulating emotion with reappraisal-focused strategies that encourage taking a different perspective has been shown to reduce loss aversion as observed both in choices and in the relative arousal responses to actual loss and gain outcomes. In the current study, we find using fMRI that behavioral loss aversion correlates with amygdala activity in response to losses relative to gains. Success in regulating loss aversion also correlates with the reduction in amygdala responses to losses but not to gains. Furthermore, across both decisions and outcomes, we find the reappraisal strategy increases baseline activity in dorsolateral and ventromedial prefrontal cortex and the striatum. The similarity of the neural circuitry observed to that seen in emotion regulation, despite divergent tasks, serves as further evidence for a role of emotion in decision making, and for the power of reappraisal to change assessments of value and thereby choices.

Keywords: emotion; reappraisal; emotion regulation; decision making; loss aversion

INTRODUCTION

Decision making is not dispassionate but is instead fundamentally supported by emotions (Loewenstein, 1996; Frank *et al.*, 2009; Phelps, 2009). Evidence of this comes from two sources. First, decision-making studies, measuring components of emotion such as arousal, have shown that physiological responses correlate with information like imminent losses (Bechara *et al.*, 1997), volatility (Lo and Repin, 2002), anger during interpersonal interactions (van't Wout *et al.*, 2006) and deception (Wang *et al.*, 2010). The second source of evidence for the involvement of emotion in decision making comes from studies manipulating emotion during choices, demonstrating the causality of the relationship (Lerner *et al.*, 2004; Winkielman *et al.*, 2005; Harlé and Sanfey, 2007; Andrade and Ariely, 2009). The neural mechanisms of decision making also include regions like the amygdala and insula (Bechara *et al.*, 1997; Gottfried *et al.*, 2003; Paulus *et al.*, 2003; Hsu *et al.*, 2005; Shiv *et al.*, 2005; Murray, 2007; Clark *et al.*, 2008), traditionally associated with emotion and physiological responses (Morris *et al.*, 1996; Whalen *et al.*, 1998; LeDoux, 2000; Critchley *et al.*, 2004). This connection between emotion and choices is further supported by studies of patients with damage to those same regions (Shiv *et al.*, 2005; De Martino *et al.*, 2010), providing compelling evidence that the mechanisms underlying emotions and choice overlap.

Emotions are also known to be actively generated in part by our thoughts or appraisals (Schachter and Singer, 1962), suggesting that by changing appraisals, we can change emotions. This concept led to a large body of research on regulating emotions with reappraisal (Gross, 1998), demonstrating its power to alter emotional responses (Ochsner *et al.*, 2002; Eippert *et al.*, 2007; Delgado *et al.*, 2008a). Neurally, dorsolateral and ventromedial prefrontal cortex (DLPFC and VMPFC) are consistently identified in the regulation of emotion, and the amygdala and striatum in representing value and processing emotion (Ochsner and Gross, 2008; Hartley and Phelps, 2010).

The behavioral and physiological consequences of the reappraisal of decision making were demonstrated in a recent study (Sokol-Hessner *et al.*, 2009). Participants showed greater skin conductance responses to losses compared to gains in a baseline condition, and this differential arousal correlated with behavioral estimates of loss aversion (the relative decision weight of losses to gains). In a second condition, participants reappraised choices from a broader perspective, reducing loss aversion behaviorally and eliminating over-arousal to losses relative to gains by decreasing loss responses.

Studies of the neural correlates of loss aversion have implicated both the striatum and the amygdala. One functional magnetic resonance imaging (fMRI) study found striatal activity at decision reflected the overall expected utility of the choice, including loss aversion (Tom et al. 2007). However, others linked amygdala activity to the endowment effect (Weber *et al.*, 2007), often interpreted as a behavioral consequence of loss aversion (Tversky and Kahneman, 1991). Similarly, patients with amygdala damage show reduced loss aversion (De Martino *et al.*, 2010). Though these latter findings linking the amygdala to loss aversion conflict with the quantitative fMRI exploration of loss aversion with functional imaging, we note that Tom *et al.* (2007) had only decisions and no outcomes. Consequently, one possible model is that the amygdala may mediate loss aversion in responses to outcomes, accounting for Weber *et al.* (2007) and De Martino *et al.* (2010), and that the weights in those outcome responses may be passed on to the striatum, leading it to represent loss aversion at the time of decision as in Tom *et al.* (2007). As reappraisal modulates loss aversion behaviorally, we would therefore expect to see changes in the striatum and amygdala as a result of regulation.

In the present study, we ask whether the neural mechanisms underlying reappraisal in decision making are similar to those known to support intentional emotion regulation. Such similarity would suggest a central role for emotions and their regulation in decision making. It would also close the distance between emotions and valuation, and

Received 6 April 2011; Accepted 9 January 2012

The authors thank M. Delgado for helpful comments. This work was supported by the James S. McDonnell Foundation to EAP; the National Institutes of Health (MH080756 and AG039283) to EAP; and the Gordon and Betty Moore Foundation and Human Frontiers Science Program to CFC.

Correspondence should be addressed to Elizabeth Phelps, Department of Psychology, New York University, 6 Washington Place, New York, NY 10003, USA. E-mail: liz.phelps@nyu.edu

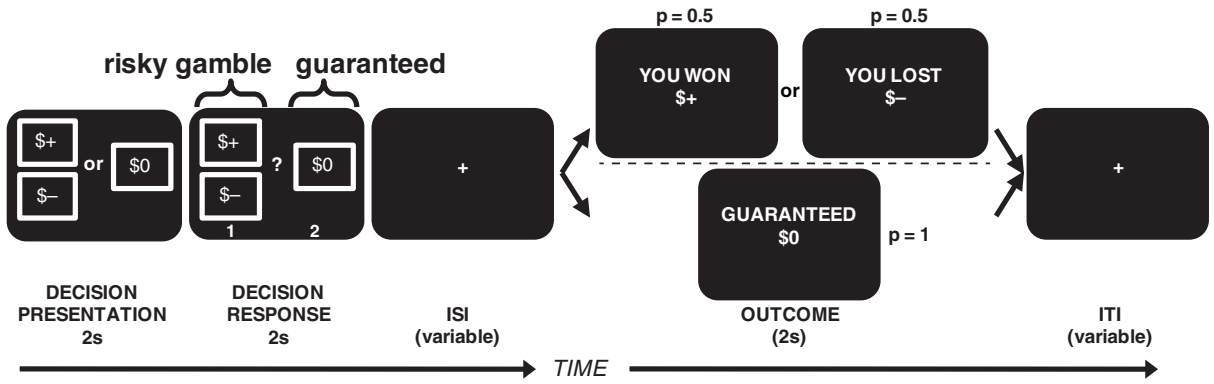


Fig. 1 A schematic of the sequence of events for a full trial. Participants made a series of forced monetary choices between gambles (winning or losing with equal $P = 0.5$) and a guaranteed alternative ($P = 1$), with outcome screens following each choice. Symbols of '+' and '−' stand in for actual monetary amounts presented on each trial. After initial presentation of the gamble and the guaranteed amount (2 s; 1TR), the appearance of button cues indicated a response period (2 s) during which participants could either accept the gamble or reject it for the guaranteed alternative. After a poisson-distributed variable interstimulus interval (ISI; 2–8 s, mean 4.1 s), the outcome screen was presented (2 s) consisting of a win or lose screen with equal probability if the gamble had been accepted, otherwise the guaranteed alternative if the gamble had been rejected. Finally, a poisson-distributed variable intertrial interval (ITI; 4–12 s, mean 6.4 s) separated each trial from the next.

emotion regulation and reappraisal in choice, arguing that they are simply instantiations of the same processes and mechanisms in different contexts.

In a within-subjects design, participants were scanned while making risky monetary choices in each of two conditions. In the 'Attend' condition, participants considered each choice on its own merit, as if it was the only choice they were making. In the 'Regulate' condition, participants took a broader perspective and considered each choice in its greater context, as one of many. We estimated participants' loss aversion, risk attitudes and consistency over choices in each condition. Analyses of the fMRI data focused on correlates of loss aversion and its reduction, as well as the application of the 'Regulate' intentional strategy.

EXPERIMENTAL PROCEDURES

Participants

Sixty-three participants (34 female, mean age 19.8 ± 3.1 years) took part in the study. Of those, nine were removed for excess motion, and seven were excluded for other reasons (See 'Detailed Participant Exclusions' in Supplementary Data for more details). The remaining 47 participants (27 female, mean age 20.1 ± 1.7 years) were entered into the decision analysis. For analysis of outcomes, seven participants were excluded for not having enough outcome trials [exclusion criterion: fewer than 10 trials in 2 or more outcome categories (e.g. 'Attend' win, 'Regulate' loss)]. The outcomes analyses include the remaining 40 participants (24 female, mean age 20.2 ± 1.7 years). One participant was excluded from the loss aversion coefficient (represented by λ) correlational analyses for having an 'Attend' log(λ) value greater than three standard deviations above the mean. All correlations with λ were performed on the remaining 39 participants. All participants gave informed consent as approved by the University Committee on Activities Involving Human Subjects at New York University, and in accordance with the Declaration of Helsinki.

Behavioral procedure

Participants were thoroughly instructed in all details and contingencies of the task, successfully completed a brief quiz assessing comprehension of the instructions, practiced use of the strategies with the experimenter and did a practice block of trials before scanning.

Immediately after giving informed consent, participants were endowed with $30, told the money was theirs to risk during the study, and asked to place it in their wallets or purses. After the task, 10% of all the trials in which feedback was presented (30 out of 300 trials) were randomly selected. Participants were paid the $30 plus the sum of their actual outcomes in those trials. Participants could lose up to the entire $30 endowment, and could gain up to a theoretical maximum of an additional $662. All participants also received a $75 ($25/h) subject fee upon completion of the study.

Participants completed two identical sets of choices (Figure 1) with different intentional cognitive strategies. For the 'Attend' strategy, participants were asked to consider each choice in isolation from any context, as if it was the only choice in the entire study. For the 'Regulate' strategy, participants were asked to consider each choice in a greater context, remembering that each choice was one of many or part of a portfolio. The conceptual nature of these strategies was emphasized by asking participants not to keep a running tally of their previous outcomes or overall earnings. Similar to typical studies of emotion regulation (e.g. Ochsner *et al.*, 2002), detailed strategy instructions were read aloud, and participants were given a chance to ask questions about the strategies. They were then encouraged to repeat the strategies back to the experimenter in their own words. After a brief set of practice trials completed with the experimenter, participants completed a longer set of practice trials alone, after which they could again ask questions about the strategies. The full text of the strategies is in the Supplementary Data.

The choices presented to participants were identical for the two instructed strategies, but the win/loss outcomes varied randomly across trials. Each 'set' of 150 choices was designed to allow the dissociation of several aspects of behavior (see below, 'Behavioral Model' section). Out of the 150 choices, 120 were between a mixed gamble (positive and negative possible outcomes) and a guaranteed amount of zero, and 30 were between gain-only gambles (positive and zero possible outcomes) and positive guaranteed amounts (see Supplementary Data for exact monetary amounts). Participants had to either accept the gamble, in which case they won or lost with equal probability, or reject it for the guaranteed amount. Each decision was immediately followed by its outcome, prior to the next trial beginning. See Figure 1 for trial details and timing. In addition to the 300 'full' trials (consisting of choice, inter-stimulus interval (ISI), outcome, and inter-trial interval (ITI); 150 in each 'Attend' and 'Regulate'), there were 64 partial trials (consisting only of choice, partial trial indicator and ITI; 32 in each 'Attend' and 'Regulate') to allow accurate separation of decision and outcome blood oxygenation level-dependent (BOLD) activity (Ollinger *et al.*, 2001a, 2001b). The partial trial indicator following the

response period consisted of 1s of normal (white) fixation and 1s of a red fixation cross.

Each block was completed using one of the two strategies (14 blocks each for 'Attend' and 'Regulate', for 28 blocks total; 4 blocks per functional run). Blocks were preceded by a cue (4s; followed by 2s fixation) indicating which strategy to use for the following trials. There were no gaps between blocks, other than the ITI following the last trial of the block, after which the cue for the next block was displayed. Blocks were pseudorandomly ordered such that no strategy occurred more than four times in a row at any point (including across runs). Participants completed one of four counterbalanced task orders which were independently randomized along the following dimensions: order of condition blocks ('Attend', 'Regulate'), gamble outcomes ('win', 'lose'), and gamble order within each condition block.

Behavioral model

Choice behavior was estimated with a prospect theory-inspired (Kahneman and Tversky, 1979) three parameter model (Sokol-Hessner *et al.*, 2009). Gains and losses were modeled with Equations (1) and (2), respectively. The resulting subjective utility estimates were used in the softmax function in Equation (3), translating the subjective difference between the gamble and the guaranteed amount into a probability of gamble acceptance.

$$u(x^{+}) = x^{\rho} \tag{1}$$

$$u(x^{-}) = -\lambda \times (-x)^{\rho} \tag{2}$$

$$p(\text{gamble acceptance}) = \left(1 + exp\{-\mu(u(gamble) - u(guaranteed))\}\right)^{-1} \tag{3}$$

Lambda (λ, the loss aversion coefficient) appears only in the utility function for losses [Equation (2)]. It represents the multiplicative weighting of the subjective value of losses relative to gains. When $\lambda > 1$, losses are overvalued relative to gains of the same size ('loss averse'). When $\lambda = 1$, gains and losses are valued equally ('gain-loss neutral'). When $\lambda < 1$, gains are overvalued relative to losses ('gain-seeking'). Rho (ρ, the curvature of the function) represents risk attitudes and diminishing sensitivity to changes in value as the absolute value increases. Mu (μ, the logit sensitivity) represents the consistency of participants' decisions across multiple choices.

The model was estimated for each individual participant separately in the 'Attend' and 'Regulate' conditions with a Nelder–Mead simplex maximum likelihood procedure in Mathematica (Wolfram Research, Champaign, IL, USA). Overall model significance for each participant in each condition was evaluated against a random-choice model with a likelihood ratio test, determining whether the probability of the data observed was significantly higher given the estimated parameters. Within-subject changes in parameters were similarly evaluated with likelihood ratio tests of the full model (containing all 'Attend' and 'Regulate' parameters) against reduced models which restricted parameter values to be identical in 'Attend' and 'Regulate'.

Scanning parameters

Scanning was performed at NYU's Center for Brain Imaging with a 3T Siemens Allegra head-only scanner and a Nova Medical head coil (model NM011). High-resolution anatomical images were acquired using a T1-weighted protocol (Field of view (FOV) = 256, 176 slices, 1 × 1 × 1 mm). Functional imaging used a single-shot gradient echo echo-planar imaging (EPI) sequence (TR = 2000 ms, TE = 30 ms, FOV = 192, flip angle = 90°), acquiring 7 functional runs of 421 volumes, each with 36 contiguous 3 mm isovoxel oblique axial slices aligned parallel to the AC–PC plane. Data were preprocessed with BrainVoyager software (Brain Innovation, Maastricht, The Netherlands), including motion correction, slice-time correction and spatial smoothing (4 mm FWHM Gaussian kernel). Functional runs were coregistered to the high-resolution anatomical after which all scans were transformed to Talairach space (Talairach and Tournoux, 1988). Data used in general linear models (GLMs) were temporally high-pass filtered (period = 128 s) with SPM8's filtering tool (Statistical Parametric Mapping 8, http://www.fil.ion.ucl.ac.uk/spm/) prior to analysis. Trial-triggered averages were taken from data that had not been temporally high-pass filtered. Analysis was performed with BrainVoyager and custom Matlab scripts (Mathworks, Natick, MA, USA).

GLMs were estimated on a fixed-effects level for each participant. The results were then subjected to random effects group-level contrasts in order to functionally define regions of interest (ROIs) for use in other analyses.

Analyses of decisions included all 47 participants. The GLM used for these analyses included, separately for 'Attend' and 'Regulate', a main effect (indicator) regressor for mixed valence decisions and a parametric regressor with the subjective expected utility of the decision (calculated using the participant's estimated value functions) at the time of gamble presentation in the mixed-valence trials. For completeness, the GLM also included main effect regressors (separately for 'Attend' and 'Regulate') for mixed-valence win outcomes, mixed-valence loss outcomes, mixed-valence guaranteed outcomes, gain-only decisions, gain-only outcomes and block cues.

Analyses of outcomes were performed with the 40 participants with enough trials to support estimation (see Experimental Procedures: Participants). In order to eliminate statistical issues associated with having few trials of a given type in a single functional run, participants' functional runs were temporally concatenated to form one long run. The GLM used for these analyses included, separately for 'Attend' and 'Regulate', a main effect (indicator) regressor for mixed-valence win outcomes, another for mixed-valence loss outcomes and parametric regressors with the win amount in dollars, and similarly with the loss amount. For completeness, the GLM also included main effect regressors (separately for 'Attend' and 'Regulate') for mixed valence decisions, mixed-valence guaranteed outcomes, gain-only decisions, gain-only outcomes and block cues. Additional parametric regressors included the subjective expected utility of the decision (calculated using the participant's estimated value functions) at the time of gamble presentation, and the prediction error associated with an outcome at the time of outcome presentation, calculated as the difference between the subjective utility of the outcome and the subjective expected utility of the gamble.

All parametric outcome predictors were orthogonalized against the relevant main effect regressors, and the prediction error regressors were subsequently orthogonalized against the main effect and parametric regressors.

In all GLMs, nuisance predictors included indicators for the decision and outcome periods when participants failed to respond in time, the occurrence of partial trial indicators, and motion estimates (six total: translation and rotation in each of three orthogonal planes). The outcome analyses (performed on the concatenated data) also included a constant factor for each functional run. All predictors except the motion estimates and run constants were convolved with the BrainVoyager hemodynamic response function (HRF).

The blocked nature of our task made it possible for two different patterns to be observed in BOLD activity as a result of the perspective-taking regulation strategy. First, it is possible that transient responses to events (e.g. loss outcomes) were altered by regulation,

such that the observed β-values from a general linear model would be different between conditions ('Attend' or 'Regulate'). However, because the conditions occurred in blocks, it is additionally possible that there were longer lasting changes consistent with this perspective shift, independent of individual trial events (e.g. Donaldson *et al.*, 2001; Visscher *et al.*, 2003). That is, regulation in this setting could include not just altering an event-specific response, but also maintaining a perspective across any particular type of event, manifesting in a baseline shift in BOLD activity (in contrast to the transient responses to events). To get at any potential baseline shifts across blocks, we used the technique of trial-triggered averaging (e.g. Buckner *et al.*, 1996), which is not constrained by assumptions about the shape of the hemodynamic response. Beginning with the timepoint at the start of the event of interest (e.g. decision), we calculated individuals' average BOLD signal at each timepoint during that event, and then combined across individuals to produce a group-level average of the mean BOLD signal at each timepoint. We then compared these average BOLD signal time courses across conditions ('Attend' or 'Regulate'). The data used for this analysis was non-high-pass filtered BOLD activity extracted from ROIs.

RESULTS

Behavioral results

Estimates of the behavioral model parameters across 47 participants were consistent with previous results using this choice paradigm (Sokol-Hessner *et al.*, 2009), and in many other paradigms including naturally occurring field data (Camerer *et al.*, 1997; Genesove and Mayer, 2001; Haigh and List, 2005). Mean 'Attend' parameter values (with standard errors of the mean) were $\lambda = 1.62$ (0.14; loss aversion), $\rho = 0.88$ (0.04; risk attitudes), and $\mu = 3.26$ (0.61; consistency over choices). Since the distribution of the loss aversion coefficient λ across people is typically right-skewed, taking its log is more conducive to standard statistical testing. The mean $\log(\lambda)$ value in the 'Attend' condition was 0.34 (0.08), corresponding to $\lambda = 1.41$. In the 'Regulate' condition, mean parameter values were $\lambda = 1.33$ (0.11), $\rho = 0.91$ (0.04) and $\mu = 2.93$ (0.38). The mean $\log(\lambda)$ value was 0.17 (0.07), corresponding to $\lambda = 1.19$.

To compare estimates between 'Attend' and 'Regulate' at the group level, we performed two-tailed paired *t*-tests of participants' parameter estimates in 'Attend' *vs* those in 'Regulate'. These tests indicated a significant difference for λ [loss aversion; $t(46) = 4.52$, $P < 5 \times 10^{-5}$; using $\log(\lambda)$, $t(46) = 4.94$, $P < 2 \times 10^{-5}$], but no difference in either risk-aversion [ρ; $t(46) = 0.90$, $P < 0.38$] or consistency [μ; $t(46) = 0.77$, $P < 0.45$]. Thus, there is a consistent, selective effect of the 'Regulate' strategy in decreasing loss aversion from 'Attend' to 'Regulate' ($\lambda_{ATTEND} - \lambda_{REGULATE}$, as a percentage of λ_{ATTEND}) by an average of 14% (Figure 2).

We found that 37 individuals (out of 47 participants; 79%) showed some decrease in λ from 'Attend' to 'Regulate', comparable to previous findings (86% in Sokol-Hessner *et al.*, 2009). Because of the unique, quantitative nature of our task, we were able to characterize individual differences in the strength of that effect. We examined individuals' behavior for significant differences in value parameters between 'Attend' and 'Regulate' using likelihood ratio tests (LRTs; see Supplementary Data for more details). Out of 47 participants, 16 had significant shifts in λ (all 'Regulate' < 'Attend') at a threshold of $P < 0.05$. We identified these participants as 'Regulators'. The remaining 31 participants who did not show a significant decrease in loss aversion we identified as 'Non-Regulators'. LRTs performed on the other parameters found 8 out of 47 significant shifts in ρ (two 'Regulate' < 'Attend'), and 9 out of 47 in μ (6 'Regulate' < 'Attend'). Since these differences were neither large nor systematic, the remainder of the analysis focuses on λ, the loss aversion coefficient.

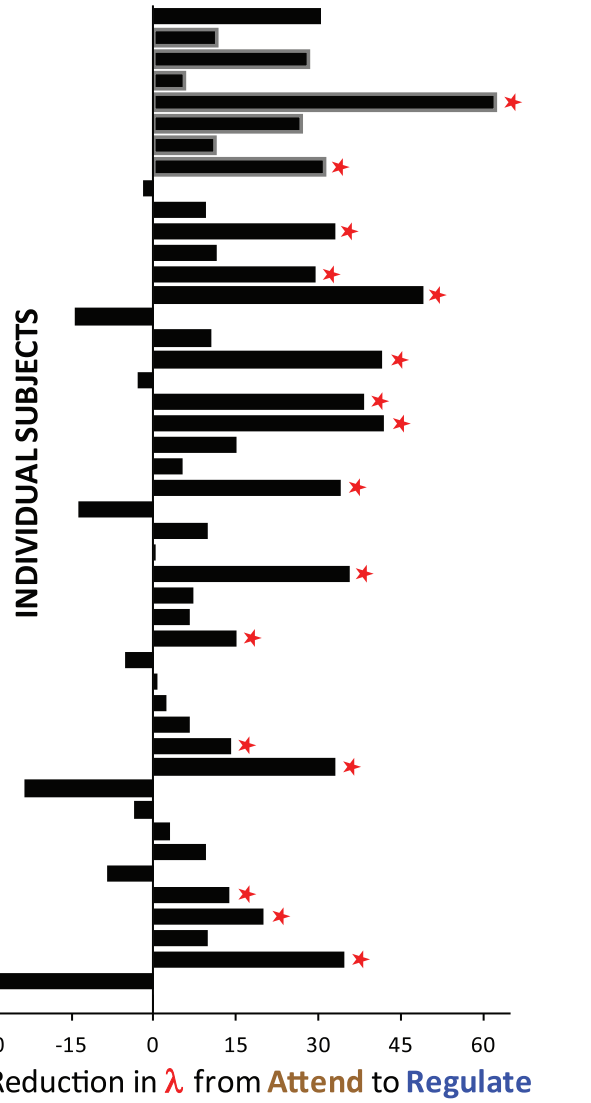


Fig. 2 Regulation reduced loss aversion. Percent reduction in behavioral estimates of individuals' loss aversion from 'Attend' to 'Regulate' ($100 \times (\lambda_{ATTEND} - \lambda_{REGULATE}) / \lambda_{ATTEND}$). A positive number indicates less loss aversion in the 'Regulate' condition. Bars outlined in gray were subjects excluded from the analysis of outcomes (see Experimental Procedures: Participants). Red stars indicate individuals whose shift in loss aversion was individually significant at the $P < 0.05$ level. Participants are descendingly ordered by loss aversion, with the most loss averse at the top, and the least loss averse at the bottom.

LRTs assessing the overall significance of the estimated models in both 'Attend' and 'Regulate' were overwhelmingly significant (all $Ps < 10^{-6}$). We also calculated the mean predicted likelihood of participants' choices given the estimated parameters. Across participants, the average predicted likelihood of a choice given the estimates was 0.75 (s.e. = 0.01) in 'Attend' and 0.73 (s.e. = 0.01) in 'Regulate', demonstrating that choices were predicted imperfectly, but much better than chance (See Supplementary Data for more details).

Imaging results

We performed two types of analysis on the fMRI data. First, we examined event-specific, transient responses by analyzing parameter estimates (β's) of activity across the brain. Second, because of the

Table 1 Contrast and correlation activations

Brain region (+ or − is the contrast value sign)	Brodmann's area (BA)	Talairach coordinates (*x, y, z*)	Number of voxels (1 mm^3)
Loss aversion at decision: 'Attend' decision subjective expected value > + ($n = 47$); $P < 0.001$ (unc); cluster threshold = 81 mm^3;			
+ Right striatum		8, 5, 6	567
+ Left striatum		−8, 4, 5	131
− Lingual gyrus	19	8, −63, 0	478
+ Lingual gyrus	19	−13, −69, −5	2671
+ Midbrain		−8, −24, −6	82
+ Middle frontal gyrus	46	−43, 42, 15	98
+ Precentral gyrus	6	−46, −1, 32	85
Loss aversion at outcome ('Attend'): Correlation: 'Attend' λ with (Attend Lose > Win) ($n = 39$); $P < 0.005$ (unc); cluster threshold = 81 mm^3;			
+ Left amygdala		−22, 2, −19	163
Loss aversion at outcome ('Regulate'): Correlation: 'Regulate' λ with (Regulate Lose > Win) ($n = 39$); $P < 0.005$ (unc); cluster threshold = 81 mm^3;			
− Inferior frontal gyrus	13	38, 27, 14	109
− Parahippocampal gyrus		34, −15, −23	430
− Cerebellum		38, −39, −25	99
− Cuneus	18	17, −83, 22	255
− Inferior parietal lobe	40	−64, −33, 30	132
Regions responding to value: Attend Win > Attend Lose ($n = 40$); $P < 0.001$ (unc); cluster threshold = 81 mm^3;			
+ Ventromedial prefrontal cortex	24	−8, 32, 3	213
+ Right Caudate head		8, 4, 1	924
+ Left Caudate head		−12, 2, −2	897
+ Anterior cingulate	24	15, 29, 11	615
+ Medial frontal gyrus	10	−6, 51, 11	342
+ Supplementary motor area	6	−8, −26, 54	182
+ Right parietal lobe		29, −26, 33	828
+ Right parietal lobe		30, −28, 31	113
+ Right frontal lobe		23, −1, 28	340
+ Left frontal lobe		−28, −12, 28	178
+ Thalamus		−6, −33, 16	105
Regions related to application of the regulation strategy: Regulate decision ME > Attend decision ME ($n = 16$); $P < 0.005$ (unc); cluster threshold = 81 mm^3;			
+ Right dorsolateral prefrontal cortex	9	31, 37, 30	92
+ Supplementary motor area	6	6, −12, 59	196
+ Motor cortex	4	−3, −35, 59	86
+ Right thalamus		6, −22, 7	99

blocked nature of the reappraisal task, we thought there might be baseline shifts in activity as a function of condition (i.e. 'Attend' or 'Regulate'), in addition to any event-specific effects. In order to investigate this possibility, we analyzed trial-triggered averages of fMRI BOLD signal to look for baseline shifts in activity across decision and outcome. See Table 1 for detailed contrast results.

Correlates of loss aversion at decision and outcome

In our analysis of β's, we looked for correlates of loss aversion separately at decision and outcome. A previous study of loss aversion examined activity at the time of decision and found that activity in the ventral striatum and other regions reflected the overall expected utility (including the estimated degree of loss aversion) of the potential losses and gains being considered (Tom *et al.*, 2007). Since gain and loss values were presented simultaneously at the time of decision and were correlated (see Methods in Supplementary Data), it was not possible to independently analyze the BOLD response to losses or to gains at decision. Instead, we calculated the expected utility of the mixed valence gambles in the baseline 'Attend' condition using participants' individually estimated value functions, including their unique λ estimate. This parametric regressor was then entered into a whole-brain analysis, identifying regions of the brain whose activity correlated with the expected utility (including loss aversion) of the gamble being considered. Among the regions whose activity at decision correlated with this regressor was the bilateral striatum (Table 1; see also Supplementary Data), consistent with previous results suggesting a unified representation in that region of expected utility at decision (e.g. Hsu *et al.*, 2005; Preuschoff *et al.*, 2006).

In analyzing outcome-related activity for correlates of behavioral loss aversion, we were able to separately estimate the BOLD responses to loss outcomes and gain outcomes (since only one outcome occurred at any given time), and then do second-level correlations and contrasts with those estimates. We performed a correlation of the log of individuals' λ values (loss aversion) in 'Attend' with the voxelwise contrast of 'Attend' Loss > 'Attend' Win across the entire brain (both main effect, or binary predictors). This analysis revealed a region of the left amygdala as the sole neural correlate at outcome of behavioral loss aversion under these conditions [$r(37) = 0.58$ $P < 0.0002$; Figure 3A; Figure 3B is a replotting of the correlation for illustrative purposes only; see Table 1 for whole-brain correlation details]. Previous findings related behavioral loss aversion to physiological arousal responses to loss *vs* gain outcomes in a parallel fashion (Sokol-Hessner *et al.*, 2009). Since the amygdala is known to mediate arousal responses across a variety of contexts (Phelps *et al.*, 1998; Garavan *et al.*, 2001; Williams *et al.*, 2001; Glascher and Adolphs, 2003; McGaugh, 2004), these findings serve as further evidence that the aforementioned arousal–loss aversion relationship may be amygdala mediated. A similar whole-brain correlation of the behavioral loss

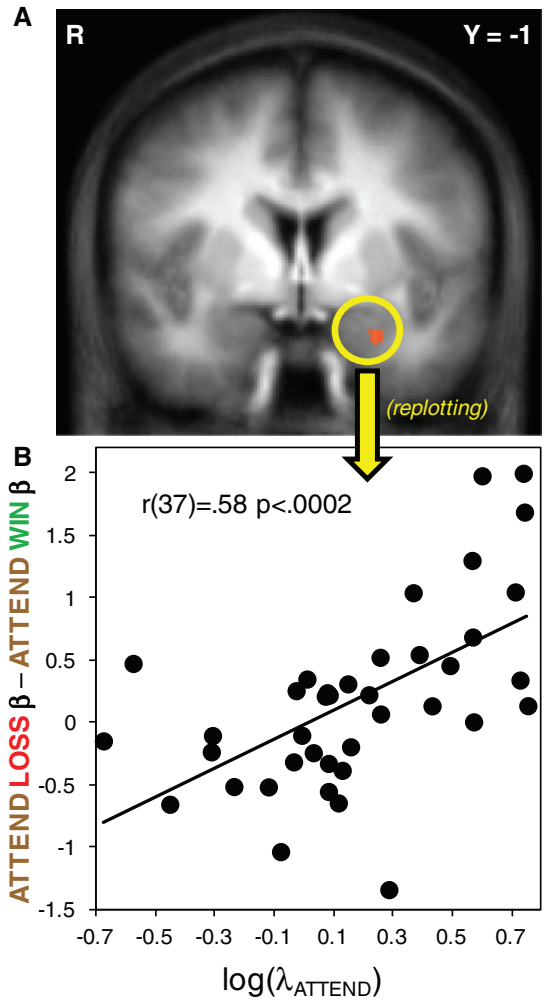


Fig. 3 Whole-brain correlation between loss aversion and outcome activity. (**A**) Whole-brain voxelwise correlation between individuals' estimated λ_{ATTEND} and the contrast values for 'Attend' Loss – 'Attend' Win. Map thresholded at $P<0.005$, voxel extent threshold = 81 mm^3; (**B**) Replotting of the correlation for illustration only.

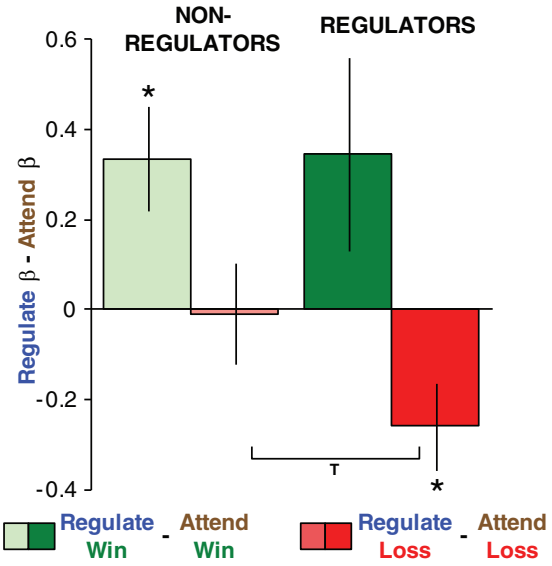


Fig. 4 Successful regulators reduce amygdala responses to loss outcomes. β estimates are extracted from the left amygdala region identified in Figure 3 and Table 1. *Y*-axis is the β estimate in 'Regulate' minus that in 'Attend' for either wins (greens) or losses (reds). Positive numbers indicate increased activity in 'Regulate', negative numbers indicate reduced activity in 'Regulate'. Asterisks indicate significantly different from zero at $P<0.05$. "T" indicates a significant group difference (one-tailed two-sample unequal variance *t*-test, $P=0.05$).

aversion coefficient from the 'Regulate' condition with the contrast of 'Regulate' Loss > 'Regulate' Win did not identify any of our predefined regions of interest (Table 1). Additionally, estimates of activity extracted from the left amygdala ROI did not show a strong relationship with loss aversion in the 'Regulate' condition [$r(37)=0.23$ $P<0.16$]. Fisher's *r*-to-*z* transformation indicated that the 'Attend' and 'Regulate' correlations were weakly different ($z=1.82$, $P=0.07$).

Transient effects of regulation at outcome

In our previous behavioral and physiological study, we found that individuals who successfully reduced their loss aversion with the emotion regulation strategy ('Regulators') showed reductions in their physiological arousal responses to loss outcomes (Sokol-Hessner *et al.*, 2009). In the present study, there were two ways to examine changes in outcome responses—on a group level (within and between 'Regulators' and 'Non-Regulators'), and using more continuous tests (correlations with regulation success). In both cases, we analyzed the main-effect parameter estimates of activity extracted from the left amygdala region identified in the correlation with loss aversion (see previous section and Table 1), and analyzed those β's for changes from 'Attend' to 'Regulate'.

Using the first, group-based approach, we looked at changes in activity to losses and to gains for the 'Regulators'. Similar to our previous study's arousal results, the 'Regulator' participants showed a strong reduction in their amygdala responses to losses [mean 'Regulate' Loss β – 'Attend' Loss $\beta=-0.26$; $t(13)=2.21$, $P<0.05$], while 'Non-Regulators' showed no such change (mean 'Regulate' Loss β – 'Attend' Loss $\beta=-0.01$; $t(24)=0.08$, $P<0.95$), a difference that was significant between groups [one-tailed two-sample unequal variance *t*-test; $t(36.25)=1.67$, $P=0.05$]. In the case of win outcomes, both 'Non-Regulators' and 'Regulators' showed similarly sized increases in their left amygdala responses ('Regulators' mean 'Regulate' Win β – 'Attend' Win $\beta=0.35$; $t(13)=1.62$, $P<0.13$; 'Non-Regulators' mean 'Regulate' Win β – 'Attend' Win $\beta=0.34$; $t(24)=2.90$, $P<0.008$) (Figure 4).

Taking the second, correlational approach to examining the relationship between regulation success and outcome processing, we performed correlations across all participants (both 'Regulators' and 'Non-Regulators') of individuals' percent reduction in λ (loss aversion) with the reduction in left amygdala responses to loss outcomes, and to win outcomes. Regulation success was marginally significantly correlated in the left amygdala ROI with reduction in BOLD responses to loss outcomes (Percent reduction in λ correlated with 'Attend' Loss β – 'Regulate' Loss β; $r(37)=0.26$, $P<0.08$), but was not correlated with change in responses to gain outcomes (Percent reduction in λ correlated with 'Attend' Win β – 'Regulate' Winβ; $r(37)=-0.11$, $P<0.49$), though the difference between the Loss β and Gain β correlations was not significant (Fisher's *r*-to-*z* transformation, $z=1.6$, $P=0.11$).

The findings from both group-level and correlational approaches implicate the regulation of loss outcome responses in the successful attenuation of behavioral loss aversion, directly echoing previous results with physiological arousal (Sokol-Hessner *et al.*, 2009).

Baseline effects of regulation across decision and outcome

Two final sets of contrasts were used to examine responses in regions of the brain related to regulation and choice behavior, in keeping with

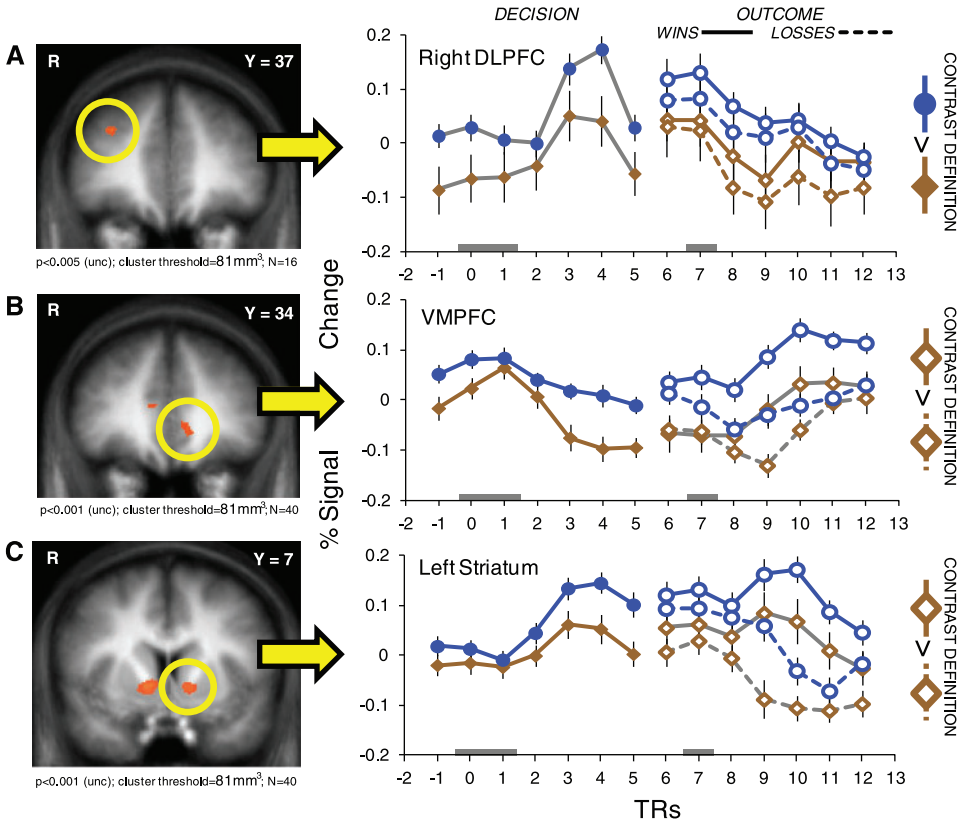


Fig. 5 Trial-triggered averages for activity in (**A**) right DLPFC, (**B**) VMPFC and (**C**) left striatum. Brown diamonds represent 'Attend' activity, and blue circles represent 'Regulate' activity. Decision activity is indicated with filled-in markers, outcome activity with outlined markers, and wins and losses with solid and dotted lines, respectively. The contrasts used to define the ROIs are indicated on the right, and their respective lines are plotted in gray on the graph. Decision activity is locked to the time of decision presentation (TRs 0 and 1, indicated by gray block on *X*-axis). Outcome activity is locked to the presentation of the outcome (labeled TR 7 on the graph, indicated by gray block on *X*-axis). Error bars are standard error of the mean

the expectation of regulation-related effects at decision and changes in the processing of outcomes as a consequence of regulation. The regions of interest were defined as follows. First, the contrast of the main effect of a 'Regulate' decision *vs* that of an 'Attend' decision ('Regulate' Decision > 'Attend' Decision) was performed on the 'Regulators', identifying a region of the right DLPFC related to the application of the regulation strategy. The DLPFC has been repeatedly implicated in studies of emotion regulation (Ochsner *et al.*, 2002, 2004; Banks *et al.*, 2007; Eippert *et al.*, 2007; Delgado *et al.*, 2008a, 2008b; Ochsner and Gross, 2008; Hartley and Phelps, 2010). Second, areas related to value computation, including the bilateral striatum and VMPFC, were identified by contrasting estimates of BOLD activity to gain outcomes with that to loss outcomes ('Attend' Win > 'Attend' Lose; see Table 1 for full list of regions identified in both contrasts).

Since the regulation task was blocked (choices were in sets of 25; see Experimental Procedures section), we were able to examine whether any changes might have occurred in baseline levels of BOLD activity as a function of regulation by using trial-triggered averaging (see 'Methods' section). In contrast to the previously discussed event-specific transient responses represented by β estimates of activity, we expected to observe baseline increases in activity over the entire time course as a result of the condition ('Attend' or 'Regulate'). For each of the aforementioned regions of interest, trial-triggered averages were calculated for all participants with sufficient data for outcome analyses ($n = 40$).

As mentioned above, the first contrast ('Regulate' Decision > 'Attend' Decision) identified voxels in the DLPFC. Confirming the transient-focused contrast of β's used to define this region of DLPFC, the trial-triggered averages across the decision period exhibited greater activity in the 'Regulate' condition as opposed to the 'Attend' condition [$t(6) = 8.2$, $P < 0.0002$]. Interestingly, that increase in baseline activity persisted throughout the outcome phase [during wins, $t(6) = 4.9$, $P < 0.003$; during losses, $t(6) = 6.2$, $P < 0.0008$].

Trial-triggered averages from the striatum and VMPFC, identified in the second contrast ('Attend' Win > 'Attend' Lose), exhibited a parallel pattern to DLPFC activity. Separate ANOVAs performed on the left striatum and the VMPFC also showed increased activity in the 'Regulate' condition as compared to 'Attend' at decision [repeated measures ANOVA, condition (2) x TR (7); Left striatum main effect of condition $F(1,39) = 4.1$, $P < 0.05$; VMPFC main effect of condition $F(1,39) = 5.1$, $P < 0.03$], as well as outcome [repeated measures ANOVA, condition (2) x outcome type (2) x TR (7); Left striatum main effect of condition $F(1,39) = 7.9$, $P < 0.008$; VMPFC main effect of condition $F(1,39) = 14.8$, $P < 0.001$] (Right striatum results were similar to the left striatum; See Supplementary Table S2 for full ANOVA results). This result was further confirmed by planned paired *t*-tests for both the striatum [left striatum at decision $t(6) = 4.5$, $P < 0.004$; during wins, $t(6) = 14.5$, $P < 7 \times 10^{-6}$; and during losses, $t(6) = 6.6$, $P < 6 \times 10^{-4}$], and for the VMPFC [at decision $t(6) = 5.5$, $P < 0.002$; during wins, $t(6) = 22.6$, $P < 5 \times 10^{-7}$; and during losses, $t(6) = 4.5$, $P < 0.005$] (Figure 5). The data from both striatum and VMPFC suggest that baseline shifts, like those observed in DLPFC above, may also extend into regions more generally associated with value representation.

DISCUSSION

In the present study, we examine the BOLD correlates of loss aversion during a risky decision-making task and the effect of intentionally reappraising the meaning of the choice on decisions and brain activity. We find striking similarities both to previous studies directly assessing emotional responses in decision making, as well as to studies of emotion regulation in non-choice domains. Our three main results are: (i) amygdala activity to losses *vs* gains correlates with estimates of behavioral loss aversion; (ii) individuals' degree of success in regulating their choices is correlated with changes in amygdala responses to losses only—a pattern that directly echoes previous findings with physiological emotional responses (Sokol-Hessner *et al.*, 2009); and (iii) baseline increases in BOLD activity during reappraisal in regions of the brain, including DLPFC, VMPFC and striatum, that mirror regulation-related activity found in other studies of emotion regulation (Ochsner *et al.*, 2002, 2004; Banks *et al.*, 2007; Eippert *et al.*, 2007; Delgado *et al.*, 2008a, 2008b). Together, these results suggest that the observed BOLD correlates of reappraisal during decision-making overlap with those from emotion regulation. As perspective taking, by definition, alters appraisals, a component of emotion (Scherer, 2005) and emotion regulation (Gross, 1998), these findings confirm the importance of emotion regulation in decision making. Specifically, they suggest value computation includes emotional components that can be intentionally shifted, just like other emotional responses.

Behaviorally, other studies on emotion regulation differ from the current study in that their quantitative analyses of regulation success focused on the group level (Ochsner *et al.*, 2002, 2004; Banks *et al.*, 2007; Eippert *et al.*, 2007; Delgado *et al.*, 2008a, 2008b; Wager *et al.*, 2008; Urry *et al.*, 2009). While we performed group-level analyses, the nature of our task also enabled a second level of analysis, in which we were able to quantitatively investigate the strength or significance of our effect on an individual–participant basis. This approach was as unique to the study of emotion regulation as it was critical in characterizing some of our effects.

In addition to this study, we are aware of two others that have quantitatively estimated individuals' loss aversion, and examined the relationship to neural function. First, Tom *et al.* (2007), found a unified representation of expected utility (which included loss aversion) in VMPFC and striatal responses (among other regions; but not the amygdala) at the time of decision over mixed valence gambles. We also found bilateral striatal activity at decision representing expected utility, implicating the striatum in loss aversion. The second study, De Martino *et al.* (2010), observed two patients with bilateral amygdala lesions as they made choices in a task nearly identical to that in Tom *et al.* (2007), and found that neither patient was loss averse (λ's of 0.76 and 1.06; both less than matched controls). In our study, amygdala responses to loss outcomes relative to gain outcomes correlated with loss aversion, implicating the amygdala in its representation. Despite the fact that these findings indicate different regions of the brain in loss aversion (the striatum, Tom *et al.*, 2007; the amygdala, De Martino *et al.*, 2010), we believe our findings and those of the previous two studies can be accounted for in a unified model, proposed below.

The current study, in combination with Sokol-Hessner *et al.* (2009), links responses (neurally and physiologically) to outcomes with estimates of behavior from decisions. It is possible that responses at outcome may be incidentally linked to decisions, without influencing them. Alternatively, and we think more likely, our findings are consistent with a model in which anticipated responses to outcomes might guide behavior at decision. This latter model, in line with extant theories (LeDoux and Gorman, 2001; Delgado *et al.*, 2008c; Seymour and Dolan, 2008; Talmi *et al.*, 2008; De Martino *et al.*, 2010), suggests that amygdala responses to outcomes may signal emotional salience. These signals modulate activity in regions including the striatum and VMPFC, which have well documented connections with the amygdala (Amaral *et al.*, 1992). This modulation would lead activity in those regions at decision to reflect loss aversion.

Though further testing of this model will clearly be necessary, it can account for the conclusions of previous studies. As Tom *et al.* (2007) had decisions without outcomes, BOLD activity could have reflected stored values or weights, perhaps from previous experience. De Martino *et al.* (2010) might then have observed no loss aversion in patients in the same task because of a complete absence of an amygdala signal, during or prior to the study. By imaging decisions and outcomes in the present study, we could confirm Tom *et al.* (2007), and observe the hypothesized amygdala signal from De Martino *et al.* (2010) both in baseline behavior and as it changed during reappraisal.

It is additionally notable that the proposed model is similar to modulatory models of the role of emotion and the amygdala in capturing attention (Taylor and Fragopanagos, 2005; Pourtois and Vuilleumier, 2006; Stanley *et al.*, 2009), altering memory (Phelps *et al.*, 1998; McGaugh, 2004; Kensinger and Schacter, 2008), and learning contingencies (Phelps *et al.*, 2004; Schiller *et al.*, 2008). The present study suggests a similar modulatory role in decision making.

Further supporting this hypothesis that affective salience plays a role in loss aversion, the pattern of amygdala responses to outcomes exhibits striking similarities to the pattern previously found for arousal responses (Sokol-Hessner *et al.*, 2009). In that study, skin conductance responses to losses (relative to gains) correlated with loss aversion. Individuals who reduced their loss aversion reduced their arousal responses to losses relative to gains, driven by a reduction in the response to losses. The present study showed a similar correlation between loss aversion and the response to losses *vs* gains in the amygdala, and linked the reduction in loss aversion with reduction in amygdala activity to losses. Though neural data are not evidence of emotion (Phelps, 2009), it is compelling that amygdala activity exhibits the same pattern observed in research with emotional responses (Sokol-Hessner *et al.*, 2009), consistent with amygdala mediation of physiological arousal responses (Garavan *et al.*, 2001; Glascher and Adolphs, 2003). These parallels suggest that relative emotional responses to outcomes may support loss aversion and its regulation.

In addition to the effects discussed above of reappraisal on participants' responses to events, like winning or losing money, our blocked design also allowed us to observe consequences of reappraisal on longer timescales. The shifts we found in baseline BOLD activity using trial-triggered averaging suggest that taking a different perspective may also involve maintaining a tonic mindset over the course of a block. Such shifts indicate that perspective taking might be similar to regulatory fit (Higgins, 2005; Avnet and Higgins, 2006) or manipulations of mood (Lerner *et al.*, 2004; Harlé and Sanfey, 2007; Andrade and Ariely, 2009).

That the DLPFC showed a baseline shift is consistent with a putative role in strategic representation and control (Miller and Cohen, 2001; Badre and D'Esposito, 2007), the (non-intentional) regulation of value and decision making (Knoch *et al.*, 2006a, 2006b; Hare *et al.*, 2009; Bhatt *et al.*, 2010; Figner *et al.*, 2010), and the neural mechanisms supporting emotion regulation (Ochsner and Gross, 2008; Hartley and Phelps, 2010). This suggests that similar neural mechanisms may support regulation in financial situations. Of course, DLPFC localization varies (Ochsner and Gross, 2008; Hartley and Phelps, 2010), and there is currently no consensus on its functional organization (Miller and Cohen, 2001; Badre and D'Esposito, 2007; for more discussion, see Supplementary Data).

Baseline shifts were also found in other brain regions. These include the VMPFC, associated with expected utility (Hampton *et al.*, 2006; Tom *et al.*, 2007; Weber *et al.*, 2007; Hare *et al.*, 2008, 2009), extinction

of conditioned stimuli (Phelps *et al.*, 2004; Kalisch *et al.*, 2006; Schiller *et al.*, 2008) and emotion regulation (Ochsner *et al.*, 2004; Delgado *et al.*, 2008b), as well as the striatum, strongly linked with value representation (Hsu *et al.*, 2005; Hampton *et al.*, 2006; Kable and Glimcher, 2007; Tom *et al.*, 2007; Delgado *et al.*, 2008c; Hare *et al.*, 2008). Our findings would, therefore, argue that the conceptualization of these regions' function should include a degree of mutability in response to intentional control.

The present study provides BOLD evidence for the similarities between perspective taking and emotion regulation, and the overlap between emotion and value. We connect loss aversion with amygdala activity, and show that as in emotion regulation, taking a perspective that reduces loss aversion also reduces amygdala responses, and increases prefrontal activity. In combination with previous work, these findings suggest emotional responses are part of value computation, and that those responses, and therefore value itself, can be intentionally controlled. Decision making and valuation are neither as dispassionate as some may have hoped, nor as far outside our conscious control as others may have feared. Instead, the act of choice, much like attention, perception and learning, is multiply determined and perhaps most importantly, within our control.

SUPPLEMENTARY DATA

Supplementary data are available at *SCAN* online.

Conflict of Interest

None declared.

REFERENCES

Amaral, D.B., Price, J.L., Pitkanen, A., Carmichael, S.T. (1992). Anatomical organization of the primate amygdaloid complex. In: Aggleton, J.P., editor. *The Amygdala: Neurobiological Aspects of Emotion, Memory, and Mental Dysfunction*. New York: Wiley-Liss, pp. 1–66.

Andrade, E.B., Ariely, D. (2009). The enduring impact of transient emotions on decision making. *Organizational Behavior And Human Decision Processes*, *109*(1), 1–8.

Avnet, T., Higgins, E.T. (2006). How regulatory fit affects value in consumer choices and opinions. *Journal of Marketing Research*, *43*(1), 1–10.

Badre, D., D'Esposito, M. (2007). Functional magnetic resonance imaging evidence for a hierarchical organization of the prefrontal cortex. *Journal of Cognitive Neuroscience*, *19*(12), 2082–99.

Banks, S.J., Eddy, K.T., Angstadt, M., Nathan, P.J., Phan, K.L. (2007). Amygdala-frontal connectivity during emotion regulation. *Social Cognitive and Affective Neuroscience*, *2*(4), 303–12.

Bechara, A., Damasio, H., Tranel, D., Damasio, A.R. (1997). Deciding advantageously before knowing the advantageous strategy. *Science*, *275*(5304), 1293–5.

Bhatt, M., Lohrenz, T., Camerer, C.F., Montague, P.R. (2010). Neural signatures of strategic type in a two-person bargaining game. *PNAS*, *107*(46), 19720–5.

Buckner, R., Bandettini, P., O'Craven, K., et al. (1996). Detection of cortical activation during averaged single trials of a cognitive task using functional magnetic resonance imaging. *PNAS*, *93*, 14878–83.

Camerer, C., Babcock, L., Loewenstein, G., Thaler, R.H. (1997). Labor supply of new york city cabdrivers: one day at a time. *Quarterly Journal of Economics*, *112*(2), 407–441.

Clark, L., Bechara, A., Damasio, H., Aitken, M.R.F., Sahakian, B.J., Robbins, T.W. (2008). Differential effects of insular and ventromedial prefrontal cortex lesions on risky decision-making. *Brain*, *131*(5), 1311–22.

Critchley, H.D., Wiens, S., Rotshtein, P., Ohman, A., Dolan, R.J. (2004). Neural systems supporting interoceptive awareness. *Nature Neuroscience*, *7*(2), 189–95.

De Martino, B., Camerer, C.F., Adolphs, R. (2010). Amygdala damage eliminates monetary loss aversion. *PNAS*, *107*, 3788–92.

Delgado, M.R., Gillis, M., Phelps, E.A. (2008a). Regulating the expectation of reward via cognitive strategies. *Nature Neuroscience*, *11*(8), 880–1.

Delgado, M.R., Nearing, K.I., Ledoux, J.E., Phelps, E.A. (2008b). Neural circuitry underlying the regulation of conditioned fear and its relation to extinction. *Neuron*, *59*, 829–38.

Delgado, M.R., Schotter, A., Ozbay, E., Phelps, E.A. (2008c). Understanding overbidding: using the neural circuitry of reward to design economic auctions. *Science*, *321*(5897), 1849–52.

Donaldson, D., Petersen, S., Ollinger, J., Buckner, R. (2001). Dissociating state and item components of recognition memory using fmri. *Neuroimage*, *13*(1), 129–42.

Eippert, F., Veit, R., Weiskopf, N., Erb, M., Birbaumer, N., Anders, S. (2007). Regulation of emotional responses elicited by threat-related stimuli. *Human Brain Mapping*, *28*(5), 409–23.

Figner, B., Knoch, D., Johnson, E.J., et al. (2010). Lateral prefrontal cortex and self-control in intertemporal choice. *Nature Neuroscience*, *13*(5), 538–9.

Frank, M.J., Cohen, M.X., Sanfey, A.G. (2009). Multiple systems in decision making: a neurocomputational perspective. *Current Directions in Psychological Science*, *18*(2), 73–7.

Garavan, H., Pendergrass, J.C., Ross, T.J., Stein, E.A., Risinger, R.C. (2001). Amygdala response to both positively and negatively valenced stimuli. *Neuroreport*, *12*(12), 2779–83.

Genesove, D., Mayer, C. (2001). Loss aversion and seller behavior: evidence from the housing market. *Quarterly Journal of Economics*, *116*(4), 1233–60.

Glascher, J., Adolphs, R. (2003). Processing of the arousal of subliminal and supraliminal emotional stimuli by the human amygdala. *The Journal Of Neuroscience*, *23*(32), 10274–82.

Gottfried, J.A., O'Doherty, J., Dolan, R.J. (2003). Encoding predictive reward value in human amygdala and orbitofrontal cortex. *Science*, *301*(5636), 1104–7.

Gross, J.J. (1998). Antecedent- and response-focused emotion regulation: divergent consequences for experience, expression, and physiology. *Journal of Personality and Social Psychology*, *74*, 224–37.

Haigh, M.S., List, J.A. (2005). Do professional traders exhibit myopic loss aversion? An experimental analysis. *Journal of Finance*, *60*(1), 523–34.

Hampton, A.N., Bossaerts, P., O'Doherty, J.P. (2006). The role of the ventromedial prefrontal cortex in abstract state-based inference during decision making in humans. *Journal of Neuroscience*, *26*(32), 8360–7.

Hare, T.A., Camerer, C.F., Rangel, A. (2009). Self-control in decision-making involves modulation of the vmpfc valuation system. *Science*, *324*(5927), 646–8.

Hare, T.A., O'Doherty, J.P., Camerer, C.F., Schultz, W., Rangel, A. (2008). Dissociating the role of the orbitofrontal cortex and the striatum in the computation of goal values and prediction errors. *Journal of Neuroscience*, *28*(22), 5623–30.

Harlé, K., Sanfey, A.G. (2007). Incidental sadness biases social economic decisions in the ultimatum game. *Emotion*, *7*(4), 876–81.

Hartley, C.A., Phelps, E.A. (2010). Changing fear: the neurocircuitry of emotion regulation. *Neuropsychopharmacology*, *35*(1), 136–46.

Higgins, E.T. (2005). Value from regulatory fit. *Current Directions in Psychological Science*, *14*(4), 209–13.

Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., Camerer, C.F. (2005). Neural systems responding to degrees of uncertainty in human decision-making. *Science*, *310*(5754), 1680–3.

Kable, J.W., Glimcher, P.W. (2007). The neural correlates of subjective value during intertemporal choice. *Nature Neuroscience*, *10*(12), 1625–33.

Kahneman, D., Tversky, A. (1979). Prospect theory - analysis of decision under risk. *Econometrica*, *47*(2), 263–91.

Kalisch, R., Korenfeld, E., Stephan, K.E., Weiskopf, N., Seymour, B., Dolan, R.J. (2006). Context-dependent human extinction memory is mediated by a ventromedial prefrontal and hippocampal network. *The Journal of Neuroscience*, *26*(37), 9503–11.

Kensinger, E.A., Schacter, D.L. (2008). Memory and emotion. In: Lewis, M., Haviland-Jones, J.M., Barrett, L.F., editors. *Handbook of Emotions*. Guilford Press, pp. 601–17.

Knoch, D., Gianotti, L.R.R., Pascual-Leone, A., et al. (2006a). Disruption of right prefrontal cortex by low-frequency repetitive transcranial magnetic stimulation induces risk-taking behavior. *Journal of Neuroscience*, *26*(24), 6469–72.

Knoch, D., Pascual-Leone, A., Meyer, K., Treyer, V., Fehr, E. (2006b). Diminishing reciprocal fairness by disrupting the right prefrontal cortex. *Science*, *314*, 829–32.

Ledoux, J.E. (2000). Emotion circuits in the brain. *Annual Review of Neuroscience*, *23*, 155–84.

Ledoux, J.E., Gorman, J.M. (2001). A call to action: overcoming anxiety through active coping. *American Journal of Psychiatry*, *158*(12), 1953–5.

Lerner, J.S., Small, D.A., Loewenstein, G.F. (2004). Heart strings and purse strings: carryover effects of emotions on economic decisions. *Psychological Science*, *15*(5), 337–41.

Lo, A.W., Repin, D.V. (2002). The psychophysiology of real-time financial risk processing. *Journal of Cognitive Neuroscience*, *14*(3), 323–39.

Loewenstein, G. (1996). Out of control: visceral influences on behavior. *Organizational Behavior and Human Decision Processes*, *65*(3), 272–92.

Mcgaugh, J.L. (2004). The amygdala modulates the consolidation of memories of emotionally arousing experiences. *Annual Review of Neuroscience*, *27*, 1–28.

Miller, E.K., Cohen, J.D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience*, *24*, 167–202.

Morris, J.S., Frith, C.D., Perrett, D.I.J., et al. (1996). A differential neural response in the human amygdala to fearful and happy facial expressions. *Nature*, *383*(6603), 812–5.

Murray, E.A. (2007). The amygdala, reward and emotion. *Trends in Cognitive Science*, *11*(11), 489–97.

Ochsner, K.N., Bunge, S.A., Gross, J.J., Gabrieli, J.D.E. (2002). Rethinking feelings: an fmri study of the cognitive regulation of emotion. *Journal of Cognitive Neuroscience*, *14*(8), 1215–29.

Ochsner, K.N., Gross, J.J. (2008). Cognitive emotion regulation: insights from social cognitive and affective neuroscience. *Current Directions in Psychological Science*, *17*(2), 153–8.

Ochsner, K.N., Ray, R.D., Cooper, J.C., et al. (2004). For better or for worse: neural systems supporting the cognitive down- and up-regulation of negative emotion. *Neuroimage*, *23*(2), 483–99.

Ollinger, J.M., Corbetta, M., Shulman, G.L. (2001a). Separating processes within a trial in event-related functional MRI - II. Analysis. *Neuroimage*, *13*(1), 218–29.

Ollinger, J.M., Shulman, G.L., Corbetta, M. (2001b). Separating processes within a trial in event-related functional MRI - I. The method. *Neuroimage*, *13*(1), 210–7.

Paulus, M.P., Rogalsky, C., Simmons, A., Feinstein, J.S., Stein, M.B. (2003). Increased activation in the right insula during risk-taking decision making is related to harm avoidance and neuroticism. *Neuroimage*, *19*(4), 1439–48.

Phelps, E.A. (2009). The study of emotion in neuroeconomics. In: Glimcher, P.W., Camerer, C.F., Fehr, E., Poldrack, R.A., editors. *Neuroeconomics: Decision Making And The Brain*. London, UK: Academic Press, pp. 233–50.

Phelps, E.A., Delgado, M.R., Nearing, K.I., Ledoux, J.E. (2004). Extinction learning in humans: role of the amygdala and VMPFC. *Neuron*, *43*, 897–905.

Phelps, E.A., Labar, K.S., Anderson, A.K., O'Connor, K.J., Fulbright, R.K., Spencer, D.D. (1998). Specifying the contributions of the human amygdala to emotional memory: a case study. *Neurocase*, *4*(6), 527–40.

Pourtois, G., Vuilleumier, P. (2006). Dynamics of emotional effects on spatial attention in the human visual cortex. *Progress in Brain Research*, *156*, 67–91.

Preuschoff, K., Bossaerts, P., Quartz, S.R. (2006). Neural differentiation of expected reward and risk in human subcortical structures. *Neuron*, *51*(3), 381–90.

Schachter, S., Singer, J.E. (1962). Cognitive, social and phsyiological determinants of emotional state. *Psychological Review*, *69*(5), 379–99.

Scherer, K.R. (2005). What are emotions? And how can they be measured? *Social Science Information*, *44*(4), 695–729.

Schiller, D., Levy, I., Niv, Y., Ledoux, J.E., Phelps, E.A. (2008). From fear to safety and back: reversal of fear in the human brain. *Journal of Neuroscience*, *28*(45), 11517–25.

Seymour, B., Dolan, R.J. (2008). Emotion, decision making, and the amygdala. *Neuron*, *58*(5), 662–71.

Shiv, B., Loewenstein, G.F., Bechara, A., Damasio, H., Damasio, A.R. (2005). Investment behavior and the negative side of emotion. *Psychological Science*, *16*(6), 435–9.

Sokol-Hessner, P., Hsu, M., Curley, N.G., Delgado, M.R., Camerer, C.F., Phelps, E.A. (2009). Thinking like a trader selectively reduces individuals' loss aversion. *PNAS*, *106*(13), 5035–40.

Stanley, D., Ferneyhough, E., Phelps, E.A. (2009). Neural perspectives on emotion: impact on perception, attention, and memory. In: Berntson, G.G., Cacioppo, J.T., editors. *Handbook of Neuroscience for the Behavioral Sciences*. Hoboken, New Jersey: John Wiley & Sons, pp. 2.

Talairach, J., Tournoux, P. (1988). *Co-Planar Stereotaxis Atlas of the Human Brain: An Approach to Medical Cerebral Imaging*. Stuttgart, New York: Thieme Medical Publishers.

Talmi, D., Seymour, B., Dayan, P., Dolan, R.J. (2008). Human pavlovian instrumental transfer. *Journal of Neuroscience*, *28*(2), 360–8.

Taylor, J.G., Fragopanagos, N.F. (2005). The interaction of attention and emotion. *Neural Networks*, *18*, 353–69.

Tom, S.M., Fox, C.R., Trepel, C., Poldrack, R.A. (2007). The neural basis of loss aversion in decision-making under risk. *Science*, *315*, 515–8.

Tversky, A., Kahneman, D. (1991). Loss aversion in riskless choice: a reference-dependent model. *Quarterly Journal of Economics*, *106*(4), 1039–61.

Urry, H.L., Van Reekum, C.M., Johnstone, T., Davidson, R.J. (2009). Individual differences in some (but not all) medial prefrontal regions reflect cognitive demand while regulating unpleasant emotion. *Neuroimage*, *47*(3), 852–63.

Van 'T Wout, M., Kahn, R., Sanfey, A.G., Aleman, A. (2006). Affective state and decision-making in the ultimatum game. *Experimental Brain Research*, *169*(4), 564–8.

Visscher, K., Miezin, F., Kelly, J., et al. (2003). Mixed blocked/event-related designs separate transient and sustained activity in fMRI. *Neuroimage*, *19*, 1694–708.

Wager, T.D., Davidson, M.L., Hughes, B.L., Lindquist, M.A., Ochsner, K.N. (2008). prefrontal-subcortical pathways mediating successful emotion regulation. *Neuron*, *59*, 1037–50.

Wang, J.T., Spezio, M., Camerer, C.F. (2010). Pinocchio's pupil: using eyetracking and pupil dilation to understand truth telling and deception in sender-receiver games. *American Economic Review*, *100*(3), 984–1007.

Weber, B., Aholt, A., Neuhaus, C., Trautner, P., Elger, C.E., Teichert, T. (2007). Neural evidence for reference-dependence in real-market-transactions. *Neuroimage*, *35*, 441–7.

Whalen, P.J., Rauch, S.L., Etcoff, N.L., Mcinerney, S.C., Lee, M.B., Jenike, M.A. (1998). Masked presentations of emotional facial expressions modulate amygdala activity without explicit knowledge. *Journal of Neuroscience*, *18*(1), 411–8.

Williams, L., Phillips, M., Brammer, M., et al. (2001). Arousal dissociates amygdala and hippocampal fear responses: evidence from simultaneous fMRI and skin conductance recording. *Neuroimage*, *14*(5), 1070–9.

Winkielman, P., Berridge, K.C., Wilbarger, J.L. (2005). Unconscious affective reactions to masked happy versus angry faces influence consumption behavior and judgments of value. *Personality and Social Psychology Bulletin*, *31*(1), 121–35.

SUPPLEMENTARY MATERIALS
Article Title: Emotion Regulation Reduces Loss Aversion by Decreasing Amygdala Responses to Losses
Authors: Sokol-Hessner, P, Camerer, CF, Phelps, EA

Behavioral estimation procedure

The estimation procedure was identical to that used in Sokol-Hessner et al (2009), and that paper can be referenced for more details and ancillary tests of the model. In brief, an exponential function was used to model participants' utility functions over gains and losses (Tversky and Kahneman, 1992). Curvature of the function was constrained to be identical in the gain domain and the loss domain (i.e. $\rho^+ = \rho^-$). The utility functions were as follows:

$$u(x) = \begin{cases} x^{\rho^+} & \text{if } x \geq 0 \\ -\lambda \cdot (-x)^{\rho^-} & x < 0 \end{cases}$$

The loss aversion coefficient (λ), represents the multiplicative weight on losses relative to gains. The exponential function captures risk attitudes and diminishing sensitivity. Lower values of ρ indicate more diminishing sensitivity and therefore increasing risk aversion in the gain domain and risk seeking in the loss domain. Conversely, higher values of ρ indicate less risk aversion in the gain domain, and less risk seeking in the loss domain. A ρ of 1 indicates a linear value function, and therefore risk-neutrality and an absence of diminishing sensitivity.

The probability of choosing the gamble instead of the guaranteed amount was given by the logit (softmax) function:

$$F(p,x_1,x_2,c) = \left(1 + \exp\left\{-\mu\left(U(p,x_1,x_2) - u(c)\right)\right\}\right)^{-1}$$

where p is the probability of winning the gamble, x_1 and x_2 are the outcomes in the gamble, and c is the guaranteed alternative. The parameter μ in the logit function captures the consistency of participants' choices. Low (high) estimates of μ indicate less (more) consistency over choices.

Denoting the choice of the subject in trial i as y_i, where $y_i = 1$ if the subject chose the gamble, and 0 if the guaranteed alternative, we fit the data using maximum likelihood, with the log likelihood function:

$$\sum_{i=1}^{150} y_i \log\left(F(p,x_1,x_2,c)\right) + (1 - y_i)\log\left(F(p,x_1,x_2,c)\right)$$

The estimation was performed in Mathematica v5.2 with the Nelder-Mead simplex algorithm (Nelder and Mead, 1965).

The standard errors were calculated using the negative of the inverse of the Hessian matrix evaluated at the estimated values for the parameters. The Hessian matrix consists of the second partial derivatives of the log likelihood function, and the negative of the Hessian is called the observed information matrix, also the asymptotic variance-covariance matrix. The square root of the diagonal variance terms yields the standard error estimates. The intuition is that the Hessian is an indication of the relative steepness (flatness) of the likelihood surface near the parameter estimates, and thereby indicates more (less) precise parameter estimates.

Significance Tests

Likelihood ratio tests (LRTs; Greene, 2003) were used on individual subjects' data for two purposes: to assess overall model fit, and to compare parameters between conditions. In both cases, the test compares the likelihood of the observed choices given the "full model" (least constrained; most parameters) against the reduced model (more constrained, fewer parameters). The likelihood ratio statistic, expressed in log, is $-2(\log(L(\Theta_0))-\log(L(\Theta)))$, where Θ stands in for the vector of parameters. That statistic is asymptotically distributed as a Chi-squared distribution with k degrees of freedom, where k is the number of parameter restrictions on the model.

In assessing overall model fit, the comparison was between the full model and a null model in which ρ, λ, and μ were constrained to 0 (a random choice model). In this case, k = 3df.

In assessing significant differences of individual parameters between "Attend" and "Regulate", we performed LRTs separately for ρ, λ, and μ, in which the reduced model was constrained such that $\theta_{\text{ATTEND}} = \theta_{\text{REGULATE}}$ (k = 1df).

An additional way to assess the power of the model in accounting for behavior is to calculate a measure of the geometric average predicted probability of the choices observed (random = 0.5, perfect prediction = 1; Ceiling expected prediction is roughly 0.85 (Camerer, 1989)). If the likelihood for choice c_i is $p(c_i)$, the log likelihood for all choices for a participant is given by:

$$\sum_{i=1}^{150} \log\left(p(c_i)\right)$$

Dividing the overall log likelihood by the number of choices (150) yields the average log likelihood per choice, and exponentiating that average log likelihood yields the geometric mean of the predicted likelihoods. Intuitively, this number represents the mean likelihood of observing a given participant's choices, given the estimated model.

Monetary Choice Amounts

For the exact monetary amounts, see Table S1. For the 120 mixed-valence trials (choices between a gamble with a positive and a negative possible outcome, and a

guaranteed amount of $0), gain values were from the set {$2, $4, $5, $6, $8, $9, $10, $12}. Loss values were derived by multiplying each gain value by factors from -2 to -1/4 in steps of 1/8. The gain-only trials consisted of choices between a gamble with positive and $0 possible outcomes, and a positive guaranteed amount. The catch, or partial trials were mixed valence in nature, though outcomes were never shown for these trials. In order to prevent participants from seeing the same choices twice in a given condition, though their gain values were from the same set as the 120 mixed valence trials, the corresponding loss values were calculated by multiplying each gain value by the factors -0.2, -0.4, -0.8, and -1.6. The guaranteed amount was always $0 in catch trials.

Additional notes on replication of Tom et al. (2007)

In replicating the analyses performed in previous research on loss aversion and decision-making (Tom et al., 2007), we were unable to execute exactly the same analyses. This was largely due to the manner in which we matched loss values with gain values in our mixed-valence trials. That is, we took a static set of gain values, and multiplied each by a set of negative multiplicative factors to yield loss values (see Monetary Choice Amounts, above, Table S1, and Figure S1). Therefore, at decision, gain and loss values correlated significantly with each other ($r(118) = -0.65$ $p < 2 \times 10^{-15}$). This correlation precluded the entering of potential gain values as separate from potential loss values in analyses of BOLD signal at the time of decision.

However, the analysis from Tom et al (2007) identified overlapping regions in modulating their activity depending on the size of potential losses and potential gains, and found their relative activity to be related to loss aversion. Seeing as these potential gains and potential losses were being processed at the same time (during the presentation of a decision), that is equivalent to saying that these regions' activity tracked the subjective expected value of the mixed valence gamble being considered. Therefore, we performed an analysis with the subjective expected value of the mixed valence trials entered as a regressor (see main paper).

Localizing Dorsolateral Prefrontal Cortex (DLPFC)

In localizing regulation strategy-related activity to the DLPFC, there are a number of reasons the relevant results may have been less robust than expected.

First, As the strategy participants applied in "Regulate" was broad in scope, including phrases like "as if you were a trader," "not your money," "win some, lose some," "portfolio," and "as one of many" (see below for the full language of the strategy), it is possible that participants selectively applied different portions of the strategy.

Second, it is true that both "Attend" and "Regulate" consisted of some strategic content. In spite of that, we conceptualized of "Attend" as the baseline behavior in this study, seeing as it is relatively unlikely that someone would sequentially face 150 monetary choices all at once – unless they were a trader.

Finally, and perhaps most importantly, the exact localization of function in the dorsolateral prefrontal cortex in tasks such as this one is often a topic of debate, not surprisingly given our limited understanding of the functional organization of prefrontal cortex in general (Miller and Cohen, 2001; Amodio and Frith, 2006; Badre and D'Esposito, 2007; Ochsner and Gross, 2008; Hartley and Phelps, 2010). A recent review of 16 studies of emotion regulation noted extensive prefrontal variability across studies, and argued that such differences could be driven by subtle shifts in the strategy employed, let alone the stimuli in question, or the direction of regulation (Ochsner and Gross 2008), and even given such factors, distinctions were limited to broad anatomical terms. For example, the authors of that review suggested that dorsal regions of prefrontal cortex may be engaged by the selective attention necessary for reinterpretation, while medial and ventral regions are preferentially activated by other aspects of regulation. Given that, as noted above, the perspective-taking employed in this study consisted of a number of different components, it is all the more notable that there did appear to be a common locus of strategy-related activity in the DLPFC.

Whole-brain Regulator Outcome Contrast

In addition to examining the left amygdala ROI (as discussed in the main text), we also looked at the whole-brain level for changes in activity to loss outcomes. To do so, we performed a whole-brain analysis in the "Regulator" participants, looking for regions of the brain with significantly reduced responses to loss outcomes from "Attend" to "Regulate" (a contrast of "Attend" Loss > "Regulate" Loss). This contrast revealed a region of the right amygdala (Figure S2; Table S3). Extracting parameter estimates for all of our participants from this region, we observed that "Regulator" participants showed no significant difference between "Attend" and "Regulate" activity in this region of the brain for win outcomes (in contrast to the difference observed for loss outcomes), and "Non-Regulator" participants had no differences between activity in "Attend" and "Regulate" either for wins or for losses (all n.s.).

Detailed Participant Exclusions

We ran 63 participants. Sixteen participants were excluded from all analysis for a variety of reasons, which we detail below.

One participant reported intentionally closing their eyes during some of the outcomes in the task, because they felt anxious about those outcomes. They wrote "*In Attending (after choosing), I closed my eyes so I didn't see if I won or lost… Not so in reappraising.*"

One participant fell asleep during the scan.

One participant aborted the study during the 6th of 7 functional scans, causing the loss of all behavioral data collected to that point.

One participant had a morphological abnormality (e.g. a cyst or a growth of some kind) in their brain, discovered during the anatomical scan.

One participant indicated in their post-scan debriefing that they did not believe the experiment, thought the money at stake was not real, and did not understand how

they were being paid. It was important to us that participants believed and understood the experiment in its entirety.

Two participants' data could not be used because the fMRI scanner experienced severe spikes in the frequency domain (k-space) during collection. This overlaid 2D sinusoidal gradients of varying frequency, orientation, and intensity on the axial slices of their functional scans, rendering the data unusable.

Nine participants had excess motion (>3mm in any translational direction), a normal proportion of subjects (14%) for scans of this length.

In the analyses on the remaining participants, we sought to increase our statistical power in each analysis by including as many participants as possible. This approach was necessitated by the variance in loss aversion across subjects, and in the strength of the effect of regulation (normal for strategic manipulations).

Full Text of "Attend" and "Regulate" Instructions
These instructions were read aloud to participants as they read along silently. The strategies were practiced verbally with the experimenter, as well as on practice trials, prior to the study.

ATTEND:
When you see "ATTEND" before a block of trials, focus on each of the following monetary decisions in complete isolation from all other decisions. Tell yourself it's the only gamble that matters, that this one might be the one you get paid for. As such, you might win the positive amount, but you could just as easily lose the negative amount, and have to give that money back to the experimenter. Approach each trial as if you are making only this one choice in today's study.

Concentrate on the values in that one gamble, its possible outcomes, and the guaranteed alternative. Ask yourself how you would feel if you won the positive amount, how you would feel if you lost the negative amount, and how you feel about the guaranteed amount. Just let any thoughts or emotions about that particular choice occur naturally, without trying to control them.

It is important that you focus on the monetary decision in front of you at that time, in isolation from any context.

REAPPRAISE:
When you see "REAPPRAISE" before a block of trials, think of each of the following monetary decisions in the context of all the previous and following choices during REAPPRAISE blocks. That is, treat it as one of many monetary decisions, which will constitute a "portfolio". Remind yourself that you are making many of these similar decisions. Do not keep a running total – simply approach these gambles keeping in mind their context.

Imagine you are considering one of the monetary decisions in this task right now.

One way to think of this instruction is to imagine yourself a trader. You take risks with money every day, for a living. Imagine that this is your job, and that the money at stake is not yours – it's someone else's. Of course, you still want to do well (your job depends on it). You've done this for a long time, though, and will continue to. All that matters is that you come out on top in the end – a loss here or there won't matter in terms of your overall "portfolio". In other words, you win some and you lose some.

It is important that you focus on these monetary decisions in the context of all the other monetary decisions you will be making today during the REAPPRAISE blocks.

Table S1: Exact monetary amounts in the task

Gain Values	Loss Values	Guaranteed Alternative
Mixed-Valence Trials		
{$2, $4, $5, $6, $8, $9, $10, $12}	Gain Values x {-1/4:-1/8:-2}	$0
Gain-Only Trials		
$2.00	$0.00	$1.00
$3.00	$0.00	$1.00
$4.00	$0.00	$2.00
$4.00	$0.00	$2.00
$5.00	$0.00	$2.00
$5.00	$0.00	$3.00
$7.00	$0.00	$3.00
$8.00	$0.00	$3.00
$7.00	$0.00	$4.00
$8.00	$0.00	$4.00
$12.00	$0.00	$4.00
$12.00	$0.00	$5.00
$13.00	$0.00	$5.00
$10.00	$0.00	$6.00
$12.00	$0.00	$6.00
$12.00	$0.00	$6.00
$13.00	$0.00	$6.00
$19.00	$0.00	$8.00
$18.00	$0.00	$9.00
$25.00	$0.00	$9.00
$17.00	$0.00	$10.00
$22.00	$0.00	$10.00
$23.00	$0.00	$10.00
$25.00	$0.00	$10.00
$26.00	$0.00	$10.00
$24.00	$0.00	$12.00
$26.00	$0.00	$12.00
$30.00	$0.00	$12.00
$22.00	$0.00	$13.00
$28.00	$0.00	$13.00
Catch/Partial Trials		
{$2, $4, $5, $6, $8, $9, $10, $12}	Gain Values x {-1.6, -0.8, -0.4, -0.2}	$0

Table S2: Full ANOVA Results

	df	F	p
Left Striatum – Decision			
Condition	1,39	4.075	0.050
Timepoint	6,234	14.694	< 0.001
Condition x Timepoint	6,234	3.406	0.003
Left Striatum – Outcome			
Condition	1,39	7.919	0.008
Outcome	1,39	16.093	< 0.001
Timepoint	6,234	9.420	< 0.001
Outcome x Timepoint	6,234	11.754	< 0.001
VMPFC – Decision			
Condition	1,39	5.139	0.029
Timepoint	6,234	21.871	< 0.001
Condition x Timepoint	6,234	3.405	0.003
VMPFC – Outcome			
Condition	1,39	14.770	< 0.001
Outcome	1,39	7.189	0.011
Timepoint	6,234	13.852	< 0.001
Condition x Time	6,234	7.028	< 0.001

- All ANOVAs were repeated measures within-subjects.
- For decision activity, Condition (“Attend” or “Regulate”) x Timepoint (from -1 to 5 TRs around the decision occurring at TR 0)
- For outcome activity, Condition (“Attend” or “Regulate”) x Outcome (Win or Lose) x Timepoint (from -1 to 5 TRs around the outcome occurring at TR 0)
- Only significant main effects or interactions are listed for clarity.

Table S3: Additional Contrast Results

Reduction in Loss Responses in Regulation: Regulate Lose ME < Attend Lose ME (N=14); p < 0.005 (unc); cluster threshold = 81mm^3;			
+ Right Amygdala		19, -8, -19	88
+ Precuneus/Angular gyrus	19/39	46, -70, 39	391
- Cuneus	18	22, -87, 19	537
- Middle occipital gyrus	19	-25, -84, 8	402
+ Anterior cingulate	32	4, 42, 7	110
- Cerebellum		-22, -35, -23	113

Figure S1: Mixed Valence Gamble Values

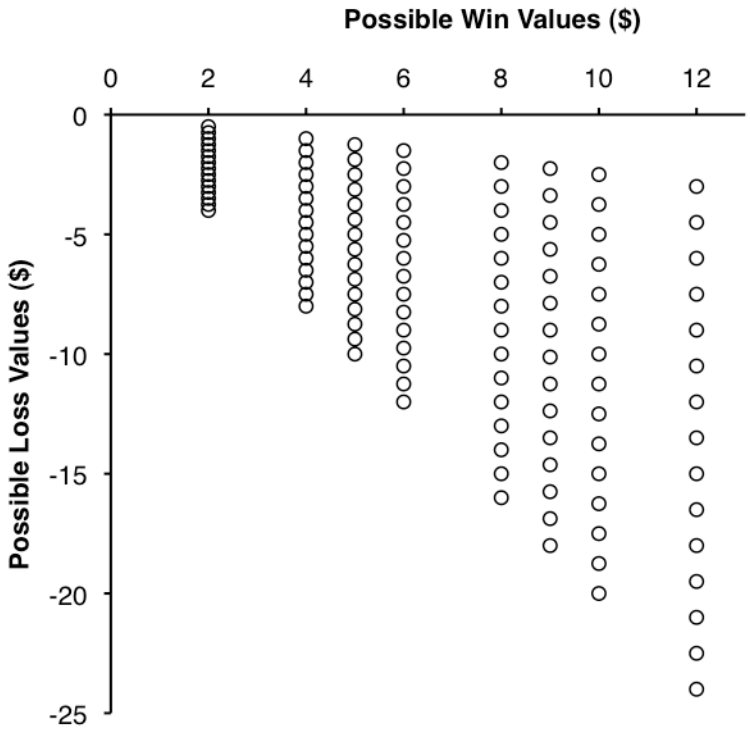
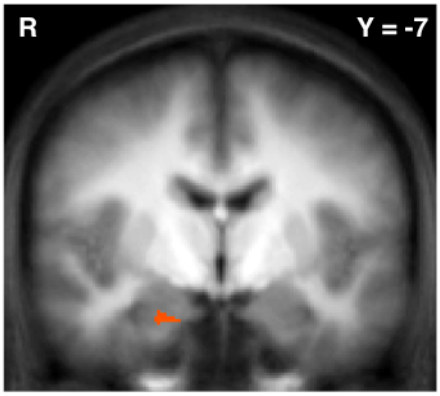


Figure S2: Regulation success is related to changes in amygdala activity to losses. For Regulators at outcome (N=14), a contrast of “Attend” Loss – “Regulate” Loss identifies a region of right amygdala.



p<0.005 (unc); cluster threshold=81mm^3; N=14

Attend Loss > Regulate Loss

References

Amodio, D. M. and C. D. Frith (2006) Meeting of minds: the medial frontal cortex and social cognition. Nature Reviews Neuroscience 7(4): 268-277.

Badre, D. and M. D'Esposito (2007) Functional magnetic resonance imaging evidence for a hierarchical organization of the prefrontal cortex. Journal of Cognitive Neuroscience 19(12): 2082-2099.

Camerer, C. F. (1989) An experimental test of several generalized utility theories. Journal of Risk and Uncertainty 2(1): 61-104.

Greene, W. H. (2003). Econometric Analysis. Upper Saddle River, NJ, Prentice Hall.

Hartley, C. A. and E. A. Phelps (2010) Changing fear: the neurocircuitry of emotion regulation. Neuropsychopharmacology 35(1): 136-146.

Miller, E. K. and J. D. Cohen (2001) An integrative theory of prefrontal cortex function. Annual Review of Neuroscience 24: 167-202.

Nelder, J. A. and R. Mead (1965) A Simplex-Method for Function Minimization. Computer Journal 7(4): 308-313.

Ochsner, K. N. and J. J. Gross (2008) Cognitive emotion regulation: Insights from social cognitive and affective neuroscience. Curr Dir Psychol Sci 17(2): 153-158.

Tom, S. M., C. R. Fox, C. Trepel and R. A. Poldrack (2007) The Neural Basis of Loss Aversion in Decision-Making Under Risk. Science 315: 515-518.

Tversky, A. and D. Kahneman (1992) Advances in Prospect-Theory - Cumulative Representation of Uncertainty. Journal of Risk and Uncertainty 5(4): 297-323.