Superstar Effects in Golf Tournaments

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Abstract

This paper uses random assignments in golf tournaments to examine superstar and peer effects in high-skill work environments. I expand the definition of a superstar to the top 5 players in the PGA Tour from 2002 to 2006 besides just Tiger Woods. Through tournament-by-category fixed effect regressions I find that there is a superstar effect at the field level when such dominant players participate in a tournament. The presence of a superstar is associated with an increase in 1.15 strokes for the rest of the field. Additionally, players tend to exhibit less risky behavior when superstars participate.

Introduction

Tournament style contests are a common feature across academia and business. Competition rewards like tenure and promotion stir innovation and increase effort amongst competitors (Lazear and Rosen, 1981). However, what happens if a competitor knows they are going to lose due to the presence of a superstar worker? For everyone else, the incentive to succeed might diminish because the expected payout is lower. If true, relative pay schemes may become ineffective in the presence of a superstar. On the other hand, superstars in a workplace may offer extensive opportunities for knowledge spillover. Even if there is no real competition anymore, the total productivity of the team may increase from efficiency gains and crowd out the negative incentive effects. Properly understanding the effect of superstars in a workplace has important implications for hiring decisions, incentive schemes, and the organization of labor within a firm. These are decisions managers need to make in order to maximize productivity.

Numerous studies have found peer effects in low-skill, effort-based workplaces (Mas and Moretti, 2009, Bandiera et al., 2010, Falk and Ichino, 2006). However, there are many differences between fruit-picking studies and their relationship to the many modern day highly-skilled jobs. The total output of a firm or team is observable, but often the individual's contribution is difficult to determine. Sports provide an avenue for observing high-skill labor in a statistically conscious environment. In particular, golf tournaments are an excellent case to study peer effects and superstar effects because of their random assignment of group pairings, fixed relative reward system, meaningful high-level player statistics, extensive opportunities for knowledge spillovers, and non-team based tournament competition. Individual players are competing for their own benefit, but the pairings they belong to still create a group environment where knowledge is shared through observation. This is analogous to many high skill industries where employees on a team compete for a promotion. Employees and players are motivated by self-interest, but can still be affected by their peers and vice versa.

Beyond peer effects, the literature has been highly contentious over the existence of superstar effects in golf tournaments. This paper attempts to step into this void and resolve the current dispute by examining superstar effects within tournament pairings and by examining superstar effects at the field level. Unlike previous studies like Brown (2011) and Connolly and Rendleman (2014), I use a tournament-by-category fixed effects model with the inclusion of controls for each player's handicap (skill).[1] This model is based off the study by Guryan, Kroft, and Notowidigdo (2009) who only looked at peer effects within a group and the effect of Tiger Woods within a group. By expanding my set of superstars to include household names such as Phil Mickelson, Vijay Singh, Ernie Els, Retief Goosen and Tiger Woods, I detect an adverse superstar effect at the field level, but not within golf pairings. The use of tournament-by-category fixed effects and inclusion of player skill control variables enables me to address superstar effects from a different perspective that controls for tournament prize sizes, course conditions, course difficulty, and other unmeasurable variables.

Ultimately, I find that superstars do influence players adversely at the field level, but not at the pairing level. More specifically, players perform worse by 1.15 strokes per superstar when a superstar is in the field. Superstars also cause decreased risk taking, which is the opposite of the optimal strategy predicted by the PGA Tour incentive distribution scheme. I hypothesize that

[1] Tournament-by-category fixed effects include separate dummy variables for each skill level of players within a tournament. Further details on how player categories are assigned can be found in the Data Description section (pg. 8) and in Appendix A.

the decrease in risky behavior is the result of players being afraid to fail in front of the increased attention that superstars bring.

Literature Review

Tournaments have been extensively examined for incentive effects, and more recently peer effects and superstar effects. Lazear and Rosen (1981) and Ehrenberg and Bognanno (1990) examined the incentive effects within tournaments and found that the the larger the total prize is the better players perform in the final round of a tournament. In particular, Ehrenberg and Bognanno (1990) used professional golf tournaments from the 1984 PGA Tour to show that the structure and size of tournament prizes does influence player performance. However, Ehrenberg and Bognanno found there was no significant effect of prize size or prize distribution for play in the first or second round. In PGA Tour events not making the cut means players do not make any money from the tournament so all players have a big incentive to play well in the first two rounds. These findings are especially revealing because in 1984 sponsorship opportunities were much less frequent and prizes were considerably less. This study only uses data in the first and second round, but recognizes that financial incentives are more prevalent today given the higher prize pools and much greater sponsorship opportunities.[2] Even just playing well with a superstar in a pairing for one round or making a highlight play has the opportunity to boost a player's career in today's televised version of golf.

Beyond tournament prize and incentive effects, peer effects has been a contentious topic amongst labor and sports economists. The seminal paper by Mas and Moretti (2009) finds

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[2] Players only receive a prize if they are one of the top 70 players after the second round. http://www.pgatour.com/news/2008/01/11/cut_rule.html

positive productivity spillover effects when looking at cashiers in a supermarket. They argue that social pressure is the main mechanism by which peer effects occur because cashiers become more productive when they are able observed by highly productive workers nearby. On the other hand the study by Guryan, Kroft, and Notowidigdo (2009) finds no evidence for peer effects or superstar effects within professional golf pairings. Guryan, Kroft, and Notowidigdo look at a wide range of peer effect possibilities within a golf pairing including the effect of the average ability, maximum ability, and minimum ability of playing partners. They also look at the effect of playing with a player in the top 10% or 25% and bottom 25% or 10%. Finally, they look at the effect of being paired with Tiger Woods. In each case, they find no evidence for peer effects. Though they note that the estimate for playing with Tiger Woods is large and close to significant, but not quite. Unlike the Mas and Moretti (2009) paper, they state that golf tournaments are devoid of complementary technologies in the production function. For example, cashiers share a scare resource – baggers. These baggers assist cashiers and tend to assist the longest lines to keep queues short, which could increase the productivity of lower-skilled workers and show up as peer effects.

Other studies have looked at peer effects in collegiate swimming and track. Yamane and Hayashi (2015) found that swimmers swim slower when they are behind, which is very similar to superstar effects. It shows that participants tend to give up when they see their competition is far ahead of them. In contrast, studies such as Ozbeklik and Smith (2014) have looked at risk taking in professional golf match-play tournaments by examining the standard deviation of a player's score relative to par on holes grouped by difficulty. They find that lower ranked players and trailing players tend to play riskier. In their view, players are not giving up when they are behind, but instead are simply adopting riskier strategies.

A few recent studies have looked specifically at superstar effects on the entire field in a golf tournament, though again, the results have been mixed. Brown (2011) and Tanaka and Ishino (2012) found an adverse effect when Tiger Woods and Jumbo Azaki, respectively, participated in a tournament. They found that their presence hurt the field by well over a stroke over the course of a tournament. Both Brown and Tanaka and Ishino explained the adverse incentive effect as a result of the decrease in expected payoff for non-superstar players. These studies have been heavily disputed by Connolly and Rendleman (2014) who argue that there are no superstar effects on the field. By correcting errors in Brown's data and adopting a random effects model, Connolly and Rendleman find that Tiger Wood's presence in a tournament has no significant effect on the field. Finally, Connolly and Rendleman argue that Tiger Woods was not special and that there were are other superstars in the field.[3] They estimate that about 5% of players could take on the superstar role and effect the field, which is something this paper builds upon.

There is clear disagreement between these 3 golf papers – Brown (2011), Tanaka and Ishino (2012), and Connolly and Rendleman (2014) – and others outside of golf over the existence of peer effects and superstar effects. The rest of this paper will look at resolving these disagreements. First, I examine if expanding the set of superstars will show any significant superstar effect. After all, Tiger Woods's dominance was not complete, and TV broadcasts did not just follow Tiger Woods. Unlike previous studies I use a tournament-by-category fixed

[3] In fact Connolly and Rendleman (2014) find that Tiger Woods does not even identify as a superstar.

effects model with the inclusion of controls for each player's handicap (skill). Again, the use of tournament-by-category fixed effects enables me to address superstar effects from a different perspective that controls for tournament prize sizes, course conditions, course difficulty, and other unmeasurable variables. Finally, I examine how a superstar effects players' risk taking behavior, and show that superstar players really are "super".

Data Description

This study uses the dataset created by Guryan, Kroft, and Notowidigdo (2009), which features panel data from PGA Tour events over the course of 3 years: 2002, 2005, and 2006.[4] These 3 years encompass 81 tournaments with 17,492 observations of player rounds. Though I observe each player and some tournaments over time, I treat each tournament as a separate event. This insures that any changes in the course difficulty or layout or prize pool will be controlled.[5] Table 1 and Figure 1 provide descriptive statistics about the dataset. Table 1 breaks down player scores and skills across the field and within different categories of players. Figure 1 shows the distribution of skill levels between Category 1, 1A, 2 players and Category 3 players.

Unlike many other studies, the data used in this paper excludes tournaments where group pairings are done non-randomly and removes tournaments that feature more than one course (i.e. a North and South course). These events tend to give preference to the best players since they often get later tee times, which allows them to watch other players and observe course conditions

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[4] This dataset is published online by the *American Economic Journal: Applied Economics*, and is available at https://www.aeaweb.org/articles?id=10.1257/app.1.4.34

[5] Connolly and Rendleman (2014) criticize Brown (2011) for failing to control for courses that change their layout or par-difficulty over time.

as well as the standings. Non-random tournaments include events like the Masters, the US Open, and Player's Championship where players are paired up strategically to increase TV viewership.

As mentioned earlier, I expand the number of superstars beyond just Tiger Woods. While Tiger Woods was clearly a dominant figure in his prime, he still only won a quarter of the tournaments he entered. He definitely was beatable and there were other players dominating the game at the same time. As such, I select the top 5 players over the years 1999-2006 and identify them as superstars: Tiger Woods, Phil Mickelson, Ernie Els, Vijay Singh, and Retief Goosen. These players had the most top 5 rankings from 2002-2006 by a large margin. I also summed each player's rank over the course of these 5 years and no other player had less than twice as large of a summation. Oddly enough, the superstar with the worst average rank was Phil Mickelson who was commonly viewed as Tiger's main competition during his prime. To keep track of a superstar's presence in a tournament I derive an intensity variable that is a measure of the number of superstars that play in a tournament (0-5). In total, superstars play in 51 of the 81 tournaments observed, and on average there are about 1.52 superstars in the field.

In professional golf tournaments players are randomly paired with 1 or 2 other similar players in their respective categories (1, 1a, 2, 3). Each category is based on prior performance and standing in the PGA Tour Player Rankings.[6] For each year, Guryan et al. contacted the PGA Tour and affirmed the category of each player and confirmed which tournaments used non-random pairing systems in order to drop them from the dataset.

Specifically, the data includes per round scores, adjusted handicap (ability) for each year, average playing partner handicap (ability), and years of experience on the PGA Tour. I restrict

[6] More details can be found on the PGA Tour website and in Appendix A.
http://www.pgatour.com/news/2015/pga-tour-priority-ranking.html

the analysis to only the first two rounds because the groupings in round 1 and 2 are the same. The groupings also account for time-of-day differences based on when a pairing starts their round.

In terms of data statistics the average score in a tournament is 71.158, which is about par on a normal 71 or 72 par course. Interestingly, the difference between scoring in the top 10% versus the bottom 10% is an 8 stroke difference and only a 4 stroke difference to the mean. This signifies that every stroke matters a great deal in a tournament. Even if a player is unlikely to win making the cut results in a monetary reward, which can be greatly magnified by sponsorship opportunities.[7]

The Guryan dataset also features innate skill measurements for each player which are based on the mean slope-rating of the dataset.[8] These have been created by using player handicaps from 1999, 2000, and 2001 for the 2002 measurements. As well as using the 2003 and 2004 handicaps for the 2005 and 2006 data. This implementation differs from the standard USGA handicap by indexing based off of the average slope rating (difficulty of the course) of the tournament courses used in this dataset instead of an arbitrary default value.

Empirical Approach

I begin by exploring superstar effects within golf pairings (i.e. when paired with a superstar player). Again, I use tournament-by-category fixed effects instead of player fixed effects as Brown (2011) and Tanaka and Ishino (2012) do.[9] Instead, I follow Guryan, Kroft, and

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[7] The top 70 players make the cut, and if more than 78 players make the cut due to ties there is another cut after round 3. http://www.pgatour.com/news/2008/01/11/cut_rule.html

[8] Further details on how skill measurements are made for each player can be found in Appendix B.

[9] I have also done regressions using player fixed effects and found similarly statistically significant results, though coefficient values have decreased slightly.

Notowidigdo (2009) who found no differences between using player-fixed effects versus simply controlling for a player's innate ability (handicap). This allows me to control for differences in course conditions, course difficulty, weather, purse size, and more for each different category (1, 1A, 2, 3) of players. Including by-category fixed effects in addition to tournament-fixed effects recognizes that different skill levels will react differently to tournaments. Some tournaments might be much easier for the best players, or much harder for more mediocre players. For example, many of the best players heavily prefer super fast greens but for amateurs superfast greens would be impossible to play on. Either way, tournament-by-category fixed effects allows me to ignore differences in prize pool incentives, which means my results are not dependent on financial incentives. Though of course, sponsorship opportunities still exist.

My basic specification for measuring superstar effects within a golf pairing is:

(1) $$score_{igtr} = \beta_0 + \beta_1 Ability_i + \partial_1 SuperstarPairing_g + \gamma_{tc} + e_{igtr}$$

Where *i* is the player index, *g* is group pairing index, *t* is the tournament index, *r* is the round index, and *c* is the category a player belongs to. β_0 is the intercept, β_1 is the coefficient for the player's predetermined ability(handicap). ∂_1 is the dummy coefficient for whether or not a player plays with a superstar in his group. γ_{tc} is the set of tournament-by-category fixed effects.

One of the main problems in any peer effects study is the reflection problem (Manski, 1993). Simply using the baseline score of each player in a group does not eliminate the endogeneity problems of common shocks. For example, if one round has particularly good conditions for scoring well, then we would incorrectly find that a partner's score increase causes a player's score to increase too. This in turn could also increase the partner's score. While this may be partly true, the common shock of good conditions is the real reason for the better performance. By using predetermined measures of ability I can find the effect a highly-skilled individual has on a player regardless of tournament conditions with the caveat that calculating and measuring innate ability is a difficult task. Still, these results confirm the results of Brown (2011) as well as Connolly and Rendleman (2014) before they imposed additional restrictions on Brown's model.

While there is no evidence for a superstar effect within golf pairings there might be an effect at the field level. In order to model the effects of a superstar on the field I create an intensity variable that takes a value 0-5 depending on the number of superstars in the field. I also include a dummy variable for whether or not a superstar is in the same group as a player. This acts like an interaction term for the effect a superstar has on the field, and any additional effects if he is also in a player's group. I also control for the differences in round one and round two scores, recognizing that players are more likely to play better in round two after they have become more familiar with the course. Thus the model is:

$$(2)\ score_{igtr} = \beta_0 + \beta_1 Ability_i + \partial_1 TournSuperstars_t + \partial_2 SuperstarPairing_g + \partial_3 round2_r + \gamma_{tc} + e_{itgr}$$

Where ∂_1 is the intensity dummy coefficient for the number of superstars in the field. ∂_2 is the dummy variable for if a superstar is in a player's group in addition to the field. ∂_3 is the dummy variable for round two. All other variables are the same. I still use tournament-by-category fixed effects.

In addition to looking at the broad effect a superstar has on the field I also look at the effect a superstar has within specific categories of players. I specify:

$$(3)\ score_{itr} = \beta_0 + \beta_1 Ability_i + \partial_1 TournSuperstars_t + \partial_2 (TournSuperstars * Category)_{tc} + \partial_3 round2_r + \gamma_t + e_{itr}$$

Where all variables are the same except ∂_2 is now the interaction term between the number of superstars that participate in a tournament and a dummy variable that takes a 1 when a player is in the specified category. Though, I use tournament fixed effects instead of tournament-by-category fixed effects to avoid collinearity with my interaction term. I run four separate regressions where I change the interaction term for each particular category − 1, 1A, 2, or 3.

After examining the existence of field wide superstar effects I explore the underlying mechanism by which superstar effects occur. I examine the standard deviation of a player's score in a tournament where superstars are present.[10] More specifically, I examine the standard deviation of a player's score relative to the scores of other players in the same category, round, and tournament in the resulting 610 observations. By examining the standard deviation within a category I am able to measure the effect superstars have on the field's risk taking behavior across different player skill levels. I am able to interpret these coefficients as changes in risky behavior because I am controlling for the differences in difficulties of each tournament through tournament fixed effects, and I am controlling for the average player abilities for each category in a tournament. As such, my results are not reflective of a stronger or worse field, or a harder or weaker tournament. Instead they show differences in player risk taking behavior. I specify:

(4) $sd(score)_{trc} = \beta_0 + \beta_1 Ability_{tc} + \partial_1 TournSuperstars_t + \partial_2 round2_r + \gamma_t + e_{tr}$

Where all independent variables are the same as equation (2) . However, I drop tournament-by-category fixed effects in favor of just tournament fixed effects due to sample size.

[10] My model follows the Ozbeklik and Smith (2014) specification except for the inclusion of tournament fixed effects.

I then include an interaction term to detect if there is an additional effect a superstar has on each category of players, which I measure in model (5):

$$(5)\quad sd(score)_{trc} = \beta_0 + \beta_1 Ability_{tc} + \partial_1 TournSuperstars_t + \partial_2 (TournSuperstars * Category)_{tc} + \partial_3 round2_r + \gamma_t + e_{tr}$$

Where ∂_2 is the dummy variable for the superstar effect on a particular category of players(s) in the field. I model category 1, category 1a, category 2, and category 3 interaction dummies in separate regressions. Otherwise, all other variables are the same.

In order to prove the robustness of my superstar effect results I test whether previous winners have any effect on the field. In a perfectly incentive based world players would react the same to superstars as they do to players who recently won tournaments. Like superstars, the presence of previous winners in a tournament should signal to competing players that there is less of a chance of them winning. Ultimately, the question is whether there is anything truly special about superstars?

I use the same exact regression equations – (2), (4) and (5) – but replace my superstar intensity variables with a new intensity variable for the number of previous winners in a tournament. I only keep track of the previous 6 winners because after a few weekends players will recognize if a player is not performing as well. I model the following specification based on equation (2):

$$(6)\quad score_{itr} = \beta_0 + \beta_1 Ability_i + \partial_1 TournPrevWinners_t + \partial_2 round2_r + \gamma_{tc} + e_{itr}$$

Where ∂_1 is the intensity dummy coefficient for the number of previous winners in a tournament, and all other variables are the same.

Likewise, I do the same thing for equations (4) and (5) where I examine risk behavior through the standard deviation of a player's score. I model:

(7) $sd(score)_{trc} = \beta_0 + \beta_1 Ability_{tc} + \partial_1 TournPrevWinners_t + \gamma_t + e_{tr}$

(8) $sd(score)_{trc} = \beta_0 + \beta_1 Ability_{tc} + \partial_1 TournPrevWinners_t + \partial_2 (TournPrevWinners * Category)_{tc}$

$+ \gamma_t + e_{tr}$

Where all variables are the same as equations (3) and (4) except ∂_1 is the intensity dummy coefficient for the number of previous winners in a tournament, and ∂_2 is the dummy coefficient for the interaction term for the number of previous winners in a tournament and the specific category looked at in the particular regression.

Econometric Results

Similar to Guryan, Kroft, and Notowidigdo (2009) I find that there are no superstar effects within golf pairings even after expanding the set of superstars to be greater than just Tiger Woods. These results can be seen in Table 2 and are especially interesting because group-pairings offer tremendous opportunities for players to learn from the best players in the world. Knowledge spillover opportunities are extensive in golf from the tee-shot to approach shots to putting. While order of play does matter, it should even out over the course of two rounds. Plus, the player who scores the best on the previous hole tees off first on the next hole. Thus, superstars should still allow other players to see the best path to the hole is, what the wind is doing, and how fast the greens are. The lack of a significant effect means that players are not taking advantage of their opportunities to perform better. Either players are putting in less effort or they are simply trying to be play safer while in the spotlight. Another explanation is that superstar players are only paired with category 1 players, who represent the highest skilled players in the world. While this is true to a certain extent, superstar players are by far and away the best players in the world. The average stroke difference between a superstar player and a category one player is over 1 stroke, which could be the difference between winning and losing. And even the best non-superstar category 1 players will still have something to gain by observing a superstar play.

What is significant towards score is a player's handicap. In this regard I find the exact same results as Guryan, Kroft, and Notowidigdo (2009). A 0.67 improvement in handicap results in a 1 stroke improvement in round score. I also check if it is the relative difference in skill between a player and his superstar partner that matters. However, as regression (2) shows, there is no significant effect. In regression (3) I also control for the average ability of playing partners (including the superstar), which reflects that players can learn from both partners. Remember that the vast majority of golf pairings contain 3 players. Though this is also not significant. For robustness I have also tried the relative difference between a player and his best partner and find the non-significant results. Likewise, for each category of players I have examined what happens when they play with the top players within their respective categories and findno significant results. As such, I choose not to report these results.

While I find no effect within pairings I find that there is a large and significant adverse effect at the field level when superstars participate in a tournament. As Table 3 shows, each superstar in a tournament worsens a player's score by roughly 1.15 strokes. Again, there is no significant effect from being paired with a superstar even when controlling for the field level effect. In regression (2) in Table 3 I include an interaction term between a player's handicap and the number of superstars in a tournament in order to control for differences in affect within a category of player skill. Though this interaction term proves insignificant, this regression shows my results in regression (1) are robust -- all coefficients remain significant at the 1% level. These results support the studies by Brown (2011) and Tanaka and Ishino (2012), but show that players are performing worse regardless of the tournament prize pool. By including tournament-by-category fixed effects I find that players must be performing worse due to some other mechanism.

In Table 4 I dive deeper into the superstar effects within particular categories of players through an interaction term with the number of superstars in a tournament and a dummy variable for the specified player category. These results confirm that there is still a superstar effect across the field. Additionally, there is an additional superstar effect for category 1, 1A, and 2 players. Category 1 players perform slightly better than the rest of the field by -0.154 strokes per superstar in the field. This makes sense considering that category 1 players are the best players in the world and these players are more used to playing with superstars. Regardless, there is still a net 1.10 adverse effect on a player's score for category 1 players. Category 1A and 2 players perform slightly worse compared to the rest of the field when they play with superstars. They perform worse by an additional 0.1 strokes. Category 3 players do not have a significant additional effect when they play in the same tournament with superstars, which may indicate that these low skilled players are simply happy to be playing with notable professional golfers no matter their status.

In order to examine the mechanism by which adverse superstar effects occur I look at whether players are playing riskier when superstars are present by examining the standard deviation of a player's score. Riskier strategies make sense in golf tournaments because given the convex prize distribution, players always have a greater marginal benefit of finishing one rank higher than the marginal cost of finishing one rank lower. The same is true in the presence of a superstar who are expected to take the top prize. Plus, players have even more to gain by dethroning him because of all the news coverage and sponsorship opportunities today.

Table 5 shows that the exact opposite is true. Players actually play less risky when superstars are present. The -1.785 stroke convergence to the mean is both large and statistically significant. Again, I am able to interpret these coefficients as changes in risky behavior because I am controlling for the differences in difficulties of each tournament through tournament fixed effects, and I am controlling for the average player abilities for each category in a tournament. As such, my results are not reflective of a weaker field or a harder tournament. Instead they show that players actually play safer or less risky in the presence of superstars.

By ignoring their best strategic maneuvers players could simply be giving up. After all, players should be concerned mostly about first place finishes in golf tournaments because they offer the greatest prizes and guarantee PGA Tour membership status for the next 2 years.[11] However, a more likely scenario is that players are simply playing safer in the presence of superstars because they are motivated more by the fear of failure than their chances of winning. Superstars draw greater media attention and, therefore, scrutiny for every single player. Also,

[11] Though marginal prize distribution matters, the overwhelming majority of the tournament effects literature suggests that the biggest determinant is the top prize (Ehrenberg and Bognanno, 1990).

anyone would be excited to say that they got to play with a superstar such as Tiger Woods, and even more so if that person did not make a fool out of himself in that particular tournament.

I also expand these results by looking at a superstar's effect on risk across different categories of players. I measure this through an interaction term between the number of superstars in a tournament and a particular category of players in that tournament. Table 6 shows that there is no distinct additional superstar effect for each category of players, but there is still a negative or less risky effect for the field in regressions (2), (3), and (4) − which corresponds to the interaction term with category 1A, 2, and 3 players respectively. Perhaps, the lack of significant field wide superstar effect may indicate that the best players are more used to playing with superstars, or that his category contains more than just 5 superstars.

Therefore, I examine whether previous winners have any effect on the field similar to superstars. After all there is no reason that just the top 5 players should be the only superstars in the sport of golf. Surely players who are in the 6-10 rank range should also adversely affect the field. As seen in Table 7 in regression (1), the previous 6 winners in a tournament adversely affect the field by 0.427 strokes at a 5% significance level. More than likely, the smaller but significant effect of previous winners participating in a tournament is the result of top-tier players who could also qualify as superstars such as Jim Furyk. What is clear though is that superstar players have a much greater and significant effect on the field compared to simply the previous winners − nearly three times as large and significant at the 1% level.

Further proof that the previous winners have less of an effect on the field can be found in Table 7 in regression (2) where I examine the effects previous winners have on a player's risk taking. There is no significant effect of the previous winners on the standard deviation of player scores. Additionally, the point estimate is positive rather than negative. If significant this would signify that players take more chances when a non-superstar, previous winner is in the field. Regardless, these results show that only superstars have an effect on a player's risk taking. Finally, looking at the effect previous winners have on specific categories of players in Table 8 shows no further evidence that these players have any effect at all on player behavior. Therefore, there is a major distinction between superstar players and simply winning players that extends beyond tournament incentive explanations.

Conclusion

While tournament theory suggests that very skilled workers will negatively affect their less skilled peers, economic literature has failed to confirm empirically the theoretical prediction of superstar effects. Unlike previous superstar effect studies in golf tournament literature, this paper uses tournament-by-category fixed effects instead of player fixed effects to control for all of the different possible course conditions that might affect each category of players differently.

This study shows that while there are no superstar effects within professional golf pairings, there is a 1.15 stroke adverse effect at the field level. There is also an additional adverse effect for category 1A and 2 players. Despite using another model that controls for player skill directly with player handicaps, my results are consistent with Brown (2011) and Tanaka and Ishino (2012). However, by controlling for tournament incentive effects I show that category 1 players actually experience slightly less of an effect, -0.154 strokes, compared to the rest of the field in the presence of superstars. This may show that what really drives superstar effects is simply the spotlight that they bring. I expand this theory by examining risky behavior and show that superstars lead to lower risk taking, which is the opposite of what a convex prize distribution tournament model predicts. These effects cannot be explained simply through incentives because players are ignoring opportunities to increase their expected payoff by choosing riskier strategies and failing to learn from superstars in a golf pairing. As such, players appear to be playing safer in the presence of superstars because they are too afraid to fail in front of the increased attention that they bring. Finally, my results also show that there is a clear distinction between superstar players and players that have won in the last 6 tournaments. Previous winners have a smaller adverse effect on the field. Specifically, they adversely affect player scores by 0.427 strokes, but previous winners do not cause players to change their risk taking behavior.

These results show that superstars effect the field beyond simple tournament incentive mechanisms. How exactly players are underperforming when they play with superstars still needs further examination. Further studies should consider looking at different measures of performance such as putting, driving, and greens hit in regulation to examine player concentration and effort in the presence of superstars. Regardless, superstar effects apply beyond just professional golf tournaments. Most workplace tournaments are similar to golf in that players are not eliminated in head-to-head competition. Employees still stick around and fight for lower opportunities besides the top prize. As such, overall productivity may very well decrease as a result of the placement of top-tier personnel who nullify the competition structure within a firm.

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Table 1 - Descriptive Statistics								
Variable	Observations	Mean	SD	Percentiles				
				10th	25th	50th	75th	90th
Score	17492	71.158	3.186	67	69	71	73	75
Handicap (Ability)	17492	-2.855	0.922	-3.811	-3.397	-2.928	-2.448	-1.837
Superstars in the Field	17492	1.516	1.514	0	0	1	3	4
Superstars' Handicap (Ability)	244	-4.350	0.651	-4.926	-4.744	-4.299	-4.074	-4.018
Category 1 Players' Handicap (Ability)	6377	-3.142	0.767	-4.101	-3.618	-3.204	-2.650	-2.173
Category 1A Players' Handicap (Ability)	6818	-2.812	0.731	-3.673	-3.233	-2.871	-2.427	-2.034
Category 2 Players' Handicap (Ability)	2998	-2.856	0.895	-3.728	-3.365	-3.017	-2.505	-1.871
Category 3 Players' Handicap (Ability)	1299	-1.677	1.450	-3.131	-2.505	-1.653	-1.128	-0.288

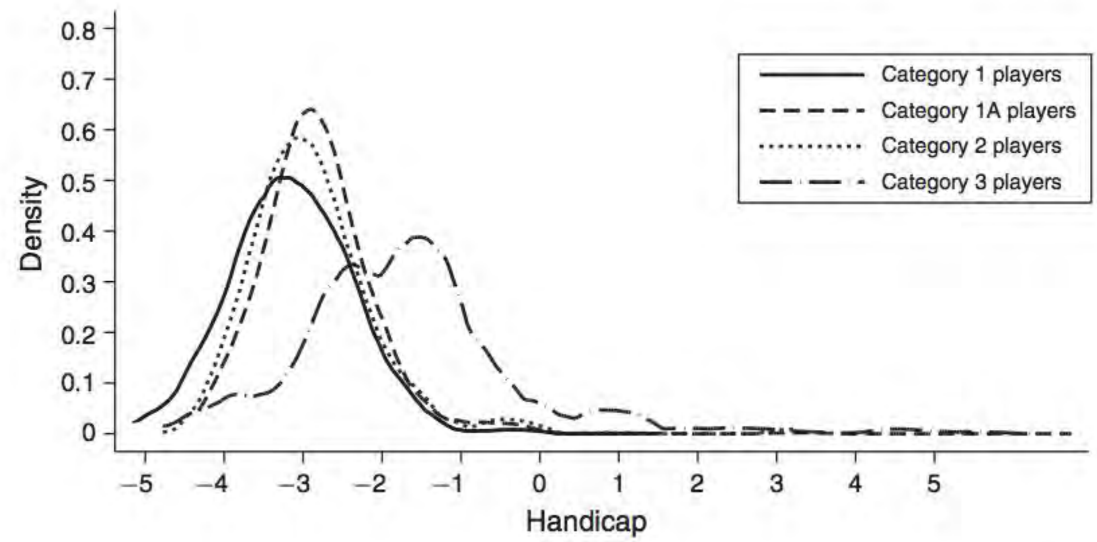

Figure 1 - Handicap (Skill) Distribution by Player Category (Guryan, Kroft, and Notowidigdo, 2009)

Table 2 (Weighted) - The Effect of Being Paired with a Superstar on Score			
	(1) Player's Score	(2) Player's Score	(3) Player's Score
Player's Handicap	0.673*** (0.039)	0.621** (0.270)	0.672*** (0.039)
Paired with a Superstar	-0.350 (0.407)		-0.369 (0.407)
Handicap Difference between Player and Superstar		-0.028 (0.059)	
Average Handicap of Playing Partners			-0.030 (0.041)
Tournament x Category x Round Fixed Effects	Yes	Yes	Yes
R^2	0.1521	0.2306	0.1521
N	17492	448	17492

Table 3 (Weighted) - Superstar Effects on the Field		
	(1) Player's Score	(2) Player's Score
Player's Handicap	0.622*** (0.040)	0.660*** (0.058)
Number of Superstars in the Field	1.147*** (0.200)	1.082*** (0.209)
Round 2 Dummy Variable	-0.269*** (0.052)	-0.269*** (0.052)
Paired with a Superstar	0.082 (0.172)	0.082 (0.172)
Player Handicap x Number of Superstars in the Field		-0.024 (0.025)
Tournament x Category Fixed Effects	Yes	Yes
R^2	0.1554	0.1555
N	17492	17492

Table 4 (Weighted) - Superstar Effects on the Field with Interactions for Particular Categories				
Score Per Round:	**(1) Cat 1 Players**	**(2) Cat 1A Players**	**(3) Cat 2 Players**	**(4) Cat 3 Players**
Player's Handicap	0.671*** (0.037)	0.701*** (0.037)	0.708*** (0.037)	0.702*** (0.038)
Number of Superstar(s) in the Field	1.253*** (0.195)	1.201*** (0.196)	1.246*** (0.195)	1.292*** (0.194)
Number of Superstar(s) in the Field x Player Category	-0.154*** (0.026)	0.093*** (0.027)	0.100*** (0.038)	0.064 (0.065)
Round 2	-0.271*** (0.053)	-0.271*** (0.053)	-0.270*** (0.053)	-0.270*** (0.053)
Tournament Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.1403	0.1387	0.1383	0.1337
N	17492	17492	17492	17492

Table 5 - Detecting Risky Behavior on the Field	
:	**(1) Standard Deviation of Score per Round**
Player's Handicap	0.085 (0.039)
Superstar(s) in the Field	-1.785** (0.370)
Round 2 Dummy	0.053 (0.089)
Tournament Fixed Effects	Yes
R^2	0.1946
N	610

Table 6 - Detecting Risky Behavior with Interactions for Particular Categories				
Standard Deviation of Score per Round:	**(1) Cat 1 Players**	**(2) Cat 1A Players**	**(3) Cat 2 Players**	**(4) Cat 3 Players**
Player's Handicap	0.085 (0.039)	0.092 (0.044)	0.084 (0.041)	0.100 (0.046)
Number of Superstar(s) in the Field	-1.527 (1.277)	-2.082** (0.456)	-1.721** (0.513)	-1.728*** (0.247)
Number of Superstar(s) in the Field x Player Category	0.006 (0.025)	0.013 (0.006)	-0.003 (0.008)	-0.016 (0.011)
Tournament Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.1930	0.1933	0.1930	0.1933
N	610	610	610	610

Table 7 - Previous Winners on the Field		
	(1) Score per Round	**(2) Standard Deviation of Score per Round**
Player's Handicap	0.443*** (0.031)	0.058 (0.025)
Previous Winner(s) in the Field	0.427** (0.187)	0.352 (0.343)
Round 2 Dummy	-0.264*** (0.046)	0.052 (0.089)
Tournament-by-Category Fixed Effects	Yes	Yes
R^2	0.1571	0.1956
N	17248	610

Table 8 - Detecting Risky Behavior - Previous Winners with Interactions for Particular Categories				
Standard Deviation of Score per Round:	**(1) Previous Winner(s) in the Field x Cat 1 Players**	**(2) Previous Winner(s) in the Field x Cat 1A Players**	**(3) Previous Winner(s) in the Field x Cat 2 Players**	**(4) Previous Winner(s) in the Field x Cat 3 Players**
Player's Handicap	0.059* (0.023)	0.048* (0.015)	0.052 (0.030)	0.034 (0.043)
Previous Winner(s)	2.225 (1.756)	0.636 (0.543)	0.498 (0.569)	0.279 (0.265)
Previous Winner(s) in the Field x Player Category	0.057 (0.044)	-0.017 (0.012)	-0.011 (0.014)	0.023 (0.023)
Tournament Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.1953	0.1946	0.1944	0.1946
N	610	610	610	610

Appendix A - Player Categories and Random Assignment

According to Guryan, Kroft, and Notowidigdo (2009) players are placed in one of four categories: 1, 1A, 2, and 3 based on their past performances over their career. Players are paired up with players in their category. The categories are assigned based on the following rules:

1. Category 1 players are tournament winners, and the top 25 money winners from the previous year, and PGA Tour life members.
2. Category 1A players include former champions of the four majors and The Players Championship (e.g., former British Open champions John Daly and Nick Faldo), as well as tournament winners who no longer qualifiy for Category 1 and who played in five or more PGA Tour events in the prior year.
3. Category 2 players include those in the top 125, players with 50 or more career cuts made, and players in the top 50 of the World Golf Rankings.
4. Category 3 includes all others, such as local qualifiers. These golfers get the first and last tee times of each session. When Annika Sorenstam became the first woman in 58 years to play in a PGA Tour event, she was a Category 3 player and was assigned the earliest and latest tee times in her two rounds.

Players might be paired with players from a different category if the number of players in a given category is not a multiple of three. In that case, Category 1A players are paired with Category 1 players and Category 3 players are paired with Category 2 players.

Appendix B - Player Handicap (Skill) Measurements

Player handicaps are created using scores from 1999, 2000, and 2001 for player observations in 2002. Likewise, scores from 2003 and 2004 are used for player observations in 2005 and 2006.

According to Guryan, Kroft, and Notowidigdo (2009) a simple average of scores from prior years understates differences in ability across players because better players tend to self-select into tournaments played on more difficult golf courses. They address this problem using a simplified form of the official handicap correction used by the United States Golf Association (USGA). For the purpose of computing the handicap correction, the USGA estimates the difficulty of most golf courses in the United States. Using scores of golfers of different skill levels, the USGA assigns each course a *slope* and a *rating*, which are related to the estimated slope and intercept from a regression of score on ability. They normalize the slopes of the courses in the dataset so that the average slope is one. They then use the ratings and adjusted slopes of the course to regression-adjust each past score, indexed by *n*. Specifically, for each past score they compute

$$h_n = (score_n - rating_c)/adjusted\ slope_c$$

where c indexes golf courses. For each golfer, in each year, they take the average of h_n for the scores from the previous two or three years to be the measure of ability. This ability measure is essentially an estimate of the number of strokes more than 72 (i.e., above par) that a golfer typically takes in a round, on an average course, that is used for professional golf tournaments. As is true for golf scores generally, higher values are worse. Thus, the measure of ability is positively correlated with a golfer's score. This correction differs from the official USGA handicap correction. The official correction predicts scores on the average golf course for which the slope is 113, whereas they calibrate to the average course slope in the sample (135.5). This adjustment ensures that the measure of ability is in the same units as the dependent variable strokes per round.