High Stakes Behavior with Low Payoffs: Inducing Preferences with Holt-Laury Gambles

by

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Abstract:
Kahneman and Tversky (1979) argued that risky decisions in high stakes environments can be informed using questionnaires with hypothetical choices. Yet results by Holt and Laury (2002) and Harrison et al (2005) suggest that questionnaire responses and decisions in hypothetical and low monetary payoff environments do not well predict decisions in higher monetary payoff environments. This raises the question of whether investigating decision making in high stakes environments requires using high stakes. Here we show that one can induce preferences using the binary-lottery reward technique (e.g., Berg et al., 1986) in order to study high-stakes decision making with low-stakes. In particular, we induce preferences such that decisions in a low-stakes environments reflect well the choices made in the high stakes environment of Holt and Laury (2002). This finding is of interest to anyone interested in studying high-stakes decision behavior without paying high stakes.

Introduction

Many pressing economic issues, from financial system bailouts to asset market bubbles to CEO salaries, involve decisions in high stakes environments. In order to test theories relevant to these environments one might need to wait for months (or years) for the appropriate data to become available. If the situation is pressing, and advice is needed quickly, laboratory experiments are often recommended. Yet laboratory experiments, due to their reliance on typically relatively small pecuniary rewards, may be limited in their ability to study behavior in very high stakes environments. Here we argue that this limitation is not as severe as it might at first seem. Indeed, this paper demonstrates a preference-induction procedure (Berg et al., 1986) that allows researchers to study high-stakes behavior in a cost-effective low-stakes environment.

The role of stake-size has been long debated. For example, Kahneman and Tversky (1979) defended hypothetical choices by arguing that subjects have no reason not to tell the truth. Also, Camerer and Hogarth (1999) argued that choices may involve differential productive effort, which can affect what the experimenter observes. Even when choices involve dollars, cognitive costs may lead to distortions from a subject's true preferences. Camerer and Hogarth (1999) asserted further that experiments using salient rewards have not overturned "anomalies" observed in hypothetical choice environments. Harrison (1994), on the other hand, argued that changing incentives affects choices in the Allais Paradox and also preference reversals. His observations may suggest concerns for experiments using small cash payments.

Responding to such concerns, Holt and Laury (2002) (henceforth, HL) conducted risk-elicitation games using high stakes.Their study (details in section 2.2) focuses on a sequence of paired lottery comparisons under both hypothetical and real-dollar payments. They find that choices under hypothetical payments do not vary with stake-size, while people display increasing risk aversion as real dollar stakes increase. HL's finding emphasizes the importance of salient rewards, but also leaves as an open concern whether one can learn about high-stakes decision making using small-stakes environments. This concern is reinforced by experiments reported by Fehr-Duda et al. (2010), which point to the importance of emotions in influencing high-stakes decisions.

Despite these concerns, this paper reports evidence that one can use low stakes experiments to produce choices that well-reflect decisions made in that same environment when stakes are much higher. In particular, we show that one can induce preferences (Roth and Malouf, 1979 and Berg et al., 1986) in such a way that high-stakes behavior is generated in a low-stakes environment.

2 Background

2.1 Background on Inducing

The preference-induction technique (Roth and Malouf, 1979; Berg et al., 1986) has found multiple uses. Several reviews of the technique exist and suggest that risk aversion can be induced successfully, though there remain mixed results for risk-seeking and risk neutral preferences (for reviews see Davis and Holt, 1993; Roth, 1995; Camerer, 2003).

Two studies have focused on examining anomalies: Harrison (1994) and Selten et al. (1999). Harrison finds that induction mitigates anomalies, while Selten et al. (1999) finds it does not (and in particular, preference reversals continue to appear). However, Berg, Dickhaut, and Rietz (2003) reexamined the Selten et al. (1999) data, and showed that inducing in fact significantly alters the preference reversals, thus reversing the claims of Selten et al. (1999).

2.2 Background on Holt and Laury

The basic HL design is the following: subjects in each treatment made ten decisions between two gambles (illustrated in Table 1a.) One gamble was a "safe" gamble with a small payout difference between the two possible payouts, while the other was "riskier" with a higher difference between payoffs. As seen in the table, the seven treatments run included four degrees of increasing actual stake sizes and three corresponding hypothetical high stakes treatments where subjects' instructions asked what they would do in the event they faced the decisions in an actual high stake environment. Subjects received payment based on one randomly selected draw from their ten decisions.

<Table 1>

The HL results revealed that, for low payoffs, there was no distinction between hypothetical and real payoffs; however, as stakes increased by factors of 20, 50, and 90 there was a marked divergence between the results with payoffs and the results without payoffs. While increasing hypothetical stakes does not lead to changes in decisions, increasing actual stakes leads to higher levels of risk aversion. Figures 1 and 2 describe these results. Note that higher actual payoffs shift the distributions to the right. Their analysis shows that subject decision making can be characterized using a version of the power-expo utility function. We induce this utility function in our experiment.

HL is an ideal study on which to base our analysis for several reasons. First, replicating HL's increasing stake sizes provides us the opportunity to use several different mappings of stake-sizes to choice probabilities, providing evidence on the robustness of the inducing procedure. Second, subjects' decisions in HL involve only individual monetary risk, enabling a clean analysis of the inducing procedure itself absent confounds due to strategic choice.

3 Experimental Design

Our goal is to generate high-stakes behavior in a low-stakes environment. To do this, we incorporate the inducing procedure of Berg et al. (1986) into the HL experimental design, thereby inducing the HL power-expo utility function (equation 1). HLs reported original parameter estimates for the equation were $r=0.269$ (0.017), and $\alpha=0.029$ (0.0025) (Standard Errors in parentheses.)

(1) $$U(X) = \frac{1 - \ exp(-\alpha x^{1-r})}{\propto}$$

We study five treatments. The first four coincide with the four actual stakes treatments in HL (section 2.2 above): Low payouts, 20x payouts, 50x payouts, and 90x payouts. Often times we would like to examine decisions people make under very high sums, thus we expand the manipulation beyond incentives used by HL. The fifth treatment does not occur in HL, but predicts decisions that would occur in 180x the payouts of the HL low payoff treatment. We refer to these treatments as the DHATJ treatments within the tables and figures. Appendix A contains a transcript of the instructions.

3.1 Stage 1

In Stage 1, subjects make a decision between two lotteries, A and B. The Stage 1 decision is the subject's only decision in the experiment. Subjects receive points from the outcomes of their chosen lottery instead of earning cash as in HL. Table 2 lays out each of these ten decisions. As shown, in the first decision, there is a 10% (90%) chance of the high (low) number of points. As subjects proceed through the decisions, the chance increases (decreases) by 10 percentage points with each decision. After a subject makes their decision (A or B) they roll a ten-sided die which determines the number of points they receive. A roll of 1 in the first decision means the subject receives the high number of points, a 1 or 2 in the second decision means they receive the high number of points, a 1, 2, or 3 in the third, and so on.

<Table 2>

Table 3 lays out the points that make up the high and low payouts of each lottery (A and B) in the five treatments. The table indicates that the points earned in each of our treatments coincide precisely with the dollars earned in the corresponding HL treatment (third and seventh columns.) For example if a subject would earn 40 dollars in the HL treatment, they would earn 40 points in our treatment.

<Table 3>

3.2 Stage 2

The conversion of the points, earned in Stage 1, into monetary cash earnings occurs in stage 2. The points a subject receives in Stage 1 translate into chances (Bernoulli trial probabilities) to win a $2.50 prize (more points implies greater probability of the prize.) Table 3 shows the probability that a subject wins the prize for each of the possible number of points earned in each treatment (fourth and eighth columns.) See the supplementary materials for the exact transformations of points to probability for each treatment. Subjects roll a 100-sided die on their desk to determine if they win the prize. For example, when a subject has a 2% chance of the prize, if the die lands with sides 1 or 2 facing up they win the prize, otherwise they do not. Likewise, if a subject has a 73% chance of the prize, with any side between (and including) 1 and 73 facing up, they win the prize. After having rolled the 100-sided die the subject knows that either they have earned $2.50 or earned nothing.

3.3 Discussion

It is worth emphasizing several features of our design. First, the only difference between treatments is in the point payouts (and the related prize probabilities.) Second, note that while the probability of winning the prize changes between treatments, the prize remains at a constant $2.50 in all cases. Thus, while in HL the amount subjects can win increases dramatically through the treatments, in our treatments subjects never receive the opportunity to earn more than $2.50 for any decision (subjects always participate in a low-stakes experiment.) Finally, with the use of the Berg et al., (1986) methodology, there are no wealth effects in our design. Wealth effects are not a problem in this design because we pay subjects in points for their Stage 1 decision. Assuming expected utility maximization, subjects should prefer to choose the point-maximizing option, and this is independent of wealth levels, see Berg et al. (1986) for details. The advantage is that we can pay subjects for each of the ten HL decisions instead of only one randomly selected decision.

3.4 Procedures

Upon arriving to the experiment, the experimenter directs subjects to the appropriate room where they read the instructions in private and listen to the instructions read aloud by the experimenter. The instructions include paid practice to ensure subjects understand the procedures. After the instructions, subjects make their first decision between lotteries A and B. Subjects then roll a ten-sided die at their desk (with the monitor watching) to determine the number of points they receive, which is recorded. The subject follows that roll, immediately, with the roll of a 100-sided die to determine if they win a $2.50 prize. This procedure repeats for each of the ten HL decisions, meaning a subject can earn up to a maximum of $25 regardless of which treatment the subject is participating in.) Subjects receive an additional seven dollars for showing up, and receive their cash payments immediately prior to leaving the laboratory.

3.5 Hypotheses

HL’s hypothetical treatments provide data on how subjects make Stage 1 decisions in the above design, when faced with hypothetical large payments. They found that decisions under hypothetical high stakes were no different from decisions under actual low stakes and significantly different from actual high stakes. Likewise, if preference-induction works, then induced high-stakes behavior should be significantly different from behavior in the HL hypothetical high-stakes environments .

Hypothesis 1 *The distribution of safe choices (choice A) from our real stakes choice data, based on induced preferences, will be statistically distinguishable from the Holt-Laury distribution of safe choices for each hypothetical high stakes treatment.*

Likewise, successfully inducing high stakes subject decision-making behavior requires subjects’ decisions in the induced high stakes environment not to significantly differ from subject behavior under actual high stakes. Hypothesis 2 captures this requirement, using the HL data from their actual stakes treatments as a comparison group. While HL did not use George Mason students, the inducing procedure (using the risk-aversion parameter estimates of HL) should allow us to induce George Mason students to behave as-if they had the same level of risk-aversion as HLs original subjects.

Hypothesis 2 The *distribution of safe choices (choice A) from our real stakes choice data, based on induced preferences, will be statistically indistinguishable from the Holt-Laury distribution of safe choices for each real stakes treatment.*

5 Results

The experiments took place at the Interdisciplinary Center for Economic Science (ICES) at George Mason University, with subjects randomly recruited from the George Mason student body. In addition to any amount earned in the experiment, each subject received seven dollars for arriving to the laboratory on time. Subjects spent about 90 minutes in the laboratory.

We report data from 98 subjects in five treatments: 19 in the Low treatment, 20 in the x20 treatment, 17 in the x50, 21 in the x90, and 21 in the x180. These samples are similar to the sample sizes used by HL in their very high stakes treatments (19 and 18 in their x50 and x90 treatments respectively.) We compare the decisions made by these subjects in our induced stakes environments to the decisions made by the subjects in the comparable experimental treatments in HL.

Result 1: *The distribution of safe choices (the proportion of subjects who chose choice A) from our choice data based on induced preferences is statistically different from the Holt-Laury distribution of safe choices for each of the three Holt-Laury hypothetical high stakes treatments.*

This result supports Hypothesis 1. The three graphs in Figure 1 show that subjects systematically approach induced preference environments differently than they approach hypothetical high stakes environments. Kolmogorov-Smirnov and Kruskal-Wallis tests show significant differences at standard levels for all three treatments. For the Kolmogorov-Smirnov tests: $p=0.046$, $p=0.087$, and $p=0.016$ for the x20, x50, and x90 treatments respectively. For the Kruskal-Wallis: $p=0.032$, $p=0.006$, $p=0.006$ for these same conditions, respectively.

Result 2: *The distribution of safe choices (choice A) from our choice data based on induced preferences is statistically indistinguishable from the Holt-Laury distribution of safe choices for each of the four Holt-Laury real stakes treatments.*

This result supports Hypothesis 2. As the four graphs in Figure 2 show, the distribution of safe choices in each of our induced preference treatments follows that of the distribution of safe choices in HL. We find no significant difference between these two distributions in any of the four treatments with either Kolmogorov-Smirnov two-tailed tests or Kruskal-Wallis two-tailed tests ($p > .10$ in all cases.)

<Figure 2>

Result 3: *The actual distribution of safe choices (choice A) with induced preferences, under simulated high stakes that are 180 times that of Holt-Laury's low stakes, follows the distribution of safe choices predicted by the Holt-Laury power-expo utility function.*

Figure 3 shows what the predicted noisy distribution of decisions would be (using HL's power-expo function) under an actual 180x stakes environment compared to the actual decisions of subjects in our experiment under an induced 180x stakes environment. A chi-squared goodness-of-fit test shows no significant difference between these two distributions (P>0.25).

<Figure 3>

The non-parametric tests used in the three results above provide support for our hypotheses. Parametric analysis, through use of maximum likelihood estimation, can provide further evidence that we are inducing high stakes behavior. The more powerful nature of the parametric analysis not only makes it easier to find a difference between our data and the HL data if one exists, but also uses the information that each of the ten decisions a subject makes are correlated. The non-parametric tests do not incorporate the correlation between the decisions of each subject.

We reach result 4, below, by calculating the maximum likelihood estimates (using the methods of Harrison 2008) of the power-expo utility parameters of HLs equations 1 and 2. We slightly modify HL's original equations by including parameters μ_2, r_2, and α_2, which act to capture any differences between our data and HL's (δ is a dummy variable equal to one for our data and zero for HL's data.) If induction is successful, μ_2, r_2, and α_2 should be zero.

(2) $$\Pr(\text{choose option A}) = \frac{U_A^{1/(\mu_1+\mu_2\delta)}}{U_A^{1/(\mu_1+\mu_2\delta)} + U_B^{1/(\mu_1+\mu_2\delta)}}$$

(3) $$U(x) = \frac{1-\exp\left(-\left(\alpha_1+\alpha_2\delta\right)x^{1-(r_1+r_2\delta)}\right)}{\alpha_1+\alpha_2\delta}$$

Result 4: *The noise, μ, relative risk aversion, r, and absolute risk aversion, α, parameters calculated from the induced high stakes sessions' decisions do not differ significantly from the parameters calculated from the HL actual high stakes session's decisions.*

As summarized in result 4, maximum likelihood estimations of μ_2, r_2, and α_2 each are not significantly different from zero (p=.267, p = .111, and p=.472 respectively.) Thus, our estimates do not differ significantly from what HL originally reported: μ_1= 0.134 (.009), r_1=0.267 (.0255) and α_1=0.029 (0.004). HLs reported original parameter estimates were μ_1=0.134 (0.0046), r_1=0.269 (0.017), and α_1=0.029 (0.0025) Standard Errors are in parentheses.

Result 5: *The use of induced high stakes environments in experiments is less costly than the use of actual high stakes environments.*

Table 4 displays result 5 in greater detail. The first column of the table lists the expected costs of paying one subject for one randomly selected lottery from their ten lottery choices made in a standard actual-stakes HL session. The second column shows the comparable cost when using an induced high stakes environment instead. As seen, the expected cost differences are substantial. As discussed briefly in the design section, in the induced stakes environment, experimenters can pay subjects for all ten lottery decisions without wealth effects concerns. The fourth column in the table lays out the expected cost per subject when paying for each decision. Comparison to the third column demonstrates that even if one could pay for all ten decisions under actual high stakes without wealth effects, the cost per subject increases rapidly. As a comparison, our induced stakes environment has an expected cost per observation of about 22 dollars in the 180x stakes treatment when paying for all ten decisions, while paying for one decision in an actual 180x stakes environment has an expected cost of over 388 dollars per observation.

<Table 4>

6 Discussion

The importance of salient rewards, long emphasized by Vernon Smith and formalized with his seminal "Induced Value Theory" (Smith, 1976), is a defining feature of experimental economics. It separates experimental economics research from much related work on decision making occurring in other social science and business school environments. Unfortunately, some may misconstrue this emphasis to entail an inability to use laboratory investigations to study behavior and decisions in very high stakes environments, unless a large amount of money is available to spend. Here we have argued that this limitation is not as severe as it might at first seem. In particular, we have demonstrated that using the "induced preference" procedure (e.g., Berg et al., 1986) one is able to generate high-stakes behavior using a low-stakes environment.

We focused on the behavior reported by Holt and Laury (2002). They found that risk attitudes varied systematically with the magnitude of payoffs. Moreover, they estimated a utility function that captured the relation between choice and size of payoff. This paper specifically showed that, in a low-stakes environment, the Berg et al. (1986) procedure can be used to generate choices in this risk task that follow the same patterns Holt and Laury found in their high-stakes conditions.

Economically important decisions under risk often occur in high-stakes environments, lending special importance to our study. In future research we intend to induce preferences within game and market environments. Experimenters can implement a preference induction procedure in any environment where the appropriate data exist to inform participant preferences (e.g., research inference of trader risk-aversion from financial market data). Further development of preference inducement would be valuable; it holds the promise of becoming a key tool for the empirical study of new mechanisms.

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Table 1

A. Holt - Laury Paired Lottery-Choice Decisions: Low Payout Treatment

	Gamble A (Safe)		Gamble B (Risky)	
	Chance of Receiving 2 Dollars	Chance of Receiving 1.6 Dollars	Chance of Receiving 3.85 Dollars	Chance of Receiving 0.1 Dollars
Decision 1	10%	90%	10%	90%
Decision 2	20%	80%	20%	80%
Decision 3	30%	70%	30%	70%
Decision 4	40%	60%	40%	60%
Decision 5	50%	50%	50%	50%
Decision 6	60%	40%	60%	40%
Decision 7	70%	30%	70%	30%
Decision 8	80%	20%	80%	20%
Decision 9	90%	10%	90%	10%
Decision 10	100%	0%	100%	0%

B. Holt - Laury Treatments

Treatment	Gamble A		Gamble B	
Low	$2.00	$1.60	$3.85	$0.10
x20	$40.00	$32.00	$77.00	$2.00
x50	$100.00	$80.00	$192.50	$5.00
x90	$180.00	$144.00	$346.50	$9.00
Hypothetical x20*	$40.00	$32.00	$77.00	$2.00
Hypothetical x50*	$100.00	$80.00	$192.50	$5.00
Hypothetical x90*	$180.00	$144.00	$346.50	$9.00

***In the hypothetical treatments dollar amounts listed are hypothetical amounts only.**

Table 2

DHATJ Paired Lottery-Choice Decisions: Low Payouts

	Option A		Option B	
	Chance of Receiving 2 Points	**Chance of Receiving 1.6 Points**	**Chance of Receiving 3.85 Points**	**Chance of Receiving 0.1 Points**
Decision 1	10%	90%	10%	90%
Decision 2	20%	80%	20%	80%
Decision 3	30%	70%	30%	70%
Decision 4	40%	60%	40%	60%
Decision 5	50%	50%	50%	50%
Decision 6	60%	40%	60%	40%
Decision 7	70%	30%	70%	30%
Decision 8	80%	20%	80%	20%
Decision 9	90%	10%	90%	10%
Decision 10	100%	0%	100%	0%

Table 3
Holt-Laury and DHATJ Treatment Comparrison

Treatment	Choice	Dollars in HL/ Points in DHATJ	Chance of $2.50 Prize in DHATJ	Treatment	Choice	Dollars in HL/ Points in DHATJ	Chance of $2.50 Prize in DHATJ
Low	A	2	61%	90	A	180	79%
		1.6	52%			144	71%
	B	3.85	97%		B	346.5	99%
		0.1	7%			9	1%
20	A	40	65%	180	A	360	89%
		32	56%			288	83%
	B	77	97%		B	693	100%
		2	2%			18	1%
50	A	100	73%				
		80	64%				
	B	192.5	99%				
		5	1%				

Note that in HL (DHATJ) chance of receiving the high number of Dollars (Points) for choice A or B increases by round starting with 10%, in round 1, and increasing to 100%, in round 10.

Table 4
Cost Comparrison

	Expected Cost per Observation If Paying For 1 of 10 Choices		Expected Cost per Observation If Paying For All 10 Choices	
	HL	**DHATJ**	**HL**	**DHATJ**
Low	$2.41	$1.67	$24.87	$17.06
x20	$47.18	$1.71	$486.18	$17.44
x50	$113.73	$1.85	$1,168.98	$18.75
x90	$204.71	$1.97	$2,104.16	$19.85
x180	$388.17	$2.19	$3,974.67	$21.99

Expected costs calculated by power-expo utility maximizing behavior by all agents.

Figure 1
HL-Hypothetical vs. DHATJ Comparrison

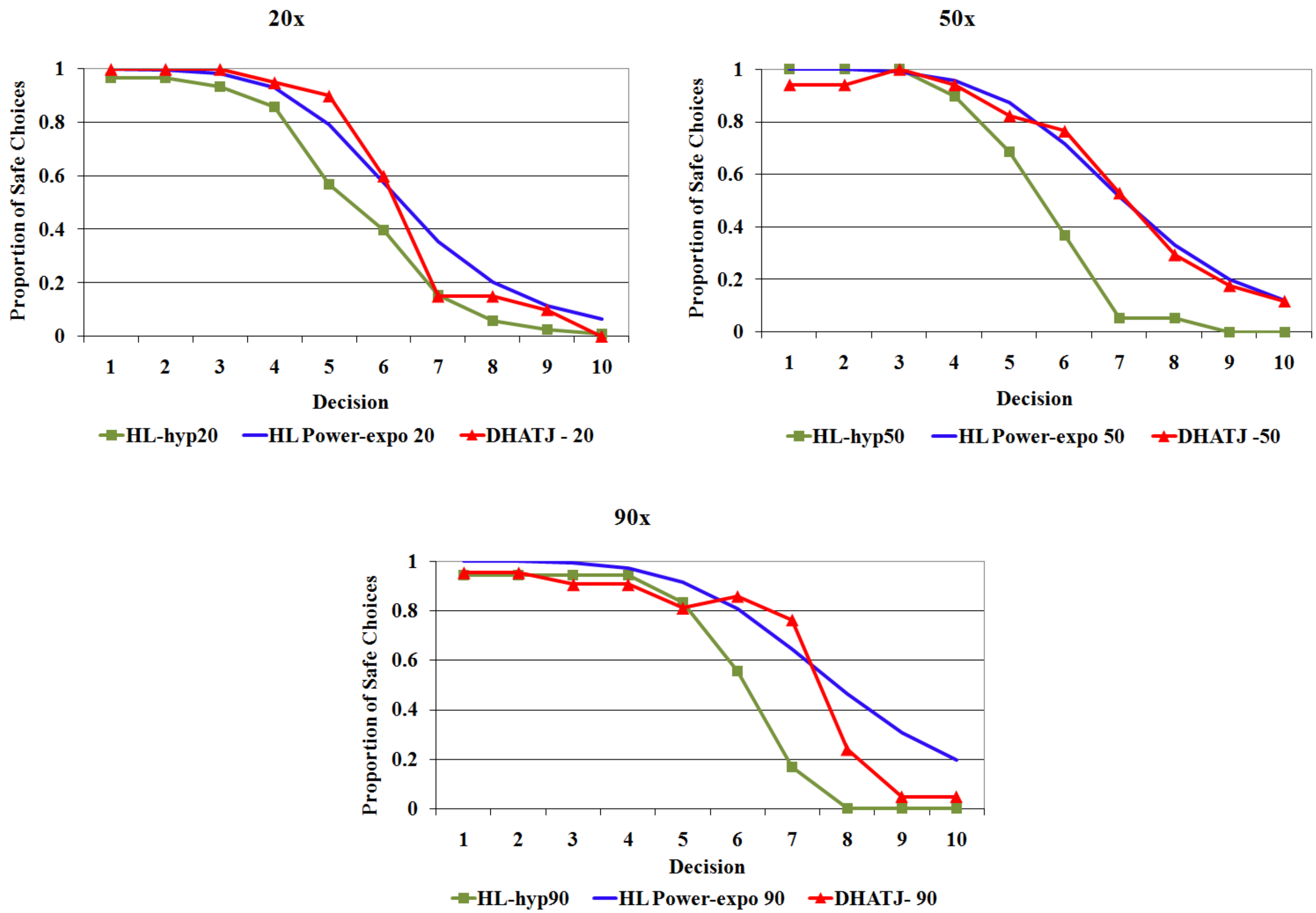

Figure 2
HL vs. DHATJ Comparrison

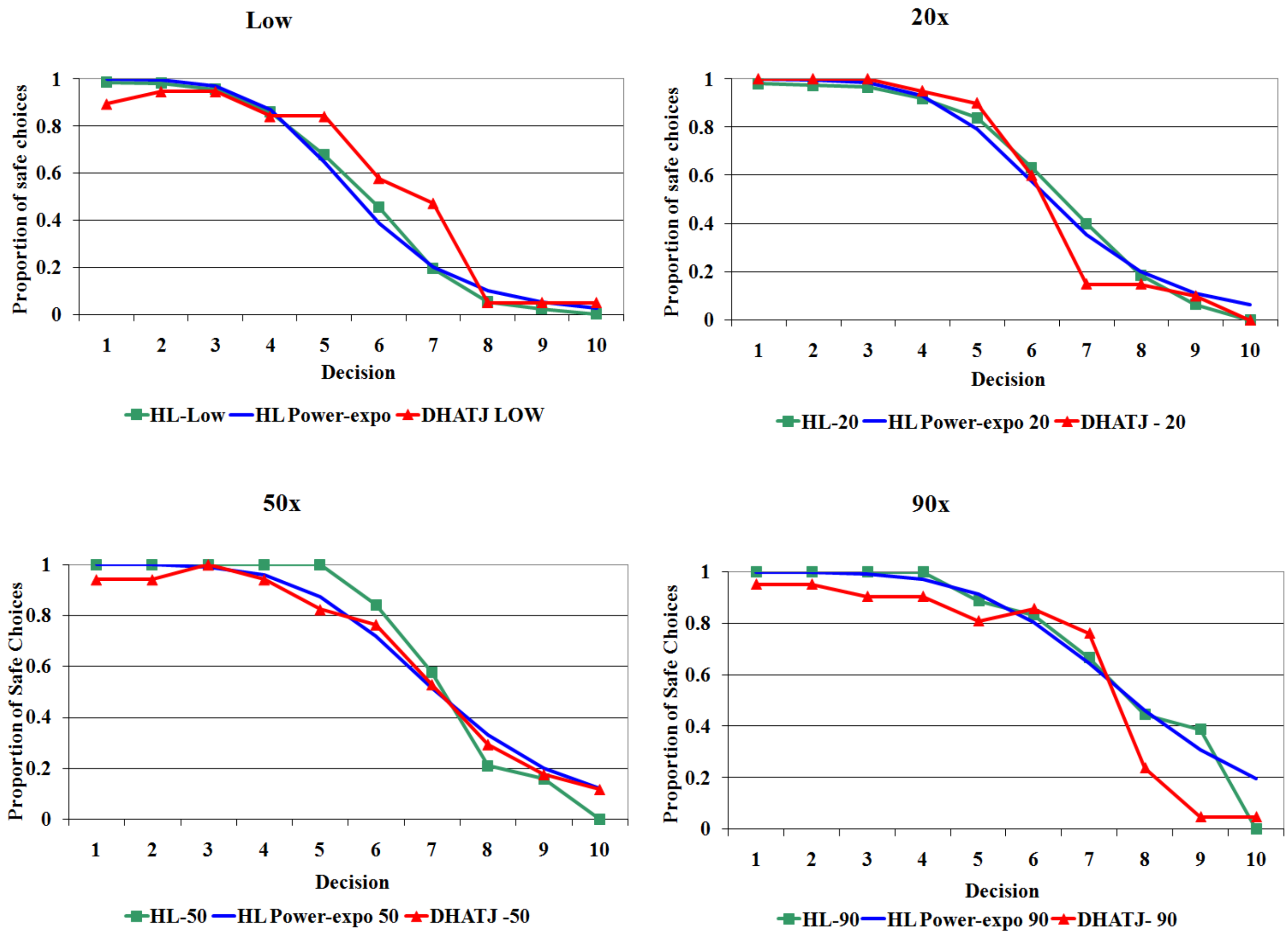

Figure 3
DHATJ Induced High Stakes 180x HL