Risk-Taking Dynamics in Tournaments: Evidence from Professional Golf

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Abstract

We use a unique dataset comprised of observations from ten years of professional golf tournaments to analyze golfers' risk-taking strategies. We focus on analyzing the decisions golfers made when hitting their second shots on par five holes, a shot that often forces golfers to play daringly or conservatively, with little in between. Successful gambles often lead to profitable outcomes when executed well, but leave golfers open to tail-end risks for poorly struck shots. Our analysis yields three interesting findings, all of which are closely related to previous studies of strategic risk. First, the strategies golfers adopt hew closely to the way economic agents in other settings cope with uncertainty. Second, golfers' decisions are dynamic throughout tournaments, especially when playing relatively well early in a tournament and near the halfway mark of a tournament when the worst-performing half of the field is cut. We use regression discontinuity tools to show meaningful differences between the decisions made by golfers on either side of the cut score. Last, we argue golfers' willingness to take risks was affected by Superstar Tiger Woods, a finding that suggests a strategic component of the Superstar Effect needs to be considered alongside the effort component, as discussed in Brown (2011).

Keywords: Risk Strategies, Tournaments, Superstar Effect

JEL: D4, D81, Z2

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I. Introduction

The incentive effects provided by tournaments are an often-studied topic, and the overwhelming dimension of interest in these studies is effort. Beginning with pioneering applied studies like Ehrenberg and Bognanno (1990a, b), a number of important studies have provided strong evidence in support of the theoretical propositions discussed in Lazear and Rosen (1981). In this paper, we use a dataset from the professional golf world that has many unique properties to study strategic decisions, an often difficult metric to contemplate analytically because of constraints that affect data collection.

Studies of sporting contests often allow for highly controlled settings that enable accurately measured choices. In this spirit, we utilize data on a particular type of decision professional golfers face in nearly every competitive round they play – the decision of how much risk to take with their second shots on par five holes.[2] This commonly made and often-critical decision forces golfers to consider the returns from hitting a longer second shot, a high-risk, high-reward strategy, or playing a shorter, more conservative, "lay-up" shot.[3] If executed correctly, a good, risky second shot to a par five green can give a golfer a leg up on his competition, an action that increases the chances of a golfer receiving a valuable remunerative reward for strong relative performance in the tournament.

[2] On page 1323 of Ehrenberg and Bognanno (1990a), the authors presage studies of this sort by writing, "Players can also choose conservative or risky strategies, and, depending on a player's ability to the rest of the field or his rank after each round, different strategies may be pursued. Models that also included the choice of strategies that differ in risk undoubtedly would yield additional empirical implications."

[3] Each golfer faces the same optimal decision on the first shot; hit the ball as far as they can while staying in play for their second shot. To the extent that ability, distance of first shot, and where they land their first shot matters, these are controlled for in this study – thus allowing us to focus on the risky decision of the second shot itself.

To conduct this study, we use the extraordinary ShotLink database, which uses geospatial technology to track precisely golfers' on-course locations during tournaments, to test golfers' risk choices on these particular shots and present three major findings. First, we analyze the extent to which golfers' decisions align with previous studies of risk taking. We show that the likelihood of golfers taking a riskier shot increases as their ranking in a tournament improves and that golfers become more conservative when faced with conditions that enhance the uncertainty surrounding their decisions, such as the weather or severity of the on-course hazards they faced worsened on a particular shot. Our findings align with previous studies of competitors' behavior in tournaments that have a rank-order feature. Studies like Chevalier and Ellison (1997), Mago, Sheremata, and Yates (2013), and Adams and Waddell (2018) show agents' decisions in tournaments change with their relative standing in a tournament and at various junctures of a tournament and comport with the general consensus on the way uncertainty impacts risk taking. Though we analyze decision making at all stages of golf tournaments, we pay particular attention to the second round of PGA Tour tournaments, after which the tournament field is cut by slightly over half. We use regression discontinuity techniques to show that golfers on the immediately wrong side of the cut line are about two percentage points more likely to take on risky behavior compared to their better-performing competitors, who have performed just well enough not to be cut from the field.

We close the paper by considering more closely a strategic dimension for the Superstar Effect that goes beyond the discussion in Brown (2011). Like that study, we consider tournaments with and without the incomparable Tiger Woods, but our dataset spans seasons before and after his sex scandal, which robbed him of his supernatural golfing powers (and conveniently for us, occurred after the 2009 season was over).[4] We find that before his public embarrassment, golfers in the tournaments he entered did not change their risk-taking behavior relative to other tournaments, which supports the conclusion of Brown. However, we find that after his public embarrassment there is evidence of a significant difference in the levels of risks golfers take in tournaments with and without Woods. Thus, there is evidence that golfers that had to face the Superstar version of Woods were exhibiting both strategic decisions as well as effort choices, the implications of which we discuss.

This paper is divided into four other sections. The second section discusses risk taking in golf and presents a simple model of second shot decisions. The third section describes the data and the model we employ to analyze golfers' decisions. The fourth section presents the three sets of results that comprise our findings. The final section offers concluding remarks.

II. Risk in Golf

Most excellent professional golfers have developed the ability to gauge when it is best for them to adopt appropriately risky strategies and, often, follow through on their decision with their incredible physical gifts. In this section we describe the particular decision that we study in this paper and the decision professional golfers of all qualities face in nearly every round: the decision of what to do with their second shot on par five holes.

Golf courses that host professional events consist of 18 holes, which vary by length and par value, a measure of the number of strokes a high-caliber player should take to complete the hole. Par-five holes, the type of hole of interest to this paper, are generally the longest holes on a golf course, with par-three holes being the shortest type of hole. Golfers start all holes by hitting a shot from the tee box, a well-manicured area on which it is legal for golfers to improve the

[4] Woods was named PGA Tour Player of the Year 10 times, between 1997 and 2009, the last full season he played prior to his extramarital affairs unwinding his life. Since then, he has only won the award once, in 2013.

conditions from which they strike the shot by using a short wooden peg called a tee. Par-three holes are designed such that the golfer is supposed to reach the green, the part of the hole where the actual hole is located, with his tee shot and then take two putts to complete the hole in par. Par-four and par-five holes are designed such that the golfer hits a long shot from the tee, often with a club called a driver, which is designed to launch the ball further than other clubs the golfer might carry.[5] On par four holes, golfers' second shots are expected to reach the green, where they should take two putts to complete the hole in par.

[Table 1]

Following this pattern, par five holes are designed such that the second shot is played short of the green, which sets the stage for a short third shot to the green. However, professional golfers tend to be able to hit a golf ball a very long way, and this often leads to them facing the option of attempting to reach the green with their second shot. The benefit of this decision is that with a successful, aggressive second shot the golfer stands an increased chance to make a relatively low score on the hole, thereby helping him gain ground over his competition, a must-do for those wanting to be successful in the rank-order tournaments that define professional golf.

As seen in Table 1, going for it leads to a lower average score compared to the average score when an alternative, conservative strategy is used, but the risky option has a higher standard deviation in most instances. Often golfers face high-risk, high-reward outcomes when they go for the green. This trade-off exists because a golfer loses some control over the direction of a second shot that must be hit a long way. Attempting to reach the green in two shots opens

[5] *The Rules of Golf* stipulate that golfers can use up to 14 clubs in a competitive round (These clubs vary by length to leverage imparted changes positively with length and the angle of the club face - the part of the club that strikes the ball to the ground where launch angle varies with this characteristic). Golfers can hit a driver the furthest of all clubs because they can impart the most leverage with the lowest launch angle with this club compared to the other clubs, which are shorter and launch the ball higher after impact.

the golfer to the possibility of a relatively low or high score on a hole, depending on the success of that second shot.[6] Laying up is the more conservative strategy, and it eliminates tail-end risks but at the cost of perhaps making it more difficult to earn a relatively low score and gain ground on the competition.

Of course, professional golfers play for prize money, so the efficacy of their risk strategies affects the money they earn in an event. In this study, we use data from ten seasons of play on the Professional Golf Association (PGA) Tour (2004-2013), which uses the same payout structure for all of the tournaments that comprise the dataset. As has been discussed in many previous studies of professional golf (e.g. Ehrenberg and Bognanno,1990a, b or McFall, Knoeber, and Thurman, 2009), the prize structure in PGA Tour events is highly nonlinear, which means small advantages over the course of a tournament can lead to large increases in compensation. Given that the PGA Tour rewards golfers for their relative performance, a golfer who posts a lower score on a par five hole increases his chances for a bigger prize at the end of the tournament.[7] Given this prize structure, the successful execution of a risky second shot can boost a golfer's earnings quickly.

The best professional golfers thrive on par five holes. Long hitters, like Tiger Woods in the prime of his career, had many opportunities to play smart, aggressive second shots into par five greens, thereby gaining strokes on the competition. But golfers who favor a safer approach to playing the game (Jim Furyk, for instance) also have played par five holes well in their most successful seasons. Table 2 illustrates the strong relationship between golfers' earnings and their

[6] Well-designed par five holes force golfers to deal with extreme temptation on the second shot. A successful second shot could lead to a low score for the hole. However, a small hiccup on the hole can ruin a tournament. Of course, the more harrowing the shot, the more exciting it is for fans to watch golfers attempt risky gambits.
[7] The purses for many tournaments were over $6 million in the 2013 season. See http://www.sbnation.com/golf/2015/8/16/9162213/2015-pga-championship-prize-money-purse-payout for a description of the way prize money is distributed in PGA Tour events.

performances on par five holes. The table lists the leading money winners for each season from 2004 to 2013 and those golfers' absolute and relative performances on par five holes during those seasons. In those ten years, only one golfer, Luke Donald, managed to top the annually calculated money earnings list while performing outside of the top five golfers on par five holes. [Table 2]

We view golfers' decisions over these second shots as an example of agents deciding between the marginal value of a risk against the expected return from their alternative lay-up strategy. The size of the value of adopting a risky strategy varies across golfers, who have different strengths and weaknesses, and holes, which have different design characteristics that may heighten the risk golfers face. To model golfers' second-shot decisions, we assume a golfer wants to adopt a level of risk that enables him to maximize the value of the score he earns on a hole, which he does by minimizing the number of strokes he takes to complete the hole. We view the level of risk that a golfer chooses for his second shot as being chiefly a function of the distance he must cover in order for a second shot to be successful, with the aforementioned factors shifting the quantity of risk faced.[8] We assume that the marginal cost of risk increases at an increasing rate with the distance a shot must traverse because the choice of heightened aggressiveness means the golfer has less and less control over the ball.

The data we use in this study allows us to observe several circumstances in which the value of a second-shot risk shifted. Perhaps most influential of these circumstances is a golfers' position in the tournament standings at the time of a decision. The closer a golfer is to the top of

[8] Aggressiveness in this context relates to how far a golfer wants to hit the ball with his second shot. To hit a ball a longer distance, a golfer needs to select a club that is more unwieldy to use (a 3-wood, say) compared to a club used to hit a shot a shorter distance (a pitching wedge, for instance). Therefore, we can view golfers moving along their marginal cost curve the further they wish to hit the ball.
We contrast this view of aggressiveness with one in which a golfer simply swings harder in order to get the ball to go longer distances.

the tournament standings, the more and more valuable a successful second shot becomes, thereby increasing the value of risk at all distances to the hole. Similarly, the design of a hole can vary the cost of a penalty for the loss of control of an aggressive play. We also incorporate information maps of tournament courses to identify holes on which golfers faced water or sand-filled bunkers on a second-shot decision. Also, golfers have different strengths and weaknesses when it comes to golfing skills, such as putting, power, and playing from sand. Depending on the golfers' relative skill-sets the cost of each unit of risk can vary by the golfer. Additionally, the conditions of the shot itself can change the cost of aggression. For instance, the type of on-course environment upon which the ball rests can affect tremendously a golfers' ability to control a shot, as do the weather conditions that prevail at the time a shot was struck.[9] Finally, as Brown (2011) shows, the addition of superstars in a field (Tiger Woods, in the case of that study) can affect a golfer's performance and implicitly their choice of risk.

Because the difference in the distance an aggressive or conservative second shot must travel is large, we view the level of risk a golfer adopts on the second shot as a choice between a relatively high or low level of risk (r_h or r_l), a view that is similar to models of choices made in some contract decisions (Laffont and Martimort, 2002). A golfer choosing to attempt to reach the green requires an adoption of a high level of risk, and to play these risky shots, he must estimate four key values to arrive at an optimal level of risk. These values are 1) the probability of hitting a successful risky second shot, 2) the value of the score they believe they will earn given a successful risky second shot, 3) the value of the score they will earn given an unsuccessful risky

[9] The density of air increases with humidity. This increased density causes the ball to travel reduced distances because the ball meets more resistance compared to flying in drier conditions. Wind is a golfer's worst enemy, especially when gusty conditions prevail. Small deviations in wind speed can impact a ball's trajectory in enormous ways.

second shot, and 4) the value of the score they estimate they will earn if they play with a low level of risk, the golfer's reference value for the hole.

Let the probability of playing a successful second shot, given a high level of risk, r_h, be Prob(success|r_h), which falls at an increasing rate with the size of r_h. Let V[E(score|r_h)] be the weighted average of a golfer's score given his perceived likelihood of striking a shot successfully with a relatively high level of risk. Finally, define ΔV = V[E(score|r_h)] - V[E(score|r_l)], where r_l represent occasions in which golfers choose a low level of risk. When $\Delta V = 0$, we assert a risk neutral golfer is indifferent between going for the green and laying up.

Equation 1 shows our view of a golfer's second-shot decision:

$$V[E(score|r_h)] = Prob(r_h)(V(E(score|success)) + (1\text{-}Prob(r_h))(V(E(score|unsuccessful))$$
$$= V(E(score|unsuccessful) + Prob(r_h)(\Delta V_h) \qquad (1),$$

where ΔV_h = V(E(score|success)) – V(E(score|unsuccessful) is the risk premium the golfer faces over the second shot. The size of these values change with the exogenous risk shifters that we previously discussed, thus constantly altering the amount of risk a golfer chooses to take on with every shot.

III. Data and Methods

The ShotLink database allows us to observe aspects of nearly every shot taken on the PGA Tour. Second shots on par-five holes are our main interest in this study, and ShotLink contains fields that show the distance from the hole a golfer was when he struck such a shot, thereby allowing us to measure movements along a marginal cost and marginal benefit of risk curves. We can measure shifts in these curves because ShotLink allows us to observe the environment from which a second shot was struck (fairway, which is the environment from which it is easiest to control a second shot, rough, or sand). We also calculate measures of golfers' skill sets with golfer-specific characteristics within different facets of the game. These skill sets include: how far a golfer can hit a ball (driving distance), how accurately a golfer can hit a ball (driving accuracy and a number of measures on iron and wedge play), and the quality of a golfers' short game (shots taken near or on the green, which include pitching, chipping, and putting). With these measures, we capture risk shifts across golfers who are in the same position relative to a hole but view differently the situation because of their relative strengths. Finally, we merged weather data for each day and location of competition and, for each hole in the dataset, we coded different hazards, like bunkers or water, that the golfers faced when contemplating their second shots. The addition of these variables make this dataset unique in the annals of applied economics work on golf tournaments.

A critical aspect to this study is the extent to which we can accurately determine the strategy a golfer employed for his second shot. Unfortunately, ShotLink does not provide information on golfers' intentions. If it did, we would anticipate a binomial variable that would be turned on when a golfer attempted to reach a green with his second shot and remain off otherwise. In lieu of this variable, we must analyze the data to determine which avenue golfers took when they made their second-shot strategy choices.

The method we employ to discern between strategies is to first identify second shots taken on par five holes that ended on the green, for these were obviously the product of a risky decision. Then, we use a subjective field in the ShotLink database called *around the green,* which is set to one when a shot finishes around the green (but not on the green) and zero, otherwise. Finally, we count as risky attempts the shots that ended in hazards (areas like water or off the course) near the green that required golfers to be penalized prior to striking their next shot. This last step allows for us to accurately measure when a golfer takes the risky second shot, because without the third step we would be overcounting non-risky attempts, which would bias our results.

As a final layer of insurance toward generating accurate data, we also check the results we generated using our definition of “around the green” against different definitions of shots near the green. Specifically, we identify shots that ended inside of separate circles of 30 and 40 yards from the hole and add to these shots the aforementioned wayward shots that required penalties. The results we generate with these different ways of identifying risky strategies are consistent with the method that uses the *around the green* variable. Thus, below we only report results using *around the green* for brevity, as these results are robust across counting methods.[10]

[Table 3]

In total, we analyze ten seasons of data in this study (2004-2013). Table 3 displays some useful statistics regarding the par five holes that comprise the dataset. The dataset contains 376 tournaments in total, with 4,116 par five holes played across 1,506 tournament rounds. The average score on a par five holes in these tournaments is 4.69 shots per hole. The hardest hole was the 2011 version of the 14th hole at Pebble Beach Golf Links. The easiest hole was the first hole at Trump National Doral in 2009.[11] There were five occasions in which a golfer scored a two on a par five (a very rare albatross, in golf lexicon) and one occasion in which a 13 was carded.

Our baseline regression model is equation 2:

$$\Pr(Go-for-it)_{ijt} = \beta_0 + \beta_1 Yards-to-Pin_{ijt} + \beta_2 Yards-to-Pin_{ijt}^2 +$$

[10] More than 40% of the shots are listed as “around the green” in the ShotLink dataset. We also include any shots that landed on the green or in the water/had a penalty involved, as these shots did not end around the green and would not have been characterized as such. We believe that these mishits suggest that a golfer attempted to reach the green and failed spectacularly at it. See Table A1 in the appendix to see how our definition of “around the green” changes with extra interpretations of the evidence presented in ShotLink.

[11] The first hole at Doral has since been re-designed. It is no longer the pushover that it once was.

$$+\beta_3 Purse_t + \beta_4 TRank_{ijt} + \beta_5 TRank_{ijt}^2 + \beta_6 Purse * TRank_{ijt} + \beta_7 (Purse * TRank)_{ijt}^2 +$$

$$\Gamma \ N_i + \Theta \ S_{ijt} + \Phi \ Year_t + \varepsilon_{ijt} \qquad (2)$$

The left-hand variable measures the likelihood of golfer i attempting to reach the green with his second shot while playing hole j of tournament t. This variable takes on a value of one when a golfer attempts to reach the green with his second shot (go-for-it) and zero otherwise. Because we view the distance a golfer has to traverse as being an important variable for capturing the amount a golfer can forecast the way a shot will turn out, $yards\text{-}to\text{-}pin_{ijkt}$ and $yards\text{-}to\text{-}pin^2_{ijkt}$ allow us to control for movements along golfers' benefit and cost of risk curves. We expect the likelihood of a gamble to fall with distance.

Other observable fields within ShotLink allow us to estimate a golfer's tournament ranking when he made a second-shot decision, which is valuable because the allocation of tournament purses are based on relative performance and rewarded in an invariant method across tournaments. We can gain a measure of the value of a risk by interacting tournament ranking with the size of the purse. As golfers' relative standing in a tournament improves, the size of the benefits and costs of any risk they take grow exponentially, given the non-linear way prizes are distributed in PGA Tour events. We capture these effects with $Purse_t$, $TRank_{ijt}$, and interactions of those two variables.

The other controls change the benefit and cost of risk at all yardage levels and vary across each golfer and time. The N-vector controls for golfer-specific characteristics such as their ability to manage various parts of the sport, including hitting the ball long distances, hitting the ball accurately, and putting. The S-vector controls, many of which are unique to empirical research conducted on golf, account for shot-specific characteristics like the weather faced over a shot, the on-course environment from which a shot was struck (fairway, rough, or sand, for instance), which can increase the uncertainty of a risk given that the golfer's ability to control the ball changes, and the hazards arrayed around the green (water or bunkers) to which the golfer was deciding to attempt to reach with his second shot. We also control for yearly fixed effects, captured in the Y-vector, to hold constant technology changes that have occurred in golf. Finally, we assume the error term, ε_{ijkt}, to be mean zero but not i.i.d. Golfers face an array of obstacles on each hole that are largely unobservable to us, so we use standard errors that are clustered at the hole level.

[Table 4]

In Table 4 we list the summary statistics of variables of interest limited to the golfers that were 175 to 275 yards from the hole before the second short (the data our sample is limited to). The mean distance from the pin is 242.5 yards, so most of these golfers are far enough from the hole that they are making the conscious decision to go for it on the second shot. In these tournaments the players are ranked between 1 and 180, with the average at 47.5 (there are observations after the cut that limit the sample to the highest ranked golfers). The average purse for a tournament in our sample is almost $6.3 million and about 52 percent of the shots taken take the gamble. Tiger Woods played in 27 percent of the tournament observations we have in our sample. We also have controls for player characteristics and environmental factors. For instance, 20.8% of the holes in this sample have water in front of the hole and 64 percent of these shots are taken from the fairway.[12]

IV. Results

[12] These results are generated with second shots that are 175 to 275 yards from the hole. This is because if the shot is closer than 175 yards almost all golfers go for the green, thus there is no ability to analyze risk taking. And shots over 275 yards are so far from the hole that very few golfers end up going for it – so it may be risk taking from other issues rather than the typical choice variables we analyze.

In this section, we measure the way various factors impact golfers' risk decisions. We start by discussing regression results generated from using equation 2, the baseline specification, to show that golfers' risk decisions are largely consistent with standard economic thinking about the way uncertainty affects peoples' decisions. We then follow other studies of strategic decision like Levitt and Miles (2011), Chevalier and Ellison (1997), and Adams and Waddell (2018), which analyze risk taking in non-golf and golf settings, taking into account the impact of competitors' standing in a competition on their decision making. We use regression discontinuity tools to show that golfers around the cut score behave differently immediately before the tournament field is cut roughly in half. Finally, we amend equation 2 to test the results presented in Brown (2011) to determine if Tiger Woods's presence in a tournament influenced a golfer's strategy.

The baseline model allows us to accomplish the task of considering golfers' decisions in the least complex environment from which they can play a second shot, the fairway, the portion of a hole before the green where grass is mown shortest. It is in this environment where golfers will be able to make the cleanest amount of contact with their club on their ball because on-course irritants like long grass or sand will not corrupt the moment of contact. Professional golfers, though, do not always play their second shots from the fairway. Often, golfers will have to consider the effects that longer grass will have on the quality of the contact they will make on the ball with their club, and generally speaking, playing from areas that are not the fairway means reconciling a loss of control on a shot, and that adds uncertainty to a second-shot gamble a golfer is considering. The ShotLink data allow us to identify two environments on holes in which grass is longer than the fairway – the intermediate rough and the primary rough. Additionally, golfers sometimes have to contend with the effects of hitting from sand in strategically arrayed bunkers on many holes. Lastly there are other environments – like pine straw or, what ShotLink calls "native areas" from which golfers who hit wayward drives must navigate. Like (non-fairway) grass, hitting from sand or the native areas adds uncertainty to the quality of the strike that a golfer can impart on a shot.[13] To study the effect that playing from these less manicured areas has on golfers' decision making, we add to equation 2 four indicator variables that capture the large majority of the observations that occurred from non-fairway environments. We call this specification equation 2′.

We show two sets of results in Table 5, both of which are generated using OLS. Results in Column 1 come from estimates that limit observations to shots that only were on the fairway, while the results in Column 2 include shots taken from all course environments. Both of these specifications contain information on golfer characteristics. Columns 3 and 4 repeat the first two columns, save for switching golfer characteristics with golfer fixed effects. We can learn much from this specification regarding the way golfers internalize risk.[14]

[Table 5]

First, and most critically, the estimates on the distance from the hole variables, *yards-to-pin* and *yards-to-pin^2,* show that golfers are less likely to take a risk as the distance they must traverse to the hole increases (the peak in columns two and four are 175, the minimum in this data; with a peak of 194 in columns one and three, close to the minimum). This evidence supports the notion that the return to risk taking diminishes as yardage to the hole increases. Using results from the second column in Table 5, we estimate that the likelihood of golfers taking a second shot gamble from 200 yards from the hole is about 7.4 percentage points larger

[13] Additionally, golfers might find in these non-fairway areas a tree that blocks the direct path the ball would take to the green. Golfers in the fairway generally have a clear path to the green.
[14] Results from using a probit estimate instead of OLS can be found at https://docs.google.com/document/d/1EF_v5T5PJ4ZDlIWx7KVQT3SZ3YDVSzeKC127QNaAA84/edit?usp=sharing

than when golfers are 225 yards from the hole. This difference is not only economically significant but statistically significant at less than the 1% level.

Additionally, these results speak to the seriousness that professional golfers weigh uncertainty from the environment they must navigate when thinking of these second shots. Consider the coefficient estimates on the four non-fairway environment indicator variables. These estimates are relative to the likelihood of a gamble taking place from the fairway, are precisely measured, and indicate the seriousness with which golfers are trying to limit the deleterious effects of uncertainty that come from playing from these environments. All four coefficient estimates are less than zero and accurately measured at less than the 1% significance level. Golfers guard closely against the uncertainty created by less than perfect lies by playing more conservatively than they do in the fairway, where forecasting a ball's flight is easier to accomplish. The changes to risk decisions are shown in Figure 1.

[Figure 1]

The unique fields that we created to merge with the ShotLink data, weather and hole characteristics, allow for us to consider exogenous shifters of risk that no doubt influence golfers' second-shot decision making. For instance, the average daily temperature for each round played, which is important because golf balls, like all projectiles, tend to fly further as air warms. So, we would expect to see the likelihood of second shot gambles rise with temperature, because golfers could expect for their ball to fly further on warmer days, thereby reducing the marginal cost of traversing any distance between them and the hole.

Finally, we find that golfers dial back significantly on risk taking when the hole they are attempting to reach with the second shot requires them to navigate a water hazard. When a golfer's ball lands in a water hazard, he must pay a penalty of at least one shot on his score for the hole, so misplayed risks are more costly, and therefore it is unsurprising to find golfers playing more conservatively in these instances. The results in Table 5 show that when water is right, left, or in front of the green, golfers are less likely to take on risk, which is consistent with our prior notions of golfers' behavior. We highlight the coefficient estimate on water fronting the green for it shows best the impact the severe penalty for hitting a shot in the water has on golfers' behavior. When water is in front of a green, a golfer trying to reach the green has to traverse the entire distance to the green through the air, and that reality heightens the risk associated with a second-shot gamble because there is less margin for error on these shots. The estimate on this indicator variable from the results shown in the fourth column of Table 5 show golfers are 6.8 percentage points less likely to attempt to reach the green with their second shot when they face water in front of the green compared to occasions without such a hazard.

On to our second and third questions of interest: how is a golfer's risk-taking decision influenced by his standing in a tournament? We answer this question by first analyzing a golfer's decision given his place in the tournament's standings, much like Chevalier and Ellison (1997) did with mutual fund managers during their fiscal year evaluations. We then hone in on the decisions made at the end of second rounds, when fields are cut in roughly half, with the best performers moving on and collecting a paycheck for their performance in the final two rounds.

Starting with the view of within-tournament performance, we use equation 2 and its fixed-effects counterpart (only shots from fairways) and estimate the specifications at three junctures of a typical tournament, the first two rounds, the third round, and the fourth round. We posit that golfers' behavior might differ in the first two rounds because, after the second round, roughly the worst performing half of a field is cut from the tournament. Golfers want to avoid getting cut because cut golfers do not get any prize money from the tournament purse, which means being at, or near, the cut score matters a lot. For instance, Adams and Waddell (2018) show that golfers perform better at the end of the second rounds when they are in danger of getting cut. We then treat differently the third and fourth rounds because the burden of making the cut is relaxed and the relative proximity to the end of a tournament is greater in the fourth round, when golfers' notions about what their final position (and the size of their earnings) in a tournament might be.[15]

We have competing ideas about how golfers' decision making will be affected by their tournament standing. First, successful gambles will likely elevate a golfer in a tournament's standings, and the higher he is in a tournament's standings, the larger and larger monetary benefits of a successful risk will be. All the same, however, can be said of costs that must be reconciled if a gamble does not payoff. This is why we would not be surprised to see evidence that suggests that golfers who are performing well might take fewer risks toward the end of a tournament in order to mitigate a loss from a gamble gone wrong that would send them tumbling down the tournament's standings and reduce their earnings. We could also imagine relatively poor performing golfers throwing caution to the wind because they have little to lose and much to gain from pulling off a successful gamble, much like the lower performing money managers in Chevalier and Ellison (1997).

[Table 6]

The results in Table 6 support the hypothesis of amplified risk at the highest rankings of a tournament, but only through the third round of a tournament – when golfers are jockeying for position prior to the final round. It is in the final round of a tournament, when golfers are most

[15] To illustrate the difference between first and second-place in a typical PGA Tour event, consider that the winner receives 18% of the tournament's purse, which is 7.2% more than the runner-up. In an $8 million event, that difference amounts to about $570,000.

able to hone in on their expected pay from their relative performance, that we see a drop in the relative differences in the probability of golfers of different standing taking gambles. We use these regression results to construct Table 7A and 7B, which show the difference in the predicted probability of a second-shot gamble being taken by golfers at various places in a tournament's standings.

[Table 7A]

[Table 7B]

Consider the top row of results in either table. The first three columns in this row show the differences in the likelihood of the tournament leader taking a second-shot gamble compared to golfers ranked 30th, 60th, or 120th in the tournament. First, note that, save for one instance, these three differences are all positive and significant at less than the 1% level, suggesting that golfers who start strongly in a tournament are more likely to take a risk compared to their slower-starting rivals. Second, note that the rate at which this difference in the golfers' willingness to take on risks slows after 60th place (last column). This finding is important because most tournament fields are cut after the second round to the lowest 70 scores and ties. A golfer who is near 60th place in a tournament's standings before the cut is made needs to tread carefully lest he fall outside of the cut line and not play for pay during the last two rounds of competition. Once golfers reach the third round, when the consequences of being cut fall away, their relative willingness to take on risk starts to flatten across a tournament's standings. In the third round, top-ranked golfers and golfers ranked around 30th place are significantly more likely to take on risk compared to golfers in 60th place. Finally, by the time tournaments reach the final round, the differences in golfers' willingness to take risks are negligible.

We find this set of results to be interesting compared to previous studies of risk-taking in tournament settings. Chevalier and Ellison (1997) found that money managers ranked in the bottom of yearly rate of return rankings tended to take on more risk in late stages of fiscal years, so that they might improve their relative standing and not lose investors who are put off by a bad relative performance. Our results suggest that the likelihood of a golfer taking on second-shot risks drops with his position on a leaderboard, at least through the first three rounds of a tournament. Toward the end of the tournament, differences in risk taking melts away with golfers' relative standings.

The explanation as to why we see differences in risk-taking strategies across these two types of contests is related to the nature of the incentives faced by the competitors. The mutual fund managers in the kinds of tournament Chevalier and Ellison (1997) study are not competing strictly in rank-order space. Their absolute performance likely matters, too. Though it is probably nice to be able to advertise that a particular fund performed best in a given year, the reward for doing so is not explicitly defined like in a golf tournament. By contrast, our findings suggest that golfers are willing to take on more risk the larger is the *net benefit* of a risk, and in the rankings of money managers, this necessarily does not characterize rewards paid to those managers.

The findings regarding golfers' decisions before the cut is made deserves further attention, because we can study with regression discontinuity techniques the extent to which golfers' risk decisions varied as the cut became imminent near the end of the second round, like Adams and Waddell (2018). We follow the framework from Lee and Lemieux (2010) for identifying instances in which discontinuity is an appropriate tool and find studying golfers' decisions near the cut line to fit comfortably within the framework. In particular, the method of cutting that occurs in tournaments clears a critical hurdle for using discontinuity because golfers are unable to adjust the cut score with their behavior. While golfers can estimate the cut score as they ponder their second shots, they know their actions will not alter the cut score because there too many golfers participating in the tournament to allow for such an occurrence. Like the assumption of a single firm being unable to alter the price in a completive market, the collective, non-collusive actions of the tournament field always overwhelm the actions of a single golfer.

To explore the idea of discontinuity, we first test the likelihood of golfers on either side of the cut line gambling with their second shots as being equal. For this comparison, we use a subsample of the data that is limited to second shots on par five holes that occurred on the last nine holes (holes 28-36 of a tournament) before the cut occurred. We assert that golfers had a clear estimate of the score that would need to be achieved in order to avoid being cut while they pondered their second shots. So, we determine the cut score (in relative to par terms) for all the tournaments that were conducted under stroke play rules and discarded the tournaments that did not cut the field from these calculations.[16] We then subtract from a tournament's cut score each golfer's score relative to par on a hole-by-hole basis in order to determine how far above or below the cut score a golfer was when he his second shot. In technical terms, $from\ cut_{ijt} = cut\ score_t - current\ score_{ijt}$, which meant that when Phil Mickelson's score was one shot higher than the cut score when he played the 18th hole of the second round of the 2008 Buick Invitational, the value of *from cut* for that observation is -1.[17]

We show the results of various tests of mean equality in Table 8. The first two columns include all golfers on either side of the cut line, no matter the value of *from cut.* The first column

[16] A few tournaments used an alternative scoring method, called the Stableford system, for conducting play. Additionally, there are a few events, namely those conducted by the World Golf Association, that did not cut golfers from the field. We dropped observations from these tournaments while conducting the discontinuity analysis.

[17] Mickelson decided to go for the green on that day. He made a par five on the hole and missed the cut by one shot.

limits observations to second shots taken in the fairway, while the second column includes shots taken from any course environment. For either test, the null hypothesis – that the likelihood of golfers gambling with their second shots in the final nine holes before the cut is equal, no matter which side of the cut line golfers were on – can be rejected at less than the 1% level.

We also perform the same tests but limit further the sample of golfers by eliminating those who were more than three strokes from either side of the cut score. The middle columns of Table 8 show results of both tests for golfers who were less than four shots from either side of the cut. Again, for the shots that were taken from the fairway, there is no reasonable way to argue that golfers' decisions are the same across the cut line, as the p-value of the test of equality is near zero. However, the null cannot be rejected for golfers who in other environments. This same pattern holds for the last set of tests, when we include only golfers whose scores were on the cut line or one shot worse than the cut line during those last nine holes. Evidently, golfers know that some gambles are never worth taking.

[Table 8]

These results suggest that golfers who were on the wrong side of the cut line tended to take more risk with their second shot relative to their opponents who were treading carefully near the correct side of the cut line. The economic explanation for this deviation is fairly obvious – golfers who were in jeopardy of missing the cut felt more pressure to take a risk and seek a successful outcome in order to inch back over to the other side of the cut line.

To measure more closely the differences in risk-taking strategies near the cut line, we identify golfers whose scores on the last nine before the cut line are four shots on the good or bad side of the cut line and amend equation 2 (or equation 2′) to include three additional variables that help identify golfers' position around the cut line. The first variable, explained above, is *from cut*$_{ijkt}$. The second is an indicator variable, *making cut*$_{ijkt}$, that is turned on when a golfer's score was better than the cut score at the time of observation. Finally, we interact *from cut* and *making cut* to create *better from cut*$_{ijkt}$.[18]

The results of two regression estimates are shown in Table 9. All results are from a subsample of the data that includes only golfers who were three or fewer shots from the cut score during the final nine holes of the second round. The results in the first column represent estimates from analyzing only shots taken in the fairway, while the second column includes all shots. We used OLS to generate these results, but also find similar results with probit estimates.[19]

[Table 9]

The regression results support the tests of mean equality, golfers behaved differently immediately around the cut score, with golfers on the wrong side of the cut score taking on more risk than their competitors who are protecting the precious ground they have gained. The results in column 1 show that golfers who were on the wrong side of the cut score were about 2 percentage points more likely to take a second-shot gamble compared to the golfers on the other side.

Figure 2 shows the extent to which the incentives to take on risk change as golfers' standing goes from making the cut to missing the cut. The vertical axis shows the predicted likelihood of taking a second shot risk from the model used to generate the results in the first column of Table 9, and the horizontal axis shows values of *from cut*. The graph shows clearly that the incentive to gamble is discontinuous at zero strokes from the cut, the most tenuous position in terms of earning the right to continue competing. Golfers nearest to but on the wrong

[18] We exclude tournament-ranking variables in these specifications.

[19] For brevity's sake, these results are not presented here. These estimates can be requested from the authors.

side of the cut score are about two percentage points more likely to adopt a risky strategy than those with a score equal to the cut score.

[Figure 2]

The last task we set out to accomplish in this paper is to measure the extent to which Tiger Woods's presence in tournaments influenced golfers' risk decisions. We are able to perform this task in an interesting way because our dataset spans two eras of Woods's amazing career. In the first era, from 2004 to 2009, he was clearly the game's superstar, as discussed in Brown (2011). In November 2009, though, his life and career unraveled in humiliating public fashion, as we all discovered the tawdry details of his marital infidelities.

In the first six seasons of the dataset, Woods was named PGA Player of the Year five times, while in the remaining four years after the scandal, he won the award once. So our dataset provides us a good opportunity to explore the way golfers made decisions against Superstar and Disgraced Woods. Brown (2011) convincingly showed golfers were exerting less effort (and thereby performing worse) against Superstar Woods, which corroborated theoretical claims in Rosen (1986) about optimal effort allocation against superior competition. Brown also discusses the possibility of golfers taking too much risk against Woods, in hopes of pulling off a lucky shot in order to keep pace with him. If golfers were adopting suboptimal risk strategies against Woods, then their performance would likely suffer. Without untangling the effects of strategic decisions from effort decisions, conclusions about performance suffering due to lower than normal effort would be erroneous. Brown determines that the evidence shows strategy did not affect golfers' poor performance when playing against Superstar Woods.

The passage of time has provided us with higher quality data to retest this conclusion from Brown. Further, Woods's scandal allows us to determine if golfers' strategies changed in the presence of Disgraced Woods. In order to measure strategy changes, we alter the fixed effects version of equation 2′. We include three indicator variables, (1) $Super\_TW_t$, (2) $After\_Scandal_t$, and (3) $Disgraced\_TW_t$, which are turned on for tournaments in which either Superstar Woods entered (1, between 2004 and 2009), took place after the November 2009 scandal broke (2), or Disgraced Woods entered a tournament (3, 2010 and beyond). Further, and conveniently, the scandal happened after the official PGA Tour events were done for the 2009 season.[20] We interact these indicator variables with yards to pin_{ijt}, and yards to pin^2_{ijt} to obtain equation 3:

$$
\begin{aligned}
&\Pr(Go-for-it)_{ijt} \\
&= \beta_0 + \beta_1 Yards-to-Pin_{ijt} + \beta_2 Yards-to-Pin^2_{ijt} + \beta_3 Super\_TW_t \\
&+ \beta_4 Super\_TW Yards-to-Pin_t + \beta_5 Super\_TW\ \ Yards-to-Pin^2_{ijt} \\
&+ \beta_6 AfterScandal_t + \beta_7 After\ Scandal\ Yards-to-Pin_{ijt} \\
&+ \beta_8 AfterScandal\ Yards-to-Pin^2_{ij} + \beta_9 Disgraced\_TW\quad_t \\
&+ \beta_{10} Disgraced\_TW Yards-to-Pin_{ijt} \\
&+ \beta_{11} Disgraced\_TW Yards-to-Pin^2_{ijt} \\
&\qquad +\beta_{12} Purse_t + \Gamma\ \ N_i + \Theta\ \ S_{jt}\ \ + \varepsilon_{ijt}\ \ ,
\end{aligned}
$$

where N_i is a vector containing golfer identities, S_{ijt} are hole-specific characteristics like bunker and water locations or weather information, and ε_{ijt} is a mean-zero, normally distributed error term.

This specification enables us to test two hypotheses on golfers' risk taking not in or in the presence of Woods. First, we can determine if golfers' willingness to take on risk differed in tournaments Woods entered compared to tournaments he did not, in either era of his career. Second, we can compare if there was a significant difference in the willingness of golfers to take

[20] There were a few unofficial tournaments that happened after this event, but no tournaments of any meaning were played, and they had a relatively small purse size (these were exhibitions with a limited field). Thus, the Superstar Era of our data is 2004-2009 and the Disgraced Era is the following years.

on risk in the presence of Woods, across the two eras of his career. If golfers did behave differently after Superstar Woods lost his luster, then this would be evidence in support of the idea that golfers altered their risk-taking decisions when outclassed. We test these hypotheses by estimating the difference in the likelihood of going for the green from 240 yards, roughly the mean yardage golfers faced for their second shots in the dataset.

[Table 10]

We display the results of two fixed-effect regressions in Table 10. The first column contains all shots in the dataset, while the second column contains only shots taken in the final rounds of tournaments. With the results from the first column, we detect weak evidence supporting the hypothesis that golfers behaved differently in the presence of either Woods. When playing against Superstar Woods, they did not alter their behavior at any stage of a tournament, as the point estimates of the likelihood of taking on different risk choices from 240 yards from the hole do differ significantly from zero.[21] As for the Disgraced Woods Era, the pattern is slightly different. We find that at all stages of the tournament, golfers were about 2.7 percentage points less likely to go for the green from 240 yards in tournaments Woods entered compared to those in which he did not compete. In the fourth round, golfers' willingness to gamble fell even further when Disgraced Woods entered a tournament. We estimate that they were 4.3 percentage points less likely to take a gamble in tournaments Disgraced Woods entered compared to those he did not. This estimate is significant at less than the five percent level.

These results suggest that golfers in the era of Superstar Woods gambled at roughly the same rates in tournaments with or without him in the field. Since his fall from grace, golfers have been gambling less when he competes compared to when he does not, especially in the final

[21] For illustrative purposes, the difference in the likelihood of gambling from 240 yards with and without Woods in the Superstar Era = Pre_TW_Played + 240*Pre_TW_Yds to Pin + 240^2Pre_TW_Yds to Pin^2.

rounds of tournaments. We interpret these findings to be evidence of golfers in the Superstar Woods Era taking on too much risk when he played, a result consistent with a Superstar Effect in the strategic dimension. However, they dialed back to more optimal levels of risk when playing against Disgraced Woods. Thus, we hypothesize, if Woods was not a superstar in the early years they would have decreased these risks in those same tournaments - but since he was, they continued to take the extra risks in the big tournaments as their only chance to beat him.

Brown (2011) carefully dismisses the idea of performance differences being explained by risk-taking differences across tournaments in the Superstar Era. Similar to this study, that study considers various types of risky shots, including attempts at reaching greens with long shots. But these attempts are considered with only the high-level data available then. The passage of time has conferred upon us two advantages – more detailed data and the opportunity to observe golfers competing against Woods after his fall from superstardom, Disgraced Woods. It is the golfers' behavior in the Disgraced Woods Era, when they clearly took fewer risks when competing against him that leads us to believe that Superstar Woods pushed golfers to take on too much risk in order to compete against the most brilliant version of him. This conclusion begs the question to what extent should we reconsider the Superstar Effect of which Brown found evidence given that golfers took on too much risk when playing Superstar Woods.

To begin, it is helpful to consider the way Superstar Woods altered professional golf. Clearly, golfers adopted riskier strategies in the years following Woods's domination of the sport. During this time, technological advances were impacting the sport, which would have impacted risk taking, so we stop short of drawing a clear line of causality between his presence and changes in the sport. Consider, though, the differences in risk strategies golfers employed across the two eras. From all environments, the difference in the average likelihood of a golfer going for the green with his second shot is 1.6 percentage points bigger in the post-scandal years. This difference is significant at less than a 1-percent level. For shots from the fairway, the difference in the likelihood is larger, as golfers were 2.8 percentage points more likely to go for the green with their second shot in the post-scandal years. Given this knowledge, it is not surprising to find the difference-in-the-differences of golfers' willingness to gamble with their second shots in the presence of Woods is negligible. Therefore, in the presence of Disgraced Woods, golfers' risk-taking behavior is very similar to the way it was throughout the era of Superstar Woods. However, on the occasions he did not compete in the Disgraced Woods Era risk taking *increased* relative to the other types of tournaments.[22]

Given the relative change in golfers' behavior across the two eras, is there evidence that suggests their scores have changed in accordance with their decision making? Evidence supporting the affirmative would imply golfers became more comfortable with higher scores from lower levels of risk when competing against Disgraced Woods. In the Superstar Era, the average score in tournaments in which Woods entered was 0.036 strokes per hole larger than when he did not compete. By contrast, the same difference in the Disgraced Woods Era was 0.043 strokes per hole.[23] Thus, in the Disgraced Woods Era, scores have increased by 0.007 strokes per hole in the presence of Woods, an amount that can attributed to golfers adopting more conservative strategies when Disgraced Woods competed because they no longer needed the extra risks for the chance to keep up with him.

[22] We view Woods as being a Babe Ruth figure in golf because he forced golfers to respond to his dominance, and nature of the game was changed. See Groothuis, Rotthoff, and Strazicich (2017) for a discussion on changes wrought by Ruth's dominance.

[23] Average score during the Superstar Years was 4.669 strokes on 180614 holes when he did not play and 4.705 when he did. In the Disgraced Years, the averages are 4.656 on 116966 holes and 4.70 on 42106 holes.

It is typical for a PGA Tour course to feature three par five holes, so we surmise that the difference in the way golfers strategized across eras amounts to about 0.021 strokes per round. Brown (2011) reports per round effects from the Superstar Effect of between 0.5 and 2.0 shots per round, our estimate of the size of a strategic component that might also explain part of the performance differences in the face of overwhelmed competition makes sense and suggests that the effort component is actually larger than originally estimated.

V. Conclusion

In this study, we analyze risk-taking strategies in professional golf by focusing on the second-shot decisions made by professional golfers on par-five holes in PGA Tour tournaments held between 2004 and 2013. Our dataset consists of over 200,000 second shots and support a number of previous studies on risk taking, both in and out of rank-order contests. First, golfers adopt more conservative strategies when they face elements that increase the uncertainty of an aggressive play, like unruly weather or costly hazards, a finding that is consistent with several classic studies on risk taking. Second, we show risk taking is dynamic throughout tournaments and use regression discontinuity to show golfers' risk-taking responds strongly to the moment when the tournament's cut nears. Lastly, we use the Tiger Woods sex scandal to test notions of the Superstar Effect. We find that golfers' behavior changed little in the presence of Woods during his peak performing years (pre-2010) but did after his sex scandal wiped out his golfing prowess (post-2009). We surmise this difference supports the notion that golfers took more risk competing against Superstar Woods than with which they were comfortable, which means a strategic component must be added to the effort component of the Superstar Effect discussed in Brown (2011). Our findings suggest economists should seek more opportunities to study further the implications of a strategic component of the Superstar Effect.

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Table 1- Gambling Golfers Must Reconcile Risk of High Scores					
	All Distance	175-200 yds	200-225 yds	225-250 yds	250-275 yds
Mean Score Gamble	4.35	4.17	4.29	4.36	4.43
(Obs, SD)	(129542, 0.689)	(9629, 0.645)	(30187, 0.684)	(50128, 0.688)	(39484, 0.69)
Mean Score No Gamble	4.79	4.73	4.76	4.78	4.77
(Obs, SD)	(116356, 0.646)	(1748, 0.673)	(12218, 0.665)	(35885, 0.647)	(66401, 0.641)
Mean Score Gamble	4.33	4.14	4.26	4.35	4.41
from Fairway	(105753, 0.685)	(7509, 0.637)	(23776, 0.677)	(41246, 0.686)	(33138, 0.688)
Mean Score No Gamble	4.71	4.62	4.67	4.70	4.72
from Fairway	(51908, 0.633)	(554, 0.621)	(4085, 0.655)	(14868, 0.641)	(32363, 0.626)
Mean Score Gamble	4.43	4.27	4.39	4.44	4.51
Not Fairway	(23789, 0.699)	(2120, 0.662)	(6421, 0.702)	(8882, 0.693)	(6346, 0.704)
Mean Score No Gamble	4.85	4.79	4.81	4.83	4.87
Not Fairway	(64448, 0.650)	(1194, 0.690)	(8133, 0.665)	(21017, 0.646)	(34038, 0.646)

Table 2- Leading Money Winners Perform Very Well on Par 5 Holes			
Year	Leading Money Winner	Average Score- Par 5 Holes	Par 5 Scoring Rank
2004	Vijay Singh	4.47	1
2005	Tiger Woods	4.52	1
2006	Tiger Woods	4.43	1
2007	Tiger Woods	4.48	2
2008	Vijay Singh	4.52	1
2009	Tiger Woods	4.43	1
2010	Matt Kuchar	4.56	3
2011	Luke Donald	4.55	7
2012	Rory McIlroy	4.49	1
2013	Tiger Woods	4.57	4

Table 3- Summary Statistics of Par Five Holes Analyzed

Year	Number Tournaments	Number Holes Completed	Average Score	Average Score Easiest Hole	Average Score Hardest Hole
2004	39	36016	4.65	4.24	5.08
2005	38	50894	4.70	4.05	5.11
2006	39	52283	4.69	4.19	5.27
2007	39	50041	4.68	4.24	5.16
2008	41	50041	4.70	4.30	5.29
2009	35	42408	4.68	4.20	5.13
2010	34	42774	4.67	4.24	5.18
2011	39	45808	4.68	4.26	5.33
2012	38	45585	4.67	4.16	5.29
2013	34	42302	4.68	4.30	5.14
Total	376	458152	4.69		

TABLE 4- Summary Statistics (Only observations in which golfers were 175 to 275 yards from the hole before second shot.)

VARIABLES	N	Mean	Standard Deviation	Min	Max
Yards to Pin	246,013	242.5	22.05	175	275
Yards to Pin Squared	246,013	59,286	10,403	30,625	75,625
Tournament Rank	246,013	47.60	36.37	1	180
Unit Purse	246,013	6.294	1.294	3	10.35
Gambled	246,013	0.527	0.499	0	1
Difference in Rank	246,013	-152.1	177.7	-996	151
Difference in Rank Squared	246,013	54,723	115,349	0	992,016
Tiger Woods Played	246,013	0.273	0.446	0	1
Player Characteristics:					
Season Drive Distance	245,986	289.4	8.781	238.6	330.8
Season Drive Accuracy	245,986	0.621	0.0562	0.143	0.929
Season Greens in Regulation	245,986	0.647	0.0328	0.306	0.833
Season Scramble Percentage	245,986	0.572	0.0418	0.111	0.844
Season Sand	245,962	0.484	0.0804	0	1
Season Putting Distance	245,986	1.260	0.0929	0.202	2.184
Environmental Factors:					
Water Right	243,109	0.187	0.390	0	1
Water Left	243,109	0.131	0.337	0	1
Water Front	243,109	0.208	0.406	0	1
Water Long	242,487	0.0860	0.280	0	1
Sand Left	243,109	0.493	0.500	0	1
Sand Right	243,109	0.594	0.491	0	1
Sand Front	243,109	0.569	0.495	0	1
Sand Long	243,109	0.324	0.468	0	1
Average Temperature	240,313	69.18	9.028	40	88
Fairway	246,013	0.641	0.480	0	1

Fairway Bunker	246,013	0.0596	0.237	0	1
Fairway Rough	246,013	0.228	0.420	0	1
Intermediate Rough	246,013	0.0643	0.245	0	1
Other Environment	246,013	0.00675	0.0819	0	1

Table 5 - Golfers' Second-Shot Decisions Are Consistent with Economic Theory (Standard Errors in Parentheses)

Explanatory Variables	(1) Linear Prob Coeff Est	(2) Linear Prob Coeff Est	(3) Linear Prob Coeff Est (Golfer FE)	(4) Linear Prob Coeff Est (Golfer FE)
Yards to Pin	0.0330***	0.0187***	0.0327***	0.0185***
	(0.0034)	(0.0027)	(0.0033)	(0.0027)
$(\text{Yards to Pin})^2$	-8.49e-05***	-5.34e-05***	-8.44e-05***	-5.31e-05***
	(7.50e-06)	(5.93e-06)	(7.30e-06)	(5.81e-06)
Fairway Bunker		-0.544***		-0.544***
		(0.0145)		(0.0146)
Primary Rough		-0.417***		-0.417***
		(0.0152)		(0.0152)
Intermediate Rough		-0.140***		-0.140***
		(0.0108)		(0.0107)
All Other Environments		-0.560***		-0.557***
		(0.0172)		(0.0171)
Unit Purse	-0.0125*	-0.0144**	-0.0147**	-0.0169***
	(0.0067)	(0.0066)	(0.0067)	(0.0064)
Water to the Right	-0.0104	-0.0321	-0.0101	-0.0320
	(0.0248)	(0.0232)	(0.0243)	(0.0229)
Water to the Left	-0.0152	-0.0280	-0.0161	-0.0291
	(0.0300)	(0.0297)	(0.0301)	(0.0298)
Water in Front	-0.0562**	-0.0675***	-0.0560**	-0.0675***
	(0.0234)	(0.0226)	(0.0234)	(0.0226)
Water Long	-0.0288	-0.0120	-0.0288	-0.0120
	(0.0422)	(0.0378)	(0.0416)	(0.0372)
Bunker to the Left	0.0436**	0.0329*	0.0454**	0.0342*
	(0.0206)	(0.0186)	(0.0204)	(0.0185)
Bunker to the Right	0.0128	-0.00729	0.0132	-0.00698

	(0.0210)	(0.0196)	(0.0209)	(0.0196)
Bunker in the Front	0.0263	0.0241	0.0262	0.0238
	(0.0183)	(0.0173)	(0.00538)	(0.0053)
Bunker Long	-0.0192	-0.0161	-0.0195	-0.0163
	(0.0206)	(0.0196)	(0.0206)	(0.0196)
Average Temperature	0.0010	0.0005	0.0011	0.0006
	(0.0007)	(0.0008)	(0.0007)	(0.0008)
Tournament Rank	0.0005	-0.0001	0.0008	7.53e-05
	(0.0008)	(0.0008)	(0.0008)	(0.0009)
(Tournament Rank)^2	-2.44e-06	5.56e-08	-3.58e-06	-8.41e-07
	(3.02e-06)	(3.07e-06)	(3.04e-06)	(3.10e-06)
Tournament Rank	-0.0002	-9.99e-05	-0.0002	-0.0001
x Unit Purse	(0.0001)	(0.0001)	(0.0001)	(0.0001)
(Tournament Rank)^2	1.17e-07*	8.20e-08	1.35e-07**	9.63e-08
x Unit Purse	(6.90e-08)	(6.97e-08)	(6.82e-08)	(6.99e-08)
Golfer Characteristics	Yes	Yes	No	No
Yearly Fixed Effects	Yes	Yes	Yes	Yes
Environmental Fixed Effects	No	Yes	No	No
Golfer Fixed Effects	No	No	Yes	Yes
Shot From	Fairway Only	All Surfaces	Fairway Only	All Surfaces
Constant	-3.579***	-1.602***	-2.327***	-0.409**
	(0.409)	(0.347)	(0.177)	(0.172)
Observations	150,264	235,070	150,276	235,095
R-squared	0.139	0.275	0.148	0.281
All Rounds	Yes	Yes	Yes	Yes

Notes: These results are from estimating equation 2, which has a dependent variable of the probability of a golfer going for the green (gambling) with his second shot on a par five hole. The results in the first column is from a subsample of shots that were struck from only the fairway, while the last column are the results from the full sample of observations (probit estimates have also been done, but are not listed here for brevity. These results can be requested from the authors). Robust standard errors in parentheses. We cluster standard errors by each hole in the dataset. *** indicates a coefficient estimate that is measured at less than the 1% level, ** indicate less than 5% level, and * indicate less than 10%. The columns that match (1 and 3; 2 and 4) have slightly different numbers of observations because there are a few golfers in the dataset that we do not have all the individual characteristics, but can still use athlete level fixed effects.

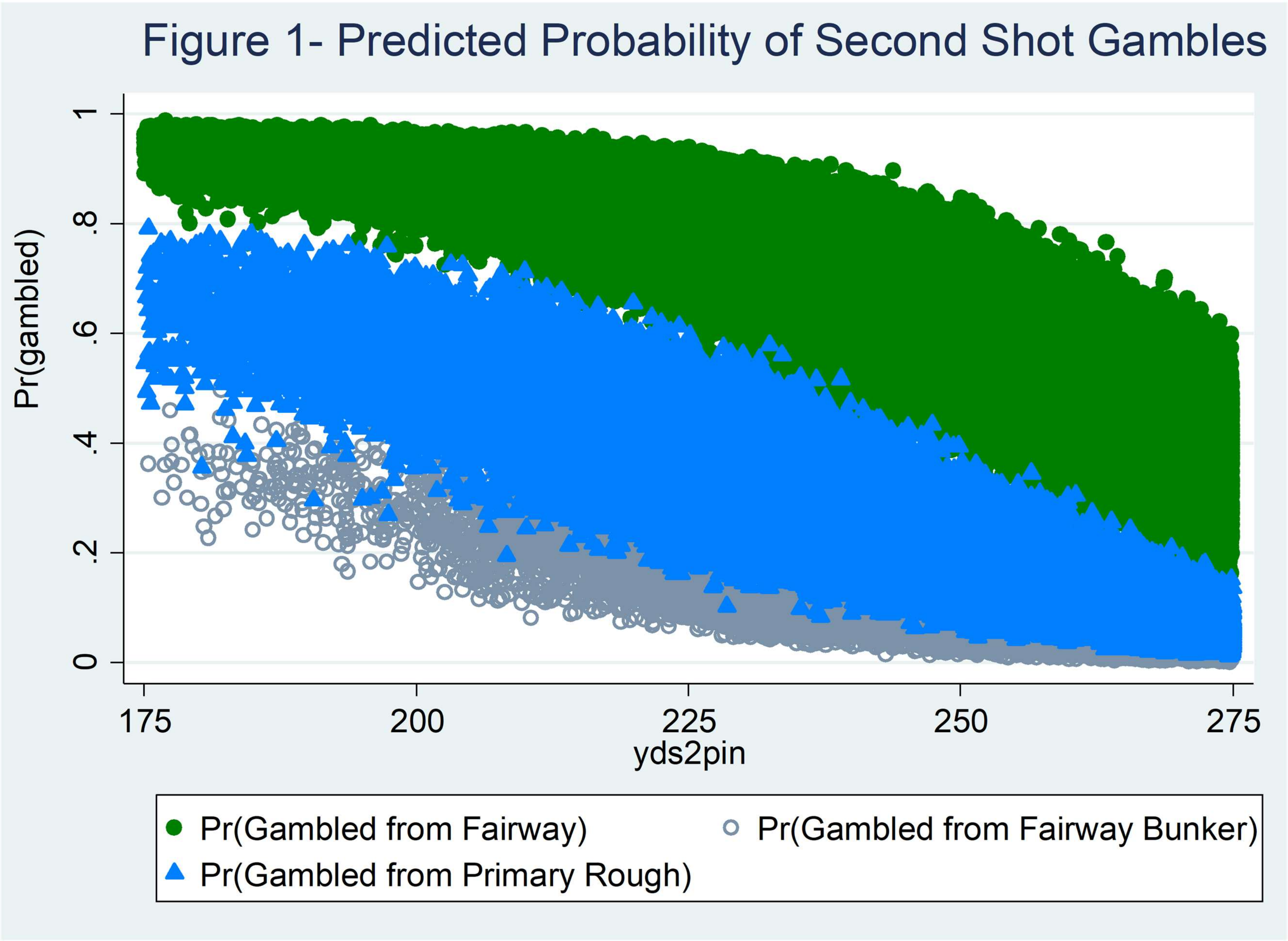

Figure 1- Predicted Probability of Second Shot Gambles
Pr(gambled)
0
.2
.4
.6
.8
1
175
200
225
250
275
yds2pin
Pr(Gambled from Fairway)
Pr(Gambled from Fairway Bunker)
Pr(Gambled from Primary Rough)

Table 6 – Golfers' Second-Shot Decisions Vary by Tournament Round (SE in parentheses)

	Column 1	Column 2	Column 3
VARIABLES	Linear Prob Coeff Est	Linear Prob Coeff Est	Linear Prob Coeff Est
	First Two Rounds	Round 3	Round 4
Yards to Pin	0.0293***	0.0401***	0.0288***
	(0.0018)	(0.0029)	(0.0030)
$(\text{Yards to Pin})^2$	-7.79e-05***	-0.000101***	-7.58e-05***
	(4.03E-06)	(6.27E-06)	(6.48E-06)
Rank	-8.88e-05***	-0.000105***	-9.70e-05***
	(1.14E-05)	(2.09E-05)	(1.93E-05)
Unit Purse	-0.0149***	0.0003	-0.0271***
	(0.0043)	(0.0052)	(0.0080)
Water to the Right	-0.0108	-0.0077	-0.0212
	(0.0124)	(0.0156)	(0.0184)
Water to the Left	-0.0236*	-0.0034	0.0049
	(0.0133)	(0.0197)	(0.0181)
Water in Front	-0.0516***	-0.0482***	-0.0981***
	(0.0102)	(0.0145)	(0.0150)
Water Long	-0.0322	-0.0276	-0.0169
	(0.0199)	(0.0303)	(0.0271)
Bunker to the Left	0.0525***	0.0590***	0.0360***
	(0.0089)	(0.0121)	(0.0120)
Bunker to the Right	0.0171**	0.0066	0.0044
	(0.0087)	(0.0129)	(0.0121)
Bunker in the Front	0.0264***	0.0335***	0.0128
	(0.0075)	(0.0108)	(0.0104)
Bunker Long	-0.0194**	-0.0216*	-0.0044

	(0.0085)	(0.0112)	(0.0114)
Average Temperature	0.0009*	0.0009	0.0014**
	(0.0005)	(0.0007)	(0.0007)
Tournament Rank	0.0002	0.0048***	-0.0023
	(0.00071)	(0.0017)	(0.0020)
(Tournament Rank)^2	5.57E-07	-3.07e-05***	1.57E-05
	(2.59E-06)	(1.08E-05)	(1.33E-05)
Tournament Rank	-0.0002	-0.0008***	0.0004
x Unit Purse	(0.0001)	(0.0003)	(0.0003)
(Tournament Rank)^2	1.16e-07**	7.04e-07***	-5.95e-07*
x Unit Purse	(5.89E-08)	(2.58E-07)	(3.34E-07)
Constant	-1.777***	-3.110***	-1.738***
	(0.214)	(0.329)	(0.34)
Yearly Fixed Effects	Yes	Yes	Yes
Observations	89,553	30,702	29,699
R-squared	0.132	0.146	0.124
All Rounds	No	No	No

Notes: These results are from linear probability estimates of Equation 2, which has a dependent variable of the probability of a golfer going for the green (gambling) with his second shot on a par five hole. All observations used to generate these results are from shots struck from only the fairway. Robust standard errors in parentheses. We cluster standard errors by each hole in the dataset. *** indicates a coefficient estimate that is measured at less than the 1% level, ** indicate less than 5% level, and * indicate less than 10%.

Table 7A- Best Performing Golfers Press Their Advantage before Last Round					
	Difference in Likelihood of Golfers Gambling Based on Tournament Ranking at Time of Shot Decision (SE)				
	1 v. 30	1 v. 60	1 v. 120	30 v. 60	60 v. 120
First Two Rounds	0.021*** (0.004)	0.034*** (0.006)	0.036*** (0.007)	0.013*** (0.002)	0.004 (0.005)
Round 3	0.004 (0.006)	0.018* (0.009)	N/A	0.014*** (0.004)	N/A
Round 4	-0.005 (0.008)	0.002 (0.01)	N/A	-0.056 (0.037)	N/A

Table 7B- Best Performing Golfers Press Their Advantage before Last Round					
	Difference in Likelihood of Golfers Gambling Based on Tournament Ranking at Time of Shot Decision (SE)				
	1 v. 30	1 v. 60	1 v. 120	30 v. 60	60 v. 120
First Two Rounds	0.019*** (0.007)	0.031*** (0.010)	0.036*** (0.012)	0.013*** (0.004)	0.004 (0.006)
Round 3	0.001 (0.007)	0.012 (0.011)	N/A	0.012** (0.005)	N/A
Round 4	-0.005 (0.009)	-0.001 (0.012)	N/A	-0.058 (0.556)	N/A

Notes: Tables 7A and 7B show the difference in the likelihood that golfers ranked at various positions in a tournament will take risks at various stages of the tournament. The results in these tables are from the estimation of equation 2 and the fixed effects version of equation 2, both of which seek to explain the likelihood that a golfer would have taken the risky option of attempting to reach a par five green with his second shot. ***- difference is significant at the 1% level, **- differences are significant at the 5% level, and *- differences are significant at the 10% level.

Table 8- Mean Test of Equality of Prob(Gamble)

	All Strokes from Cut		B/t 4 and -4 Strokes From Cut		B/t 1 and -2 Strokes from Cut	
	Prob(Gamble) Unconditional Fairway	Prob(Gamble) Unconditional Non-Fairway	Prob(Gamble) Conditional Fairway	Prob(Gamble) Conditional Non-Fairway	Prob(Gamble) Conditional Fairway	Prob(Gamble) Conditional Non-Fairway
Making Cut	0.395 (20609)	0.137 (13118)	0.401 (11471)	0.147 (7114)	0.405 (6744)	0.151 (4086)
Missing Cut	0.465 (20351)	0.165 (10300)	0.436 (10795)	0.148 (5733)	0.426 (7472)	0.149 (4068)
Test of Equality Result	p = 0	p = 0	p = 0	p = 0.97	p = 0.01	p = 0.84

Notes: These results show the probability of golfers gambling with their second shots in the second nine of the second rounds of PGA Tour tournaments. We compare likelihoods of golfers who are on the safe and wrong sides of the cut score, which is determined after the second round of tournaments. The first two columns include all golfers, no matter their distance from the tournament's cut score, while the third through sixth columns limit the sample of golfers to those within varying distances of the cut score. The last row shows results from testing for equality across the two types of players.

Table 9- Second Shots Decision are Discontinuous at Cut Line (OLS)

Explanatory Variables	Column 1 Fairway Discontinuity	Column 2 All Shots Discontinuity
Making_Cut	0.021**	0.015**
	0.011	0.008
From_Cut	-0.014*	-0.012**
	0.007	0.006
Observations	11177	16741
R-squared	0.16	0.26
All Rounds	N- Second Only	N- Second Only

Notes: These results are from an OLS estimation of an amended equation 2, with the variables *from cut, better than cut,* and *making cut* added to the specification. We use a subsample of observations that includes only shots taken during golfers' second nines of their second round of tournaments (just before the cut is made). *From cut* values are less than zero for golfers with scores worse than the cut line, so golfers on the wrong side of the cut score are significantly more likely to take risks at this stage of the tournament compared to golfers within the cut line. The first column of results limits the observations to only shots taken in the fairway. The second column of results includes shots taken from all environments. ***- difference is significant at the 1% level, **- differences are significant at the 5% level, and *- differences are significant at the 10% level.

Figure 2- Discontinuity of Risk Taking around Tournament Cut Score

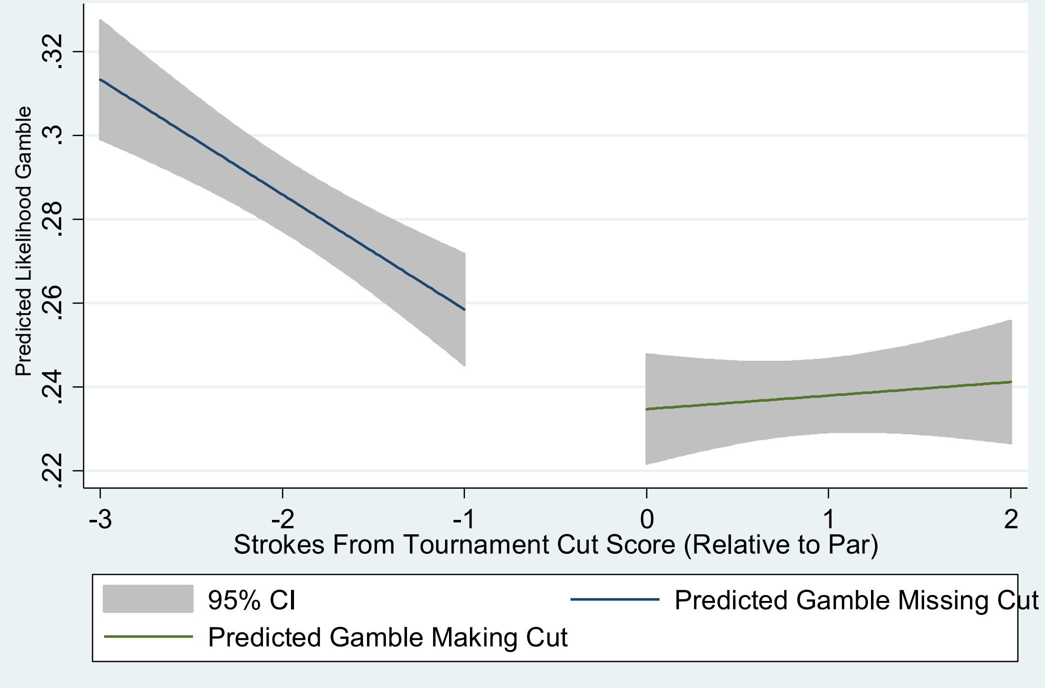

Table 10 – Impact Superstar and Disgraced Tiger Woods Had on Risk Taking

VARIABLES	(1) FE Est All Rounds	(2) FE Est Last Round
Yards to Pin	0.021***	0.023***
	(0.003	(0.004)
(Yards to Pin)^2	-5.78e-05***	-6.32e-05***
	(6.18e-06)	(9.54e-06)
Pre TW Played	0.892	1.864**
	(0.561)	(0.889)
Pre TW Yards to Pin	-0.007	-0.016**
	(0.005)	(0.008)
Pre TW (Yards to Pin)^2	1.53e-05	3.47e-05**
	(1.11e-05)	(1.70e-05)
After Accident	0.140	0.234
	(0.433)	(0.678)
After Yards to Pin	-0.001	-0.002
	(0.004)	(0.006)
After (Yards to Pin)^2	3.05e-06	4.85e-06
	(8.12e-06)	(1.27e-05)
DisgracedTW Played	0.551	2.436**
	(0.741)	(0.966)
DisgracedTW Yards to Pin	-0.005	-0.021**
	(0.006)	(0.008)
DisgradedTW (Yards to Pin)^2	9.53e-06	4.33e-05**
	(1.39e-05)	(1.82e-05)
Fairway Bunker	-0.546***	-0.551***
	(0.015)	(0.016)
Primary Rough	-0.418***	-0.406***
	(0.015)	(0.016)

Intermediate Rough	-0.140***	-0.131***
	(0.011)	(0.0133)
All Other Environments	-0.558***	-0.563***
	(0.017)	(0.023)
Water to the Right	-0.034	-0.040
	(0.023)	(0.028)
Water to the Left	-0.027	-0.007
	(0.029)	(0.031)
Water in Front	-0.0673***	-0.102***
	(0.023)	(0.026)
Water Long	-0.012	-0.0004
	(0.037)	(0.044)
Bunker to the Left	0.035*	0.030
	(0.018)	(0.021)
Bunker to the Right	-0.007	-0.012
	(0.019)	(0.021)
Bunker in the Front	0.024	0.014
	(0.017)	(0.019)
Bunker Long	-0.016	-0.005
	(0.019)	(0.021)
Average Temperature	0.0008	0.0008
	(0.0007)	(0.0009)
Unit Purse	-0.016***	-0.0200***
	(0.005)	(0.007)
Shot From	Fairway Only	All Surfaces
Constant	-0.872**	-1.133**
	(0.338)	(0.513)
Observations	235,095	46,331
R-squared	0.281	0.285

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: These results are from linear probability estimates of Equation 3, which has a dependent variable of the probability of a golfer going for the green (gambling) with his second shot on a par five hole. All observations used to generate these results are from shots struck from only the fairway. Robust standard errors in parentheses. We cluster standard errors by each hole in the dataset. *** indicates a coefficient estimate that is measured at less than the 1% level, ** indicate less than 5% level, and * indicate less than 10%.

Appendix

Definitions of golfer-specific and hole-specific variables.
Drive Distance- the average distance of two drives per round.
Drive Accuracy- the percentage of fairways a golfer hits on non-par three holes in a round.
Greens in Regulation- the percentage of greens a golfer hits in regulation.
Scramble- the percentage of holes in which a golfer made a par and did not hit a green in regulation.
Sand Saves- the percentage of holes in which a golfer made a par from a greenside bunker.
Average Putt Distance- the average distance from the hole a golfer was when a putt was holed.
Last Round- an indicator variable with a value of one on occasions in which a shot was struck in the last round of a tournament.

Table A1 – Definitions of “around the green”

Coding Step	Definition of "around the green"	Observations	Pct of Gambled
1	Strict ShotLink Definition	339,015	40.50%
2	Step 1 + Shots around Green	339,015	57.20%
3	Step 1 + Step 2 + Water/Penalties	339,015	59.22%