國立臺灣大學社會科學院經濟學系
碩士論文

Department of Economics
College of Social Sciences
National Taiwan University
Master Thesis

多期競賽中以「高風險」戰術求勝的理論與實驗

Rational Long Shot in Dynamic Tournaments with Interim Performance Feedback

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中華民國 101 年 8 月

August, 2012

誌謝

兩年半的碩士生活轉眼即逝，將以這篇論文畫下句點。在大家幫助下順利完成實驗設計、程式撰寫、受試者募集、實驗進行到資料分析及最後的論文編撰之後，才知道研究進行時的高低起伏是如此難耐卻又快樂的過程。

在此感謝 TASSEL 的夥伴們:特別是陳之翰、郭彥、助理吳曉芳及同學林偉倫在實驗設計及進行過程中無私的支持陪伴和奉獻心力，以及大師兄陳暐和劉書彧於百忙之中抽空幫忙。最重要感謝這段期間我的指導教授：王道一老師對我悉心的指導、鼓勵和協助。不僅在知識上，更在態度上表現出以身作則地表現出對研究的要求和熱情，不論在研究或生活上，都改變了我許多。另外也要特別感謝陳之翰同學在這過程中對我的支持和鼓勵和包容。很多次遇到瓶頸時若沒有你和老師的鼓勵和支持，不會有最後這篇文章。

最後，特別感謝我的家人：爸爸媽媽及外婆。您們是我的動力，謝謝您們一直以來對我的支持和包容，特別是這幾年的碩士生涯以及在最後鼓勵我盡力完成。願榮耀歸於您們。

李易珊 民國 101 年 8 月 16 日

多期競賽中以「高風險」戰術求勝的理論與實驗

李易珊、王道一

民國 101 年 8 月 16 日

中文摘要

本文提出一個理性模型來解釋在贏者全拿的多期競賽中，人們為何會使用違反直覺的戰術，例如在籃球中的「長射」。此模型可合理解釋為何在共同基金市場，職業運動，和高階主管卡位等激烈競爭中，領先和落後者皆存心使用「高風險」的戰術以贏得最後勝利。由於此結論直接來自輸贏的機率，不受參與者的風險偏好影響，因此，一般認為是「高風險」的戰術，其實不見得跟參與者的風險偏好有關。接著我們用經濟學實驗來驗證這種即時公佈成績的多期競賽，發現實驗結果在下列三方面皆與理論預測相符：第一：78%的競爭者選擇和理論預測相同的戰術。第二：迴歸分析顯示：當理論預測人們應使用「保守」（論件計酬）的戰術時，95%的受試者選擇與理論相符。而當理論預測人們應使用「高風險」（長射）的戰術時，71%（81%當此為優勢策略）的受試者行為與理論相符。即使控制受試者之能力、性別及風險偏好後，此結果仍顯著不變。第三：受試者最終相對成績的分佈亦與理論預測相符。此外，當參與者大幅領先、使得理論預測兩種戰術一樣好的時候，男性與比較愛好風險的參與者更傾向選擇「高風險」的戰術。

關鍵字：運動經濟學，風險，共同基金，競爭，給薪制度

Rational Long Shot in Dynamic Tournament with Interim Performance Feedback

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16th August, 2012

Abstract

We propose a rational model to explain the use of counter-intuitive tactics in dynamic (two-person) tournaments. The model predicts when and why both leaders and trailers sometimes intentionally take "risky" tactics in order to win the final victory in high incentive tournaments in the mutual fund market, professional sports, competition for executive positions and so on. We then conduct a controlled laboratory experiment on this dynamic tournament with interim performance feedback, and find results that coincide with theoretical predictions in the following three ways: First, players follow model prediction 78% of the time. Second, regression analysis shows that 95% of players follow prediction when theory suggests the "safe" (piece-rate) tactic, while when theory suggests the "risky" (long shot) scheme, trailers follow this prediction 74% (81% when it dominant) of the time, even after controlling for players' ability, gender and risk attitude. Also, we find that gender and risk preferences play a role in leaders' behavior when theory predicts indifference. Finally, the experimental distribution of final performance difference is also close to what theory predicts.

Keywords: Risk-taking, Sport Economics, Contests, Competition, Mutual Funds

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1 Introduction

Tournaments have been widely adapted in various professions. In sports, winner-take-all athletic contests are used in professional golf (Brown, 2011), professional tennis (Sunde, 2009; Lallemand, Plasman and Rycx, 2008), the National Basketball Association (Grund, Hcker and Zimmermann, 2010), and the National Football League (Romer, 2006). In finance and corporations, there are yearly competitions in mutual fund and Hedge fund market (Brown, Harlow and Starks, 1996; Brown, Goetzmann and Park, 2001; Taylor, 2003*a*), in software algorithms creation (Boudreau, Lacetera and Lakhani, 2011), and competitions for executive positions (Iii, Main and Crystal, 1988; Kale, Reis and Venkateswaran, 2009; Graffin, Carpenter and Boivie, 2011). This incentive scheme has become so popular that Frank and Cook (1995) describe it as present in "virtually every part of our economic life."

Since Lazear and Rosen (1981), economists have studied how winner-take-all tournaments as an incentive scheme can induce higher effort. In particular, when players are risk-neutral and homogenous, Lazear and Rosen (1981) show that compensation schemes based on workers' relative position in the firm (tournament) elicit higher or even maximum effort levels than those based on absolute level of output (piece rate). Nalebuff and Stiglitz (1983) and O'Keeffe, Viscusi and Zeckhauser (1984) extend this to various two-contestant tournament rules, including winning by a certain margin, payment by relative performance,[1] endogenous precision and unfair tournaments. Nalebuff and Stiglitz (1983) and Green and Stokey (1983) discuss how the number of players and prizes affect effort level. Player heterogeneity and incomplete information can also affect players effort level (Lazear and Rosen, 1981, and O'Keeffe et al., 1984). For a survey of the literature, see McLaughlin (1988). Experimental studies testing theoretical prediction show mixed result.[2]

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[1] In Nalebuff and Stiglitz (1983), payment equals to a fixed amount plus a linear function of the difference of two individuals' level of output.

[2] Consistent with theory, experimental evidence show that increasing the prize spread do induce higher effort (Orrison, Schotter and Weigelt, 2004), while both player heterogeneity (Orrison et al., 2004; Harbring, Irlenbusch, Krkel and Selten, 2007; Eriksson, Teyssier and Villeval, 2009; Brown, 2011) and interim

Despite its importance, there are possible side effects of using tournaments to induce high performance. In particular, studies show that tournaments may induce agents to tactically take excessive risk. For example, Taylor (2003*b*) argues that when the midyear performance gap is large, winning managers are more willing to gamble under tournament compensation plans, and Basak and Makarov (2012) develop a theory to explain this phenomenon. Whereas other empirical studies show that mutual funds (Brown et al., 1996) and their managers (Chevalier and Ellison, 1999; Kempf, Ruenzi and Thiele, 2009) with a poor midyear performance increase risk to catch up with midyear winners. Interestingly, both front runners and trailers have been proposed to take more "risk" and potentially choose reckless moves in tournaments.

Note that these tactics occur in real life dynamic tournaments where there are end game effects and interim performance feedback. Mutual funds and their managers increase portfolio risk in order to window dress their performance level, knowing they are midyear leaders (or trailers) and anticipating the upcoming year-end performance rating (Brown et al., 1996; Brown et al., 2001; Taylor, 2003*a*). In sport tournaments, there are various counter-intuitive tactics to win the final victory by seemingly losing in the middle. For example, in the final minutes of Super Bowl XLVI , New England coach Bill Belichick intentionally told his defense to let their opponent, the Giants, score on the next play when there were 69 seconds left and New England were leading 17-15. By doing so, New England's offense would have a little more time to drive down the field and hopefully score, increasing their winning probability from 1.9% to 4.5% according to the online statistics outfit PredictionMachine.com.[3] Another example is the Badminton scandal in the 2012 Olympics: Four women double teams intentionally threw their matches in order to secure a more favorable draw in the next round, because the winner in that round will

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performance feedback (Casas-Arce and Martnez-Jerez, 2009) lower players' incentive to exert high effort or lower their quality (Eriksson, Poulsen and Villeval (2009)). However, other experimental studies show that tournaments yield greater variance in effort levels compared to piece-rate schemes (Bull, Schotter and Weigelt, 1987; Nalbantian and Schotter, 1997; Eriksson, Teyssier and Villeval, 2009), and hence have reduce overall efficiency. Instead, Harbring and Irlenbusch (2008) shows that "a balanced fraction of winner" and "loser prizes" enhance production.

[3] In fact, had they allow the Giants to score one possession earlier, their winning probability could have jump to 10.3%. For more details, see Futterman (2012).

encounter the former champion team of the 2008 Olympics. These examples show that in real-life dynamic tournaments, when knowing their interim performance level, players tend to employ rationalizable tactics depending on their current performance and timing, in order to win the final victory.

Most theoretical models cannot investigate how interim performance feedback in tournaments and end game effects induce these "risky" or "ugly" tactics. First, the canonical models of single-period tournaments are all static and do not allow for interim performance feedback or end game effects (Lazear and Rosen, 1981, Nalebuff and Stiglitz, 1983, and O'Keeffe et al., 1984). Second, in most dynamic tournament models, there are no room for "tactic", since players' strategies consist of only effort levels that increase performance (e.g. Casas-Arce and Martnez-Jerez, 2009, Fershtman and Gneezy, 2011, and Altmann, Falk and Wibral, 2012). Finally, in the few dynamic tournament models that do take tactics into consideration, most have performance levels that are either exogenous or positively correlated with effort. This either makes players feel destined or makes choosing tactics effectively choosing effort levels (e.g. Nieken and Sliwka, 2010; Hwan Baik, Cherry, Kroll and Shogren, 1999), and hence, cannot allow for situations in which players choose tactics intentionally to *reduce* their interim performance.

To focus on the choice of tactics depending on players' current performance and timing in tournaments, we consider a dynamic tournament, in which players are paired to play matching pennies against each other without rematch for 24 rounds and each choose their scoring schemes round-by-round.[4] In each round, players first learn the current performance of both players and hence the present score difference between himself and his opponent. Then, players choose their scoring scheme (tactic) for themselves and play matching pennies three times. Precisely, subjects choose for that round either a "piece-rate" scoring scheme of winning one point per match won, or a "long-shot" scheme of winning nine points if and only if they win all three matches in that round. Points are

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[4] The matching pennies task makes the performance level endogenous and meanwhile rules out the effect of effort in this tournament. Also, the winning rate of matching pennies serves as the measure for ability.

accumulated for 24 rounds, and the player who wins more points at the end of the last round wins the tournament. Notice that if both players are equipped with the same ability in playing matching pennies, one expects to earn on average 1.5 points under the piece-rate scheme, but merely 1.25 points under the long-shot, which means choosing the long-shot lowers the average performance (number of points earned) of a subject, although he or she might take a leap in scores when winning all the matches in that round.

We then conduct laboratory experiments to test our theory. We first verify that our behavioral assumption for the theoretical model is applicable to our data. Precisely, data support our behavioral assumption that each player has roughly half the chance to win in matching pennies. We then show that subjects indeed choose the long shot scheme mostly when the theoretical model predicts so. The only exception is the set of triangular regions in the state space theory predicts it is *the leader* who should take the long shot. In fact, estimating an equilibrium plus noise model, we find that the rational model captures around 78% of subject behavior. Moreover, prediction power of the rational model is much stronger when theory predicts piece-rate, but increases across all regions as the tournament proceeds. Panel data regressions focused on the last third of the game (where regions with different predictions are all presented) confirm that subjects choose the long-shot scoring strategy in the tournament when players fall behind and are trailing, consisting with theory. Furthermore, personal characteristics, such as gender and risk preferences, play an important role, but only when theory predicts indifference. In fact, regression results confirm that trailers overwhelmingly choose the long-shot scheme when theory is silent, such as when they are losing for sure.[5] In contrast, male subjects and those who are less risk-averse choose the long shot when they are indifferent as leaders. Interestingly, replacing the final step-wise payoff function with a logistic function (so subjects also care about final score differences) can explain these findings. Finally, we show the distribution of final score differences also coincides with theory.

The remaining of the paper is organized as follows. Section 2 derives the theoretical

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[5] This can be an indicator that trailers do care about their relative performance levels rather than only caring about their monetary payoffs. See section 2.1.2 for more details.

prediction of this game. Section 3 describes the experiment to test the prediction. Section 4 reports the experimental results, and Section 5 concludes.

2 Theoretical Prediction

To focus on the choice of tactics depending on players' current performance and timing in tournaments, we consider a dynamic tournament, in which players are paired to play matching pennies against each other without rematch for R rounds. In each round, players play matching pennies three times. Assuming each player has half the chance to win the underlying matching pennies game, we consider a dynamic tournament where the extensive-form game depicted in Figure 1 is played R times: First, players simultaneously choose their "tactic" or scoring scheme $F_{i,r}$ for round r ($\leqq R$).[6] They can either choose for themselves a piece-rate scheme or a long-shot scheme. $F_{i,r} \in \{L(m), P(m)\}$ Then, Nature decides the number of matches won by players i (among the matching pennies games played) in that round, $(m_{i,r})$, and hence points earned by each player $(Score_{i,r})$ based on their tactics.

$$\begin{array}{rcll} Score_{i,r} & = & F_{i,r}(m_{i,r}) & : m_{i,r} \longrightarrow \mathbb{Z} \\ L(m) & = & 9 & \textit{if } m_{i,r} = 3 \\ & = & 0 & \textit{otherwise} \\ P(m) & = & m & \end{array}$$

Note that "payoffs" in this game tree are points, not the actual expected utilities of each node. Since this is a winner-take-all tournament, only players with the highest scores in their group win the prize at the end of round R.[7] We define the score difference of in the end of each round r in this tournament as $z_{i,r} = \sum_{t=1}^{r} Score_{i,t} - \sum_{t=1}^{r} Score_{-i,t}$, and player i's payoff if terminal node z is reached as, $u_i(z_i) = \mathbb{1}_{[z_i, R>0]} + 0.5 \times \mathbb{1}_{[z_i, R=0]}$.

Hence, by assuming an increasing utility function over monetary payoffs, the expected

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[6] $i = 1, 2$.

[7] The winner will be randomly determined if there is a tie at the end of the tournament.

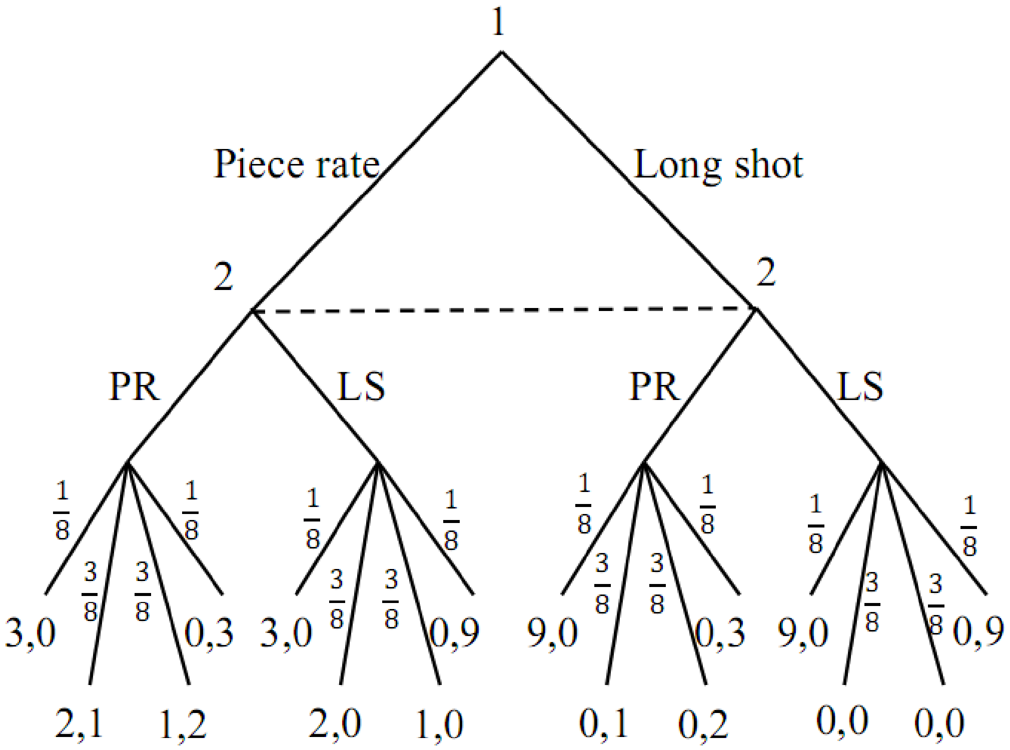

Figure 1: The Stage Game of the Tournament

utility of choosing each scoring strategy is a monotonic transformation of the corresponding winning probability under that strategy. Thus, the choice of strategy is independent of one's risk preference.[8] Thereafter, we can find the subgame perfect Nash equilibrium for each possible score difference in each round by applying backward induction. Specifically, we firstly find the best response which yields the highest winning probability for each possible score difference in the last round and solve for pure strategy Nash equilibria (if there is any). If there is none, we solve for the mixed strategy Nash equilibrium. We then plug in the winning probabilities yielded by the equilibrium strategies to be the expected payoffs of the reduced game for the corresponding score differences. The same procedure is applied repeatedly all the way back to the first round, in which the Nash equilibrium of the final reduced game is the subgame perfect Nash equilibrium of the original game.

For example, consider the situation that player i is trailing by four points in the beginning of the last round. Since this is the last round and the trailer can at most

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[8] Strictly speaking, we require utility function to be linear in winning probabilities and assume perfect reduction of compound lottery.

Round 24		Trailer	
Score Difference: -4		Piece Rate	Long Shot
Leader	Piece Rate	(1, 0)	(0.875, 0.125)
	Long Shot	(1, 0)	(0.875, 0.125)

Table 1: Backward Induction Example: $(z_1, z_2) = (4, -4)$, $r = R$

win 3 points under the piece-rate scheme, his/her winning probability for choosing piece rate is zero, regardless of the opponent's strategy. On the other hand, player i has a 0.125 probability of winning if he/she chooses the long-shot scheme (by winning all three matches and earn nine points). Hence, the payoff matrix at this state is shown in Table 2, and the Nash equilibrium requires trailers to choose the long shot and leaders to be indifferent between the two scoring schemes. Equilibrium winning probabilities are 0.875 for the leader and 0.125 for the trailer (which are to be plugged in as payoffs for two scoring schemes for $z_i = 4/z_i = -4$ and $r = R$ in the reduced game).

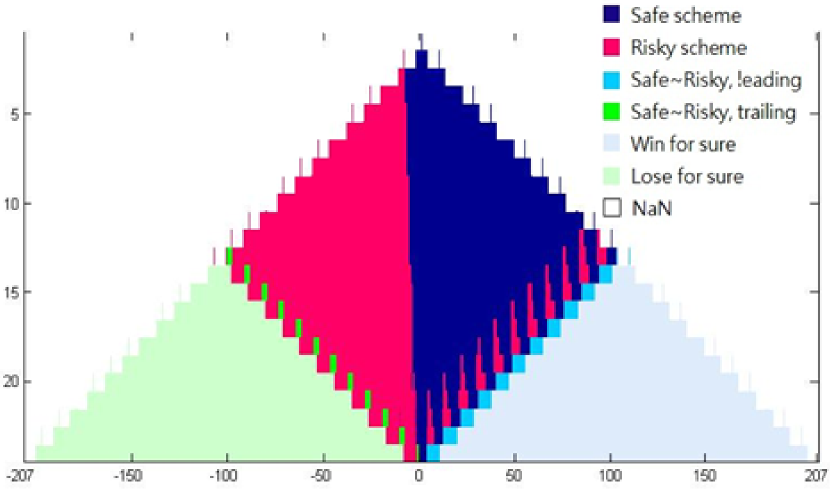

Figure 2: Subgame Perfect Nash Equilibrium for the Tournament with $R = 24$ (All Possible Score Differences).

Figure 2 depicts the subgame-perfect Nash equilibrium of this dynamic tournament with $R = 24$. The top blue cell indicates that at the beginning of round 1, when the only possible score difference is zero, the best strategy for both players is to adopt the piece-rate scheme, for it yields higher expected points and is equipped with a smaller variance than the long-shot scheme. It would be intuitive to predict that trailers who are only

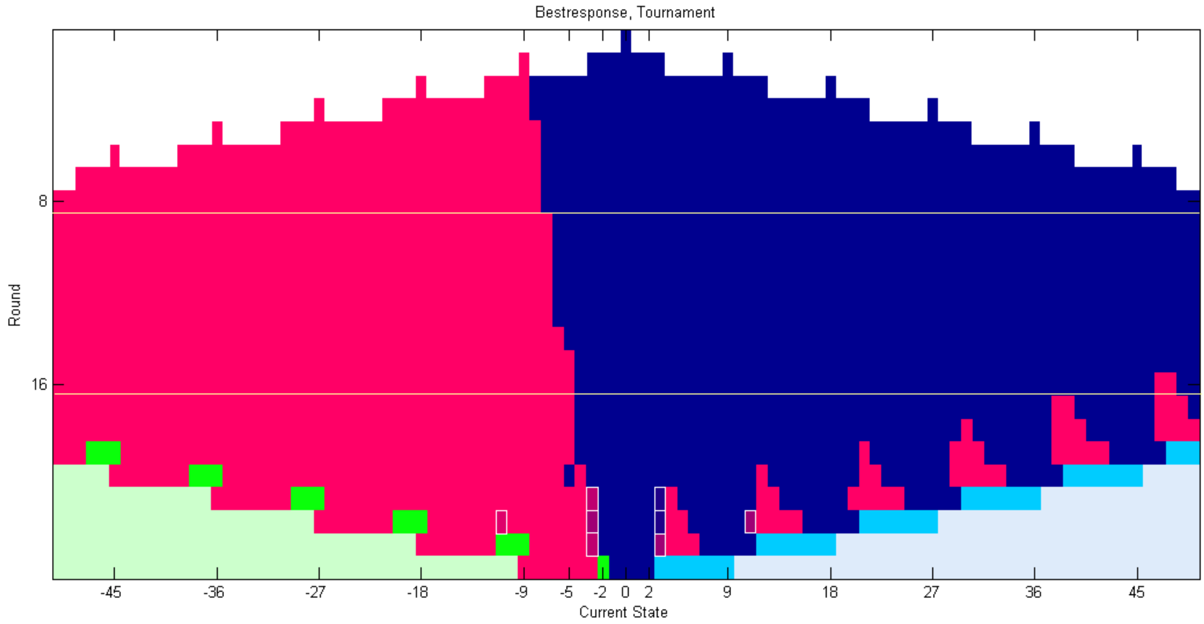

Figure 3: Subgame Perfect Nash Equilibrium for the Tournament with $R = 24$ (Magnified to show $z_i \in [-50, 50]$)

slightly behind and most leaders should keep taking advantage of the piece-rate. Indeed, this is shown by the deep blue area which indicates that employing the piece-rate scheme is the best response in these score differences. However, as the tournament proceeds, trailers are forced to turn to the long-shot scheme to catch up. This is portrayed by the red area on the left side. The long-shot scheme has its downside, i.e. the lower expected points. Thus, it is optimal only when trailers are trailing by more than two points. This is because trailers trailing by only one or two points should take advantage of the higher expected points resulted from the piece-rate scheme. However, once the trailer is trailing by a lot, the long-shot scheme is always a best response for which it enables the trailer to leap in scores if they are lucky.

The faded-green blocks at the bottom-left indicate score differences where the trailers are losing for sure and therefore indifferent between two schemes. Whereas the mirror image of these score differences, the light-blue blocks at the bottom-right, consists of their opponents' positions, in which leaders win for sure. The bright-green blocks embedded among the red region indicate score differences where trailers are at the brink of elimination, and hence, indifferent between the long-shot and piece-rate schemes given their opponents are choosing the piece-rate scheme. Similarly, the sky-blue blocks at the right indicate score differences in which leaders are indifferent between the two schemes given their trailing opponents are employing the long-shot.

The most surprising part of the equilibrium prediction is the triangular red areas at the right side, which indicates leaders who are close to but still steps away from winning for sure should employ the long-shot scheme, hoping to a leap from their current state to the winning-for-sure region. These areas are sparse because leaders are facing a difficult tradeoff between winning probabilities and expected points when they are close to winning for sure. Specifically, when winners are only two points away from winning for sure, they should take advantage of the small variance and high expected points provided by the piece-rate scheme. However, earning three points in one round by applying the piece-rate scheme is as difficult as earning nine points by employing the long-shot. Therefore, when leaders are more than two points but within nine points away from the winning-for-sure region, adopting the long-shot strategy is optimal.

2.1 Properties of the Subgame Perfect Nash Equilibrium

2.1.1 Winning Probabilities

Figure 4 plots the winning probabilities (yielded by best responses) for different score differences at different stage of the tournament. The thicksolid line is the winning probability over final score differences. [9] Since a player wins a big prize only when winning the tournament, this thick solid line shows the utility function over the tournament result if we assume players only care about their monetary payoffs. The other lines are the winning probabilities for different score differences in Round t yielded by best responses derived by applying backward induction.[10] Although the best strategies shown in Figure

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[9] For final score differences higher or equal to +1, the winning probabilities are 1. For final score differences below or equal to -1, the winning probabilities are zero. Hence, the winning probability for score difference equal to zero is 0.5 since the winner will be randomly drawn

[10] For example, the dark (red) dash line is the winning probability in the beginning of the last round. The winning probabilities for relative scores equaling to -10 and below are literally zero since the maximum

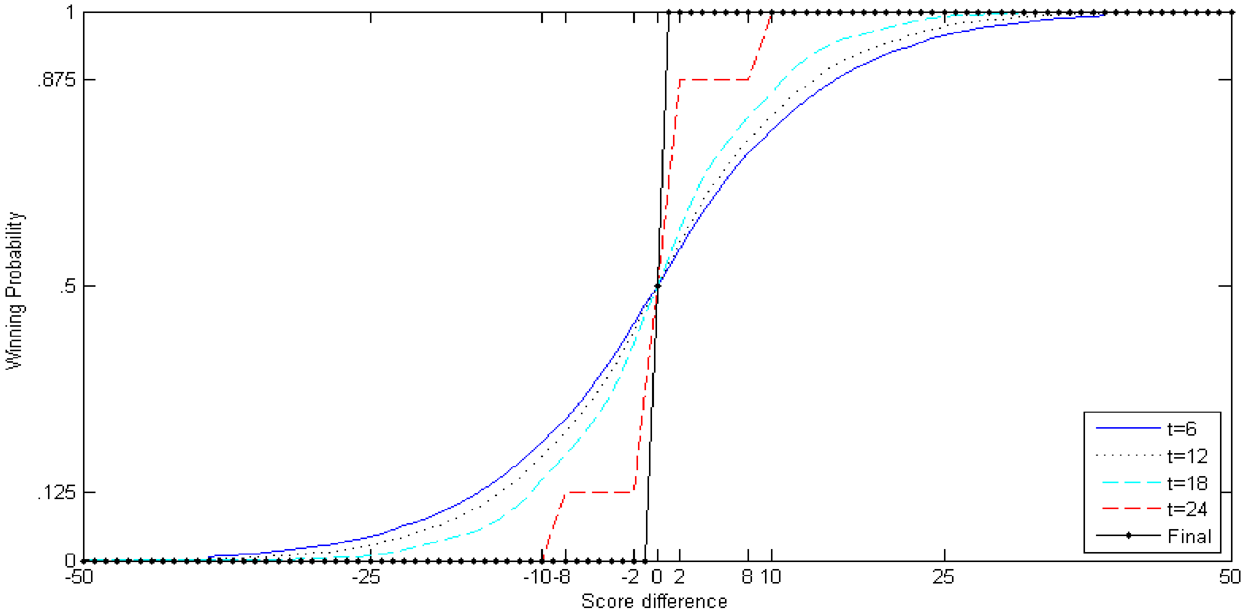

Figure 4: Winning Probability as a Function of Score Difference and Round

2 are non-monotonic over score differences, the winning probabilities are monotonically increasing over score differences. Besides, as t decreases, the winning probability becomes flatter and flatter because there is more chance to come back. In contrast, the steep winning probability curves when t is large is resulted from the finite time horizon of the tournament.

2.1.2 Caring about Final Score Differences

It is possible that players in the tournament not only care about their final monetary payoff, but also the final score differences they lead or trail by. We model this as a logistic function:

$$u_i(z_i) = \frac{\exp(\lambda z_i)}{1 + \exp(\lambda z_i)}$$

where large λ approximates the step function and $\lambda = 0$ indicates players completely ignoring the tournament structure of the game. This function is increasing, indicating

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points a player may win is 9 per round. That is why those scores are in losing-for-sure region in Figure 2. And when relative score is 10 or above, the winning probability is one since the player win for sure. Between 10 and -10 we see steep increases caused by the discrete nature of the long shot and the piece rate schemes.

that players want to lead but not to trail, and concave (convex) above (below) $z_i = 0$, implying that players take zero as their reference point and have decreasing marginal utility over absolute score differences. In addition, it incorporates the winner-take-all step-wise utility function as a limiting case, since $u_i(z_i) \to \mathbf{1}_{[z_i > 0]}$ as $\lambda \to \infty$.

Figure 5 illustrates how the parameter of logistic function (λ) smooth out the payoff functions as $\lambda \to 0$. The larger λ is, the more players perceive the game as a tournament and care less about winning or losing by a lot. For example, the *logistic(2)* utility function (solid line) resembles the step function, although player's marginal utility still increases slightly as they lead by more points (or trail less). As the parameter of logistic function(λ) decreases, player care more about their final score differences and perceive the game less as a tournament. The *logistic(0.05)* utility function (dash-dot line) shows an utility function that is almost linear over final score differences. Players with this utility function would aim to maximize (minimize) the points they are leading (trailing) by, instead of maximizing the probability of winning the tournament.

We solve for the subgame-perfect Nash equilibrium replacing the original step function with a logistic payoff function and show how this payoff function changes the equilibrium of this tournament. First of all, because of the logistic payoff function. the winning probability will never be 1 or 0. Hence, the winning/losing-for-sure regions disappear in the equilibrium based on the logistic utility functions. For example, Figure6 shows the equilibrium strategies with *logistic(2)* payoff function, in which losing-for-sure trailers now choose the long shot scheme instead of being indifferent between two scoring schemes. Aside from this difference and the disappearance of winning/losing-for-sure regions, the equilibrium almost is identical to the original one. In contrast, Figure 9 shows the equilibrium based on logistic(0.05) payoff function which is almost linear. Since players care only about difference in performance, they always choose the piece-rate scheme which yields higher expected points (compared to the long-shot). Figure 7 and Figure 8 show intermediate cases based on *logistic(1)* and *logistic(0.5)* utility functions respectively. These two figures demonstrate the transition of equilibrium from players who care nothing but winning to those who only care about score differences. In particular, one can see how the triangular regions where leaders choose the long-shot and the winner indifferent regions disappear as λ decreases.

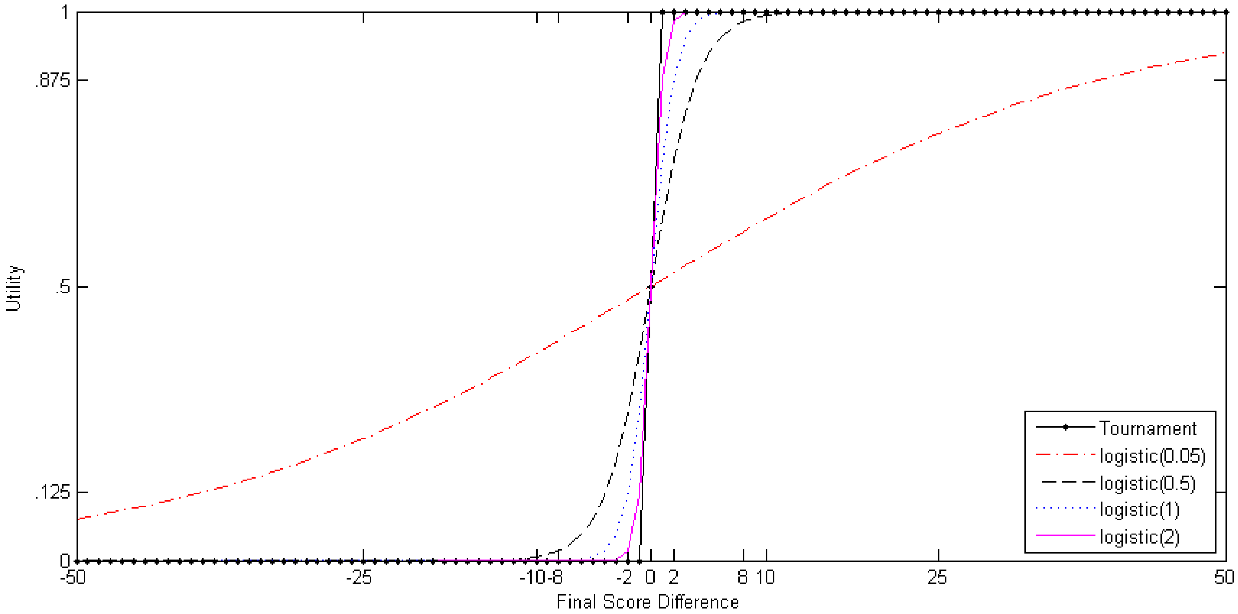

Figure 5: Various Logistic Payoff Functions of Final Score Difference

3 Data and Experimental Strategy

We conducted a lab experiment to observe how people choose between a long-shot and a piece-rate scoring scheme as their score differences change throughout the above tournament. In particular, subjects are paired to compete in a 24-round tournament without rematch, and only winners (highest one in points in each pair) earn NT\$400 (approximately US\$13.5),[11] and losers earn nothing beyond the show-up fee.[12] In each round, each subject first chooses their own scoring scheme for that round, then the two subjects play matching pennies three times against each other to earn points according to their own scoring scheme. Subjects may choose (for that round) a “piece-rate” strategy of winning

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[11] 400 New Taiwan Dollars is approximately four times the minimum hourly wage in Taiwan (which is NT\$103).

[12] The winner is randomly determined if there is a tie at the end of this 24 rounds tournament.

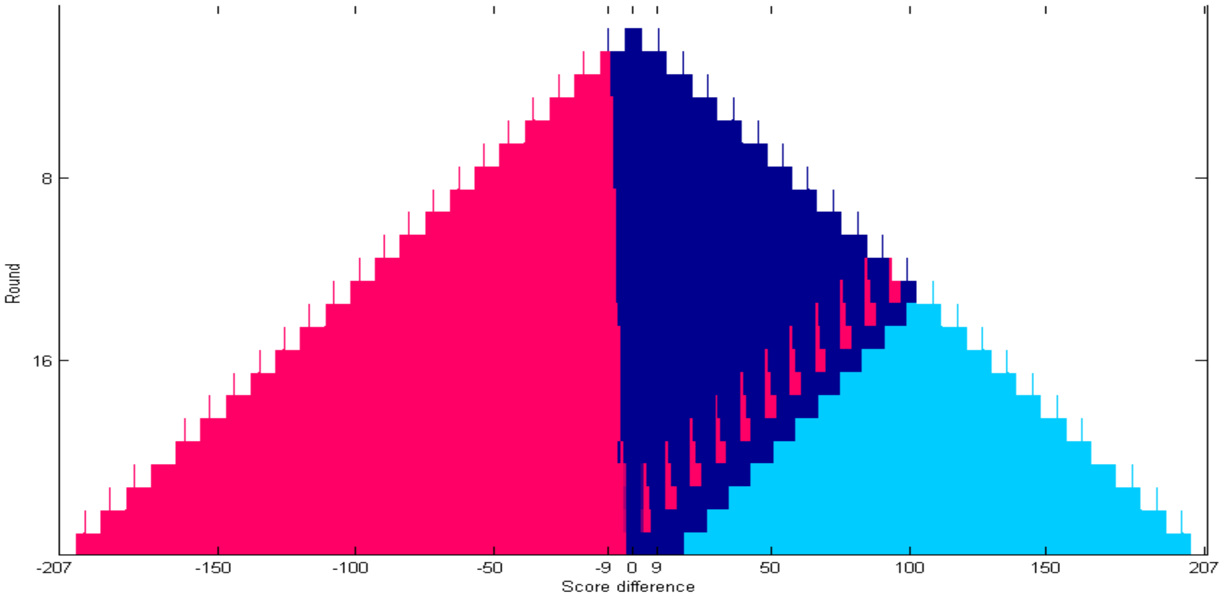

Figure 6: Subgame-perfect Nash Equilibrium with Logistic(2) Payoff Function

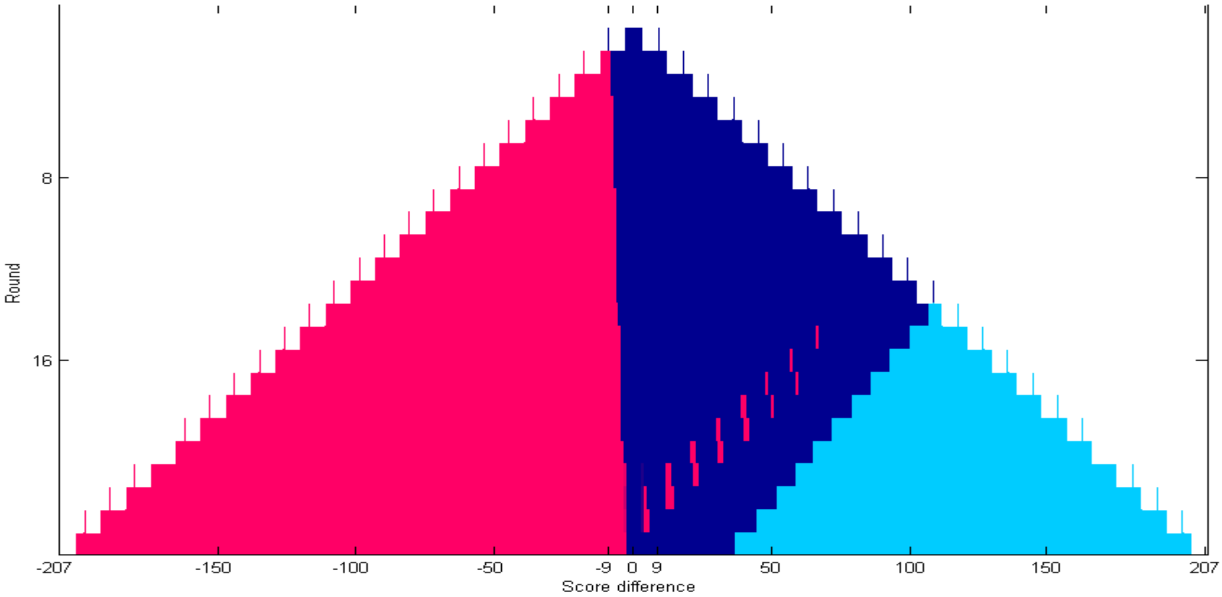

Figure 7: Subgame-perfect Nash Equilibrium with Logistic(1) Payoff Function

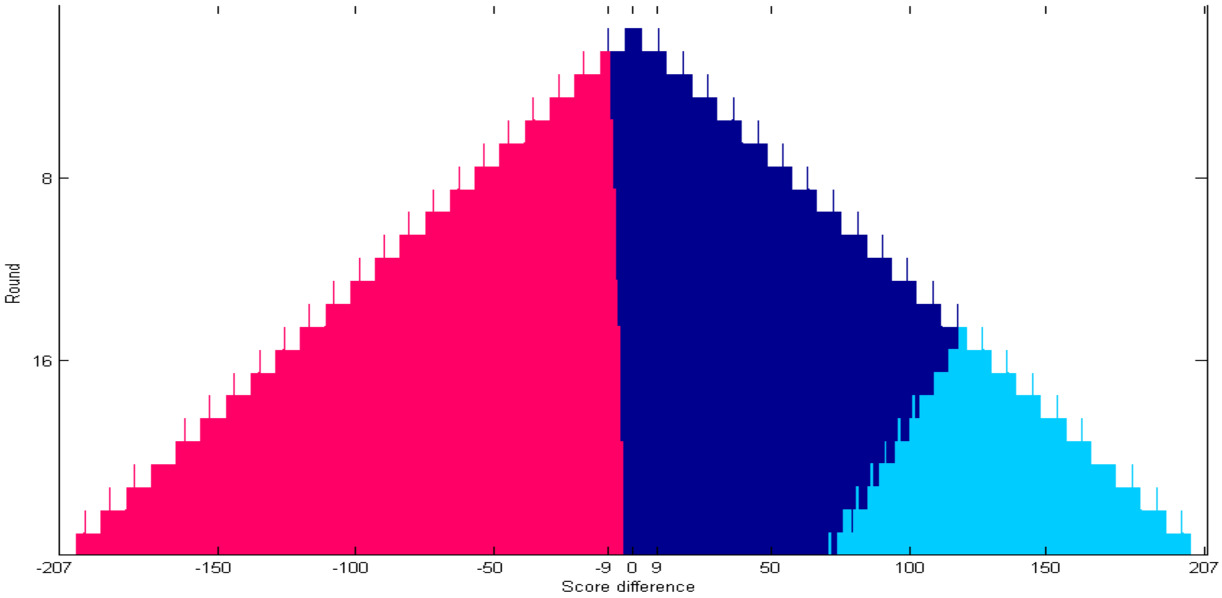

Figure 8: Subgame-perfect Nash Equilibrium with Logistic(0.5) Payoff Function

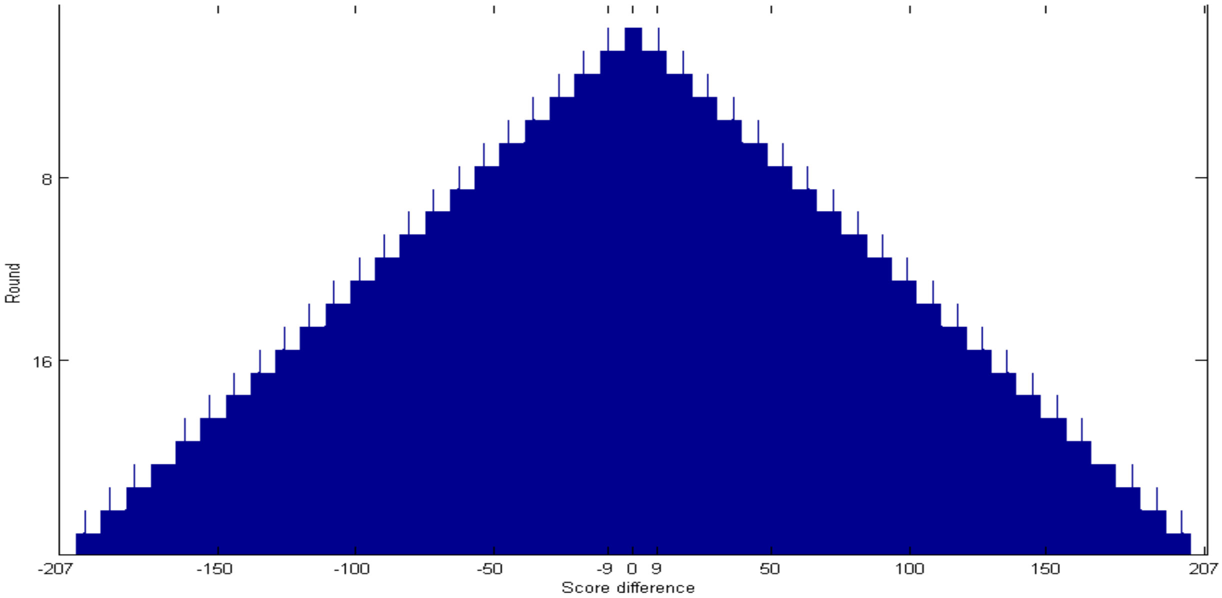

Figure 9: Subgame-perfect Nash Equilibrium with Logistic(0.05) Payoff Function

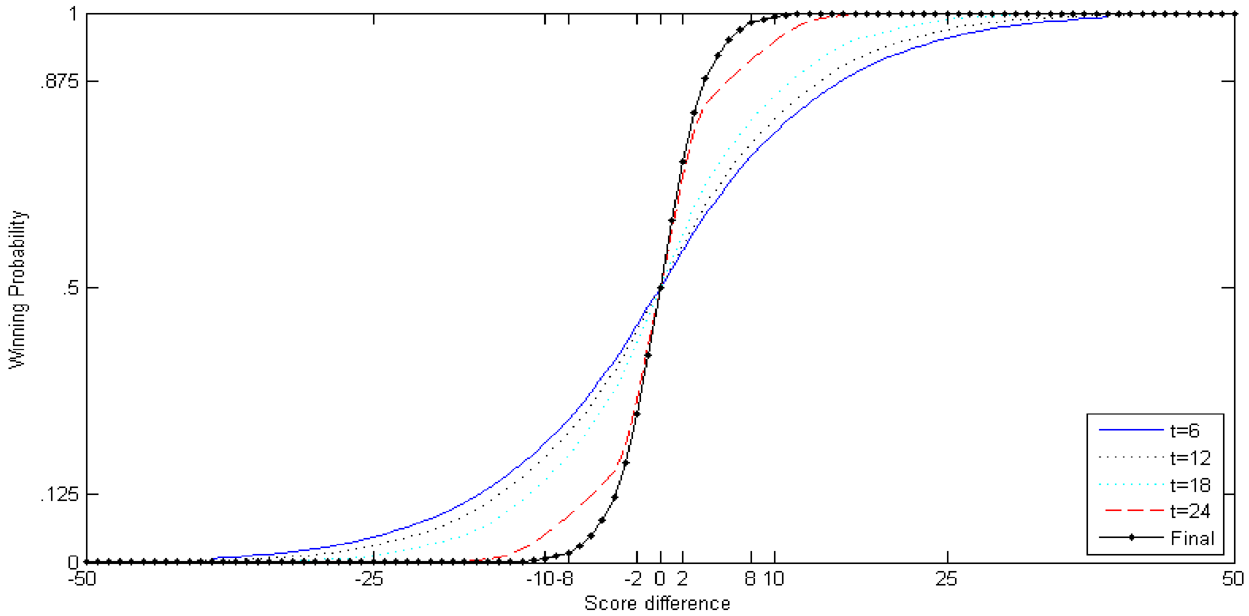

Figure 10: Winning Probabilities for the Equilibrium with Logistic(0.05) Payoff Function (Every 6 Rounds)

one point per match won, or a "long-shot" scheme of winning nine points if and only if he/she wins all three matches in that round.

The matching pennies outcomes are reported after each match (so players receive immediate feedback to foster learning and be more involved in playing against each other), and the scores of both subjects are reported after each round. Therefore, subjects can adjust their tactics in the beginning of each round according to their most current score performance and their opponent's performance in the game.

To test our prediction on how score differences affect player's action in this tournament, we control for personal characteristics which may yield similar effects, including ability,gender and risk prederence. In particular, we used the matching pennies tasks to minimize the effect of effort on scores and choices, and used players' "past winning rate" as a proxy to control for their ability in this task. Gender, which may affect risk-taking choices in competitions, was elicited in a questionnaire at the end of this experiment to avoid experimenter demand effects. Finally, risk preference was measured by conducting the Holt and Laury risk preference elicitation task of Holt and Laury (2002) in the beginning of the experiment. In the Holt and Laury task each subject was asked to choose between paired lotteries in 10 different scenarios, and the switching point of the choices was used to infer one's risk preference. One of scenarios was randomly drawn and the chosen lottery realized, which yields an expected payoff around 7 US dollars. The same Holt and Laury task was conducted after the tournament concluded to check for robustness and measure potential wealth effects (which we find none).

The following analysis uses data obtained from six experimental sessions conducted at the Taiwan Social Science Experimental Laboratory (TASSEL) in National Taiwan University (NTU). 108 subjects in total were recruited from students in National Taiwan University. However, we focus on the data of players who have "rationalizable" risk preference (i.e. have a unique switching point) in the Holt and Laury (2002) task; this leaves us with 2204 data points from 96 subjects playing 24 rounds.

4 Result

The results section proceeds as follows. Section 4.1 reports subject performance on matching pennies and verify our behavioral assumption that each player has half the chance to win in a matching pennies. Section 4.2 reports subject's choice of scoring schemes, and find them coinciding with what the theoretical (tournament) model predicts in most regions. The only exception is the triangular region that leaders should take long shots. In fact, an equilibrium plus noise model is estimated to demonstrate the prediction power of the rational model in different regions. Section 4.3 discusses the drive for picking the long-shot scoring strategy in the tournament.

4.1 Matching Pennies

We first test our behavioral assumption on matching pennies in the theoretical model: each player has half the chance to win a match. In particular, we conduct binomial tests on the matching pennies results ($MP = 1$ if won, $MP = 0$ if lost) at both the individual and group level. At the individual level, we test whether the 72 matching pennies results of each subject follow a binomial distribution with $p = 0.5$. Table4.1 shows that only 2 out of 96 subjects fail this binomial test at the 5% level. At the group-level, we find the average number of matches won by the better player is not significantly ($p - value = 0.555$ for the two-sided binomial test) different from the theoretical prediction of 38.3895.[13] Including twelve more subjects that failed to have unique switching points in the Holt-Laury task does not change even that quantitative result, leading to only 4 out of all 108 subjects failing the individual binomial test at the 5% level and a group-level p-value of 0.118.[14] Hence, our behavioral assumption for the theoretical model, i.e. equal winning rates, is indeed applicable for our experimental data. This allows us to proceed and compare choices and performance level data with prediction to see how this rational tournament model performs.

	Number of winners, losers, ties (N)	Individual level test # of failed subjects	group level test 2-sided p-value (n)
All data	50,50,8 (108)	4 #won:21,27,45,51	0.1181 (54)
exclude outliers (multiple switching points)	44,44,8 (96)	2 # won:21,27	0.5460 (48)
exclude outliers & their partners	38,38,8 (84)		0.6139 (42)

Table 2: Binomial Test Results for Matching Pennies

4.2 Comparison between Lab Data and Prediction

In Figure 11, we report the fraction of long-shot players in each possible state using colors. Red stands for all players choosing long-shot and blue stands for all players choosing piece-rate. The colors in between indicate that some players at that state chose the long

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[13] When $x_1, x_2 \overset{\text{i.i.d.}}{\sim} B(72, 0.5)$, the average number of matches won by "better players" following the binomial distribution with $p = 0.5$ is $E[\max\{x_1, x_2\}] = \sum_{x_1=1}^{72} \sum_{x_2=1}^{72} \max\{x_1, x_2\} \cdot f(x_1, x_2) = 38.3895$.

[14] Excluding both those who failed to have unique switching points and their partners strengthens our results (Table 2, row 3).

shot while others with the same score difference employed the piece-rate scheme. The thick black lines illustrate the main boundaries between regions with different predictions based on our theoretical model. The regions below the two bottom boundaries are score differences that leaders win for sure (region at the bottom right) and losers lose for sure (region at the bottom left). The most important boundary is the vertical black line lying within the interval [-9,-2]. The model predicts that the long-shot scheme should dominate on the left side of this boundary, and the piece-rate strategy on the right (except for the triangular regions where long shots are best responses for leaders).

Matching the theoretical prediction with actual choices of our experimental subjects, we find in Figure 11 the majority of the piece-rate region blue and the majority of the long-shot region in the left side red (although there are still some blues, especially at the beginning of the tournament). In the winning-for-sure and losing-for-sure regions where theory is silent, most of the cells are red, although people are indifferent in these two regions. The only region that theory does not capture choices of most subjects is the triangular regions where long shots are best responses, while the majority of them in Figure 11 is blue.

To provide a measure of how the rational model performs, we estimate an equilibrium plus noise model. Precisely, suppose the rational model predicts that subjects should choose the piece-rate scheme at a certain score difference, the econometric model allows subject to have ϵ probability to actually choose the long shot instead; so the probability of playing the piece-rate scheme is $1-\epsilon$. When the model predicts subjects should choose the long-shot strategy, the econometric model predicts that they choose the long-shot scheme with probability $1-\epsilon$, and choose the "wrong" scheme (piece-rate) with probability ϵ.

We use maximum likelihood estimation to find the best-fitting ϵ for this model, using 2204 data points. Figure 12 depicts the absolute values of log-likelihood associated with different ϵ's between zero and 0.5. It turns out that the overall best-fitting parameter for this model is $\epsilon = 0.2170$, indicating that people follow the rational model prediction roughly 78 percent of the time, with at most 22% noise. Given the computational complexity of the equilibrium and subjects playing this game only once, the noise is surprisingly low.

To further see how this model performs in regions with different prediction as the tournament proceeds, we estimate different ϵ_i for rounds 1–8, 9–16 and 17–24, separately for the long shot region in the left and the piece-rate region in the right. For the long shot region in the left, ϵ_i is 0.62 for round 1–8, 0.57 for round 9–16, and drops to 0.31 for round 17–24. The ϵ_i for the piece-rate region also decrease from 0.14 for round 1–16 to 0.09 for the last 8 rounds, which indicates learning. However, a thorough investigation of individual learning patterns is beyond the scope of this paper. The counterintuitive triangular regions where leaders are predicted to choose the long shot yield an error rate of $\epsilon_i = 0.95$, which means 95% of our subjects employ the piece-rate scheme instead. This is not consistent with the rational model which predicts that players should choose the long-shot when they are leading by these amounts. Interestingly, this is consistent with the equilibrium using a logistic utility function with low λ, indicating subjects care about the margin of victory/loss, in addition to their monetary payoffs.

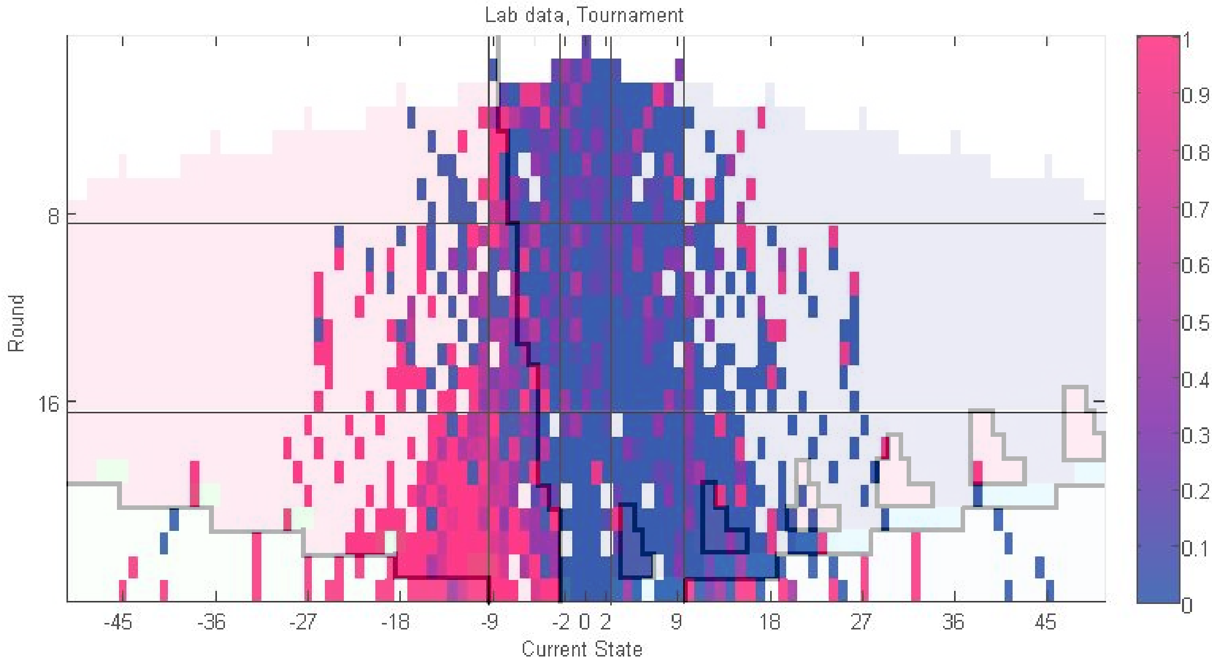

Figure 11: Fraction of Subjects Choosing the Long Shot Strategy

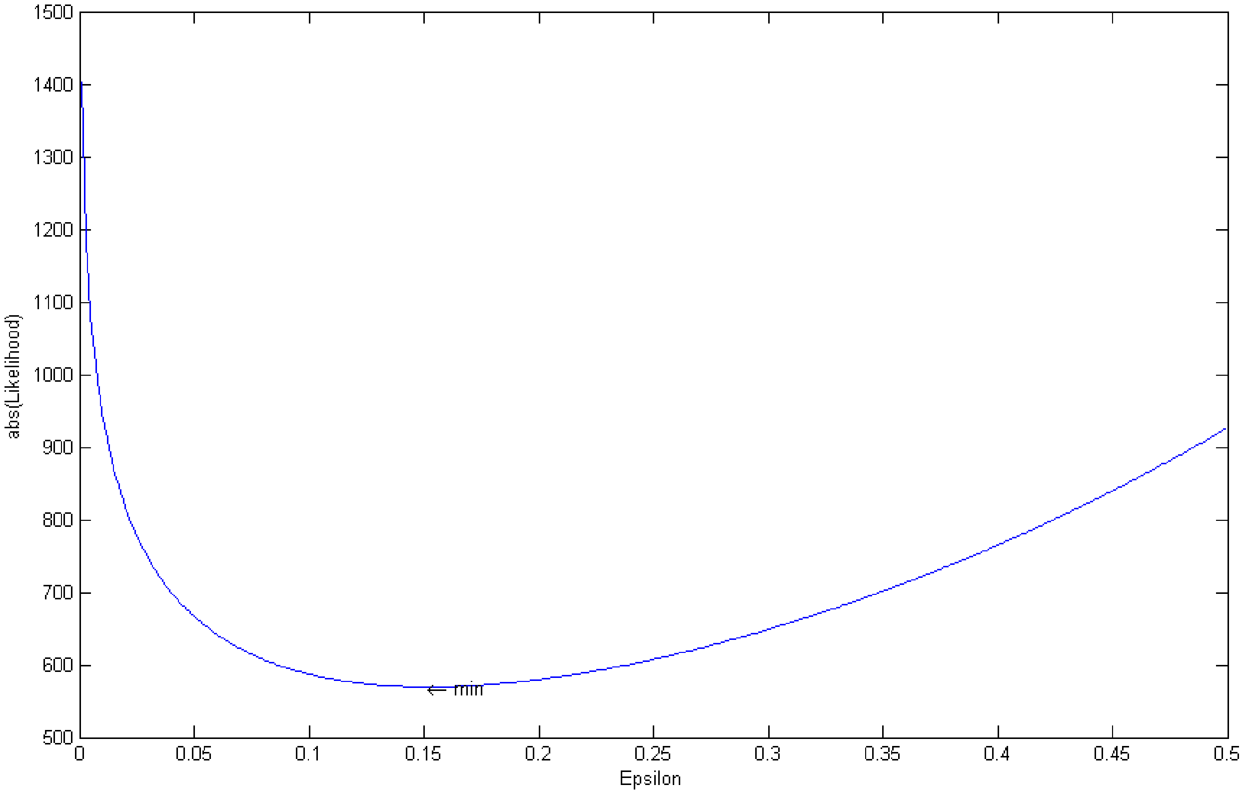

Figure 12: Maximum Likelihood Estimation for Error Rate ϵ

4.3 Regression Analysis

In 4.3.1 we first discussed the relation between choosing the long-shot scheme and falling behind (and have negative score differences) in this tournament. Section 4.3.2 predicts subjects' long shot choices in this tournament using the theoretical predictions and other personal characteristics (such as gender, risk preference and ability). We focus on the data of the last third of the game (round 17 to round 24) where regions with different theoretical predictions are all presented.

4.3.1 Granger Causality of Long Shot Choice and Score Difference

Figure 11 shows that most players choose the long shot when trailing behind. But choosing the long-shot can also lower one's average scores. Hence, we conduct a Granger causality test to clarify the relation between trailing behind and choosing the long shot.

Table 3 provides panel logit model estimates explaining the relation between choosing the long-shot scheme and trailing behind. Column (1) shows that subjects choose the long-shot scheme 42.4% more often after knowing they are currently trailing. Column (2) indicates choosing the long-shot scheme has insignificant effect on trailing behind (11.4% with $p = 0.3274$). Hence, we conclude that trailing behind Granger causes choosing the long-shot strategy.

4.3.2 Score Differences, End Game, and Personal Characteristics

Table 4 reports panel logit regression results that explain choosing the long-shot scoring scheme in this tournament using whether one is trailing behind, the theoretical predictions and other personal characteristics. The dependent variable $\mathbf{LS}_t$ is a dummy variable for picking the long shot. The independent variables are dummies for trailing behind (*Trailing*), regions with different theoretical predictions (*LS_dominant*(d), *LS_trailer*(d), *LS_leader*(d), *Indiff_leader*(d), *Win_for_sure*(d), *Indiff_trailer*(d), *Lose_for_sure*(d)), controlling for relative risk-averse parameter (*RRA*), gender (*Male*(d)) and player's ability (*PastWinningRate*).

Panel Logit	(1)	(2)
Dependent variable	**LS**$_t$ (d)	**Trailing**$_t$ (d)
LS$_{t-1}$ (d)	.515***	.114
	(10.55)	(0.98)
LS$_{t-2}$ (d)	.275***	.0212
	(4.47)	(1.86)
Trailing$_t$ (d)	.424***	
	(5.08)	
Trailing$_{t-1}$ (d)	-.0139	.799***
	(-1.47)	(19.35)
Trailing$_{t-2}$ (d)		.380***
		(3.91)
N	746	746

Marginal effects; t statistics in parentheses; (d) for discrete change of dummy variable from 0 to 1.
$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 3: Granger Causality Test (Last 8 (17-24) Rounds

Column (1) shows that trailing behind in general significantly increasing the chances of choosing the long-shot scoring by 56.2%. This is consistent with the Granger causality test. Column (2) estimates the marginal probability of choosing the long-shot in regions with different theoretical predictions. The results significantly coincide with theoretical prediction in most regions, except for the triangular regions in which leaders are to choose the long shot (*LS_leader* = 1). In particular, subjects trailers in the long-shot region (*LS_trailer* = 1) choose the long shot 74.1% of the time more than subjects in the piece-rate region (baseline) ($p < 0.001$). This effect is even stronger (81% more) when long shot is the dominant strategy (*LS_dominant* = 1).

In regions where trailers are indifferent between the two scoring strategies (*Indiff_trailer* = 1 or *Lose_for_sure* = 1), subjects choose the long shot 79% or 81% of the time. On the other hand, players who are guaranteed a win (*Win_for_sure* = 1) seem to be playing around by choosing the long shot half of the time, while most other players who are leading and indifferent between two scoring strategies (*Indiff_leader* = 1) choose the piece-rate scoring strategy.

As reported in column (3), the results do not change even if we control for past winning rate (proxy for ability), risk preferences (*RRA* measured by the Holt-Laury task), and gender. These three controls seem to have no significant effects on choices. The results in Column (2) and (3) are all significant at the 0.1% level, and they are robust to employing a panel Probit model.

To investigate whether risk preferences and gender play a role in certain stages of the tournament, we interact *RRA* and gender (*Male*) with four regional dummies (*LS*, *PR*, *Ind_trail/L*, *Ind_lead/W*). Column (4) shows the effects of risk attitude and gender on subject's choice of scoring strategy take place only when theory predicts that players are indifferent between two scoring strategies. When subjects are already winning for sure or close to winning for sure, there is an interactive effect in which male players and those who are less risk-averse are more likely to choose the long shot. These two controls have no significant effect in any other regions in this tournament.

5 Performance Distribution

Aside from prediction on scoring schemes (subjects' strategic choices), this rational model also predicts the time series of the score distribution (performance distribution for each round) in dynamic tournaments. Since this prediction enables us to test if players follow best response in each steps by simply comparing their performance distribution with the theoretical one, it provides another clear and convenient measure on the rational model's prediction power. This is of empirical relevance since regulators of the financial sector also care about the entire distribution of mutual fund performance, in addition to the winner's performance.

We calculate the theoretical prediction of the number of players (out of 108) for each performance level z_i starting from round 1 to the end of round 24 (final) in this tournament, assuming that every player employs equilibrium strategies and each player has half the chance to win matching pennies.

We first calculate the probability mass function of score differences subjects may reach

	(1) **LS**	(2) **LS**	(3) **LS**	(4) **LS**
Trailing(d)	0.562^{***}			
	(7.87)			
LS_dominant(d)		0.810^{***}	0.806^{***}	0.815^{***}
		(19.44)	(19.44)	(18.64)
LS_trailer(d)		0.741^{***}	0.706^{***}	0.665^{***}
		(12.74)	(9.14)	(5.29)
LS_leader (d)		-0.0953	-0.0894	-0.141
		(-0.91)	(-0.82)	(-1.32)
Indiff_leader (d)		-0.0316	-0.0269	-0.128
		(-0.26)	(-0.22)	(-1.21)
Win_for_sure (d)		0.503^{***}	0.515^{***}	0.425^{*}
		(4.74)	(4.90)	(2.05)
Indiff_trailer (d)		0.788^{***}	0.784^{***}	0.805^{***}
		(17.33)	(17.49)	(17.55)
Lose_for_sure (d)		0.806^{***}	0.799^{***}	0.836^{***}
		(19.38)	(18.89)	(18.74)
RRA(*r*)			-0.102	
			(-1.00)	
*RRA *LS*				-0.0656
				(-0.46)
*RRA *PR*				0.0371
				(0.25)
*RRA *Ind_trail/L*				-0.350
				(-0.75)
*RRA *Ind_lead/W*				-0.450^{*}
				(-2.26)
Male (d)			0.120	
			(1.38)	
*Male *LS* (d)				0.237
				(1.43)
*Male *PR* (d)				0.0209
				(0.17)
*Male *Ind_trail/L* (d)				-0.140
				(-0.99)
*Male *Ind_lead/W*(d)				0.491^{*}
				(1.99)
PastWinningRate			-0.271	-0.257
			(-0.98)	(-0.92)
N	746	746	746	746

Marginal effects; *t* statistics in parentheses; (d) for discrete change of dummy variable from 0 to 1.
$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 4: Panel Logit Regression for the Last 8 (17-24) Rounds

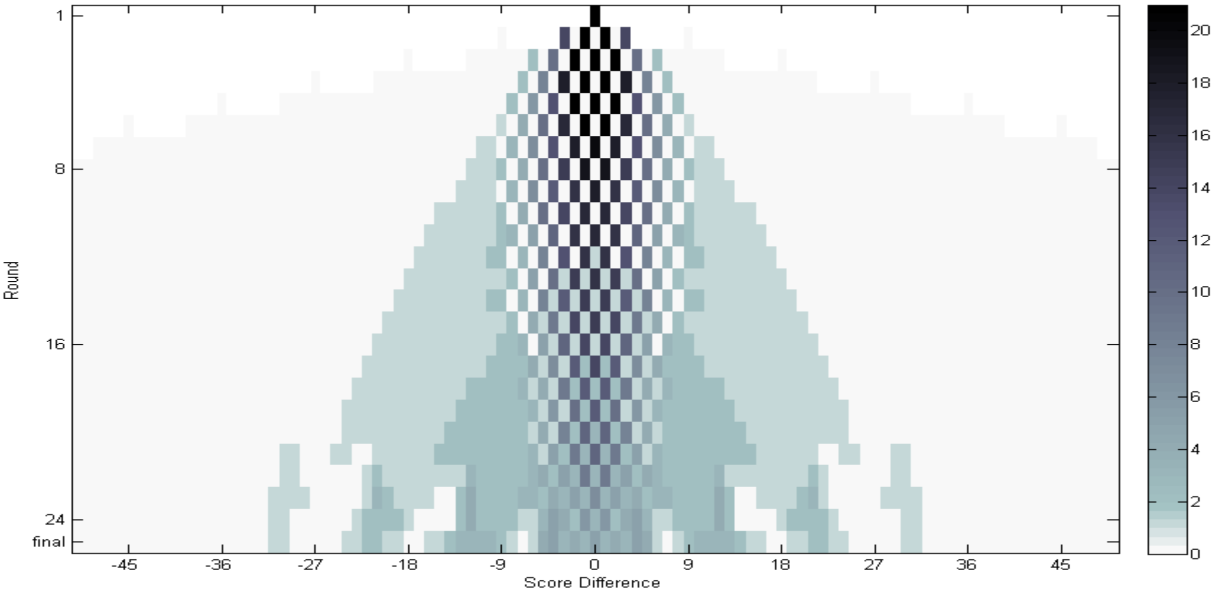

Figure 13: Theoretical Performance Distribution (Time Series of Score Differences)

in the next round when subjects and their opponents both apply best response in this round. For example, zero is the state (score difference z_i) for everyone at the beginning of round 1 and the best response in this state is to choose the piece-rate scheme, so theory predicts the performance distribution in the beginning of round 2 based on the score distribution that both player choose the piece rate. Therefore the score distribution at the beginning of round 2 is $(0.125, 0.375, 0.375, 0.125)$ for performance levels $(-3, -1, 1, 3)$ (c.f. Figure 1). To calculate the performance distribution for round 3, we repeat the same procedure for performance levels $z_i = -3, -1, 1, 3$ in round 2. By applying the same calculation all the way down to the last round, we obtain the performance distribution where all players employ best responses all the time. This theoretical prediction is shown in Figure 13 (frequencies higher or equal to 21 are all shown in black). Note that Figure 13 looks like a “checker’s board” in the middle since z_i cannot be an even number when both players are choosing the piece-rate.

We obtain the symmetric performance distribution of this tournament by averaging the probability for a certain state and that for their opponent’s state and plugging in this averaged probability to these two states. Finally, by multiplying these probability density functions by number of subjects, 108, and round the number to integers, we predict the frequency of each state for 24 rounds and the final performance distribution.[15]

Figure 14 shows observed frequencies for different performance levels from round 1 to the end of round 24. The checker's board predicted by Figure 13 is recognizable in Figure 14.

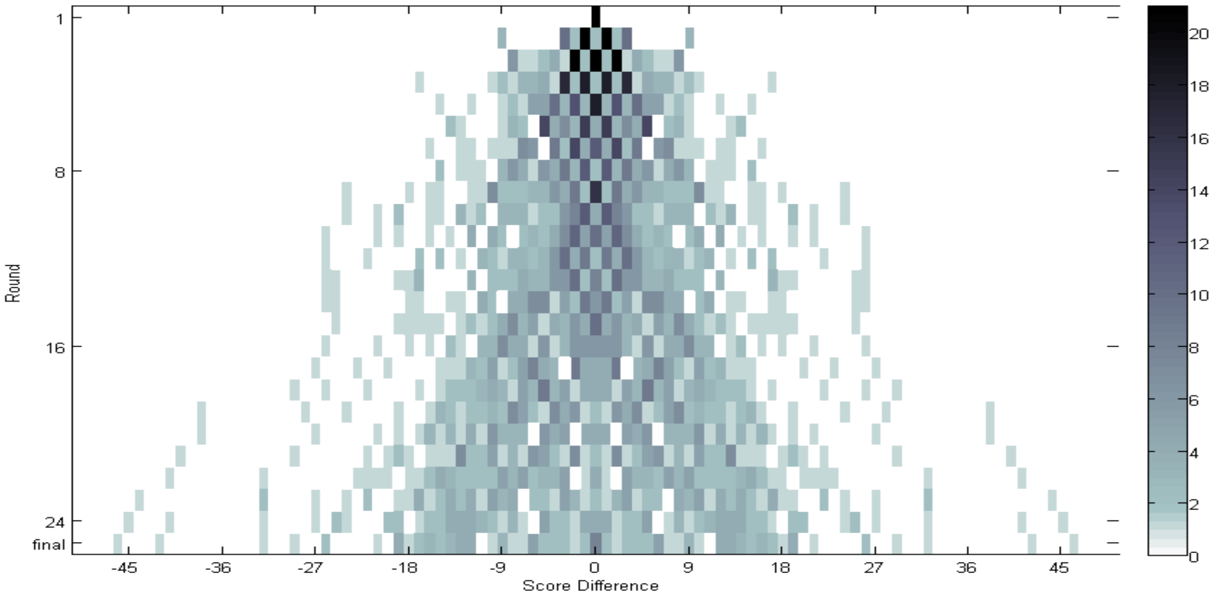

Figure 14: Performance Level Frequencies from Round 1 to Round 24

Figure 15 compares the experimental and theoretical distribution of final score differences. We conduct the Kolmogorov-Smirnov Goodness of Fit test to test if the distribution of final performance level data is from the same distribution of theoretical one. Since our theoretical cumulative distribution function of performance level is discrete, while the original Kolmogorov-Smirnov test is used for continuous distributions, we use resampling to generate the Kolmogorov-Smirnov statistic distribution to calculate the p-value. Specifically, we first obtain Kolmogorov-Smirnov statistic for our 54 data points

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[15] The reason for taking average is that we paired players to play against each other in this tournament, so half of players must be leaders, and their opponents must be trailers with performance level symmetric to theirs. Hence, the performance distribution of our 108 subjects in this tournament consists of 54 paired independent observations, in which nature draws 54 performance levels from "the performance distribution that all players employee best responses all the time" and then paired these performance levels with the corresponding performance level of their opponents.

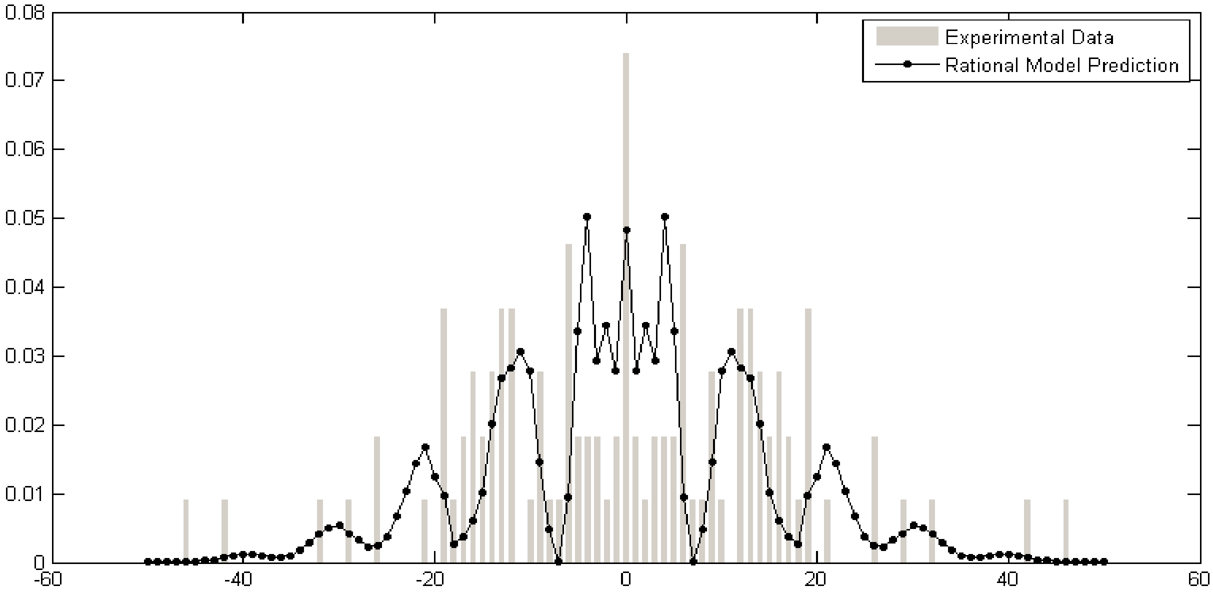

Figure 15: Distribution for Final Score Difference: Theoretical Prediction and Data

of winner's final scores, which is 0.1955. Then we generate 50,000 sets of performance level data by resampling, so that each set consists of 54 data points randomly draw from the theoretical performance distribution of winners. Next, we compute the test statistic for each set, and construct the distribution of Kolmogorov-Smirnov statistics. Finally, we obtain the p-value of 0.1955 by comparing it with this Kolmogorov-Smirnov statistics distribution.

Figure 16 depicts the cumulative density function for the Kolmogorov-Smirnov statistics distribution we obtain. Since the p-value for Kolmogorov-Smirnov statistic of our data (0.1955) equals to 0.0943, we conclude the performance level distribution of our subjects is insignificantly different from the theoretical one at the 5% level.

6 Conclusion

In this paper we propose a model which rationalizes the use of counter-intuitive tactics in dynamic (two-person) tournaments. When players only care about the outcome of the tournament instead of relative performance, this model suggests that trailers and leaders

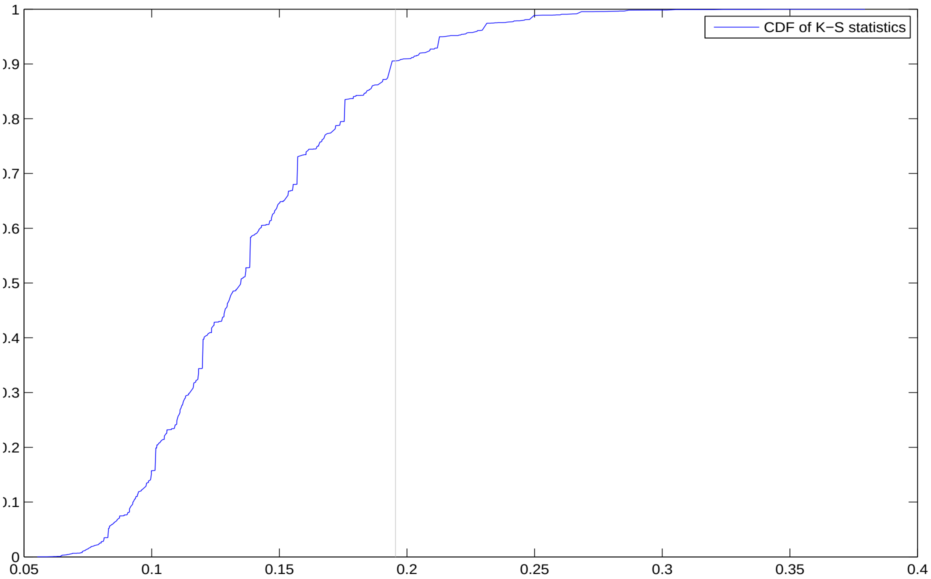

Figure 16: CDF for Kolmogorov-Smirnov Statistics

almost winning for sure both have incentive to employ a long shot tactic, even when it lowers expected performance. This explains why in high incentive tournaments, such as those in mutual fund markets, professional sports and executive promotion, both leaders and trailers intentionally take “risky” tactics in order to win the final victory. When players care about their relative performance levels, this model predicts that the chosen tactic depends on the degree players care about the final score difference. Notice that these theoretical predictions are robust to all types of risk preference as long as the winning probability enters the utility function linearly. Furthermore, this model is highly flexible in assumptions and provides precise and testable predictions for dynamic tournaments. For any given player perception of final performance, players’ ability, number of periods and payoffs of tactics to choose from, this rational model provides prediction for best tactics, winning probabilities and performance level distributions for each round in dynamic tournaments.

Evidence from controlled laboratory dynamic tournaments with interim performance feedback coincides with most of our model predictions: First, the estimated equilibrium-plus-noise model shows that players follow the tournament model prediction 78% of the time, despite the complexity involved when calculating the best tactics. Moreover, regression analysis shows that in the last 8 rounds, when theory suggests piece-rate, 95% of players follow this prediction. When theory suggests the long shot, trailers follow this prediction 74% (81% when it dominates piece rate) of the time, but leaders do not. These results are robust after controlling for players' ability, gender and risk attitude. Thirdly, we find that gender and risk preferences play a secondary role in leaders' behavior when theory predicts indifference. Finally, we verify that final performance in the laboratory is not significantly different from the theoretical distribution by conducting a Kolmogorov-Smirnov test. Hence, in all of our tests, the tournament model consistently displays its prediction power on tactic choices.

There are still several open questions to be resolved in future work. The most obvious one is to test whether playing the tournament multiple times will enable subject to learn to follow theoretical predictions. Since the equilibrium plus noise model shows a decrease in error rates as the tournament proceeds, it is highly possible that subjects will behave as what theory predicts after learning. This issue is important particularly because "tactics" are more common in professional contests where players have abundance experience about the contests they are involved in.

Another area that deserves further investigation is to generalize the model to cope with real-life tournaments and to investigate whether professional players in these tournaments follow theory as well. For example, it will be interesting to see whether this model can be extended to predict intentionally losing in professional sports, such as American football players letting the other side score in Super Bowl XLVI and badminton players throwing their matches in the 2012 Olympics.

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Appendix: Results of Two Holt and Laury Tasks

In this experiment we conducted the paper-based Holt and Laury task[16] twice. The first Holt and Laury task was conducted at the very beginning of the experiment, before subjects knew anything about the rest of the experiment.The only thing they knew at that time was they will get at least NT$100 as their show-up fee. Subjects were told that payoffs from this task will count only if “the coin they toss at the end of this experiment session turns out to be a head.” The second Holt and Laury task was conducted after subjects knew whether they won the big prize in the tournament (*PRIZE*=NT$400 for winners, *PRIZE*=NT$0 for losers). Subjects learned from the instruction of the second task that if the coin they toss turn out to be tails they will earn the payoffs from the second task.

The Holt-Laury task elicits a risk-attitude proxy by asking subjects to make choices (C) between a safe lottery (S) and a risky lottery (R) in ten different scenarios. Both lotteries have a high payoff and a low payoff, these four payoffs (S^h, S^l, R^h, R^l)are fixed across scenarios. In our experiment, S^h =NT$200,$S^l$ = NT$160, R^h = NT$385, R^l = NT$10.[17] The probability of winning the high payoff (p^h) of the chosen lottery monotonically varies from 0.1 to 1 in scenario 1 to scenario 10.

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[16] See the experimental instructions in the Appendix for the Holt and Laury task table.

[17] The exchange rate is 1:30. (US$1 = NT$30)

Since the 4 possible payoffs are fixed and only the payoff probability distribution varies monotonically over scenarios one's preference is rationalizable only if he or she has a unique switching point (i) in choices across scenarios For example, One's preference cannot be expressed by a vNM expected utility function if his choices flip back and forth between safe and risky lotteries in ten scenarios. Specifically, a rational person will choose the risky lottery in scenario 10 – since the probability of winning the high payoff (P^h) is 1 and the high payoff of the risky lottery is much higher than that of the safe lottery. As P^h becomes lower, the risky lottery becomes less and less attractive, and may have lower expected utility than that of the safe lottery starting from a certain scenario. Then, a rational subject will switch to the safe lottery at the scenario and will never switch back.)

Given the number of safe lottery chosen, the 4 possible payoffs the payoff probability distribution in 10 scenarios we can estimate the relative risk-averse parameter (r) of our subjects assuming vNM expected utility functions In the following analysis, we assume the value function: $u(x) = x^{1-r}/(1-r)$. Table A1 report the relation between the value of relative risk-averse parameter (r) and risk attitude.

RRA	Risk preference
$r < 0$	Risk-loving
$r = 0$	Risk-neutral
$r > 0$	Risk-averse

Table A.1: Relation between Risk-preference Parameter and Risk Attitude

x is one of the 4 possible payoffs plus $PRIZE$ divided by 100, which makes the 4 possible payoffs exactly the same 4 numbers shown in the original US dollar version. This ensures that our estimated risk-preference parameter is comparable with previous studies.

Table A.2 reports the estimated interval and median ($\dot{r}$) of relative risk-averse parameter (r) corresponding to 11 possible switching points ($i = 0 \ldots 10$) for winners and losers. The difference between winners and losers is that $PRIZE$ is NT\$400 for winners and NT\$0 for losers. Notice that since subjects were asked to perform the first Holt-Laury task before knowing anything about the rest of the experiment, the possible payoffs they perceive in the first task are exactly the same as losers in the second task ($PRIZE = 0$). Hence, the estimated risk-preference parameters corresponding to switching points in the first task are the same as those for Losers. Similarly, if winners do not take $PRIZE$ into account when performing their second Holt-Laury task, they will have the same switching point in the second task because the payoffs they perceive in second Holt-Laury task are exactly the same as those in the first task.

The switching point for risk-neutral subjects is 4 for both winners and losers. This suggests that risk neutral subjects will always choose 4 safe choices regardless their tournament result and how they perceive their payoffs. Risk-loving subjects will choose less than 4 safe choices and risk-averse subjects will choose more than 4 safe choices.

SP	Winners		Losers	
	$\dot{r}$	r	$\dot{r}$	r
0		$r < -5.66$		$r < -1.71$
1	-4.49	$-5.66 < r < -3.33$	-1.33	$-1.71 < r < -0.95$
2	-2.57	$-3.33 < r < -1.80$	-0.72	$-0.95 < r < -0.49$
3	-1.18	$-1.80 < r < -0.55$	-0.315	$-0.49 < r < -0.14$
4	0.02	$-0.55 < r < 0.59$	-0.005	$-0.14 < r < 0.15$
5	1.15	$0.59 < r < 1.71$	0.28	$0.15 < r < 0.41$
6	2.32	$1.71 < r < 2.93$	0.545	$0.41 < r < 0.68$
7	3.67	$2.93 < r < 4.41$	0.825	$0.68 < r < 0.97$
8	5.515	$4.41 < r < 6.62$	1.17	$0.97 < r < 1.37$
9-10		$6.62 < r$		$1.37 < r$

Table A.2: Inferred Risk-preference Parameters (r)

Figure A.1 illustrates the predicted relationship between switching points (i.e. number of safe choices) in two Holt and Laury tasks for winners and losers Points locate on the 45-degree line suggests that subjects do not change their risk attitude. Points above the 45-degree line means subjects become more risk-averse (choose less safe choices) in the second task. On the contrary, Points below the 45-degree line means subjects become more risk-loving in the second Holt-Laury task.

Theory predicts that losers will keep the same switching point in the second task, while winners taking their prize under consideration when performing the second task will become more like risk neutral no matter they were risk-loving or risk-averse in the first task.

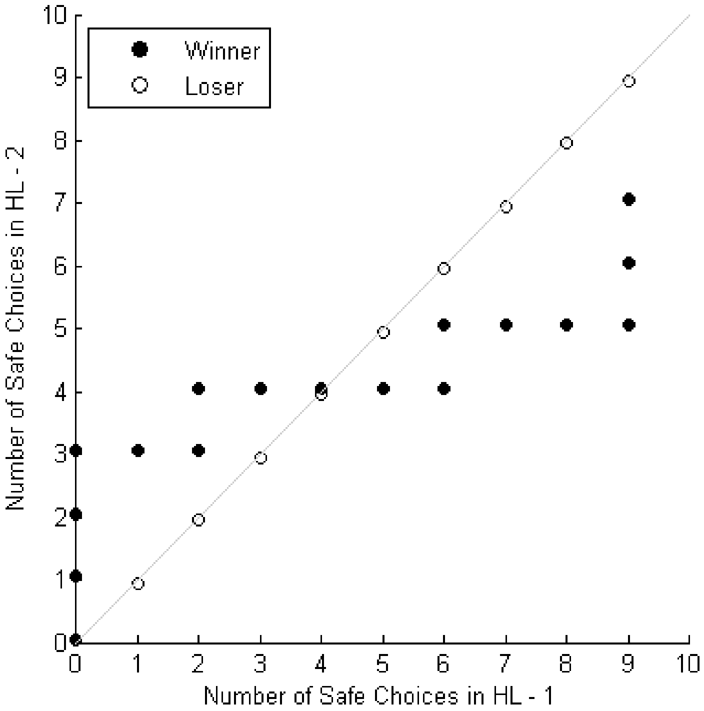

Figure A.1: Prediction of Switching Points in the Two Holt-Laury Tasks

Figure A.2 reports the number of safe lottery chosen in the two Holt-Laury tasks by 96 subjects. 12 other subjects who have more than one switching point in either task are excluded from our data set. We find:

1. Most subjects choose the same switching point in two Holt-Laury tasks regardless their risk preference. (The modes are (4,4) and (6,6), both having 18 observations.)
2. Most subjects are risk-averse in both tasks. This result coincides with what previous literature indicates
3. Contrary to Figure A.1, the difference in switching points between winners and losers is not significant. This indicates winners do not take the prize they won into account when performing their second Holt-Laury task.

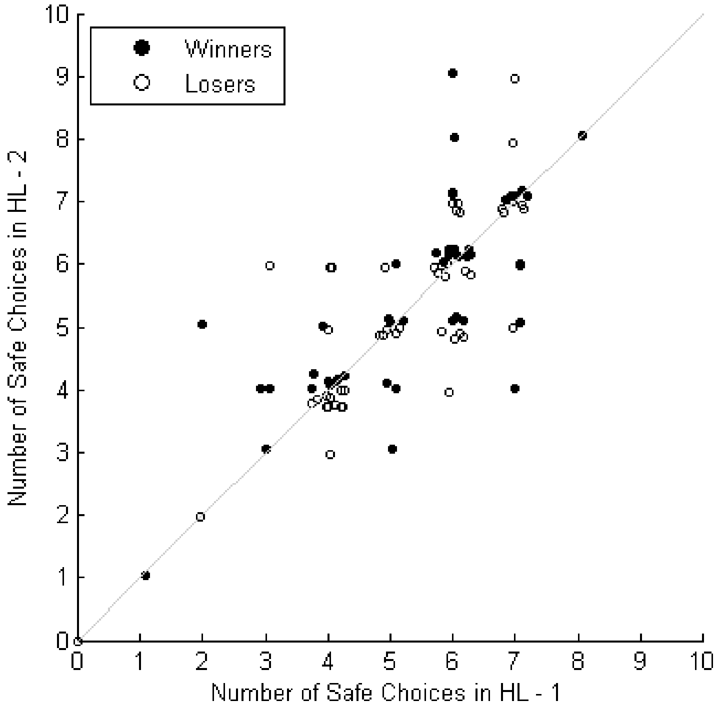

Figure A.2: Subjects' Choices in Two Holt-Laury Tasks

In order to confirm the third point, we regress subjects' switching point in the second task (*SP2*) on their switching point in the first task (*SP1*), dummy variable for winners (*Winner*) and their interactive term (*SP1_Win*) to test if winning the big prize has an effect on switching points in the second Holt-Laury task. The result is shown in Table A.3. Since the coefficients of *Winner* and *SP1_Win* are not significantly different from zero, we conclude that winning the big prize has no effect on the second switching point.

Hence, in the regressions reported in Table 4, we use the corresponding risk-averse parameter ($\dot{r}$) reported in Table A.2 as our proxy for risk preference. Specifically, the risk-averse parameter ($\dot{r}$) equals to the median of the set of corresponding r to the switching point i.[18][19]

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[18] The first switching point is the same as the switching point for losers in Table A.2.

[19] For unbounded intervals, we use the lower bound.

	SP2
SP1	0.873***
	(9.24)
Winner(d)	0.454
	(0.61)
SP1_Win	-0.101
	(-0.74)
Cons	0.780
	(1.53)
N	96

t statistics in parentheses; (d) for discrete change of dummy variable from 0 to 1.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Relation the Second Switching Point to the First One and Prize

第一部份實驗

學號：
姓名：

請寫下您在決策一～十的選擇。

實驗結束後，實驗者會請您擲一次硬幣。若硬幣為正面，則會再請您擲兩顆十面骰。第一顆骰子的數字將決定採用的決策，接下來根據您在該決策中的選擇（A 或 B 彩券）及第二顆骰子的數字決定您此部份的獎金。若硬幣為反面，則此部分的選擇不影響您的實驗報酬。

決策	A 福袋	B 福袋	您的選擇（A 或 B）
決策一	1：得 200 元 2～10：得 160 元	1：得 385 元 2～10：得 10 元	
決策二	1～2：得 200 元 3～10：得 160 元	1～2：得 385 元 3～10：得 10 元	
決策三	1～3：得 200 元 4～10：得 160 元	1～3：得 385 元 4～10：得 10 元	
決策四	1～4：得 200 元 5～10：得 160 元	1～4：得 385 元 5～10：得 10 元	
決策五	1～5：得 200 元 6～10：得 160 元	1～5：得 385 元 6～10：得 10 元	
決策六	1～6：得 200 元 7～10：得 160 元	1～6：得 385 元 7～10：得 10 元	
決策七	1～7：得 200 元 8～10：得 160 元	1～7：得 385 元 8～10：得 10 元	
決策八	1～8：得 200 元 9～10：得 160 元	1～8：得 385 元 9～10：得 10 元	
決策九	1～9：得 200 元 10：得 160 元	1～9：得 385 元 10：得 10 元	
決策十	1～10：得 200 元	1～10：得 385 元	

TASSEL 實驗說明 p.1

實驗報酬

本實驗結束後，你將得到定額車馬費新台幣 100 元，以及你在實驗中獲得的「法幣」所兌換成之新台幣。（「法幣」為本實驗的實驗貨幣單位。）你在實驗中能獲得的「法幣」會根據你所做的決策、別人的決策，以及隨機亂數決定，每個人都不同。每個人都會個別獨自領取報酬，你沒有義務告訴其他人你的報酬多寡。請注意：本實驗中的「法幣」與新台幣兌換的匯率為 1:1。

實驗說明

本實驗為兩人各自選擇計分方式的猜硬幣決策實驗，共有四十輪決策，每一輪兩人對猜硬幣三次。實驗開始前，電腦將隨機配對，兩人一組，往後均維持此分組。每輪開始前，你和另一位受試者會先各自選擇自己的**計分方式**，接著兩人進行三次的對猜硬幣決策實驗。計分方式有兩種：

1. **分次計算**：每贏一次可得一分，輸一次得零分。
2. **三次一起計算**：一輪三次都贏才得九分，否則得零分。

選擇時請用滑鼠點擊計分方式選項前的圓圈選擇，並按下確定。

接下來進行三次猜硬幣決策實驗。每次猜硬幣，兩人各自選擇猜**「正面」或「反面」**，以期達成不同的目標：兩人當中，有一個人要試圖讓自己的選擇與另一個人的選擇相同，另一個人則要試圖讓他的選擇與第一個人不同。達成目標的人為該次的贏家，另一人則為輸家。每次雙方螢幕上會分別顯示「您的目標為：**（與對手）相同**」或「您的目標為：**（與對手）相反**」。請用滑鼠點選螢幕的「正面」或「反面」按鈕選擇。

實驗報酬計算

二十四輪決策結束後，您的總得分將與電腦隨機選取的一個標準做比較。若您的總得分高於此一標準，則可得到獎金法幣 400 元。若您的總得分低於標準，則無法得到獎金。若您的總得分正好等於標準，則有一半的機會(由電腦亂數決定)可以得到獎金。電腦選取標準的方式如下：每一輪電腦都會從 0~3 的數字中抽取一個數字，其機率分配如右表所示。將二十四輪的數字相加，則得到最後的標準。

0	1	2	3
1/8	3/8	3/8	1/8

每輪結束後，螢幕都會顯示您該輪的得分及該輪電腦隨機抽取的數字，閱讀後請按「確認」。

TASSEL 實驗說明 p.2

問答階段

在正式實驗開始之前，螢幕上會先顯示一些問題並請您輸入正確答案。這些問題的目的是為了確認您了解此實驗的規則。**所有問題都被正確回答後，您將進入練習階段。**如果您對這些問題或本實驗有任何疑問，請在此時舉手。實驗者會過來解答。

練習階段

此階段的目的為幫助您熟悉正式實驗的操作介面及計分方式。請注意，**練習階段的得分僅供您熟悉本遊戲的計分方式，與您的最後總得分或現金報酬均無關。**練習結束後，螢幕將顯示「！實驗正式開始！」，然後進入正式實驗。在正式實驗中所獲得的「法幣」，實驗結束後都會兌換成新台幣付給您。

請注意:

1. **您選擇的計分方式只影響自己，另一位參與者的分數不受影響。**
2. **二十四輪結束後，您累計的分數須高於或等於標準才有機會得到獎金。**
3. **電腦會為每一位參與者各自隨機選取標準，因此您所看到的標準只影響自己，與其他參與者是否獲得獎金無關。**

第三部份實驗

學號：
姓名：
性別：

請寫下您在決策一～十的選擇。

實驗結束後，實驗者會請您擲一次硬幣。若硬幣為反面，則會再請您擲兩顆十面骰。第一顆骰子的數字將決定採用的決策，接下來根據您在該決策中的選擇（A 或 B 彩券）及第二顆骰子的數字決定您此部份的獎金。若硬幣為正面，則此部分的選擇不影響您的實驗報酬。

決策	A 福袋	B 福袋	您的選擇（A 或 B）
決策一	1：得 200 元 2～10：得 160 元	1：得 385 元 2～10：得 10 元	
決策二	1～2 ：得 200 元 3～10：得 160 元	1～2 ：得 385 元 3～10：得 10 元	
決策三	1～3 ：得 200 元 4～10：得 160 元	1～3 ：得 385 元 4～10：得 10 元	
決策四	1～4 ：得 200 元 5～10：得 160 元	1～4 ：得 385 元 5～10：得 10 元	
決策五	1～5 ：得 200 元 6～10：得 160 元	1～5 ：得 385 元 6～10：得 10 元	
決策六	1～6 ：得 200 元 7～10：得 160 元	1～6 ：得 385 元 7～10：得 10 元	
決策七	1～7 ：得 200 元 8～10：得 160 元	1～7 ：得 385 元 8～10：得 10 元	
決策八	1～8 ：得 200 元 9～10：得 160 元	1～8 ：得 385 元 9～10：得 10 元	
決策九	1～9 ：得 200 元 10：得 160 元	1～9 ：得 385 元 10：得 10 元	
決策十	1～10：得 200 元	1～10：得 385 元	