Forecasts of Relative Performance in Tournaments: 
Evidence from the Field

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Abstract

This paper investigates the quality of individuals’ forecasts of relative performance in tournaments. We ask players in luck-based and skill-based tournaments to make point forecasts of rank. We use a proper scoring rule to reward forecast accuracy. We also offer players the possibility of choosing among different bets whose payments are contingent on relative performance. The main finding of the paper is that players’ forecasts and betting behavior reveal overestimation of relative performance. Experience across skill-based tournaments improves players’ forecasts but experience across luck-based tournaments does not. The paper tests alternative theories for overestimation of relative performance. We find evidence against the reference group neglect explanation and also against the correlation between risk preferences and skill explanation. We find weak evidence in favor of the self-serving bias explanation.

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1 Introduction

Tournaments are one of the most frequently used incentive schemes in organizations.\footnote{A rank-order tournament is an incentive scheme where the managers of a firm establish a fixed set of prizes and then award the largest prize to the worker who produces the largest output, the second largest prize to the worker who produces the second largest output, and so on.} For example, salespeople are often paid bonuses that depend on their sales relative to those of the other salespeople in the firm. Most managers are involved in promotion tournaments: vice-presidents compete to be promoted to president and senior executives compete to become CEO. Elections, litigation, auctions, athletic contests, and racing games can also be viewed as tournaments.\footnote{See Rosen (1988) for a detailed discussion of these and other examples of tournaments.}

Economic theory tells us that individuals’ expectations of relative performance in tournaments are one of the main determinants of their effort or investment choices. Surprisingly, very few studies in Economics investigate whether individuals’ expectations of relative performance are rational or not.\footnote{The experimental work by Clark and Friesen (2003) and Hoelzl and Rustichini (2005) are two exceptions. We discuss these and related studies in Section 5. We are unaware of studies that test the rationality of individuals’ forecasts of relative performance using field data.} This paper tries to fill this gap in the literature.

If individuals’ forecasts of relative performance in tournaments are rational then they must be unbiased and efficient. Forecasts are unbiased when there is no systematic tendency for overestimation or underestimation of relative performance. Forecasts are efficient when individuals’ use all available information to make them. Evidence from social psychology suggests that, across a wide variety of tasks, people display a systematic tendency to overestimate their relative skill. However, in almost all of these studies, individuals are not given monetary incentives to make accurate predictions.

We test the rationality of forecasts of relative performance using field data from two poker tournaments—UCSD’s 2004 Winter and Spring Poker Classics—and one chess tournament—Sintra’s 2005 Chess Open. We use field data instead of experimental data for two main reasons. First, the costs associated with organizing these type of tournaments in the lab are quite large. Second, experience with a task influences the quality of individuals’ forecasts of relative performance. In a real world tournament players have very heterogenous experience levels which can not be replicated in the lab.\footnote{For example, in a chess tournament participants had, on average, been to 60 chess tournaments before. This level of experience with chess tournaments can not be replicate in the lab since each tournament lasts several hours.} We select poker and chess tournaments because of the different role that skill and luck play in determining rank in these tournaments. A poker tournament is a luck-based tournament: luck plays a large role in determining players’ positions. By contrast, a chess tournament is a skill-based tournament: skill is the main factor that determines players’ positions.

Before the start of each tournament we distribute a survey to participants
where we ask them, among other things, to provide a point forecast of their relative performance. We use financial incentives for rewarding forecast accuracy. The forecast error of each player is the difference between his point forecast and his objective performance. Thus, the presence or absence of bias in forecasts can be evaluated at the aggregate level and at the individual level. We also let individuals choose between receiving a sure payment and nine different bets whose payments are contingent on relative performance. This gives us an alternative measure of expectations of relative performance, based on the observation of choices among alternatives, that can be compared with the point forecasts.

The main finding of the paper is that players’ forecasts of relative performance are biased: on average, a poker player overestimates relative performance by 7 to 10 percentiles and a chess player by 6 to 7 percentiles. Thus, the tendency towards overestimation identified in the social psychology literature is also present in players’ forecasts of relative performance in luck-based tournaments as well as in skill-based tournaments. More importantly, the tendency towards overestimation is present even when players are given monetary incentives for making accurate forecasts. However, the degree of overestimation that we find is not as large as the ones often reported in the social psychology literature.

Poker players’ forecasts of relative performance are not distinguishable from random guesses. More precisely, taking into account the overestimation bias, forecasts of poker players in the Winter Poker Classic are a random guess in the percentile interval [21, 99] and, in the Winter Poker Classic, a random guess in the interval [15, 99]. By contrast, chess players’ forecasts are significantly better than random guesses.

Players’ betting behavior also reveals overestimation of relative performance. In the Spring Poker Classic, 78.6% of players chose bets that pay when performance is above the median. In Sintra’s Chess Open 63.8% of chess players chose bets that pay when performance is above median. In fact, we find that poker players’ betting behavior seems to reveal more overestimation of relative performance than their point forecasts: in the Spring Poker Classic, 78.6% of players chose bets that paid them when their performance was above the median but only 62.8% of players forecasted that their performance would be above median.5

The paper states a theoretical result that compares a risk neutral player’s optimal bet to his optimal point forecast. This result shows that the betting problem, by comparison with the forecasting problem, creates an asymmetry between overestimation and underestimation of relative performance. In the forecasting problem, a risk neutral player who overestimates or underestimates relative performance by the same amount faces the same loss. By contrast, in the betting problem, a risk neutral player who overestimates relative performance by 10% incurs a larger loss than if he underestimates relative performance by 10%. This implies that the optimal bet of a risk neutral player should be smaller than his optimal point forecast. In other words, for risk neutral players, the choice of bet question is a more stringent test of overestimation of relative performance.

5This does not happen when we compare chess players’ bets and point forecasts.
than the point forecast question.

Experience across poker tournaments does not improve poker players’ forecasts of relative performance. On average, an inexperienced poker player overestimates relative performance only by 3 percentiles and an experienced poker player by 14 percentiles. The mean absolute forecast error of an inexperienced poker player is identical to that of an experienced poker player: 30 percentiles. By contrast, experience across chess tournaments improves chess players’ forecasts. On average, an inexperienced chess player overestimates relative performance by 14 percentiles and an experienced chess player only by 2 percentiles. The mean absolute forecast error of an inexperienced chess player is 28 percentiles and that of an experienced poker player is 12 percentiles.

Our rich dataset allows us to identify what type of player is more likely to overestimate, underestimate, or have an accurate perception of relative performance. The data from poker tournaments show that the more experienced and less skilled players tend to overestimate relative performance and that the less experienced and more skilled players tend to underestimate relative performance. The more experienced and more skilled chess players have accurate perceptions of relative performance whereas the less experienced and less skilled chess players tend to overestimate relative performance.

Additionally, we find that chess players’ forecasts of relative performance are not efficient: chess players could have made better forecasts of relative performance if they had used their knowledge about the quality of the competition to make their forecasts. We also find that chess players’ are overconfident about their forecasts of relative performance. To test for the presence of overconfidence in forecasts of relative performance we asked chess players to provide 90% confidence intervals for their point forecasts. Out of forty confidence intervals only fifteen contained the actual relative performance of the player. Finally, the paper tests three alternative explanations for overestimation of relative performance: reference group neglect, correlation between risk preferences and skill, and the self-serving bias in causal attributions. We find evidence against the first two explanations and weak evidence in favor of the third explanation.

The rest of the paper proceeds as follows. Section 2 presents and discusses the findings in luck-based tournaments. Section 3 presents and discusses the findings in skill-based tournaments. Section 4 tests three theories for overestimation of relative performance. Section 5 reviews related research. Section 6 concludes the paper. The Appendix contains the surveys that were handed out to players in each tournament, theoretical results about individuals’ optimal point forecasts and optimal choices of bet, and statistical results.

\footnote{We have no data to test either the efficiency of poker players’ forecasts or the degree of confidence that poker players place in their forecasts.}
2 Luck-Based Tournaments

To study the quality of individuals’ forecasts of relative performance in luck-based tournaments we distributed and collected surveys at two poker tournaments held at Viejas Casino in San Diego.

The first tournament—“Winter Poker Classic”—was held on March, 7th, 2004. 155 UCSD students played the “Texas Hold’em” game until a final winner was decided. Each player paid a $10 participation fee before the game and received $1500 valued chips during the game. Once the player used up all chips, she would get eliminated and had to leave the table. There were 155 players in the tournament, each paying an entry fee of $10. The total prize pool was $1670. The second tournament—“Spring Poker Classic”—was held on May, 23rd, 2004. In this tournament there were 167 players each paying an entry fee of $20. The total prize pool was $3000. The prize structure of each tournament is depicted in Table I in the Appendix. To obtain players’ forecasts of relative performance we asked them the following question:

Of all the individuals participating in the poker tournament, what percentage do you think will be eliminated before you?

We assumed that a player’s elimination order is a good measure of his relative performance in the tournament. Since the Casino only monitored the elimination order of the top 18 players (those who receive prizes) we had to monitor the order of elimination of the remaining players. Based on each player’s forecast of relative performance and his monitored elimination order, we could calculate the forecast error of each player, $E_i$, defined as

$$E_i = F_i - P_i,$$

where $F_i$ is player $i$’s forecast of relative performance and $P_i$ is player $i$’s relative performance. Furthermore, to let players have incentives to make correct forecasts, we paid monetary rewards according to a quadratic scoring rule. The reward of player $i$, $R_i$, as a function of player $i$’s forecast error, was determined by the rule

$$R_i = \begin{cases} \$10 - \left(\text{Int} \ (|E_i|)\right)^2, & \text{if Int} \ (|E_i|) \leq 4 \\ \$0, & \text{if Int} \ (|E_i|) > 4 \end{cases},$$

7 In Texas Hold’em each player gets two cards face down, to be combined with five community cards dealt face up in the middle - the first three simultaneously (called the flop), then a fourth (the turn), then a fifth (the river) - to make the best five-card hand. Since each player shares five-sevenths of his cards with his opponents, the difference between the best and the second-best hand - all the difference in the world, bankrollwise - is quite a bit subtler than in seven-card stud. Even more crucial, stud is always played with fixed bet sizes, whereas Hold’em, with four betting rounds instead of five, has traditionally lent itself to a no-limit format.

8 In the first half hour of this tournament, players who were close to running out of chips could of rebuy chips. This is why the total prize pool is greater 155 times the entry fee. In this tournament the Casino had no profit since all buy-ins were converted into prizes.

9 In this tournament the total prize pool is less than the sum of the entry fees ($3340). Thus, the Casino profited $340 from the tournament.
where \( \text{Int} (x) \) is the closest integer which is smaller than \( x \). Thus, in the Winter
Poker Classic, we paid $10 if the forecast error less was than or equal to 1%, $9 if it was more than 1% and less than or equal to 2%, $6 if it was more than 2% and less than or equal to 3%, $1 if it was more than 3% and less than or equal to 4%, and $0 otherwise.\(^{10}\) In the survey, players do not know the formula of the scoring rule, but are told their payoffs from their forecasts based on the formula of the scoring rule.\(^{11}\)

Propositions 1 and 2 in the Appendix show that the quadratic scoring rule is an incentive compatible scoring rule for a risk neutral player or for a player with an unimodal and symmetric distribution of beliefs. In other words, the optimal point forecast of a risk neutral player or of a player whose beliefs are unimodal and symmetric is the mean belief of relative performance. Alternatively, we could have chosen a truth telling incentive scheme where individuals would be paid something when they are exactly correct and nothing otherwise. This rule induces risk neutral players to report the mode rather than the mean.

2.1 Distribution of Forecasts

There were 155 players in the Winter Poker Classic and 167 players in the Spring Poker Classic. We handed out surveys to all players. Each player filled his survey individually and returned it to us right after he finished it. Players returned 139 surveys in the Winter Poker Classic and 145 surveys in the Spring Poker Classic. From the 139 surveys that we gathered in the Winter Poker Classic we obtained 135 forecasts of relative performance. From the 145 surveys that we gathered in the Spring Poker Classic we obtained 129 forecasts of relative performance.

Table II shows us the distribution of forecasts of poker players in both tournaments for each interval of 10 percentiles starting in the interval [0,10] and ending in the interval [90,99]. In the Winter Poker Classic 25.9% of forecasts are below the 50th percentile and 63.1% of forecasts are above it. The mean forecast of relative performance in the Winter Poker Classic was the 62.67th percentile. In the Spring Poker Classic 33.3% of forecasts are below the 50th percentile and 55.7% of forecasts are above it. The mean forecast of relative performance in the Spring Poker Classic was the 58.29th percentile. In both the Winter and the Spring Poker Classics the mode of the distribution of forecasts

\(^{10}\) Similarly, in the Spring Poker Classic we use the following rule

\[ R_i = \begin{cases} 
20 - \text{Int}(|E_i|)^2, & \text{if } \text{Int}(|E_i|) \leq 5 \\
0, & \text{if } \text{Int}(|E_i|) > 5
\end{cases} \]

that is, we paid $20 if the forecast error less was than or equal to 1%, $19 if it was more than 1% and less than or equal to 2%, $16 if it was more than 2% and less than or equal to 3%, $11 if it was more than 3% and less than or equal to 4%, $4 if it was more than 4% and less than or equal to 5%, and $0 otherwise.

\(^{11}\) In the Spring Poker Classic players were told that they could receive the earnings from their forecasts if they showed up at a pre-specified location at UCSD. In the Winter Poker Classic players were asked for their addresses and the rewards for players' forecasts and choice of bet were mailed to them.
is the 50th percentile, with approximately 11% of forecasts.\footnote{In the Winter Poker Classic, the second most forecasted percentile is the 80th percentile, with approximately 8% of forecasts. In the Spring Poker Classic the second most forecasted percentile is the 90th percentile, with approximately 10% of forecasts.}

### 2.2 Bias of Forecasts

From the 155 players that took part in the Winter Poker Classic we were able to monitor the relative performance of 135 players. Among the 135 players whose relative performance we monitored and the 135 players who provided forecasts of relative performance we have a total of 122 poker players whose order of elimination and forecast of relative performance are both known. The mean forecast of relative performance of these 122 players was the 63.09th percentile and their mean relative performance was the 53.07th percentile. Thus, the mean forecast error of these 122 poker players is 10.02 percentiles. In other words, the average player in this group of 122 poker players overestimated relative performance by approximately 10 percentiles.

To show that the mean forecast error of these 122 players is significantly different from zero we run the ordinary least squares regression

\[
E_i = a + \varepsilon_i, \tag{1}
\]

where \(E_i\) is the forecast error of player \(i\) and \(a\) is the intercept. Running this regression we find that the constant term has a \(t\)-statistic equal to 3.02. Thus, we find that, with a significance level of 0.25\%, the mean forecast error of the 122 players in the Winter Poker Classic is greater than zero.

From the 167 players that took part in the Spring Poker Classic, 144 individuals were observed and ordered according to their elimination time. Among the 144 players whose relative performance we monitored and the 128 players who provided forecasts of relative performance we have a total of 116 poker players whose order of elimination and forecast of relative performance are both known. The mean forecast of relative performance of these 116 poker players was the 57.97th percentile and their mean relative performance was the 50.60th percentile. Thus, the mean forecast error of these 116 poker players is 7.38 percentiles. That is, the average player in this group of 116 poker players overestimated relative performance by 7.38 percentiles.

To show that the mean forecast error of these 116 players is significantly different from zero we use the same procedure as in the Winter Poker classic. Running the ordinary least squares regression in (1) with the Spring Poker Classic data we find that the intercept term has a \(t\)-statistic equal to 2.03 which implies that, with a significance level of 2.5\%, the mean forecast error of the 116 players in the Spring Poker Classic is greater than zero.

Since we could not obtain forecast errors for the whole population in both the Winter and the Spring Poker Classics this raises the question as to whether the mean forecast errors obtained for the 122 players in the Winter Poker Classic and for 116 players in the Spring Poker Classic are representative of the mean
forecast errors of the whole population. We have three comments to make regarding this issue.

First, note that the 122 poker players in the Winter Poker Classic make up 79% of the population in that tournament and that the 116 poker players in the Spring Poker Classic make up 70% of the population in that tournament. Thus, we have obtained mean forecast errors for a large majority of the population in both tournaments.

Second, in the Winter Poker Classic we lost the order of elimination of 20 players in the first 45 minutes because tables were reshuffled and there were tables in three different rooms. After the first 45 minutes we obtained the order of elimination of every single player (the tournament’s duration was 3 hours). Thus, the players whose order of elimination was not monitored are among the worst performers in the tournament. As we shall see, players who perform worse are the ones who overestimate relative performance the most. So, the mean forecast error of the 122 players in the Winter Poker Classic is a lower bound of the mean forecast error of the population.13

Third, in the Spring Poker Classic we monitored the order of elimination of 144 poker players (86% of the population) and obtained forecast errors for 116 players. Thus, we have 28 players in the Spring Poker Classic whose order of elimination was monitored but whose forecast errors are not known. The mean relative performance of these 28 poker players is equal to the 48.90th percentile. As we pointed out before, the mean relative performance of the 116 players was the 50.60th percentile. Thus, there is no significant difference between the mean relative performance of the group of 28 players and the group of 116 players. If that is the case we do not expect that there would be significant differences in mean forecast errors between the two groups. This leads us to believe that the mean forecast error of the 116 players in the Spring Poker Classic is representative of the mean forecast error of the whole population.

2.3 Precision of Forecasts

To study the precision of poker players’ forecasts of relative performance we run the ordinary least squares regression

\[ P_i = a + bF_i + \varepsilon_i, \]

where \( a \) is the intercept and \( b \) the slope. To understand what information this regression can give us about the precision of poker players’ forecasts let us consider two extreme scenarios. First, suppose that poker players’ forecasts of relative performance are very precise. In this case we would have a very good fit and the R-squared would be very close to one. The estimated coefficient for the intercept would be very close to 0 and the estimated coefficient for the slope would be very close to 1. Alternatively, suppose that poker players’ forecasts of relative performance are just a random guess in the interval \([50 - \delta_L, 50 + \delta_R]\),

13This lower bound should be very close to the actual value since the 122 players make up 79% of the population.
with \( \delta_i \in [0, 50] \) with \( i = L, R \). In this case we would have a very bad fit and the R-squared would be very close to 0. The estimated coefficient for the intercept would be very close to 50 and the estimated coefficient for the slope would be very close to 0. The results obtained for the two poker tournaments are summarized in Table III. We see from Table III that the fit of both regressions is very bad: the \( R \)-squared is equal to 0.6% and the mean absolute error in forecasts in approximately 30 percentiles. We also see that in both tournaments the estimated coefficient for the intercept is close to 50 and that the estimated coefficient for the slope is not significantly different from 0. In effect, for both tournaments, we cannot reject the hypothesis that \( a = 50 \) and \( b = 0 \) at 5% significance level. 14

Thus, poker player’s forecasts of relative performance in both tournaments are not distinguishable from random guesses. More precisely, taking into account the overestimation bias, forecasts in the Winter Poker Classic seem to be a random guess in the interval [21,99] and forecasts in the Spring Poker Classic seem to be a random guess in the interval [15,99]. Not surprisingly, the lack of precision of poker players’ forecasts in both tournaments implied that their earnings from taking the survey are quite low.

Table IV summarizes players’ earnings from taking the survey in each tournament. The first two columns in Table IV tell us how many players were paid each type of reward for their point forecasts in the Winter Poker Classic. The total monetary rewards for point forecasts in the Winter Poker Classic were $86. This corresponds to an average reward of $.70, a value that is not significantly different, at a 5% significance level, from the expected reward of a random guess: $.50. 15

The third and the forth columns in Table IV tell us how many players were paid each type of reward for their forecasts in the Spring Poker Classic. The total reward paid for point forecasts in this tournament was $149. This corresponds to an average reward of $1.28, a value that is not significantly different, at 5% significance level, from the expected reward of a random guess: $1.35. 16

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14 In the Winter Poker Classic, the \( F \) statistic for the hypothesis test that \( a = 50 \) and \( b = 0 \) is equal to 1.05 and the 5 percent critical value for \( F_{(2,120)} \) is 3.09. Since \( F = 1.05 < 3.09 = F_{(2,120)} \), we can conclude that there is no evidence in the data to reject the hypothesis that the players’ forecasts in the Winter Poker Classic are random guesses. In the Spring Poker Classic, the \( F \) statistic for the same test is equal to 41 and the 5 percent critical value for \( F_{(2,114)} \) is 3.09. Since \( F = 41 < 3.09 = F_{(2,114)} \), we can conclude that there is no evidence in the data to reject the hypothesis that the players’ forecasts in the Spring Poker Classic are random guesses.

15 In the Winter Poker Classic, the expected reward of a random guess of a player who is neither on the bottom 5% nor on the top 5% is given by \( .02(\$10 + \$9 + \$6 + \$1) = \$ .52 \). The expected reward of a random guess of a player in the bottom 5% or the top 5% is given by \$ .26. Thus, the expected reward of a random guess is equal to \( .9 \times \$ .52 + .1 \times \$ .26 = \$ .50 \).

The \( t \) statistic for the hypothesis test that the average reward for a forecast is not different from the expected reward of a random guess is equal to .79 and the 5 percent critical value is equal to \( t_{50}(121) \approx 1.65 \). Thus, we cannot reject the hypothesis that players’ forecasts in the Winter Poker Classic were random guesses.

16 In the Spring Poker Classic, the expected reward of a random guess of a player who is neither on the bottom 5% nor on the top 5% is given by \( .02(\$20 + \$19 + \$16 + \$11 + \$4 + \$1) = \$1.42 \). The expected reward of a random guess of a player in the bottom 5% or the top 5% is
2.4 Betting Behavior

In the Spring Poker Classic players were also asked to choose among different bets whose payments depended on their relative performance in the tournament. The question was worded as follows:

Consider the ten lotteries below. Choose one of the lotteries
We pay you $2.00 for sure
We pay you $2.22 if you are eliminated after 10% of players and $0 otherwise
We pay you $2.50 if you are eliminated after 20% of players and $0 otherwise
We pay you $2.86 if you are eliminated after 30% of players and $0 otherwise
We pay you $3.33 if you are eliminated after 40% of players and $0 otherwise
We pay you $4.00 if you are eliminated after 50% of players and $0 otherwise
We pay you $5.00 if you are eliminated after 60% of players and $0 otherwise
We pay you $6.66 if you are eliminated after 70% of players and $0 otherwise
We pay you $10.00 if you are eliminated after 80% of players and $0 otherwise
We pay you $20.00 if you are eliminated after 90% of players and $0 otherwise

The answers to this question are summarized in the last three columns of Table IV. A total of 140 players answered the betting question. In the first column we have the reward of each bet, in the second column, the number of players that were paid for a specific choice of bet, and, in the third column, the share of players who chose each bet. For example, 48 players in the Spring Poker Classic chose the bet that paid $20.00 if a player was eliminated after 10% of the players and $0 otherwise but only 6 players were paid $20.00 for that choice. These 48 players represent 34.4% of the number of players who made a choice of bet.

Let us start by discussing the precision of poker players’ choices of bet. Table IV shows us that the average reward for choice of bet was $2.01. This is exactly the same value as the expected value of a random bet: $2.00. Thus, the rewards that poker players’ received from their bets are no better than the rewards they would have received if they had made random bets.

given by $.71. Thus, the expected reward of a random guess is equal to .9 × $1.42 + .1 × $.71 = $1.35.

The t statistic for the hypothesis test that the average reward for a forecast is not different from the expected reward of a random guess is equal to −.17 and the 5 percent critical value is equal to t_{59}(115) ≈ 1.65. Thus, we cannot reject the hypothesis that players’ forecasts in the Spring Poker Classic were random guesses.

17 If a player’s performance is worse than the 10th percentile and makes a random choice of bet his expected reward is (1/10) × $2 + (9/10) × $0 = $.2. If a player’s performance is better than the 10th percentile and worse than the 20th percentile and makes a random choice of bet is expected reward is (1/10) × $2 + (1/10) × $2.22 + (8/10) × $0 = $1.422. Doing the same for players in the other deciles we obtain expected rewards for players in each decile. Thus, if all players made random choices of bet the average reward for choice of bet should be approximately equal to

$$\frac{1}{10}($.2 + $.422 + $.672 + ... + $5.857) \approx $.2.$$
Table IV also tells us that 21.4% of players chose bets that pay when their relative performance is below median and 78.6% of players chose bets that only pay when their relative performance is above median. Ranking bets from 5 (the sure thing) to 55 (the $4 bet) to 95 (the $20 bet) we find that the average choice of bet of the 140 poker players in the Spring Poker Classic is 68.4. This is approximately the bet that pays $6.66 if a player is eliminated after 70% of the population and $0 otherwise.

2.5 Experience and Forecasts of Relative Performance

Among other things we also asked players in the Winter and Spring Poker Classics to report the number of poker tournaments that they had played in the past. This allows us to check whether more experience with poker tournaments improves players’ forecasts of relative performance.

Pooling the Winter and Spring Poker Classics’ data we have a total of 200 poker players who provided forecasts of relative performance, who reported the number of poker tournaments they have played before, and whose relative performance was monitored.

On average, a poker player who participated in the Winter and Spring Poker Classics has played in 5 poker tournaments before. Taking this into consideration we divide poker players into four groups according to number of tournaments played before: 0 tournaments, 1 to 4 tournaments, 5 to 15 tournaments, and 16 or more tournaments. Table VI displays the mean forecast (MF), the mean position (MP), the mean forecast error (ME), and the mean absolute forecast error (MAE) for each group. Table VI shows that both the mean forecast and the mean performance are increasing with experience. It also shows that the mean forecast error is larger for players who have had no previous experience with poker tournaments than for players who have played from 1 to 4 tournaments. However, the mean forecast errors of the two groups of poker players who have more experience across tournaments are the largest.18 The last column in Table VI also shows that the mean absolute error is similar across the

18If we run the ordinary least squares regression $ME_i = a + bExp_i + \epsilon_i$, where $Exp_i$ is the number of poker tournaments a player in the Spring Poker Classic has been in the past, we find that

$$ME_i = 4.838 + 0.139Exp_i.$$  

(1.25)  (.53)

We see that the slope of this regression is positive but not significantly different from zero. This confirms that experience with poker tournaments does not reduce mean forecast error.
four experience groups. Overall, we can say that experience does not improve poker players’ forecasts of relative performance.

Since we have a large number of players we can study the impact of experience on forecasts of relative performance conditional on relative performance. To this purpose we divide the 200 poker players into groups according to their experience and relative performance. We use the same division as before in terms of experience and we divide players into quintiles according to their relative performance. The mean forecast errors of each group are summarized in Table VII. We also see from Table VII that poker players whose performance is in the 1st, 2nd, and 3rd quintiles overestimated their relative performance whereas poker players whose performance is in the 4th and 5th quintiles underestimated their relative performance. We also see from this table that poker players who are the worst performers and who have more experience are the ones who have a greater tendency to overestimate relative performance. On the other hand, poker players who are the best performers and who have less experience are the ones who have a greater tendency to underestimate relative performance. In fact, for poker players in the 1st, 2nd, and 3rd performance quintiles, overestimation of relative performance is increasing with experience whereas for poker players in the 4th and 5th performance quintiles, underestimation of relative performance is decreasing with experience.

Let us now consider precision of forecasts according to experience and relative performance. The mean absolute errors of each group are depicted in Table VIII. We see from Table VIII that the impact of experience on the precision of poker players’ forecasts of relative performance varies with relative performance. The mean absolute forecast error of poker players whose relative performance is in the 1st and 2nd quintiles increases with experience. However, the mean absolute forecast error of poker players whose relative performance is in the 4th and 5th quintiles decreases with experience. In sum, experience with poker tournaments seems to improve the quality of the forecasts of the better players and to worsen the quality of the forecasts of the worse players.

2.6 Discussion of Findings

Poker players’ forecasts of relative performance fail the rationality test: they are biased towards overestimation of relative performance. On average, a poker player in the Winter Poker Classic overestimated relative performance by at least 10 percentiles and a poker player in the Spring Poker Classic by 7 percentiles. We test alternative explanation for this finding in Section 4.

\[ MAE_i = a + b \text{Exp}_i + \varepsilon_i, \]

where \( \text{Exp}_i \) is the number of poker tournaments a player in the Spring Poker Classic has been in the past, and \( \varepsilon_i \) is the error term. We find that

\[ MAE_i = 6.85 - 0.047 \text{Exp}_i. \]

We see that the slope of this regression is not significantly different from zero. This confirms that experience with poker tournaments does not increase the precision of forecasts.
Let us now discuss poker players’ betting behavior in the Spring Poker Classic. The average choice of bet of the 140 poker players in the Spring Poker Classic is 68.4. This is approximately the bet that pays $6.66 if a player is eliminated after 70% of the population and $0 otherwise. Poker players’ bets seem to reveal more overestimation of relative performance than their point forecasts. In effect, while 78.6% of players chose bets that paid them when their performance was above the median only 62.8% of players forecasted that their performance would be above median.\(^{20}\)

In the Appendix we state theoretical results that characterize players’ optimal point forecasts and optimal bets. Proposition 4 shows us that the optimal bets of risk neutral players may differ from their optimal point forecasts. Proposition 4 part (i) shows us that if an individual is risk neutral and his density of beliefs is uniform with support on \([a, 1]\) then the individual is indifferent between any bet in \([a, 1]\). Thus, we can not make any inference about beliefs of relative performance from observing the betting behavior of a risk neutral player with uniform beliefs with support on \([a, 1]\). Proposition 4 part (ii) tells us that if an individual is risk neutral and his density of beliefs is uniform with support on \([a, b]\), with \(b < 1\), then the individual’s optimal bet is \(a\). Finally, parts (iii) and (iv) of Proposition 4 show that and if an individual is risk neutral and his density of beliefs is unimodal and symmetric or unimodal and positively skewed then his optimal bet is lower than his optimal point forecast.\(^{21}\) One distribution that satisfies the conditions stated in Proposition 4 parts (iii) and (iv) is the Beta\((\alpha, \beta)\) distribution with \(1 < \beta \leq \alpha\).\(^{22}\)

The intuition behind parts (ii), (iii) and (iv) of Proposition 4 is that the

\(^{20}\)If we restrict our attention to players who have simultaneously provided a point forecast and made a choice of bet we can compare the distribution of point forecasts to the distribution of choices of bet. This comparison is summarized in Table V. Table V shows us that poker players who believed that they would perform below the 70th percentile chose bets that were greater than their point forecasts and that poker players who believed that they would perform above the 70th percentile chose bets that were similar to their point forecasts. The mean forecast of the 42 poker players who forecasted a performance below the 50th percentile is the 28.93th percentile and their mean choice of bet is 44.0. The mean choice of bet of the 14 players who forecasted a performance above the 50th percentile was above the median only 62.8% of players forecasted that their performance would be above median.\(^{20}\)

\(^{21}\)We cannot show that a risk neutral individual with a unimodal and negatively skewed density of beliefs chooses an optimal bet lower than his optimal point forecast. In fact, this need not be the case. Consider the following example, let \(g(x) = \frac{2(x-0.5)^2}{(0.5-0.5)^2} \) for \(0.5 < x < b\), with \(b \in (0.5, 1]\). In this case the distribution of beliefs is negatively skewed, \(c^* = 1 - \sqrt{1 - (b^2 - b + 1)}\) and \(E(X) = \frac{2}{(0.5-0.5)^2} \left( \frac{b^3}{3} - \frac{b^2}{2} + \frac{1}{2b} \right)\). If \(b = 0.98\) we have \(c^* = 0.86 > 0.82 = E(X)\). However, it is also easy to check that for any \(b \in (0.5, 0.962)\) we have \(c^* < E(X)\) whereas for any \(b \in [0.962, 1]\) we have \(c^* > E(X)\). Thus, for this negatively skewed distribution of beliefs we have \(c^* < E(X)\) for most values of the parameter \(b\).

\(^{22}\)To illustrate Proposition 4 part (iii) suppose that an individual is risk neutral and that his beliefs have the distribution Beta\((2,2)\). If beliefs have the density Beta\((2,2)\) we have that

\[g(x) = 6(x - x^2),\]

and

\[G(x) = 3x^2 - 2x^3.\]
betting problem, by comparison with the forecasting problem, creates an asymmetry between overestimation and underestimation of relative performance. In the forecasting problem, a player who overestimates relative performance by 10% faces the same cost as the player who underestimates relative performance by 10%. By contrast, in the betting problem, a player who overestimates relative performance by 10% incurs larger costs than if he underestimates relative performance by 10%.

Thus, if we assume that poker players’ are approximately risk neutral and that the distribution of beliefs of the poker players’ who forecasted a below median performance is unimodal and positively skewed, then the data is inconsistent with the implications of Proposition 4: poker players who forecasted below median performance make choices of bet larger than their point forecasts. However, since we did not assess poker players’ preferences towards risk we cannot claim that players reveal more overestimation of relative performance in their bets than in their point forecasts.

Poker player’s forecasts of relative performance in both tournaments are not distinguishable from random guesses. More precisely, taking into account the overestimation bias, forecasts in the Winter Poker Classic seem to be a random guess in the interval [21,99] and forecasts in the Spring Poker Classic seem to be a random guess in the interval [15,99]. Additionally, in the Spring Poker Classic, the rewards that poker players’ received from their bets are no better than the rewards they would have received if they had made random bets.

There are three possible explanations (not necessarily mutually exclusive) for these findings: (1) most poker players were very inexperienced in poker tournaments so they had very little information about their relative skill, (2) the fact that luck plays a large role in a Texas Hold’em Poker tournament, or (3) the degree of financial incentives was not enough to motivate people to think hard enough about their relative skill. Let us consider each explanation in detail.

It is true that most poker players in the Winter and Spring Poker Classics were inexperienced. However, as we have seen, the more experienced poker players’ mean absolute forecast error is as large as the mean absolute forecast error of the less experienced poker players. So, we do not think that lack of experience is the main reason behind the large forecast errors observed. Luck does seem to play a large role in poker tournaments. If that is the case, then maybe the precision of players’ forecasts was low not because they were making random guesses of their relative performance but because relative performance was very random.

The optimal bet is given by

\[
\frac{1}{1 - e} = \frac{6(c - c^2)}{1 - 3c^2 + 2c^3}
\]

or

\[c^* = 1/4 < 1/2 = E(X).\]

So, in this example the optimal point forecast is 1/2 and the optimal bet is 1/4.
Could it be that the lack of precision in poker players' forecasts is due to insufficient financial incentives? Yes, the size of monetary incentives may have been too small. Still, the impact of monetary incentives depends on the dispersion of players’ beliefs of relative performance. For example, if a poker player in the Spring Poker Classic is risk neutral and has uniform beliefs with support on [0, 99], then she does not expect to receive any reward for her point forecast with 90% probability and she is indifferent between all bets. Thus, if players’ beliefs of relative performance are very spread out, then players’ expected rewards from taking the survey are small and do not depend much on their forecasts or bets. By contrast, if the distribution of a player’s beliefs of relative performance is tight, then the impact of monetary incentives is larger. In sum, we cannot rule out the possibility that stronger monetary incentives would improve the precision of players' forecasts and reduce the size of the overestimation bias.

3 Skill-Based Tournaments

Could it be that our findings in luck-based tournaments extend to skill-based tournaments? To address this question we chose the game of chess. It is obvious that in chess luck plays a much smaller role than in poker. It is also the case that chess players tend to have more information about their relative skill than poker players. In chess each player has an Elo rating. The Elo rating system in chess is a means of comparing the relative strengths of chess players, devised by Arpad Elo. Players gain or lose rating points depending on the Elo rating of their opponents. If a player wins a game of chess in a rated tournament, they gain a number of rating points that increases in proportion to the difference between their rating and their opponent’s rating.23 The fact that luck plays a smaller role in chess than in poker and that chess players have more information about their relative skill leads us to expect that chess players’ forecasts of relative performance should be more precise than those of chess players.

Sintra’s Chess Open was held in July, 17th, 2005 in Sintra, a village near Lisbon. There were 93 chess players in the tournament. Players had to pay an entry fee of either 3 or 6 euros.24 Players’ ages ranged from 10 to 75 years old. On average, a chess player in the tournament had 36 years of age. Some players had never been to a chess tournament before and others had been to more than two hundred chess tournaments before. On average, a chess player in the Sintra Chess Open had been to 60 chess tournaments before. Of the 93 chess players 3 were women. The total prize pool was 1100 euros.25 The prize structure of the tournament is depicted in Table IX.

23The central statistical assumption of the ELO system is that any player’s tournament performances, spread over a long enough career, will follow a normal distribution. A detailed description of the formulæ and theory behind the system can be found at http://home.clear.net.nz/pages/petanque/ratings/descript.htm.
24Members of the chess clubs only had to pay 3 euros while non-members had to pay 6 euros.
25The prizes for this tournament were obtained from sponsors of the Sintra Chess Club.
Like in poker tournaments, we asked chess players to predict their relative performance under a quadratic scoring rule. Chess players were also asked to choose among different bets whose payments were contingent on their relative performance in the tournament. They were asked to report their own Elo rating and to provide their best estimate of the percentage of players in the tournament who have a smaller Elo rating. Many players ended up receiving their rewards at the end of the tournament while some opted by receiving them by mail.

3.1 Distribution of Forecasts

We handed out 70 surveys of which 65 were returned. We did not hand out surveys to 23 players who arrived late at the tournament.\(^{26}\) From the 65 surveys that were returned we obtained 60 forecasts of relative performance. Table X gives us an idea of the distribution of forecasts of these 60 chess players. Table X shows us the distribution of forecasts of chess players for each interval of 10 percentiles starting in the interval \([0,10]\) and ending in the interval \([90,99]\). The two most forecasted percentiles were the 60th percentile and the 85th percentiles, with approximately 8% of forecasts in each. In Sintra’s Chess Open 38.3% of forecasts are below the 50th percentile and 56.7% of forecasts are above it. The mean forecast of relative performance in Sintra’s Chess Open was the 54.37th percentile.

3.2 Bias of Forecasts

The relative performance of each chess player in the tournament was calculated by the organization of the tournament using the Swiss method. The mean relative performance of the 60 chess players who provided forecasts was the 47.37th percentile. Thus, the mean forecast error of the group of 60 chess players is 7 percentiles. In other words, the average chess player in this group overestimated relative performance by 7 percentiles.

We use the same procedure as in poker tournaments to show that forecast errors are biased, that is, we run the ordinary least squares regression \(E_i = a + \varepsilon_i\), where \(E_i\) is the forecast error of player \(i\). We find that the intercept term has a \(t\)-statistic equal to 2.31 which implies that, with a significance level of 2%, the mean forecast error of the 60 chess players is greater than zero.

What about the level of bias of the whole population? Does it differ significantly from 7 percentiles? Since we now have the relative performance of all players in the tournament we can back out the missing forecasts of the 33 players from their relative performance.\(^{27}\) We use ordinary least squares to find the marginal impact of position on forecasts. That is, we run the regression

\(^{26}\)Players who arrived late at the tournament had their first round opponents’ waiting for them and had lost playing time in that round. We decided to not hand out surveys to these players.

\(^{27}\)These 33 players can be divided into three groups: 23 players who arrived late at the tournament, 5 players who did not want to return the survey, and 5 players who returned the survey but who did not provide a forecast of relative performance.
\[ F_i = a + bP_i + \varepsilon_i \] and find that

\[
F_i = 19.102 + 0.745P_i. 
\]

We use the estimated coefficients in (2) to predict the forecasts of the 33 players according to their relative performance.\(^{28}\) If we do that we find that the mean forecast of the whole population would be equal to 55.94. Since the mean relative performance of the whole population is equal to 49.47, the mean forecast error would be equal to 6.47. Thus, the bias for the whole population should be slightly smaller than the bias displayed by the group of 60 players. This happens because overestimation of relative performance is decreasing with relative performance and the mean relative performance of the group of 33 players is the 53.31th percentile which is greater than the mean relative performance of the group of 60 players.\(^{29}\)

### 3.3 Precision of Forecasts

To study the precision of chess players’ forecasts we use the same approach as with poker players, that is, we run the ordinary least squares regression

\[
P_i = a + bF_i + \varepsilon_i. 
\]

The results are summarized in Table XI. We see from Table XI that the R-squared of the regression is 45.9% and that the mean absolute error is 17.03. The estimated coefficient for the intercept is 13.867 which is closer to 0 than to 50. The estimated coefficient for the slope is 0.616 which is closer to 1 than to 0. Thus, chess players’ forecasts of relative performance are closer to the perfect fit model than to the random guess model. As expected, chess players’ forecasts of relative performance are more precise than those of poker players. As we mention before, this may happen for two reasons: (1) luck plays a smaller role in chess than in poker, or (2) chess players have more information about their relative skill than poker players.

The earnings that chess players received from taking the survey are summarized in Table XII. The first two columns in Table XII tell us how many players received each type of reward for their forecasts in Sintra’s Chess Open. The total monetary rewards for point forecasts in Sintra’s Chess Open were $110. This corresponds to an average reward of $1.83, a value that is significantly higher, at a 5% significance level, from the expected reward of a random guess: $.50.\(^{30}\)

\(^{28}\)We could not use this approach in poker tournaments since we did not know the rank of most of the players who did not provide forecasts of relative performance.

\(^{29}\)Recall that 23 out of the 33 players whose forecasts are missing are players who were not handed out a survey because they arrived late at the tournament. A high skilled player may stand to lose less by arriving late at the first round of the tournament than a low skilled player since higher skill may more than compensate for the lost in playing time due to lateness. This may be reason why arriving late at the tournament is correlated with a smaller overestimation of relative performance.

\(^{30}\)The t statistic for the hypothesis test that the average reward for a point forecast is not
3.4 Preferences Towards Risk

To have an idea of players preferences towards risk in the domain of gains we asked them the following question:

Consider the 10 lotteries below, whose prizes depend on the draw of a random number between 0 and 100 (the random number will be generated by the tournament manager after the start of the event). Choose one of the options.

We pay you 1.00 for sure
We pay you 1.11 if the random number is above 10 and 0 otherwise
We pay you 1.25 if the random number is above 20 and 0 otherwise
We pay you 1.43 if the random number is above 30 and 0 otherwise
We pay you 1.67 if the random number is above 40 and 0 otherwise
We pay you 2.00 if the random number is above 50 and 0 otherwise
We pay you 2.50 if the random number is above 60 and 0 otherwise
We pay you 3.33 if the random number is above 70 and 0 otherwise
We pay you 5.00 if the random number is above 80 and 0 otherwise
We pay you 10.00 if the random number is above 90 and 0 otherwise

This question allows us to have an idea of players’ risk preferences under objective uncertainty. All lotteries have the same expected value but different levels of risk. Thus, a risk averse player prefers the sure thing, a risk neutral player is indifferent between every lottery, and a risk seeking player prefers the most risky lottery.31

A total of 57 players answered the choice of lottery question. The last three columns of Table 12 show that 12 players chose the sure thing, 35 players chose lotteries with an intermediate risk level, and 10 players chose the most risky lottery. Thus, players’ choices of lottery show that at the most there are 12 players who are risk averse in the domain of gains. They also show that at most there are 10 players who are risk seeking in the domain of gains. Thus, we must have at least 35 players who are risk neutral in the domain of gains.32

different from the expected reward of a random guess is equal to 2.78 and the 5 percent critical value is equal to $t_{5\%}(59) \approx 1.67$. Thus, we can reject the hypothesis that players’ forecasts in Sintra’s Chess Tournament were random guesses.

31Since a risk neutral player is indifferent between all the lotteries this question does not allow a perfect distinction between risk neutrality and the two other types of preferences towards risk at the individual level. However, at the aggregate level, if the mean choice of lottery of a group of players is close to the sure thing than there is evidence that the group is risk averse. By contrast, if the mean choice of lottery of a group of players is closer to the most risky lottery there is evidence that the group is risk seeking.

32The interpretation that players’ choices of lottery tell us something about their preferences towards risk may be incorrect. In the survey, the choice of lottery question was asked after the choice of bet question. It could have been the case that players’ answers to the choice of lottery question were anchored in their answers to the choice of bet question. This possibility cannot be ruled out since, in effect, a total of 30 players made identical choices of bet and of lottery.
3.5  Betting Behavior

The answers to the choice of bet question are summarized in the middle columns of Table 12. A total of 58 players answered the choice of bet question. The last line in the last column in Table 12 tells us the average reward for choice of bet was $1.65. We can compare this number to the average reward of a random choice of bet: $1.00. The observed average reward for choice of bet is significantly greater than the average reward of random choices of bet.33

Overall, 36.2% of chess players chose bets that pay when their relative performance is below median and 63.8% of chess players chose bets that only pay when their relative performance is above median. Ranking bets from 5 (the sure thing) to 55 (the $2 bet) to 95 (the $10 bet) we find that the average choice of bet of these 58 chess players is 54.0. This is close to bet 55: the bet that pays $2.00 if a player is eliminated after 50% of the population.

Table XIII compares chess players’ choices of bet to their point forecasts. Table XIII shows us that chess players’ who forecasted that they would perform below the 50th percentile tend to choose bets greater than their point forecasts and that chess players’ who forecasted that they would perform above median tend to choose bets smaller than their point forecasts.34 In fact, the mean forecast of the 22 chess players who forecasted a performance below the median is the 20.18th percentile and their mean choice of bet is 27.73. By contrast, the mean forecast of the 35 chess players who forecasted a performance above the median is the 74th percentile and their mean choice of bet is 69.57.

3.6  Experience, Skill, and Forecasts

A total of 49 chess players provided forecasts of relative performance and reported the number of chess tournaments they have played before. On average, a chess player who participated in Sintra’s Chess Open has played in 60 chess tournaments before. Taking this into consideration we divide players into four groups according to number of tournaments played: 0 tournaments, 1 to 6 tournaments, 7 to 50 tournaments, and 50 or more tournaments. The table below displays the mean forecast, mean position, mean forecast error, and mean absolute forecast error for each group. Table XV shows that the less experienced chess players tend to overestimate relative performance more than the more experienced chess players. Table XV also shows that, unconditional on relative performance, more experience with chess improves the precision of chess players’ forecasts of relative performance.

We divide the 49 players into groups according to their relative performance and number of tournaments played. We divide players into quintiles according to

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33 The t statistic for the hypothesis test that the average reward for choice of bet is not different from the expected reward of a random choice of bet is equal to 2.02 and the 5 percent critical value is equal to $t_{5\%}(57) \approx 1.67$. Thus, we can reject the hypothesis that players’ choices of bet in Sintra’s Chess Tournament were random choices.

34 There are only two exceptions to this pattern: the 3 chess players who made forecast in the [30,39] percentile interval and the 3 chess players who made forecasts in the [70,79] interval.
relative performance. Table XVI displays the mean forecast errors for each group (the number of players in each group is small so there is not much confidence in the numbers in the table). This happens for two reasons: (1) there is a strong correlation between experience and relative performance, that is, on average, a more experienced chess player performs substantially better than a less experienced chess player and (2) the less experienced chess players overestimate relative performance. Table XVII displays the precision of forecasts, measured by mean absolute error.

How does relative skill influence chess players’ forecasts of relative performance? Assuming that the Elo rating of each player is a good measure of relative skill we can use the Elo ratings to answer this question. Thus, we divide the 60 players who provided forecasts of relative performance into quintiles according to Elo rating. Table XVIII summarizes the findings for each quintile. Table XVIII shows us that the low skill players are the ones who overestimate relative performance more. Overestimation of relative performance is higher for the high skilled than for the average skill players, but the difference is small. Table 18 also shows us that the low skill players have much larger forecast errors than high skill players.

### 3.7 What Explains Relative Performance?

Of the 93 players that took part in the tournament 70 had an Elo rating and 33 did not. If luck is not very important in determining rank and the Elo rating is a good measure of relative skill at chess, then we expect that there is a strong positive correlation between a player’s Elo rating and his performance in the tournament. This is was indeed the case: the correlation between a player’s Elo and the percentage of players who performed worse than him was 80.70%.

The Elo rating is a measure of relative skill that takes into consideration the past performance of a player. This means the it should underestimate the skill of young players and overestimate the skill of old players. Since we also asked players for their age we can check if age also has an influence in relative performance controlling for the influence of Elo. To do this we run the ordinary least squares regression

\[ P_i = a + bELO_i + cAGE_i + \varepsilon_i, \]

where \( AGE_i \) is the age of player \( i \) measured in years. The results of this regression are summarized in Table XIX. As we expected the results of the regression in Table 19 show us that, the impact of age, conditional on Elo rating, on relative performance is negative.

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35 Among the 93 players who took part in the tournament there were 23 players without an Elo rating. To rank the 23 without Elo rating in terms of relative skill we use their relative performance in the tournament.

36 Since we knew the positions of all the players and 70 players had an Elo rating the number 80.70% is obtained by calculating the correlation between for the position of the 70 players who had an Elo rating and their Elo rating.
3.8 Efficiency of Forecasts

For chess players’ forecasts of relative performance to be rational they would have to be unbiased and efficient. We already know that forecasts of chess players are biased. Can we say anything about efficiency? If a chess player makes an efficient forecast of relative performance then he must use all the available information that he has about his relative skill to make that forecast. Since we also asked players to provide their best estimate of the percentage of the population in the tournament with a lower Elo rating we can check what happens if we include this assessment as an explanatory variable in regression (3). Thus, to test the hypothesis that chess players’ forecasts are efficient we run two regressions: one with the explanatory variable Lower Elo and the other without it. That is we compare

\[ P_i = a + bF_i + \varepsilon_i, \]

and

\[ P_i = a + bF_i + cLElo_i + \varepsilon_i, \]

where \( LElo_i \) is player \( i \)’s subjective assessment of the percentage of the population that has a lower Elo rating. The results for both regressions are displayed in Table XX. The results from the two regression in Table XX show us that chess players’ forecasts are not efficient. The model with the explanatory variable Lower Elo (regression 1) has a better fit than the model without it (regression 2). In other words, chess players could have made better forecasts if they had taken into consideration their own subjective assessments of the percentage of the population with a smaller Elo rating.

3.9 Overconfidence

To find out if chess players were overconfident in their forecasts of relative performance we asked each player to provide a 90 percent confidence interval for his best estimate of what percentage of people would be ranked below him. The precise question was worded as follows

"Please provide a 90% confidence interval for your best estimate of what percentage of people will be ranked below you. For example, suppose your answer to the previous question was \( X \) and you think that with 90% chances the percentage of people ranked below you will be between \( Y \) and \( Z \), with \( Y \leq X \leq Z \). Then your answer to this question would be \( [Y, Z] \). Now, answer the question by providing an interval: ______ ."

Amongst the 60 players who provided forecasts of relative performance only 40 players provided confidence intervals for their forecasts. The average interval width of these 40 chess players was 15.47 percentiles. There was considerable variance in confidence interval width.\(^{37}\) Out of the 40 confidence intervals provided only 15 contained the actual relative performance of the player. This

\(^{37}\) Only 3 players provided confidence intervals that did not contain their point forecast of relative performance.
corresponds to a hit rate of 35 percent, well below 90 percent. Thus, there is evidence of overconfidence in chess players’ forecasts of relative performance.

The fact that the average width of the 90% confidence intervals of these 40 chess players is equal to 15.47 percentiles tells us that the distribution of beliefs of relative performance of these players is quite tight. This implies that from the average chess player’s perspective the expected rewards for the forecast question and for the betting question are not irrelevant. To see this suppose that a chess player is risk neutral and has uniform beliefs of relative performance with support in $[0, 99]$. The expect payoff of this chess player’s optimal point forecast—the 50th percentile—is approximately 50 cents. The expected reward of this chess player’s optimal bet—the sure thing—is $1.00. We see that for a chess player with these beliefs of relative performance the expected rewards from the forecast and bet questions are quite small. Now, suppose that a chess player is risk neutral but has uniform beliefs of relative performance with support in $[40, 60]$. The expect payoff of this chess player’s optimal point forecast—the 50th percentile—is approximately $2.50. The expected reward of this chess player’s optimal bet—the bet that pays $1.67 if the player is better than 40% of the population and $0 otherwise—is $1.67. In sum, if chess players have tight distributions of beliefs of relative performance, as it seems to be the case given their stated confidence intervals, then their perceived expected rewards from taking the survey are larger than the actual expected rewards.

3.10 Discussion

Chess players’ forecasts of relative performance fail the rationality test: they are biased towards overestimation of relative performance. On average, a chess player in the Sintra’s Chess Open overestimated relative performance by approximately 7 percentiles. The finding that chess players forecasts of relative performance are, like poker players’ forecasts, biased towards overestimation is somewhat surprising since chess players have usually more information about the quality of their competitors: each player knows his own Elo rating and chess players are aware of how their Elo rating compares to the Elo ratings of competitors.

Chess players’ forecasts of relative performance are not random guesses. Experience with chess tournaments improves chess players forecasts of relative performance. Chess players who have played more chess tournaments exhibit less overestimation of relative performance and smaller absolute forecast errors. Thus, the inexperienced chess players are the ones responsible for the overestimation observed in the population.

Let us now discuss the betting behavior of chess players. As we have seen the average choice of bet of chess players’ coincides with their average point forecast. Thus, on average, chess players’ bets seem to reveal the same degree of overestimation of relative performance as their point forecasts. Since we have an idea about chess players’ preferences towards risk we can check whether the bets and point forecasts of risk neutral players are consistent with the predictions of Proposition 4. Table XIV shows us that the 12 risk neutral players
who forecasted a below average performance chose bets larger than their point forecasts. However, the 22 risk neutral players who forecasted an above average performance chose bets smaller than their point forecasts. The choices of bet and point forecasts of the risk neutral players who forecasted a below average performance are inconsistent with Proposition 4.

We tried to measure chess players’ risk preferences by offering them the choice between 10 different lotteries all with the same expected value but with different levels of risk. There were two problems with this approach. First, the fact that all lotteries have the same expected value does not allow a clear distinction between a risk neutral and risk averse individual or between a risk neutral and a risk seeking individual. Second, many chess players seem to have anchored the answer to the choice of lottery question in the answer to the betting question. These two aspects can certainly be improved upon in future research.

4 Why a Bias in Forecasts?

As we have shown forecasts of relative performance in tournaments are biased: there is a systematic tendency towards overestimation of relative performance. Why does this happen? There are several alternative explanations for this bias. First, individuals may overestimate their relative performance due to reference group neglect. If an individuals is not aware that the people who chose to participate in the tournament are more skilled than a random person then he will overestimate his relative skill. Second, if low skilled players are risk averse and high skilled players are risk seeking, then forecasts may be biased towards the positive side even though there is no overestimation of relative performance. Third, individuals may also overestimate relative performance due to the self-serving bias in causal attributions, the tendency that people have to attribute failure to bad luck and success to skill. Forth, skill investment and egocentric comparisons can lead individuals to overestimate relative skill. Fifth, relative optimism may lead players to think that they are more lucky than others. We will now see what the data can tell us about the first three explanations.

4.1 Reference Group Neglect

According to the reference group neglect explanation, individuals overestimate relative performance in tournaments because they fail to realize that better players will self select to play in tournaments. Thus, according to this explanation, overestimation of relative performance should come hand in hand with underestimation of the quality of competitors. Knowledge of one’s own Elo and the quality of the competition (measured by Elo rating) allows a precise test of the reference group neglect hypothesis. To test this hypothesis we asked each

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38 As far as we know this explanation for overestimation of relative skill is new.
39 This explanation is formalized in Santos-Pinto and Sobel (2004).
40 We can not test the last two explanations with our data.
player to provide his own Elo rating and his best estimate of the percentage of players in the tournament who have an Elo rating less than his.41 The organization of the tournament knew the Elo rating of each player and this information was made available to us. This allows us to check the quality of each player’s information about his own Elo rating. This information also allows us to check the quality of each player’s information about the level of skill of his competitors, measured by the share of the population with an Elo rating less than his.

A total of fifty nine players answered the question about their own Elo rating. Thirty nine players either knew their own Elo rating or knew that they had no Elo rating. Fourteen players were mistaken about their Elo rating.42 Six players stated that they could not recall their Elo rating.43 Two players thought they did not have an Elo rating but they had an Elo rating. Thus, approximately 78 percent of the players who answered the question about own Elo rating had very accurate information about own Elo rating.

A total of forty five chess players provided an estimate of the percentage of players in the tournament who had a smaller Elo rating. The average estimate of the quality of the competition was that 48.04 percent of the population had a lower Elo rating. However, on average, the actual percentage of the population with a smaller Elo rating was 49.22 percent. That is, on average, this group of players overestimated the quality of competitors by 1.18 percentiles.44 However, this group of players overestimated relative performance by 5.70 percentiles.45 This finding is inconsistent with the reference group neglect explanation for overestimation of relative performance.

4.2 Correlation between Risk Preferences and Skill

It is possible to construct examples where risk aversion or risk seeking preferences may lead a player to make an optimal point forecast that is different from his mean belief of relative performance.46 Propositions 1 and 2 show us that two necessary conditions to construct those examples is that individuals are not risk neutral and their distribution of beliefs is skewed. These two conditions give us intuition on how risk preferences may influence an individual’s optimal point forecast.

41 See questions Q4 and Q5 in Appendix C.
42 Of the 14 players who were mistaken about their Elo rating, 7 were less than 10 points away from their actual rating.
43 However, these 6 players were able to provide an estimate of their ranking in terms of Elo rating. This suggests that they had an idea of their Elo rating even though they were not able to recall it.
44 The standard deviation of estimate error was 16.09 percentiles, which indicates that chess players’ precision in forecasting the quality of their competitors is similar to the precision of their forecasts of relative performance.
45 The average forecast of relative performance of these 45 players was the 56.34th percentile whereas the average relative performance was the 50.64th percentile.
46 We are unable to state general results that characterize how risk aversion or risk seeking preferences lead optimal point forecasts to differ from mean beliefs of relative performance.
Consider a risk seeking player with a negatively skewed distribution of beliefs. We expect that the optimal point forecast of this type of player should be higher than his mean belief of relative performance since the utility from the increase in risk associated with making a forecast higher than the mean belief should be greater than the loss in utility from the decrease in the probability of earning the higher rewards. By contrast, we expect that the optimal point forecast of a risk seeking player with a positively skewed distribution of beliefs should be lower than his mean belief of relative performance. In this case, the utility from the increase in risk associated with making a forecast lower than the mean belief should be greater than the loss in utility from the decrease in the probability of earning the higher rewards.47

Now, consider a population of players where the low skilled players have positively skewed distributions of beliefs of relative performance and the high skilled players have negatively skewed distributions. Additionally, suppose that players do not have a tendency to either overestimate or underestimate relative performance. If risk preferences are uncorrelated with skill, then the mean point forecast of the population should be equal to the mean belief of relative performance. This happens because the number of risk averse and risk seeking players with positively (or positively) skewed distributions of beliefs is similar. However, if risk preferences are correlated with skill, then the mean point forecast of the population should differ from the mean belief of relative performance. For example, if low skilled players are risk averse and high skilled players are risk seeking, then the mean point forecast of the population should be higher than the mean belief of relative performance. In this case, what looks like overestimation of relative performance is really the result of a correlation between risk preferences and skill.48

In Sintra’s Chess Open we have information about chess players’ preferences towards risk, skill, and forecasts, and so it is possible to test this hypothesis. Table XIV summarizes the relevant data. Out of the 56 players who made a choice of lottery we classify 34 as being risk neutral, 12 as being risk averse, and 10 risk seeking. Out of the 34 risk neutral players, 22 players performed below median and overestimated relative performance by 13 percentiles and the remaining 13 players performed above median and underestimated relative performance by 2.3 percentiles. Out of the 12 risk averse players, 6 players performed below median and overestimated relative performance by 1.6 percentiles and the

47Similarly, if an individual is risk averse and has a negatively skewed distribution of beliefs we expect that his optimal point forecast is lower than his mean belief of relative performance since the utility from the decrease in risk associated with making a forecast lower than his mean belief may be greater than the loss in utility from the decrease in the probability of earning the higher rewards. By contrast, if an individual is risk averse and has a positively skewed distribution of beliefs we expect that his optimal point forecast is higher than his mean belief of relative performance since the utility from the decrease in risk associated with making a forecast higher than his mean belief may be greater than the loss in utility from the decrease in the probability of earning the higher rewards.

48Similarly, if low skilled players are risk seeking and high skilled players are risk averse, then the mean point forecast of the population should be smaller than the mean belief of relative performance. In this case, what looks like underestimation of relative performance is really the result of a correlation between risk seeking behavior and skill.
remaining 6 players performed above median and overestimated relative performance by 5.5 percentiles. Finally, out of the 10 risk seeking players, 4 performed below median and overestimated relative performance by 8 percentiles and the remaining 6 performed above median and underestimated relative performance by 0.4 percentiles. Thus, we see that the 22 risk neutral players who performed below median account for most of the overestimation observed in the population. We also see that there does appear to exist a correlation between risk preferences and performance. In sum, the data does not support the hypothesis that the bias in chess players’ forecasts comes from a correlation between risk preferences and skill.

4.3 Self-Serving Bias in Causal Attributions

According to this explanation players overestimate relative performance because they attribute success to skill and failure to luck. At the beginning of the tournament we asked players: “How do you think your position in this tournament will be determined?” Players could choose among 7 different options where the role of skill and luck varied. On average, players thought that skill is more important than luck but that luck plays a large role in determining relative performance.49

Two days after the Spring Poker Classic was over we sent an email to those players who had given us their email contact. In that email players were told their relative performance and reminded them of their forecast. Additionally, players were asked once again “How do you think your position in the poker tournament was determined?”

There would be strong support for the self-serving bias explanation if: (1) the attributions of players who overestimated relative performance (players who failed to attain their forecasted performance) changed in the direction of luck becoming more important after the tournament than before the tournament and (2) the attributions of players who underestimated relative performance (players who succeeded in surpassing their forecasted performance) changed in the direction of skill becoming more important after the tournament than before the tournament.

We sent emails to 98 players in the Spring Poker Classic but only received replies from 25 players. Out of these 25 players we have 12 players who did not change their attributions, 10 players who changed their attributions according to the self-serving bias, and 3 players who changed their attributions in the opposite direction as the one consistent with the self-serving bias. Thus, we some support for the self-serving bias explanation. However, the low reply rate casts doubts about the validity of this finding.

5 Related Literature

Hoelzl and Rustichini (2005), Moore (2002), Moore and Kim (2003) examine forecasts of relative performance in an experimental setting with monetary in-
centives. While their designs differ, the papers all identify a subject’s beliefs about relative performance by asking the subject whether a reward should be based on a test of skill or the outcome of a random device. The experiments reveal overestimation of relative performance when more than half of the subjects prefer to be rewarded on the basis of their performance on the test than on the basis of a randomization device that selects a winner with probability one half. These papers observe that the extent of overestimation increases when the test becomes easier (and even find evidence of underestimation when relative performance on difficult tests determines monetary payoffs). More people voted for performance-based payment for easier tasks than for hard ones. Monetary payments significantly reduced overestimation of relative performance.

As Hoelzl and Rustichini (2005) point out, the drawback of this measure of beliefs of relative performance is that subjects are facing the choice between a lottery with objective uncertainty—outcome of the random device—and lottery with subjective uncertainty—the outcome of the test of skill. Thus, if subjects suffer from ambiguity aversion, this measure is likely to underestimate the subjective perception that subjects have of their relative performance.

Clark and Friesen (2003) design an experiment to measure the rationality of individuals’ forecasts in two types of tournaments: (1) maximizing a two variable unknown function by moving contiguously from cell to cell on a spreadsheet and (2) decoding five letter words. They use a similar approach as the one used in this paper in that they provide subjects with a quadratic scoring rule that rewards forecasts accuracy. They find support for rational expectations of relative performance in tournaments.

6 Conclusion

This paper shows that players in tournaments tend to overestimate relative performance. Overestimation is present in players’ forecasts even with financial incentives for accurate forecasts. The paper shows that players are also willing to bet on their overly favorable views of relative performance. Thus, players’ betting behavior confirms the tendency for overestimation of relative performance found in players’ forecasts.

The paper shows that overestimation is present in luck-based tournaments as well as in skill-based tournaments. Overestimation is also present even when players have a good idea of the quality of the competition. Still, the degree of overestimation that we find is not as large as the ones often reported in studies in the social psychology literature.

There are several limitations to our measure of beliefs of relative performance. Previous studies (Brown, 1995, 1998) found that affine transformations of the payoff function that see the subjects threatened with the prospect of losing money result in more accurate forecasts than when earnings remain positive (due to loss aversion from the part of the subjects).50 This is an important

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50 A significant body of empirical evidence shows that people are loss averse. See for example, Tversky and Kahneman (1991).
aspect that we could not address since there was no way that players could lose money if they made poor forecasts or picked the wrong bet.

As Hoelzl and Rustichini (2005) show, monetary incentives can reduce overestimation of relative performance. We provided monetary incentives to players for making accurate forecasts and bets. However, the size of monetary incentives may have been too small even after taking into consideration that players’ distributions of beliefs of relative performance are excessively tight. If that was the case, then players’ had neither strong incentives to provide accurate forecasts nor to make accurate bets. We cannot rule out the possibility that the overestimation bias would disappear if players would have been given stronger monetary incentives.
References


7 Appendices

7.1 Surveys

UCSD's 2004 Winter Poker Classic - Survey

You are about to answer a survey that asks you to make a prediction of your position in this poker tournament. Depending upon how well you make your prediction you may be able to earn up to $10. Clipped to this survey is a sticker with a number that matches the number on this particular survey sheet. You will need to put this sticker on your shirt so that we can identify you during the tournament. You will also need to keep the sticker and present it in order to collect your payment tomorrow, Monday, from 10:00 am to 4:00 pm near the entrance of Jamba Juice in Price Center at UCSD (if you can't make it tomorrow please contact us at the email address provided on the back of the sticker).

Q1: Please read the following question carefully:

Of all the individuals participating in this poker tournament what percentage do you think will be eliminated before you?

Before you answer note that while the poker tournament is taking place we will record the order of elimination of each participant by writing down the number in his or her sticker. The order of elimination is determined exclusively by the moment in time when each participant leaves the table where he/she is playing. Thus, it will be possible to find out what percentage of people will be eliminated before you. After you are eliminated from the tournament, we will compare your prediction with the ratio of the actual number of individuals eliminated before you to the total number of players. We will then pay you for your prediction as follows:

- $10 if the prediction is less than 1% away from your position;
- $9 if the prediction is more than 1% and less than 2% away from your position;
- $6 if the prediction is more than 2% and less than 3% away from your position;
- $1 if the prediction is more than 3% and less than 4% away from your position;
- $0 otherwise.

Now, answer the question by choosing a whole number between 0 and 99 (recall that the number you choose represents your best estimate of what percentage of people will be eliminated before you):

Q1: How many hours per month (within the last year) do you play poker? Circle one (for the purpose of this question any poker game counts, whether in a tournament or not, whether against "live" opponents or using poker software, or over the internet)
Q2: How many poker tournaments have you played before? Circle one (for the purpose of this question consider that a poker tournament involves monetary bets and at least 20 players)

Q3: The average UCSD poker player has___________than/as the average UCSD poker player who chose to play in this tournament today. Choose one of the options below to fill in the blank.

a much, much higher level of skill
a substantially higher level of skill
a slightly higher level of skill
approximately the same level of skill
a slightly lower level of skill
a substantially lower level of skill
a much, much lower level of skill

Q4: How do you think your position in this tournament will be determined?
Choose one

Only by your relative skill at playing poker
More by your relative skill than by luck, and luck plays a small role
More by your relative skill than by luck, and luck plays a large role
As much by your relative skill as by luck
More by luck than by your relative skill, and relative skill plays a large role
More by luck than by your relative skill, and relative skill plays a small role
Only by luck

Q5: Below we list 7 skills that may matter for being a good player of Texas Hold’em. Please mark the 3 skills that you consider to be the most important.

Ability to control emotions
Ability to assess the quality of the opponents
Ability to know when and how to bluff
Ability to read the opponents’ body language and getting tells
Ability to know when to play aggressively or defensively
Ability to assess the opponents’ range of hands
Ability to calculate and recalculate the odds

Q6: Below we list the same 7 skills as above. Please mark the 3 skills you think you are better at.

Ability to control emotions
Ability to assess the quality of the opponents
Ability to know when and how to bluff
Ability to read the opponents’ body language and getting tells
Ability to know when to play aggressively or defensively
Ability to assess the opponents’ range of hands
Ability to calculate and recalculate the odds
UCSD’S 2004 SPRING POKER CLASSIC - SURVEY

You are about to answer a survey that asks you to make a prediction of your position in this poker tournament. Depending upon how well you make your prediction you may be able to earn up to $20. The survey also asks you to choose between different lotteries whose outcomes depend on your position in the tournament. Depending how well you make your choice of lottery and how well you perform in the tournament you may earn up to an additional $20. Clipped to this survey is a sticker with a number that matches the number on your survey sheet. You will need to put this sticker on your shirt so that we can identify you during the tournament. We will send you your payment by mail if you provide us your name and address. If you prefer, you can provide us only your email address and we will tell you your payment by email and schedule an appointment to pay you. We guarantee the confidentiality of all personal information in this survey.

Q1: Please read the following question carefully:

Of all the individuals participating in this poker tournament what percentage do you think will be eliminated before you?

Before you answer note that, while the poker tournament is taking place, we will record the order of elimination of each participant by writing down the number on his or her sticker. The order of elimination is determined exclusively by the moment in time when each participant leaves the table where he/she is playing. Thus, it will be possible to find out what percentage of people will be eliminated before you. After you are eliminated from the tournament, we will compare your prediction with the ratio of the actual number of individuals eliminated before you to the total number of players. We will then pay you for your prediction as follows:

- $20 if the prediction is less than 1% away from your position;
- $19 if the prediction is more than 1% and less than 2% away from your position;
- $16 if the prediction is more than 2% and less than 3% away from your position;
- $11 if the prediction is more than 3% and less than 4% away from your position;
- $4 if the prediction is more than 4% and less than 5% away from your position;
- $0 otherwise.

Now, answer the question by choosing a whole number between 0 and 99 (recall that the number you choose represents your best estimate of what percentage of people will be eliminated before you. Numbers close to zero indicate that you will be among the first to be eliminated, numbers close to 99 indicate that you will be among the last to be eliminated): ____________

Q2: Now, consider the ten lotteries below. Choose one of the lotteries

- We pay you $2.00 for sure
- We pay you $2.22 if you are eliminated after 10% of the players and $0 otherwise
- We pay you $2.50 if you are eliminated after 20% of the players and $0 otherwise
- We pay you $2.86 if you are eliminated after 30% of the players and $0 otherwise
- We pay you $3.33 if you are eliminated after 40% of the players and $0 otherwise
We pay you $4.00 if you are eliminated after 50% of the players and $0 otherwise.
We pay you $5.00 if you are eliminated after 60% of the players and $0 otherwise.
We pay you $6.66 if you are eliminated after 70% of the players and $0 otherwise.
We pay you $10.00 if you are eliminated after 80% of the players and $0 otherwise.
We pay you $20.00 if you are eliminated after 90% of the players and $0 otherwise.

Your answers to the questions that follow are very valuable for the purpose of this survey. It should not take you more than 3 to 4 minutes to answer them.

Name: ___________________________ E-mail: _____________________________
Address: _____________________________________________________________

Q3: Did you participate in the 2004 UCSD’s Winter Poker Classic? ? Yes ? No

Q4: How many poker tournaments have you played before? For the purpose of this question consider that a poker tournament involves monetary bets and at least 20 players: ________

Q5: How many hours per month (within the last year) do you play poker? For the purpose of this question any poker game counts, whether in a tournament or not, whether against "live" opponents or using poker software, or over the internet: ________

Q6: Consider all poker players present in this tournament. How good a poker player are you compared with all poker players in this tournament? Answer this question by providing a ranking ranging from 0 (I am at the very bottom) to 50 (I am exactly average) to 99 (I'm at the very top): ________

Q7: Consider all poker players in UCSD. How good a poker player are you compared with all poker players at UCSD? Answer this question by providing a ranking ranging from 0 (I am at the very bottom) to 50 (I am exactly average) to 99 (I'm at the very top): ________

Q8: How do you think your position in this tournament will be determined? Choose one
- Only by your relative skill at playing poker
- More by your relative skill than by luck, and luck plays a small role
- More by your relative skill than by luck, and luck plays a large role
- As much by your relative skill as by luck
- More by luck than by your relative skill, and relative skill plays a large role
- More by luck than by your relative skill, and relative skill plays a small role
- Only by luck

Q9: Below we list 7 skills that may matter for being a good player of Texas Hold’em. Please mark the 3 skills that you consider to be the most important.
- Ability to control emotions
- Ability to assess the quality of the opponents
- Ability to know when and how to bluff
Ability to read the opponents’ body language and getting tells
Ability to know when to play aggressively or defensively
Ability to assess the opponents’ range of hands
Ability to calculate and recalculate the odds

Q10: Below we list the same 7 skills as above. Mark the 3 skills you think you are better at.
Ability to control emotions
Ability to assess the quality of the opponents
Ability to know when and how to bluff
Ability to read the opponents’ body language and getting tells
Ability to know when to play aggressively or defensively
Ability to assess the opponents’ range of hands
Ability to calculate and recalculate the odds

SINTRA’S 2005 CHESS OPEN - SURVEY

You are about to answer a survey that, among other things, asks you to make a prediction of your relative position in this chess tournament. Depending upon how well you make your prediction you may be able to earn up to 10 (Question 1). The survey also asks you to choose between different lotteries whose prizes depend on your relative position in the tournament (Question 3) or on the draw of a random number (Question 10). Depending on your choice of lottery, how well you perform in the tournament, and the draw of the random number you may earn up to an additional 20. We will send you your payment by mail if you provide us your name and address. If you prefer, you can provide us only your e-mail address and we will tell you your payment by e-mail and then you can give us your address if you wish to receive it by mail. This survey is confidential.

Name:_____________________E-mail:___________________
Address:____________________________________________
Zip code:___________________ Age:_________ Sex: ? M ? F

Q1: Please read the following question carefully:
Of all the individuals participating in this chess tournament what percentage do you think will be ranked below you?

Before you answer note that, after the tournament is over, we will compare your prediction with the ratio of the actual number of players ranked below you to the total number of players. We will then pay you for your prediction as follows:
10 if the prediction is less than 1% away from your position;
9 if the prediction is more than 1% and less than 2% away from your position;
6 if the prediction is more than 2% and less than 3% away from your position;
1 if the prediction is more than 3% and less than 4% away from your position;
0 otherwise.

Now, answer the question by choosing a whole number between 0 and 99 (recall that the number you choose represents your best estimate of what percentage
of people will be ranked below you. Numbers close to zero indicate that you predict that you will be among worst players in the tournament, numbers close to 99 indicate that you predict that you will be among the best players in the tournament): ____________

Q2: Please provide a 90% confidence interval for your best estimate of what percentage of people will be ranked below you. For example, suppose your answer to the previous question was X and you think that with 90% chances the percentage of people ranked below you will be between Y and Z, with Y ≤ X ≤ Z. Then your answer to this question would be [Y, Z]. Now, answer the question by providing an interval: ____________

Q3: Consider the 10 lotteries below, whose prizes depend on your ranking in the tournament. Choose one of the options:

- We pay you 1.00 for sure
- We pay you 1.11 if at least 10% of players are ranked below you and 0 otherwise
- We pay you 1.25 if at least 20% of players are ranked below you and 0 otherwise
- We pay you 1.43 if at least 30% of players are ranked below you and 0 otherwise
- We pay you 1.67 if at least 40% of players are ranked below you and 0 otherwise
- We pay you 2.00 if at least 50% of players are ranked below you and 0 otherwise
- We pay you 2.50 if at least 60% of players are ranked below you and 0 otherwise
- We pay you 3.33 if at least 70% of players are ranked below you and 0 otherwise
- We pay you 5.00 if at least 80% of players are ranked below you and 0 otherwise
- We pay you 10.00 if at least 90% of players are ranked below you and 0 otherwise

Q4: What is your Elo rating? ________ If you can’t answer this question choose one of the options below
- I don’t have an Elo rating
- I have an Elo rating but I can’t recall it

Q5: What is your best estimate of the percentage of players in this tournament who have an Elo rating less than yours? ____________

Q6: How many chess tournaments have you played before? Consider that a chess tournament involves monetary prizes and at least 20 players: ____________

Q7: Consider all chess players in this tournament. How good a chess player are you compared with all chess players in this tournament? Answer this question by providing a ranking ranging from 0 (I am at the very bottom) to 50 (I am exactly average) to 99 (I’m at the very top): ____________

Q8: Consider the chess players in this tournament who have a similar level of experience as yourself. How good a chess player are you compared with the chess players in this tournament who have a similar level of experience as yourself? Answer this question by providing a ranking ranging from 0 (I am at the very bottom) to 50 (I am exactly average) to 99 (I’m at the very top): ____________

Q9: How do you think your position in this tournament will be determined? Choose one
- Only by your relative skill at playing chess
More by your relative skill than by luck, and luck plays a small role
More by your relative skill than by luck, and luck plays a large role
As much by your relative skill as by luck
More by luck than by your relative skill, and relative skill plays a large role
More by luck than by your relative skill, and relative skill plays a small role
Only by luck

Q10: Consider the 10 lotteries below, whose prizes depend on the draw of a random number between 0 and 100 (the random number will be generated by the tournament manager after the start of the event). Choose one of the options.
We pay you 1.00 for sure
We pay you 1.11 if the random number is above 10 and 0 otherwise
We pay you 1.25 if the random number is above 20 and 0 otherwise
We pay you 1.43 if the random number is above 30 and 0 otherwise
We pay you 1.67 if the random number is above 40 and 0 otherwise
We pay you 2.00 if the random number is above 50 and 0 otherwise
We pay you 2.50 if the random number is above 60 and 0 otherwise
We pay you 3.33 if the random number is above 70 and 0 otherwise
We pay you 5.00 if the random number is above 80 and 0 otherwise
We pay you 10.00 if the random number is above 90 and 0 otherwise

Q11: Below we list 7 skills that may matter for being a good chess player. Please mark the 3 skills that you consider to be the most important.
Ability to use time wisely (good clock management)
Ability to spot weaknesses in an opponent’s game
Ability to recall past games and typical moves
Ability to simulate mentally future moves including opponent’s moves
Ability to identify an opponent’s strategy or lack of it
Ability to control emotions
Ability to spot weaknesses in your own game

Q12: Below we list the same skills as above. Mark the 3 skills you think you are better at.
Ability to use time wisely (good clock management)
Ability to spot weaknesses in an opponent’s game
Ability to recall past games and typical moves
Ability to simulate mentally future moves including opponent’s moves
Ability to identify an opponent’s strategy or lack of it
Ability to control emotions
Ability to spot weaknesses in your own game
7.2 Forecasting Problem

Suppose that an individual’s beliefs of relative performance are a continuous random variable \( X \). Let beliefs have density \( g(x) \), continuous and with support in \([a, b]\), with \( 0 \leq a < b \leq 1 \). Suppose this individual has initial wealth \( \bar{w} \) and utility of wealth \( U(w) \). Let \( f \) represent the individual’s point forecast, with \( f \in [0, 1] \). This individual’s wealth—a continuous version of the discrete quadratic scoring rule—is given by

\[
 w = \bar{w} + \left[ w_0 - (x - f)^2 \right],
\]

with \( w_0 \geq 1 \). The optimal point forecast of this individual is given by

\[
 \max_{f \in [0, 1]} \int_a^b U(\bar{w} + w_0 - (x - f)^2)g(x)dx. \tag{4}
\]

We will call (4) the point forecast problem. The first-order condition to (4) is given by

\[
 \int_a^b U'(\bar{w} + w_0 - (x - f^*)^2)2(x - f^*)g(x)dx = 0.
\]

and the second-order condition by

\[
 \int_a^b [U''(\bar{w} + w_0 - (x - f^*)^2)2(x - f^*)^2 - U'(\bar{w} + w_0 - (x - f^*)^2)]g(x)dx < 0.
\]

If an individual is risk averse we have \( U' > 0 \) and \( U'' < 0 \) and the second-order condition is verified. If an individual is risk neutral we have \( U' > 0 \) and \( U'' = 0 \) and the second-order condition is also satisfied. If an individual is risk seeking we have \( U' > 0 \) and \( U'' > 0 \) and we can’t tell if the second-order condition is satisfied or not. However, if \( \bar{w} \) is sufficiently large the second-order condition is also satisfied for a risk seeking individual. We can now state the following results.

**Proposition 1** If an individual is risk neutral, then \( f^* = E(X) \)

**Proof.** If an individual is risk neutral, then the first-order condition to the point forecast problem is given by

\[
 \int_a^b (x - f^*)g(x)dx = 0,
\]

or

\[
 f^* = E(X),
\]
that is, the optimal point forecast of a risk neutral individual is his mean belief of relative performance.

**Proposition 2** If an individual’s beliefs of relative performance are unimodal and symmetric, then $f^* = E(X)$

**Proof.** Let the distribution of beliefs have support in $[a, b]$. Using integration by parts, the first-order condition to the point forecast problem is equivalent to

$$U(\bar{w} + w_0 - (b - f^*)^2)g(b) - U(\bar{w} + w_0 - (a - f^*)^2)g(a) = \int_a^b U(\bar{w} + w_0 - (x - f^*)^2)g'(x)dx.$$

or,

$$U(\bar{w} + w_0 - (a - f^*)^2)g(a) + \int_a^E(X) U(\bar{w} + w_0 - (x - f^*)^2)g'(x)dx =$$

$$U(\bar{w} + w_0 - (b - f^*)^2)g(b) + \int_{E(X)}^b U(\bar{w} + w_0 - (x - f^*)^2)(-g'(x))dx.$$

If $a \leq f^* < E(X)$ and $g$ is symmetric and unimodal, then the first term in the LHS is greater than the first term in the RHS and the value of the integral in the LHS is greater than the value of integral in the RHS. But then the value of the LHS is greater than the value of the RHS, a contradiction. If $E(X) < f^* \leq b$ and $g$ is symmetric and unimodal, the first term in the LHS is smaller than the first term on the RHS and the value of the integral in the LHS is smaller than the value of integral in the RHS. But then the value of the LHS is smaller than the value of the RHS, a contradiction. Thus, it must be that $f^* = E(X)$.  

**Q.E.D.**

**Proposition 3** If an individual’s beliefs of relative performance have the uniform distribution with support $[a, b]$, with $0 \leq a < b \leq 1$, then $f^* = E(X)$.

**Proof.** Using integration by parts, the first-order condition to the point forecast problem is equivalent to

$$U(\bar{w} + w_0 - (b - f^*)^2)g(b) - U(\bar{w} + w_0 - (a - f^*)^2)g(a) =$$

$$\int_a^b U(\bar{w} + w_0 - (x - f^*)^2)g'(x)dx.$$

If beliefs have the uniform distribution, then $g'(x) = 0$ for all $x$ and $g(a) = g(b)$, so the above condition reduces to

$$U(\bar{w} + w_0 - (b - f^*)^2) = U(\bar{w} + w_0 - (a - f^*)^2),$$

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or
\[ f^* = \frac{a + b}{2} = E(X), \]
that is, the optimal point forecast of an individual with uniform beliefs of relative performance is his mean belief of relative performance. \( Q.E.D. \)

### 7.3 Betting Problem

Suppose that an individual has beliefs of relative performance given by the density \( g(x) \), with support in \([a, b]\), with \(0 \leq a < b \leq 1\). Suppose this individual has initial wealth \( \bar{w} \) and utility of wealth given by \( U(w) \). Let \( c \) represent the choice of bet, with \( c \in [0, 1] \). This individual’s wealth—a continuous version of our discrete bets choice—is given by

\[
w = \begin{cases} 
\bar{w} + \frac{w_0}{1-c}, & x \geq c \\
\bar{w}, & x < c 
\end{cases},
\]

with \( w_0 \geq 1 \). The optimal bet of this individual is the solution to

\[
\max_{c \in [0, 1]} \Pr[X < c]U(\bar{w}) + \Pr[X \geq c]U \left( \bar{w} + \frac{w_0}{1-c} \right)
\]
or

\[
\max_{c \in [0, 1]} G(c)U(\bar{w}) + [1 - G(c)]U \left( \bar{w} + \frac{w_0}{1-c} \right).
\]

We will call (5) the betting problem. We can state the following result.

**Proposition 4** If an individual is risk neutral and his beliefs of relative performance are

(i) uniform with support \([a, 1]\), with \(0 \leq a \), then his optimal bet is any \( c^* \in [a, 1] \);

(ii) uniform with support \([a, b]\) with \(0 \leq a < b < 1\) then \( c^* = a < E(X) = f^* \);

(iii) unimodal and symmetric, then \( a < c^* \leq \text{Mode}(X) = E(X) = f^* \);

(iv) unimodal and positively skewed, then \( a \leq c^* \leq \text{Mode}(X) < E(X) = f^* \).

**Proof:** Let start by proving (i). If an individual is risk neutral and has uniform beliefs with support in \([a, 1]\) then the objective function of the betting problem is \( \bar{w} + w_0/(1-a) \). Since this individual’s utility does not depend on his choice of bet he must be indifferent between any bet in \([a, 1]\).

Let us show (ii). If an individual is risk neutral and has uniform beliefs with support in \([a, b]\) with \(0 \leq a < b < 1\), then the objective function problem of the betting problem is \( \bar{w} + \frac{b-a}{b-a} \frac{w_0}{1-c} \). It is clear that for this case the optimal bet is \( c^* = a \).

Let us show (iii). If an individual is risk neutral and has unimodal and symmetric beliefs, then the first-order condition to the betting problem becomes

\[-g(c^*) \frac{w_0}{1-c^*} + [1 - G(c^*)] \frac{w_0}{(1-c^*)^2} = 0\]
or

\[ 1 - G(c^*) = g(c^*)(1 - c^*). \]

This is equivalent to

\[ \int_{c^*}^{1} g(x) dx = \int_{c^*}^{1} g(c^*) dx. \] (6)

If we can show there exists an \( x_0 \) strictly greater than \( c^* \) such that \( g(c^*) < g(x_0) \) then it must be that \( c^* < \text{Mode}(X) \) since \( \text{Mode}(X) = \max g(x) \). Suppose, by contradiction that: (1) for all \( x > c^* \) we have \( g(x) \leq g(c^*) \) and (2) that there exists an \( x_0 > c^* \) such that \( g(x_0) \leq g(c^*) \). By the well know result that one can integrate inequalities, assumptions (1) and (2) imply that

\[ \int_{c^*}^{1} g(x) dx < \int_{c^*}^{1} g(c^*) dx, \]

which contradicts (6). Thus, we must either have that (a) \( g(x) = g(c^*) \) for \( x \geq c^* \), or (b) there exists an \( x_0 > c^* \) such that \( g(c^*) < g(x_0) \). Case (a) is a degenerate case. If case (b) holds then we know that \( c^* < \text{Mode}(X) \). So, for a unimodal and symmetric density of beliefs we have that \( c^* < \text{Mode}(X) = E(X) \).

To finish the proof we still need to show that the second-order condition to the betting problem is satisfied. This condition is given by

\[ -g'(c^*) \frac{w_0}{1 - c^*} - 2g(c^*) \frac{w_0}{(1 - c^*)^2} + 2 \left[ 1 - G(c^*) \right] \frac{w_0}{(1 - c^*)^3}, \]

which simplifies to

\[ -g'(c^*) \frac{w_0}{1 - c^*}. \]

We see that the second-order condition is satisfied whenever \( g'(c^*) > 0 \). But, if \( c^* < \text{Mode}(X) = E(X) \) and the distribution is unimodal and symmetric, then it must be that \( g'(c^*) > 0 \).

Finally, let us show (iv). When \( g'(a) > 0 \) the proof is similar to that of (iii) with the exception that for a unimodal and positively skewed density of beliefs we have that \( \text{Mode}(X) < E(X) \). Note that when \( g'(a) > 0 \) the second-order condition is satisfied and \( a < c^* < \text{Mode}(X) < E(X) \). When \( g'(a) < 0 \) we have a corner solution: \( c^* = \text{Mode}(X) = a \).

Q.E.D.

7.4 Statistical Appendix
Figure 1: Forecasts and Performance in Winter Poker Classic.

Figure 2: Overestimation Across Deciles in Winter Poker Classic.
Figure 3: Forecasts and Performance in Spring Poker Classic

Figure 4: Overestimation Across Deciles in Spring Poker Classic
Figure 5: Forecasts and Performance in Sintra Chess Tournament

Figure 6: Overestimation Across Deciles in Sintra Chess Tournament.
Table I
UCSD’s 2004 Poker Classic Prizes

<table>
<thead>
<tr>
<th>Rank</th>
<th>Prize</th>
<th>Rank</th>
<th>Prize</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st place</td>
<td>$447 (27%)</td>
<td>1st place</td>
<td>$792 (27%)</td>
</tr>
<tr>
<td>2nd place</td>
<td>$209 (12%)</td>
<td>2nd place</td>
<td>$370 (12%)</td>
</tr>
<tr>
<td>3rd place</td>
<td>$164 (10%)</td>
<td>3rd place</td>
<td>$290 (10%)</td>
</tr>
<tr>
<td>4th place</td>
<td>$149 (9%)</td>
<td>4th place</td>
<td>$264 (9%)</td>
</tr>
<tr>
<td>5th place</td>
<td>$134 (8%)</td>
<td>5th place</td>
<td>$238 (8%)</td>
</tr>
<tr>
<td>6th place</td>
<td>$119 (7%)</td>
<td>6th place</td>
<td>$211 (7%)</td>
</tr>
<tr>
<td>7th place</td>
<td>$104 (6%)</td>
<td>7th place</td>
<td>$185 (6%)</td>
</tr>
<tr>
<td>8th place</td>
<td>$89 (5%)</td>
<td>8th place</td>
<td>$158 (5%)</td>
</tr>
<tr>
<td>9th place</td>
<td>$75 (4%)</td>
<td>9th place</td>
<td>$132 (4%)</td>
</tr>
<tr>
<td>10th-18th places</td>
<td>$20 (12%)</td>
<td>10th-18th places</td>
<td>$40 (12%)</td>
</tr>
<tr>
<td>Sum</td>
<td>$1670 (100%)</td>
<td>Sum</td>
<td>$3000 (100%)</td>
</tr>
</tbody>
</table>

Table II
Distribution of Players’ Forecasts in UCSD’s Poker Classics

<table>
<thead>
<tr>
<th>Forecast</th>
<th>Winter Poker Classic</th>
<th>Spring Poker Classic</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0,9]</td>
<td>1 0.7</td>
<td>1 0.8</td>
</tr>
<tr>
<td>[10,19]</td>
<td>6 4.4</td>
<td>5 3.9</td>
</tr>
<tr>
<td>[20,29]</td>
<td>11 8.2</td>
<td>19 14.6</td>
</tr>
<tr>
<td>[30,39]</td>
<td>8 5.9</td>
<td>5 3.9</td>
</tr>
<tr>
<td>[40,49]</td>
<td>9 6.7</td>
<td>13 10.1</td>
</tr>
<tr>
<td>[50,59]</td>
<td>19 14.1</td>
<td>17 13.2</td>
</tr>
<tr>
<td>[60,69]</td>
<td>20 14.8</td>
<td>17 13.2</td>
</tr>
<tr>
<td>[70,79]</td>
<td>14 10.4</td>
<td>16 12.4</td>
</tr>
<tr>
<td>[80,89]</td>
<td>22 16.3</td>
<td>16 12.4</td>
</tr>
<tr>
<td>[90,99]</td>
<td>25 18.5</td>
<td>20 15.5</td>
</tr>
<tr>
<td>Total</td>
<td>135 100.0</td>
<td>129 100.0</td>
</tr>
</tbody>
</table>
### Table III
Ordinary Least Squares Regression
Results for Poker Tournaments

<table>
<thead>
<tr>
<th>Variable</th>
<th>Winter Poker Classic</th>
<th>Spring Poker Classic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>47.770 (7.10)*</td>
<td>45.321 (6.35)*</td>
</tr>
<tr>
<td>Forecast</td>
<td>0.084 (0.85)</td>
<td>0.096 (0.85)</td>
</tr>
</tbody>
</table>

\[ n = 122 \quad n = 116 \]
\[ R^2 = 0.006 \quad R^2 = 0.006 \]
\[ \text{MAE} = 29.66 \quad \text{MAE} = 31.34 \]

Dependent variable: relative performance
\( t \) statistics in parentheses
*Significant at 0.05 level

### Table IV
Poker Players’ Earnings from Forecasts and Choice of Bet

<table>
<thead>
<tr>
<th>Winter Poker Classic</th>
<th>Spring Poker Classic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Point Forecast</td>
<td>Point Forecast</td>
</tr>
<tr>
<td>Reward</td>
<td>Paid</td>
</tr>
<tr>
<td>$0</td>
<td>107</td>
</tr>
<tr>
<td>$1</td>
<td>4</td>
</tr>
<tr>
<td>$6</td>
<td>6</td>
</tr>
<tr>
<td>$9</td>
<td>4</td>
</tr>
<tr>
<td>$10</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>$20</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Rewards | $86 | Rewards | $149 | Rewards | $281.79 |
Players  | 122 | Players  | 116  | Players  | 140    |
Average  | $70 | Average  | $1.28| Average  | $2.01  |
Table V
Comparison of Players' Forecasts and Choices of Bet in the Spring Poker Classic

<table>
<thead>
<tr>
<th>Forecasts</th>
<th>P</th>
<th>MF</th>
<th>MB</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0,9]</td>
<td>1</td>
<td>7.0</td>
<td>15.0</td>
</tr>
<tr>
<td>[10,19]</td>
<td>5</td>
<td>13.0</td>
<td>33.0</td>
</tr>
<tr>
<td>[20,29]</td>
<td>18</td>
<td>23.2</td>
<td>37.2</td>
</tr>
<tr>
<td>[30,39]</td>
<td>5</td>
<td>32.0</td>
<td>63.0</td>
</tr>
<tr>
<td>[40,49]</td>
<td>13</td>
<td>43.5</td>
<td>56.5</td>
</tr>
<tr>
<td>[50,59]</td>
<td>17</td>
<td>50.8</td>
<td>71.5</td>
</tr>
<tr>
<td>[60,69]</td>
<td>16</td>
<td>63.2</td>
<td>66.3</td>
</tr>
<tr>
<td>[70,79]</td>
<td>15</td>
<td>73.5</td>
<td>73.0</td>
</tr>
<tr>
<td>[80,89]</td>
<td>15</td>
<td>82.6</td>
<td>83.0</td>
</tr>
<tr>
<td>[90,99]</td>
<td>20</td>
<td>92.2</td>
<td>93.5</td>
</tr>
<tr>
<td>Total</td>
<td>125</td>
<td>58.2</td>
<td>66.7</td>
</tr>
</tbody>
</table>

Table VI
Forecasts of Relative Performance and Experience with Poker Tournaments

<table>
<thead>
<tr>
<th>Tourn.</th>
<th>P</th>
<th>MF</th>
<th>MP</th>
<th>ME</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>82</td>
<td>52</td>
<td>47</td>
<td>5</td>
<td>32</td>
</tr>
<tr>
<td>1-4</td>
<td>65</td>
<td>57</td>
<td>56</td>
<td>1</td>
<td>29</td>
</tr>
<tr>
<td>5-15</td>
<td>28</td>
<td>72</td>
<td>57</td>
<td>15</td>
<td>30</td>
</tr>
<tr>
<td>≥16</td>
<td>25</td>
<td>77</td>
<td>60</td>
<td>16</td>
<td>28</td>
</tr>
</tbody>
</table>

Table VII
Mean Forecast Error According to Experience and Performance Quintil

<table>
<thead>
<tr>
<th>Nº Tourn.</th>
<th>1st ME</th>
<th>2nd ME</th>
<th>3rd ME</th>
<th>4th ME</th>
<th>5th ME</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>41</td>
<td>21</td>
<td>22</td>
<td>17</td>
<td>9</td>
</tr>
<tr>
<td>1-4</td>
<td>41</td>
<td>6</td>
<td>25</td>
<td>13</td>
<td>17</td>
</tr>
<tr>
<td>5-15</td>
<td>75</td>
<td>3</td>
<td>38</td>
<td>5</td>
<td>12</td>
</tr>
<tr>
<td>≥16</td>
<td>65</td>
<td>5</td>
<td>45</td>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Nº Tourn.</th>
<th>1st MAE</th>
<th>2nd MAE</th>
<th>3rd MAE</th>
<th>4th MAE</th>
<th>5th MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>41</td>
<td>21</td>
<td>25</td>
<td>17</td>
<td>28</td>
</tr>
<tr>
<td>1-4</td>
<td>41</td>
<td>6</td>
<td>26</td>
<td>13</td>
<td>32</td>
</tr>
<tr>
<td>5-15</td>
<td>75</td>
<td>3</td>
<td>43</td>
<td>5</td>
<td>30</td>
</tr>
<tr>
<td>≥16</td>
<td>66</td>
<td>5</td>
<td>45</td>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>

Table VIII
Mean Absolute Error According to Experience and Performance Quintil

<table>
<thead>
<tr>
<th>Nº Tourn.</th>
<th>1st MAE</th>
<th>2nd MAE</th>
<th>3rd MAE</th>
<th>4th MAE</th>
<th>5th MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>41</td>
<td>21</td>
<td>25</td>
<td>17</td>
<td>28</td>
</tr>
<tr>
<td>1-4</td>
<td>41</td>
<td>6</td>
<td>26</td>
<td>13</td>
<td>32</td>
</tr>
<tr>
<td>5-15</td>
<td>75</td>
<td>3</td>
<td>43</td>
<td>5</td>
<td>30</td>
</tr>
<tr>
<td>≥16</td>
<td>66</td>
<td>5</td>
<td>45</td>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>
### Table VIII
Sintra’s Chess Open Prizes

<table>
<thead>
<tr>
<th>Rank</th>
<th>Monetary Prize</th>
<th>Symbolic Prize</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st place</td>
<td>$300 (27%)</td>
<td>Trophy</td>
</tr>
<tr>
<td>2nd place</td>
<td>$180 (16%)</td>
<td>Trophy</td>
</tr>
<tr>
<td>3rd place</td>
<td>$120 (11%)</td>
<td>Trophy</td>
</tr>
<tr>
<td>4th place</td>
<td>$75 (7%)</td>
<td>Medal</td>
</tr>
<tr>
<td>5th place</td>
<td>$50 (5%)</td>
<td>Medal</td>
</tr>
<tr>
<td>6th-10th places</td>
<td>$30 (14%)</td>
<td>Medal</td>
</tr>
<tr>
<td>11th-15th places</td>
<td>$25 (11%)</td>
<td>Medal</td>
</tr>
<tr>
<td>16th-20th places</td>
<td>$20 (9%)</td>
<td>Medal</td>
</tr>
<tr>
<td>Sum</td>
<td>$1100 (100%)</td>
<td>-</td>
</tr>
</tbody>
</table>

### Table X
Distribution of Players’ Forecasts in Sintra’s Chess Open

<table>
<thead>
<tr>
<th>Forecast</th>
<th>Players</th>
<th>Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0,9)</td>
<td>6</td>
<td>10.0</td>
</tr>
<tr>
<td>[10,19]</td>
<td>4</td>
<td>6.7</td>
</tr>
<tr>
<td>[20,29]</td>
<td>5</td>
<td>8.3</td>
</tr>
<tr>
<td>[30,39]</td>
<td>3</td>
<td>5.0</td>
</tr>
<tr>
<td>[40,49]</td>
<td>5</td>
<td>8.3</td>
</tr>
<tr>
<td>[50,59]</td>
<td>5</td>
<td>8.3</td>
</tr>
<tr>
<td>[60,69]</td>
<td>10</td>
<td>16.7</td>
</tr>
<tr>
<td>[70,79]</td>
<td>3</td>
<td>5.0</td>
</tr>
<tr>
<td>[80,89]</td>
<td>11</td>
<td>18.3</td>
</tr>
<tr>
<td>[90,99]</td>
<td>8</td>
<td>13.3</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>100.0</td>
</tr>
</tbody>
</table>

### Table XI
Ordinary Least Squares Regression

<table>
<thead>
<tr>
<th>Sintra Chess Open</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>Forecast</td>
</tr>
</tbody>
</table>

\[ n = 60 \]
\[ R^2 = 0.459 \]
MAE = 17.03

Dependent variable: relative performance
\( t \) statistics in parentheses
*Significant at 0.05 level
Table XII
Chess Players’ Earnings from Forecasts, Choice of Bet, and Choice of Lottery

<table>
<thead>
<tr>
<th>Point Forecast</th>
<th>Choice of bet</th>
<th>Choice of Lottery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reward</td>
<td>Paid</td>
<td>Reward</td>
</tr>
<tr>
<td>$0</td>
<td>48</td>
<td>$1</td>
</tr>
<tr>
<td>$1</td>
<td>0</td>
<td>$1.11</td>
</tr>
<tr>
<td>$6</td>
<td>0</td>
<td>$1.25</td>
</tr>
<tr>
<td>$9</td>
<td>10</td>
<td>$1.43</td>
</tr>
<tr>
<td>$10</td>
<td>2</td>
<td>$1.67</td>
</tr>
<tr>
<td>$200</td>
<td>7/10</td>
<td>17.2</td>
</tr>
<tr>
<td>$2.50</td>
<td>0/4</td>
<td>6.9</td>
</tr>
<tr>
<td>$3.33</td>
<td>2/3</td>
<td>5.2</td>
</tr>
<tr>
<td>$5.00</td>
<td>5/13</td>
<td>22.4</td>
</tr>
<tr>
<td>$10.00</td>
<td>3/7</td>
<td>12.1</td>
</tr>
</tbody>
</table>

Rewards: $110
Players: 60
Average: $1.83

Rewards: $95.5
Players: 58
Average: $1.65

Rewards: $43.45
Players: 57
Average: $0.76

Table XIII
Comparison of Players’ Forecasts and Choices of Bet in Sintra’s Chess Open

<table>
<thead>
<tr>
<th>Forecasts</th>
<th>P</th>
<th>MP</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0,9]</td>
<td>6</td>
<td>23.1</td>
</tr>
<tr>
<td>10,19</td>
<td>4</td>
<td>16.4</td>
</tr>
<tr>
<td>20,29</td>
<td>5</td>
<td>29.9</td>
</tr>
<tr>
<td>30,39</td>
<td>3</td>
<td>36.6</td>
</tr>
<tr>
<td>40,49</td>
<td>4</td>
<td>40.3</td>
</tr>
<tr>
<td>50,59</td>
<td>5</td>
<td>34.4</td>
</tr>
<tr>
<td>60,69</td>
<td>10</td>
<td>45.4</td>
</tr>
<tr>
<td>70,79</td>
<td>3</td>
<td>64.5</td>
</tr>
<tr>
<td>80,89</td>
<td>10</td>
<td>71.8</td>
</tr>
<tr>
<td>90,99</td>
<td>7</td>
<td>78.8</td>
</tr>
<tr>
<td>Total</td>
<td>57</td>
<td>47.6</td>
</tr>
</tbody>
</table>

Table XIV
Comparison of Players’ Performance, Forecasts, and Risk Preferences in Sintra’s Chess Open

<table>
<thead>
<tr>
<th>Perf.</th>
<th>Risk Averse</th>
<th>Risk Neutral</th>
<th>Risk Seeking</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0,49]</td>
<td>P</td>
<td>MF</td>
<td>MP</td>
</tr>
<tr>
<td>6</td>
<td>21.9</td>
<td>20.3</td>
<td>1.6</td>
</tr>
<tr>
<td>50,99</td>
<td>6</td>
<td>81.2</td>
<td>75.7</td>
</tr>
<tr>
<td>Total</td>
<td>12</td>
<td>46.6</td>
<td>43.4</td>
</tr>
</tbody>
</table>
Table XV
Forecasts of Relative Performance and Experience with Chess Tournaments

<table>
<thead>
<tr>
<th>Chess Tourn.</th>
<th>P</th>
<th>MF</th>
<th>MP</th>
<th>ME</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>7</td>
<td>30</td>
<td>15</td>
<td>15</td>
<td>24</td>
</tr>
<tr>
<td>1-6</td>
<td>10</td>
<td>39</td>
<td>25</td>
<td>14</td>
<td>30</td>
</tr>
<tr>
<td>7-50</td>
<td>14</td>
<td>44</td>
<td>44</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>≥50</td>
<td>18</td>
<td>72</td>
<td>69</td>
<td>3</td>
<td>13</td>
</tr>
</tbody>
</table>

Table XVI
Mean Forecast Error According to Experience with Chess Tournaments and Performance Quintil

<table>
<thead>
<tr>
<th>Chess Tourn.</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
<th>5th</th>
</tr>
</thead>
<tbody>
<tr>
<td>ME</td>
<td>P</td>
<td>ME</td>
<td>P</td>
<td>ME</td>
<td>P</td>
</tr>
<tr>
<td>0</td>
<td>20</td>
<td>5</td>
<td>-19</td>
<td>1</td>
<td>22</td>
</tr>
<tr>
<td>1-6</td>
<td>12</td>
<td>4</td>
<td>35</td>
<td>4</td>
<td>-20</td>
</tr>
<tr>
<td>7-50</td>
<td>-12</td>
<td>1</td>
<td>-3</td>
<td>7</td>
<td>10</td>
</tr>
<tr>
<td>≥50</td>
<td>-49</td>
<td>1</td>
<td>32</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Table XVII
Mean Absolute Error According to Experience with Chess Tournaments and Performance Quintil

<table>
<thead>
<tr>
<th>Chess Tourn.</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
<th>5th</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>P</td>
<td>MAE</td>
<td>P</td>
<td>MAE</td>
<td>P</td>
</tr>
<tr>
<td>0</td>
<td>25</td>
<td>5</td>
<td>19</td>
<td>1</td>
<td>22</td>
</tr>
<tr>
<td>1-6</td>
<td>20</td>
<td>4</td>
<td>47</td>
<td>4</td>
<td>20</td>
</tr>
<tr>
<td>7-50</td>
<td>12</td>
<td>1</td>
<td>11</td>
<td>7</td>
<td>10</td>
</tr>
<tr>
<td>≥50</td>
<td>49</td>
<td>1</td>
<td>32</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Table XVIII
Forecasts of Relative Performance According to Elo Quintil

<table>
<thead>
<tr>
<th>Elo Quintiles</th>
<th>P</th>
<th>MF</th>
<th>MP</th>
<th>ME</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st</td>
<td>11</td>
<td>37.5</td>
<td>14.9</td>
<td>22.6</td>
<td>31.3</td>
</tr>
<tr>
<td>2nd</td>
<td>15</td>
<td>31.2</td>
<td>33.3</td>
<td>-2.1</td>
<td>17.6</td>
</tr>
<tr>
<td>3rd</td>
<td>12</td>
<td>52.9</td>
<td>44.8</td>
<td>8.1</td>
<td>19.0</td>
</tr>
<tr>
<td>4th</td>
<td>12</td>
<td>71.2</td>
<td>63.8</td>
<td>7.4</td>
<td>10.3</td>
</tr>
<tr>
<td>5th</td>
<td>10</td>
<td>89.3</td>
<td>87.5</td>
<td>1.8</td>
<td>6.3</td>
</tr>
</tbody>
</table>

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### Table XIX
Ordinary Least Squares Regression Results Including Age and Elo

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>35.04 (-2.87)*</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.37 (-2.89)*</td>
<td></td>
</tr>
<tr>
<td>Elo</td>
<td>0.058 (9.36)*</td>
<td></td>
</tr>
</tbody>
</table>

\[ n = 45 \]
\[ R^2 = 0.68 \]
\[ \text{Adjusted } R^2 = 0.67 \]

Dependent variable: relative performance  
\( t \) statistics in parentheses  
*Significant at 0.05 level

### Table XX
Ordinary Least Squares Regressions Results for Test of Efficiency of Forecasts

<table>
<thead>
<tr>
<th>Regression 1</th>
<th>Regression 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>Constant</td>
<td>Constant</td>
</tr>
<tr>
<td>11.67 (2.00)*</td>
<td>11.39 (2.30)*</td>
</tr>
<tr>
<td>Forecast</td>
<td>Forecast</td>
</tr>
<tr>
<td>0.69 (7.54)*</td>
<td>0.45 (4.17)*</td>
</tr>
<tr>
<td>Lower Elo</td>
<td>0.32 (2.68)*</td>
</tr>
</tbody>
</table>

\[ n = 44 \]
\[ R^2 = 0.57 \]
\[ \text{Adjusted } R^2 = 0.56 \]

\[ n = 44 \]
\[ R^2 = 0.70 \]
\[ \text{Adjusted } R^2 = 0.67 \]

Dependent variable: relative performance  
\( t \) statistics in parentheses  
*Significant at 0.05 level
Table XXI
Ordinary Least Squares Regression
Results Including Elo and Match

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sintra’s Chess Open</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-10.94 (-0.79)</td>
</tr>
<tr>
<td>Elo</td>
<td>0.04 (4.82)*</td>
</tr>
<tr>
<td>Match</td>
<td>2.34 (0.50)</td>
</tr>
</tbody>
</table>

n = 42
$R^2 = 0.40$
Adjusted $R^2 = 0.38$

Dependent variable: forecast of relative performance
t statistics in parentheses
*Significant at 0.05 level