The Journal of Risk and Uncertainty, 22:3; 251–261, 2001
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The Medium Prizes Paradox: Evidence From a Simulated Casino*

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Abstract

Mainstream explanations to gambling specify conditions under which human agents are locally risk loving. Such theories, however, fail to explain the typically observed prize distribution of a few large prizes and a large number of medium ones—hence the *medium prizes paradox.* In the current study we show that adaptive learning models recently proposed in the literature offer a solution. Simulations of such models predict that multiple medium prizes will slow down the decrease (over time) in agents' inclination to gamble. We run a laboratory experiment that supports this explanation and shows that the positive effect of medium prizes on the inclination to gamble increases with time.

Keywords: gambling, reinforcement, learning

JEL Classification: C91, D81, D83

The phenomenon of gambling is inconsistent with expected utility theory unless the notion of risk-aversion is abandoned. The consensus that human agents are generally risk averse is virtually unchallenged and appears to be supported by the prevalence of insurance in all aspects of life and hedging in financial markets. Nonetheless, gambling is widespread, fast rising in popularity (Clotfelter and Cook, 1989) and accounts for 10% of leisure expenditures in the United States (Christiansen, 1998). From Friday night poker and March Madness office pool, to casinos, race tracks and state lotteries—saying that gambling is popular seems like a gross understatement.

Devereux (1968) defines "gambling" as taking an unnecessary risk, which is expected to result in a loss. Mainstream explanations to gambling typically involve local risk-loving type of assumptions. In their frequently cited article, Friedman and Savage (1948), suggest that the co-existence of insurance and gambling might be explained by an S-shaped utility function that is concave at the low wealth levels and convex at the higher wealth levels. As an interpretation, Friedman and Savage suggest that winning a large prize could move people to a higher social class and hence people would tend to be risk-seeking with respect to high sums. Similar explanations to risk-seeking behavior were

*This research was supported by the Israel-USA Binational Science Fund and the National Science Foundation.

raised by Ng (1976) who discussed the need to finance large indivisible expenditures, Robson (1996) who claimed large prizes would increase one's "competitive strength," and Saddler (2000) who claimed that large prizes would help escaping the "poverty trap." Although such models could help explain gambling activity in general,[1] they cannot explain the typical multi-prizes structure of lotteries in practice. If gamblers are indeed risk seeking, then the gamble organizers can increase their revenues by switching to a single-prize lottery that pays less (in expectation) but seems equally-attractive to risk seeking agents. We call this enigma "*The Medium Prizes Paradox*."

One possible way to resolve the paradox is by looking at generalized expected utility models. A solution of this type was proposed by Quiggin (1991) based on Quiggin's (1982) rank dependent expected utility (RDEU) model. RDEU posits that whereas certainty and near certainty are easy to comprehend, low probability events are overweighted and high probability events are underweighted. This provides a justification for multiple prizes, even very small ones that do not contribute much to the expected value of the gamble. The multiple-prizes design reduces the probability of losing (i.e., not winning any prize) from near certainty (in a single large prize design) to some smaller probability for which significant underweighting applies. The anticipated loss associated with the gamble thus falls and the gamble seems much more attractive (Quiggin, 1991).[2]

A similar explanation can be proposed based on *Prospective Reference* theory (Viscusi, 1989). According to this theory, choice is based on a weighted average of the expected utility calculated using the true probabilities and the expected utility calculated using uniform probabilities over all non-null outcomes. Though the motivation for this formulation lies in Bayesian updating, this theory has been shown to be successful in non-repeated settings as well (Carbone and Hey, 1994, 2000). Prospective Reference theory predicts that multiple prizes with small probabilities will raise expected utility.

Notwithstanding the contribution of RDEU and Prospective Reference theory, there is an alternative simple explanation to the medium prizes paradox. The motivation comes from Skinner (1953, p. 104), who pointed out the importance of reinforcement schedules, and suggested casinos as one of many examples where such schedules could be studied. In addition, we have witnessed in recent years several breakthroughs in the modeling of "learning" and adaptive behavior. In general, the learning literature shows that the effect of economic incentives on human behavior is best captured by simple *adaptive learning* models (see, for example, Borgers and Sarin, 1997; Brandts and Holt, 1996; Camerer and Ho, 1999; Cheung and Friedman, 1997; Crawford, 1995; Erev and Roth, 1998; Fudenberg and Levine, 1998; Stahl, 1996; Van Huyck, Cook, and Battalio, 1997). In these models, actions that did better in the observed past tend to increase in frequency while actions that did worse tend to decrease in frequency. A simple adaptive learning model would resolve the medium prizes paradox by asserting gambling to be a transitory state in the learning process—a state which may be prolonged if the right reward structure is selected. Namely, the reward structure proposed to prolong gambling activity involves frequent smaller prizes. The multi-prizes gamble is thus preferred to the single large prize design since it is more successful in maintaining the gamblers' initial inclination to gamble farther away into the future.

Of course, there may be more than one reason for the medium prizes paradox and the two explanations raised above (underweighting the probability of loss and prolonging the agents' inclination to gamble) might in fact contribute together to the prevalence of multi-prizes gambles in reality. One goal of the current paper is to evaluate the relative importance of the two factors. To achieve that goal we study behavior in a simulated casino in which the two effects can be easily isolated. In particular, we examine two different casinos. In the first, the gamble pays a single large prize with some small probability. In the second, the gamble has a simple multi-prizes design. The players in our casinos are allowed to gamble repeatedly for 100 to 200 trials. Players are informed of the payoff distribution of the corresponding gamble. Thus, the perceptual factors that are captured by the RDEU model (and Prospective Reference theory) should affect the gamblers' behavior from the very first trial. The learning-based advantage of medium prizes, on the other hand, should evolve with experience and appear in later periods. Our experimental results show that while behavior is quite similar (across the two casinos) in the first 40 rounds, a significant difference evolves later on. Our results thus suggest that the learning story outlined above provides a better explanation to the medium prize paradox.

The article proceeds as follows: Section 1 describes the two casinos under investigation. Section 2 demonstrates that (under the assumption that the agents are initially indifferent between "gambling" and "not gambling") seven different learning models from the recent literature predict the emergence of an advantage to the medium-prize lottery. Section 3 presents the experimental results. The potential implications of the results are discussed in Section 4.

1. The simulated casino

Players had to choose between two fixed alternatives in each round: a safe alternative and a gamble (the word "safe" and "gamble" are used here for expositional purposes; the players were given the two choices in neutral terms). The safe alternative always paid 9, 10 or 11 tokens with equal probabilities. This prospect was designed to abstract the no gambling option. The small variability in payoffs was introduced to reflect some exogenous uncertainty concerning the opportunity cost of gambling. The alternative prospect, the gamble, had a lower expected value (9 tokens rather than 10 tokens) but it introduced a possibility of winning a large prize of 9000 tokens. The exact structure of the gamble varied across two treatments. In the single-prize treatment the gamble paid 9000 tokens with probability 0.001 and zero otherwise. In the multiple-prizes treatment the gamble paid 9000 tokens with probability 0.0001, 54 tokens with probability 0.15, and zero otherwise.

In the simulations, 1000 virtual agents behaving according to a pre-specified learning model played each treatment for 200 rounds. In the experiments, forty Technion students played the single-prize treatment while other (different) forty students played the multiple-prizes treatment. The exact number of repetitions for each subject was determined by randomly drawing an integer between 100 and 200. The random number of repetitions was implemented in order to eliminate end-game effects. Appendix A provides more details on the experimental design.

2. Simulating learning to resolve the paradox

Recent studies suggest that behavior in repeated choice tasks can be approximated by simple adaptive learning models. In this section, we use computer simulations to predict the behavior of adaptive agents for seven different learning models of this type. We show that all seven models make the same qualitative prediction: starting with equal propensity to gamble in both treatments, over time the gambling rate in the single-prize treatment falls much more rapidly than the gambling rate in the multiple-prizes treatment. The medium prizes paradox might thus be resolved by concluding that the multiple medium prizes structure prolongs the gambling activity through slower learning and thus increases the revenues of the gamble-organizer in the long run.

In particular, we simulated seven leading models of learning: Bush and Mosteller (1955), Cheung and Friedman (1997), Tang (1996), Fudenberg and Levine (1998), Camerer and Ho (1999), Sarin and Vahid (2001), and Erev, Bereby-Meyer, and Roth (1999). We further simulated the dynamics version of prospective reference theory (Viscusi, 1989), in which a subject Bayesian updates his subjective probabilities starting with a uniform prior over outcomes.

Table 1 presents the predicted average (over all periods) gambling rate for the eight models, with the corresponding standard deviations. The predictions were derived by a computer simulation in which 1000 virtual agents, behaving according to each model's assumptions, played each treatment for 200 times. The simulations of the learning models, with the exception of Prospective Reference theory, began under the assumption of uniform initial propensities; that is, equal probabilities for "gambling" and "not gambling" at the outset.

The parameters for the different models were taken from previous studies that focused on estimating the parameters that best approximate subjects' behavior over a number of different tasks. In particular, the values of the parameters for the first five models were taken from Bereby-Meyer and Erev (1998) that estimated the parameters that give the best approximations for subjects' behavior in three different binary choice tasks. The parameters for Sarin and Vahid (2001) and Erev, Bereby-Meyer, and Roth (1999) were taken from the original articles. These articles focused on estimating the parameters that give the best approximation for a large set of tasks. The initial prior for Prospective Reference Theory is taken from Carbone and Hey (1994).[3]

Table 1 demonstrates that the same qualitative results are obtained for all eight models under consideration. In all eight cases the average betting rate (across 200 repetitions) in the multiple-prizes casino was significantly higher than the average betting rate in the single-prize casino. These results therefore confirm our hypothesis that the multiple-prizes structure prolongs the gambling activity of adaptive economic agents.

To illustrate the logic behind the learning models, Appendix B describes the assumptions of the last learning model in our list (Erev, Bereby-Meyer, and Roth 1999). The

Table 1. Average gambling rates for different learning models

Model	Single-prize treatment (%)	Multiple-prizes treatment (%)
Bush and Mosteller (1955)	0.5 (0.7)	15.8 (35.5)
Cheung and Friedman (1997)	8.4 (24.6)	22.6 (21.3)
Tang (1996)	0.5 (0.7)	13.1 (30.6)
Fudenberg and Levine (1995)	11.0 (23.8)	23.0 (21.9)
Sarin and Vahid (2001)	0.5 (0.2)	1.4 (0.1)
Camerer and Ho (1999)	9.2 (19.2)	27.0 (16.6)
Erev, Bereby-Meyer, and Roth (1999)	15.6 (11.6)	37.6 (13.1)
Viscusi (1989)	31.8 (21.9)	75.6 (25.5)

Standard deviation across players is presented in parentheses next to the mean.

plot on the left of Figure 1 shows the average gambling rates (over the 1000 simulations) in the first period, in the first 20 periods, and in 4 blocks of 40 trials, for that model. The corresponding experimental data is presented on the right. In the next section we examine the experimental data in detail.

3. The experimental data

We first examine the behavior in the first round of play. If indeed the RDEU and Prospective Reference theory could resolve the medium-prizes paradox, then the subjects would be expected to gamble more in the multiple-prizes treatment from the outset. The average (across the 40 subjects) gambling rate in the single-prize casino was 0.45; the average gambling rate in the multiple-prizes casino was 0.57. The difference between the two rates is statistically insignificant ($p = 0.13$) and both rates are not significantly different from 0.5 (p-values of 0.46 and 0.44, respectively). These results suggest that the first period effect predicted by RDEU and Prospective Reference theory is not statistically significant.

We next examine whether the average gambling rate across all periods significantly differs across the two treatments. The average gambling rate in the single-prize casino was 26.6% (S.D. of 29.1%); the average gambling rate in the multiple-prizes casino was 37.7% (S.D of 24.6%), a statistically significant difference ($p = 0.034$, one tail).

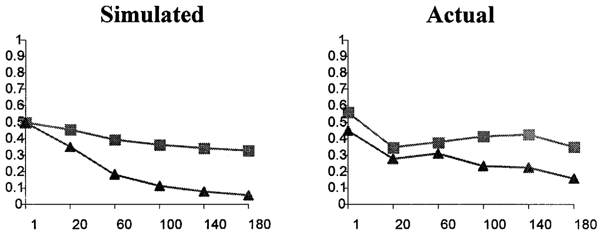

Figure 1. Simulated versus actual dynamic paths. The triangles represent the single-prize treatment and the squares represent the multiple prizes treatment.

Table 2. Average gambling rates per blocks of 40 rounds

	Single-prize treatment		Multiple-prizes treatment		
Block	*N*	Average	*N*	Average	*p*-value (one tail)
1	40	0.279	40	0.347	0.121
2	40	0.309	40	0.378	0.164
3	40	0.234	40	0.415	0.006
4	32	0.225	31	0.424	0.012
5	18	0.160	14	0.352	0.045

Finally, we split the 200 periods into five blocks of 40 periods each.[4] The average gambling rate per block and the one-tailed t-test for comparison of means across treatments are presented in Table 2.

Table 2 shows that the average gambling rates in the two casinos in the first 40 rounds of play were not significantly different ($p = 0.121$, one tail). The differences stayed statistically insignificant in the next 40 rounds of play (rounds 41–80) as well. As time progressed, however, the single-prize treatment pulled away from the multi-prize treatment as the gambling rate sharply declined in the first treatment. The differences across treatments thus become statistically significant in the last three blocks of the experiment.

4. Concluding discussion

It is hard to dismiss the Friedman and Savage type of explanations to gambling and betting. The arguments are simply too intuitive not to be true. When one buys a lottery ticket, surely some of the motivation lies in the hope of buying a new home, putting the kids through college, and getting that Ferrari you always wanted, as would be consistent with the large indivisible expenditure explanation and the higher social class explanation. The other part of the motivation possibly lies is the dream of investing the money in some profitable enterprise, consistent with the competitive advantage explanation and moving on to better access to technology. These notions are not testable in our experimental setting, as we would not be able to back up prizes large enough to test these claims. Nonetheless, these theories would not explain the multiple medium and small prizes in gambles from slot machines to lotteries.

We discussed and investigated the medium-prizes paradox in gambling. We discovered that although substantial gambling behavior could be observed in a simulated casino, in the range of prizes we offered, risk loving did not appear to play a major role in players' behavior (else behavior in the first round would reveal a preference towards the single large prize). Similarly, we rejected the theory of rank dependent utility as a possible explanation. Instead, gambling was shown to be a phase in a process of learning—a phase that may last a while due to small yet frequent positive reinforcements. In other words, gambling could be prolonged by a reward structure comprised of frequent medium prizes.

The implications of this demonstrated effect of multiple small-to-medium rewards are far reaching beyond the realm of gambling. The effect is capitalized on, for example, in advertising. “Look under the cap” type of promotions for soft drinks typically offer a few large prizes (cars, vacations), many medium prizes (walkmans, watches) and numerous small prizes (a free can, a discount coupon to other firm products). The same logic suggests that special attention to small reinforcements should also be taken into consideration in product design and in customer service. More generally, greater attention to small frequent rewards might also be quite effective in different arenas like education and crime prevention.

Appendix A: Experimental design

In the experiment, 80 Technion students (40 in each treatment) were seated at separate terminals and presented with five dice on a computer screen. They were told that each die had ten sides with numbers from 0 to 9 and that each side had an equal chance of occurrence. The five dice, combined from left to right, would form a number from 00000 to 99999. It was explained that all numbers from 00000 to 99999 had an equal chance of occurring. In addition to the on-screen dice, there were two buttons on the screen. Subjects were told they could choose button 1 or button 2 each period. A mouse click on either button would then roll the dice. The rolling action appeared on the screen and lasted few seconds to replicate casino slot machines, create excitement, and give subjects a few seconds to observe the last roll’s payoffs and contemplate their next move. The number resulting from the roll translated into “tokens” according to a “payoff” table that was handed out to the subjects in advance. In particular, we had two treatments: (1) single large prize; (2) multiple-prizes.

In each treatment, pressing the first button corresponded to the (safe*) payoff schedule below, with prizes of 9, 10, and 11 equally likely, yielding an expected value of 10 with small variance in payments. When the subject selected this option, the resulting number X was translated to payoffs (in tokens) in the following key:

9 tokens	$0 \le X < 33{,}333$
10 tokens	$33{,}333 \le X < 66{,}666$
11 tokens	$66{,}666 \le X \le 99{,}999$

The second button corresponded to a second payoff schedule (the gamble). In treatment 1, when the subject chose payoff schedule 2 (button 2) the number X resulting from the role was translated to tokens by the following key:

0 tokens	$0 \le X < 99{,}900$
9000 tokens	$99{,}900 \le X \le 99{,}999$

* Words such as “safe,” “bet,” or “gamble” were strictly avoided in the instructions. Nonetheless, we use them here for expositional purposes and the reader’s convenience.

In treatment 2, when the subject chose payoff schedule 2 (button 2), the resulting number was translated to tokens by the following key:

0 tokens	$0 \leq X < 84{,}900$
54 tokens	$84{,}990 \leq X < 99{,}990$
9000 tokens	$99{,}990 \leq X \leq 99{,}999$

Subjects were presented with the two conversion-tables corresponding to the treatment to which they were assigned (each subject participated in only one treatment). The method in which the number resulting from the roll is translated to tokens (for each one of the two buttons) was also explained to the subjects verbally.

Subjects were told in advance that they would play the game repeatedly for 100 to 200 rounds, with any number of rounds between 100 and 200 equally likely. Payment was in private and in cash at the end of the experiment. Subjects were given a show-up fee of $3 plus an additional $1 for every 300 tokens.

Appendix B: Erev, Bereby-Meyer, and Roth (1999)

As an example to a specific learning model we briefly outline Erev, Bereby-Meyer, and Roth (1999) model. This model was found to provide nice approximations of actual behavior in more than 80 decision tasks (including n-person strategic games, team games, two-person games in which the players could not reciprocate, and different individual decision tasks). Interestingly, the good predictions were obtained even without estimating parameters to each task: It turns out that one set of the model's two parameters (estimated on nine individual decision tasks) captures the actual behavior patterns in all 80 tasks.

When no losses are possible (as in the current gambling task), the model can be summarized by the following assumptions:

L1: Initial propensities. The decision maker has an equal initial propensity to play each one of his strategies: G, for "gamble" and N for "not gamble." The initial propensity to select strategy j (at round 1) is given by $q_j(1)$.

L2: Average updating. The propensity to play strategy j in round $t+1$ is a weighted average of the initial propensity ($q_j(1)$) and the average payoff obtained from playing j in the first t rounds ($\text{AVE}_j(t)$). The weight of the initial propensity is a function of a "strength of initial propensities" parameter $N(1)$. The weight of the average past payoff is a function of the number of times strategy j was actually chosen in the past ($C_j(t)$). Specifically,

$$q_j(t+1) = q_j(1)\frac{N(1)}{C_j(t)+N(1)} + \text{AVE}_j(t)\frac{C_j(t)}{C_j(t)+N(1)} \tag{1}$$

L3: Exponential response rule. The probability $p_j(t)$ that a decision maker selects the j-th pure strategy at time t is given by,

$$p_j = e^{q_j(t)\lambda/S(t)} \Big/ \sum \left(e^{q_k(t)\lambda/S(t)}\right) \tag{2}$$

where the sum is over all pure strategies k, λ is a parameter that determines reinforcement sensitivity, and $S(t)$ is a measure of the absolute deviation of the payoffs that the decision maker has experienced up to time t. Thus, the probability of selecting a given strategy increases with the propensity to select it (which increases with the average payoff from past selections). The division by the absolute deviation measure, $S(t)$, implies that noisy reinforcements reduce reinforcement sensitivity (and thus lead toward more uniform choice probabilities).

The absolute deviation, $S(t)$, is estimated by the average absolute difference between the recent payoff (x at trial t) and the accumulated average payoff in the first t trials ($A(t)$). Following the logic of equation 2, $S(t)$ is updated as follows:

$$S(t+1) = S(t)W'(t) + |A(t) - x|(1 - W'(t)) \qquad (2')$$

where $W'(t) = (t + mN(1))/(t + mN(1) + 1)$ and m is the number of pure strategies (in the current case 2). For the initial value $S(1)$ we take the expected absolute difference between the payoff from random choice and "the expected payoff given random choice" (9.5 in the current setting).

The average payoff $A(t)$ is calculated in a similar manner:

$$A(t+1) = A(t)W'(t) + x(1 - W'(t)) \qquad (3)$$

where $A(1)$ is the expected payoff from random choice (9.5).

Altogether, the model has two initial propensity parameters (the value of $q_j(1)$ for each strategy j) and two free parameters, λ and $N(1)$, that represent the shape of the learning model. Roth and Erev (1995) simplified the model by assuming uniform initial propensities. In particular they set $q_j(1) = A(1)$ for all j. Given this simplification, they find that the parameters that best fit their data are: $N(1) = 30$, $\lambda = 2.8$.

Notes

1. Unfortunately the models fail at this task as well. Machina (1982) for instance notes that gambling behavior is unrelated to initial wealth. This fact contradicts the "local risk-loving" explanations outlined above.
2. Note, however, that the expected value assigned by the RDEU model to a single-prize lottery may still be higher than the value assigned to a multi-prize lottery with the same expected payoff. In particular, our calculations suggest that the generalized expected utility models estimated by Tversky and Kahneman (1992) (and see Wakker, Erev, and Weber, 1994) assign a higher expected value to the single prize lottery in the specific application studied in this article.
3. The initial prior of the implied dynamic Viscusi (1989) is a weighted average of uniform probabilities over non-null outcomes and the true probabilities. Carbone and Hey (1994) set the weight on the uniform component of the initial prior equal to 0.1. The Bayesian motivation in Viscusi (1989) implies a weight on the initial prior and Bayesian updating from there. We find that giving the initial prior the weight of 1 period is sufficient to have a remarkable effect on the dynamic path.
4. Since each subject played 100–200 periods, not all subjects have all five blocks of data.

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