Learning or Framing?: Effects of Outcome Feedback on Repeated Decisions from Description

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Abstract

Two experiments document effects of experienced outcome feedback on risk behavior in a repeated description-based decision task. In Study 1, participants were initially strongly risk-seeking in the loss domain, but became less so across 100 repeated trials with outcome feedback. No significant trend was observed for gain problems. Participants then experienced an additional 100 trials of the reflected gain or loss problem. Trends in risk preferences across these Set 2 trials were similar to those in Set 1, however, initial Set 2 levels of risky-option choices were shifted towards EV-maximization, suggesting a cross-domain effect of prior experience. Study 2 attempted to distinguish between reinforcement-learning and monetary reference-point explanations of these cross-domain effects by "endowing" participants facing 100 gain (loss) trials with a large starting loss (gain). Endowment with a large prior gain mimicked the effects of 100 prior gain trials for loss-domain decisions, favoring the reference-point account.

Keywords: repeated decisions; decisions from experience; risky choice; risk-seeking

Behavioral decision research over the past decade has established that decisions from experience (DFE) differ from description-based decisions (DBD) in key ways (for reviews see Hertwig & Erev, 2009; Rakow & Newell, 2010). However, there is a lack of consensus about the underlying reasons for the description-experience gap (e.g., Camileri & Newell, 2009; Hadar & Fox, 2009; Hau, Pleskac & Hertwig, 2010). In part this may be because in typical studies of decisions from experience all information about payoff distributions of the choice options is acquired through outcome feedback. Thus, comparing typical studies of DBD and DFE contrasts not only single-trial decisions to repeated decisions with outcome feedback, the usual focus of discussion, but simultaneously compares decisions under risk, with known payoffs and probabilities, to decisions under uncertainty, with consequences that are initially unknown (cf. Hadar & Fox, 2009). Thus, simple DBD-DFE comparisons confound the *informational* effects of outcome feedback (i.e., information relevant to estimating probabilities of outcomes, thus to strategy selection) and the *hedonic* effects of experienced outcomes (i.e., possible reinforcement learning).

Some empirical evidence suggests that repeated experience with outcome feedback can modify behavior even in description-based decisions. Yechiam, Barron and Erev (2005) found that for a description-based decision problem involving choice between two risky losses, choices of the riskier option that had slightly higher expected value (EV) were more common in the "experience" condition where participants received outcome feedback across 100 trials. Jessup, Bishara, and Busemeyer (2008) studied behavior in repeated trials of two description-based risky decision problems in the Gain domain, finding that the overall proportion of risk-seeking or risk-avoiding choices differed according to whether the decision maker was given outcome feedback or not. In a study of probability-matching behavior where the probabilities of the binary outcomes were known from the outset, Newell and Rakow (2007) found that outcome feedback affected the tendency to select the normative (more likely) outcome.

Several mechanisms could account for effects of experience on risk preferences. Reinforcement learning models have been proposed to account for behavior in repeated decision tasks with initially unknown outcomes (e.g., March, 1996; Yechiam and Busemeyer, 2005; Erev, Ert, Roth, et al., 2010). One such account that takes a clear position on what is learned and how it might generalize is March's (1996) proposal that simple reinforcement learning might impart domain-specific *risk attitudes*, or generalized preferences between risky and riskless decision options for gains and (separately) for losses.

Another possibility is that reinforcement learning mechanisms act so as to make description-based decisions more "rational" by encouraging EV-maximization. Such a shift might occur implicitly, by shifting decision weights to be more nearly linear with the objective probabilities (Hertwig, Barron, Weber & Erev, 2004; Jessup et al., 2008; Hau et al., 2008). Alternatively, effects of experience in description-based decisions may arise via explicit strategy choices, if experience promotes more frequent adoption of EV-maximizing strategies (e.g., Erev & Barron, 2005).

Finally, effects of experience on description-based decision making might be caused by framing effects as postulated by Prospect Theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). It is usually assumed in Prospect Theory that previous outcomes are ignored; under this default "segregation framing" no changes in risk preferences across repeated trials are to be expected. However, under certain task conditions prior gains and/or losses might be incorporated into the evaluation of a new problem's outcomes ("aggregation framing"), thereby changing an individual's reference point for the decision (Kahneman & Tversky, 1979; Redelmeier & Tversky, 1992; Thaler & Johnson, 1990).

These alternate classes of explanation for possible effects of experience on DBD tasks are explored in the two empirical studies and analyses reported below.

STUDY 1

Study 1 was designed to verify if people's risk preferences can change over repeated trials with outcome feedback in a description-based decision task, and if any observed changes in risk preference would generalize between the domains of gains and losses.

Method

Materials. Six simple decision problems were used; three basic problems in the gain domain and corresponding versions in the loss domain. The three basic gain problems were: Problem G1 = ($5; $100, .1), Problem G2 = ($9; $100, .1), and Problem G3 = ($9; $20, .5). So, for example, Problem G1 offered a choice between receiving $5 with certainty and a 10% chance of receiving $100. The three loss versions (L1, L2, and L3) simply substituted losses for gains.

Participants. The participants were 96 undergraduate and graduate students, recruited by posted flyers or from courses, and paid for their participation.

Procedure. The participants responded to decision problems shown on a computer screen. Each participant saw 100 trials of one of the Gain (or Loss) problems, followed by 100 trials of the corresponding Loss (or Gain) problem. After the first set of trials participants were shown their cumulative gains or losses. There were six experimental groups, with 16 participants in each condition.

On each trial, descriptions of the two choice options were presented, with the left-right position counterbalanced. The participant made a choice, and the payoff for that trial was shown. The cumulative amount won or lost could be checked at any time by clicking an icon.

Actual pay for the participants varied depending on the outcomes of their decisions. A base payment of $10 was adjusted by 0.5% of the participant's total amount of winnings (for the 100 Gain trials) and losses (for the 100 Loss trials).

Results

The main dependent variable was the probability of selecting the sure-thing option across the 100 trials. To facilitate data analysis, trial-by-trial choices were averaged within 20-trial pseudo-blocks.

Participants in this repeated-trials situation were strongly risk-seeking for losses. However, the proportion of sure-thing choices changed across the 100 trials: For the three Loss problems the overall proportion of sure-thing choices in the initial block of trials was .14, rising to .37 in the final block. For the three Gain problems the overall trend was flat, from .49 in the initial block to .48 in the final block. The trends by individual problem are shown in Figure 1.

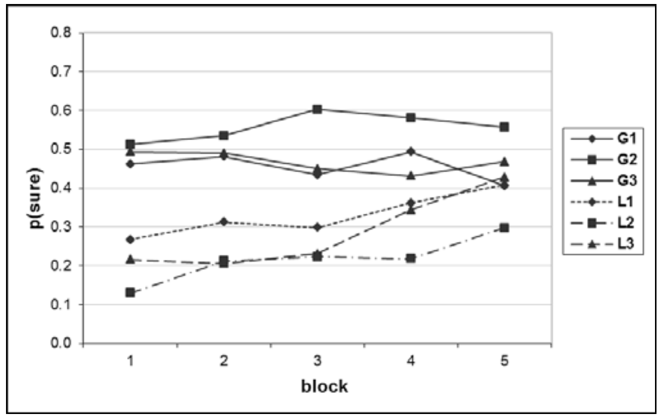

Figure 1: Proportion of sure-thing choices across blocks of Set 1 trials, by problem (G1-G3 = Gain domain problems, L1-L3 = Loss domain problems).

The interaction between Block and Domain was significant, $F(4,360) = 7.153$, $p<.001$, using the Huynh-Feldt correction for sphericity, $\varepsilon = .73$, thus the trends for Gains and Losses were tested separately. For Loss problems, the effect of Block was significant, $F(4,188) = 10.721$, $p<.001$, $\varepsilon = .50$, but not for Gain problems, $F(4,188) = 0.217$, $p=.902$, $\varepsilon = .84$. Thus, a significant learning trend is observed in the Loss domain, consisting of an increasing probability of selecting the sure thing option (the option with higher EV). This suggests that the longer-term effect of outcome feedback in the Loss domain is to reduce risk-seeking, perhaps by moving decision makers towards EV-maximization.

For Set 2 trials, Figure 2 shows initial mean levels and the trend for sure-thing choices compared to Set 1 performance. The initial-block proportion of sure thing choices for Set 2 Gain trials is .39, compared to .49 for the initial block of Set 1 trials. This difference, though sizeable, is not significant, $t(94) = -1.347$, $p=.181$. For Losses the mean proportion of sure-thing choices is .29 for the initial block of Set 2 trials, compared to .14 for the initial block of Set 1 trials; this effect is significant: $t(94) = 2.717$, $p=.008$. These "intercept effects" demonstrate an effect of prior experience (in the first set of 100 trials) on initial performance in Set 2 trials.

Figure 2 also shows the overall mean trend across blocks in Set 2 (the Set 1 trends are shown for comparison) for Gains and Losses. The learning trends across blocks in Set 2 trials are similar to the patterns for Set 1 trials. For Gain problems, the proportion of sure-thing choices is essentially flat across the five blocks of the Set 2 trials (.39 in Block 1 versus .36 in Block 5). However, there is a steady increase in the proportion of sure-thing choices across blocks for Loss problems (from .29 in Block 1 to .40 in Block 5). The Time (Block) effect for Gains is not significant, $F(4,188) = 0.227$, $p=.825$ with Huynh-Feldt correction (ε =.57), while the Time (Block) effect for Loss problems is marginally significant, $F(4,188) = 2.674$, $p=.057$, ε =.659.

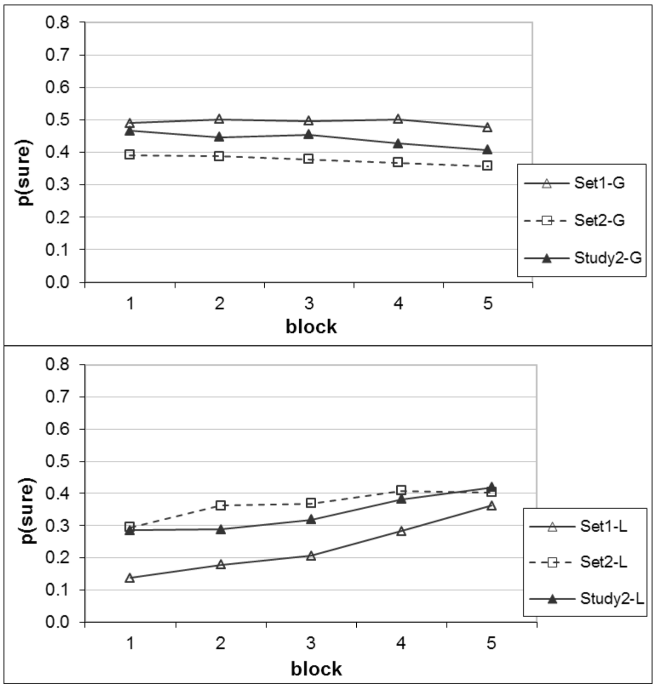

Figure 2: Mean change in proportion of sure-thing choices for problems across 100 trials in Study 1-Set 1, Study 1-Set 2, and Study 2. Top panel: overall means for Gain problems. Bottom panel: overall means for Loss problems.

Sequential Analysis. To further evaluate the viability of reinforcement-based accounts, a sequential analysis of trial-level responses was conducted for the Study 1 Set 1 data. This analysis involved computing separate "learning curves" across trials t+1 to t+10 based on whether trial *t* (varied from *t* =1 to 90) was a sure-thing response resulting in a fixed gain (or loss, depending on condition), a risky response that did not result in a gain (loss), or a risky response that resulted in a large gain (loss). The mean proportion of sure-thing responses for each trial *t+1* to *t+10* is shown in Figure 3.

For Gain problems, a sure-thing response on trial *t* tends to be followed by another sure-thing response at trial *t+1*, and this proportion declines over the next 4-5 trials; a corresponding increase is observed for several trials following a risky response. It seems that decisions by participants to try the sure-thing or the risky-option are often decisions to try a given option for *several* trials, not just one (cf. Biele, Erev, and Ert, 2009). For Losses, there is some hint of a similar pattern, but the Loss curves following a risky response (and the "total" pattern) have a positive slope, reflecting the general rise in the proportion of sure-thing choices observed across blocks.

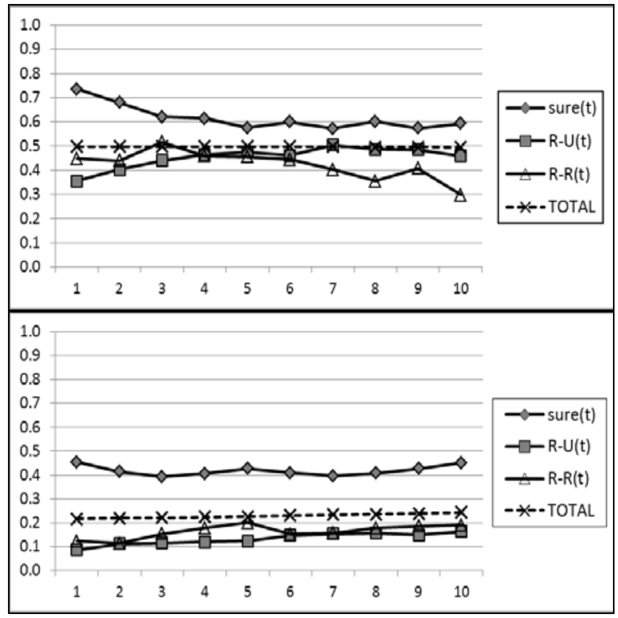

Figure 3: Trends in the proportion of sure-thing choices (Y axis) across the 10 trials following a sure-thing response, an unreinforced risky-choice response, and a reinforced risky-choice response. Top panel: Gain problems. Bottom panel: Loss problems.

The primary question, though, concerns whether effects of reinforcement learning can be detected in these curves. Such an effect should be discernable in a divergence of the curves following a reinforced risky response (curve "R-R") and an unreinforced risky response (curve "R-U"). For Gains, a divergence is indeed discernable across trials *t*+1 to *t*+3, however the direction is such that participants seem to switch *away* from the risky response for a few trial following a reward "hit". This behavior is inconsistent with reinforcement learning but consistent with the gambler's fallacy (cf. Yechiam & Busemeyer, 2006; Barron & Leider, 2010). For Losses, the pattern is different. Across the first five or so trials following a "punished" risky response (curve R-R), the mean level of sure-thing responses is elevated, compared to the curve for unreinforced risky responses (curve R-U). This pattern *is* consistent with reinforcement learning.

Discussion

The results of Study 1 show that risk preferences can change as a result of experience across repeated trials of a description-based decision problem, at least for loss-domain problems. In both Set 1 and Set 2 trials, participants were initially risk-seeking for Loss problems, but increased their proportion of sure-thing choices across blocks.

Importantly, the sequential analyses described above demonstrate that simple reinforcement learning models cannot fully explain choices in the repeated DBD paradigm, because participants were actually *less* likely to select the risky option for several trials after a successful risky choice, exhibiting "negative recency" (cf. Barron & Leider, 2010).

The present study is the first to our knowledge to explore possible cross-domain effects of experience on repeated decisions. Our results show that experience with 100 prior trials of a Gain-domain decision problem decreases the initial level of risk seeking for Set 2 trials in the Loss domain. The complementary effect, in which prior Loss trials decreased initial risk aversion for Gain problems, was sizable (a 10% change) but not significant. This finding cannot be explained by simple reinforcement learning models (which do not address generalization of learned associations between gain and loss domains), nor by March's (1996) idea of learned generalized risk preferences. After all, if participants in the Set 1 Loss condition are learning a generalized aversion to risk, then the proportion of sure-thing choices for Set 2 Gain trials should be increased, not decreased. And if the learned risk preferences are domain-specific (March's actual suggestion), then they could not explain any cross-domain shifts.

Thus we are left with two candidate mechanisms that could explain both trial-by trial changes in risk preferences and the cross-domain "intercept" effects: learning of more rational (EV-maximizing) behavior (perhaps mediated by learning of more linear decision weights), and framing or reference-point effects, as postulated by Cumulative Prospect Theory (Tversky & Kahneman, 1992). To elaborate on the latter explanation, under the assumption of aggregation framing accumulating losses in the Loss domain trials would move participants away from the reference point, reducing the curvature of the value function in the neighborhood of the aggregated decision outcomes, thereby reducing risk seeking behavior incrementally over trials. Second, aggregation framing might be triggered especially for initial Set 2 trials (causing the intercept effects) because participants were explicitly shown their cumulative Set 1 outcomes before beginning Set 2. Thus, the shift in initial risk propensity for Set 2 Loss trials might be a "house money" effect (Thaler & Johnson, 1990) whereby participants take into account their cumulative Set 1 gains, inuring them to small certain losses in Set 2.

STUDY 2

Study 2 was designed to compare framing effects and EV-learning as potential explanations for the cross-domain "intercept" effects observed in Study 1. One way to distinguish predictions of the two accounts is to offer participants comparable gains or losses that are not associated with individual decision trials. If the previous winnings/losses had their influence through framing effects, then simply endowing decision makers with a large initial windfall gain (or a large loss) should have similar effects. In contrast, if the Study 1cross-domain "intercept" effects were caused by learning of more linear subjective decision weights (or any other type of reinforcement learning), then endowing subjects with a large initial gain or loss should not lead to shifts in risk preferences.

Method

The procedure of Study 2 was similar to that of Study 1. However, each participant experienced only 100 trials of a single decision problem in the domain of either gains or losses. Before these 100 trials, each participant was awarded either a large gain (before the Loss domain trials) or a large loss (before the Gain domain trials). The proportions of sure-thing choices were then observed across these 100 decision trials.

Materials. Study 2 used the same six decision problems used in Study 1.

Participants. The participants (N=78) were recruited in the same manner as Study 1 participants.

Procedure. Before beginning the learning trials, each participant was given the choice of three envelopes. In each envelope was a positive or negative number that was described to the participant as a monetary gain or loss. Subjects in the Loss condition were awarded a large initial gain, and participants in the Gain condition were awarded a large initial loss. The amounts used for endowment of the initial large gain or loss were generated for individual participants based on a normal distribution with mean and standard deviation matched to the distribution of cumulative outcomes earned by participants for each corresponding problem in Study 1 Set 1 trials. It was explained to the participant that the gain (loss) shown in the envelope was his/her starting position, and that the outcomes of all subsequent decision trials would be combined with this initial stake to determine the participant's final outcome position, which would determine his/her pay (as in Study 1).

Participants then responded to each of 100 repeated trials of a decision problem shown on the screen. There were 12-14 participants in each condition (i.e., for each decision problem). The interface for each decision trial was identical to that used in Study 1.

Results

The mean proportion of sure-thing choices in the first and last block of trials is shown in Table 1 for all six decision problems. For Study 2 Gain trials, the mean first-block proportion of sure-thing choices was .47, versus .49 for Study 1 Set 1 Gain trials (see Figure 2). This difference was not significant, $t(86) = 0.322$, $p=.748$. Thus, the "endowment" manipulation of a large initial loss had virtually no effect on initial risk preference levels for Gain problems. However, for Study 2 Loss trials the initial (first-block) propensity to select the sure-thing option (.29) was significantly higher than the initial level (.14) shown in Study 1 Set 1 Loss trials, $t(84) = -2.602$, $p=.011$, and was virtually identical to the initial level of .30 shown by participants in Study 1 Set 2 Loss trials after they had experienced 100 Gain trials (see Figure 2).

Table 1. Study 2 trials: Initial and final block proportions of sure-thing choices for six decision problems, with mean initial endowments. (N=78 participants total).

Problem:	Mean Endowment:	Initial Block	Final Block
G1 ($5; $100, .1)	-$718.72	.56	.28
G2 ($9; $100, .1)	-$975.85	.51	.64
G3 ($9; $20, .5)	-$922.43	.34	.34
(Gain overall)	-$872.33	.47	.41
L1 (-$5; -$100, .1)	$738.29	.18	.29
L2 (-$9; -$100, .1)	$946.82	.31	.50
L3 (-$9; -$20, .5)	$951.19	.35	.45
(Loss overall)	$878.77	.29	.42

Thus, the effects of 100 preceding Gain trials on initial risk preferences for the Set 2 Loss problems (Study 1) is roughly equivalent to the effects of receiving a single windfall gain of comparable magnitude (Study 2), nudging people toward a (maximizing) strategy of favoring small sure losses. However, a large initial loss does not affect behavior in repeated Gain trials.

Changes in risk propensity across the five blocks of Study 2 learning trials were also assessed. The interaction between Block and Domain was significant, $F(4,304) = 3.692$, $p=.016$, Huynh-Feldt $\varepsilon=.681$, indicating that the trends across blocks differed for Gains and Losses. For Gains, there was a non-significant decline in the proportion of sure-thing choices, from .47 in Block 1 to .41 in Block 5, $F(4,156) = 0.551$, $p=.621$, $\varepsilon=.639$. For Losses there was a large (significant) increase in the proportion of sure-thing choices across blocks, from .29 in Block 1 to .42 in Block 5, $F(4,148) = 4.393$, $p=.013$, $\varepsilon=.552$. These trends closely resemble those for Study 1 Set 1 trials, though the curves are shifted in their "intercepts" or initial levels (Figure 2).

Discussion

The results of Study 2 replicate the Study 1 finding that making repeated decisions with outcome feedback has the long-term (100 trials) effect of reducing risk-seeking in the Loss domain. However, the major goal of this study was to investigate whether the cross-domain "intercept" effects of prior experience found in Study 1 are due to framing/aggregation of monetary outcomes or to learning in the direction of EV-maximization.

The obtained results show that merely endowing participants with a large initial gain has an effect on initial risk propensity for Loss trials, significantly increasing the proportion of sure-thing choices in the first block of Loss trials. The size of the effect is comparable to the effect found in Study 1 where participants actually experienced 100 previous gain trials, suggesting that framing processes are a sufficient explanation for the effects of prior Gain trials on initial risk-seeking propensity in the Loss domain. Participants may have felt that they were "playing with the house money" (Thaler & Johnson, 1990). In contrast, for Gain problems, there was no significant effect of "endowing" participants with a large initial loss (cf. Fatás, Jiménez, and Morales, 2011).

General Discussion

The present empirical results confirm and extend previous findings (e.g., Chen, 2001; Yechiam & Busemeyer, 2005; Jessup et al., 2008) that experienced outcome feedback can change people's choice propensities in a repeated *description-based* risky decision task (involving losses), even though complete information about outcomes and contingencies is given at the outset (cf. Newell & Rakow, 2007, for similar conclusions involving a prediction task).

It is interesting to compare initial preferences (first-trial and first-block) in this repeated-trials task with available data on preferences for the same problems in a standard single-trial description-based decision paradigm (Chen & Corter, 2006). In that study, for single trials, the mean proportion of sure-thing choices for Gain problems G1-G3 was .54. Here, the first-trial mean proportion of sure thing responses for Gain problems was .52, a nearly identical level, and .49 for all 20 first-block trials. For Loss problems, the single-trial level of sure-thing responses (from Chen & Corter, 2006) was .46, compared to .27 for first-trial and .14 for first-block trials here. Thus, it seems that in the Loss domain merely *knowing* that one will face repeated trials of a risky decision problem intensifies risk seeking.

Study 1 and Study 2 document a number of other asymmetries between the Gain and Loss domains: experiencing outcome feedback for each trial can affect description-based decisions in the Loss domain, but does not seem to do so for Gains. Also, the effect of a "windfall" gain can affect initial decisions under (described) risk in the Loss domains (decreasing risk seeking), while a large one-time loss does not significantly affect decisions in the Gain domain. The specific asymmetries echo previous findings (e.g., Schneider, 1992; Chen & Corter, 2006) that decision makers show more inconsistency in choice when decisions are framed in terms of losses, and are consistent with Dunegan's (1993) suggestion that Gain and Loss problems may invoke different types of processing. Finally, our analysis of sequential effects in Study 1 show that a risky-gain payoff does not act as a positive reinforce, but an experienced risky loss does seem to act as a punishment, reducing subsequent choices of that option.

These results shed light on possible mechanisms whereby experience might affect description-based decisions. Simple reinforcement learning between the sure-thing and risky options, suggested by March (1996) to create domain-specific risk preferences, cannot account for the full pattern of our results. One possible mechanism causing EV-consistent responses to increase with substantial experience is learning affecting the decision-weight function that brings the function closer to linear, thus making choices more consistent with EV-maximization. But another possibility involves conscious selection among strategies (cf. Erev &

Barron, 2005), specifically, that more participants are *explicitly* calculating EV and basing their decisions on that criterion. Both types of processes, implicit learning of more linear decision weights and conscious selection of strategies, may in fact affect behavior in sequential description-based decisions. Thus, dual-systems accounts of cognition (e.g., Sloman, 1996; Camerer, Loewenstein, & Prelec, 2005) may be needed to provide complete descriptions of decision behavior in such situations.

Acknowledgments

Study 1 reported here was conducted as part of the first author's dissertation research (Chen, 2001). He wishes to thank the members of his dissertation committee, especially Ido Erev and Elke Weber, for their helpful advice. We also thank Yi-Chun Chen for her assistance in running Study 2.

References

Barron, G., & Erev, I. (2003). Small feedback-based decisions and their limited correspondence to description-based decisions. *Journal of Behavioral Decision Making, 16(3*), 215-233.

Barron, G., & Leider, S. (2010). The role of experience in the Gambler's Fallacy. *Journal of Behavioral Decision Making, 23(1)*, 117-129.

Biele, G., Erev, I., & Ert, E. (2009). Learning, risk attitude and hot stoves in restless bandit problems. *Journal of Mathematical Psychology, 53*, 155–167

Camilleri, A. R., & Newell, B. R. (2009). The role of representation in experience-based choice. *Judgment and Decision Making, 4*(7), 518.

Camerer, C. F., Loewenstein, G. W., & Prelec, D. (2005). How neuroscience can inform economics. *Journal of Economic Literature, 43(1)*, 9-64.

Chen, Y.-J. (2001). The role of learning in risk preferences for single- and multiple-play gambles. Unpublished Ph.D. dissertation, Teachers College, Columbia University.

Chen, Y.-J., & Corter, J. E. (2006). When mixed options are preferred in multiple-trial decisions. *Journal of Behavioral Decision Making, 19(1)*, 17-42.

Dunegan, K. J. (1993). Framing, cognitive modes, and image theory: Toward an understanding of a glass half full. J*ournal of Applied Psychology, 78(3)*, 491-503.

Erev, I. & Barron, G. (2005). On adaptation, maximization, and reinforcement learning among cognitive strategies. *Psychological Review, 112*, 912–931.

Fatás, E., Jiménez, F., & Morales, A. J. (2011). Controlling for initial endowment and experience in binary choice tasks. *Journal of Risk and Uncertainty, 43*, 227–243.

Hadar L, & Fox C. (2009). Information asymmetry in decision from description vs. decision from experience. *Judgment and Decision Making*, 4(4), 317-325.

Hau, R., Pleskac, T. J., & Hertwig, R. (2010). Decisions from experience and statistical probabilities: Why they trigger different choices than a priori probabilities. *Journal of Behavioral Decision Making, 23,* 48–68.

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science, 15(8)*, 534–539.

Hertwig, R., & Erev, I. (2009). The description-experience gap in risky choice. *Trends in Cognitive Sciences, 13,* 517-523.

Jessup, R. K., Bishara, A. J., & Busemeyer, J. R. (2008). Feedback produces divergence from Prospect Theory in descriptive choice. *Psychological Science, 19,* 1015-1022.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An analysis of decision under risk. *Econometrica, 47(2),* 263-292.

March, J. G. (1996). Learning to be risk averse. *Psychological Review*, *103*, 309–319.

Newell, B. R. & Rakow, T. (2007). The role of experience in decisions from description. *Psychonomic Bulletin and Review, 14,* 1133-1139.

Rakow, T., & Newell, B. R. (2010). Degrees of uncertainty: An overview and framework for future research on experience-based choice. *Journal of Behavioral Decision Making, 23,* 1–14.

Redelmeier, D. A., & Tversky, A. (1992). On the framing of multiple prospects. *Psychological Science, 3*, 191–193.

Schneider, S. L. (1992). Framing and conflict: Aspiration level contingency, the status quo, and current theories of risky choice. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 18,* 1040-1057.

Sloman, S. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin, 119,* 3–22.

Thaler, R., & Johnson, E. (1990). Gambling with the house money and trying to break even: effects of prior outcomes on risky choice. *Management Science, 36(6),* 643–660.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 9,* 195–230.

Yechiam, E., Barron, G., & Erev, I. (2005). The role of personal experience in contributing to different patterns of response to rare terrorist attacks. *The Journal of Conflict Resolution*, 49(3), 430-439.

Yechiam. E., & Busemeyer, J.R. (2005). Comparison of basic assumptions embedded in learning models for experience based decision-making. *Psychonomic Bulletin and Review, 12(3),* 387-402.