Supporting Information

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SI Text

Counterbalancing. We conducted a 4 × 3 × 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…−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 $w(0.5) \approx 0.45$ (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.

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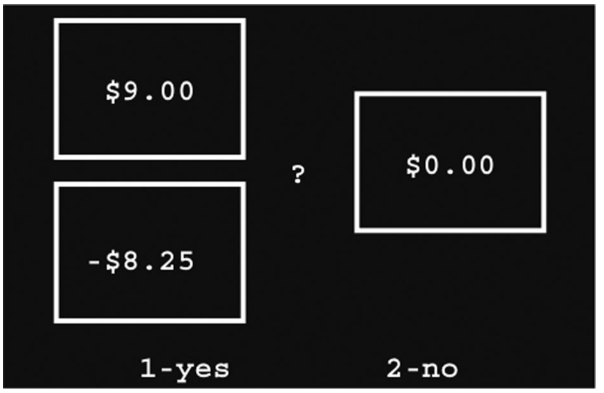

Fig. S1. A sample screenshot from the study. The 2 boxes on the left represent the gamble's possible gain and loss amounts (*Top* and *Bottom*, respectively). The box on the right represents the guaranteed amount. Participants had to indicate whether they wanted to accept the gamble.

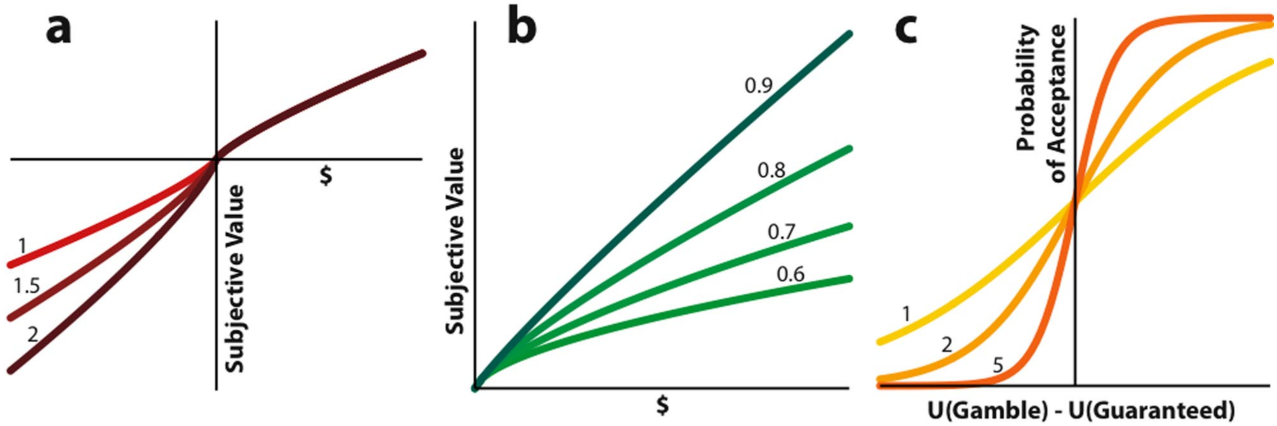

Fig. S2. Examples of functions from the behavioral model used to quantify choice behavior. (*a*) Stylized gain-loss value functions showing representative λ values. On the x axis is objective value (e.g., $5, $10). On the y axis is the subjective value to the individual. As λ values increase, the value 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.

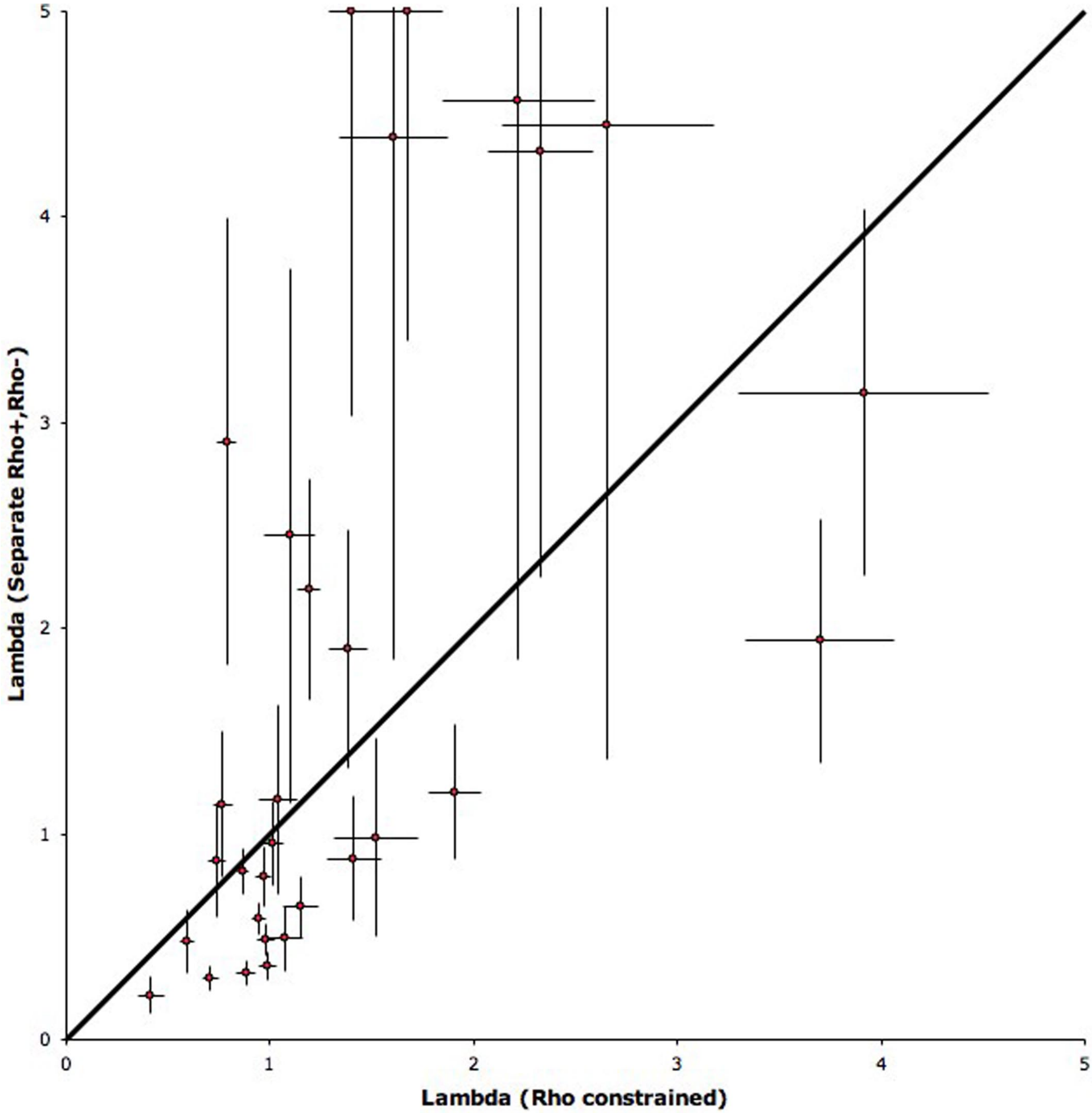

Fig. S3. Estimates of the loss aversion parameter λ in unconstrained (separate ρ^+ and ρ^-) and constrained ($\rho^+ = \rho^-$) models.

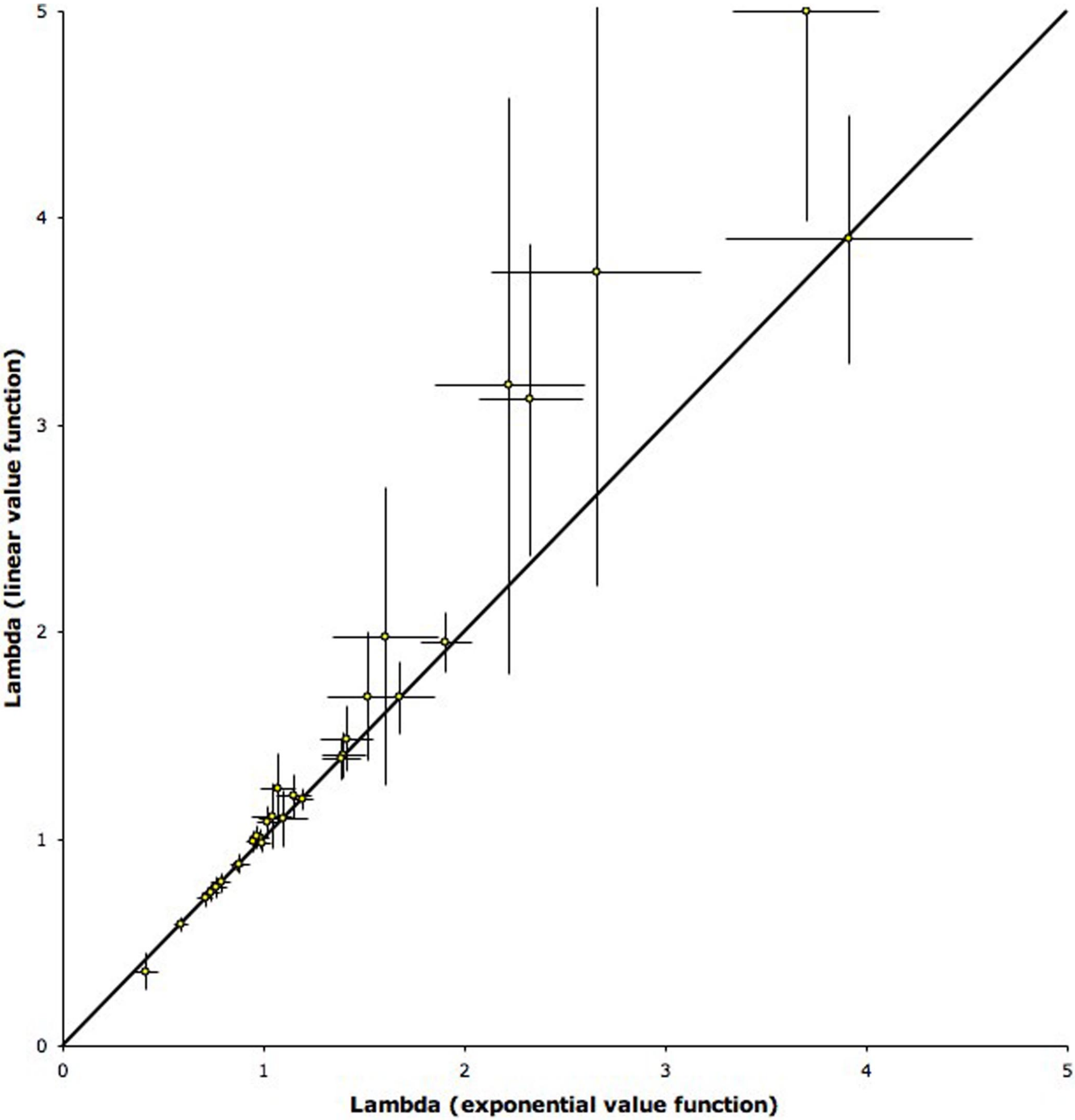

Fig. S4. Estimates of the loss aversion coefficient λ from exponential ($\rho^+ = \rho^-$) and linear ($\rho^+ = \rho^- = 1$) models.

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%

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