The joint effect of the classic choice phenomena, and the role of experience

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Experimental studies of human choice behavior have documented clear violations of rational economic theory and triggered the development of the influential field of behavioral economics. Yet, the impact of these careful studies on applied economic analyses and on policy decisions is not large. One justification for the tendency to ignore the experimental evidence involves the assertion that the behavioral literature highlights contradicting deviations from maximization, and it is not easy to predict which deviation is likely to be more important in specific situations. The prominent decision theorist David Schmeidler (personal communication, 2002) has expressed this concern bluntly: his theoretician's humor suggests that the contradicting nature of the different phenomena implies that they cancel each other out and thus can be ignored. The Nobel laureate Alvin E. Roth (see Erev et al., 2010) adds that he likes the psychological research, but asks that the authors of the different papers would add a toll-free phone number, and be ready to answer questions concerning the conditions under which the different phenomena are expected to drive behavior.

Kahneman and Tversky (1979) tried to address this problem by proposing a model (prospect theory) that captures the joint effect of four of the most important deviations from maximization. Specifically, they focus on the certainty effect (Allais paradox, Allais, 1953), the reflection effect, overweighting of low probability extreme events, and loss aversion (see top four rows in Table 1). The current paper extends this and similar efforts (see e.g., Thaler & Johnson, 1990; Brandstätter, Gigerenzer, & Hertwig, 2006; Birnbaum, 2008; Wakker, 2010; Erev et al., 2010) by facilitating the derivation and comparison of models that capture the joint impact of the four "prospect theory effects" and ten additional phenomena. The additional phenomena that we consider are shown in Table 1 and include six tendencies that were documented in studies of decisions without feedback (risk aversion in the St. Petersburg problem, Bernoulli, 1738/1954; ambiguity aversion, Ellsberg, 1961; the break even effect, Tahler & Johnson, 1990; the get something effect, Payne, 2005; the splitting effect, Birnbaum, 2008; and the magnitude effect of losses, Ert & Erev, 2013), and four phenomena that were documented in the study of repeated decisions with feedback (underweighting of rare events and reversed reflection effect, Barron & Erev, 2003; the payoff variability, Busemeyer & Townsend, 1993; and the correlation effect, Diederich & Busemeyer, 1999).

At the first stage of our investigation we tried to replicate the different phenomena under the same "standard" setting (Hertwig & Ortmann, 2001). Specifically, we focused on choices with real monetary consequences in a space of experimental tasks wide enough to replicate all the phenomena illustrated in Table 1. The results suggest that all 14 phenomena emerge in our setting. Yet, their magnitude tends to be smaller than their magnitude in the original demonstrations.

The second part of our investigation examines the robustness of the suggested behavioral tendencies by studying 60 additional problems that were randomly selected from an 11-dimensional space of tasks that includes the replication problems examined in the first stage. The results highlight the robustness of the distinct phenomena. In addition, our analysis suggests that the main behavioral tendencies can be summarized with a model assuming that each choice is based on the decision maker's best estimate of the expected value and a small number of mental simulations. Each simulation implies a draw from one of four distributions: the objective (unbiased) payoff distribution, and three subjective (biased) distributions. Additionally, the model assumes that feedback increases the probability of drawing from the objective distribution. Thus, the model suggests that the initial (pre-feedback) behavior reflects three biases that lead to the 10 "description" (decisions without feedback) phenomena, and experiencing feedback increases maximization. Yet, because the number of mental simulations is small, feedback also implies reliance on small samples and leads to underweighting of rare events.

In the third part of the current project we organize a choice prediction competition in which other researchers are challenged to develop models that can capture the results of the first two experiments, and predict the results of a third experiment that we plan to run. The third experiment will be similar to the first two experiments, but will focus on an independent draw of 60 other problems from the current 11-dimensional space of tasks.

Table 1.

Typical Examples of Fourteen Phenomena and Their Replications in the Current Study.

	Classical Demonstration		Current Replication	
Phenomenon	Problems	%B Choice	Problems	%B Choice
	Phenomena observed in studies of decisions without feedback			
1. Certainty effect/Allais paradox (Kahneman & Tversky, 1979; following Allais, 1953)				
	A: 3000 with certainty B: 4000, .8; 0 otherwise	20%	A: 3 with certainty B: 4, .8; 0 otherwise	42%
	A’: 3000, .25; 0 otherwise B’: 4000, .20; 0 otherwise	65%	A′: 3, .25; 0 otherwise B′: 4, .20; 0 otherwise	61%
2. Reflection effect (Kahneman & Tversky, 1979)				
	A: 3000 with certainty B: 4000, .8; 0 otherwise	20%	A: 3 with certainty B: 4, .8; 0 otherwise	42%
	A’: -3000 with certainty B’: -4000, .8; 0 otherwise	92%	A′: -3 with certainty B′: -4, .8; 0 otherwise	49%
3. Over-weighting of rare events (Kahneman & Tversky, 1979)				
	A: 5 with certainty B: 5000, .001; 0 otherwise	72%	A: 2 with certainty B: 101, .01; 1 otherwise	55%
4. Loss aversion (Ert & Erev, 2013; following Kahneman & Tversky, 1979)				
	A: 0 with certainty B: -100, .5; 100 otherwise	22%	A: 0 with certainty B: -50, .5; 50 otherwise	34%
5. Low Magnitude eliminates loss aversion (Ert & Erev, 2013)				
	A: 0 with certainty B: -10, .5; 10 otherwise	48%	A: 0 with certainty B: -1, .5; 1 otherwise	49%
6. St. Petersburg paradox/risk aversion (Bernoulli, 1738/1954)				
	A fair coin will be flipped until it comes up heads. The number of flips will be denoted by the letter k. The casino pays a gambler 2^k. What is the maximal amount of money that you are willing to pay for playing this game?	Modal response: less than 8	A: 9 with certainty B: 2, 1/2; 4, 1/4; 8; 1/8; 16, 1/16; 32, 1/32; 64, 1/64; 128, 1/128; 256 otherwise	38%
7. Ellsberg paradox/ Ambiguity aversion (Einhorn & Hogarth, 1986; following Ellsberg, 1961)				
	Urn K includes 50 Red, and 50 White balls. Urn U includes 100 balls, each either Red or White with unknown proportions. Choose between:		A: 10 with probability .5; 0 otherwise B: 10 with probability ‘p’; 0 otherwise (‘p’ unknown constant)	37%
	A: 100 if a ball drawn from K is Red; 0 otherwise	47%		
	B: 100 if a ball drawn from U is Red; 0 otherwise	19%		
	C: Indifference	34%		

8. Break even effect (Thaler & Johnson, 1990)				
	A: -2.25 with certainty B: -4.50, .5; 0 otherwise	87%	A: -1 with certainty B: -2, .5; 0 otherwise	58%
	A': -7.50 with certainty B': -5.25 .5; -9.75 otherwise	77%	A′: -2 with certainty B′: -3 .5; -1 otherwise	48%
9. Get something effect (Ert & Erev, 2013, following Payne, 2005)				
	A: 11, .5; 3 otherwise B: 13, .5; 0 otherwise	21%	A: 1 with certainty B: 2, .5; 0 otherwise	35%
	A’: 12, .5; 4 otherwise B’: 14, .5; 1 otherwise	38%	A′: 2 with certainty B′: 3 .5; 1 otherwise	41%
10. Splitting effect (Birnbaum, 2008; following Tversky & Kahneman, 1986)				
	A: 96; .90; 14, .05; 12 .05 B: 96; .85; 90, .05; 12, .10	73%	A: 16 with certainty B: 1, .6; 50, .4	49.9%
			A′: 16 with certainty B′: 1, .6; 44, .1; 48, .1; 50, .2	50.4%
Phenomena observed in studies of repeated decisions with feedback				
11. Under-weighting of rare events (Barron & Erev, 2003)				
	A: 3 with certainty B: 32, .1; 0 otherwise	32%	A: 1 with certainty B’: 20, .05; 0 otherwise	29%
	A’: -3 with certainty B’: -32, .1; 0 otherwise	61%	A′: -1 with certainty B′: -20 .05; 0 otherwise	64%
12. Reversed reflection (Barron & Erev, 2003)				
	A: 3 with certainty B: 4, .8; 0 otherwise	63%	A: 3 with certainty B: 4, .8; 0 otherwise	65%
	A’: -3 with certainty B’: -4, .8; 0 otherwise	40%	A′: -3, with certainty B′: -4, .8; 0 otherwise	40%
13. Payoff variability effect (Erev & Haruvy, 2010; following Busemeyer & Townsend, 1993)				
	A: 0 with certainty B: 1 with certainty	96%	A: 2 with certainty B: 3 with certainty	100%
	A’: 0 with certainty B’: -9, .5; 11 otherwise	58%	A': 6 if E; 0 otherwise B': 9 if not E; 0 otherwise P(E) = 0.5	84%
14. Correlation effect (Grosskopf et al., 2006; following Diederich & Busemeyer, 1999)				
	A: 150+N_1 if E; 50+N_1 otherwise B: 160+N_2 if E'; 60 +N_2 otherwise	82%	A: 6 if E; 0 otherwise B: 9 if not E; 0 otherwise	84%
	A': 150+N_1 if E; 50+N_1 otherwise B': 160+N_2 if E; 60 +N_2 otherwise N_i ~ N(0,20), P(E) = P(E') = .5	98%	A’: 6 if E; 0 otherwise B’: 8 if E; 0 otherwise P(E) = 0.5	98%

Note. The notation *x*, *p* means payoff of *x* with probability *p*. In the classical demonstrations the choice rates are for one-shot decisions in the no-feedback phenomena and for mean of the final 100 trials (of 200 or 400) in the with-feedback phenomena. In the current replications, choice rates are for five consecutive choices without feedback in the no-feedback phenomena and for the final block of 5 trials (of 25) in the with-feedback phenomena.

Space of Choice Problems

The previous studies that demonstrated the behavioral phenomena summarized in Table 1 used diverse experimental paradigms. For example the Allais paradox/certainty effect was originally demonstrated in studies that examined choice among fully described gambles (Allais, 1953; Kahneman & Tversky, 1979), while the Ellsberg paradox was originally demonstrated in studies that focused on bets on the color of a ball drawn from partially described urns (Ellsberg, 1961; Einhorn & Hogarth, 1986). In addition, within the same experimental paradigm different payoff distributions give rise to different behavioral phenomena. In other words, the differences among the various demonstrations of Table 1's behavioral phenomena involve multiple dimensions. Thus, it is possible to think of Table 1's classical demonstrations as points in a multidimensional space of "choice tasks". This abstraction clarifies the critique against behavioral decision research: The critique rests on the observation that the leading models were designed to capture specific points in this space of choice problems, where different models address different points, and the boundaries of the different models are not always clear. As a result, it is not clear which one of these models should be used to predict behavior in a new choice task.

The current research tries to address this critique by facilitating the study of a space of choice tasks wide enough to give rise to all 14 phenomena summarized in Table 1. We started by trying to identify the critical dimensions of this multidimensional space. Our effort suggests that the main properties of Table 1's problems include at least 11 dimensions. Nine of the 11 dimensions can be described as parameters of the payoff distributions. These parameters include: L_A, H_A, pH_A, L_B, H_B, pH_B, nLotOut, LotShape and Corr. In particular, each problem in the space is a choice between Option A that provides either H_A (with probability pH_A) or L_A (with probability 1-pH_A), and Option B that provides either an outcome of a lottery that has expected value of H_B (with probability pH_B) or L_B (with probability 1-pH_B). In addition to its expected value (H_B) the lottery's distribution is determined by the parameters LotNum (which defines the number of possible outcomes in the lottery) and LotShape (which defines whether the distribution is symmetric around its mean, right-skewed, or left-skewed, or is undefined if LotNum = 1) as explained in Appendix A. Corr determines the sign of the correlation between the payoffs of the two options.

The tenth parameter, Ambiguity (Amb) captures the precision of the initial information the decision maker receives concerning the probabilities of the outcomes in Option B. We focus on the two extreme cases: Amb = 1 implies no initial information concerning these probabilities (they are replaced with undisclosed parameters), and Amb = 0 implies complete information and no ambiguity (as in Allais, 1953; Kahneman & Tversky, 1979).

The 11th dimension in the space is the amount of feedback. As Table 1 shows, some phenomena emerge in decisions without feedback, and other phenomena emerge when the decision maker can rely on feedback. We studied this dimension within problem. That is, decision makers faced each problem first without feedback, and then with feedback (the obtained and the forgone outcomes following each choice).

Experiment 1's main hypothesis is that this 11-dimensioanl space is sufficiently large to give rise to the classical phenomena from Table 1.[1] Moreover, we assume that despite the diversity of experimental paradigms used to demonstrate these phenomena in the past, they could all be replicated within the abstract framing of choice between gambles used by Allais (1953) and Kahneman and Tversky (1979). Yet, to be on the safe side, in addition to the 11 dimensions, we have added to Experiment 1 a couple of framing manipulations ("accept/reject" and "coin-toss") that previous studies noted as important to a couple of the

[1] We clearly had to limit the range of values each of the 11 dimensions may take, which inevitably added technical constraints to the space of problems we actually study. For example, the manner by which the lottery parameters define its distribution limits the possible lottery distributions in the space (see Appendix A). Hence, Experiment 1's genuine hypothesis is that even the limited 11-dimensional space is sufficiently large to replicate the classical phenomena.

phenomena in Table 1 (loss aversion, see Erev & Ert, 2013; and the St. Petersburg paradox, see Erev, Glozman, & Hertwig, 2008, respectively). Under the "accept/reject framing" Option B is presented as the acceptance of a gamble, and Option A as the status quo (rejecting the gamble). Under the "coin-toss framing" the description of the lottery uses the coin-toss game framing used by Daniel Bernoulli (1738/1954) to describe the St. Petersburg's paradox.[2] Hence, each of the 30 problems studied in Experiment 1 (Table 2) is uniquely defined by the first 10 parameters described above plus a framing manipulation (and, as noted, the 11th, feedback dimension is studied within problem).

Naturally, other dimensions and manipulations than those we have described above exist, and could in theory affect the results. One such dimension is whether the choice problem is played for hypothetical or for real money. We have chosen to focus only on problems played for real money, as we believe they are more representative of choice behavior in natural settings. Another reason for the focus on real money is the observation that this focus reduces noise (Camerer & Hogarth, 1999).[3]

Experiment 1: Replications

Experiment 1 was designed to explore whether the current 11-dimensional space is wide enough to replicate the 14 choice phenomena summarized in the left hand side of Table 1. A second goal of Experiment 1 was to clarify the boundaries and the relative importance of these phenomena. Finally, the experiment was designed to test the robustness of a couple of the phenomena to certain framing manipulations, which previous research suggested matter. In order to achieve these goals we studied the 30 choice problems summarized in Table 2.

[2] Examples of the experimental screen, including of the various framing manipulations, are shown in Appendix B.

[3] Admittedly, our initial inclination was to model this noise rather than exclude hypothetical problems. We changed our mind after a pilot study in which more than the 30% of the subjects preferred the hypothetical gamble "-1000, .1; +1" over the status quo (zero with certainty).

Table 2.

The Thirty Problems Studied in Experiment 1.

	Option A			Option B			Lottery				B-rate				
											No-FB	With-FB			
Prob.	H	pH	L	H	pH	L	Num	Shape	Corr.	Amb	1	2	3	4	5
1	3	1	3	4	0.8	0	1	-	0	0	.42	.57	.57	.60	.65
2	3	0.25	0	4	0.2	0	1	-	0	0	.61	.62	.62	.64	.62
3	-1	1	-1	0	0.5	-2	1	-	0	0	.58	.60	.60	.58	.56
4	1	1	1	2	0.5	0	1	-	0	0	.35	.51	.54	.50	.54
5	-3	1	-3	0	0.2	-4	1	-	0	0	.49	.46	.42	.38	.36
6	0	0.75	-3	0	0.8	-4	1	-	0	0	.38	.40	.40	.42	.41
7	-1	1	-1	0	0.95	-20	1	-	0	0	.48	.63	.62	.62	.64
8	1	1	1	20	0.05	0	1	-	0	0	.39	.38	.33	.34	.29
9	1	1	1	100	0.01	0	1	-	0	0	.47	.40	.39	.39	.39
10	2	1	2	101	0.01	1	1	-	0	0	.55	.45	.43	.42	.42
11	19	1	19	20	0.9	-20	1	-	0	0	.13	.22	.21	.20	.21
12	0	1	0	50	0.5	-50	1	-	0	0	.34	.41	.43	.44	.38
13[a]	0	1	0	50	0.5	-50	1	-	0	0	.36	.37	.40	.37	.36
14	0	1	0	1	0.5	-1	1	-	0	0	.49	.45	.42	.41	.38
15	7	1	7	50	0.5	1	1	-	0	0	.78	.84	.88	.83	.85
16	7	1	7	50	0.5	-1	1	-	0	0	.71	.79	.81	.83	.83
17	30	1	30	50	0.5	1	1	-	0	0	.24	.33	.33	.30	.29
18	30	1	30	50	0.5	-1	1	-	0	0	.23	.33	.40	.33	.33
19[b]	9	1	9	9	1	9	8	R-skew	0	0	.37	.39	.36	.31	.30
20	9	1	9	9	1	9	8	R-skew	0	0	.38	.38	.39	.36	.36
21	10	0.5	0	10	0.5	0	1	-	0	1	.37	.42	.47	.48	.51
22	10	0.1	0	10	0.1	0	1	-	0	1	.82	.84	.78	.71	.66
23	10	0.9	0	10	0.9	0	1	-	0	1	.15	.16	.26	.33	.32
24	-2	1	-2	-1	0.5	-3	1	-	0	0	.48	.52	.48	.48	.45
25	2	1	2	3	0.5	1	1	-	0	0	.41	.50	.46	.46	.49
26	16	1	16	50	0.4	1	1	-	0	0	.50	.65	.61	.60	.55
27[c]	16	1	16	48	0.4	1	3	L-skew	0	0	.50	.57	.60	.58	.57
28	6	0.5	0	9	0.5	0	1	-	-1	0	.91	.87	.83	.85	.84
29	2	1	2	3	1	3	1	-	0	0	.97	.98	.99	.99	1.0
30	6	0.5	0	8	0.5	0	1	-	1	0	.94	.97	.96	.98	.98

Note. B-rates are mean choice rates for Option B, presented in five blocks of five trials each: No-FB is the block without feedback, and With-FB are the blocks with feedback.

[a]An accept/reject type problem (the problem is replaced with a proposal to accept or reject a game of chance with Option B's outcomes). [b]A coins-toss type problem (Option B is construed as a game of chance similar to that used by Bernoulli, 1738/1954). Its implied payoff distribution is described in Row 6 of Table 1. [c]The implied payoff distribution is described in Row 10 of Table 1.

Method

One Hundred and twenty five students (63 male, $M_{\text{Age}} = 25.5$) participated in Experiment 1. Sixty participants were run at the Hebrew University of Jerusalem, and 65 were run at the Technion. Each participant faced each of the 30 decision problems, presented in Table 2, for 25 trials. The order of the 30 problems was random. Participants were told that they were going to play several games, each of which for several trials, and their task in each trial is to choose one of the two options on the screen for real money. The instructions also stated that at the end of the study one of the trials would be randomly selected, and that the participants' obtained outcome in that trial would be realized as their payoff (see examples of the experimental screen and a translation of the instructions in Appendix B). In the first five trials of each problem, the participants did not receive feedback after each choice; thus they had to rely on the description of the payoff distributions. Full feedback (the outcome of each of the two prospects) was provided after each choice starting at Trial 6; that is, in the last 19 trials the participants could rely on the description of the payoff distributions and on feedback concerning the outcomes of previous trials.[4] The final payoff (including show-up fee) ranged between 10 and 110 Shekels ($M = 41.9$)

Results and Discussion

The main experimental results, mean B-rates (choice rates of Option B over the 125 participants) are presented in the right-hand columns of Table 2. The raw data (nearly 94,000

[4] In addition, we also compared two order conditions in a between-subject design. Sixty participants (thirty in each location) were assigned to the "By Problem" (ByProb) order: They faced each problem for one sequence of 25 trials. The other participants were assigned to the "By Feedback" (ByFB) order. This order condition was identical to the ByProb condition with one exception: The participants first performed the five no-feedback trials in each of the 30 problems (in one sequence of 150 trials), and then faced the remaining 20 trials with feedback of each problem (in one sequence of 600 trials, and in the same order of problems they have played in the no-feedback trials). Our analyses suggested almost no differences between the two conditions, therefore we chose to focus on the choice patterns across conditions, and report these subtle differences in the "effects of location and order" section.

lines) can be found in the online supplemental material[5], and below we clarify the implications of the results to the 14 phenomena.

The Allais paradox/certainty effect. The Allais paradox (Allais, 1953) is probably the clearest and most influential counterexample to expected utility theory (von Neumann & Morgenstern, 1944). Kahneman and Tversky (1979) show that the psychological tendency that underlies this paradox can be described as a certainty effect: Safer alternatives are more attractive when they provide gain with certainty. Figure 1 summarizes our investigation of this effect using variants of the problems used by Kahneman and Tversky (Row 1 in Table 1) to replicate Allais' common ratio version of the paradox. Analysis of Block 1 (first 5 trails, without feedback, or "No-FB") shows the robustness of the certainty effect in decisions from description: The safer prospect (A) was more attractive in Problem 1 when it provided a positive payoff with certainty (A-rate of 58%, B-rate of 42%, *SD* = 0.42), than in Problem 2 when it involved some uncertainty (A-rate of 39%, B-rate of 61%, *SD* = 0.44). The difference between the two rates is significant, $t(124) = -3.69$, $p < .001$. However, feedback eliminates the paradox. The difference between the two problems over the four With-FB blocks (B-rate of 60%, *SD* = 0.37 in Problem 1, and B-rate of 62%, *SD* = 0.39 in Problem 2) is insignificant: $t(124) = -0.59$.

Prob.	Option A	Option B
1	(3, 1)	(4, .8; 0)
2	(3, .25; 0)	(4, .2; 0)

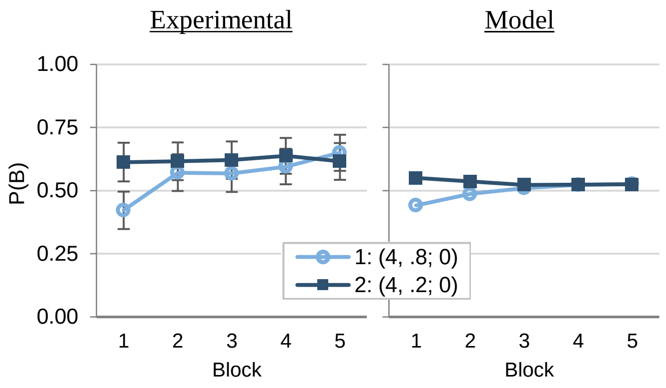


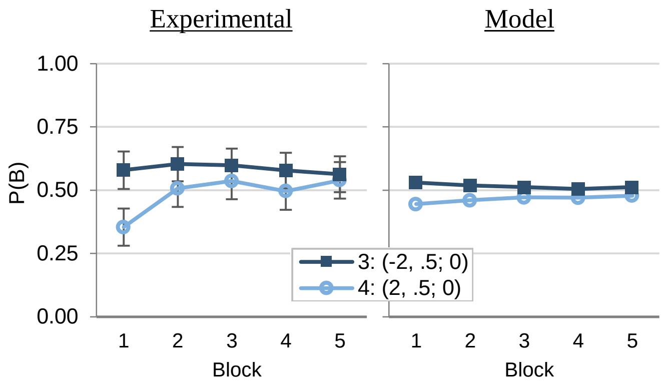
Figure 1. Problems Which Test The Allais Paradox/Certainty Effect in Experiment 1. The notation (x, p; y) refers to a prospect that yields a payoff of *x* with probability *p* and *y* otherwise. Option B's choice proportions

[5] See http://departments.agri.huji.ac.il/cpc2015

are shown in five blocks of five trials each (Block 1: “No-FB”, Blocks 2-5: “With-FB”). The experimental results are given with 95% CI for the mean. (The right-hand plot presents the prediction of the baseline model described below).

The reflection and the reversed reflection effects. Comparison of Problem 3 and Problem 4 in Figure 2 demonstrates the reflection effect (Kahneman & Tversky, 1979, and Row 2 in Table 1) in the No-FB block: Risk aversion in the gain domain (B-rate of 35%, *SD* = 0.42 in Problem 4) and risk seeking in the loss domain (B-rate of 58%, *SD* = 0.42 in Problem 3). The difference is significant, $t(124) = -4.99$, $p < .001$. Feedback reduces this effect. The B-rate in the With-FB blocks (2 to 5) is 52% (*SD* = 0.37) in Problem 4 and 59% (*SD* = 0.35) in Problem 3. This difference is insignificant, $t(124) = -1.59$. Comparison of Problem 1 with Problem 5 reveals a weaker indication of the reflection effect. The results in the No-FB block show risk aversion in the gain domain (B-rate of 42%, *SD* = 0.42 in Problem 1), and near risk neutrality in the loss domain (B-rate of 49%, *SD* = 0.42 in Problem 5), an insignificant difference, $t(124) = -1.24$. Feedback reverses the results and leads to lower risk-taking rate in the loss domain (B-rate of 40%, *SD* = 0.37 in Problem 5) than in the gain domain (B-rate of 60%, *SD* = 0.37 in Problem 1). The reversed reflection pattern (see Barron & Erev, 2003; and Row 12 in Table 1) over the four With-FB blocks, that may indicate learning toward maximization, is significant, $t(124) = 3.90$, $p < .001$.

Prob.	Option A	Option B
3	(-1, 1)	(-2, .5; 0)
4	(1, 1)	(2, .5; 0)



Prob.	Option A	Option B
5	(-3, 1)	(-4, .8; 0)
1	(3, 1)	(4, .8; 0)

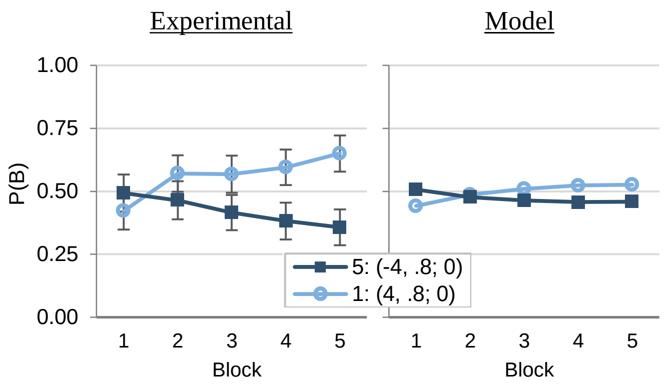


Figure 2. Problems Which Test The Reflection Effect in Experiment 1. The notation (x, p; y) refers to a prospect that yields a payoff of *x* with probability *p* and *y* otherwise. Option B's choice proportions are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"). The experimental results are given with 95% CI for the mean.

The weighting of rare events. Figure 3 summarizes our investigation of the weighting of rare events. An analysis of the No-FB block shows that the modal choice in Problem 10 reflects overweighting of the rare (probability .01) event. The participants tend to prefer the long shot gamble. Yet, the magnitude of this effect is not large; the mean rate (55%, *SD* = 0.44) is not significantly different from 50%, $t(124) = 1.15$. Moreover, Problems 7, 8, 9 show no indication for initial overweighting of rare events. One explanation for the difference between these findings and Kahneman and Tversky's (1979, and Row 3 in Table 1) strong indications for overweighting of rare events in decisions from description involves the definition of the term rare. The classical demonstrations focus on a 1/1000 event, and we studied 1/20 and 1/100 events. It is possible that the tendency to overweight rare events increases with their rarity.[6] This explanation is supported by the observation that our results for the positive rare outcomes reveal higher B-rate in the 1/100 case (mean of 51% in Problems 9 and 10, *SD* = 0.38) than in the 1/20 case (B-rate of 39%, *SD* =0.43, in Problem 8); this difference is significant, $t(124) = 3.32$, $p = .001$.

Prob.	Option A	Option B
7	(-1, 1)	(-20, .05; 0)
8	(1, 1)	(20, .05; 0)
9	(1, 1)	(100, .01; 0)
10	(2, 1)	(101, .01; 1)

Prob.	Option A	Option B
11	(19, 1)	(-20, .1; 20)

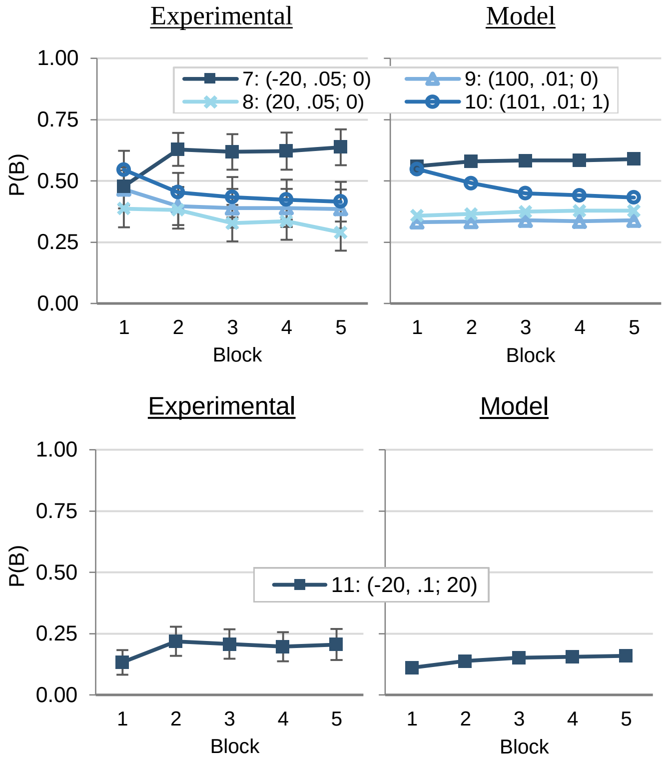


Figure 3. Problems Which Test The Weighting of Rare Events in Experiment 1. The notation (x, p; y) refers to a prospect that yields a payoff of *x* with probability *p* and *y* otherwise. Option B's choice proportions are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"). The experimental results are given with 95% CI for the mean.

Figure 3 also shows that the emergence of underweighting of rare events in decisions with feedback is robust (Barron & Erev, 2003, Lejarraga & Gonzalez, 2011; and Row 11 in Table 1). Experience reduces sensitivity to the rare event in all five problems. In the four equal expected value problems (7, 8, 9 and 10) the choice rate following feedback reflects

[6] Another possible explanation for the weaker indication of initial overweighting of rare events that we observed relative to Kahneman and Tversky (1979) is the fact that our subjects were asked to make five repeated decisions (rather than only one) with no feedback. To examine this explanation we ran an experiment in which 60 subjects faced each of the 30 problems using Kahneman and Tversky's paradigm: One decision per each of the 30 problems without any feedback. The results reject this explanation: They show that the reduction of the number of no-feedback choices from 5 to 1 has little effect: the correlation between the B-rates in the current no-feedback trials and this one-shot replication, over the 30 problems, was 0.94. In addition, analysis of Figure 3's problems shows that the one-shot design did not increase the weighting of rare events.

clear indication of underweighting of rare events: The choice rate of the prospect that leads to the best payoff most of the time is 63% (*SD* = 0.37), 67% (*SD* = 0.39), 61% (*SD* = 0.42), and 57% (*SD* = 0.44), in problems 7, 8, 9 and 10 respectively (and all four values are significantly larger than 50%, *t*(124) = 3.82, 4.77, 2.90, 1.72 respectively). Problem 11 highlights one boundary of underweighting of rare events. When the difference in expected value is sufficiently large (19 versus 16) experience did not eliminate the tendency to prefer the high expected value option over the risky alternative that leads to better payoff most of the time (90% of the trials).

Loss aversion and the magnitude effect. The loss aversion hypothesis implies a preference of the status quo over a symmetric fair gamble (e.g., a gamble that provides equal probability to win or lose *x*, Row 4 in Table 1). Figure 4 summarizes our investigation of this hypothesis. Evaluation of the No-FB block in Problem 12 shows that the status quo was preferred over equal chances to win or to lose 50 in 66% (*SD* =0.43, significantly more than 50%, *t*(124) = 4.25, *p* < .001) of the cases. Problem 13 focuses on the same objective task as Problem 12 with a different framing. The results show that in the current setting, the observed behavior is robust to the framing: 64% (*SD* = 0.42, significantly more than 50%, *t*(124) = 3.66, *p* < .001) of the choices reflect rejection of the gamble.[7] Problem 14 replicates the finding that low stakes eliminate the initial loss aversion bias (Ert & Erev, 2013; Harinck et al., 2007; and see Row 5 in Table 1): The gamble was selected in 49% (*SD* = 0.44) of the cases. The difference between Problems 14 and 12 in the No-FB block is significant, *t*(124) = -3.64, p < .001. The results for the last four blocks show that the feedback eliminated the magnitude effect, but did not eliminate the general tendency to select the status quo over the fair gamble.

[7] Ert and Erev (2008, 2013) observed stronger support for loss aversion in the accept/reject framing manipulation than in the abstract presentation. We believe that the lack of difference here reflects the fact that our subjects were faced with many abstract problems, and this experience eliminated the format effect.

Prob.	Option A	Option B
12	(0, 1)	(50, .5; -50)
13[a]	Reject B	Accept a game that gives equal chances to win or lose 50
14	(0, 1)	(1, .5; -1)

Prob.	Option A	Option B
15	(7, 1)	(50, .5; 1)
16	(7, 1)	(50, .5; -1)
17	(30, 1)	(50, .5; 1)
18	(30, 1)	(50, .5; -1)

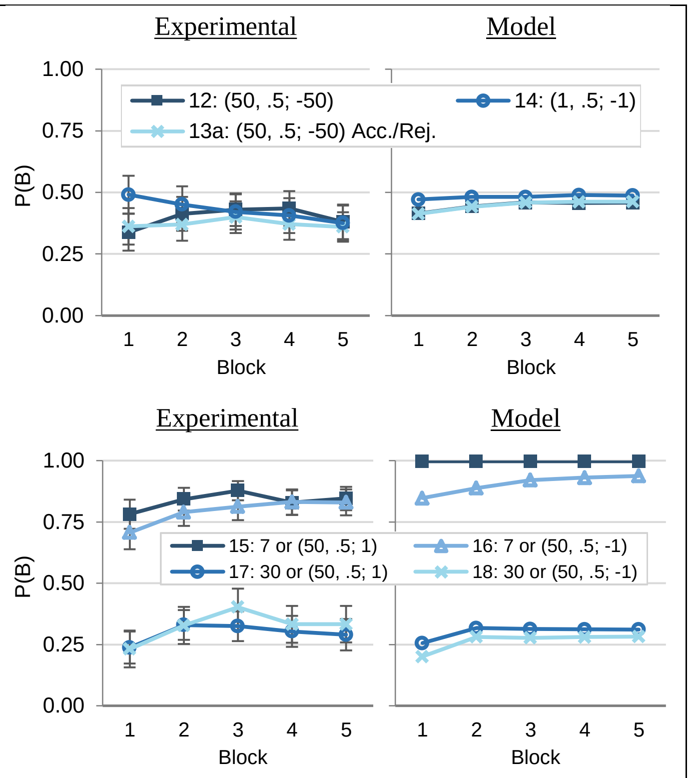


Figure 4. Problems Which Test Loss Aversion and Magnitude Effects in Experiment 1. The notation (x, p; y) refers to a prospect that yields a payoff of *x* with probability *p* and *y* otherwise. Option B's choice proportions are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"). The experimental results are given with 95% CI for the mean.

We added Problems 15, 16, 17, and 18 (lower panel in Figure 4) to study one boundary of loss aversion: The observation that in certain settings the addition of losses to the higher EV option can increase its attractiveness (Yechiam & Hochman, 2013). Our results do not reveal this "loss attention" pattern. Rather, they show similar sensitivity to the expected values in all cases. It seems that our dominant alternative was not dominant enough.

St. Petersburg paradox. Our experimental paradigm differs from the St. Petersburg problem (Row 6 in Table 1) in many ways. Most importantly, we study choice rather than bidding, and avoid the study of hypothetical tasks (and for that reason cannot examine a problem with unbounded payoffs). Nevertheless, the main behavioral tendency demonstrated by the St. Petersburg paradox, the observation of risk aversion in the gain domain, can be examined in our setting. Figure 5 summarizes our investigation. We studied two framings of a bounded variant of the St. Petersburg problem. In Problem 19, the participants were asked to select between 9 with certainty, and a coin-toss game with the same expected value. In Problem 20, the game's possible outcomes and their objective probabilities were listed on the screen. The results reveal a tendency to avoid the game that was slightly increased by experience. The B-rates in the No-FB Block were 36% (*SD* = 0.42), and 38% (*SD* = 0.43) in the "coin-toss"(St. Petersburg) and the "abstract" variants respectively. Both rates are significantly lower than 50%, $t(124) = -3.61$ and -3.22, $p < .001$. In addition, the results over all 5 blocks show slightly lower B-rate in the coins format (34% vs. 37%) this difference is in the direction of the mere presentation hypothesis suggested by Erev, Glozman, and Hertwig (2008) but the difference in the current setting is insignificant.

Prob.	Option A	Option B
19[b]	(9, 1)	A fair coin will be flipped until it comes up heads but no more than 8 times. The number of heads will be denoted *k*. You will get 2^k.
20	(9, 1)	(2, 1/2; 4, 1/4; 8, 1/8; 16, 1/16; 32, 1/32; 64, 1/64; 128, 1/128; 256)

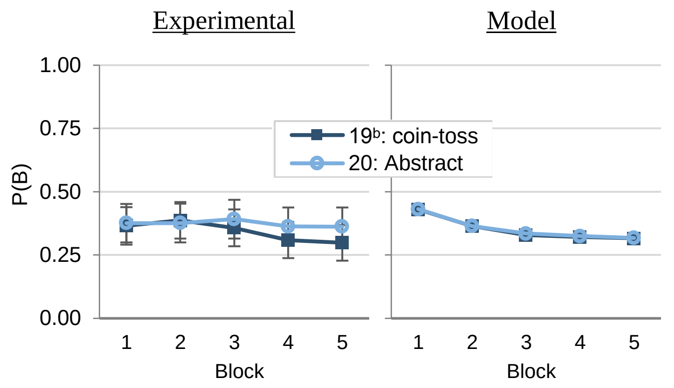


Figure 5. Problems Which Test The St. Petersburg's Paradox in Experiment 1. The notation (x_1, p_1; x_2, p_2; …; y) refers to a prospect that yields a payoff of x_1 with probability p_1, a payoff of x_2 with probability p_2,…, and *y* otherwise. Option B's choice proportions are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"). The experimental results are given with 95% CI for the mean.

Ambiguity aversion/Ellsberg paradox. Ellsberg (1961; see Row 7 in Table 1) shows a violation of subjective expected utility theory that can be described as indication of ambiguity aversion. Figure 6 summarizes our analysis of this phenomenon. The first block in Problem 21 reveals ambiguity aversion: The typical choice (63%, *SD* = 0.41) favors the prospect "10, .5; 0" over the ambiguous prospect "10 or 0 with unknown probabilities." This value is significantly larger than 50%, $t(124) = 3.49$, $p < .001$. Problem 22 reveals that when gaining in the non-ambiguous option (A) occurs with low probability, people favor the ambiguous option (ambiguity-rate of 82%, *SD* = 0.30). Problem 23 shows a strong tendency to avoid the ambiguous option when gaining in the non-ambiguous option is associated with high probability (ambiguity-rate of 15%, *SD* = 0.30). Both rates are significantly different from 0.5, $t(124) = 12.0$, and -13.1, $p < .001$, and are in line with previous findings of studies in decisions in uncertain settings without feedback (e.g., Camerer & Weber, 1992). Evaluation of the effect of experience reveals that feedback eliminates these attitudes towards ambiguity (see Ert & Trautmann, 2014 for similar findings). The average choice rate of the ambiguous option over the four With-FB blocks in these problems was 49%.

Prob.	Option A	Option B
21	(10, .5; 0)	(10, *p*; 0) *p* = .5 unknown
22	(10, .1; 0)	(10, *p*; 0) *p* = .1 unknown
23	(10, .9; 0)	(10, *p*; 0) *p* = .9 unknown

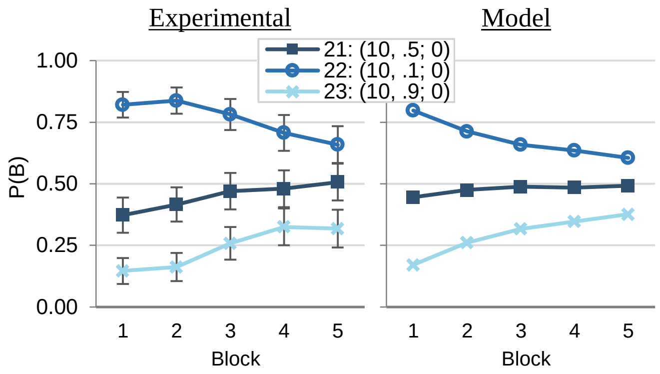
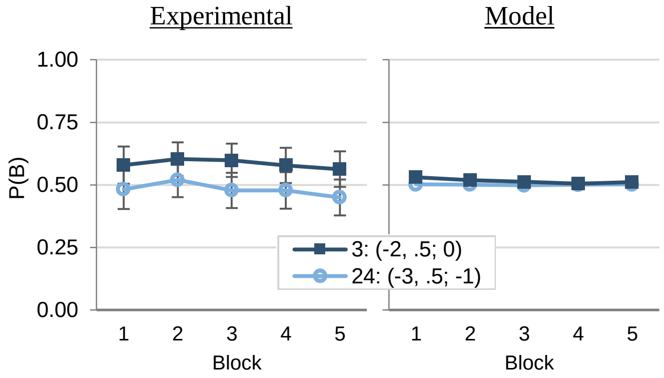


Figure 6. Problems Which Test Ambiguity Attitudes in Experiment 1. The notation (x, p; y) refers to a prospect that yields a payoff of *x* with probability *p* and *y* otherwise. In these problems, the probabilities of the outcomes in Option B are undisclosed to participants ([a] ambiguous problem). Option B's choice proportions are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"). The experimental results are given with 95% CI for the mean.

The break even effect. Thaler and Johnson (1990, Row 8 in Table 1) notice that people are more likely to take risk in the loss domain when this risk can cover all their losses and leads to a break-even outcome. The results, summarized in Figure 7, document the break even effect in the No-FB block. Our participants took significantly more risk in Problem 3 (B-rate of 58%, *SD* = 0.42) and Problem 5 (B-rate 49%, *SD* = 0.42) when the risk can eliminate the loss, than in Problem 24 (B-rate of 48%, *SD* = 0.44) and Problem 6 (B-rate 38%, *SD* = 0.42) when the loss cannot be avoided, $t(124) = -2.01$, $p = .047$ and $t(124) = -2.12$, $p = .036$ respectively. Feedback did not eliminate this difference in the first pair (3 and 24), but did eliminate it in the second pair (5 and 6). The B-rates over the four With-FB blocks are 59% (*SD*=0.35) in Problem 3 and 48% (*SD* = 0.37) in Problem 24 and the difference is significant, *t*(124) = -2.76, *p* = .007. However, in both Problem 5 and Problem 6 the B-rates over the four With-FB blocks is 41%.

Prob.	Option A	Option B
3	(-1, 1)	(-2, .5; 0)
24	(-2, 1)	(-3, .5; -1)



Prob.	Option A	Option B
5	(-3, 1)	(-4, .8; 0)
6	(-3, .25; 0)	(-4, .2; 0)

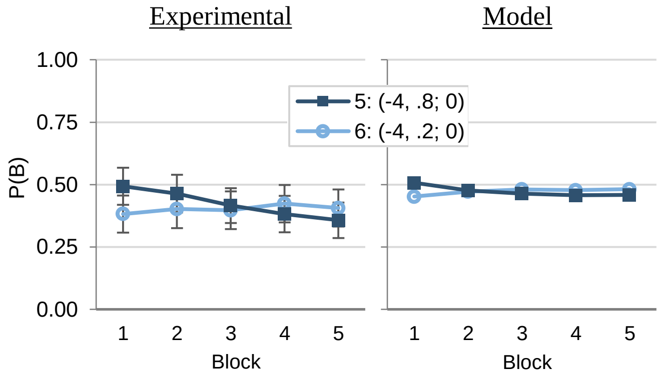
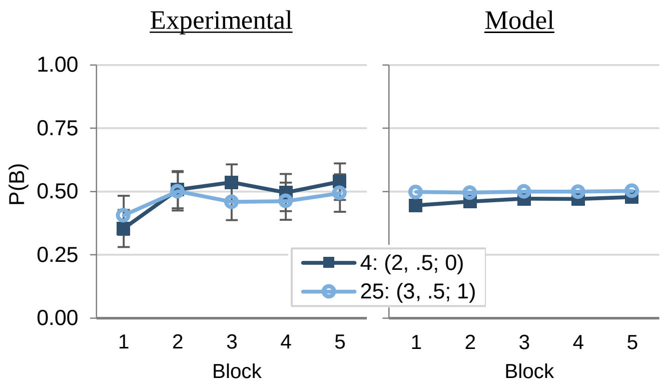


Figure 7. Problems Which Test The Break Even Effect in Experiment 1. The notation (x, p; y) refers to a prospect that yields a payoff of *x* with probability *p* and *y* otherwise. Option B's choice proportions are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"). The experimental results are given with 95% CI for the mean

The get something effect. Payne (2005) shows that people are more likely to take action that increases the probability of positive outcome than an action that does not affect this probability (Row 9 in Table 1). Our analysis of this tendency, summarized in Figure 8, focuses on the comparison of Problem 4 with Problem 25, and the comparison of Problem 9 with Problem 10. Both comparisons reveal that in the No-FB block our participants took less risk when the safer prospect (A) guaranteed a gain (B-rate of 35%, *SD* = 0.42 in Problem 4, and B-rate of 47% *SD* = 0.44 in Problem 9) relatively to the problems in which both options guaranteed a gain (B-rate of 41%, *SD* = 0.44 in Problem 25, and B-rate of 55%, *SD* = 0.44 in Problem 10). The effect is not large, but the difference between the two pairs is significant in a one-tail test, $t(124) = -1.87$, $p = .032$. Feedback eliminated this effect.

Prob.	Option A	Option B
4	(1, 1)	(2, .5; 0)
25	(2, 1)	(3, .5; 1)



Prob.	Option A	Option B
9	(1, 1)	(100, .01; 0)
10	(2, 1)	(101, .01; 1)

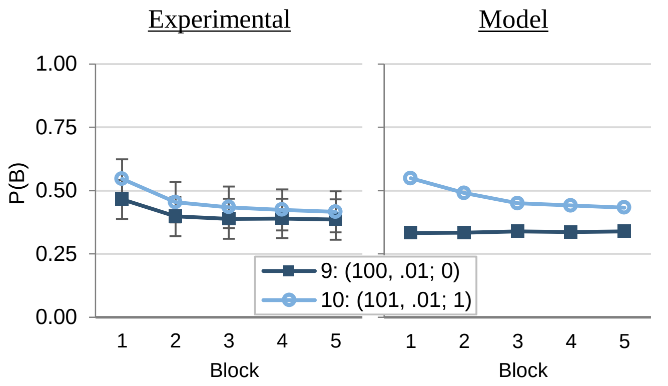


Figure 8. Problems Which Test The Get Something Effect in Experiment 1. The notation (x, p; y) refers to a prospect that yields a payoff of *x* with probability *p* and *y* otherwise. Option B's choice proportions are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"). The experimental results are given with 95% CI for the mean.

The splitting effect. Studies of decisions from description show that splitting an attractive outcome to two distinct outcomes can increase the attractiveness of a prospect even when it reduces its expected value (see Birnbaum, 2008; Tversky & Kahneman, 1986; and Row 10 in Table 1). Figure 9 summarizes our effort to replicate this effect in our paradigm. Specifically, we examine the effect of replacing the outcome 50 (in Problem 26) with the outcomes 44, 48 and 50 (in Problem 27). The results of the No-FB block show a slight increase in the predicted direction: from 49.9% (*SD* = .42) to 50.4% (*SD*= .42). This difference is insignificant, but note that the expected value of the riskier option decreased while its choice rate slightly increased. Feedback reverses the effect and moves behavior toward maximization.

Prob.	Option A	Option B
26	(16, 1)	(50, .4; 1)
27	(16, 1)	(50, .2; 48, .1; 44, .1; 1)

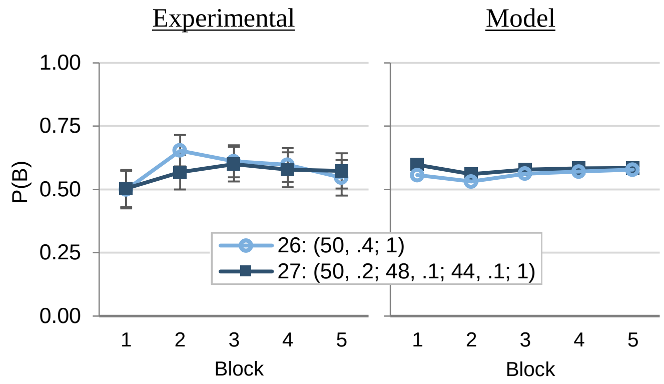


Figure 9. Problems Which Test The Splitting Effect in Experiment 1. The notation (x_1, p_1; x_2, p_2; …; y) refers to a prospect that yields a payoff of x_1 with probability p_1, a payoff of x_2 with probability p_2,…, and *y* otherwise. Option B's choice proportions are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"). The experimental results are given with 95% CI for the mean.

The payoff variability and correlation effects. Studies of decisions from experience demonstrate that payoff variability moves behavior toward random choice (Busemeyer & Townsend, 1993; and Row 13 in Table 1), and positive correlation between the payoffs of the different alternative reduces the payoff variability effect and facilitates learning (Diederich & Busemeyer, 1999; and Row 14 in Table 1). Figure 10 summarizes our effort to replicate these effects in the current setting. A comparison of Problem 28 with Problem 29 documents the payoff variability effect: Lower maximization rate in the high variability problem even though the expected benefit from maximization is higher in this problem. This difference was observed in the No-FB block (max-rate of 91%, SD = 0.21 in Problem 28; in comparison with max-rate of 97%, SD = 0.15 in Problem 29), and it was intensified in the With-FB blocks (max-rate of 85%, SD = 0.19 in Problem 28; in comparison with max-rate of 99%, SD = 0.06 in Problem 29). Both reflections of the payoff variability effect are significant, $t(124)$ = 3.56, and 8.56, $p < .001$. Comparison of Problems 28 and 30 highlights the significance of the correlation effect. The positive correlation between the payoffs significantly increased the maximization rate in the With-FB blocks from 85% in Problem 28 to 97% (SD = 0.10) in

Problem 30, *t*(124) = 7.39, *p* < .001. Notice that the correlation effect implies the pattern predicted by regret theory (Loomes & Sugden, 1982). The negative correlation that impairs maximization implies regret in 50% of the trials. The current results suggest that feedback intensifies the impact of regret.

Prob.	Option A	Option B
28	6 if Event E; 0 otherwise.	0 if Event E; 9 otherwise.
	p(Event E) = .5	
29	2 with certainty	3 with certainty
30	6 if Event E; 0 otherwise.	8 if Event E; 0 otherwise.
	p(Event E) = .5	

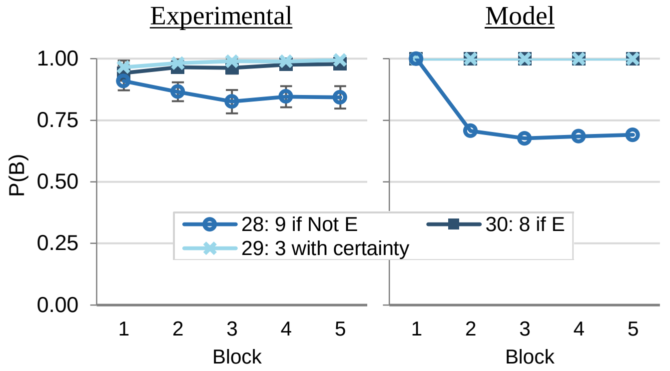


Figure 10. Problems Which Test The Payoff Variability and Correlation Effects in Experiment 1. The notation (x, p; y) refers to a prospect that yields a payoff of *x* with probability *p* and *y* otherwise. Option B's choice proportions are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"). The experimental results are given with 95% CI for the mean.

Effects of location and order. Recall that Experiment 1 was run in two locations, Technion and the Hebrew University (HU), under two order conditions (as explained in Footnote 3). Differences were found to be minor. The correlation between HU and Technion, and the correlation between the two order conditions were 0.92 or higher. Moreover, for the purposes of the current study any existing differences were of little interest, as all the behavioral phenomena from Table 1 were reproduced in both locations and most emerged in both locations and order conditions.[8]

Experiment 2: Randomly Selected Problems

As noted above, Experiment 1 focuses on 30 carefully selected points in a 11-dimensional space of choice tasks. On one hand, the focus on these points facilitates the demonstration that our space is wide enough to replicate the classical choice phenomena. On

[8] Some behavioral phenomena, such as the splitting effect and loss aversion were more easily demonstrated in the ByFB condition, and other phenomena such as the break even effect and the reversed reflection effect were more easily demonstrated in the ByProb condition. Yet in general, qualitative differences were mild.

the other hand, the focus on demonstrations of well-known phenomena does not shed light on parts of the space that received less attention in previous research. Thus, the attempt to develop a model based on Experiment 1 results can lead to over fitting of the classical phenomena. Experiment 2 is designed to reduce this risk of over-fitting. In this experiment, we study 60 problems that were randomly selected from the space of problems described above. Since the two framing manipulations did not reveal interesting effects in Experiment 1, Experiment 2 focuses only on the abstract representation. Appendix C shows the problem-selection algorithm. Table 3 details the 60 problems selected.

Method

One-hundred and sixty-one students (81 male, $M_{\text{Age}} = 25.6$) who did not take part in Experiment 1 participated in Experiment 2. Each participant faced one set of 30 problems from Table 3: Eighty-one participants faced Problems 31 through 60 and the rest faced Problems 61 through 90. The experiment was run both at the Technion (*n* = 81) and the Hebrew University of Jerusalem. The apparatus and design were similar to that of Experiment 1. In particular, participants faced each problem for 25 trials, the first five trials without feedback (No-FB) and the rest with full (including the forgone outcome) feedback (With-FB). Participants were paid for one randomly selected trial in one randomly selected problem plus a show-up fee.[9] The final payoff ranged between 10 and 144 Shekels (*M* = 47.7).

Results and Discussion

The mean choice rates per block and by feedback type (i.e. No-FB or With-FB) for each of the 60 problems are summarized in Table 3. The raw data is given in online

[9] The show-up fee was determined for each participant individually such that the minimal possible compensation for the experiment was 10 Shekels: It was the maximum between 25 shekels and the sum of 10 Shekels and the maximal possible loss in the problem that was randomly selected to determine the payoff. For example, if Problem 31 was selected, the show-up fee was 54 Shekels, but if Problem 32 was selected the show-up fee was 25 Shekels. This procedure was not disclosed to participants in advance and they only knew in advance their expected total payoff.

supplemental material. It is constructive to distinguish between full information problems, which provided participants with complete descriptions of both options' distributions (i.e. Amb = 0) and the 11 ambiguous problems which included one option with unknown probabilities (Amb = 1).

Table 3.

Definitions and Choice Rates of The Problems in Experiment 2.

	Option A			Option B			Lottery				B-rate					
											No-FB	With-FB				
Prob.	H	pH	L	H	pH	L	Num	Shape	Corr	Amb	B1	B2	B3	B4	B5	All
31	4	1	4	40	.6	-44	1	-	0	1	**.23**	.31	.34	.41	.37	**.36**
32	24	.75	-4	82	.25	3	1	-	0	0	**.68**	.68	.67	.67	.69	**.68**
33	-3	1	-3	14	.4	-22	1	-	0	0	**.33**	.28	.31	.25	.22	**.26**
34	7	1	7	27	.1	4	3	Symm	0	0	.39	.45	.43	.41	.40	.42
35	-5	1	-5	47	.01	-15	1	-	0	0	**.18**	.09	.04	.03	.05	**.05[a]**
36	28	1	28	88	.6	-46	4	R-skew	0	0	.39	.55	.56	.60	.57	.57[a]
37	23	.9	0	64	.4	-7	1	-	0	0	.38	.41	.42	.37	.37	.39
38	24	1	24	34	.05	28	1	-	0	0	**.91**	.98	.99	1.0	1.0	**.99**
39	29	1	29	33	.8	6	5	Symm	0	0	.50	.69	.70	.68	.66	**.68[a]**
40	3	.8	-37	79	.4	-46	7	L-skew	0	0	.49	.54	.61	.60	.56	.58
41	29	1	29	44	.4	21	5	Symm	0	0	**.68**	.73	.74	.68	.68	**.71**
42	-6	1	-6	54	.1	-21	1	-	0	1	.61	.48	.25	.23	.20	**.29[a]**
43	14	1	14	12	.9	9	1	-	0	0	**.13**	.04	.00	.00	.01	**.01[a]**
44	23	1	23	24	.99	-33	1	-	0	0	**.27**	.44	.47	.49	.47	.47[a]
45	13	1	13	13	1	13	9	Symm	0	0	.50	.56	.59	.53	.52	.55
46	37	.01	9	30	.6	-37	1	-	0	0	**.20**	.27	.27	.31	.30	**.29**
47	11	1	11	57	.2	-5	6	L-skew	0	0	**.22**	.20	.21	.16	.15	**.18**
48	-2	1	-2	24	.5	-24	1	-	0	1	.39	.49	.52	.45	.42	.47
49	23	1	23	23	1	23	3	Symm	0	0	.54	.50	.49	.48	.48	.49
50	4	1	4	4	1	4	9	Symm	0	0	.44	.66	.60	.57	.57	.60
51	42	.8	-18	68	.2	23	1	-	0	0	**.79**	.71	.74	.72	.70	**.72**
52	46	.2	0	46	.25	-2	1	-	0	0	.36	.26	.25	.22	.22	**.24**
53	28	1	28	42	.75	-22	1	-	0	0	.36	.43	.42	.42	.42	.42
54	18	1	18	64	.5	-33	1	-	0	0	**.32**	.30	.31	.32	.29	**.30**
55	43	.2	19	22	.25	17	9	Symm	-1	0	**.21**	.16	.09	.07	.07	**.10**
56	-8	1	-8	-5	.99	-34	1	-	0	0	**.76**	.88	.91	.90	.89	**.90**

57	49	.5	-3	33	.95	17	9	Symm	-1	0	**.77**	.71	.70	.73	.75	**.72**
58	85	.4	-7	40	.25	24	1	-	0	0	.60	.51	.52	.54	.56	.53
59	17	.25	16	43	.4	2	1	-	0	0	.51	.52	.52	.49	.49	.51
60	51	.1	21	38	.6	1	1	-	0	0	.37	.38	.34	.29	.30	**.33**
61	26	.25	25	29	.05	24	7	R-skew	0	0	**.67**	.62	.62	.60	.56	.60
62	25	1	25	45	.2	17	1	-	0	0	**.32**	.32	.35	.34	.34	**.34**
63	17	1	17	60	.1	15	5	Symm	0	0	**.68**	.70	.67	.66	.69	**.68**
64	52	.1	-8	5	.9	-43	1	-	0	1	**.35**	.55	.70	.72	.68	**.66**[a]
65	12	.4	-16	-5	1	-5	1	-	0	0	**.33**	.40	.44	.45	.45	.43
66	45	.6	2	54	.1	20	5	L-skew	0	0	.43	.35	.40	.44	.43	.40
67	85	.25	4	54	.25	11	1	-	1	0	.45	.47	.46	.48	.43	.46
68	12	1	12	102	.2	-14	1	-	0	0	.39	.27	.29	.32	.31	**.30**
69	49	.5	11	31	.95	21	3	Symm	0	1	.39	.29	.37	.40	.45	**.38**
70	18	1	18	35	.75	-19	1	-	0	0	.38	.55	.58	.60	.58	.58[a]
71	13	.6	-20	76	.2	-26	1	-	0	0	.38	.25	.29	.23	.28	**.26**
72	-9	1	-9	13	.25	-8	1	-	0	0	**.82**	.96	1.0	1.0	1.0	**.99**[a]
73	2	1	2	51	.05	0	7	Symm	0	0	.37	.38	.39	.39	.41	.39
74	44	.05	16	14	.9	10	3	Symm	0	1	**.13**	.05	.02	.00	.00	**.02**[a]
75	13	1	13	50	.6	-45	1	-	0	0	**.35**	.44	.42	.44	.50	.45
76	35	.01	16	20	.5	13	5	Symm	0	1	**.68**	.71	.71	.68	.64	**.68**
77	1	1	1	38	.4	-9	1	-	0	0	.65	.66	.65	.60	.63	**.64**
78	19	1	19	44	.05	9	1	-	0	0	**.11**	.12	.11	.14	.12	**.12**
79	32	.01	19	65	.01	9	1	-	0	0	**.14**	.07	.04	.02	.02	**.03**[a]
80	3	1	3	50	.4	-36	1	-	0	0	.47	.37	.41	.41	.43	.40
81	10	.25	2	-1	.9	-32	1	-	0	1	**.14**	.04	.01	.01	.01	**.02**[a]
82	25	1	25	26	.01	25	7	Symm	0	1	.55	.72	.77	.81	.82	**.78**[a]
83	9	1	9	64	.01	9	1	-	0	0	**.87**	.96	.98	.98	.99	**.98**[a]
84	27	1	27	22	.99	-7	1	-	0	0	**.08**	.02	.00	.00	.00	**.01**
85	20	1	20	70	.25	6	1	-	0	0	.43	.45	.49	.46	.44	.46
86	71	.5	-11	61	.75	-49	1	-	0	1	**.13**	.23	.30	.32	.25	**.28**[a]
87	-2	1	-2	4	.99	-34	7	Symm	0	0	**.81**	.96	.98	.96	.98	**.97**[a]
88	17	.05	-7	13	.25	-15	1	-	0	1	**.68**	.57	.51	.44	.37	.47[b]
89	17	1	17	44	.1	17	1	-	0	0	**.88**	.96	.99	1.0	1.0	**.99**[a]
90	10	1	10	31	.75	-49	1	-	0	0	.42	.55	.53	.56	.55	.55

Note. B-rates are mean choice rates for Option B, presented according to blocks of five trials each or according to availability of feedback: No-FB (no feedback) or With-FB (with feedback). The rightmost column shows the mean B-rate across all 4 With-FB blocks. Values in bold (in the No-FB and All-With-FB columns) are significantly different from .5 at $p < .05$ significance level (corrected for multiple testing according to Hochberg's, 1988, procedure).

[a] Difference between rates in the No-FB and the With-FB trials is significant in .05 significance level (corrected according with Hochbreg's, 1988, procedure)

Full information problems. The results show a preference for the option with the higher expected value (EV) when such an option exists. In problems in which the payoff description allowed for an EV-based choice[10], the maximization rate (i.e. choice rate of the higher-EV option) in the No-FB trials was 64% (*SD* = 0.18). In 26 problems this maximization rate significantly differed from 50% (at .05 significance level corrected with Hochberg's, 1988, procedure for multiple comparisons), and in 24 of these this rate was higher than 50%. Only in two problems (Problem 44 and Problem 61, see Figure 11) the maximization rate in the No-FB trials was significantly lower than 50%. The initial deviation from maximization in both these problems may reflect overweighting of rare events.[11] Figure 11 shows that feedback reduced these deviations but did not reverse them.

Prob.	Option A	Option B
44	(23, 1) [EV=23]	(-33, .01; 24) [EV= xx]
61	(25, .75; 26) [EV= xx]	(23, .025; 24, .95; 25, .0125; 29, .00625; 37, .00313; 53, .00156; 85, .00078; 149, .00078) [EV= xx]

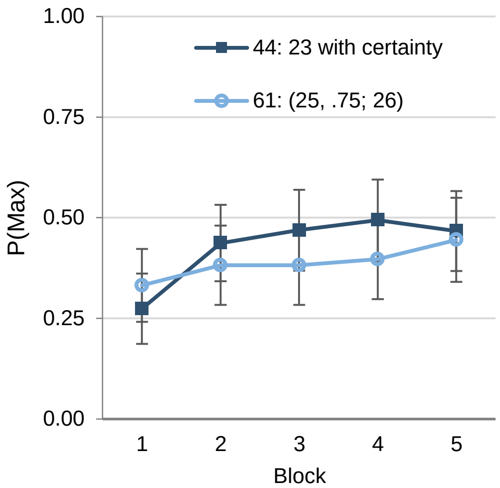


Figure 11. Problems with Initial Low Maximization Rates in Experiment 2. The notation (x_1, p_1; x_2, p_2; …; y) refers to a prospect that yields a payoff of x_1 with probability p_1, a payoff of x_2 with probability p_2,…, and *y* otherwise. Maximization rates are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"), and are given with 95% CI for the mean.

Feedback increased the tendency for maximization. Total maximization rate in the With-FB trials was 67% (*SD* = 0.21). In 10 of the 11 problems in which choice rates in the

[10] Of the 60 problems, in addition to the 11 ambiguous problems, three problems included options with identical EVs, thus 46 problems' descriptions allowed for an EV-based choice.

[11] Interestingly, although Problem 61 is similar to Problem 25 from Experiment 1 in many respects, the observed choice rates differ: they suggest overweighting of the rare event in Problem 61, but not in Problem 25.

No-FB and With-FB trials significantly differed, maximization rates were higher in the With-FB trials. Analysis of these 10 problems reveals they share a common property. In all ten problems, the option which maximizes expected value also provides a higher payoff most of the time (see Erev & Roth, 2014). Congruently, in the only problem in which feedback significantly decreased maximization rates (Problem 39, see Figure 13), the maximizing option provided a better payoff in only 20% of the trials. Figure 12 confirms the generality of this finding. It examines all 46 relevant problems and shows that the higher the proportion of better payoffs generated by the maximizing option, the larger the increase in maximization rates brought upon by feedback (and vice versa). The correlation between the two is 0.65, 95% CI [0.45, 0.79].

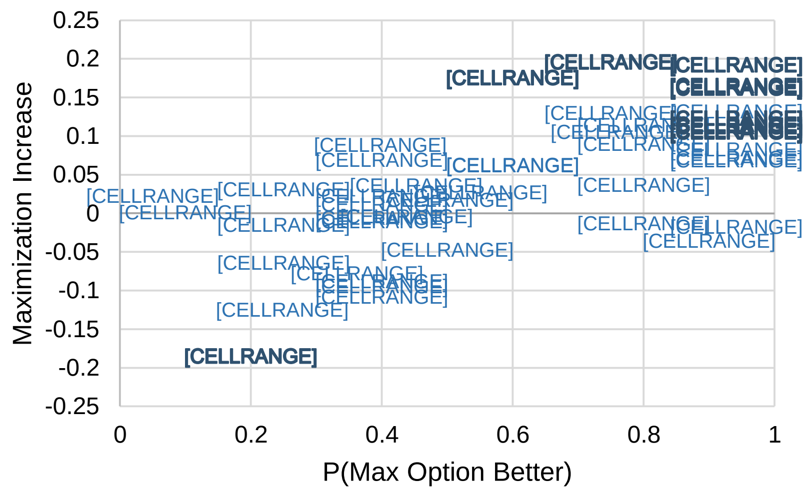


Figure 12. Increase in Choice of the Maximizing Option between With-FB and No-FB trials as a Function of the Probability that the Maximizing Option is the Better Alternative in a Random Trial. Each data-point represent one problem and is marked with the number of that problem (see Table 3). The bold dark markers represent problems with maximization increase significantly different from zero. The correlation is .65.

Figure 13 demonstrates this observation in four problems: two problems (36 and 70) in which feedback moved participants towards maximization and two problems (39 and 52) in which it moved participants away from maximization, consistent with learning to choose the option that is better most of the time. Note in addition that the initial maximization rates in three of these problems are in the direction predicted by several phenomena given in Table 1 (loss aversion in Problems 36, 52, 70, break even effect in Problem 52, and the certainty effect in Problems 36, 70).

Prob.	Option A	Option B	P(Max. Better)
36	(28, 1)	(-46, .4; 86, .3; 88, .15; 92, .15)	60%
	[EV= 28]	[EV= xx]	
39	(29, 1)	(6, .2; 31, .05; 32, .2; 33, .3; 34, .2; 35, .05)	20%
	[EV= 29]	[EV= xx]	
52	(46, .2; 0)	(46, .25; -2)	25%
	[EV= xx]	[EV= xx]	
70	(18, 1)	(35, .75; -19)	75%
	[EV= 18]	[EV= xx]	

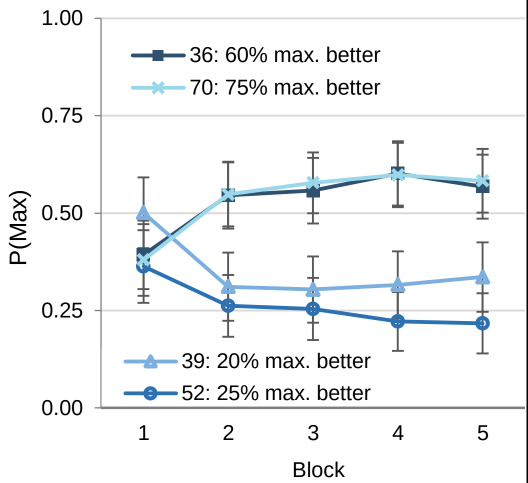


Figure 13. Problems that Demonstrate the Typical Effect of Feedback in Experiment 2. The notation (x_1, p_1; x_2, p_2; …; y) refers to a prospect that yields a payoff of x_1 with probability p_1, a payoff of x_2 with probability p_2,…, and *y* otherwise. P(Max. Better) is the probability that the maximizing option is the better alternative in a random trial. Maximization rates are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB") and are given with 95% CI for the mean.

Figure 14 summarizes the results in the three problems which include two options that have identical EVs. All three problems are a choice between a safe gain, and a multi-alternative symmetric-distribution gamble with the same expected value. The observed choice rates in the No-FB trials (Block 1) suggest risk neutrality; the gamble's choice rates were 50%, 54% and 44% for problems 45, 49, and 50 respectively (*SD* = 0.45, 0.46, and 0.44). In none of the problems is the difference from 50% statistically significant: $t(80)$ = -0.07, 0.75, and -1.3 respectively. These results differ from the common observation of risk aversion in the gain domain (e.g. Kahneman & Tversky, 1979), and consistent with recent demonstrations that feedback can lead to risk seeking in the gain domain (Ludvig & Spetch, 2011; Tsetsos, Chater & Usher, 2012). The initial risk neutrality can be the product of the multi-outcome symmetric distribution used here. Another feasible explanation involves the fact that in Problems 45 and 49 (where we observe the higher risk seeking rates) the worst possible outcome from the gamble is high relatively to the safe alternative.

Prob.	Option A	Option B
45	(13, 1)	(9, .00391; 10, .03125; 11, .10938; 12, .21875; 13, .27344; 14, .21875; 15, .10938; 16, .03125; 17, .00391)
49	(23,1)	(22, .25; 23, .5; 24, .25)
50	(4, 1)	(0, .00391; 1, .03125; 2, .10938; 3, .21875; 4, .27344; 5, .21875; 6, .10938; 7, .03125; 8, .00391)

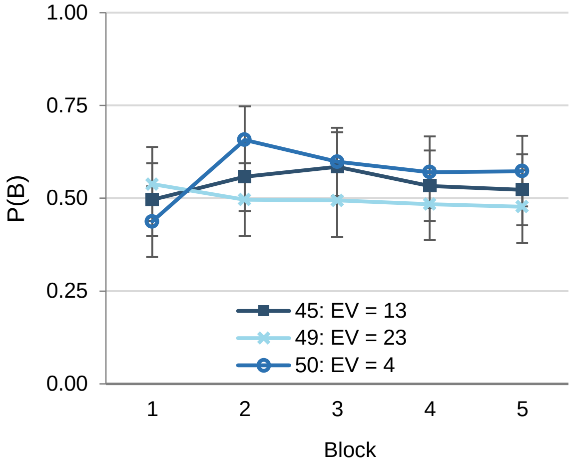
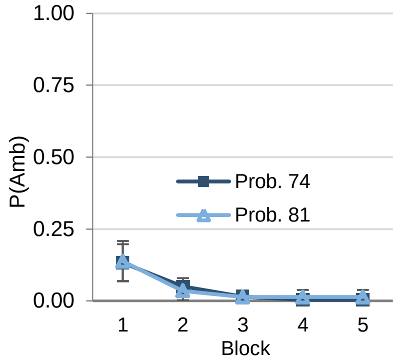
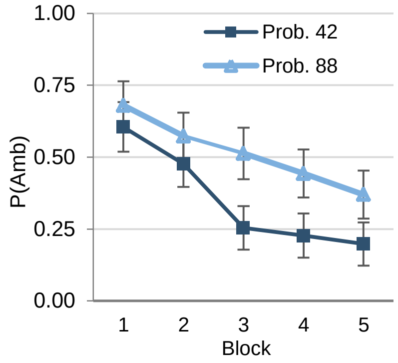
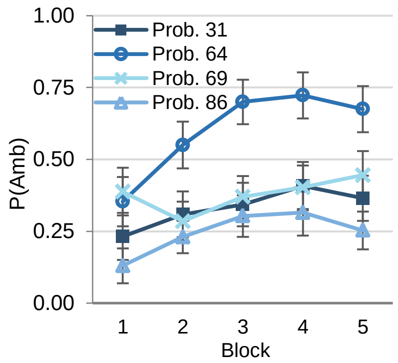


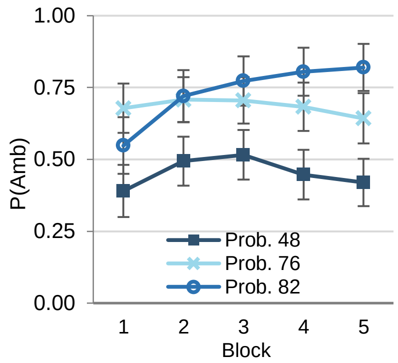
Figure 14. Problems with Identical Expected Values in Experiment 2. The notation (x_1, p_1; x_2, p_2; …; y) refers to a prospect that yields a payoff of x_1 with probability p_1, a payoff of x_2 with probability p_2,…, and y otherwise. Proportions of the riskier choice are shown in five blocks of five trials each (Block 1: "No-FB", Blocks 2-5: "With-FB"), and are given with 95% CI for the mean.

Ambiguous problems. Figure 15 summarizes the results in the 11 ambiguous problems. The 11 problems are classified based on two measures: The objective difference between the expected values (top two panels vs. bottom two panels), and the estimated difference between the expected values under the assumption that all the ambiguous option's outcomes are equally likely (right two panels vs. left two panels). The results show that the initial behavior (No-FB trials) reflects a tendency to maximize expected return assuming uniform probabilities: The choice rate of the ambiguous option in the first block tends to be lower in Figure 15's left panels than it is in its right panels. In addition, initial behavior also seems to reflect some pessimism. Feedback tends to increase maximization: the choice rates of the ambiguous option in Figure 15 tend to decrease in the top panels (where the ambiguous option is objectively inferior to the alternative) and increase in the lower panels (where the opposite is true).

<table>
<tr><td></td><td>Amb. Estimated EV Low</td><td>Amb. Estimated EV High</td></tr>
<tr><td>Amb. Real EV Low</td><td>


<table>
<tr><td><u>Prob.</u></td><td><u>Option A</u></td><td><u>Option B</u></td></tr>
<tr><td>74</td><td>44, .05;
16, .95</td><td>10, 13, 14, or 15
[.1, .0225, .45, .225]</td></tr>
<tr><td>81</td><td>10, .25;
2, .75</td><td>-32 or -1
[.1, .9]</td></tr>
</table>
</td><td>


<table>
<tr><td><u>Prob.</u></td><td><u>Option A</u></td><td><u>Option B</u></td></tr>
<tr><td>42</td><td>-6, 1</td><td>-21 or 54
[.9, .1]</td></tr>
<tr><td>88</td><td>17, .05;
-7, .95</td><td>-15 or 13
[.75, .25]</td></tr>
</table>
</td></tr>
<tr><td>Amb. Real EV High</td><td>


<table>
<tr><td><u>Prob.</u></td><td><u>Option A</u></td><td><u>Option B</u></td></tr>
<tr><td>31</td><td>4, 1</td><td>-44 or 40
[.4, .6]</td></tr>
<tr><td>69</td><td>49, .5;
11, .5</td><td>21, 30, 31, or 32
[.05, .2375, .475, .2375]</td></tr>
<tr><td>64</td><td>52, .1;
-8, .9</td><td>-43 or 5
[.1, .9]</td></tr>
<tr><td>86</td><td>71, .5;
-11, .5</td><td>-49 or 61
[.25, .75]</td></tr>
</table>
</td><td>


<table>
<tr><td><u>Prob.</u></td><td><u>Option A</u></td><td><u>Option B</u></td></tr>
<tr><td>48</td><td>-2, 1</td><td>-24 or 24
[.5, .5]</td></tr>
<tr><td>76</td><td>35, .01;
16, .99</td><td>13, 18, 19, 20, 21, or 22
[.5, .03125, .125, .1875, .125, .03125]</td></tr>
<tr><td>82</td><td>25, 1</td><td>23, 24, 25, 26, 27, 28, or 29
[.00016, .00094, .99234, .00312, .00234, .00094, .00016]</td></tr>
</table>
</td></tr>
</table>

Figure 15. Problems with Ambiguous Options in Experiment 2. The 11 problems are classified according to whether (a) the ambiguous option is better than the alternative on average (has higher real EV; top vs. bottom panels), and (b) the ambiguous option is better than the alternative under the assumption that all its outcomes are equally likely (has higher estimated EV; left vs. right panels). In Option A each payoff is followed by its probability. In Option B all payoffs are displayed in succession with their respective (undisclosed) probabilities in the brackets that follow. Proportions of the ambiguous (B) choice are shown in five blocks of five trials each (Block 1: “No-FB”, Blocks 2-5: “With-FB”), and are given with 95% CI for the mean.

A baseline model: Best Estimate And Simulation Techniques (BEAST)

The main goal of the current section is to propose a model that can capture the joint effect of, and the interaction between, the fourteen phenomena discussed above. Specifically, we try to develop a simple model that can reproduce the initial choice rates and the effect of feedback in all 90 problems. We chose to start with the assumption that people try to maximize payoff, and use two classes of techniques to achieve this goal. The first implies an attempt to compute the expected values, the second uses mental simulations that (we speculate) were found to lead to good outcomes in similar situations in the past (Marchiori et al., in press; and see Plonsky, Teodorescu & Erev, under review). The assumption that people are sensitive to the expected value (EV) was introduced to capture the observation that over the 60 (non-ambiguous) problems in which one of the options had higher EV, the maximization rate was 68%. We chose to use "techniques" rather than "subjective utilities and weighting functions" to clarify the fact that our model assumes quick changes in the observed choice biases in response to feedback (and the biases do not capture a stable property of the individual as assumed in the leading models that use subjective functions).[12]

The baseline model, referred to as Best Estimate And Simulation Techniques (BEAST), assumes that Option A is strictly preferred over option B, after *r* trials, if and only if:

$$[BEV_A(r) - BEV_B(r)] + [ST_A(r) - ST_B(r)] + e(r) > 0 \qquad (1)$$

where $BEV_A(r) - BEV_B(r)$ is the advantage of A over B based on the best estimation of the expected values, $ST_A(r) - ST_B(r)$ is the advantage of A over B based on mental simulations,

[12] Another reason for our choice is the fact that we were not able to find a "subjective utilities and weighting functions" model that fits the current data well. We considered several generalizations of cumulative prospect theory (the best known subjective function model, Tversky & Kahneman, 1992), and all of them were outperformed by the model described below even when the analysis was focused on the no feedback blocks with full information (the conditions addressed by prospect theory). One of the goals of the current competition is to examine if other researchers can find variants of these models that fit the data better.

and e(r) is an error term.[13] In trivial choices, when one of the options dominates the other, e(r) = 0.[14] In all other cases e(r) is drawn from a normal distribution with a mean 0 and standard deviation σ_i (a property of agent *i*).

When the payoff distributions are known (as in the non-ambiguous problems in our study), the best estimations of the expected values are the actual objective ones. That is, $BEV_j(r)$ equals the expected value of option *j*, EV_j (for all *r*). The simulation-based estimate of option *j*, $ST_j(r)$, equals the average of κ_i (a property of *i*) outcomes that are each drawn (from option *j*'s possible outcomes) in one mental simulation.[15]

Each simulation uses one of four techniques. Simulation technique *Unbiased* implies random and unbiased draws, either from the options' described distributions or from the options' observed history of outcomes. Before obtaining feedback (decisions in trials 1 to 6) the draws are taken from the objective distributions using a *luck-level* procedure: The agent first draws a luck-level, a uniform number between zero and one. Then, for each prospect, the agent uses the same luck-level as a percentile in the prospect's cumulative distribution function and draws the outcome that fits that percentile.[16] When the agents can rely on feedback (trials 7 to 25) they first sample one of the previous trials (all trials are equally likely to be sampled), and the drawn outcomes for both options are those observed in that trial.

The other three techniques are "biased": they can be described as a mental draw from distributions that differ from the objective distributions. The probability of choosing one of

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[13] When the left-hand side of Inequality 1 equals exactly zero, we assume random choice between the options.

[14] In dominance, we mean either deterministic dominance or first-order stochastic dominance. In the first 90 problems, the set of trivial problems includes problems 28, 29, 30, 38, 43, 72, 74, 81, 83, 84 and 89.

[15] For example, consider an agent with $\kappa_i = 3$ who faces Problem 17 ("30" or "50, .5; -1") based on the following simulation results {30, 50}, {30, 50} and {30, -1} and the error term e(t) = -2. Equation 1 yields $(30 - 24.5) + (90/3 - 99/3) - 2 = 0.5$. Thus, the model implies an A choice.

[16] That is, the outcome drawn is the result of $F^{-1}(x)$ where x is the luck-level and F is the prospect's cumulative distribution function. For example, in Problem 2 ("3, .25; 0" or "4, .2; 0"), luck level of .67 yields the draw {0, 0}, luck level of 0.77 yields the draw {3, 0}, and luck level of .87 yields the draw {3, 4}.

the biased techniques decreases when the participants receive feedback. Specifically, it equals:

$$PBias(t) = \beta_i / (\beta_i + 1 + t^{\theta i}) \quad (2)$$

where $\beta_i > 0$ captures the magnitude of the agent's initial tendency to use one of the biased techniques, t is the number of trials with feedback, and $\theta_i > 0$ captures agent *i*'s sensitivity to feedback.[17]

Notice that when κ_i is small, even unbiased sampling can lead to deviations from maximization; it implies reliance on small samples, and thus underweighting of rare events. The assumption that the probability of using the unbiased techniques increases with feedback was introduced to capture the observation that feedback decreased the weighting of rare events.

The three biased techniques are each used with equal probability, PBias(t)/3. Simulation technique *Uniform* yields each of the possible outcomes with equal probability (see a related idea in Birnbaum, 2008) using the luck-level procedure described above (the draws are made from the uniform cumulative distribution function even after feedback is obtained). This technique enables the model to capture overweighting of rare events and the splitting effect.

Simulation-technique *Contingent Pessimism* is similar to the priority heuristic (Brandstätter et al., 2006); it depends on the sign of the best possible payoff (SignMax), and the ratio of the minimum payoffs (RatioMin). When SignMax > 0, and RatioMin $\leq \gamma_i$ ($0 < \gamma_i < 1$ is a property of *i*), this simulation yields the worst possible payoffs for each option (MIN_A and MIN_B). This helps the model capture loss aversion and the certainty effect. When

[17] For example, assuming $\beta_i = 3$, and $\theta_i = .5$ the probability of using one of the bias techniques in each of the κ_i simulations is 3/(3+1) =.75 when $t = 0$ (trials 1 to 6), 3/(3+1+1) = .6 when $t = 1$ (Trial 7), and 3/(3+1+3.36) = .407 when $t = 19$ (Trial 25).

one of the two conditions is not met, the current simulation implies random choice among the possible payoffs (identically to technique Uniform). RatioMin is computed as:

$$\text{RatioMin} = \begin{cases} 1, & \text{if } \mathrm{MIN_A} = \mathrm{MIN_B} \\ \dfrac{\mathrm{Min}\left(|\mathrm{MIN_A}|,|\mathrm{MIN_B}|\right)}{\mathrm{Max}\left(|\mathrm{MIN_A}|,|\mathrm{MIN_B}|\right)}, & \text{if } \mathrm{MIN_A} \neq \mathrm{MIN_B} \text{ but } \mathrm{sign}(\mathrm{MIN_A}) = \mathrm{sign}(\mathrm{MIN_B}) \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

For example, RatioMin = 0 in Problem 9 ("1" or "100, .01; 0"), and 0.5 in Problem 10 ("2" or "101, .01; 1"). The contingencies capture two regularities. The sensitivity to SignMax implies less pessimism (less risk aversion) in the loss domain, hence the reflection effect. The second, RatioMin contingency, implies less pessimism when the minimal outcomes appear similar (have the same sign and are close in magnitudes). This implies that the addition of constant to all the payoffs, decreases risk aversion in the gain domain. In addition, it implies higher sensitivity to rare events in problems like Problem 10 and Problem 61 (large RatioMin), than in problems like Problem 9 and Problem 25 (small RatioMin).

Simulation technique *Sign* implies high sensitivity to the payoff sign. It is identical to technique *Unbiased* with one important exception: Positive drawn values are replaced by *R*, and negative outcomes are replaced by -*R*, where *R* is the payoff range (the difference between the best and worst possible payoffs in the current problem; e.g., 100 in Problem 9 and Problem 10).[18]

When the probabilities of the different outcomes are unknown (as in the problems with ambiguous Option B), they are initially estimated with a pessimistic bias (Gilboa & Schmeidler, 1989). The initial expected value of the ambiguous option is estimated as a weighted average of three terms: EV_A, MIN_B, and UEV_B, which is the estimated EV from Option B under the assumption that all the possible outcomes are equally likely. We assume

[18] For example, in Problem 9 ("1" or "100, .01; 0"), all the positive outcomes are replaced by +100 (the value of L), and the 0 stays 0.
.

the same weighting for EV_A and UEV_B, and capture the weighting of MIN_B with $0 \leq \varphi_i \leq 1$: an ambiguity aversion trait of *i*. That is,

$$BEV_B(0) = (1-\varphi_i)(UEV_B + EV_A)/2 + \varphi_i MIN_B, \tag{4}$$

For example, assuming $\varphi_i = 0.05$, $BEV_B(0)$ in Problem 22 ("10, .5; 0" or "10, *p*; 0") equals .95(5+1)/2 + .05(0) = 2.85. In the no feedback trials (1 to 6) the probabilities of the *m* possible outcomes are estimated under the assumption that the subjective probability of the worst outcome SP_{MINB} is higher than 1/m, and each of the other m−1 subjective probabilities equal $(1-SP_{MINB})/(m-1)$. Specifically, SP_{MINB} is computed as the value that minimizes the difference between $BEV_B(0)$ and the estimated expected value from Option B based on the subjective probabilities: $SP_{MINB} \cdot MIN_B + (1-SP_{MINB})U_{Bh}$, where $U_{Bh} = (mU_B - MIN_B)/(m-1)$ denotes the average of the best m−1 outcomes. This assumption implies that

$$SP_{MINB} = \begin{cases} 0, & \text{if } BEV_B(0) > U_{Bh} \\ 1, & \text{if } BEV_B(0) < MIN_B \\ \dfrac{U_{Bh} - BEV_B(0)}{U_{Bh} - MIN_B}, & \text{otherwise} \end{cases} \tag{5}$$

That is, in Problem 22 with $\varphi_i = 0.05$, $SP_{MINB} = (10 - 2.85)/(10 - 0) = 0.715$.

Each trial with feedback in the ambiguous problems moves $BEV_B(t)$ toward EV_B. Specifically,

$$BEV_B(t+1) = (1 - 1/T) \cdot BEV_B(t) + (1/T) \cdot O_B(r) \tag{6}$$

where *T* is the expected number of trials with feedback (20 in the current setting) and $O_B(r)$ is the observed payoff generated from the ambiguous Option B at trial *r*.[19]

The six properties of each agent are assumed to be drawn from uniform distributions between 0 and the model's parameters: $\sigma_i \sim U(0, \sigma)$, $\kappa_i \sim (1,2, 3, ..., \kappa)$, $\beta_i \sim U(0, \beta)$, $\theta_i \sim U(0, \theta)$, $\gamma_i \sim U(0, \gamma)$, and $\varphi_i \sim U(0, \varphi)$. Namely the model has six free parameters: σ, κ, β,

[19] For example, in Problem 22 with $\varphi_i = 0.05$, observing $O_B(6) = 0$ implies that $BEV_B(7) = (1 - 1/20) \cdot 2.85 + (1/20) \cdot 0 = 2.707$.

γ, φ, θ. Notice that only four of these parameters are needed to capture decisions under risk without feedback (the class of problems addressed by prospect theory). These parameters are σ, κ, β, and γ. The parameter φ captures attitude toward ambiguity, and θ abstracts the reaction to feedback.

We estimated BEAST's parameters using the Mean Squared Deviation (MSD) measure and 14 additional constraints that correspond to the 14 qualitative phenomena summarized in Table 1. Specifically, we used a grid search procedure to find the set of parameters that minimizes the MSD over the 450 B-rates (90 problems times 5 blocks) and also reproduces the 14 qualitative phenomena. Best fit was obtained with the parameters $\sigma = 7$, $\kappa = 3$, $\beta = 2.6$, $\gamma = .5$, $\varphi = .07$, and $\theta = 1$. The MSD score is 0.007. The right-hand graphs in Figures 1 through 10 present the predictions of BEAST with these parameters.

Experiment 3: A Choice Prediction Competition

The current results suggest that distinct deviations from maximization summarized in Table 1 can be reliably observed in our experimental paradigm. In addition, our analysis suggests that the coexistence of distinct deviations in contradicting directions (e.g., over- and under-weighting of rare events), does not imply that it is difficult to predict the joint effect of the different behavioral tendencies. The joint effect of these tendencies can be captured with a single quantitative model.

The main shortcoming of our analysis is the fact that BEAST, the quantitative model we proposed, lives up to his name: it is not elegant in the sense that it includes many post hoc assumptions that were introduced to capture the current results. Thus, it is possible that it over-fits the data. It is also possible that this over-fitting led us to favor the "expected value plus mental simulations" assumption while the underlying processes are better captured by some refinement of models like prospect theory that assume a more elegant generalization of the expected value rule. We chose to address this shortcoming by organizing a choice prediction competition (see Arifovic, McKelvey & Pevnitskaya, 2006; Erev et al., 2010; Erev, Ert & Roth, 2010; Ert, Erev & Roth, 2011) using a generalization criterion (Busemeyer, & Wang, 2000). Specifically, we plan to run a third experiment, using Experiment 2's design, and challenge other researchers to participate in an open competition that focuses on the prediction of the results of this experiment. To participate in the competition, participants will be asked to send us a model implemented in a computer program that reads the 10 parameters of each problem as input, and provides the predicted B-rates in five blocks of five trials as output. The competition's winning model will be the model with the lowest mean squared deviation score. The winning participant (or participants) will be invited to co-author the final draft of the current paper.

The problems that will be studied in Experiment 3 (the competition study) will be sampled from the space of problems that was studied above (using the algorithm described in Appendix C), and the subjects will be drawn from the same students population (Technion and HU). Yet, Experiment 3 will examine different problems than the problems studied in Experiments 1 and 2, and will use subjects who did not take part in those experiments.

The participants in the competition are encouraged to use the data of Experiments 1 and 2 to build and estimate their models. The raw data from these experiments and the current summary of this data, as well as examples of acceptable submissions (specifically, using BEAST as an example) can be downloaded from the competition's website (http://departments.agri.huji.ac.il/cpc2015).

The call for the competition will be distributed over the mailing lists of leading scientific societies focused on decision research, and experimental and behavioral economics on November 2014. The details of registration to the competition are specified in the competition's website. The predictions submission deadline is May 1, 2015 (at Midnight

EST). Experiment 3 will be run in early 2015, but the parameters of the selected problems, and the experimental results will not be revealed until May 2, 2015.

Requirements

In order to facilitate the accumulation of knowledge we chose to impose four requirements on the submitted models. First, the model should replicate the 14 qualitative phenomena described in Table 1 (the exact replication criteria are detailed in the competition's website). Second, the submission has to be implemented in a computer program (using either SAS, Matlab, or R as programming language) with no more than 250 code-lines (where each ";" mark is treated as the end of a line, the number of code-lines of BEAST in the SAS version is 220). The final two requirements involve the verbal description of the model: it should be short and it should be clear. The maximal allowed length of this verbal description is 1500 words (the number of words in the current description of BEAST is 1249). The clarity of the verbal description will be evaluated by asking three independent skilled programmers (Technion students) to reproduce the model and its output only based on the verbal description. The three programmers will be preselected for this job based on their ability to program BEAST using its above description, and to program cumulative prospect theory based on the description in Tversky and Kahneman (1992).

Competition Criterion: Mean Squared Deviation (MSD)

The current competition focuses on the prediction of the mean B-rates in each of the five blocks of trials for each choice problem. As in Erev et al.'s (2010) competitions, the accuracy of the prediction will be evaluated using a mean squared deviation (MSD) score. We will first compute the squared difference between the observed and predicted rates in each block of five trials, in each of the 60 problems, and then compute the mean over the 300 scores.

The MSD criterion, which has been also used by previous studies (e.g., Erev, Ert, Roth, 2010; Erev, Ert, Roth, Haruvy et al., 2010; Ert et al., 2011), has several advantages over other model estimation techniques (e.g., likelihood criteria). In particular, the MSD score underlies traditional statistical methods (like regression and the t-test) and is a proper scoring rule (Brier, 1950; Selten, 1998) which is less sensitive to large errors than other measures.

Relationship to Previous Competitions

Notice that the current competition addresses the critique of our previous competitions (see Spiliopoulos & Ortmann, 2013), which asserted that competitions are typically run as a single implementation they might be susceptible to auxiliary assumptions, therefore "before running a tournament it is important to very carefully select the implementation details based on prior studies and knowledge" (Spiliopoulos & Ortmann, 2013, p. 243). The deviation point of the current competition, which focuses on the replication of 14 well-known behavioral phenomena, follows this proposition. Furthermore, we believe that the requirement from models to be clear on their description so other researchers could easily use them, can facilitate model's parsimony and usability.

Plan and Hypotheses

Our plan is to complete the current paper in May 2015 after analyzing the competitions' results. We will then add a description of the results obtained in the competition study (Experiment 3), and the description of the winning model.

We hypothesize that the winning model will be similar to BEAST with respect to the assumed behavioral tendencies. Specifically, it is likely to assume: high sensitivity to the expected values and the existence of a dominant option, several initial biases that diminish with feedback, and a tendency to rely on small samples that does not diminish overtime. We do not have clear predictions about the exact quantification of these tendencies, and hope that the quantification under the winning model will be more elegant than the one under BEAST. We also hope that the current project will clarify the existence of distinct deviations from maximization which do not cancel each other out, and the fact that the effort to capture them in a general model allows useful prediction of behavior.

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Appendix A: Derivation of Noise in Multi-Outcome Problems

Problems in which LotNum is larger than 1 are multi-outcome problems in which Option B includes more than two possible outcomes. In this case, the high outcome in Option B (H_B) is split into more than one outcome, according to a lottery's distribution. There are three types of lottery distributions, *Symm*, *R-skew*, and *L-skew*, and all have expected value equal to H_B (i.e. the lottery maintains the original expected value of Option B).

In problems with LotShape "Symm", the lottery's possible outcomes are generated by adding the following terms to H_B: -*k*/2, -*k*/2+1, …, *k*/2-1, and *k*/2, where *k* = LotNum – 1 (hence the lottery includes exactly LotNum possible outcomes). The lottery's distribution around H_B is binomial with parameters *k* and ½. In other words, the lottery's distribution is form of discretization of a normal distribution with mean H_B. Formally, if in a particular trial the lottery (rather than L_B) is drawn (which happens with probability pH_B), Option B's generated outcome is:

$$\begin{cases} \boldsymbol{H_B} - \frac{\boldsymbol{k}}{2}, & \boldsymbol{with\ probability} \binom{\boldsymbol{k}}{0}\left(\frac{1}{2}\right)^{\boldsymbol{k}} \\ \boldsymbol{H_B} - \frac{\boldsymbol{k}}{2} + 1, & \boldsymbol{with\ probability} \binom{\boldsymbol{k}}{1}\left(\frac{1}{2}\right)^{\boldsymbol{k}} \\ \vdots & \\ \boldsymbol{H_B} - \frac{\boldsymbol{k}}{2} + \boldsymbol{k}, & \boldsymbol{with\ probability} \binom{\boldsymbol{k}}{\boldsymbol{k}}\left(\frac{1}{2}\right)^{\boldsymbol{k}} \end{cases}$$

In problems with LotShape "R-skew", the possible outcomes are generated by adding the following terms to H_B: $C^+ + 2^1$, $C^+ + 2^2$, …, $C^+ + 2^n$, where *n* = LotNum and $C^+ = -n - 1$. In problems with LotShape "L-skew", the possible outcomes are generated by adding the following terms to H_B: $C^- - 2^1$, $C^- - 2^2$, …, $C^- - 2^n$, where $C^- = n + 1$ (and *n* = LotNum). Note C^+ and C^- are constants that keep the lottery's distribution at H_B. In both cases (R-skew and L-skew), the lottery's distribution around H_B is truncated geometric with the parameter ½ (with the last term's probability adjusted up such that distribution is a well-defined). That is, the distribution is skewed: very large outcomes in R-skew and very small outcomes in L-skew are obtained with small probabilities. For example, if LotShape = R-skew and LotNum = 5 (in which case, C^{+} = -6), the lottery's implied distribution is:

$$\begin{cases} \boldsymbol{H_B} - 6 + 2, & \textbf{\textit{with probability}}\ 1/2 \\ \boldsymbol{H_B} - 6 + 4, & \textbf{\textit{with probability}}\ 1/4 \\ \boldsymbol{H_B} - 6 + 8, & \textbf{\textit{with probability}}\ 1/8 \\ \boldsymbol{H_B} - 6 + 16, & \textbf{\textit{with probability}}\ 1/16 \\ \boldsymbol{H_B} - 6 + 32, & \textbf{\textit{with probability}}\ 1/16 \end{cases}$$

and if LotShape = L-skew and LotNum = 5 (i.e. C^{-} = 6), the implied distribution is:

$$\begin{cases} \boldsymbol{H_B} + 6 - 2, & \textbf{\textit{with probability}}\ 1/2 \\ \boldsymbol{H_B} + 6 - 4, & \textbf{\textit{with probability}}\ 1/4 \\ \boldsymbol{H_B} + 6 - 8, & \textbf{\textit{with probability}}\ 1/8 \\ \boldsymbol{H_B} + 6 - 16, & \textbf{\textit{with probability}}\ 1/16 \\ \boldsymbol{H_B} + 6 - 32, & \textbf{\textit{with probability}}\ 1/16 \end{cases}$$

Appendix B: Translated Instructions and Examples of the Experimental Screen

The instructions to participants in the ByProb condition (see Footnote 3 in main text) were:

> *"This experiment consists of many games which you will play one after the other. In every game there are multiple trials and in every trial you will have to choose between two options presented on the screen. The choice will be made by clicking on the button that corresponds with the option you have selected, which will be located below that option.*
>
> *Following some of the trials there will appear on the selected button the outcome you obtained by selecting that option (this outcome will appear in black font). On the other button there will appear the outcome you could have obtained had you selected the other option (the forgone outcome will appear in dull font).*
>
> *In the end of the experiment one trial will be selected at random from all the experiment's trials and your obtained outcome in that trial will be your payoff for the performance in the experiment. Trials in which outcomes did not appear on the screen may also be selected to count as your payoff.*
>
> *Please note: The more trials you have with larger obtained outcomes, the larger the chances you would get a larger monetary pay in the end of the experiment."*

The initial instructions to participants in the ByFB condition were:

> *"This experiment consists of many games which you will play one after the other. In every game there are multiple trials and in every trial you will have to choose between two options presented on the screen. The choice will be made by clicking on the button that corresponds with the option you have selected, which will be located below that option.*
>
> *In the end of the experiment one trial will be selected at random from all the experiment's trials and your obtained outcome in that trial will be your payoff for the performance in the experiment.*
>
> *Please note: The more trials you have with larger obtained outcomes, the larger the chances you would get a larger monetary pay in the end of the experiment."*

After completing all (150) No-FB trials (five per problem), the participants in the ByFB condition were shown the following instructions:

> *"The first part of the experiment is over.*
>
> *In the second part of the experiment, there will appear on the selected button the outcome you obtained by selecting that option (this outcome will appear in black font).*
> *On the other button there will appear the outcome you could have obtained had you selected the other option (the forgone outcome will appear in dull font).*
>
> *The rest of the instructions remain unchanged."*

Screenshot examples of the experimental paradigm are given in Figures B1 through B5: Figure B1 demonstrates a problem with abstract representation and Amb = 0; Figure B2 demonstrates a problem with abstract representation and Amb = 1; Figure B3 demonstrates the coin-toss framing manipulation; Figure B4 demonstrates the accept/reject framing manipulation; and Figure B5 demonstrates the feedback given to participants following a choice. Note the location of each option on the screen was counterbalanced and the information regarding correlation between options (bottom row on the screen) only appeared if both options had more than one possible outcome (i.e. when correlation information was relevant).

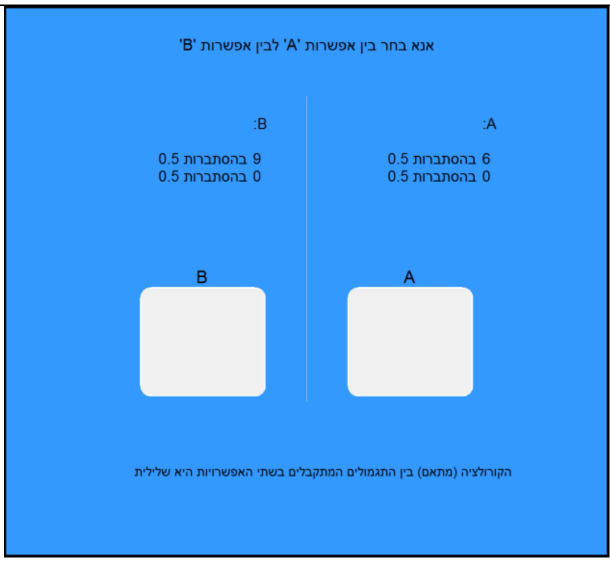

Figure B1. Example of the experimental screen in an abstract problem with Amb = 0. The top row reads: "Please choose between Option A and Option B". Option A on the right reads: "6 with probability 0.5; 0 with probability 0.5" and Option B on the left reads: "9 with probability 0.5; 0 with probability 0.5". The line below the two buttons reads: "The correlation between the obtained payoffs in the two options is negative".

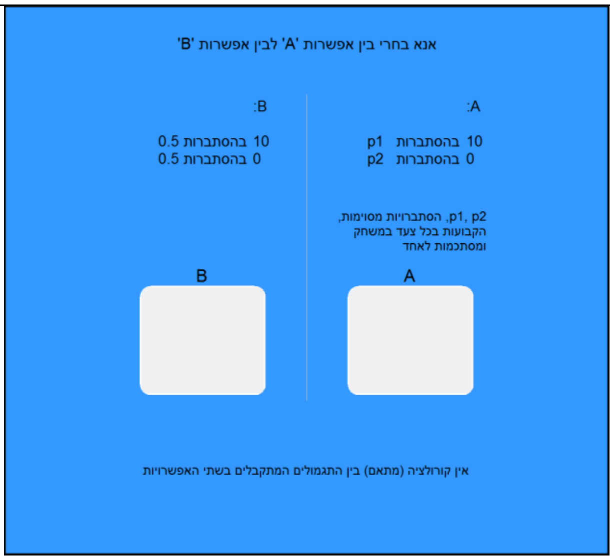

Figure B2. Example of the experimental screen in an abstract problem with Amb = 1 (ambiguous problem). The top row reads: "Please choose between Option A and Option B". Option A on the right reads: "10 with probability p1; 0 with probability p2" and below that: "p1 and p2 are probabilities which remain constant in every trial of this game and sum to one". Option B on the left reads: "10 with probability 0.5; 0 with probability 0.5". The line below the two buttons reads: "There is no correlation between the obtained payoffs in the two options."

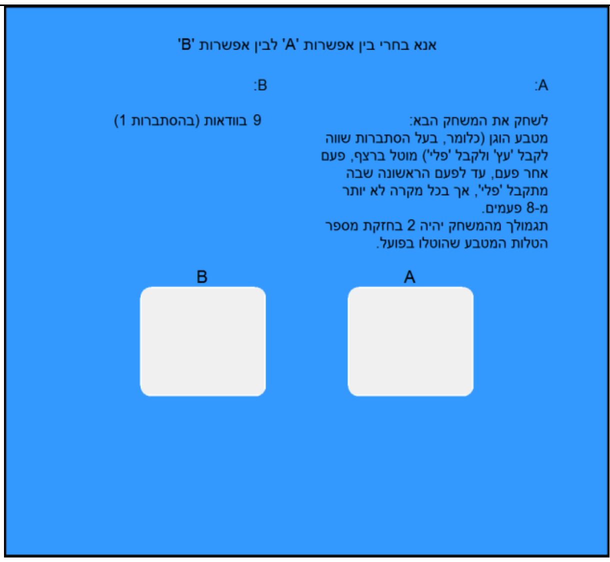

Figure B3. Example of the experimental screen in a problem framed with a “coin-toss” manipulation. The top row reads: “Please choose between Option A and Option B”. Option A on the right reads: “Playing the following game: A fair coin (i.e. with equal chance for Heads or Tails) will be flipped consecutively until it comes up Heads, but not more than 8 times; Your payoff will be 2 to the power of actual flips of the coin”, and Option B on the left reads: “9 with certainty (with probability 1)”

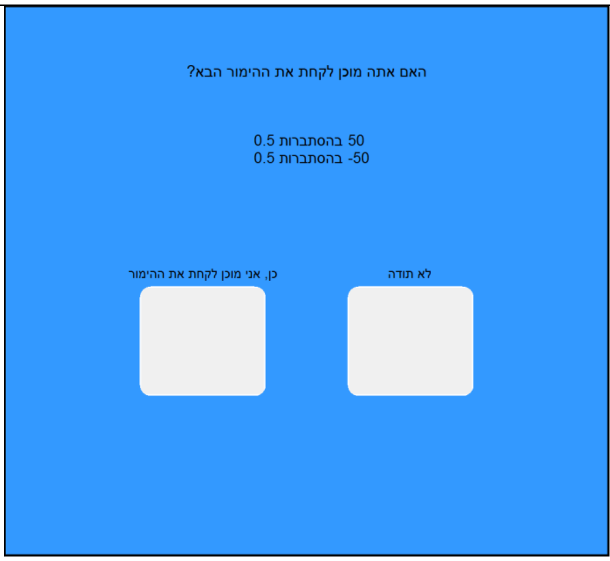

Figure B4. Example of the experimental screen in a problem with framed with “accept/reject” manipulation. From the top, the Hebrew reads: “Are you willing to take the following gamble? 50 with probability 0.5; -50 with probability 0.5”. The option on the right reads: “No thanks” The option on the left reads: “Yes, I am willing to take the gamble”.

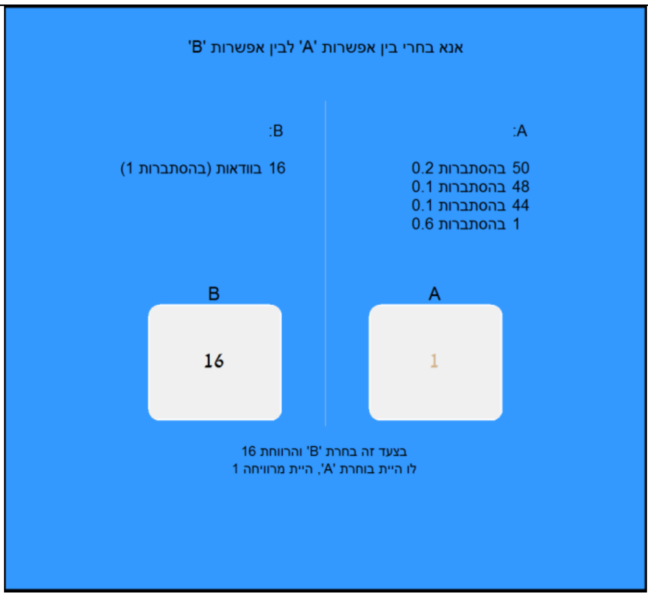

Figure B5. Example of the experimental screen when full feedback is given (blocks 2-5). The participant here chose Option B. The top row reads: "Please choose between Option A and Option B". Option A on the right reads: "50 with probability 0.2; 48 with probability 0.1; 44 with probability 0.1; 1 with probability 0.6", and Option B on the left reads: "16 with certainty (with probability 1)". Below the two buttons the lines reads: "In this trial you chose 'B' and gained 16; Had you chosen 'A', you would have gained 1".

Appendix C: The Problem Selection Algorithm

The 60 problems in Experiment 2 were generated according to the following algorithm (the algorithm will be used also to determine the problems in Experiment 3).

1. Draw randomly EV_A' ~ Uni(-10, 30) (a continuous uniform distribution)
2. Draw number of outcomes for Option A, N_A: 1 with probability .5; 2 otherwise.

   2.1. If $N_A = 1$ then set $L_A = H_A$ = Round(EV_A'); $pH_A = 1$

   2.2. If Ns = 2 then draw pH_A uniformly from the set {.01, .05, .1, .2, .25, .4, .5, .6, .75, .8, .9, .95, .99, 1}

   2.2.1. If $pH_A = 1$ then set $L_A = H_A$ = Round(EV_A')

   2.2.2. If $pH_A < 1$ then draw an outcome *temp* ~ Triangular[-50, EV_A', 120]

   2.2.2.1. If Round(*temp*) < EV_A' then set L_A = Round(*temp*);

   H_A = Round{[EV_A' – $L_A(1 – pH_A)$]/pH_A}

   2.2.2.2. If Round(*temp*) > EV_A' then set H_A = Round(*temp*);

   L_A = Round[(EV_A' – $H_A \cdot pH_A$)/$(1 - pH_A)$]

   2.2.2.3. If $H_A > 150$ or $L_A < -50$ then stop and start the process over

3. Draw difference in expected values between options, *DEV*: $\boldsymbol{DEV} = \frac{1}{5}\sum_{i=1}^{5} U_i$, where

   U_i ~ Uni[-20, 20]

4. Set EV_B' = EV_A + *DEV* , where EV_A is the real expected value of Option A.
5. Draw pH_B uniformly from the set {.01, .05, .1, .2, .25, .4, .5, .6, .75, .8, .9, .95, .99, 1}

   5.1. If $pH_B = 1$ then set $L_B = H_B$ = Round(EV_B')

   5.2. If $pH_B < 1$ then draw an outcome *temp* ~ Triangular[-50, EV_B', 120]

   5.2.1. If Round(*temp*) < EV_B' then set L_B = Round(*temp*);

   H_B = Round{[EV_B' – $L_B(1 – pH_B)$]/pH_B}

   5.2.2. If round(temp) > EVs' ten set H_B = Round(*temp*);

   L_B = Round[(EV_B' – $H_B \cdot pH_B$)/$(1 – pH_B)$]

5.2.3. If $H_B > 150$ or $L_B < -50$ then stop and start the process over

6. Set lottery (see Appendix A):

   6.1. With probability 0.5 the lottery is XX. Set LotNum = 1 and LotShpae = “-“

   6.2. With probability 0.25 the lottery is skewed. Draw *temp* uniformly from the set {-7, -6, … ,-3, -2, 2, 3, … , 7, 8}

      6.2.1. If *temp* > 0 then set LotNum = *temp* and LotShape = “R-skew”

      6.2.2. If *temp* < 0 then set LotNum = -*temp* and LotShape = “L-skew”

   6.3. With probability 0.25 the lottery is symmetric. Set LotShape = “Symm” and draw LotNum uniformly from the set {3, 5, 7, 9}

7. Draw Corr: 0 with probability .8; 1 with probability .1; -1 with probability .1

8. Draw Amb: 0 with probability .8; 1 otherwise.

In addition, in some cases the generated problem was not used for technical reasons. These cases are: (a) when there is a positive probability for an outcome larger than 256 or an outcome smaller than -50; (b) Options are indistinguishable from participants’ perspective (i.e. have the same distributions and Amb = 0); (c) Amb = 1 but Option B has only one possible outcome; and (d) At least one option has no variance but the options are correlated.

BEAST results (OCT 25):

The SAS System

Obs	kapa	sig	teta	beta	fi	eta	_TYPE_	_FREQ_	msd1	msd
1	3	8	1	3	0.05	1.5	0	90	0.86524	0.73117

The SAS System

dt	r	g	av1	ap1	av2	bv1	bp1	bv2	bp2	nvb	rb1	rb2	rb3	rb4	rb5	pred1	pred2	pred3	pred4	pred5
KT	0	1	1	1.00	1	0	0.95	20	0.05	2	0.39	0.38	0.33	0.34	0.29	0.34	0.35	0.36	0.36	0.36
KT	0	2	-1	1.00	-1	-20	0.05	0	0.95	2	0.48	0.63	0.62	0.62	0.64	0.59	0.59	0.60	0.60	0.60
KT	0	3	1	1.00	1	0	0.99	100	0.01	2	0.47	0.40	0.39	0.39	0.39	0.32	0.33	0.33	0.33	0.32
KT	0	4	2	1.00	2	1	0.99	101	0.01	2	0.54	0.46	0.44	0.43	0.42	0.54	0.46	0.44	0.42	0.41
KT	0	5	3	1.00	3	0	0.20	4	0.80	2	0.43	0.57	0.57	0.60	0.65	0.43	0.49	0.50	0.51	0.51
KT	0	6	0	0.75	3	0	0.80	4	0.20	2	0.62	0.62	0.62	0.64	0.62	0.53	0.52	0.52	0.52	0.51
KT	0	7	-3	1.00	-3	-4	0.80	0	0.20	2	0.49	0.46	0.42	0.38	0.36	0.52	0.49	0.47	0.46	0.46
KT	0	8	-3	0.25	0	-4	0.20	0	0.80	2	0.38	0.40	0.39	0.42	0.40	0.47	0.48	0.48	0.48	0.48
KT	0	9	0	1.00	0	-50	0.50	50	0.50	2	0.34	0.42	0.43	0.44	0.38	0.41	0.44	0.46	0.47	0.46
AcRj	0	10	0	1.00	0	-50	0.50	50	0.50	2	0.36	0.37	0.40	0.38	0.36	0.42	0.45	0.45	0.45	0.46
KT	0	11	0	1.00	0	-1	0.50	1	0.50	2	0.49	0.45	0.42	0.41	0.38	0.48	0.48	0.48	0.49	0.49
KT	-1	12	0	0.50	6	0	0.50	9	0.50	2	0.91	0.86	0.83	0.84	0.84	0.87	0.73	0.68	0.68	0.69
KT	0	13	2	1.00	2	3	1.00	3	0.00	1	0.97	0.98	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00
KT	1	14	0	0.50	6	0	0.50	8	0.50	2	0.94	0.96	0.96	0.98	0.98	0.86	0.91	0.92	0.93	0.94
KT	0	15	-2	1.00	-2	-3	0.50	-1	0.50	2	0.48	0.52	0.48	0.48	0.45	0.50	0.50	0.50	0.50	0.50
KT	0	16	-1	1.00	-1	-2	0.50	0	0.50	2	0.58	0.61	0.60	0.58	0.57	0.54	0.53	0.53	0.52	0.51
KT	0	17	1	1.00	1	0	0.50	2	0.50	2	0.35	0.51	0.54	0.49	0.54	0.43	0.45	0.46	0.47	0.47
KT	0	18	2	1.00	2	1	0.50	3	0.50	2	0.41	0.50	0.46	0.46	0.49	0.49	0.49	0.50	0.49	0.50
KT	0	19	7	1.00	7	1	0.50	50	0.50	2	0.78	0.84	0.88	0.83	0.85	1.00	1.00	1.00	1.00	1.00
KT	0	20	7	1.00	7	-1	0.50	50	0.50	2	0.71	0.79	0.82	0.83	0.83	0.83	0.89	0.91	0.92	0.93
KT	0	21	30	1.00	30	1	0.50	50	0.50	2	0.24	0.33	0.33	0.31	0.29	0.28	0.30	0.31	0.31	0.31
KT	0	22	30	1.00	30	-1	0.50	50	0.50	2	0.23	0.33	0.40	0.33	0.34	0.20	0.24	0.26	0.26	0.26
Amb	0	23	0	0.50	10	0	0.50	10	0.50	2	0.37	0.42	0.47	0.48	0.51	0.47	0.48	0.50	0.50	0.49
Amb	0	24	0	0.90	10	0	0.90	10	0.10	2	0.82	0.84	0.78	0.71	0.66	0.76	0.68	0.65	0.63	0.61
Amb	0	25	0	0.10	10	0	0.10	10	0.90	2	0.15	0.16	0.26	0.32	0.32	0.23	0.30	0.34	0.36	0.38
StPb	0	26	9	1.00	9	2	0.50	4	0.25	8	0.37	0.39	0.36	0.31	0.30	0.45	0.37	0.34	0.33	0.32
KT	0	27	9	1.00	9	2	0.50	4	0.25	8	0.38	0.38	0.39	0.36	0.36	0.45	0.37	0.34	0.33	0.32
KT	0	28	16	1.00	16	1	0.60	50	0.40	2	0.50	0.65	0.61	0.60	0.55	0.58	0.59	0.60	0.59	0.60
KT	0	29	16	1.00	16	1	0.60	44	0.10	4	0.51	0.57	0.60	0.58	0.57	0.64	0.62	0.62	0.62	0.61
KT	0	30	19	1.00	19	-20	0.10	20	0.90	2	0.13	0.22	0.21	0.20	0.21	0.11	0.14	0.14	0.14	0.14
Amb	0	31	4	1.00	4	-44	0.40	40	0.60	2	0.23	0.31	0.34	0.41	0.37	0.25	0.36	0.41	0.44	0.46

dt	r	g	av1	ap1	av2	bv1	bp1	bv2	bp2	nvb	rb1	rb2	rb3	rb4	rb5	pred1	pred2	pred3	pred4	pred5
KT	0	32	-4	0.25	24	3	0.75	82	0.25	2	0.68	0.68	0.67	0.67	0.69	0.79	0.67	0.63	0.62	0.61
KT	0	33	-3	1.00	-3	-22	0.60	14	0.40	2	0.33	0.28	0.31	0.25	0.22	0.36	0.33	0.32	0.31	0.31
KT	0	34	7	1.00	7	4	0.90	26	0.03	4	0.39	0.45	0.43	0.41	0.40	0.55	0.45	0.42	0.40	0.39
KT	0	35	-5	1.00	-5	-15	0.99	47	0.01	2	0.17	0.09	0.04	0.03	0.05	0.24	0.16	0.13	0.12	0.11
KT	0	36	28	1.00	28	-46	0.40	86	0.30	4	0.39	0.55	0.56	0.60	0.57	0.45	0.51	0.53	0.54	0.54
KT	0	37	0	0.10	23	-7	0.60	64	0.40	2	0.38	0.41	0.42	0.37	0.37	0.40	0.43	0.45	0.45	0.46
KT	0	38	24	1.00	24	28	0.95	34	0.05	2	0.91	0.98	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
KT	0	39	29	1.00	29	6	0.20	31	0.05	6	0.50	0.69	0.70	0.68	0.66	0.42	0.46	0.48	0.48	0.49
KT	0	40	-37	0.20	3	-46	0.60	-41	0.01	8	0.49	0.54	0.60	0.60	0.56	0.64	0.62	0.61	0.60	0.61
KT	0	41	29	1.00	29	21	0.60	42	0.03	6	0.68	0.73	0.74	0.68	0.68	0.70	0.64	0.63	0.63	0.62
Amb	0	42	-6	1.00	-6	-21	0.90	54	0.10	2	0.60	0.48	0.26	0.23	0.20	0.70	0.46	0.33	0.29	0.27
KT	0	43	14	1.00	14	9	0.10	12	0.90	2	0.13	0.04	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
KT	0	44	23	1.00	23	-33	0.01	24	0.99	2	0.27	0.44	0.47	0.49	0.47	0.37	0.48	0.53	0.56	0.57
KT	0	45	13	1.00	13	9	0.00	10	0.03	8	0.50	0.56	0.58	0.53	0.52	0.45	0.47	0.47	0.47	0.47
KT	0	46	9	0.99	37	-37	0.40	30	0.60	2	0.20	0.27	0.27	0.31	0.30	0.18	0.27	0.30	0.31	0.32
KT	0	47	11	1.00	11	-5	0.80	0	0.01	7	0.22	0.20	0.21	0.16	0.15	0.26	0.27	0.28	0.28	0.28
Amb	0	48	-2	1.00	-2	-24	0.50	24	0.50	2	0.39	0.49	0.52	0.45	0.42	0.55	0.56	0.56	0.57	0.56
KT	0	49	23	1.00	23	22	0.25	23	0.50	3	0.54	0.50	0.49	0.48	0.48	0.50	0.50	0.50	0.50	0.50
KT	0	50	4	1.00	4	0	0.00	1	0.03	8	0.44	0.66	0.60	0.57	0.57	0.40	0.44	0.45	0.45	0.45
KT	0	51	-18	0.20	42	23	0.80	68	0.20	2	0.79	0.71	0.74	0.72	0.70	0.79	0.66	0.63	0.61	0.60
KT	0	52	0	0.80	46	-2	0.75	46	0.25	2	0.36	0.26	0.26	0.22	0.22	0.36	0.40	0.42	0.41	0.42
KT	0	53	28	1.00	28	-22	0.25	42	0.75	2	0.36	0.43	0.42	0.42	0.42	0.32	0.41	0.45	0.46	0.47
KT	0	54	18	1.00	18	-33	0.50	64	0.50	2	0.32	0.30	0.31	0.32	0.29	0.26	0.32	0.34	0.35	0.35
KT	-1	55	19	0.80	43	17	0.75	18	0.00	9	0.20	0.16	0.09	0.07	0.07	0.05	0.06	0.06	0.05	0.05
KT	0	56	-8	1.00	-8	-34	0.01	-5	0.99	2	0.76	0.88	0.91	0.90	0.89	0.63	0.73	0.77	0.79	0.80
KT	-1	57	-3	0.50	49	17	0.05	29	0.00	9	0.77	0.71	0.70	0.73	0.75	0.84	0.79	0.77	0.76	0.76
KT	0	58	-7	0.60	85	24	0.75	40	0.25	2	0.60	0.51	0.52	0.54	0.56	0.66	0.59	0.57	0.56	0.56
KT	0	59	16	0.75	17	2	0.60	43	0.40	2	0.51	0.52	0.52	0.49	0.49	0.54	0.55	0.56	0.56	0.56
KT	0	60	21	0.90	51	1	0.40	38	0.60	2	0.37	0.38	0.34	0.29	0.30	0.27	0.37	0.40	0.41	0.42
KT	0	61	25	0.75	26	23	0.03	24	0.95	8	0.67	0.62	0.62	0.60	0.56	0.50	0.40	0.36	0.34	0.33
KT	0	62	25	1.00	25	17	0.80	45	0.20	2	0.32	0.32	0.35	0.34	0.34	0.37	0.33	0.31	0.31	0.30
KT	0	63	17	1.00	17	15	0.90	58	0.01	6	0.68	0.70	0.67	0.66	0.69	0.84	0.80	0.78	0.78	0.78
Amb	0	64	-8	0.90	52	-43	0.10	5	0.90	2	0.35	0.55	0.70	0.72	0.68	0.31	0.48	0.56	0.58	0.59
KT	0	65	-16	0.60	12	-5	1.00	-5	0.00	1	0.33	0.40	0.44	0.45	0.45	0.46	0.48	0.49	0.49	0.49
KT	0	66	2	0.40	45	20	0.90	28	0.01	6	0.43	0.35	0.40	0.44	0.43	0.55	0.44	0.41	0.40	0.39
KT	1	67	4	0.75	85	11	0.75	54	0.25	2	0.45	0.47	0.46	0.48	0.43	0.45	0.48	0.49	0.49	0.50
KT	0	68	12	1.00	12	-14	0.80	102	0.20	2	0.39	0.27	0.29	0.32	0.31	0.26	0.29	0.30	0.31	0.31
Amb	0	69	11	0.50	49	21	0.05	30	0.24	4	0.39	0.29	0.37	0.40	0.45	0.47	0.49	0.50	0.51	0.52
KT	0	70	18	1.00	18	-19	0.25	35	0.75	2	0.38	0.55	0.58	0.60	0.58	0.43	0.53	0.56	0.58	0.58

dt	r	g	av1	ap1	av2	bv1	bp1	bv2	bp2	nvb	rb1	rb2	rb3	rb4	rb5	pred1	pred2	pred3	pred4	pred5
KT	0	71	-20	0.40	13	-26	0.80	76	0.20	2	0.38	0.25	0.29	0.23	0.28	0.37	0.35	0.34	0.33	0.33
KT	0	72	-9	1.00	-9	-8	0.75	13	0.25	2	0.82	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
KT	0	73	2	1.00	2	0	0.95	48	0.00	7	0.37	0.38	0.39	0.39	0.41	0.37	0.37	0.36	0.36	0.35
Amb	0	74	16	0.95	44	10	0.10	13	0.23	4	0.13	0.05	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
KT	0	75	13	1.00	13	-45	0.40	50	0.60	2	0.35	0.44	0.42	0.44	0.50	0.30	0.38	0.41	0.43	0.43
Amb	0	76	16	0.99	35	13	0.50	18	0.03	6	0.68	0.71	0.71	0.68	0.64	0.52	0.54	0.54	0.54	0.54
KT	0	77	1	1.00	1	-9	0.60	38	0.40	2	0.65	0.66	0.65	0.60	0.63	0.56	0.62	0.64	0.64	0.65
KT	0	78	19	1.00	19	9	0.95	44	0.05	2	0.11	0.12	0.11	0.14	0.12	0.16	0.10	0.09	0.08	0.08
KT	0	79	19	0.99	32	9	0.99	65	0.01	2	0.14	0.07	0.04	0.02	0.02	0.18	0.12	0.10	0.08	0.08
KT	0	80	3	1.00	3	-36	0.60	50	0.40	2	0.47	0.37	0.41	0.41	0.43	0.23	0.28	0.30	0.31	0.31
Amb	0	81	2	0.75	10	-32	0.10	-1	0.90	2	0.14	0.04	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00
Amb	0	82	25	1.00	25	23	0.00	24	0.00	5	0.55	0.72	0.77	0.81	0.82	0.50	0.56	0.57	0.56	0.55
KT	0	83	9	1.00	9	9	0.99	64	0.01	2	0.87	0.96	0.98	0.98	0.99	1.00	1.00	1.00	1.00	1.00
KT	0	84	27	1.00	27	-7	0.01	22	0.99	2	0.08	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
KT	0	85	20	1.00	20	6	0.75	70	0.25	2	0.43	0.45	0.49	0.46	0.44	0.50	0.47	0.46	0.45	0.45
Amb	0	86	-11	0.50	71	-49	0.25	61	0.75	2	0.13	0.23	0.30	0.32	0.25	0.17	0.35	0.42	0.44	0.46
KT	0	87	-2	1.00	-2	-34	0.01	1	0.02	8	0.81	0.96	0.98	0.96	0.98	0.82	0.87	0.89	0.90	0.90
Amb	0	88	-7	0.95	17	-15	0.75	13	0.25	2	0.68	0.57	0.51	0.44	0.37	0.51	0.43	0.39	0.37	0.35
KT	0	89	17	1.00	17	17	0.90	44	0.10	2	0.88	0.96	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
KT	0	90	10	1.00	10	-49	0.25	31	0.75	2	0.42	0.55	0.53	0.56	0.55	0.35	0.45	0.47	0.48	0.49

Code

```
libname out '';


data a; set out.lhset123; dtype=desctype;
if dtype='Am' then dtype='Amb';
rezef=1; if condi=300 then rezef=2;
array rb{5} rb1-rb5;
****; do i=1 to 5; rb{i}=mean(rb{i},lag(rb{i})); end; if rezef=2;*****
collaps over rezefs;
rezef=1;

nsim=10000; ***number of simulations;

****parameters************************************************************
***;
do kapa=3; *3**sample size;
do sig=8; *6**noise standard deviation;
do teta=1; *.8**the diminishing effect of number of previous trial with
feedback in this problem;
do pbias=3; *2.6the initial tendency to select the biased dist, .8 implies
equal prob;
do wamb=.05;
do eta=1.5;**1.3;
output;
end; end; end; end; end; end;
```

```
data a; set a;
array rb{5} rb1-rb5;
array pred{5} pred1-pred5;
array va{2} av1-av2;
array vb{10} bv1-bv10;
array pa{2} ap1-ap2;
array pb{10} bp1-bp10;
array tpb{10} tpb1-tpb10;
eva=av1*ap1+av2*ap2;
tmpsum=0;
*nvb=n(of bv1-bv10);

**number of outcomes;
nva=0; nvb=0;
 do qq=1 to 2; if pa{qq}>0 then nva=nva+1;  end;
 do qq=1 to 10; if pb{qq}>0 then nvb=nvb+1; end;


**max and min;
 minv=min(bv1,av1); maxv=max(vb{nvb},av2);
 utmp=mean(of bv1-bv10);

 mina=av1; minb=bv1; maxa=va{nva}; maxb=vb{nvb};

***detecting dominance*******************;
dom=1; maxd=0; mind=0;
do zz =0 to 1 by .005;
sumr=0; sums=0;
do qq=1 to 2; sums=sum(sums,pa{qq}); if sums>zz then do; vs=va{qq}; qq=2;
end; end;
do qq=1 to nvb; sumr=sum(sumr,pb{qq}); if sumr>zz then do; vr=vb{qq};
qq=nvb; end; end;
diff=vs-vr; if diff<mind then mind=diff; if diff>maxd then maxd=diff;
if mind<0 and maxd>0 then do; zz=1; dom=0; end;
end;
if dtype='Amb' then do; dom=0; if mina>maxb or minb>maxa then dom=1; end;

***initial values to be used later;
 do i=1 to 5; pred{i}=0; end;


******************************************Simulations**********************
******;
do sim=1 to nsim;

teti=teta*ranuni(0);
sigi=ranuni(0)*sig; if dom=1 then sigi=0;
kapi=round(.5+ranuni(0)*kapa);
iamb=ranuni(0)*wamb;
ibias=pbias*ranuni(0);
ieta=eta*(ranuni(0));


*****The expected values;
evb=0; tmpev=0; tmpsum=0;
do i=1 to nvb; evb=sum(evb,vb{i}*pb{i});  end;
tevb1=evb;

evb1=evb;
```

```
if dtype='Amb' or dtype='Am' then do;
 tevb1=max(0,(1-iamb)*mean(utmp,eva));
 tevb1=(1-iamb)*mean(utmp,eva)+iamb*(bv1);
 tpb1=max(0,(hr-tevb1)/(hr-lr));
do i=2 to nvb; tpb{i}=(1-tpb1)/(nvb-1); end;
/*tevb1=0;
tpb1=1/nvb+iamb;
do i=2 to nvb; tpb{i}=1/(nvb)-iamb/(nvb-1); end;
do i=1 to nvb; tevb1=sum(tevb1,vb{i}*tpb{i});  end;*/
end;
tevb=tevb1;

b=0;
do r=1 to 25;

tt=1+(max(0,r-5))**teti;
rbet=tevb-eva+sigi*rannor(0)*25/(tt+25); ***initial noisy bias;
if (r-1)/5=round((r-1)/5) then b=b+1;

***taking a sample of kapa***************************************;
do i= 1 to kapi;

rndexp=ranuni(0);
rnds=ranuni(0);
rndr=ranuni(0);

if r<7 or corr=1 then rndr=rnds; **sens to prostive correlation, no
sensitivity to negative corr;
*if corr=1 then rndr=rnds; **sens;
if r>6 and corr=-1 then rnds=1-rndr;
***Choosing the type/distribution of the
draw**********************************;
draw='odis';  ***draw from the objective distribution;
if rndexp<ibias/(ibias+tt) then do; ***with tt=1 this implies that all 5
distributions are equally likely, when tt increases the objective is more
likely;
rndd=round(.5+ranuni(0)*3);  **all the 4 bias distributions are equally
likely;
  if rndd=1 then draw='eqli';  **draw from equiliy likely;
  if rndd=2 then draw='dims';
  if rndd=3 then draw='pess';  **draw the worst payoff;

end;

***Unbias: draw from the true
distribution*************************************************************
************;
if draw='odis' then do; sums=0; sumr=0;
do qq=1 to 2; sums=sum(sums,pa{qq}); if sums>rnds then do; vs=va{qq}; qq=2;
end; end;
do qq=1 to 10; sumr=sum(sumr,pb{qq}); if sumr>rndr then do; vr=vb{qq};
qq=10; end; end;
sums=0; sumr=0;
if dtype='Amb' and r<7 then do qq=1 to 10; sumr=sum(sumr,tpb{qq}); if
sumr>rndr then do; vr=vb{qq}; qq=10; end; end;
end; ***of draw=odis;


 ***Uniform: draw from the all the probability are equaly likly ********;
 if draw='eqli' then do;
```

```
   oa=round(.5+rnds*nva);
   ob=round(.5+rndr*nvb);
   vs=va{oa};vr=vb{ob};
 end; ***of draw=eq. likely;


 ***Contingent pessimism: draw from the pessimistic or median (in case of
more than 2)
distribution***********************************************************
************;
rndr=ranuni(0);
if draw='pess' then do; sumr=0;
  vs= av1; ****basic payoff from s;
  vr= bv1; ****basic payoff from r;
aa=max(abs(av1),.001);
bb=max(abs(bv1),.001);
/*if (sign(av1) =sign(bv1) and min(aa/bb,bb/aa)>1-ieta) or maxv=<0 or
(mean(bv1, vb{nvb})=evb and nvb>2) then do;*/
if ((sign(av1) =sign(bv1) and min(aa/bb,bb/aa)>1-ieta)) or maxv=<0  then
do;
 oa=round(.5+rnds*nva);
 ob=round(.5+rndr*nvb);
 vs=va{oa};vr=vb{ob};
end;
end;**of cont pess;

***Sign: draw from distribution with diminishing sensitivity*******;
if draw='dims' then do; sums=0; sumr=0;
  do qq=1 to 2; sums=sum(sums,pa{qq}); if sums>rnds then do;
vs=(kapi)*(maxv-minv)*sign(va{qq}); qq=2; end; end;
  do qq=1 to 10; sumr=sum(sumr,pb{qq}); if sumr>rndr then do;
vr=(kapi)*(maxv-minv)*sign(vb{qq}); qq=10; end; end;
  sums=0; sumr=0;
 if dtype='Amb' and r<7 then do qq=1 to 10; sumr=sum(sumr,tpb{qq}); if
sumr>rndr then do; vr=(kapi)*(maxv-minv)*sign(vb{qq}); qq=10; end; end;
end;  ***of draw=dimsen;

rbet=rbet+(vr-vs)/kapi;

end;**of kapi samples;

tmpo=ranuni(0); sumr=0;
  do qq=1 to nvb; sumr=sum(sumr,pb{qq}); if sumr>tmpo then do; vout=vb{qq};
qq=nvb;  end; end;
  if dtype='Amb' and r>5 then do; nt=20; tevb=tevb*nt/(nt+1)+vout/(nt+1);
end;

***** updating the statistics*************;
if rbet>0 then pred{b}=pred{b}+1/(nsim*5);
if rbet=0 then pred{b}=pred{b}+.5/(nsim*5);


end; ** or r trials;


end;***of nsim;
*if (bv2=101 or problem=61) and pred1<.5 then pred1=-100;
if (bv2=101) and pred1<.5 then pred1=-10;
msd1=100*(rb1-pred1)**2;
msd=20*((rb1-pred1)**2+(rb2-pred2)**2+(rb3-pred3)**2+(rb4-pred4)**2+(rb5-
pred5)**2);
```

```
data a; set a;
 agree=0; if (pred1>=.5 and rb1>=.5) or (pred1<=.5 and rb1<=.5) then
agree=1;
 game = problem;
 pred1 = round(pred1, .01);
 pred5 = round(pred5, .01);


proc sort out=b; by kapa sig teta pbias wamb eta;* xminp;
proc means data=b noprint; by kapa sig teta pbias wamb eta;* xminp;
var msd1 msd;
output out=o mean= msd1 msd;

proc sort; by msd;

proc print;

run;

proc print  data=a round;
var dtype corr game av1 ap1 av2 ap2 bv1 bp1 bv2 bp2 bv3 bp3 bv4 bp4 eva evb
nvb rb1-rb5  pred1-pred5 msd;* dom mind maxd;* pred lagi;run;

run;
```