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A Comparison in the Returns to Skills on the European Tour and the PGA Tour

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Abstract: This study uses 2015 data from the PGA Tour and the European Tour to analyze differences in the returns to shot making skills between these two top professional golf tours. As the European Tour grows to become a competitive alternative to the PGA Tour, a player will be faced with a decision of which tour to compete to maximize the economic payoff. A model similar to Shmanske (1992) was used to run OLS regressions and quantile regressions. The quantile regressions were used to determine differences in the returns across various points on the earnings distribution. The findings suggest that a player on the PGA Tour requires a different skill set to be competitive than a player on the European Tour. The PGA Tour results are consistent with past studies on returns to skills in (e.g. Moy and Liaw 1998 and Alexander and Kern 2005). Driving distance and putting skills are significant determinants of earnings on the PGA Tour. Iron play and putting skills are significant determinants of earnings on the European Tour. This study adds to previous golf economics studies by investigating returns to skills on the European Tour and comparing those differences to the PGA Tour.

I. Introduction

There are two major professional golf tours that young players aspire to one day compete on: the PGA Tour and the European Tour. The PGA Tour is the worldwide leading professional golf tour and has been the center of many golf economic studies to date. The European Tour is a growing professional golf tour that has been scarcely analyzed in sports economic research and it is currently the second biggest professional golf tour in the world in terms of prize earnings. These golf tours each host 40 to 50 tournaments a year that allow for professional golfers a chance to make a large sum of money. The PGA Tour hosts the majority of its tournaments in the United States, while the European Tour hosts the majority of its tournaments in Europe. A prize purse is pre-determined and distributed amongst the players that make “the cut”. The cut comes after two rounds of competition and limits the field to the 70 players with the best scores. At the end of the tournament, the tours distribute 18% of the total prize pool to the tournament winner, 10.8% to second place, 6.8% to third place, 4.8% to fourth place, and down to .2% for seventieth place. In 2015 The Players Championship on the PGA Tour had the largest prize purse, which totaled $10,000,000. In the same year the BMW Masters had the largest purse on the European Tour totaling $8,000,000. Both of these tours require a player to earn a membership to play in unlimited events on their respective tour.

While the biggest names in professional golf typically are found on the PGA Tour, many talented professionals earn a healthy living on the European Tour. Some professionals choose to compete on both tours. In 2015, there were 12 players that were in the top 150 money earners on both the European Tour and the PGA Tour. The European Tour has seen recent growth in the size of its prize purses, yet not quite the size of the PGA Tour. Currently, many young golfers will participate on the European Tour to gain experience and some prize earnings before hoping for an eventual move to the PGA Tour. The European Tour has stated it hopes to make big changes over the next three to five years and provide a comparable alternative to the PGA Tour, both in terms of prize money and player experiences. That makes the European Tour worth studying in economics. My research will add to the literature by telling professional golfers what it takes to be competitive on the European Tour as compared to the PGA Tour and how they can develop their skills for the highest expected earnings on each tour. It will also tell a player what tour will naturally suit their skill set for the highest expected earnings. It will be the first paper to calculate returns to skills for professional golfers on the European Tour.

The final results of the study show that putting and iron play are the two most significant determinants of earnings on the European Tour and putting while driving distance are the two most significant determinants of earnings on the PGA Tour. Driving the golf ball was not found to be a significant determinant of earnings on the European Tour. These results show that a player who is a good iron player should pursue the European Tour, given financial comparability, and a player that has a long driving distance should pursue the PGA Tour.

In Part II of this paper, I will conduct a review of the current economic literature in professional golf. In Part III, I will go over the data and methodology used in the study before discussing the results in Part IV. The final section, Part V, will draw conclusions from this research.

II. Literature Review

Lazear and Rosen (1981) pioneered the research in golf economics. They analyzed rank order tournament theory through the lens of professional golf. This study has lead other sports economists to examine various topics throughout professional golf. Research into how skills affect golfers' prize earnings at the professional level has been going on for quite some time.

Davidson and Templin (1986) was the first paper to examine the relation between a golfer's skills and the prize earnings. These studies are created on the theoretical model of human capital theory and human capital investment; that is, what skills and attributes contribute to the most economic value in labor. In golf terms, this means which skills will contribute to the highest expected winnings. These studies use a similar theoretical model as Mincer (1974) where earnings have a direct relation to schooling and experience. Mincer (1974) uses a log of the wage as the dependent variable and then vectors of a worker's schooling years, *S*, and experience, *Exp*, as a series of independent variables in his model:

$$\text{lnwage} = \beta_0 + \beta_1 S + \beta_2 \text{Exp} + \beta_3 \text{Exp}^2 + \varepsilon$$

Although there are some issues with this model, it is still relevant as a solid theoretical framework for human capital investment. Davidson and Templin (1986), along with many later studies, directly links shot making skills to prize earnings and attempts to determine the value of marginal product (VMP) of professional golfer's skills. The theory is that a player's earnings are a direct result of their shot making skills. Davidson and Templin (1986) included a series of skill measures that made up a vector of independent variables. The dependent variable is the player earnings for a year. This paper found a positive correlation between driving skills, hitting greens in regulation, putting skills and the dependent variable, prize earnings. After Davidson and Templin (1986), sports economists had a theoretical framework to work from and expand on. Shmanske (1992) contributed to the literature by being the first study to include experience factors in the model with the idea being that a combination of skills and experience affect a player's prize earnings. Many later returns to skills in professional golf studies have used this regression approach to determine the expected earnings of players, and the findings of these studies are very similar. Driving distance, putting average and greens in regulation percentage are significant determinants of prize earnings and driving accuracy and sand save percentage are sometimes significant in these studies. These early papers laid a theoretical foundation for other studies in this field.

Moy and Liaw (1998) examines returns to skills in professional golf on the three main professional golf tours in the United States, the Ladies Professional Golf Association (LPGA) Tour, the Senior PGA Tour and the PGA Tour. The motive of the paper was to determine if a difference exists in the returns to skills between the three tours. The LPGA Tour is the leading tour for women professional golfers in the world. Similarly, the Senior PGA Tour is the top global tour for professional players over the age of 50. Their methodology is similar to Davidson and Templin (1986) where a player's earnings are the dependent variable and vector of skill measures makes up the independent variables. The data used in this study is from the 1993 professional golf season. The data shows a large difference in the mean prize earnings of the three tours, with the LPGA Tour professionals earning much less than the other two tours. The paper finds differences in the importance of certain shot making skills for the different tours. PGA Tour professionals require a complete skill set to achieve the highest expected earnings. On both the Senior PGA Tour and the LPGA Tour, the players can maximize their expected earnings by having a good short game and being a good iron player. Green in regulation percentage measures iron play. Driving the golf ball is less important on the Senior PGA Tour and LPGA Tour. This paper does not add a control for experience, which was introduced in Shmanske (1992). Therefore, the coefficients are likely overestimated in this study. This paper relates very closely to my study, as I will also be analyzing differences in the returns to skills between two professional tours.

Nero (2001) used returns to skills to determine the efficiency of the world's top professional players based on their year-long averages. After calculating a player's returns to skills, Nero (2001) calculated a player's comparative performance. The data used in this study was from the PGA Tour season in 1996. The data set included a vector of skill measures and a control for the amount of tournaments the player entered. Again, this paper did not include a control for a player's experience, so it is likely that the coefficients are slightly overestimated. After estimating returns to skills using OLS, study looks to find if players make their predicted earnings based on their skills. The author also wanted to find out which player earned the most prize earnings given their statistical averages in the estimated equation. Nero (2001) uses the estimated equation to measure this. The study takes a player's statistical averages and plugs them back into the estimated equation to figure out what that player could have expected to earn in that season. The study takes the expected earnings of that player and draws comparisons to the actual earnings. Nero (2001) finds that Tom Lehman earned the most money in that year relative to his performance. Based on the model, Tom Lehman could have expected to earn $418,749 in that season. Instead, he actually earned $1,780,159. He therefore was the most efficient golfer from that year. Conversely, Paul Azinger was determined to be the most inefficient golfer from that year; he earned less than half of his predicted earnings based on his statistics. There are several reasons this could happen. For example, a player could play far above their statistical average in a tournament with a larger prize purse and therefore collect more earnings. Although interesting, this research does not necessarily help golfers realize what they need to improve to increase their expected earnings.

As time went on, professional golf saw some distinct changes. As cited in the Alexander and Kern (2005) study, there were some major changes to the technology in the golf clubs and the golf balls. The clubs were made to hit the ball longer and balls were made more aerodynamic in order to fly longer. Golf course designers began adding length to their courses in order to make them more challenging. This gave Alexander and Kern (2005) the motivation in their study to test to see if the rates of returns to skills on the PGA Tour had changed since the early 1990's. Many professional golfers and analysts began to hypothesize that golf was now a test of who could be the best driver of the golf ball. Alexander and Kern (2005) tested this idea to see if driving offered higher returns as opposed to short game skills and specifically putting. The time period the authors examine includes the PGA Tour seasons from 1992-2001 and the number of observations per year varies depending on the attainable data. The methodology is similar to Shmanske (1992), where shot making skills, experience factors, and a control for the number of events entered make up a set of independent variables. The data included in this paper are based on statistics kept by the PGA Tour with some minor adjustments in hopes to create better measures of skills. One problem I see in the data set is the short game measure the authors call CHIP. The base statistic of this measure is the scrambling statistic kept by the PGA Tour. The scrambling statistic measures the percentage of the time a player makes a par after missing the green in regulation. Therefore, this statistic is not a pure measure of short game because a player is not necessarily within 30 yards of the green, the accepted range where shots are then considered parts of the short game, when they miss the green in regulation. A player's ball could hypothetically be 200 yards from the green after the stroke taken in attempt to hit the green in regulation. The scrambling statistic does not account for that scenario. The overall findings in this paper suggest that driving skills have seen a small increase in the marginal returns over time. Even with that, putting is found to still be the most significant determinant in maximizing earnings on the PGA Tour.

Other sports economists have tried to analyze returns to skills in golf using alternative methods. Scully (2002) found a fundamental error in the theoretical models that were used in past papers (e.g. Davidson and Templin 1986, Shmanske 1992, Shmanske 2000 and Alexander and Kern 2005). Scully argues that shot making skills do not have a direct link to winnings and therefore, a single equation model cannot be used. He states that shot making skills, *X*, directly affect scoring average, *SA*, and then scoring average affects the overall finish and therefore prize earnings, *Prize*. Therefore, he created a two-equation model where scoring average is some function of skills and prize earnings is some function of a players scoring average. He also adds two other independent variables to the second equation: the player's age, *Age*, and number of tournaments entered in that season, *Events*. His multi-equation model takes the form:

$$SA = \beta_0 + \beta_1 X + \varepsilon$$

$$\ln Prize = \beta_0 + \beta_1 \ln SA + \beta_2 \ln Events + \beta_3 \ln Age + \varepsilon$$

His data set included PGA Tour statistics from 2000. Scoring average and number of tournaments for that year were statistically significant. He concluded that lowering the season scoring average by one-tenth of a stroke added close to $32,000 to the expected yearly prize earnings and entering one more event added $16,700 to the expected prize earnings.

Callan and Thomas (2007) later tried to build off Scully's theory by also using a multi-equation approach, but their goal was similar to that of Shmanske (1992). They too wanted to find the VMP of professional golfer's skills, but agree with Scully (2002) that prize earnings are indirectly affected by shot making skills. Instead, a player's shot making skills and experience level will contribute to the average round score. This average round score, along with the number of events played will contribute to the average tournament rank of that player. Finally, this tournament rank and the number of tournaments completed (the number of times a player makes money in a tournament) will be the factors that affect the prize earnings of a player. They monetize each shot making skill based on yearly earnings in order to calculate VMP of the shot making skills. The data used in this paper were from the year 2002 on the PGA tour and it looks at a cross section of 194 players. They find results similar to past studies. The study also runs OLS estimates to compare the findings of their model to what the findings would show using single equation methods. Callan and Thomas find that single equation methods overestimate the coefficients on driving accuracy, driving distance and sand saves and these studies underestimate greens in regulation percentage and putting. This issue is something to keep in mind when looking at results from past papers. The theory of Scully (2002) and Callan and Thomas (2007) has shown improvement over other previous papers when comparisons to the original OLS methods were also conducted.

Shmanske (2008) introduced another idea to try to improve on past works in the area of returns to skills in professional golf. Until this point, the data used in the methodology of other studies had been yearlong averages of statistics kept on the PGA Tour. These averages do not take into account the fact that some players do not play certain events. At some events, some statistics will be skewed because of the golf course or location. For example, at a course located in a place of high altitude, the golf ball will travel a further distance and the driving distance statistic will be positively skewed for the players that competed in that event. Similarly, at a course with firm greens, a player can expect to hit fewer greens in regulation and the green in regulation percentage statistic will be negatively skewed. To combat this problem, Shmanske (2008) compiled tournament level data to account for this problem. This study uses data from the 2006 season and it includes the top 100 money earners on the PGA Tour from the 2005 season. The data is adjusted on a per tournament basis based on the averages from that event of all of the players entered. This study reported similar results as the past literature, however it showed improvement in explaining the returns to skills in professional golf because the results again had a higher R-squared than previous OLS estimates.

Calculating returns to skills can still be developed even further. Kahane (2010) tried looking at returns to skills with consideration for the skewed distribution of payouts on the PGA Tour using data from 2004 to 2007. Kahane notes that from 2004 to 2007, Tiger Woods, Vijay Singh and Phil Mickelson won 36% of the tournaments played on the PGA Tour. Kahane used a model similar to that of Shmanske (1992) where shot making skills directly affect the earnings of the professional players. After Callan and Thomas (2007) showed improvements in the methodology to calculate returns to skills, one would assume this methodology would not have been used. In order to account for the skewed distribution, Kahane uses a quantile regression approach to show how the different shot making skills affect players along the earnings distribution. For example, if a player in the 90^{th} percentile increased their greens in regulation percentage by one percentage point or putting average by one stroke, their expected prize earnings increase would be much smaller than a player in the 10^{th} percentile. Conversely, if an earner in the 10^{th} percentile increased their average driving distance by one yard, their expected earnings increase would be much greater than a player earning in the 90^{th} percentile. Kahane (2010) is one of the first papers to take into account the skewness in the earnings distribution when looking at returns to shot making skills in golf. Because of the earnings skewness on both the PGA Tour and the European tour, I will be using a methodology similar to this study in my research. After Scully (2002) and Shmanske (2008) showed improvement in the methodology of this literature, it seems interesting that studies such as this one still uses the original methodology. One would speculate that this methodology was used out of ease. The improved methodologies are more complicated and require tedious work.

After reviewing the current literature, it is evident that there are many ways returns to skills can move beyond the current research. Since Davidson and Templin (1986), many sports economists have succeeded in making improvements on each other’s work. My work will contribute to this literature because I will be using data set from the European Tour. Much like Moy and Liaw (1998), my research will analyze the returns to skills of another tour, the European Tour, as it relates to the world’s top professional tour, the PGA Tour. To do this, I will be using a model similar to Kahane (2010) and the quantile regression approach. As Kahane (2010) cites, this will help account for the skewed distribution of earnings. Similar to the PGA tour, the top money earners on the European Tour make far more money than the rest of the players because of the pay out structure. The quantile regression approach will allow me to compare the percentiles on player’s statistics. I will also be running an OLS regression to see the overall returns to skills on the European Tour as well. This paper will give a solid foundation in future research on the European Tour and also any comparisons that will be made in the research of golf economics.

III. Data and Methodology

The model to be used in this paper is similar to that of Shmanske (1992) and Moy and Liaw (1998). The data sample used in this regression is a cross section of yearlong averages from the 2015 seasons on the PGA Tour and the European Tour. It includes a sample of the top 150 money earners on each tour from that year. All data is available to the public and can be found on the PGA Tour website (pgatour.com), the European Tour website (europeantour.com), and ESPN.com. The model takes the form:

$$\text{logearn} = \beta_0 + \beta_1\text{events} + \beta_2\text{drdist} + \beta_3\text{dracc} + \beta_4\text{putts} + \beta_5\text{gir} + \beta_6\text{ss} + \beta_7\text{pro} + \beta_7\text{pro}^2 + \varepsilon$$

The dependent variable, logearn, is the log of the player's earnings throughout the entire year. The reason the earnings are used in log form is because the percentage increases will make the results easier to compare and rescale an unequal distribution. To this point, the earnings on the PGA Tour still exceed the earnings on the European Tour. In 2015, Jordan Spieth earned the most money on the PGA Tour with $12,030,465. On the European Tour, Rory McIlroy was the leading money earner with 4,727,253 Euro. The independent variables are statistics kept and defined by the PGA tour and European Tour. The statistics included are year-end averages. The data set consists of long game measures (*drdist*, *dracc*, and *gir*), short game measures (*putts* and *ss*), an experience factor (*pro* and pro^2), and a control for the number of events played in during the year (*events*). These skill statistics and experience factors have a direct effect on a player's earnings. Combined, these variables make up a complete professional player. A more in-depth definition of the variables is included below using definitions from pgatour.com.

The *events* variable is simply the number of events entered in the year. No player on either tour competed in every tournament in 2015. That is most likely because a full schedule would lead to players becoming very fatigued and not allow them perform at their highest level. On both the PGA Tour and the European Tour, the top money earner played in a fewer number of tournaments than the average professional player. It is expected that this coefficient will be positive because playing in more events gives a player more chances to make money.

Driving distance, *drdist*, is the average number of yards per measured drive. These drives are measured on 2 holes per round. Care is taken to select two holes that face in opposite directions to counteract the effect of the wind. Drives are measured at the point at which they come to rest whether they are in the fairway or not. One would expect a positive coefficient because a farther drive leaves a player closer to the hole, therefore making the next shot easier leading to a lower score. Driving accuracy percentage, *dracc*, is the percent of time a tee shot comes to rest in the fairway (regardless of club). One would expect a positive coefficient because a more accurate player has a better chance to shoot lower scores.

Greens in regulation percentage, *gir*, is the percent of time a player was able to hit the green in regulation. A green is considered hit in regulation if the ball is touching the green after the player hit the ball on the green in regulation stroke. Subtracting 2 from the par of the hole determines the green in regulation stroke. For example, a player's second shot on a par 4 is considered the green in regulation stroke. The greater the greens in regulation percentage, the more accurate the player is with their irons, so a positive coefficient is expected.

Putting average, *putts*, and sand save percentage, *ss*, are used as measures of a player's short game. Putting average is the average number of putts it takes the player to complete the hole after hitting the green in regulation. Having a fewer number of putts leads to lower scores, so a negative coefficient is expected. Sand save percentage is the percentage of the time a player is able to hit the ball in the hole in two shots or less when in sand trap next to the green. If a player is more likely to get the ball "up and down", they will have lower scores, on average, so a positive coefficient is expected.

Pro and pro^2, are the number of years a player has played professional golf and the square of that amount of years. One would expect that a player would have increased earnings with the amount of experience but with diminishing returns as the player gets older. Therefore, one would expect years pro to be positive but the square to be negative.

The statistics show that players on the PGA Tour are, on average, hit their drives farther and in the fairway a higher percentage of the time than the European Tour players. The data also shows that the PGA Tour players average fewer puts per green in regulation hit. European Tour players are better short game players and have a higher average sand save percentage. The players on the European Tour also hit a higher average of greens in regulation that PGA Tour players. A full summary of the statistics for both the PGA Tour and European Tour are shown below in Table 1 and Table 2 respectively.

Table 1: PGA Tour- Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
events	150	25.18	4.766	12	36
earn	150	1,873,092	1,619,685	578,571	12,030,465
drdist	150	291.0	9.254	270	317.7
dracc	150	62.23	4.942	51.52	76.88
putts	150	1.766	0.0230	1.699	1.826
gir	150	66.58	2.609	58.10	73.52
ss	150	50.83	6.180	37.35	63.27
pro	150	12.77	6.279	2	34
pro2	150	202.2	196.3	4	1,156
logearn	150	14.20	0.653	13.27	16.30

Table 2: European Tour- Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
events	150	23.11	5.643	9	33
earn	150	751,041	770,998	117,469	4,727,253
drdist	150	288.6	8.579	263.4	311.4
dracc	150	61.20	5.607	49.20	74.20
putts	150	1.777	0.0269	1.712	1.842
gir	150	69.46	3.899	62.20	85.19
ss	150	55.75	8.653	20	78.40
pro	150	12.65	6.348	2	34
pro2	150	200.1	188.1	4	1,156
logearn	150	13.11	0.907	11.67	15.37

The model presented above will be used in part one of my methodology to conduct Ordinary Least Square (OLS) regressions and Quantile Regressions. The OLS regressions will be used to analyze the returns to skills using the mean of the top 150 players on each tour. Outliers in a data set would likely affect the estimates calculated using a mean. This is especially true in professional golf earnings. The quantile regressions will be used to account for the skewed distribution in earnings on both of these professional golf tours. On the PGA Tour, the top 15 earners won 29.8% of the prize money distributed to the top 150 players and on the European Tour the top 15 earners won 34.6% of the prize money distributed to the top 150 players. The distribution of the earnings is shown in Table 3 and Table 4. Therefore, the mean does not give a true estimate of the returns to skills for every professional golfer competing on these tours. The quantile regression approach will be used to analyze both ends of the data and the median, so a player will know what skills will maximize the expected earnings of the lowest earners and the highest earners. A young player might be interested in how to maximize their earnings when he first enters either tour and will most likely earn less money than the average player. Conversely, a player looking to become one of the top players in the world will know the shot making skills that contribute to the highest expected earnings on the top tours. The quantile regressions will analyze the 5^{th} percentile, the 20^{th} percentile, the 50^{th} percentile, the 80^{th} percentile, and the 95^{th} percentile.

In part one of my methodology, I used separate regression analysis to seek differences in the returns to skills on these two major professional golf tours. In part two of my methodology, I will determine if there is significance in the returns to skills between the PGA Tour and the European Tour. To do this, I will add a dummy variable, *tour*, to the data set to signify if a player competed on the European Tour or the PGA Tour. The dummy variable will equal 1 if a player was a member of the European Tour and 0 if the player was a member of the PGA Tour. This model will include a set of all of the variables included in the first model, which are represented by vector *Z*. I will also include a set of interaction terms by multiplying all of the skill variables, the experience variables and event control variables, represented by vector *X*, by the *tour* dummy variable. This analysis will show if there is a significant difference in the returns to the shot making skills on the two tours. It is important to note that the currency on European Tour money list is the Euro and the currency on the PGA Tour is the United States dollar. I have converted the Euro to the dollars for the European Tour players to unify the currency to allow for proper analysis. The conversion that was used was from December 31, 2015 and the variable is named *earndollars*. The conversion rate at this time was 1.09 dollars to every 1 Euro. I hypothesize that there will be significant differences in the short game statistics between the two tours. I expect larger returns to putting average on the European tour, which would be signified by a negative coefficient on the interaction team. I expect larger returns to sand save percentage on the European Tour, as well, which would be signified by a positive coefficient on the interaction term. The model used in part two of the methodology takes the form:

$$\mathbf{log(earndollars) = \alpha + \delta_1 Z + \delta_2 tour + \delta_3 X + \varepsilon}$$

IV. Results

The results of the Ordinary Least Squares regression are shown in Table 5 as a side-by-side comparison of the PGA Tour and the European Tour. The results for the 5th percentile, the

20th percentile, the 50th percentile, the 80th percentile, and the 95th percentile are shown in Table 6, Table 7, Table 8, Table 9, and Table 10, respectively, as a side-by-side comparison between the PGA Tour and the European Tour. The standard errors are shown below the coefficients in parentheses.

First, I will discuss the results shown in the OLS estimates. Again, the OLS estimates use the mean of the sample and do not take into account the skewness of the earnings distribution. Beginning with the PGA Tour, all of the skill variables have the expected sign and are statistically significant. Driving distance and putting average are significant at the 1% level. On the European Tour, putting average, green in regulation percentage, and sand save percentage are statistically significant and have the expected sign. Interestingly, the driving statistics are insignificant and have the inverse of the expected sign. These results show that driving the golf ball is not a significant determinant of earnings on the European Tour. The green in regulation percentage coefficient is .159 on the European Tour compared to just .0438 on the PGA Tour. That means if a player can increase his year long average of green in regulation percentage, he can expect his earnings to increase 15.9% on the PGA Tour compared to just 4.38% on the PGA Tour. The putting average coefficients are quite high, but in theory, it is not possible for a player to lower his putting average by a full shot. If a professional player on the PGA Tour could lower his putting average by one standard deviation, which is .023 strokes, that player's expected earnings would increase by 32.82%. Interestingly, these OLS estimates for the PGA Tour are not drastically from the 50th percentile of earners, or the median. All of the skill variables are significant at the median and the coefficients are quite similar. There is a difference between the OLS estimates and the median percentile of earners in the significance of shot making skills and coefficients on the European Tour. In the 50th percentile of players, sand save percentage is a significant determinant of earnings. There is also a large difference in the coefficients for putting average. With the OLS estimates, a player can expect to increase his earnings by 48.61% by lowering his putting average by one standard deviation. A player earning in the 50^{th} percentile can expect to increase his earnings by 65.02% by improving his putting average by one standard deviation. The differences in these results are due to the skewness of the earnings distribution.

The 5^{th} and 20^{th} percentiles of earners represent a wide makeup of players. Some of the earners in these percentiles are new players and some of them are players that had a down year and did not make as much money as they could have. A new professional that is looking to make money early in their careers can use these estimates to understand what the necessary skills are in maximizing their expected earnings in the first few years. At the 5^{th} percentile on the PGA Tour, all of the independent variables were found to be statistically significant at the 1% level. This shows that a young player on the PGA Tour can increase his expected earnings by improving any of the various shot making skills. At the 5^{th} percentile on the European Tour, it is again the short game variables and green in regulation percentage that are statistically significant. The coefficients on putting average and green in regulation percentage are still much greater on the European Tour than the PGA Tour. From the 5^{th} percentile to the 20^{th} percentile, there is no change in the significance in the independent variables. However, the coefficients on green in regulation percentage and putting became larger showing a higher increase in expected earnings if a player were to improve these statistics. The green in regulation coefficient rose to .185 from .167. A player earning money at the 20^{th} percentile can expect an 18.5% increase in earnings by improving his green in regulation percentage by 1% over the course of a year. At the 20^{th} percentile on the PGA Tour, sand save percentage and green in regulation percentage are no longer significant. The driving variables and putting average remain significant. A new player looking to play on the PGA Tour can expect an increase in his earnings by becoming a better driver of the golf ball and being a good putter.

The 80^{th} percentile and 95^{th} percentile are used to examine the returns to skills of the elite players on these two professional tours. In the 80^{th} percentile on the European Tour, putting average and green in regulation percentage are significant determinants of earnings. A player in the 80^{th} can expect to earn 11.56% more in prize earnings than a weaker player in the 5^{th} percentile with a one standard deviation improvement in putting average. In the 95^{th} percentile on the European Tour, driving accuracy percentage is statistically significant. This is the first percentile where a driving statistic is statistically significant. The only skill statistic that is not significant at the 95^{th} percentile is driving distance. These results show that a top player on the European Tour can increase his earnings by becoming better at any part of the game.

One would argue that a player earning in 80^{th} percentile and the 95^{th} percentile on the PGA Tour is considered one of the best players in the world. A player in the 80^{th} percentile and the 95^{th} percentile can increase their expected earnings by making the same improvements. Putting average and driving distance are both statistically significant. The coefficients are also quite close in number as well. These results suggest that all of the players at the top of the PGA Tour are similar in ability. The best way for a player to increase his expected earnings is to become a better putter. By improving putting statistics, a player can quickly lower scores. The winner of a PGA Tour event is usually the player that makes a few more putts than the other players and these results certainly show that.

The results in Part 2 of my methodology indicate significant differences in the returns to skills between the European Tour and the PGA Tour. The results are displayed in Table 11 and are reported through the interaction terms. The three areas where there is a significant difference in the earnings are events played, green in regulation percentage and putting average at the 1 percent level. The positive coefficient on the events interaction term show that there are greater returns for a player that chooses to play in more events on the European Tour than if a player were to compete in more events on the PGA Tour. The positive coefficient on the green in regulation interaction and the negative coefficient on the putting average interaction show that there are higher returns to iron play and putting on the European Tour. The coefficient of .0523 on the green in regulation interaction term shows that there is an extra 5.23% return to a marginal increase in green in regulation percentage on the European Tour. The coefficient of -6.229 on the putting average interaction term is a bit harder to interpret because a player's putting average cannot fully be decreased by 1 point. What this does show, however, is that there is more than a 50 percent greater return to putting average on the European Tour than the PGA Tour. These results enforce what was shown in the OLS regression and the quantile regressions.

V. Discussion

The purpose of calculating returns to skills in professional golf is to determine what shot making skills lead to the highest expected earnings. These results tell a player what is worth practicing in order to improve. Using the quantile regressions, a player earning in a specific percentile will know what skills they should improve to make themselves more money for their specific skill level. Analysis of the PGA Tour and the European Tour will tell a player which tour suits their game and will lead them to the highest expected earnings. Furthermore, a player looking to play on the European Tour as opposed to the PGA Tour will know what skills they should improve to do so and vice versa.

After analyzing the results, we can tell what skill set fits each tour. A player that is a solid iron player and a good putter would be a better fit for the European Tour. A player that drives the ball long and is a good putter would be a better fit for the PGA Tour. If a new player were looking to break into the professional golf scene, they would need to be a complete player to compete on the PGA Tour as a lower money earner. If a new player were looking to compete on the European Tour, he can maximize his expected earnings by improving his short game and hitting more greens in regulation. Interestingly, driving statistics are not significant on the European Tour. There are two potential reasons for this. First, the styles of courses played on the European Tour are much different than most courses played in the United States. European golf is known for "links" style golf. Links style golf courses typically have wide landing areas and very few trees. This allows players to hit the ball in a variety of directions and have a straight shot to the green on their next shot. In the United States, courses usually have skinnier fairways that are lined with trees. This punishes the player for hitting the ball off of the ideal target line. Another potential reason why driving statistics are insignificant on the European Tour is due to the weather. The weather is often worse on the European Tour and the links style courses have no protection from the wind. This makes short game skills much more important. When the wind blows strongly or it's raining, all players will struggle with long game shots. This puts a higher burden on the short game and the players that have the best short game in bad weather will normally win. The results shown in this study for the PGA Tour are similar to that of results shown in previous studies. Because no other economic study has investigated returns to skills on the European Tour, this study will be a baseline for further research on that tour. In other studies that have used OLS methods, the results in this study for the PGA Tour are quite similar. Moy and Liaw (1998) found that in order for a player to be competitive on the PGA Tour, they would need to have a complete skill set. The OLS results in my study also showed that a player is required to have a complete set of skills to be competitive on the PGA Tour. The results shown in the quantile results of this study have some similarities to the study conducted in Kahane (2010). Kahane (2010) found that putting was a larger determinant of earnings for players at higher percentiles. That is also true in this study. Although putting is statistically significant for both the top and bottom earners on the PGA Tour, the larger coefficient on putting average for the 95th percentile of earners show that the top players can expect a larger increase in earnings with a marginal increase in the putting average. The results shown in this study are similar to past studies that explore returns to skills on the PGA Tour and lay a foundation for further studies on the European Tour.

Currently, the PGA Tour has larger prize payouts than the European Tour. It would make financial sense for the top players presently playing on the European Tour to make the change to the PGA Tour, if possible. The results of this study will also tell professional players hoping to do that if their playing style will fit the change. As previously mentioned, all shot making skill variables are statistically significant on the PGA Tour at the 5th percentile. Based on the 95th percentile coefficients and significance levels, a top player on the European Tour would translate well to the PGA Tour.

Another interesting piece of the data set are the players that choose to compete on both the PGA Tour and the European Tour. There are 12 players that are members of both tours and competed in the minimum events to be listed on the respective money list. Eleven of the 12 players are from outside of the United States. Patrick Reed is the only golfer from the United States that competes on both tours. Paying as a member of both tours can be very difficult. A player needs to compete in a minimum number of events to be able to maintain his status on the tour. Most of the events the European Tour and the PGA Tour organize are played Thursday through Sunday of the same weeks throughout the year. Players that opt to compete on both tours must choose which events that want play, which means they will miss the event on the other tour. Rory McIlroy entered 12 events on each tour and finished 1st on the money list on the European Tour and 4th on the money list on the PGA Tour. His winnings totaled $5,152,706 on the European Tour and $4,683,312 on the PGA Tour.[1] When one considers that the European Prize purses are smaller the PGA Tour, it is clear to see that Rory McIlroy played much better on the European Tour. One explanation for this can be found by looking at his statistics. Rory McIlroy's had better short game statistics relative to the other players and short game statistics are a significant determinant of earnings on both tours. However based on my results, the returns to short game skills are greater on the European Tour. This means all else equal, Rory McIlroy would be expected to receive higher earnings on the European Tour as opposed to the PGA Tour. Henrik Stenson was another player that chose to compete on both the European Tour and the PGA Tour. He competed in 15 events on the PGA Tour and 16 events on the European Tour. Henric Stenson was a top 20 money earner on both tours, however he earned much more money on the PGA Tour than the European Tour even when accounting for the smaller prize purses. Henrik Stenson earned $1,860,272 when competing on the European Tour and $4,755,070 during his time playing on the PGA Tour. Henrik Stenson is known for his driving and iron play and that shows in his statistics relative to other professionals. Driving statistics are significant determinants of earnings on the PGA Tour, which means that he is an example of a player who would be expected to have higher earnings on the PGA Tour.

V. Conclusion

Eventually, the European Tour officials expect to be a competitive alternative to the PGA Tour. When that happens, players will have to make a decision on which tour they would like to

[1] The European Tour dollar amount was converted to United States dollars from the Euro.

compete. Financially, the study will tell the player which tour they should attempt to gain status on. Of course, finances are not they only reason a player would choose one tour over the other; there are other factors that play into that decision.

There are also a few limitations to the model that has been used in this study. A large factor in a golfer's results is the mental strength of a player. A player in a better mental position will typically play better than another player that is mentally weaker but possesses the same skill set. There is no measure to classify golfers based on their mental strength. If there was some measure of mental strength, that would help the accuracy of a returns to skills model. Similarly, outside factors could have a positive or negative effect on a player's performance. For example, when Tiger Woods was going through some struggles with his personal life, his golf was certainly negatively affected. Again, if there were a way to measure such problems, the model would become more accurate.

Another potential problem with this study is the use of simple regression analysis. Scully (2002) introduced an improved methodology that produced slightly more accurate results. Because the results are not substantially better, I chose to go with a more simple methodology to make the process easier.

Returns to skills have been widely studied in the area of sports economics. Because golfers act as a solo entity with no interdependence, professional golf is a great medium for studies within labor economics. Returns to skills in professional golf studies can be taken further to analyze whether or not players are learning from studies done in returns to skills in professional golf. The results from a study analyzing the learning behavior of players could be taken beyond the scope of sports economics. A study could take a panel of players over a set amount of time to see if they have altered their skill sets to maximize their expected earnings. A study such as that would give insight into the labor force to see if employees will alter their strengths in order to maximize the economic payoff. To this point, there have been multiple sports economic studies that function as a lens into the behavior of workers and this is another example of how sports economics can go beyond just the world of sports. These are a few ways golf economics can be taken further and these are just a few ideas.

This study gives a foundation for future studies of the European Tour and other professional tours worldwide. Many professional golfers do not start out on the European Tour or the PGA Tour. Professional players have to work their way up through a series of “mini” tours. Mini tours are smaller tours with tiny prize purses that hardly total up to a living income. These tours are worth studying because it would help players decide whether or not to try and play professional golf for a living. It would tell aspiring players if their skill set is complete enough to compete with other professional golfers that are just starting their careers. These are just a few ideas for future studies in the area of professional golf and ways to build off what has already been done. This study has broken the norm of using data from the PGA Tour and paves the way for other economists to continue research in professional golf.

Table 3: PGA Tour- Distribution of Player Earnings

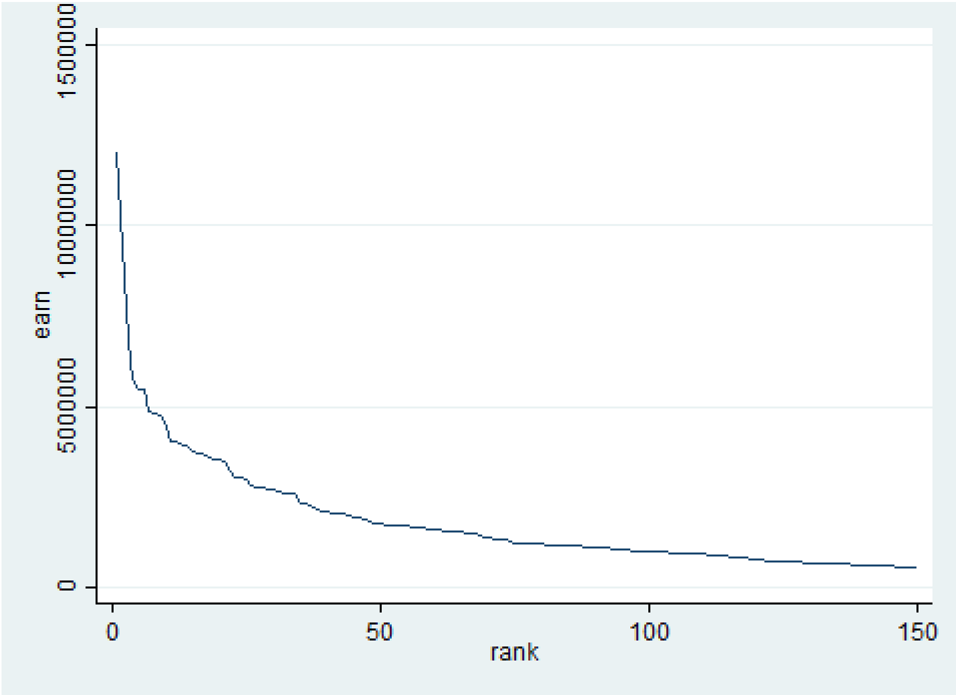

Table 4: European Tour- Distribution of Player Earnings

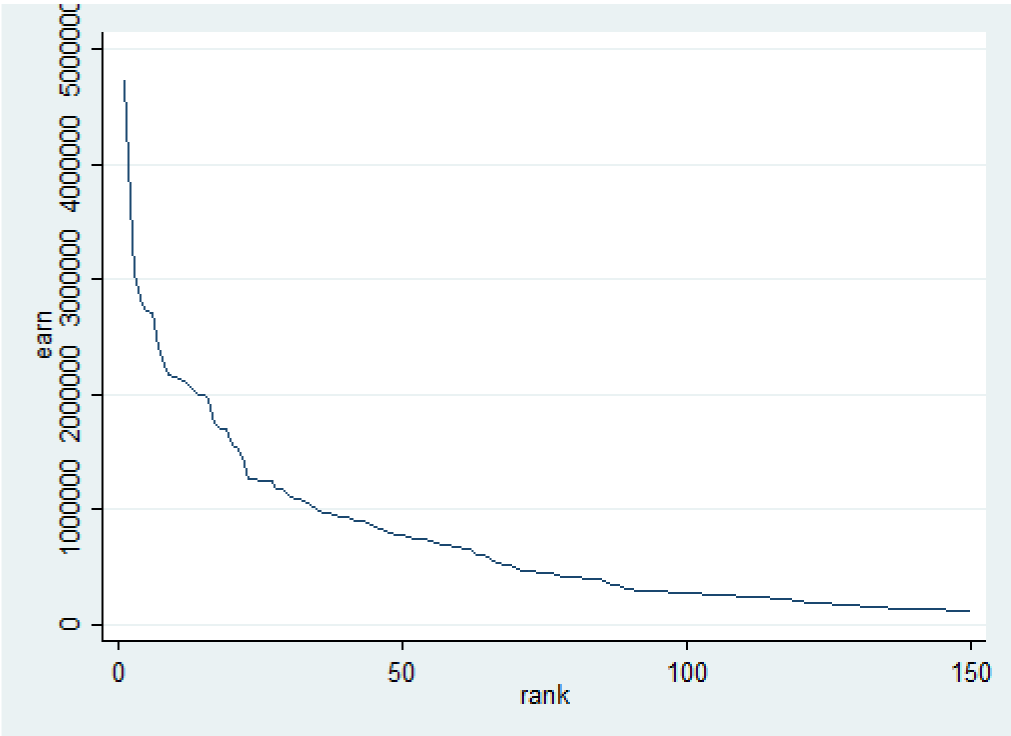

Table 5: OLS Regression Results

VARIABLES	(1) PGA	(1) Euro
events	0.00176	0.0457***
	(0.00958)	(0.00872)
drdist	0.0347***	-0.00701
	(0.00673)	(0.00741)
dracc	0.0231*	-0.00839
	(0.0123)	(0.0112)
putts	-14.27***	-18.07***
	(1.818)	(1.801)
gir	0.0438**	0.159***
	(0.0197)	(0.0150)
ss	0.0157**	0.0111**
	(0.00682)	(0.00546)
pro	0.0276	-0.0148
	(0.0236)	(0.0277)
pro2	-0.000685	0.000307
	(0.000744)	(0.000924)
Constant	23.90***	35.15***
	(4.160)	(3.665)
Observations	150	150
R-squared	0.501	0.634

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

Table 6: Quantile Regression- 5^{th} Percentile

VARIABLES	(1) PGAq5	(1) Euroq5
events	0.0128***	0.0744***
	(0.00255)	(0.0143)
drdist	0.0266***	-0.00590
	(0.00179)	(0.0122)
dracc	0.0249***	-0.00414
	(0.00328)	(0.0185)
putts	-10.94***	-12.81***
	(0.485)	(2.957)
gir	0.0303***	0.167***
	(0.00525)	(0.0246)
ss	0.0105***	0.0174*
	(0.00182)	(0.00896)
pro	0.0327***	-0.0419
	(0.00629)	(0.0455)
pro2	-0.00063***	0.00141
	(0.000198)	(0.00152)
Constant	20.43***	22.91***
	(1.109)	(6.017)
Observations	150	150

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

Table 7- Quantile Regression- 20th Percentile

VARIABLES	(1) PGAq20	(1) Euroq20
events	0.0589***	0.0589***
	(0.0143)	(0.0143)
drdist	-0.00912	-0.00912
	(0.0122)	(0.0122)
dracc	-0.00395	-0.00395
	(0.0184)	(0.0184)
putts	-17.09***	-17.09***
	(2.954)	(2.954)
gir	0.185***	0.185***
	(0.0246)	(0.0246)
ss	0.0187**	0.0187**
	(0.00896)	(0.00896)
pro	-0.0751	-0.0751
	(0.0455)	(0.0455)
pro2	0.00243	0.00243
	(0.00152)	(0.00152)
Constant	30.93***	30.93***
	(6.012)	(6.012)
Observations	150	150

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

Table 8: Quantile Regression- 50th Percentile

	(1)	(1)
VARIABLES	Euroq50	PGA50
events	0.0501***	0.00135
	(0.0134)	(0.0119)
drdist	-0.00545	0.0390***
	(0.0114)	(0.00834)
dracc	-0.00412	0.0257*
	(0.0173)	(0.0153)
putts	-24.17***	-14.33***
	(2.773)	(2.254)
gir	0.157***	0.0498**
	(0.0230)	(0.0244)
ss	0.00299	0.0194**
	(0.00841)	(0.00846)
pro	0.00880	0.0274
	(0.0427)	(0.0293)
pro2	-0.000425	-0.000773
	(0.00142)	(0.000922)
Constant	45.59***	21.99***
	(5.642)	(5.156)
Observations	150	150

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

Table 9: Quantile Regression- 80th Percentile

VARIABLES	(1) PGAq80	(1) Euroq80
events	0.00283	0.0334**
	(0.0177)	(0.0137)
drdist	0.0365***	0.00740
	(0.0124)	(0.0116)
dracc	0.00985	0.00736
	(0.0227)	(0.0177)
putts	-14.99***	-17.11***
	(3.354)	(2.829)
gir	0.0380	0.149***
	(0.0363)	(0.0235)
ss	0.0171	0.00975
	(0.0126)	(0.00858)
pro	0.0319	0.00854
	(0.0435)	(0.0436)
pro2	-0.00137	-0.000264
	(0.00137)	(0.00145)
Constant	26.27***	29.73***
	(7.673)	(5.757)
Observations	150	150

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

Table 10: Quantile Regression- 95th Percentile

VARIABLES	(1) PGAq95	(1) Euroq95
events	-0.0329*	0.0158***
	(0.0184)	(0.00436)
drdist	0.0246*	0.00186
	(0.0129)	(0.00370)
dracc	0.0335	0.0257***
	(0.0236)	(0.00561)
putts	-14.82***	-13.76***
	(3.486)	(0.899)
gir	0.00310	0.146***
	(0.0378)	(0.00748)
ss	0.00904	0.0160***
	(0.0131)	(0.00273)
pro	0.00864	0.00998
	(0.0453)	(0.0138)
pro2	-0.000914	-0.000739
	(0.00143)	(0.000461)
Constant	32.17***	24.89***
	(7.975)	(1.830)
Observations	150	150

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

Table 11: (Methodology Part 2) Interaction Terms Results

VARIABLES	(1) logearndollars
events	-0.00620
	(0.00869)
drdist	-0.00706
	(0.00657)
dracc	-0.0112
	(0.00998)
putts	-11.84***
	(1.590)
gir	0.107***
	(0.0130)
ss	0.00994**
	(0.00484)
pro	-0.0239
	(0.0245)
pro2	0.000498
	(0.000819)
tour	4.888
	(4.600)
eventstour	0.0520***
	(0.0116)
drdisttour	4.70e-05
	(0.00930)
dracctour	0.00280
	(0.0141)
puttstour	-6.229***
	(2.255)
girtour	0.0523***
	(0.0186)
sstour	0.00120
	(0.00685)
protour	0.00917
	(0.0347)
pro2tour	-0.000191
	(0.00116)
Constant	30.35***
	(3.251)
Observations	300
R-squared	0.730

Standard errors in parentheses

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

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