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Feedback Produces Divergence from Prospect Theory in Descriptive Choice

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Abstract

Recently, Barron & Erev (2003) demonstrated that individuals making experience-based choices underweight small probabilities, in contrast to the overweighting observed during decisions in a typical descriptive paradigm. Here we tested whether the reception of trial by trial feedback in a repeated descriptive paradigm would engender choices more correspondent with the experiential or descriptive paradigms. The results of a repeated gambling task indicated that individuals receiving feedback underweighted small probabilities, relative to their no feedback counterparts, implicating feedback as a critical component during the decision making process, even in the presence of fully specified descriptive information. A model comparison at the individual subject level suggested that feedback drove individuals' decision weights towards objective probability weighting.

Feedback Produces Divergence from Prospect Theory in Descriptive Choice

On June 19th, 1986, a college student died in his dorm room from cocaine intoxication. This was no ordinary student: it was Len Bias, who two days earlier was drafted second overall by the Boston Celtics basketball team. Bias – whose talent was sometimes compared to Michael Jordan's– was about to sign a contract worth more than imaginable while growing up; unfortunately, a poor decision cut short all of his opportunities.

Even though it was well established by this time that cocaine use, in rare circumstances, could result in death, it might be said that Bias "underweighted" the small probability of this most terrible outcome. He had observed the repeated choices of his friends who consistently obtained the pleasant outcome of drug use as opposed to the fatal outcome (*The New York Times*, 1987). This is a real-world example of the important difference between descriptive and experiential choice. Although Bias almost certainly knew *descriptively* that cocaine use had as a possible outcome the rare event of death, he also *experienced* (through his friends and his own use) that this tragic outcome was rare. Recent laboratory experiments confirm that people make different decisions based on experiential versus descriptive information (Barron & Erev, 2003). We are interested in 1) what makes people choose differently across these two paradigms and 2) what theoretical component of the decision process incorporates the dynamics causing this difference.

Descriptive choice paradigms are the basis of most models of decision making. In the descriptive paradigm, participants choose between options, with possible outcomes and probabilities of each outcome fully described[1]. For many years, economists assumed that individuals behaved according to a rational theory called expected utility theory (EUT; Bernoulli, 1738/1954; von Neumann & Morgenstern, 1944); Kahneman and Tversky later proposed prospect theory (PT; 1979; Tversky & Kahneman, 1992) to account for many systematic violations of EUT observed in descriptive choice. PT incorporated into EUT, among others, three new concepts: overweighting of small probabilities (where small probability events are considered more likely to occur than in reality), the risk reflection effect (where people avoid risk when choosing between gains but seek risk when choosing between losses), and loss aversion (where losses have more impact than gains of equal magnitude). The first two concepts allow PT to account for an interesting pattern of preferences for risky choices. To illustrate, consider the following option pairs:

A1: 3 for sure

B1: 4 with probability .8; else 0

A2: 3 for sure

B2: 32 with probability .1; else 0

When all outcomes are positive, A1 is preferred over B1, whereas B2 is preferred over A2; but when all outcomes are negative, B1 is preferred over A1 whereas A2 is preferred over B2. Thus, the following four-fold pattern is observed in descriptive choice: risk aversion when the risky gamble has a high probability to win or low probability to lose, and risk seeking when the risky gamble has a low probability to win or a high probability to lose.

Because humans can understand and work with symbols representing probabilities and values, descriptive choice is possible; but, non-humans are unable to choose descriptively; therefore, choices by animals represent experiential choice. In contrast to the predictions of PT, the choices of bees (Real, 1987) are best described as underweighting of small probabilities, a behavioral pattern also observed in human experiential choice (Benartzi & Thaler, 1995; Thaler, Tversky, Kahneman, & Schwartz, 1997; Weber, Shafir, & Blais, 2004; Newell & Rakow, in press)

To gain a better understanding of the difference between experiential and descriptive choice, Barron & Erev (2003) examined several core concepts of PT using an experiential choice paradigm. Specifically, participants learned about the distribution of outcomes through repeated choice and subsequent feedback; no descriptive information about possible outcomes and their likelihoods of occurring were given beyond the post-choice feedback. Remarkably, they observed that in all but one of the cases they tested the patterns of preference were the opposite of what PT predicted. For example, underweighting of small probabilities was observed in experiential choice rather than the overweighting posited by PT. In other words, the converse of PT best predicted the results!

Naturally, several possible explanations exist for this discrepant behavior between descriptive and experiential paradigms. First, the experiential paradigm requires individuals to learn about payoff distributions whereas the descriptive paradigm informs individuals about payoff distributions; thus, learning represents a key component of the experiential choice paradigm. As a result, learning is typically not included in theories derived from descriptive choice; in contrast, theories derived from experiential choice include learning mechanisms, typically reinforcement learning (e.g., Sutton & Barton, 1998; Erev & Barron, 2005; Busemeyer & Stout, 2002).

Second, the experiential paradigm requires repeated choice whereas the descriptive paradigm is often conducted using a single choice. Hertwig, Barron, Weber, and Erev (2004) sought to eliminate this methodological difference as an explanation by allowing participants in the experiential condition to "sample" from the options in order to learn about the distribution of payoffs, but the observed samples were not considered choices. After sampling to their satisfaction, participants made a single choice for which they would receive payment. Thus, participants in both the descriptive and experiential conditions made one relevant choice; again, participants in the experiential condition behaved conversely to PT (Hertwig et al., 2004).

It's possible that the underweighting of rare events in this paradigm may simply result from sampling bias (Fox & Hadar, 2006; Hertwig et al., 2004; Rakow, Demes, & Newell, 2007). That is, in the experiential condition, participants do not know the true payoff distribution: they only observe a small sample. With small samples, rare events are likely to be underrepresented, and so resultant behavior would correspond with small probability underweighting. For example, when a sample of N=7 draws is taken from a distribution paying 64 with a probability of .05, otherwise nothing, the 64 outcome will rarely occur, effectively rendering the expected payoff equal to 0. However, even in experiments with relatively large samples (e.g., Barron & Erev, 2003, used >100 trials), small probabilities are underweighted. Consequently, the sampling bias explanation cannot account for the entire paradigmatic difference.

Third, the experiential paradigm requires feedback whereas the descriptive paradigm does not. Yechiam and Busemeyer (2006) observed that when given descriptive information and feedback about the outcome of their choice, individuals reverse preference with experience.

Specifically, individuals were given an endowment and then chose repeatedly between the following two risky gambles:

A3: Lose 8 with probability .005; else lose 2

B3: Lose 300 with probability .005; else lose 1

Individuals initially preferred the riskier option (B3), but after feedback eventually came to prefer the safer option (A3)[2]. However, some unique features of this task prevent strong conclusions about PT-convergent versus divergent behavior: 1) the payoff structure involved only risky gambles as opposed to completely safe alternatives, 2) individuals were guaranteed to lose money on each trial, and 3) the probabilities involved were extreme and very rarely experienced. These features preclude this work from being considered a strong test of PT assumptions.

On the basis of the above results, we hypothesized that feedback is the crucial arbiter dictating whether participants underweight or overweight small probabilities. To test this feedback hypothesis in isolation, we held constant the repeated nature of the two methods and eliminated the necessity of learning about payoff distributions, allowing only the feedback component to vary. Further, we wanted to specifically focus on the observation that when outcomes are positive, small probabilities are overweighted in descriptive choice but are underweighted in experiential choice. Consequently, we tested both the upper and lower portions of the probability spectrum insuring that any observed underweighting was not attributable to expected value adherence with repeated choice.

We predicted that when outcome feedback was not given, individuals would conform to PT and overweight small probabilities, thus preferring a small certain win over a risky high probability gamble, but preferring a risky low probability gamble over the same small certain win. Conversely, when given feedback, we predicted individuals would underweight small probabilities and show the opposite choice pattern.

Additionally, we were interested in discerning which theoretical component of the decision process incorporated the dynamics producing such behavioral disparities between the two paradigms. In correspondence with our prediction that people would overweight small probabilities when not receiving feedback but underweight them when receiving feedback, we predicted that the theoretical analysis would reveal that the feedback manipulation affected a probability weighting parameter.

The model used for this theoretical analysis was a modified version of decision field theory (Busemeyer & Townsend, 1993). Decision field theory is a dynamic and stochastic model of choice accounting for a wide variety of empirical findings within both the descriptive and experiential choice paradigms (Busemeyer & Diederich, 2002; Busemeyer, Johnson, & Jessup, 2006). In decision field theory, attention switches between outcomes with the amount of attention applied to each outcome a function of the probability of receiving that outcome. This attention-switching activity results in a relative preference for each outcome at each moment and these preferences change over time until preference for one option surpasses a threshold, at which point that option is chosen. Other probabilistic choice models could have been applied to this data set; consequently, our model analysis was not a test of decision field theory but rather a tool for examining which parameters changed because of the feedback manipulation.

To address the prediction concerning the weighting of small probabilities, a probability weighting function modified the attention-switching activity of decision field theory (Prelec, 1998). In this model, small probabilities can be overweighted (probability weighting parameter λ<1), underweighted (λ>1) or objectively weighted (λ=1). The exact computation for decision field theory and the probability weighting function can be found in the Appendix.

Methods

Twenty nine participants were recruited from Indiana University and completed 120 trials for both conditions (counterbalanced) of a repeated measures design experiment. The High Probability (HP) condition consisted of a choice between the following two options:

Option HP_S: win 3 cents for sure

Option HP_R: win 4 cents with probability .8; else 0

The Low Probability (LP) condition consisted of these choices:

Option LP_S: win 3 cents for sure

Option LP_R: win 64 cents with probability .05; else 0

Participants were randomly assigned to No Feedback (NFB; n = 15) and Feedback (FB; n = 14) groups. Both groups received all descriptive information about the gambles and made repeated choices. The only difference was that the FB group received feedback indicating their winnings on the previous trial whereas the NFB group did not.

Because we anticipated that individuals would experience boredom when confronted with the exact same decision repeatedly, especially when not receiving feedback, the win amount for the risky gamble varied slightly on each trial, with the minimum expected value for the risky gamble equated with the sure thing option. A total of five different expected values were shown for the risky gamble (range(EV) = [3, 3.4]) for both conditions, and the five different expected values were equated across both conditions. The risky gamble with an expected value of 3.2 was shown twice as often as the other four gambles. Furthermore, a post-task item assessed the extent to which participants were bored by the task on a 1-5 Likert scale, ranging from ‘Very slightly or not at all’ to ‘Extremely’.

Participants received instruction and training and completed several practice trials before beginning the procedure. Further, they learned that the amount of money they would earn depended on their choices. On each trial, they observed pie charts indicating the amount of money that could be won with the size of the pie pieces indicating the probability of winning the displayed amounts. At the end of the experimental session, they were paid $7 for their time as well as the amount of their cumulative winnings.

Note that four patterns of responding were possible: 1) individuals could adhere to expected value and consequently prefer the risky gamble in each pair (HP_R and LP_R), 2); individuals could be risk-averse and choose the sure thing in each pair (HP_S and LP_S), 3); individuals could choose in accordance with PT and thus overweight small probabilities (choosing HP_S and LP_R), 4); or they could choose in opposition to PT and underweight small probabilities (choosing HP_R and LP_S).

Results

Statistical Analyses

Figure 1 shows the preference for the sure thing option relative to the risky gamble (LP condition in the upper portion, HP condition below) for the FB and NFB groups, plotted as a function of blocks of ten trials. We hypothesized that descriptive choice with no feedback would result in overweighting of small probabilities whereas descriptive choice with feedback would result in underweighting of small probability events. This prediction was supported by the data. The probability of choosing the sure thing was analyzed with a mixed ANOVA, using Condition (LP or HP) and Block (12 blocks of ten trials each) as within subjects factors, and Group (NFB or FB) as a between subjects factor. There was a significant Group x Condition interaction ($F_{1,27} = 4.76$, $p < .05$, Cohen's $f = .41$) . No other comparison was significant at the .05 level.

[*Insert Figure 1*]

Whereas the NFB group behavior generally conformed to theories derived from a descriptive paradigm (e.g., PT), participants in the FB condition behaved otherwise, underweighting the small probabilities relative to their NFB counterparts. Consequently, feedback alone was enough to drive participants to underweight small probability events. It is possible that the NFB group experienced more boredom in the task than the FB group and that this boredom accounts for any observed behavioral difference. However, responses to the boredom assessment item did not significantly differ across groups ($t_{24} = 1.25$, $p = .22$).

Theoretical Analyses: Which Parameter did Feedback Alter

The FB group may have appeared to underweight small probabilities relative to those in the NFB group, but which theoretical component in decision field theory varied between groups to produce the differential behavior? There are several possibilities including changes to the (a) weight or attention given to probabilities, (b) utility function capturing risk seeking and risk aversion tendencies, or (c) threshold controlling the tendency to maximize utility or choose randomly; these concepts are represented by the free parameters λ, α, and θ, respectively.

Decision field theory was fit to the choice probabilities for each individual's data. Table 1 shows the medians of the best fitting parameters that maximized the likelihood of each subject's choices. The decision field theory likelihoods were compared to the likelihoods of a baseline model which perfectly reproduced the marginal choice probabilities for each gamble pair. This comparison used the Bayesian Information Criterion (BIC; Schwarz, 1978, which penalizes models for each additional parameter; thus, adding extra parameters will not necessarily improve the BIC (see the Appendix for information concerning the estimation procedure, baseline model, and computation of the BIC). The BIC indicated that decision field theory provided a superior fit on 13 out of 15 NFB participants and 11 out of 14 FB participants and consequently fit the data quite well[3]. Figure 2 presents the observed choice behavior and model predictions. The plots were generated by obtaining the predictions from the best fitting parameter values at the individual level and using the mean of these predictions.

[*Insert Figure 2*]

We then compared the obtained best fitting parameters across the two conditions. As a reminder, we predicted that the probability weighting parameter λ would account for the different choice behavior across groups. As predicted, the λ parameter was higher in the FB group than the NFB group, indicating that individuals who received feedback underweighted small probabilities relative to their NFB counterparts. A Mann Whitney U test of the three free parameters revealed that only the probability weighting parameter λ differed significantly between groups, $z=2.25$, $p<.05$. However, as Table 1 demonstrates, $\lambda \approx 1$ for the FB group, and thus does not reflect underweighting, but rather objective weighting of small probabilities.

[*Insert Table 1*]

To summarize, the data conformed to our predictions of PT-convergent behavior when feedback was *not* provided (as indicated by overweighting of small probabilities) but PT-divergent behavior when feedback *was* provided (as indicated by relative underweighting of small probabilities). A theoretical analysis supported the above finding, showing that feedback specifically altered the probability weighting parameter. But, this analysis also revealed that feedback coupled with description drives subjective probabilities towards their objective values.

Discussion

The results of this study implicate feedback as the crucial arbiter between experiential and descriptive choice. Apparently, feedback overwhelms descriptive information and drives individuals toward the objective probabilities (as indicated by $\lambda \approx 1$ in FB group). Due to the task design, the difference cannot be attributed to sampling bias.

The findings are interesting for a variety of reasons. First, that feedback alone drives individuals to the objective probabilities bears relevance to many current studies. For example, in most studies testing behavioral models of choice, feedback is often not provided. However, neuroimaging studies concerned with substrates and networks of reward and decision mechanisms typically provide feedback after each trial. Consequently, the observed neural substrates of choice may not correspond with the neural mechanisms actually used in the behavioral studies that inspired them!

Second, these results suggest that previous observations of small probability underweighting in experience-based tasks might possibly be described as objective probability weighting coupled with risk aversion. In several of the cases reporting underweighting of unlikely events, a utility parameter was not applied to the outcomes; the failure to do so could produce the appearance of underweighting. However, these other cases (e.g., Barron & Erev, 2003; Hertwig et al., 2004) also differed from our experiment by not including descriptions in the experiential condition. Thus, feedback coupled with description might be needed for approximately objective weighting.

These results do not implicate feedback as the sole factor determining whether or not small probability events are overweighted, as several other factors could still be involved; the fact that the median best fitting probability weighting parameter across NFB individuals was higher than usual attests to this. This mildly atypical finding could have been driven by the small outcomes, parametric modulation of the risky outcomes, or repeated nature of the task. However, this does not minimize the observation of significantly different behavior based only on the reception of feedback.

Though a particular model analysis (decision field theory) was reported here, we actually considered multiple models, as our objective was to use a model applicable both when feedback was and was not given (and thus no learning occurred). For the FB participants, we compared 11 other models, including models with delta and Bayesian learning rules, and also a softmax choice rule (Sutton & Barto, 1998). The softmax choice rule was also fit to the NFB participants. However, these models produced inferior BIC scores relative to the no learning implementation of decision field theory; the inferiority of the learning models was likely due to the swiftness of learning. Possibly, the feedback coupled with the descriptions combined to produce rapid learning (c.f. Stout, Rock, Campbell, Busemeyer, & Finn, 2005). The softmax choice rule, though its BIC score was slightly inferior to that obtained by decision field theory across all subjects, produced the same conclusions: only the probability weighting parameter differed significantly between groups.

To conclude, these results indicate that individuals respond differently depending upon whether they receive feedback after their choices, even when provided with complete descriptive information. Further, this suggests that feedback plays a crucial role in differentiating between experiential and descriptive choice behavior. The observed behavioral difference has implications for behavioral choice theories in economics and psychology as well as neurophysiological studies seeking to uncover the neural substrates underlying choice behavior.

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Appendix

Decision Field Theory

In decision field theory, preference for an option accumulates at each time step in accordance with a diffusion process until preference for an option exceeds a preset threshold. This particular implementation of decision field theory corresponds with a Wiener process (see Busemeyer & Townsend, 1993, Appendix):

$$\Pr(x_i \mid X) = \frac{e^{4\cdot\left(\frac{d}{\sigma}\right)\cdot\left(\frac{\theta}{\sigma}\right)} - e^{2\cdot\left(\frac{d}{\sigma}\right)\cdot\left(\frac{\theta}{\sigma}\right)}}{e^{4\cdot\left(\frac{d}{\sigma}\right)\cdot\left(\frac{\theta}{\sigma}\right)} - 1} \qquad \text{(A1)}$$

where the term on the left denotes the probability of choosing option i out of the set of all options X. The drift rate d is the difference between the mean valences of the two options, the diffusion rate σ is the square root of the sum of the variance of the two options, and the threshold θ represents the absorbing boundary to which preference accumulates. The drift rate d is computed as follows:

$$d = V_A - V_B \qquad \text{(A2)}$$

V_i represents the mean valence for option i and is derived according to:

$$V_i = \sum_{j=1}^{N} w_{ij} \cdot x_{ij}^{\alpha} \qquad \text{(A3)}$$

In the above equation, w_{ij} represents the attention weight given to outcome j when considering option i, and x_{ij}^{α} represents the utility of outcome j produced by option i. The parameter α is a utility parameter; $\alpha<1$ denotes decreasing sensitivity to differences in outcome magnitude as magnitude increases. The attention weights were computed from a formula proposed by Prelec (1998) which takes the following form:

$$w = e^{(-(-\log p)^{\lambda})} \qquad \text{(A4)}$$

Here, p is the objective probability of an outcome and λ is the probability weighting parameter. The diffusion rate σ was computed as follows:

$$\sigma = \sqrt{\sum w_{ij} \cdot (x_{ij}^{\alpha} - V_i)^2} \qquad \text{(A5)}$$

Consequently, the parameters d and σ were derived from the stimuli and the parameters λ and α were free to vary. The third free parameter was the standardized threshold, θ/σ.

Maximum Likelihood Estimation

The parameter values which maximized the likelihood of the data were estimated according to:

$$LL_M = C + \sum_i^N \ln(\hat{y}_M) \cdot y_i \qquad \text{(A6)}$$

where LL is the log likelihood of the data given the model parameter values, y_i is the number of times option i was chosen, $\hat{y}_M$ represents the predicted choice proportion for the model M ; N=10 different gamble pairs, five in each condition. C is a constant that cancels out and is thus ignored. Maximum likelihood estimation was performed in Matlab using the robust combination of a simplex search (Nelder & Mead, 1965) and multiple random starting points.

Baseline Model

The baseline model used here experiment assumed that a multinomial process generates choices (see Busemeyer & Stout, 2002). This baseline model perfectly reproduces the marginal choice probabilities for each of the gamble pairs and consequently has a SSE of 0. However, the model has one free parameter for each of the gamble pairs and is thus punished by the BIC due to the large number of free parameters.

Model Comparison

The BIC was used to compare the performances of the baseline model and decision field theory. The formula for the BIC is:

$$BIC = 2 \cdot (LL_{DFT} - LL_B) + k \cdot \ln N \qquad \text{(A7)}$$

Here, k represents the difference in the number of degrees of freedom for the two models being compared (7) and N is the number of data points (i.e., 240 trials, since the models are compared at the individual level). In this formulation, positive BIC values indicate better model performance for decision field theory than the saturated model.

Author Note

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Footnotes

[1]*Descriptive choice* is distinct from *descriptive theories of choice* that seek to describe *how* people choose, in contrast with *normative theories* which explain *what people should* choose.

[2] At first glance these results seem to contradict other work using completely described gambles with a similar payoff structure, using groups making a single descriptive choice (to be played 100 times) or 100 choices with feedback after every trial (Yechiam, Barron, & Erev, 2005). In that work, individuals choosing descriptively preferred the safe option but those choosing experientially preferred the risky option. However, that experiment consisted of 100 trials whereas the Yechiam and Busemeyer (2006) task consisted of 400 trials, analyzed in blocks of 50. Consequently, it's possible that on the first trial individuals preferred the safe option, then quickly moved towards the risky option and only after 100 trials began the approach towards expected value maximization, favoring the safe option.

[3]Median R^2 values were .91 and .84 for the NFB and FB groups, respectively. It is possible that these values could be improved upon because we 1) maximized the likelihood rather than R^2 and fit the individual as opposed to the group data. We also tested the nested models within this decision field theory implementation and found that the three parameter version produced superior BIC scores.

Table 1

Median BIC and Best Fitting Parameter Values Separated by Group

Group	BIC	λ	$1/\theta$	α
NFB	19.78	0.90	0.04	0.92
FB	19.94	0.98	0.13	0.98

Note. All data was fit at the individual level. BIC is positive where decision field theory outperformed the baseline model. Parameters: λ is a decision weight parameter from Prelec (1998); θ controls the extent to which a participant behaves deterministically; α is a utility parameter. NFB = No Feedback; FB = Feedback; BIC = Bayesian Information Criteria.

Figure Captions

Figure 1. Choice probability for the sure thing for the feedback (dashed lines) and no feedback (solid lines) groups, in 12 blocks of 10 choices. The upper portion shows choice probability from the low probability gamble pair. The plots on the far right indicate the overall mean choice behavior collapsed across blocks. The error bars represent the standard error of the mean.

Figure 2. Aggregate model fits for feedback (dashed lines) and no feedback groups (solid lines). These were obtained by fitting the model to the observed individual data ('X' for feedback and 'O' for no feedback) and averaging the predictions across participants. There were five different risky gambles in each condition and the sure thing was always 3 cents. The vertical axis gives the choice probability for the sure thing and the horizontal axis gives the value of the risky gamble. The probability of winning the risky amount in the LP gamble (left) was 0.05 and 0.80 in the HP gamble. The error bars represent the standard error of the mean for the observed choice probabilities.

Figure 1

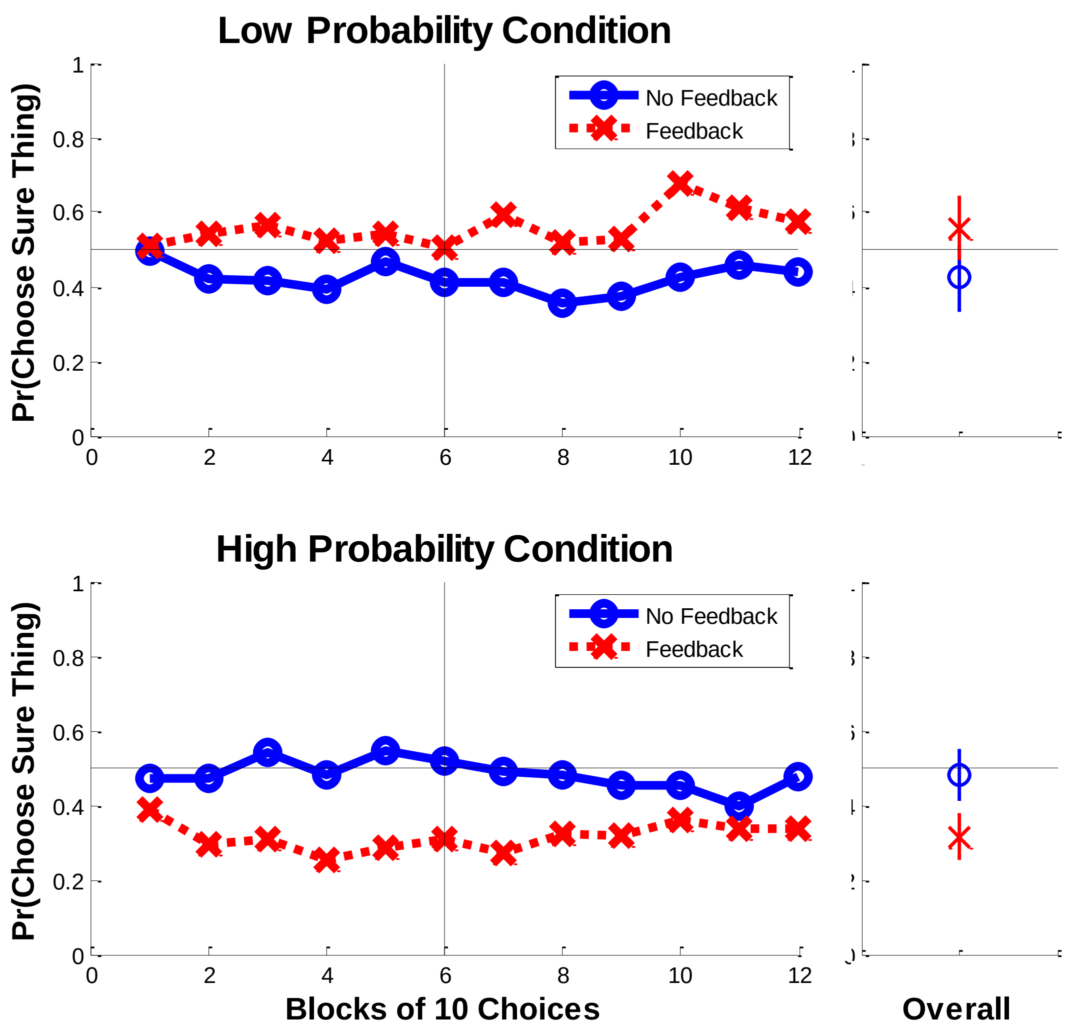
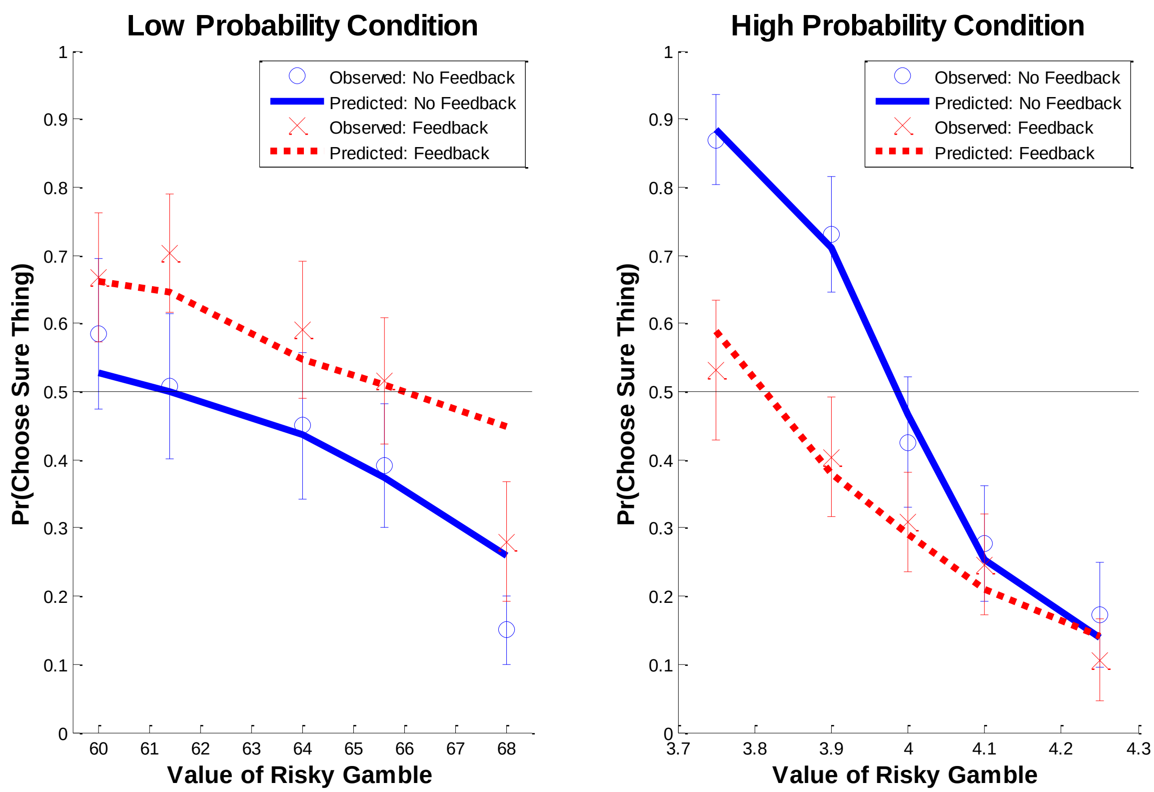

Low Probability Condition
High Probability Condition
No Feedback
Feedback
Pr(Choose Sure Thing)
Blocks of 10 Choices
Overall
0
0.2
0.4
0.6
0.8
1
0
2
4
6
8
10
12

Figure 2


Low Probability Condition
High Probability Condition
Observed: No Feedback
Predicted: No Feedback
Observed: Feedback
Predicted: Feedback
Pr(Choose Sure Thing)
Value of Risky Gamble
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
60
61
62
63
64
65
66
67
68
3.7
3.8
3.9
4
4.1
4.2
4.3