PEER EFFECTS IN THE PROFESSIONAL GOLF ASSOCIATION

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ABSTRACT

PRESTON MARTIN COUCH. Peer effects in the Professional Golf Association. (Under the direction of DR. CRAIG A. DEPKEN II)

In this analysis I will determine the execution of professional golfers in the final two rounds of a four round tournament. This paper investigates if a player's performance influences another player's performance using tee shots on par three holes. I use a fixed effects regression model to determine if there are significant spill overs in player performances when paired together. Important variables used throughout this paper include distance to the pin after the shot, a player's world ranking, and the money each player wins for his performance. The preferred model fails to find any statistically significant evidence that suggest one player's performance influences their playing partner's performance.

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TABLE OF CONTENTS

INTRODUCTION	1
LITERATURE REVIEW	4
DATA DESCRIPTION	8
EMPIRICAL ANALYSIS	13
CONCLUSION	22
REFERENCES	24
APPENDIX A: TABLES	25
APPENDIX B: FIGURES	29

INTRODUCTION

This paper analyzes if players in the Professional Golf Association affect and influence their playing partner's performance. Throughout the analysis I utilize data generated and gathered from the Professional Golf Association. The game of golf can be traced back to the early fifth-tenth century in Scotland. Today, the PGA Tour is considered the most elite golf tour in the world, and has the toughest requirements to retain a PGA player card, which is a required to compete.

During every round of a tournament, players can witness their playing partner's shots and scores. Being able to observe other player's shots can in fact generate a number of opportunities to gain knowledge and motivation for a player's next shot (Guryan, Kroft, and Notowidigdo, 2009). This knowledge is perceived as an advantage to most professional golfers.

Players can easily gain knowledge throughout a round of golf by observing another player hit a shot similar to theirs. However, the question is how will each player adjust to the knowledge gained. For example, wind can play a major role in a golf tournament, specifically when aiming to hit the green. Most golfers have adequate knowledge about where on the green is a good and safe play**.** Players must be able to measure the wind correctly in order to accurately hit the ball where they desire. The direction and strength of the wind can create uncertainty in about which club is appropriate in order to land the ball where desire.

For example, imagine there is a strong wind present, Player A hits first off the tee, and lands in the water, 20 yards short of the green. This might change Player B's perception of how strong the wind is, and Player B may choose a longer club so to hit a longer shot then they first anticipated. Hence by observing the previous player's shot, Player B can indeed gain useful knowledge about the conditions which can lower the risk of hitting a bad shot.

This knowledge can also be useful for a player's strategy purpose. Consider another example, Jack Nicklaus and Arnold Palmer are partnered together and are tied going into the last two holes. If Jack Nicklaus lands in the water off the tee, then Arnold Palmer might contemplate playing a "safer" shot then he first anticipated when walking to the tee. A player's strategy can quickly change after observing a similar shot, especially from the tee box.

Motivation can also play a factor when hitting second from the tee box. Consider the previous example, but instead Jack Nicklaus hits a great shot that stops right next to the hole. This could mentally motivate Arnold Palmer or, counter intuitively, hurt him, depending on Palmer's original strategy. By observing a great shot, this could encourage Arnold Palmer to hit just as good of a shot as Jack Nicklaus.

Whether it's a positive or negative effect, the knowledge and motivation gained by observing other players hit similar shots can easily affect a golfer's performance. In order to be a great golfer, players must have a strong mental ability to modify their approach in the right direction when unknown circumstances present themselves. Most of Hall of Fame golfers, like Arnold Palmer and Jack Nicklaus, could properly take the knowledge gained from watching their player partner's shot and use it to help them make better judgements and create positive motivation.

In an effort to put all the players on the same playing field, I have chosen to restrict the data used in this analysis to the last two rounds of a tournament. Thus, the pairings are not random, as the pairings in the last two rounds are determined by each player's individual performance in the previous rounds of the tournament. This is unlike the first two rounds of a tournament where the pairings are normally 'said' to be random.

During the last two rounds of a tournament, players are usually paired into groups of two. The order in which player tees off is clearly stated in the rule book of golf. Rule 10-2A states, that the player with the lowest score on the previous hole has the honor of teeing off first at the next hole. If both players were to tie on the previous hole, then the order of play on the teeing ground is the same as the previous hole (USGA).

EXISTING LITERATURE

Side by side peer performance has been studied in many fields, more heavily in education and the workplace, but lately more attention has been focused on peer effects within a competitive environment. I will now discuss a few studies that are related to this paper.

One piece of literature that is similar to the question at hand is a study done by Jonathan Guryan, Kory Kroft, and Matthew Notowidigdo (2009), which focuses on peer effects in the workplace. Some of the data was derived and supported from golf player pairings on the PGA Tour. In their thorough analysis, they found insignificant evidence that supports the theory of player partner's performance influencing one own's performance.

After analyzing the data, they stated that they were *"able to rule out peer effects larger than .043 strokes, for every increase by one stroke in their player partner's performance"* (Guryan, Kroft, and Notowidigdo, 2009). In their study, they were aiming to analyze random groupings in tournaments, so they decided to use the first two rounds when pairings are supposed to be selected by random. However, some studies argue that the selections in the first two rounds of a PGA tournament are not random, but are biased and selected to boost TV ratings and ticket sales. In my paper, I decided to focus more on the last two rounds of golf tournaments when pressure and prize money was a considerate factor.

The psychology of peer effects in performances can be dated back to the late 18th century. Norman Triplett (1898) validated that one's individual performance can influence one's peer's performance. Triplett found that bicyclists posted a better time when they were racing with a fellow competitor, compared to when they raced alone. His paper finds that observing a peer perform a similar task in a competitive environment, it can have a positive influence in one's own performance.

Ehrenberg and Bognanno (1990) argue that the payout structure in the PGA substantially influences a player's performance. They explain how complex and skewed the payout structure for tournaments are in the PGA. However, they also explained that the payout structure was needed to be how it is, in order to prevent colluding within the players. They acknowledge that the marginal return is substantially higher in the top standings of a tournament, when compared to lower standings. They found that performance effects are easily more noticeable in the last two rounds when pressure and fatigue are major factors.

Haraguchi and Waddell (2007) look at a golfer's performance relative to monetary payouts. Using a spatial econometrics approach, they find a positive monetary marginal effect on player performance when players were tied in the final round of a tournament. Haraguchi and Waddell also sorted players by standing and ability, creating more precise predictions for whether other player's performance influences one's own.

Mas and Moretti (2009) analyze data in the retail industry to analyze what peer effects have on worker's performance in a supermarket. In their analysis, they find significantly positive peer effects within workers at the supermarket when working along with highly productive coworkers. However, since working in a retail environment can be viewed more as a team environment they find that employees were able to free-ride on other coworkers when it was possible without detection. However, in most PGA events free riding is not attainable as each player's position is solely based on their individual performance. This study and many others alike focus on how low skilled labor performance is affected by social and peer effects. Motivated from these papers, I will determine if peer effects occur on performance in the highly skilled workforce of professional golfers.

In 2001, Bruce Sacerdote looks at another aspect of peer effects. Sacerdote collected data describing freshman students at Dartmouth University to determine the peer effects at a prestigious college. He finds a positive correlation within roommates GPA. That is, if one roommates GPA is relatively high then this can help increase the other roommates GPA accordingly (Sacerdote, 2001). His findings are aligned with most peer effect performance theories discussed. Here, however, once Sacerdote accounts for the fixed effects within the college student's GPA, the coefficients and significance in his analysis drops majorly.

Baumeister (1984) conducted six experiments to determine what impact pressure can have on someone's performance. He noticed in each case of added pressure that there was an increase in the person's continuous attention to the task at hand. In all six experiments that he conducted, he found that as one's self attention increased due to pressure moments, their performance decreased (Baumeister, 1984). He points out that as one's own attention to the task at hand increases due to a substantial amount of pressure, that this could in fact disturb the nature of the performance. This can easily be related to a golf stroke as the execution of the stroke is mostly muscle memory. If a player is so concentrated on the thought of performing well, then the player might lose focus on his instincts and his muscle memory, therefore resulting in an undesirable shot. This has been observed a numerous of times in the PGA, as some players can't handle the pressure when it comes down to the wire of a tournament and therefore they end up choking and performing worse than expected.

DATA DESCRIPTION

The data I analyze in this paper were mainly collected from the shot link system created by the PGA Tour. The system collects data on the majority of the players throughout a season. Including tee times, group pairings, payouts, shot statistics, and course statistics. The data collected was for ten seasons, from 2004 to 2014. The data covered 344 tournaments over ten years, with most tournaments compromising of around 125 to 150 players. By using these different variables, we hope to analyze peer effects in the PGA.

Traditional Four Round Tournaments

I limit this study to four round tournaments, which are the norm on the PGA Tour. There are two main types of play on the PGA Tour, match play and stroke play. Stroke play means that each stroke of each hole is added up to reach your total round score. Unlike other sports, in golf the players are trying to attain the lowest score possible, so the lowest combined score for all four rounds at the end of the tournament wins. Match play is different in that the golfers are only considering their score for each hole, thereafter the winner of that hole will gain one point, the player with the most points after 18 holes, wins. I restrict the data to stroke play because I believe there is more “on the line” when every stroke counts towards your overall position.

In a basic four round tournament, the pairings of the players are said to be selected at random in the first two rounds, however some would disagree. After the first two rounds, most tournaments will have a cut where they eliminate about half of the players based on overall standings.

In rounds three and four, player pairings are decided by the players individual score or standing within the tournament at the end of the previous round. The last two rounds are usually made of player pairings of two, as oppose to three or four in the first two rounds. In this paper, I only look at the last two rounds of a four round tournament for several reasons. First and mainly, because we are solely interested in players whose performances have been similar in each tournament. This will allow us to observe peer effects when the players have similar incentives and obstacles.

Secondly, I am only interested in players who make the cut after the second round, as these players have qualified to earn money, and therefore have a significant incentive to perform well the rest of the tournament. As expected, the higher the performance and finish, the higher the payout is for each player. However, the payoffs on the PGA Tour tend to be very skewed. That is, the top 10% of players who make the cut, earn over 50% of the total prize money allocated to all players (Rinehart, 2009). PGA events give a whopping 18% to the winner of the tournament, while second and third place take home only 10.8% and 6.8%, respectively. All of these statistics are shown in Figure 1.

One stroke can end up costing golfers three quarters of a million dollars in major tournaments. This convex prize distribution can create enormous pressure on every shot for players who are near the top of the leaderboard. However, the convexity of the payouts is needed in order to prevent colluding within the sport. By looking at Figure 1, we are easily able to see the skewness in the monetary payoffs for PGA tournaments. I limit the observations to the top 10 pairings in order to establish similar player skill between players. By doing so, the noise of each player's skill ability difference should be limited.

Variables

The PGA Tour has several variables on each player for each shot, however not every variable is relevant to our study. The remainder of the section will explain in detail each relevant variable we include in our analysis.

Par 3's

During the course of a round of golf, players consider a number of variables on every shot. These variables could be: 1) the distance to the pin, green, bunker, or water; 2) the lie of the ball; downhill, uphill, if its buried deep in the rough, will it fly out or slowly come out of the rough, is the ball above your feet or below, players stance; 3) Pressure from each shot; is the player in the lead or trying to come back, will the player be rewarded millions or just thousands, is it a major; 4) The golf balls direction of projectile, considering; the wind, weather, is there a tree or obstacle in the direction you want to hit.

All of these variables can interfere with each shot a player takes. In order to eliminate so much noise and uncertainty, I limit the focus to only tee shots on par three holes. Tee shots will eliminate unidentified variables like a player's stance and the ball's lie. Further, par three's are normally designed to require only one shot to get from tee to green.

Top Ten Purses

In this analysis, I distinguish between a regular tournament and a top-ten payout tournament. There are many reasons to distinguish a top-ten purse tournament from a regular tournament. The first is the overall monetary payout. The combined total purse in a major championship, for example, is far greater than the average payout for non-major tournaments. This is mainly because the qualifications and skill levels are much greater than a regular tournament. The total purse price is correlated with the tournaments TV revenue and ticket sales. The higher the total payout, the greater the incentive is for more players wanting to compete. Thus, the PGA must set higher standards in order to qualify for these tournaments. Second, endorsement opportunities will increase the incentive for players to perform well in majors and other top tournaments. Third, many analyst and fans rely heavily on degree of difficulty within each tournament, and the number of majors won when deciding where that golfer will rank in the best players of all time column. All of these reasons can help explain why the incentive to perform well in a top tournament is larger than in regular tournaments. Therefore, this variable tests whether competing in a top-purse prize tournament changes the peer effects between players.

Rankings

The world ranking system incorporated by the PGA tour is perplexing. This system uses a range of variables such as the strength of competitors in each tournament and the number of top finishes in order to determine the rankings of the top golfers in the world. By knowing the rankings of players and how far apart playing partners are from one another, I will be able to analyze if there’s an effect present. We would think an intimidation effect could come into play at some point. We will analyze the ranking differential within each pairing to determine if the rank of their pairing partner is of any significance at all.

Distance

Data on the distance (in inches) to the hole after the shot was taken. It will be used to show the quality of each player's shot. Hole placements are not always the same every year and round. Tournament officials determine hole positions on the greens in order to challenge golfers and to create excitement. They know where to place the hole for easy locations and hard pin locations depending on the course conditions for the day. Sometimes players will not try to land the ball right next to the hole, especially on par 3's as it is usually very risky to do so. Most players are okay with aiming at a safer and bigger landing spot farther away from the hole. I limit the data to tee shots that landed on the green only. I will use the distance to the pin after the shot for player two as the dependent variable in all models.

EMPIRICAL ANALYSIS

The research applies ordinary least squares (OLS) and a fixed-effects model to analyze the effects on the playing partners shot effects. By conducting a Hausman test, I was able to determine that the fixed effects model is superior to the random effects model. As a result, I will show the fixed effects model of the analysis in a baseline model and make changes to determine if a better model is obtainable.

The following models will include the variables $DISTANCE_1$, $DISTANCE_0$, $PLAYERRANK_1$, $PLAYERRANK_0$, $MONEY_1$, $MONEY_0$, $PLAYERAGE_1$, $PLAYERAGE_0$. Variables with a “0” subscript correspond to the first player to shoot off the tee box. Variables with a “1” subscript correspond to the second player to shoot off the tee box. It is important to note the observation level of the data. Each variable though out this paper is observed on year, tournament, partnership, player, and hole levels. Meaning each observation is sorted into categories (year, tournament, partnership, player, hole) to analyze the data properly.

Throughout the analysis I will restrict observations to certain criteria. For example, the primary model is associated with observations from all stroke play tournaments in the PGA. Since I believe there could be more “on the line” for tournaments when payouts are substantially more, I will re-estimate all the models, limiting observations to all top-ten total purse tournaments. We suspect that monetary and intangible awards could create more pressure for players, which could alter player performances. I will also restrict the observations to shots that only land on the green. I choose to do this in order to get a more realistic variables when it come down how far apart player’s are when they land on the green.

The main model in equation (1) is as follows:

$$DISTANCE_1 = \alpha + \beta_1 DISTANCE_0 + \varepsilon\ , \tag{1}$$

where $DISTANCE_1$ is the distance to the hole in inches after the shot when the player teed off second; α are the fixed effects; β_1 is the estimated parameter; $DISTANCE_0$ is the distance to the hole in inches after the shot when the player teed off first; and ε is a zero mean error term.

The estimated results of Equation (1) are recorded in the first column of Table 1. Equation 1 will produce intuition on how player one can affect player two's shot from the tee box. Looking at the results from this simple regression, the model presents an R^2 value of fifth-teen percent and shows that the independent variable, $DISTANCE_0$ is insignificant at the ninety-five percent confidence interval.

The parameter on $DISTANCE_0$ is not significantly less from one. This suggests that we can not certainly say that player two's landing distance to the pin is significantly smaller than player one's distance after the shot. Interpretation of $DISTANCE_0$ is "for every one inch increase in $DISTANCE_0$, $DISTANCE_1$ is expected to increase by .02 inches." For example, suppose player one and player two are both expected to land the ball twenty feet from the hole, on average. However, instead player one lands the ball 30 feet from the hole, a difference of plus ten. Now player two is expected to hit the ball 20.20 feet away from the hole, a difference of only 0.2 feet. Analyzing this model, one might propose that player two has a higher probability of hitting their ball closer to the hole then player one does, on average. However, it doesn't seem to be a significant affect.

I now extend the analysis to consider more variables with the same dependent variable. The next model, Equation (2) is as follows:

$$DISTANCE_1 = \alpha + \beta_1 DISTANCE_0 + \beta_2 MONEY_1 + \beta_3 MONEY_0 + \varepsilon \quad , \quad (2)$$

where the distance variables are the same as Equation (1); the β's are the estimated parameters; $MONEY_1$ is, the money eventually won by the player who teed off second; $MONEY_0$ represents the money won by the player who teed off first.

Equation (2) helps test if payouts have any influence on performance within partner pairings. The estimation results of Equation (2) are reported in the second column of Table 1. From interpreting the results, this model has an R^2 value of twenty-eight percent. The results show that $DISTANCE_0$ is still statistically insignificant at the ninety-five percent confidence interval. $MONEY_1$, the monetary payout player two receives, is statistically significant at the ninety-five percent level. However, $MONEY_0$ is insignificant at the ninety-five percent confidence interval. I still believe these variables to be relevant specifically at the top of the leaderboard, when one stoke can cost a player hundreds of thousands.

The next model adds two more independent variables, with the same dependent variable. The next model, Equation (3) is as follows:

$$DISTANCE_1 = \alpha + \beta_1 DISTANCE_0 + \beta_2 MONEY_1 + \beta_3 MONEY_0 +$$
$$\beta_4 PLAYERRANK_1 + \beta_5 PLAYERRANK_0 + \varepsilon \quad , \qquad (3)$$

where distance and money variables are the same as Equation (2); the β's are the estimated parameters; $PLAYERRANK_1$ is the rank at the beginning of the season of the player who teed off second; and $PLAYERRANK_0$ represents the rank at the beginning of the season of the player who teed off first.

The results from Equation (3) are recorded in the third column of Table 1. This model tests if a player's rank can affect a player's performance from the tee box.

Analyzing the results, the model has an R^2 just greater than twenty-eight percent. Like the previous models, the results show that $DISTANCE_0$ is statistically insignificant at the ninety-five percent confidence interval.

The parameter on $DISTANCE_0$ from Equation (3) is slightly greater than zero, at 0.022, but insignificant. The results reported in this paper are similar to those of Guryan, etc., (2009). In Guryan's paper, he was *"able to rule out peer effects larger than 0.043"*. Even though the estimated parameter in this paper are insignificant, the estimated peer effect are somewhat similar to what Guryan, etc. reported in their paper.

$MONEY_0$, the monetary payout player one will receive has a negative correlation to $DISTANCE_1$. This means the more money player one makes for the tournament, then player two's shot should land father away from the hole, on average. Like the previous models, $MONEY_0$ remains statistically insignificant. However, we believe that these variables are relevant to the foundation of the model.

$PLAYERRANK_1$ is negatively correlated with $DISTANCE_1$. This parameter is as expected, a higher (better) golf ranking will tend to lower the distance to the hole for the same player. For every one rank increase for any golfer, it will shorten his distance to the hole by 0.12 inches when teeing off second, on average. $PLAYERRANK_0$ is positively correlated to $DISTANCE_1$, however is insignificant at the ninety-five percent interval. This suggests that as a pairing partner's rank improves, the distance to the pin after the shot should increase, for player two, on average. $PLAYERRANK_1$ was statically significant, but $PLAYERRANK_0$ shows to be insignificant at the ninety-five percent confidence interval. Still, we believe that player rankings could in fact influence their playing partners shot. Intimidation could hinder or improve a performance of certain golfers in the PGA.

Like above, the next model will have additional independent variables along with the same dependent variable ($DISTANCE_1$). The new model, Equation (4) is as follows:

$$DISTANCE_1 = \alpha + \beta_1 DISTANCE_0 + \beta_2 MONEY_1 + \beta_3 MONEY_0 + \beta_4 PLAYERRANK_1 + \beta_5 PLAYERRANK_0 + \beta_6 PLAYERAGE_1 + \beta_7 PLAYERAGE_0 + \varepsilon \text{ , (4)}$$

where distance, money, and player-rank variables are the same as they are in the previous equation; the β's are the parameters to be estimated; $PLAYERAGE_1$ represents the player's age at the start of the season of the player who shot second off the tee box; and $PLAYERAGE_0$ represents the players age at the start of the season of the player who shot first from the tee.

The estimated results for Equation (4) are reported in the fourth column in table 1. This model will serve to clarify if players age can have an influence on player's performance off the tee. Interpreting these results, the model has an R^2 marginally exceeding twenty-eight percent and only shows one variable being statically significant at the ninety-five percent confidence interval. Like before, $DISTANCE_0$ is statistically insignificant, as well as $MONEY_0$ and $PLAYERAGE_0$. $PLAYERRANK_1$ remains negatively correlated with $DISTANCE_1$, i.e., for every one rank increase (better), this will shorten the distance to the hole by 0.11 inches when teeing off second, on average. Money variables remain negatively correlated to $DISTANCE_1$ and are insignificant; however, we still believe these variables to be an important aspect to our model. One note worth mentioning, is that $PLAYERRANK_1$ changes from being significant in Equation (3), to being insignificant in this model.

$PLAYERAGE_1$ is negatively correlated to $DISTANCE_1$, however it is statistically insignificant at the ninety-five percent interval. This means, that as a player two increases in age each year (one unit), then his distance to the hole should decrease by 2.9 inches, on average. $PLAYERAGE_0$ is positively correlated with $DISTANCE_1$, however is weakly insignificant at the ninety-five percent confidence interval. Interpreting this variable, the results show that as player one's age increase every year (one unit), the distance to the pin for player two is suppose increase by 35 inches. We believe the to be major a red flag, as this parameter is too large for comfort. We believe that Equation (3) seems to be a better fit for the model because of this high parameter and having only one variable that is statistically significant.

Both Shots Hit the Green

I now restrict the data for observations where both shots (player one and player two) hit the green. I believe this sample will provide better useful knowledge for when both player's hit the green, which is a little more then half the time.

The following data are reported in Tables 3 and 4. When comparing all observations and the sample when both players hit the green, $DISTANCE_1$ seems to drop in magnitude for each model above. In most cases, the coefficient for DISTANCE1, dropped by at least half of what it was when we consider all observations. This is as expected, as one would assume player's who both hit the green will be closer to each other then verses pairings where one might be on the green and one might not.

Most of the variables have the same correlation to DISTANCE1 when comparing all observations to the sample when both player's hit the green. However, looking at the sample, we now have no variables that are statisciatlly significant at the ninety-five percent confidence interval. The coeffiecnt for player-rank and player age variables do seem to rise significantly when we limit the sample the to both players hitting the green. The constant for the sample drops almost in half for most of the models above. This is as expected. The smaller sample only looks at shots that landed on the green, whereas all the observations considers shots that landed on the green, surrounding area, in the bunkers, or in the water. We should expect the average distance to the pin after the shot should significantly drop once we limit the observations to the smaller sample.

Top Ten Purses

Professional golfers must deal with different levels of stress throughout a season. Tournament payouts can contribute to the levels of intensity and nervousness each player will face. To determine if performance is effected when the payouts are large we will now we restrict the data to the top ten purses for each season. This will help me analyze if player one's shot will affect player two's shot when the amount of money on the line is large. I re-estimate the equations above but limiting the observations to only the top ten purses.

The results using top-ten purses are reported in columns five through eight of Table 2. When comparing the models above for all tournaments versus top ten purse tournaments there doesn't seem to be much movement in any of the variables. The estimated parameter for $DISTANCE_0$ seems to significantly decrease for most models when we restrict the data to the top ten purses.

I suspect this is because there are better players in these higher payout tournaments. Accordingly, these better players are more focused due to the higher monetary and intangible incentive. However, I also suspect that there is some form of “choking” occurring in these top purse tournaments. Players can easily get choked up on one or two holes, and feel so far behind that they don’t believe they can get back into contention. This choking theory along with better players competing is why I believe we see such a change in the $DISTANCE_0$ variable. I believe that the added pressure from the increased monetary and intangible incentives influences player two’s shot after observing player one hit a similar shot. Looking at the results, there seems to be a negative impact on the player who tee’s off second, on average.

The models shown using the top-ten payout show a lot of variables dropping in the level of significance. Actually none of the variables in all four models are significant at the ninety-five percent confidence interval. However, the low number of observations within the top-ten purse tournaments could explain this.

Rankings

Ranking differentials within parings in the PGA happens occasionally. Professional golfers are paired in groups of two for the last two rounds in most tournaments. The pairings are determined by each player’s performance throughout each round. This means that a golfer ranked one hundred in the world could be paired with the number one ranked golfer in the final round. I tried to test if player rankings within a pairing can influence each other’s performance on the course. Trying to determine if a rank differential greater than 20, 40, and 60 ranks would show any effect on $DISTANCE_1$. However, the results were not as expected.

I included the same variables as Equation (3), but with additional interaction terms of rank differentials and $DISTANCE_0$. Since we limit the data the final two rounds and top pairings according with the leader board, we don't see that many rank differentials within the top pairings. The results show that there are not enough observations for the interaction terms in order to get an obtainable result. Maybe moving forward, I will try to find if there are enough observations in a bigger data set.

CONCLUSION

The objective of this paper is to analyze the connection between professional golfers and any peer effects to determine if one player's performance can influence another player's performance. The purpose is to see if the most skilled golfers in the world seem to have any peer effects on their competitors within their workplace. Data describing the PGA tour players cover over the period from 2005 to 2015 is used to test the hypothesis that player's performance can in fact influence their peer's production. This study was specifically analyzed for data on the tee box and for par three holes.

The technique used in this analysis is a fixed effect estimator model. The dependent variable (DISTANCE1), is estimated in each of the models with additional independent variable adjustments to each model. I identified various independent variables that may provide insight into how far PGA golfers land their tee shots from the hole on par three's. Once I identified the appropriate models, the analysis then tested and reported the significance of each model and its relationship.

Contrary to many of the studies analyzed in this paper, that PGA players can affect other player's performance. The results from this research, shows that there doesn't seem to be concrete evidence in support of this hypothesis. My study finds there are significant effects within one's own performance, but fails to finds statistically significant evidence in all models that support peer influences on other players. When looking at the top-ten purse tournaments, the results don't seem to show any evidence in support of the theory.

When starting this research, I thought there would be a significant effect in favor of the hypothesis. However, one might not be surprised by this finding when they think about the skill level and degree of difficulty required succeed as a PGA golfer. These athletes are the best in the world at golf and should not be influenced by how other player perform. I would be interested in analyzing a paper written in depth on the psychological aspect of peer effects within the PGA tour. I would assume the pressure aspect and "choking" theory could come into play more heavily when looking at the psychological peer effects between golfers.

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APPENDIX A: TABLES

Table 1. All tournaments

VARIABLES	(1) distance1	(2) distance1	(3) distance1	(4) distance1
distance0	0.0203	0.0290	0.0219	0.0259
	(0.0124)	(0.0219)	(0.0229)	(0.0230)
money1		-9.72e-05***	-9.36e-05**	-9.56e-05**
		(3.74e-05)	(3.87e-05)	(3.88e-05)
money0		-9.88e-06	-2.28e-05	-1.98e-05
		(4.47e-05)	(4.65e-05)	(4.66e-05)
playerrank1			-0.117*	-0.114*
			(0.0611)	(0.0612)
playerrank0			0.0147	0.0149
			(0.0593)	(0.0593)
playerage1				-2.890
				(20.89)
playerage0				35.40*
				(21.18)
Constant	345.3	333.8**	374.7**	-1,079
	(287.1)	(169.1)	(176.3)	(1,351)
Observations	13,163	7,569	7,229	7,168
R-squared	0.149	0.280	0.285	0.283
Number of holeid	4,653	3,943	3,850	3,841

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2. Top-Ten tournaments

VARIABLES	(5) Top Ten	(6) Top Ten	(7) Top Ten	(8) Top Ten
distance0	-0.0274	0.0148	0.0286	0.0415
	(0.0325)	(0.0516)	(0.0552)	(0.0575)
money1		-4.93e-05	-6.61e-05	-6.09e-05
		(7.58e-05)	(7.88e-05)	(8.01e-05)
money0		-0.000144	-0.000166	-0.000166
		(9.97e-05)	(0.000103)	(0.000105)
playerrank1			-0.405	-0.414
			(0.274)	(0.280)
playerrank0			-0.222	-0.237
			(0.322)	(0.327)
playerage1				-14.37
				(66.62)
playerage0				-13.70
				(67.80)
Constant	491.0	191.5	294.6	1,450
	(538.1)	(496.8)	(520.0)	(4,010)
Observations	3,191	2,206	2,134	2,081
R-squared	0.364	0.477	0.466	0.460
Number of holeid	1,126	1,000	983	975

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3. Both shot hit the green

VARIABLES	distance1	distance1	distance1	distance1
distance0	0.0102	0.0887	0.0735	0.0731
	-0.0267	-0.072	-0.0747	-0.0758
money1		3.57E-05	4.30E-05	2.81E-05
		-8.13E-05	-8.20E-05	-8.30E-05
money0		-0.000116	-0.000106	-0.000134
		-0.000121	-0.000125	-0.000128
playerrank1			-0.0748	-0.0955
			-0.176	-0.177
playerrank0			0.0292	0.0487
			-0.194	-0.195
playerage1				16.24
				-59.35
playerage0				-88.8
				-55.97
Constant	184.7	177.9**	200.2**	4,178
	-153.8	-90.1	-94.2	-3,496
Observations	5,241	3,093	2,975	2,956
R-squared	0.407	0.825	0.842	0.843
Number of holeid	2,851	2,192	2,132	2,124

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4. Both shots hit the green (Top-Ten)

VARIABLES	(5) Top Ten	(6) Top Ten	(7) Top Ten	(8) Top Ten
distance0	0.0074*	0.0365	0.0645*	0.0376*
	(0.0132)	(0.0220)	(0.1130)	(0.0211)
money1		-0.000680	-6.60e-05	8.88e-05
		(0.00229)	(0.000441)	(0.000327)
money0		0.00263	0.000138	0.000170
		(0.00578)	(0.000504)	(0.000510)
playerrank1			-0.281	-0.304
			(3.957)	(4.456)
playerrank0			-1.731	-0.015
			(2.773)	(2.307)
playerage1				-33.93
				(113.73)
playerage0				-26.85
				(39.93)
Constant	263.2	119.3	190.0	3156.0
	(312.5)	(309.5)	(332.8)	(8891.0)
Observations	1172	824	802	785
R-squared	0.97	0.951	0.955	0.954
Number of holeid	657	537	529	522

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX B: FIGURES

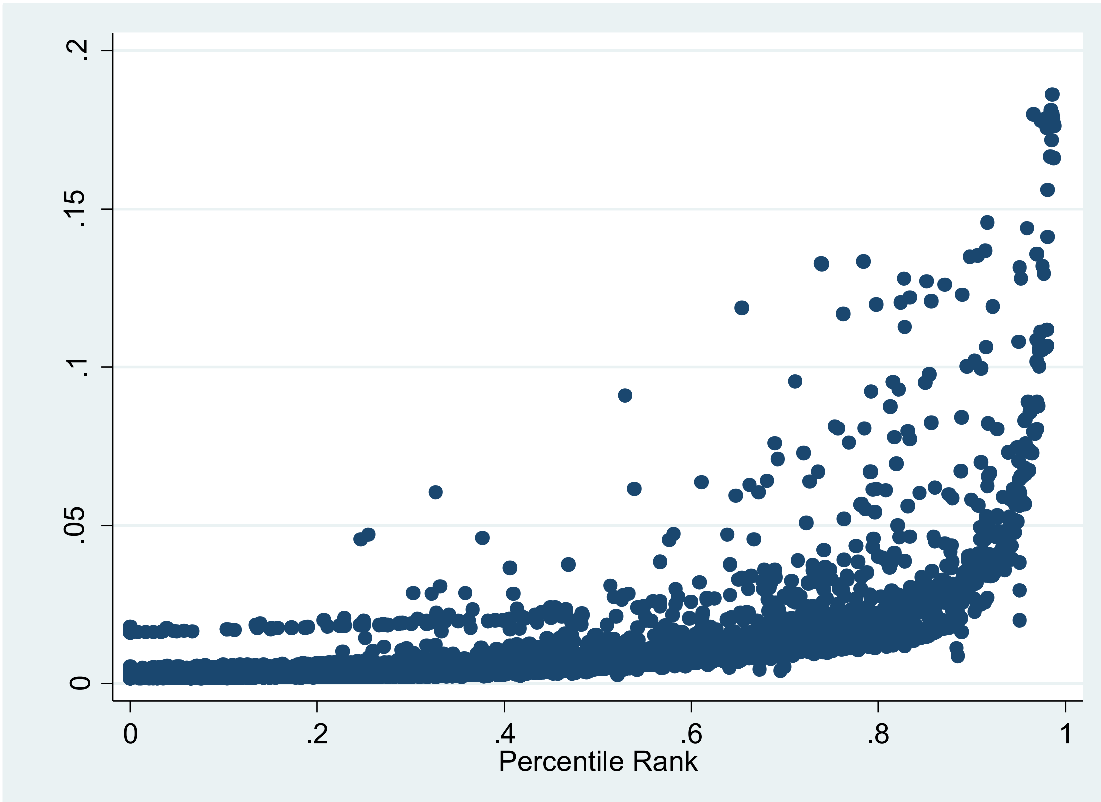

Figure: 1. Payout structure for PGA tournaments