Risk and Effort in Rank Order Tournaments:

The Case of the 2004 PGA Tour

By

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Abstract:

This paper seeks to examine whether golfers respond to the different incentives they face in professional golf tournaments. Specifically, it examines whether they vary their risk and their effort in a way that can be explained economically. The paper uses three models, looking at how golfers near the projected cut respond on the second round of competition and how they respond on the final day of competition, both in terms of their expected score and their variation. Most of the tests were not statistically significant, but the raw numbers seem to suggest that golfers do respond to the different incentives they face in a way that the economic model would predict.
Introduction

The sport of golf has a long and illustrious history. Dating back to Scotland in the fifteenth century, golf has evolved from a game favored by the British aristocracy to a global sport played by millions. In this past century, golf also evolved into a professional sport, with organized leagues holding organized tournaments. In the last decade, probably in great deal due to Tiger Woods, golf has blossomed in popular sporting attraction. Resultantly, with increased popularity came increased advertising, and the tournament money available has grown enormously.

In America, the most prestigious golfing league, capturing the best players and offering the biggest possible salaries, is undoubtedly the PGA Tour. The PGA Tour organizes many tournaments throughout the year. A standard tournament is a four day affair and is open to 144 or 156 entrants (Bronars and Oettinger 2001). Every golfer in the field competes against the other golfers and plays two eighteen hole rounds, one each day. After the first two days, the seventy golfers (plus ties) that have the fewest strokes combined from the first two rounds pass the cut (Bronars and Oettinger 2001). The other golfers are cut from the tournament and receive no earnings.

The golfers who pass the cut are certain of receiving some payment, yet the earnings depend completely on the size of the total purse and on the golfer’s rank compared to the field. The first through fifth golfers in a standard tournament, earn “18.0%, 10.8%, 6.8%, 4.8%, and 4.0% of the total purse, respectively, while the 10th, 25th, 50th, and 70th (last) place finishers receive 2.7%, 0.88%, 0.252%, and 0.2% of the total purse, respectively” (Bronars and Oettinger 2001). Thus, finishing in the top of the field carries much greater rewards than does passing the cut but finishing in the bottom of
the field. Further, the difference in pay from the first to the second place finishers is quite substantial when compared to the difference in pay between, for example, the thirtieth and thirty-first finishers.

Because golf enthusiasts would love to play in tournaments on the PGA Tour, the PGA naturally limits membership on the Tour and further restricts participation in individual tournaments. Any golfer who won a tournament in the previous year, any player who has won a “major” tournament (the Masters, the US Open, the British Open, and the PGA Championship) in the previous ten years, and other players who meet certain thresholds in other categories are allowed on the Tour and are granted an exemption for the year, meaning they can enter any tournament they wish and will retain their spot on the Tour for at least two years. Spaces then become limited for non-exempt golfers who are on the Tour. They enter tournaments by placing well in qualifying tournaments or by being granted an exemption from a tournament’s sponsors. Non-exempt golfers also face the possibility of losing their status of a Tour professional and face greater incentives to perform well to stay on the Tour. As a result, the PGA Tour is a very competitive organization, and this competitiveness bears out in tournament scoring.

The PGA Tour, like many sports organizations, meticulously collects data concerning its players, and to the economist’s delight, the PGA Tour publishes a great deal of the data that it collects. As such, the sport of golf has become a valuable place in which to study many economic questions. For example, a line of literature on golf seeks to answer if the adage, “Drive for show, putt for dough,” has any truth. Specifically, it examines the relative worth of golfers’ statistics, such as driving distance, percentage of
greens in regulations, average putts per hole, etc., to calculate the relative worth of different golf shots, to let golfers know where they stand amongst other professional golfers and to allow players to better tailor their practicing.

Another line of literature, the one that this paper concerns, is built on the theories of tournament structures. Specifically, the payoffs in each tournament, described above, are fixed well in advance of the actual tournament. Further, payoffs do not depend on one’s output, i.e. number of strokes, but rather on how one’s output compares to the rest of the field. This type of tournament, known as rank-order tournaments, affects how players behave in every situation the golfers face. For example, the tournament structure theory would argue that a player tied for the lead with one hole left on the final day of competition could be expected to perform differently than the player who is tied for last with one hole left on the final day of competition.

At the same time, the player who has a chance to win or lose hundreds of thousands of dollars on the final hole also faces many pressures. One might predict that this golfer will focus thoroughly on this hole, play smartly, perhaps even aggressively, to ensure a victory, and thereby his score, relative to what he might otherwise shoot in a different situation, is better. At the same time, there could be conflicting pressures. Specifically, this golfer might over-think his shots or swing with too tensely. The pressure might get to a golfer, causing him to play poorly on the final hole because the knowledge that hundreds of thousands of dollars ride on his next drive might be too much to bear.

This paper seeks to examine how golfers actually respond to different situations in a standard tournament setting. Specifically, I question whether golfers respond in the
ways that tournament structure theory would predict, given different marginal returns to performance. In this paper, I first will describe the relevant literature that has examined this question, focusing on both the theory of how different tournament incentives affect behaviors and on how others have used statistics from the PGA Tour to test whether this theory describes actual golfer behavior on the Tour. I will then describe how I intend to improve on the past literature to be able to better answer the question. The next section will describe the data that I have collected as well as the regressions that I used to answer the question. Finally, I will detail my results.

Literature Review

Lazear and Rosen (1981) pioneered the study of tournament incentive effects. In their seminal essay, they examined rank-order tournaments, tournaments in which payoff did not depend directly on output but rather on how one’s output compared to the rank of others, and focused mostly on how to setup a tournament that would allocate resources so that all participants behave efficiently. While this essay is not concerned about discovering the optimum way to structure PGA Tour events, but rather it takes the structure as given, Lazear and Rosen’s findings nevertheless relate to the theory of how PGA professionals are expected to compete.

Lazear and Rosen (1981) showed that the participants select their inputs based on the spread of payoffs associated with ranks. For example, in a two player rank-order tournament, if both contestants are paid equally at the end of the tournament, neither has an incentive to exert much effort because his payoff is known in advance. If, however, the winner receives the whole purse and the loser receives nothing, then both will have an
incentive to compete against one another, assuming that both players feel that they have a reasonable chance to win. This incentive is particularly intense when the talents of both contestants are known to be equal and their luck is believed to be equal as well.

Lazear and Rosen (1981) focused their work especially on payoffs inside of a firm, yet the results generalize to the PGA as well. Within a golf tournament, inputs such as practice and even skill are fixed. However, a golfer has the ability to change his level of effort, which, at least in the scope of golf, seems to relate mostly to the golfer’s level of concentration. Moreover, a professional golfer can also change his strategy, which includes questions of whether he plays safely, attempting to minimize risk, or play aggressively, taking on risk in the hope that this strategy could promise him thousands of dollars of increased earnings. (For the purpose of this paper, I consider decisions such as this to fall under the category of risk.) In light of these inputs, a golfer should try harder when faced with the prospect of winning (or, conversely, losing) a large amount of money, and he might want to take on more risk when he has a chance of winning a large amount of money and feels that there is not a high probably of losing money.

Whereas Rosen and Lazear (1981) created clear formulas on how to examine participants expected input, the two-person case that they look at is much easier than a golf tournament, as golf starts out as roughly a 150 person competition, and ends possibly with many golfers vying for first place in a tournament. Further, in golf, positions are continually updated, and players often can look at the leader board and know where they stand in relation to other players. As a result, players face different marginal returns to performance as the tournament progresses, and it is reasonable to assume that players know how they stand in relation to other players at all times. Because of these properties,
there are no ex ante formulae to use to calculate the optimal level of effort before the tournament. Instead, the optimal level of effort will change throughout the tournament for each golfer depending on the golfer’s past play and on the field around him.

Ehrenberg and Bognanno (1990) applied Rosen and Lazear’s (1981) theory to see whether golfers’ behaviors in tournament settings lie in accord. Using data from the 1984 PGA Tour, Ehrenberg and Bognanno tested two hypotheses. First, they noted that distribution of purse according to ranks is virtually identical across tournaments; the only differences between tournaments that would vary incentives across tournaments are purse sizes. Ehrenberg and Bognanno (1990) predicted that, because golfers have an extra incentive to score well when the purse size is greater, golfers should play better as when the purse increases.

For their second hypothesis, they tested whether golfers respond differently on the fourth day of the tournament depending on where they find themselves with respect to the field. The intuition behind this is that golfers will respond by exerting more effort if they find themselves closer to the lead, especially when there are many golfers who can possibly win at the start of the fourth round. Such golfers have incentives to score better than their competitors who are not in place to win the tournament or do not have to contend with as many golfers for the win.

However, before performing their statistical analyses, they separated all players into two groups: exempt and non-exempt players. As I briefly stated in the introduction, on the PGA Tour, participation in tournaments is restricted by the following rules. The rules guiding these restrictions are rather technical (for the interested reader, they can be found at http://www.pgatour.com/players/pgatour-exempt), yet Ehrenberg and Bognanno
summarized these rules by writing that all players who have won a tournament within the last year or a major (the U.S. Open, the Masters, the British Open, or the PGA Tour Championship) in the last ten are all exempt and can enter any tournament they wish. All other players on the Tour are not guaranteed entry into every tournament and thus they must work to see that they remain relatively high on the money earned list (actually in the top 125) to ensure that they can still play in their desired tournaments. Because the non-exempt players care not only about winnings from an individual tournament, but rather about earnings over the whole year, Ehrenberg and Bognanno expected that non-exempt golfers will not respond as much as do exempt golfers to differences in marginal returns to performance in a given tournament.

Describing their theory, Ehrenberg and Bognanno wrote, “Our empirical work is based on two-contestant tournament models with heterogeneous competitors. Assuming that an individual’s score is linearly related to his effort/concentration level, a tournament-specific effect (due to course difficulty and weather conditions), and random factors and that effort/concentration has positive and increasing marginal cost, one can show that a player’s final score in a tournament setting will depend on the prize differential for winning, measures of his and his opponent’s ability and tournament specific factors” (Ehrenberg and Bognanno 1990). Using this theory, they tested their first hypothesis, regressing an individual’s score in the following equation:

\[ s_{ji} = a_0 + a_1 \text{TPRIZE}_i + a_2 \mathbf{x}_i + a_3 \mathbf{y}_j + a_4 \mathbf{z}_i + \nu_{ij} \]

where \( s_{ji} \) represents individual \( j \)’s score in tournament \( i \), \( \text{TPRIZE}_i \) represents the total prize available at tournament \( i \), \( \mathbf{x}_i \) is a vector controlling for course difficulty and weather conditions, \( \mathbf{y}_j \) is a vector serving as a proxy for the player \( j \)’s ability, \( \mathbf{z}_i \) is a vector...
controlling for the quality of the other players in the field who made the cut, and $v_{ij}$ represents an error term (Ehrenberg and Bognanno 1990). They found that the coefficient $a_1$ was negative, as predicted—greater purses lead to lower scores—and that the coefficient is slightly greater in magnitude for exempt players. Further, they found that an increase of $100,000$ of prize money results in an expected 1.1 shot decrease in players’ scores.

Ehrenberg and Bognanno then tested whether total prize money affects players during the first two days of competition, rather than the full four days of competition. To do this, they used the same equation, but $z_i$ now measured the quality of the whole field and the weather variables only included the first two days of play. In this regression, they found that total prize money has a much smaller effect, one that is not statistically significant. They attributed this finding to their belief that play during the first two days occurs when players are somewhat refreshed and can easily concentrate. However, on the final two days, as fatigue sets in, it requires more energy to remain concentrated, creating a divergence across tournaments with different purses.

To test their second prediction that golfers’ scores in the final round will improve if they are closer to the lead and if more competitors are bunched around the lead, they again used regression analysis. They regressed the final round score on the following variables: the decrease in money a player would experience if he dropped one rank in the field, the increase in money a player would experience if he improved one rank in the field, and the average of the absolute changes in money if a player improves or drops one place. These three variables measure the money associated with the competitor’s current rank, yet they tell nothing about the distribution of the rest of the field. To measure this,
Ehrenberg and Bognanno also use the following three variables along with those already mentioned: first, the increase in money if the golfer improved his score relative to those around him by one stroke; second, the increase in money the golfer would receive by improving his score by two strokes relative to those around him; finally, the increase in money a golfer would receive by improving his score by three strokes relative to those around him. Finally, they included in this regression measures of how the player scored in the first three days of competition, how the remaining field scored in the first three days of competition and they included measures of the weather for the first three days and for the final day of the competition.

For non-exempt players, they found no evidence that marginal returns to performance influenced the players’ final round scores. However, for exempt players, they found that a marginal return of one standard deviation above the mean for the rest of the field resulted in a 1.0-1.7 shot decrease in the final round, demonstrating that, as predicted, players with greater marginal returns to performance will perform better in the final round of competition.

I find a few aspects of Ehrenberg and Bognanno’s paper less than convincing. First, golfers are continually updating their decisions as the fourth round progresses. The fourth round is also long – a lot can happen in the final eighteen holes. Ehrenberg and Bognanno cannot capture the actual decisions of the players because they assume that golfers are only motivated by their place at the beginning of the final round.

Second, Ehrenberg and Bognanno do not take into account notions of risk. In many competitions, especially the majors, the winner receives a disproportionate return, not only in the tournament’s purse but also in new sponsorships and an increased public
persona, which promises further monetary rewards. Thus, golfers in contention for the lead in the final day of competition usually do not play to secure their spot in, say, seventh place, but rather increase the risk in their shot selection to create a chance of winning. Such an increase in risk could offer better scores, but on average might create worse scores. This behavior, which very likely exists, cannot be captured in Ehrenberg and Bognanno’s model because risk and shot selection does not exist. As such, while their model certainly has its merits, I do feel that it can be improved.

Finally, and perhaps most importantly, Ehrenberg and Bognanno do not incorporate into their regression any measure of what will happen if they fall a few strokes relative to the field. While a player might have the chance to win an extra hundred thousand dollars, he likely also faces the possibility that many people right below him could overtake his rank, causing him to suffer a loss of possibly more than he stands to gain. Such a situation should influence the golfer’s decisions by, for example, making him play not to capture the players far ahead of him but rather trying to fend off those behind him.

Orzag (1994) took issue with Ehrenberg and Bonanno’s (1990) work. Gathering data from the 1992 PGA Tour, Orzag ran a similar model to test whether Ehrenberg and Bognanno’s findings occur in other years. Instead of reaching the same conclusion, Orzag found that there is no statistical evidence to show that greater total purses lower a golfer’s score on average.

Discovering why his findings differed from Ehrenberg and Bognanno’s, Orzag noted an odd relationship that existed in the 1984 data set that did not exist in the 1992 data set. Specifically, in the 1984 data set, weather had a strong relationship with total
prize. In a tournament, the total prize is set far in advance, so theoretically it should have no bearing on the weather. However, Orzag ran a regression using weather as the independent variable and total prize as the dependent variable. In 1984, the $t$-statistic on weather was 14.0, which is highly significant, but in 1992, the $t$-statistic was only -0.89, which is not statistically significant. Orzag did not posit a reason why the 1984 data would have this strange relationship, but he nevertheless suggested that with such a relationship in place, it is better to drop the weather term altogether from the regression, assuming that weather is orthogonal to the other explanatory variables.

Without the weather term, Orzag found that the total prize of the tournament in 1984 data set is significantly different from zero, with a $t$-statistic of -1.93, but he finds no such significance for total prize in the 1992 data set ($t$-statistic is -0.60). Further, he tests if there is a statistical difference between the coefficients of the total prize terms, and finds that there is not any statistical difference. From this, he suggested that the weather term probably biased the results in Ehrenberg and Bognanno’s (1990) paper to the extent that in Ehrenberg and Bognanno’s (1990) paper, total purse was highly significant, but its significant faded dramatically once weather is discounted. Further, Orzag (1994) argued that weather could have been correlated with the error term, impacting the veracity of the all of the coefficients that Ehrenberg and Bognanno found.

Finally, Orzag suggested two reasons why the relationship between total prize available and scoring either did not exist or no longer holds. First, the PGA Tour in 1984 was less popular than it was in 1992. The average tournament prize in 1984 was $440,000, and in 1992 it jumped to $1.1 million (Orzag 1994). Further, in this period, golf became a national televised sport. For these reasons, Orzag posits that while total
prize money increased, making golfers score better, pressure to succeed also increased. With extra pressure comes the possibility that golfers will succumb to the situation, resulting in worse scores as the prize increases. If Orzag was correct in this point, then in today’s competitions, greater purses should result in far worse scoring, as golf has enjoyed a popularity far surpassing its 1992 level and with this increased popularity, the monetary stakes involved have blossomed. For example, in 2004, the purse in The Players Championship at Sawgrass, not even a major tournament, totaled $8,000,000, and many other tournaments had purses above $5,000,000 (data found at http://www.pgatour.com/tournaments/schedules/r/2004). With such high stakes and increased viewership, if Orzag’s hypothesis holds, one should not be surprised to see higher prizes correlated with worse scoring.

Secondly, Orzag suggested that, in golf, increased concentration does not correlate with better performance, attacking the heart of Ehrenberg and Bognanno’s (1990) thesis. He provides this non-economic reasoning by referring to his individual experience, and provides a quote from Fred Couples, a PGA Tour professional, who said, “You try real hard and you can’t make anything, and you don’t try at all, and everything goes in the hole – go figure!” (Orzag 1994).

While I personally share Orzag’s belief as it relates to golf, I understand that my behavior and professional’s behavior vastly differ. Instead, I would defer to the actual regression analysis in determining whether or not professional golfers’ behavior is accurately predicted by tournament structure theory. Further, his paper suffered the same drawbacks as does Ehrenberg and Bognanno’s. Risk was not included nor was any measure of expected loss, which could correlate with risk-aversion.
Melton and Zorn (2000) finally addressed the notion of risk. They argued that since payoffs in golf tournaments are asymmetric, promising more of a reward for improving one place than a loss for decreasing one place, risk-taking should occur in tournament settings. Further, they wrote that a player looks at his position in relation to the field and at the apparent strategies of other players before deciding on how much risk he should take. Because of these intuitions, they believed that a player will decide the level of risk he takes, and that greater risk results in greater variance in scores.

Moreover, they reasoned that players will be affected differently depending on their rank. Specifically, players near the bottom of the field, who have higher (worse) scores, should take on extra risk because better performance relative to others promises upside while downside loss that would occur for more risk-taking is minimal, due to the flattening of the payoffs for worse ranks. Melton and Zorn further felt that players at the top of the field face conflicting pressures. While these players would like to take on additional risk, they are also more risk-averse because they face the prospect that they would lose a sizeable portion of money by slipping to lower places. Thus, they hypothesized that the better positions result in lower levels of risk.

To test this hypothesis, they first grouped the field into four quartiles based on score after two rounds of play. They did not look at the players’ scores for the first two rounds because they argued a cut affects players’ decisions, prompting them to take on more (or less) risk to survive the cut. They also broke the field into four groups after three rounds of play to test how players respond in the final round.

Melton and Zorn (2000) then looked at the variances of each of the quartiles and find that variance is statistically significantly greater at the worse quartiles. They
conclude, then, that lower quartile players take on additional risk, which creates greater variances, when compared to players with better ranks.

While I believe that variance can tell a lot about a player’s level of risk-taking, I am not certain that variance alone can substitute as risk. Most obviously, it would seem that players at the bottom of the field have less of an incentive to concentrate because the range of their monetary reward is quite limited and well-defined. For these players, extra concentration does not promise a great enough benefit, and these players therefore are more likely to just get through the round by playing more nonchalantly. Not concentrating on a round could easily increase variance, which would create an alternative reason for their findings. Variance alone, therefore, should not be a proxy for risk-taking, especially when it is used to compare the top players to the bottom players in a field, as the two categories face different incentives in their play.

Moreover, variance alone cannot act as a substitute for ability. The variance of a group of golfers with similar ability will most likely be lower than the variance of a group of golfers with varied ability. Given that the top golfers on the tour continually perform well in most of the tournaments they enter, and given that earnings is highly stratified on the PGA Tour, it is very likely that the top ranks in tournaments, on average, consist of an abnormally high percentage of the best golfers on the PGA Tour. In contrast, the bottom ranks of a tournament could be composed of good golfers playing poorly, average golfers playing at their expected level of success, or perhaps even bad golfers playing well (remember, to be in this group, it only takes two strong rounds to pass the cut), it is reasonable to believe that the worse quartiles will have higher variance, even if risk has been factored out. A better test of variance would relate scores to players’ abilities.
Finally, Bronars and Oettinger (2001) completed the relevant literature on the behavioral incentives of golf tournaments. (Their paper is only a draft, and Oettinger specifically asked that I do not quote his findings, which have changed since 2001. However, he allowed me to discuss their insights and methodology, which still apply to the paper they hope to publish in the near future.)

Bronars and Oettinger (2001) tried to extend Ehrenberg and Bognanno’s (1990) paper by focusing on whether a higher purse at a tournament causes improved behavior and by focusing on whether a golfer responds to marginal differences in return to performance. However, they believed that using a single year cross-sectional data to measure these variables would be rife with biased estimates. They wrote, for example, that one cannot possibly capture all of the variables that describe the level of difficulty of the course, the excellence of the field and other exogenous variables that would affect a player’s score, while trying to determine if a higher prize elicits better behavior. Further, they wrote that using cross-sectional data will be biased because better golfers are more likely to end near the top at tournaments, making it seem as if those near the top score better, and they are more likely to enter tournaments in which the total purse is greater, making it seem as if the total purse improves golfers’ scores.

To solve this problem, Bronars and Oettinger (2001) argued that using panel data minimizes this risk. They therefore used data from 1996 to 2001, capturing the performance of 120 golfers throughout the years in 40 different tournaments. Overall, this captured 12,658 golfer-tournament-year observations (Bronars and Oettinger 2001). Further, they measured each golfer’s performance in a tournament relative to his performance for the year and thus control for year to year variations in a golfer’s play.
Further, they argued, as I have mentioned above, that golfers do not choose the level of effort before the tournament begins and maintain this level for four days. Instead, they receive continued feedback and update their level of effort and their strategy throughout the tournament. Therefore, instead of using final round score, they base each golfer’s output at the level of the hole. They further restricted their sample to the final few holes of the tournament, where incentives to take risks are the greatest, and they restricted their sample to the final few groups teeing off in the competition. The final groups are usually the ones containing the tournament’s leaders, and these golfers usually have the most complete information because all other competitors have finished their play by the time that the final groups arrive on the final holes.

For their first hypothesis, they tested whether golfers’ expected scores are decrease as the size in the tournament’s purse increases. Like in Ehrenberg and Bognanno’s (1990) model, Bronars and Oettinger (2001) measured score using purse size and other explanatory variables. Specifically, they used the regression:

\[
\text{SCORE}_{ijt} = X_{ijt}^\gamma + \beta \text{PURSE}_{jt} + \epsilon_{ijt}
\]  

(2)

Where \( \text{SCORE}_{ijt} \) represents the average score over all rounds for player \( i \) in tournament \( j \) in year \( t \), \( X_{ijt} \) represents other observable determinants of performance, \( \text{PURSE}_{jt} \) is the total prize available to all golfers of tournament \( j \) in year \( t \), and \( \epsilon_{ijt} \) represents the error term, encompassing all other non-observable factors.

To test whether final round score is affected by the marginal returns to performance, they also followed the ideas behind Ehrenberg and Bognanno’s (1990) paper. Specifically, they used the following regression:

\[
\text{FRSCORE}_{ijt} = X_{ijt} \pi + \delta \text{MR}_{ijt} + \epsilon_{ijt}
\]  

(3)
MR\textsubscript{ijt} represents “an estimate of the expected increase in golfer i’s winnings if the final round score distribution were shifted to the left by one stroke (through additional effort)” (Bronars and Oettinger 2001). This means, I believe, that they were calculating how much more money a golfer would win if he shot one score better (lower) on the final day, assuming that everyone else performed as they did. This measure, of course, will take into account the tournament’s total prize, which increases MR for all ranks, and the golfer’s final rank.

Finally, their third test dealt with the hypothesis that some players have an incentive to take risks while others do not. Specifically, they believe that a player closely trailing another with few people directly behind him has an incentive to take on extra risk. At the same time, a player either leading the tournament or not closely trailing another, while many possible contenders are directly behind him, has an incentive to reduce the risk in his level of play. They then measured risk by looking at atypical scores. Particularly, they measured the number of times a player scores either two shots below par (an “eagle”) or two shots or more above par (at least a “double bogey”).

Much of the work in Bronars and Oettinger (2001) was a great improvement over earlier papers. The amount of data that they have collected is stunning compared to earlier papers, and it allowed them to test their hypothesis by minimizing influences that would bias their explanatory variables. However, I believe that a weakness in their paper lies in how they measure risk. Specifically, they look only at eagles and double bogeys. An eagle occurs very infrequently in regular play. Actually, for holes in which par is three or four, eagles almost never occur. For a hole that is a par five, there is a greater chance for an eagle, although this chance still remains small. In light of this, it is
virtually impossible to capture when a player takes on greater risk and succeeds in par three and par four holes. Instead, a player taking greater risk and succeeding might end up turning into a score of one below par (a “birdie”) rather than a normal score of par.

Additionally, measuring only double bogeys or worse does not seem to capture risk. A professional who scores this likely has made a mistake on the hole. Perhaps he has missed the fairway on his drive and hit it out of bounds. Perhaps he lost his ball and had to take a penalty stroke. Perhaps he hit his ball into the water hazard in the hole. The point is that there are many foreseeable instances in which a golfer’s score is a double bogey, and risk might not capture the reason for this. Instead, given the players they are looking at (the best in the tournament over the final few holes), and knowing that as a tournament’s purse increases, the level of viewership increases, it is possible, as Orzag (1994) suggested, that these players who performed poorly over the final few holes actually succumbed to the immense amount of pressure that they face.

A better test that they could have performed is the Chi-Square Goodness of Fit, which instead of testing outliers in the distribution, tests the distribution itself. With this, they could have looked at greater variance, which is what they wanted to discover in the first place, as variance was used as a proxy for risk. Because of this, while they searched for the right question, their means might have actually given them false results, as they end up measuring bad scores, not risk.

In this paper, I hope to extend the analyses of the previously mentioned authors. I believe that a few questions remained unanswered. First, do players perform better or worse when the tournament’s purse is greater? Second, do golfers respond as theory would predict to different marginal returns to performance in the final round. Third, and
perhaps even most interestingly, do golfers near the lead in the final round take on additional risk to try to win the tournament?

**Economic Theory**

It might seem that a professional golfer faces the problem of minimizing his score, but theoretically this should not be the case. Imagine, for example, that a golfer finds himself in the lead after three days, with the next closes golfer trailing by five shots. The golfer in the lead does not have an incentive on the fourth day to try to minimize his score, as attempting to score well could result in him taking risks that jeopardize his lead. Instead, the golfer’s main incentive is to hold on to the lead that he has, ensuring that he is paid the maximum amount possible. This line of reasoning should actually apply to all golfers; given each golfer’s situation, he should adopt a strategy that maximizes his expected income.

In constructing the model that follows, I make a few crucial assumptions. I first assume that all golfers are risk-neutral. They attempt to maximize their expected earnings, which varies directly with their expected utility. I further assume that a golfer enters a tournament with a pre-existing ability that he cannot change in the tournament itself. His ability is a probabilistic distribution that takes the shape of a standard bell curve, centered on his scoring average. Moreover, I assume that all golfers are the same in terms of the variance of their scores. The only thing that changes from one golfer to the next is ability. The golfer has two theoretical choices to make in competition: he can vary his level of effort and he can vary his level of risk.
He will decrease his level of effort when he feels that the returns to effort are outweighed by the extra cost of concentrating for the whole round. A golfer who decreases his level of effort should play worse than the golfer who concentrates, though this is a speculative statement, not grounded in economic reasoning. Further, I assume that a golfer who decreases his level of effort will decrease his variance, as ability rather than tournament incentives or concentration, will be the major factor affecting his play. Because the golf tournament design pays players on top of the leaderboard handsomely and differentiates between the top few golfers, while the worse golfers who pass the cut earn relatively similar figure, one would expect that golfers vying for the lead and the top several positions exhibit full effort, as their returns to effort are staggering. On the other hand, players who know that they do not have a great chance to finish well in the tournament face a disincentive to expend effort. It will likely be the golfers with the worse ranks who do not exhibit full effort.

Likely more than deciding level of effort, a golfer’s major decision during a tournament should be selecting his optimum level of risk. I assume that a golfer’s decision on risk affects his output in two crucial ways. If a golfer elects to take on more risk, he will flatten and widen his bell curve, making both higher and lower scores more likely, as more risk should lead to more variance in scoring. Second, more risk should yield a higher expected score. This is true because on the golf course, there are more ways to fail on a hole than ways to succeed. A golfer who tries to take riskier shots opens himself up to the possibility that his drives do not land on the fairway, his ball flirts with water hazards, etc. He thus faces a choice with some ambivalence: given his ability, he can choose to increase his variance, which results in a higher expected payout given the
payoff structure of golf tournaments, but he simultaneously must choose to increase his expected score, which results in a lower payout.

In deciding how much risk to take in his shots, he is guided by a few considerations. First, a player can look at the field and his relationship to the field to know who he must compete against. I assume that the ability of each golfer is common knowledge and can be represented by the golfer’s Official World Ranking at the end of the 2004 season. Second, a golfer can look at the distribution of his competitors around him. He would notice, for example, that there are many players in a slightly better position, but hardly anyone slightly worse than he is. With his knowledge of others’ abilities and their relation to him, a golfer can form a rational belief about how the field around him will compete. This belief will be continually updated with new information, and a golfer should use this belief in determining his level of risk. (Under this theory, golfers do not disregard all information that they receive and simply “play their own game.” Using standard economic assumptions, a rational golfer should want to know what the field looks like, because only with this knowledge can he formulate his best response).

Second, a golfer knows his own ability. This can influence his decision-making in several ways. For example, suppose Vijay Singh, the highest rated player of the 2004 year, finds himself in a position one stroke worse than the projected cut after one day. He knows that the golfers around him have less ability than he, and thus he should understand that by playing his typical game, perhaps by even limiting the risk he takes, his ability alone will propel him to a higher rank, which should let him pass the cut. On the other hand, imagine a relatively bad golfer who has just played atypically well and
finds himself one stroke better than the projected cut after one round. He knows that by playing his standard game, he will likely fall to a worse rank compared to those around him, so he might choose to take on a large amount of risk, knowing that only by doing so will he have a chance to pass the cut. Ability, theoretically, should be a crucial part of a golfer’s decision-making.

Finally, a golfer should take into account the expected gain and the expected loss his faces by improving or worsening his score, respectively. To understand why this is the case, imagine a golfer finds himself in second place toward the end of the tournament, which promises $600,000 in earnings. If he wins, he will earn $1,000,000, while if he falls to third place, he will earn $300,000. Assume that he can select between either finishing in second place or facing a half-half chance that he finishes in first or third, the riskier alternative. If, as we assume, the golfer is risk-neutral, and if this adequately captures his thinking, then this golfer should select to play with risk and take the gamble. Alternatively, a golfer might face a situation in which he cannot reasonably improve his rank, but can easily fall if he plays with risk. He should adopt a less risky strategy. The choice governing how much risk to select depends heavily on the projected benefits and costs of using such risk, which depend on a player’s position in the tournament.

Data

For this paper, I have collected data on the 2004 PGA Tour for mostly all of the professionals who competed. All of the data that I have collected is published information, and most of it has been obtained on the PGA Tour’s web site, www.pgatour.com. For the data that I could not find on this web site, I used
www.google.com to search for my specific question, and I usually was directed to Sports Illustrated’s web site, www.cnnsi.com or USA TODAY’s web site, www.usatoday.com.

For each player, I have recorded each of the tournaments in which he played. Further, in each tournament, I have collected the scores for each player’s round in which we competed. I further collected data concerning the tournament’s purse size, actual payouts at the end of the fourth round, and the distribution of payouts announced before the tournament, which can differ from the actual payout in the case of ties in rank. From this data, I was able to calculate each player’s average score and total earnings over the season, and I was able to manipulate the data to rank players at the end of each round and calculate expected payout, if these players remained at their rank, and gain or loss if the players changed ranks.

I write that I have collected “mostly all” of the data on the 2004 professional golfers because, to my knowledge, there is no player that I know of who has been left out of the data collections. However, it is entirely possible that a few players have been overlooked. This is true because to find the data, I had to look at the professional golfers on the 2005 (current) tour and then search their tournament results during the 2004 season. I further updated my list by looking at each tournament’s leaderboard and filling in any missing players who were paid (i.e. passed the cut) but were not yet on my list. Thus, I could have omitted the results of players on the 2004 PGA Tour who did not make a cut and subsequently dropped to a lower tour, most likely the Nationwide Tour, or quit golf altogether. I do not believe, however, that this represents a large portion of the data, nor do I believe that this omission will significantly impact my findings, as only one of my models deals with behavior before the cut.
I further collected data on each player’s ability using the Official World Ranking, which is published weekly. The Official World Ranking system observes golfers’ performances over two years of competition, giving the most recent tournaments the most rank. The world ranking covers both performance in tournaments and the strength of the field in order to determine how successful golfers have been. The world ranking system both ranks players in relation to one another and gives players an absolute ranking, the latter of which I used. Most of the ranks fall below 1.0, but the best golfers all have ranks above 1.0. Tiger Woods and Vijay Singh, for example, had ranks of 11.90 and 12.97, respectively, showing that there is a great difference of ability on the PGA Tour. Further, I used the rank at the end of the 2004 season to best capture how the golfers played throughout both the 2004 and 2003 seasons.

Finally, let me mention that I dropped a few tournaments from the 2004 season from the data set. I deleted the Ryder Cup because these players did not compete for money and because the Ryder Cup was not a standard four round stroke play tournament. I deleted the Mercedes Championship, the TOUR Championship, the WGC American Express Championship and the WGC NEC Invitational because none of these tournaments cut the field in half at any time. Instead, all of the golfers who competed knew they would earn something, which changes their incentives throughout the tournaments. I deleted The INTERNATIONAL because none of the players had round by round scores, and I finally deleted the WGC Accenture Match Play Championship because the tournament was not a stroke play competition. All of the other tournaments from the 2004 season were used in the data set.
Model 1: Do golfers respond to the incentive to make the cut?

Perhaps the most obvious time to engage in a risky strategy is when one is promised upside if the risk succeeds and limited downside if the risk fails. If this is true, then one would expect players to engage in risky strategies to try to make the cut. As previously mentioned, all professional golfers who pass the cut in a standard tournament are assured of taking home a paycheck, while all golfers who do not make the cut receive no earnings. Further, golfers who finish the first round a few strokes worse than the player who is ranked 70th (where the cut usually takes place) understand that they do not have a great chance at passing the cut unless they play well enough on the second round. These golfers who are expected to be cut, then, have the greatest incentive to increase their variance to give themselves the greatest chance of scoring well. Golfers who are in a position to pass the cut, on the other hand, especially the worse golfers, have an incentive to lower their risk to maximize the chances that they pass the cut and get paid.

At the same time, players’ abilities form another crucial part of the decision on how much risk to take. A great golfer who is a few shots worse than the projected cut might want to just play regularly and hope that his skill alone will propel him above others so that he will make the cut. A poor golfer, on the other hand, might try to be exceptionally risk-taking if faced with the same position because he assumes that his standard round will cause him to continue to drop ranks, causing him to be cut.

As a result of these intuitions, in each tournament, I have ranked all of the golfers according to their first round score. I then have grouped the golfers into the following groups: those one stroke better than the projected cut, those at the projected cut, those one stroke worse than the projected cut, those two strokes worse than the projected cut, those
three strokes worse than the projected cut and those four strokes worse than the projected cut. All else equal one would expect that the worse group a golfer falls into, the higher the variance of his next round score will be.

Moreover, I then break these groups into two parts: those of the best golfers and those of the worse golfers. The logic behind this, again, is that the better golfers will respond differently than the worse golfers given the same position because the better golfers could rely on the knowledge that ability alone will help them better succeed. I divided the golfers based on whether or not their World Golf Ranking was above a 1.75, which corresponds to the best 75 golfers in the world, which is roughly the ability of Jesper Parnevik. While this is an arbitrary cutoff, it will demonstrate the difference that skill makes in determining a player’s level of risk.

Having grouped the golfers first by score and then by ability, I look at the distribution of their second round scores. Still, I correct for ability by, instead of measuring the distribution of their second round scores alone, I measure the second round score subtracted by their average score. Having done this, I look at the distribution of the second round scores less the golfers’ average scores across my groups, and I compare group to group by using a Chi-Square Goodness of Fit test. This test will let me know whether or not the distributions of the two groups are significantly different from each other. It states nothing about the average score of the two groups, but rather only looks at the variance of the groups, which is helpful because there is the possibility that a higher level of risk will lead to worse scores, making scoring average not completely useful. If I can conclude that the distributions are statistically different from one another, then I can
calculate the variances of the groups to see which one is greater. My results are described below in the results section.

**Model 2: Do golfers respond to risk incentives on the final day of competition?**

As mentioned, the payout structure of a tournament is very asymmetric. The golfer who finishes in first place receives 18% of the total purse, which often promises that first place takes home about $1,000,000 in earnings. In contrast, twenty-third place receives 1.04% of the purse, and everyone below twenty-third place receives less than one percent. In fact, the difference between fiftieth place and seventieth place is less than two thousand dollars, while the difference between first and second can be around three hundred thousand dollars. Because of the distribution, the worst ranks after two days know more or less what they will receive in earnings, while the best few ranks face tremendous variation. At the same time, there are a group of ranks which do not earn much in their current position, will not lose much if they fall a few ranks, but stand to gain much if they can score well and enter the top few spots.

I looked at the distribution of the purse according to ranks (which is attached, see Figure One at the top of the next page), and based on this distribution, I divided the field into three groups: those with ranks 1 to 14 after three days of play, those with ranks 15-30 after three days of play, and those with ranks 31 and above. The highest group falls in positions in which they stand to receive a great amount of money if they maintain their current rank, gain even more money if they improve a few ranks, and lose a lot of money if they fall in the ranking. Because of these characteristics, golfers in this group might take on risk if, based on the distribution of golfers, they could improve their rank but not
easily fall in rank. Yet, at the same time, the prospect that they might lose a lot of money could make them more risk averse.

The group of golfers ranked 16-30 fall in a position in which they stand to receive a large sum of money (averaging around $50,000) if they maintain their current rank, do not face a strong prospect of losing money, but do face the possibility that, if they play well, their expected earnings could more than double. These golfers, then, might try to take on great risk because doing so promises the chance at a large sum of money, while the downside to such risk remains relatively small.

The golfers in the group ranked 31 and above, for the most part, can form a strong prediction of how much money they will receive, mostly irrespective of how well they play in the final round. The 31\textsuperscript{st} golfer can expect somewhere near $30,000 and, forty
ranks below, the 70th ranked golfer can expect around $7,000, showing that there is not as much room for improvement within the group. Because these golfers face little downside to risk, they could be expected to play with a risky strategy to try to make their way up to higher groups, even though they cannot expect an increase in pay near what those in the group 16-30 can. At the same time, this group faces the strongest disincentive to expending effort because they are more or less certain of how they will finish. Because of these conflicting pressures, their variance should be high, but perhaps not as high as those in group 16-30 who do not face a disincentive to concentrate.

As in Model 1, I placed all of the golfers who passed the cut into these three groups, ranked on the cumulative scores of the first three rounds. Again, I measured the final round score less the golfer’s average score to isolate ability, and I divided the groups into two, based on whether or not the golfer’s world rank was above 1.75. Having done this, I test whether the distributions of the six groups is statistically different from one another by using the Chi-Square Goodness of Fit test. Again, my results can be found below.

Model 3: Do golfers’ scores improve based on the money they stand to gain by playing well?

Much of the literature on golf has attempted to see if golfers play better when the size of the purse increases, which is a difficult question on many fronts. For one, when the size of the purse increases, better golfers choose to enter the tournament, making the field more difficult. Additionally, there could be a correlation with purse size and the difficulty of the course that would seemingly make purse size lead to worse scoring.
(Just think how the scores in the British Open and the US Open are awfully high.)

Because of these characteristics, some of the golfers, especially the worse ones, might expect to make less money as the purse size increases, changing incentives altogether.

The easier question to answer which still retains the spirit of this quest is whether golfers respond to immediate incentives to make or lose a lot of money. For example, if a golfer stands to make a hundred thousand dollars extra if he plays well, can we expect this golfer to play well? If a golfer stands to lose a hundred thousand dollars if he messes up, should we expect him to play well or alternatively mess up? Questions such as these target whether golfers respond to different marginal returns to performance, and they can be more easily answered.

To answer these questions, an ideal place to look at whether golfers respond to different marginal returns to performance is the final day of competition, when golfers can form a strong belief about how much money they will earn. To study this, I sorted golfers in each tournament according to the combination of their scores for the first three rounds. Having sorted them, I then ranked the players and calculated the expected payoff each will receive if he maintains his rank in the final round. I also corrected for ties by using the same formula that the PGA Tour uses: all tied players split the profit that each tied rank would receive; this means, for example, that if five people were tied in tenth place, they would split the earnings associated for places ten through fourteen.

I also then tried to capture the distribution around the golfers, which will affect their beliefs about how the tournament will end. To do this, I looked at the marginal improvement in earnings that each golfer would receive if he lowered his score by one stroke and the marginal decrease in his earnings if he raised his score by one stroke.
relative to the field. These measurements would help capture the distribution at each
golfer’s rank, at the number of golfers one shot better and at the number of golfers at one
shot worse than each player. It is, I believe, important to capture how much money each
golfer stands to lose by raising his score by one stroke, even though Bronars and
Oettinger (2001) did not, because golfers will look both ahead and behind them in
calculating their optimum strategy. Further, take for example a golfer who is in second
place at the end of the third round. He will compete differently if third place is two shots
behind him than if ten people are tied for third place and are all one stroke behind him.

Having calculated this, I used a regression model that incorporated the golfer’s
first three rounds, which should be the best predictor of how the golfer is going to play on
the fourth day of the tournament, and the golfer’s world rank, which should be the best
indicator of how good the golfer is across tournaments. Finally, I use a fixed-effects
regression model so that I can isolate the natural variation in score that will occur based
on the difficulty of the course. Having done this, I regress the fourth round scores on the
golfers’ position, ability, expected marginal increase and expected marginal loss. I also
include another regression using another variable, called risk, which measures the
golfer’s expected marginal improvement added to his expected marginal decline (which
is a negative number), representing what the golfer stands to make if he varies his score.

The regressions are as follows, and the results are detailed below in the results section:

\[
\text{Fourth}_j = a_1 \text{Score}_i + a_2 \text{Ability}_i + a_3 \text{ExpIncr}_j + a_4 \text{ExpLoss}_i + a_5 \text{Course}_j 
\]

\[
\text{Fourth}_j = b_1 \text{Score}_i + b_2 \text{Ability}_i + b_3 \text{Risk}_i + b_4 \text{Course}_j 
\]

Where \( \text{Fourth}_j \) represents the fourth round score for golfer \( i \) in tournament \( j \), \( \text{Score}_i \)
represents the combined first three rounds for golfer \( i \) in tournament \( j \), \( \text{Ability}_i \) measures
the golfer’s Official World Rank, \( \text{ExpIncr}_j \) represents his expected increase in pay if he
improves one shot relative to the field, $\text{ExpLoss}_{ij}$ measures if he falls one shot relative to the field, $\text{Course}_j$ corrects for the difficulty of the course in each tournament, and $\text{Risk}_{ij}$ looks at the difference in earnings if he gains one shot and if he falls one shot relative to the field.

Results: Model 1

For Model 1, I created six groups based on each player’s relation to the projected cut after the first round. I specifically looked at all players in all tournaments who were one stroke better than the projected cut, at the projected cut, one stroke worse than the projected cut, and two, three, and four strokes worse than the projected cut. The following spreadsheet describes the initial statistics of each group, before I have performed any testing:

<table>
<thead>
<tr>
<th>Group's Relation to Projected Cut</th>
<th>Observations</th>
<th>Mean (2nd Rd. Less Player's Avg.)</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 stroke under</td>
<td>746</td>
<td>-0.26</td>
<td>3.22</td>
</tr>
<tr>
<td>At projected cut</td>
<td>919</td>
<td>-0.28</td>
<td>3.05</td>
</tr>
<tr>
<td>1 stroke worse</td>
<td>719</td>
<td>-0.12</td>
<td>3.15</td>
</tr>
<tr>
<td>2 strokes worse</td>
<td>558</td>
<td>0.22</td>
<td>3.17</td>
</tr>
<tr>
<td>3 strokes worse</td>
<td>375</td>
<td>-0.07</td>
<td>3.13</td>
</tr>
<tr>
<td>4 strokes worse</td>
<td>285</td>
<td>-0.48</td>
<td>3.2</td>
</tr>
</tbody>
</table>

Observing these statistics, it appears as if players who are one stroke better than the cut take on great risk, while those at the projected cut play most conservatively. Perhaps this is true because players at the cut try to lower their risk so they can pass the cut after the second day of competition, whereas players who are one stroke better than the projected cut have overlooked the cut itself, believing that they will get into the next
two days of competition. Further, the theory that risk should increase the farther away players are from the cut does not appear to be supported by the data. At the same time, perhaps golfers behave differently depending on ability. Below, I have listed the actual Chi-Square Goodness of Fit Test statistics, which gives a more precise read of the data. I have compared each group to the group one stroke worse, and I have tested a few groups that are two strokes apart to see if there is a difference between groups that is too subtle to come out between groups only one stroke different.

Table 2

<table>
<thead>
<tr>
<th>Group's Relation to Cut</th>
<th>Group Tested Against</th>
<th>Degrees of Freedom</th>
<th>Pearson Chi-square</th>
<th>Level of Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1</td>
<td>At projected cut</td>
<td>21</td>
<td>18.37</td>
<td>0.626</td>
</tr>
<tr>
<td>At projected cut</td>
<td>1</td>
<td>20</td>
<td>35.79</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>21</td>
<td>27.65</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>21</td>
<td>31.86</td>
<td>0.061</td>
</tr>
<tr>
<td></td>
<td>-1</td>
<td>21</td>
<td>28.02</td>
<td>0.109</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>3</td>
<td>29.63</td>
<td>0.1</td>
</tr>
</tbody>
</table>

From this table, we can see that the distributions between many of the groups are not statistically different. However, the distribution between the group at the projected cut and the group one stroke worse than the projected cut is statistically significant to the .02 level of significance. Observing their distributions from Table 1, it seems as if golfers in the group one stroke worse than the projected cut take more risk, and hence have a higher variance, than the group of golfers at the projected cut. This finding supports the theory that players will take on more risk when the face the situation in which expected earnings are low (in this case, not passing the cut promises no money) while the potential upside to
risk is high (at least $7,000, even if the golfer finishes in last place once he passes the cut).

We can understand risk better once we group the golfers by their ability. In the following table, I have listed the statistics for each of these groups once divided into two parts: the best golfers and the rest. Again, I divide them based on whether or not their Official World Rank is above 1.75, which I take to serve as a proxy for the arbitrary divide of the best golfers from the rest of the professionals on the PGA Tour.

Table 3

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>-1</td>
<td>High</td>
<td>175</td>
<td>-0.43</td>
<td>3.06</td>
</tr>
<tr>
<td>-1</td>
<td>Low</td>
<td>571</td>
<td>-0.21</td>
<td>3.28</td>
</tr>
<tr>
<td>At cut</td>
<td>High</td>
<td>215</td>
<td>-0.01</td>
<td>2.87</td>
</tr>
<tr>
<td>At cut</td>
<td>Low</td>
<td>704</td>
<td>-0.36</td>
<td>3.11</td>
</tr>
<tr>
<td>1</td>
<td>High</td>
<td>134</td>
<td>-0.01</td>
<td>3.29</td>
</tr>
<tr>
<td>1</td>
<td>Low</td>
<td>585</td>
<td>-0.15</td>
<td>3.12</td>
</tr>
<tr>
<td>2</td>
<td>High</td>
<td>133</td>
<td>-0.28</td>
<td>3.37</td>
</tr>
<tr>
<td>2</td>
<td>Low</td>
<td>425</td>
<td>-0.2</td>
<td>3.11</td>
</tr>
<tr>
<td>3</td>
<td>High</td>
<td>64</td>
<td>0.24</td>
<td>3.29</td>
</tr>
<tr>
<td>3</td>
<td>Low</td>
<td>311</td>
<td>-0.14</td>
<td>3.1</td>
</tr>
<tr>
<td>4</td>
<td>High</td>
<td>50</td>
<td>-0.7</td>
<td>3.74</td>
</tr>
<tr>
<td>4</td>
<td>Low</td>
<td>235</td>
<td>-0.43</td>
<td>3.08</td>
</tr>
</tbody>
</table>

Here, many of the intuitions from the theory seem to bear out in the data. For example, the better golfers who are one stroke better than the cut have a lower variance than the worse golfers in the same group. As noted before, this could be due to the fact that these worse golfers feel like that they have a chance at making the cut, but they understand that they must have a high variance to increase the chances that they play well. All of the other groups for the worse golfers actually have a lower variance, which might suggest that these golfers acutely feel the desire to pass the cut when they are one stroke better than the projected cut, and this desire wanes the worse they have scored in
the first round because they may not feel that they have as strong a chance of passing the cut. Effort, to them, becomes relatively more costly.

The strongest players’ data too seems to support the economic theory of risk that we have described. At the projected cut, these golfers have minimized their variance likely because they understand that they must first pass the cut before competing for a paycheck, and they understand that since they are the best golfers in the world, ability alone could propel them over the cut. As a result, they try to remove all of the possibilities that could give them a bad (and perhaps very good) and play a much less risky strategy to pass the cut. It is also evident that these great golfers really try to vary their scores when they had a poor first round because they still feel quite able to play well and pass the cut. The standard deviation for the group that is four strokes worse than projected cut is 3.74, roughly 30% greater than the standard deviation of the group of golfers at the projected cut.

Nevertheless, while these numbers seem to suggest that the data supports the economic model of risk in a tournament setting, we must first use statistical tests to verify this. Again, below is the Chi-Square Goodness of Fit Tests that examines whether the distributions of various groups are significantly different from one another.

Table 4

<table>
<thead>
<tr>
<th>First Group (To Cut, Ability)</th>
<th>Tested Against (To Cut, Ability)</th>
<th>Degrees of Freedom</th>
<th>Pearson Coefficient</th>
<th>Level of Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1, High</td>
<td>-1, Low</td>
<td>21</td>
<td>24.67</td>
<td>0.262</td>
</tr>
<tr>
<td>At cut, High</td>
<td>At cut, Low</td>
<td>18</td>
<td>16</td>
<td>0.592</td>
</tr>
<tr>
<td>1, High</td>
<td>1, Low</td>
<td>20</td>
<td>20.29</td>
<td>0.44</td>
</tr>
<tr>
<td>2, High</td>
<td>2, Low</td>
<td>20</td>
<td>24.4</td>
<td>0.225</td>
</tr>
<tr>
<td>3, High</td>
<td>3, Low</td>
<td>18</td>
<td>12.03</td>
<td>0.845</td>
</tr>
<tr>
<td>4, High</td>
<td>4, Low</td>
<td>17</td>
<td>18.46</td>
<td>0.36</td>
</tr>
<tr>
<td>-1, Low</td>
<td>At cut, Low</td>
<td>21</td>
<td>27.75</td>
<td>0.147</td>
</tr>
<tr>
<td>At cut, Low</td>
<td>1, Low</td>
<td>20</td>
<td>32.12</td>
<td>0.042</td>
</tr>
</tbody>
</table>
In this table, it is evident that most of the tests do not reveal a result of statistical difference. This could be due to two causes: first, the distributions among the tested groups are really the same, or second, there is not enough data for the Goodness of Fit Test to yield a strong result. While either may be the case, it seems somewhat unlikely that the distributions that were tested are actually the same, given that the variance numbers for both groups seem to follow the pattern that the theory advocates; good golfers use risk when they are far behind, and the worse golfers use risk when they have a chance to win, but expend less effort the less their chances of passing the cut.

Results: Model 2

In this model, we divided up the data into three relevant groups based on the scores of the first three rounds combined. The groups were those players ranked between 1 and 14, including ties, those ranked from 15-30, including ties, and those ranked 31 and above. We then divided these groups into the players ranked above 1.75 and those ranked below 1.75 to see if ability changes golfers’ strategies heading into the final round of the tournament. Again, in order to best isolate ability, we tested the each player’s final round score less his average score for the 2004 season and then compared these findings
across different groups. The summary statistics of each of the six groups are in the following table.

Table 5

<table>
<thead>
<tr>
<th>Group Ranks</th>
<th>Ability</th>
<th>Observations</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 to 14</td>
<td>High</td>
<td>323</td>
<td>0.29</td>
<td>3.56</td>
</tr>
<tr>
<td>1 to 14</td>
<td>Low</td>
<td>384</td>
<td>0.24</td>
<td>3.19</td>
</tr>
<tr>
<td>15 to 30</td>
<td>High</td>
<td>241</td>
<td>0.24</td>
<td>3.2</td>
</tr>
<tr>
<td>15 to 30</td>
<td>Low</td>
<td>535</td>
<td>0.42</td>
<td>3.62</td>
</tr>
<tr>
<td>31+</td>
<td>High</td>
<td>259</td>
<td>0.8</td>
<td>3.5</td>
</tr>
<tr>
<td>31+</td>
<td>Low</td>
<td>866</td>
<td>0.69</td>
<td>3.29</td>
</tr>
</tbody>
</table>

Here again, we see evidence that theoretical model of risk and effort might capture the data. Perhaps the most noticeable numbers in the table is how the golfers ranked thirty and above fall off dramatically in their final round. This might be due to the fact that these golfers have little incentive to concentrate because they can already predict, within a few thousand dollars, how much they will be paid, regardless of how they score, unless it is amazingly well.

Further, we see that the worse golfers ranked 15 to 30 decrease their variance from their average scores, especially when compared to the best golfers with similar ranks. It could be the case that the worse golfers in this group are assured of taking home an atypically high paycheck and thus become relatively more risk-averse than the best golfers because the worse ones seek to protect the paycheck that they are promised. On the other hand, the better golfers might be more risk-taking because they feel that they have a legitimate chance at winning the tournament, which will add much more to their yearly income than would finishing somewhere around tenth rank. Thus, they take risks and hope to end in first place, knowing that they have ability on their side. Again, though, these are only suggestions from the data. We must test the distributions against
one another before we can definitively conclude that the data fully supports the theory. The following table records the Chi-square Goodness of Fit results from various tests of the groups.

<table>
<thead>
<tr>
<th>First Group (Rank, Ability)</th>
<th>Tested Against</th>
<th>Degrees of Freedom</th>
<th>Pearson Coefficient</th>
<th>Level of Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 to 14, High</td>
<td>1 to 14, Low</td>
<td>21</td>
<td>21.8</td>
<td>0.411</td>
</tr>
<tr>
<td>15 to 30, High</td>
<td>15 to 30, Low</td>
<td>21</td>
<td>22.55</td>
<td>0.368</td>
</tr>
<tr>
<td>31+, High</td>
<td>31+, Low</td>
<td>24</td>
<td>14.89</td>
<td>0.924</td>
</tr>
<tr>
<td>1 to 14, Low</td>
<td>15 to 30, Low</td>
<td>21</td>
<td>23.86</td>
<td>0.300</td>
</tr>
<tr>
<td>15 to 30, Low</td>
<td>31+, Low</td>
<td>24</td>
<td>26.86</td>
<td>0.311</td>
</tr>
<tr>
<td>1 to 14, High</td>
<td>15 to 30, High</td>
<td>20</td>
<td>18.89</td>
<td>0.529</td>
</tr>
<tr>
<td>15 to 30, High</td>
<td>31+, High</td>
<td>21</td>
<td>16.83</td>
<td>0.721</td>
</tr>
</tbody>
</table>

Again, none of these results are significant, and it even seems like there is no difference between the groups of both high and low ability that are ranked 31 or higher. At the same time, the statistics from Table 5 seem to suggest that the economic model captures some of the behavior. Further, it is interesting to note that the test statistics are more significant for the golfers of higher ability than they are for lower ability. Perhaps this suggests that the best golfers have the strongest response to changing incentives because they know that they will more often find themselves in the position to win the tournament or simply make a lot more money over the year. As such, they might feel freer to take risks, whereas the worse golfers, who find themselves in this situation less often, would rather make sure that they secure the money they have so far earned, opting out for the chance to win tournaments by playing risky.

Nevertheless, none of these tests approaches a high level of significance. Perhaps these tests are not significant because there are so many factors that affect a player’s score that it is difficult to even study how much effect any one of these factors, such as
incentives, has on either distribution or average score for these golfers. This naturally suggests that we use a regression model to attempt to isolate the effect of these various factors that all might influence a player’s behavior and final score.

Results: Model 3

The third model investigated whether golfers respond to the different incentives they face throughout the tournament settings focused on predicting final round score. The more specific question we were looking to answer addressed how golfers responded to the opportunity to make a great deal of money by improving one stroke relative to the rest of the field. Our economic model predicted that golfers should take more risk, perhaps scoring worse in the process, when the disparity between the money a golfer stands to gain is large compared to the money that the golfer stands to lose. This money, of course, depends both on his rank in the tournament and on the distribution of the field around him.

Again, because the course makes a large difference in the golfers’ scores, I have factored out the specific course effects by using fixed effects linear regressions. The first regression measured both the money the golfer could earn by improving one stroke relative to the field and the money that the golfer could lose by falling one stroke relative to the field. The second regression combined the two terms into a variable called “Risk” to see if golfers respond as predicted when there is a large disparity between these two terms. The following table presents the finding of this regression analysis.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Regression 1</th>
<th>Regression 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>WorldRank</td>
<td>-0.3599</td>
<td>-0.3595</td>
</tr>
<tr>
<td>(t-stat)</td>
<td>(-11.33)</td>
<td>(-11.32)</td>
</tr>
<tr>
<td>Combined First Three Rounds</td>
<td>0.0582</td>
<td>0.0548</td>
</tr>
<tr>
<td>(t-stat)</td>
<td>(3.33)</td>
<td>(3.77)</td>
</tr>
<tr>
<td>Expected Increase</td>
<td>0.000000136</td>
<td></td>
</tr>
<tr>
<td>(t-stat)</td>
<td>(1.30)</td>
<td></td>
</tr>
<tr>
<td>Expected Decrease</td>
<td>0.000000758</td>
<td></td>
</tr>
<tr>
<td>(t-stat)</td>
<td>(0.53)</td>
<td></td>
</tr>
<tr>
<td>Risk</td>
<td></td>
<td>0.00000116</td>
</tr>
<tr>
<td>(t-stat)</td>
<td></td>
<td>(1.34)</td>
</tr>
<tr>
<td>Adjusted R-Squared</td>
<td>0.3068</td>
<td>0.307</td>
</tr>
</tbody>
</table>

One of the more surprising things about Table 7 is the low amount of variation in the fourth round score that these factors can explain. Second, it is interesting to note that none of the terms associated with how much money a golfer stands to gain or lose in the final round is significant. Further, this table seems to not support the economic theory that golfers play better when the stand to make or lose more money because they try harder and expend more effort in scoring well. Instead, it might support Orzag’s (1994) claim that golfers experience somewhat more of a choke factor. For example, the coefficient on the Expected Increase term is positive and suggests that if a golfer can make an extra $100,000 by improving one stroke relative to the field, he is expected to score 1.36 shots worse in the final round than if he faced the opportunity of making no money by improving one stroke. This finding could be inline with the theory that he will take more risk to try to win this money and hence might play worse.

However, the coefficient on the term representing the amount of money he will lose if he falls one stroke relative to the field is also positive. This means that if a golfer might lose $100,000 by falling one stroke relative to the field, he can be expected to score
.758 strokes worse, which, in a sense, measures the choke factor. However, the t-statistic on this term is too far near zero to make any definitive statement on whether or not Orzag’s hypothesis or the economic theory forwarded in this paper (or neither) are true.

In the second regression, the coefficient on the “risk” term states that if a golfer stands to gain $100,000 more than he stands to lose in the final round by improving one stroke verses falling one stroke, respectively, then he is expected to score 1.16 shots worse in the final round, which both supports the theory that the golfer plays with a lot of risk and the theory that the golfer effectively chokes in the final round.

Conclusions

This paper sought to analyze whether or not golfers respond to different incentive that they face in the course of a tournament setting. In asking how golfers responded, it was first necessary to develop an economic model that sought to explain a priori how golfers would think about the situations they face and respond rationally. In this model, I first used the standard economic assumption that golfers attempt to maximize their utility on the tour, which, for the purposes of this paper, meant that they try to maximize their income, not minimize their scoring. As such, golfers face two major choices during the course of their play. First, they must decide how much effort and concentration to expend during the course of the round. I argued that these golfers should use the most concentration when the cost to effort is relatively low compared to the sum of money that they stand to gain. This will occur when the amount of money that they stand to gain or lose varies substantially. In other words, they will expend the most effort and energy
when they are atop the leaderboard or when they face a field that is highly bunched near them.

The second choice that they must face is how much risk to play with. Risk will increase their variance, allowing them to increase the chance that they score very well, while it also increases the chance that they play very poorly. A golfer will then use risk to maximize his income when he faces a situation in which he could gain a great deal of money by improving a few strokes relative to those around him while he does not face the prospect of losing a large amount of money by falling a few strokes. As also noted, because at every rank except first and last, the money that a golfer makes by improving one rank is always greater than the amount of money that a golfer loses by falling one rank. As such, one expects golfers to frequently play with risk, with the level of risk depending on the actual position of each player.

To test this economic theory, I first investigated a situation in which many golfers are expected to play with a lot of risk: the cut. Golfers who face the likely prospect that they will be cut understand that if they are cut, they will not make any money for competing, while if the pass the cut, they are assured of making at least $7,000. The more remote the golfer’s chances are of making the cut, the more risk the golfer should take in his second round. Of course, at some point, the golfer will not believe that he can pass the cut with a reasonable probability, which would make the cost of competing relatively higher. This golfer might not compete with as much risk, making his variance decrease.

I found that golfers at the projected cut played conservatively, especially the better golfers, which is a finding that the economic model supports because these golfers
know that by sheer ability, they can expect to make the cut. As a result, they lower their risk. I also found that the great golfers seem to respond the most to these incentives, pursuing very risky strategies the farther away from the projected cut they are. However, many of these results and findings were not statistically significant, likely because the number of great golfers who are four shots below the projected cut after one round of play is not relatively high. These tests would benefit with having more data, as the differences among golfers in different groups should emerge, assuming that the theory is correct.

The second test that I performed looked at how golfers respond on the final round of competition. I divided the golfers into three groups that all faced different incentives. I predicted that the group of golfers ranked 15 to 30 would take the most risk in the final round because they faced a situation in which improving their rank could promise a large financial gain, while maintaining or even decreasing their rank would not impose a large financial loss. I also predicted that the group of golfers ranked 31 and above would not have as large an incentive to compete because they knew, more or less, how much they would make and could not change this, except if they had a tremendously strong performance. For golfers ranked 1 to 14, I predicted that overall they would take on less risk, but noted that in some cases, golfers might try to take on tremendous risk to increase their chances of winning the tournament, which has tremendous financial rewards.

The economic theory seemed to be supported in many ways, although most of the tests were not statistically significant. First, the players who were ranked 31 and above averaged at least .7 strokes higher than their average on the final round, evidence that they did not exhibit the same level of effort as did the other groups, which all had a lower
average score. Additionally, it appeared as if, once again, the best golfers responded most strongly to the different incentives they faced. These golfers were apparently more risk prone than their counterparts, likely because the former tried to win tournaments and often finish high on the leaderboard, while the latter tried to play conservatively to retain the money that they seemed to have earned in their previous rounds.

Finally, I ran two regressions to see how golfers’ final round scores relate to the amount of money that they stand to gain and lose. I found that their overall ability and their first three rounds were highly significant, but that the money that they stood to gain or lose was not significant. Further, these variables could only explain thirty percent of the variation in the dependent variable, the fourth round scores.

This paper, however, suffers many limitations. First, golf decisions are made a shot at a time. How a golfer is playing midway through the round might affect his expectations, and developments that occur with other players during the round will also affect his expectations, and hence his strategy. Because of my limited amount of data (which was still over 6,000 player-tournaments), I had to treat golf as if decisions were made at the beginning of the round and were unchanged as the round proceeded, clearly unreflective of what actually occurs. The paper would benefit from having data at the level of the hole rather than the round for each player, and having shot by shot data would be even better. Perhaps with this extra data, the economic theory that I forwarded, if true, would be more observable. Additionally, data from several years of golf would improve the testability of the theory, which is another limitation that I faced.

Nevertheless, from these tests, it seems as if golfers are motivated by the different incentives that they face, although they are motivated differently. For example, much of
their decision making seemed to revolve around their ability, and thus players similarly group behaved differently because they entered their rounds with different expectations.

Perhaps a larger lesson to take from these investigations, though, is that while incentives might matter somewhat in golfer’s behavior, golf is still a game of luck. Financial motivations, skill, and recent past performance could only capture about one third of the variation in something as immediate as the final round of play. Golfers make choices in the face of uncertainty, and they likely understand that much of what happens in the final round, and even in the tournament itself, is not fully under their control. Nevertheless, one could still try to impose rationality into a system rife with luck and uncertainty, which is what I have tried to do. Hopefully, with more data, future searches into the PGA Tour in particular, and observable rank order tournaments as a whole, will reveal that participants do behave fully rationally, as economics would predict.
WORKS CITED


