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The Impact of Age on the Ability to Perform under Pressure: Golfers on the PGA Tour

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Abstract

This paper is about aging and the ability to perform under pressure on the PGA tour. Performance increases with golfing skill, but may first increase and then decrease with age as experience interacts with changes in physical condition. Similarly, mental fortitude or the ability of a golfer to perform under pressure may first increase and then decrease with age as experience interacts with changes in the ability to concentrate. Net performance on the tour is the result of both physical golfing skill and the ability to perform under pressure. We control for changes in physical skill and focus on the mental side of the game. The role of experience suggests an inverted U shaped relationship between age and mental performance that could vary significantly across golfers. We use Order-m FDH to calculate a measure of performance under pressure, and we confirm an inverted U-shaped curve with age. Along the way, we examine the ability to perform under pressure at the level of the individual golfer.

Keywords: age, efficiency, order-m FDH, golf, performance under pressure.

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I. Introduction

The ability to perform under pressure is a critical component of success on the Professional Golfers Association (PGA) tour. Golf is the ultimate exercise in individual accountability; the golfer reaps the benefits of good shots and suffers the consequences of transgressions. There is no opponent responsible for his circumstance as in tennis or a batter in baseball facing a pitcher and fielders. There are no teammates to inflate or deflate his performance as in basketball or football. The setting is perfect for the application of performance to the mental capacity of the individual golfer.

Corey Pavin won the U.S. Bank Championship and a $720,000 paycheck on the PGA tour in 2006 at forty-six years of age after not winning for ten years; Pavin won fourteen times on the tour in his younger years. At the eve of his career, Jack Nicklaus won the Masters at age 46. Rocco Mediate (45 years old) went head-to-head with Tiger Woods (32 years old) for five rounds in the 2008 U.S. Open at Torrey Pines, only to lose on the first playoff hole. Rocco had not won for six years and only won five times in his career. Some golfers peak during their younger years, only to have a fleeting resurgence at the end. At the same time, it took Phil Mickelson twelve years of competition on the PGA tour before he won his first major, the Masters in 2004. And the older is Tiger Woods, the more successful he becomes, with an occasional relative lapse. The relationship between age and performance on the PGA tour is complex.

Performance depends upon the physical ability to make great shots and the mental fortitude to manage the pressure and the course. This paper focuses on the mental side. Golfers become wiser with experience (hopefully), and this includes an enhanced ability to manage four pressure packed rounds from Thursday through Sunday. But age takes its toll and the ability to concentrate deteriorates. Up to some point, the experience effect dominates, and the net effect of age on the ability to perform under pressure is positive; beyond some point, age trumps experience and the ability to perform under pressure diminishes. This is a classic tradeoff. Some golfers manage the aging process better than others. It is interesting to investigate whether or not there is any regularity to the aging process. One might expect an inverted “U” shaped relationship between age and mental performance that could vary across golfers but be confounded by the late and dramatic successes of golfers such as Corey Pavin, Jack Nicklaus and almost Rocco Mediate. The objective of this paper is to reveal this relationship between age and managing pressure in general and at the level of the individual golfer. As Pavin and Nicklaus demonstrate, it is critical to adopt a technique that is robust to the impact of outliers.

Age and mental performance is the focus, but the observed relationship between age and performance includes the physical side of the game. As a golfer gets older, physical golfing ability might improve at first and then deteriorate, deteriorate monotonically, or exhibit other patterns and nonlinearities. It is essential to employ a methodology that quantifies the ability to perform under pressure while controlling for the change in physical skills. We embed a golfer into a frontier production function framework in which physical golfing inputs produce performance. The efficiency scores – the difference between best-practice (frontier) performance and actual performance - provide measures of the mental side of the game.

Two ingredients are necessary to identify the net effect of age on the ability to manage pressure: unconditional and conditional on age efficiency scores. The unconditional scores are based upon comparisons with all golfers regardless of age. The conditional scores are based upon comparisons with golfers in an age bracket. The ratio of the unconditional score to the conditional score enables us to explore the general relationship between age and performance. We label this statistic the age efficiency ratio (AER).

The Daraio and Simar (2005) methodology that utilizes order-m frontiers is used to measure golfer efficiency. This approach uses the standard FDH methodology to measure production efficiency in a probabilistic production framework so as to mitigate the influence of outliers (such as Tiger Woods, for example). Age is treated as an environmental (exogenous) variable. Efficiency scores capture how well a golfer converts golfing ability inputs into performance on the tour. Efficiency scores are calculated with and without age. The impact of age is based upon a ratio of these scores. This approach enables us to identify the influence of age on the mental side of the game for the individual golfer and in general. The global conclusions on age are based upon non-parametric regression that captures the nonlinear complexity of age on performance.

This paper provides a quantitative measure of the ability to perform under pressure for golfers on the PGA tour; determines the general impact of aging on the ability to perform under pressure; and identifies the impact of age on performance for individual golfers. Section II continues with a brief review of the economic literature on golf. Section III discusses the data. Section IV summarizes the methodology. The results are in Section V and the final section concludes.

II. Literature Review

Possibly because economists enjoy watching spectator sports and there are reams of data collected on professional sports, there is an abundance of sport economics articles. Professional golfing is no exception, and many of these articles investigate the returns to golfer skills. Alexander and Kern (2005) determine whether the returns to various golf skills have changed over the period 1992-2001. Their results show that the return to driving distance has increased relative to that of putting ability. Yet putting ability is still by far the single most important determinant of earnings. Scully (2002) finds that golfer prize money is determined by golfer performance, as measured by a scoring average that is normally distributed. This creates a non-linear relationship between performance and earnings.

Chatterjee, Wiseman and Perez (2002) analyze the nature and extent of improvement in golf by investigating the performance of the top players in the Masters tournament throughout the history of that event. They conclude that golfers are obtaining lower scores over time and that the variation of the scores has declined. These findings are indicative of rapid and improved performance and increased competition. Coate and Golfbaum (2004) also find that the performance of lesser skilled professional golfers has improved relative to higher skilled golfers. They argue that increased investment in skills across the skill distribution can nonetheless lead to relative performance gains by lesser skilled golfers because their marginal product of acquired skill exceeds that of the better players.

Rishe (2001) examines whether the earnings gap between the PGA and Senior Tour golfers is due to differences in average skill levels or the rates of return to these skills and finds the gap is primarily due to differences in the rates of return to performance. These measured lower rates of return to skills may be due to the mental side of the game, an input that is not measured in Rishe's study, as we do in this article.

Shmanske (1992) examines human capital formation as determined by practice. He first estimates production functions relating golfers' earnings to skills and finds that putting and driving distance are the most important skills. These are inputs we use in our measure that adjusts for performance. Production functions relating a golfer's skill level to practice time show little support for diminishing marginal product of practice, with return on putting worth over $500 per hour. Shmanske (2000) also examines the relationship between skills and earnings on the PGA Tour compared to the LPGA and concludes that women are not underpaid compared to men, controlling for skill levels. He finds that the most valuable skills are putting for men followed by driving distance, but greens in regulation for women.

Shmanske (2007) argues that the PGA Tour disproportionately rewards one-time, exceptional performance rather than consistent steady play. The payout is skewed to the top scores; the winner receives 18 percent of the purse, but 70th place only receives 0.2 percent of the purse. Likewise, Hood (2008) in a simulation model that uses players' average and variability of performance demonstrates that greater variation in performance increases earnings as compared to consistent performance. The implication is that a player that has just one exceptional weekend, but otherwise is a mediocre player relative to his peers, might average more earnings during the season than a highly consistent golfer who did not have that exceptional weekend. Our hypothesis is that the exceptional weekend is evidence of handling the pressure and this golfer dominates the generally consistent player who fades on one day of a tournament.

Finally, Fried, Lambrinos, and Tyner (2004) measure the efficiency of the golfer using Data Envelopment Analysis, where the technical efficiency scores are interpreted as a Performance under Pressure Index. A similar index is computed in this paper but using Order-m Free Disposal Hull techniques. They also define and compute an Athletic Ability Performance Index AAPI that is a composite measure of a golfer's physical skills that represents earnings per event under the assumption that the golfer handles the pressure (the mental side) at a best-practice level.

III. Data

The data consists of measures of output, inputs and the exogenous factor of age for golfers on the Professional Golfers Association Tour in 2004, 2005 and 2005 subject to playing in at least 14 events that year. The output measure is earnings per event (E). The input measures are greens in regulation (GIR), driving total (DT)[1], save percentage (SP), and Putting (PUTT). These data are annual averages by golfer for the years, 2004, 2005 and 2006. The exogenous factor is the golfer's age (AGE). The data are from the golf section of the ESPN website.[2]

GIR is the percentage of greens hit in regulation over the season. Regulation is par minus two that allows for making par for the hole with two putts. DT is the sum of the player's rank for driving distance (average yards per drive) and drives in fairway

[1] Drive total is the sum of the rankings of driving distance and accuracy (percentage of drives in the fairway). We could include the two components of DT separately, but a more parsimonious specification increases the differentiation in efficiencies. We take advantage of this opportunity to reduce the number of inputs.
[2] The website is http://sports.espn.go.com/golf/statsIndex.

(percentage of drives in the fairway). The lower is DT, the better is the golfer. However, since a production framework requires higher values of an input to correspond to higher output, DT values for each golfer are transformed by taking the maximum DT value plus one (the value of 368) over the three years and subtracting each golfer's DT value. This conversion results in larger (better) values of the converted DT values corresponding to a larger input into the golf production process. The discussion in the text, however, is in terms of the unconverted values. SP is the percentage of pars a player makes when he fails to reach the green in regulation. PUTT is the average putts per hole reached in regulation. The lower is PUTT, the better is the golfer.[3] AGE is the golfer's age in 2004, 2005 and 2006.

Table 1 contains the descriptive statistics by year. The data are remarkably stable over the time period. Despite the reputed improvement in golfing technology, golfers do not hit greens in regulation, save par, or putt any better in 2006 than in 2004. Since DT is an aggregation of rankings in yards per drive and drives in fairway, it masks any improvements in driving distance and accuracy as a result of superior club technology. However, mean driving distance is 288 yards in 2004 and 2005, and 289 yards in 2006. Drives in fairway are 63% in 2004, 64% in 2005 and 63% in 2006. Driving distance and accuracy have not improved over this three year period. Exchanging 2004 equipment for 2006 equipment is not justified according to the numbers, at least for a professional golfer. Earnings per event is also relatively stable over the three years, falling from $46.5K to $44.9K between 2004 and 2005 and then rising to in 2005 to $50.8K. We feel comfortable pooling the three years, yielding a dataset with 593 golfers.

[3] Thus PUTT is converted using the same procedure applied to DT. The maximum observed value of PUTT is almost 2.00, so each golfer's observed PUTT value is subtracted from 2.00. The discussion in the text is in terms of the unconverted values.

IV. Method

The efficiency of individual golfers is computed using output oriented FDH (Free Disposal Hull). The output efficiency of a golfer is based upon comparing the output of a golfer to the output of other golfers that use the same if not fewer of all the inputs of the golfer being evaluated. The problem with FDH computations is that they are sensitive to outliers. If the output of a golfer is very high, like a Tiger Woods, then the efficiency of other golfers are measured relative to the output of Tiger Woods, given that Tiger Woods uses the same or fewer inputs than the golfers being evaluated. Our output is revenue per event, which is measured accurately, and the inputs are performance variables that are also carefully measured. Thus we do not expect data measurement error. However, Tiger Woods is an outlier in the population of golfers. A Tiger Woods is exceptional, and it is not fair to judge the performance of a more typical professional golfer with the exceptional golfer.

Thus the concept of order-m statistics, developed by Daraio and Simar (2005), is used to compute the efficiency of individual golfers. The concept is based upon a probabilistic specification of the production function. The production process is described by the joint probability measure of (X, Y), where X are inputs and Y are outputs. This joint probability completely characterizes the probabilistic production function. Under an output orientation, this joint probability can be written as:

$$F_{Y|X}(y|x) = \text{Prob}(Y \leq y \mid X \leq x) \qquad [1]$$

The expected order-m frontier for a fixed integer value of $m \geq 1$ is the expected value of the maximum of m random variables $Y^1, \ldots, Y^m$ drawn from the conditional distribution function of Y, given that X≤ x. Essentially, a golfer's efficiency is computed in reference to a random sample of m other golfers drawn with replacement who use the same or fewer inputs than the golfer being evaluated. This can be done by Monte-Carlo methods, or more efficiently by numerical integration.

The estimator by integration is given by:

$$\theta_m(x,y) = E[\max(Y^1,\ldots..,Y^m)|X\leq x] = \int_0^{\infty}(1-[F_{Y\,|\,X}(y\,|\,x)]^m)dy \qquad [2]$$

or

$$\theta_m(x,y) = \theta(x,y) + \int_0^{\theta(x,y)}(1-[F_{Y\,|\,X}(y\,|\,x)]^m)dy, \qquad [3]$$

where $\theta_m(x,y)$ is the order-m efficiency estimate for each golfer, which is computed from the FDH output efficiency estimate plus the defined integral. These can be computed using nonparametric integration methods as shown by Daraio and Simar.[4]

To estimate efficiency conditional upon the age of the golfer, the equations are modified so that the output y is not only conditional upon the inputs x, but also conditional upon z, the age of the golfer. Equation [3] is then modified as:

$$\theta_m(x,y|z) = \theta(x,y|z) + \int_0^{\theta(x,y|z)}(1-[F_{Y\,|\,X,z}(y\,|\,x,z)]^m)dy\,. \qquad [4]$$

A nonparametric estimate requires a kernel estimator for z with a bandwidth. A triangle distribution is used as the kernel and various bandwidths (h) are utilized for the age variable z.[5]

[4] We thank Leopold Simar for providing the Mathlab code and helping us with implementation.
[5] The order-m efficiency of each golfer conditional upon age was also computed from Mathlab software code provided by Simar.

V. Results

A. *Interpreting the Model*

The output variable is earning per event[6], which is simply the total earnings of the golfer in a given year divided by the number of events that the golfer played. The four inputs are Drive Total, Greens in Regulation, Putting Average (lower is better), and Save Percentage, as discussed in the data section. Data from 2004, 2005, and 2006 are combined into one data set under the assumption that there was no technological change over that three year period; the underlying structure between output and inputs remained stable. This provides a large reference set of 593 golfers. Obviously, playing conditions at specific events varied, but over the total events in each year at various locations, average playing conditions should be uniform. Many golfers played each of those three years, and that provides an opportunity to explore the consistency of a golfer's performance over time.[7]

We interpret efficiency to be a measure of the ability of a golfer to perform under pressure, encompassing managing the course and the mind (the mental side of the game) over four pressure-packed rounds. The data consists of annual averages. Two golfers can have similar playing statistics (inputs) and very different earnings per event (output) as illustrated in Table 2. Padraig Harrington in 2005 achieves his annual average playing

[6] We choose to use earnings as the output rather than scoring because earning is what ultimately matters. It is true that winnings are the result of relative scoring for a given tournament, but the best score varies by tournament according to course conditions, course difficulty, the players in the field, and the weather. Earnings is a common denominator across tournaments.

[7] Golfers play different tournaments and these tournaments have different purse sizes, playing conditions, and competition. This could affect efficiency scores. To some extent, players have the freedom to choose what tournaments to enter. We assume that they optimize this decision to make as much money as possible. Given this assumption, we calculate their ability to perform under pressure.

statistics as a result of putting four excellent rounds together and winning tournaments, whereas Hidemichi Tanaka achieves similar (superior) playing statistics as a result of playing excellently in the opening rounds, perhaps into the final round, but falling apart down the stretch and missing the big prize. Harrington dominates Tanaka in the FDH score. If Harrington and Tanaka were the only two golfers in the data set, Harrington would have an efficiency score equal to one and Tanaka equal to 0.12; Tanaka is producing 0.12 of efficient earnings per event. The efficiency score captures the critical element of ability that is not measured by standard golfing statistics – the mental side of the game. Table 4 contains an interesting sample of efficiency scores for various golfers and years.

For the fan, the intrigue of golf lies in the importance of the mental side of the game. It is captivating to watch players dueling down the stretch on a Sunday afternoon as the pressure of each drive, approach, chip and putt mounts, speculating on who will crack, and who will hold it together. Adam Scott's performances in the 2007 Memorial and St Jude tournaments are examples. Scott led the Memorial at the conclusion of round two on Friday, shooting a ten under par 62 that tied the PGA record for a single round, but he failed to hold it together on Saturday and Sunday and tied for fifth. At the Stanford St. Jude the following week, he led the tournament after three rounds, was tied for the lead after eleven holes on Sunday, but on the thirteenth hole he missed a five foot par putt for boogie, put his tee-shot into a lake on the fourteenth and three-putted for a triple boogie. He finished the tournament in seventh place, earning $201K compared to $1 million that went to the winner (Woody Austin). In another instance, Aaron Baddeley led the 2007 US Open at Oakmont by two strokes over Tiger Woods going into the final round on Sunday. He double boogied the first hole on Sunday, shot 80, finished thirteenth, and won a mere $124,000 compared to $1.26M that went to the eventual winner, Angel Cabrera. Every golfer on the tour is capable of driving the ball far and accurately, chipping, and putting excellently. Very few golfers on the tour are capable of maintaining that level of excellence over the four rounds of a pressure packed tournament and winning the big prize at the end.

B. *Unconditional Efficiency Scores*

Unconditional FDH and order-m efficiency scores are summarized in Table 3 for various values of m. As expected, with m = 500, the efficiency statistics are very similar to standard FDH results; the only difference is in the maximum value, which exceeds one for m = 500. A score greater than one occurs if the golfer being evaluated is not in the random comparison set and performs at best-practice. Even with a high value of m, there is the possibility of the sample not including an efficient golfer, resulting in an efficiency score exceeding one, given the large number of draws. In fact, for m equal to the sample size (593), the results would not be identical to standard FDH since sampling is with replacement.

As the value of m decreases, efficiency scores tend to increase. This is due to reduced dimensionality and the greater likelihood of obtaining efficiency scores greater than one. With m equal to 10, for example, each golfer is evaluated relative to a random draw (with replacement) of only ten other golfers. However, note that the results are the average of repeating the random draws an infinite number of times, which mitigates the dimensionality effect. Moreover, as m decreases, it is increasingly likely that random draws will not include the golfer being evaluated, and if this golfer is efficient, the efficiency score will be greater than one.

Table 4 contains the order m = 500 efficiency scores[8], the ranking according to annual earnings, and annual earnings for a sample of interesting golfers for 2004 – 2006. Generally, golfers ranked high according to total earnings have high efficiency scores, and vice versa, but not always. This is an important characteristic of a frontier production function approach; performance evaluation is conditional upon inputs. Golfers with excellent performance measures can have low efficiency scores if they are dominated by other golfers with similarly excellent performance measures and the same or lower inputs. Golfers with poor performance measures can have high efficiency scores if they dominate other golfers with similarly poor performance measures and higher inputs. Rankings are fundamentally based upon the ability to extract the maximum earnings (output), given inputs. This is a very different ranking methodology than rankings based upon an absolute characteristic such as total earnings or annual earning per event. In fact, the rank correlation coefficient between total earnings and our m-500 efficiency scores is only 0.36.

Consider some intriguing examples based upon individual golfer efficiency scores:

- Phil Mickelson is ranked third in 2005, earned $5.7 million, and his efficiency score is 0.79. Given Mickelson's athletic golfing ability as measured according to the 2005 annual averages, he could have earned $7.2M had he managed the course and his mind

[8] The results are similar for other values of m. The advantage of m = 500 is that most scores are less than or equal to one, which is consistent with the efficiency literature and facilitates interpretation.

up to best practice over the season. In terms of earnings per event rather than total earnings, Mickelson's would have ranked second with $344K/event, behind Tiger Woods with $506K/event and ahead of VJ with $267K/event. Tiger and VJ are efficient in 2005. Mickelson illustrates that *highly ranked and very successful golfers can be inefficient*; Mickelson did very well in 2005, but he did not perform up to his potential. Woods in 2004 and Furyk in 2005 are additional examples of high earnings but inefficiency.

- Jesper Parnevik in 2005 is ranked 109th, earned only $733K in total ($31K/event), but his efficiency score is 1.00. Given Parnevik's athletic golfing ability in 2005, he managed the course and the mind up to best practice and extracted the maximum earnings (actually earnings/event) possible. *Relatively unsuccessful golfers can be efficient.* Comparing Tanaka in 2005 and in 2006 also illustrates this point. His efficiency increased significantly from 0.12 to 1.00, but his earnings per event decreased from $20K to $2K. He played very poorly on average in 2006: drives in fairway fell by almost ten percentage points from 68.5% to 58.9%, drive total ranking deteriorated to 318th from 177th, greens in regulation fell from 66.9% to 57.9%, putts increased from 1.78 to 1.82. Save Percentage did improve from 50% to 53.9%. However, Tanaka was efficient in 2006 despite earning much less because he is compared to a different set of golfers with lower inputs; the standard has changed and he performs well relative to the lower standard. *Relatively unsuccessful golfers can be efficient.*

- In contrast, Woods and Furyk are ranked one and two in 2006, earning \$9.9M and \$7.2M respectively, and are efficient. Tiger and Jim played up to their potential and did very well. *Highly successful golfers can also be efficient.*
- Hidemichi Tanaka is ranked 117 in 2005, earned \$20,180 per event and \$686K in total, and his efficiency score is 0.12. Tanaka did not manage the course and the mind particularly well. Given his athletic golfing ability in 2005, he had the potential to earn \$5.7M in total, that would have put him tied with Mickelson for third on the money list. *Relatively unsuccessful golfers can be inefficient and have great potential.*
- A comparison of Geoff Ogilvy in 2005 and 2006 is an intriguing story. Efficiency increased from 0.36 to 1.00, earnings per event increased from \$74K to \$218K and total earning increased from \$1.9M to \$4.4M. Ogilvy went from 33rd on the money list to 5th. Moreover, he accomplished this with essentially no change in his average golfing inputs. The data suggests that Ogilvy mastered the mental side of the game in 2006. Golf is a game played "between the ears," and for Ogilvy, managing the course and his mind up to best practice in 2006 was worth millions of dollars. Interestingly, had Ogilvy been efficient in 2005, he would have earned \$205K per event and \$5.3M. *The mental side of the game is a powerful determinant of success on the PGA Tour.*

C. *Conditional Efficiency Scores*

Conditional on age efficiency scores are summarized in Table 5 for m = 30 and various bandwidths (h). Conditional scores are higher than unconditional scores on average because golfers are compared to other golfers of a similar age. The tighter is the age bracket as determined by the bandwidth, the higher are average efficiency scores.

1. The General Relationship between Age and Performance

Golfers become wiser with experience (hopefully) and, beyond some point, athletic prowess and mental toughness diminish. This is a classic tradeoff. Our methodology permits us to focus on age and mental fortitude, controlling for the physical aspect. Some golfers manage the aging process better than others. It is interesting to investigate whether or not there is any regularity to the aging process. One might expect an inverted "U" shaped relationship as the ability to manage the pressure improves with experience at first, but eventually age takes its toll and the ability to concentrate deteriorates.

To explore this proposition, consider the age efficiency ratio (AER) that is the ratio of the unconditional to the conditional on age order-m FDH efficiency scores. Where the unconditional and conditional efficiency scores are equal, the AER equals one. Such a golfer is evaluated equally in terms of the mental side of the game relative to all golfers in the sample and relative to golfers in his age bracket. Handicapping for age does not improve the efficiency score. This golfer is managing his age excellently. He can hold his own relative to the entire field without making any special provision for his age. Where the conditional score is higher than the unconditional score, the AER is less than one. Handicapping for age improves the efficiency score. This golfer is not managing his age as well. The performance of other golfers outside his age bracket dominates him by more than the performance of golfers in his age bracket.

Figure 1 plots the AER against age for m=500 and a bandwidth of h=5. The fitted line is a nonparametric regression using a logistic kernel function with a bandwidth of 1.64. The figure suggests that experience dominates age up to around 36 years old, after which performance drops off. Few golfers remain on the PGA tour after age 50. The data supports an inverted "U" shaped relationship between age and performance. It is important to recognize in interpreting this figure that sample selection is occurring. Golfers that realize that their performance is falling or whose performance falls so much that they do not qualify for tournaments are not included in the data set as these golfers leave the tour or join the senior tour for golfers fifty or older. If these golfers were included, then it is possible that the deterioration in relative efficiency would be measured as much more severe.

To verify the concave relationship between efficiency and age, the relationship is also estimated with ordinary least squares regression using age and age squared as independent variables. The function peaks at 35 years old. Unlike the non-parametric regression, this approach produces a smooth functional estimate. The regression results are contained in Table 6. Although an inverted U shape is confirmed, the adjusted R squared value is only 0.04, implying that there is much more than age explaining variation in relative efficiency.

2. Individual Conditional Efficiency

The conditional scores combine the influences of output performance based upon the standard inputs with the influence of age. With h = 5 and m = 500, the conditional efficiency score is the average of an infinite number of scores based upon samples of 500 drawn with replacement from the age bracket two years on either side of the age of the golfer being evaluated. Table 7 focuses on the same set of golfers included in Table 4. The table includes conditional efficiency scores, the age efficiency ratio, the predicted age efficiency ratio and age.

In 2006, Jim Furyk and Phil Mickelson are both 36, they are both conditionally and unconditionally efficient, they both have approximately equal AERs (1.00) and manage their ages better than predicted, yet Mickelson earns $224K per event and Furyk earns $300K per event. How is this possible? First of all, compared to a predicted AER equal to 0.885, Furyk and Mickelson are managing the influence of age better than average. Second, they have substantial differences in their earnings per event because they are not compared to each other. As illustrated in the table below, Furyk is a better golfer in terms of the inputs than Mickelson, so best practice implies higher earnings per event.

At the level of an individual golfer, the ability to manage age can vary over time. Jesper Parnevik is an example. The story begins in 2004. Parnevik is conditionally and unconditionally inefficient. He fails to leverage his golfing ability into maximum earnings per event both relative to all golfers, and relative to golfers near him in age. His AER is below that predicted for golfers in his age group. Course management and the pressure of the tour are holding him back. Parnevik works on his game between 2005 and 2006 with mixed results. See table 8. He hits the ball further with less accuracy, but his DT improves. He hits fewer greens in regulation, putting is unchanged, and his SP falls by ten percentage points. This puts Parnevik in a different comparison set of golfers, both unconditioned and conditioned on age, resulting in his efficiency scores rising to one. His AER rises to 1.00, and he manages his age better than predicted. In all likelihood, this result is driven by his exceptionally poor save percentage; 515 out of 593 golfers have higher (better) save percentages. Conditionally and unconditionally, there are no golfers with worse values of SP (and the other three inputs) who earn more per event than Parnevik. This demonstrates the strict requirements of an FDH based methodology. But nonetheless, given that Parnevik can only save par 41.9 percent of the time that he does not hit the green in regulation, he is managing his 40 years of age very well.

There is an interesting turnaround in 2006. Parnevik's game improves compared to 2005, particularly in the accuracy dimensions. He hits more drives in the fairway without sacrificing distance, his DT rank improves from 231 to 209, and his SP rises six percentage points from 41.9 to 47.9. Everything is relative in this framework; the conditional and unconditional comparison sets change and Parnevik's unconditional efficiency falls to 0.31, and his conditional efficiency falls to 0.48. His AER is 0.65 and he is managing his 41 years of age below predicted. He should be doing better, but even so, he is earning $58K per event and $1.3M in total, which far exceeds $31K per event and $733K in total for 2005, although not quite as good a year as 2004. Managing age, the course and the mind, given inputs, are very different concepts than financial success.

The final example is a comparison of Luke Donald and Geoff Ogilvy in 2005. Both golfers are 28 years old and young, but Ogilvy manages his age better than predicted and Luke manages his age slightly worse than predicted. However, Donald earns more than Geoff per event and in total. Based on the statistics shown in table 8, Ogilvy appears to have slightly better golfing inputs, particularly DT, although Donald is more accurate and better at saving par. Donald earns more per event even though he has inferior golfing inputs because his unconditional efficiency score is higher, 0.79 compared to 0.36. Managing the mental side of the game translates into financial success on the tour. But this is not the same as managing age, where Ogilvy exceeds Donald. Ogilvy's conditional and unconditional efficiency scores are low, but essentially equal, producing an AER equal to 1.06. Ogilvy leverages his inputs into earnings just as well relative to all golfers as he does relative to golfers in his age bracket. Contrast this to Donald, who is efficient in his age bracket and inefficient (0.79) relative to all golfers in the sample. Unlike Ogilvy, to be efficient, Donald's performance has to be handicapped by age. Donald is not managing his young age as well as Ogilvy.

VI. Conclusions

The allure of golf transcends the standard measures of golfing athletic ability. The ordinary hacker is incredulous to observe (typically on a television screen) drives of 350 yards, sinking long putts and saving par from deep in the woods. True excitement arises from watching the mental strain of contending golfers struggling to hold it together as they battle down the stretch on a Sunday afternoon with hundreds of thousands of dollars and glory at stake.

This paper is about the mental side of the game. We used a frontier statistical technique to obtain a quantitative measure of the ability to manage the pressure. The essence of this measure of mental fortitude is that controlling for golfing athletic ability (the inputs), golfers who earn more per event achieve a higher efficiency score. The higher the efficiency score, the better the ability to manage the pressure. Mental toughness is the missing golf statistic on the PGA Tour.

The effect of aging on athletic success is a fascinating and complex question. We investigated this issue in the context of the mental side of the game. Experience increases with age and may improve mental fortitude at first, but eventually age trumps experience and the ability to handle the pressure diminishes. This interaction suggests an inverted U shaped relationship between the ability to perform under pressure and age. We calculated efficiency scores unconditional and conditional on age and plot the ratio against age to uncover a relationship. Based upon a nonparametric regression, we found evidence to support the inverted U shaped relationship with the ability to perform under pressure peaking around 36 years old. We were also able to identify individual golfers who manage their age better and worse than predicted.

In the future golfers will continue to hit long and spectacular drives, sink unbelievable putts, and extricate themselves from trouble, but it is the mental battle that is the ultimate attraction of the game.

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Table 1: Descriptive statistics

		2004 (n=196)		2005 (n = 202)		2006 (n=195)	
Variable	Definition	Mean	SD	Mean	SD	Mean	SD
E ($)	Earnings per event	46,548	54,990	44,996	5,3868	50,898	63,995
GIR (%)	Greens in regulation	65	2.85	65	2.80	65	2.80
DT(yards)	Driving total	196	51	202	49	196	52
SP (%)	Save percentage	49	5.5	49	6.3	49	5.8
PUTT (n)	Average putts for greens reached in regulation	1.78	0.02	1.78	0.03	1.78	0.02
AGE (years)	Age of Golfer	35.9	6.4	35.9	6.6	35.9	6.6

Table 2: Tanaka and Harrington statistics

Golfer	*E($)*	*DT*	*GIR*	*PUTT*	*SP*
Tanaka (2005)	20,000	177	66.9	1.78	50.0
Harrington (2005)	174,000	242	62.7	1.78	47.1

Table 3: FDH Output Efficiencies and Order-m FDH Output Efficiencies, N=593

	FDH	*m = 500*	*m = 30*	*m = 20*	*m = 10*
Average	0.55	0.55	0.64	0.69	0.81
Standard Deviation	0.32	0.32	0.39	0.43	0.53
Minimum	0.07	0.07	0.10	0.10	0.11
Maximum	1.00	1.15*	3.48*	4.14*	5.56*
Number of Efficient Golfers	139	139	162	173	212

* Efficiency can be greater than one since the reference set may not include the golfer being evaluated. That golfer may lie above the reference set. The value m is the m-order statistic used to trim the number of comparison golfers.

Table 4: Efficiency Scores, Ranking and Earnings, m-order = 500, Years 2004-2006

Golfer	*2004*				*2005*				*2006*			
	Rk	Eff	Tot$	E(K)	Rk	Eff	Tot$	E(K)	Rk	Eff	Tot$	E(K)
Woods	4	0.80	5.4M	282	1	1.05	10.7M	506	1	1.15	9.9M	663
Furyk	-	-	-	-	4	0.85	4.3M	164	2	1.02	7.2M	301
A. Scott	7	1.01	3.7M	233	15	1.00	2.6M	136	3	1.07	4.9M	262
V. Singh	1	1.07	2.4M	376	2	1.04	8M	267	4	0.98	4.6M	170
G. Ogilvy	61	0.21	1.2M	48	33	0.36	1.9M	74	5	1.00	4.4M	218
Mickelson	3	1.08	5.8M	263	3	0.79	5.7M	271	6	1.00	4.2M	224
L. Donald	35	0.82	1.6M	78	17	0.79	2.5M	138	9	0.78	3.2M	177
Goosen	6	1.05	3.9M	243	8	1.00	3.5M	194	19	0.83	2.6M	145
Els	2	1.00	5.8M	362	-	-	-	-	28	0.74	2.3M	129
Garcia	9	1.00	3.2M	180	10	1.00	3.2M	161	49	1.00	1.6M	92
Parnevik	40	0.37	1.6M	65	109	1.00	733K	31	71	0.31	1.3M	58
Tanaka	104	0.37	795K	29	117	0.12	686K	20	224	1.00	69K	2

Notes: Rk = rank according to total winnings, Eff = Efficiency sore, Tot$ = total winnings in millions, E(K) = earnings per event in thousands

Table 5: Order-m FDH Output Efficiencies Conditional upon Golfer Age, N = 593

	Eff-m30	*Eff-m30,h=10*	*Eff-m30,h=7*	*Eff-m30,h=5*
Average	0.64	0.67	0.70	0.72
Standard Dev.	0.39	0.35	0.34	0.32
Minimum	0.10	0.11	0.10	0.10
Maximum	3.48	2.84	2.57	2.28
Number of Efficient Golfers	172	194	224	250

Notes: The value m is the m-order statistic used to trim the number of comparison golfers. The value h is the bandwidth used for the nonparametric estimate using a triangle distribution for the kernel.

Table 6: Dependent Variable: AER (m=500, h=5, n=593)

Independent Var.	*Coefficient*	*Standard Error*	*Prob Value*
Constant	0.23	0.30	0.44
Age	0.07	0.02	0.00
Age squared	-0.001	0.0002	0.00

Notes: Adjusted R-squared = 0.04; F[2,590] = 13.76 (Prob value = 0.00)
The value m is the m-order statistic used to trim the number of comparison golfers. The value h is the bandwidth used for the nonparametric estimate using a triangle distribution for the kernel.

Table 7: Conditional Efficiency Scores, m=500,h=5, n = 593

	2004				2005				2006			
Golfer	Age	CEff	AER	PrAER	Age	CEff	AER	PrAER	Age	CEff	AER	PrAER
Woods	29	1.00	0.8	0.82	30	1.00	1.05	0.825	31	1.00	1.15	0.83
Furyk	34	-	-	0.875	35	0.84	1.01	0.88	36	1.00	1.02	0.885
A. Scott	24	1.00	1.01	0.78	25	1.00	1.00	0.785	26	1.00	1.07	0.79
V. Singh	41	1.00	1.07	0.81	42	1.00	1.04	0.79	43	1.00	0.98	0.78
G. Ogilvy	27	0.20	1.05	0.805	28	0.34	1.06	0.81	29	1.00	1.00	0.82
Mickelson	34	1.00	1.08	0.875	35	0.75	1.05	0.88	36	1.00	1.00	0.885
L. Donald	27	0.82	1.00	0.805	28	1.00	0.79	0.81	29	1.00	0.78	0.82
Goosen	35	1.00	1.05	0.88	36	1.00	1.00	0.885	37	0.83	1.00	0.83
Els	35	1.00	1.00	0.88	36	-	-	0.885	37	0.74	1.00	0.83
Garcia	24	1.00	1.00	0.78	25	1.00	1.00	0.79	26	1.00	1.00	0.79
Parnevik	39	0.57	0.65	0.83	40	1.00	1.00	0.82	41	0.48	0.65	0.81
Tanaka	33	0.88	0.42	0.87	34	0.12	1.00	0.875	35	1.00	1.00	0.88

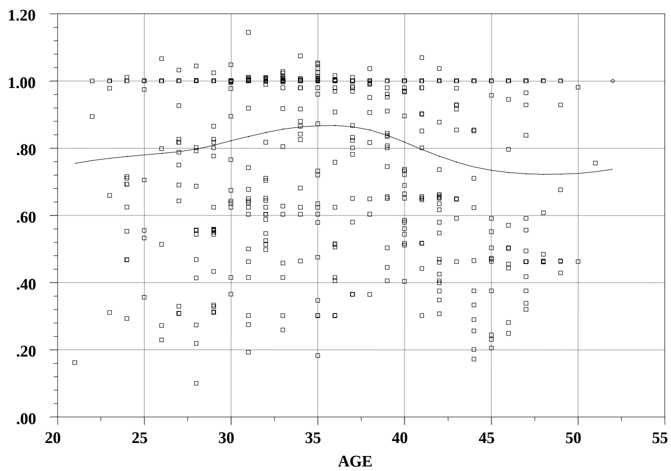
Notes: CEff=Conditional efficiency, AER=Age efficiency ratio, PrAER=Predicted age efficiency ratio.

Table 8. Golfing Performance Inputs of Various Golfers

Golfer	*DIS*	*DIF*	*DT*	*GIR*	*PUTT*	*SP*
Furyk 2006	282	73.8	167	70.7	1.73	47.6
Mickelson 2006	301	58.6	176	68.3	1.74	40.4
Parnevik 2004	288	60	242	66.1	1.76	51.9
Parnevik 2005	292	57.6	231	61.1	1.76	41.9
Parnevik 2006	291	61.4	209	64.4	1.75	47.9
Ogilvy 2005	298	60.7	169	66.7	1.75	57.2
Donald 2005	285	64.3	210	68.4	1.77	59.8

Notes: DIS is Driving Distance, DIF is Drives in Fairway, other variables defined in Table 1.

Figure 1. Age Efficiency Ratio (AER) as a Function of Age, with Non-Parametric Curve Fitted using a Logistic Kernel Function with a Bandwidth of 1.64



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