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Risk taking in competition: Evidence from match play golf tournaments ☆

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ABSTRACT

We test hypotheses regarding risk taking behavior of competitors in settings characterized by one-on-one, single elimination tournaments. We draw data from 579 professional golf matches and over 18,000 holes from 2003 to 2013 in tournaments where match-play scoring is used rather than stroke-play. Because of the uniqueness of the data, we are able to provide clean empirical tests of how risk taking is affected by horizon effects (holes remaining), peer effects arising from heterogeneity in player abilities, match status (whether behind or ahead), and the difficulty of the task/project (hole). The findings are applicable to corporate settings where only a few rivals compete for a prize, such as a winning bid, a promotion, market share dominance, and patents. Other applications include litigation contests and political elections.

1. Introduction

There is an extensive literature on the incentive effects of tournaments, with most studies finding that tournament reward structures have positive effects on the effort levels of participants. The effects on risk taking are less well studied and much less clear. Tournaments are characterized by rank structure, with compensation at the top increasing by increasing increments, especially at the last stage. However, as Alchian (1988, 92) points out in reviewing this literature, “Whether that last large increment is the carrot that motivates gamblers to achieve ultimate success… or represents a measure of marginal product of someone in top authority is not something about which I am confident. I can argue both ways convincingly… to myself”. The concern is that winning a tournament could reflect superior effort or talent; alternatively, it could reflect risk taking that paid off. Armen Alchian's remark suggests that a potentially useful line of inquiry is to determine whether we can isolate risk-taking behavior in tournament settings and assess whether it varies in systematic ways depending on competitive conditions. These are important issues as excessive risk taking motivated by tournament compensation can lead to negative consequences for an organization. For example, a firm may establish an internal tournament to become CEO. Candidates, depending on their perceived rankings relative to other candidates, may try to increase their win probabilities by selecting high-risk strategies or undertaking high-risk projects that have large payoffs to the candidate under a success scenario, but low expected value for the firm (i.e., negative NPV).

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While the relation between expected reward and effort should be positively monotonic regardless of the number of competitors in the field, the relation between expected reward and risk-taking is less clear, especially when the number of competitors is large and competitors vary in ability. The reason for the difference is that expending effort unambiguously improves expected performance whereas increasing risk, though it reduces expected performance, can increase win probability if the variance increase is large enough. Whether it is rational to take more risk depends on the upper tail of the distribution of the player's possible outcomes relative to the competitors' and on the payoff structure. If the field is large and the prize is concentrated at the top, there may be no realistic way to win except by aggressively taking risk, but if the prize is distributed more evenly, it may be optimal to play a safer strategy. Possibly because of the ambiguity of predictions, there have been few studies of risk taking in tournament competition. This is unfortunate because in some cases it is hard to distinguish between higher effort and higher risk taking.

Match-play data from professional golf is particularly well suited for investigating risk-taking incentive effects in tournaments.[1] The matches resemble the simplest possible two-person tournament that allows for clear theoretical predictions about risk taking by weaker players and trailing players in matches. In a single-elimination tournament, in each round an agent is matched against only one competitor. Within the round, the performances and the relative abilities of the rest of the competitors do not matter to the two players in the match. The strategic interactions across competitors are simplified in match play so that issues of sabotage or collusion are minimized. In contrast to a tournament consisting of multiple participants, in a one-on-one match, all of the relevant strategic interactions are observed and the number of variables that must be controlled is limited (e.g., the matched players play the hole at the same time and under the same weather conditions). In addition, there is no uncertainty about the rewards, as the participants know the prizes ex ante for each tournament and at each stage. The relative ability of each player can be inferred from their historical performance (in our case the Official World Golf Ranking prior to the tournament). These types of objective measures of ability are rarely available in data apart from individual sports. The rankings allow us to construct an index of player heterogeneity and evaluate how risk taking varies with relative abilities of the matched players. These features of match play make it particularly well suited to test hypotheses related to risk taking.[2]

In single-elimination tournaments, the rational behavior of risk-neutral agents leads to several clear predictions about risk taking; among them: the greater the difference in ability between a weaker and a stronger player, the more risk the weaker player is expected to take; the greater the lead held by the leading player, the more risk the lagging player is expected to take, and this effect should be stronger toward the end of the tournament, as the probability of winning without taking additional risk declines; when confronting a set of risky opportunities where the player can choose the level of risk to take, the players will choose to increase risk in situations where the expected payoff (i.e., win probability) to increasing risk is highest and to limit risk when the expected payoff to risk is negative.

Expectations of risk taking are less clear for the leading player and the stronger player. In a competition against nature, where nature is weaker, the leading or stronger player would be expected to adopt a safer strategy. Bronars (1986) shows that followers have incentives to choose risky strategies, while leaders have incentives to "lock in" leads. However, Nieken and Sliwka (2010) argue that increased risk-taking by a closely trailing player in a tournament can induce additional risk taking by the player who is in the lead. An example they offer is car racing—if the leader were to see a car very close behind, she would drive a bit faster and more recklessly, so the distance between the two also matters. Thus, the theoretical prediction for risk taking by leading players is unclear and may well involve mixed strategies.

Because of the advantages of match-play data, we are able to consider a rich set of conditions that may influence risk taking, including peer effects (relative abilities of the competitors), match status (leads and lags), match horizon (holes left in the round), and the expected payoff to risk taking, which varies by hole difficulty (as inferred by the skewness of observed scores on the hole). Our findings support the expectations of increased risk taking for lagging players and weaker players when matched with stronger players, but do not support higher risk taking for leading players. Leading players take less risk generally and play more conservatively as their lead increases. Stronger players play riskier strategies when paired with weaker players but they reduce risk as their leads increase, especially late in the match.

Our study has important implications for similarly structured competitions that are single-elimination and involve small numbers of competitors, where, in the end, a single winner is determined. Examples include promotion competitions for top managerial positions; bidding competitions in procurement auctions; litigation contests for brand names or patent rights; and competitions for first-mover advantage in markets with significant network economies. While each of these examples has been examined in theoretical papers to illustrate the applicability of tournament theory, there is little empirical work examining determinants of risk taking.

2. Hypotheses development

In tournament settings, players choose costly actions or effort levels that affect the probability of winning and a player's probability of winning depends positively on her own effort, negatively on the opponents' effort, and on random components of performance. Most of the literature on tournaments focuses on effort effects. While the compensation structure of tournaments is

[1] Golf has been used as the context for several important economic studies, and follows the long tradition of economists, including Armen Alchian, of using sports markets to inform us about economic behavior. Ehrenberg and Bognanno (1990a,b) were the first use golf data to study the incentive effects of tournament compensation and show that larger and more highly skewed compensation structures are associated with higher levels of performance. Also, see Brown (2011), Pope and Schweitzer (2011) and Guryan et al. (2009), who among others, use stroke-play golf data to study aspects of competition.

[2] In a paper using professional tennis data, Sunde (2010) points out the advantages of match play data, and tests for effort effects in final-round matches.

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designed to elicit greater effort, it can also increase the players' incentives to adopt risky strategies intended to increase the probability of winning. Strategic risk taking occurs when a competitor deliberately increases the variance of outcomes and may occur, for example, when the competitor is clearly behind in the tournament (e.g., the "Hail Mary" pass). It may also occur when a competitor is confronted with an opponent who is more capable, so that the weaker competitor may need to increase variance to have a chance of winning. This proposition follows, according to Rosen (1988), from the "option value" quality of the competition —prizes are fixed in advance and losses are limited, so greater risk-taking increases expected rewards among weaker players or those who are trailing. In golf, the analogy would be that the normal strategy or effort level would have an expected score of par on a given hole. But by selecting a longer club and going for the green in fewer strokes than regulation (say going for the green in 2 strokes on a par 5), the player increases the chance of a birdie (1 under par) but also increases the chance of a bogie (1 over par). In this example, selection of the longer club is a variance-increasing strategy.

Theory suggests that the competitors' strategies are developed in the context of a non-cooperative game and that behavior, including the choice of risk, is determined by comparing expected returns with their costs, conditional upon the rival's choices. The choice of when to increase risk depends on features of the tournament, including the number of competitors. Because we use the case of match play (two competitors), the features we focus on are: 1) relative abilities of the competitors in the match, 2) the dynamics of relative position—who is leading and who is behind, 3) the match horizon (number of holes remaining to be played), and 4) the difficulty of the hole (in our setting a hole is analogized to a project and risk taking is expected to vary with the difficulty of the hole (as indicated by skewness of the distribution of observed scores on the hole)).

Building on the basics of tournament theory and focusing on the four features above, we test the following primary hypotheses:

H1. The propensity to take risk is greater for lower-ranked (lower ability) players, the greater is the difference in the rankings.

H2. The propensity to take risk on a hole is greater for the trailing player, the greater is the difference in scores (holes won).

H3. The propensity to take risk is greater for the trailing player, the fewer holes there are remaining in the match.

H4. The propensity to take risk on difficult holes is greater when players are behind because the alternative is a high probability of elimination.

H1 is a test of how heterogeneity in abilities, other things constant, affects risk taking. We expect lower-ranked players to have a greater propensity to take risk than higher-ranked players who, by their previous performance, have demonstrated superior capabilities. We expect this propensity to be greater earlier in the match than later, because later the score differences are more likely to dominate the choice to take risk.

H2 tests the effects of leads and lags on the riskiness of player strategy. The probability that a trailing player can win a match by conservative play decreases as the score difference increases and as the number of holes remaining (opportunities to catch up) decreases (H3). The player hopes that by increasing variance, some lucky breaks will enable him to overcome the other player's lead.

In a tournament setting like match play, the competitors face multiple challenges (holes) over the course of the tournament that can be analogized, to projects in a corporate setting, stages in the political contest (primary vs. general election), or various motions in litigation. These projects are likely to vary in expected return to risk taking. The more difficult ones, other things the same, involve lower expected returns for taking risk. A golf example is the difference between an easy hole (with high birdie potential) and a more difficult hole (with high bogie potential). Professional golfers can be expected to take more risk on those holes that are easier (H4). If a player is significantly behind, however, H2 comes into play and the combination suggests that the lagging players will also take risk on the more difficult holes, where the probability of winning the hole due to taking extra risk is low.

Empirical implications for leading players and the more skilled players are less clear because of the game-theoretic nature of their actions and because the competition is dynamic in that past performance affects the expected payoffs to future holes. In golf match-play competition, the winner of the match is the first player to win 10 contests (holes), where ties count as half-wins.[3] This dynamic setting may induce the leader to reduce risk to lock in the lead, especially late in the match (Bronars). Alternatively if the lead is not large, there may be an incentive to choose a risky strategy. If the trailing player is close in score to the leader and the trailing player chooses to play a risky strategy, then the leader may increase risks in response (Nieken and Sliwka, 2010). Alternatively, the leader may choose to rely on the existing lead and any ability difference and play a safe strategy.

Because of the incentive of the lower-ranked player to play a high risk strategy when the players are of disparate abilities, predictions for the initial strategy of the higher ranked player are ambiguous. In a dynamic setting, incentives will evolve as score differential changes and the match nears the end. As explained above, the score status (rather than relative abilities) is expected to dominate the choice of risk taking as the match progresses and as players with larger leads have incentives to reduce risk as the match nears the end.

[3] The dynamic aspect "best-of-N" contests can give rise to an economically-based momentum effect, as recognized by several recent studies. These studies indicate that leaders have greater economic incentives to exert more effort than do trailing players. Malueg and Yates (2010) illustrate this with best-of-three sets tennis matches between equally-skilled players, where a player who is up one set is more likely to win the second set; if the players split sets, each is equally likely to win the third. The leading player has a higher expected value of the prize, net of effort cost, and this causes the leader to exert more effort in the third set. Also, see McFall et al. (2009) for a golf example. The evidence is mixed, however, as Ferrall and Smith (1999) do not find evidence of a momentum effect for team sports. Thus far, this literature has focused on effort effects and it is not obvious how incentives for risk taking would be affected.

3. Previous literature on incentives and tournament competition

The theoretical literature on tournament competition examines incentive effects and economic efficiency when competitors are promoted and paid based on relative performance (see the seminal papers by Lazear and Rosen (1981) and Tullock (1980) and the survey of the literature by Prendergast (1999)).[4] Of particular relevance for our paper is Rosen's (1986) study of incentive properties of prizes in single-elimination events, where rewards are increasing in survival during the competition. He points out that survival competition is prevalent in many markets, including promotion tournaments within corporations, and provides the motivation for our study of match play.[5]

A few theoretical studies have examined the risk-taking decision in tournament settings. Cabral (2003), for example, analyzes a two-firm game where firms can choose both effort and a low or high variance strategy. He formalizes the intuition that laggards have little to lose and are more likely to adopt riskier strategies when they are behind, whereas leaders adopt safer strategies. He adopts an infinite time horizon and does not address the question of when the trialing player adopts the riskier strategy.[6]

There also are a few empirical papers that examine risk taking in tournaments. Becker and Huselid (1992) show that higher prizes result in faster, though riskier, driving by professional NASCAR drivers, as proxied by more caution flags at tournaments with higher prizes. Using stroke-play PGA golf data, where each player competes against the entire field, Hood (2008) finds that players have some control over the variability of their scores and that playing a risky strategy even if it worsens their expected score (increases the number of strokes), increases expected payoff because of the interaction of the extreme convexity of the payoffs and the effect of risk taking on the distribution of scores. Using a non-sports setting, Knoeber and Thurman (1994) study the broiler chicken industry where growers' rewards are determined based on relative performance. They find that higher rewards result in better performance (more pounds of chicken produced relative to the cost of chicks and feed), and that the growers who are unlikely to win the tournament take riskier actions (measured as the variance in the grower's cost over growing cycles) to improve their prospect of winning.

Kini and Williams (2012) test the proposition that higher tournament incentives result in greater risk taking in the form of risker policies selected by senior managers involved in internal CEO contests. They find that more intensive competitions, proxied by more convex earnings structures related to promotion, result in greater risk taking as reflected by higher firm measures of R&D intensity, firm focus, and leverage. Coles et al. (2012) examine industry-wide promotion tournament incentives for CEOs and find that the larger tournament prizes and larger gaps between CEO pay and pay among competing firms are associated with riskier internal investment decisions and financial policies. Both of these papers on CEO labor markets contemplate multiple competitors for the position and find that the variance of performance increases with the pay gap between the winner and runners-up. The findings are inferential, as the authors observe policy outcomes, but do not observe the risk-taking choices of individual competitors and cannot link risky projects to specific decision-makers who are candidates for CEO positions.

Using the example of mutual fund manager competition, Brown et al. (1996), Chevalier and Ellison (1997), and Chen et al. (2011) illustrate the effects of incentives on risk taking. Chevalier and Ellison (1997) show that while managers are rewarded as a linear function of assets under management, flows into mutual funds are not linearly related to fund performance. Investors tend to allocate capital to mutual funds based on previous performance, so that funds that have under-performed the market are predicted to take too little risk, while those that have out-performed have an incentive to take excessive risk.[7]

In a paper that considers how relative skill levels can affect tournament outcomes, Guryan et al. (2009) use random assignment of playing partners in stroke play golf tournaments and test for peer effects. They do not find that the ability of playing partners affects performance, which contrasts with evidence from other studies of peer effects. They suggest that perhaps workers learn from professional experience not to be affected by social forces. Their analysis is different than ours in that our focus is not on behavioral bias arising from being paired with a better player. Instead we are interested in risk taking that occurs when a lower-ability player is matched in single elimination with a higher-ability player and how that varies over the course of the match and with relative score.

Brown (2011) examines a particular type of peer effect when the field of competitors includes a dominant player or "superstar". In her study of stroke-play competition, the presence of a superstar is associated with reduced performance of other competitors. Interestingly, the adverse superstar effect is larger for highly-skilled golfers in that their win probabilities are most adversely affected by the presence of a superstar.

[4] Many empirical studies document effort effects. Ehrenberg and Bognanno (1990a,b) are the first to use golf stroke-play data for studying effort and find that prize money has a significantly positive impact on player effort, as indicated by lower scores. While reviewing much of the empirical literature, Szymanski (2003) more broadly discusses contest theory and points out that more work is needed to better understand how various aspects of contest structure affect incentives of participants.

[5] Noe and Parker (2005), for example, provide an application of the theory by modeling competition in internet markets as winner-take-all where competitors spend heavily on marketing and advertising and only a few firms emerge as winners and most end up losing money.

[6] See also Hvide (2002) who builds on the Lazear–Rosen model and considers how moderating the compensation can reduce risk taking among agents while maintaining effort.

[7] While most studies that consider risk are concerned with taking too much risk, there is also the flipside concern of taking too little (a CEO candidate who is "winning" may decide to play conservatively and forego risky projects with positive NPVs). This concern is touched on in behavioral studies of loss aversion. For example, Pope and Schweitzer (2011) find that professional golfers are less likely to make birdie putts than to make otherwise similar par putts. They conclude that this behavior reflects irrational loss aversion—players are more concerned about failing to make par than about failing to make birdie. As another example, Romer (2006) considers the decisions National Football League coaches face on fourth down between kicking and going for the first down. He finds that the decisions reflect departures from what would clearly maximize teams' chances of winning. He points out that there is little evidence as to why individuals avoid such risks, suggesting that conventional risk aversion cannot explain the results.

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Harbaugh and Klumpp (2005) analyze how players of different abilities strategically use effort to maximize their probabilities of winning in elimination tournaments. In their model, underdogs use more effort in the beginning of the tournament, whereas favorites use more effort in the later rounds. While their paper is about effort effects, the implication is that the asymmetric abilities and match horizon are factors that influence player behavior.[8]

To summarize, numerous empirical studies document that tournament incentives elicit effort responses. There is less evidence of incentive effects for risk taking. Significant issues for previous studies are the intractability of measuring competitor attributes (relative ability), the challenges of tracking the dynamics of risk taking among multiple competitors across changing tournament conditions, and the inability to isolate and measure individual risk-taking choices in many competitive settings.

4. Background on golf and PGA Tour tournaments

The USGA Rules of Golf define golf as "playing a ball with a club from the teeing ground into the hole by a stroke or successive strokes in accordance with the Rules."[9] Golf courses normally consist of 18 holes. Each hole has a "tee box" and "putting green," but each is unique as to how the holes are laid out, the terrain between the tee box and green (which may include bunkers, water hazards, and trees), and the size and contours of the green. Each hole is assigned a value, or "par", which is the modal score for a professional player (3, 4, or 5). The par value of a hole represents the number of strokes that professional golfers normally require to finish the hole, and score cards represent performance on each hole relative to par. Golfers who complete a hole one or two strokes under par have shot a "birdie" or an "eagle", respectively. Golfers who complete a hole one or two strokes over par earn a "bogie" or "double bogie", respectively. Following Pope and Schweitzer (2011) and Brown (2011), among others, we use a player's dispersion of hole scores from par as an indicator of taking risk.

Golf is a precision sport requiring great accuracy. Players choose the clubs they use to advance the ball from the tee to the green, so both club selection and shot selection can affect variance (measured here as standard deviation relative to par). There is a clear trade-off between accuracy and distance. For example, off the tee, an iron generally is more accurate and safer than a driver, but will not travel as far. In addition to club selection, shot selection can affect variance. A draw will go farther than a fade but is harder to hit reliably. If a player lands his tee shot behind a tree, he can take the safe way out and try to hit safely (laterally) into the fairway, which counts as an additional stroke without materially advancing the ball. Or, the player can try to advance the ball toward the green by fading it around the tree or using a high-lofted club to go over the tree.

4.1. Stroke-play and match-play formats

In professional golf tournaments there are two primary formats for scoring. The more common is stroke play where the golfers accumulate the strokes over the entire match, and the one who has taken the fewest strokes at the completion of the tournament wins. A professional stroke-play tournament normally consists of 72 holes of golf, or four rounds played over four days. Cash prizes are awarded on the basis of the players' ranks after the final round.

The second format for scoring is match play where each player competes against a single opponent in each round and only winning or losing against that player matters. Hence, in match play, the player competes against opponents one-at-a-time in contrast to stroke play where the player competes against the entire field of golfers. In match play, the players do not count their cumulative strokes over the match; instead, each hole is a separate competition that is won, lost, or tied. The player with the lower accumulated score on a hole wins the hole and the player who wins more holes wins the round for the day and advances, whereas (in all but the penultimate round) the loser of the round is eliminated. The winner of the final round wins the tournament.

Although there are variations in match play, the type we consider is one-on-one single elimination. Match scores are kept hole by hole and if the players tie on a hole, say with a par each, then the hole is "halved." The match is played on an 18-hole course and once a player has won more holes (or is "up" more holes) than there are holes remaining to be played, the trailing player cannot win and the match is over. For example, if after 12 holes Player A is up 7 with 6 left to play, then Player A is said to have won the match "7 and 6." A match can extend beyond 18 holes if the players are tied, in which case there is a sudden death playoff, where the first player to win a hole, wins the match.

A complicating feature of match play for data purposes is the possibility of an opponent conceding a hole. Each hole is a separate competition and the absolute number of strokes taken by the players does not matter, only winning or losing the hole does. Hence, if one player has already completed the hole with a birdie, for example, and the opponent would be putting for par, the opponent cannot win and may as well concede the hole.[10] When a player concedes a hole, the opponent's win is recorded, but a stroke score is not recorded for the player who has conceded. We also observe cases in the data where a win is recorded but neither the score of the winner nor the loser is recorded. This raises an empirical issue because the probability of conceding is likely to reflect risk taking. While conceding complicates our analysis, it also is useful since it provides a hole-specific indication of risk taking. We describe how we deal with this measurement issue below.

[8] Also, see Abrevaya (2002), who studies the effects of asymmetric abilities of competitors and, using data from professional bowling, shows that performance in a ladder-style tournament depends on whether a competitor has advanced up the ladder and on the competitor's long-run ability.

[9] http://www.usga.org/Rule-Books/Rules-of-Golf/Rule-01/.

[10] See: https://www.usga.org/Rule-Books/Rules-of-Golf/Rule-02/.

4.2. Risk taking and match-play strategy

Much has been written about the optimal strategy for match play and how it differs from that for stroke play. In particular, there is extensive discussion in the popular golf literature of whether and when a risky strategy is rational in match play. Should a player take risk and put pressure on the opponent or play steadily without taking risks and let the opponent make mistakes? Similar questions arise in work-related promotion tournaments or other settings where the rivalry is between two dominant players. Pairwise competition is more game-theoretic than group competition as there is only one other opponent and each reacts to the other's actions or circumstances.

In contrast to stroke play, in match play the opponent who matters in any given round is easily identifiable and is competing on exactly the same hole at the same time. So course conditions, time of day and other factors that would require explicit controls in stroke play are implicitly controlled for. Reactions must be immediate in match play because each hole is either won or lost (or is halved). If, for example, one competitor hits a fantastic shot, the other may believe that it is important to hit an equally good shot. If an opponent chunks a shot, that may open up the opportunity to play safe and reduce risk on that hole. Thus, decisions about risk taking are directly related to match dynamics such as the player's standing in the match at the start of a hole, number of holes remaining, and other observable match-specific features. We are able to track who is leading in the match at the start of each hole and by how much, so that we can determine how those factors affect risk taking on a given hole.

A common type of risk taking occurs on holes where players can "go for it"—attempt to reach the green in one shot less than is expected for par. Off the tee, a player on a par 5, for example, is expected to reach the green with the third shot and then two-putt for par. However, he might choose to go for the green on the second shot and still hope to two-putt for a birdie—taking the extra risk to reach the green in two may payoff, but there is a chance that aggressive play may result in landing in a hazard or long grass and that the risky attempt could lead to a bogie or worse. We regard holes with low average relative-to-par scores as those where risk taking is relatively safe so that even a player who is ahead might decide to go for it. Other holes present a high risk of a negative outcome relative to par (high bogie potential holes). On these, a player who is ahead might be expected to "play it safe", but a player who is behind might still feel compelled to take risk.

Risk taking can also occur on the green. For example, suppose a player faces a tricky downhill breaking putt. In stroke play, the player would be careful not to run the ball too far past the hole and might leave it short to make a score of par more likely, because a high score on an individual hole can ruin the round. By putting it too far past the hole, the player could easily end up taking two additional putts. But in match play, shot selection depends on how things stand on the hole. If the opponent has already holed the ball with a score of par, then our player, who is putting for par, must go for it—missing and going well past the hole is no worse in this case than being short a few inches. If he does not make the putt, he loses the hole no matter how many additional putts he needs to complete the hole.

4.3. The World Golf Championship (WGC) Accenture match-play tournament

For our analysis, we use data from the WGC-Accenture Match Play Championship, which is one of the annual World Golf Championships, staged in late February each year, and is a single-elimination match play event. The field consists of the top 64 players in the world, as determined by Official World Golf Rankings, which is a rank-ordered measure of the top 200 professional golfers. Invited players are seeded according to these rankings.[11]

The prize money for the 2013 tournament was $8.5 million, with the winner taking $1.4 million and the Walter Hagen Cup. Throughout the time period studied, the winner's share has remained approximately constant ranging from 16% in the years 2009–2012 to 17.5% in 2003. The matches in our sample have been played at three locations (La Costa Resort Carlsbad, 2001–2006; the Gallery Golf Club, Marana, Arizona, 2007–2008; and since 2009 at the Ritz Carlton Golf Club, Dove Mountain in Marana, Arizona).

5. Data and results

We use data provided by the PGA Tour through their extensive ShotLink database. We use hole-by-hole scores for each player who competed in the WGC Accenture Match Play Championship 2003–2013. The dataset includes 579 professional golf matches and 18,940 player-hole observations.[12]

[11] PGA match play tournaments use a 64-player field with standard tournament bracket rules and four brackets. The players are ranked from 1 to 64 using their rankings, with the top four players given No. 1 seeds. The next four players are awarded No. 2 seeds, with the remainder of the field seeded in order down to the final four players, who are seeded 16th. The groups are then placed in one of the four brackets, each containing one seed from 1 to 16. The first-round matchups feature No. 1 against No. 16, No. 2 against No. 15, etc. If a player in the top 64 as of the tournament's cutoff date (usually the Monday before the event), skips the competition, the No. 65-ranked player is invited, etc. See: http://www.worldgolfchampionships.com/accenture-match-play-championship/leaderboard.html.

[12] In our sample period between 2003 and 2013 there are 704 matches played in the WGC Accenture Match Play Championship. However, we dropped observations from 125 matches because of the inconsistencies in the data and uncertainties over conceded holes. Dropped holes included the final rounds from 2003 to 2010 when the final game was played over 36 holes.

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5.1. Measuring risk taking

Risk taking is measured in two basic ways. The first is by the percentage of holes that are conceded. As noted below, data on conceded holes provides some of our clearest evidence of risk taking by hole. If conceded holes are systematically related to differences in player ranking, relative scores prior to the hole, or holes remaining to be played, then they provide a measure of risk taking on the hole.[13]

Second, we measure risk taking as the standard deviation of relative-to-par scores on a hole or over a set of holes Hence, both birdies and bogies (−1 and +1 relative to par) are reflective of risk taking. Standard deviation, in turn, is measured in two ways—in descriptive Tables 2 and 3, we use hole-specific cross-sectional standard deviations of relative-to-par scores and compare player risk taking across holes of varying difficulty and across holes at different stages of the tournament. In the regression analyses in Tables 4 and 5, we use player-specific standard deviations over a round or subsets of holes within a round (e.g., the first 6 holes in the round versus the last 6).

While conceded holes indicate risk taking, these holes also pose a challenge for empirical study. If a player concedes a hole, we do not observe the stroke score for the player who concedes, and frequently do not observe the score of the player who wins the hole. Hence, there is a negative bias in the reported relative-to-par scores and standard deviations are measured with error. To see this, consider Table 1, which shows the distribution of observations in our data sorted by relative match score prior to the observed hole in play. For example, prior to completion of hole 1, the only possible score is 0 and 1158 observations of hole 1 are included in the database, of which 29 players conceded the hole. For each possible relative-to-opponent score–where the player is either up (+) relative to his opponent, or down (−), or even (0)–we first show the percentage of holes conceded, followed by the number of holes conceded and the total number of observations, separated by a comma. So, for example, on hole 2, there are 292 players who were −1 (as a result of losing hole 1), and 7 of those (2.4%) conceded the hole. The final rows show the totals for percentage conceded, number conceded, and number of observations of the various combinations of hole and relative score.

While the overall percentage of conceded holes is small, ranging from 0.86% on hole 5 to 3.58% on hole 17, the patterns of conceded holes indicate systematic increases in risk taking as the number of holes remaining declines, especially toward the end of the match. The propensity to take risk resulting in hole concession is particularly acute when a player is well behind and is facing a high probability of elimination. For example, 14 out of 121 players (11.6%) who were trailing by 2 with only 2 holes remaining, conceded hole 17 compared to 1 out of 121 players (0.8%), who were leading by 2 with 2 remaining and conceded the hole.

To further illustrate the issue with conceded holes in the raw data, consider Fig. 1. Panel A shows the average relative score at the beginning of each conceded hole. A negative value indicates that on average players who conceded were losing the match at the start of the hole. The figure shows how the average relative score on conceded holes varies as the match progresses. The figure illustrates that a player is more likely to concede a hole when the player is behind, and especially when there are only a few holes remaining. By the start of hole 18, the most negative relative score is −1 (since players who were further than one hole behind at that point could not possibly win the match). Table 1 shows that by hole 18 only 352 scores were reported, compared to 1158 on each of the first 9 holes. In Table 1, all of the players who conceded hole 18 were −1 at the start of the hole. Correspondingly, the average score of players conceding that hole, as plotted in Panel A of Fig. 1, is −1.0.

Panel B divides players into three groups—those who are behind, tied, or ahead, and shows that the percentage of holes conceded at each point in the match is especially high for those players who are behind and as the match nears the final holes. As the match nears completion, players who are behind adopt increasingly risky strategies.

To address the concern about bias resulting from omitted scores on conceded holes, we impute scores for these holes by assuming that the winner earns the mean score in that round for the hole in question and by assuming that the loser earns a score that is two strokes higher. This assumption is reasonable because normally a score difference of one would not be recorded as a conceded hole; rather holes are recorded as conceded when expected score differences between players are large. Hence, it would not be surprising for the loser's expected score to be even higher than 2 (e.g. +3 or more). The robustness of results to alternative assumptions is assessed below.

5.2. Descriptive statistics

5.2.1. Risk taking by leading and trailing players

Table 2 contains data on player risk taking measured by the standard deviation of the relative-to-par scores by hole group (early or late in the round) for players who are classified by match status (ahead or behind). Standard deviations are calculated for each player over three groups of holes: 1–6, 7–12, and 13–18+. The table provides a way to evaluate H2 and H3, as it is organized to contrast performance results as the match progresses for players who are leading vs. trailing, as indicated by the relative scores in column 1. Players who are behind take significantly more risk than those who are ahead, and this result is much more pronounced as the match nears the end—holes 13–18+. These results, the significantly higher standard deviations for

[13] Conceded holes could occur not because of risk-taking by the player who concedes the hole but because the opponent makes a tremendous shot (e.g., a hole in one), making it impossible for the conceding player to win the hole. However, the overall pattern in Table 1 is consistent with concessions occurring in predictable situations—i.e., the percentage of holes conceded is high when a player is far behind and toward the end of the match, when rational risk taking is likely to occur.

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Table 1
Conceded holes by hole in play and relative score prior to hole. The table shows numbers of holes played, numbers conceded, and percentage conceded by hole number and relative match score as of the start of the hole in play. For example, a relative score of −9 on hole 10 means that the player has lost all 9 previous holes, and will face elimination if he fails to win any subsequent hole of the 9 remaining.

Match score	Hole number																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
−9																		
Pct. conceded										0.0%								
No. conceded, Obs.										0,1								
−8																		
Pct. conceded									0.0%									
No. conceded, Obs.									0,1									
−7																		
Pct. conceded								0.0%			20%	0.0%						
No. conceded, Obs.								0,1			1,5	0,7						
−6																		
Pct. conceded							0.0%	0.0%	0.0%	0.0%	0.0%	11.1%	8.3%					
No. conceded, Obs.							0,1	0,1	0,3	0,9	0,13	1,9	1,12					
−5																		
Pct. conceded						0.0%	0.0%	0.0%	0.0%	9.1%	0.0%	0.0%	12.2%	8.6%				
No. conceded, Obs.						0,1	0,4	0,7	0,17	2,22	0,15	0,28	5,41	3,35				
−4																		
Pct. conceded					0.0%	0.0%	3.7%	0.0%	0.0%	0.0%	4.6%	4.5%	3.3%	5.7%	7.3%			
No. conceded, Obs.					0,10	0,17	1,27	0,38	0,53	0,50	3,66	3,67	2,61	4,70	5,69			
−3																		
Pct. conceded				7.7%	3.0%	1.7%	1.5%	1.4%	1.2%	2.2%	5.2%	1.9%	2.0%	7.6%	7.1%	11.3%		
No. conceded, Obs.				2,26	1,33	1,60	1,69	1,73	1,83	2,92	5,97	2,105	2,102	8,106	7,98	12,106		
−2																		
Pct. conceded			3.5%	0.0%	1.4%	2.1%	0.0%	2.1%	4.6%	2.8%	5.2%	0.7%	4.3%	1.6%	4.6%	1.8%	11.6%	
No. conceded, Obs.			3,85	0,118	2,147	3,143	0,139	3,146	6,132	4,144	7,136	1,138	6,139	2,122	6,131	2,113	14,121	
−1																		
Pct. conceded		2.4%	3.6%	2.6%	1.2%	0.8%	0.5%	2.9%	1.7%	1.8%	4.5%	0.0%	2.1%	2.9%	0.8%	2.9%	3.1%	7.7%
No. conceded, Obs.		7,292	10,278	7,266	3,251	2,237	1,223	6,204	3,181	3,166	7,156	0,145	3,141	4,139	1,129	4,138	4,130	10,130

0																		
Pct. conceded	2.5%	1.7%	1.6%	1.5%	0.7%	0.4%	2.6%	2.3%	0.9%	3.2%	1.1%	0.7%	2.1%	1.5%	1.5%	2.5%	2.7%	0.0%
No. conceded, Obs.	29,1158	10,574	7,432	5,338	2,276	1,242	6,232	5,216	2,218	6,188	2,180	1,152	3,140	2,134	2,132	3,118	3,112	0,84
+1																		
Pct. conceded		1.7%	1.1%	1.5%	0.8%	3.0%	1.8%	1.5%	0.6%	3.6%	3.2%	0.0%	0.0%	5.8%	2.3%	1.5%	0.0%	0.0%
No. conceded, Obs.		5,292	3,278	4,266	2,251	7,237	4,223	3,204	1,181	6,166	5,156	0,145	0,141	8,139	3,129	2,138	0,130	0,130
+2																		
Pct. conceded			1.2%	1.7%	0.0%	2.8%	0.7%	2.7%	1.5%	0.0%	2.2%	1.5%	0.0%	0.8%	1.5%	0.0%	0.8%	
No. conceded, Obs.			1,85	2,118	0,147	4,143	1,139	4,146	2,132	0,144	3,136	2,138	0,139	1,122	2,131	0,113	1,121	
+3																		
Pct. conceded				0.0%	0.0%	0.0%	0.0%	1.4%	1.2%	2.2%	1.0%	1.0%	0.0%	0.9%	1.0%	1.9%		
No. conceded, Obs.				0,26	0,33	0,60	0,69	1,73	1,83	2,92	1,97	1,105	0,102	1,106	1,98	2,106		
+4																		
Pct. conceded					0.0%	0.0%	3.7%	0.0%	1.9%	0.0%	3.0%	3.0%	1.6%	1.4%	0.0%			
No. conceded, Obs.					0,10	0,17	1,27	0,38	1,53	0,50	2,66	2,67	1,61	1,70	0,69			
+5																		
Pct. conceded						0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.4%	0.0%				
No. conceded, Obs.						0,1	0,4	0,7	0,17	0,22	0,15	0,28	1,41	0,35				
+6																		
Pct. conceded							0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%					
No. conceded, Obs.							0,1	0,1	0,3	0,9	0,13	0,9	0,12					
+7																		
Pct. conceded								0.0%			20%	0.0%						
No. conceded, Obs.								0,1			1,5	0,7						
+8																		
Pct. conceded									0.0%									
No. conceded, Obs.									0,1									
+9																		
Pct. conceded										0.0%								
No. conceded, Obs.										0,1								
Totals																		
Pct. conceded	2.51%	1.90%	2.07%	1.73%	0.86%	1.55%	1.30%	1.99%	1.47%	2.16%	3.20%	1.13%	2.12%	3.15%	2.74%	3.00%	3.58%	2.84%
No. conceded	29	22	24	20	10	18	15	23	17	25	37	13	24	34	27	25	22	10
Observations	1158	1158	1158	1158	1158	1158	1158	1158	1158	1156	1156	1150	1132	1078	986	834	615	352

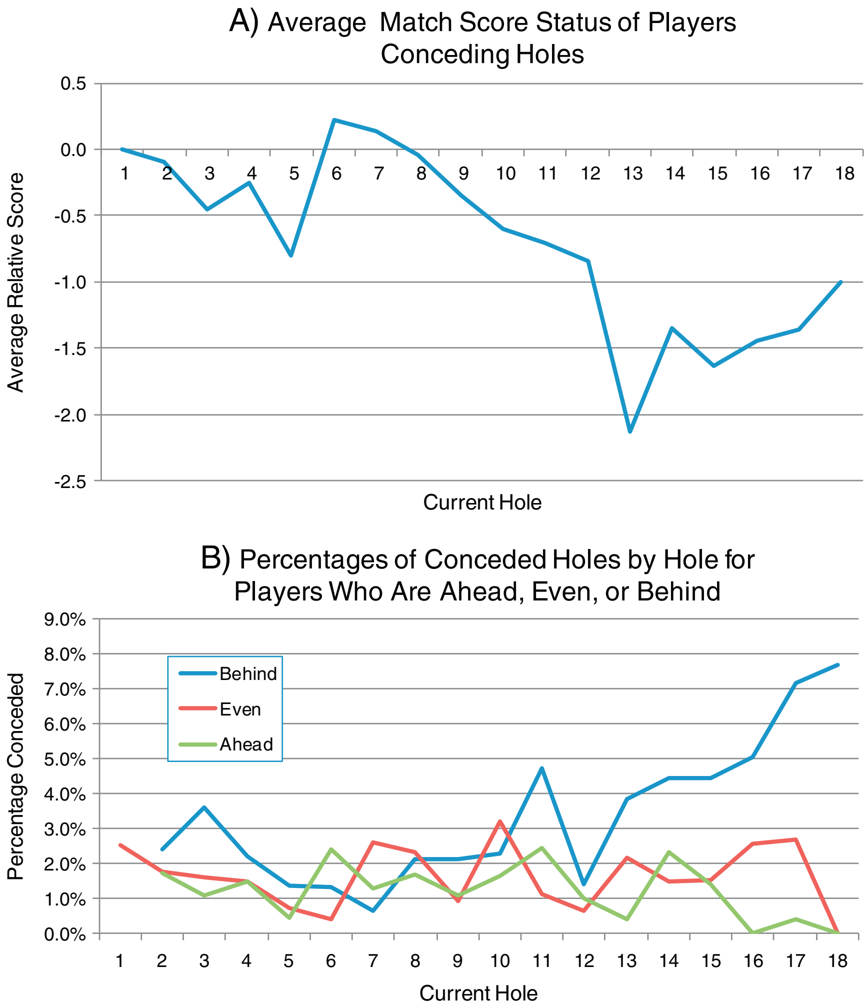

Fig. 1. Evidence of risk taking through percentages of holes conceded. Using raw data on hole scores, panel A shows the average match score status of players conceding holes. Match score is measured as net holes won minus lost as of the start of the hole. As the match progresses the likelihood of the next hole being conceded increases as players fall behind, especially on holes 9–18. Panel B shows the percentages of holes conceded by players who are behind, ahead, or tied in the match, by hole 1–18.

trailing players late in the match, are consistent across all categories of score differences ranging from −/+2 to −/+5 and overall. The magnitude of the effect is generally more pronounced the further ahead is the leading player.[14]

5.2.2. Risk taking by project risk-return attributes

In corporate settings where tournaments determine winners and losers in promotions, the competitors confront challenges, assignments, and projects over time. The theoretical literature suggests that the most able competitors will rise to the top, as indicated by successes over the course of the tournament. However, success (or failure) can also be due to taking risk. Because risk taking is not random and different types of projects offer different risk-return trade-offs, we expect that risk taking will vary across different types of projects.

Table 3 provides a way to evaluate H4 by examining risk taking across three categories of holes that vary in terms of expected return-to-risk payoffs. We classify holes as most difficult, where risk taking is less likely to payoff, or "highest bogie potential holes", those of "moderate difficulty", and holes that are easy, where risk taking is more likely to payoff, or "highest birdie potential". The expected return to taking risk is highest for holes with high birdie potential and is particularly compelling when a player is behind late in the match. To classify holes by difficulty, we rely on the distribution of the observed mean relative-to-par score for each hole across all players for a tournament year, 2003–2013 (a hole-year). The holes with reported scores that are

[14] Results are robust to using an assumed score difference of +1 instead of +2 for conceded holes, in that the differences in standard deviation are the same sign (higher standard deviations for players who are behind) and are significant when the scores of players are most disparate. As noted, the assumption of a +1 score difference for conceded holes is conservative.

Table 2
Performance and risk measures by hole group and match status. The table shows mean relative-to-par score and mean standard deviation of relative-to-par scores for players sorted by cumulative score in the match F-statistics are the ratios of variances of relative-to-par scores for leading and trailing players (holes won–holes lost) through the preceding hole (column 1). Statistics are reported by hole: 1–6, 7–12, or >12. Standard deviations of relative-to-par scores are computed by hole group for each player in each match. For each hole group and match score, statistics are reported for the player who is behind and the player who is ahead. Differences in mean scores and standard deviations are reported for expositional convenience. Cells with only one observation are dropped. F-statistics are tests of differences in standard deviation of relative-to-par scores between leading and trailing players. F-stat: *** = .01; ** = .05; * = .10.

Match score	Holes 1–6				Holes 7–12				Holes >12			
	Players behind	Players ahead	Diff. between	F-stat [p-value]	Players behind	Players ahead	Diff. between	F-stat [p-value]	Players behind	Players ahead	Diff. between	F-stat [p-value]
[−/+7]												
Mean					−0.147	−0.07	−0.077					
Std dev					0.979	0.727	0.251	1.81				
Obs.					13	13		[0.30]				
[−/+6]												
Mean					0.087	−0.136	0.223		−0.194	−0.194	0.000	
Std dev					0.778	0.683	0.095	1.298	0.870	0.576	0.294	2.276
Obs.					36	36		[0.44]	12	12		[0.16]
[−/+5]												
Mean					0.014	−0.105	0.119		−0.045	−0.163	0.118	
Std dev					0.736	0.681	0.054	1.166	0.993	0.713	0.280	1.938
Obs.					93	93		[0.46]	76	76		[0.004] ***
[−/+4]												
Mean	−0.074	−0.074	0.000		−0.029	−0.089	0.060		−0.043	−0.098	0.055	
Std dev	0.616	0.675	−0.060	1.203	0.731	0.744	−0.013	1.036	0.806	0.686	0.121	1.381
Obs.	27	27		[0.64]	301	301		[0.76]	200	200		[0.020] **
[−/+3]												
Mean	−0.044	−0.17	0.126		−0.006	−0.151	0.145		−0.019	−0.111	0.092	
Std dev	0.725	0.642	0.083	1.274	0.696	0.659	0.038	1.117	0.812	0.695	0.117	1.365
Obs.	119	119		[0.18]	519	519		[0.20]	412	412		[0.002] ***
[−/+2]												
Mean	−0.021	−0.026	0.005		−0.074	−0.158	0.084		0	−0.082	0.082	
Std dev	0.685	0.718	−0.033	1.099	0.758	0.722	0.036	1.101	0.773	0.643	0.129	1.442
Obs.	525	525		[0.28]	835	835		[0.16]	629	629		[0.000] ***
[−/+1]												
Mean	−0.046	−0.086	0.040		−0.095	−0.141	0.046		0.017	−0.062	0.079	
Std dev	0.723	0.703	0.020	1.058	0.716	0.722	−0.006	1.015	0.674	0.679	−0.005	1.016
Obs.	1466	1466		[0.28]	1075	1075		[0.80]	808	808		[0.82]
Total												
Mean	−0.040	−0.076	0.036		−0.060	−0.141	0.080		−0.004	−0.085	0.081	
Std dev	0.713	0.703	0.010	1.028	0.729	0.712	0.018	1.051	0.758	0.673	0.085	1.268 ***
Obs.	2137	2137		[0.50]	2872	2872		[0.18]	2137	2137		[0.00]

right skewed are classified as "highest birdie potential hole" so that the mass of the distribution is concentrated on the left; those that are left skewed are classified as "highest bogie potential holes" so that the mass of the distribution is concentrated on the right; the middle difficulty holes are those with normal distributions. We then rank all hole-years by this approach and divide them into the three groups in each year.

For each difference in match score and each type of hole, Table 3 reports the mean score and cross-sectional standard deviation of scores for the players who are ahead versus behind. For each pair of statistics of leading and trailing players, we compute the difference in mean scores and cross-sectional standard deviations and we test the statistical significance of the difference in standard deviation using a variance-ratio test. The results show that for the highest bogie potential holes, there is more risk taking (overall) for players who are behind and that the trailing player generally takes more risk the further behind he is. The effect is even stronger for the high birdie potential holes. While not shown, these results are stronger still in the final holes of the match (as in Table 2).[15]

5.3. Regression analysis by hole group

To more comprehensively study risk taking across holes grouped by order of play, (i.e., hole groups 1–6, 7–12, >12), we estimate the following regression equation:

$$Risk_{ihm} = \alpha + \beta_1\ Rank\ Diff_i + \beta_2\ Higher\ Rank_i * Rank\ Diff_i + \beta_3\ Accum\ \mathrm{Score}_{ih} + \beta_4\ Higher\ Score_i * Accum\ Score_{ih} + \beta_5\ Hole_h + \varepsilon_{ih},$$

[15] Again, results are robust to using alternative assumptions for conceded holes subject to the caveat in note 13.

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Table 3
Performance and risk measures by hole difficulty. The table shows mean relative-to-par score and mean standard deviation of relative-to-par scores for players sorted by cumulative score in the match (holes won–holes lost) through the preceding hole (column 1). Statistics are reported by holes grouped by hole difficulty (easiest–highest birdie potential, moderate, hardest–highest bogie potential), as indicated by mean-relative-to-par score and skewness of the distribution. Standard deviations of relative-to-par scores are computed by hole difficulty group for each player in each match. For each hole difficulty group and match score, statistics are reported for the player who is behind and the player who is ahead. Differences in mean scores and standard deviations are reported for expositional convenience. Cells with only one observation are dropped. F-statistics are tests of differences in standard deviation of relative-to-par scores between leading and trailing player. F-statistics are the ratios of variances of relative-to-par scores between leading and trailing players. F-stat: *** = .01; ** = .05; * = .10.

Match score	Holes 1–6				Holes 7–12				Holes >12			
	Players behind	Players ahead	Diff. between	F-stat [p-value]	Players behind	Players ahead	Diff. between	F-stat [p-value]	Players behind	Players ahead	Diff. between	F-stat [p-value]
[−/+7]												
Mean	−0.416	−0.130	−0.286						0.167	0.000	0.167	
Std dev	1.123	0.846	0.277	1.761					0.753	0.632	0.120	1.417
Obs.	7	7		[0.48]					6	6		[0.68]
[−/+6]												
Mean	−0.333	−0.491	0.158		0.000	−0.375	0.375		0.339	0.244	0.095	
Std dev	0.770	0.688	0.082	1.251	0.535	0.518	0.017	1.067	0.809	0.434	0.375	3.473
Obs.	19	19		[0.64]	8	8		[0.92]	21	21		[0.006]***
[−/+5]												
Mean	−0.312	−0.577	0.264		−0.050	−0.033	−0.017		0.300	0.162	0.138	
Std dev	1.005	0.593	0.412	2.871	0.687	0.612	0.075	1.260	0.766	0.670	0.096	1.305
Obs.	53	53		[0.00]***	59	59		[0.38]	58	58		[0.32]
[−/+4]												
Mean	−0.352	−0.467	0.115		−0.083	0.028	−0.111		0.342	0.223	0.120	
Std dev	0.739	0.712	0.028	1.079	0.535	0.589	−0.053	1.007	0.751	0.632	0.119	1.414
Obs.	200	200		[0.50]	144	144		[0.96]	184	184		[0.02]**
[−/+3]												
Mean	−0.277	−0.443	0.166		0.026	−0.065	0.092		0.213	0.111	0.102	
Std dev	0.801	0.651	0.149	1.511	0.676	0.594	0.082	1.294	0.659	0.631	0.028	1.090
Obs.	373	373		[0.00]***	305	305		[0.02]**	372	372		[0.40]
[−/+2]												
Mean	−0.341	−0.430	0.090		0.024	0.000	0.024		0.188	0.119	0.069	
Std dev	0.763	0.696	0.067	1.201	0.680	0.614	0.066	1.225	0.684	0.653	0.031	1.096
Obs.	664	664		[0.018]**	583	583		[0.014]**	742	742		[0.22]
[−/+1]												
Mean	−0.338	−0.415	0.076		0.027	−0.032	0.059		0.188	0.169	0.020	
Std dev	0.732	0.681	0.051	1.156	0.607	0.628	−0.021	1.072	0.673	0.667	0.006	1.017
Obs.	1166	1166		[0.014]**	1059	1059		[0.26]	1123	1123		[0.78]
Total												
Mean	−0.331	−0.431	0.100		0.017	−0.025	0.042		0.207	0.149	0.057	
Std dev	0.760	0.682	0.078	1.252	0.635	0.616	0.019	1.070	0.684	0.654	0.030	1.096
Obs.	2482	2482		[0.00]***	2158	2158		[0.12]	2506	2506		[0.02]**

where *Risk* is measured as the standard deviation of relative-to-par scores over hole group h, for player i, in match m with a given opponent. *Rank Diff* is the difference in the value of the World Wide Golf ranks between player i and the opponent in the match. As the variable is constructed, the higher ranked (stronger) player in a match has a positive value of *Rank Diff* and the lower ranked (weaker) player has a negative value. *Higher Rank* is a binary indicator variable that takes on the value of 1 for the higher-ranked player in a match. *Higher Rank* ∗ *Rank Diff* is the interaction of *Higher Rank* and *Rank Diff*. As the model is structured, the coefficient on *Rank Diff* measures the partial effect of the weaker player's rank difference on the dependent variable and the coefficient on the interaction with *Higher Rank* measures the difference in partial effects between higher- and lower-ranked players in the match. Summing these two coefficients yields the partial effect of *Rank Diff* for the higher-ranked player. The spline specification of the model allows for a slope difference between higher and lower ranked players but restricts the estimates to be the same at the point where the rank difference between the players is zero.

Accum Score is accumulated match score (net holes won minus lost) for player i at the start of hole h ($h \in H$), and takes on a negative value for the trailing player, a positive value for a leading player, or 0 if the match is even. *Higher Score* is a binary indicator variable that takes on the value of 1 for the player in a match who is leading at the start of the hole. *Higher Score* ∗ *Accum Score* is the interaction between *Higher Score* and *Accum Score*. The coefficient on *Accum Score* measures the partial effect of the weaker player's score on the dependent variable and the coefficient on the interaction with *Higher Score* measures the difference in partial effects between leading and trailing players in the match. *Hole* is the number of the hole, h, that is being played (can take on a value of 1–18+). Here, again, summing these two coefficients yields the partial effect of *Accum Score* for the player who is ahead at the start of the hole.

Table 4 shows the result of four regression models of risk taking by hole group, ranging from early to late in the match. The standard deviation of the relative-to-par score is measured for a player over a group of holes (here ordered by hole order in the match), so that the tests are different than those using hole-specific cross-sectional variations (as in Table 1 and below in the Table 6 regressions, where conceded hole percentage is used as a measure of risk). Panel A results in Table 4 are without player

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Table 4
Risk taking by hole group. Risk taking, the dependent variable, is measured as the standard deviation of relative-to-par score for observed players over the hole group, determined by whether the observation occurs during the first six, second six, or the final holes of a match. *Rank Diff* is the arithmetic difference in the rankings of the two players paired in the match so that the higher ranked (lower-ranked) player has a positive (negative) value. *Higher Rank* is a binary variable that equals one for the higher ranked player. Rankings are from the Official World Golf Ranking, measured just prior to the tournament. *Accum Score* is net holes won minus lost by the player at the start of the hole. *Higher Score* is a binary variable that equals one for the player who is ahead in the match. *Hole* is the number of the hole being played. Models with player fixed effects appear in Panel B. Wald tests of the significance of summed coefficients appear below the regressions. F-stats for robust standard errors: *** = .01;** = .05;* = .10, two-tailed tests.

		All holes (s.d. by group)	Holes 1–6	Holes 7–12	Holes > 12
Panel A: without player fixed effects					
Rank Diff	Coef.	−0.000316**	−0.000255	−0.000721***	0.000187
	p-Value	0.028	0.282	0.001	0.563
Higher Rank * Rank Diff	Coef.	0.001106***	0.000942**	0.001775***	0.000356
	p-Value	0.000	0.019	0.000	0.517
Accum Score	Coef.	−0.01247***	−0.033012***	−0.004598	−0.013071**
	p-Value	0.000	0.000	0.103	0.021
Higher Score * Accum Score	Coef.	0.007061*	0.035594***	0.001903	−0.002993
	p-Value	0.051	0.047	0.674	0.736
Hole	Coef.	−0.001944***	−0.004469**	−0.000059	0.004439*
	p-Value	0.000	0.049	0.975	0.091
Constant	Coef.	0.643367***	0.639037***	0.633591***	0.554483***
	p-Value	0.000	0.000	0.000	0.000
Model F-stat	Prob. > F	0.000***	0.000***	0.004***	0.000***
Number of observations	Obs.	18908	6946	6934	5028
Rank + rank interaction	Sum coef.	0.000791***	0.000687***	0.001054***	0.000542
	p-Value	0.000	0.002	0.000	0.064
Score + score interaction	Sum coef.	−0.005409***	0.002582	−0.002695	−0.016064***
	p-Value	0.006	0.618	0.277	0.000
Panel B: with player fixed effects					
Rank difference	Coef.	−0.000125	0.000234	−0.000922***	0.000683
	p-Value	0.495	0.42	0.000	0.119
Higher Rank * Rank Diff	Coef.	0.001209***	0.000791*	0.001836***	0.000471
	p-Value	0.009	0.071	0	0.467
Accum. Score	Coef.	−0.010265***	−0.031899***	−0.003009	−0.013545**
	p-Value	0.000	0.000	0.290	0.020
Higher Score * Accum Score	Coef.	0.004423	0.031313***	−0.000610	−0.003644
	p-Value	0.227	0.000	0.894	0.681
Hole	Coef.	−0.001819***	−0.003912*	0.000121	0.002672
	p-Value	0.000	0.063	0.945	0.28
Model F-stat	Prob. > F	0.000***	0.000***	0.000***	0.0000***
Number of observations	Obs.	18908	6946	6934	5060
Rank + rank interaction	Sum coef.	0.001084***	0.001025**	0.000914***	0.001153***
	p-Value	0.000	0.000	0.000	0.000
Score + score interaction	Sum coef.	−0.005842***	−0.000586	−0.003618	−0.017189***
	p-Value	0.004	0.908	0.148	0.000

fixed effects and panel B results are with player fixed effects. The four models are measured, respectively, using all observations but with standard deviation measured over hole groups, and using only the observations for hole groups 1–6, 7–12, and >12. Because many players compete in only one year and lose in the first round, the imposition of fixed effects may result in understating the effects of *Rank Diff*. However, excluding fixed effects may incorrectly ascribe erratic play to deliberate risk taking. Because of the use of binary variables and interactions to differentiate between higher and lower rank and score, we use Wald tests to assess the significance of the summed coefficients. The summed coefficients and Wald test p-values appear below the regressions in each panel.

5.3.1. Rank difference and risk taking

To evaluate H1, we consider the relative abilities of the players. The coefficient β_1 measures the impact of rank difference on risk taking (standard deviation of relative-to-par scores) of lower rank players. Because *Rank Diff* is negative for the lower-ranked player, a negative coefficient means that the greater the difference in rank between that player and the opponent, the more risk the weaker player is taking. In the first round, players are seeded by rank so that the highest-ranked players face the lowest-ranked players. For example, in one first round match Tiger Woods, ranked 1, is matched against the player who was ranked 66 at the time, so *Rank Diff* would be −65 for the weaker player and 65 for Woods. The coefficient of −0.000316 over All Holes indicates that (other things equal) the expected increase in risk taking for the weaker player in this pairing is a 0.0205 increase in the standard deviation of relative to par scores. This compares to standard deviation of 0.6871 over all observations (sample statistics not reported), an increase of 3.0%. As shown, given the negative sign across the various categories, weaker players take additional risk on all the holes when paired with higher-ranked players. In the fixed effects models, the coefficient over all holes is weaker and the coefficient estimate varies materially by hole group. However, these results must be interpreted with caution. With fixed effects included, the player fixed effect will fully explain the standard deviation of relative-to-par scores for any player who competes in only one year and loses in the first round. Hence these observations are effectively dropped from the analysis. Thus, many of the observations that are most important for studying the effects of rank differences in matches are effectively dropped and the coefficient estimates based on the remaining observations are likely to be upwardly biased. We can, nonetheless, still compare the effects of rank difference for the higher-ranked player and between the higher- and lower-ranked player in a match.

In a competition against a materially weaker player, one might expect the stronger player to play conservatively and simply rely on the difference in ability. But in the match-play setting, we find evidence of game-theoretic risk taking. The coefficient, β_2, on the interaction of *Higher Rank* with *Rank Diff* is positive and significant in each model except for the last hole group, both without and with fixed effects. More importantly, the summed coefficients of the interaction and that on *Rank Diff* are also positive in all models and the Wald tests are highly significant. The Wald tests indicate that (all else equal) the stronger players actually play riskier strategies when they are paired with weaker players. Returning to the Tiger Woods pairing as an example, the estimated increase in risk taking is 0.0514, an increase of about 7.5% relative to the average. In this comparison, except for the effects of effectively dropping observations of players who only compete once and lose on the first day, the inclusion of fixed effects does not materially affect our conclusions. Thus, the differences in risk taking are not due to differences in player consistency that are correlated with rank.

5.3.2. Match status and risk taking

The results from Table 4 also provide evidence on H2—how match status (a player's lead or lag) affects risk taking. The coefficient, β_3, on *Accum Score* shows the effect on risk for the player who is behind in the match. Consistent with expectations, and with results from Tables 2 and 3, the negative coefficient indicates that risk taking is greater for players who are further behind. Trailing by 3 strokes is associated with a 0.0374 (5.4%) higher level of risk taking. The coefficient, β_4, on *Higher Score* ∗ *Accum Score* shows the difference in risk taking by the player who is ahead relative to the player who is behind. As indicated by the summed coefficients and associated Wald test, especially toward the end of the match, players who are ahead generally take relatively less risk than the players who are behind and play more conservatively as their lead increases. Based on all holes, a player who is up 3 reduces risk by 0.0162 (2.4%) of the average. Based on the hole group results, their tendency to reduce risk appears to be greater later in the match. This could be indicative of an effort to preserve a lead by playing more conservatively as the match nears completion.

5.4. Regression analysis by hole difficulty

Table 5 shows results of the following model, which adds two additional terms to the previous equation:

$$Risk_{ihm} = \alpha + \beta_1\ Rank\ Diff_i + \beta_2\ Higher\ Rank_i * Rank\ Diff_i + \beta_3\ Accum Score_{ih} + \beta_4\ Higher\ Score_i * Accum\ Score_{ih} + \beta_5\ Hole_h + \beta_6\ \text{Accum Score}_{ih} * \text{Hole}_h + \beta_7\ \text{Accum Score}_{ih} * \text{High Score}_i * \text{Hole}_h + \varepsilon_{ih},$$

where the player's standard deviation is measured over holes grouped by difficulty, and all other terms are defined above. Here, because the models are not grouped by order of play, we include interactions of *Hole* with *Accum Score*, and of *Hole* with *Accum Score* and *Higher Score*. The rationale for the regression model in Table 5 is to examine how relative rank, relative score, and match horizon affect risk taking on holes of varying difficulty (H4). We include the interactions of *Hole* with score variables to assess whether risk taking is different later in the match (H3). However, our ability to assess this is limited because the measure of risk taking does not vary hole-by-hole. Rather, it must be measured as the standard deviation over several holes (grouped by hole difficulty). Later, we are able to use the conceded holes data to examine an indication of risk taking by hole.

As shown, as *Rank Diff* increases, the weaker players take more risk, especially on the most difficult (highest bogie potential) holes. This seemingly counterintuitive result indicates that relative rank does not significantly affect risk taking on the easier (highest birdie potential) holes. The players appear to go for birdies no matter with whom they are matched, but when *Rank Diff* is large, the low-ranking players are pressured into taking more risk even on the holes where the expected payoff is low. The corporate analogy would be to a weaker manager taking high risk on bad projects in the hope of a lucky outcome. Based on the summed coefficients, stronger players appear to increase risk taking with greater rank differences on all types of holes.

The score difference results are similar to those in Table 4. The further behind a player is, the more risk he takes, and this is particularly true for the more difficult holes, where the expected payoffs of added risk are low. In contrast, players who are in the lead reduce risk, especially on the relatively safe birdie holes (which result is most evident in the fixed effects models). The propensities of players to vary risk on holes with relatively good or bad expected payoffs have implications for management. In particular, a vulnerable manager might undertake projects that expose the firm to excessive risk. Conversely, a secure manager could avoid risks that might be of long-run value to shareholders.

The full partial effect of accumulated score is more difficult to assess in Table 5 than in Table 4, because of the interactions between *Accum Score* and *Hole*. Based on a three-hole difference in accumulated score, we evaluated the partial effect of the accumulated score at holes 3 and 16. For the trailing player, the increase in risk taking by the trailing player is estimated to be 0.0947 (13.8% of the mean), and at hole sixteen it is estimated to be 0.0433 (6.3% of the mean). Of course the probability of a

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Table 5
Risk taking by hole difficulty. Risk taking, the dependent variable, is measured as the standard deviation in relative-to-par score for observed players over holes grouped by hole difficulty. Difficulty is determined for each tournament-year and is measured by the relative-to-par score on the holes. Highest Birdie Potential Holes are those with the lowest relative-to-par scores (exhibit right skewness) and Highest Bogie Potential holes are those with the highest relative-to-par scores (exhibit left skewness). *Rank Diff* is the arithmetic difference in the rankings of the two players paired in the match so that the higher ranked (lower-ranked) player has a positive (negative) value. *Higher Rank* is a binary variable that equals one for the higher ranked player. Rankings are from the Official World Golf Ranking, measured just prior to the tournament. *Accum Score* is net holes won minus lost by the player at the start of the hole. *Higher Score* is a binary variable that equals one for the player who is ahead in the match. *Hole* is the number of the hole being played. Models with player fixed effects appear in Panel B. Wald tests of the significance of summed coefficients appear below the regressions. F-stats for robust standard errors: *** = .01;** = .05;* = .10, two-tailed tests.

		All holes (s.d. by hole diff)	Highest birdie potential holes	Moderate difficulty holes	Highest bogie potential hole
Panel A: without player fixed effects					
Rank difference	Coef.	−0.000456***	−0.000125	−0.000359	−0.000953***
	p-Value	0.001	0.577	0.143	0.000
Higher Rank * Rank Diff	Coef.	0.001055***	0.001009**	0.000685	0.001547***
	p-Value	0.000	0.011	0.113	0.000
Accum Score	Coef.	−0.035538***	0.000471	−0.041047***	−0.030425***
	p-Value	0.000	0.962	0.000	0.003
Higher Score * Accum Score	Coef.	0.027408***	−0.037525**	0.037531**	0.013111
	p-Value	0.002	0.020	0.013	0.449
Hole	Coef.	0.000936	−0.002938***	0.000090	0.000501
	p-Value	0.119	0.008	0.924	0.697
Accum Score * Hole	Coef.	0.001319**	−0.002134**	0.001988**	0.001126
	p-Value	0.011	0.017	0.028	0.232
Accum. Score * Higher Score * Hole	Coef.	−0.001399*	0.004317***	−0.002081	−0.000526
	p-Value	0.092	0.003	0.140	0.330
Constant	Coef.	0.567572***	0.660734***	0.533420***	0.559075***
	p-Value	0.000	0.000	0.000	0.000
Model F-stat	Prob. > F	0.000***	0.000***	0.000***	0.0000***
Number of observations	Obs.	18940	6337	6185	6350
Rank + rank interaction	Sum coef.	0.000599***	0.000928***	0.000339	0.000644**
	p-Value	0.000	0.000	0.184	0.016
Score + score interaction	Sum coef.	−0.008130	−0.029118***	−0.005974	−0.014230*
	p-Value	0.1536	0.000	0.724	0.095
Score * Hole + Score * High Score * Hole	Sum coef.	−0.000080	0.001517**	0.000130	0.000369
	p-Value	0.876	0.014	0.918	0.524
Panel B: with player fixed effects					
Rank Difference	Coef.	−0.000635***	0.000030	−0.000988***	−0.000967***
	p-Value	0.000	0.912	0.001	0.001
Higher Rank * Rank Diff	Coef.	0.001421***	0.000555	0.001922***	0.001847***
	p-Value	0.000	0.194	0.000	0.000
Accum Score	Coef.	−0.031926***	−0.004493	−0.032388***	−0.025325**
	p-Value	0.000	0.633	0.001	0.011
Higher Score * Accum Score	Coef.	0.022199**	−0.033894**	0.027651**	0.011782
	p-Value	0.013	0.027	0.049	0.474
Hole	Coef.	0.000679	−0.001759*	−0.000418	0.000069
	p-Value	0.250	0.091	0.634	0.955
Accum Score * Hole	Coef.	0.001100	−0.001294	0.001254	0.000737
	p-Value	0.030	0.126	0.136	0.410
Accum Score * Higher Score * Hole	Coef.	−0.000938	0.003364**	−0.001101	−0.000261
	p-Value	0.249	0.016	0.398	0.862
Model F-stat	Prob. > F	0.000***	0.000***	0.000***	0.000***
Number of observations	Obs.	18940	6337	6185	6350
Rank + rank interaction	Sum coef.	0.000786***	0.000641**	0.000962***	0.000933***
	p-Value	0.000	0.015	0.000	0.001
Score + score interaction	Sum coef.	−0.009727*	−0.032486***	−0.006374	−0.010808
	p-Value	0.0831	0.000	0.608	0.170
Score * Hole + Score * High Score * Hole	Sum coef.	0.000163	0.001566**	0.000278	0.000252
	p-Value	0.747	0.014	0.855	0.595

player being behind by three is much greater later in the match, so the appearance of declining risk taking later in the match is most likely to be an indication that there are practical limits on the ability to increase risk. A player who is behind by nine after nine holes, for example, probably cannot realistically increase risk much more than a player who is behind by three could. For the player who is leading, we find significant evidence that risk taking varies by how many holes are remaining, except on birdie holes (where the player takes somewhat higher risk later in the match). Rather, the important driver of risk taking for this player is the lead, which results in more conservative play.[16]

[16] We ran the regressions with alternative assumptions for conceded holes; the results are strengthened for the +3 assumption, but for the (too conservative) +1 assumption, some of the coefficients become less significant.

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Table 6
Conceded holes—risk taking by hole group. The dependent variable is a binary variable that equals one if a player concedes the hole. *Rank Diff* is the arithmetic difference in the rankings of the two players paired in the match so that the higher ranked (lower-ranked) player has a positive (negative) value. *Higher Rank* is a binary variable that equals one for the higher ranked player. Rankings are from the Official World Golf Ranking, measured just prior to the tournament. *Accum Score* is net holes won minus lost by the player at the start of the hole. *Higher Score* is a binary variable that equals one for the player who is ahead in the match. Hole is the number of the hole being played. Models with player fixed effects appear in Panel B. Wald tests of the significance of summed coefficients appear below the regressions. F-stats for robust standard errors: *** = .01;** = .05;* = .10, two-tailed tests.

		All holes	Holes 1–6	Holes 7–12	Holes >12
Panel A: without player fixed effects					
Rank difference	Coef.	−0.000170**	−0.000263**	−0.000076	−0.000174
	p-Value	0.015	0.014	0.494	0.264
Higher Rank * Rank Diff	Coef.	0.000198	0.000300	0.000047	0.000279
	p-Value	0.109	0.114	0.809	0.308
Accum Score	Coef.	0.013936***	−0.013351*	0.017845**	0.077484***
	p-Value	0.000	0.099	0.032	0.000
Higher Score * Accum Score	Coef.	−0.017343***	0.003369	−0.028084**	−0.076998**
	p-Value	0.000	0.782	0.047	0.024
Hole	Coef.	−0.000398	−0.002492**	−0.001548	−0.000791
	p-Value	0.186	0.044	0.326	0.687
Accum Score * Hole	Coef.	−0.001849***	0.002120	−0.001963**	−0.006476***
	p-Value	0.000	0.208	0.018	0.000
Accum Score * Higher Score * Hole	Coef.	0.002015***	−0.000051	0.002882**	0.006361***
	p-Value	0.000	0.984	0.041	0.007
Constant	Coef.	0.019008***	0.020814***	0.032848**	0.021414
	p-Value	0.000	0.000	0.032	0.482
Model F-stat	Prob. > F	0.000***	0.006***	0.084*	0.0000***
Number of observations	Obs.	18962	6946	6934	5082
Rank + rank interaction	Sum coef.	0.000028	0.000036	−0.000029	0.000106
	p-Value	0.692	0.735	0.795	0.497
Score + score interaction	Sum coef.	−0.003407	−0.009982	−0.010239	0.000486
	p-Value	0.236	0.217	0.217	0.981
Score * Hole + Score * High Score * Hole	Sum coef.	0.000166	0.002070	0.000919	−0.000114
	p-Value	0.522	0.219	0.267	0.937
Panel B: with player fixed effects					
Rank Difference	Coef.	−0.000044	0.000000	0.000002	−0.000166
	p-Value	0.652	1.000	0.989	0.411
Higher Rank * Rank Diff	Coef.	0.000054	−0.000076	−0.000016	0.000354
	p-Value	0.705	0.728	0.942	0.265
Accum Score	Coef.	0.017166***	−0.011480	0.016535**	0.095965***
	p-Value	0.000	0.158	0.045	0.000
Higher Score * Accum Score	Coef.	−0.020513***	0.003054	−0.025748*	−0.099524***
	p-Value	0.000	0.802	0.066	0.004
Hole	Coef.	−0.000407	−0.001691	−0.001095	−0.001482
	p-Value	0.178	0.171	0.481	0.455
Accum Score * Hole	Coef.	−0.002018***	0.002584	−0.001637**	−0.007787***
	p-Value	0.000	0.125	0.046	0.000
Accum Score * Higher Score * Hole	Coef.	0.002227***	−0.000993	0.002491*	0.008037***
	p-Value	0.000	0.698	0.075	0.001
Model F-stat	Prob. > F	0.000***	0.000***	0.000***	0.000***
Number of observations	Obs.	18962	6946	6934	5082
Rank + rank interaction	Sum coef.	0.000010	−0.000076	−0.000014	0.000188
	p-Value	0.901	0.536	0.910	0.291
Score + score interaction	Sum coef.	−0.003347	−0.008426	−0.009212	−0.003559
	p-Value	0.247	0.299	0.261	0.866
Score * Hole + Score * High Score * Hole	Sum coef.	0.000210	0.001591	0.000854	0.000250
	p-Value	0.420	0.344	0.295	0.864

5.5. Conceded holes by rank difference and hole difficulty

As noted, it is difficult to assess the importance of proximity to the end of the round when risk taking must be measured as the standard deviation of results over several holes, as in the prior two tables. The conceded holes data, in contrast, enables us to examine hole-specific risk taking and also provides a different perspective on risk taking associated with rank differences and score differences. Table 6 uses the same set of explanatory variables as does Table 5, but is focused on the occurrence of a conceded hole as an indication of risk taking.[17] Because the dependent variable is hole-specific, we are able to examine risk taking over holes grouped by order. For *Rank Diff* there is some indication that in the early holes of the match, the lower-ranked player

[17] Table 6 is estimated with linear probability models because of the highly unbalanced sample. When we fit a probit model to all of the data, the coefficients and significance levels are similar to those reported in Table 5, but for subsamples of the data, the maximum likelihood function in probit does not always converge.

takes more risk the greater the difference in rank. This becomes non-significant later in the round, as should be expected. Later in the round, score difference is expected to be more important than rank difference. The coefficient on *Rank Diff* for holes 1–6 indicates that in the previously mentioned match of Tiger Woods with a much lower-ranked player, the increase in risk taking by the weaker player would be 1.71 percentage points. This coefficient, however, is not significant in the fixed-effects model.

With regard to conceded holes, the trailing player takes additional risk, especially later in the round. This is hard to see because the coefficient on *Accum Score* is positive and that on the interaction with hole is negative. Evaluating the full partial effect as of the start of hole 16, based on the model for all holes, a player who is behind by 3 with only a 3 holes remaining increases the conceded hole probability by 4.7 percentage points. The result is similar in the fixed effects models. Interestingly, the leading player's risk taking by this measure is not sensitive to relative score or holes remaining.

We also examined conceded holes by hole difficulty. Results (not reported) are similar to those in Table 5. Lower ranked players are more likely to concede difficult (bogie) holes, as are higher ranked players, but to a lesser extent. We find the same complexity related to accumulated scores, indicating higher probabilities of conceding when a player is behind late in the match.

5.6. Summary of results and additional robustness tests

We demonstrate that risk taking is affected by the relative abilities of competitors, player lead or lag, match horizon, and the difficulty of the task. The findings support our four hypotheses that are focused on trailing players and players who are lower ranked than their opponents. Players who are trailing take more risk. The result holds whether risk is measured as percent of holes conceded or as the cross-sectional standard deviation of relative-to-par score. In regressions of standard deviation over hole groups, lagging players take more risk the further behind they are. Also, lower-ranked players take more risk as the relative strength of their opponent increases except near the end of the match, where relative score is likely to be more important. In regressions on conceded holes, relative rank is an important determinant of risk taking early in the match but becomes less important than score difference as the match progresses.

No previous study has directly examined the effects of project difficulty in settings where competitors undertake identical projects or tasks that comprise a tournament (i.e. identical golf holes). We find that lower ranked and trailing players take more risk on difficult holes (those holes with left-skewed score distributions that are the high bogie potential holes), the further behind they are and the closer to the end of the match. Lower ranked and trailing players appear to go for birdies (those holes with right-skewed score distributions) no matter with whom they are matched.

Contrary to the notion that the winning strategy for high-ability players is to play conservatively and wait for the opponent to make mistakes, our results show that higher-ranked players take more risk on both highest birdie and highest bogie potential holes the greater the difference in ranking relative to their opponents. Leading players, however, take less risk generally and play more conservatively as their lead increases.[18]

As additional robustness checks, we ran regressions in Tables 4–6, including both player and year fixed effects together. Results are not materially different from those reported. First-round matches are more likely to be those where the rank difference is largest due to non-random seeding. While these matches provide the greatest opportunity to study rank difference, we nonetheless tested sensitivity of results to dropping them. In Tables 4 and 5 models, *Rank Diff* sometimes loses significance, but this appears to be due to the lower power associated with the much lower sample size. Results in Table 6 are similar to those reported. Given that the participants in the tournament are the top 64 players in the world and everyone invited to the tournament generally accepts the invitation to play, there is no self-selection problem and the full-sample results are more meaningful.

We also considered order of play as a potential explanatory variable. The ShotLink database does not include shot-by-shot data for the Accenture tournament, but we can determine which player tees off first on each hole. Inclusion of a binary variable indicating which player in the match tees off first, however, does not affect the results in any material way.

Finally, we considered whether the presence of a “superstar” affects match play. We follow Brown (2011) and identify Tiger Woods as the dominant player during the tournament years of our study. As stated above, Brown finds an adverse performance effect (higher scoring) for players, especially the top players, when Woods is in the field. We re-ran the regressions in Tables 4–6, leaving out matches of players who are paired with Woods and the results are not affected. The results are also robust to leaving out the two years (2010, 2011) when Woods chose not to compete in the tournament.

6. Discussion

Most studies of tournament focus on effort and the design of incentive structures to elicit maximum effort. But if competitors can choose both effort and risk, then it can be difficult to distinguish the two when looking at outcomes. In this paper we focus on risk taking and the conditions that elicit it, and we identify some interesting patterns. The findings are useful for thinking about small numbers competition in corporate settings like corporate promotion tournaments or bidding contests between firms (e.g., Airbus and Boeing) R&D races, competitions to select architectural designs, etc. Match play data from professional golf tournaments provides a simple framework for imposing *ceteris paribus* conditions so that we can more convincingly isolate the features of tournaments that influence risk taking.

[18] A possible extension would be to analyze how risk-taking behavior differs in match play, where each hole is a separate winner-takes-all contest, vs. stroke play, where the cumulative score on holes is what matters and the competition is the entire field of players.

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By helping to identify attributes of the competition that can lead to behavior that firms may want to monitor, the findings have managerial implications for organizations that establish competitions among employees or suppliers. For example, the results suggest that competitors with lower ability, or those who fall behind quickly, may take on more risk and be more inclined to increase risk on difficult projects (those with low expected returns to risk taking). If these types of conditions are identifiable early on, then the overseers of the organization can monitor and perhaps influence the decision making and actions of competitors to align with organizational objectives. Moreover, if deliberate risk taking is unobservable, then to assure a good outcome, tournament features should be designed to limit the ability of competitors to affect outcomes through their risk taking choices. Other implications include that the value of monitoring laggards increases as the tournament nears an end and where there appears to be a clear leader. The findings also suggest that adjusting the convexity of payoffs to flatten the reward structure can modify risk taking by competitors.

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