# Quitters Never Win: The (Adverse) Incentive Effects of Competing with Superstars

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Internal competition may motivate worker effort, yet the benefits of competition may depend critically on workers' relative abilities: large skill differences may reduce efforts. I use panel data from professional golf tournaments and find that the presence of a superstar is associated with lower performance. On average, golfers' first-round scores are approximately 0.2 strokes worse when Tiger Woods participates relative to when Woods is absent. The overall tournament effect is 0.8 strokes. The adverse superstar effect varies with the quality of Woods's play. There is no evidence that reduced performance is attributable to media attention intensity or risky strategy adoption.

## I. Introduction

Proponents of internal competition contend that within-firm contests fuel employee efforts. Indeed, tournament-style competitions—in which firms reward relative performance—are found in many contexts, pitting workers against each other for tenure, promotion, and awards.[1] While common intuition suggests that rivalry may encourage workers to exert more effort, this may not always be the case.

Economic theory suggests that the benefits of tournament competition depend critically on the degree to which competitors are relatively

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[1] General Electric, 3M, Bloomingdale's, Procter & Gamble, IBM, Digital, Johnson & Johnson, General Motors, and Hewlett-Packard all use between- and within-team competition to provide incentives for quality and innovation (Eisenhardt and Gahmic 2000; Marino and Zábojník 2004).

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equal in underlying ability. When individuals of grossly unequal talents compete, the less talented may (optimally) give up whereas the high-ability worker coasts to victory. That is, relative performance schemes may falter in the presence of a superstar. While an adverse "superstar effect" is an intriguing theoretical possibility, is there any empirical validity to this worry? I test the simple hypothesis—consistent with the extant literature on contests and tournaments—that the presence of a superstar in a rank-order tournament can lead to reduced effort from other participants.[2] Professional golf tournaments, where effort relates relatively directly to performance, present an opportunity to examine empirically the influence of a superstar.

This paper uses data from Tiger Woods and the PGA TOUR (formerly the Professional Golfers' Association of America's Tournament Players Division) to identify the adverse incentive effect of superstars in tournaments. The data include round-by-round scores for all players in every PGA tournament from 1999 to early 2010 and hole-by-hole scores for tournaments from 2002 to early 2010. I estimate the impact of the superstar's presence on the scores of other golfers, first examining all regular and major tournaments and then exploiting Woods's unexpected absences from the tour in 2008 and 2010. Results are robust to several specifications. To my knowledge, this is the first paper to investigate the impact of superstars in rank-order tournaments.

The main results of the paper are as follows:

1. The presence of a superstar in a tournament is associated with reduced performance from other competitors. In general, the adverse superstar effect is larger for higher-skilled golfers relative to lower-skilled players
2. Reduced performance is not attributable to the adoption of risky strategies. Players do not appear to be "going for the green" more in the presence of a superstar. Moreover, the variance of players' hole-by-hole scores in PGA tournaments is not statistically significantly higher when Woods is in the field relative to when he does not participate.
3. Superstars must be "super" to create adverse effects: The adverse superstar effect is large in periods in which Woods is particularly successful and disappears during periods in which he is performing relatively poorly on the course.

Other features of tournaments have been explored empirically in

[2] I use the term "superstar" in the same spirit as Sherwin Rosen in his paper "The Economics of Superstars" (1981). He describes the superstar phenomenon as a concentration of output among a few individuals; I use the term to describe a dominant player. That is, a superstar provides consistently superior performance relative to the field of competitors.

several settings. Knoeber and Thurman (1994) compare tournament and linear payment schemes using data from a sample of U.S. broiler producers. They examine the impact of prizes on performance level and variability and, in contrast with my findings, conclude that less able producers adopt riskier strategies. Eriksson (1999) uses industry data from Denmark and suggests that wider pay dispersion leads to greater employee effort. Sunde (2003) and Lallemand, Plasman, and Rycx (2008) examine professional tennis data to study heterogeneity in elimination tournaments. They find that the lower-ranked players tend to underperform in uneven matches. Brown and Minor (2011) study the effect of a strong future opponent on current effort choice in match-pair elimination tournaments and also test their theoretical predictions with professional tennis data.

Tournament theory also has been examined in a laboratory setting: Bull, Schotter, and Weigelt (1987) find that disadvantaged contestants provide more effort than predicted by tournament theory. Political races can be framed as tournaments: Levitt (1994) uses field data on campaign expenditure in U.S. House elections and finds that political spending is highest in close races.

Other research has used data from professional golf. Ehrenberg and Bognanno (1990*a*) use a subsample of PGA tournaments in 1984 to show that larger prizes lead to lower scores, a result I do not observe in my analysis. While some of their specifications control for the ability of players surrounding a competitor on the final day of play, they do not discuss how competitors' skill heterogeneity affects performance. In another paper, Ehrenberg and Bognanno (1990*b*) use data from the 1987 European PGA Tour and find again that higher prize levels result in lower scores. However, Orszag (1994) questions the robustness of these results and finds that tournament prizes have little impact on performance. Guryan, Kroft, and Notowidigdo (2009) use data on random partner assignments in the first two rounds of PGA events in 2002, 2003, and 2005 and find no evidence of peer effects. Connolly and Rendleman (2008) examine the performance of 253 players from 1998 to 2001 to identify the role of luck in professional wins. Pope and Schweitzer (2011) use precise putting data from the PGA Tour to study the presence of loss aversion in high-stakes competition.

The work of Lazear and Rosen (1981) provides a foundation for understanding the incentive effects of tournaments, and Prendergast (1999) surveys the recent literature. Several studies, including Green and Stokey (1983), Nalebuff and Stiglitz (1983), Dixit (1987), and Moldovanu and Sela (2001), have extended the theoretical literature on tournaments, yet none has focused on the impact of a superstar on tournament incentives.

The paper is organized as follows: First, to motivate my empirical study, I present in Section II results from the contest literature that highlight the impact of player asymmetries on participant effort. In Section III, I outline the important features of professional golf and describe the PGA Tour data used in my analysis. I present the econometric analysis and consider several alternative explanations for the observed adverse superstar effect. Section IV concludes by reframing the results in terms of the economic significance of the performance effect for professional golfers.

## II. Contests with Heterogeneous Players

Results in the contest literature capture the impact of changes in players' relative abilities on effort and form the basis for my empirical tests.[3] In particular, recent work has generalized the imperfectly discriminating Tullock (1980) contest to consider the impact of heterogeneous abilities and asymmetric valuations on participants' effort. Stein (2002) presents a rent-seeking contest model with $n$ heterogeneous participants competing for a single prize, and Szymanski and Valletti (2005) consider three-person contests with multiple prizes. In the following section, I present the Tullock-style contest framework and highlight the results of Stein (2002) and Szymanski and Valletti (2005). In addition, I present a simple numerical example of a multiple prize contest with asymmetric players.

### A. *n Heterogeneous Players and One Prize*

Consider a contest in which $n$ heterogeneous players compete for prize $R$ by choosing effort level $x_i$. Let the ability parameter $\lambda_i$ reflect player $i$'s prior relative chance of winning, where $\lambda_1 > \lambda_2 > \cdots > \lambda_n \geq 1$. Let each player's contest success function take on a logit form so that a player's probability of winning the contest is

$$p_i = \frac{\lambda_i x_i}{\sum_{j=1}^{n} \lambda_j x_j}.$$

For simplicity, I assume that the cost of effort is linear. The expected payoff to player $i$ is

$$\pi_i = \frac{\lambda_i x_i}{\sum_{j=1}^{n} \lambda_j x_j} R - x_i.$$

Using the first-order condition for a representative participant, Stein (2002) presents the following expression:

[3] Nitzan (1994) and Konrad (2009) provide excellent surveys of contest modeling.

$$\frac{\partial x_i}{\partial \lambda_j} = \frac{(n-1)RB^2}{n^2\lambda_i\lambda_j^2}\left[1 - \frac{2(n-1)B}{n\lambda_i}\right] \quad \text{for } i \neq j,$$

where

$$B = n\left(\sum_{i=1}^{n}\frac{1}{\lambda_i}\right)^{-1}$$

is the harmonic mean of the relative ability measures.

When $j = 1$ and $i > 1$, we can see that $\partial x_i/\partial\lambda_1 < 0$ when $\lambda_i < [2(n-1)B]/n$.[4] This inequality always holds in the two-player case; that is, in a two-player contest, the presence of a superstar always leads to lower equilibrium effort from the other player.

When $n > 2$, the inequality condition implies that the superstar will have an adverse incentive effect on effort of a player $i \neq 1$ when the superstar is substantially more able than this competitor. This comparative static result supports the main testable prediction of the current paper: Increases in the ability of the most skilled player lead to lower equilibrium effort from low-ability players. Similar results have been presented for two-player contests with general rent-seeking technology (Baik 1994) and a range of returns to scale parameters (Nti 1999).

### *B. Heterogeneous Players and Multiple Prizes*

To consider asymmetric contests with multiple prizes, I examine a contest in which three players compete for two prizes. Let the total prize pool be $R$ and let $\alpha > 1/2$ denote the fraction of the total prize awarded to the winner. The player in second place wins a prize of $(1-\alpha)R$ and the player in third place receives 0. Consider a simple asymmetry in which player 1 is $\lambda > 1$ times more skilled than the other two (identical) players. In contrast, Szymanski and Valletti (2005) offer a model in which players differ in their costs of effort; their results are similar and are discussed below.

The probability that player $i$ wins second prize is equal to the sum of the probabilities that each of the other competitors won first prize, conditional on player $i$ not having won the first prize himself.

In a two-prize event, player 1's expected payoff reflects the probability that he wins the first prize, $\alpha R$, and the probability that he wins the second prize, $(1-\alpha)R$, instead:[5]

[4] Stein (2002) does not outline explicitly this condition. In his proposition 4′ (p. 334), he states that an increase in the ability of any player will decrease the effort (or expenditure) of all other players.

[5] Although the current model is not sequential, Szymanski and Valletti (2005) suggest this helpful intuition for calculating the probability that a player wins second prize: Think of this probability as "the probability of winning the first prize in a second contest from which the winner of the first prize in the full contest has been eliminated" (470).

$$\pi_1 = \frac{\lambda x_1}{\lambda x_1 + x_2 + x_3}\left[\alpha + (1-\alpha)\left(\frac{x_2}{\lambda x_1 + x_3} + \frac{x_3}{\lambda x_1 + x_2}\right)\right]R - x_1.$$

Similarly, the expected payoffs for players 2 and 3 are

$$\pi_2 = \frac{x_2}{\lambda x_1 + x_2 + x_3}\left[\alpha + (1-\alpha)\left(\frac{\lambda x_1}{x_2 + x_3} + \frac{x_3}{\lambda x_1 + x_2}\right)\right]R - x_2,$$

$$\pi_3 = \frac{x_3}{\lambda x_1 + x_2 + x_3}\left[\alpha + (1-\alpha)\left(\frac{\lambda x_1}{x_2 + x_3} + \frac{x_2}{\lambda x_1 + x_3}\right)\right]R - x_3.$$

Differentiating the payoff functions and equating the first-order conditions suggests that players 2 and 3 pursue a common strategy. Solving the system yields an equilibrium in which each player maximizes his own payoff, given his opponents' strategies. To illustrate the change in effort resulting from a change in the players' relative abilities and the purse-sharing rule, I solve the system numerically.

Figure 1 presents three sets of numerical solutions characterizing the

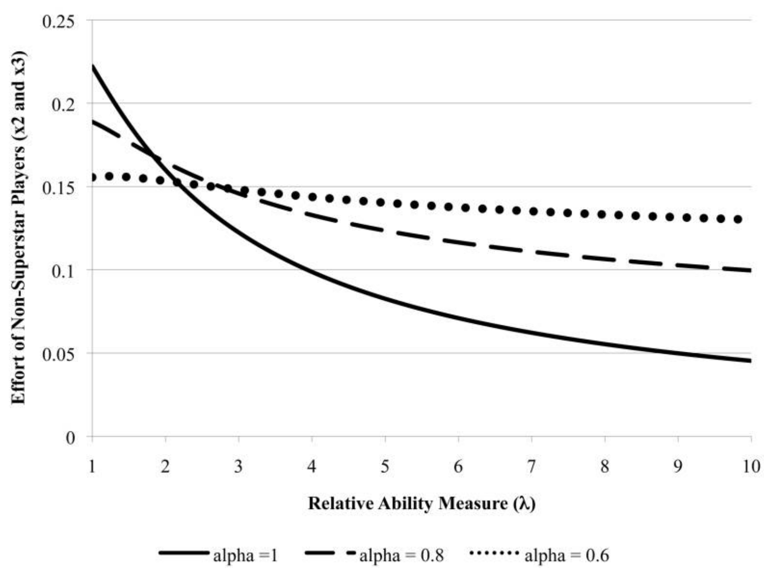


FIG. 1.—Numerical solutions for a three-player and two-prize model. The figure illustrates numerical solutions to the system of equations presented in Section II for a tournament with three players competing for two prizes. Alpha ($\alpha$) describes the purse-sharing rule, where the winner receives a fraction $\alpha$ of the total purse, the second-place player receives a fraction $1-\alpha$ of the total purse, and the third-place player receives 0. The vertical axis measures the effort of the two, identical nonsuperstar players in the tournament. The horizontal axis measures the relative ability advantage of the superstar player, where the superstar is $\lambda$ times more skilled than the regular, nonsuperstar players.

relationships between effort, prize distribution, and relative ability. Respectively, the three series depict tournaments in which the winner takes all ($\alpha = 1$), 80 percent of the purse is awarded to the winner ($\alpha = 0.8$), and 60 percent of the purse is awarded to the winner ($\alpha = 0.6$).

In each example in figure 1, the efforts of players 2 and 3 ($x_2$ and $x_3$) decline as player 1's skill advantage increases. That is, the efforts of the regularly skilled players fall as the superstar becomes more skilled.

In the figure, as the relative ability of the strongest player increases, the curve for the contest with a single prize ($\alpha = 1$) decreases more rapidly than the curves for two-prize scenarios ($\alpha = 0.80$ and 0.6). That is, the adverse effort effect of increasing the superstar's ability is dampened by the existence of a consolation prize. The intuition is straightforward: given the chance to win a second-place prize, the weaker players will exert more effort (relative to their effort in the single-prize case) even if they will almost certainly not win the top prize.

From figure 1, one can also note the effect of increasing the first prize under different levels of player asymmetry: When the asymmetry is small, the weak players' efforts are increasing in the size of the first prize; yet with a larger asymmetry, the weak players' efforts decrease as the first prize increases. Informally, as the superstar's relative ability improves, the regularly skilled players shift their focus from the size of the first prize to the size of the second prize. Szymanski and Valletti (2005) provide a formal presentation of this intuition in the proof of their proposition 2 (p. 474).

In the following sections, I describe the data and empirical approach used to test my main empirical hypothesis: The presence of a superstar competitor will lead to lower effort (and, therefore, performance) from regularly skilled players in rank-order tournaments, relative to players' effort when the superstar is not in the competition.

## III. The Presence of a Superstar

Professional golf offers a real-world laboratory in which to examine the effect of a superstar on his competitors; the participants are professionals making real decisions that affect their financial success and future career, the competitive stakes are significant, and the data are rich.

PGA Tour golfers are highly trained professional athletes who exert considerable effort both before and during competitive rounds. Before events, effort is about focused preparation: in the several days leading up to the first round, a golfer may choose to hit balls on the driving range, play practice rounds, and carefully study the course. Preparation may be both physically taxing and costly in terms of opportunity costs: in 2001, players' fees for attending corporate outings range from \$100,000 per day for David Love III to \$1 million per day for Tiger

Woods.[6] During competition, a player may take extra care to consider his lie, the target, the weather conditions, and his club selection. These pre-event and midround activities require considerable effort—practice and patience may be both physically and mentally costly—but result in improved performance. In fact, it is the close relationship between effort and performance that makes golf data particularly suitable for this study.

The objective of golf is to complete each hole with the fewest strikes of the ball. "Par" describes how the course is designed to be played by an experienced golfer. Players are "under" and "over" par if they complete a hole in fewer or more strokes than par, respectively. Professional golf tournaments typically consist of four rounds (Thursday to Sunday). Final positions are assigned according to players' total scores for the event. A "cut" is made after the second round. In most tournaments, only the top 70 golfers and those tied for seventieth position play the third and fourth rounds.[7]

All players who make the cut earn prize money, and those who miss the cut receive no prize. In the case of a tie for first place, additional playoff holes determine the tournament winner. While purse size differs by tournament, the prize distribution is fixed and nonlinear on the PGA Tour. The top 15 golfers earn approximately 70 percent of the total purse; tournament winners receive 18 percent of the purse, and second through fifth positions earn 10.8, 6.8, 4.8, and 4 percent, respectively. The golfer in seventieth position receives 0.2 percent of the purse.

The presence of a superstar, Tiger Woods, is a key feature of professional golf and is critical for identification in my paper. Woods won his first PGA tournament within weeks of turning professional in 1996. Between 1996 and 2006, he collected 54 PGA wins including 12 major titles and failed to make the cut in only four of the 219 tournaments in which he competed. Displaying remarkable consistency, he earned top three finishes in 92 of those events and top 10 finishes in 132 events. Woods was the PGA Player of the Year eight times between 1997 and 2006. Over those years, he was consistent and dominant: when Woods played, there was a high probability that he would play very well.

[6] These fees were reported in *USA Today*'s article "Woods' Presence Pushes Appearance Fees Sky High" published May 18, 2001. Note that the PGA Tour explicitly prohibits appearance fees in official PGA events.

[7] Some events use a 10-stroke rule to determine the cut; e.g., in the U.S. Open, the cut includes the low 60 scorers (and ties) and any player within 10 strokes of the leader. Given the cut, Woods's participation in an event may mean that fewer regular players advance to the final rounds. When player and tournament characteristics are held fixed, competition between fewer players should lead to increased effort and improved performance. This mechanical effect works against the predicted superstar effect and is counter to what I observe in the data.

### A. PGA Tour Data

I use a panel data set of 269 PGA tournaments from 1999 to 2006 in my main analysis and also present additional results using data from 2007 to 2010.[8] While past related work has relied on data from selected tournaments from a single season (e.g., Ehrenberg and Bognanno 1990*a*, 1990*b*; Orszag 1994), multiyear, player-level data allow me to identify between- and within-tournament changes while controlling for player-specific variation. The panel nature of the data represents a strength of the current analysis: since golf courses have unique features that make cross-course comparison challenging, I can examine players' performances on the same course over many years.

Round-level scores are available for all players in all tournaments from 1999 to 2010, and hole-by-hole scores are available from 2002 to 2010.[9] From the data, I can identify players who made or failed to make the cut, withdrew, or were disqualified. Weather data from the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA) were matched to players' scores.[10] To control for crowd size, tournament popularity, and the intensity of media coverage, I obtained viewership data for all major television networks, as well as some PGA Tour ticket sales estimates.

I also matched players' scores to monthly average Official World Golf Rankings (OWGR), which measure the top 200 professional golfers' relative quality.[11] Golfers accumulate OWGR points on the basis of their finishing positions and the field strength in professional tournaments (U.S. and international) in the previous 2 years, and the points are time weighted. The most points are awarded for top finishers in the major tournaments, followed by difficult PGA Tour events; events on lower-status international tours earn the smallest number of points. Rankings are simply the rank order of players by their accumulated points.

Figure 2 presents the mean tournament score relative to par for high-ranked, low-ranked, and unranked golfers who made the cut in PGA

[8] Data from 94 small-field and alternate tournaments are omitted since they select only lower- or higher-skilled players, respectively.

[9] Tournament scores were gathered from the PGA Tour's Shotlink data, *Golfweek* magazine's Web site (http://www.golfweek.com), and the Golf Channel (http://www.thegolfchannel.com). Additional golf course information was collected from the Golf Course Superintendents Association of America Web site (http://www.gcsaa.org). Player data were gathered from the PGA Tour Web site (http://www.pgatour.com).

[10] Because not all event locations are NOAA weather station sites, tournaments are matched to the closest NOAA site. The closest site was selected by hand to ensure geographic similarities. For example, a coastal golf course was matched with the closest coastal weather station.

[11] OWGR data were gathered from http://www.officialworldgolfranking.com.

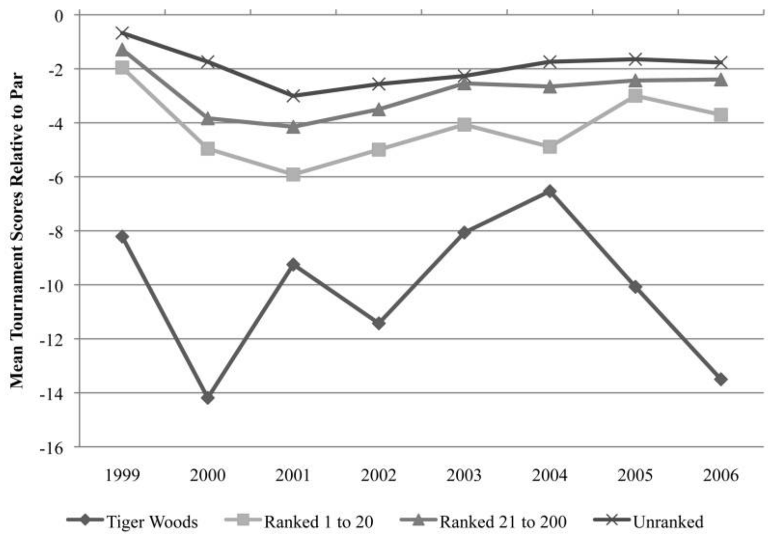


FIG. 2.—Mean scores for PGA Tour events, 1999−2006. Only players who made the cut are included. Regular and major events are included; values for small-field and alternate events are not presented. Ranks reflect players' OWGR at the time of the event. Values for Tiger Woods are presented separately and therefore are omitted from the statistics for top-ranked players.

Tour events between 1999 and 2006.[12] In all years, mean scores are below zero ($p$-values < .01), as even average unranked PGA Tour players post scores that are better than par. Scores exhibit another consistent pattern: top-ranked players' scores are significantly better (lower) than unranked players' scores in every period ($p$-value < .01). The superstar play of Tiger Woods is also evident in figure 2: his scores are always significantly lower than the mean scores of other golfers ($p$-value < .01).

### B. *Performance With and Without the Superstar*

My main empirical analysis examines Woods's impact on the performance of other golfers on the PGA Tour. Theory presented in Section II suggests that the presence of a superstar reduces other competitors' efforts, and this should lead to worse performance. Simple comparisons of mean scores of golfers in the presence and absence of a superstar

[12] In 2007, the PGA Tour introduced the Fed Ex Cup, a season-long contest in which players accumulate points on the basis of their performance in regular tour events. The top five finishers in the Fed Ex Cup earn between $3 million and $10 million in tax-deferred retirement funds. Finishers between 125th and 150th position receive $32,000. Since the introduction of the Fed Ex Cup may have changed players' incentives in certain events, I focus the bulk of my analysis on the years before 2007.

provide a suggestive start. Figure 3 presents the average score relative to par of all players in events across time from 1999 to 2006, excluding Woods's scores. From the figure, we can observe that scores from many of the events with Woods appear substantially higher (worse) than scores from events in which he did not participate. Note that while these raw data may also reflect differences in weather conditions, courses, purse sizes, and tournament characteristics, figure 3 motivates the identification strategy for this paper. Controlling for event-specific effects and individual player heterogeneities, the empirical analysis in the following sections tests whether scores in the presence of the superstar are higher than scores when Woods is not in the field.

Figure 4 presents a summary of the difference between average scores relative to par for tournaments in which Woods did and did not participate. Since players vary in terms of ability, the difference is presented separately for ranked and unranked players by year. *T*-tests reject the null hypotheses that players' scores are equal with and without the superstar for all years except 2006 ($p$-values $< .05$).[13]

Table 1 presents summary statistics for different hole-level scores in rounds from 2002 to 2006. On average, golfers have slightly fewer eagles (two strokes under par) per round in tournaments with Woods, relative to when they are not competing with the superstar; a $t$-test rejects the equality of means at a $p$-value of .06. However, players post more bogeys (one stroke over par) and double bogeys (two strokes over par) when the superstar is present; the differences are small in magnitude but are statistically significantly different from zero at $p$-values of .07 and .04, respectively. These data show that more high scores and fewer low scores are posted in tournaments with Woods relative to when he does not compete.

Woods's consistency and dominance imply that other players are competing over a smaller (residual) purse in tournaments that he enters. Since the expected prize is a key determinant of equilibrium effort, in principle, one ought to see the same level of performance from competitors in tournaments with a similar, smaller purse in which Woods does not participate. That is, one test of contest theory would be to match tournaments by residual purse to see if there are performance differences across tournaments with and without Woods. The theory predicts that we should observe little or no difference in performance. Of course, since tournaments are matched solely by purse size, this prediction ignores other potential influences that also affect scores, such as weather and course conditions.

[13] Nonparametric Wilcoxon signed-rank tests yield identical results. In general, the distributions of the scores of other golfers are statistically different when Woods participates in a tournament relative to when he does not.

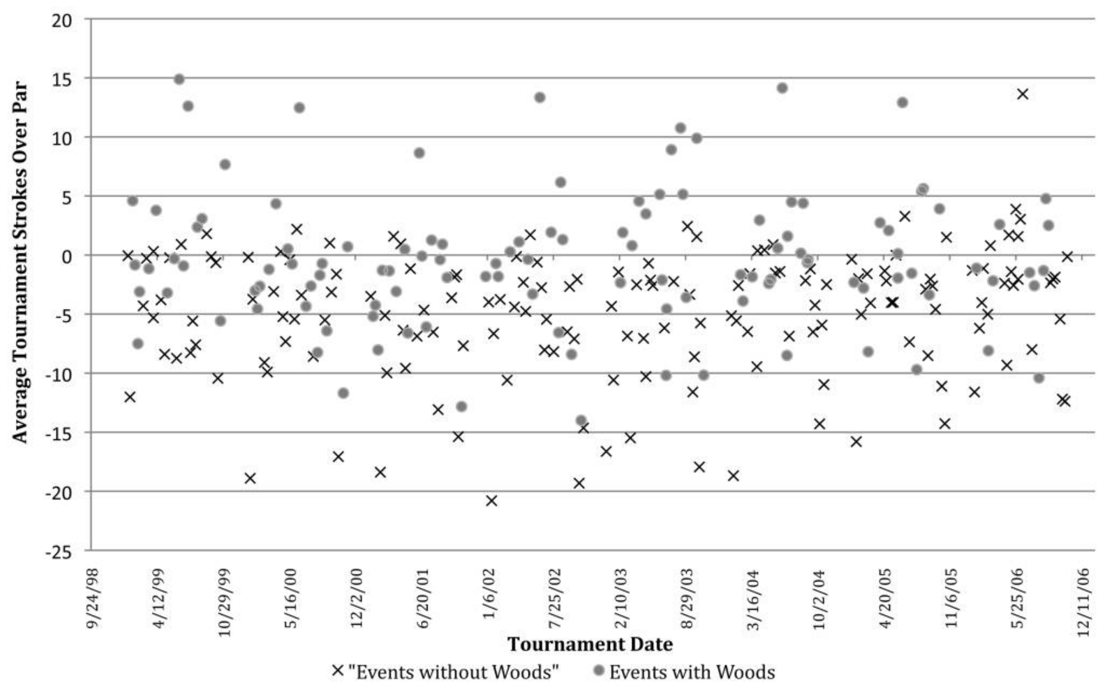


Fig. 3.—Scores relative to par over time for tournaments with and without Tiger Woods. This figure presents average final tournament scores for all players (except Woods) who made the cut in regular PGA Tour, World Golf Championship, and major events between 1999 and 2006.

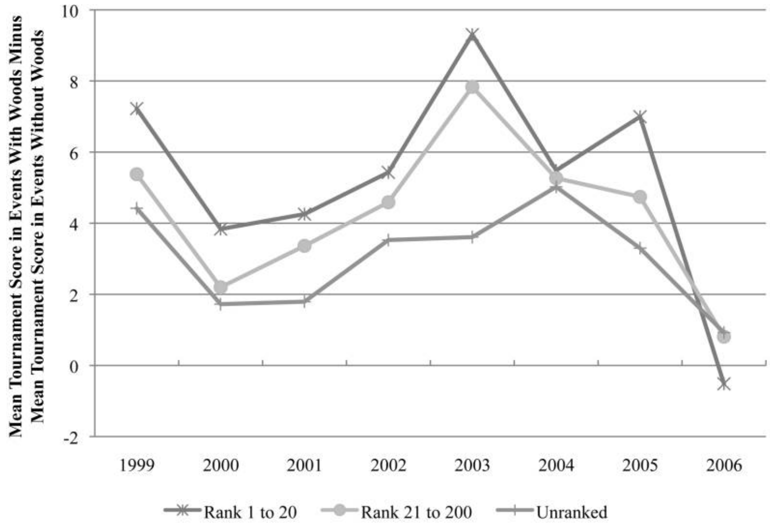


FIG. 4.—Differences in tournament scores for events with and without Tiger Woods. Only scores from players who made the cut are included in the calculations. Regular and major events are included; small-field and alternate events are excluded. With Tiger Woods indicates that Woods played in the tournament, and without Tiger Woods includes only tournaments in which Woods did not participate. Ranks reflect players' OWGR at the time of the event. Scores for Tiger Woods are excluded.

TABLE 1
AVERAGE NUMBER OF EAGLES, BIRDIES, PARS, BOGEYS, AND DOUBLE BOGEYS IN TOURNAMENTS WITH AND WITHOUT TIGER WOODS FROM 2002 TO 2006

| | Average Number per Round in Tournaments | | |
|---|---|---|---|
| | With Tiger Woods | Without Tiger Woods | $H_0$: Equal Number With and Without Tiger Woods (Unpaired $t$-Test) |
| Eagle (2 strokes under par) | .080<br>(.004) | .093<br>(.006) | $p$-value = .065 |
| Birdie (1 stroke under par) | 3.815<br>(.021) | 3.866<br>(.033) | $p$-value = .194 |
| Par (equal to par) | 11.323<br>(.026) | 11.354<br>(.038) | $p$-value = .515 |
| Bogey (1 stroke over par) | 2.510<br>(.020) | 2.448<br>(.028) | $p$-value = .069 |
| Double bogeys (2 strokes over par) | .242<br>(.006) | .218<br>(.009) | $p$-value = .035 |

NOTE.—Values in parentheses are standard deviations. Only scores from players who made the cut are included. Regular and major events are included; small-field and alternate events are excluded. With Tiger Woods indicates that Woods played in the tournament, and Without Tiger Woods includes only tournaments in which Woods did not participate. Scores for Tiger Woods are excluded.

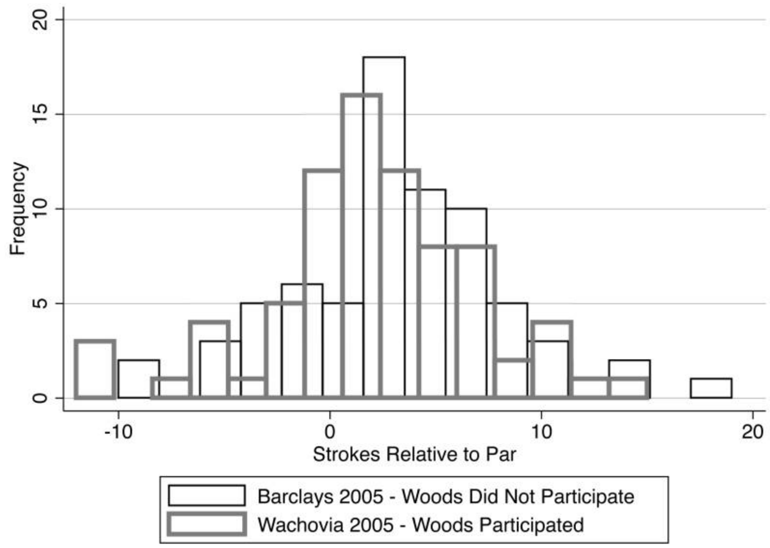


Fig. 5.—Distribution of tournament scores for Barclays Classic and Wachovia Championship in 2005. Only scores from players who made the cut are included. Woods's final score in the Wachovia Championship is excluded.

To perform this simple test, I compute Woods's expected prize for a given event from his median finishing rank in that tournament and compute the residual purse for the other competitors. I then matched these events to tournaments in which Woods did not compete. To avoid comparisons across substantially different seasons, I required matches to occur within 3 months of each other. I eliminated all pairs in which the difference in the residual and actual purse sizes was greater than $100,000.[14] For example, on the basis of his past performance in the event, Woods had an expected finish of fourth place in the 2005 Wachovia Championship, leaving a residual purse of $5,809,675. I matched this event with the 2005 Barclays Classic with a total purse of $5,772,655. Figure 5 compares the distribution of players' tournament scores between these two events; indeed, these distributions are not statistically different.[15]

This procedure yielded 25 plausible matches. In each case, I computed $t$-statistics and Wilcoxon rank-sum tests of tournament scores. In

[14] To avoid purse differences biasing the comparison toward worse performance with the superstar, I required any difference in purse size to be due to a larger residual purse in events with Woods. I also matched on tournament type (i.e., major vs. regular).

[15] Using a two-sample Kolmogorov-Smirnov test, I do not reject the null of equality of distributions ($p$-value = .77). Similarly, using a $t$-test and Wilcoxon rank-sum test, I do not reject the null of equal means ($p$-values = .16 and .18, respectively).

16 of the 25 comparisons, players' performances were significantly worse when Woods was present. I could not reject the null hypothesis that players' scores were equal in four cases. These simple comparisons suggest that, even conditional on having an equal residual purse, an average competitor may play worse in the presence of a superstar.

While theory would suggest that few (if any) of the matches should be statistically remarkable, these comparisons do not control for different fields of competitors, weather conditions, and course-specific effects. Indeed, the mean magnitude of the differences is 2.3 strokes—much higher than one might expect—suggesting that other features of tournaments and golf courses deserve particular attention. This initial test motivates a more detailed regression approach, where I can account for course- and player-specific heterogeneities, weather, and the competitiveness of the field.

### C. *Econometric Specification*

The hypothesis outlined in Section II suggests the following initial econometric specification:

$$\begin{aligned}\text{strokes}_{ij} = {} & \beta_1\text{star}_j \times \text{HRanked}_i + \beta_2\text{star}_j \times \text{LRanked}_i \\ & + \beta_3\text{star}_j \times \text{URanked}_i + \alpha_1\text{HRanked}_i + \alpha_2\text{LRanked}_i \\ & + \gamma_0 + \gamma_1 X_i + \gamma_2 Y_j + \varepsilon_{ij},\end{aligned} \tag{1}$$

where $\text{strokes}_{ij}$ is the score, in terms of strokes above or below par, for player $i$ in tournament $j$; $\text{star}_j$ is a dummy variable that equals one when the superstar is present in the tournament; $\text{HRanked}_i$ is a dummy variable indicating that the player is ranked in the top 20 by the OWGR; $\text{LRanked}_i$ is a dummy variable indicating that the player is ranked 21–200 by the OWGR; and $\text{URanked}_i$ is a dummy variable indicating that the player is unranked (or ranked above 200) at the time of the event. In addition, I include $X_i$, a matrix of player-course fixed effects that capture an individual player's course-specific heterogeneities, and $Y_j$, a matrix of event-specific controls described below.[16] Finally, $\varepsilon_{ij}$ is the error term. I estimate the equation using ordinary least squares with a robust variance estimator that is clustered by player-year to allow for correlation

[16] Of course, player-course fixed effects capture finer heterogeneities than course-level fixed effects. "Slope" is another coarse measure of course difficulty. The slope ratings of many tour courses are censored at the maximum. While the United States Golf Association slope rating may represent course difficulty during nonprofessional play, the rating is not indicative of tour event difficulty.

across an individual golfer's tournaments in a given year.[17] Because the variable of particular interest is the presence of the superstar, Woods's scores are omitted from the regressions.

The reference group in all regressions is composed of unranked players competing in a tournament in which Woods is not present. The coefficients on the superstar dummy interactions with rank categories ($\beta_1$, $\beta_2$, and $\beta_3$) capture the effect of Woods's presence on players' scores. In the reported results, I present these "total" superstar effects by player types.

The matrix of event controls, $X_j$, includes the following variables:

- Major dummy: I use an indicator for the four major tournaments (U.S. Open, British Open, PGA Championship, and the Masters), which are prestigious, attract a strong field of players, and are notoriously challenging.[18]
- Temperature and wind speed: I use the average daily temperature (in Fahrenheit) and resultant wind speed (tenths of a mile per hour) to control for the weather conditions during tournaments. In reported specifications, I use upper and lower temperature quartile dummy variables to indicate temperatures that are hot (above 80 degrees) and very cold (below 62 degrees).
- Lagged rainfall: Inches of rain accumulated over the 3 days before the event also controls for playing conditions. Rain may make the course easier, since moist greens are soft, slow, and forgiving.
- Total purse: Purse variables reflect tournaments' monetary incentives. In all reported specifications, I include the total purse in thousands of dollars deflated by the monthly consumer price index and the square of the purse value.
- Field quality: The competitiveness of the field of players is proxied by the average OWGR rank points of the participants (excluding Woods). For each player, I calculate this average excluding his own

[17] Concerns about player-level correlation reflect the individual nature of the activity and the argument that some players may be particularly affected by the presence of the superstar. Player-year clusters account for the correlation of a player's ability within a season and correlation between observations from the same player being repeatedly "treated" by Woods's presence in the same year. Standard errors are slightly larger when I cluster by player but present the same pattern of statistical significance. Since golfers' performances may be correlated within a tournament, I also consider clustering by event. The standard errors on all coefficients are higher than when clustering by player-year but lead to a similar pattern of statistical significance. The exception is regression 3 in table 2 below, where the coefficient on the effect for players ranked twenty-first to 200th is not statistically significant. These results are not reported.

[18] An indicator for World Golf Championship events, part of a series of tournaments that attract players from the PGA, European, and Japanese golf tours, is absorbed by the player-course fixed effects.

contribution to the strength of the field.[19] Section III.A provides details on the OWGR.

- Viewership: I use daily household television viewership data gathered by the Nielsen Company to proxy for the intensity of fan- and media-related attention at events. The data include estimates of the number of viewers of tournament coverage on major television networks. If a tournament has been shown on several networks, I aggregate the viewership figures to total number of households viewing the coverage. In round-level analyses, I use daily household viewing statistics. For tournament-level regressions, I further aggregate the data to reflect the total number of viewing households across the entire event. Coarse PGA Tour ticket sales data are available only for 2009; however, attendance appears positively and significantly correlated with tournaments' total television viewership.

The set of controls included in the main specification aim to capture individual-, course-, and event-specific variation that could affect players' performances, and they allow me to isolate the impact of the superstar competitor. For example, there are significant course design heterogeneities on the tour, yet differences in the difficulty of specific courses are captured by the player-course dummies. Moreover, if a specific golfer plays remarkably better (or worse) on a particular course, then the player-course dummies also capture these heterogeneities. If intense media attention improves (or hurts) players' performances, then the television viewer controls should capture these effects. Variation in Woods's schedule allows me to identify his impact on other players' performance; he did not always participate in the same events on the same courses each year. In Section III.E, I exploit several unexpected changes in his tour schedule.

In short, the econometric specification used in the following analysis allows me to answer the following question: Controlling for weather conditions, the competitiveness of the field, the number of spectators, and the size of the tournament prize, how does player $i$'s score on course $j$ change in the presence or absence of a superstar competitor?

### *D. Tournaments from 1999 to 2006*

Since players make critical effort-related decisions prior to the start of events, one might expect any effect of a superstar in the tournament field to appear in the first round. Columns 1 and 2 of table 2 report results using players' first-round scores in regular and major PGA tour-

[19] This adjustment reflects the fact that a player faces a set of opponents that excludes himself.

TABLE 2
Regression Results for Scores in Regular and Major Tournaments, 1999–2006: Strokes Relative to Par

| | Tournament Types | | | |
|---|---|---|---|---|
| | First Round Regulars and Majors (1) | First Round Regulars (2) | Tournament Regulars and Majors (3) | Tournament Regulars (4) |
| Superstar effect for players: | | | | |
| Ranked 1–20 | .596** | .535* | 1.358** | .996 |
| | (.281) | (.302) | (.726) | (.786) |
| Ranked 21–200 | .161 | .141 | .804*** | .672** |
| | (.113) | (.117) | (.318) | (.328) |
| Unranked | .202 | .212 | .596 | .311 |
| | (.126) | (.131) | (.396) | (.400) |
| Observations | 34,986 | 29,167 | 18,805 | 15,651 |
| Adjusted $R^2$ | .29 | .21 | .48 | .38 |

Note.—All specifications include controls for players' rank, strength of the field, wind, rain and temperature, purse size, television viewership, tournament type, and course-player fixed effects. Values in parentheses are standard errors, clustered by player-year. Other variable coefficients are suppressed. Major events are the PGA Championship, U.S. Open, British Open, and Masters. Scores for Tiger Woods are excluded.

* Statistically significant at a $p$-value of .10.

** Statistically significant at a $p$-value of .05.

*** Statistically significant at a $p$-value of .01.

naments: between 140 and 170 golfers start in each event. Approximately half of any tournament field makes the cut after the second round.

In the first round, the performance of top-ranked players appears affected by the superstar. For major and regular events, top golfers' first-round scores are 0.6 strokes higher when Woods is in the field relative to when he is not. In an examination of only regular events, the superstar effect is 0.54 strokes for the first round. The magnitude of the effect is substantial, particularly when one considers that an average of two (and as many as eight) players share first place after the first round of tournament play. Moreover, when we account for ties, the top two first-round scores in a tournament differ by an average of only 0.8 strokes. Note that unranked players' scores are not significantly different when Woods participates. This nonresult aligns with the intuition that players who are low in the distribution of relative skill or who expect to finish in the nearly flat portion of the tournament prize distribution may not be adversely affected by a top competitor. For example, the difference between fortieth-place and forty-first-place prizes in an average regular tournament is less than $1,000; thus, a one-position shift in the distribution has little marginal impact on players' performances.

Regressions 3 and 4 report results from players who made the cut in

PGA Tour events in regular and major events. Recall that golfers who make the cut play all tournament rounds and are guaranteed a cash prize. In an examination of major and regular events, the tournament scores of ranked players are significantly higher when Woods is present: estimates suggest that the effect is between 1.3 and 0.7 strokes, depending on player rank. In only regular events, the superstar effect for top 20 players is positive but not statistically significant. In general, however, the size of the superstar effect is substantial for good PGA Tour golfers: on average, fewer than two strokes separate first and second place in PGA tournaments.

The superstar effect is not sensitive to the specification of particular control variables. Although not reported, the estimates are robust across alternative specifications of the purse and temperature measures, including linear and quadratic terms.[20]

### *E. Woods's Unexpected Absences*

Concerns about nonrandom participation decisions may complicate the identification of the superstar effect in the performance data of professional golfers. One might wonder whether Woods plays only the most difficult courses or if particularly talented players avoid tournaments in which Woods is in the field. If either claim were true, a simple comparison of scores with and without Woods could be misleading.

In a laboratory experiment, otherwise homogeneous players could be assigned publicly known ability levels. In the treatment rounds, one player could be randomly assigned relatively high ability, and the effect of his presence could be measured by changes to the effort of other players. In the ideal field experiment on the PGA Tour, golfers would commit to their playing schedules at the start of each year and Woods would compete unexpectedly at randomly determined events. His current ability would be public knowledge, and other competitors would not be allowed to adjust their playing schedules or long-run training in response to Woods's appearances. Indeed, in this experiment, it would be as though Woods fell from the sky to compete.

Of course, both of these scenarios have strengths and substantial drawbacks: Laboratory experiments are feasible to conduct but may not elicit natural behavior from competitors. In contrast, a multiyear field

[20] Although coefficients are not reported because of space constraints, higher purses actually appear to induce slightly higher scores: raising the purse by $100,000 is associated with a 0.04 increase in the first-round score. While this result is counter to the findings in Ehrenberg and Bognanno (1990*a*, 1990*b*), Orszag (1994) concludes that changes in tournament prize money did not significantly affect golfers' scores. One plausible explanation for the current result is that the purse variable is capturing unmeasured changes in course difficulty. The controls for the quality of the field are negative for the regressions in table 2, suggesting that stronger fields may lead to lower scores.

experiment might produce realistic results—athletes would compete for real prizes—but an experiment of this scale would be impossible to conduct.

In this section, I describe a feasible empirical strategy that exploits several unanticipated changes in Woods's playing schedule. Most simply, I compare a player's performance in a tournament in which Woods was expected to but did not actually play with the player's performance in adjacent years in which Woods was expected to and actually did compete. In these scenarios, players prepared similarly in the months leading up to the competitive season but faced a different competitive environment at the start of the events. Given the timing of announcements about Woods's absences, it is reasonable to expect that players could not adjust the intensity of their long-term training programs but could adjust the intensity of the preparation activities for any given tournament.

Woods's playing season has been significantly interrupted on several occasions, leading to his unexpected absence from competition:

- Knee surgery: In June 2008, Woods announced that he would miss the remainder of the season to undergo knee surgery. After the Masters Tournament in April 2008, Woods had scheduled arthroscopic knee surgery. He returned to play in mid-June, winning the U.S. Open. Two days after his victory, he announced that he would undergo more extensive surgery to repair his knee and leg. Woods's visible physical reaction to his knee pain during the U.S. Open highlights the unexpected nature of this withdrawal. During his medical leave, he missed eight events in which he had regularly participated in previous years: three regular events and several late season playoff events.
- Personal difficulties: In November 2009, Woods announced an indefinite absence from golf to manage issues in his personal life. This well-publicized withdrawal was unanticipated: media reports suggested that few people, if any, would have been able to forecast the series of events that led to Woods's announcement. Woods returned to play in the Masters Tournament in April 2010. During this break, Woods missed a World Golf Championship event and the Arnold Palmer Invitational Tournament in which he had participated in previous years.

TABLE 3
Tournament Scores in Selected Events With and Without Tiger Woods

| | Knee Surgery 2007–9 | | Personal Issues 2009–10 |
|---|---|---|---|
| | July | August | March |
| Ranked 1–20: | | | |
| With Woods | −4.00 | 4.51 | 4.60 |
| | (3.61) | (7.29) | (4.16) |
| Observations | 5 | 35 | 5 |
| Without Woods | −8.00 | −.17 | −1.00 |
| | (5.24) | (5.06) | (6.04) |
| Observations | 9 | 18 | 9 |
| Ranked 21–200: | | | |
| With Woods | 2.01 | 3.84 | 5.84 |
| | (4.70) | (10.05) | (5.20) |
| Observations | 86 | 136 | 44 |
| Without Woods | −5.97 | 2.63 | 1.87 |
| | (4.93) | (6.44) | (5.07) |
| Observations | 73 | 57 | 47 |
| Unranked: | | | |
| With Woods | 4.13 | −2.68 | 6.48 |
| | (4.69) | (11.43) | (4.14) |
| Observations | 53 | 59 | 23 |
| Without Woods | −4.09 | 5.80 | 3.21 |
| | (4.58) | (7.82) | (5.75) |
| Observations | 70 | 5 | 19 |

Note.—Values in parentheses are standard deviations. Months and years of interest reflect the timing of Woods's unexpected absences from competition. Only scores from players who made the cut are included. With Woods indicates that Woods played in the tournament, and Without Woods includes the same tournaments in which Woods did not participate in the year of interest. Scores for Tiger Woods are excluded.

These unexpected events provide an opportunity to examine the robustness of the adverse superstar effect without selection bias.[21]

Table 3 reports the scores in the same tournaments with and without Woods over the periods of interest; the mean scores labeled With Woods consider events in which he actually participated, and the values labeled Without Woods reflect scores from those same events when Woods was unexpectedly absent. When Woods underwent surgery in 2008, mean scores for top-ranked players were approximately 4.6 strokes better than when Woods played ($p$-value $< .01$). Scores for lower-ranked and un-

[21] In May 2006, Woods left the tour for 3 months after the death of his father after a long illness. Woods and several of his close friends on the tour withdrew immediately from the Wachovia Championship in Charlotte, NC. He missed three events. Although few could have anticipated the exact timing of this event, widespread media reports suggested a rapid and severe decline in Woods's father's health in the 2 months prior to his death. I can identify no statistically significant improvement (or decline) in Woods's competitors' performances during this absence.

TABLE 4
Regression Results for Woods's Unexpected Absences: Strokes Relative to Par

| | Knee Surgery in 2008: July–September 2007–9 | | Personal Issues in 2009 and 2010: January–March 2009–10 | |
|---|---|---|---|---|
| | First Round (1) | Tournament (2) | First Round (3) | Tournament (4) |
| Superstar effect for players: | | | | |
| Ranked 1–20 | .244 | 3.919*** | 1.125 | 2.754 |
| | (.614) | (1.462) | (.930) | (2.038) |
| Ranked 21–200 | .317 | 5.647*** | 1.510*** | 3.519*** |
| | (.309) | (.956) | (.447) | (1.050) |
| Unranked | .119 | 5.755*** | 1.210*** | 3.554*** |
| | (.377) | (1.094) | (.484) | (1.351) |
| Observations | 2,676 | 1,616 | 2,339 | 1,172 |
| Adjusted $R^2$ | .21 | .58 | .18 | .36 |

Note.—All specifications include controls for wind, rain and temperature, purse size, and course- and player-level fixed effects. Values in parentheses are standard errors, clustered by player-year. Other variable coefficients are suppressed. Scores for Tiger Woods are excluded.

* Statistically significant at a $p$-value of .10.

** Statistically significant at a $p$-value of .05.

*** Statistically significant at a $p$-value of .01.

ranked players also improved by 5.3 and 3.9 strokes, respectively ($p$-value = .01). During Woods's unexpected absence in early 2010, high-ranked, low-ranked, and unranked players had significantly better mean scores ($p$-values < .1, .01, and .05, respectively).[22] These summary statistics are suggestive: mean scores suggest a large adverse superstar effect in these periods of interest.

Table 4 reports the results for the event studies for first-round (regressions 1 and 3) and tournament (regressions 2 and 4) scores, controlling for player-, course-, and event-specific variation. For Woods's absence due to injury, I include data from three years (before, during, and after the event). Since late season events include playoff and nonstandard events, I examine only regular tournaments and World Golf Championships from July to September. For the second analysis, I include data from January to March of the 2009 and 2010 seasons.

Although the estimated coefficients are positive, I find no statistically significant adverse superstar effect on golfers' first-round performance in the window around Woods's knee surgery. However, competitors' tournament scores are significantly worse. As described at the beginning

[22] Differences in mean scores from events in which Woods played and mean scores from all events in which he did not participate are similar in magnitude and statistical significance.

of Section III, players face effort-related decisions before events, during rounds, and between tournament days. If players prepare differently when they expect to face a superstar, then we might expect evidence of a performance effect early in the event. If players prepared for these tournaments expecting Woods to be in the field, then a substantial portion of their effort may have already been expended; this would bias the first-round effect toward zero. Coefficients in regressions 1 and 2 suggest that, in some cases, the observable outcome of the adverse effect—high scores—may accumulate over multiple days of play. Even when we control for the course, conditions, purse size, and individual heterogeneities, players' scores were four to five strokes higher when Woods participated in the competition; the estimates for ranked and unranked players are not statistically distinguishable.

Comparing golfers' performances in 2009 and 2010, I find a statistically significant adverse superstar effect for ranked and unranked players in both first-round and final scores. On average, tournament scores were 3.5 strokes higher when Woods was in the field.

The magnitude of these coefficient estimates is remarkable: one stroke in the first round and three, four, or five strokes per tournament are astonishingly large changes in players' performances. Examining microdata for players who participated in the same event across Woods's presence and absence, I can identify individuals who posted final scores that were higher in the presence of the superstar. For example, Jim Furyk shot $-3$ in 2007 and $-6$ in 2009 when Woods played in the AT&T National and $-9$ in 2008 when Woods did not participate; Vijay Singh shot $+15$ in 2007 and even par in 2009 in the World Golf Championship–Bridgestone when Woods was in the field but $-10$ in 2008 when Woods was absent. Of course, the estimated adverse superstar effect reflects a mean decline in performance: approximately 10 percent of golfers actually played better in the presence of a superstar in the years around Woods's knee surgery.

The precision of the estimates in table 4 may reflect the small sample sizes since Woods missed only two or three events in each case. Moreover, identification in the specification with individual and course fixed effects hinges on individual golfers playing the same event across multiple years with and without the superstar. However, despite these demands on the data, the results are consistent with an adverse superstar effect. In general, first-round and tournament-level estimates suggest that golfers play worse on average when Woods is in the field relative to when he does not participate.

### *F. "Hot" and "Cool" Periods*

Although his career has been extraordinary, Woods's "superstardom" has varied across time. In 2003 and 2004, Woods failed to win a major event, and media reports claimed that "Tiger slump gives rivals hope" and "Woods' year a major disappointment."[23] Results in table 2 include a single indicator for the presence of the superstar, the empirical analogy of fixing players' relative skill, $\lambda$, in Section II. If, instead, I allowed $\lambda_1$ to take on high and low values relative to $\lambda_i$ for $i > 1$, then I would expect players' efforts to respond accordingly. When the superstar was relatively "hot" (large $\lambda_1$), effort would be low and the superstar effect should be large. When the superstar was relatively "cool" (small $\lambda_1$), effort would be high and the superstar effect should be small. To operationalize these predictions, I estimate equation (1) with hot and cool indicators for Woods's more and less successful periods, respectively. Estimates of the variables of interest are reported in table 5.

I identify hot and cool periods by calculating the difference between Woods's average score and other ranked players' average score in the previous month. When Woods's performance is not remarkably better than other golfers' performances—score differences in the bottom quintile—he is in a cool period. When Woods's scores are remarkably lower than his competitors' scores—score differences in the top quintile—he is in a hot period. Score differences in the second to fourth quintiles represent Woods's typical performance.[24]

Regressions 1 and 2 examine first-round scores, and regressions 3 and 4 use overall tournament scores. During Woods's hot periods, the superstar effect is large and statistically significant; in regular and major events, tournament scores of top-ranked players are approximately two strokes higher when Woods participates ($p$-values $< .01$). Woods's impact appears early: top-ranked players' first-round scores are approximately one stroke higher when Woods competes. The scores of players ranked outside of the top 20 are also statistically higher when Woods participates during his hot periods. For these players, first-round scores are approximately 0.6 strokes higher and overall scores are approximately 0.97 higher in regular events when they face a hot superstar.

Cool periods have the opposite effect on the superstar coefficients: some golfers may actually play better when Woods is perceived to be weaker (and beatable). The adverse superstar effect disappears for all ranked players, and tournament-level coefficients are negative and statistically significant for unranked competitors ($p$-values $< .1$).

[23] Headlines by Majendie of BBC.co.uk (April 14, 2003) and Potter of USAtoday.com (August 17, 2003), respectively.

[24] Results are similar when I use 1-month-lagged quartiles of score differences and hot/cool years as reported by the media; these estimates are not reported.

TABLE 5
Regression Results for "Typical," "Hot," and "Cool" Periods: Strokes Relative to Par

| | Tournament Type | | | |
|---|---|---|---|---|
| | First Round Regulars and Majors (1) | First Round Regulars (2) | Tournament Regulars and Majors (3) | Tournament Regulars (4) |
| Ranked 1–20: | | | | |
| Typical superstar effect | .358 | .381 | 1.016 | .792 |
| | (.302) | (.332) | (.833) | (.927) |
| Hot superstar effect | .982*** | 1.388*** | 2.074*** | 2.276*** |
| | (.321) | (.379) | (.775) | (.961) |
| Cool superstar effect | .279 | −.418 | .500 | −.753 |
| | (.439) | (.501) | (1.049) | (1.330) |
| Ranked 21–200: | | | | |
| Typical superstar effect | −.088 | −.065 | .669** | .519 |
| | (.127) | (.130) | (.365) | (.373) |
| Hot superstar effect | .611*** | .744*** | 1.377** | 1.414*** |
| | (.139) | (.152) | (.369) | (.400) |
| Cool superstar effect | −.220 | −.299* | −.332 | −.265 |
| | (.171) | (.173) | (.486) | (.519) |
| Unranked: | | | | |
| Typical superstar effect | .129 | .222 | .433 | .310 |
| | (.152) | (.153) | (.460) | (.465) |
| Hot superstar effect | .523*** | .602*** | 1.387*** | .974* |
| | (.149) | (.159) | (.504) | (.522) |
| Cool superstar effect | −.294 | −.342 | −1.151* | −1.110* |
| | (.216) | (.215) | (.663) | (.632) |
| Observations | 34,986 | 29,167 | 18,805 | 15,656 |
| Adjusted $R^2$ | .29 | .58 | .48 | .38 |

Note.—All specifications include controls for players' rank, strength of the field, wind, rain and temperature, purse size, television viewership, tournament type, and course-player fixed effects. Values in parentheses are standard errors, clustered by player-year. Other variable coefficients are suppressed. Major events are the PGA Championship, U.S. Open, British Open, and Masters. The difference between the average score posted by ranked players and the score posted by Tiger Woods was calculated for all months. Cool and hot periods represent the first and fifth quintiles of these values, respectively, lagged by 1 month. Missing percentile values were replaced with data from the previous available month. Scores for Tiger Woods are excluded.

* Statistically significant at a $p$-value of .10.

** Statistically significant at a $p$-value of .05.

*** Statistically significant at a $p$-value of .01.

### G. *Risky Strategies*

Do golfers employ riskier strategies when they face the superstar relative to their play in more "winnable" tournaments? Risky shot taking should widen the distribution of scores relative to more conservative play. That is, we might expect a player pursuing a risky strategy in the presence of a superstar to post more eagles (two strokes under par) and more double bogeys (two strokes over par). Instead, table 1 reports the opposite: more eagles and fewer doubles are posted when Woods is not in the field.

While golfers aim to minimize their total strokes on the course, they face a salient trade-off between distance and accuracy. Players can pursue risky strategies through shot and club selection; for example, players often face the choice to "go for the green" by attempting a longer and riskier shot than required to earn par. Par for a hole is established by determining the number of shots required to get to the green plus two putts. That is, a good golfer on a par 5 hole is expected to land on the green with his third shot and two putts for par. In practice, however, a player might choose to aim for the green on his second shot on a par 5. A successful shot may lead to a better score, whereas an unsuccessful shot that lands in a water hazard or long grass may result in a difficult follow-on shot and a worse score. Risky shots may also be attempted off the tee: players may choose to use a higher-loft club (e.g., an iron or higher wood) instead of a driver. While he loses distance, the player expects to gain accuracy with this more conservative club choice.[25]

Players may also make risk-related decisions on the green, where strong putts that push the ball well past the hole are also risky. Lighter putts that finish short of the hole lower the probability of a successful end but may make the next putt more straightforward. Moreover, downhill putts are considerably more difficult than uphill putts, so leaving a difficult downhill putt is a risky move. In their study of loss aversion, Pope and Schweitzer (2011) consider missed putts that finish short of the cup (safe) or well past the cup (risky).

Table 6 presents regression results using two measures of risky play: variance and whether a player goes to the green when presented with the opportunity to take the riskier shot off the fairway.

Variance is calculated by examining players' hole-by-hole scores relative to par within each round of a tournament. For example, a player who finishes one over par after 18 holes with 12 pars, five bogeys, two birdies, and one eagle will have a variance measure of 0.76. In contrast, a golfer who finishes one over par with 17 pars and a bogey will have a variance measure of 0.05. In these data, players' average risk measure is 0.47 (standard deviation of 0.28).[26] Results of regression 1 do not suggest that players are adopting riskier strategies in the presence of the superstar: coefficient estimates are very small in magnitude and not statistically different from zero. The variance in scores in rounds 3 and 4 tends to be higher than the variance in the first two rounds of play.

[25] Unfortunately, club selection data are currently unavailable for the PGA Tour.

[26] The measure ranged from 0 to 4.1; several players scored exactly par on every hole of their round, whereas others posted both eagles and quadruple bogeys in a single round.

TABLE 6
Regression Results for Risky-Strategy Measures

| | Dependent Variable | |
|---|---|---|
| | Variance of Strokes Relative to Par in Regular Events, 2001–6 (1) | Went for It Measure (Greens Attempted/Total Opportunities) Regulars Events, 2002–6 (2) |
| Ranked 1–20 | .001 | .016 |
| | (.023) | (.055) |
| Ranked 21–200 | −.005 | −.005 |
| | (.009) | (.039) |
| Unranked | .013 | .025 |
| | (.012) | (.041) |
| Round 2 | −.002 | .003 |
| | (.006) | (.072) |
| Round 3 | .027*** | −.013 |
| | (.008) | (.078) |
| Round 4 | .034*** | −.017 |
| | (.008) | (.046) |
| Observations | 29,166 | 7,423 |
| Adjusted $R^2$ | .29 | .41 |

Note.—All specifications include controls for wind, rain and temperature, purse size, and player-course fixed effects. Values in parentheses are standard errors, clustered by player-year. Other variable coefficients are suppressed. Only data from players who made the cut are included.
* Statistically significant at a $p$-value of .10.
** Statistically significant at a $p$-value of .05.
*** Statistically significant at a $p$-value of .01.

This finding may reflect the fact that golfers who make the cut after round 2 may adopt riskier strategies once guaranteed a cash prize.

The second risk measure, reported in column 2 of table 6, is the fraction of opportunities in which the player attempted a risky going for it shot in a tournament. Since 2002, the PGA Tour has recorded players' attempts to land on a green in fewer shots than expected. For example, a player might choose to aim for the green on his second shot on a par 5 or with a long drive on a par 4 hole. In general, players will have three to five such opportunities per round. If a player goes for it in two of five opportunities in a round, this is coded as 0.4. On average, players attempted a riskier shot 49 percent of the time (standard deviation of 20 percent). While this measure is crude, it provides a robustness check on the analysis of variance-related results. In regression 2, the estimated coefficients do not achieve statistical significance under a variety of specifications, including a probit specification that accounts for the bounded dependent variable; again, regression results do not suggest that players are adopting riskier strategies in events with the superstar competitor.

Brown and Li (2010) use detailed approach shot and putting data to examine how tournament rank and absolute score differences between top players affect their adoption of risky strategies. They examine 10–40-foot first putts that missed (either long or short) by more than 25 inches, the median distance for unsuccessful second putts, and control for the grade putt from ball to cup. They calculate the percentage of the first putts that were risky in each round and find no difference in shot-level risk-related outcomes when Woods participates.

### *H. Alternative Explanations*

According to many media reports, Woods's rise to superstardom has increased fan interest in professional golf. Indeed, television coverage and ratings have increased dramatically since 1999: on average, total viewership per event increased approximately 10 percent each year between 1999 and 2007.[27] Moreover, tournaments in which Woods participated tend to draw larger viewing audiences; when we control for tournament type, events with Woods attracted substantially more television viewers. One might worry that the estimated superstar effect is a function of Woods's popularity; that is, one might wonder if competitors are responding not to the change in the competition but to the larger crowds or increased media attention. Television viewer and ratings data, purchased from the Nielsen Company for the entire panel of tournaments from 1999 to 2010, allow me to consider this alternative explanation for the observed adverse superstar effect.

To control for event popularity, media presence, and crowd size, I include television viewership controls in all of the specifications. Although not reported in the main tables of the paper, in regressions examining the performance impact of the superstar's participation in tournaments, coefficient estimates for the viewership variable were negative but not statistically significant at conventional levels. These results suggest that while more viewership may be imprecisely associated with better performance, media attention is not driving the observed decrease in players' performances in tournaments with the superstar.

Moreover, when Woods plays in a televised event, he dominates the coverage: according to Repucom, a brand analysis firm, networks showed Woods nearly 30 percent of the time during first-round coverage and nearly 19 percent of the time during the final round of the 2010 Masters.[28] In contrast, relatively unknown competitors receive little airtime; for example, in the same event, Y. E. Yang placed eighth but was

[27] Author's estimate using data from the Nielsen Co.

[28] As reported by the *New York Times* on April 22, 2010 (http://onpar.blogs.nytimes.com/2010/04/20/a-look-at-woodss-tv-presence/).

never shown on television. If nonsuperstar players are receiving little media attention when Woods competes, then it is unlikely that distraction is driving the adverse performance results.

A recent paper by Guryan et al. (2009) examines the first two rounds of tournaments in 2002, 2005, and 2006 and finds that being paired with Woods has no statistically significant effect on golfers' performance. Their results help address two other alternative explanations for the superstar effect. First, one might wonder whether it is a positive audience effect—and not the undesirable media pressure considered above—that drives the current superstar result. In this case, you might argue that players perform better under intense media attention and thus play worse when Woods is consuming the spotlight. If this were true, we would expect players paired with Woods to benefit from his popularity. Guryan et al. show that players sharing Woods's attention do not play differently. Second, these authors' results provide evidence that the observed performance effect is not due to intimidation on the course. Golfers playing near the superstar should be particularly affected by intimidation—more than those who teed off minutes or hours before—yet this does not appear to be the case.

## IV. Conclusion

While there are many situations in which tournament-style internal competition improves worker performance, tournament and contest theory suggests that large inherent skill differences between competitors can have the perverse effect of reducing effort incentives. The main contribution of this paper is to investigate whether this theoretical possibility matters in practice. Using a rich panel data set of the performance of PGA Tour golfers, I present evidence that a "superstar effect" is in fact present in professional golf tournaments.

Understanding the economic magnitude of the adverse incentive effects is also useful. Consider the following counterfactual: How much would Tiger Woods's earnings have been reduced if all of his competitors played as well as they did when he was not in the field? In my main results, I identify a superstar effect of approximately one stroke for players ranked in the top 200 in the world. I simulate the distribution of prizes if all ranked players' tournament scores had been one stroke better when they competed against Woods; that is, I removed the estimated superstar effect from players' scores. In 34 of the 136 tournaments that I studied, the simulated improvement in competitors' performance had no effect since Woods was sufficiently alone in the score distribution to avoid a rank-order shift. In 20 events, the simulation shifted at least one golfer into a tie with Woods in the final tournament standing; in the remaining events, Woods shifted from a tie at a higher prize position to a tie at a lower prize position.

My calculations suggest that Woods's PGA Tour earnings would have fallen from $54.4 million to $48.4 million between 1999 and 2006 had his competitors' performance not suffered the superstar effect. By my estimates, Woods pocketed nearly $6 million in additional earnings because of the reduced effort of other golfers—prize money that would otherwise have been distributed to other players in the field. Viewed in this light, the superstar effect is economically substantial.

To understand the impact of the effect on Woods's competitors, I ask: What if a single average player were able to overcome his own adverse performance by exerting effort and post scores that were one stroke better in tournaments with the superstar? I simulate the total winnings of each of the ranked players, assuming that his scores were one stroke lower in all events with Woods between 1999 and 2006. On average, a golfer would have earned approximately $28,000 more. Given that an average top 200 player played in 12 events with Woods and earned $3.4 million from the PGA Tour during the 8-year period, the return to effort seems small. For example, in the simulation, a one-stroke improvement by David Love III would have increased his average per-tournament earnings by approximately $10,000—considerably less than his reported daily rate for corporate appearances. Of course, the estimates do not reflect improved endorsement opportunities that would have resulted from better tournament play.

Still, these simulations provide compelling evidence: while the overall economic significance of the adverse superstar effect is strikingly large, individual competitors may simply say: "Why should I exert more costly effort when the marginal payoff in the presence of a superstar is low?"

The implications of the superstar effect extend beyond professional golf; in principle, organizations in which internal competition is a key driver of incentives should be cautious in using a "best-athlete" recruiting strategy. For example, sales managers and law firms should be aware of the impact of introducing a superstar associate on the cohort's overall performance. Understanding the superstar effect is a first step toward learning how to best structure situations in which competition exists between players of very heterogeneous abilities.

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