Skills, Effort, and Performance in Tournaments: A Dynamic Model and Empirical Analysis

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Abstract

We develop a dynamic model of skill acquisition and performance in a tournament setting. Comparative statics suggest how the distribution of performance may change in response to changes in total and relative compensation. The model is explored empirically by examining trends in professional golf earnings distributions. The empirical work indicates that the performance of lesser skilled professional golfers has improved relative to higher skilled golfers in periods of rising real purses and increases in purse spreads that favor the better golfers. We argue that increased investment in acquired skills across the skill distribution can lead to relative performance gains by the lesser skilled players because their marginal product of acquired skill exceeds that of the better players.

Keywords: Tournament Theory, Performance, Sports Economics

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1. Introduction

The sixth U.S. Open Golf Tournament was held at the Chicago Golf Club in 1900. It was the first U.S. Open to attract the best players from Great Britain and 55 professionals competed for a total purse of $850, with $200 going to the winner. Harry Vardon’s 72 hole score of 313 won the event. The fifth, tenth, twentieth, thirtieth, and fortieth place finishers were 14, 25, 32, 42, and 50 strokes behind Vardon.\(^1\) Michael Campbell won the 2005 U.S. Open in Pinehurst, North Carolina, with a 72 hole score of 280. The fifth, tenth, twentieth, thirtieth, and fortieth place finishers were 5, 7, 9, 11, and 12 strokes behind Campbell. One hundred and fifty professionals competed for $6,250,000 in prize money, with $1,170,000 going to Campbell. Existing static tournament models cannot explain compression in performance with rising purses over time.

In this paper we develop a dynamic model of skill acquisition in a tournament setting that explains the compression in performance (and improvements in performance) that occur with an increase in purses. The model assumes agents develop their stock of skills outside of competition in response to the reward structures they face. It contrasts with existing static tournament models that presume an exogenous stock of skill and consider the intensity of use of the given skills.

Lazear and Rosen (1981) developed the seminal work in tournament theory. They demonstrated that labor compensation by a rank order tournament can be superior to other compensation schemes when it is difficult to observe the effort of workers. Green and Stokey (1983) extended the Lazear and Rosen (LR) model to explicitly consider multiple competitors and a common external shock. Szymanski and Valletti (2004) demonstrated formally that

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\(^{1}\) This information is from Johnson (1995).
efficiently designed tournaments will not be winner take all if competitors are heterogeneous in ability. The latter point is important because the principal theoretical result of tournament theory that has been subject to empirical testing is that competitors will put forth more effort in a tournament setting the larger the absolute differences in compensation between ranks at finish. Szymanski (2003) and Frick (2003) provide recent reviews of this literature, which relies extensively on the professional sports laboratory. Road racing, stock car racing, bowling, horse racing, tennis, and golf have been studied. Golf has particular advantages when considering the incentive effects of purses and purse spreads in that outputs (scoring) of the participants and the prize structures of the tournaments are readily identified and participants compete in a single event rather than in match play. Professional road racing also has these advantages but is subject to strategic behaviors which add noise to the performance measures (Frick (2003)).

Two basic approaches to empirically examine the agent’s response to reward have been employed. Both approaches appear in Ehrenberg and Boganno (1990a) and Ehrenberg and Boganno (1990b). The first is the cross-sectional approach, taking advantage of the distribution of total purse offerings across tournaments in a give year. Since awards are distributed using the same fixed proportion of the total purse, an increase in the total purse means an increase in purse spread between rank-order compensation. Ehrenberg and Boganno (1990a, 1990b) studied individual total scoring in four day tournaments on the 1984 U. S. Professional Golf Association (PGA) tour and on the 1987 European PGA tour respectively. Both analyses found a significant relationship between purse size and performance. The authors attributed the finding of a purse effect to increases in effort and concentration in tournaments with larger purses.

The challenge of the cross-sectional approach is to control for idiosyncratic factors that affect performance in a particular tournament. These include factors such as weather,
differences in course difficulty, and the quality of the pool of competitors. Analysis of the 1992 American PGA tour by Orxzag (1994) finds an insignificant purse affect. Orszag’s reexamination of Ehrenberg and Boganno’s 1984 tournament results suggests that the purse effect could be spurious. Melton and Zorn (2000) finds a statistically significant purse effect in the 1994 and 1995 Senior PGA tour, but with an estimated performance improvement of only 0.3 strokes from increasing the purse from $800,000 to $900,000, the incentive affect on performance appears small.

The second approach exploits the convex nature of the compensation schedule. Professional golf tournaments distribute the total purse among players based on their rank in performance. The payment schedule is convex in that the step size between ranks increases with improvement in rank (e.g., 0.002% of purse to the 70th placed finisher, 0.0022% to the 69th, …, 7% to third, 11% to second, and 18% first). Examining how individuals appear to change effort during the course of four rounds in the tournament as their rank (and thus marginal benefit to effort) changes is a natural indicator of the strength of the purse effect. Ehrenberg and Boganno (1990a, 1990b) analyzed the effects on fourth round scoring of the marginal prize gain from improving from the third round rank. Greater marginal prize gains were associated with lower final round scoring in both cases, which they interpret as an indication that the more highly skilled tour professionals may be more responsive to purse spreads.

One reason for the inconclusiveness of the empirical research may be its emphasis on how intensely given stocks of skills are used at a moment in time, rather than on the acquisition of skills over time. Commenting on Ehrenberg and Boganno (1990a), Lazear (1995, p. 34) observes that “one would not think effort would be particularly sensitive to incentive pay,” in a sports tournament setting. That is, competitors might be expected to put forth their best efforts
on each day of competition. Our theoretical and empirical analysis captures how competitors might alter their stock of skills in preparation for the tournament.

In the next section, we develop a dynamic model of skill acquisition that takes place outside of the course of play. The training builds on the competitor’s skills that are employed during competition. We use the model to help understand trends in professional golf earning distributions and in the performance of U.S. and European professional golfers over time. We also examine the improvement in scoring with increases in purse over time among above average and below average PGA tour golfers in the U.S. A common thread in our empirical work is that less skilled professional golfers are gaining on better skilled golfers over time in spite of the purse spread changes that favor the better golfers. We show theoretically that the relative gains of the less skilled players might have a straightforward economic explanation. The model suggests that better players maintain greater stocks of acquired skill with lower marginal products than lesser players. Endogenous decisions to increase investment in acquired skill in response to increases in the reward structure can lead to relative performance gains by the lesser players who have higher marginal products.

The behavioral model of effort contrasts with the non behavioral explanation of compression in performance favored by Schmidt (2004) and Schmidt and Berri (2003). These authors argue that the compression in performance that they find in baseball occurs as a result of population grow, an explanation offered by Gould (1996). The notion is that a greater number of individuals will occupy the right most tail of the skill distribution, which is bounded on the right by a “wall” fixed by human limitations. If, say, the top 1000 golfers compete professionally, performance levels will be subject to less variation as the overall population grows. This theory, however, cannot explain the increased levels of investment in skills of the modern athlete.
compared to athletes of past decades and its role in performance compression and enhancement. Only in the past decade or two, for example, has training year round become the rule rather than the exception in professional baseball, football, basketball, and golf. We believe it is not coincidence that the increased investment in skills correlates with increases in reward structures. Our model offers the tools to explain how the increased investment in skills can result in compression as well as improvement in performance among tournament participants.

2. Model

In the dynamic model developed in this section, \( I \) agents, indexed \( i = 1, \ldots, I \), compete in repeated tournaments with prizes distributed based on the competitors’ relative ranking. Each agent is endowed with a level of “innate skill”. The competitors improve their expected performance with “acquired skill,” a form of human capital that is maintained through the input of resources such as effort. Agents choose a level of acquired skill to maximize utility.

Behavior is implied by model derive from the traditional and very general assumption of a concave utility function, a concave production function transforming acquired skill into performance, and a concave production function for training that transforming effort into skill. The interesting behavior generated by the model is the product of the mapping from performance to expected payoff. By the nature of the reward structure, this function is convex over much of the performance range, reflecting the increasing step size for improved tournament rank, but is concave in range of the top performers, reflecting there is no financial compensation for the top ranked competitor to improve performance. It is the attempt to retain generality in the functions that produces the many different scenarios that contribute to compression in performance.

2.1 The agent's optimization problem
Agent $i$ maximizes the present discounted value of the expected stream of future utility,

$$\max \sum_{t=0}^{\infty} (1 + \theta)^{-t} E(U(m_{i,t}, x_{i,t}))$$

s.t. $U(m_{i,t}, x_{i,t}) = u(m_{i,t}) - x_{i,t}$, $m_{i,t} \geq 0$, $x_{i,t} \geq 0$, $i = 1, \ldots, I$,

$$m_{i,t} = H(I + 1 - r_{i,t}, M_t)$$

$$r_{i,t} = r(y_{i,t}, y_{-i,t})$$

$$y_{i,t} = z_{i,t} + \eta_{i,t}$$

$$z_{i,t} = a_i + f(k_{i,t}) + \varepsilon_{i,t}$$

$$k_{i,t+1} = (1 - \delta)k_{i,t} + g(x_{i,t}).$$

Borrowing from Green and Stokey (1983), the instantaneous utility function is determined by the competitor's tournament earnings, $m_{i,t}$, and the expenditure of inputs used in the acquisition of acquired skills, $x_{i,t}$. Utility is additively separable with $u' > 0$, $u'' \leq 0$.

Competitor $i$ receives earnings in period $t$ based on relative rank, $r_{i,t}$, and the size of the total purse, $M_t$. The function $H$ in (3) captures purse distributing according to rank. The function $H$ is an increasing step function with increasing step size with each improvement in rank. Tournament rank is based on relative performance where $r$ in (4) simply sorts players by performance $y_{i,t}$ relative to that of other competitors, $y_{-i,t}$.

The $z_{i,t}$ term in (5) is the individual's own contribution to his or her performance in the tournament at time $t$. The value of $z_{i,t}$ is determined according to (6). The $\eta_{i,t}$ term in (5)

\footnote{At low levels of compensation, some steps are of equal size, but the overall trend is for increasing compensation for each step improvement in rank.}
captures common shocks that affect all competitors. These may be transitory shocks, such as performance altering weather, or permanent shocks, such as the introduction of a new technology. The $a_i + f(k_i)$ term in (6) is the deterministic component of performance based on an additive combination of innate skill, $a_i$, and the stock of acquired skill, $k_{i,t}$. The only exogenous difference between competitors is the endowment of $a_i$. The function $f$ maps acquired skill to performance with $f' > 0$, $f'' \leq 0$, and $f' \to 0$ as $k \to \infty$. The term $\epsilon_{i,t}$ is an idiosyncratic iid shock to individual performance with mean zero and variance $\sigma^2_\epsilon$.

Agent $i$'s stock of acquired skill at time $t$ is determined by the transition function (7). The parameter $\delta$ is the depreciation rate for acquired skill. The function $g$ captures the production of acquired skill through inputs $x_{i,t}, g' > 0$, $g'' \leq 0$. At the steady state, $x_i = g^{-1}(\delta k_i)$.

Performance functions for competitors with two different levels of innate skill are shown in Figure 1. For a given $k$, low and high innate skill competitors have the same marginal product. At $k = k_a$ in Figure 1 $z'_L(k_a) = z'_H(k_a) = f'(k_a)$, $f_H(k_a) > f_L(k_a)$. For a given performance level the player with less innate skill has a lower marginal product of $k$. For $k_h < k_i$ such that $E(z_H(k_h)) = E(z_L(k_i))$, $z'_L(k_i) = f'(k_i) < f'(k_h) = z'_H(k_h)$.

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3 The implication of a multiplicative relationship between innate and acquired skill, say $a_i f(k_i)$, is interesting as well. If high skilled competitors benefit from a higher marginal produce of investment, this makes possible (though still not ensuring) a separating equilibrium reminiscent of Spence (1973). Larger purses will increase the desire for the top skilled players to ensure their dominance. In this case, performance distributions would expand rather than compress.

4 The choice between setting $f$ to be concave or $g$, is arbitrary and interchangeable. An alternate model of skill allows high skilled agents to more easily acquire human capital (see…). This would require $g(x_{i,t}, a_i)$, or
2.2 Analysis

A condition for the agents to invest in acquired skills is that the expenditure of effort has a reward. The presence of an increasing payoff to performance does not create an incentive for investment if the difference in performance between one competitor and the next is too great to be overcome by acquiring skills. Formally, define for consecutively ranked players in $a$,

**Condition A:** There exists some $k_{i,t}, k_{i,t} < \kappa < \infty$ such that for $a_i < a_{i+1}$,

$$a_i + f(k_i) > a_{i+1} + f(0).$$

The upper bound $\kappa$ ensures that the superior performance comes with a finite level of acquired skill. The more closely spaced the competitors are in $a_i$, the more competitive is the environment and the lower $\kappa$ can be for Condition A to be true. Define the environment to be competitive if at least one competitor chooses to maintain a positive stock of acquired skill.

Let $h(y_{i,t}, y_{-i,t})$ be a continuous function approximation of the discrete function $H$,

$$m_{i,t} = h(y_{i,t}, y_{-i,t}) \approx H(I + 1 - r(y_{i,t}, y_{-i,t})).$$

As such, $h$ is an increasing and convex function as the competitor improves relative performance. Of course, one a competitor’s performance attains the top ranked position, $h$ is flat with regards to further improvements in performance. Thus, we have $h_t(y_{i,t}, y_{-i,t}) > 0$ and $h_l(y_{i,t}, y_{-i,t}) > 0$ for $y_{i,t} \leq y_t^*$ and $h_l(y_{i,t}, y_{-i,t}) = 0$ for $y_{i,t} > y_t^*$. The upper bound $y_t^*$ is the performance necessary to earn the top rank in the period $t$ tournament. Let $h_t(y_{i,t}, y_{-i,t}) = h(y_{i,t}, y_{-i,t})$ alternatively, $f(k_{i,t}, a_i)$ with $f_{k,a} > 0$. The implications of the model are not altered by this alternate specification since $f^{Hi}(k_i, a_i) > f^{Lt}(k_i, a_i)$ would remain true.
so that the subscript \( t \) on \( h \) reflects the time \( t \) realization of \( y_{-t,i} \). The clustering of competitor performance or a large gap in scores between adjacent ranked competitors can result in

\[ h_t'(y_{-t,i}) \geq 0, \text{ with } h_t''(y_{-t,i}) \in R. \]

To reduce the number of special cases that need to be examined, assume a competitive environment (see Condition A) with a smooth distribution of innate skills and with a density that is either constant or decreasing as innate skill rises for the population participating in the tournaments. Consider \( h^*(y) = E(h(y)) \). The uncertainty is in what mapping from performance \( y \) to rank \( r \). Assume homogeneous beliefs so that the expectations function is shared by all competitors. By the nature of the tournament compensation structure, \( h^* \) is increasing and convex at low levels of performance due to the underlying convexity in \( h \). Performance that is perceived to approach (or surpass) the unknown \( y_i^* \) will realize decreasing marginal benefit to improved performance so that \( h^* \) becomes concave for high \( y_i \).

Using (2), (5), (6), and (8) to express utility as a function of acquired skill produces

\[
U(k_{i,t}, x_{i,t}) = (u(h_i(a_i + f(k_{i,t}) + e_{i,t}, M_i)) - x_{i,t}
\]

\[
k_{i,t} \geq 0, \quad x_{i,t} \geq 0.
\]

As with Green and Stokey (1983), the aggregate shock, \( \eta_i \), is not a component of the optimization problem since it does not alter rank.

The Euler equation requires that \( x_{i,t} \) solves

\[
E(u'(m_{i,t})h'(y_{i,t})f'(k_{i,t})) = (\delta + \theta) / g'(x_{i,t}).
\]

The steady state level of acquired skill for player \( i \) depends on the player’s innate skill level, on the size of the total purse, and, due to the nonlinearity of \( u \) and \( h \), \( \sigma^2_e \) (as a first approximation),
\[ k_i^* = k(a_i, M'; \sigma_i^2) \]. The steady state level of effort can be solved from (7) as \( x_i^* = g^{-1}(\delta k_i^*) \). To reduce notation clutter, the \( i \) subscripts are dropped but remain implied. The LHS of (10) captures the marginal benefit of acquired skill while the RHS is the marginal cost of maintaining it. The steady state requires,

\[ E(u'(k_i^*)h'(k_i^*)f''(k_i^*)) = (\delta + 0)/g'(\delta k_i^*) \]

**Proposition 1:**

a) The Marginal Benefit of acquired skill (MB) is asymptotically decreasing with MB \( \rightarrow 0 \) as \( k \rightarrow \infty \).

b) It is possible that for individual \( i \) there exists a range of \( k_i \), \( 0 \leq k_{i1} \leq k_i \leq k_{i2} < \infty \) for which MB is increasing in \( k_i \).

**Proof:** The fact that \( f' \rightarrow 0, f'' \rightarrow 0, \) and \( h' < \lambda < \infty \) as \( k \rightarrow \infty \) ensures that the marginal benefit converges to zero as \( k \rightarrow \infty \). The derivative of the LHS of (10) produces

\[ E(u'' h' f'+u' h'' f''+u' h' f') \]

The second derivative, \( u'' \), \( f'' \), and \( g'' \) are all negative, but \( h'' \) in the second term includes a range that is positive. QED

The second order condition on the optimization problem is

\[ E(u'' h' f'+u' h'' f''+u' h' f')g'+g'' E(u' h' f') < 0 \]. (11)

**Proposition 2:** Given \( k \), MB is increasing in \( a_i \).

**Proof:** This follows directly from (10) given the assumption of a competitive environment. Both \( y_i \) and \( m_i \) are increasing \( a_i \). With \( h'' > 0 \), MB is increases in \( a_i \). The possible exception is the top ranked player by innate skill. This player may face \( h'' < 0 \). QED
Proposition 2 captures the increased benefit of possessing greater innate skill. The gain derives from competing on a steeper portion of the tournament payoff function.

The three functions $u, f,$ and $g$ are all concave and their impact on the decision process is redundant. The decreasing marginal utility, the decreasing marginal benefit to acquired skill on performance, and the decreasing marginal product in converting effort into acquired skill each works to a decreasing benefit to increased effort. All of the interesting behavior produced by the model derives from the convexity in the reward structure with the sudden kink that stops rewarding improved performance to the top performing competitor. Without altering the comparative statics that are the basis of our analysis, we can substantially reduce notation and increase the clarity of the issues that govern behavior by imposing linearity in two of the three functions. The remaining concave function serve the role played by all three in bounding effort. We choose to keep the concavity in $f$.\(^5\)

As in Green and Stokey (1983), consider only the symmetric Nash Equilibrium in which all agents share the same response function to their optimization problem. This eliminates possible multiple equilibrium that can arise as a result of beliefs about the investment decisions made by other competitors. Equations (10) and (11) become

\[
E(h'(z(k^*))f'(k^*)) = \phi(\delta + \theta) \quad \text{and} \quad (10')
\]

\[
E(h'' f' + h' f'') < 0 \quad (11')
\]

where $\phi = 1/u'g'$ is a constant.

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\(^5\) A linear utility function has the added benefit of eliminating risk aversion associated with the stochastic tournament prize that would affect the optimal steady state $k^*$ without altering the comparative statics for the issues considered.
2.3 Solutions

The shape of the MB curve can be classified into three categories.

Case 1: MB is everywhere decreasing in $k$.

Case 2: MB is decreasing in $k$ for $k < k_{1i}$, increasing for $k_{1i} < k < k_{2i}$, and decreasing $k_{2i} < k$ for $0 < k_{1i} < k_{2i} < \infty$.

Case 3: MB is increasing in $k$ for $0 < k < k_{2i}$ and decreasing $k_{2i} < k$ for $0 < k_{2i} < \infty$.

**Proposition 3**: $k_{1i}$ and $k_{2i}$ are decreasing functions of $a_i$.

Proof: The increasing portion of the MB curve is the result of a steeply increasing region of $h'$. For higher levels of $a_i$, this steep portion of the expected payoff is faced at lower levels of $k_i$.

**Proposition 4**: $k_i^*$ is an continuous non-decreasing function of $a_i$ with the possibility of a single jump at $a_i^* \geq 0$.

Proof: A jump occurs if an increasing portion of the MB curve crosses the MC curve.

Figure 2 displays a possible progression of MB curves produced by examining competitors in the population with increasing levels of $a_i$. The lowest skilled agent (curve I) cannot effectively compete for a tournament prize. The return to investing in additional acquired skill is everywhere less than the cost. If an increasing portion of the MB curve exists, it is far to the right and below the MC.

As innate skill rises the MB curve shifts up and the rising section migrates left. With sufficient innate skill, the MB curve crosses the MC. This may occur, as depicted by curve II, at $k = 0$, or at the peak of the rising section if $MB|_{peak} > MB|_{k=0}$. If the latter is the case, then $k^*$ jumps from $k^* = 0$ to $k^* = k^+ > 0$. Here, $k^+$ produces the peak in the MB curve for the agent $a_i$ for which all agents $j$ with $a_j < a_i$ have MB everywhere below MC. If the former is the case,
then as $a_i$ continues to rise, the increasing portion of the MB curve eventually rises to cross the MC. The jump in $k^*$ occurs when

$$\int_{k^-}^{k^+} (h'(k) f'(k) - \phi(\delta + \Theta)) dk .$$  (12)

exceeds zero. Here, $k^-$ and $k^+$ are the lesser and greater values of $k$ for which MB = MC and for which MB has a downward slope.

Further increases in innate skill can move the increasing portion of the MB curve completely above the MC as in Curve IV. A situation that can exist in a competitive environment only for the top ranked competitor according to innate skill is capture in Curve V.

It is possible that an individual competitor so overwhelms the competition that greater innate skill would allow him to reduce his investment in acquired skill producing a $k(a_i)$ that is decreasing in $a_i$. All remaining competitors compete on the convex portion of $h^e$. Steady state $k(a_i)$ is increasing in $a_i$. Figure 3 captures one possible function for $k(a_i)$ in which players with innate skill $a_i < a$ choose to maintain $k(a_i) = 0$ and at $a_i = a^*$ $k(a_i)$ jumps from $k^-$ to $k^+$. 

Figure 3 about here

2.4 Model implications

We are interested in characterizing how the distribution of performance changes in response to changes in the competitive environment. Let $m_{r,j} = p_r M_j$, $\sum p_r = 1$ so that the proportion paid to each rank is fixed.\(^6\) As $M_j$ increases, the purse spread, the monetary reward difference between earnings at each rank, increases as well. Furthermore, the higher a $a_i$

\(^6\)U.S. PGA Golf tournament awards are based on a percent of the tournament's purse. The winner receives 18% of the total purse, or $p_1 = 0.18$. The percent of the purse declines with the player’s position. The lowest positive award goes to the 70\(^{th}\) player who earns 0.2% of the total purse.
competitor’s rank the greater the increase in purse spread induced by the increase in $M$. These two features are captured by

$$\partial(\partial h(k_i)/\partial k_i)/\partial M > 0 \quad (13)$$

and

$$\partial(\partial^2 h(k_i)/\partial k_i^2)/\partial M > 0, \quad (14)$$

respectively. A change in $M_i$ should result in a change to $k_i^*$, and thus overall performance. The reaction will not be uniform across players, so the change in $M_i$ change the distribution of performance as well as the level.

The nature of the population’s response to an increase in the purse depends on the concavity of $f$ and convexity of $h$. The change in individual $i$’s performance is

$$\frac{\partial f(k_i^*)}{\partial M} = \frac{\partial f(k_i^*)}{\partial k_i^*} \frac{\partial k_i^*}{\partial M}. \quad (15)$$

Both components of the RHS of (15) are positive. The change in acquired skill, $\frac{\partial k_i^*}{\partial M}$, is positive by applying (13) to (10’). Further, we are interested in whether there will be a compression or expansion in performance among the competitors. To determine this, consider

$$\frac{\partial^2 f(k_i^*)}{\partial a_i} = \frac{\partial^2 f(k_i^*)}{\partial k_i^2} \frac{\partial k_i^*}{\partial M} + \frac{\partial f(k_i^*)}{\partial k_i^*} \frac{\partial^2 k_i^*}{\partial M \partial a_i}. \quad (16)$$

Concavity in $f$ ensures that the first term of (16) is negative while the second term is positive.

The $\frac{\partial^2 k_i^*}{\partial M \partial a_i}$ term is assured to be positive for two reasons. The increase in $M$ induces an increase in $h^*$ in (10’). Since the high innate skill players maintain a higher $k^*$, they exist on a
flatter portion of \( f \). For the same change in \( h' \), they must make a larger adjustment in \( k^* \) to satisfy the FOC. According to (14), the change to \( h' \) experienced by the high skilled players is larger than that experienced by the low skill players and thus the required adjustment to \( k^* \) is even larger. The relative magnitudes of \( f' \) and \( h' \) determine the relative magnitudes of the two terms in (16). Greater concavity in \( f' \) increases the magnitude of the negative first term and decreases the magnitude of the positive second term. The greater the convexity of \( h \), the larger is \( \frac{\partial^2 k^*_i}{\partial M\partial a_i} \).

Earnings are determined by realized tournament rankings. With repeated tournament play, a player’s rank according to earnings is asymptotically equivalent to his or her rank according to \( z_j \). Rank by earnings does not indicate how close performance is one rank to the next. The proximity of player performance is suggested by the distribution in earnings. Given \( \sigma_\varepsilon \), improved relative performance by lower ranked competitors allows greater overlap in individual performance distributions which produces greater variance in realized rank in tournaments. A greater variance in rank results in a more equitable distribution of earnings. This characteristic will be exploited in the empirical section to determine whether increases in the real value of tournament purses have produced a compression or expansion in the performance distribution.

Case 2 type competitors captured in curve III of Figure 2 offer another mechanism by which the earnings distribution becomes more equal with increases in \( M \). As depicted in Figure 3, the jump in \( k(a_i) \) divides the population into two groups of competitors characterized by high and low \( k_i \). Though there is only epsilon difference in innate skill between the \( a_i = a^* \) and \( a_j \rightarrow a^* \) from below, the difference in \( k_i \) produces a large divide in performance that results in a divide
in earnings as well. The value of \( a^* \) declines as \( M \) increases. The greater proportion of players choosing the high \( k_i \) values then the more equitable the performance and the earnings.

Those interested in Gould’s theory on performance compression may be interested in applying the model to considering the impact of an exogenous compression of innate skill on the endogenous \( k_i^* \). The closer spacing of the competitors’ skill increases the marginal benefit to acquired skill. This will lead to an increase in effort, and thus steady state acquired skills, throughout the population of competitors. Whether this behavioral component would increase or decrease compression would require further analysis.

3. Empirical Findings

In the introduction to this paper we noted that there have been performance gains by lesser skilled professional golfers relative to better skilled professional golfers, at least as evidenced by U.S. Open scoring distributions in recent years in comparison to those of one hundred years ago. From (13) relative performance gains by lesser skilled players occur when all players augment their acquired skill given the greater marginal product inherent in the lower stock of acquired skills maintained by the lesser players. It may also be true that some lesser competitors (Case 3) jump to higher skill levels in response to real purse increases, leading to even more compression in the performance distribution than would otherwise occur. This situation might be particularly relevant to our comparison of U.S. Open scoring across a century. Many of the professional golfers one hundred years ago were professional only in the sense they were willing to take prize money. Only a handful of them could earn enough money from golf to justify a substantial commitment to improving their skills. In this section we take a closer look at performance and earnings distributions in professional golf with more recent data.
3.1 Trends in the U.S. and European PGA Annual Prize Money Earnings Distributions

In section 2.3 it was shown that compression in the scoring distribution would combine with convexity in the reward structure to produce a more equitable distribution of prize money. The trends in the U.S. and European PGA annual prize money earnings distributions examined in this section are towards more earnings equality. The growth in prize money since 1953 for the Americans and since 1971 for the Europeans are shown in Figure 4.7 There was a well organized professional golf tour in the U.S. in the 1920's but “the tour became more structured after World War II and exploded in the late 1950s and early 1960s.”8 U.S. tour prize money grew from $3.2 million in 1952 (2002 dollars) to $189 million in 2002. European tour prize money grew from £3.5 million in 1982 (2002 pounds) to £47 million in 2002.

Figure 4 about here

Data are available on the prize money received by each player on these tours in each year. In Figures 5 and 6 the ratios of the prize money earnings of the 200th, 150th, 100th, 50th, and 20th ranked players to the fifth ranked player are presented for the U.S. tour for each year since 1952. The decline in these ratios with time are statistically significant and proportionately greater the larger the ratios. For example, the 200th to 5th ratio, the 100th to 5th ratio, and the 20th to 5th ratio fell from 241, 38, and 2.5 in 1955 to 35, 5, and 1.6 in 2002. The differences in the rates of decline in all ratios are statistically significant, with the exception of the 200th to the 5th

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7 U.S. prize money data provided to the authors by the PGA tour for 1953 to 1979. Prize money data since 1980 and are available at pgatour.com. European tour prize money data are available at europeantour.com. The European data presented here date from 1980 because the 1970s data includes earnings by non tour members (e.g., Americans at the British Open) while the later data does not.

in comparison to the 150th to the 5th. Declines in similar prize money distribution ratios are also
evident for the European tour. In Figures 7 and 8 the ratios of the prize money earnings of the
150th, 100th, 50th, and 20th ranked player to the fifth ranked European player are presented. The
larger two ratios decline significantly with time, the smaller two do not, and differences in the
rate of decline are significant between the larger two ratios and between the larger two ratios and
the smaller two ratios.

Figure 5 about here
Figure 6 about here
Figure 7 about here
Figure 8 about here

Trends in truncated Gini coefficients calculated for the top 200, top 150, and top 100
players on each tour also provide evidence of growing equality in earnings on the U.S. and
European PGA tours. These are presented in Table 1. The growth in earnings equality with
increasing real purses on the two tours is consistent with relative gains in performance by the
lesser skilled players.

Table 1 about here

3.2 Trends in the World Ranking of U.S. and European PGA Tour Members

In this section we consider more directly performance gains by less skilled professional
golfers relative to more skilled professional golfers during a period of real purse increase. Since
1986 the performances of players on the U.S., European, Japanese, South African, Asian, and
Australasia professional golf tours have been used to compile a "world" ranking or a joint
ranking of these players. Points for this ranking depend on a player's order of finish in a
tournament and the quality of the field that competes in the tournament. The world rankings are used to determine eligibility for several tournaments each year that are restricted to the higher world ranked players, and they are used to fill some of the places in other prestigious tournaments, including the "major" tournaments. The prize monies for these tournaments are among the highest, and thus a player's world ranking is of consequence.

Table 2 shows the proportion of U.S. and European players ranked in the top 200 according to the world rankings at years end for each year, 1986 to 2002. The data show the number of U.S. players exceeds the number of European players in each year but that the U.S. advantage declines over time. In 1986, 52% of the top 200 players were on the U.S. tour and 17% were on the European tour. In 2002, these numbers were 44% and 24%, respectively.

Regression models are presented below using the 1986 to 2002 world ranking data. The dependent variable is the "adjusted" world ranking of U.S. and of European tour players and the independent variables are own tour ranking and an interaction of own tour ranking and year counter starting at one for 1986. The adjusted ranking is obtained by eliminating from the sample players ranked in the top 200 that did not compete on the U.S. and European tours. The U.S. and European players were then re-ranked while maintaining their relative positions in the world rankings.

For U.S. tour players the results are

\[
\text{adjusted world rank} = -0.06 + 1.27 \text{ (U.S. tour rank)} + 0.013 \text{ (U.S. tour rank)} \times \text{ (year)}
\]

\[
t = -0.0 \quad t = 143.1 \quad t = 18.4
\]

\[
R^2 = 0.96, \quad n=1585.
\]

means: \text{adjusted world rank} 68.6, \text{U.S. tour rank} 48.9

For European tour players the results are
\[ \text{adjusted world rank} = 8.17 + 3.29 (\text{Eur. tour rank}) - 0.03 (\text{Eur. tour rank}) \times (\text{year}) \]

\[ t = 9.17 \quad t = 60.6 \quad t = -8.25 \]

\[ R^2 = 0.90, \quad n=727 \]

These regression results indicate that a U.S. player of a given rank on the U.S. tour had a higher world ranking than a European player of the same rank on his tour. Given the greater purses and purse spreads on the U.S. tour, the better world performance of American golfers is a straight forward prediction of tournament theory. The regression results also show that the American advantage declined with time. The estimated US tour rank effect increases from 1.28 to 1.49 between 1986 and 2002. The estimated European tour rank effect declines from 3.26 to 2.76 over the same period. Interpreting these results within the context of our model, the growth in purses on both tours leads to an increase in investment in acquired skill on both tours but the larger marginal products on the European tour results in relative performance gains.

The first order conditions reveal that, consistent with Green and Stokey, \( \eta_t \) drops out of the agent’s optimization problem. The implication is that technology improvements and other common shocks to performance do not alter behavior. This follows from the presumption that technology improvements are skill neutral. Many technological innovations in sports equipment would appear to favor the less skilled players by making the equipment more forgiving of errors in technique, and thus our assumption may appear, at first glance, to be counter intuitive. Clearly, technology can compensate for a low skill competitor’s deficiency in skill. That the increased in performance would translate into increased competition and a compression of scores requires that the top players are unable to also take advantage of the performance enhancements
offered by the new technology. This would not appear to be the case.⁹

A technology based explanation for the compression in performance is also inconsistent with our empirical findings. If this assumption is relaxed to allow relative gains in performance from technological change to accrue to lesser skilled players, a technology based explanation of earnings compression emerges. The results in this section are not consistent with this view. Technological change favoring the lesser players would cause compression in performance across the tours but would not change the relative rankings of U.S. and European players.

### 3.3 Tournament Scoring at the Bob Hope Desert Classic, 1980-2002

In this section we directly estimate purse effects on performance over time for better skilled and less skilled professional golfers on the U.S. PGA Tour. The U.S. PGA tour each year consists of about 40 tournaments played in different locations each week from mid January to mid November. Almost all tournaments are four day competitions, 18 holes per day. An analysis of the relationship between purses and tournament scoring over time on the tour is complicated by the fact that the golf courses on which tournaments are staged have not stayed the same and by changes in ball and club technology. The golf courses on which the tour professionals compete have changed for three reasons. First, some tournaments have been replaced in the schedule by other tournaments in different cities. Second, existing tournaments in a given city have used different courses in the metropolitan area. Third, courses traditionally used in existing tournaments have been made more difficult. This has been accomplished in a

---

⁹ Consider the introduction of the graphite tennis racket. It is clearly more forgiving than the old wood rackets, enabling amateur tennis players to improve their game. But, the top players in tennis take advantage of the forgiveness as well, substantially increase the ball speed and ball control.
number of ways including lengthening the holes, narrowing the fairways, adding bunkers or other hazards, growing the rough, increasing the speed of the greens, and, most recently, placing the flag sticks closer to bunkers or to the edges of the greens. Between 1993 and 2003, for example, the average total yardage of PGA tournament courses increased from 6981 to 7105 yards.¹⁰

Golf ball and golf club technologies have also changed.¹¹ Tour players claim the biggest technological change has been in the distance the golf ball travels when struck with the swing speeds achieved by a professional golfer. Although the United States Golf Association limits the liveliness of golf balls, its testing has been at swing speeds less than those of golf professionals.¹² Changes in the golf driver (the club used to begin most golf holes) have also resulted in added distance. Titanium has been used to make driver club heads larger and driver club faces thinner.

¹⁰ Authors calculations from data at www.pgatour.com. A good example of a course change to increase scoring difficulty is the alterations at Augusta National in 2002 and 2006. In 2002 the course yardage was increased from 6,985 to 7,270, trees were added along fairways, bunkers were expanded, and fairways were narrowed by extending the rough. In 2006, the course was lengthened again to 7,445 yares.

¹¹ Ball and club improvements partially explain why many courses traditionally used on the tour have been made longer and more difficult; course “integrity” can be maintained by preventing scores from going too low.

¹² Jack Nicklaus, one of the best golfers of all time and a noted golf course designer: “It's the golf ball. All of the balls do that. Its ridiculous. Absolutely ridiculous.... Because of equipment -- not equipment, just the golf ball. And the way they test golf balls, they monitor tests at 110 miles an hour. I swing at 110 miles an hour. I can't make the golf ball go anyplace. If you swing at 110 to 130 miles an hour, it's like the difference between a category 2 and category 3 hurricane. It's not a little bit. [The golf ball] just explodes.” (“Golf balls making courses obsolete,” May 30, 2003, http://www.golfserv.com/gdc/news/article.asp?id=13625)
in order to create a trampoline effect at impact.\textsuperscript{13} Data on the average driving distance of PGA tour professionals appears to reflect these technological changes. The data show a modest increase in average driving distance from 257 yards to 260 yards between 1980 and 1993 and then an increase to 280 yards by 2002.\textsuperscript{14} Frank Thomas, who was in charge of equipment and ball testing for the for the United States Golf Association throughout this period, agrees that the increase in driving distance is due to the livelier balls and improved drivers.\textsuperscript{15}

The issue of changes in course difficulty in an analysis of the relationship between golf scoring and purse over time can be circumvented if course layouts can be identified that have not changed in difficulty. Tournaments in which amateurs play with the pros for several rounds can provide venues that have been consistent over time on the days the amateurs play. There are four such tournaments held each year. These are the AT&T Pebble Beach Nation Pro Am, The Bob Hope Chrysler Classic, The Walt Disney World Golf Classic, and the Las Vegas Invitational. Generally in these tournaments a pro is paired with three amateurs for each round but the final one. One purpose of this format is to raise money; amateurs pay sizeable fees for the privilege of participating. The presence of amateurs in the field on days when the pros are competing means the courses on these days must be set up to facilitate amateur play. If pin placements are too

\textsuperscript{13} Popular Mechanics Magazine (2003) reports the trampoline effect is greatest at high swing speeds. http://popularmechanics.com/science/sports/2003/1/feel_the_tension/. Tiger Woods has “complained all year that some players were using hot drivers that exceeded the (United States Golf Association) limits for the springlike effect.” Miami Herald, September 30, 2003.

\textsuperscript{14} See pgatour.com

difficult, greens too fast, or rough too thick, amateurs will take too long to complete 18 holes of play.

The Bob Hope Chrysler Classic is contested on four separate courses each year. Four courses are required because of the usual complement of pros (about 130 start the tournament) plus three amateurs for each pro. Each pro plays on a different course on each of the first four days. Amateurs play with the pros on the first four days. On the fifth and final day, only the pros compete.\(^{16}\) Two of the courses, Bermuda Dunes and Indian Wells, have been used in the tournament every year since 1980, which is the first year for which comprehensive data on PGA tour players have been maintained by the PGA Tour. According to the course superintendents and to the tournament office, these courses have changed little since 1980.\(^{17}\) The scoring data for our research are the pros’ scores on these two courses on those days they compete with the amateurs from 1980 to 2002. About 5,720 scores are available (130 pros x 2 courses x 22 years).\(^{18}\) The average daily scores of the tour players at Indian Wells and Bermuda Dunes on the days they played with the amateurs declined from 72.4 in 1980 to 68.8 in 2002, or by 3.6. Because both the 1980 tournament, and to a lesser extent the 2002 tournament, had days of inclement weather, a purer measure of the trend in score decline is from a comparison of the average scores in 1981 and 2001, years in which the weather is described by the PGA tour as perfect on all tournament days.\(^{19}\) This comparison shows a decline of 2.7, from 71.2 to 68.5.

\(^{16}\) The Hope is one of the rare five day, 90 hole tournaments.

\(^{17}\) There have been some changes in course yardage that are controlled for in the empirical analysis.

\(^{18}\) Daily scores and course assignments obtained from the Desert Sun newspaper.

\(^{19}\) The PGA tour records weather conditions for each day of each tournament. In the case of the Hope Tournament weather conditions are usually "perfect". Statistics for wind and rain days at the Hope are presented in Table 3.
The average score at all PGA tournaments declined by 1.22 between 1980 and 2002, from 72.26 to 71.04. The smaller decline tour wide may be due to increases in PGA course difficulty in the latter part of the period. Annual prize money on the PGA tour increased from 26 million to 189 million in 2002 dollars in the 1980-2002 period. The score declines at the Hope do not necessarily result from enhanced skill levels of PGA tour players. Improved technology or the attraction of better players to the Hope field are among those factors that could also be responsible for improved scoring over time.

We begin the analysis of the relationship between purse size and scoring with the Hope data by relating the daily score of a player to weather, prize money, the player’s quality or rank, and course length. More specifically, with individual player subscripts suppressed,

\[ \text{Score}_{dt} = f(\text{wind}_{dt}, \text{rain}_{dt}, \text{real\,purse}_t, \text{rank}_t, \text{length}_{dt}). \]

Scores on day \( d \) in year \( t \) are related to wind and rain conditions on that day, the real total purse of all tournaments for that year, the player’s rank on the prize money list for that year, and the adjusted length or yardage of the course (Bermuda Dunes or Indian Wells) on which the score was recorded. The length variable is adjusted to reflect technological improvements after 1993. The yardage for each course is reduced in each year by 14 times the increase in driving distance over the 1993 tour average. The factor of 14 comes from the fact that the driver will be used up to 14 times in an 18 hole round on a course with four par threes, four par fives, and 10 par fours. The real purse variable references the total purse for all tournaments on the PGA tour in each year because we assume tour pros improve their skills in response to earnings possibilities in all tournaments. The real purse also determines the purse spread given the fixed payout schedule in the period.
Two sets of generalized least squares estimates for daily scoring at the Hope tournament, 1980-2002, are presented in Table 2. In regression 1 the scoring model estimates are for the better one half of the players according to rank on the money list. In regression 2, the estimates are for the lesser one half of the players. The real purse variable is negatively related to scoring in each equation and greater in absolute value for the lesser players, although the difference in the coefficients is not statistically significant ($t = 1.1$). The increase in real PGA purses and the real purse regression coefficients imply daily score reductions of 1.9 and 2.4 between 1980 and 2002 for the better one half and lesser one half of the players, respectively. We interpret these results as supportive of an incentive effect of purse size on the acquisition of skills and on scoring and broadly supportive of gains in performance of lower ranked players relative to higher ranked players as real purses have increased.\(^{20}\)

4. Summary and Conclusion

We examined the steady state properties of a dynamic model of skill acquisition to understand performance in a tournament setting. Empirically, we examined trends in professional golf earning distributions and in the relative performance of U.S. and European professional golfers. We also estimated the relationship between real purses and scoring among above average and below average PGA tour golfers in the U.S. The empirical work indicated that the performance of less skilled professional golfers is improving relative to better skilled

\(^{20}\) It is also interesting to note that the coefficients of the weather variables and the length variables are greater in absolute value for the better players, with the difference in the weather coefficients being statistically significant. These coefficients imply that higher ranked players take greater advantage of favorable scoring opportunities (shorter yardage, better weather) than lesser ranked players.
golfers in periods of rising real purses and increases in purse spreads that favor the better golfers.

We argued that this anomaly might have a straightforward explanation. It is that the better players have greater stocks of acquired skill and lower marginal products of acquired skill than the lesser players and therefore increased investment in acquired skill across the skill distribution lead to relative performance gains by the lesser players.
Bibliography


Figure 1 Expected individual performance as a function if $k_i$ for high and low innate skill competitors
Figure 2 MB curves for five different levels of innate skill
Figure 3 Steady state acquired skill, $k^*_i$, as a function of innate skill, $a$
Figure 4 U.S. and European Tour Purses by Year
Figure 5 U.S. Prize Money Ratios 5th Ranked Player to 200th, 150th, and 100th, 1952-2002
Figure 6 U.S. Prize Money Ratios of 5th Ranked Player to 50th and 20th, 1952-2002
**Figure 7** European Prize Money Ratios of 5th Ranked Player to the 150th and 100th, 1980-2002
Figure 8 European Prize Money Ratios of 5th Ranked Player to 50th and 20th, 1980-2002
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Table 1: Gini Coefficients for U.S. and European PGA Tours
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Other PGA tours are: Japanese, South African, Asian, Australasia.
Table 3
Results of Regressing Daily Scoring on Real PGA Purse and Other Variables, Above Median Rank Players and Below Median Rank Players, Hope Tournament, 1980 - 2002

<table>
<thead>
<tr>
<th>Variable</th>
<th>Above Median Rank</th>
<th>Below Median Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>t stat.</td>
</tr>
<tr>
<td>Wind</td>
<td>1.5918</td>
<td>11.39</td>
</tr>
<tr>
<td>Rain</td>
<td>0.2908</td>
<td>1.14</td>
</tr>
<tr>
<td>Rank</td>
<td>0.0134</td>
<td>7.22</td>
</tr>
<tr>
<td>Realpurse</td>
<td>-0.0011</td>
<td>-9.79</td>
</tr>
<tr>
<td>Length</td>
<td>0.0019</td>
<td>7.85</td>
</tr>
<tr>
<td>constant</td>
<td>56.9024</td>
<td>34.76</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.1400</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td>2910</td>
<td></td>
</tr>
</tbody>
</table>

The t statistics are from Huber robust standard errors clustered on year

Daily scoring is for the Indian Wells and Bermuda Dunes courses. Wind and Rain indicates wind or rain on that day according to the PGA tour media guide. Rank is player’s rank on money list for that year. Realpurse is total prize money (2002 dollars) divided by 100,000 on PGA tour for that year. Length is course length in yards adjusted for technological improvements after 1993. Full sample means and (standard deviations) are: Daily scoring 70.11 (2.97); Wind .16 (.37); Rain .04 (.21); Rank 110.5 (67.4); Realpurse 766.0m (469.3m); Length 6610.8 (219.3).