Does a Coworker's Skill Level Impact Performance?

Evidence from Professional Golf

Seth Pope

Professor Gary Smith

Department of Economics

Pomona College

23 April 2023

No. 16 UMBC stuns No. 1 Virginia 74-54 to make NCAA history. Before this 2018 matchup, sixteen seeds were 0-135 against number one seeds in the NCAA tournament. So, what happened? How did a no-name school defeat the giant from the ACC who was picked by most to make it to the Final Four? In sports, we often hear about playing down to the level of one's competition. The idea is that one does not play to their own full potential due to the low ability level of their competitors. Perhaps Virginia drastically underestimated UMBC and played down to what they thought was the level of their competition. Or maybe, UMBC played up to the level of their competition?

Evidence as far back as Triplett (1898), who found that cyclists raced faster against each other than against the clock, suggests that social interaction plays an essential role in individual performance. Manski (1993) was the first to develop a specific theoretical framework to discuss this peer effects concept. Falk and Ichino (2006), Cornelissen et al. (2017), and Buechel et al. (2018) further developed and expanded on Manski's framework. The economic importance of peer effects has been justified in numerous studies, such as Falk and Ichino (2006), who found in a lab study that pair peer effects raise productivity (especially in low-productivity workers).

The mechanisms through which peer effects increase productivity are three-fold: learning from their co-workers about how to perform a specific task, workers exerting extra hard when they see their co-workers working hard or know their co-workers are watching, or that the nature of the production of one worker directly influences the productivity of another worker (such as on an assembly line). This study will focus on the first two mechanisms, which are behavioral.

Using professional golf as a case study, this paper will examine what impact peer effects have on performance in a highly competitive, high-skill labor market. Similar to Guryan, Kroft, and Notowidigdo (2009), who found little to no convincing evidence of peer effects in professional golf using tee time randomization, this study will exploit the randomization of tee times on the PGA Tour to examine peer effects. The study will use more recent data from the 2021-2022 PGA Tour season, as well as improved player and competitive ability metrics (strokes-gained) created in the years since the prior study's release. Furthermore, this study will restrict the sample to just the first and second-round pairings, which are done randomly. Third and fourth-round pairings cannot be used, as hot players in the current tournament are paired together. A study using these third and fourth rounds could be subject to various other factors, such as regression to the mean.

This paper is structured as follows: Section I provides further detail on prior peer effects literature. Section II describes the data. Section III details the methodology. Section IV contains the results and robustness checks. Finally, Section V discusses the study's conclusions, implications, and limitations.

I. Prior Literature

While other studies have attempted to examine peer effects in the workplace rather than in a lab, such as Mas and Moretti (2009) and Bandiera, Barankay, and Rasul (2009), these studies are flawed due to the non-random assignment of peers. Without the random assignment of peers, other characteristics or factors could impact productivity, causing the covariance of peer ability and the error term to be greater than zero.

Previous observational studies conducted by Sacerdote (2001) and Zimmerman (2003) at Dartmouth and Williams Colleges exploit the random assignment of dorm roommates to study peer effects. Both found that peer effects most likely impacted higher education performance. While these studies are more informative than other observational studies due to randomization, they are not directly applicable to the workplace due to the lack of direct monetary incentives.

Professional sports make for an ideal case study to examine peer effects in the workplace due to randomization, strong monetary incentives for the athletes, and data availability.

Prior studies in golf analyzing peer effects have found conflicting conclusions. Guryan, Kroft, and Notowidigdo (2009) use the randomization of playing partners in the first and second rounds of professional golf tournaments to show that there is little to no evidence that peer effects impact performance on the PGA Tour. However, the authors use a limited dataset, and their measure of player ability is slightly antiquated..

Meanwhile, Brown (2011) uses panel data from professional golf to show that the presence of a superstar at a tournament is associated with a worse performance by all the other players competing in the tournament (not just Tiger's direct playing partners). Brown (2011) finds that overall performance is 0.8 strokes worse when Tiger Woods participates relative to when Tiger Woods is absent; moreover, she finds that the adverse effects vary with the quality of Tiger Woods's play. Brown's study appears empirically sound due to the presence of various robustness checks (such as Tiger's knee injury in 2008 and personal issues in 2009); however, the lack of randomization still creates some questions about the validity of her results, specifically related to self-selection bias.

In contradiction to Guryan, Kroft, and Notowidigdo (2009) and Brown (2011), Hickman and Metz (2018) use putting data to show that learning by observing peers positively affects performance on the PGA Tour. With regards to this study, their results suggest that playing with better players can help one learn and improve upon their own abilities. Surprisingly, Hickman and Metz (2018) also find a significant negative relationship between performance and the quality of the most recent shots by their competitors. This second result is also of particular interest as it suggests that players can be discouraged by a playing partner's successes.

Concerning this study, Hickman and Metz's second conclusion indicates that playing with someone well above one's skill level could discourage and negatively impact performance (most likely canceling out any positive learning peer effects).

II. Data

The data come from three sources: DraftKings.com, the PGA Tour, and ESPN. Initial tee time level data were collected from every tournament in the 2021-2022 PGA Tour season by scraping DraftKings.com web pages. DraftKings.com provides a plethora of sports gambling data for the five major American sports, European soccer, MMA, NASCAR, and MMA. From DraftKings, I specifically used first and second-round tee time data from the 2021-2022 PGA Tour season, the most recently completed on the PGA Tour. Two PGA tour tournaments (The Puerto Rico Open and The Barbasol Championship) were dropped due to a lack of data availability on DraftKings.com. The QBE Shootout and Zurich Classic were removed as these events are team events on the PGA Tour. The Dell Matchplay, Barracuda Championship, and Tour Championship were also dropped due to each event's different scoring format from the other tournaments on tour. Finally, the AT&T Pebble Beach Pro-Am was dropped due to amateurs (celebrities) playing with the professionals. Unfortunately, there is no reliable ability metric for these celebrities online.

The data were then restricted to just the first and second rounds, as these tee times are created randomly. Third and fourth-round tee times are created using players' performances in the first and second rounds. Due to the lack of randomization, including data from these rounds could result in significant errors. Perhaps a player who overperformed in round one or two has some sort of regression to the mean in round three or four. Connolly and Rendleman (2008) as well as Rendleman (2020) show that there is considerable evidence of regression to the mean both for amateur and professional golfers. Alternatively, hot players paired together could remain hot and over-perform their baseline ability. Finally, pressure increases dramatically, specifically in the tournament's fourth round, perhaps creating even more errors.

Next, first and second-round scoring data at each tournament collected by the PGA Tour using their proprietary Shotlink Plus system were merged into the dataset. In cooperation with CDW and Microsoft, the PGA Tour created the ShotLink Plus system in 2017. The ShotLink Plus system uses artificial intelligence (relying on past, basic data from 2000-2017) to gather and sort data from: reporting on-course volunteers, fairway lasers, cameras, and Trackman radars. The system is revolutionary in compiling and “disseminat[ing] scoring and statistical data on every shot by every player in real-time.” Using this ShotLink Data, the PGA Tour also creates and releases summary statistics for each season. The critical summary statistic for this paper will be strokes-gained. The strokes-gained metric was created by Broadie (2012) in his novel paper “Assessing Golfer Performance on the PGA Tour.” The metric refers to how many strokes better the professional golfer in question was in the tournaments he played during the prior season relative to how the average professional on the PGA Tour would have done. Broadie’s strokes-gained metric is now considered the gold standard when conducting golf research and has been used by Connolly and Rendleman (2012) as well as Hickman and Metz (2018). Additionally, sports odds companies like DraftKings.com use the metric to help them construct their betting lines. For our data, strokes gained overall from the 2019-2020 season were used (to remain independent from the 2021-2022 scoring data). Using this metric means that data from rookies and pros who only played a few events had to be dropped; however, this is not necessarily bad, as their unknown history makes it more challenging to estimate their skill level and future play. Finally, demographic data, such as age and career earnings, from ESPN was merged into the dataset.

Once all merged together, 4,248 observations across 37 tournaments and 174 players were left. Summary statistics for these observations are displayed in Table 1.

The dependent variable Score_{iktr} refers to player *i*'s score in a specific group *k* at tournament *t* during round *r*. Figure 1 indicates that the mean score in our sample is 70.38, and the median is 70. This mean score is slightly better than the PGA Tour average score during the 2021-2022 season of 71.092. Our sample mean score is marginally better than the tour average due to the elimination of rookies and the fact that we only look at first and second-round scoring. Players tend to score better during the first and second rounds as pin positions are more accessible, and players are less pressured to perform well. Our distribution of scores is also slightly right-skewed, which makes sense as it is challenging to shoot under par and pretty easy to mess up and shoot a high score.

The first control variable Ability_i refers to player *i*'s strokes gained overall statistic from the previous PGA Tour season (2020-2021). The mean strokes gained overall of 21.97, displayed in Figure 1, suggests that our sample had a slightly better ability level than the average PGA Tour player in the 2020-2021 season. This statistic is expected given that the poorest-performing players from the previous season are usually demoted to the mini-tour level in the following season.

The next variable of $\text{AverageAbility}_{-i,ktr}$ is the average ability, as measured by strokes-gained, of group *k* at tournament *t* in round *r*, not including the ability level of player *i*. Typically, in the first two rounds of a PGA Tour event, four players are paired together making this variable the average of the other three players' scores. The smaller standard deviation than

$Ability_i$ reinforces that pairings are made randomly. If pairings were not made randomly, one would see a larger standard deviation value as highly skilled players paired altogether (all positive) and poorly scored players paired altogether (all negative) would increase the variation dramatically. However, when better-than-average and worse-than-average players are paired together, their skill level nullifies, thus creating values closer to the mean with less variation. A similar effect is seen in $AverageScore_{-i,ktr}$, which was calculated by taking the average of the scores of the other players in group *k* besides player *i* at a tournament *t* during round *r*.

Both Round? and Morning? are dummy variables that equal zero in round one and the morning, respectively, and equal one in round two and the afternoon, respectively.

Age and Career Earnings (in millions) refer to player demographic data that will be used in robustness checks. The mean age of the players is 34.79, with 52-year-olds Phil Mickelson and KJ Choi as the oldest players and 23-year-old phenom Matthew Wolff as the youngest. Phil Mickelson is our dataset's most accomplished player, having already earned $95 million on the PGA Tour in tournaments alone (not counting endorsements, other tours, etc.). Martin Trainer is the least accomplished player, having already earned a quite respectable $13 million.

III. Empirical Framework

The empirical framework closely follows the tradition of Sacerdote (2001), Zimmerman (2003), and Guryan, Kroft, and Notowidigdo (2009). Using this prior literature, specifically Guryan, Kroft, and Notowidigdo (2009), the following linear regression model was created:

1) $Score_{iktr} = \alpha_1 + \beta_1 * AverageAbility_{-i,ktr} + \beta_2 * AverageAbility^2_{-i,ktr} + \beta_3 * Ability_i + Round? + Morning? + \delta_t + \lambda_p + e_{iktr}$

The dependent variable of interest $Score_{iktr}$ refers to player *i*'s score in a specific group *k* at tournament *t* during round *r*. $Ability_i$ is a measure of player *i*'s ability level; in this case, it is the player's prior year strokes-gained statistic. $\text{AverageAbility}_{-i,ktr}$, the independent variable of interest, refers to the average ability, as measured by strokes-gained, of group *k* at tournament *t* in round *r*, not including the ability level of player *i*. $\text{AverageAbility}^2_{-i,ktr}$ is the $\text{AverageAbility}_{-i,ktr}$ term squared, and then adjusted to positive or negative depending on the sign of the first term. Round? is a dummy variable that is zero if the score is from round one and one if the score is from round two. δ_t is a tournament-level fixed effect term, and λ_p is a player-level fixed effect term. Finally, e_{iktr} is the error term.

The beta coefficient for the independent variable of interest, $\text{AverageAbility}_{-i,ktr}$, is expected to be negative, highly significant, and of large size. Using prior literature as a guide, this coefficient is hypothesized since playing with better players should lower one's score (a good thing in golf). However, there may be a choking effect when playing with players who are significantly better than player *i*. As such, expanding on previous literature, an $\text{AverageAbility}^2_{-i,ktr}$, was added to model this diminishing relationship. Figure 1 and Figure 2 display these relationships.

Ability_i is a control term and is expected to have a strong negative correlation with player *i*'s score, as players with better ability ratings should theoretically shoot lower scores. However, the player-fixed effects could greatly impact the sign, size, and significance of this coefficient.

Round? and Morning? are both dummy variables to account for any time effects that may affect multiple players (such as pin positions, weather, etc.). I expect the coefficient for Round? to be negative and significant because players tend to shoot lower scores on Thursday during round one as the course is generally set up the easiest, and there is practically no pressure. Similarly, I expect the coefficient for Morning? to be negative and significant because it is easier to shoot a lower score in the morning when there is less wind and fresher greens.

Since $AverageAbility_{-i,ktr}$ in Equation 1 is a predetermined characteristic, the estimates of β_1 and β_2 are unlikely to be biased due to the presence of unobserved common shocks. These common shocks may affect the standard errors of our regression but will not bias the coefficients directly. However, replacing $AverageAbility_{-i,ktr}$ with $AverageScore_{-i,ktr}$, and $AverageAbility^2_{-i,ktr}$ with $AverageScore^2_{-i,ktr}$ is perhaps an even more interesting specification. As described by Guryan, Kroft, and Notowidigdo (2009), this new outcome-on-outcome specification explores "how performance relates to the contemporaneous performance of peers, rather than just to peers' predetermined skills." However, the coefficients of interest in this new methodology could easily be biased by common shocks that occur to all the individuals within a given grouping. Nonetheless, Equation 2, as described below, was estimated due to the theoretical importance of the results.

2) $Score_{iktr} = \alpha_1 + \gamma_1 * AverageScore_{-i,ktr} + \gamma_2 * AverageScore^2_{-i,ktr} + \gamma_3 * Ability_i + Round? + Morning? + \delta_t + \lambda_p + e_{iktr}$

The independent variable of interest $AverageScore_{-i,ktr}$ is the average score of player *i*'s playing companions in group *k* during round *r* of tournament *t*. An upward-facing parabolic relationship is hypothesized with regards to $AverageScore_{-i,ktr}$ as watching others in one's group play well will likely improve one's own score. However, I expect this impact to be decreasing, as each shot one's group plays better likely matters less and less. Moreover, I think that watching others play extremely well (to the left of the axis of symmetry of the parabola) could put extra substantial pressure on one's performance, causing a choking effect where one would be projected to play less well than if their group performed slightly worse. Figure 3 and Figure 4 display these relationships. Note that the gamma coefficients from the equation above should be considered upper estimates of any potential peer effects due to the positive bias that may occur because of common shocks.

IV. Results

The results of estimating Equation 1 are displayed in Table 2. Columns 1-4 contain the results with and without player and tournament-specific fixed effects. The coefficients for our dependent variables of interest $AverageAbility_{-i,ktr}$ and $AverageAbility^2_{-i,ktr}$ are minuscule and of varying signs in the four different alterations of the regression. These coefficients suggest that the ability level of one's playing partners on the PGA Tour does not really make a difference in how one scores on a given day. The positive coefficients for both variables in Column 4 (when all fixed effects are added in and the adjusted r-squared is the highest) suggest that, if anything, playing with a better group in terms of ability actually makes one score slightly worse.

The results of estimating Equation 2 are displayed in Table 3. Columns 1-4 contain the results with and without player and tournament-specific fixed effects. Interestingly, we find significant, sizable coefficients for our dependent variables of interest $AverageScore_{-i,ktr}$ and $AverageScore^2_{-i,ktr}$. As expected, the gamma coefficient for $AverageScore_{-i,ktr}$ was negative, and the gamma coefficient for $AverageScore^2_{-i,ktr}$ was positive, suggesting an upward-facing quadratic relationship concerning Player *i* score (as displayed in Figure 5). These gamma coefficients suggest that players on tour do, in fact, play up or down to the level of competition in their group on that given day. Additionally, it perhaps indicates the existence of a choking effect when playing with players who are performing extraordinarily well (shooting 65 or better). Differencing $AverageScore_{-i,ktr}$ and $AverageScore^2_{-i,ktr}$ by the overall average score of all plates who competed in a given round was also modeled out. However, this differencing did not make a significant difference to the adjusted r-squared of the models nor the coefficients. Furthermore, this differencing made the coefficients slightly more difficult to interpret.[1]

Unsurprisingly, the coefficients for Round? were positive and Morning? were negative in all regression results. These coefficients suggest that players play better in the first round than in the second round and that getting early morning tee times is a significant scoring advantage. As expected, the coefficients for $Ability_i$ varied in sign, size, and significance depending on the inclusion or exclusion of player-specific fixed effects.

Tables 4-7 contain robustness checks focusing on player age and career earnings. Table 4 and Table 5 display similar regression results to those found in Table 2, Column 4 but instead run on four subsamples (quartiles) of player age or career earnings. Table 6 and Table 7 contain similar results to that of Table 3, Column 4 but instead, run on four subsamples (quartiles) of player age or career earnings. Table 4 and Table 5 confirm that the insignificant, minuscule beta coefficients for $AverageAbility_{-i,ktr}$ and $AverageAbility^2_{-i,ktr}$ occur regardless of one's age or earnings.

Table 6, Column 1 suggests that how others play in one's group on a given day makes a particular difference in how younger players perform. This impact appears to fade with age but not completely go away, as can be seen by the diminishing coefficients across the columns in Table 6 for $AverageScore_{-i,ktr}$ and $AverageScore^2_{-i,ktr}$. The coefficients for $AverageScore_{-i,ktr}$ and $AverageScore^2_{-i,ktr}$ in Table 7, Column 2 suggest that player's in the second quartile of earnings are most affected by how their playing partners perform that day. The coefficients in Table 7, Column 4 suggest that more accomplished players are barely impacted at all by how the other players in their group are performing. Intuitively, this makes sense as these players are probably

[1] Readers are welcome to reach out if they would like to see more detailed results from this modeling

not concerned with the small paycheck from this tournament (given what they previously earned) and are solely trying to win.

V. Conclusion

Initial results using $AverageAbility_{-i,ktr}$ and $AverageAbility^2_{-i,ktr}$ suggest that the ability level of the other players in one's group does not make a difference in how a PGA Tour player performs on a given day. Despite the definite existence of some positive bias, results (as well as the robustness checks) using $AverageScore_{-i,ktr}$ and $AverageScore^2_{-i,ktr}$ suggest that how one's playing partners are performing on a given day definitely impacts how one performs on that day on the PGA Tour. The robustness checks suggest that this impact fades slightly with age and almost entirely goes away with more prior success. This suggests peer effects make less of an impact with regards to older, more experienced people (which is intuitive as they theoretically have already reaped these benefits earlier in their careers).

The results have significant implications for sports betting in golf, especially as more live betting is promoted by companies such as DraftKings and alternative tours like LIV Golf. Regarding live betting, one should place bets on players who are not performing quite as well as their playing partners. Alternatively, one could bet against someone who is severely outperforming his playing partners. Moreover, the initial results suggest that pairings with players of high or low ability do not really matter for sports betting lines. Instead, the results suggest that timing should have the most significant impact on opening betting lines (with morning times outperforming afternoon times by almost half a shot across all regression specifications).

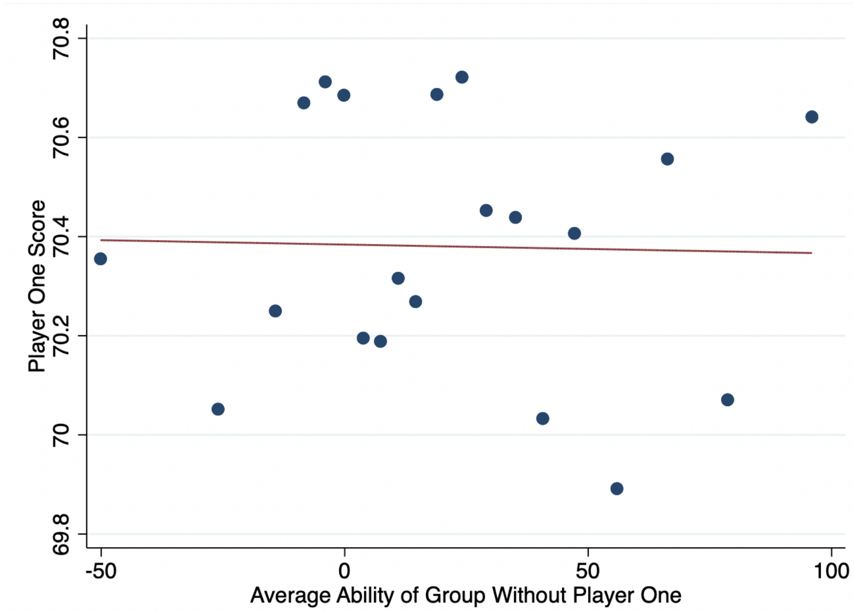
Regarding peer effects, the results suggest that ability level might not make as big of a difference as prior studies suggested. We hypothesize that ability likely still does impact productivity through the learning mechanism if skill differences are significant enough. However, our data do not contain enough skill variation to demonstrate this significantly, given that everyone on the PGA Tour plays at the highest level of professional golf (where ability level only varies slightly).

Nonetheless, the most considerable peer effects likely occur at the daily level, with how others are performing on that day making the largest difference in scoring. Furthermore, these daily peer effects are much larger for less experienced, younger tour professionals. Concerning implications, these results suggest that seeing other people's productivity and work is an essential motivator for one's own work and success. Furthermore, with regard to younger workers, the learning mechanism through which peer effects increase productivity is of particular importance. With the continued rise of remote work, employers must figure out how to still reap these productivity gains. I specifically believe the effectiveness of the learning mechanism will decrease dramatically, as younger workers will miss out on key mentoring opportunities and career development opportunities. Future empirical research must be done to quantify these peer effect losses caused by remote work and see if they outweigh some of the benefits of asynchronous work (schedule flexibility, autonomy, etc.).

Table 1: Summary Statistics for 2021-2022 PGA Tour Season Data

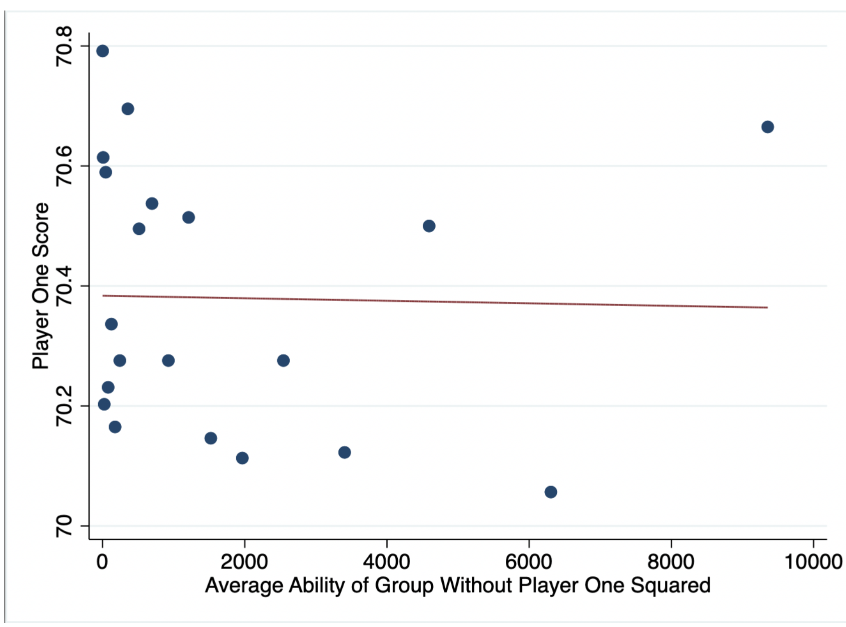
Variable	Mean	Standard Deviation	Minimum	Maximum	Median
$Score_{iktr}$	70.38	3.21	60	84	70
$Ability_{i}$	21.97	43.97	-114.03	134.28	15.49
$AverageAbility_{-i,ktr}$	21.24	35.38	-99.74	129.12	16.56
$AverageAbility^{2}_{-i,ktr}$	1702.93	2469.73	0.00	16672.62	605.91
$AverageScore_{-i,ktr}$	70.39	2.58	63	80	70
$AverageScore^{2}_{-i,ktr}$	4961.85	365.64	3969	6400	4900
Round?	0.50	0.50	0	1	0.50
Morning?	0.50	0.50	0	1	0.50
Age	34.79	5.88	23	52	34
Career Earnings (in millions)	18.40	14.60	1.57	95.00	13.00

Figure 1: Average Ability of the Group Without Player *i* vs. Player *i* Score



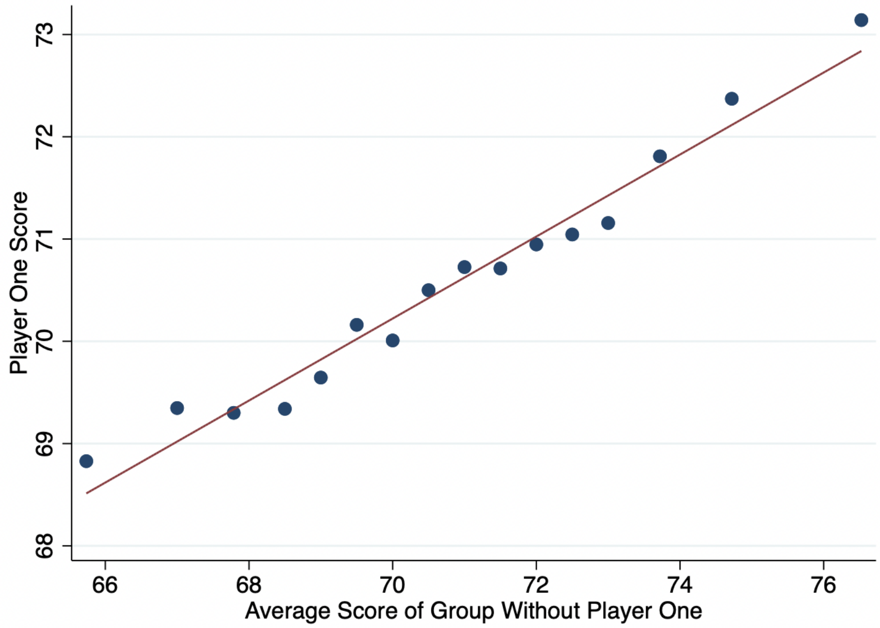
Note: Average Ability was binned into 20 groups for readability

Figure 2: Average Ability of the Group Without Player *i* Squared vs. Player *i* Score



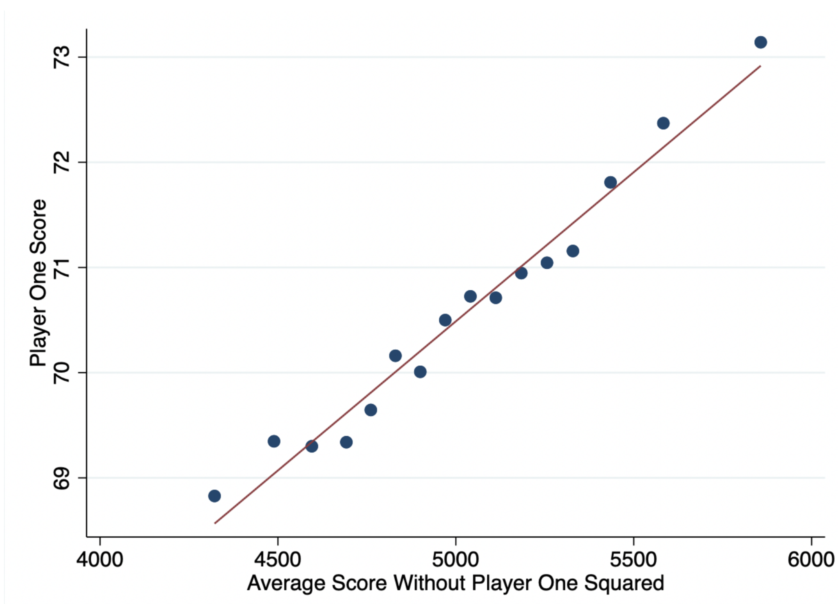
Note: Average Ability was binned into 20 groups for readability

Figure 3: Average Score of the Group Without Player *i* vs. Player *i* Score



Note: Average Score was binned into 16 groups for readability

Figure 4: Average Score of the Group Without Player *i* Squared vs. Player *i* Score



Note: Average Score was binned into 16 groups for readability

Table 2: Regression of Player *i* Score on Average Ability of Group *k* Without Player *i*

	(1)	(2)	(3)	(4)
Observations	4248	4248	4248	4248
R-squared	0.0218	0.220	0.0852	0.276
adj. R-squared	0.0206	0.213	0.0455	0.238
VARIABLES	Player *i* Score	Player *i* Score	Player *i* Score	Player *i* Score
Average Ability of Group *k* Without Player *i*	0.00262	-0.000596	0.00419	0.000772
	[0.183]	[0.745]	[0.044]	[0.688]
Average Ability of Group *k* Without Player *i* Squared	2.90e-05	-2.12e-05	5.08e-05	1.72e-05
	[0.299]	[0.407]	[0.089]	[0.526]
Ability of Player *i*	-0.00890	-0.0113	0.0246	0.00757
	[0.000]	[0.000]	[0.029]	[0.459]
Round?	0.462	0.462	0.462	0.462
	[0.000]	[0.000]	[0.000]	[0.000]
Morning?	-0.377	-0.376	-0.379	-0.376
	[0.000]	[0.000]	[0.000]	[0.000]
Constant	70.43	71.28	71.53	72.05
	[0.000]	[0.000]	[0.000]	[0.000]
Tournament-Specific Fixed Effects	No	Yes	No	Yes
Player-Specific Fixed Effects	No	No	Yes	Yes

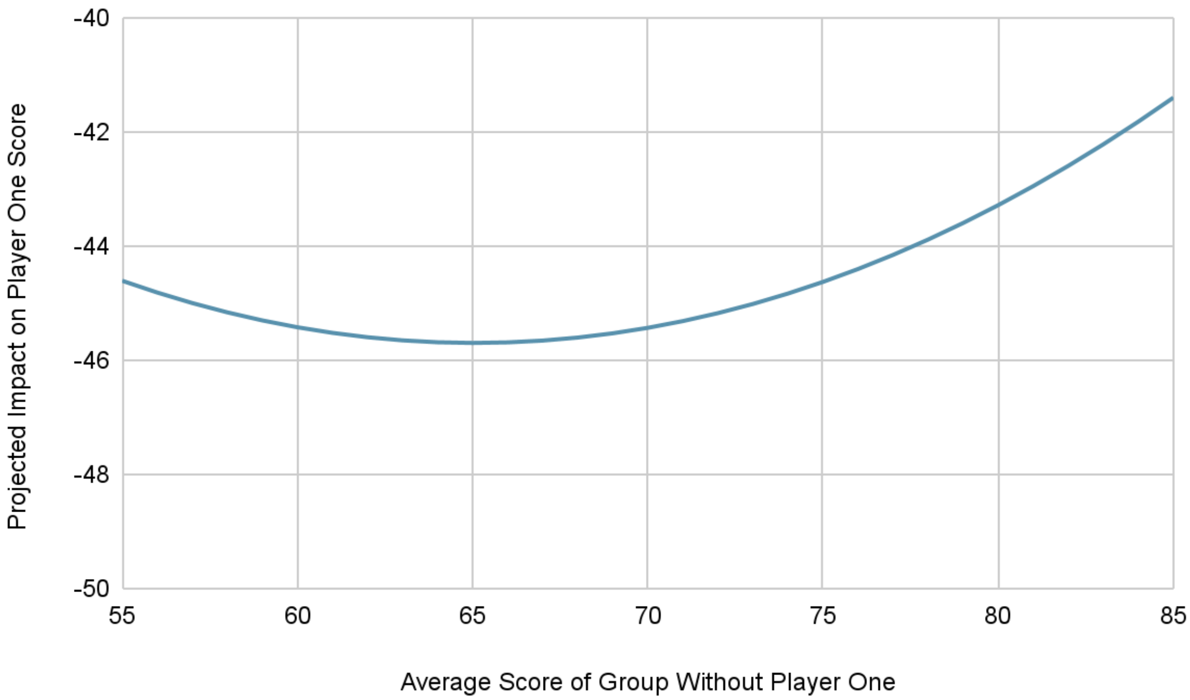
Two sided p-values in brackets

Table 3: Regression of Player *i* Score on Average Score of Group *k* Without Player *i*

	(1)	(2)	(3)	(4)
Observations	4248	4248	4248	4248
R-squared	0.119	0.228	0.177	0.283
adj. R-squared	0.118	0.220	0.141	0.246
VARIABLES	Player *i* Score	Player *i* Score	Player *i* Score	Player *i* Score
Average Score of Group *k* Without Player *i*	-1.293	-1.237	-1.471	-1.405
	[0.059]	[0.066]	[0.034]	[0.039]
Average Score of Group *k* Without Player *i* Squared	0.0119	0.00961	0.0132	0.0108
	[0.014]	[0.043]	[0.007]	[0.025]
Ability of Player *i*	-0.00743	-0.0113	0.0280	0.0103
	[0.000]	[0.000]	[0.009]	[0.312]
Round?	0.281	0.400	0.279	0.400
	[0.003]	[0.000]	[0.002]	[0.000]
Morning?	-0.248	-0.340	-0.250	-0.343
	[0.008]	[0.000]	[0.007]	[0.000]
Constant	102.6	110.6	109.7	117.4
	[0.000]	[0.000]	[0.000]	[0.000]
Tournament-Specific Fixed Effects	No	Yes	No	Yes
Player-Specific Fixed Effects	No	No	Yes	Yes

Two sided p-values in brackets

Figure 5: Average Score of the Group Without Player *i* vs. Projected Impact on Player *i* Score Modeled Using Gamma Coefficients



Note: Axes were truncated to include only realistic scores for PGA professionals (55-85)

Table 4: Regression of Player *i* Score on Average Ability of Group *k* Without Player *i* By Age Quartiles

	(1)	(2)	(3)	(4)
Observations	966	1174	1050	1058
R-squared	0.316	0.272	0.301	0.311
adj. R-squared	0.258	0.215	0.245	0.246
VARIABLES	Player *i* Score (1st Quartile Age)	Player *i* Score (2nd Quartile Age)	Player *i* Score (3rd Quartile Age)	Player *i* Score (4th Quartile Age)
Average Ability of Group *k* Without Player *i*	0.0111	-0.00381	0.00587	-0.00225
	[0.054]	[0.314]	[0.082]	[0.567]
Average Ability of Group *k* Without Player *i* Squared	-0.000107	0.000105	9.39e-06	-1.10e-05
	[0.103]	[0.047]	[0.859]	[0.870]
Ability of Player *i*	-0.0126	-0.0150	-0.0131	-0.0225
	[0.235]	[0.297]	[0.001]	[0.060]
Round?	0.673	0.525	0.429	0.238
	[0.000]	[0.002]	[0.010]	[0.169]
Morning?	-0.494	-0.298	-0.339	-0.391
	[0.007]	[0.075]	[0.043]	[0.024]
Constant	70.02	71.44	69.92	72.76
	[0.000]	[0.000]	[0.000]	[0.000]
Tournament-Specific Fixed Effects	Yes	Yes	Yes	Yes
Player-Specific Fixed Effects	Yes	Yes	Yes	Yes

Two sided p-values in brackets

Table 5: Regression of Player *i* Score on Average Ability of Group *k* Without Player *i* By Career Earnings Quartiles

	(1)	(2)	(3)	(4)
Observations	1058	1060	1064	1066
R-squared	0.278	0.258	0.312	0.321
adj. R-squared	0.216	0.199	0.253	0.264
VARIABLES	Player *i* Score (1st Quartile Career Earnings)	Player *i* Score (2nd Quartile Career Earnings)	Player *i* Score (3rd Quartile Career Earnings)	Player *i* Score (4th Quartile Career Earnings)
Average Ability of Group *k* Without Player *i*	-0.00284	-0.00152	0.00294	0.00239
	[0.465]	[0.698]	[0.431]	[0.609]
Average Ability of Group *k* Without Player *i* Squared	1.69e-05	-9.33e-06	1.51e-05	1.92e-05
	[0.830]	[0.870]	[0.776]	[0.731]
Ability of Player *i*	-0.00215	-0.0106	0.0105	-0.0197
	[0.904]	[0.004]	[0.311]	[0.105]
Round?	0.467	0.473	0.335	0.571
	[0.009]	[0.007]	[0.046]	[0.001]
Morning?	-0.249	-0.462	-0.527	-0.249
	[0.166]	[0.008]	[0.002]	[0.144]
Constant	70.71	70.40	72.31	71.83
	[0.000]	[0.000]	[0.000]	[0.000]
Tournament-Specific Fixed Effects	Yes	Yes	Yes	Yes
Player-Specific Fixed Effects	Yes	Yes	Yes	Yes

Two sided p-values in brackets

Table 6: Regression of Player *i* Score on Average Score of Group *k* Without Player *i* By Age Quartiles

	(1)	(2)	(3)	(4)
Observations	966	1174	1050	1058
R-squared	0.317	0.280	0.311	0.316
adj. R-squared	0.260	0.224	0.256	0.252
VARIABLES	Player *i* Score (1st Quartile Age)	Player *i* Score (2nd Quartile Age)	Player *i* Score (3rd Quartile Age)	Player *i* Score (4th Quartile Age)
Average Score of Group *k* Without Player *i*	-2.395	-2.043	-1.210	-0.651
	[0.091]	[0.123]	[0.362]	[0.646]
Average Score of Group *k* Without Player *i* Squared	0.0174	0.0155	0.00968	0.00543
	[0.082]	[0.097]	[0.301]	[0.588]
Ability of Player *i*	-0.0120	-0.0128	-0.0114	-0.0232
	[0.257]	[0.375]	[0.005]	[0.050]
Round?	0.608	0.472	0.352	0.195
	[0.001]	[0.005]	[0.035]	[0.260]
Morning?	-0.489	-0.237	-0.276	-0.372
	[0.007]	[0.159]	[0.099]	[0.032]
Constant	152.4	138.3	107.1	91.53
	[0.003]	[0.003]	[0.023]	[0.069]
Tournament-Specific Fixed Effects	Yes	Yes	Yes	Yes
Player-Specific Fixed Effects	Yes	Yes	Yes	Yes

Two sided p-values in brackets

Table 7: Regression of Player *i* Score on Average Score of Group *k* Without Player *i* By Career Earnings Quartiles

	(1)	(2)	(3)	(4)
Observations	1058	1060	1064	1066
R-squared	0.290	0.265	0.316	0.328
adj. R-squared	0.229	0.206	0.258	0.272
VARIABLES	Player *i* Score (1st Quartile Career Earnings)	Player *i* Score (2nd Quartile Career Earnings)	Player *i* Score (3rd Quartile Career Earnings)	Player *i* Score (4th Quartile Career Earnings)
Average Score of Group *k* Without Player *i*	-1.491	-3.308	-1.828	0.282
	[0.303]	[0.017]	[0.181]	[0.835]
Average Score of Group *k* Without Player *i* Squared	0.0117	0.0238	0.0135	-0.000966
	[0.252]	[0.015]	[0.159]	[0.920]
Ability of Player *i*	-0.00122	-0.0107	0.0125	-0.0160
	[0.945]	[0.002]	[0.222]	[0.185]
Round?	0.363	0.421	0.295	0.504
	[0.044]	[0.016]	[0.079]	[0.003]
Morning?	-0.197	-0.453	-0.499	-0.221
	[0.272]	[0.010]	[0.003]	[0.193]
Constant	117.4	184.9	133.9	56.52
	[0.022]	[0.000]	[0.006]	[0.238]
Tournament-Specific Fixed Effects	Yes	Yes	Yes	Yes
Player-Specific Fixed Effects	Yes	Yes	Yes	Yes

Two sided p-values in brackets

References

Bandiera, Oriana, Iwan Barankay, and Imran Rasul. 2009. “Social Connections and Incentives in the Workplace: Evidence from Personnel Data.” *Econometrica* 77 (4): 1047–94.

Broadie, Mark. 2012. “Assessing Golfer Performance on the PGA Tour.” *Interfaces* 42 (2): 146–65.

Brown, Jennifer. 2011. “Quitters Never Win: The (Adverse) Incentive Effects of Competing with Superstars.” *Journal of Political Economy* 119 (5): 982–1013.

Buechel, Berno, Lydia Mechtenberg, and Julia Petersen. 2018. “If I Can Do It, so Can You! Peer Effects on Perseverance.” *Journal of Economic Behavior and Organization* 155: 301–14.

Connolly, Robert A, and Richard J Rendleman. 2012. “What It Takes to Win on the PGA Tour (If Your Name Is ‘Tiger’ or If It Isn't).” *Interfaces* 42 (6): 554–76.

Cornelissen, Thomas, Christian Dustmann, and Schönberg Uta. 2017. “Peer Effects in the Workplace.” *The American Economic Review* 107 (2): 425–56.

Falk, Armin, and Andrea Ichino. 2006. “Clean Evidence on Peer Effects.” Journal of Labor Economics 24 (1): 39–57.

Guryan, Jonathan, Kory Kroft, and Matt Notowidigdo. 2007. Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments. *NBER Working Paper Series*, No. W13422. Cambridge, Mass: National Bureau of Economic Research.

Hickman, Daniel C, and Neil E Metz. 2018. “Peer Effects in a Competitive Environment: Evidence from the Pga Tour.” *Economic Inquiry* 56 (1).

Manski, Charles F. 1993. “Identification of Endogenous Social Effects: The Reflection Problem.” *The Review of Economic Studies* 60 (3): 531–42.

Mas, Alexandre, and Enrico Moretti. 2009. “Peers at Work.” *American Economic Review* 99 (1): 112:145.

Richard J. Rendleman Jr. 2020. “The Relative Roles of Skill and Luck Within 11 Different Golfer Populations.” *Journal of Quantitative Analysis in Sports* 16 (3): 237–54.

Sacerdote, Bruce. 2000. Peer Effects with Random Assignment: Results for Dartmouth Roommates. *NBER Working Paper Series*, No. 7469. Cambridge, MA.: National Bureau of Economic Research.

Triplett, Norman. 1898. “The dynamogenic factors in pacemaking and competition.” *American Journal of Psychology* 9: 507–533.

Zimmerman, David J. 2003. “Peer Effects in Academic Outcomes: Evidence from a Natural Experiment.” *The Review of Economics and Statistics* 85 (1): 9–23.