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IZA DP No. 10755

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ABSTRACT

Do Tournaments with Superstars Encourage or Discourage Competition?

To test and replicate the superstar effect reported by Brown (2011) we empirically study contests where a single entrant has an endogenously higher probability of winning. Unlike the previous literature, we test for the presence of the superstar effect in several different contexts. Ultimately, we collect and explore data from four sources: men's and women's professional golf, and men's and women's professional alpine skiing. Our baseline study of men's professional golf serves as a replication of Brown's (2011) study. Empirically, we find little robust evidence of the superstar effect in any of our datasets. In our replication exercise, we approximate the findings of Brown (2011), however, we cannot reject the null that the presence of a superstar has no impact on high ranked competitors. In our other settings, we cannot reject the null that superstars have no influence on the performances of highly ranked competitors.

JEL Classification: C2, J3, M52, D03
Keywords: superstar, tournaments, incentives

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I like to win. If I lose, I'm not very happy.
Hermann "The Herminator" Maier

When I first came on tour, I was playing for money.
Now I'm playing to win golf tournaments [...]
Annika Sörenstam

I'm never tired of winning, and I'm never tired of skiing.
Lindsey Vonn

I want to be what I've always wanted to be: dominant.
Tiger Woods

1. Introduction

Firms are often faced with finding means to incentivize workers to maximize both individual and group effort. One mechanism that has gained popularity and has been widely implemented is the use of rank order tournaments (Lazear and Rosen 1981). Examples of such tournaments include athletic events (Taylor and Trogdon 2002; Sunde 2009; Coffey and Maloney 2010), workplace promotion and CEO compensation (Main et al. 1993; Chan 1996; Bognanno 2001; DeVaro 2006; Eriksson 1999), and research and development contests (Taylor 1995; Terwiesch and Xu 2008; Terwiesch and Ulrich 2009).

Given their prevalence, economists have widely studied rank order tournaments, both empirically and theoretically, to understand how their design influences individual and group effort. In most cases, researchers have shown that increasing the steepness of the prize gradient leads to increased performance (Kale et al. 2009; Ehrenberg and Bognanno 1990; Moldovanu and Sela 2001; Freeman and Gelber 2010). Researchers have also shown how the prize gradient affects the strength of the field when entry into the tournament is endogenous (Cason et al. 2010; Morgan, Orzen, and Sefton 2012). Recent work has begun to examine how the composition of the field impacts behavior, for instance, given differences in the competitive attitudes amongst genders (Niederle et al. 2013; Booth and Nolen 2012).

Most relevant to this study is the growing literature examining the impact of participants' heterogeneity on effort (Bhattacharya and Guasch 1988; Ryvkin 2009, 2011, 2013). Empirically, recent work has begun to focus on the potential disincentive to exert costly effort when facing a superstar competitor or a favored participant. One of the most influential empirical papers is Brown's (2011) study, which highlights the disincentive to exert effort on the PGA Tour using exogenous variation associated with Tiger Woods peak performance in the early 2000s. Brown finds that when Tiger Woods was at the top of his game, golfers in the same tournament tended to underperform relative to their performance in tournaments in which Tiger did not participate. Thus, Tiger's presence exogenously reduced the probability of victory for the other players and led to reduced effort. Several other studies have reinforced Brown's findings. For example, Connolly and Rendleman (2009) with PGA data, as well as Tanaka and Ishino (2012) with Japanese golf data report similar relationships. In addition, Frank (2012) discovers effects among amateur golfers that are consistent with Brown's (2011) findings. In other contexts, Boudreau et al. (2016) find that the presence of star computer programmers has a similar effect on less skilled programmers. Finally, Herbertz and Sliwka (2013) show that non-favored participants reduce their efforts in tournaments in which a participant is favored to win.

While these findings show that the presence of a favorite or superstar may lead to reduced effort, empirical work on peer-effects in non-competing work environments suggests rather positive effects on the effort when low productivity individuals are matched with high productivity individuals (Falk and Ichino 2006; Bandiera, Barankay, and Rasul 2009; Lyle 2007, 2009; Mas and Moretti 2009).[1] In addition, recent theoretical contributions by Kräkel (2009),

[1] At the same time Bandiera, Barankay, and Rasul (2009) report a negative effect on the output of high productivity individuals when matched with a low productivity individual.

Stracke and Sunde (2014), and Gürtler and Gürtler (2015) demonstrate that heterogeneous abilities can actually increase the effort provision within tournaments. Thus, it is not clear if the superstar effect can be generalized, or alternatively, how large a star has to be to create disincentives amongst peers.

Along these lines, several questions have been raised regarding Brown's (2011) initial study. For instance, Guryan, Kroft, and Notowidigdo (2009) test for peer effects using the PGA Tour's quasi-random pairing algorithm and find no evidence that being paired with Tiger Woods leads to worse performance throughout the tournament. While their intent was to study peer effects, one must question the superstar effect if players who are directly competing with Tiger are not intimidated by his presence. More directly, a comment by Connolly and Rendleman (2014) challenges Brown's (2011) results by noting that the results are (1) not robust to changes in the sample specification, the addition of missing tournament data, and (2) not robust to alternative clustering that accounts for common (unobservable) shocks within a given tournament.[2]

Our purpose in this paper is to test whether or not the superstar effect is generalizable to other settings. While the recent literature has provided a sharp critique of Brown (2011), there are several examples and counter-examples documenting the disincentives generated by competition with a superstar noted above. Thus, we extend the literature by expanding the set of environments in which we test for the superstar effect. Tiger Woods, while at his peak, was a special player who completely dominated the field, thus the results in Brown (2011) may be Tiger specific. We examine a variety of contexts that vary according to their physical demands,

[2] In Brown (2011), the author notes that the findings are qualitatively similar to changes in clustering (p997, fn. 17).

mental demands, and pay structures. More specifically, in addition to the original environment of men's golf, we test for the superstar effect in three new environments: 1.) women's golf, a natural analogue to the original study, 2.) men's World Cup Alpine Skiing and 3.) women's World Cup Alpine Skiing. For each of these environments there exists a natural superstar: Annika Sörenstam, Hermann Maier, and Lindsey Vonn. We explain the choice of these environments and superstars in more detail below.

Due to certain differences in observables between the datasets, such as the availability of TV ratings for all contests, we first replicate the main findings from Brown (2011) with a dataset we have compiled of PGA Tournament events to show how our baseline results differ with the omission of certain controls. We also show how these results change in response to concerns raised by Connolly and Rendleman (2014). This provides a starting point for our main analysis focusing on the LPGA Tour and the International Ski Federation (FIS) World Cups for men and women. As in Brown (2011), we exploit variation in the participation of the superstars to determine how the performance of entrants varies both when the superstars compete and do not compete in a given tournament. Given the panel nature of our data, we control for a wide variety of confounds, such as individual's average performance on a particular course or slope. This allows us to determine how each athlete's performance changes with the participation of the superstar relative to an athlete's average performance.

Empirically, we find little robust evidence of the superstar effect in any of our datasets. In our replication exercise, we approximate the findings of Brown (2011), however, we cannot reject the null that the presence of a superstar has no impact. In our other settings, we cannot reject the null that superstars have no influence on the performance of highly ranked competitors. In fact, while we do not emphasize the result, we find weak evidence that in some contexts, such as women's alpine skiing, competing against a superstar improves performance amongst low ranked competitors, lending support to the hypothesis put forth by Stracke and Sunde (2013) and Gürtler and Gürtler (2015).

2. Theoretical Background

In the environment that we consider, there are two main features that may influence the effort decisions of participants (1) the relative ability of other participants and (2) the presence of multiple prizes (and their structure). Below we present two models from the existing literature to highlight how each of these features affects effort decisions. First, we review a model by Stein (2002), who considers the impact that heterogeneous players have on effort in a contest. We then discuss how the presence of multiple prizes influences effort, following the work of Symanski and Valletti (2005). The discussion that follows will closely mirror that found in Brown (2011).

In Stein's model, there are *n* players who invest effort in the hopes of winning a single prize, *R*. Each participant has a relative ability level, θ_i, that orders the participants from most to least skilled, $\theta_1 > \theta_2 > \theta_3 > \cdots > \theta_n \geq 1$. This relative ability suggests that for the same effort level, the first player is more likely than the second player to win the prize. We follow the literature, and assume that the success function takes the logistic form, and for simplicity, assume that the cost of effort is homogeneous and linear for each participant, and is thus normalized to one. Under these assumptions, we can write the expected profit function for a given player *i* as follows

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

We then solve for the optimal effort, and, to understand how an increase in relative ability affects effort, we take derivatives with respect to individual ability

$$\frac{dx_i}{d\theta_j} = \left[\frac{(n-1)R\,\Gamma^2}{n^2\theta_i\theta_j^2}\right]\left[1 - \frac{2(n-1)\,\Gamma}{n\theta_i}\right].^3$$

For effort to be decreasing in the ability of a rival, the second term in brackets must be less than zero. From this expression, it is easy to see that this is the case when $\theta_i \leq \frac{2(n-1)\Gamma}{n}$. In the case with two players, this inequality is always satisfied, thus, the presence of a superstar always reduces effort. However, as *n* increases *>2*, the relative ability of the superstar must be sufficiently large for this inequality to hold.[4]

While the relative ability of players may influence effort, the presence of multiple prizes may affect effort as well. As Szymanski and Valletti (2005) note, if either of them were to enter a foot race against a world class runner, such as Ussain Bolt, they would not exert effort in the presence of a single prize. However, the introduction of a second prize is sufficient to encourage effort amongst these amateur athletes. To provide intuition, we consider the three person contest presented in Szymanski and Valletti (2005). In their model, three players compete to win a share of the prize purse, *R,* whereby the first place finisher receives a share of the purse $0.5<k<1$, the second place finisher receives $(1-k)$, and the third place finisher receives zero. Unlike Stein (2002), heterogeneity in ability can be introduced by allowing the effort cost to vary across players. We assume that cost is linear and that the success function is logistic, however, express the payoff more generally for compactness. Under these assumptions, we can define the expected payoff function as follows

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[3] $\Gamma = n\left(\sum_{i=1}^{n}\frac{1}{\theta_i}\right)^{-1}$ is the harmonic mean of the relative abilities of the players.

[4] Broadly, this finding is consistent with more recent work by Bourfeau, Lakhani, and Menietti (2016), Moldovanu and Sela (2001), who show that as participants are added to a contest, the effort response can be positive or negative depending on one's own ability.

$$\pi_i = p_i kR + \sum_{j \neq i} p_j p_{i-j} (1-k)R - c_i x_i.$$

The first term is the expected value of winning the first prize, the second term is the expected value conditional on not winning the first prize, and the third term is the effort cost. As in Szymanski and Valletti (2005), we allow one "strong" or "superstar" player to have a lower cost of effort, while the two weaker players are symmetric $(c_1 < c_2 = c_3)$.[5] To solve the game, we differentiate the expected profit with respect to x_i, which yields the following first order condition

$$\frac{d\pi_i}{dx_i} = \frac{dp_i}{dx_i} kR + \sum_{j \neq i} \left(\frac{dp_j}{dx_i} p_{i-j} + p_j \frac{dp_{i-j}}{dx_i} \right) (1-k)R - c_i.$$

Given the cost and the logistic formulation for the success functions, equilibrium effort for each type (strong, weak) can be solved implicitly (as described in Sisak, 2009). Szymanski and Valletti show that as the superstar becomes more dominant (as the cost approaches zero), the efforts of the weak players decline, such that in the limit, the weak players behave as if they are in a two player contest, competing only for the second prize. Because these weak players are effectively competing for second place, the allocation of the purse towards the second place is highly important. For a fixed cost of effort for the superstar, increases in *k*, lead to reductions in effort by the weaker players.

In what follows, we describe how we arrived at the contests that we examine within the paper and then provide some evidence that these settings should be influenced by superstars.

[5] This deviates from Brown (2013) who address differences in ability including a parameter, $\lambda > 1$, that exogenously increases the likelihood of winning in the success function. Brown then considers how increasing λ affects effort.

That is, we provide evidence that an individual in each sport is more skilled by an order of magnitude than their closest rivals, and that the prize structure has a steep prize gradient.

3. Selection Criteria

The empirical exercise that follows involves making several ad hoc choices regarding the selection of athletic events and individuals whom are classified as superstars. To select the events and athletes, we considered several criteria:

1. *Each event must be an individual sport and the individual must compete alone.*[6]

The first restriction has several consequences for our sample. For example, even though sports such as swimming and track have obvious superstars, such as Michael Phelps and Usain Bolt, they simultaneously complete against their competitors, which may give rise to peer effects, violating the assumption that effort is predetermined. This type of feedback effect has been documented empirically by Coffey and Maloney (2010). This restriction also eliminates sports such as tennis, where players compete in matches that are winner take all. In golf, each golfer is the only individual to take a stroke on a given hole, while in alpine skiing events, each racer goes down the course one by one.

2. *Each sport must be scored on an objective or rank order scale, such that no part of the score is based on subjective judgment.*

This restriction effectively eliminates sports that have a portion of their scoring determined by judges. For instance, this eliminates prominent athletes such as Sean White in events like the

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[6] In golf, athletes play in pairs and groups, however, no player completes at the same time as another.

snowboarding halfpipe, or dominant figure skaters like Katarina Witt and Dick Button. The reasoning here was twofold, first, it is difficult to measure performance when the subjective part of the scoring is highly idiosyncratic to the judges and secondly, in some contests, such as figure skating, there have been rampant cases of corruption amongst judges and national federations (Zitzewitz, 2014).

3. *Each sport must have a clear superstar, whereby (i) an individual wins the majority of major events for consecutive years in a row and (ii) is the top three money winner multiple years in a row.*

Several sports satisfy conditions (1) and (2), but fail to produce a superstar. For example, the shot put satisfies (1) and (2), as throwers step into the ring one by one, and have their effort marked and measured in meters, however, there is not a dominant thrower who has won multiple World Championships or Olympic games. Similarly, professional bowling satisfies (1) and (2), but there is not a clearly dominant bowler. Alternatively, a sport may have a clear superstar by the stated definition, however, they may be so dominant that there is not sufficient variation in the data to identify an effect. On the professional darts tour, Englishman Phil Taylor has been the dominant force dating back to the early 1990s. Given his longevity and dominance, the existing data do not provide sufficient variation to identify an effect of his participation on rivals.

4. *There should be a clear superstar in both the men's and women's fields of the event.*

It has been heavily documented in the economics literature that men and women respond to economic settings differently (see Croson and Gneezy 2009 for a review). By observing men and women competing in the same event, we can test to see if the incentive effect of a superstar is generalizable to both sexes.

After careful consideration, we believe that we have identified two sports where both the men and women have a clear superstar: alpine skiing and golf. In golf, we follow Brown (2011) and identify Tiger Woods as a superstar in men's golf. In the women's game, Annika Sörenstam is the outstanding player of her generation. In the alpine skiing events, we believe we denote Herman Maier and Lindsey Vonn as superstars. In what follows, we discuss what qualifies each individual as a star, and provide evidence that the competitions have steep prize gradients.

Evidence of Super Stardom

As we previously noted, there are two conditions that are key for a player to have a negative effect on their rivals effort (1) the star must be significantly more skilled than their rivals (2) the contest needs to have multiple prizes with a sufficiently steep prize gradient.

Table 1: Superstars

Name	Tiger Woods	Annika Sörenstam	Hermann Maier	Lindsey Vonn
Sport	Men's golf	Women's golf	Alpine Ski	Alpine Ski
Time active	1996-	1992-2008	1996-2009	2000-
Superstar years/season	1999-2006	2000-2006	1998-2001 2004-2005	2008-2013
During superstar seasons (corresponding numbers in brackets for the runner ups):				
- #wins	79(42)	72(31)	49(29)	52(20)
- prize money in millions	$63.4 (32.6)	$15.5 (8.4)	2.9 CHF (2.0)	2.5 CHF(1.9)

Active period are the years in which the athletes competed in professional events. Woods turned professional when joining the PGA tour, Sörenstam when joining the Ladies European Tour (she joined the LPGA in 1994) and for Maier and Vonn when they first participated in a FIS World Cup race.

We begin by discussing how dominant each superstar was in their own sport. Table 1 provides career statistics for the superstars and the time periods for which we consider them as the dominant athletes in their sports. Tiger Woods was dominant at the peak of his career, amassing

79 wins, while his closest rival, Phil Mickelson accumulated 42 wins. Within a given season, Woods's earnings were significantly larger than any other player in the field. In Figure 1, Panel (a), we present the earnings distribution over the final ranks of the 2005 PGA Tour, the year of the Tiger slam, normalized to Woods's tour earnings. Tiger's closest rival in 2005, Vijay Singh, had earnings that were 75 percent of Woods's, while Phil Mickelson's were only 53 percent. Tiger's earnings were equal to the cumulative sum of 94 other golfers who were awarded prize money on the tour (35 percent of all golfers awarded money).

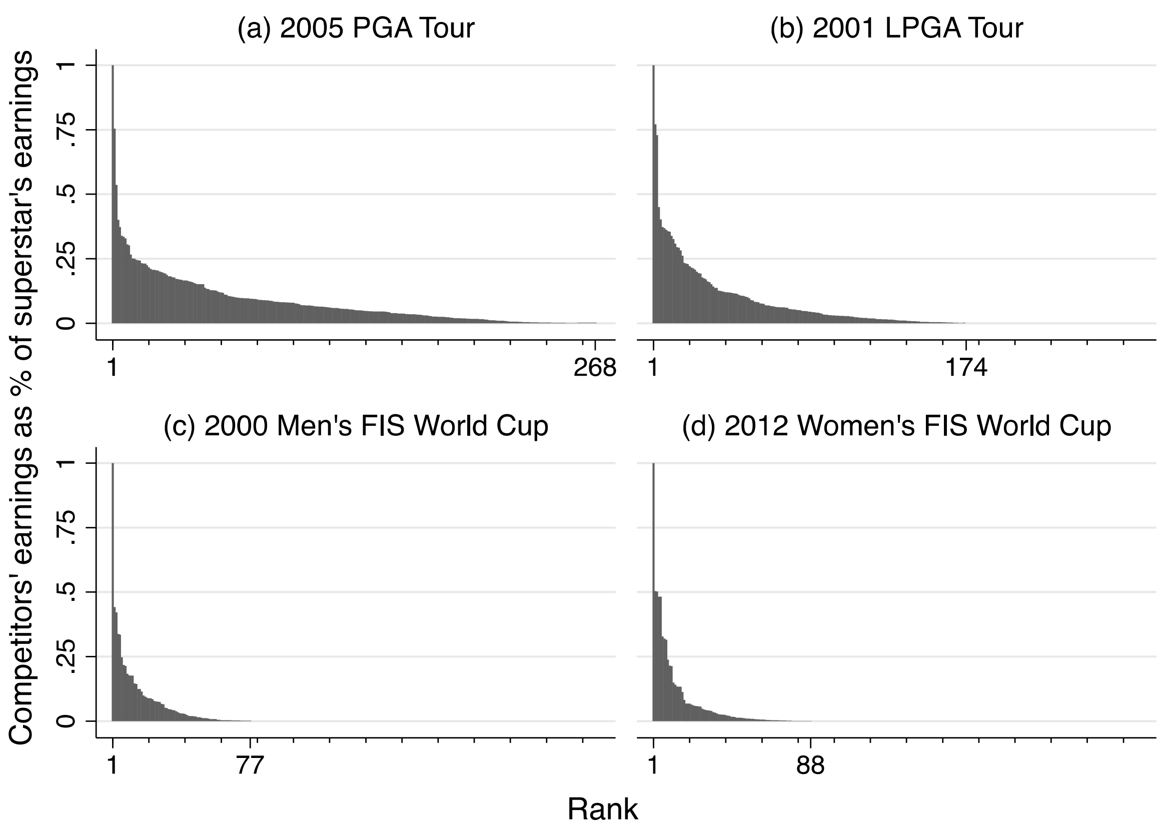

Figure 1: Season earnings relative to superstars' earnings by sport.
Only athletes with positive earnings included

In the women's draw, Annika Sörenstam was potentially an even larger star than Woods. Sörenstam has the most career wins of any female golfer in history and is the LPGA Tour's all-time leader in earnings. Over the sample period, Sörenstam amassed 72 wins, 31 wins more than her closest rival and contemporary, Karrie Webb. Over an eleven year period, 1995 to 2005, Sörenstam was the top money earner and tour champion eight times. In Figure 1, Panel (b), we present the earnings distribution from the 2001 LPGA Tour. In 2001, Sörenstam's closest rival, Se Ri Pak, earned 77 percent of Sörenstam's earnings, while Karrie Webb, the second closest rival, earned 72 percent. Her earnings were larger than those of 74 golfers combined, representing 42 percent of golfers receiving prizes on the LPGA Tour.

In the men's alpine skiing data, we denote Hermann Maier as a superstar. Maier dominated the FIS competition from 1998 to 2005 by winning 49 races. During this time he won the overall cup 4 times, and reached the podium 19 times in the 4 events that comprise the overall cup.[7] Over his career he amassed 54 FIS wins, and was a podium finisher 96 times. His closest contemporary, Stephan Eberharter, had 29 wins, however, many of these came during the 2002 and 2003 seasons, which Maier missed due to a horrific motorcycle accident. Upon his return, Maier continued to dominate the field. While we do not directly observe the earnings distribution of the FIS World Cup for seasons prior to 2012, we can construct the earnings distribution based on the prize structure and the observed finish of each racer in each event, and then aggregate over the athlete for the entire season. In Figure 1, Panel (c), we present the constructed distribution for the 2000-01 season, one of several years that Maier was the overall champion. Maier's closest rivals (Benjamin Raich and Stephan Eberharter) earned 44 and 42 percent of Maier's earnings respectively. His earnings were larger than 50 skiers who posted earnings, 64 percent of all money winners in FIS competition. Many other entrants earned zero money.

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[7] In 1998, Maier won 2 gold medals at the Olympic Games in the Giant Slalom and the Super-G.

Amongst female alpine skiers, we have identified Lindsey Vonn as a superstar. Between 2008 and 2012, Vonn won 52 races and was the overall points leader in the World Cup four times (losing the 5th by a mere 3 points).[8] Overall, Vonn has won 19 World Cup titles (4 overall, and 15 discipline specific titles) from 2008-2015.[9] In all races combined, Vonn has won 67 races and has appeared on 113 podiums. Her closest rival, Maria Höfl-Riesch, has 27 wins and 81 podiums. Given her success on the slopes, she has also earned significantly more than the majority of the field. In Figure 1, Panel (d), we present the FIS World Cup earnings totals for the 2012 season (relative to Vonn). Vonn's closest two rivals earned 50.3 and 50.2 percent of her earnings during the season. She also had more earnings than 63 other skiers who earned money, representing 70 percent of prize winners on the circuit.

While the scale of earnings is lower in the FIS World Cup than either the men's or women's golf tour, the earnings gradient is much steeper. In part, the difference in the earnings gradient are a function of the prize structures in each event, which we now discuss. Thus, in a relative sense, both Maier and Vonn are relatively more dominant than either Woods or Sörenstam.

Even though our superstars earn significantly more than their closest rivals, the disincentive to compete may be offset by a relatively flat prize structure, as discussed by Szymanski and Valletti (2005). In each of our settings, the prize gradients allocate a large share of the purse to the winner. In Figure 2, we present the prize structure for each sport. In Panel (a), we present the prize structure for the PGA Tour. On the PGA Tour, the purse from a tournament is divided such that the first place finisher earns 18 percent, second prize 10.8 percent, while the

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[8] http://data.fis-ski.com/dynamic/athlete-biography.html?sector=AL&competitorid=30368&type=sum-WC

[9] In 2010, Vonn won a gold and a bronze medal Olympic games (Downhill and Super-G).

70th ranked player earns only 0.2 percent.[10] Provided that the average golf tournament has 144 entrants, roughly half of all participants receive a prize, with the top 10 finishers earning 60.5 percent of the purse. In Panel (b) of Figure 2, we present the prize structure for the LPGA Tour. On the LPGA Tour, the top earner receives 15 percent of the purse, the second place finisher receives 9.2 percent, while the 75th finisher receives approximately 0.18 percent.[11] In each case, the first place finisher receives about 1.6 times the prize of the second place finisher.

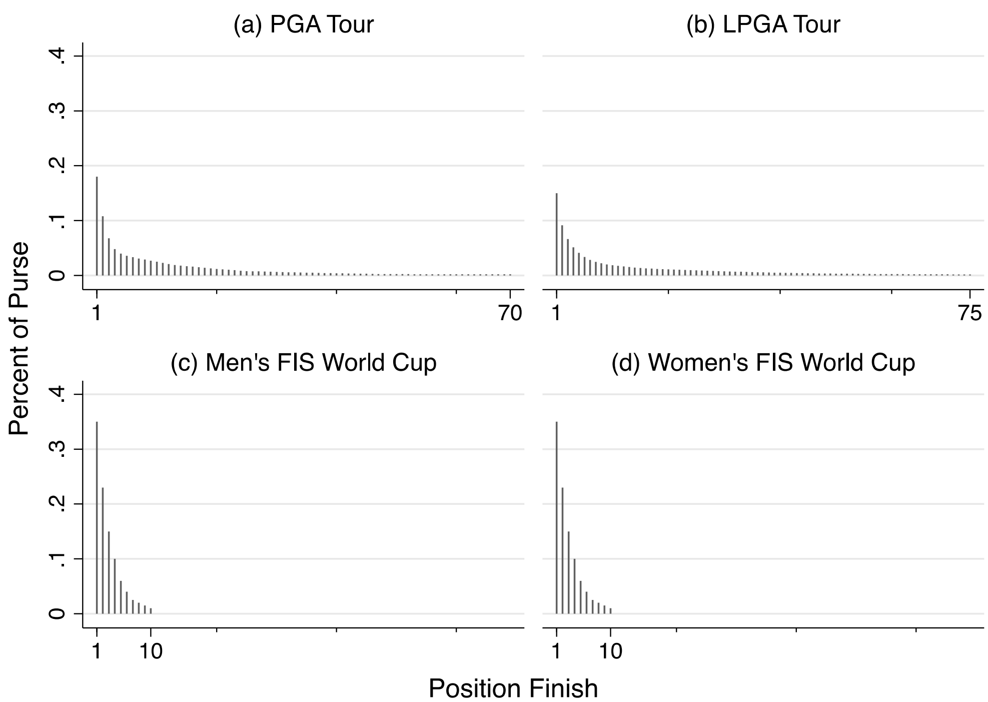

Figure 2: Price gradient by sport.

In Panels (c) and (d), we plot the prize structure for the average alpine event on the FIS-World cup for men and women respectively. The prize structure of each event (Downhill, Super G, Slalom, Giant Slalom) varies slightly and occasionally varies from location to location, yet these

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[10] http://golftips.golfsmith.com/calculate-payout-professional-golf-tournaments-20519.html
[11] Author Calculation from LPGA results found here: http://www.lpga.com/tournaments

deviations are usually small. The purse for each alpine during our sample is 100,000 Swiss Francs (this amount was recently increased to 110,000 Swiss Francs)[12] and is the same for both the men's and women's competition. Across alpine events, the first place finisher receives a share of 30 to 35 percent of the purse (32.6 percent average for females, 33 percent average for males), while the second place finisher receives between 20 and 23 percent (21.4 percent average for females, 20.5 percent average for males) of the purse.[13] Up to this year, the FIS World Cup only paid the top 10 finishers (with a few exceptions), creating a steep gradient throughout the distribution, as some races can have has many as 80 entrants.

This exercise demonstrates that the prize structures are steep in both professional golf and alpine skiing. In golf, the ratio of prizes for first to second place are approximately 1.6, while in skiing they are 1.5 times larger. This slightly flatter structure at the top may be due to safety concerns, as noted by Che and Humphreys (2013).[14] However, overall, fewer entrants are eligible for a prize in skiing than in golf, suggesting that throughout the entire field, skiing has the steeper prize gradient.

4. Empirical Strategy

Before we describe the data in detail, we outline our empirical strategy. To identify the impact of competing with a superstar, we specify a regression model that relates an individual's performance in a given event, in a given season, to an indicator that equals 1 if the superstar is competing in the same event at the same time, and is zero otherwise. Given the panel nature of

[12] Prior to the 2016-17 Season, the FIS World Cup had a purse of 100,000 Swiss Francs per event.
[13] The prize structure is computed from data reported in http://bmsi.ru/media/6b08ea81-e01e-463f-a88f-82d99e1c828f/priz11.pdf.pdf
[14] One should note that in professional skiing and golf the largest part of an athlete's income is based on advertising and endorsements. The likelihood of signing such a profitable contract increases with the number of wins; regardless of the prize structure of the events.

the data, we are able to examine how a given athlete's performance varies when they compete both in the presence of the superstar and without the superstar, while controlling for their average performance at the same event/course. We are also able to control for several observables, which may also influence performance, such as extreme weather events or the strength and composition of the field.

More formally, we follow the empirical specifications outlined in Brown (2011) relating individual performance to the superstar as follows:

$$y_{ijt} = \beta_1 HRank_{it} \times star_{jt} + \beta_2 LRank_{it} \times star_{jt} + \beta_3 URank_{it} \times star_{jt} + \alpha_1 HRank_{it} + \alpha_2 LRank_{it} + \gamma_0 + \gamma X_{jt} + \phi Z_{it} + \varepsilon_{ijt}. \qquad (1)$$

In this specification, y_{ijt} is an individual performance measure for athlete i in event j, during season t. Depending on the specification, y_{ijt} will be either a measure of strokes net of par, or the race time in an alpine skiing event. $HRank_{it}, LRank_{it}$, and $URank_{it}$ are indicator variables equal to 1 if athlete i is high ranked, low ranked or unranked during season t[15], $star_{jt}$ is an indicator variable equal to 1 if the star is in the event. We allow the star variable to vary over time, as some athletes may not be stars over their entire career. X_{jt} is a set of event-specific controls described below, while Z_{it} is a set of individual specific controls, and ε_{ijt} is a random error term. In some specifications we will allow the errors to have arbitrary correlation within player throughout the season as in Brown (2011), while in others we will allow the error terms to be correlated within events in a specific season (as in Connolly and Rendleman, 2014). Both error structures may be reasonable. For example, an individual athlete may be streaky, such that their performance in the current event is correlated with their performance in prior events.

[15] For Golf the cutoffs are 20 and 200, these are roughly the 90th and 25th percentile of ranking. For skiing the cutoffs are chosen to match these percentiles giving 10 and 50.

Additionally, the performance of athletes within a tournament may also be correlated, for instance, because golfers face the same pin locations, which move from day to day within the tournament. Similarly, skiers' times may be correlated in an event because of the gate locations, which vary season to season at the same resort, or unobserved snow conditions. Given that both approaches have their merits and shortcomings, we also cluster on both the player-year and event-season following the procedure outlined by Cameron, Gelbach, and Miller (2012). All specifications omit the scores of the superstar from the dataset.

The choice of X_{jt} and Z_{it} differ by data set. For PGA events, X_{jt} contains an indicator denoting whether or not the tournament is a major, time varying weather data: temperature, wind speed, rainfall, as well as information on the size of the purse (in real 1982-84 dollars) and purse squared. We allow the purse to have a differential effect for high, medium, and low ranked individuals by interacting the purse with the ranking indicators. Finally, X_{jt} includes a measure of the field's quality, as measured by the average World Golf ranking points for all other players in the tournament excluding the superstar. In the LPGA dataset, X_{jt} contains the same variables, except the weather variables, and an indicator if the tournament was held for three rounds. In both cases Z_{it} is a set of player-course fixed effects to control for a players' average performance on a given course over time.

In the alpine skiing dataset, X_{jt} contains a measure of the strength of the field, as measured by the average player ranking of all tournament participants excluding the superstar. Z_{it} contains player-tournament location fixed effects, and time varying observables of the skier: their age and age squared.

Following the predictions derived in the model, we expect that the coefficients on the interactions terms, β_1, β_2, and β_3, should all be positive, as higher scores relative to par, and slower ski times suggest decreased performance. One possible shortcoming of our empirical design is that we are estimating the net effect of competing with a superstar. If the superstar also creates a positive peer effect, then the interpretation of β_1, β_2, and β_3 should be the composite effect of the peer effect and the disincentive effect. To an extent, our empirical design limits the impact of peer effects as each sample includes periods in which Woods, Sörenstam, Maier, and Vonn compete, but are not designated as superstars. Thus, for peer effects to drive our findings, there must be a differential peer effect when these athletes are at the peak of their career. Empirically, there is some evidence from golf that peer effects are limited (Guryan, Kroft, and Notowidigdo; 2009).

5. Data

Here we briefly outline each dataset that we have constructed. We first describe our golf datasets, and note any differences from Brown (2011), we then proceed to describe the alpine skiing data.

For the men's golf dataset, we begin by collecting every PGA Tour event from 1999-2006 seasons via the PGA Tour's Shotlink database. This data includes the individual tournament level score for every golfer as well as tournament level information, such as the event purse. We combine these sources with tournament weather events (temperature, wind, and rainfall) and Official World Golf Rankings. Unlike Brown (2011) and Connolly and Rendleman (2014), we omit information regarding television ratings, as we do not have this information for all of the athletic contests we study. Thus, our baseline will also serve as a test for the severity of omitted variables bias, which may be important when evaluating the other events.

We construct two separate datasets, one that is aimed at replicating the results presented by Brown to the best of our ability, and a second that includes several tournaments that were excluded by Brown but meet the inclusion criteria. First, we omit small field tournaments (Mercedes and The Tour championship), tournaments held opposite Majors and World Golf Championship events, and tournaments scheduled for five rounds. This reduces the sample from 368 to 311 tournaments, which correspond to those used by Connolly and Rendleman (2014). In specifications that examine the total score over all four rounds, we omit four tournaments that were cut short due to severe weather conditions. We further omit tournaments following the detailed descriptions in both Brown (2011) and Connolly and Rendleman (2014) to derive our dataset that is comparable to Brown, consisting of 264 tournaments, 261 for four rounds. Lastly we require that the tournament be held each year during our sample period, this gives 272 tournaments (268 for all four rounds) for our full data set and 232 tournaments (229 for all four rounds) when replicating the results found in Brown (2011).[16]

The dataset for LPGA is similar to the PGA data set. We obtain round by round scores and purse amounts from www.golfstats.com. As with Woods we limit our data set to tournaments over the time when Sörenstam was at the peak of her career, 2000 – 2006, resulting in 227 events. We then drop 3 tournaments that were cut short due to severe weather, leaving us with 224 events when analyzing the entire event score. As with the PGA dataset we require tournaments be held each year during our data set, giving 147 tournaments (144 for event level scores). There are two major differences between the PGA and LPGA datasets. First, we do not observe weather data for each event. Secondly, the LPGA did not have an official ranking system until 2007.

16 All results are qualitatively similar if we drop this condition.

We address these concerns in the following way: First, given that we observe the weather correlates in the men's sample, we test to see how sensitive the superstar coefficient is to the omitted variables bias. When we do this, we cannot reject the equality of the coefficients, reducing concerns of omitted variables bias in the women's sample. To address the missing LPGA player ranking data, we construct our own ranking based on individual level performance data from our sample and the formulas associated with the PGA's current ranking system.[17]

For alpine skiing we collected data for all World Cup events from the International Ski Federation (FIS) and include information on event type (Downhill, Super G, or Giant Slalom), time to finish event, location, and date. Our main dependent variable for alpine skiing will be the time to finish an event. In addition, we include a second dependent variable that measures if an athlete did not finish an event (due to a crash or missing a gate). As in the LPGA there is no official ranking system, so again we implement our own raking system.[18] When looking at men's skiing we use observations from the 1997 to 2010 seasons and focus at the three events in which Maier primarily competed (Downhill, Super G, and Giant Slalom). For women's skiing we use observations from the 2002 – 2014 seasons and work with the two events that Vonn primarily competed in: Super G and Downhill.

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[17] All participants who complete an event are awarded points based upon the finish position: first place receives 50 points, second receives 30, third receives 20, … , 65th receives 0.75, and below receives 0, if the tournament is a major these values are doubled and all those who finish earn 0.75 points. These points are then weighted over the past two years according to the following system. The first 13 weeks have full weight while the remaining 91 weeks decrease in equal increments to 0. The weighted points are then divided by the total number of tournaments played in the past two years.

[18] We adopt the previously discussed procedure for alpine skiing by adjusting the point system. Points are awarded using the same scale the FIS uses to determine season winners, first receives 100 points, second receives 80 points, …, 30th receives 1 point, and below receives 0.

Before we proceed to the formal results, we first present some initial evidence that is suggestive of a superstar effect in golf and skiing. In Table 2, we present the differences in means of strokes net of par for PGA and LPGA players by ranking category when they play with and without a superstar. From this exercise, we can see that players on the PGA score between 2.97 and 6.02 shots worse when a superstar is in the tournament, with stronger effects found for high ability players. In the women's draw, we find that playing with a superstar increases a players score by 1.26-2.39 strokes per tournament. Both of these results are consistent with the superstar hypothesis, however, this simple difference in means is unconditional, and there are a variety of factors that we have previously mentioned that might influence performance, such as the difficulty of the course when superstars select into a tournament.

Table 2: Difference in Means for Golf Events

Panel A: Men's Golf (PGA)

	High Ranked			Low Ranked			Unranked		
	Star	No Star	Difference	Star	No Star	Difference	Star	No Star	Difference
Strokes	-1.593	-7.615	6.022***	-0.302	-4.913	4.611***	-0.060	-3.035	2.974***
SE	(7.819)	(6.197)	(0.355)	(7.890)	(6.274)	(0.135)	(8.107)	(6.169)	(0.180)
N	1,106	670	1,776	5183	5919	11,102	1,952	5,062	7,014

Panel B: Women's Golf (LPGA)

	High Ranked			Low Ranked			Unranked		
	Star	No Star	Difference	Star	No Star	Difference	Star	No Star	Difference
Strokes	-1.468	-4.931	2.396***	2.069	0.208	1.363***	5.565	4.300	1.264***
SE	(7.582)	(6.434)	(0.397)	(7.278)	(6.602)	(0.174)	(8.120)	(6.915)	(0.602)
N	1,260	461	1,721	4,301	2,629	6,930	644	233	877

Table reports mean strokes net of par. Star is mean score in tournaments when the superstar is present; No Star is mean score in tournaments when the star is not present. Scores are event scores using the full data set, all estimates omit the superstar and players who did not make the cut. Standard deviations are in parenthesis below the estimates, for the estimated difference the standard error is given in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, using a two tailed t test.

In Table 3, we report these differences using the time to finish an event from the alpine skiing data. Table A.1. in the appendix analogously reports the differences for the frequencies of finishing an event with the superstar present and without. Compared to the golf data, the pattern provided by the skiing data in Table 3 is less clear. In the men's Super G, we see that competing with a superstar actually improves times for highly ranked individuals by 1.9 seconds.

Table 3: Difference in Mean Time for Alpine Skiing Events

Panel A: Men's FIS

	High Ranked			Low Ranked			Unranked		
	Star	No Star	Difference	Star	No Star	Difference	Star	No Star	Difference
Downhill									
Time	114.079	114.29	-0.211	115.209	115.995	-0.786	116.699	118.933	-2.234***
SE	(0.623)	(0.695)	(1.013)	(0.341)	(0.367)	(0.535)	(0.441)	(0.506)	(0.713)
N	437	715	1,152	1559	2,475	4,034	851	1248	2,099
Super G									
Time	85.338	87.280	-1.942***	85.361	88.375	-3.013***	87.747	88.818	-1.071**
SE	(0.507)	(0.428)	(0.678)	(0.257)	(0.233)	(0.357)	(0.343)	(0.302)	(0.465)
N	237	393	630	888	1,390	2,278	457	699	1,156
Giant Slalom									
Time	145.502	145.22	0.280	147.183	146.45	0.737	148.146	147.693	0.453
SE	(0.575)	(0.480)	(0.753)	(0.378)	(0.322)	(0.498)	(0.977)	(0.762)	(1.223)
N	327	492	819	830	1,170	2,000	125	177	302

Panel B: Women's FIS

	High Ranked			Low Ranked			Unranked		
	Star	No Star	Difference	Star	No Star	Difference	Star	No Star	Difference
Downhill									
Time	101.381	97.498	3.882***	101.763	98.512	3.250***	103.575	100.11	3.066***
SE	(0.650)	(0.513)	(0.825)	(0.329)	(0.269)	(0.425)	(0.651)	(0.449)	(0.776)
N	316	493	809	1252	1862	3114	384	703	1087
Super G									
Time	80.479	79.377	1.101**	81.411	80.108	1.303***	82.056	81.017	1.009**
SE	(0.360)	(0.303)	(0.481)	(0.190)	(0.160)	(0.253)	(0.383)	(0.262)	(0.450)
N	243	410	653	950	1546	2496	356	599	955

Table reports mean strokes net of par. Star is mean time in races when the superstar is present, No Star is mean time in tournaments when the star is not present. All estimates omit the superstar and players who did not finish the event. Standard errors are in parenthesis below the estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, using a two tailed t test.

More generally, the presence of a superstar tends to improve times on the men's side in Super G and Downhill. In the women's events, we see that competing against a superstar can increase a racer's time by up to 3.8 seconds in the downhill, and more generally, increases racers' times. In what follows, we control for a variety of features than may influence these unconditional differences in means.

6. Results

We first begin by reporting the results from our replication exercise, and then proceed to discuss the results from the other environments.

A. Replicating the Tiger Woods Superstar Effect

In Table 4, we present the results of from our replication exercise that correspond to equation (1). In Panel A, we present results that use the first round score as the outcome of interest. [19] In column 1, we re-print the coefficient estimates from Brown (2011). In column 2 we present our closest replication of her sample, while in column 3 we use a sample that includes additional events, following the criteria outlined in Connolly and Rendleman (2014). For each specification, we report three sets of standard errors, those clustered on the player-year (in parenthesis, used in Brown, 2011), errors clustered on the event (in brackets, reported in Connolly and Rendleman, 2014), and errors that are clustered on both dimensions, the player-year and event (in curly brackets). We do this so the reader can see how the statistical inference changes under varying assumptions associated with the error structure.

Our replication exercise closely matches the results reported by Brown (2011), as a t-test of the coefficients cannot reject equality. We find that playing against a superstar increases a player's score by 0.868 strokes, and this result is statistically significant at the 5% level when

[19] In Table A.2. in the appendix, we present additional results where we consider alternate definitions of player ranking by examining the number of wins and top finishes during the previous two seasons (i.e., won a tournament, finished in top 5, top 10, etc.). In Table A.3., we also estimate the potential superstar effect separately for each round in the tournament.

clustering the standard errors at the player-year level. Furthermore, the effect is concentrated in highly ranked players, who have the most at stake when playing against Tiger.

Table 4: PGA Results

	Panel A			Panel B		
	First Round, Majors Included			Event Scores, Majors Included		
	Brown	Replication	All Data	Brown	Replication	All Data
HRank×Star	0.596	0.868	0.680	1.358	1.170	1.092
	(0.281)**	(0.287)***	(0.263)***	(0.726)**	(0.712)	(0.660)*
	--	[0.364]**	[0.353]*	--	[1.196]	[1.134]
	--	{0.359}**	{0.350}*	--	{1.062}	{1.028}
LRank×Star	0.161	0.329	0.174	0.804	0.119	0.056
	(0.113)	(0.120)***	(0.111)	(0.318)**	(0.322)	(0.296)
	--	[0.231]	[0.245]	--	[0.878]	[0.816]
	--	{0.206}	{0.216}	--	{0.736}	{0.693}
URank×Star	0.202	0.366	0.218	0.596	0.026	-0.058
	(0.126)	(0.139)***	(0.126)*	(0.396)	(0.428)	(0.389)
	--	[0.241]	[0.243]	--	[0.940]	[0.848]
	--	{0.213}*	{0.215}	--	{0.788}	{0.724}
N obs	34,986	32,851	38,735	18,805	16,923	19,892
N Tournaments	269	232	272	269	229	268

Standard Errors in parenthesis are clustered by player year, standard errors in brackets are clustered by tournament, standard errors in curly braces are clustered by player year and tournament, All estimate omit the superstar. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ with respect to that standard error.

Brown are results as reported in Brown (2011), Replication is our best attempt at replicating Brown (2011) and All Data only excludes tournaments listed in paper

When we allow the errors to be correlated within tournament the standard errors increase slightly but the estimated coefficient is still statistically significant at the 5% level for high ranked players. When clustering the standard errors at both the player-year level and the tournament level the results remain qualitatively similar.

When we move to the larger sample (column 3), as suggested by Connolly and Rendleman (2014), the point estimate drops to 0.680. As more tournaments are added to the sample, precision increases, but due to the smaller point estimate, the significance level decreases under the assumption that errors are correlated within tournament. When clustering on both dimensions the standard errors are comparable to allowing for correlation within each tournament.

In Panel B of Table 4, we report the results using the tournament event score as the outcome of interest. This data differs from the first round score data in that it drops players who do not make the cut at the conclusion of the second day. Again, we report Brown's original point estimates, as well as our replication using both samples. Our estimates, reported in columns 5 and 6, are smaller in magnitude, but given the large standard errors, cannot be rejected as different from Brown's original estimates. Unlike Brown, we do not find strong evidence of a superstar effect over the entire tournament, regardless of the sample or the assumptions regarding the error structure. Since the only major difference in the samples are television viewership, these differences may be attributed to that omission.[20]

As previously noted, when we study the LPGA Tour and World Cup Skiing, we do not observe weather data, which likely influences performance (faster/slower greens, slushy/icy slopes). To test for the severity of the potential omitted variables bias (for golf), we re-estimate equation (1) on our PGA dataset, but omit the weather covariates. The results of this exercise are reported in Table A.4. in the appendix. When we omit the weather variables, the point estimates

[20] Connolly and Rendleman (2014) successfully replicated event scores when including television viewership data. They also show that when the tournament sample size increases and the errors are allowed to be correlated within tournament, that the superstar effect loses statistical significance.

are generally larger, however, the estimates are not statistically different from the baseline estimates reported in Table 4. This provides some confidence that the potential omitted variables bias is not so large as to invalidate our main findings.[21]

Overall, in our re-examination of the previously documented superstar effect generated by Tiger Woods, we find that the original results reported in Brown (2011) are highly sensitive to the assumed error structure and the inclusion of omitted tournaments (as previously noted by Connolly and Rendleman, 2014). While it is reasonable to allow errors to be correlated within a player throughout the season to allow for serial correlation across tournaments, it is also likely that scores within a tournament are correlated due to unobservable variables, such as the moisture content of the grass, which can affect fairway and green speeds, or the pin location, which varies from day to day, and can affect the difficulty of the course. When we allow the error structure to depend on both of these sources of correlation, we generally cannot reject the null hypothesis of no superstar effect. Of course, allowing for a richer error structure naturally decreases the precision of the estimates, and imposes a stricter test of the data. In what follows, we examine other settings to see how generalizable the superstar effect may be, while remaining agnostic in regards to the true error structure.

B. Generalizing the Superstar Effect

The mixed evidence from the PGA Tour raises several questions. Is it limited to males playing professional golf, to Tiger Woods, or does it depend critically on the assumptions on unobservables? In what follows, we examine three additional venues, women's golf, and men's and women's professional alpine skiing. The theoretic models of the superstar effect suggest that

[21] This is in the spirit of work by Altonji, Elder, and Tabor (2005) and Oster (2015), who develop formulas to quantify the severity of omitted variables bias.

there will be a disincentive effect when (i) the superstar is significantly more talented than the closest rival and (ii) the prize structure is sufficiently convex. In our other settings, both conditions are more likely to hold than in the PGA Tour. As we noted previously, Sörenstam was a more dominant competitor than Tiger Woods, and the prize gradient in FIS is steeper than either golf event.

While the LPGA Tour receives less attention than the men's tour, it had an equally if not more dominant competitor than Tiger Woods: Anika Sörenstam. During the peak of her career, Sörenstam's margin of victories over her next closest rival was larger than Tiger's margin over Phil Mickelson. Therefore, understanding how a potentially brighter star than Woods impacts the competition in a similar environment will be useful in understanding the robustness of the superstar effect.

To estimate the potential impact that Sörenstam had on her rivals' performance, we re-estimate equation (1) using the sample of LPGA events described in the data section. Here we briefly describe the main findings, reported in Table 5. As before, we continue to report multiple sets of standard errors so the reader can see how the statistical significance changes with the error structure. Table 5 reports the effect a superstar has on a high, low, and unranked golfer in the first round, second round, third round, fourth round, and overall effect across all four rounds.[22]

For brevity, we focus our discussion on the first round scores and the overall tournament performance, which closely mirrors the discussion in Brown (2011). In column 1, we report that highly ranked female players perform worse (have a higher score) in the first round when

[22] The number of observations decreases after the second round due to the winnowing of the field at the conclusion of the second round, and after the third round due to tournaments that were scheduled for three rounds.

Sörenstam plays in the tournament, however, regardless of the error structure, the estimated effect is not statistically different from zero. Low tier and unranked players also perform worse (more strokes above par) when Sörenstam participates in the tournament; however, the effect is also imprecisely estimated.

Table 5: LPGA Results

	1stRound	2ndRound	3rdRound	4thRound	Event
HRank×Star	0.119	-0.369	0.059	-0.029	-0.570
	(0.292)	(0.282)	(0.300)	(0.426)	(0.655)
	[0.423]	[0.363]	[0.413]	[0.489]	[0.923]
	{0.429}	{0.363}	{0.380}	{0.448}	{0.931}
LRank×Star	0.096	-0.239	-0.186	-0.312	-0.814
	(0.106)	(0.105)*	(0.158)	(0.197)	(0.279)***
	[0.266]	[0.244]	[0.265]	[0.325]	[0.681]
	{0.255}	{0.217}	{0.230}	{0.267}	{0.623}
URank×Star	0.062	0.196	0.038	-0.776	0.102
	(0.293)	(0.341)	(0.712)	(0.793)	(1.216)
	[0.402]	[0.373]	[0.686]	[0.766]	[1.426]
	{0.461}	{0.358}	{0.574}	{0.641}	{1.538}
N Obs	17,403	17,173	9,804	7,460	9,794
N Tournaments	147	147	144	113	144

Standard Errors in parenthesis are clustered by player year, standard errors in brackets are clustered by tournament, standard errors in curly braces are clustered by player year and tournament. All estimates omit the superstar. *p<0.10, **p<0.05, ***p<0.001 with respect to that standard error.

The picture becomes even less clear when examining the estimates over the entire four rounds of the tournament. In column 5, we report the estimated coefficients using the overall tournament strokes net of par. We find that over the entire event, the presence of Sörenstam leads to an improvement in tournament outcomes for high and low ranked competitors (although the estimate is not statistically different from zero for high ranked players), and reverses sign for low ranked players (also not statistically different from zero). The effect for low ranked players is not consistently significant across rounds and choice of standard errors. The lack of statistical significance for these findings is robust to alternate definitions/classification of highly ranked golfers.[23]

Our findings create some doubt as to how generalizable the superstar effect is to stars other than Tiger Woods, or at the very least suggest that there may be differences in how males and females respond to superstar competitors. One criticism of the LPGA dataset is that it omits climatic variables that might be correlated with an athletes score. Unless the climate variables are correlated with the decision of Sörenstam to enter the tournament, the estimated superstar effect will not be biased by this omission. In the PGA Tour sample, we demonstrate that excluding climate variables did not affect the superstar coefficient estimate, suggesting that Tiger Woods's entry into a tournament and climate variables are uncorrelated, while this does not conclusively document that Sörenstam does not choose to enter on the basis of climatic conditions, it seems like a stretch that golfers on the LPGA Tour would respond differently to rain and cold than their male counterparts. Similarly, we do not control for media exposure/TV ratings. While media exposure may create pressure, affecting the score of a golfer, TV ratings will only bias the superstar coefficient if differential media exposure, conditional on the purse of the tournament, is correlated with the superstar's decision to enter the tournament. Both of these conditions seem unlikely, therefore, we believe that it is unlikely that our estimates suffer from this type of omitted variables bias.

At this point, it is unclear whether or not men and women respond differently to superstars, or if Tiger Woods was just a special athlete. In what follows, we turn our discussion to men's and women's FIS World Cup Alpine Skiing. We examine alpine skiing because it

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[23] In the appendix, we report estimates using alternative definitions of highly skilled by specifying that an athlete has finished in the top N places in the previous two season (Table A.5).

represents a completely different set of skills for the athlete, yet in each event, there is a well-regarded star (Herman Maier and Lindsey Vonn). In what follows, we report coefficient estimates for two outcome variables: the overall time in the race and the probability of finishing the race. We report both measures, as the presence of a superstar competitor may lead less skilled skiers to take riskier paths down the mountain in an attempt to gain a time advantage. This type of risk taking may be the only way to offset the skill differential. Examining finishing times in isolation may be misleading if a large proportion of skiers adopt this risk taking strategy and do not complete the race and thus do not have an official race time.

In Panel A of Table 6, we report the coefficient estimates from the men's field. We report 6 outcomes: the race time in three events (Downhill, Super G, and Giant Slalom) and an indicator that denotes whether or not the racer completed the race. In the men's downhill, the presence of Maier has no statistically significant impact on highly ranked skiers. For lesser ranked skiers, it appears as though Maier's presence leads to an increase in the number or racers finishing, yet increases their run times. The increase in the likelihood of finishing is statistically significant regardless of the error structure assumption, while the slower race times have relatively large standard errors under the various assumptions.[24] The rules of the FIS may partially influence our findings. In the downhill, racers are allowed several practice runs throughout the week, which may allow lower ranked competitors to study the lines taken down the slope by more experienced and more skilled competitors. If these paths down the slope are

[24] In our baseline, we estimate linear probability models, which may allow predicted probabilities to lie outside of the [0,1] interval. Therefore, as a robustness check, we also estimated the model using a logit error structure. The results of this specification are reported in the Appendix, Table A.6. Additionally, we also consider alternative definitions of highly ranked skiers. Our estimates are robust to the alternate definitions. The results from these regressions are reported in Appendix Table A.7.

riskier or require more skill, then the lower ranked competitors may be making a tradeoff between risk and effort, independent of any disincentive effect.[25]

In the Super G and Giant Slalom, Maier's participation had little impact on the race times of highly ranked skiers. The lowest ranked skiers finished at higher rates when Maier participated, and in the case of the Giant Slalom remains marginally statistically significant under the various error assumptions. However, the mid-tier skiers were not influenced by Maier in either the Super G or Giant Slalom. Again, the rules governing skiing may partially explain why fewer skiers where influenced by Maier's participation. In both the Super G and Giant Slalom, skiers are not permitted to make practice runs, but instead are only allowed to visually inspect the course one hour before the event begins. In the case of the Giant Slalom, the gates are repositioned between runs, limiting the scope for learning between runs down the slope by watching your competitors run.

We now turn our attentions to the women's FIS World Cup events to see if we find a similar pattern. In Panel B of Table 6, we report the estimated effect that Linsey Vonn's participation has on her competitors' race times and likelihood of completing an event. Because Vonn specialized in the Downhill and Super G (the speed events), we limit our study to these competitions. In Column 1, we present the results from the downhill event. When Vonn participates, the likelihood of finishing a race increases for highly ranked skiers (less likely to not finish), and they have faster race times (neither coefficient is statistically significant). Under the assumption that errors are only correlated within skier throughout the season, we find that Vonn's participation leads to faster race times for low ranked skiers, which is suggestive of

[25] Millner and Pratt (1991) demonstrate that more risk-averse experimental subjects reduce effort in contests. Similar findings in the experimental literature are summarized in Dechenaux, Kovenock, and Sheremeta (2015).

positive peer effects. Under alternative error term assumptions, this effect is statistically indistinguishable from zero. In the Super G, we find that Vonn's participation has no effect on highly ranked skiers (for either outcome), and causes low ranked skiers to have slower times. This effect is only statistically significant when we cluster the standard errors on the skier-season. Under the alternative error assumption's Vonn's participation has no impact on skiers of any ranking in any competition.[26]

Discussion

Previous research has documented the superstar effect in men's professional golf (Brown, 2011). We document that these findings are highly sensitive to sample selection (Connolley and Rendelman 2014), as well as the assumptions governing the error structure, calling into question the robustness of the initial findings in the literature. Our focus in this paper is to see whether or not other settings may allow us to identify the superstar effect using the same source of variation that Brown (2011) used in her study of professional golfers. Across three different athletic contests, (6 if each FIS event is counted as a separate competition), we fail to document any relationship between *highly ranked* athletes and the presence of a superstar in the contest. Instead, we document that lower ranked athletes actually perform better in the presence of the superstar, suggesting that there may be positive peer effects rather than a disincentive to exert effort amongst the closest rivals to the superstar.

[26] Again, as a robustness check to complement our estimated linear probability models, we also estimated the model using a logit error structure. The results of this specification are reported in the Appendix, Table A.6. In addition, we again consider alternative definitions of highly ranked skiers and our estimates are robust to alternate definitions. The results are reported in Appendix Table A.7.

Table 6: FIS Alpine Skiing Results

	Panel A: Men's Alpine Skiing						Panel B: Women's Alpine Skiing			
	Downhill		Super G		Giant Slalom		Downhill		Super G	
	Pr(¬*finish*)	Time	Pr(¬*finish*)	Time	Pr(¬*finish*)	Time	Pr(¬*finish*)	Time	Pr(¬*finish*)	Time
HRank×Star	3.206×10^{-4}	1.277	0.020	0.360	0.036	1.465	-0.039	-0.930	0.025	0.677
	(0.023)	(0.985)	(0.042)	(0.607)	(0.041)	(0.762)*	(0.028)	(1.135)	(0.046)	(0.809)
	[0.024]	[2.071]	[0.040]	[1.444]	[0.041]	[2.048]	[0.029]	[3.555]	[0.053]	[1.782]
	{0.028}	{2.162}	{0.046}	{1.475}	{0.046}	{2.054}	{0.028}	{3.549}	{0.055}	{1.831}
LRank×Star	-0.048	1.879	0.008	0.130	0.011	1.206	0.018	-2.271	-0.019	1.129
	(0.013)***	(0.471)***	(0.025)	(0.322)	(0.031)	(0.544)**	(0.017)	(0.582)***	(0.022)	(0.446)**
	[0.019]**	[2.081]	[0.040]	[1.336]	[0.031]	[1.908]	[0.018]	[3.562]	[0.027]	[4.569]
	{0.020}**	{2.099}	{0.042}	{1.338}	{0.037}	{1.899}	{0.020}	{3.540}	{0.028}	{1.642}
URank×Star	-0.083	2.078	-0.076	0.951	-0.083	2.250	-0.023	-1.989	-0.025	1.130
	(0.022)***	(0.592)***	(0.037)**	(0.492)*	(0.033)**	(1.773)	(0.041)	(1.523)	(0.047)	(0.818)
	[0.028]***	[1.879]	[0.056]	[1.554]	[0.044]*	[2.604]	[0.049]	[4.270]	[0.063]	[1.639]
	{0.028}***	{1.871}	{0.056}	{1.554}	{0.046}*	{2.594}	{0.049}	{4.589}	{0.060}	{1.666}
N obs	8,299	7,285	5,163	4,069	7,318	3,121	5,555	5,010	4,972	4,104
N events	151	151	90	90	117	117	108	108	92	92

Standard Errors in parenthesis are clustered by player year, standard errors in brackets are clustered by tournament, standard errors in curly braces are clustered by player year and tournament. All estimates omit the superstar. When using the probability of not finishing as the dependent variable a linear probability model is used. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ with respect to that standard error.

Given the heterogeneous abilities amongst the athletes, this finding is consistent with recent findings by Gürtler and Gürtler (2015*)* and previous studies in the peer effects literature (for instance Sacerdote 2001, Zimmerman 2003, Lyle 2009). These findings also seem to be weaker in the female samples, which possibly suggest that peer effects differ by gender (Zimmerman 2001, Lundborg 2006), although we may simply lack statistical power.

7. Conclusion

Recently, there has been a growing literature that examines the role that participant heterogeneity has on individual effort in rank order tournaments. One suggestion has been that the presence of a superior competitor will lead other entrants in the tournament to reduce their effort. We further test this hypothesis by collecting data from four unique athletic settings with natural superstars.

To identify the effect of a superstar athlete on their competitor's performance, we collect individual level data from four athletic contests, men's golf, women's golf, men's alpine skiing, and women's alpine skiing. We then use the entry decision of the superstar in a specific tournament/event as a source of exogenous variation. Exploiting within athlete-tournament variation, we find that professional athletes are not discouraged by the presence of superior talent. If anything, we find weak evidence that the presence of a superstar competitor leads to increases in individual effort among the weakest competitors, which is consistent with the large literature on peer effects. We also find that the potential peer effects are stronger for male competitors than females. Our findings highlight the importance of replication and the use of alternative samples to explore the robustness of previously documented phenomena.

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Appendix A.: Additional Tables

Table A.1.: Difference in Mean Finishes for Alpine Skiing Events

Panel A: Men's FIS

	High Ranked			Low Ranked			Unranked		
	Star	No Star	Difference	Star	No Star	Difference	Star	No Star	Difference
Downhill									
Pr(¬*finish*)	0.073	0.082	-0.009	0.095	0.113	0.018*	0.136	0.181	0.045***
SE	(0.260)	(0.274)	(0.015)	(0.294)	(0.317)	(0.009)	(0.343)	(0.358)	(0.015)
N	477	771	1,248	1,732	2,791	4,523	1,004	1,524	2,528
Super G									
Pr(¬*finish*)	0.146	0.118	-0.028	0.176	0.169	-0.007	0.319	0.293	-0.027
SE	(0.354)	(0.324)	(0.026)	(0.381)	(0.375)	(0.015)	(0.455)	(0.466)	(0.023)
N	280	446	726	1,090	1,673	2,763	686	988	1,674
Giant Slalom									
Pr(¬*finish*)	0.226	0.197	-0.029	0.455	0.465	0.010	0.831	0.882	0.052***
SE	(0.419)	(0.398)	(0.026)	(0.498)	(0.499)	(0.016)	(0.375)	(0.322)	0.014)
N	429	613	1,042	1,586	2,186	3,772	998	1,506	2,504

Panel B: Women's FIS

	High Ranked			Low Ranked			Unranked		
	Star	No Star	Difference	Star	No Star	Difference	Star	No Star	Difference
Downhill									
Pr(¬*finish*)	0.097	0.079	-0.019	0.092	0.070	-0.022**	0.181	0.142	-0.040*
SE	(0.297)	(0.269)	(0.019)	(0.289)	(0.256)	(0.009)	(0.386)	(0.349)	(0.021)
N	350	535	885	1,379	2,003	3,382	469	819	1,288
Super G									
Pr(¬*finish*)	0.155	0.107	-0.049**	0.141	0.141	3.89×10^{-4}	0.245	0.249	0.005
SE	(0.363)	(0.309)	(0.025)	(0.348)	(0.348)	(0.013)	(0.433)	(0.430)	(0.025)
N	296	459	755	1,137	1,800	2,937	482	798	1,280

Star is mean time in races when the superstar is present, No Star is mean time in tournaments when the star is not present. All estimates omit the superstar and players who did not finish the event. Standard errors are in parenthesis below the estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: PGA Round by Round Scores Using Number of Top Finishes in the Past Two Years

	1stRound	2ndRound	3rdRound	4thRound	Event
Top1×Star	-0.033	0.047	-0.067	-0.008	-0.037
	(0.075)	(0.068)	(0.079)	(0.085)	(0.178)
	[0.075]	[0.075]	[0.080]	[0.090]	[0.167]
	{0.088}	{0.081}	{0.081}	{0.094}	{0.188}
Top5×Star	-0.013	0.049	0.005	-0.011	0.010
	(0.025)	(0.025)**	(0.031)	(0.032)	(0.062)
	[0.026]	[0.025]*	[0.031]	[0.031]	[0.067]
	{0.028}	{0.027}*	{0.027}*	{0.033}	{0.068}
Top10×Star	-0.005	0.018	0.008	-0.008	0.003
	(0.015)	(0.015)	(0.020)	(0.021)	(0.039)
	[0.016]	[0.016]	[0.021]	[0.021]	[0.044]
	{0.017}	{0.017}	{0.017}	{0.022}	{0.044}
Top20×Star	-0.004	0.018	0.004	-0.010	-0.002
	(0.010)	(0.010)*	(0.014)	(0.014)	(0.026)
	[0.011]	[0.011]*	[0.014]	[0.015]	[0.032]
	{0.011}	{0.011}	{0.011}	{0.015}	{0.030}
Top30×Star	4.297×10^{-4}	0.019	0.006	-0.012	4.892×10^{-4}
	(0.008)	(0.008)**	(0.011)	(0.012)	(0.022)
	[0.009]	[0.009]**	[0.012]	[0.012]	[0.026]
	{0.009}	{0.009}	{0.009}	{0.012}	{0.025}
N obs	38,735	38,102	20,782	19,892	19,892
N Tournaments	272	272	268	268	268

Standard Errors in parenthesis are clustered by player year, standard errors in brackets are clustered by tournament, standard errors in curly braces are clustered by player year and tournament. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ with respect to that standard error.

Table A.3: PGA Round by Round Estimates

	Round 1	Round2	Round3	Round4
HRank×Star	0.680	-0.092	0.342	0.172
	(0.263)***	(0.281)	(0.333)	(0.341)
	[0.353]*	[0.364]	[0.435]	[0.434]
	{0.350}*	{0.360}	{0.418}	{0.422}
LRank×Star	0.174	-0.209	0.117	-0.074
	(0.111)	(0.112)*	(0.153)	(0.160)
	[0.245]	[0.250]	[0.298]	[0.286]
	{0.216}	{0.219}	{0.256}	{0.249}
URank×Star	0.218	-0.277	-0.036	-0.066
	(0.126)*	(0.136)**	(0.202)	(0.214)
	[0.243]	[0.237]	[0.323]	[0.318]
	{0.215}	{0.210}	{0.279}	{0.281}
N obs	38,735	38,102	20,782	19,892
N tournaments	272	272	268	268

Standard Errors in parenthesis are clustered by player year, standard errors in brackets are clustered by tournament, standard errors in curly braces are clustered by player year and tournament. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ with respect to that standard error.

Table A.4: PGA Results excluding weather controls

	First Round, Majors Included		Event Scores, Majors Included	
	Replication	All Data	Replication	All Data
HRank×Star	0.751	0.681	1.296	1.318
	(0.292)**	(0.271)**	(0.728)*	(0.675)*
	[0.386]*	[0.367]*	[1.286]	[1.195]
	{0.378}**	{0.363}*	{1.128}	{1.069}
LRank×Star	0.231	0.179	0.241	0.302
	(0.117)**	(0.108)*	(0.321)	(0.294)
	[0.260]	[0.248]	[0.976]	[0.891]
	{0.228}	{0.219}	{0.814}	{0.754}
URank×Star	0.132	0.118	0.014	0.090
	(0.138)	(0.127)	(0.428)	(0.389)
	[0.271]	[0.257]	[1.035]	[0.939]
	{0.234}	{0.225}	{0.865}	{0.797}
N obs	32,851	38,735	16,923	19,892
N tournaments	232	272	229	268

Standard Errors in parenthesis are clustered by player year, standard errors in brackets are clustered by tournament, standard errors in curly braces are clustered by player year and tournament. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ with respect to that standard error.

Table A.5: LPGA Round by Round Scores Using Number of Top Finishes in the Past Two Years

	1stRound	2ndRound	3rdRound	4thRound	Event
Top1×Star	-0.055	0.028	0.076	0.073	0.169
	(0.105)	(0.105)	(0.112)	(0.129)	(0.248)
	[0.120]	[0.096]	[0.114]	[0.127]	[0.240]
	{0.125}	{0.120}	{0.121}	{0.126}	{0.260}
Top5×Star	0.016	-0.010	0.014	0.003	0.029
	(0.029)	(0.028)	(0.031)	(0.044)	(0.071)
	[0.036]	[0.026]	[0.033]	[0.043]	[0.064]
	{0.036}	{0.030}	{0.033}	{0.040}	{0.067}
Top10×Star	0.016	-0.003	0.007	0.001	0.013
	(0.018)	(0.017)	(0.020)	(0.027)	(0.043)
	[0.022]	[0.016]	[0.021]	[0.024]	[0.040]
	{0.022}	{0.018}	{0.021}	{0.023}	{0.042}
Top20×Star	0.006	-0.010	0.002	4.956×10^{-4}	-0.009
	(0.011)	(0.011)	(0.013)	(0.017)	(0.028)
	[0.014]	[0.010]	[0.014]	[0.017]	[0.027]
	{0.014}	{0.011}	{0.014}	{0.016}	{0.028}
Top30×Star	0.004	-0.011	-0.001	3.459×10^{-4}	-0.015
	(0.009)	(0.009)	(0.011)	(0.015)	(0.023)
	[0.011]	[0.008]	[0.011]	[0.014]	[0.023]
	{0.011}	{0.009}	{0.011}	{0.013}	{0.023}
N	16,973	16,754	9,622	7,254	9,706

Standard Errors in parenthesis are clustered by player year, standard errors in brackets are clustered by tournament, standard errors in curly braces are clustered by player year and tournament. * p < 0.10, ** p < 0.05, *** p < 0.01 with respect to that standard error.

Table A.6: Fixed Effects Logit Probability of Not Finishing

	Panel A: Men's Alpine Skiing			Panel B: Women's Alpine Skiing	
	Downhill	SuperG	Giant Slalom	Downhill	Super G
HRank×Star	-0.008	0.210	0.223	-0.595	0.229
	(0.294)	(0.336)	(0.217)	(0.392)	(0.325)
LRank×Star	-0.524	0.073	0.041	0.319	-0.155
	(0.137)***	(0.162)	(0.103)	(0.226)	(0.172)
URank×Star	-0.735	-0.464	-0.701	-0.192	-0.162
	(0.189)***	(0.203)**	(0.189)***	(0.337)	(0.259)
N	3,059	1,915	3,638	1,322	1,670
N Events	151	90	117	108	92

Standard Errors in parenthesis are clustered by player year, standard errors in brackets are clustered by tournament, standard errors in braces are clustered by player year and tournament. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ with respect to that standard error.

Note: Observations are dropped if the outcome variable is constant within a fixed effects unit, hence the reduction in sample size.

Table A.7: Alternative Specifications for Top Finishes

	Panel A: Men's Alpine Skiing						**Panel B: Women's Alpine Skiing**			
	Downhill		Super G		Giant Slalom		Downhill		Super G	
	Pr(¬*finish*)	Time	Pr(¬*finish*)	Time	Pr(¬*finish*)	Time	Pr(¬*finish*)	Time	Pr(¬*finish*)	Time
Top1XStar	1.926×10^{-4}	-0.016	0.000	0.079	0.019	-0.131	-0.009	0.454	0.010	-0.273
	(0.008)	(0.419)	(0.033)	(0.520)	(0.020)	(0.372)	(0.015)	(0.627)	(0.027)	(0.489)
	[0.008]	[0.229]	[0.032]	[0.467]	[0.021]	[0.273]	[0.016]	[0.403]	[0.025]	[0.438]
	{0.009}	{0.281}	{0.036}	{0.518}	{0.023}	{0.300}	{0.016}	{0.480}	{0.027}	{0.468}
Top5XStar	0.005	-0.009	0.017	-0.061	0.003	-0.051	-0.006	0.246	0.001	-0.135
	(0.003)	(0.133)	(0.011)	(0.167)	(0.008)	(0.144)	(0.006)	(0.197)	(0.009)	(0.179)
	[0.003]	[0.116]	[0.009]	[0.115]	[0.007]	[0.140]	[0.008]	[0.218]	[0.010]	[0.153]
	{0.004}	{0.134}	{0.011}	{0.139}	{0.008}	{0.142}	{0.008}	{0.204}	{0.011}	{0.179}
Top10XStar	0.004	0.016	0.009	-0.124	0.004	-0.052	-0.005	0.161	0.001	-0.131
	(0.002)	(0.089)	(0.007)	(0.107)	(0.005)	(0.115)	(0.005)	(0.136)	(0.006)	(0.126)
	[0.002]	[0.085]	[0.006]	[0.101]	[0.005]	[0.136]	[0.005]	[0.185]	[0.008]	[0.120]
	{0.002}	{0.094}	{0.007}	{0.110}	{0.006}	{0.138}	{0.005}	{0.169}	{0.008}	{0.137}
Top20XStar	0.003	0.019	0.007	-0.107	0.007	-0.066	-0.003	0.092	0.001	-0.123
	(0.002)	(0.061)	(0.005)	(0.069)	(0.004)	(0.095)	(0.003)	(0.098)	(0.005)	(0.089)
	[0.002]	[0.070]	[0.005]	[0.077]	[0.004]	[0.142]	[0.004]	[0.173]	[0.006]	[0.112]
	{0.002}	{0.075}	{0.005}	{0.080}	{0.004}	{0.140}	{0.004}	{0.161}	{0.006}	{0.120}
Top30XStar	0.003	0.029	0.006	-0.120	0.008	-0.077	-0.002	0.085	0.002	-0.113
	(0.001)	(0.053)	(0.004)	(0.063)	(0.004)	(0.101)	(0.003)	(0.092)	(0.004)	(0.082)
	[0.002]	[0.073]	[0.005]	[0.079]	[0.004]	[0.169]	[0.004]	[0.182]	[0.006]	[0.118]
	{0.002}	{0.075}	{0.005}	{0.082}	{0.004}	{0.167}	{0.004}	{0.172}	{0.006}	{0.122}
N	8,299	7,285	5,163	4,064	7,318	3,121	5,555	5,555	4,972	4,930

Standard Errors in parenthesis are clustered by player year, standard errors in brackets are clustered by tournament, standard errors in braces are clustered by player year and tournament. * p < 0.10, ** p < 0.05, *** p < 0.01 with respect to that standard error.