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Prize and Risk-Taking Strategy in Tournaments: Evidence from Professional Poker Players

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ABSTRACT

Prize and Risk-Taking Strategy in Tournaments: Evidence from Professional Poker Players

This study examines whether people optimally respond to prize incentives for risk taking in tournaments. I exploit the television game show World Poker Tour as a natural experiment. The results show that professional players strategically choose the degree of risk taking depending on the incentives implied by the prize structure they face. I find that they are more sensitive to losses than to gains.

JEL Classification: M5, D8

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1 Introduction

Many firms use rank-order tournaments to motivate, assess, and compensate their workers. Rank-order tournaments are advantageous when it is costly to evaluate individual performance in absolute term and when such measure, even if it is affordable, is likely to be contaminated by common shock (Prendergast 1999). Examples are the competition among vice presidents for promotion (Main *et al.* 1993) and rank-based contracts with suppliers (Knoeber and Thurman 1994). Lazear and Rosen (1982) show that firms can induce the first best level of effort by using a tournament.

On the other hand risk-taking incentives are intrinsic in rank-order tournaments. Trailers have an incentive to take high-risk actions during the course of competitions, in particular near the end, because the prize is the same whether they lose by a little or a lot as long as ranking does not change. Many examples can be found in business contexts, such as risk taking by mutual funds and broiler chicken farmers (Chevalier and Ellison 1997, Knoeber and Thurman 1994) as well as in professional sports (Bronars 1987, Becker and Huselid 1992, Bronars and Oettinger 2001). In sports, risky behaviors are not troublesome, but rather enjoyable. Spectators enjoy uncertain results and are excited at upsets by underdogs. On the other hand, in business organizations, risky behaviors and uncertain outcomes could hurt profitability. They might increase the variability of year-to-year performance, make evaluation and future planning difficult, and finally destroy investors' confidence in the market.

In this study I exploit the popular television game show "World Poker Tour" on Travel Channel in the United States as a natural experiment for examining risk-taking behaviors in rank-order tournaments. Poker tournaments are suitable for the purpose of this study since risk taking, such as bluffing and "all-in," is the most essential component of the game strategy, while the problem of effort choice is quite trivial. They also provide a unique opportunity to evaluate risk taking behavior under well-defined rules in the face of high monetary incentives, which is not affordable in a lab experiment. Furthermore I expect that unobserved heterogeneity in preferences should be minimal since most players are homogenous in quality. Lastly it is unlikely that professional players make systematic mistakes in statistical calculation.

I examine whether professional players strategically choose the degree of risk taking in response to the prize incentives they face. I exploit variation in risk-taking incentives both within a tournament and across tournaments. The incentives would change for each individual player within a tournament depending on his or her current position on prize structure. Some players face relatively large expected gains and small expected losses in prize from a risk-taking strategy than others. Also the incentives would be different across tournaments since prize structures, such as total prize and its distribution, significantly differ tournament by tournament. Poker tournaments should provide a clear view of how people respond to risk-taking incentives in rank-order tournaments.

2 A Simple Model of Risk Taking Strategy

In a poker game called *No Limit Texas Hold'em*, each player is given a pair of cards (the so-called "hole cards"). There are five "community cards" in the end, and the player with the best seven-card poker wins al the money wagered. As community cards are revealed in three stages–"Flop" (three cards), "Turn" (one), and "River" (one), players choose whether to check, fold, or call and how much to raise without knowing other players' hole cards.

Suppose that there are six players on table. Consider a player i with c_i number of chips at a moment. Subscript i also denotes the current rank. Let w_j denote the prize for final rank j. So $w_j > w_k$ if $j < k$. Let $p_j(c_i)$ denote the subjective probability of player i that he will end up with final rank j, where j = 1, 2, ..., 6. It is reasonable to assume that the probability distribution has a mode at w_i, that is $p_i(c_i) \geq p_j(c_i)$ for all $j \neq i$.

For simplicity assume that players choose only whether to call or fold for a certain amount of bet. In other words my model does not consider how much to bet; players can bet more chips only by participating more frequently. Suppose that there are n players who calls a bet, x chips. If player i participates and wins, total chips increase by $(n-1)x$, but if he loses, total chips decrease by x. Of course, x is smaller than or equal to c_i because players cannot bet more chips than what they have. The probability distribution of final ranks will accordingly change to $p_j(c_i + (n-1)x)$ or $p_j(c_i - x)$, respectively.

First consider a middle-ranked player, that is $i \neq 1$ or 6.[1] Let π_i represent his luck (good

[1] I assume that there are always six players. In reality it is possible that a player of $i \neq 6$ is not middle ranked as some players are eliminated by bankruptcy.

or bad hands). That is, it represents the probability of winning. The probability distribution of final ranks will be that of a "compound lottery" of $p_j(c_i + (n-1)x)$ and $p_j(c_i - x)$ with weight π. Let $p_j(c_i, x)$ denote the new probability distribution.[2] It is reasonable to assume that the distribution of $p_j(c_i, x)$'s is more spread out than that of $p_j(c_i)$'s because betting always entails some risk taking. Player i participates if and only if:

$$\Sigma_{j=1}^{6} p_j(c_i, x) U(w_j) \geq \Sigma_{j=1}^{6} p_j(c_i) U(w_j). \tag{1}$$

The participation constraint can be rewritten to:

$$\Sigma_{j \neq i} \frac{p_j(c_i, x) - p_j(c_i)}{\Sigma_{k \neq i}[p_k(c_i, x) - p_k(c_i)]} U(w_j) \geq U(w_i). \tag{2}$$

Alternatively,

$$\Sigma_{j<i} \frac{p_j(c_i, x) - p_j(c_i)}{\Sigma_{k \neq i}[p_k(c_i, x) - p_k(c_i)]} U(w_i + g_{ij}) + \Sigma_{j>i} \frac{p_j(c_i, x) - p_j(c_i)}{\Sigma_{k \neq i}[p_k(c_i, x) - p_k(c_i)]} U(w_i - l_{ij}) \geq U(w_i),$$

where g_{ij} represents the gain in prize and l_{ij} the loss in prize when ranking changes from i to j. Notice that $p_j(c_i, x^*) - p_j(c_i) > 0$ because the distribution is more spread out by betting.[3] Therefore the left-hand side of the inequality is sort of a weighted sum of gains and losses.

The participation constraint clearly shows that if other things are equal, the larger g increases the incentive to take risk. On the other hand, the larger l decreases the incentive for risk taking. Notice that g's and l's are different across individual players depending on their relative position on the prize structure. In the sample of poker tournaments I will use later, when we consider only gains and losses from one-rank change, that is $g_{i,i-1}$ and $l_{i,i+1}$, the average gain is \$282,356 for the second rank and \$35,772 for the fifth rank. And the average loss is \$151,173 for the second rank and \$22,064 for the fifth rank. They also differ significantly across tournaments because each tournament has different prize structure. It is therefore testable whether individual players' risk taking behaviors (betting more frequently

[2] I omit π because it does not play a significant role for empirical purpose. I assume that it is statistically identical for all players. In other words the probability that a player has good or bad hands is same across individuals by the law of large number.

[3] I assume that $p_j(c_i) = p_j(c_i, x = 0)$. That is, the probability distribution does not change much when the player does not bet. Note that the assumption is not always true because the distribution could change by changes in other players' chips even though the player does not participate.

and probably more chips) are affected by expected gains and losses they face.

The result here explains why prize structures are usually convex in poker games or sports events where spectators enjoy uncertainty, suspense, and upsets. The convexity implies that g's are larger than l's regardless of ranking. It increases risk-taking incentives overall.

Risk-taking strategy is relatively trivial for top-ranked and bottom-ranked players. Top-ranked player face no expected gains from a risky strategy and so should try to lock in the current ranking. They would participate only when they have good hands. Top-ranked players' incentives should be minimal among players. On the other hand, bottom-ranked players would have relatively stronger incentives for risk taking than others because they have nothing to lose. For these players the current position is a guaranteed place no matter what they do.

Lastly, the participation constraint also depends on marginal changes in probability distribution by risk-taking strategy. For example, if $p_j(c_i, x) - p_j(c_i)$ is small for $j < i$, it is likely that the player will not participate. This suggests that when the player follows the leaders very closely, risk taking strategy does not improve the probability of advancing significantly and so risk taking is not so attractive. Instead he might prefer more prudential plays to wait for the best chance. On the other hand, if $p_j(c_i, x) - p_j(c_i)$ is small for $j > i$, the player is likely to fold his cards. That implies that if the player leads the followers by relatively large gaps, it is more attractive to take risk. Even if he loses some chips, it is not likely that the followers catch up with him. Risk-taking incentives depend on chip spreads among players as well as prize structure.

3 Data from *World Poker Tour*

The data I use in this study are about individual players' performance, ranking, and money prize in different tournaments. Information at the tournament level, such as total prize and variance, is collected from the official website of "World Poker Tour" (www.worldpokertour.com). The data are available for 27 tournaments in season one (2002-2003) and season two (2003-2004). For these tournaments we can observe predetermined prize structures, six players at the final table, their initial chips, and final ranking. Each player starts with different number of starting chips, which are cumulated through preliminary rounds. There is no information on preliminary rounds.[4] The final round is an elimination tournament in which one is out of the table if and only if he or she is bankrupt. All chips will be eventually concentrated to the final winner's hands.

Table 1 presents prize structures for 27 tournaments. Total money prize is huge; it is on average 1.4 million dollars. Total prize varies significantly across tournaments. The biggest tournament is *WPT Championship*, 5.4 million dollars. The distribution of prize over ranking is very unequal and convex. The final winner takes almost a half of total prize. Top three players take 81 percent of total money. Compared to the last-place prize, the first prize is 11 times larger, the second prize is 5.4 times larger. But the fourth prize is 1.9 times larger, and the fifth prize is only 1.3 times larger. As with total prize, the distribution is also significantly different across tournaments.

As mentioned, it is possible to identify individual players' initial and final rank. The extent to which players' ranks change during a tournament is informative in the sense that there are more changes if more players take high-risk strategies. For the purpose of this study it would be interesting to examine if there is any systematic relationship between prize structure and ranking changes. I examine two features of prize structure; dispersion and total prize. If ranking changed only by luck, they should be independent of rank changes. By regression I find $[\textit{Changes in Rank}] = 6.28 - 1.72 \times [\textit{Prize Dispersion}] - 0.34 \times [\textit{Total Prize}]$ where $N = 27$ and $R^2 = 0.18$.[5] The estimates for prize structure are statistically significant at 10% and 1% significance level, respectively. Figure 2 shows that there is a small but negative relationship between changes in rank and prize dispersion. It also shows the relationship between changes in rank and total prize. The result for prize dispersion is consistent with the standard expectation that higher dispersion should decrease changes in rank after controlling for mean as long as players are risk averse. The result for total prize is consistent with the experimental finding of Kachelmeier and Shehata (1992) that people become more risk averse at higher stake. This simple look at the data already confirms that players' risk-taking behaviors depend on prize structure.

[4] There are 80-150 entrants in a tournament. The buy-in dollars (minimum entry fee) are significantly different, ranging from 300 to 25,000.

[5] I measure changes in rank by number of players whose final rank is different from initial rank. Prize dispersion is measured by coefficient of variation (standard deviation divided by mean). The unit of total prize is 1 million dollars.

The more detailed data at the individual-player level can be collected for only 12 tournaments from the World Poker Tour DVD collection (season one).[6] The data contain more information since we can actually watch each episode and follow individual players' performance (chips) and ranking within a tournament. I keep record of chip counts whenever they are shown to viewers. It is not possible to construct the complete history of changes in chips because chip counts are not displayed on the play-by-play basis. I collect the data on individual holding of chips only until there remain at least three players, first, because I focus on middle-ranked players and, second, because chip counts are not usually available after only two players remain.

Table 2 shows some descriptive statistics. There are 286 observations for middle-ranked players and additional 106 observations for bottom-ranked players. Players are categorized as bottom-ranked players when they are ranked the last among surviving players. The first thing to be noted in Table 2 is that bottom-ranked players are riskier than middle-ranked players in terms of the amount of chips they bet. Bottom-ranked players bet 60 percent on average while middle-ranked players bet about 30 percent of their chips. This is because bottom-ranked players bet almost same amount of chips as middle-ranked players do even though they hold only a half of chips. By the convexity of prize structure, the expected gain in prize by one-rank advancement is much larger than the expected loss by one-rank retreat. The expected gain in prize by advancing a rank is much smaller in size for bottom-ranked players ($27,022) than for middle-ranked players ($100,192). However the expected loss by a risk-taking strategy is zero for bottom-ranked players, which explains higher risk taking by bottom-ranked players.

4 Empirical Analysis

4.1 Measure of Risk Taking

The model shows that players take risk by participating and betting more frequently when there exists a stronger incentive for risk taking. So I measure the degree of risk taking for an individual player's strategy by the absolute value of variation in chips over the tournament. This is in the same spirit of Knoeber and Thurman (1994) in which they measure the degree

[6]I dropped one tournament, *Aruba Poker Classic*, since its game format is very different from the others.

of risk taking in production by a measure of variability in output.[7] Specifically my measure of risk taking is $\Delta c_{ink} = |c_{\cdot,n,k} - c_{i,n-1,k}|$ where $|\cdot|$ means absolute value. $c_{i,n,k}$ represents the amount of chips of the i-th ranked player at the n-th chip count display in tournament k. It measures the change in chips between the (n-1)-th and n-th chip count. Only the absolute value of chip change is considered because we are interested in the degree of risk taking itself, not actual outcomes (success or failure) of risk-taking strategy.

It should be kept in mind that Δc_{ink} is likely to underestimate a player's actual willingness to take risk. Poker game is an interactive game. A player cannot raise money unless at least one other player call his bet. The optimal bet is somewhere between the amount of chips a player likes to bet and the amount of bet he thinks other players will call.

The chip change in absolute value, Δc_{ink}, might be mechanically positively correlated with the amount of chips that the player initially holds at the (n-1)-th chip count. In other words Δc_{ink} could simply reflect the fact that players with more chips bet more and have more changes in absolute value. This suggests that we need to control for the amount of chips at the previous chip count, $c_{i,n-1,k}$.[8] For robustness check I also experiment with an alternative variable ($\%\Delta c_{ink}$), which measures the percentage change in chips between two chip count displays.

4.2 Broadcasting Bias

I can observe individual players' chips only when a tabulated report of individual chip counts is shown to viewers. The editors of the TV show determine how many times and when to show chip counts. As a result, the measure of Δc_{ink} does not represent actual fluctuation in individual holding of chips and actual degree of risk taking. My findings in this paper should be taken with a grain of salt in this aspect.

However it seems reasonable to assume that Δc_{ink} approximates quite well actual changes in chips. I assume that the editors of the TV show would want to maximize the excitement of viewers. Then they should inform viewers of changes in chips whenever there are significant

[7]However the variability in output might not represent risk taking strategy in the case of agricultural production. The variability could reflect mismanagement or technological defects. If so, the correlation between output variability and ranking could reflect simply heterogeneous managerial capabilities or differences in technology.

[8]Instead we could control for total number of chips. But it does not change the results.

changes in chip spread or ranking. It is not likely that chip counts are shown when chips change little. Chip counts are almost always shown when a player is bankrupt and eliminated from the tournament. So we can identify at least to which players the chips that the eliminated player held are redistributed.

Also it should be noted that changes in chips between chip counts are likely to underestimate actual degree of risk taking because the measure of Δc_{ink} omits some minor fluctuations. If so, my estimate of the incentive effect on risk taking strategy would be a lower bound.

4.3 Specification and Results

The basic estimation equation is:

$$\Delta c_{ink} = \alpha_1 g_{ink} + \alpha_2 l_{ink} + \beta_1 \sigma^-(c_{ink}) + \beta_2 \sigma^+(c_{ink}) + X_{ink}\gamma + \epsilon_{ink}, \tag{3}$$

where n increases within a tournament and $n = 1, 2, \ldots, N_k$. Explanatory variables g and l are crucial for the purpose of this paper. g_i is the gain in money prize by advancing one rank.[9] It is the prize gap between w_i and w_{i-1}. And l_i is the marginal loss in money prize by one rank. It is the prize gap between w_i and w_{i+1}. Formally I specify that $g_i = w_{i-1} - w_i$ and $l_i = w_i - w_{i+1}$. The model predicts that α_1 is positive and α_2 is negative.

Individuals' risk incentives depend not only on neighboring prizes, but generally the whole prize structure, $\{w_1, ..., w_i, ..., w_6\}$, as shown in the model. Including the detailed information on risk incentives, such as $w_{i-2} - w_i$ and $w_i - w_{i+2}$, reduces the sample size. Thus g_i is a proxy for incentives from higher prizes and l_i represents incentives from lower prizes.

One might wonder whether risk-taking incentives could change between chip counts because individual plays between chip counts are omitted and unobservable. Then g and l constructed based on the ranking at the (n-1)-th chip count would not measure risk-taking incentives that can explain changes in chips between chip counts. Table 3 addresses the issue; it shows that ranking changes little between chip counts, even though chips change a lot as seen in Table 2. About 50 percent of players do not change ranking at all, and 35 percent change only one rank. It is reasonable to assume that risk-taking incentives are rather constant between chip counts.

[9] For simplicity I will omit subscripts unless necessary.

$\sigma^-(c_{ink})$ and $\sigma^+(c_{ink})$ represent chip spreads from the nearest leader and follower, respectively. Formally, $\sigma^-(c_{ink}) = (c_{i-1} - c_i)$ and $\sigma^-(c_{ink}) = (c_i - c_{i+1})$. For example, as a player leads the nearest follower by a relatively large gap, it is likely that his current ranking is guaranteed. Then, risk taking is more attractive. On the other hand, as he is trailed by the nearest leader by a small gap, it is likely that he can catch up by normal plays. Risk taking is then not necessary. The coefficients for both variables are expected to be positive. However, unlike g and l, chip spreads might change much between chip count displays. So the measures of chip spreads at the (n-1)-th display could only weakly represent actual concerns about leaders and followers.

X_{ink} is a vector of a constant and control variables, including $c_{i,n-1,k}$, $\underline{w}_{nk}$, N_k, and n. The minimum prize ($\underline{w}_{nk}$) at the n-th chip count is included. Note that it is not constant within a tournament because it increases as players are eliminated. It is a guaranteed amount of prize at the moment of the tournament. The coefficient is therefore expected to be positive.[10] I also control for the number of chip counts in the tournament (N_k) because I expect that more frequent chip counts should capture more fluctuations in chips. The maximum number of chip counts differ across tournaments by the editorial decision. The smallest N_k is 3 and the largest one is 16 in the sample. n is included since variation in chips would be higher as a tournament approaches the end and smaller number of players remain.

Lastly ϵ_{ink} is the error term. I assume it is independent of explanatory variables, but allow for correlation across individual players for a pair of n and k. Since poker game is a zero-sum game, there are always winners and losers. Even if we consider the absolute values of chip changes, they are likely to be negatively correlated among players.[11] I correct standard errors by clustering for a pair of n and k.

Table 4 shows the results for the sample of middle-ranked players. As expected, the degree of risk taking depends on the incentives that individual players face. An increase in the gain in prize increases risk taking. An decrease in the loss also increases risk taking. The average holding of chips is 242,760. The estimates in column (4) suggest that an average player with 242,760 chips would put on risk about 6.1 percent of chips in response to one

[10] It should be kept in mind that $\underline{w}_{nk}$ is strongly and positively correlated with total prize. The correlation coefficient is over 0.9. The coefficient for minimum prize could capture any effect of total prize.

[11] Consider that two players who win some chips from others play each other. If a player wins, then his chips in absolute vale increase, while the loser's chips in absolute value decrease.

standard deviation increase in g (\$101,059). On the other hand, he would reduce his bet by about 14.2 percent in response to one standard deviation increase in l (\$48,455). The finding that players are more sensitive to losses than to gains is consistent with the hypothesis of loss aversion (Kahneman and Tversky 1979). The hypothesis that $|\alpha_1| = |\alpha_2|$ is rejected except column (1).

The results show that the more chips a player holds, the more chips he bets. An extra chip increases the absolute value of chip change by about 0.1, much less than one chip.[12] As expected, I find that as a player is trailed by the nearest leader by a larger gap or as he leads the nearest follower by a larger gap, he would bet more. The effect of chip spread from the nearest follower is however statistically and economically insignificant. This result suggests that risk taking is more dependent on chip spread from the leader.

In column (5) I include players' age and its squared term. Mostly some background information about players, such as age, career, and residence, are introduced for viewers in the beginning of show. But I cannot identify age for some players, which reduces the sample size. Figure 3 is a motivation, which suggests a U-shaped relationship between age and risk taking. Below average age 46, as players are younger, they are more aggressive; their chips fluctuate more in absolute value. For older players the relationship is not significant. I find the same results about age from regression in column (5).

Other results are also consistent with expectation. The minimum prize significantly increases the absolute value of chip change. The more frequently chip counts are displayed to viewers, the more variation in chips players have. Lastly, as tournament approaches the end, players bet more chips and the absolute value of chip fluctuation increases significantly.

Table 5 presents the results for the sample of middle-ranked and bottom-ranked players. For bottom-ranked players l is zero since there is nothing to lose. The chip spread from the nearest follower is not available for bottom-ranked players, so I have to interact $(\sigma^+(c))$ with the indicator for middle-ranked players (*Middle Rank*). The results are overall very similar to those in Table 4. The effect of l is larger in absolute value. This implies that bottom-ranked players would take more risk because they have nothing to lose in rank-order tournaments. Again the hypothesis that $|\alpha_1| = |\alpha_2|$ is strongly rejected across the board.[13]

[12] I include the quadratic term of c_{n-1} for the case of nonlinearity, but find it insignificant.

[13] I also run regressions with interacted terms between risk-taking incentives and chip spreads because, for

Table 6 and 7 presents the results for different specifications for robustness check. In Table 6 I use percentage change in chips ($\%\Delta c_{ink}$) as an alternative dependent variable. The results are virtually equivalent to the previous ones. For middle-ranked players one standard deviation increase in g would increase the absolute value of percentage change in chips by 2 to 5 percent. On the other hand, one standard deviation increase in l should decrease it by 8.6 to 11.4 percent. As with the previous results, the effects are significantly asymmetric in size. The results do not change qualitatively when we include bottom-ranked players. Most of other variables except N_k and n become statistically insignificant. Table 7 shows the results when some additional control variables are included. I include rank-specific dummy variables for the case that there is any direct effect of ranking. I also include tournament characteristics of prize structure (total prize and prize dispersion). The results do not change much. Additional variables are not statistically significant.

5 Conclusion

This study examines whether people optimally respond to risk-taking incentives in rank-order tournaments at high stake. I exploit professional poker tournament as a natural experiment. I find that professional players choose the degree of risk taking depending on monetary incentives, i.e. expected gains and losses implied from their relative position on the prize structure. Holding other things equal, a larger expected gain or smaller expected loss would strengthen the incentive for risk taking. I also find that the effects of expected gains and losses are highly asymmetric. Players are significantly more responsive to expected losses that gains.

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example, players could be more responsive to the expected gains from risk-taking strategies when it is less likely that they are caught up with by followers. However I find that the interacted terms are not significant both economically and statistically while they do not change other estimates qualitatively.

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Table 1: Prize Structure for 27 Tournaments[1]

	Mean	Median	SD	Min	Max
First Prize (w_1)	606,151	500,000	502,048	100,000	2,278,356
Second Prize (w_2)	323,795	278,240	291,146	38,000	1,372,223
Third Prize (w_3)	172,622	139,120	153,198	18,000	706,903
Fourth Prize (w_4)	118,725	83,472	106,854	10,000	457,406
Fifth Prize (w_5)	82,953	62,604	73,105	7,000	332,660
Last Prize (w_6)	60,889	46,715	51,645	6,000	232,862
Total Prize	1,365,135	1,091,430	1,165,011	183,000	5,380,410

[1] Prizes are denominated in the US dollars.

Table 2: Descriptive Statistics of Crucial Variables[1]

	Variable	Mean	SD	Min	Max
Middle-Ranked Players (N = 286)					
Absolute Variation in Chips	Δc	62,235	92,881	0	798,000
Current Chips	c_{n-1}	242,760	204,839	26,000	1,239,000
Percentage Variation in Chips	$\%\Delta c$	30.0%	33.3%	0%	173.1%
Chip Spread from Nearest Leader	$\sigma^{-}(c)$	156,997	226,275	0	1,813,000
Chip Spread from Nearest Follower	$\sigma^{+}(c)$	73,200	79,653	0	511,000
Gain in Prize by One-Rank Change	g	100,192	101,059	3,000	505,261
Loss in Prize by One-Rank Change	l	47,108	48,455	1,000	253,312
Bottom-Ranked Players (N = 106)					
Absolute Variation in Chips	Δc	60,890	79,607	0	391,000
Current Chips	c_{n-1}	111,716	107,271	5,000	666,000
Percentage Variation in Chips	$\%\Delta c$	60.3	55.2	0	246.9
Chip Spread from Nearest Leader	$\sigma^{-}(c)$	65,829	72,081	500	371,000
Chip Spread from Nearest Follower	$\sigma^{+}(c)$	–	–	–	–
Gain in Prize by One-Rank Change	g	27,022	31,464	1,000	153,135
Loss in Prize by One-Rank Change	l	0	0	0	0

[1] Prizes are denominated in the US dollars.

Table 3: Changes in Rank between Chip Count Displays

Middle-Ranked Players

Rank Change	Frequency	Percent (%)
0	140	48.95
1	115	40.21
2	24	8.39
3	6	2.10
4	1	0.35

All Players except Top Rank

Rank Change	Frequency	Percent (%)
0	204	52.04
1	140	35.71
2	35	8.93
3	12	3.06
4	1	0.26

Table 4: Middle-Ranked Players[1]

	(1)	(2)	(3)	(4)	(5)
g_i	.164	.241	.192	.178	.181
	(.076)	(.076)	(.074)	(.075)	(.096)
l_i	-.396	-.870	-.792	-.797	-.746
	(.209)	(.286)	(.270)	(.267)	(.246)
c_{n-1}	.184	.116	.113	.118	.070
	(.060)	(.059)	(.060)	(.057)	(.058)
$\sigma^-(c)$		.119	.117	.101	.119
		(.054)	(.055)	(.054)	(.058)
$\sigma^+(c)$		-.002	.010	-.038	.010
		(.108)	(.107)	(.105)	(.101)
$\underline{w}$		.787	.673	.801	.722
		(.443)	(.408)	(.413)	(.336)
N_k			-3439	-5795	-5301
			(1688)	(1697)	(2371)
n				5837	6269
				(1775)	(1940)
Age					-5825
					(2760)
Age Squared					62.5
					(35.3)
Constant	19724	4759	44762	43457	163722
	(8992)	(14095)	(20004)	(19389)	(53561)
$R^2 =$	.153	.213	.228	.257	.280
F-test for $\|\alpha_1\| = \|\alpha_2\|$	[.175]	[.008]	[.009]	[.001]	[.004]
Number of Observations			286		255

[1] Robust standard errors in parentheses are calculated by clustering. p-values are in brackets.

Table 5: Middle-Ranked and Bottom-Ranked Players[1]

	(1)	(2)	(3)	(4)	(5)
g_i	.232	.228	.201	.135	.141
	(.076)	(.072)	(.074)	(.073)	(.087)
l_i	-.729	-.964	-.920	-.796	-.793
	(.175)	(.256)	(.249)	(.242)	(.243)
c_{n-1}	.184	.184	.179	.174	.139
	(.054)	(.053)	(.055)	(.051)	(.047)
$\sigma^-(c)$		.112	.111	.091	.109
		(.051)	(.051)	(.051)	(.055)
$\sigma^+(c)\times$Middle Rank		-.081	-.070	-.105	-.079
		(.100)	(.098)	(.096)	(.093)
Middle Rank		-681	58.5	-9492	-3785
		(8588)	(8494)	(8280)	(8841)
$\underline{w}$		.718	.638	.775	.719
		(.363)	(.335)	(.330)	(.320)
N_k			-2610	-5270	-5052
			(1435)	(1457)	(1858)
n				5967	6461
				(1643)	(1765)
Age					-4694
					(2148)
Age Squared					48.3
					(26.0)
Constant	20119	3026	33263	35632	138114
	(7088)	(11974)	(17488)	(16575)	(43169)
$R^2 =$	.189	.248	.257	.292	.307
F-test for $\lvert\alpha_1\rvert = \lvert\alpha_2\rvert$	[.001]	[.001]	[.001]	[.001]	[.001]
Number of Observations	392				349

[1] Robust standard errors in parentheses are calculated by clustering. p-values are in brackets. Middle Rank is an indicator of middle-ranked players.

Table 6: Percentage Change in Chips[1]

	(1)	(2)	(3)	(4)
g_i	.000050	.000020	.000053	.000032
	(.000029)	(.000033)	(.000038)	(.000042)
l_i	-.000235	-.000178	-.000242	-.000154
	(.000067)	(.000078)	(.000088)	(.000090)
$R^2 =$	.041	.121	.120	.161
F-test for $\|\alpha_1\| = \|\alpha_2\|$	[.0001]	[.0072]	[.0012]	[.0427]
Number of Observations	286		392	

[1] Robust standard errors in parentheses are calculated by clustering. p-values are in brackets. Other variables included are $\sigma^-(c)$ and $\sigma^+(c)$ in column (1), $\sigma^-(c)$, $\sigma^+(c)$ c_{n-1}, $\underline{w}$, N_k, and n in column (2). Included are $\sigma^-(c)$, $\sigma^+(c)\times$Middle Rank, and Middle Rank in column (3), $\sigma^-(c)$, $\sigma^+(c)\times$Middle Rank, Middle Rank, c_{n-1}, $\underline{w}$, N_k, and n in column (4).

Table 7: Robustness Checks[1]

Sample	g_i	l_i	Controls	$\lvert\alpha_1\rvert = \lvert\alpha_2\rvert$
Middle	.144	-.638	Basic, Dummies for Rank	[.077]
	(.073)	(.313)		
Middle	.146	-.652	Basic, Dummies for Rank,	[.086]
	(.083)	(.298)	Tournament Characteristics	
Middle & Bottom	.109	-.695	Basic, Dummies for Rank	[.010]
	(.074)	(.260)		
Middle & Bottom	.092	-.676	Basic, Dummies for Rank,	[.014]
	(.090)	(.253)	Tournament Characteristics	

[1] Robust standard errors in parentheses are calculated by clustering. p-values are in brackets. For the sample of middle-ranked players, basic control variables include c_{n-1}, $\sigma^-(c)$, $\sigma^+(c)$, $\underline{w}$, N_k, and n. For the sample of middle-ranked and bottom-ranked players, basic control variables include c_{n-1}, $\sigma^-(c)$, $\sigma^+(c)\times$Middle Rank, Middle Rank, $\underline{w}$, N_k, and n. Tournament characteristics include total prize and coefficient of variation in prize.

Figure 1: Convex Prize Structures

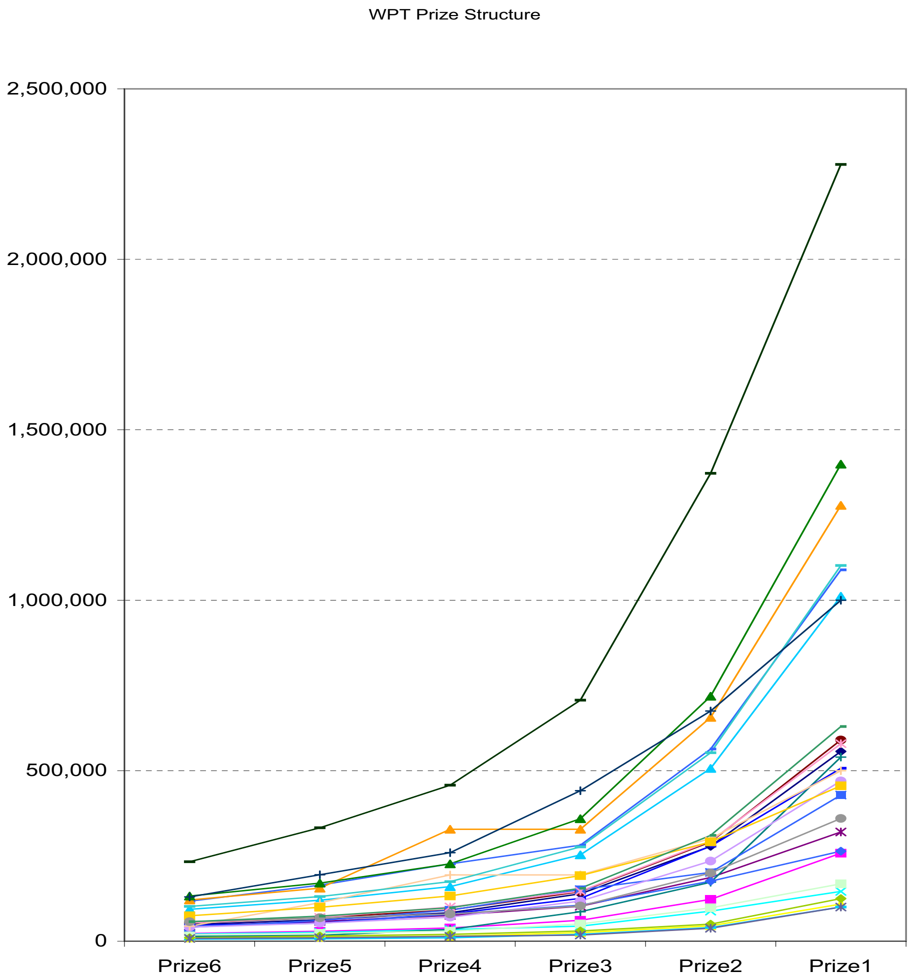
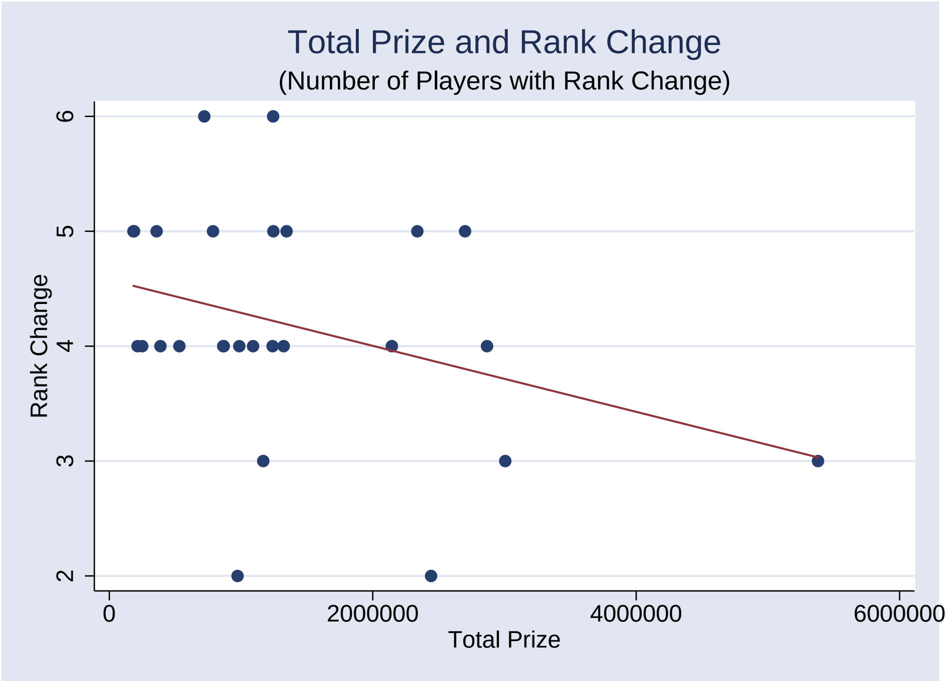
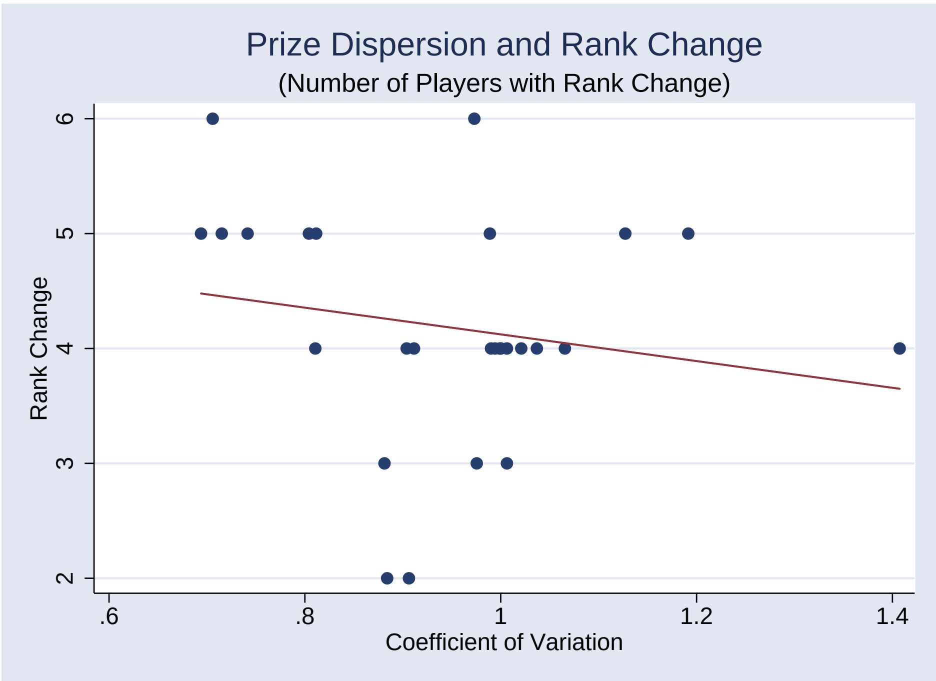


Figure 2: Prize Structure and Rank Change



(a) Total Prize and Rank Change



(b) Prize Dispersion and Rank Change

Figure 3: Age Profile of Risk Taking