Thinking like a trader selectively reduces individuals' loss aversion

Peter Sokol-Hessner[a], Ming Hsu[b], Nina G. Curley[a], Mauricio R. Delgado[c], Colin F. Camerer[d], and Elizabeth A. Phelps[a,1]

[a]Department of Psychology, New York University, 6 Washington Place, New York, NY 10003; [b]Beckman Institute for Advanced Science and Technology, Department of Economics, University of Illinois at Urbana-Champaign, 405 North Mathews Avenue, Urbana, IL 61801; [c]Department of Psychology, Rutgers University, 101 Warren Street, Newark, NJ 07102; and [d]Division of the Humanities and Social Sciences, California Institute of Technology, 1200 East California Boulevard, Pasadena, CA 91125

Edited by Edward E. Smith, Columbia University, New York, NY, and approved February 4, 2009 (received for review July 19, 2008)

Research on emotion regulation has focused upon observers' ability to regulate their emotional reaction to stimuli such as affective pictures, but many other aspects of our affective experience are also potentially amenable to intentional cognitive regulation. In the domain of decision-making, recent work has demonstrated a role for emotions in choice, although such work has generally remained agnostic about the specific role of emotion. Combining psychologically-derived cognitive strategies, physiological measurements of arousal, and an economic model of behavior, this study examined changes in choices (specifically, loss aversion) and physiological correlates of behavior as the result of an intentional cognitive regulation strategy. Participants were on average more aroused per dollar to losses relative to gains, as measured with skin conductance response, and the difference in arousal to losses versus gains correlated with behavioral loss aversion across subjects. These results suggest a specific role for arousal responses in loss aversion. Most importantly, the intentional cognitive regulation strategy, which emphasized "perspective-taking," uniquely reduced both behavioral loss aversion and arousal to losses relative to gains, largely by influencing arousal to losses. Our results confirm previous research demonstrating loss aversion while providing new evidence characterizing individual differences and arousal correlates and illustrating the effectiveness of intentional regulation strategies in reducing loss aversion both behaviorally and physiologically.

arousal | emotion regulation | decision-making

We are not at the whim of our emotions—rather, research on emotion regulation suggests we have a degree of control over our affective state and can reduce or enhance the emotional impact of a given stimulus in real time (1). We are able to do this intentionally, and when doing so, we not only report decreased negative affect (1–3) but also show signs of decreased physiological responding (4, 5) and decreased activity in brain areas that are closely linked to emotions and affect (1–3). Emotion regulation research so far has primarily used pictures (1–5), but any stimulus that results in an emotional response could theoretically be the target of regulation. We propose to examine a specific role for emotions in economic choice behavior and to observe the effects of an intentional cognitive regulation strategy on both behavior and associated emotional responses.

It is widely acknowledged that emotion plays a role in decision-making, drawing on evidence from numerous behavioral studies using emotional stimuli as well as physiological, neuroimaging, and lesion studies. For example, one study demonstrated that irrelevant emotional states induced by film clips could eliminate or even reverse the endowment effect (higher selling than buying prices) in subsequent choices (6). Another study on consumption behavior of drinks showed that the subliminal presentation of emotional faces not only altered participants' ratings of various drinks but also the actual amount they drank and the price they were willing to pay for the drink (7). These startling results clearly demonstrate an effect of emotional stimuli on decisions, even when these stimuli are irrelevant or below awareness. Self-reports of affect have been used to explore the effect of subjective feelings on choices (8, 9), widening the possible measures of the affective experience. Neuroimaging studies (10–13) and studies with brain-damaged patients (11, 14–16) have repeatedly demonstrated the involvement and necessity of brain regions including the amygdala and insula in decision-making, although these particular areas are arguably best known for their association with a range of tasks involving emotion and physiological responding (17–20). This overlap suggests there are some common underlying mechanisms involved in reward, choice, and emotion. For example, a now-classic study using the Iowa Gambling Task illustrated the close relationship between physiological arousal and choices in normal participants but showed that brain-damaged patients, who did not show normal arousal responses, also did not show normal choice patterns (14). A similar study with the same patients (and others) showed behavior consistent with diminished sensitivity to losses (16), further establishing the necessity of emotion-related brain regions in mediating aspects of decision-making. The current study builds on this research by using behavioral models and physiological measures to investigate a specific and quantifiable role for emotional responses in risky monetary decision-making.

Given the aforementioned work suggesting emotions may play a central role in the anticipation and processing of losses, the phenomenon of loss aversion is of obvious interest. In 1979, Kahneman and Tversky (21) suggested that losses loom larger than equivalent gains, a property called "loss aversion." Loss aversion subsequently came to be conceptualized as a multiplicative overweighting of losses relative to gains represented by a parameter λ (21). Laboratory studies have since demonstrated that humans can show loss aversion for objects such as mugs (22), money (23), and simulated investments (24, 25). This work has been supported by analyses of real world data that show similar behavior in, among other situations, stock markets (26–28), the pricing and purchasing of consumables (29, 30) and condominiums (31), and the choice of work hours by cabdrivers (32). It has been suggested that loss aversion might have a specific, evolutionarily conserved neurobiological basis (as opposed to being epiphenomenal or cultural in origin). Supporting this claim, work with primates has shown that our genetic cousins also exhibit loss aversion in a fiat currency economy (33). Loss aversion appears to exist across both domains and species, and because decision-making in the context of possible losses has been linked to emotional responses, loss aversion is an excellent candidate

Author contributions: P.S.-H., M.H., M.R.D., C.F.C., and E.A.P. designed research; P.S.-H. and N.G.C. performed research; M.H. and C.F.C. contributed new reagents/analytic tools; P.S.-H., M.H., and N.G.C. analyzed data; and P.S.-H., C.F.C., and E.A.P. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

Freely available online through the PNAS open access option.

[1]To whom correspondence should be addressed. E-mail: liz.phelps@nyu.edu.

This article contains supporting information online at www.pnas.org/cgi/content/full/0806761106/DCSupplemental.

NEUROSCIENCE

PSYCHOLOGY

measure for examining the effect of intentional regulation strategies on emotion-related aspects of choice behavior.

In determining a strategy that might affect loss aversion, we return to research on intentional emotion regulation with a focus on reinterpretation (often termed "reappraisal") (1, 2, 34). As opposed to other kinds of emotion regulation techniques, reinterpretation is distinguished by changing the meaning of a stimulus with the goal of altering the resulting affective state. The stimulus remains physically identical, but the perceiver thinks about it in a different way, perhaps focusing on different aspects of it, taking a different perspective, or putting it in some greater context that changes its immediate meaning. Such reinterpretation of a disturbing image of injured people could include imagining that the people in the image are just actors with makeup performing a stunt, or recognizing that even a small cut can sometimes bleed quite a bit, making things look much worse than they actually are. In the context of monetary decisions, reinterpretation of a particular outcome could include putting it in a greater context as one of many outcomes (35) or taking a different perspective on a choice, perhaps imagining that oneself is an experienced professional trader, rather than an excitable amateur investor. These kinds of strategies are sometimes recommended to investors in articles (36) or investment guides. For example, one investment company reminded their clients that "it is the return of the entire portfolio that matters, not the individual parts. Stay focused on how your investments are performing as a whole, rather than each one, to get over the inevitable bumps in the road toward reaching your goals." These reinterpretations are not in the spirit of denial ("it does not exist, look away, think of something else") but rather focus on the affect-inducing object and attempt to change its meaning for the participant.

In the current study, we examine loss averse behavior, its physiological correlates, and the impact of an intentional regulation strategy on these variables. Emotion is a complex construct, and one commonly accepted theoretical approach is to consider emotion as consisting of multiple component processes (37), including facial and vocal expression, subjective feelings, action tendencies, bodily responses, and cognitive appraisals. For the following study, we focus on the latter 3 components. Participants' choices are our objective measure of action tendencies, modeled on an individual participant basis with quantitative parametric behavioral models conventionally used in economics. We measure participants' skin conductance to quantify bodily arousal responses, and relate such responses to behavior. Finally, cognitive appraisal is operationalized as the intentional cognitive regulation strategy that we instruct participants to use. This strategy is similar to other emotion regulation strategies in its reinterpretive nature, despite its content being more relevant to economic decisions. We observe both behavioral and physiological consequences of the strategy, suggesting that emotional responses are related to the observed behavior. By combining the above variables and individual level behavioral and physiological analyses, we can explore subtle effects within subjects, and can speak directly to the effects of our strategy on a given individual, rather than being limited to group analysis.

Participants made a series of forced monetary choices between a binary gamble ($P = 0.5$) and a guaranteed amount ($P = 1$) (Fig. S1). All choice outcomes were realized immediately after decision (e.g., "you won"). One hundred and forty choices constituted a "set," from which we quantified 3 aspects of behavior: the weighting of losses relative to gains (loss aversion, λ), attitudes toward chance (risk aversion, ρ), and consistency over choices (logit sensitivity, μ) (Fig. S2). The values in the set were selected a priori to allow accurate estimation of a range of possible values of λ, ρ, and μ. The participants completed 2 full sets of choices: one while using the "Attend" strategy, which emphasized each choice in isolation from any context, "as if it was the only one,"

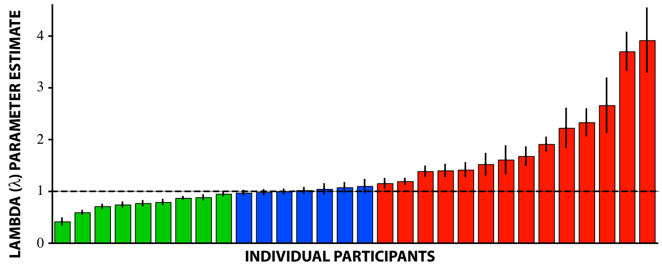

Fig. 1. Individual loss aversion coefficients (λ) when using the Attend strategy in Study 1. Green indicates $\lambda < 1$ (gain seeking), blue indicates λ is not different from 1 (gain-loss neutral), and red indicates $\lambda > 1$ (loss averse). Error bars are standard error of the mean.

and the other using the "Regulate" strategy, emphasizing choices in their greater context, "as if creating a portfolio" (complete instructions included in the *SI Text*). This allowed separate quantification of Attend and Regulate behavior for each subject. Choices were presented in pseudorandomly ordered blocks of 10 with a given strategy, and block order, gamble order, and gamble outcome were counterbalanced across participants. The conceptual nature of the strategies was emphasized and participants were thoroughly instructed and quizzed on all procedures. In Study 1, the participants were initially endowed with \$30 and were paid this sum plus actual gains or losses from 10% of the trials selected at random upon completion of the study. Study 2 had an identical behavioral session as Study 1, but the participants returned for a separate session in which their skin conductance response (SCR, a measure of sympathetic nervous system activity) was recorded during the choice task as a measure of arousal. See *Methods* and *SI Text* for more detail.

Results

Study 1 Results.

Attend Results. Mean parameter estimates (with standard errors) were $\lambda = 1.40$ (0.15), $\rho = 0.83$ (0.04), and $\mu = 2.57$ (0.29). Because of the multiplicative nature of the loss aversion parameter λ, taking the log can avoid biases in calculating the mean. The mean $\log(\lambda)$ value was 0.198 (0.09) and was significantly greater than zero ($t(29) = 2.113$, $P < 0.05$), indicating that the group was on average loss averse. Translating that value out of the log scale by raising the constant e to that value gave a mean λ of 1.22.

The range of parameter values were λ: 0.41–3.91, ρ: 0.37–1.23, and μ: 0.71–6.53. Individual λ values are found in Fig. 1. These values indicate that there are 9 gain seeking, 7 gain-loss neutral, and 14 loss averse participants in our sample, where gain seeking is defined as having a λ significantly less than 1, gain-loss neutral is defined as having a λ not significantly different from 1, and loss averse is defined as having a λ significantly greater than 1.

Regulate Results. Mean parameter estimates (with standard errors) were $\lambda = 1.17$ (0.15), $\rho = 0.87$ (.04), and $\mu = 2.39$ (0.29). The mean $\log(\lambda)$ value was -0.0005 (0.10), and was not significantly different from zero ($t(29) = -0.005$, not significant (n.s.)). This corresponded to a mean $\lambda = 0.999$. Paired t tests with the Attend data were conducted to determine the effect of the cognitive strategy within-subjects on the parameters estimated. An effect was observed for the loss aversion coefficient λ ($t(29) = 3.64$ $P < 0.0011$), but not for ρ ($t(29) = 1.66$ $P < 0.11$) or μ ($t(29) = 0.79$ $P < 0.44$).

Although 26 out of 30 subjects showed decreases in loss aversion when using the Regulate strategy, there was variability across individuals in the strength of the effect. To capture some

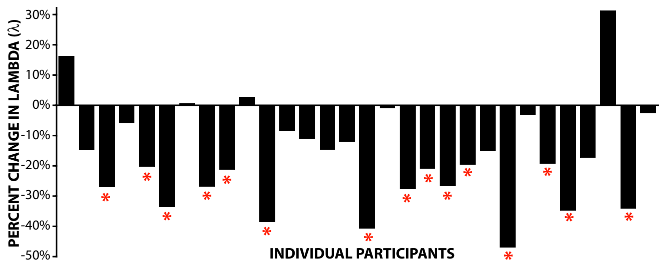

Fig. 2. Percent change in loss aversion due to the cognitive strategy in Study 1, expressed as ($\lambda_{\text{Regulate}} - \lambda_{\text{Attend}}$) as percent of λ_{Attend}. A negative value indicates less loss aversion during Regulate trials. Participants are in the same order as Fig. 1. Changes in loss aversion exceeding the 0.05 criterion cutoff are marked with red asterisks.

of this variability and quantify the strength of this effect, we performed likelihood ratio tests on the parameters (see *Methods* and *SI Text*) to identify individuals with differences in parameters between the conditions stronger than a cutoff P value of 0.05. Of 30 subjects, 15 exceeded the criterion for changes in λ, 3 for changes in estimated ρ values, and 2 for changes in their estimated μ values. Overall, individuals' loss aversion as measured during the attend instruction (λ_{Attend}) was reduced by an average of 16% (standard error 3.09%) during the regulate instruction ($\lambda_{\text{Regulate}}$) (See Fig. 2). This effect was independent of λ_{Attend} ($r < 0.03$, n.s.).

Counterbalancing (including block order, gamble outcome, and gamble order within block) had no effects on parameter estimates or the effectiveness of the Regulate strategy. See *SI Text* for more details.

Study 2 Results.

Behavioral Results. The behavioral results in Study 2 confirmed those of Study 1. Mean Attend parameter estimates (with standard errors) were $\lambda = 1.31$ (0.13), $\rho = 0.88$ (0.03), and $\mu = 2.97$ (0.28). Mean Regulate parameter estimates (with standard errors) were $\lambda = 1.15$ (0.12), $\rho = 0.92$ (0.03), and $\mu = 2.60$ (0.23). Paired t tests between the Attend and Regulate conditions confirmed a strong effect for the loss aversion coefficient λ ($t(28) = 6.91$ $P < 1.6 \times 10^{-7}$). There was no significant effect on ρ ($t(28) = 1.82$ $P < 0.08$), or μ ($t(28) = 1.40$ $P < 0.17$).

Physiological Results. Because amounts of money won or lost varied both within participants and between participants, SCR at outcome in units of microsiemens (μS; square-root transformed to reduce skewness) were normalized by the amount of money won or lost on a given trial, giving each participant an average Gain SCR score and average Loss SCR score with units of $\sqrt{\mu S}/\$$. In addition to the Gain and Loss SCR scores, we created an SCR difference score of Loss − Gain as a physiological measure of loss aversion.

On average, losses were more arousing than gains in the Attend condition (Loss − Gain = 0.0092 $\sqrt{\mu S}/\$$, $t(28) = 1.89$, $P < 0.035$ one-sample t test, one-tailed), but not in the Regulate condition (Loss − Gain = 0.0017 $\sqrt{\mu S}/\$$, $t(28) = 0.24$, $P < 0.40$ one-sample t test, one-tailed). However, although 28 of the 29 subjects in Study 2 showed a decrease in loss aversion with the regulation strategy, there was extensive variability in the strength of the effect. To characterize that variability, we separated participants using likelihood ratio tests. We divided them based on whether they exceeded the cutoff for changes in their λ coefficient between Attend and Regulate, creating 2 groups: Regulators ($P < 0.05$), and Nonregulators ($P > 0.05$). Only Regulators showed a significant decrease in the Loss − Gain SCR difference score from Attend to Regulate (Attend = 0.0102 $\sqrt{\mu S}/\$$, Regulate = −0.0102 $\sqrt{\mu S}/\$$, $t(13) = 2.04$, $P < 0.031$ one-tailed paired t test), whereas Nonregulators showed a nonsignificant increase (Attend = 0.0089 $\sqrt{\mu S}/\$$, Regulate = 0.0128 $\sqrt{\mu S}/\$$, $t(14) = 0.49$, $P < 0.64$ two-tailed paired t test) (see Fig. 3).

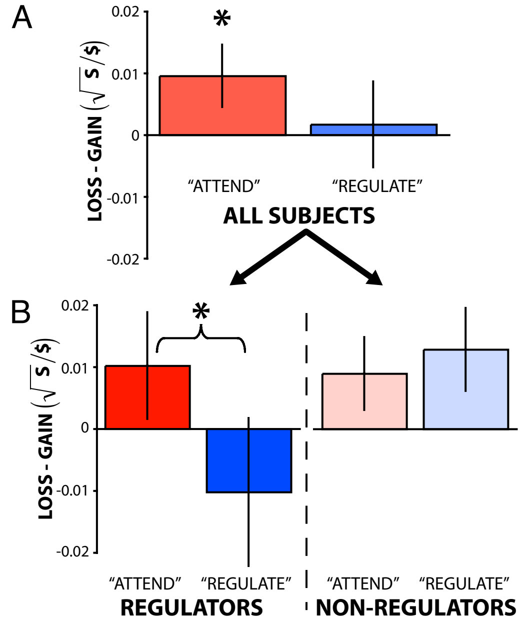

Fig. 3. Average Loss − Gain ($\sqrt{\mu S}/\$$) SCR difference scores from Study 2. (A) Across all subjects, arousal is greater per dollar to losses than gains, but only in the Attend condition. (B) Regulators (exceeded cutoff for decrease in λ) show a significant decrease in the difference score, while Nonregulators (did not exceed cutoff for decrease in λ) do not. Error bars are standard error of the mean.

We also conducted ANOVAs on the Gain and Loss SCR scores. A 2 × 2 × 2 repeated measures ANOVA with factors of Outcome (Loss, Gain), Strategy (Attend, Regulate), and Group (Regulators, Nonregulators), revealed a trending interaction between all 3 factors ($F(1, 27) = 3.70$ $P < 0.065$), but no other interactions nor main effects (all P's > 0.29). To examine what might be driving the 3-way interaction, we conducted separate 2 × 2 repeated measures ANOVAs on the Gain and Loss SCR scores. The Loss SCR score ANOVA showed a trending interaction between Strategy and Group ($F(1,27) = 3.791$ $P < 0.062$, all other P's > 0.37), but an identical ANOVA on just the Gain SCR score had no significant main effects or interactions (all P's > 0.48), illustrating that the initial 3-way interaction was driven in large part by changes in the Loss SCR score.

Individuals' Loss − Gain SCR difference scores also positively correlated with their respective behavioral loss aversion (λ) coefficients in both the Attend condition ($r(27) = 0.394$, $P < 0.035$) (See Fig. 4), and the Regulate condition ($r(27) = 0.403$, $P < 0.031$).

Model Estimation. To test the significance of the estimated parameters, we performed a likelihood ratio test for each individual in each condition, contrasting the likelihood of the data given the estimated parameters for that condition with the likelihood of the data given a random choice model. This showed that for subjects of Study 1 in both conditions (60 sets of parameters total), all estimated models had a $P < 5 \times 10^{-5}$, and 56 out of 60 models had a $P < 1 \times 10^{-10}$ (Participants' models in Study 2 had similar significance levels). For more details on validity tests of the model, see *Methods*.

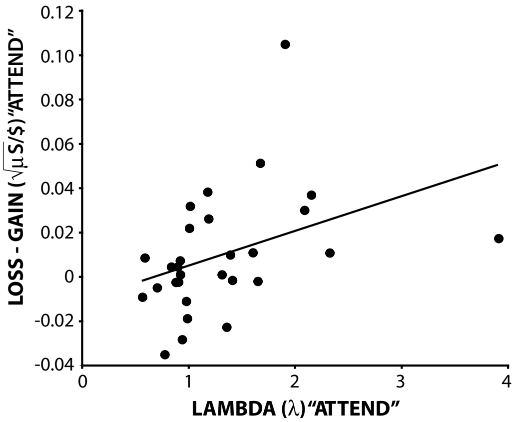

Fig. 4. Individuals' physiological SCR difference score Loss − Gain ($\sqrt{\mu S}/\$$) plotted against their behavioral loss aversion coefficient λ in the Attend condition in Study 2. Removal of candidate outliers strengthens the correlation.

Discussion

Our results support the idea that taking a perspective similar to that of a trader can alter choices and arousal responses related to loss aversion. Building upon the evidence that emotions have a role in decision-making (6–9, 12), and that there might be an important role in decision-making for the anticipation of emotional responses to losses (16), we show that loss aversion is linked to physiological arousal responses to loss outcomes relative to gain outcomes and that these measures are reliably and systematically affected by perspective-taking.

In Study 1, we showed that an intentional reinterpretive regulation strategy had a specific and strong effect in decreasing individuals' initial levels of loss aversion. No other measurements of behavior showed significant changes as a result of using the strategy. Study 2 demonstrated that behavioral loss aversion was correlated with a physiological arousal measure, specifically the SCR per dollar to loss outcomes relative to gain outcomes. Furthermore, Study 2 showed that only the individuals most successful at reducing their degree of loss aversion by taking a different perspective had a corresponding reduction in the physiological arousal response to loss outcomes.

One goal of this study was to find an ecologically plausible reinterpretive strategy that could lead to a change in the emotional significance of some of the components of decision-making. In this context, it appears that "thinking like a trader" may reduce the subjective impact of loss outcomes. Just as recent work demonstrating that individuals' anticipation of loss may shift their choices (38), it appears that participants in our study similarly anticipated their responses to gains and losses and chose accordingly (39). Given the correlational nature of this study, however, future manipulations that alter arousal directly will be necessary to demonstrate causality.

This is not the first study to show the effect of perspective-taking on loss-averse behavior. For example, a study by Thaler et al. (25) applied an ecologically plausible situational manipulation (based on the frequency of feedback for risky investments) in a between-subjects design. They showed that temporally bracketing choices decreased the occurrence of behavior consistent with loss aversion [similar to results found by Gneezy and Potters (24)]. Other studies have hypothesized that emotional attachment and cognitive perspective might modulate loss aversion and, more specifically, that having the intention to trade some good or currency would reduce loss aversion for that item, potentially through affective and/or cognitive means (40–42). This study builds upon these ideas, combining intentional regulation, cognitive perspective taking, and physiological measurements of arousal. We have shown that not only do different individuals' perspectives alter their choices but also that within an individual, choosing to take a different perspective can reliably reduce their loss aversion.

In addition, our demonstration of changes in arousal due to the intentional regulation strategy coincides with evidence from studies of the cognitive regulation of emotion illustrating significant behavioral (1–3), physiological (4, 5), and neural (1–3) changes associated with the intentional use of regulation strategies to reappraise emotional stimuli. Because the "trader perspective," or portfolio approach, that our regulation strategy encourages is similarly reinterpretive, it is possible that a related mechanism is at work. In that context, this study may provide some insight into what separates professional traders and gamblers from amateurs. It is possible that professionals and amateurs are fundamentally different people from the start, but it is also possible that professionals have learned not just facts about investments, but strategies for addressing the normal emotional responses that might prevent amateurs from making the same decisions, given the same information (36, 43, 44). Indeed, professional sports card dealers (45), condominium investors (rather than owners) (31), and experienced cab drivers (32) show less apparent response to loss than less experienced agents.

Our results also shed light on a simmering debate about the nature of loss aversion (42, 46): do losses hurt as much as our decisions to avoid them suggest, or are we overzealous at the time of decision in predicting that losses will hurt disproportionately, when in fact they are not any worse than gains are good? In other words, is loss aversion due to a basic hedonic property of our reaction to losses, as are simple basic preferences for food, sleep, sex, and warmth? Or is it a kind of error in judgment caused by an exaggerated fear of losses relative to their actual impact (47), perhaps due to an underappreciation of our capacity for emotional adaptation to negative events (48)? Our results support the former, "hedonic," interpretation, that losses do hurt more than gains feel good, because differential physiological arousal responses are linked to actual feedback about loss and gain, and therefore, at least to some degree, loss aversion may not be a judgment error. However, our results also support the latter, "judgmental error," interpretation to some extent by demonstrating that cognitive strategies can systematically reduce loss aversion behaviorally and physiologically; so whatever "fear of loss" may exist is not so basic as to be immutable, but is instead subject to regulation. At least it appears there is some hope for the "amateur" decision-maker, in that a simple reinterpretation might mitigate one dimension of the difference between amateurs and professionals. We can change how we decide, and although we may be sensitive to losses, we can make ourselves less so.

Methods

Subjects. In Study 1, 30 participants (13 male, mean age 22 ± 3 years) completed the experiment. In Study 2, 52 participants (19 male, mean age 21 ± 3 years) completed the behavioral session. Twelve were excluded based on highly imprecise parameter estimation*, 4 for noiseless performance†, 2 for outlier behavior (>3 SD from the mean), and 2 for instruction-related issues. Of the remaining 32 participants, one was excluded for SCR nonresponding and one could not make a second session. The remaining 30 participants completed the physiological session, in which one participant was dropped for experimenter error. The behavioral and physiological data from the

*The measure used at the time to define significance in the model was later replaced with the likelihood ratio test (see the *SI Text*).

†For participants whose decisions can be fit perfectly (with no noise parameter), there is a range of parameter values which fit equally well, and no standard procedure for choosing one of these sets of values over the others. Problems with noiseless data are common in such estimations.

remaining 29 participants is presented. The experiment was approved by the University Committee on Activities Involving Human Subjects at New York University.

Procedure—Study 1 and Study 2 Behavioral Session. Participants were endowed with $30 immediately following completion of informed consent. They were told the money was theirs to risk during the study and were asked to place it in their wallets or purses. At the end of the study, the endowment was adjusted by the actual value of the outcome of 28 randomly selected trials (10% of all trials), given their choices. Participants could lose a maximum of $30 (returning the entire endowment) and win a theoretical maximum of $572. All participants also received a $15 subject fee upon completion of the study.

Participants were thoroughly instructed and quizzed on task details and strategy use. See *SI Text* for more details.

There were 2 cognitive regulation strategies (for the complete wording, see *SI Text*). For the Attend strategy, participants were instructed to consider each monetary choice in isolation from all other choices, to make each of those decisions as if it was the only choice they were making for the study, and to let any emotions or thoughts occur naturally, without trying to control them. We conceived of this instruction to mirror the everyday approach to decisions for most people—that is, one at a time, individually. For the Regulate strategy, participants were instructed to consider each monetary choice in the context of the other choices in that category, as if they were creating a portfolio. The instruction included phrases like "imagine yourself [as] a trader," "you do this all the time," and "treat it as one of many monetary decisions, which will sum together to produce a 'portfolio.'" This strategy was intended to be what a professional trader might do when making many portfolio-style decisions. The conceptual nature of the strategy was emphasized by asking participants to not keep a running total of their previous outcomes. We were not concerned with isolating the efficacious parts of our instructions, but with observing effects given an ecologically relevant general approach of considering choices in their context. Future research could unpack the effects of these various strategic components.

The presented choices were identical for both instructed strategies, except for the random outcomes of the risky gambles. Each set of 140 choices consisted of 120 choices between mixed-valence gambles (positive and negative possible outcomes) and guaranteed amounts of zero, and 20 choices between gain only gambles (positive and zero possible outcomes) and positive guaranteed amounts. Each decision was resolved immediately after choice with the outcome of the gamble or the guaranteed amount, depending on participants' choices (see *SI Text* for the exact monetary amounts). Participants completed choices in blocks of 10, using one cognitive strategy during each block. The blocks were pseudorandomly ordered such that no strategy ever occurred more than 3 times in a row. Participants completed one of 4 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.

Before each block of 10 trials, the regulation instruction was displayed for 5 s. Each trial consisted of the presentation of a monetary choice (4 s), a response period (2 s), and the choice outcome (1 s), with a 1 s inter-stimulus interval between response and outcome and a 1–3 s variable inter-trial interval.

Procedure—Study 2 Physiological Session. Participants returned within 2 weeks after the behavioral session for a physiological assessment. The assessment consisted of 2 sessions at least 48 h apart. The endowment and instructions were exactly the same as in the behavioral session, including a $30 endowment, detailed task instructions, a task quiz, and strategy instruction. Over both sessions, participants completed a total of 120 choices between mixed-valence gambles and a guaranteed amount of zero. Sixty choices were completed using the Attend strategy, and 60 with the Regulate strategy. Choice values were selected a priori using participants' parameter estimates from the behavioral session to equalize the number of win, loss, and guaranteed outcomes. See the *SI Text* for more details. The choice structure had the following changes: each monetary decision consisted of an instruction (1 s) indicating which strategy to use, the presentation of a monetary choice (2 s), a response period (2 s), and the choice outcome (1 s). Because of the lagged nature of the skin conductance response, variable periods of fixation (8–11s) were inserted before and after outcomes to allow isolation of the responses to each outcome. Trial order and win/lose outcomes were randomly ordered for each subject.

SCR. SCR was measured using Ag-AgCl electrodes attached to the crease between the distal and middle phalanges of the first and second digits of the left hand. The SCR data were amplified and recorded with a BIOPAC Systems skin conductance module connected to an Apple computer. Data were recorded at a rate of 200 samples per second. SCR analysis was conducted using AcqKnowledge software (BIOPAC Systems Inc.).

SCR (in μS) was measured as the trough-to-peak amplitude difference in skin conductance of the largest response in the window 0.5 s after stimulus onset to 4.5 s after stimulus offset. A minimal response criterion was set at 0.02 μS, and responses not exceeding this threshold were scored as ''0.'' SCR data were low-pass filtered (25Hz), smoothed (3 sample kernel), and square-root transformed to reduce skewness. SCRs at outcome were normalized with the dollar amount of the outcome to produce measurements with units of $\sqrt{\mu S}/\$$.

Model. We used a 3 parameter model to estimate choice behavior. Gains and losses were estimated with Eqs. **1** and **2** respectively, and Eq. **3** (a logit, or softmax function) translated the difference between the subjective value of the gamble and the subjective value of the guaranteed amount (estimated using Eqs. **1** and **2**) into a probability of gamble acceptance between 0 and 1. All 3 functions relied on the 3 parameters described below: λ (the loss aversion coefficient), ρ (the curvature of the utility function), and μ (the logit sensitivity).

$$u(x^+) = x^\rho \quad [1]$$

$$u(x^-) = -\lambda \times (-x)^\rho \quad [2]$$

$$p(\text{gamble acceptance}) = (1 + \exp\{-\mu(u(\text{gamble})\text{-}u(\text{guaranteed}))\})^{-1} \quad [3]$$

λ (Fig. S2*a*) only appears in the equation for the calculation of the utility of losses (Eq. **2**), since it refers to the multiplicative valuation of losses relative to gains. When $\lambda = 1$, gains and losses are valued equally (''gain-loss neutral''), while $\lambda > 1$ indicates the overvaluation of losses (loss averse), and $\lambda < 1$ means gains are overvalued relative to losses (gain seeking).

ρ (Fig. S2*b*) represents risk aversion due to the presence of diminishing sensitivity to changes in value as the absolute value increases, and μ (Fig. S2*c*) refers to the sensitivity of the participant's choices to changes in the difference between subjective values of the gamble and the guaranteed amount (see *SI Text* for more details on the model).

For all participants we separately estimated Attend and Regulate λ, ρ, and μ values in Mathematica v5.2 using a maximum likelihood estimation procedure. To determine overall model significance on a per subject, per condition basis, we performed a likelihood ratio test against a random model to determine whether the probability of the data was significantly higher given the parameters we estimated. To determine the significance of within-subject changes in any given parameter, we performed a likelihood ratio test of the full model (Attend and Regulate parameters) against a reduced model which was allowed only one value of the parameter in question for both Attend and Regulate. For more details on the estimation and tests, including against alternative models, see *SI Text*.

ACKNOWLEDGMENTS. This research was sponsored by a James S. McDonnell Foundation grant to E.A.P., Moore Foundation and Human Frontier Science Program grants to C.F.C., and a National Science Foundation Graduate Research Fellowship to P.S.H.

1. Ochsner KN, et al. (2004) For better or for worse: Neural systems supporting the cognitive down- and up-regulation of negative emotion. *NeuroImage* 23:483–499.
2. Ochsner KN, Bunge SA, Gross JJ, Gabrieli JDE (2002) Rethinking feelings: An fMRI study of the cognitive regulation of emotion. *J Cognit Neurosci* 14:1215–1229.
3. Schaefer SM, et al. (2002) Modulation of amygdalar activity by the conscious regulation of negative emotion. *J Cognit Neurosci* 14:913–921.
4. Eippert F, et al. (2007) Regulation of emotional responses elicited by threat-related stimuli. *Hum Brain Mapp* 28:409–423.
5. Jackson DC, Malmstadt JR, Larson CL, Davidson RJ (2000) Suppression and enhancement of emotional responses to unpleasant pictures. *Psychophysiology* 37:515–522.
6. Lerner JS, Small DA, Loewenstein G (2004) Heart strings and purse strings: Carryover effects of emotions on economic decisions. *Psychol Sci* 15:337–341.
7. Winkielman P, Berridge KC, Wilbarger JL (2005) Unconscious affective reactions to masked happy versus angry faces influence consumption behavior and judgments of value. *Pers Soc Psychol Bull* 31:121–135.
8. Mellers BA, Schwartz A, Ho K, Ritov I (1997) Decision affect theory: Emotional reactions to the outcomes of risky options. *Psychol Sci* 8:423–429.

9. Mellers BA, Schwartz A, Ritov I (1999) Emotion-based choice. *J Exp Psychol* 128:332–345.
10. Gottfried JA, O'Doherty J, Dolan RJ (2003) Encoding predictive reward value in human amygdala and orbitofrontal cortex. *Science* 301:1104–1107.
11. Hsu M, Bhatt M, Adolphs R, Tranel D, Camerer CF (2005) Neural systems responding to degrees of uncertainty in human decision-making. *Science* 310:1680–1683.
12. Murray EA (2007) The amygdala, reward and emotion. *Trends Cogn Sci* 11:489–497.
13. Paulus MP, Rogalsky C, Simmons A, Feinstein JS, Stein MB (2003) Increased activation in the right insula during risk-taking decision making is related to harm avoidance and neuroticism. *NeuroImage* 19:1439–1448.
14. Bechara A, Damasio H, Tranel D, Damasio AR (1997) Deciding advantageously before knowing the advantageous strategy. *Science* 275:1293–1295.
15. Clark L, et al. (2008) Differential effects of insular and ventromedial prefrontal cortex lesions on risky decision-making. *Brain* 131:1311–1322.
16. Shiv B, Loewenstein G, Bechara A, Damasio H, Damasio AR (2005) Investment behavior and the negative side of emotion. *Psychol Sci* 16:435–439.
17. Critchley HD, Wiens S, Rotshtein P, Ohman A, Dolan RJ (2004) Neural systems supporting interoceptive awareness. *Nat Neurosci* 7:189–195.
18. LeDoux JE (2000) Emotion Circuits in the Brain. *Annu Rev Neurosci* 23:155–184.
19. Morris JS, et al. (1996) A differential neural response in the human amygdala to fearful and happy facial expressions. *Nature* 383:812–815.
20. Whalen PJ, et al. (1998) Masked presentations of emotional facial expressions modulate amygdala activity without explicit knowledge. *J Neurosci* 18:411–418.
21. Kahneman D, Tversky A (1979) Prospect theory—Analysis of decision under risk. *Econometrica* 47:263–291.
22. Kahneman D, Knetsch JL, Thaler RH (1990) Experimental tests of the endowment effect and the coase theorem. *J Polit Econ* 98:1325–1348.
23. Tversky A, Kahneman D (1992) Advances in prospect-theory—cumulative representation of uncertainty. *J Risk Uncertain* 5:297–323.
24. Gneezy U, Potters J (1997) An experiment on risk taking and evaluation periods. *Q J Econ 112* 2:631–645.
25. Thaler RH, Tversky A, Kahneman D, Schwartz A (1997) The effect of myopia and loss aversion on risk taking: An experimental test. *Q J Econ* 112:647–661.
26. Heisler J (1994) Loss aversion in a futures market: An empirical test. *Review of Futures Markets* 13:793–826.
27. Haigh MS, List JA (2005) Do professional traders exhibit myopic loss aversion? An experimental analysis. *Journal of Finance* 60:523–534.
28. Benartzi S, Thaler RH (1995) Myopic loss aversion and the equity premium puzzle. *Q J Econ* 110:73–92.
29. Putler DS (1992) Incorporating reference price effects into a theory of consumer choice. *Marketing Science* 11:287–309.
30. Hardie BGS, Johnson EJ, Fader PS (1993) Modeling loss aversion and reference dependence effects on brand choice. *Marketing Science* 12:378–394.
31. Genesove D, Mayer C (2001) Loss aversion and seller behavior: Evidence from the housing market. *Q J Econ* 116:1233–1260.
32. Camerer C, Babcock L, Loewenstein G, Thaler RH (1997) Labor supply of new york city cabdrivers: One day at a time. *Q J Econ* 112:407–441.
33. Chen MK, Lakshminarayanan V, Santos L (2006) How basic are behavioral biases? Evidence from capuchin monkey trading behavior. *J Polit Econ* 114:517–537.
34. Gross JJ (1998) Antecedent- and response-focused emotion regulation: Divergent consequences for experience, expression, and physiology. *J Pers Soc Psychol* 74:224–237.
35. Read D, Loewenstein G, Rabin M (1999) Choice bracketing. *J Risk Uncertain* 19:171–197.
36. O'Connell P, ed. (2001) Emotion, the Enemy of Investing *BusinessWeek Online* (Dec. 6). Available at http://www.businessweek.com/investor/content/dec2001/pi2001126_8886.htm.
37. Scherer KR (2005) What are emotions? And how can they be measured? *Social Science Information* 44:695–729.
38. Delgado MR, Schotter A, Ozbay E, Phelps EA (2008) Understanding overbidding: Using the neural circuitry of reward to design economic auctions. *Science* 321:1849–1852.
39. Loewenstein G, Weber EU, Hsee CK, Welch N (2001) Risk as feelings. *Psychol Bull* 127:267–286.
40. Ariely D, Huber J, Wertenbroch K (2005) When do losses loom larger than gains? *Journal of Marketing Research* 42:134–138.
41. Novemsky N, Kahneman D (2005) The boundaries of loss aversion. *Journal of Marketing Research* 42:119–128.
42. Novemsky N, Kahneman D (2005) How do intentions affect loss aversion? *Journal of Marketing Research* 42:139–140.
43. Lo AW, Repin DV, Steenbarger BN (2005) Fear and greed in financial markets: A clinical study of day-traders. *The American Economic Review* 95:352–359.
44. Lo AW, Repin DV (2002) The psychophysiology of real-time financial risk processing. *J Cognit Neurosci* 14:323–339.
45. List JA (2003) Does market experience eliminate market anomalies? *Q J Econ* 118:41–71.
46. Camerer C (2005) Three cheers—psychological, theoretical, empirical—for loss aversion. *Journal of Marketing Research* 42:129–133.
47. Kermer DA, Driver-Linn E, Wilson TD, Gilbert DT (2006) Loss aversion is an affective forecasting error. *Psychol Sci* 17:649–653.
48. Wilson TD, Gilbert DT (2005) Affective forecasting—Knowing what to want. *Curr Dir Psychol Sci* 14:131–134.

Supporting Information

Sokol-Hessner et al. 10.1073/pnas.0806761106

SI Text

Counterbalancing. We conducted a $4 \times 3 \times 2$ repeated measures analysis of variance (ANOVA) with factors of Order (A, B, C, and D), Parameter (λ, ρ, μ), and Condition ("Attend" and "Regulate"). There were no significant interactions with Order (all F's < 1, P's > 0.45).

Task Details. Participants silently read detailed, illustrated task instructions as the experimenter read them aloud and then completed a quiz on task instructions. If they made any mistakes, the instructions were reviewed until the quiz could be completed without mistakes. See supporting information (SI) Fig. S1 for an example screenshot from the study.

Monetary Choice Values (Behavioral Session). We performed a parameter recovery exercise in Mathematica v5.2 to find gamble values which were efficient for measuring changes in loss aversion (λ). In essence, a hypothetical participant was created by selecting a range of psychologically plausible values for the 3 model parameters (λ, ρ, μ) based on results from earlier studies (See Fig. S2). Stochastic choices were simulated, using those parameter values and Eq. **3**, over the initial monetary amounts. Given these simulated choices, we then used the maximum-likelihood procedure to estimate parameters. If the estimated parameters were close to the actual ones used to create the simulated data (and had a low variance across multiple simulations), then we could say that the modeling procedure could "recover" parameter values accurately. The method also showed that the correlation among the 3 recovered values was not too high so that the parameters were separately identified (in econometrics terminology). This method of creating our stimuli improved our ability to accurately recover a range of parameter values from actual participants given the choices made, and therefore increased the power of statistical tests to detect differences across and within subjects due to the strategies.

The monetary amounts were chosen first to accommodate a range in loss sensitivity from gain-seeking to loss averse and second with the assumption that most subjects would be risk averse, with few appreciable risk-seekers. For the 120 mixed valence gambles, gain outcomes were chosen from the set {2,4,5,6,8,9,10,12}, and corresponding loss outcomes were derived by multiplying the gain outcomes by a factor ranging from $-1/4$ to -2 in increments of 1/8 in a factorial design pairing each gain outcome with each multiplier. There are 15 multipliers in the set $\{-1/4, -3/8, -4/8 \ldots -2\}$ and 8 possible gain outcomes, which yields 120 gain-loss combinations. The 20 gain only gambles can be seen in Table S1. Possible monetary amounts thus ranged between +\$30 and −\$24.

Post hoc, we repeated the parameter recovery exercise with parameter values we recovered from our data set. The average Attend parameter values from Study 1 were used to stochastically simulate choices on the actual set of choice pairs, creating 500 pseudosamples. The estimation procedure was then applied to each pseudosample. Average recovered parameter values across the pseudosamples were $\lambda = 1.40$ (0.09), $\rho = 0.83$ (0.05), and $\mu = 2.79$ (0.74). These estimated values are very close or identical to the true values of $\lambda = 1.40$, $\rho = 0.83$, and $\mu = 2.57$. We also validated the standard error estimates by checking whether the true parameters fell within an interval 2 standard errors above and below the mean estimate (the bootstrapped 95% confidence interval) around 95% of the time. We found that this was indeed the case, with rates of parameter recovery within this interval of 93.8% (λ), 95.8% (ρ), and 96.6% (μ). Results were virtually identical when done using the average Regulate parameter values.

The results of Studies 1 and 2 underscore the value of studying decision-making on an individual-subject basis. Not only did this approach allow us to identify the substantial variability in loss aversion in our sample (Fig. 1), but if we had been restricted to group analyses, most of our results (e.g., the change in loss aversion within-subjects) would have been masked by that variability. Most importantly, it was this degree of specificity in estimation that enabled Study 2 to go beyond general statements about arousal. We were able to show that across participants, arousal specifically tracked loss aversion; we also found that our strategy appeared to reduce the arousal response to losses as opposed to enhancing the response to gains, for example. Without an individual approach, these kinds of analyses would have been impossible.

Monetary Choice Values (Physiological Session). Using individual participants' parameter estimates from the behavioral session, we created choices separately for the Attend and Regulate condition, with the end goal of equalizing the number of win, loss, and guaranteed outcomes. In each condition, we created by random selection 40 choices with an 85–95% chance of being accepted, and 20 choices with a 5–15% chance of being accepted. Gain values were bounded between \$1 and \$30, and loss values between −\$1 and −\$24.

Estimation Procedure. A parametric analysis to estimate risk-aversion and loss-aversion was conducted via a nonlinear stochastic choice model. Following Tversky and Kahneman (1), we represent subject's utility functions for money as a 2-part power function of the form

$$u(x) = \begin{cases} x^{\rho^+} & \text{if } x \geq 0 \\ -\lambda \cdot (-x)^{\rho^-} & x < 0 \end{cases} \qquad [1]$$

The loss aversion coefficient λ represents relative (multiplicative) weighting of losses relative to gains. The function's exponential form captures the empirical regularity of risk aversion (seeking) over gains (losses). As stated in the main text, ρ represents diminishing sensitivity to changes in value as the absolute value increases. Monetary amounts are raised to a power equal to this parameter value, producing an exponential curve which is concave for gains and convex for losses (if $\rho < 1$). A smaller ρ represents a higher rate of diminishing sensitivity and more risk aversion, relative to a larger ρ. A ρ value of one means there is no diminishing sensitivity (i.e., risk neutrality).

The diminishing sensitivity represented by ρ is equivalent to risk aversion in the gain domain and risk seeking in the loss domain, as demonstrated by the following example. Consider a gamble of +\$20/\$0 compared to a guaranteed amount of \$10. The objective expected value of the gamble is \$10 (expected value = probability × value, or 0.5 × \$20 + 0.5 × \$0 = \$10), as is of course the guaranteed amount. Therefore, a risk neutral individual would be indifferent between this gamble and the guaranteed amount. However, because the subjective value equation is exponential, the \$20 in the gamble is discounted relatively more than the \$10 in the guaranteed amount, thus leaving the gamble with a lower subjective value and leading the individual to reject the gamble for the guaranteed amount (risk averse behavior). As an example, if $\rho = 0.83$ (the average ρ value in the Attend condition in Study 1) the gamble would have a subjective value of 5.99, and the guaranteed amount a subjective value of 6.75.

In our analysis, we constrained the degree of curvature of the utility function, ρ, to be identical between the gains and the losses. That is, we assumed that $\rho^+ = \rho^-$. For likelihood ratio tests of this assumption, see *Significance Testing* below.

We further assume that people combine probabilities and utilities linearly, in the form $U(p,x) = p{\cdot}u(x)$. Note that also because we constrained $P = 0.5$ over all uncertain prospects, nonlinear weighting of probabilities (2, 3) applies equally to all choices, leaving our results qualitatively unchanged. [The magnitude of underweighting at p = 0.5 is small. Various studies have empirically estimated functions with w(0.5) ≈ 0.45 (see e.g., ref. 2).]

The probability that the subject chooses the uncertain prospect rather than the degenerate prospect is given by the logit or softmax function

$$F(p, x_1, x_2, c) = (1 + \exp\{-\mu(U(p, x_1, x_2) - u(c))\})^{-1} \qquad [2]$$

where x_1 and x_2 are the outcomes in the uncertain prospects, and c the outcome of the degenerate prospect. The logit parameter μ is the sensitivity of choice probability to the utility difference (the degree of inflection), or the amount of "randomness" in the subject's choices ($\mu = 0$ means choices are random; as μ increases the function is more steeply inflected at zero). Large μ values mean that participants are not sensitive to small changes in the values of the monetary amounts, and indicate greater reliance on "rule-based" decision-making (an infinite μ gives a step function, meaning that participants made decisions as if based entirely on a calculated rule). A smaller μ suggests that as the difference between the gamble and the guaranteed amount changed, so did the chance of the participant accepting the gamble. Another way to frame μ is as representing consistency over choices.

Denote the choice of the subject in trial i as y_i, where $y_i = 1$ if subject chooses the gamble, and 0 if the guaranteed alternative. We fit the data using maximum likelihood, with the log likelihood function

$$\sum_{i=1}^{140} y_i \log(F(p, x_1, x_2, c)) + (1 - y_i)\log(1 - F(p, x_1, x_2, c)) \qquad [3]$$

Because this is a nonlinear optimization problem, numerical methods must be used. We used the Nelder-Mead simplex algorithm (4) implemented in Mathematica v5.2.

The standard errors of the estimates were calculated using the negative of the inverse of the Hessian matrix evaluated at the estimated parameter values. The Hessian matrix is the matrix of second partial derivatives of the log likelihood function, and the negative of the Hessian is called the (observed) information matrix, which is also the asymptotic variance-covariance matrix. The square root of the diagonal (variance) terms gives us the standard error of the estimates.

Intuitively, the Hessian measures the degree of curvature of the maximum likelihood surface. A more inflected surface around the estimate implies a more precise estimate (as the likelihood values decrease faster as one moves away from the optimal solution).

Significance Testing. The likelihood ratio (LR) test (5) was used to assess significance of the overall model separately for each individual in each condition. The test compares the likelihood values of the full model against the null model in which ρ, λ, and μ were restricted to 0. The likelihood ratio statistic, expressed in log, is $-2(\log(L(\Theta_0))-\log(L(\Theta)))$ where Θ denotes a vector of parameters. It is distributed asymptotically as a χ^2 distribution with k degrees of freedom, where k is the number of parameter restrictions of the model (3 in this case).

Similarly, the LR test was used in assessing whether individuals' loss aversion coefficients differed from 1 (gain-loss neutral). An LR test was used to test the null hypothesis H_0: $\lambda=1$. In this case, the null distribution is a χ^2 distribution with 1 degree of freedom. In addition, we used the LR test to assess significant differences of individual parameters between attend and reappraise conditions. For each parameter $\theta \in \{\rho, \lambda, \mu\}$, an LR test was used to test the null hypothesis H_0: $\theta_{att} = \theta_{reapp}$. As before, our null distribution is a χ^2 distribution with 1 degree of freedom.

To test for the presence of individual variations in loss aversion, risk attitudes, and consistency over choices, we performed an LR test to test for the existence of random effects. That is, to see if we significantly improved our prediction of the data by fitting individual models as opposed to one overall model across our subject pool. Using the data from Study 1 participants, we compared the summed log likelihood values from the individual participants' model fits with the log likelihood of a single model fit across all subjects, separately for the Attend and Regulate conditions. In this case, the null is χ^2 distributed with 3 degrees of freedom. The likelihood ratios were 1402.34 and 1523.91 in the Attend and Regulate conditions respectively, corresponding with p values of approximately zero, and well below the numerical precision of standard statistical packages.

Curvature (ρ) Testing. We performed likelihood ratio tests on the Attend data for the 30 behavioral subjects from Study 1 in a similar manner as the Attend vs. Regulate significance tests.

First, to test the validity of the $\rho^+ = \rho^-$ assumption, we tested the unconstrained (separate ρ^+ and ρ^-) model against the constrained model ($\rho^+ = \rho^-$). These tests (see Table S2) showed that the constrained model could be rejected in 12 out of the 30 subjects at $P < 0.05$, and 9 out of those 12 at $P < 0.01$. However, using the unconstrained model worsened the accuracy of our estimates of the loss aversion parameter λ to a great degree (see Fig. S3), indicating that constraining $\rho^+ = \rho^-$ helped considerably improve identification (in terms of the variance of the parameters) of the model for certain subjects.

We also conducted likelihood ratio tests of the full model assuming an exponential value function (with the $\rho^+ = \rho^-$ constraint) against a model assuming a linear value function (or $\rho^+ = \rho^- = 1$), a common simplifying assumption. The results of these tests (see Table S3) indicate that we can reject linearity in 16 out of 30 subjects at the $P < 0.05$ level, and 14 out of those 16 at the $P < 0.01$ level. Because of biasing effects on the estimates of loss aversion (see below, *Estimated Degree of Loss Aversion*), we decided to keep an exponentially curved value function in our analyses.

The Estimated Degree of Loss Aversion. Despite a general belief that λ is around 2 (as in (1, 6, 7)), many studies report estimates closer to our average of 1.40. A summary of some other studies comparable to ours is given in Table S4, along with estimates of the average degree of loss aversion λ. Thirty percent of our subjects are estimated to have $\lambda < 1$ in the Attend condition. Comparable percentages range from 2–25% across the 5 studies which report individual-level estimates. Thus, while the number of subjects with $\lambda < 1$ is higher in our study, previous studies also show a substantial percentage of subjects with $\lambda < 1$. Many also show average loss-aversion coefficients comparable to our value of 1.40, including means of .82–1.95 (8), 1.43 (9), and 1.2 (10).

There are a variety of experimental factors that could also influence the degree of loss aversion found in any given study, although we briefly note that the findings of within-subjects designs such as ours are largely unaffected by such questions. First, risk aversion or diminishing sensitivity (See *Estimation Procedure*, above) can look like loss aversion in mixed gambles. That is, if a subject has diminishing sensitivity and some degree of loss aversion, but the model used to estimate their behavior is a linear value function with a loss aversion term, estimates of the loss aversion term will be biased upwards relative to their true loss aversion. To illustrate, we reanalyzed our data from the Study 1 participants in the Attend condition assuming a linear value function and found that it had the effect of biasing the corresponding estimates of λ upwards, as shown by paired t tests conducted on both λ ($t(29) = 2.64$ $P < 0.02$) and $\log(\lambda)$ ($t(29) = 3.06$ $P < 0.005$). The mean $\log(\lambda)$ value with the full model including exponential curvature was 0.20, whereas the mean $\log(\lambda)$ value estimated from the linear model was 0.26. These corresponded to mean λ coefficient values of 1.22 and 1.30, respectively (see Fig. S4 for plots of the λ estimates from exponential and linear value functions). Thus, the fact that many studies use linear value functions, and ours used exponential functions, could account for a part of the difference between our estimate and higher estimates found in some studies.

Because, as the previous paragraph suggests, it is impossible to disentangle loss aversion and risk aversion solely in the context of mixed-valence gambles, we included gain only trials, in which loss aversion (by definition) does not factor (20 out of the 140 choices were gain only choices).

Choice set construction can also conceivably have a biasing effect on estimates of loss aversion. For example, our choice set was constructed with the side effect that if subjects mindlessly accepted the best 50% of available gambles, we would recover a λ of roughly 1. Other choice sets might have the property that such an acceptance rule would be consistent with higher values of λ. Another possible factor could be a combination effect in which after losses, subjects might have bet more to catch up, and after gains, bet more because they perceived their winnings as "house money"—the net effect would increase betting and decrease estimates of loss aversion.

Beyond choice set construction, payment might have similarly strong effects on choice behavior. As an example, it is possible that our procedure encouraged a natural low baseline level of choice bracketing because of the payment structure (participants were paid the outcomes of a randomly selected 10% of their choices or 28 outcomes in the behavioral study rather than all outcomes or a single outcome) and/or because participants were completing 140 choices in each condition for a total of 280 choices. If participants were paid for, or were presented with, more or fewer choices, that baseline bracketing could conceivably be shifted. In a slightly different vein, it is possible that participants could perceive a "no bankruptcy clause" induced by the maximum potential loss of \$30 (the entire endowment), which could affect their choices in some systematic fashion, potentially increasing betting and thereby decreasing loss aversion estimates. Alternatively phrased, it is possible that participants' utility functions were flat below −\$30. The model we used considers the value function only in regard to independent choices. The no bankruptcy clause critique implicitly suggests a model of value that takes into account multiple choices and/or outcomes at the time of any single choice. Without a clear or obvious hypothesis as to the structure of that model, we felt unable to straightforwardly test it. This general question of payment is present in all laboratory studies on monetary decision making—if there is no endowment, then either choices must be hypothetical, or there will be a self-selection bias in the subject population willing to play with substantial sums of their own money. If those alternatives are not acceptable, then there is the aforementioned concern with endowments.

Another factor is whether feedback about outcomes is presented after each trial or not. Our design does have feedback because we were interested in psychophysiological reactions to actual loss (not just anticipated loss effects). Having a large set of choices with feedback could induce a natural "broad bracketing" in which losses are integrated with past or expected future gains and hence have less impact. It is possible that this may have resulted in some automatic regulation of losses of the kind suggested by research on emotional adaptation (11) and overestimation of the effects of losses (12). As an example, a paper comparing student and professional betting patterns with feedback suggested that "consistent with the notion that repetition might attenuate such anomalies… analysis of the data from the student sessions provides some evidence that the effect of the domain [gain or loss] is mitigated via repetition (13)."

We view our design features as creating a conservative lower boundary on measures of loss aversion compared to other types of designs and estimation methods. The fact that loss aversion is still substantial and present in a large majority of subjects is encouraging considering the design features which could minimize it. Furthermore, the fact that emotion regulation can still have a large and persistent effect in reducing loss aversion when it is modest to begin with is therefore even more remarkable.

Strategy Instructions. The following instructions were provided in written form to the subjects and were read aloud to them as they read along silently. The strategies were practiced with the experimenter before 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 is 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 of the previous and following choices during Reappraise trials. 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 is someone else's. Of course, you still want to do well (your job depends on it). You have 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 will not 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 of the other monetary decisions you will be making today during the Reappraise trials.

1. Tversky A, Kahneman D (1992) Advances in prospect-theory—cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5:297–323.
2. Prelec D (1998) The probability weighting function. *Econometrica* 66:497–527.
3. Wu G, Gonzalez R (1996) Curvature of the probability weighting function. *Management Science* 42:1676–1690.
4. Nelder Ja, Mead R (1965) A simplex-method for function minimization. *Computer Journal* 7:308–313.
5. Greene WH (2003) *Econometric Analysis* (Prentice Hall, Upper Saddle River, NJ).
6. Tom SM, Fox CR, Trepel C, Poldrack RA (2007) The neural basis of loss aversion in decision-making under risk. *Science* 315:515–518.
7. Chen MK, Lakshminarayanan V, Santos L (2006) How basic are behavioral biases? Evidence from Capuchin monkey trading behavior. *Journal of Political Economy* 114:517–537.
8. Bateman I, Kahneman D, Munro A, Starmer C, Sugden R (2005) Testing competing models of loss aversion: An adversarial collaboration. *Journal of Public Economics* 89:1561–1580.
9. Schmidt U, Traub S (2002) An experimental test of loss aversion. *Journal of Risk and Uncertainty* 25:233–249.
10. Gachter S, Johnson EJ, Herrmann A (2007) Individual-Level Loss Aversion in Riskless and Risky Choices. *CeDEx Working Paper* 1–23.
11. Wilson TD, Gilbert DT (2005) Affective forecasting—knowing what to want. *Curr Dir Psychol Sci* 14:131–134.
12. Kermer DA, Driver-Linn E, Wilson TD, Gilbert DT (2006) Loss aversion is an affective forecasting error. *Psychol Sci* 17:649–653.
13. Alevy JE, Haigh MS, List JA (2007) Information cascades: Evidence from a field experiment with financial market professionals. *Journal of Finance* 62:151–180.

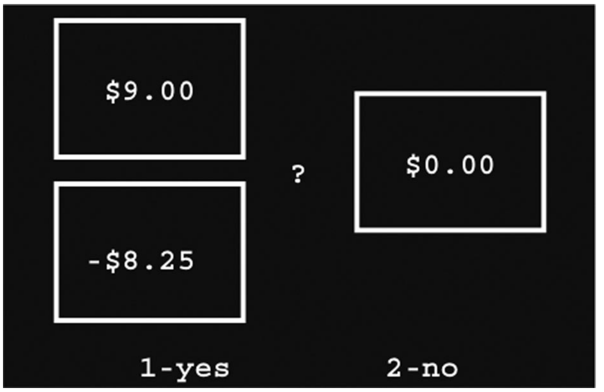

Fig. S1. A sample screenshot from the study. The 2 boxes on the left represent the gamble's possible gain and loss amounts (*Top* and *Bottom*, respectively). The box on the right represents the guaranteed amount. Participants had to indicate whether they wanted to accept the gamble.

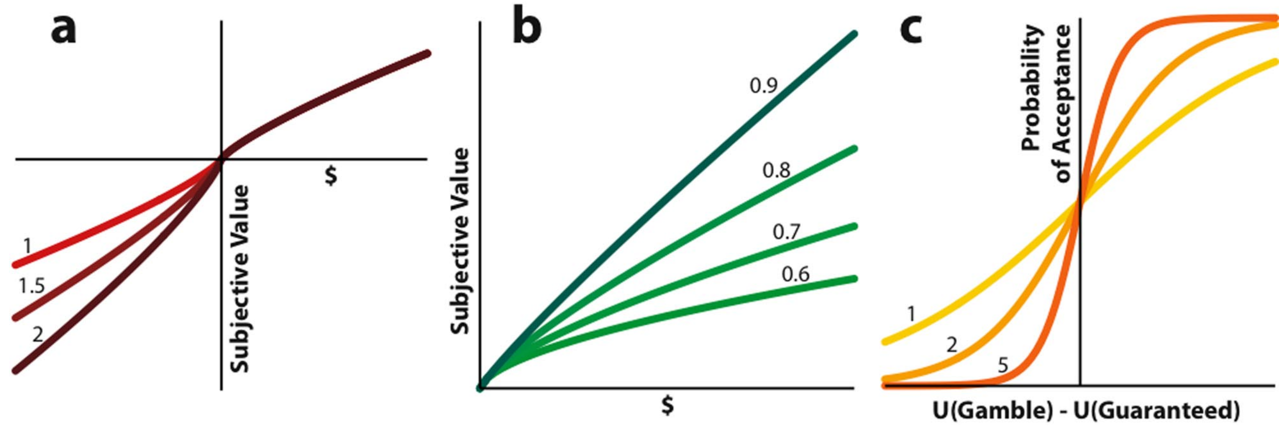

Fig. S2. Examples of functions from the behavioral model used to quantify choice behavior. (*a*) Stylized gain-loss value functions showing representative λ values. On the x axis is objective value (e.g., \$5, \$10). On the y axis is the subjective value to the individual. As λ values increase, the value function becomes steeper in the loss domain, indicating greater negative subjective value for the same objective value. (*b*) Stylized gain value functions showing representative ρ values. As in *a*, the x axis represents objective value, and the y axis represents subjective value. A smaller ρ value indicates more curvature and thus more diminishing sensitivity with increasing value. Risk aversion arises from diminishing sensitivity (see *SI Text*). (*c*) Stylized decision functions showing representative μ values. On the x axis is the difference between the subjective values of the gamble (''u(gamble)'') and the guaranteed amount (''u(guaranteed)''). On the y axis is the probability of accepting the gamble. In the middle of the graph is the indifference point, where the subjective value of the gamble and the guaranteed amount are equal, and participants are equally likely to accept or reject the gamble. As μ increases, the function shifts more quickly from rejecting the gamble to accepting the gamble and becomes less sensitive to changes in the gamble-guaranteed difference outside of the indifference point. Alternately, a high μ value means the participant was very consistent across decisions.

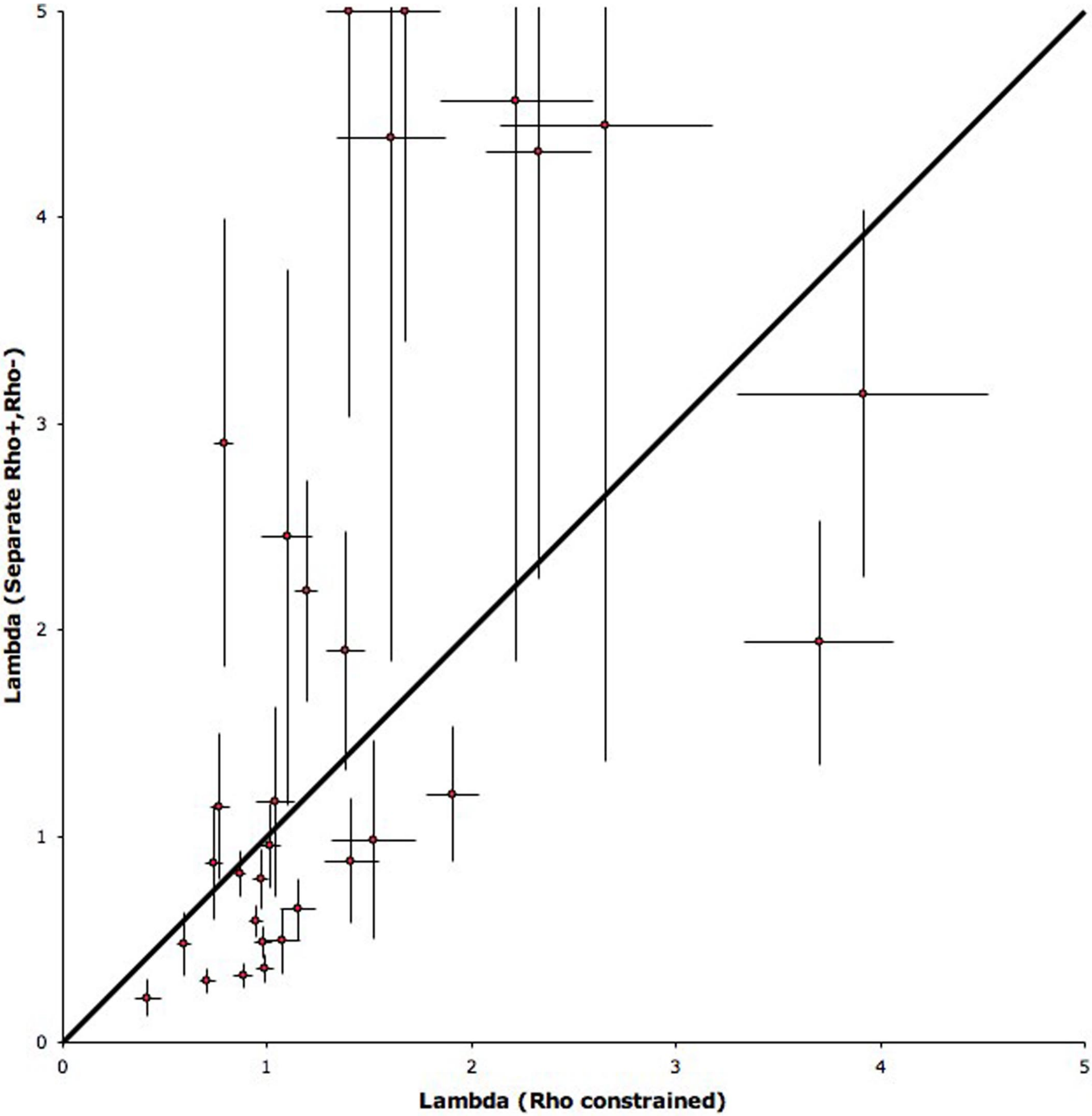

Fig. S3. Estimates of the loss aversion parameter λ in unconstrained (separate ρ^{+} and ρ^{-}) and constrained ($\rho^{+} = \rho^{-}$) models.

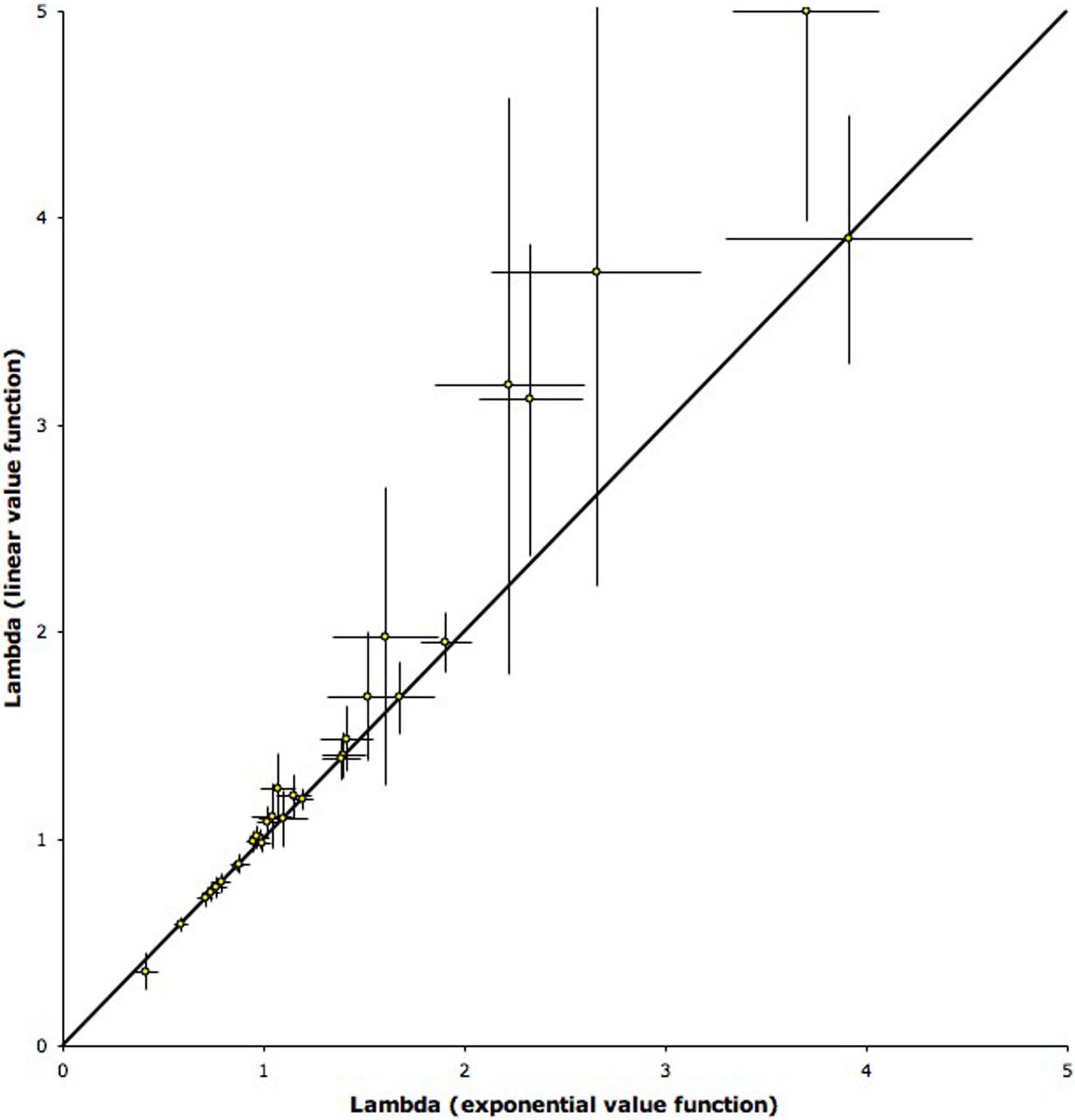

Fig. S4. Estimates of the loss aversion coefficient λ from exponential ($\rho^+ = \rho^-$) and linear ($\rho^+ = \rho^- = 1$) models.

Table S1. Monetary amounts in gain-only gambles

Gamble	Certain
2	1
3	1
4	2
5	2
7	3
8	3
12	6
12	5
12	4
13	5
13	6
19	8
22	10
23	10
25	9
25	10
26	10
26	12
28	13
30	12

Table S2. Likelihood ratio tests of unconstrained (separate ρ^{+} and ρ^{-}) versus constrained ($\rho^{+} = \rho^{-}$) models

Subject	Log Likelihood Ratio	*P* value
1	16.51	$<$0.001
2	14.42	$<$0.001
3	2.98	0.084
4	2.81	0.094
5	5.65	0.017
6	15.98	$<$0.001
7	1.31	0.253
8	10.35	0.001
9	30.35	$<$0.001
10	3.03	0.082
11	1.23	0.267
12	4.00	0.045
13	1.89	0.169
14	1.76	0.185
15	16.12	$<$0.001
16	0.30	0.587
17	3.32	0.068
18	0.10	0.758
19	7.25	0.007
20	0.09	0.768
21	2.41	0.120
22	18.20	$<$0.001
23	5.41	0.020
24	0.18	0.668
25	21.63	$<$0.001
26	1.75	0.186
27	0.46	0.497
28	2.13	0.145
29	0.82	0.365
30	0.69	0.407

($P < 0.05$ indicates rejection of the constrained model)

Table S3. Likelihood ratio tests of exponential ($\rho^{+} = \rho^{-}$) versus linear ($\rho^{+} = \rho^{-} = 1$) models

Subject	Log Likelihood Ratio	*P* value
1	0.24	0.622
2	0.05	0.827
3	22.94	<0.001
4	3.33	0.068
5	27.25	<0.001
6	7.31	0.007
7	0.55	0.459
8	33.88	<0.001
9	2.53	0.112
10	8.60	0.003
11	31.08	<0.001
12	23.65	<0.001
13	32.24	<0.001
14	8.14	0.004
15	3.32	0.069
16	0.06	0.804
17	0.11	0.738
18	35.86	<0.001
19	0.07	0.789
20	29.64	<0.001
21	2.33	0.127
22	0.09	0.759
23	6.48	0.011
24	1.54	0.215
25	0.00	0.950
26	4.28	0.038
27	0.01	0.928
28	26.28	<0.001
29	6.92	0.009
30	12.99	<0.001

($P < 0.05$ indicates rejection of the linear model)

Table S4. Estimates of loss aversion (λ) from a variety of studies

Study	λ estimate	Types of Choices & Payoff Range	Outcomes in the task?	Estimated w/risk aversion & π(p)?	% Subjects $\lambda < 1$
1	1.93 (Median), Range 0.99–6.75.	256 mixed (+/− vs. 0) gambles. Gains $10 to $40 matched with losses -$5 to -$20. Realized 3 trials.	No	No	6%
2	Using medians: 1.20, 1.25, 1.25, 1.25, 1.25, 1.40, 1.67, 2.40. Using means: 0.82, 1.08, 1.16, 1.18, 1.22, 1.24, 1.80, 1.95.	WTP/WTA/CE experiments with chocolate, chocolate vouchers, and money. Realized 1 money/chocolate exchange. Required transitivity.	No	N.A.	Not reported.
3	2.6–2.8 (mean)	Monkeys choosing fruit. Realized every choice.	Yes	No	Not reported.
4	2.25 (median)	Certainty equivalent for mixed and gain-only prospects. Not paid for choices (subject fee only). Required transitivity.	No	Yes (exponential value function, π(p) estimates)	Not reported.
5	1.43 (mean)	Certainty equivalents and risky gamble choices. Not paid for choices (subject fee only).	No	N.A.	24%
6.	N.A. (no function-fitting, only counting choices)	106 choices between pairs of tripartite gambles (both mixed valence & gain-only trials).	No	N.A.	24%
7	1.8 (mean)	Certainty equivalent hog prices with farmers. Not paid for choices (subject fee only).	No	Yes (exponential value function).	Not reported.
8	Using medians: 1.69, 0.74, 1.48, 0.43, 2.54 Using means: 2.04, 1.07, 1.71, 0.74, 8.27	"Bisection" method (choice-based certainty equivalents). Not paid for choices (subject fee only).	No	N.A. (applied multiple estimation methods)	2–25% (applied multiple estimation methods)
9	2.08 (overall). Diff. subj. groups & conditions: 2.22, 1.44, 3.97, 1.54 (medians)	Retirement fund distributions. Not paid for choices (subject fee only).	No	Yes (exponential value function).	Not reported.
10	Agg. Riskless: 2.29 (btwn-subj), 1.95 (within-subj). Indiv. Riskless: 2.62 (mean), 2.0 (median) Risky: 1.2 (median)	Riskless: WTA/WTP for a model car. Risky: 6 lottery choices. Required transitivity. Realized WTA, WTP & one lottery.	No	No	Riskless condition: 4.9% Risky condition: 16%

1. Tom SM, Fox CR, Trepel C, Poldrack RA (2007) The neural basis of loss aversion in decision-making under risk. *Science* 315:515–518.
2. Bateman I, Kahneman D, Munro A, Starmer C, Sugden R (2005) Testing competing models of loss aversion: An adversarial collaboration. *Journal of Public Economics* 89:1561–1580.
3. Chen MK, Lakshminarayanan V, Santos L (2006) How basic are behavioral biases? Evidence from Capuchin monkey trading behavior. *Journal of Political Economy* 114:517–537.
4. Tversky A, Kahneman D (1992) Advances in prospect-theory—cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5:297–323.
5. Schmidt U, Traub S (2002) An experimental test of loss aversion. *Journal of Risk and Uncertainty* 25:233–249.
6. Brooks P, Zank H (2005) Loss averse behavior. *Journal of Risk and Uncertainty*. 31:301–325.
7. Pennings JME, Smidts A (2003) The shape of utility functions and organizational behavior. *Management Science* 49:1251–1263.
8. Abdellaoui M, Bleichrodt H, Paraschiv C (2007) Loss aversion under prospect theory: A parameter-free measurement. *Management Science* 53:1659–1674.
9. Goldstein D, Johnson E, Sharpe W (2008) Measuring Consumer Risk-Return Tradeoffs. *SSRN Working Paper* Available at: http://ssrn.com/abstract=819065.
10. Gachter S, Johnson EJ, Herrmann A (2007) Individual-Level Loss Aversion in Riskless and Risky Choices. *CeDEx Working Paper* 1–23.