Performance and Risk Taking Under Threat of Elimination*

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Abstract

We revisit the incentive effects of elimination tournaments with a fresh approach to identification, the results of which strongly support that performance improves under the threat of elimination and does so, but only in part, due to increases in risk taking. Where we can separately identify changes in risk-independent performance and risk taking, our estimates suggest that at least 23 percent of the improvement in performance induced by potential elimination is due to productive increases in risk taking. These effects are concentrated among those closest to the margin of elimination and among lower-ability competitors.

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1 Introduction

Although elimination tournaments and similarly discrete outcomes of competitive environments are quite common, opportunities to consider individual behavior under the threat of elimination are rare. Having coincident measures of risk taking makes this opportunity all the more rare. In this paper, we separately identify changes in risk-taking behavior and performance due to the threat of elimination.

Of course, elimination tournaments are a particular form of contract convexity, which we might generally expect to increase risk taking. Quantifying changes in behavior due to pending elimination therefore informs an understanding of contracts somewhat more-broadly than would be implied by a strict interpretation of elimination tournaments. The shape of stock-option contracts, for example, also exhibits strong convexities in their "up or out" implications. The higher is the exercise price on the option, the more likely it is that payment will only be realized when the upside is realized and, thus, the more appealing risk-taking becomes. In fact, the vast majority of stock options are granted with exercise prices equal to the grant-date stock price (Barron and Waddell, 2008), thus implying that the only realization of monetary return is conditional on the stock price increasing—very much mimicking the "up or out" nature of elimination tournaments. Moreover, if the stock price does not exceed the exercise price, it does not matter at the margin by how much it falls short.[1] We will see empirical regularities consistent with this in the tournaments we consider, as our analysis also suggests that both performance and risk taking increase under threat of elimination.

We use hole-level Professional Golf Association (PGA) records of player performance, inclusive of objective measures of *ex ante* risk taking with *ex post* realizations, which enables hole-by-player-by-tournament-by-year analysis of performance on both sides of an objectively determined discontinuity in the expectation of elimination. With players repeatedly observed on either side of the threshold, we measure the systematic variation (within-player) in both

[1] Barron and Waddell (2008) interpret the implications of such convexity as inducing a sort of "work hard not smart" strategy. In their context, unabated, this may even leave agents prone to excessive risk taking, as though there is nothing to lose.

performance and risk taking that is explained by that discontinuity. Given the idiosyncratic nature of play—good players can have bad weekends and bad players can have good weekends—we identify off of variation within player-by-year-by-tournament.

With this fresh approach to identification, our results strongly support that performance improves under the threat of elimination and suggest a sizable role for risk taking as part of the mechanism. Where we can separately identify changes in performance and risk taking, our estimates suggest that at least 23 percent of the improvement in performance induced by potential elimination is due to productive increases in risk taking—productive in the sense that risks taken under threat of elimination are paying off with higher probability. In a world where all of the additional risk-taking opportunities (from among those the PGA flags as risk-taking opportunities) induced by the threat of elimination pay off, risk taking would account for up to 49 percent of the increase in performance. These effects are concentrated among those closest to the margin of elimination, among lower-ability competitors, and diminish as elimination approaches—we actually find performance declines in the last few opportunities for a player to escape elimination. Interestingly, risk taking seemingly plays no role in this decline.

We consider related literatures in Section 2, followed by background information and data description in Section 3. In Section 4, we present our empirical strategy, which we follow with the main results and supplemental analysis in Section 5. We offer concluding remarks in Section 6.

2 Other related literature

A large empirical literature has developed since Lazear and Rosen (1981) first demonstrated the efficacy of tournaments in promoting effort in a second-best world.[2] In a collection of papers looking at the incentive effects in a tournament environment, Ehrenberg and Bognanno (1990a,b) and Orszag (1994) together find mixed evidence of player performance responding to

[2] See Prendergast (1999) for a summary of the early literature.

monetary payoffs.[3] Exploiting variation in the design of the National Basketball Association (NBA) player draft, Taylor and Trogdon (2002) offer strong evidence of declining *ex post* performance on the elimination side of tournaments, identifying that teams having just lost the chance of a playoff birth lose significantly more often than teams that are still at the margin of making it into the playoff tournament.[4] In these ways, we anticipate that margins of elimination matter to performance.

As we use data on professional golf tournaments, we implicate several other pieces of literature. For example, Guryan et al. (2009) exploits random pairings of golfers to identify potential peer effects, finding no such relationship. However, Brown (2011) does find that the performance of non-superstars declines in the presence of superstars—a "Tiger Woods effect." Pope and Schweitzer (2011) also finds that professional golfers exhibit loss aversion, putting less accurately when at the margin of achieving a below-par score on a hole.

A somewhat large literature analyzes risk taking, generally, and often implicates areas of finance and the behavior of "C-level" executives. There are large incentives for executives, for example, to take on risk in order to make up for poor past performance. Imas (2016) summarizes the literature on risk taking after a loss and in a lab experiment finds that the effect of loss on risk taking depends on the timing of the realization of the loss. Participants who face the loss immediately after it occurs take on less risk than those who do not face the loss until the end of the experiment. Chevalier and Ellison (1997) considers mutual funds investment strategies, and find that mutual funds adopt riskier strategies when nearing the end of the calendar year in order to obtain a stronger end-of-year performance.

Other work examines the implications of up-or-out environments on risk taking in particular. In an experimental setting, Oprea (2014) explores the interaction between profit maximization, risk-taking, and survival. He finds that when profit maximization and survival

[3] In related work, Knoeber and Thurman (1994) compared a tournament scheme to a pay scheme that combines relative rankings with information about absolute productivity differences. They find that changes in prize levels that leave the prize spreads unchanged have no impact on performance in tournaments.

[4] In this context, it is argued that eliminated teams turn their attention to the pending player draft, which rewards lower performance.

can occur simultaneously, participants will choose strategies close to the optimum. However, when survival and profit maximization imply different strategies, subjects will choose survival over profit maximization, exposing themselves to greater risk in profits.[5] As another example, Cabral (2003) presents a model set in a story of investments in research and development where, in equilibrium, the industry leader chooses a safe strategy while followers choose risky strategies. This model is tested in Mueller-Langer and Versbach (2013), where the second game in sequences of two-game soccer tournaments is used as a measure of whether teams play differently when they've lost the first game. They find no such evidence that pending elimination changes behavior. Of course, as a team sport, soccer may introduce an aggregation problem that challenges identification of the causal parameter of interest.[6]

Grund et al. (2013) considers risk taking in the NBA, demonstrating that teams who are losing near the end of the game take more three-point shots, but that these riskier shots do not translate into a higher score. In weightlifting competitions, where participants choose what they intend to lift, Genakos and Pagliero (2012) finds an inverted-U relationship between participant rank and the weight they intend to lift. (Higher- and lower-ranking lifters choose to attempt heavier lifts, which is the riskier strategy.) Performance is also lower for higher-ranked lifters, which suggests that risk taking may map into realized performance differently across player ability.[7]

Ozbeklik and Smith (2017) consider risk taking in golf tournaments and find that players with lower world ranking (OWGR) are more likely to take risks in match-play golf tournaments, as are those who are playing poorly compared to their contemporaneous opponent. However, Ozbeklik and Smith (2017) defines risk as *ex post* variability of score. We, instead, separately identify *ex ante* risk taking and the *ex post* outcome of having taken that risk. In particular,

[5] Note that in our context, survival and profit maximization imply the same strategy—to make it past the cut.

[6] Taylor (2003) proposes a model that accounts for general-equilibrium effects, arguing that mutual-fund managers may best respond to the risk-taking incentives faced by other managers—those with nothing to lose—by taking more risks themselves in order to stay ahead.

[7] Increased tournament incentives in NASCAR leads to more accidents (Becker and Huselid, 1992), especially when closely ranked drivers are nearby (Bothner et al., 2007).

we use PGA-defined measures of risk-taking potential on each hole played on the PGA Tour, and conditional on this sub-sample of holes, consider whether a player takes that risk or does not.[8]

3 Background and data

Tournaments on the PGA Tour can vary in format and scoring system. The most-common scoring system is called stroke-play—it is by far the scoring system most are thinking of when they think of golf. We use only stroke-play tournaments in our analysis.[9] The winner of a stroke-play tournament is the player who completed all days of the tournament with the fewest cumulative number of strokes. However, in most stroke-play tournaments on the PGA Tour, it is also customary to cut players at the end of the second day of competition—with 18 holes in each round, that implies that elimination occurs after two times around the same 18-hole course. It is this pending threat of elimination that provides our identifying variation.

The elimination criterion used most often by PGA tournaments is to cut to 70 players, plus all ties. In a typical tournament, the "70 plus ties" rule falls in a fairly fat part of the distribution of player, so ties are not uncommon, and the number of players who actually make the cut thus varies.[10] In Figure 1 we capture the realized number of players making the

[8] McFall and Rotthoff (2016) uses stroke-level data from golf tournaments, where they define risk as a player being near the green on a shot earlier than would be expected given the par of the hole. This is potentially confounded with, for example, unobserved player ability, but is interpreted as evidence of increased risk taking in response to the presence of superstars, and evidence of reference bias—players tending to take more risk when their current rank is further away from their OWGR. Their measure of risk also differs from our measure.

[9] In a match-play tournament, players compete one-on-one for a win on each hole. The player who has fewer strokes on the most holes is the winner of this type of play. Garcia and Stephenson (2015) examines player performance under the Stableford scoring mechanism—a very small number of tournaments use this system, where points are awarded for a player's score relative to par—and finds no evidence that risk taking increases in response to this convexity.

[10] The purpose of instituting a cut to the field of competitors is primarily to speed up play, allowing players to play the third and fourth days of competition in pairs instead of in threes. In 2008, an additional cut rule was added to the PGA Tour. If more than 78 players make the day-two cut, a second "70 plus ties" cut is held at the end of day three, to reduce the field of competitors going into the last day of competition. These players are said to have made the cut, but not finished. Players who are cut at the end of day three receive a share of the tournament purse that would be consistent with having played all four days and finishing in last place.

cut on average, across all 526 tournaments in our sample.

It is also the case that every player who makes the cut shares some portion of the total purse, while no player missing the cut receives any portion of the purse. In a tournament with the median purse of $6,000,000, a last-place finish will yield $12,000. More generally, however, prizes asymptote to 0.2 percent of the purse on average. As we are identifying off of the discontinuity created at the elimination cut, we thus have in mind that the $12,000 prize is part of the explanatory to any systematic differences in behavioral we observe around the elimination margin.

In our analysis we use the hole-level panel data provided by the PGA Tour's Shotlink™—every hole played by every player in all PGA Tour events. We restrict our sample to stroke-play tournaments with four rounds of scheduled and completed play, and a "70 plus ties" elimination after the second day of competition.[11] We also restrict our analysis to tournaments that were not significantly influenced by weather (e.g., we drop tournaments where rounds were completely eliminated or where multiple rounds were played on one day instead of two). As identification is achieved around the elimination rule, we restrict our sample to where we have identification—all player-tournament-holes strictly within the first 36 holes of each tournament. We also restrict our analysis to players who completed 36 holes, reflecting that players have no obligation to complete each round, and anything falling short of two full days of competition may introduce problematic sample selection.

Our sample includes data on 2,630 players across 526 tournaments, all of them held between 2002 and 2016 inclusive. Our data include information about each player's performance on each hole. Across courses, the PGA Tour defines certain holes as "going-for-it" holes, which we use to determine whether golfers systematically take more or less risk when elimination is pending. Risk taking—"going for the green," as it would be called—is therefore defined by an attempt to reach the green in fewer strokes than would be suggested by the par on the hole. For example, on a par-five hole, instead of taking three shots to get to the green, a

[11] For example, we discard the Master's Tournament which has a cut at "50 plus ties," but also has the provision that players within 10 strokes of the leader make the cut.

player might attempt to hit the green in only two strokes. We observe whether players indeed took the riskier strategy on these holes, and whether they were successful in their attempt to reach the green. Players who fail to reach the green often land in some sort of hazard, leading to higher scores than would be expected if the risk had not been attempted.

To better control for player ability we include players' world rankings from the previous year, which also facilitates our consideration later of heterogeneity across player ability. In short, this OWGR ranking is a weighted measure of tournament success in each player's two most-recent years of competition, with points awarded according to finishing placement in any tournament and more weight given to more-difficult tournaments.[12]

4 Identification

The fundamental source of variation we exploit is the discontinuity in player expectations of making the cut, introduced by the elimination of competitors that will occur at the end of 36 holes. Specifically, the PGA Tour's "70 plus ties" rule initiates a notion of pending elimination on all holes after the first. We will therefore ask whether there are identifiable differences in performance or risk taking when playing from the elimination side of this rule on each of the holes $h \in \{2, 3, ..., 36\}$. After identifying average effects, we will explore heterogeneity in this relationship. For example, among other things, we will consider how it might change as the threat of elimination approaches, and how the threat of elimination might induce changes in performance and risk taking differentially for those who were eliminated in their most-recent tournament.

The main threat to identifying the effect of a potential elimination on player performance and risk taking is that unobserved player ability will simultaneously affect both player rank (i.e., their rank relative to the elimination discontinuity) and outcomes (i.e., strokes

[12] Recency is also given more weight, considering that golf is a game where ability is highly varying across time, so recency may better reflect current rank. These rankings are not limited to PGA Tour players, but include every professional tour, and includes the top-200 players through 2006, and the top-300 players thereafter.

taken). In particular, as players who perform worse are more likely to be cut, we would expect to find lower average performance (i.e., higher scores) on the elimination side of the discontinuity. Identifying off of within-player variation will protect identification from this potential confounder—in our preferred specifications we include player-by-year-by-tournament fixed effects, addressing the concern that retrieving the causal parameter is hampered by unobservable ability. Formally, we therefore allow for player ability to vary other than within given tournaments. In the ideal experiment, we would compare a player to himself on the same hole in the same year in the same tournament with the same cumulative number of strokes, but at a differently ranked position due to the (exogenous) performance of the competitors he faced that weekend. This reveals the fundamental econometric problem, of course, as each golfer plays each tournament-hole only once. We do get close to the ideal experiment, however, by comparing a player to himself across holes in the same tournament, where those holes are played while at differently ranked positions relative to the cut. Restricting the sample to players who are closest to the elimination margin likewise mitigates this concern, which we will do as part of our bandwidth-sensitivity analysis.

The econometric specification we are describing can be written,

$$\begin{aligned} Y_{ihty} = {} & \beta_1 \mathbb{1}(Rank_{ihty} \geq E_{hty}) + \beta_2 Rank_{ihty} \\ & + \beta_3 Rank_{ihty} \times \mathbb{1}(Rank_{ihty} \geq E_{hty}) + \delta Par_{ihty} + \gamma_{ity} + \epsilon_{ihty}, \end{aligned} \tag{1}$$

where Y_{ihty} is a placeholder for the outcome of interest (e.g., total strokes, putts, risk taken) of player i on hole h of tournament t in year y, Par_{ihty} is the par of the hole, $Rank_{ihty}$ is player i's rank in the field of competitors (after having played hole $h-1$ but before playing hole h), and E_{hty} is the elimination threshold.[13] Player-by-year-by-tournament fixed effects

[13] For 94 percent of the tournaments in our sample, half of the players will randomly be assigned to start on hole 10 in order to speed up play in the first few days of competition. We define h as the hole sequence for player i, such that that the player who starts on the course's first hole and the player who starts on the course's tenth hole start the day at $h = 1$. The results are qualitatively robust to including an out-of-order indicator, including tournament-by-year-by-order fixed effects, and to the inclusion of player-by-tournament-by-year-by-order fixed effects.

are captured in γ_{ity}. We are primarily interested in the role of $\mathbb{1}(Rank_{ihty} \geq E_{hty})$—with the threshold player i faces on hole h determined only by lagged performance, $\hat{\beta}_1$ identifies the difference in player performance that is systematic with being on the elimination side of an exogenous threat of elimination.

We consider four main outcomes in our analysis: the player's stroke total on the hole, the binary choice of whether a player "Went for it" (on the subsample of holes the PGA officially designates as "going-for-it" holes), and a variable indicating whether the player hit the green after taking that available opportunity for a riskier strategy, and how many putts were taken on a given hole. Any difference in total strokes attributable to the pending threat of elimination we interpret as some change in effort or focus, or to playing the hole differently by taking more or less risk. However, given the consensus opinion that putting is not subject to any choice over risk-related strategy, putting performance will serve to establish that risk-taking is surely not able to explain the entire increase in performance.[14] With respect to measurable returns to risk taking, we will interpret hitting the green after taking the risk as a measure of success.

Although the actual cut occurs at the end of the second day of competition, we observe each player's performance on each hole of the tournament, and can therefore recreate the status of any pending elimination that would have been faced on approach to each hole. Given the "ties" included in the PGA Tour's "70 plus ties" elimination rule, E_{hty} is a tournament-specific elimination threshold. The indicator variable $\mathbb{1}(Rank_{ihty} > E_{hty})$ therefore captures

[14] Some have suggested that leaving putts short as suggestive of a risk assessment, anticipating then that there may be something systematic with pending elimination in the prospect of putts being left short of the hole or going past the hole. Yet, this is at odds with the common "100% of short putts don't go in" adage, which also supports the interpretation that any putt left short or long is evidencing performance, not evidencing the ex ante choice over available risks. Location coordinates are available for every shot on the PGA Tour, allowing for one to consider directional vectors from the hole, for example. (Though possibly not how close to the hole a given putt may have travelled, so interpreting distance along may be misleading.) It occurs to us, however, that short/long distinctions (or such things as the potential heterogeneity that exists in left-to-right putts versus right-to-left putts, by player handedness, etc) would remain second-order to the broader question of identifying the joint association of risk taking and performance response to tournament incentives. Thus, we consider the number of putts as our risk-constant performance metric and leave additional consideration to subsequent analyses. (While some interpretations allow for putting to itself allow for risk taking (Pope and Schweitzer, 2011), the PGA does not acknowledge risk-taking opportunities with respect to putting.)

any player i with a rank worse than the "70 plus ties" cut as he approaches hole h and therefore faces elimination without some improvement. We normalize E_{hty} to zero in all figures and tables below, after accounting for ties. While elimination is according to ordinal ranking, we will also respect cardinal relationships when predicting player performance on either side of the elimination rule and, thus, define $Rank_{ihty}$ in deviations from the *stroke* total that would imply elimination (within tournament, of course, and recalculated for the entire field of players after each hole). In Figure 2, we report the distribution of rank over the pooled sample of all player-holes. In the end, if $Rank_{ihty} > 0$, then $Rank_{ihty}$ is equal to the number of strokes i must pick up in order to make the cut. If $Rank_{ihty} < 0$, then $|Rank_{ihty}|$ is equal to the number of strokes i could drop before he failed to make the cut. The interaction term in the model identifies the slope parameter on $Rank_{ihty}$ for those who face elimination as of hole h.

To the question of whether the elimination threshold is relevant to competitors, in Figure 3, we present a histogram of the elimination threshold relative to par. Across all tournaments in our sample, there is seemingly a high degree of predictability in the threshold, even before the tournament has begun. Players also have tournament-specific knowledge in the formation of their beliefs, suggesting an even-tighter distribution of deviations around the threshold than is implied in the unconditional distribution. Thus, it seems reasonable to assume that players are aware of the threshold. However, as is typical in tournaments, players move across the elimination threshold because they are playing better or worse *relative to their peers*—there is not a fixed threshold for success. As such, identifying player-specific differentials in performance and risk taking while on one side of the threshold or the other is contributed to by both own and competitor performance, and we assume that players anticipate their competitors' best response.[15]

[15] Though not reported, we consider whether players differentially responded to being on the elimination side of the threshold as a function of their most-recent play—whether they had recently picked up or lost strokes relative to par—and find no systematic variation (Appendix Table A4). In the heterogeneity analyses below, we do report the results of considering the number of threshold-crossings players make in the current tournament and their average deviation from the threshold.

Our specifications are estimated using ordinary least squares, where γ_{iyt} indicates tournament specific controls for player heterogeneity, and the estimation of ϵ_{ihty} allows for clustering at the level of player-by-year-by-tournament. As the estimated coefficients are implying changes in *hole-level* performance, note that a small change in hole-level performance can amount to sizable changes in 36-hole performance over two days of competition.

5 Results

5.1 Baseline performance results

In Column (1) of Table 1, we report estimates of a baseline specification of hole-level performance on either side of the discontinuity in players' expectations of survival that is introduced by the "70 plus ties" elimination threshold. Without including controls for player ability, the positive slope parameter on *Rank* in Column (1) is consistent with better players tending to take fewer strokes to complete a hole, on average. In Column (2), we absorb this player-specific time-invariant unobserved heterogeneity into the error structure with player fixed effects, which has the effect of reversing the sign of the estimated slope parameter. However, golf being the game it is, with players arguably experiencing hot and cold spells, there is reason to anticipate that player ability can vary across time in ways that would then escape player fixed effects. Absorbing year-specific unobserved player heterogeneity into the error structure leaves the results unchanged, suggesting that there is variation across tournaments for given player-years that misidentifies the causal parameter of interest. Thus, in Column (3) we allow for tournament-by-year player heterogeneity. To the extent players have good and bad weekends idiosyncratically, identifying the difference in player i's performance using variation within a given weekend of competition, when he is in and out of facing elimination over the course of that tournament, will be our preferred specification.[16] To the

[16] It is not uncommon for the best professional golfers to have bad weekends. For example, Jordan Spieth, the world-number-one golfer at the end of 2015, failed to make it through to the third day of competition in four of the 25 PGA Tour events he entered in 2015.

extent we have not controlled for varying player-specific heterogeneity, we anticipate the main threat to identification continuing to work against finding performance improvements on the elimination side.

In our preferred specification, the estimated discontinuity in performance at the elimination margin is therefore -0.05, suggesting that players perform relatively better (than themselves, on the same weekend) when they face elimination, and thus have nothing to lose. As the estimated parameters are per-hole performance measures, it is noteworthy to consider that the 36-hole equivalent yields a pre-cut marginal effect of -1.785 strokes—a meaningful improvement in performance given the margins that often make the difference between a player failing to make the cut and playing through to the final day of competition. The percent of players missing the cut by one stroke varies (across tournaments) from 2 to 16.5 percent, with 8.7 percent of the field of players in the average tournament missing the cut by one stroke.

We will shortly turn to consider the elasticity of risk taking with respect to potential elimination. Before doing so, in Column (4) of Table 3 we demonstrate that better putting is also induced by the threat of elimination. Importantly, with no meaningful risk-related strategies in putting, this represents a risk-held-constant, exogenous inducement into improved performance. The estimated discontinuity is -0.03, with the associated 36-hole equivalent of this marginal effect of -1.039. Given the consensus opinion that putting is not subject to any choice over risk-related strategy, this result serves to establish that risk is surely not able to explain the entire increase in performance. Specifically, increased performance on putts alone explains 58 percent of the improvement in overall score, which supports that players do indeed perform better when on the elimination side of the upcoming cut in ways that are independent of their risk taking. Without an available appeal to risk taking to explain this increase in performance, this improvement in score is most likely explained by increased focus and determination when the threat of elimination is more salient.

5.2 Baseline risk-taking results

In Table 2, we adopt our preferred specification from above but restrict the sample to those holes designated by the PGA as "going-for-it" holes. In this table, we model the variation in three risk-related outcomes: whether players went for the green on risk-taking holes, and as indications of success, whether players hit the green and the distance to the hole they faced subsequent to having taken that risk.[17] The sample size varies across columns of Table 2 as the risk-success outcomes are conditional on having taken the risk.

In general, our results in Column (1) suggest that there is a positive relationship between player rank and risk taking—a one-stroke decline in performance (an *increase* in *Rank*) is associated with a roughly 1-percent increase in the propensity to take a risk, all else equal. However, those on the elimination side of the cut choose the risky strategy 2.7 percentage points more often—a 5.4-percent increase in the probability of taking a risk when possible. Given an average of 7.2 holes (out of 36) on which it is possible to take this type of risk, this represents a potential improvement in performance of 0.19 strokes over the first two days of competition (i.e., $7.2\times.027$). Thus, at the upper bound where all risk taking pays off, taking the risk on "going for it" holes can explain up to 49 percent of the gains in measured performance.[18]

Having established playing at the margin of elimination increases risk taking (on the elimination side), in Column (2) we then consider the *ex post* realization of risk taking. Where players take risky strategies, the PGA records "success" quite simply—hitting the green on such a shot is considered success, which we capture with a binary outcome. Conditional on the risky strategy having been chosen, we find a one percentage-point increase in the probability of a successful outcome on the elimination side. When players are on the elimination side

[17] If we repeat the preferred specification of strokes, but restrict the sample to those holes designated by the PGA as "going-for-it" holes, we find similar point estimates even though there are no par-3 holes in this sub-sample, since it is expected that all golfers will always attempt to hit the green from the tee. This explains part of the decline in sample size going from Table 1 to Table 2.

[18] Restricting Table 1 Column (3) to a sample of "going-for-it" holes yields a point estimate discontinuity of -.055. Thus, where all additional risks taken reward the player with a one-stroke improvement, the fraction of gains attributable to additional risk taking is .027/.055=.49.

of the cut on a hole that affords the option to take a risk, that option is being chosen with higher likelihood. If those induced risks are similar in their riskiness (and are just opted for more often) then we would expect coincident declines in rates of success on the same side of the cut. Yet, we find *increases* in the probability of hitting the green on those risks taken from the elimination side of the elimination threshold. Assuming that selection into risk taking is monotonically increasing in the riskiness of the opportunity, the low-risk options should be played more often than the high-risk options. Risk taking therefore explains 23 percent of the gains in measured performance on "going-for-it" holes.[19]

As one last attempt to capture variation in player performance around risk taking, in Column (3) of Table 2 we consider the remaining distance to the hole after having taken a risky shot. While the PGA records failing to hit the green after choosing the risky strategy as failure, any systematic variation in the remaining distance to the hole may similarly point to improved performance. Conditional on the distance their risky shot is taken from, we find that when players face elimination they land their risky shots 13-inches closer to the hole, on average, than when they do not face elimination. Again, we interpret the data as suggestive that the threat of elimination is increasing "productive" risk taking.

5.3 Sensitivity, heterogeneity, and bandwidth considerations

In the analysis above we identify the average effect of a pending threat of elimination. Below, we wish to consider whether the elasticity of performance and risk taking is evidently different as the threat of elimination becomes more salient, and the potential sensitivity of our results to the selection of players who contribute to identification. As it turns out, these are all "bandwidth" considerations, in a way, so we group them together below.

[19] Restricting Table 1 Column (3) to a sample of "going-for-it" holes *on which risk was actually taken* yields an estimated discontinuity of -.053. Thus, accounting for rates of success, the fraction of gains attributable to additional risk taking is .012/.053=.23.

5.3.1 Responsiveness as elimination approaches

Here, we will explore the effect of pending elimination as the opportunities to influence outcomes slip away—as there are few holes remaining and the threat of elimination becomes more salient. We accomplish this by re-estimating our models while sequentially dropping the earliest holes played in each tournament.

In Figure 4, for each of our four outcome variables, we report the estimated effects of being on the elimination side of the elimination threshold across this metric. Moving to the right on the figure, we restrict the sample to fewer holes—those holes closer to the actual tournament cut at the end of the 36^{th} hole.[20] For example, the estimate reported using hole 19 as the earliest contributor is the relevant estimate for considering only the second day of play. In Panel A, the estimated discontinuity in strokes is negative throughout most of the specifications, though it attenuates as we discard early holes from the model, and actually flips sign as we identify only off of the threat of elimination over the last few holes, where it is most salient. That is, on holes 34 and 35, players are performing *worse* when on the elimination side of the cut. (Recall that it is *reductions* in score that equate with *improvements* in performance.) This would be consistent with players losing focus as the opportunities for success slip away, or evidence that players have limited capacities to maintain performance levels with the stress of elimination being felt so strongly.

Though precision is lost, the estimated discontinuity in putts, in Panel B, is seemingly invariant across the same sequence of specifications. In Panel C we plot the estimated discontinuities for risk taking, which also prove very stable throughout the 36 holes, as does the differential probability that the player hits the green on risky shots as elimination approaches (Panel D). To the extent risk taking behavior is especially salient in the second day of the tournament, and players have better information about the field, the second day is when one might want to take risks. There is a tentative evidence in favor of this argument

[20] Since we are using player-by-tournament-by-year fixed effects, the last hole we can actually discard from our sample is hole 34. Recall also that hole 1 is not identified since players are not ranked prior to posting a stroke total.

in Panel C of Figure 4—after being relatively stable in the first 18 hole (the first day), the estimated discontinuity in "going for it" starts increasing (as does, though imprecise, the corresponding discontinuity for "hitting the green" in Panel D).

Overall, then, we find consistent performance improvements associated with potential elimination that are in part driven by induced increases in successful risk taking. However, the improvements induced by the contract convexity represented in the threat of elimination do not withstand the immediacy of that threat, where significant *declines* in performance become evident as elimination approaches and there are few remaining opportunities to avoid elimination. Interestingly, however, risk taking and putting performance play little role in this eventual decline. This reversal is then most-easily attributed to differences in performance in the earlier shots of each hole.

5.3.2 The responsiveness of players who are closer to the cut on average

Here we consider parameter sensitivity to the systematic removal of players (not holes) from the sample. Players are amassed around the cutoff for the first few holes, of course, and the contributions of those player-holes introduced to the identifying variation by those who will quickly separate from the field (in either direction) may not be the ideal experimental variation off of which to identify.[21] For example, even after controlling for player ability, even the tournament's eventual winner could have easily played the first hole at one or two strokes over par, and would thus contribute one or two observations to the identifying variation, in ways that have little to do with any responsiveness to pending elimination. (Such would yield negative bias, as he subsequently performed better on the elimination side, which is what led him to eventual victory.) Clearly, the strongest and weakest players in the field, who will necessarily contribute at least a few observations around the cutoff, are hardly the marginal observations off of which we should identify. We would prefer, in the sense of the ideal experiment, to find these players randomly on each side of the elimination threshold,

[21] On average, 61 percent of the field is on the margin of being cut at hole 2.

which we might best approximate by considering the sensitivity of the point estimate to collapsing on those players who are closer to the cutoff *on average* and are therefore most likely to experience the quasi-random play from both side of the cut.

In Figure 5 we plot the histogram of players' average within-tournament ranks, revealing how different players can be from each other in their average deviation from the threshold. The truly marginal players are arguably those clustered around the cut (at zero). In Table 3 we therefore report estimates of the discontinuity as we remove players with average (tournament-specific) ranks farthest away from the threshold—roughly, then, it is both the best and worst players being eliminated as we tighten up the estimation around the discontinuity. We consider the entire sample in the first column, those within ten strokes of the cut in the second column, through to using only those with a mean rank within one stroke of the cut. Total strokes and estimates of putting responsiveness are very stable as the bandwidth collapses in this way, restricting observations to players who are truly middling in each tournament.[22]

Another possible bandwidth-sensitivity exercise would increasingly restrict the sample to tournament-year-player-holes where player ranks were nearest the cut. Given the importance of capturing unobserved player heterogeneity, in our preferred specifications we identify only off of within-player variation. As such, restricting the sample to only those player-holes where the player was close to elimination (not just close on average) quickly decreases our ability to detect any behavior of interest. More fundamentally, though, the objective in collapsing around the identifying threshold is to increase the comparability of the "treatment" and "control" groups, which this does not accomplish. For example, as previously discussed, a *Rank*-based bandwidth restriction gives increasing weight to players who will only pass through the treatment margin in the first few holes of the tournament, before they separate to either the front or back of the field of competitors. These players are in no way representative

[22] Considering the sensitivity of the average effect of Column (4) to holes closer and closer to elimination, as we did in Figure 4, yields very similar results. These are available in Appendix Figure A1, along with other supplemental results.

of the sort of marginal player off of which we wish to identify.

5.3.3 The responsiveness of players who are around the cut more often

As an alternative to removing players based on their average rank over the tournament, we can collapse on players who are close to elimination most often as a heterogeneity of sorts. In Figure 6 we report the estimated discontinuities across increasingly restricted samples. The x-axis of the figure represents the minimum number of times contributing players crossed the threshold in either direction during the first 36 holes of competition. As we move to the right—this has the sample increasingly consist of players who crossed the threshold more frequently—the estimated discontinuity in performance (in Panels A and B) more than doubles, though loses precision in the expected way. This suggests that, if anything, players most often at the margin of elimination are *more* sensitive to which side of the threshold they are on. The propensity to take risks and to succeed at those risks remains relatively constant (in Panels C and D).

5.3.4 Time of day

We continue with our consideration of heterogeneity in other dimensions by first including an analysis of what could constitute a threat to identification. Though likely to impart only attenuation bias, the time-staggered play across the field of competitors may matter insofar as early groups are less informed about the stroke totals that will contribute to the "70 plus ties" elimination threshold (i.e., the E_{hty} above).

To partially address this, we stratify the model by the hour each hole was finished. To avoid conflating the time of day and hole sequence, we control for hole sequence directly. In Figure 7 we report the estimated discontinuities, noting again that the confidence interval natural widens around observations at the end of the day, where there are fewer observations. In the end, however, we find the estimates quite robust to time of play. Even though morning players are arguably less informed than afternoon afternoon players, those in the morning are not seeming to react to potential elimination any less than those in the afternoon. This is also consistent with professional golfers knowing about where the cut line is going to be and reacting to that expectation, as we suggested in our discussion of Figure 3.

5.3.5 Player-specific ability

We next consider heterogeneous responses to the threshold at the player level. In Table 4 we stratify the sample into ranked and unranked players, and then separately estimate the discontinuity for unranked players, and then for stronger and stronger pools of ranked players.[23] Doing so reveals that higher-ranking players respond less at the margin to potential elimination. The estimated discontinuity on stroke totals for the highly ranked players is about half the size as it is for the unranked players and the estimated discontinuity on putts is also smaller.

Moreover, the risk-taking behavior and subsequent risk success of highly ranked players does not differ with pending elimination. This pattern is consistent with differences in experience—more-experienced players know better or are more comfortable with their style of play, thus being less sensitive to conditions. Essentially, a sign of maturity and expertise may well yield lower elasticities with respect to pending elimination.

It is also the case that as we collapse on higher-ranking players, we are collapsing on players who are increasingly likely to make a given cut, and thereby secure prize winnings with greater likelihood and in larger amount. Among the highly ranked, the performance increase in strokes due to the pending elimination is similar in magnitude to the performance increase in putts, implying that increased putting concentration and focus can completely explain the overall performance increase.

[23] See Appendix Table A2 for a comparison across tournaments that vary in the ability of the field of players, generally.

6 Conclusion

The PGA records enable hole-by-player-by-tournament analysis around objectively determined cutoffs, where players are routinely observed on both sides of the threshold of elimination from tournament competition. We approximate the ideal experiment by comparing a player to himself across holes in the first-two days of a single tournament—on some holes, he will be on the elimination side of the threshold, while on other holes he will be on the safe side.

We exploit an opportunity to jointly observe performance, *ex ante* risk taking, and the *ex post* realization of risk. Collectively, we paint a picture of performance, risk taking, and rates of success on risks taken, each being higher when players play from the elimination side of the elimination threshold. Our results are robust to a battery of sensitivity exercises, and strongly suggest that sensitivity to elimination is stronger in lower-ability players. In particular, while measured performance does improves, there is no evident increase in risk taking among those of highest ability.

Overall, we suggest that 23 percent of the improvement in performance induced by potential elimination is due to productive increases in risk taking. These effects are most-evident among those closest to the margin of elimination, among lower-ability competitors, and diminish as elimination approaches.

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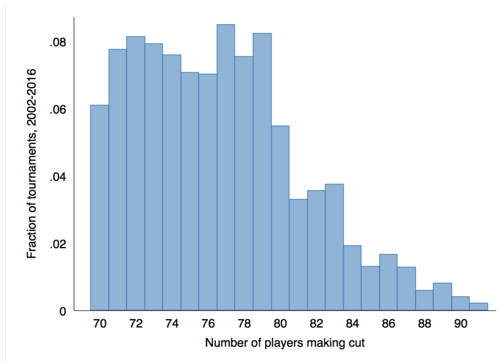
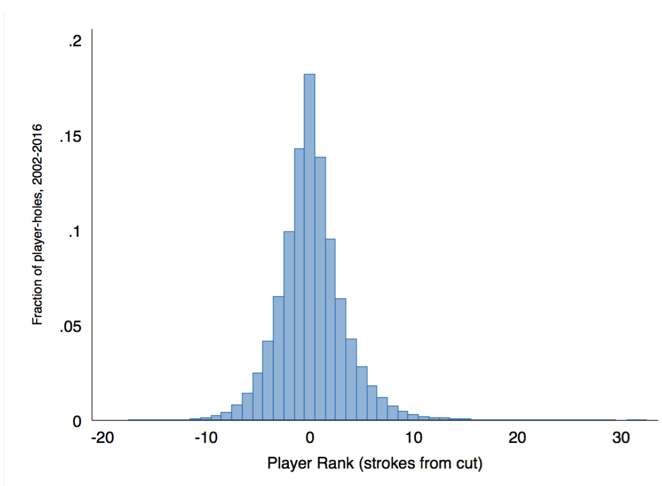
Figures

Figure 1: How many players make the "70 plus ties" cut



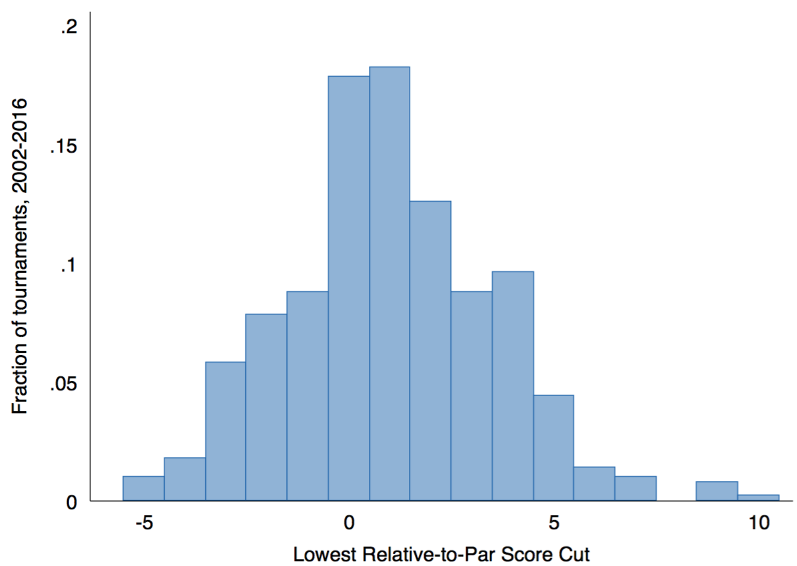
Notes: Given ties, the number of players who make the cut after 36 holes of play can exceed 70. In this figure, we plot the histogram of the number of players who make the cut in a given tournament, across all stroke-play tournaments on the PGA Tour, 2002-2016.

Figure 2: Deviations from tournament cut (*Rank*)



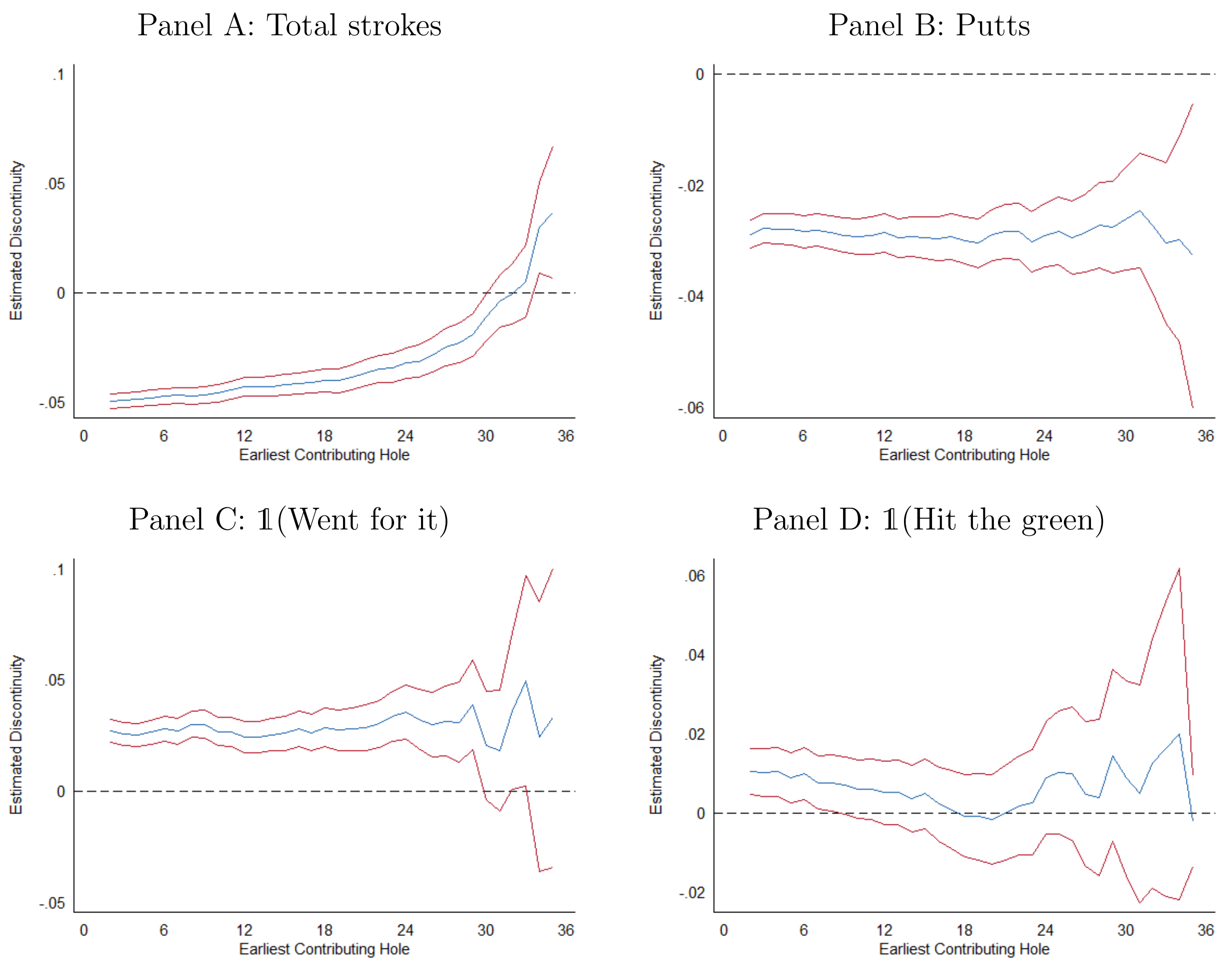
Notes: Given deviations from the implicit elimination threshold on each hole of play on the PGA Tour (E_{hty}), we plot the histogram of player rank at each hole (measured in strokes) relative to the elimination threshold, across all stroke-play tournaments on the PGA Tour, 2002-2016.

Figure 3: How predictable is the elimination threshold?



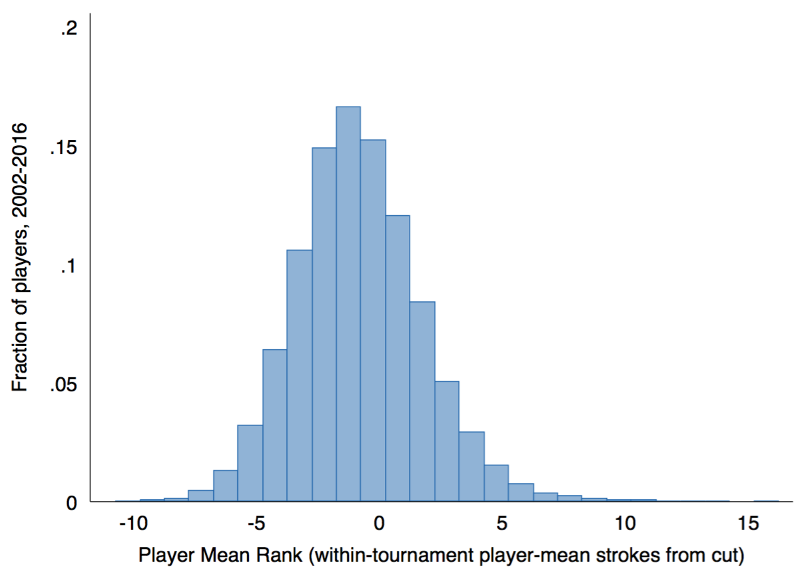
Notes: In this figure we plot the histogram of strokes *relative to par* that constituted the "70 plus ties" cut across all stroke-play tournaments on the PGA Tour, 2002-2016.

Figure 4: Does responsiveness change as elimination approaches?



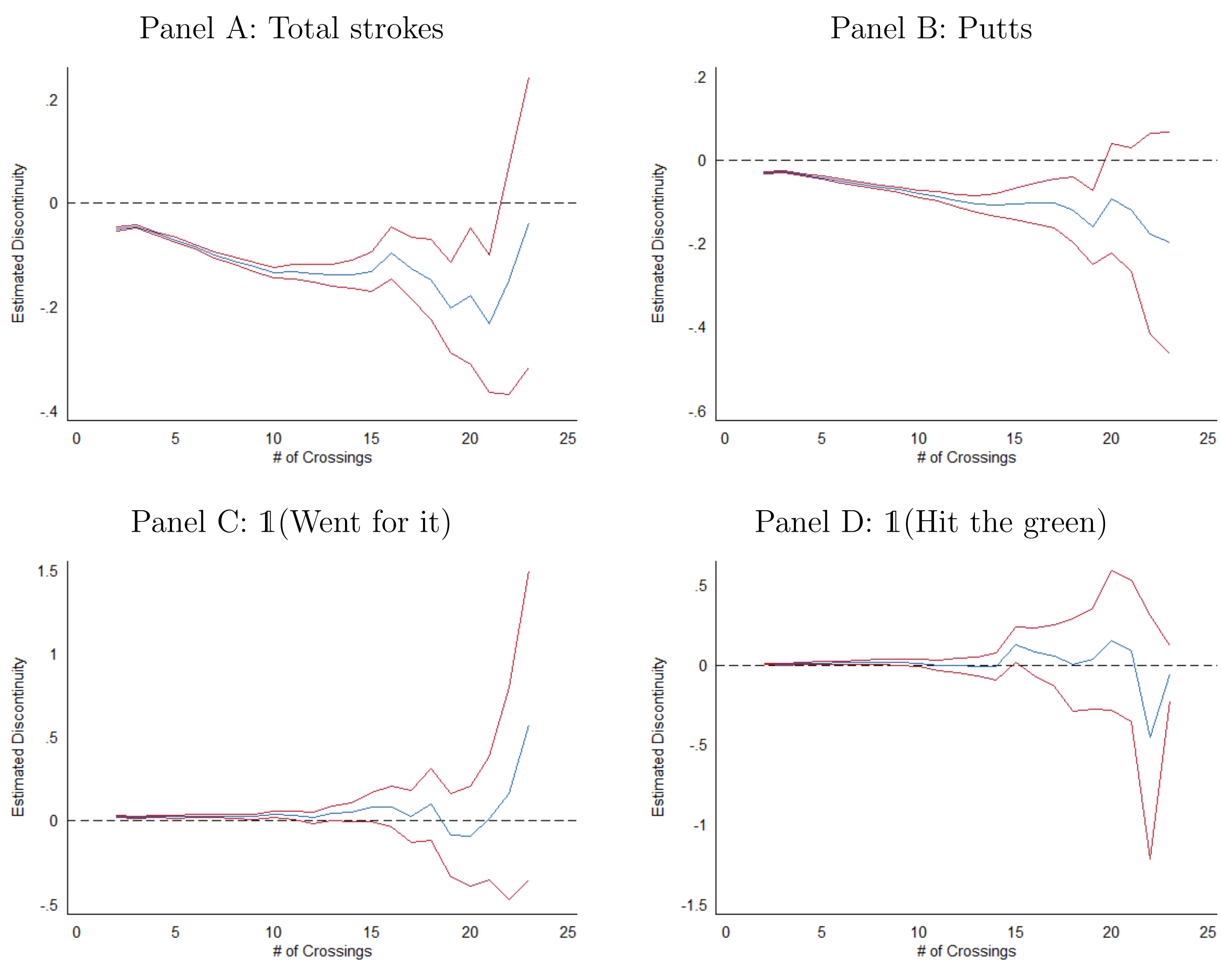
Notes: Point estimates and 95-percent confidence intervals from repeated estimations of Equation (1), restricting the sample to holes successively closer to elimination.

Figure 5: Mean rank of players



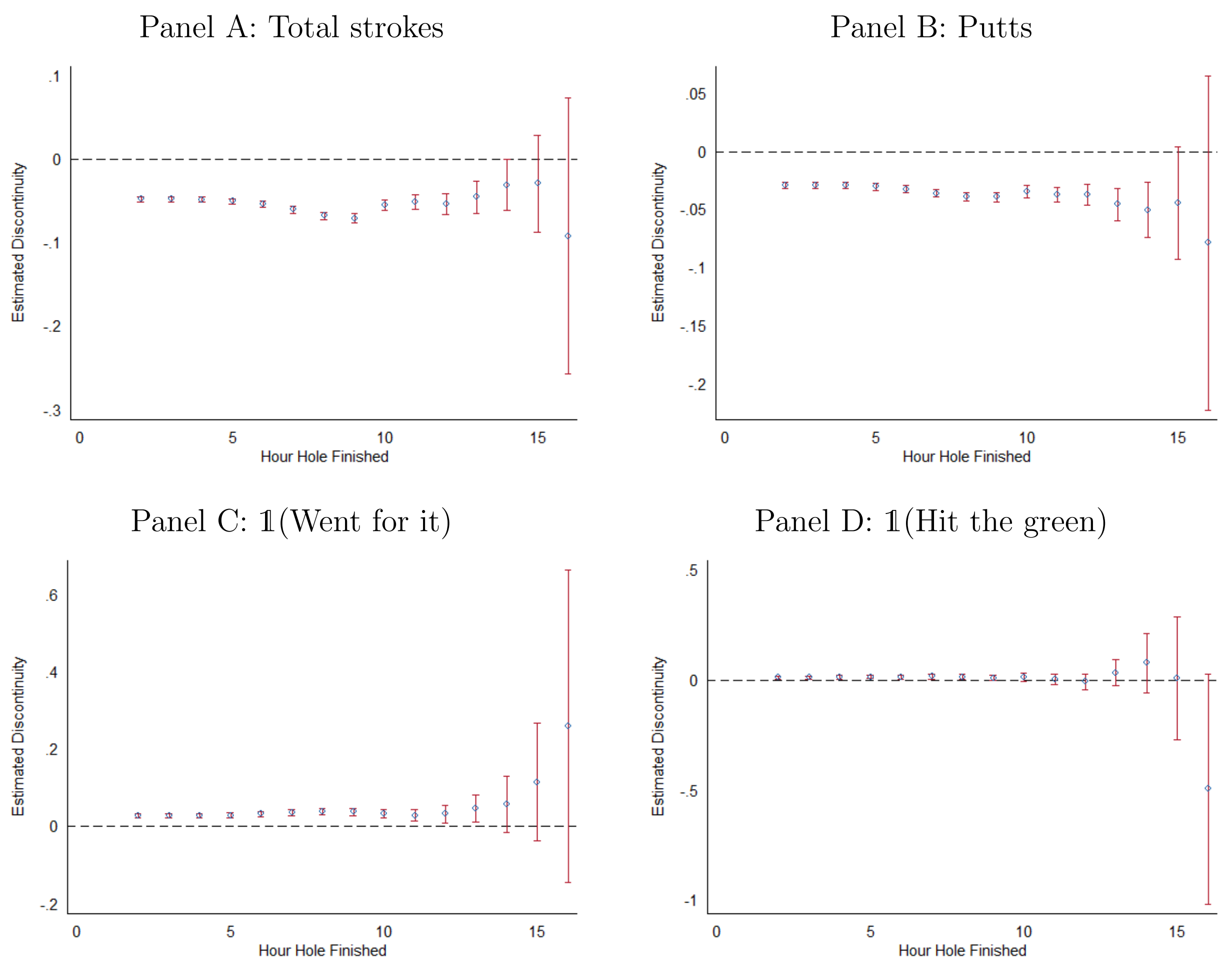
Notes: Given deviations from the implicit elimination threshold on each hole, we plot the histogram of *average* player rank (measured in strokes) relative to the elimination threshold, across all stroke-play tournaments on the PGA Tour, 2002-2016.

Figure 6: The estimated discontinuity by number of threshold crossings



Notes: Point estimates and 95-percent confidence intervals from repeated estimations of Equation (1), restricting the sample to those "closer" to elimination, defined as having more crossings of the elimination threshold.

Figure 7: Heterogeneity by hour of play



Notes: Point estimates and 95-percent confidence intervals from repeated estimations of Equation (1), stratified by the (player-specific) hour play was completed.

Tables

Table 1: The performance gains under pending elimination

	Strokes per hole			Putts only
	(1)	(2)	(3)	(4)
$\mathbb{1}(Rank \geq 70)$	-0.012***	0.002	-0.050***	-0.029***
	(0.001)	(0.0003)	(0.002)	(0.001)
$Rank$ [a]	0.0002	-0.002***	-0.063***	-.031***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
$Rank \times \mathbb{1}(Rank \geq 70)$	0.0154***	0.006***	0.013***	0.0097***
	(0.0004)	(0.0005)	(0.0007)	(0.0005)
Par	0.827***	0.827***	0.816***	-0.035***
	(0.0007)	(0.001)	(0.0007)	(0.0006)
Player FE		Yes		
Player-by-year-by-tournament FE			Yes	Yes
Observations	2,519,650	2,519,650	2,519,650	2,519,650
Number of groups		2,555	71,990	71,990
R^2	0.377	0.382	0.405	0.010
Mean	3.96	3.96	3.96	1.60
Implied change in strokes (per t)			-1.785	-1.039

Notes: Standard errors in parentheses—robust in (1), allowing for clustering at the player level in (2), and allowing for clustering at the player-by-year-by-tournament level in (3) and (4). *** p<0.01, ** p<0.05, * p<0.1. [a] In stroke play, lower integer ranks are better.

Table 2: Risk taking under pending elimination

		$\mathbb{1}$(Went for it) = 1	
	$\mathbb{1}$(Went for it)	$\mathbb{1}$(Hit green)	Distance remaining
	(1) [a]	(2) [a]	(3)
$\mathbb{1}(Rank \geq 70)$	0.027***	0.012***	-13.372***
	(0.003)	(0.003)	(3.340)
$Rank$	0.011***	0.009***	-5.557***
	(0.0006)	(0.0008)	(0.727)
$Rank \times \mathbb{1}(Rank \geq 70)$	0.003***	-0.003**	1.974*
	(0.0009)	(0.001)	(1.106)
Par	0.037***	0.130***	-146.008***
	(0.002)	(0.002)	(4.648)
Player-by-year-by-tournament FE	Yes	Yes	Yes
Observations	445,158	221,865	221,865
Number of groups	63,423	58,613	58,613
R^2	0.005	0.016	0.122
Mean (depvar)	0.498	0.242	673.323

Notes: Standard errors in parentheses, allowing for clustering at the player-by-year-by-tournament level. *** p<0.01, ** p<0.05, * p<0.1. [a] Linear-probability models, though binary response models yield qualitatively similar results.

Table 3: Bandwidth sensitivity by mean rank of player

	Absolute deviation (in strokes) from elimination threshold			
	All	$\lvert\mu_r\rvert \leq 10$	$\lvert\mu_r\rvert \leq 5$	$\lvert\mu_r\rvert \leq 1$
	(1)	(2)	(3)	(4)
Panel A: Strokes				
$\mathbb{1}(Rank \geq 70)$	-0.050***	-0.048***	-0.039***	-0.050***
	(0.002)	(0.002)	(0.002)	(0.003)
Observations	2,519,650	2,516,885	2,352,525	715,680
Panel B: Putts				
$\mathbb{1}(Rank \geq 70)$	-0.029***	-0.028***	-0.023***	-0.020***
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	2,519,650	2,516,885	2,352,525	715,680
Panel C: $\mathbb{1}$(Went for it)				
$\mathbb{1}(Rank \geq 70)$	0.027***	0.026***	0.021***	0.021***
	(0.003)	(0.003)	(0.003)	(0.005)
Observations	445,158	444,684	415,562	126,400
Panel D: $\mathbb{1}$(Hit the green) conditional on $\mathbb{1}$(Went for it)=1				
$\mathbb{1}(Rank \geq 70)$	0.012***	0.011***	0.010***	0.015***
	(0.003)	(0.003)	(0.003)	(0.005)
Observations	221,865	221,671	206,636	62,382

Notes: All specifications include par, and absorb player-by-year-by-tournament unobserved heterogeneity into the error structure. Standard errors in parentheses, allowing for clustering at the player-by-year-by-tournament level. *** p<0.01, ** p<0.05, * p<0.1

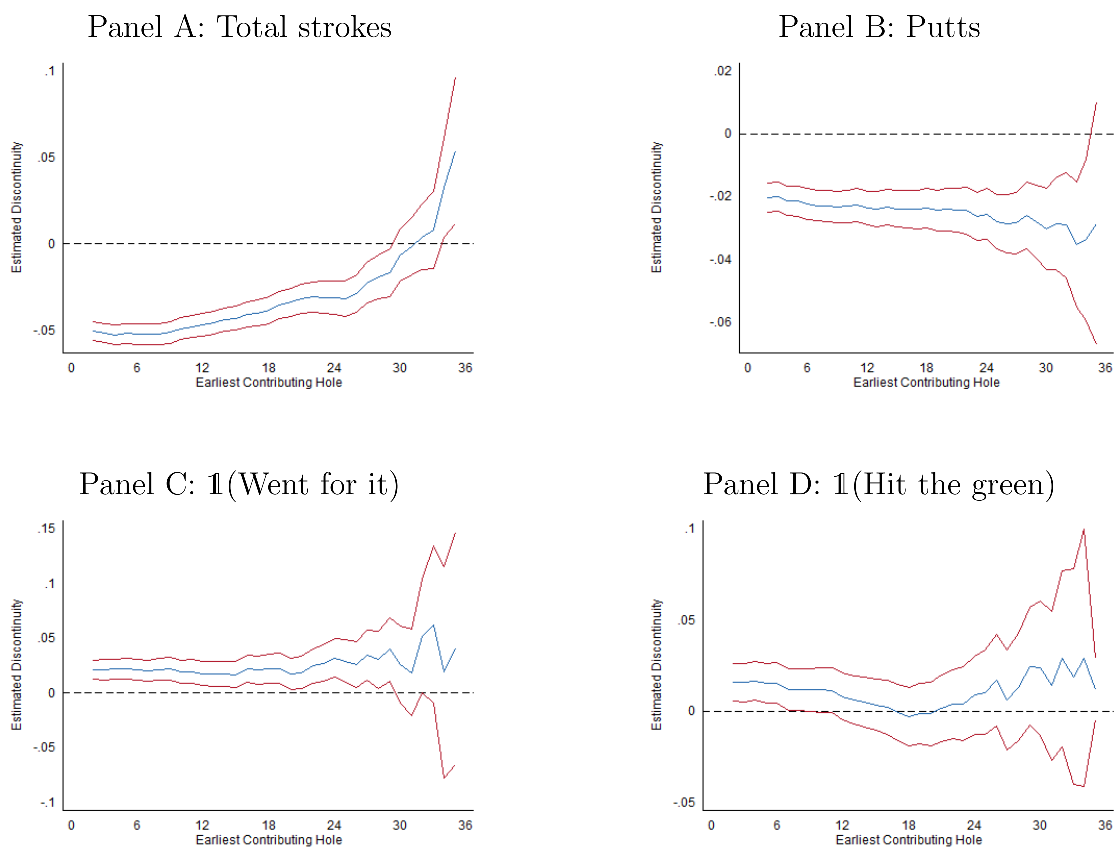
Table 4: Heterogeneity by player ability

	Unranked players	OWGR-ranked players			
		1-300	1-200	1-100	1-50
	(1)	(2)	(3)	(4)	(5)
Panel A: Strokes					
$\mathbb{1}(Rank \geq 70)$	-0.051***	-0.036***	-0.038***	-0.030***	-0.021***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
Observations	1,096,270	1,423,380	1,183,455	635,495	325,220
Panel B: Putts					
$\mathbb{1}(Rank \geq 70)$	-0.032***	-0.020***	-0.021***	-0.020***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Observations	1,096,270	1,423,380	1,183,455	635,495	325,220
Panel C: $\mathbb{1}$(Went for it)					
$\mathbb{1}(Rank \geq 70)$	0.029***	0.022***	0.020***	0.006	0.006
	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
Observations	188,045	257,113	214,492	116,356	59,776
Panel D: $\mathbb{1}$(Hit green) conditional on $\mathbb{1}$(Went for it)=1					
$\mathbb{1}(Rank \geq 70)$	0.009*	0.009**	0.007	0.009	0.012
	(0.005)	(0.004)	(0.005)	(0.006)	(0.008)
Observations	89,001	132,864	112,793	64,634	34,574

Notes: All specifications include par, and absorb player-by-year-by-tournament unobserved heterogeneity into the error structure. Standard errors in parentheses, allowing for clustering at the player-by-year-by-tournament level. *** p<0.01, ** p<0.05, * p<0.1

7 Appendix

Figure A1: Does responsiveness change as elimination approaches... for players with mean deviation from the elimination threshold $|\mu_r| \leq 1$?



Notes: Point estimates and 95-percent confidence intervals from repeated estimations of Column (4) of Table 3, restricting the sample to holes successively closer to elimination.

Table A1: "Baseline" specifications for other outcomes

	(1)	(2)	(3)
Panel A: Putts			
Rank	-0.0003	0.0005	-0.031***
	(0.0003)	(0.0005)	(0.0003)
$\mathbb{1}(Rank \geq 70)$	-0.005***	-0.002*	-0.029***
	(0.001)	(0.002)	(0.001)
$r \times \mathbb{1}(Rank \geq 70)$	0.002***	-0.001	0.010***
	(0.0004)	(0.0006)	(0.0005)
Observations	2,519,650	2,519,650	2,519,650
Panel B: $\mathbb{1}$(Went for it)			
Rank	-0.002***	-0.00003	0.011***
	(0.002)	(0.0008)	(0.0006)
$\mathbb{1}(Rank \geq 70)$	0.024***	0.021***	0.027***
	(0.002)	(0.003)	(0.003)
$r \times \mathbb{1}(Rank \geq 70)$	0.002	0.003	0.003***
	(0.0007)	(0.001)	(0.0009)
Observations	445,158	445,158	445,158
Panel C: $\mathbb{1}$(Hit green) conditional on $\mathbb{1}$(Went for it)=1			
Rank	0.006***	0.005***	0.009***
	(0.0006)	(0.001)	(0.0008)
$\mathbb{1}(Rank \geq 70)$	-0.004**	-0.001	0.012***
	(0.003)	(0.004)	(0.003)
$r \times \mathbb{1}(Rank \geq 70)$	-0.007***	-0.007***	-0.003**
	(0.0008)	(0.001)	(0.001)
Observations	221,865	221,865	221,865
Player FE	No	Yes	No
Player-by-year-by-tournament FE	No	No	Yes

Notes: All specifications include par. Standard errors in parentheses—robust in (1), allowing for clustering at the player level in (2), and allowing for clustering at the player-by-year-by-tournament level in (3) and (4). *** p<0.01, ** p<0.05, * p<0.1

Table A2: Heterogeneity by average ability of the field of competitors

		% of field with OWGR ranking		
	Full sample	≥ 30	≥ 50	≥ 70
	(1)	(2)	(3)	(4)
Panel A: Strokes				
$\mathbb{1}(Rank \geq 70)$	-0.050***	-0.050***	-0.054***	-0.057***
	(0.002)	(0.002)	(0.002)	(0.003)
Observations	2,572,654	2,354,695	1,649,900	645,015
Panel B: Putts				
$\mathbb{1}(Rank \geq 70)$	-0.029***	-0.029***	-0.030***	-0.028***
	(0.001)	(0.001)	(0.002)	(0.003)
Observations	2,572,654	2,354,695	1,649,900	645,015
Panel C: $\mathbb{1}$(Went for it)				
$\mathbb{1}(Rank \geq 70)$	0.027***	0.029***	0.031***	0.031***
	(0.003)	(0.003)	(0.003)	(0.005)
Observations	445,158	419,542	301,078	127,078
Panel D: $\mathbb{1}$(Hit green) conditional on $\mathbb{1}$(Went for it)=1				
$\mathbb{1}(Rank \geq 70)$	0.012***	0.013***	0.015***	0.019***
	(0.003)	(0.003)	(0.004)	(0.005)
Observations	221,865	208,883	153,307	66,793

Notes: All specifications include par, and absorb player-by-year-by-tournament unobserved heterogeneity into the error structure. Standard errors in parentheses, allowing for clustering at the player-by-year-by-tournament level. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Heterogeneity by par of hole

	Par 3 (1)	Par 4 (2)	Par 5 (3)
Panel A: Strokes			
$\mathbb{1}(Rank \geq 70)$	-0.036***	-0.047***	-0.056***
	(0.003)	(0.002)	(0.004)
Observations	578,327	1,496,835	444,470
Panel B: Putts			
$\mathbb{1}(Rank \geq 70)$	-0.020***	-0.029***	-0.031***
	(0.003)	(0.002)	(0.003)
Observations	578,327	1,496,835	444,470
Panel C: $\mathbb{1}$(Went for it)			
$\mathbb{1}(Rank \geq 70)$		0.014***	0.026***
		(0.004)	(0.003)
Observations		86,117	359,041
Panel D: $\mathbb{1}$(Hit green) conditional on $\mathbb{1}$(Went for it)=1			
$\mathbb{1}(Rank \geq 70)$		0.0001	0.014***
		(0.003)	(0.004)
Observations		51,592	170,273

Notes: All specifications absorb player-by-year-by-tournament unobserved heterogeneity into the error structure. Standard errors in parentheses, allowing for clustering at the player-by-year-by-tournament level. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Heterogeneity by cut outcome of most-recent tournament

	Outcome in most-recent tournament	
	Eliminated	Not eliminated
	(1)	(2)
Panel A: Strokes		
$\mathbb{1}(Rank \geq 70)$	-0.036***	-0.048***
	(0.002)	(0.002)
Observations	1,406,195	1,031,415
Panel B: Putts		
$\mathbb{1}(Rank \geq 70)$	-0.024***	-0.026***
	(0.002)	(0.002)
Observations	1,406,195	1,031,415
Panel C: $\mathbb{1}$(Went for it)		
$\mathbb{1}(Rank \geq 70)$	0.023***	0.027***
	(0.004)	(0.004)
Observations	251,455	179,957
Panel D: $\mathbb{1}$(Hit green) conditional on $\mathbb{1}$(Went for it)=1		
$\mathbb{1}(Rank \geq 70)$	0.009**	0.011**
	(0.004)	(0.005)
Observations	127,377	86,759

Notes: All specifications include par, and absorb player-by-year-by-tournament unobserved heterogeneity into the error structure. First tournament for all players discarded. Standard errors in parentheses, allowing for clustering at the player-by-year-by-tournament level. *** p<0.01, ** p<0.05, * p<0.1