Relative Salary Efficiency of PGA Tour Golfers: A Dynamic Review

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Based on one-year sample, Nero (2001) estimated golfers' earnings using four performance measures. We study the effects of the golfers' abilities and skills on their earnings by estimating a production function for four different years (1995, 2000, 2005 and 2009). Our findings suggest that the effect of each skill and ability changes over time. In this sense, our results show that previous work as Nero (2001) cannot be extrapolated to other years. We also show that a dynamic approach is needed to understand the nature of professional golfers' job performance. Our analysis is complemented by estimation of a stochastic production possibility boundary for each year under study. This allows us to classify PGA golfers according to their relative efficiency. We found that for the 2009 season Phil Mickelson was the most efficient golfer and Brian Bateman the least efficient one. The results also allow us to estimate how much a golfer would have earned given his abilities and skills assuming that he had played as well as the most efficient golfer. Camilo Villegas, for example (the Colombian golfer also known as spider man), earned US$1.8 million in 2009. If he were as efficient as Phil Mickelson was in the 2009 season, he would have earned US$7.8 million: 4.33 times more than what he actually earned.

INTRODUCTION

Studies on professional athletes' earnings shed light on the kinds of abilities that lead to generating the highest returns. In a broader sense, these studies help to advance our understanding of costs and productivity. Professional sports also provide a special opportunity for applying job performance measures to real data that is free of measurement error (Nero, 2001). Another advantage of studying professional sports is that sports statistics allow us to accurately measure athletes' productivity and find direct relations between the different components of their game and their results. It's common to find these types of studies carried out using statistics of baseball players' batting records, runs scored, and games won. Nevertheless, baseball is a team sport and thus adds an additional variable to measurements. Golf is essentially different: being a fundamentally individual sport, a golfer's productivity depends solely on his individual abilities. Surprisingly, there are few productivity studies that make use of golf statistics (Moy and Liaw, 1998; Nero, 2001; Scully, 2002; Scott and Thomas, 2007, Shmanske, 2007; Rinehart, 2009). This document evaluates the relative efficiency of PGA Tour golfers. We study the effect of golfers' abilities and skills on their earnings by estimating a production function. To this end, we use the prizes earned by professional golfers and a set of variables that represent their skills in the game to build a linear regression model that allows us to: i) determine what facets of a players' game are the most important for winning larger prizes, and ii) determine which golfers have the highest prize-derived income given their performance statistics; and finally, iii) determine which golfers have a more efficient performance than their fellow colleagues. This document also presents an estimate of the efficient boundary of PGA Tour golfers. The model produces estimates for different years. This approach enables us to answer the question "what factors determine professional golfers' salaries?" while still takes into account temporary and dynamic factors - absent in almost all previous studies (Rinehart, 2009).

Our results suggest that the effect of each skill and ability changes over time. In this sense, our results show that previous findings (Nero, 2001) based on one-year samples cannot be extrapolated and that a dynamic approach is needed to understand the nature of professional golfers' job performance. Moreover, our results demonstrate that, in general, the model quality deteriorates over time, even giving a variable with counterintuitive sign in 2009. In terms of golfers' ranking, we found that 2009's most efficient golfer was Phil Mickelson.

This article is organized as follows: The first section is the introduction, the second is the literature review, the third is the results report, and the fourth provides the conclusions.

LITERATURE REVIEW

The present article follows in the line of Nero (2001) who studies golf professionals' performance in 1996. Nero (2001) chooses the 130 golfers with the highest earnings in 1996 and performs a logarithmic regression on their earnings, the length of their drives, their accuracy, and their abilities. As also found in the present article for the years under study, for the years 1995 and 2000, Nero (2001) concludes that improvements in putting pay off more than an increase in drive distance. Additionally, Nero (2001) analyzes a golfer's maximum income given his abilities if he had been as effective as the most effective golfer, thus including his ability to deal with pressure.

Scott and Thomas (2007) model golfers' performance using a set of equations and argue that the money that they earn is an indirect result of the golfer's ability. In their calculations, a golfer's number of strokes is the result of his abilities and experience while his average ranking is a function of the number of strokes and the number of events/tournaments (Scully 2002). Lastly, a golfer's earnings are determined by his ranking and number of completed events, the last being the production equation and the first two being intermediate outcomes. Although their contribution is important, their conclusions are similar to those found in earlier articles, in which putting is the most important factor in a golfers' set of abilities.

Shmanske (2008) proposes that the use of players' annual averages does not provide an accurate estimate of players' performance, so he assembles a database that includes performance per tournament. This allows us to incorporate the particularities of each golf course into the model. Additionally, Shmanske (2008) makes use of a two-stage equation system for comparing golfers' performance with their financial achievements. In his tests he also includes the variance and asymmetry of each variable as a determining factor of the number of strokes and, consequently, of a golfer's winnings. His contribution focuses on the high R2 of his regressions.

Finally, Rinehart (2009) goes back to using annual statistics to study whether returns on golfers' performance changed between 2002 and 2009. He does not find any evidence that this has happened. His interaction variables are not significant for any of the basic ability variables.

ASSUMPTIONS

As a sport, golf is not complex in and of itself. The goal is to hit a ball with a stick from a pre-established point (a "tee") into a hole in the least possible number of strokes. Each golf course has 18 holes and a 72-stroke par. This means that it is expected that a golfer complete the course in 72 strokes. From the starting point to the hole there is an area (the fairway) over which the golfer will drive the ball. The fairway is bordered by forested areas and sand traps (bunkers) that make driving difficult if the ball lands there. Fairways are so long as to be traversed between one and three strokes. The hole is surrounded by the green, an area with highly manicured grass that makes putting easier. Each hole also has its own par. The number of strokes in which a player should complete a hole varies from three to five, two of which are putts on the green and are added to strokes required for traversing the fairway. A golfer's skill thus depends on his power and precision. Strokes on the fairway must be strong and precise: a strong golfer can reach a par five green in two strokes. Meanwhile, strokes on the green must simply be precise. Moreover, golfers must be able to recover when their strokes don't land them in friendly territory. When a golfer scores one stroke less than the hole's par, it's called a birdie. If two strokes less, then it's called an eagle. On the other hand, if a golfer scores one stroke more than the hole's par, it's a bogey. If two more, then a double bogey, and so on.

Hence, in order to measure a golfer's skill, you must know the average length of his drives (strength), the number of times that his drive lands on the fairway (drive precision), the average number of putts (putt precision), and the number of times that he completes the hole and scores par after having landed off the fairway or in bunkers (ability). Good scores on each of these parameters are expected to be statistically correlated to their winnings. It is evident that their winnings will also be correlated with the number of tournaments in which golfers participate.

Following Nero (2001), the below formula will be used to model prize money made by each golfer in a season: ($EARN_i$)[1]

$$\ln\left(EARN_i\right) = \beta_1 + \beta_2 DRIVE_i + \beta_3 PUTT_i + \beta_4 SAND_i + \beta_5 Events_i + \beta_6 DRIVEACC_i + \varepsilon_i \quad (1)$$

whereas, $DRIVE_i$ represents the average drive length, and $PUTT_i$ represents the average number of putts (strokes on the green) per player. Likewise, $SAND_i$ is the percentage of time that a player completes a hole in a maximum of two strokes after having landed in a bunker that borders the green. $Events_i$ is the number of tournaments in which a player participates each year. $DRIVEACC_i$ is the percentage of times that a drive lands on the fairway. Lastly, is a homoscedastic, non-autocorrelated zero-mean random error term. Variable definitions are contained in Table 1a while descriptive statistics for the same are reported in Table 1b. Averages shown in Table 1b reveal an improvement in drive distance from 2005 onward, increasing from 273 to 299 yards. This improvement seems to have been obtained at the cost of precision, which fell from 68% to 62%. The SAND percentage also drops from 53% in 2000 to nearly 49% in 2005 and 2009. The average number of putts falls slightly in 2009 from 1.6 in 2000 and 2005 to 1.55 in 2009.

TABLE 1a
VARIABLE DESCRIPTION

Variables	
Name	**Description**
EARN	Winnings. Amount of prize money won.
DRIVE	Drive distance. Average distance in yards.
PUTT	Putting. Average number of strokes on the green.
SAND	Getting out of bunkers. The percentage of times that a player requires a maximum of two strokes to make a hole from a bunker that borders the green.
Events	Events. The number of tournaments played per year per player.
DRIVEACC	Strokes on the fairway. The percentage of strokes that land on the fairway.

TABLE 1b
DESCRIPTIVE STATISTICS

	Year	EARN (prices as of 2009)	DRIVE	PUTT	SAND	Events	DRIVEACC
Average	2000	$ 963,670	273.17	1.60	53.70	27.61	68.26
SD	2000	$ 1,163,408	7.53	0.05	5.81	4.40	5.02
Asymmetry coefficient	2000	4.58	0.21	-0.88	-0.56	-0.52	-0.33
Average	2005	$ 1,234,738	288.57	1.62	48.67	26.10	62.81
SD	2005	$ 1,025,801	9.32	0.03	6.31	4.65	5.32
Asymmetry coefficient	2005	3.79	0.20	-0.05	-0.13	-0.32	-0.21
Average	2009	$ 1,292,000	288.11	1.55	49.65	24.36	63.18
SD	2009	$ 1,263,880	8.49	0.07	6.64	3.98	5.39
Asymmetry coefficient	2009	3.01	0.04	-0.49	-0.42	-0.45	-0.33

Using information from the PGA's (Professional Golf Association) database and employing the ordinary least squares method, Model 1 was estimated separately for the years 1995, 2000, 2005 and 2009. The results are reported in Table 2. For each of the models, Breush-Pagan, Goldfeld-Quandt, and White heteroscedasticity tests (see Appendix 1) as well as normality tests (see Appendix 2) were performed. There was not sufficient evidence in favor of heteroscedasticity in any case.

As can be seen in Table 2, all variables in the 1995 sample are significant (individually and overall), but this is not the case with the other three samples. In the case of the 2000 sample, the $SAND_i$ variable doesn't affect the prize logarithm and, therefore, the following model was used:

$$\ln\left(EARN_i\right) = \beta_1 + \beta_2 DRIVE_i + \beta_3 PUTT_i + \beta_5 Events_i + \beta_6 DRIVEACC_i + \varepsilon_i \tag{2}$$

This model is also used in Table 2. For the 2005 and 2009 samples, the coefficient associated with the $Events_i$ variable isn't significant. Therefore, the following model was used:

$$\ln\left(EARN_i\right) = \beta_1 + \beta_2 DRIVE_i + \beta_3 PUTT_i + \beta_4 SAND_i + \beta_6 DRIVEACC_i + \varepsilon_i \tag{3}$$

These models are also reported in Table 2.

It's worth noting a couple of things regarding the models. For all years, the expected coefficient signs are obtained. The only exception is the $PUTT_i$ coefficient for the year 2009, a sample for which counterintuitive results arise.

The $PUTT_i$ coefficient for 2009 is not only counterintuitive, it is also not consistent with the effect of this variable for the other two samples in question. These results may be due to:

- A multi-colinearity problem in the 2009 sample causing the change to the sign.
- A change in the way in which affects the earnings logarithm.
- There was indeed a major change in the effect of the variable.

TABLE 2
ESTIMATION OF DE DIFFERENT MODELS

	Dependent variable: ln(EARN) (Statistical t in parentheses)															
Model	1		1		2		1		3		1		3		4	
Sample	1995		2000		2000		2005		2005		2009		2009		2009	
Constant	-1.839		5.18	*	6.673	**	-2.668		-2.56		-13.457	***	-13.364	***	-73.98798	***
	(-0.719)		(1.682)		(2.292)		(-0.598)		(-0.573)		(-4.163)		(-4.135)		(-3.196)	
DRIVE	0.055	***	0.066	***	0.066	***	0.065	***	0.066	***	0.051	***	0.051	***	0.052754	***
	(8.716)		(9.802)		(9.738)		(7.008)		(7.167)		(5.87)		(5.846)		(6.118)	
PUTT	-5.242	***	-10.97	***	-11.447	***	-6.259*	**	-6.32	**	3.358	***	3.511	***	82.058122	***
	(-10.620)		(-9.233)		(-9.991)		(-2.368)		(-2.387)		(4.042)		(4.295)		(2.761)	
$PUTT^2$															-25.62248	***
															(-2.644)	
SAND	0.026	***	0.012				0.054	***	0.053	***	0.065	***	0.066	***	0.062311	***
	(3.475)		(1.457)				(5.438)		(5.349)		(7.388)		(7.534)		(7.169)	
Events	0.053	***	0.029	**	0.029	**	0.016				0.015					
	(5.123)		(2.442)		(2.441)		(1.308)				1.032					
DRIVEACC	0.077	***	0.089	***	0.089	***	0.074	***	0.075	***	0.056	***	0.057	***	0.061048	***
	(7.827)		(8.782)		(8.752)		(4.676)		(4.77)		(4.2)		(4.272)		(4.619)	
R^2	0.6264		0.5765		0.5718		0.2914		0.2852		0.3708		0.3671		0.3905	
Adjusted R^2	0.6161		0.5653		0.5628		0.2733		0.2707		0.3535		0.3533		0.3738	
F	61.03	***	51.466	***	63.427	***	16.117	***	19.648	***	21.451	***	26.538	***	23.32	***
N	188		195		195		202		202		188		188		188	

Note: (***), (**), and (*) imply rejection of the null hypothesis of no individual significance with significance levels of 1%, 5%, and 10%, respectively.

With respect to the first possible reason, different multi-colinearity tests were performed, and no evidence of this problem was found. For this reason, it was rejected as causing the counterintuitive result.

With respect to the second possible reason, the following model was used for all samples:

$$\ln\left(EARN_i\right) = \beta_1 + \beta_2 DRIVE_i + \beta_3 PUTT_i + \alpha PUTT_i^2 + \beta_4 SAND_i + \beta_6 DRIVEACC_i + \varepsilon_i \quad (4)$$

In the case of samples from the 1995, 2000, and 2005, the α coefficient is not significant. On the other hand, this coefficient is significant for the 2009 sample[2] (see Table 2). In other words, there is evidence that there is a change in the way that $PUTT_i$ affects the earnings logarithm.

In this case, Model (4) is more suitable than Model (3) for the 2009 samples (see for example the adjusted R2). According to this model, the marginal effect of an increase in the average of on-green strokes ($PUTT_i$) causes a marginal effect, the sign of which depends on the actual average. In other words, using Model 4 you get:

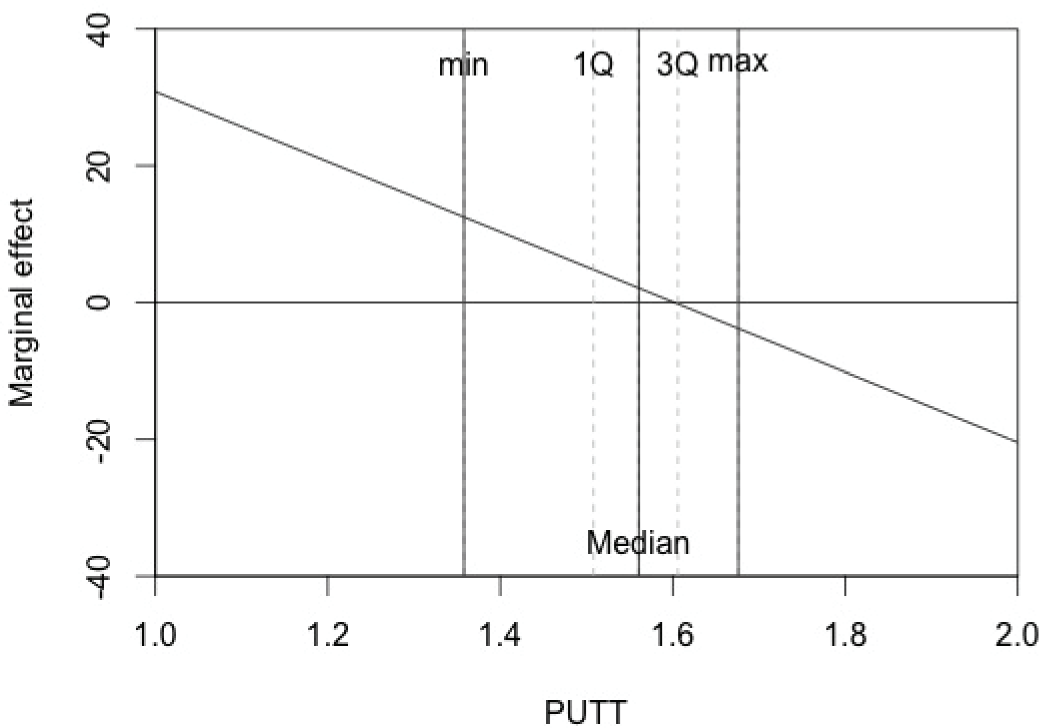
$$\frac{\Delta\% EARN_i}{\partial PUTT} = \left(\beta_{3i} + 2\alpha PUTT_i\right)\cdot 100 \qquad (5)$$

Given the estimated coefficients, if in 2009 a player has more than 1.6 average on-green strokes ($PUTT_i$), the marginal effect expressed in Model (5) is negative, as would be expected. On the other hand, if a golfer has less than 1.6 average on-green strokes, then the marginal effect is positive - a result that continues to be counterintuitive (see Figure 1).

According to the sample, only 25% of golfers have more than 1.6 average on-green strokes. Therefore, the marginal effect of $PUTT_i$ has the expected sign only for the 25% of golfers with the highest number of on-green strokes. This points to a kind of structural change in the effect of $PUTT_i$ on earnings starting in 2009.

Incidentally, the models fit relatively well, though fit seems to diminish over time: R2 goes down from 62.6% in 1995 to 39.05% in 2009.

FIGURE 1
MARGINAL EFFECT OF THE AVERAGE NUMBER OF ON-GREEN STROKES



If we compare the confidence intervals for the estimated coefficients for the different samples, we find that all the intervals for coefficients associated with the $DRIVE_i$ variable overlap each other. This means that it can be expected that the effect of said variable on prize earnings is statistically similar for all samples. The same happens with coefficients that are associated with $DRIVEACC_i$ and $SAND_i$. In the case of coefficients associated with $PUTT_i$, the intervals overlap for 1995, 2000, and 2005, but are not comparable for 2009. This means that, unlike the $Events_i$ variable for the years 2005 and 2009 and

$PUTT_i$ in 2009, there are no important changes in the effect of these variables.

TABLE 3
95% CONFIDENCE INTERVALS FOR ESTIMATED COEFFICIENTS*

Model	Sample	Lower Limit	Upper Limit	Model	Sample	Lower Limit	Upper Limit
		Constant				***SAND***	
1	1995	-6.885	3.206	1	1995	0.011	0.041
2	2000	0.929	12.417	2	2000	N.A.	N.A.
3	2005	-11.372	6.252	3	2005	0.034	0.073
4	2009	- 119.668	- 28.308	4	2009	0.045	0.079
		DRIVE				***Events***	
1	1995	0.042	0.067	1	1995	0.033	0.074
2	2000	0.053	0.080	2	2000	0.006	0.053
3	2005	0.048	0.084	3	2005	N.A.	N.A.
4	2009	0.036	0.070	4	2009	N.A.	N.A.
		PUTT				***DRIVEACC***	
1	1995	-6.216	-4.268	1	1995	0.057	0.096
2	2000	-13.706	-9.187	2	2000	0.069	0.109
3	2005	-11.540	-1.099	3	2005	0.044	0.106
4	2009	N.A.	N.A.	4	2009	0.035	0.087

* A Bonferoni correction was performed to allow for multiple comparisons

We can derive other interesting results from the estimates such as, e.g. the average elasticity of prize earnings with respect to other variables (see Table 4). In 2009, an increase of 1% in average drive yards in the vicinity of the mean resulted in an increase of 15.2% in earnings. As a matter of fact, when elasticity rates are compared, it's found that the largest elasticity for each year is associated with drive. In other words, if golfers are looking to improve their earnings by dedicating themselves to a 1% increase in any of their abilities, they will benefit most by improving drive distance. Nevertheless, perhaps a 1% improvement in driving isn't as easy to achieve as improving 1% in other aspects of the game.

This the reason that it is important to ask what part of the game matters most when trying to account for its effect on prize earnings (or more exactly, the logarithm of earnings). To answer this question, we can use standardized coefficients (see Table 5).

TABLE 4
AVERAGE ELASTICITY OF PRIZE EARNINGS

Model	Sample	Variable	Elasticity
1	1995	DRIVE	14.455
2	2000	DRIVE	18.075
3	2005	DRIVE	19.110
4	2009	DRIVE	19.110
1	1995	DRIVEACC	5.343
2	2000	DRIVEACC	6.051
3	2005	DRIVEACC	4.724
4	2009	DRIVEACC	3.857
1	1995	Events	1.374
2	2000	Events	0.811
1	1995	PUTT	-8.147
2	2000	PUTT	-18.300
3	2005	PUTT	-10.243
4	2009	PUTT	3.984
1	1995	SAND	1.384
3	2005	SAND	2.586
4	2009	SAND	3.094

TABLE 5
STANDARDIZED COEFFICIENTS

Model	Sample	Variable	Standardized coefficient	
1	1995	DRIVE	0.481	
		PUTT	-0.544	+
		Events	0.162	-
		SAND	0.255	
		DRIVEACC	0.430	
2	2000	DRIVE	0.506	
		PUTT	-0.535	+
		Events	0.131	-
		DRIVEACC	0.451	
3	2005	DRIVE	0.665	+
		PUTT	-0.177	-
		SAND	0.362	
		DRIVEACC	0.431	
4	2009	DRIVE	0.462	
		PUTT	6.060	+
		PUTT^2	-5.805	
		SAND	0.427	
		DRIVEACC	0.339	-

Note: +/- means that this standardized coefficient is the largest or the smallest in absolute value terms.

For 1995, 2000, and 2009, the largest standardized coefficient is associated with $PUTT_i$. For example, on average in 1995 a one-standard-deviation decrease[3] in the number of putts correlates to an increase of 0.544 standard deviations in the earnings logarithm, which equals USD1.6 as of 2009. These results match those found by Nero (2001), who using 1996 data, concludes that it is better to improve putting than driving.

In 2005, on the contrary, the largest standardized coefficient is that of the $DRIVE_i$ variable. This differs from the previously discussed Nero (2001) results. Here it would seem that it is better to improve driving than putting. These results point at a dynamic in the behavior of explanatory variables that couldn't be captured in the Nero (2001) study.

GOLFERS' RELATIVE EFFICIENCY

In order to determine golfers' relative efficiency, we can follow Nero's (2001) example in using a non-stochastic production boundary derived from estimated errors. Intuitively, the estimated error ($\hat{\varepsilon}_i$), represents the earnings deviation (from the logarithm) as compared to what average golfers can expect to earn given their skills. In this way, residuals show us to what extent a player is above or below their expected averages given his abilities. Thus, the largest positive error allows us to identify the golfer who earns much more than others given their skill level, i.e. the most efficient one.

TABLE 6
GOLFERS WITH THE LARGEST AND SMALLEST RESIDUALS

Year	Player with the: Largest error rate	Smallest error rate
1995	Billy Mayfair	Tim Loustalot
2000	Carlos Franco	John Daly
2005	Chris DiMarco	Hideto Tanihara
2009	Phil Mickelson	Brian Bateman

Table 6 shows golfers with the best performance and worst performance given their performance statistics. In 2009, for example, the most efficient golfer was Phil Mickelson and the least Brian Bateman.

Now if we use a deterministic approximation of an efficiency boundary, we can compare the relative performance of each golfer to the performance of each season's best golfer (Nero, 2001).

Each golfer's performance can be measured by adjusting observations so that they all fall below the earnings boundary. This is to say that the earnings frontier logarithm (LRF_i) can be calculated as follows:

$$LRF_i = \ln\left(EARN_i\right) + \max\left(\varepsilon_i\right) \tag{6}$$

Using this formula, we can infer the amount of prize money that golfers would have earned given their actual performance supposing that they had played as well as the season's best. The results for these calculations for the years 1995, 2000, and 2005 are reported in Appendix 3 while the results for 2009 are presented in Table 7 and Table 8. These two Tables show the ten most efficient and ten least efficient golfers, respectively.

TABLE 7
THE TEN MOST EFFICIENT GOLFERS IN 2009

Player	Actual earnings	Expected earnings	Boundary earnings	Efficiency
Phil Mickelson	5,332,755	847,223	5,332,755	1.00
Brian Gay	3,201,295	672,974	4,235,968	0.76
Steve Stricker	6,332,636	1,376,519	8,664,355	0.73
Brett Quigley	1,412,780	334,468	2,105,272	0.67
Jason Dufner	2,190,792	536,699	3,378,195	0.65
John Mallinger	1,717,140	455,308	2,865,892	0.60
Fred Couples	1,197,971	327,836	2,063,530	0.58
Paul Goydos	1,619,918	465,019	2,927,012	0.55
John Merrick	1,438,892	425,989	2,681,343	0.54
Padraig Harrington	2,628,377	795,291	5,005,875	0.53

TABLE 8
THE TEN LEAST EFFICIENT GOLFERS IN 2009

Player	Actual earnings	Expected earnings	Boundary earnings	Efficiency
Brad Adamonis	333,971	1,226,956	7,722,950	0.04
Shaun Micheel	257,590	985,976	6,206,124	0.04
Matthew Borchert	34,324	138,548	872,074	0.04
Steve Elkington	243,404	1,118,180	7,038,269	0.03
Rick Price	66,689	322,152	2,027,755	0.03
Darron Stiles	199,385	1,102,425	6,939,102	0.03
Kirk Triplett	155,480	1,053,318	6,630,003	0.02
Tommy Gainey	128,347	1,015,410	6,391,393	0.02
Peter Tomasulo	128,706	1,119,848	7,048,768	0.02
Brian Bateman	43,611	475,714	2,994,334	0.01

For example, in 2009 Brian Gay won 3.2 million dollars. Given his performance in the game, it would be expected that he would win 700,000 dollars. If Gay were as efficient as Mickelson, he would have won 4.2 million dollars. In this way, his "efficiency-boundary earnings" are 1.32 greater than what this golfer actually earned.

Colombian golfer Camilo Villegas won 1.8 million dollars in 2009. Given his performance in the game, it would be expected that he would win 1.2 million dollars. This is to say, he exceeded what would have been expected of him based on his averages. In terms of efficiency, Camilo Villegas ranked 62nd out of 188 players in 2009 with 23% efficiency with respect to Mickelson.

On the other hand, if Villegas had performed as efficiently as Mickelson, he would have won 7.8 million dollars. In this way, his "efficiency-boundary earnings" are 4.33 greater than what he actually earned.

CLOSING COMMENTARY

This article studies the relation between professional golfers' abilities and their performance in the years 1995, 2000, 2005, and 2009. We find that for all years in question the variables that are traditionally associated with performance are statistically significant and have the expected signs. This is with the exception of the PUTT variable, which in 2009 had a counterintuitive positive sign for three-quarters of the golfers being studied. In this case we have found a structural change in the effect of the PUTT variable on the earnings logarithm - a result which has not been documented in other studies. This may be due to the indirect relation between golfers' skills and their earnings. As suggested by Scully (2002), golfers' skills result in low scores, which are in turn awarded with prizes. This implies an indirect relation or equation system that we will analyze in future articles.

With respect to what skills are most worth improving, results show that in the last decade it was better to improve in driving than in putting. In terms of efficiency, the two measures that we have used both describe Phil Mickelson as the most efficient golfer in 2009. In future research we will delve further into the counterintuitive behaviour of the PUTT variable in samples starting in 2009 and changes in returns that occur in the sample years for the different skills that characterize a golfer's performance.

ENDNOTES

1. Prize money was deflated using the United States Consumer Price Index so as to be expressed in 2009 equivalents.
2. In order to save space, only the results from the 2009 sample are reported here.
3. This would mean decreasing the on-green putting average by 0.09.

REFERENCES

Nero, P. (2001). Relative salary efficiency of PGA Tour golfers. *American Economist,* 45, no. 2: 51-56.

Rinehart, K.L. (2009). The Economics of Golf: An Investigation of the Returns to Skill of PGA Tour Golfers. *Major Themes in Economics*, Spring, 57-70.

Callan, S.J. & Thomas, J.M. (2007). Modeling the Determinants of a Professional Golfer's Tournament Earnings. A Multiequation Approach. *Journal of Sports Economics*, 8, no. 4: 394-411.

Moy, R.L. & Liaw, T. (1998). Determinants of professional golf tournament earnings. *American Economist*, 42, 65-70.

Scully, G.W. (2002). The distribution of performance and earnings in a prize economy. *Journal of Sports Economics*, 3, no. 2: 235-245.

Shmanske, S. (2008). Skills, Performance, and Earnings in the Tournament Compensation Model: Evidence From PGA Tour Microdata. *Journal of Sports Economics*, 9, no. 6: 644-662.\

APPENDIX 1: HETEROSCEDASTICITY TESTS

The Breush-Pagan test was carried out for each of the models. In all cases, tests whose alternative hypotheses meant that an explanatory variable was causing the heteroscedasticity problem and that all the explanatory variables caused the problem were performed. Results are presented in Table 9. In no case did we find evidence of a heteroscedasticity problem. Finally, Table 11 presents the results of a Goldfeld-Quandt test for all estimated models. In this case, there was also no evidence of a heteroscedasticity problem.

TABLE 9
BREUSH-PAGAN TESTS FOR THE ESTIMATED MODELS.

Model	Sample	Ha: s_i=*f()*	Statistical-t	p-value	
1	1995	DRIVE	2.273	0.132	
1	1995	PUTT	0.005	0.943	
1	1995	Events	1.240	0.322	
1	1995	SAND	0.336	0.562	
1	1995	DRIVEACC	2.795	0.095	*
1	1995	ALL	8.884	0.114	
1	2000	DRIVE	1.987	0.146	
1	2000	PUTT	1.441	0.230	
1	2000	Events	7.703	0.164	
1	2000	SAND	2.209	0.137	
1	2000	DRIVEACC	2.627	0.105	
1	2000	ALL	1.796	0.235	
2	2000	DRIVE	2.182	0.140	
2	2000	PUTT	1.900	0.168	
2	2000	Events	4.678	0.522	
2	2000	DRIVEACC	1.612	0.204	
2	2000	ALL	1.163	0.250	
1	2005	DRIVE	0.477	0.490	
1	2005	PUTT	0.710	0.400	
1	2005	Events	1.535	0.254	
1	2005	SAND	1.381	0.166	
1	2005	DRIVEACC	0.264	0.607	
1	2005	ALL	2.800	0.061	*
3	2005	DRIVE	0.345	0.557	
3	2005	PUTT	0.756	0.385	
3	2005	SAND	2.835	0.128	
3	2005	DRIVEACC	0.064	0.800	
3	2005	ALL	4.891	0.299	
1	2009	DRIVE	0.014	0.905	
1	2009	PUTT	0.188	0.664	
1	2009	Events	0.616	0.332	
1	2009	SAND	1.457	0.227	
1	2009	DRIVEACC	0.381	0.537	
1	2009	ALL	6.450	0.265	
3	2009	DRIVE	0.016	0.901	
3	2009	PUTT	0.629	0.428	
3	2009	SAND	1.847	0.174	
3	2009	DRIVEACC	0.134	0.714	
3	2009	ALL	3.027	0.553	

Note: (***), (**), and (*) imply rejection of the null hypothesis of homoscedasticity with significance levels of 1%, 5%, and 10% respectively.

TABLE 10
WHITE TEST FOR ESTIMATED MODELS

Model	Sample	Statistical-t	p-value
1	1995	22.659	0.306
1	2000	22.326	0.250
2	2000	19.996	0.391
1	2005	21.401	0.278
3	2005	17.552	0.356
1	2009	24.356	0.227
3	2009	19.242	0.256

TABLE 11
GOLFELD-QUANDT TEST FOR ESTIMATED MODELS

Model	Sample	Ha: $s_i=X_i s$	Statistical-t	p-value	
1	1995	DRIVE	0.67	0.952	
1	1995	PUTT	1.183	0.241	
1	1995	Events	0.544	0.994	
1	1995	SAND	0.667	0.955	
1	1995	DRIVEACC	1.463	0.082	*
1	2000	DRIVE	1.353	0.101	
1	2000	PUTT	0.81	0.815	
1	2000	Events	0.446	1.000	
1	2000	SAND	1.059	0.404	
1	2000	DRIVEACC	0.873	0.718	
2	2000	DRIVE	1.186	0.233	
2	2000	PUTT	0.778	0.858	
2	2000	Events	0.448	1.000	
2	2000	DRIVEACC	0.886	0.697	
1	2005	DRIVE	1.011	0.481	
1	2005	PUTT	1.255	0.163	
1	2005	Events	0.368	1.000	
1	2005	SAND	0.726	0.917	
1	2005	DRIVEACC	0.852	0.756	
3	2005	DRIVE	0.976	0.543	
3	2005	PUTT	1.227	0.186	
3	2005	SAND	0.722	0.922	
3	2005	DRIVEACC	0.874	0.721	
1	2009	DRIVE	1.029	0.453	
1	2009	PUTT	0.748	0.887	
1	2009	Events	0.467	0.999	
1	2009	SAND	0.767	0.866	
1	2009	DRIVEACC	0.792	0.836	
3	2009	DRIVE	1.012	0.480	
3	2009	PUTT	0.673	0.952	
3	2009	SAND	0.749	0.888	
3	2009	DRIVEACC	0.837	0.773	

Note: (***), (**), and (*) imply rejection of the null hypothesis of homoscedasticity with significance levels of 1%, 5%, and 10%, respectively.

APPENDIX 2: NON-NORMALITY TESTS FOR ERRORS

Table 12 presents four traditional normality tests. There is no evidence that allows for rejecting the null hypothesis of normality for the estimated residuals in any of the models.

TABLE 12
NORMALITY TESTS FOR THE RESIDUALS IN ESTIMATED MODELS

Model	Sample	Shapiro-Wilk			Kolmogorov-Smirnov			Pearson chi-cuadrado			Jarque Bera	
		Statistical-t	p-value		Statistical-t	p-value		Statistical-t	p-value		Statistical-t	p-value
1	1995	0.991	0.332		0.054	0.192		22.149	0.076	*	0.478	1.475
1	2000	0.987	0.067	*	0.06	0.089	*	16.933	0.26		0.013	8.695
2	2000	0.985	0.033	**	0.063	0.057	*	11.005	0.686		0.005	10.52
1	2005	0.992	0.381		0.051	0.229		19.505	0.147		0.344	2.136
3	2005	0.992	0.301		0.048	0.3		34.485	0.002	***	0.324	2.256
1	2009	0.993	0.461		0.05	0.297		13.287	0.504		0.292	2.465
3	2009	0.99	0.239		0.054	0.196		16.362	0.292		0.184	3.388

Note: (***), (**), and (*) imply rejection of the null hypothesis of normality with significance levels of 1%, 5%, and 10%, respectively.

APPENDIX 3: EFFICIENCY ANALYSIS FOR THE YEARS 1995, 2000, AND 2005

TABLE 13
THE TEN MOST EFFICIENT GOLFERS IN 1995

Player	Actual earnings	Expected earnings	Boundary earnings	Efficiency
Billy Mayfair	2,172,387	548,745	2,172,387	1.00
D.A. Weibring	727,884	192,153	760,700	0.96
Corey Pavin	1,886,460	521,316	2,063,802	0.91
Mark Wiebe	237,669	71,333	282,395	0.84
Tom Lehman	1,168,735	375,855	1,487,945	0.79
Scott Simpson	1,120,263	382,955	1,516,054	0.74
Mark O'Meara	1,286,841	442,437	1,751,531	0.73
Jim Furyk	753,667	264,220	1,046,003	0.72
Marco Dawson	367,717	129,383	512,207	0.72
Lennie Clements	499,925	183,369	725,926	0.69

TABLE 14
THE TEN LEAST EFFICIENT GOLFERS IN 1995

Player	Actual earnings	Expected earnings	Boundary earnings	Efficiency
John Huston	414,679	998,903	3,954,486	0.10
Tommy Armour III	189,208	480,839	1,903,560	0.10
Fuzzy Zoeller	240,307	625,537	2,476,392	0.10
John Daly	452,932	1,239,530	4,907,086	0.09
Tom Watson	451,576	1,271,445	5,033,433	0.09
Doug Tewell	64,584	187,004	740,319	0.09
Bob Burns	83,398	242,485	959,958	0.09
Carl Paulson	90,800	273,434	1,082,480	0.08
Fulton Allem	76,353	239,418	947,816	0.08
Tim Loustalot	24,040	102,085	404,136	0.06

TABLE 15
THE TEN MOST EFFICIENT GOLFERS IN 2000

Player	Actual earnings	Expected earnings	Boundary earnings	Efficiency
Carlos Franco	1,931,820	416,967	1,931,820	1.00
Duffy Waldorf	1,724,902	390,266	1,808,113	0.95
Hal Sutton	3,814,129	1,125,578	5,214,834	0.73
Craig Stadler	787,074	244,272	1,131,717	0.70
Franklin Langham	1,999,545	641,465	2,971,923	0.67
Scott Hoch	1,705,442	557,762	2,584,127	0.66
Vijay Singh	3,206,637	1,120,530	5,191,445	0.62
Tom Lehman	2,577,059	955,378	4,426,292	0.58
Stewart Cink	2,703,175	1,005,985	4,660,754	0.58
Gary Nicklaus	503,305	190,377	882,019	0.57

TABLE 16
THE TEN LEAST EFFICIENT GOLFERS IN 2000

Player	Actual earnings	Expected earnings	Boundary earnings	Efficiency
Aaron Bengoechea	75,286	270,065	1,251,217	0.06
P.H. Horgan III	100,431	361,002	1,672,532	0.06
Casey Martin	178,467	656,636	3,042,213	0.06
Ted Tryba	310,763	1,191,446	5,519,998	0.06
David Frost	188,278	725,177	3,359,761	0.06
Sergio Garcia	1,313,557	5,441,909	25,212,504	0.05
Craig Bowden	42,708	183,841	851,738	0.05
Keith Nolan	57,317	300,764	1,393,449	0.04
Nick Faldo	344,584	2,199,156	10,188,746	0.03
John Daly	143,847	1,500,564	6,952,153	0.02

TABLE 17
THE TEN MOST EFFICIENT GOLFERS IN 2005

Player	Actual earnings	Expected earnings	Boundary earnings	Efficiency
Chris DiMarco	3,913,458	678,062	3,913,458	1.00
Bart Bryant	3,569,175	742,427	4,284,944	0.83
Tim Petrovic	1,879,785	395,544	2,282,898	0.82
Brad Faxon	1,868,037	394,163	2,274,926	0.82
Padraig Harrington	2,873,380	615,212	3,550,717	0.81
Fred Funk	3,108,805	695,832	4,016,019	0.77
Adam Scott	2,847,591	650,592	3,754,917	0.76
Peter Lonard	2,084,950	502,215	2,898,551	0.72
David Toms	4,352,270	1,099,440	6,345,457	0.69
Jim Furyk	4,674,522	1,250,446	7,216,996	0.65

TABLE 18
THE TEN LEAST EFFICIENT GOLFERS IN 2005

Player	Actual earnings	Expected earnings	Boundary earnings	Efficiency
Larry Mize	227,355	861,719	4,973,442	0.05
Will MacKenzie	302,669	1,155,828	6,670,904	0.05
Jose Coceres	296,271	1,146,451	6,616,786	0.04
Mario Tiziani	199,507	862,034	4,975,258	0.04
Charlie Wi	274,714	1,207,851	6,971,158	0.04
Brenden Pappas	306,855	1,596,211	9,212,589	0.03
Michael Long	198,189	1,056,754	6,099,092	0.03
Bradley Hughes	84,386	524,439	3,026,818	0.03
John Elliott	74,499	492,758	2,843,968	0.03
Hideto Tanihara	69,021	515,660	2,976,148	0.02