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ABSTRACT

Performance and Risk Taking under Threat of Elimination

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 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 are quite common, opportunities to consider individual behaviour under threat of elimination is not common at all. Having coincident measures of *a priori* risk taking makes this opportunity all the more rare. 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 analysis around objectively determined elimination discontinuities. With players repeatedly observed on either side of the threshold in elimination-style tournaments, we measure the systematic (within-player) variation in both performance and risk taking as explained by variation in the threat of elimination. This is in part enabled by having separate measures of performance that are independent of risk—though challenging, putting is a simple technology with fewer opportunities for risk taking.

With this fresh approach to identification, our results strongly support that performance improves under the threat of elimination and suggests a fairly 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 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. If the additional risk taking induced by the threat of elimination pays off, additional risk taking can be thought of as accounting for up to 49 percent of the increase in performance. These effects are concentrated among those closest to the margin of elimination and among lower-ability competitors.

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 draw concessionary remarks in Section 6.

2 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.[1] 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 monetary payoffs.[2] 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.[3] 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," of a sort. Pope and Schweitzer (2011) also find 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

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

[2] 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.

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

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.

Some of this work is theoretical, of course, and includes the implications of up-or-out environments on risk taking in particular. For 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.[4]

Of course, elimination tournaments are a particular form of contract convexity, which we might expect to increase risk taking. This exercise therefore informs an understanding of contracts somewhat more-broadly than than strictly elimination environments. The shape of stock-option contracts, for example, are very much "up or out" in their implications, as the higher is the strike price, the more likely 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 strike prices equal to the stock price on the grant date (Barron and Waddell, 2008), thus implying that the only realization of monetary value is conditional on the stock price increasing. Moreover, if the stock price falls short of the strike price it does not matter at the margin by how much it falls short, as gains are only realized if the stock price is higher than the strike price. 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

[4]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.

to lose. We will see the empirical regularities they find in executive compensation contracts reappearing in our empirical regularities, as our data also suggest that both performance and risk taking increase under threat of elimination.

Ozbeklik and Smith (2014) 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 (2014) 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, 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.[5]

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.[6]

[5] 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.

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

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.[7] 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 36 holes. 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.[8] In Figure 1 we capture the realized number of players making the 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

[7] 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 a Stableford scoring 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.

[8] 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.

elimination margin.

In our analysis we use the hole-level panel data provided by the PGA Tour's Shotlink™. These data therefore encompass all players 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.[9] 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 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

[9]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.

most-recent years of competition, with points awarded according to finishing placement in any tournament and more weight given to more-difficult tournaments.[10]

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. 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. Restricting the sample of players contributing identifying variation to those who are closest to the elimination margin mitigates this concern, which we will do as part of our bandwidth-sensitivity analysis. Likewise, identifying off of within-player variation will also 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

[10] 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.

unobservable ability. Formally, we thus require the assumption that player ability, or any other conflating factors, be constant across an individual tournament for a given player. 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 in the same year across holes in the same tournament, where those holes are played while at differently ranked positions relative to the cut.

Our economic specification is therefore,

$$\begin{aligned} \mathrm{Y}_{ihty} = \alpha + \beta_1 \mathrm{Par}_{ihty} + \beta_2 Rank_{ihty} + \beta_3 1(Rank_{ihty} \geq E_{hty}) \\ + \beta_4 Rank_{ihty} \times 1(Rank_{ihty} \geq E_{hty}) + \gamma_{iyt} + \epsilon_{ihty}, \end{aligned} \tag{1}$$

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, $Rank_{ihty}$ is player i's rank in the field, and E_{hty} is the elimination threshold.[11]

We consider four main outcomes in our analysis: the player's stroke total on the hole, a measure of how many putts were taken on a given 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 "going-for-it." 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. Any variation in putts alone, however, cannot be attributable to risk taking—there are no

[11]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 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.

options for taking risky putts, per se—which will help in identifying whether movement in total strokes is entirely attributable to risk. (It will not be.) With respect to the return to risk taking itself, we will interpret the player 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 $1(r_{ihty} > E_{hty})$ therefore captures anyone with a rank worse than the "70 plus ties" cut as he approaches hole h and 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 r_{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 the end, if $r_{ihty} > 0$, then r_{ihty} is equal to the number of strokes i must pick up in order to make the cut. If $r_{ihty} < 0$, then $|r_{ihty}|$ 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 r_{ihty} for those who face elimination as of hole h. In Figure 2 we report the distribution of rank r_{ihty} over the pooled sample of all player-holes.

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-tournamant. 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) would be consistent with the bias driven by better players tending to have fewer strokes on average. In Column (2), we absorb player-specific time-invariant heterogeneity into the error structure, which has the effect of reversing the sign of the estimated slope parameter. However, golf being the game it is, there is reason to anticipate that player ability can vary in ways that will escape player fixed effects. (After being cut from the 2017 Farmer's Insurance Open, Tiger Woods offered "Unfortunately, I didn't get a chance to win this golf tournament ... but I have next week.") Thus, in columns (3) and (4) we allow for year-specific player heterogeneity and tournament-by-year-specific player heterogeneity, respectively. 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.[12] This is further supported by the model of Column (4) yielding the most-negative slope parameter—omitting ability would tend to drive such estimates positive—which suggests that we are better-absorbing the effects of unobserved player ability with the less-restrictive structure.

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

[12]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.

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, we re-estimate, in Column (5), our preferred specification but with the number of putts as the dependent variable. As putting is not subject to any choice of risk-related strategy, this result serves to establish our prior that risk is surely not able to explain the entire increase in performance. The estimated discontinuity is -0.03, with the associated 36-hole equivalent of this marginal effect of -1.039. Increased performance on putts thus 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 above but restrict the sample to those holes designated by the PGA as "going-for-it" holes.[13] In this table, we attempt to explain the variation in three risk-related outcomes: whether a player went for the green on a risk-taking hole, whether a player hit the green after taking a risk, and the distance to the hole after taking a risky shot.[14] The sample size varies across columns of Table 2 as the risk-success outcomes are conditional on having taken the risk.

[13] See Table A1 for the progression of specifications leading to our preferred, as in Table 1.

[14] 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.

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 *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, or 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 pays off, risk taking can explain 49 percent of the gains in measured performance on "going-for-it" holes.[15]

In Column (2) we consider the *ex post* realization of risk taking. Where players take risky strategies, the PGA records "success" quite simply as hitting the green, 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. Risk taking therefore explains 23 percent of the gains in measured performance on "going-for-it" holes.[16] This is consistent with relatively fruitful risk taking on the elimination side, on average. We cannot separately identify the types of risk taken under threat of elimination from their success rates, but this suggests that we are identifying the effect of additional focus being brought to bear when a player faces the threat of elimination, and not merely that they are induced into taking riskier risky shots (which would decrease rates of success, all else equal).[17]

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

[15]Restricting Table 1 Column (4) 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.

[16]Restricting Table 1 Column (4) 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.

[17]Re-estimating the model while including controls for the distance to the hole *before* the shot was taken leaves our results unchanged.

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 away, so we group them together below.

5.3.1 Does responsiveness change as elimination approaches?

First, we will explore the effect of pending elimination on outcomes 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. This is also a bandwidth sensitivity of a sort, in the sense that one might think of the cleanest identifying variation existing at the actual elimination—the top 70 as of the *end* of the 36^{th} hole continuing.

In Figure 3, 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, then, we restrict the sample to fewer holes—those holes closer to the actual tournament cut at the end of the 36^{th} hole.[18] In Panel A, the estimated discontinuity in strokes is negative throughout most of the specifications, though attenuates as we discard

[18] 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.

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 35 and 36, 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 simply evidence players having limited capacity to maintain performance levels with the stress of elimination being felt so strongly. However, as the estimated discontinuity in putts, in Panel B, is invariant across the same sequence of specifications, we are inclined to attribute the inversion in effect to changes in the risk adopted by players as elimination approaches—either risk taking, per se, or the success rate of risks taken.

In Panel C we plot the estimated discontinuities for risk taking which, like putts, also proves very stable throughout the 36 holes. With one last consideration, then, it is in Panel D that we see the mechanism revealed—indeed, the differential conditional probability that the player hits the green on risky shots declines as elimination approaches.

Overall, then, a consistent story would be that the performance improvements associated with potential elimination—recall that they are in part due to successful risk taking—vanish as elimination ultimately approaches, and that this is more attributable to decreases in the success rate of any risks taken (Panel D) than to more or less risk being taken (Panel C) toward the end of day two, and, as suggest by the stability of putts, also less about risk-independent performance being any more or less responsive as elimination approaches (Panel B).

5.3.2 Is responsiveness different for players closer to the cut on average?

In further considering the sensitivity of player responsiveness to elimination, here systematically remove 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.[19] 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, 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 4 we plot the histogram of players' average within-tournament ranks, revealing how different players can be 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 20 strokes of the cut in the second column, through to using only those with a mean rank within 1 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.

5.3.3 Is responsiveness different for players who are around the cut more often?

As one last alternative, rather than removing players based on their average rank over the tournament, we can collapse on players who are close to elimination most often. In Figure 5

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

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 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.

5.3.4 Why not disaggregated player-rank sample restrictions?

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, we do not perform this exercise as 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, 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 of the sort of marginal player off of which we wish to identify.

5.4 Additional heterogeneity

5.4.1 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 6 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 consistent with professionals knowing about where the cut line is going to be and reacting to that expectation. In Figure 7 we present a histogram of the relative-to-par elimination threshold across tournaments. In short, this suggests that the threshold is predictable, with a reasonably significant ability to do so even before the tournament has begun. Thus, it isn't surprising that disparities in information don't seem to change the point estimates, especially considering that players will include knowledge of course and tournament heterogeneity.

5.4.2 Field- and player-specific ability

We next explore heterogeneous responses to the threshold. As players select into tournaments, it is interesting to consider heterogeneity by tournament, which we do by separately considering tournaments for which at least 30 percent, 50 percent, and 70 percent of the field is world ranked (according to the OWGR), respectively. Estimated discontinuities across these very different average-ability levels reveal no differential responsiveness to finding oneself on the elimination side of the cut, enough so that we are inclined to believe that differential selection into tournaments is not contributing to our results. These estimates are reported in Table 4.

We also consider heterogeneity at the player level. In Table 5 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. 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.

5.4.3 Hole difficulty

Opportunities to gain strokes vary according to the hole's par, necessitating the use of par as a control variable in our preferred specification. It is somewhat natural to then consider the potential heterogeneity across par. In Table 7 we report changes in our outcome variables across par-3, par-4, and par-5 holes separately.[20]

The estimated discontinuity in all four outcomes is somewhat larger in magnitude as the par of the hole increases. That is, players are more likely to gain strokes in response to elimination on the longer par-5 holes, where there are more opportunities to gain strokes.[21]

[20] As no par-3 holes are ever classified as "going-for-it" holes, the two risk-dependent variables cannot be estimated on par-3 holes.

[21] This is backed up by the data, with 8,559 instances of players scoring an eagle on par-5 holes and only 212 instances of the same feat on par-3 holes.

However, we see evidence of performance responding in similar ways even on the shorter par-3 holes, which again reflects that risk taking is not fully accounting for changes in performance.[22] Players are also more risk-responsive to pending elimination on par-5 holes than on par-4 holes. Concerning returns to risk, when on the elimination side of the cut players are also more likely to hit the green after taking a risk on par-5 holes.[23]

5.4.4 Does a player's history of elimination matter?

In Table 6 we stratify by whether a player's most-recent experience on the ended with him being eliminated after 36 holes, or not. Doing so suggests that those who were eliminated in their most-recent tournament were, if anything, less responsive to playing under pending elimination. As we have absorbed player-specific fixed effects into the error structure of our preferred specification, this implies that those coming of an elimination play more similarly on either side of the pending cut than do those who successfully made it to the third day of competition in their most-recent tournament. This slight increase in responsiveness to the threat among those with recent success holds across total strokes, putts, risk taking, and in the probability that risk end in success. While we have no strong priors, this is consistent with heightened expectations from recent success interacting with the current threat of elimination to produce more of a motivating device.

6 Conclusion

The PGA records enable hole-by-player-by-tournament analysis around objectively determined cutoffs, where players are routinely observed around either side of the threshold of elimination-style tournaments. We can 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

[22] Recall that there are not risks to take on par-3 holes.

[23] This can't be explained by differences in hole difficulty as more players succeed in hitting the green on par-4 holes than par-5 holes. Across all players, there is a 23-percent risk-success rate for par-5 holes and 25-percent risk-success rate for par-4 holes.

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.

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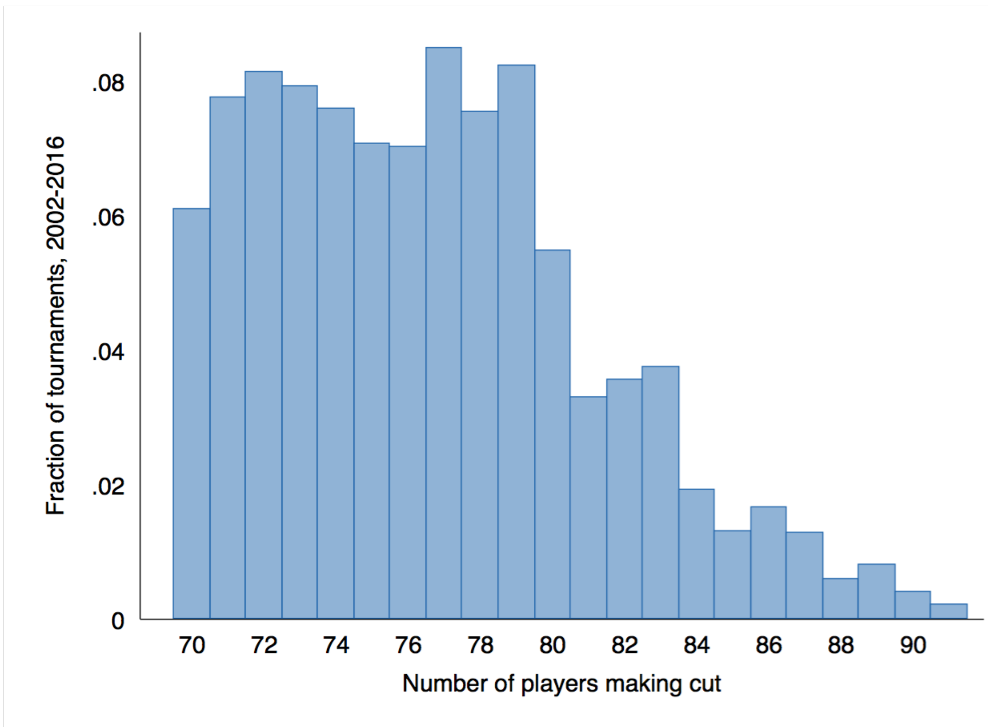
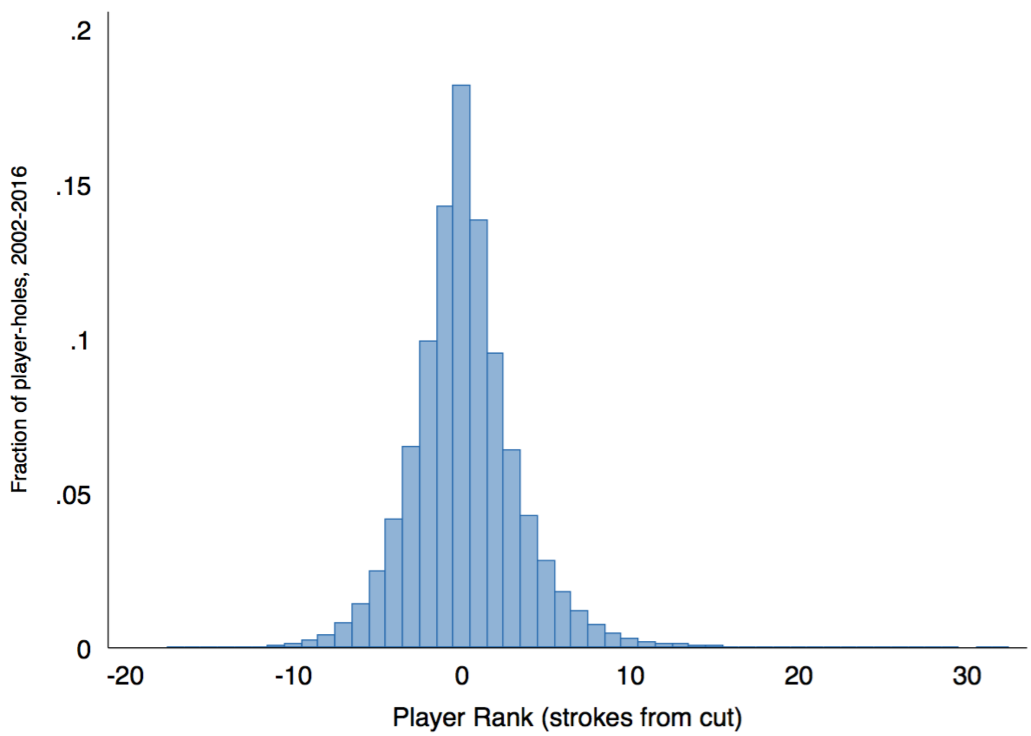
Figures

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



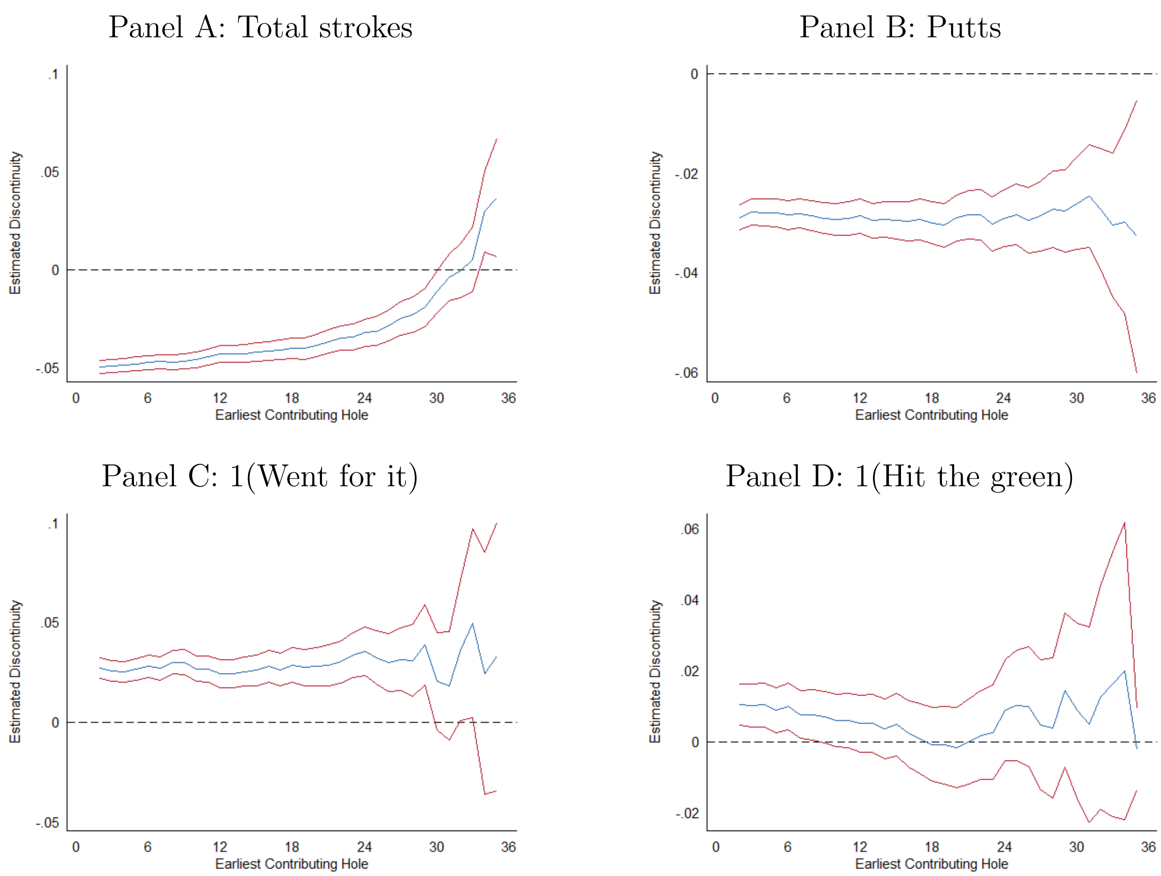
Notes: Given ties, the number of players who make the cut after 36 holes of play can exceed 70. In this figure, we plot the histogram of the number of players who make the cut in a given tournament, across all stroke-play tournaments on the PGA Tour, 2002-2016.

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



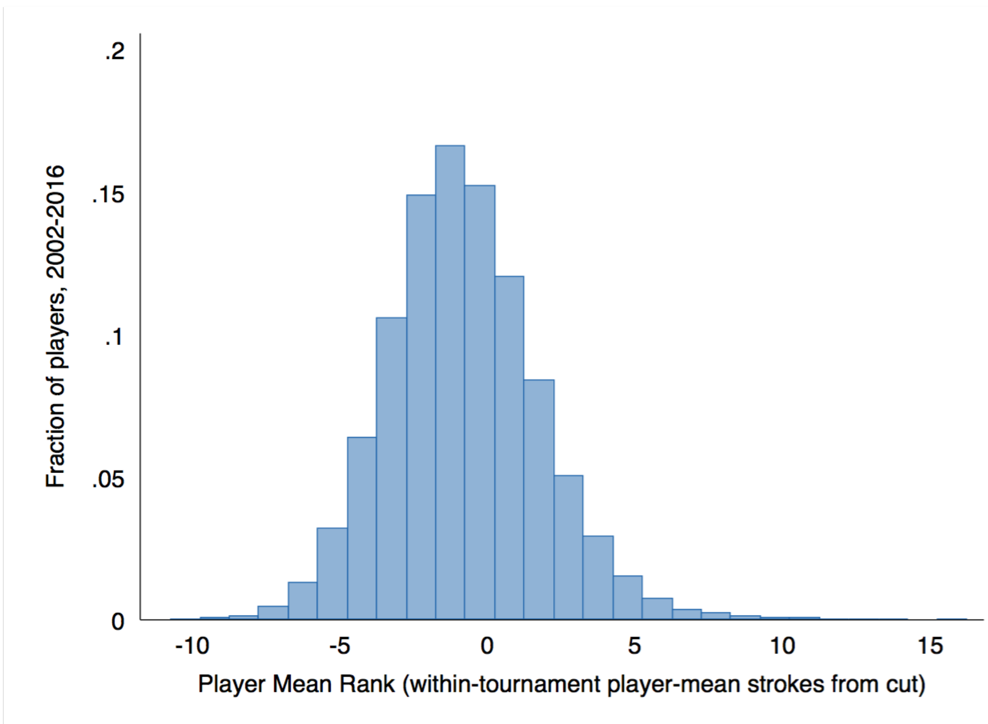
Notes: Given deviations from the implicit elimination threshold on each hole of play on the PGA Tour (E_{hty}), we plot the histogram of player rank at each hole (measured in strokes) relative to the elimination threshold, across all stroke-play tournaments on the PGA Tour, 2002-2016.

Figure 3: Does responsiveness change as elimination approaches?



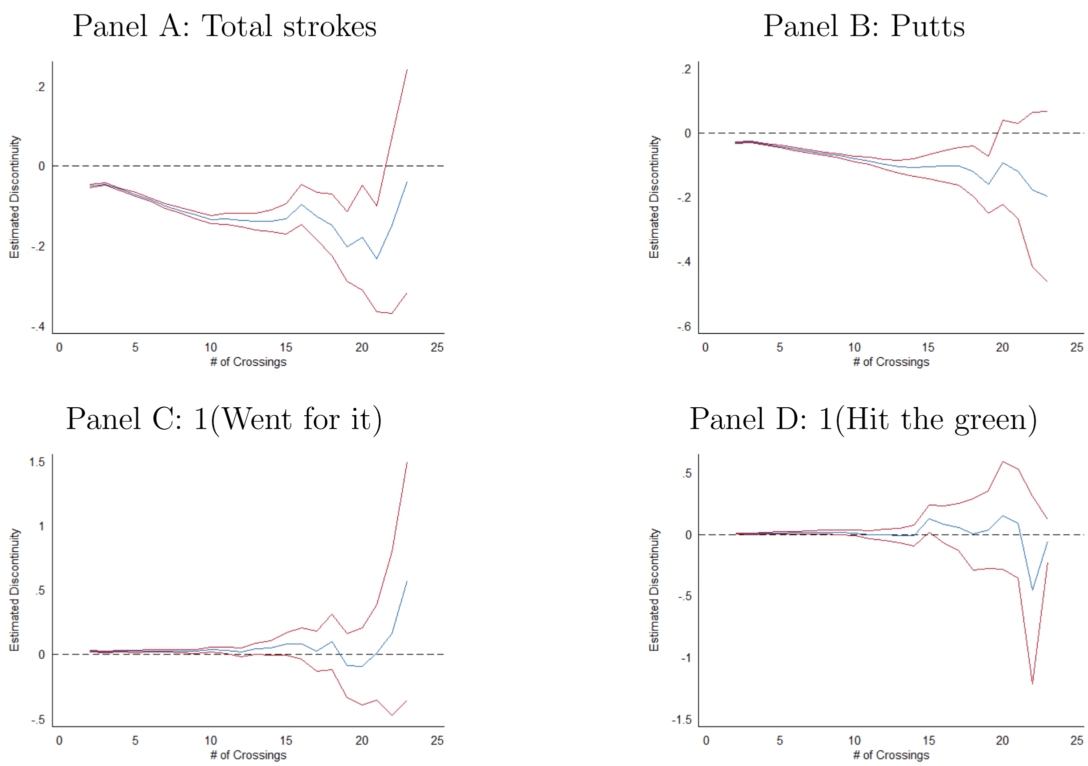
Notes: Point estimates and 95-percent confidence intervals from repeated estimations of Equation (1), restricting the sample to holes successively closer to elimination.

Figure 4: Mean rank of players



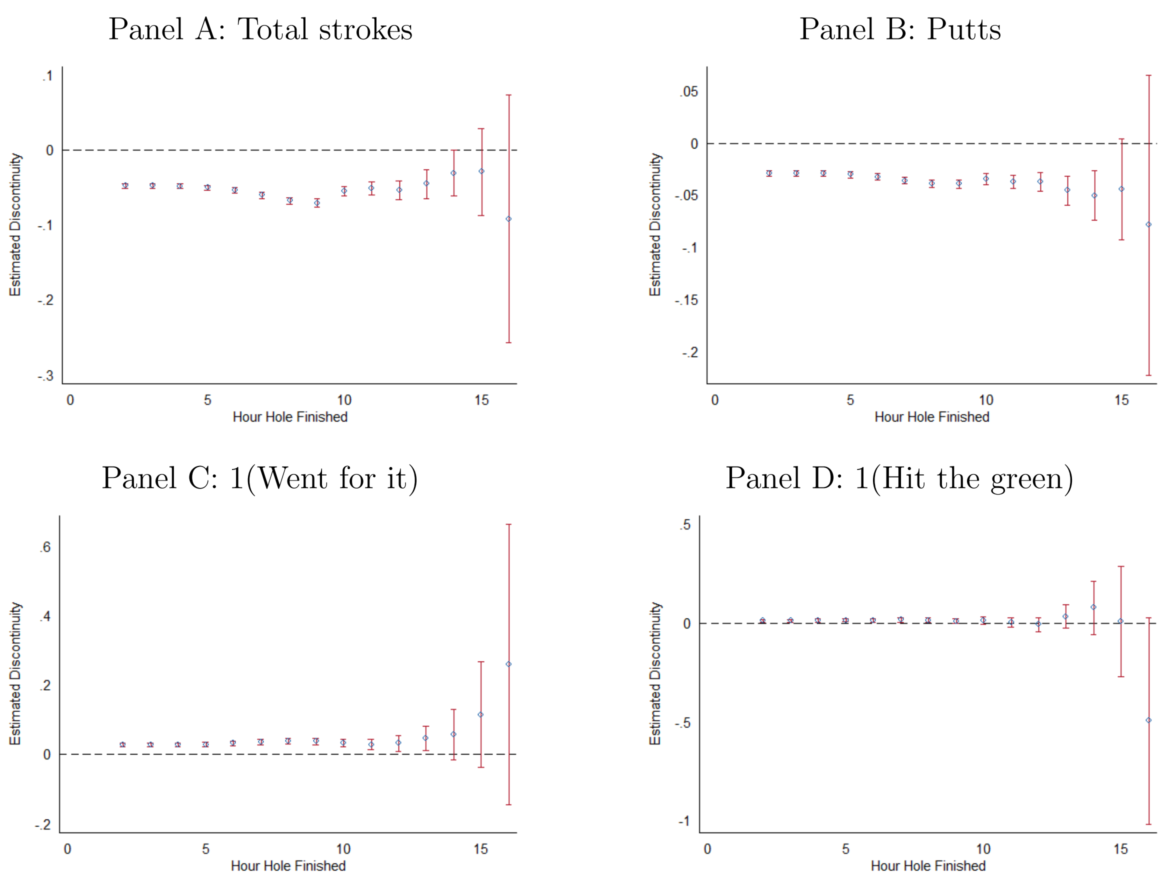
Notes: Given deviations from the implicit elimination threshold on each hole, we plot the histogram of *average* player rank (measured in strokes) relative to the elimination threshold, across all stroke-play tournaments on the PGA Tour, 2002-2016.

Figure 5: The estimated discontinuity by number of threshold crossings



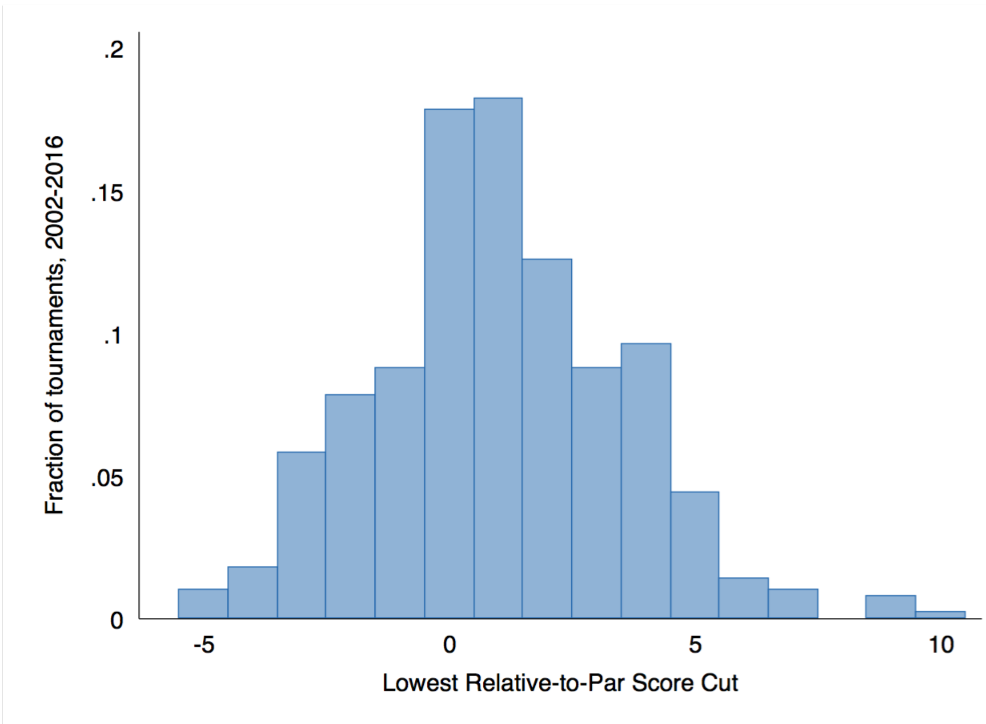
Notes: Point estimates and 95-percent confidence intervals from repeated estimations of Equation (1), restricting the sample to those "closer" to elimination, defined as having more crossings of the elimination threshold.

Figure 6: 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.

Figure 7: 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.

Tables

Table 1: The performance gains under pending elimination

	Strokes per hole				Putts only
	(1)	(2)	(3)	(4)	(5)
$1(Rank \geq 70)$	-0.012***	0.002	0.006***	-0.050***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
$Rank$	0.0002	-0.002***	-0.004***	-0.063***	-.031***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
$Rank \times 1(Rank \geq 70)$	0.0154***	0.006***	0.002***	0.013***	0.0097***
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0005)
Par	0.827***	0.827***	0.826***	0.816***	-0.035***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)
Constant	0.685***	1.263***	0.625***	0.754***	1.742***
	(0.003)	(0.075)	(0.003)	(0.003)	(0.002)
Observations	2,519,650	2,519,650	2,519,650	2,519,650	2,519,650
R^2	0.377	0.382	0.385	0.405	0.010
Player FE	No	Yes	No	No	No
Player-by-year FE	No	No	Yes	No	No
Player-by-year-by-tournament FE	No	No	No	Yes	Yes
Mean (depvar)	3.96	3.96	3.96	3.96	1.60
Number of groups		2,555	8,637	71,990	71,990
Implied change in strokes (per t)				-1.785	-1.039

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

Table 2: Risk taking under pending elimination

		1(Went for it) = 1	
	1(Went for it)	1(Hit green)	Distance remaining
	(1)[a]	(2)[a]	(3)
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)
$Rank \times 1(Rank \geq 70)$	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)
Constant	0.305***	-0.379***	699.407***
	(0.012)	(0.012)	(31.60)
Observations	445,158	221,865	221,865
R^2	0.005	0.016	0.122
Mean (depvar)	0.498	0.242	673.323
Number of groups	63,423	58,613	58,613

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. [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			
	$\lvert\mu_r\rvert \leq 20$	$\lvert\mu_r\rvert \leq 10$	$\lvert\mu_r\rvert \leq 5$	$\lvert\mu_r\rvert \leq 1$
	(1)	(2)	(3)	(4)
Panel A: Strokes				
$1(Rank \geq 70)$	-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				
$1(Rank \geq 70)$	-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: 1(Went for it)				
$1(Rank \geq 70)$	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: 1(Hit the green) conditional on 1(Went for it)=1				
$1(Rank \geq 70)$	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 average ability of the field of competitors

		% of field with OWGR ranking		
	Full sample	≥ 30	≥ 50	≥ 70
	(1)	(2)	(3)	(4)
Panel A: Strokes				
$1(Rank \geq 70)$	-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				
$1(Rank \geq 70)$	-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: 1(Went for it)				
$1(Rank \geq 70)$	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: 1(Hit green) conditional on 1(Went for it)=1				
$1(Rank \geq 70)$	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 5: 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					
$1(Rank \geq 70)$	-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					
$1(Rank \geq 70)$	-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: 1(Went for it)					
$1(Rank \geq 70)$	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: 1(Hit green) conditional on 1(Went for it)=1					
$1(Rank \geq 70)$	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

Table 6: Heterogeneity by cut outcome of most-recent tournament

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

Table 7: Heterogeneity by par of hole

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

7 Appendix

Table A1: "Baseline" specifications for other outcomes

	(1)	(2)	(3)	(4)
Panel A: Putts				
Rank	-0.0002	0.0006	0.0003	-0.031***
	(0.0003)	(0.0005)	(0.0004)	(0.0003)
$1(Rank \geq 70)$	-0.006***	-0.003*	-0.001	-0.029***
	(0.001)	(0.002)	(0.002)	(0.001)
$r \times 1(Rank \geq 70)$	0.002***	-0.0009	-0.001**	0.010***
	(0.0004)	(0.0006)	(0.0006)	(0.0005)
Observations	2,572,654	2,572,654	2,572,654	2,572,654
Panel B: 1(Went for it)				
Rank	-0.0008*	0.0008	0.001*	0.011***
	(0.0005)	(0.0009)	(0.0008)	(0.0006)
$1(Rank \geq 70)$	0.023***	0.020***	0.022***	0.027***
	(0.002)	(0.003)	(0.002)	(0.002)
$r \times 1(Rank \geq 70)$	0.0003	0.002	0.003***	0.003***
	(0.0007)	(0.001)	(0.001)	(0.0008)
Observations	466,344	466,344	466,344	466,344
Panel C: 1(Hit green) conditional on 1(Went for it)=1				
Rank	0.008***	0.006***	0.003***	0.009***
	(0.0006)	(0.001)	(0.0007)	(0.0007)
$1(Rank \geq 70)$	-0.006**	-0.004	0.001	0.011***
	(0.003)	(0.004)	(0.003)	(0.003)
$r \times 1(Rank \geq 70)$	-0.009***	-0.008***	-0.004***	-0.003***
	(0.0008)	(0.002)	(0.001)	(0.001)
Observations	235,770	235,770	235,770	235,770
Player FE	No	Yes	No	No
Player-by-year FE	No	No	Yes	No
Player-by-year-by-tournament FE	No	No	No	Yes

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