The Causality between Salary Structures and Team Performance: A Panel Analysis in a Professional Baseball League

Article *in* International journal of sport finance · May 2009

Source: RePEc

Wen-Jhan Jane
Shih Hsin University

International Journal of

Sport Finance

Volume 4 • Issue 2 • May 2009

The Role of Managers in Team Performance
David J. Berri, Michael A. Leeds, Eva Marikova Leeds, and Michael Mondello

Estimates of the Dimensions of the Sports Market in the US
Brad R. Humphreys and Jane E. Ruseski

Golf Match: The Choice by PGA Tour Golfers of which Tournaments to Enter
Stephen Shmanske

The Causality between Salary Structures and Team Performance: A Panel Analysis in a Professional Baseball League
Wen-Jhan Jane, Gee San, and Yi-Pey Ou

International Journal of Sport Finance

Volume 4 • Number 2 • May 2009

Publisher: The *International Journal of Sport Finance* is published four times a year (February, May, August, and November) by Fitness Information Technology, a Division of the International Center for Performance Excellence, West Virginia University, 262 Coliseum, WVU-PASS, PO Box 6116, Morgantown, WV 26506-6116.
Phone: 304.293.6888
Fax: 304.293.6658
Email: fitcustomerservice@mail.wvu.edu
Website: www.fitinfotech.com

The *International Journal of Sport Finance* is printed by Publishers' Graphics, Carol Stream,IL.

The *International Journal of Sport Finance* is indexed in CSA, Current Contents/Social & Behavioral Sciences, EBSCO, Intute: Social Sciences, Leisure Recreation & Tourism Abstracts, Physical Education Index, Research Papers in Economics, Social Sciences Citation Index, SPORTDiscus, SportSearch, Ulrich's, and WorldCat.

Business correspondence, subscriptions, and address changes should be mailed to Fitness Information Technology, A Division of the International Center for Performance Excellence, 262 Coliseum, WVU-PASS, PO Box 6116, Morgantown, WV 26506-6116.

ISSN: 1558-6235 (Print)
1930-076X (On-line)

FiT

International Journal of Sport Finance

Volume 4 • Issue 2 • May 2009

Original Contributions

The Role of Managers in Team Performance
David J. Berri, Michael A. Leeds, Eva Marikova Leeds, and Michael Mondello 75

Estimates of the Dimensions of the Sports Market in the USl
Brad R. Humphreys and Jane E. Ruseski 94

Golf Match: The Choice by PGA Tour Golfers of which Tournaments to Enter
Stephen Shmanske 114

The Causality between Salary Structures and Team Performance: A Panel Analysis in a Professional Baseball League
Wen-Jhan Jane, Gee San, and Yi-Pey Ou 136

Departments

Professional Bulletin Board 74

Book Review
The Economics of Intercollegiate Sports, by Randy R. Grant, John Leadley, and Zenon Zygmont
Marvin Washington 151

Professional Bulletin Board

June 8-12, 2009
Play the Game 2009
Location: Coventry, United Kingdom
Email: info@playthegame.org
Website: http://www.playthegame.org/conferences/play-the-game-2009.html

June 29-July 3, 2009
84th Annual Western Economics Association Conference
Location: Vancouver, British Columbia
Contact: Dave Berri
Email: dberri@csub.edu

October 28-30, 2009
SMA VII
Location: Cleveland, Ohio
Website: http://www.sportmarketingassociation.com/2009conference.htm

International Journal of Sport Finance, 2009, **4**, 75-93, © 2009 West Virginia University

The Role of Managers in Team Performance

David J. Berri[1], Michael A. Leeds[2], Eva Marikova Leeds[3], and Michael Mondello[4]

[1] Southern Utah University
[2] Temple University Japan
[3] Moravian College and Temple University Japan
[4] The Florida State University

David J. Berri, PhD, is an associate professor of economics in the Department of Economics and Finance. His current research focuses on the economics of sports, specifically the topics of consumer demand, competitive balance, and worker productivity.
Michael A. Leeds, PhD, is a professor of economics in the Fox School of Business and Management. His research focus is in the area of sports economics.
Eva Marikova Leeds, PhD, is an associate professor of economics and business. Her research interests include financial institutions, development economics, and sport economics.
Michael Mondello, PhD, is an associate professor in the Department of Sport and Recreation Management. His research interests focus on financial and economic issues of sport organizations.

Abstract

The role of the manager in promoting production is a little-understood phenomenon. In particular, it is difficult to separate managers' contributions from the abilities of the workers they supervise. Firms may therefore mistakenly attribute the contributions of the workers to the managers who happen to oversee them. With its plethora of performance data, the National Basketball Association (NBA) provides a natural setting to measure the contribution of a head coach to the performance of his team. We find that some highly regarded coaches deserve their accolades, but several coaches owe their success to managing highly talented teams. Conversely, some coaches with mediocre records have made significant contributions to the performance of their players. Most coaches, however, do not have a statistically significant impact on their players or their teams, making them nothing more than the "principal clerks" that Adam Smith called managers over 200 years ago.

Keywords: coaching efficiency, National Basketball Association, productivity

Introduction: The Role of Managers

The reputation of corporate managers goes through periodic upswings and downturns. As noted by Ira Horowitz (1994b), Adam Smith argued managers play an inconsequential role in the performance of a firm. Specifically, Smith separated the role of the entrepreneur from that of the manager. In Smith's view, entrepreneurs provide both the fundamental ideas and capital the organization requires for success.

Beneath the entrepreneur is a group of subordinates that oversees daily operations. From Smith's perspective, this group of subordinates does not vary in any significant way from organization to organization. In essence, the managers of daily operations are little more than "principal clerks" (Smith, 1976, pp. 54-55). This view of managers has persisted in the neoclassical model of the firm in which "top managers are homogeneous … inputs into the production process" (Bertrand & Schoar, 2003, p. 1173).

With its emphasis on static equilibrium, neoclassical theory assumes away any role for managers. In this setting, managers ensure firms operate in a technically and economically efficient manner. That is, they extract maximal output from a given set of inputs and minimize the cost of a given level of output. For a given set of inputs, a given technology, and given prices, all managers behave in exactly the same manner.

In contrast to neoclassical economics, the popular press has often regarded corporate managers, particularly CEOs, with an almost cult-like devotion. A search of Amazon.com's website showed almost 4,000 entries for Jack Welch, of which about 25 were either books by him or books whose title featured his name. These works almost uniformly praised Welch for his leadership of GE. The contrast between economic theory and popular wisdom reveals a flaw that economists have only recently begun to address. By focusing on equilibrium, the neoclassical model overlooks the key role of managers: to seek out and exploit disequilibria.

The most successful managers take advantage of market inefficiencies or find previously undiscovered niches. Such managers thus take on some of the characteristics of entrepreneurs. Unlike entrepreneurs, however, they work to redirect the inputs of existing companies rather than create new products or firms. Jack Welch, for example, did not create any new financial services. He did, however, transform GE by shifting its focus from manufacturing to financial services at a time when manufacturing was beginning to decline and the financial services sector was expanding.

Economic studies of managers have begun to recognize this role of managers and have sought to quantify their impact on the firms they head. The studies generally find that managers have a strong impact on firm policy and profitability. However, these findings are typically the result of a broad series of interactions between the CEOs, their "managerial teams," and firms as a whole. Therefore, the studies can only indirectly infer the contribution of the manager.

Sociologists, in contrast, have long recognized the role played by managers. For example, Grusky (1961) examined the nature and impact of managerial succession in firms long before the issue interested economists. In a follow-up study, Grusky (1963) recognized that sports are a natural source of data on managerial succession. He noted Major League Baseball teams provided "reliable and valid measures of rates of administrative succession and organizational effectiveness" (Grusky, 1963, p. 21). Because managers in professional sports teams all pursue identical goals by performing similar tasks, professional sports are a natural laboratory in which to investigate the contributions of managers to the performance of their organizations.

More recent studies in finance and economics have built upon Grusky's work by isolating the impact of managerial change or of specific managers. The abundant performance data available in sports allow researchers to control for the quality of inputs overseen by managers. Such studies generally adopt Adam Smith's view of managers as people who rearrange inputs of a given quality. We take this literature one step further by calculating the impact of managers on the productivity of individual players. We use this information to determine the impact of individual managers on team performance.

We compile and analyze a data set measuring the performance of individual players in the National Basketball Association (NBA) from the 1977-1978 season through the 2007-2008 campaign. We use the mobility of players and coaches over this period to isolate the impact of coaches on the teams they direct. Unlike most work on managerial performance, our study focuses on how managers affect the performance of individual players. Our results show some managers having reputations for good management skills may simply be the beneficiaries of the good teams they coach. This finding suggests recent empirical studies of CEOs may also be subject to the failure to isolate the behavior of managers.

Next, we show how managers in professional sports behave entrepreneurially by exploiting inefficiencies and discovering niches. In the section that follows, we present our measure of player performance and describe our data. In the Model of Coaching Effectiveness section, we develop a model of managerial performance, showing how much a coach contributes to a player's performance. Then, we present our estimates and use them to evaluate the impact of coaches on team performance. We finish with the conclusion.

The Economist's View of Management and Coaching

Because of the long-standing view that entrepreneurs, and not managers, matter, the economics and finance literatures have only recently begun to quantify the performance of individual managers. Some studies, such as Chevalier and Ellison (1999) and Bertrand and Schoar (2003), essentially construct matched-panel data sets allowing them to track managers as they move from firm to firm. Using such data sets allows them to separate the performance of managers from the organizations they head. Unfortunately, a manager's decision to move is often endogenous. For example, a change in CEOs could be the result of internal conflict within the organization that adversely affected the company's performance under the former CEO and whose resolution boosts the company under the new CEO. The performance of the firm could thus reflect the underlying conflict leading to the change in CEOs rather than the behavior of the CEOs themselves. Moreover, when managers move from one firm to another, they often bring a coterie of assistants with them. The fact the company effectively hires both the CEO and his "team" leads to an identification question: does the firm owe changes in performance to the manager or to the team s/he heads?

Other studies, such as Bennedsen, Perez-Gonzalez, and Wolfenzon (2006) and Johnson et al. (1985) base their analyses on truly exogenous separation: the unexpected deaths of CEOs. However, these data sets examined small samples or were geographically specific. Moreover, Johnson et al. took a very different view of managers. In their model, managers were valuable because they acquired firm-specific skills that do not necessarily apply elsewhere.

Two books by Michael Lewis demonstrate how managerial initiatives improve or fail to improve performance in professional sports. In *Moneyball* (2003), Lewis shows how Billy Beane, the general manager of the Oakland Athletics baseball team, exploited inefficiency in the evaluation of potential major league players. In their analysis of

Moneyball, Hakes and Sauer (2006) demonstrate the Athletics' success stemmed from the fact they more accurately assessed the value of players' skills. Other teams had consistently overvalued slugging percentage (the number of total bases a player advances per at-bat) and undervalued on-base percentage (the likelihood that a player successfully reaches base per at-bat). By more accurately assessing these skills, Beane acquired undervalued players and discarded overvalued ones. This allowed the Athletics to compete successfully with teams having much higher payrolls. A less noted point in *Moneyball* is the dim view Beane takes of the team's manager. Beane views his manager similar to Adam Smith, as a principal clerk carrying out the wishes of his entrepreneurial superiors.

In *The Blind Side* (2006), Lewis describes the niche that football coach Bill Walsh uncovered with the Cincinnati Bengals and later perfected with the San Francisco 49ers. Walsh developed a new product that revolutionized his field. Specifically, Walsh created the "West Coast Offense," where teams rely heavily on quarterbacks who can respond to what they see on the field and complete short passes to a variety of receivers. The West Coast Offense transformed the Bengals and then the 49ers from mediocre teams to dominant offensive machines, and it greatly enhanced the careers of key players on each team.

While Michael Lewis's case studies are highly suggestive, they neither prove nor disprove that coaches and managers in professional sports systematically affect their teams' performances. A look at two NBA coaches reveals the difficulty involved in evaluating coaching performance. Phil Jackson became head coach of the Chicago Bulls of the NBA in 1988. Over the next nine seasons, the Bulls won 74% of their regular season contests and six NBA titles. Jackson retired after winning his sixth title with the Bulls in 1998. His retirement, though, lasted only one season and in 1999 he became the head coach of the Los Angeles Lakers. Again, Jackson's team won three consecutive titles. During his first 14 seasons of coaching, Jackson compiled a record unmatched in the history of the NBA. He is the only coach with a career winning percentage greater than .700 and he has won more championships than any other coach except Red Auerbach.

Using either winning percentage or championships to measure productivity, Jackson appears to be the best coach in NBA history. However, Jackson had considerable talent at his disposal. In seven of Jackson's first nine seasons he coached the incomparable Michael Jordan. In the 147 games Jordan did not play with the Bulls in 1993-94 and 1994-95, Chicago won 60.5% of its games (http://www.nba.com). While this record was better than most coaches, it was well below Jackson's career record.

With the Lakers, Jackson was again blessed with extraordinarily talented players, particularly center Shaquille O'Neal and guard Kobe Bryant. When O'Neal was traded to the Miami Heat, the Lakers' record declined significantly even after Jackson returned from another year-long retirement. Again, it is hard to separate Jackson's ability as a coach from the talents of his players.

Phil Jackson's career record stands in stark contrast to that of Tim Floyd, Jackson's successor in Chicago. Floyd has enjoyed considerable success as a coach at the collegiate level, winning close to two-thirds of his games with three colleges. In the NBA, however, Floyd has had little success. His record with the Bulls before being dismissed part-way through the 2001-2002 season was a dismal 49-190 (http://www.nba.com).

While Tim Floyd had considerably less success with the Bulls than Phil Jackson, he also had far fewer talented players on the roster. When Jackson left, so did almost half the members of the 1997-98 championship team, including such star players as Dennis Rodman, Scottie Pippen, and Michael Jordan. At least a portion of Tim Floyd's lack of success with the Bulls can be attributed to a much shallower talent pool. Some support for the claim that Floyd was a victim of circumstance comes from his record in 2003-04 with the New Orleans Hornets. The Hornets won half their games and advanced to the second round of the playoffs, something that none of Floyd's teams in Chicago came close to doing. The contrasting stories of Phil Jackson and Tim Floyd exemplify the fundamental problem facing those interested in studying the role of managers in the success of an organization: how can one separate the performance of management from the performance of the workers?

Previous Economic Studies of Sports Coaches and Managers

The sports economics literature on the contributions of managers has built on Grusky's estimation in a number of ways. Most notably, it features more sophisticated techniques. These include an early form of frontier analysis (Porter & Scully, 1982), generalized least squares (GLS) (Chapman & Southwick, 1991), hazard models (Ohkusa & Ohtake, 1996; Scully, 1994), and the Pythagorean Theorem (Horowitz, 1994a, 1997). The literature also spans a variety of sports, including college basketball (Clement & McCormick, 1989; Fizel & D'Itri, 1996) American football (Hadley et al., 2000), and soccer (Dawson, Dobson, & Gerrard, 2000a, 2000b).

The above studies share two characteristics. First, they attempt to control for the quality of the talent at the manager's disposal. In baseball studies, for example, this often takes the form of using batters' slugging average as an explanatory variable, as first proposed by Scully (1974). Second, the studies treat talent as exogenous, as they implicitly assume the role of the manager is to manipulate inputs of a given quality. Thus, the general form of the studies can be expressed as

$$W_{it} = f(A_{it}, M_{ijt}) + \varepsilon_{it} \qquad (1)$$

where W_{it} is the winning percentage of team i in year t, A_{it} is the inherent ability level of team i in year t, and M_{ijt} is an indicator variable denoting whether manager j led team i in year t. Typically, M_{ijt} takes the form of a dummy variable, while e_{it} is a random error term reflecting unobserved factors.

Kahn (1993) and Ohkusa and Ohtake (1996) are notable exception to the above framework. Both studies test whether coaches make their players better. Kahn models Major League Baseball players' performance as a function of managerial quality. Managerial quality, in turn, is determined by regressing the manager's salary on his experience, lifetime winning percentage, and a dummy variable indicating the league in which he managed. This approach, however, has several problems. First, because the model relies on an abstract variable called "managerial quality," Kahn cannot identify the contributions of specific coaches. Second, if good managers keep their jobs longer, modeling quality as a function of experience is subject to simultaneity bias.

Ohkusa and Ohtake (1996) test whether Jovanovic's (1979) matching hypothesis holds in Japanese baseball. They regress performance measures on a player's experience and a sequence of managerial dummy variables. The coefficients reveal the impact of matching player i with manager j in year t. They find the managerial dummies do not vary by player, which lead them to reject the hypothesis that individual players benefit from playing for specific managers.

Measuring Player Performance

We build upon the work by Kahn (1993) and Okhkusa and Ohtake (1996) by carefully modeling the impact specific coaches had on the productivity of individual players and on team performance. To start, we need a measure of player performance.

Studies of baseball have benefitted from a plethora of summary metrics—such as slugging percentage, OPS (the sum of slugging percentage and on-base percentage), and linear weights—designed to measure a baseball player's performance on the field. Researchers looking at the sport of basketball, though, have far fewer options.

The traditional measure—labeled NBA Efficiency by the NBA—involves adding together a player's positive statistics (points, rebounds, steals, assists, and blocked shots) and subtracting the numbers that detract from wins (turnovers and missed shots). As Berri (1999, 2008) noted, such an approach fails to account for the differing impact these statistics have on wins.

The limitations of NBA Efficiency lead us to employ the measure detailed in Berri and Krautmann (2006), Berri, Schmidt, and Brook (2006), and Berri (2008). As these

Table 1: The Impact of Various Statistics Tracked for Players and Teams on Wins in the NBA

Player Variables	Marginal Value
Three Point Field Goal Made (3FGM)	0.06438
Two Point Field Goal Made (2FGM)	0.03179
Free Throw Made (FTM)	0.01758
Missed Field Goal (MSFG	-0.03337
Missed Free Throw (MSFT)	-0.01500
Offensive Rebounds (RBO)	0.03337
Defensive Rebounds (RBD)	0.03325
Turnovers (TOV)	-0.03337
Steal (STL)	0.03325
Opponent's Free Throws Made (DFTM)	-0.01752
Blocked Shot (BLK)	0.01744
Assist (AST)	0.02228
Team Variables	**Marginal Value**
Opponent's Three Point Field Goals Made (D3FGM)	-0.06414
Opponent's Two Point Field Goals Made (D2FGM)	-0.03168
Opponent's Turnovers (DTOV)	0.03325
Team Turnover (TMTOV)	-0.03337
Team Rebounds (TMRB)	0.03325

Note: These estimates are based on the model detailed in Berri (2008). The data employed to estimate the Berri (2008) model can be found at Basketball-Reference.com and in various issues of *The Sporting News NBA Guide*. The specific years used to estimate the Berri (2008) model began with the 1987-88 NBA season and ended in 2007-08.

works support, wins in the NBA are a function of a team's offensive and defensive efficiency; where efficiency is defined by how many points a team scores and surrenders per possession. Estimates of the relationship between wins and the efficiency metrics reveal that points, rebounds, steals, turnovers, and field goal attempts have virtually the same impact, in absolute value, on team wins. Free throw attempts and personal fouls have a smaller effect. Additional regression analysis reveals that both blocked shots and assists also have a smaller absolute impact. Given these values—detailed in Table 1—a player's marginal product (PROD) can be captured simply and accurately, as illustrated by equation (2).

$$PROD = 3FGM*0.064 + 2FGM*0.032 + FTM*0.018 + MSFG*-0.033 + MSFT*-0.015 + REBO*0.033 + REBD*0.033 + TO*-0.033 + STL*0.033 + FTM(opp.)*-0.018 + BLK*0.017 + AST*0.022 \tag{2}$$

As detailed in Berri (2008), PROD is then adjusted for the statistics tracked for the team. Then, because players play differing minutes, we calculate each player's performance per 48 minutes (ADJP48).[1]

All of the above variables are readily available for players in the NBA. Using the *Sporting News NBA Guide* and the *Sporting News NBA Register* (various years), as well as http://www.Basketball-Reference.com, we collected data from the 1977-78 through 2007-08 seasons.

The data set does not include all players in the NBA during this time period. *ADJP48* can be misleadingly high or low for a player appearing in only a handful of games or playing only a minute or two per game. To ensure reliable measures of efficiency for each year, we included only players playing at least 20 games and averaging at least 12 minutes per game. These restrictions yielded 7,887 player observations. "Player observation" refers to the fact that we might observe ADJP48 for a given player in multiple seasons.

If every player played for the same coach throughout his career, it would be impossible to separate player performance from coaching performance. Fortunately, players frequently change teams through trades or free agency, and coaches are regularly hired and fired. Of the 7,887 player observations in our sample, 3,595—or 45.6%—were with a new coach.

While frequent coaching changes were vital for our data set, they also created a problem. Just as a player with few or brief appearances might have a misleading ADJP48 value, a coach working with very few players might have a misleading impact on those players. To minimize this problem, we include only teams led by coaches who:

- had at least 15 players meeting our minutes and games played restrictions coming to the coach.
- had at least 15 players meeting our minutes and games played restrictions leaving the coach.

Given these two restrictions we were left with a sample of 62 head coaches.

Finding the Best Coach: Moving from the Traditional to the Simple

With our adjusted data, we commenced our search for the best coaches. Table 2 reports the lifetime coaching records (as of the end of the 2007-08 season) of the top 20 coaches—in terms of career winning percentage—in our sample. At the top of our list is Phil Jackson. As noted, Jackson's teams won 70% of their regular season games. Only six

Table 2: The Top 20 Coaches from 1977-78 to 2007-08
Ranked in terms of Career Winning Percentage (after the 2007-08 season)
minimum 15 qualified players come to coach, 15 qualified players depart coach

Rank	Coach	Years	Games	Wins	Losses	Winning Percentage
1	Phil Jackson	17	1,394	976	418	0.700
2	Gregg Popovich	12	934	632	302	0.677
3	K.C. Jones	10	774	522	252	0.674
4	Pat Riley	24	1,904	1,210	694	0.636
5	Paul Westphal	7	426	267	159	0.627
6	Rick Adelman	17	1,315	807	508	0.614
7	Jerry Sloan	23	1,806	1,089	717	0.603
8	Flip Saunders	13	983	587	396	0.597
9	Chuck Daly	14	1,075	638	437	0.593
10	George Karl	20	1,493	879	614	0.589
11	Jeff Van Gundy	11	748	430	318	0.575
12	Don Nelson	29	2,234	1,280	954	0.573
13	Rick Carlisle	6	492	281	211	0.571
14	Rudy Tomjanovich	13	943	527	416	0.559
15	Larry Brown	23	1,810	1,010	800	0.558
16	Mike Fratello	17	1,215	667	548	0.549
17	Del Harris	14	1,013	556	457	0.549
18	Doug Moe	15	1,157	628	529	0.543
19	Doug Collins	8	619	332	287	0.536
20	Lenny Wilkens	32	2,487	1,332	1,155	0.536

Note: These records are reported by the Sporting News NBA Register and Basketball-Reference.com [http://www.basketball-reference.com/coaches/].

other coaches in our sample had career winning percentages above 60%. At the bottom of Table 2 is coach Lenny Wilkens, who holds the career record for regular season wins. His career winning percentage of 53.6%, though, falls far behind the mark of Jackson.

Although not reported in the table, we should note the average winning percentage in our sample is 50%. Also, if we extended Table 2 to the end, our sample of 62 coaches is completed by Sidney Lowe and Tim Floyd. Lowe's career mark in five seasons was 0.257 while Floyd's was 0.280 over the same number of years.

A difficulty with focusing on career winning percentage is that wins are ultimately determined by the players on the court. Consequently, a coach with better players should be able to win more games. To measure the value of coaches we wish to see how players perform when the players join—and leave—a specific coach.

Tables 3 and 4 illustrate two simple approaches to seeing how a coach impacts player performance. Table 3 reports the top 20 coaches—from our sample of 62—who saw the highest percentage of players get better when they came to the coach. Topping this list is Dan Issel, who coached for six seasons and won 45.6% of his games as a head coach. However, of the 15 players who came to play for Issel, 12 improved.

Table 3: The Top 20 Coaches
Ranked by percentage of players who improve upon coming to the coach

Rank	Coach	Players	Improved	Percentage Improved	Winning Percentage
1	Dan Issel	15	12	80.0%	0.464
2	Don Casey	22	15	68.2%	0.357
3	Jim O'Brien	24	16	66.7%	0.517
4	Phil Jackson	41	26	63.4%	0.700
5	Mike Schuler	19	12	63.2%	0.530
6	Mike Dunleavy	51	32	62.7%	0.478
7	Rick Carlisle	24	15	62.5%	0.571
8	John Lucas	31	19	61.3%	0.401
9	Tom Nissalke	18	11	61.1%	0.388
10	Byron Scott	30	18	60.0%	0.487
11	Kevin Loughery	42	25	59.5%	0.417
12	Doc Rivers	27	16	59.3%	0.508
13	Bob Hill	29	17	58.6%	0.514
14	Doug Moe	24	14	58.3%	0.543
15	Isiah Thomas	24	14	58.3%	0.456
16	Rick Pitino	19	11	57.9%	0.466
17	Bill Fitch	39	22	56.4%	0.460
18	Doug Collins	32	18	56.3%	0.536
19	Wes Unseld	16	9	56.3%	0.369
20	Cotton Fitzsimmons	38	21	55.3%	0.518

Issel is not the only coach with a losing record to appear in Table 3. Collectively, 11 of the coaches listed lost more than they won. Again, though, we tried separating the player from the coach. Table 3 suggests although Issel's teams produced a losing record, this was because of the players not Issel.

Before we posit our conclusions, we also need to look beyond the simple view of Table 3. One issue with looking at the percentage of players who improved is that the size of the improvement is not considered. Table 4 adds that layer of complexity to our study. In Table 4, we assess how many wins the new players coming to a coach produced in their first year. The coaches are ranked in terms of the average improvement, with the top 20 coaches reported. Once again Dan Issel tops the list. On average, new players going to play for Issel produced 3.5 additional wins in their first season.

Table 4 only reports the top 20 coaches—in terms of additional wins per new player—in our sample. Similarly, the bottom of Table 4 shows six coaches who saw an average of less than one win per new player. Such a result could suggest most coaches have minimal impacts.

A Model of Coaching Effectiveness

However, before reaching the above conclusion we need to consider other factors impacting player performance. Beyond coaching, we argued player performance in a current season was impacted by the list of factors reported—with the corresponding average value in our sample—in Table 5.

Table 4: The Top 20 Coaches Again
Ranked by how many additional wins a new player produces

Rank	Coach	Players	Improved	Percentage Improved	Increase in Wins	Increase in Wins per Player
1	Dan Issel	15	12	80.0%	52.9	3.5
2	Wes Unseld	16	9	56.3%	49.8	3.1
3	Don Casey	22	15	68.2%	64.0	2.9
4	Mike Schuler	19	12	63.2%	44.2	2.3
5	Phil Jackson	41	26	63.4%	80.6	2.0
6	Jim O'Brien	24	16	66.7%	44.8	1.9
7	Doug Moe	24	14	58.3%	44.0	1.8
8	Isiah Thomas	24	14	58.3%	33.9	1.4
9	Tom Nissalke	18	11	61.1%	25.0	1.4
10	Cotton Fitzsimmons	38	21	55.3%	48.9	1.3
11	Rick Carlisle	24	15	62.5%	30.1	1.3
12	Eric Musselman	20	10	50.0%	22.8	1.1
13	Doug Collins	32	18	56.3%	35.0	1.1
14	John Lucas	31	19	61.3%	30.6	1.0
15	Rick Pitino	19	11	57.9%	17.9	0.9
16	Doc Rivers	27	16	59.3%	24.1	0.9
17	Bill Fitch	39	22	56.4%	34.2	0.9
18	Mike Dunleavy	51	32	62.7%	37.3	0.7
19	Jim Lynam	37	19	51.4%	19.1	0.5
20	Stan Albeck	38	21	55.3%	18.6	0.5

Table 5: Means of Relevant Variables

Variable	Mean
Productivity of Player (ADJP48)	0.301
Age	27.141
Games Played Past Two Seasons	141.8
Center	0.207
Power Forward	0.200
Small Forward	0.196
Shooting Guard	0.201
Productivity of Teammates (TMWP48)	0.097
Roster Stability	0.690
New Team	0.289
New Coach	0.456

Note: Player data can be found in the Sporting News NBA Guide (various years), the Sporting News NBA Register (various years), and Basketball-Reference.com

The first factor listed in Table 5 is the productivity of the player, or *ADJP48*. The lagged value of this variable captures the player's level of human capital at the end of the previous season. By itself, lagged performance explains 68% of a player's current performance. As Berri et. al. (2006) demonstrated, NBA players—relative to player productivity in baseball and football—are quite consistent over time.

Although basketball players are relatively consistent, we are interested in why performance does change. Topping the list of factors causing performance to differ over time is age. We expect when a player enters the league he will initially get better as he ages, but eventually time will negatively impact player performance.

Age is not the only physical element altering performance as injuries will also make a difference. We employ games played, across the past two seasons, as a proxy for a player's health status. All else equal, we expect fewer games played indicates more injuries and a lower level of performance. Of course, more games could also reflect the coach's opinion regarding a player's productivity. Because beliefs are based on past performance, including the lagged value of *ADJP48* captures this effect.

Beyond age and injury, the final characteristic of the player we consider is position. Berri et. al. (2006) and Berri (1999, 2008) also reported the position a player plays impacts his statistical output. Consequently, we measured *ADJP48* relative to point guards by including dummy variables for center, power forward, small forward, and shooting guard.

Players are also part of a team and two characteristics of the team were also expected to impact individual performance. The first of these was roster stability, which we expect has a positive impact on a player's performance. We measure stability as the change in the number of minutes played by a player's teammates from the previous season. A priori, greater roster stability makes players more comfortable with each other, and theoretically this should enhance performance.

The performance of these teammates also should matter. Previously, Idson and Kahane (2000) and Berri and Krautmann (2006), among others, showed a player's teammates affect his performance. In particular, we expect that as player *i's* teammates produce more, then player *i's* productivity declines. To account for such diminishing returns, we include the number of wins created by a player's teammates.

Following Grusky's (1963) claim that managerial changes negatively affect team performance, we anticipate a player's performance will decline whenever he plays for a new coach. Because we account for the impact of specific coaches below, this variable is a dummy variable equaling one if the player has moved to a new coach. While this paper is predicated on the hypothesis that specific coaches positively affect a player's performance, we expect the disruption caused by the coaching change itself to negatively impact player performance. Similarly, we also expect changing teams can also have a negative impact on performance. This variable is equal to one if the team with which a player ends the current season is different from the team he began the prior campaign.

The factors reported in Table 5 are noted as X_{it} and Y_{it} in equation (3).

$$ADJP48_{it} = \beta' X_{it} + \gamma Y_{it} + \sum_{j=1}^{62} \delta_{jt} (DCOACH_{jt} * DNC_{it}) + \sum_{j=1}^{62} \theta_{jt} (DCOACH_{jt-1} * DNC_{it}) + \eta_{it} \tag{3}$$

Where

X_{it} = A vector of individual-specific variables

Y_{it} = A vector of team-specific variables and lingering coaching effects

$DCOACH_{ijt}$ = 1 if player i played for coach j in year t (= 0 otherwise) where j spans the 62 coaches in our data set

DNC_{it} = 1 if player i played for a different coach in year t than in year t-1 (= 0 otherwise)

As noted, the individual variables in X_{it} consist of the lagged value of *ADJP48*, the player's years of experience, experience squared, the number of games played, and a dummy variable indicating the player's primary position. The individual variables in Y_{it} include roster stability, the productivity of teammates, and the dummy variables for new coach and new team. In addition, we include the lingering impact of coaching. As we describe below, we are primarily interested in how a player's performance changes as he joins and departs to and from a specific coach. Because it is possible for a coach to impact performance beyond a player's first year on the team, we also include dummy variables to capture the impact of coaches in the second and third year.

The second and third year impacts, though, are not the primary focus of our paper. The two summations in Equation (3) capture the impact of moving to or away from one of the 62 coaches examined in our study. The first sum shows how *ADJP48* changes for player i when he moves to one of the coaches in our data set. It interacts the indicator variable for playing for a new coach in year t with the indicator for whether the new coach was a specific coach in our study. Thus, if player i played for a new coach in year t and that coach was one of the 62 we examined, then $ADJP48_{it}$ changed by $\delta_g + \delta_{ijt}$ where δ_g is the generic effect of playing for a new coach and is the impact one of the 62 coaches had above and beyond a generic coach.

If moving to coach j improves player i's performance, then moving away from coach j could worsen his performance. It is tempting to hypothesize the impact should be equal and opposite in sign to moving to a coach. This would be true if the human capital that player i gains from coach j disappears if not constantly maintained or is specific to coach *j's* "system." It would not be the case if coach j provides player i with lasting skills. The second sum in Equation (3) is identical to the first sum except $DCOACH_{ijt}$ indicated player i was with coach j in the previous year. If player i played for a new coach in year t and the coach he played for in year t-1 was one of the 62 coaches in our data

Table 6A: Estimated Coefficient for Non-Coaching Independent Variables

Independent Variable	Coefficient	Standard Error	z-statistic
AdjP48, lagged*	0.1588	0.0355	4.4700
Age*	0.0465	0.0064	7.2700
Age Squared*	-0.0010	0.0001	-8.3800
Games Past Two Seasons*	0.0006	0.0001	8.1800
Center	0.0070	0.0113	0.6200
Power Forward	-0.0004	0.0099	-0.0400
Small Forward***	-0.0143	0.0084	-1.7000
Shooting Guard*	-0.0179	0.0069	-2.5800
Productivity of Teammates (TMWP48)*	-0.2996	0.0449	-6.6800
Roster Stability	0.0080	0.0069	1.1600
New Team	-0.0025	0.0025	-0.9900
New Coach	-0.0033	0.0035	-0.9300

* Significant at 1% level ** Significant at 5% level *** Significant at 10% level

Table 6B: The Coaches with a Statistically Significant Impact on Player Performance

Moving To Coach…	Coefficient	Standard Error	z-statistic
Phil Jackson*	0.045	0.013	3.550
Gregg Popovich*	0.042	0.016	2.610
Cotton Fitzsimmons*	0.042	0.013	3.170
Jim O'Brien**	0.032	0.013	2.510
Gene Shue*	0.030	0.011	2.650
Don Nelson**	0.030	0.012	2.580
Flip Saunders*	0.028	0.011	2.700
Isiah Thomas**	0.028	0.014	2.000
Rick Pitino***	0.027	0.016	1.700
Stan Albeck**	0.026	0.011	2.240
Kevin Loughery**	0.026	0.010	2.520
Mike Fratello**	0.022	0.011	1.970
Chris Ford**	0.020	0.011	1.860
Larry Brown**	0.017	0.009	1.880
Matt Guokas*	-0.046	0.014	-3.210
Second Year with Coach…			
Gregg Popovich*	0.031	0.012	2.650
Phil Jackson**	0.026	0.012	2.120
Don Nelson***	0.028	0.014	1.950
Bob Hill*	-0.046	0.014	-3.350
Third Year with Coach…			
Phil Jackson*	0.055	0.011	4.840
Moving away from Coach…			
Doug Collins*	-0.034	0.012	-2.830
Bernie Bickerstaff*	-0.033	0.012	-2.630
Jim O'Brien**	-0.031	0.015	-2.070
Paul Silas***	-0.028	0.014	-1.940
Jack Ramsay**	-0.026	0.013	-2.060
Doug Moe***	-0.025	0.013	-1.940
Kevin Loughery**	-0.025	0.011	-2.220
Rick Carlisle**	-0.023	0.011	-2.120
Don Nelson**	-0.023	0.009	-2.480
Paul Westhead***	-0.022	0.012	-1.800
Chris Ford***	0.025	0.015	1.710
Isiah Thomas**	0.036	0.014	2.570

* Significant at 1% level ** Significant at 5% level *** Significant at 10% level

set *ADJP48* changed by $\gamma_g + \theta_{ijt}$. The use of interaction variables in Equation (3) is similar to the use of differences-in-differences. It is not identical because the event (moving from one coach to another) is not fixed in time for all player observations.

Before moving on to discussing our results we acknowledge our data set is an "unbalanced" panel with a lagged dependent variable, hence an OLS estimation is inappropriate. Consequently we employed the Arellano-Bond technique. This method is specifically designed to handle unbalanced panels and essentially we use it for panel data where there are empty cells. In this case, we do not have a "balanced panel" because we do not follow a fixed number of players through the entire set of years. For example, some players disappear partway through, while others appear partway through (and may not last until the end). Consequently, standard panel techniques are not robust. This is particularly true because people do not disappear from the sample randomly but by some self-selection procedure (e.g., not good enough to make the roster).

Estimation Results

The results from estimation of Equation (3) appear in Tables 6A and 6B. For clarity, we split the results into two parts. Table 6A contains individual player and team variables. Table 6B contains the statistically significant interaction effects for players joining one of the 62 coaches and players leaving one of the 62 coaches.

Before discussing the impact of coaches, we first briefly note the results reported in Table 6A. As expected, current performance is positively linked to past productivity. This production, though, is impacted by injury, age, and position played. Specifically, the more games a player plays, the higher a player's *ADJP48*. A similar finding can be told about age early in a player's career. Advances in age, though, cause performance to decline. We estimate the turning point occurs at 24.4 years of age.

Finally, consistent with Berri et. al. (2006), we find small forwards and shooting guards tend to offer less production.

Of the team factors, only the productivity of teammates has the expected sign and level of significance. Specifically, the more productive a player's teammates the less production the player will offer. Although the effect is statistically significant, the impact of teammates is quite small. The average player—player$_i$—posts an *ADJP48* of 0.302. If player$_i$ moves from a team with average teammates to a team with players whose productivity is two standard deviations above average, player$_i$ will see his *ADJP48* value fall by 0.018. This translates into a decline of only 0.7 wins across an entire season. In sum, while diminishing returns exists in the NBA, the actual effect is minimal. While the effect of teammates is small, it trumps the impact of the remaining team factors. We do not find roster stability, switching to a new team, or switching to a generic new coach to have any statistical impact on player performance.

The impact of a generic new coach is quite similar to the effect we find for most coaches. Table 6B reports the statistically significant coaching coefficients. When you look at the impact of new, second-year, and third-year coaches, and also leaving a coach, we find 22 coaches have a statistically significant impact with respect to one of these issues. However, since our sample consists of 62 coaches, our results indicate that for 40 coaches we do not see any statistical impact.

Before we discuss the coaches having a statistically significant impact, we briefly return to Tables 2-4. These three tables report three different approaches to ranking coaches. In Table 2 we see the 20 coaches—out of our sample of 62—having the highest career winning percentage. Of these 20 names, 14 were not found to significantly impact a new player's performance and 11 names are not listed at all in Table 6B. Such a result may not surprise since career coaching records do not separate a coach from his player.

Tables 3 and 4 were an effort to isolate the coach. But the results were quite similar to what we saw in looking back at Table 2. Table 3 reports the 20 coaches having the highest percentage of player improvement while Table 4 looks at the 20 coaches who saw the greatest improvement in their new players. However, in both cases, 70% of the names listed were not found to have a statistically significant impact on new player performance. Therefore, once we control for the other factors impacting player productivity, most of the coaches who traditionally looked to be effective were found to have little effect on what a player does when he comes to the coach.

Consequently, it appears what Adam Smith thought about management in 1776 applies to most NBA coaches today. That is, most coaches do not statistically impact player performance and subsequently most NBA coaches are essentially principal clerks.

Although Smith's view applies to most coaches, we did find some exceptions. In reviewing these exceptions we note that interpreting the coaching coefficients in Table 6B is complicated. In sports featuring opposing sides, such as basketball, it is difficult to separate a player's performance from that of the player opposite him. A player might score 50 points in a game due to his own outstanding performance or to a particularly poor job by the player defending him. Thus, if all coaches do equally well, the overall quality of play could rise with no change in the standard measures of player performance: better offensive play makes no more and no less headway against better defensive play. For a coach to show a significant positive (negative) coefficient, he must do a particularly good (poor) job relative to other coaches. Our measure thus differs from that of managers in other industries, whose success need not come at the expense of other managers.

Of the 62 coaches in our data set, 14 had a statistically significant impact on *ADJP48* when a player came to the coach. Of these, Phil Jackson had the greatest impact, with a point estimate of 0.045. Players who joined a Phil Jackson-coached team saw their *ADJP48* increase by 0.026 more than players who joined a generic coach. Close behind Jackson were Gregg Popovich and Cotton Fitzsimmons, who increased *ADJP48* by 0.042. The remaining 11 coaches listed had a smaller impact. In fact, the range from the fourth coach listed, Jim O'Brien, and the 12th coach (Mike Fratello) is similar to what we see between Fitzsimmons and O'Brien. In other words, although the impact of these coaches is different from most coaches in our sample (and a generic coach) the statistically significant impacts are not much different from each other.

We can see this when we consider the confidence interval of our estimates.

Drawing a 95 percent confidence interval around the positive coefficients reported in the first part of Table 6B (Moving to Coach…) reveals these coaches are not significantly different from the others. For example, Jackson's confidence interval ranges from 0.020 to 0.070. This range overlaps the range of the last coach—Larry Brown—listed in Table 6B to have a positive impact on new players (-0.001 to 0.034). Our inability to distinguish individual coaches' impacts—even when these impacts differ from zero—is also consistent with Adam Smith's claim that managers are only "principal clerks."

Table 7:Another View of the Top NBA Coaches
Ranked by impact of coach on player performance

Moving To Coach…	Coefficient	Estimated Wins
Phil Jackson	0.045	16.7
Gregg Popovich	0.042	15.5
Cotton Fitzsimmons	0.042	15.5
Jim O'Brien	0.032	11.7
Gene Shue	0.030	11.2
Don Nelson	0.030	10.9
Flip Saunders	0.028	10.5
Isiah Thomas	0.028	10.4
Rick Pitino	0.027	9.8
Stan Albeck	0.026	9.5
Kevin Loughery	0.026	9.4
Mike Fratello	0.022	8.0
Chris Ford	0.020	7.6
Larry Brown	0.017	6.1
Matt Guokas	-0.046	-16.9
Second Year with Coach…		
Gregg Popovich	0.031	11.3
Phil Jackson	0.026	9.7
Don Nelson	0.028	10.4
Bob Hill	-0.046	-17.0
Third Year with Coach…		
Phil Jackson	0.055	20.4
Moving away from Coach…		
Doug Collins	-0.034	-12.6
Bernie Bickerstaff	-0.033	-12.1
Jim O'Brien	-0.031	-11.6
Paul Silas	-0.028	-10.2
Jack Ramsay	-0.026	-9.6
Doug Moe	-0.025	-9.3
Kevin Loughery	-0.025	-9.3
Rick Carlisle	-0.023	-8.7
Don Nelson	-0.023	-8.7
Paul Westhead	-0.022	-8.0
Chris Ford	0.025	9.1
Isiah Thomas	0.036	13.2

As noted, it is possible a coach could impact a player beyond the first year. Although hypothetical, we did not find much evidence for an impact beyond the first year with a coach. Specifically, we only found a positive impact in the second year for Popovich, Jackson, and Don Nelson and only Jackson had a positive impact in year three.

Eventually, of course, a player leaves a coach. In the last section of Table 6B we report what happens to players leaving coaches. As noted, we might expect a player to get worse if a coach is eliciting production via a specific system. For 10 coaches—out of our sample of 62—we find evidence that players get worse when they depart the coach. Of the 10 names listed, only three are listed in the first part of Table 6B. In other words, for only three coaches—Kevin Loughery, Don Nelson, and Jim O'Brien—we found a player improves when he arrives and then declines when he departs.

As was the case for our review of the impact of coaches on new players, constructing a 95% interval around the coefficients describing the impact of departing a coach shows most of the coefficients are statistically indistinguishable. The difficulty in distinguishing the coaches again reinforces the notion that managers do not have much of an impact on their players or teams.

Because coaches are ultimately judged by how their teams perform, our final table reports our effort to translate the impact coaches have on player performance into wins and losses. To do this, we convert the impact coaches have on *ADJP48* into wins. This is simply done by dividing the coaches' impact on *ADJP48* by 48 and multiplying by minutes played. Specifically, a team plays 48 minutes in a game and 82 games in a season. Hence, ignoring overtime, a team will play 19,680 minutes in a regular season. Of these, about 90% are played by players with NBA experience. If Jackson increases all of the veteran player's *ADJP48* by 0.045, then the team will win 16.7 additional wins.

Table 7 shows the results of these manipulations for the coaches having a statistically significant impact in Tables 6B. It shows that hiring one of the 14 coaches with a positive effect on *ADJP48* adds significantly to wins. Hiring Jackson, Popovich, or Fitzsimmons can add more than 15 wins across an entire season. This is enough to transform a team with a 41-41 record into a 56-26 championship contender. Phil Jackson provides a natural experiment of sorts. In 2004-05, the Lakers won 34 games without Jackson. When Jackson returned in 2005-06, the key performers on the team—Kobe Bryant and Lamar Odom—both had higher *ADJP48s*, and the team won 11 more games. While this is less than the 16 wins our model predicts, it is consistent with our prediction. The difference could be due to roster changes not accounted for by our model's assumption that only the coach changed.

Conclusion

Basic economics tells us that an appropriate reward system should be based on an employee's marginal revenue product. In industry, it should reflect a manager's impact on the company's profits; in professional sports, it should reflect a manager's contribution to the team's wins. Unfortunately, it is generally difficult to separate the performance of the manager from the quality of workers or athletes whom he supervises. For this reason, coaches in professional sports are evaluated in terms of the wins and losses of the teams under their direction. Such an evaluation, though, ignores the fact coaches work with different endowments of playing talent. This paper measures the impact coaches have on the performance of their players.

Our point estimates show that some NBA coaches add substantially to the performance of their players and to the number of games their teams win. Two of these coaches, Phil Jackson and Gregg Popovich, are acknowledged as being among the most successful coaches in NBA history, winning a combined 13 NBA championships.

Other coaches we identified had significantly less success. In fact, of the other coaches having a positive impact on newly acquired players, only Larry Brown has won an NBA title. Furthermore, Gene Shue, Isiah Thomas, Kevin Loughery, and Chris Ford all posted losing records.

Our most surprising finding was that most of the coaches in our data set did not have a statistically significant impact on player performance relative to a generic coach. Even the most successful coaches by our metric—Jackson, Popovich, and Fitzsimmons—were statistically discernable only from the very worst-rated coaches. We therefore find little evidence that most coaches in the NBA are more than the "principal clerks" that Adam Smith claimed managers were more than 200 years ago.

References

Bellotti, B. (1992). *The points created basketball book 1991–92.* New Brunswick, N.J.: Night Work Publishing.

Bennedsen, M., Perez-Gonzalez, F., & Wolfenzon, D. (2006). Do CEOs matter? Unpublished manuscript.

Berri, D. (2008). A simple measure of worker productivity in the National Basketball Association. In B. Humphreys & D. Howard (Eds.) *The business of sport* (pp. 1-40). Westport, CT.: Praeger.

Berri, D. (1999). Who is most valuable? Measuring the player's production of wins in the National Basketball Association. *Managerial and Decision Economics, 20*(8), 411–427.

Berri, D., Brook, S., Fenn, A., Frick, B., & Vicente-Mayoral, R. (2005). The short supply of tall people: Explaining competitive imbalance in the National Basketball Association. *Journal of Economics Issues*, *39*(4), 1029-1041.

Berri, D., & Krautmann, A. (2006). Shirking on the court: Testing for the disincentive effects of guaranteed pay. *Economic Inquiry*, *44*(3), 536-546.

Berri, D., Schmidt, M., & Brook, S. (2006). *The wages of wins: Taking measure of the many myths in modern sports.* Palo Alto, CA: Stanford University Press.

Bertrand, M., & Schoar, A. (2003). Managing with style. *Quarterly Journal of Economics, 118*(4), 1169-1208.

Blass, A. (1992). Does the baseball labor market contradict the human capital model of investment? *The Review of Economics and Statistics, 74*(2), 261-268.

Bradbury, J. C. (in press). Peak athletic performance and ageing: Evidence from baseball. *Journal of Sports Sciences.*

Chapman, K., & Southwick, L. (1991). Testing the matching hypothesis: The case of Major League Baseball. *American Economic Review, 81*(5), 1352-1360.

Chevalier, J., & Ellison, G. (1996). Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance. *Journal of Finance, 54*(3), 875-899.

Clement, R., & McCormick, R. (1989). Coaching team production. *Economic Inquiry*, *27*(2), 287-304.

Dawson, P., Dobson S., & Gerrard B. (2000a). Stochastic frontiers and the temporal structure of managerial efficiency in English soccer. *Journal of Sports Economics*, *1*(4), 341-362.

Dawson, P., Dobson S., & Gerrard B. (2000b). Estimating coaching efficiency in professional team sports: Evidence from English Association football. *Scottish Journal of Political Economy, 47*(4), 399-421.

Fizel, J., & D'Itri, M. (1997). Managerial efficiency, managerial succession and organizational performance. *Managerial and Decision Economics*, *18*(4), 295-308.

Fort, R., Lee, Y., & Berri, D. (2008). Race and coaching efficiency in the NBA. *International Journal of Sport Finance*, *3*(2), 84-96

Grusky, O. (1961) Corporate size, bureaucratization, and managerial succession. *The American Journal of Sociology, 67*(3), 261-69.

Grusky, O. (1963). Managerial succession and organizational effectiveness. *The American Journal of Sociology, 69*(1), 21-31.

Hadley, L., Poitras, M., Ruggiero, J., & Knowles, S. (2000). Performance evaluation of National Football League teams. *Managerial and Decision Economics*, *21*(2), 63-70.

Hakes, J., & Sauer, R. (2006). An economic evaluation of the *Moneyball h*ypothesis. *Journal of Economic Perspectives, 20*(3), 173-185.

Heeren, D. (1994). *Basketball abstract 1994–95 edition.* Indianapolis, IN: Masters Press.

Horowitz, I. (1994a). Pythagoras, Tommy Lasorda, and me: On evaluating baseball managers. *Social Science Quarterly*, *75*(1), 413-419.

Horowitz, I. (1994b). On the manager as principal clerk. *Managerial and Decision Economics, 15*(5), 187-194.

Horowitz, I. (1997). Pythagoras's petulant persecutors. *Managerial and Decision Economics, 18*(4), 343-344.

Idson, T., & Kahane, L. (2000). Team effects on compensation: An application to salary determination in the National Hockey League. *Economic Inquiry, 38*(2), 345-357.

Johnson, B., Magee, R., Nagarajan, N., & Newman, H. (1985) An analysis of the stock price reaction to sudden executive death: Implications for the management labor market. *Journal of Accounting and Economics*, *7*(1-3), 151–174.

Jovanovic, B. (1979). Job matching and the theory of turnover. *Journal of Political Economy, 87*(5), 972-990.

Kahn, L. (1993). Managerial quality, team success, and individual player performance in Major League Baseball. *Industrial and Labor Relations Review*, *46*(3), 531-547.

Lee, Y., & Berri, D. (2008). A re-examination of production functions and efficiency estimates for the National Basketball Association. *Scottish Journal of Political Economy*, *55*(1), 51-66.

Lewis, M. (2003) *Moneyball: The art of winning an unfair game.* New York: W.W. Norton.

Lewis, M. (2006). *The blind side: Evolution of a game.* New York: W.W. Norton.

Ohkusa, Y., & Ohtake, F. (1996). The relationship between supervisor and workers – The case of professional baseball in Japan. *Japan and the World Economy, 8*, 475-488.

Porter, P., & Scully, G. (1982). Measuring managerial efficiency: The case of baseball. *Southern Economic Journal*, *48*(3), 642-650.

Scott, F., Long, J., & Sompii, K. (1985). Salary vs. marginal revenue product under monopsony and competition: The case of professional basketball. *Atlantic Economic Journal*, *13*(3), 50–59.

Scully, G. (1994). Managerial efficiency and survivability in professional team sports. *Managerial and Decision Economics*, *15*(5), 403-411.

Scully, G. (1974). Pay and performance in Major League Baseball. *American Economic Review, 64*(6), 917-930.

Smith, A. (1776). *An inquiry into the nature and causes of the wealth of nations* (1963 edition). Chicago: R.D. Irwin.

Zimbalist, A. (1992). *Baseball and billions.* New York: Basic Books.

Endnote

[1] For details on ADP48 one is referred to Berri et. al. (2006) and Berri (2008). We would note here that the team adjustments involve incorporating the team variables listed in Table 1. Following Scott, Long, and Sompii (1985), these variables are allocated across players by minutes played. Such an adjustment accounts for team defense and team pace. Additionally, as detailed in the aforementioned works, performance is also adjusted for the blocked shots and assists of teammates. Finally, we adjusted each player's ADJP48 by the average value in each season. This was done by subtracting the average value from each season from each player's value. Then the average value across all 31 seasons was added. This last step was done to adjust for the change in pace we see across the seasons in our sample.

International Journal of Sport Finance, 2009, **4**, 94-113, © 2009 West Virginia University

Estimates of the Dimensions of the Sports Market in the US

Brad R. Humphreys[1] and Jane E. Ruseski[1]

[1] University of Alberta

Brad Humphreys is an associate professor in the Department of Economics. He holds the chair in the economics of gaming. His current research focuses on the economic impact of professional sports, and the economics of sports gambling.

Jane Ruseski is an assistant professor in the Department of Economics. Her current research focuses on the economics of participation in sport and physical activity and the relationship between sport participation and health.

Abstract

We examine the dimensions of the sports market in the United States. We investigate sports participation, sports viewing, and the supply and demand sides of the sports market. Our estimates of the value of economic activity in the sports market range from $44 to $60 billion in 2005. The 49,169 firms in the industry employed just over one million workers. About 118 million people participated regularly in sports in 2005, and more than 277 million individuals attended spectator sporting events.

Keywords: sports industry, industry size and scope, sport participation

Introduction

Sport is a complex activity encompassing spectacles like the Olympic Games and informal pick-up games on urban basketball courts; a recreational jogger, a runner in the Boston Marathon—a competition with thousands of participants—and people watching the Boston Marathon on television all participate in sport in some way. Academic research on sports can be found in many disciplines, spanning the humanities, social sciences, laboratory sciences, law, and business. In this paper, we document the size of the sports industry in the United States from an economic perspective.

A sizable literature on the economic impact of specific sports or sporting events already exists, in part because of the ease of defining the limits of events like a golf tournament or season of professional baseball. Relatively little attention has been paid in the past to estimating value of economic activity in the sports market, perhaps because of difficulties formulating an economic definition of sport. In our opinion, a thorough accounting of the size of the sports industry is an important undertaking for several reasons. First, such an estimate provides some general context for research on sport finance and economics. Second, the sport industry receives significant subsidies from national, state, and local governments. These subsidies take many forms, including facility construction and operation, training for elite athletes, and promotion of participation in sport for health benefits, among others. Any full cost-benefit analysis of sports subsidies should take into account the relative importance of the sport industry in the economy. Finally, unlike other industries, the sport industry has a cultural significance extending well beyond its economic boundaries. An estimate of the overall importance of the sport industry must start with an estimate of the economic dimensions of the industry.

The first step is to define sport, a topic that lies outside the discipline of economics. Several definitions have been proposed. Sociologist Jay Coakley (2003) characterized sports as activities involving gross motor skills, competition, and an organized set of rules. Economist Rodney Fort (2006) qualifies Coakley's competition criteria to include only competition based on objective scoring and further restricts sports to activities only using simple devices, like bats and balls, or no devices at all. These definitions, and others, like the criteria that some participants must receive a financial reward for success, suffer from the limitation that many sport-like activities exist. For example, hot dog eating and bass fishing would both appear to qualify as a sport under these definitions.

One key issue in defining sport involves identifying criteria that separate sport from games of skill like chess or poker and from recreational activities like dancing, hiking, fishing, and gardening. A secondary issue involves identifying criteria that appropriately define competition in a way to distinguish sport from exercise. For example, running has a competitive dimension but jogging does not. Weightlifting is an Olympic sport, bodybuilding is a professional sport, and competitions based on an athlete's performance on fitness equipment like stationary rowing machines, elliptical trainers, and stationary bicycles exist, blurring the already murky distinction between exercise and sport.

Defining sport in a way that allows estimation of the value of economic activity in the sports industry in a straightforward manner is very difficult. We proceed by making arbitrary, but defensible decisions about which activities constitute sport, exercise, recreation, and games of skill. Those better equipped to answer this difficult question can extend this research, or show that our results are not robust to alternative definitions.

An Economic Definition of Sport

The second step is to define the sport market in economic terms. Gratton (1998) discussed a general method for estimating the economic dimensions of the sports industry from national income and product accounts, and points out that economic interest in sport extends well beyond the boundaries of professional sports. While a national income and product accounting approach has some appeal, because of the well-developed methodology and the existence of rich set of frequently updated accounts for many developed economies, it also has a number of weaknesses. First, on the national product side, the researcher is at the mercy of the existing production classification system. The North American Industrial Classification System (NAICS) does not identify the sports industry. The sports industry makes up only a fraction of the activity in any existing industry classification, leading to overestimates of the size of the sports industry from national product accounts. Second, on the national income side, the published spending data are not detailed enough to identify the size of consumer spending on sports, no mater how broadly defined. Third, in the US all levels of government are involved in the provision of sports facilities and other important activities on the supply side of the sports market, and national income and product accounts do not contain detailed estimates of government spending. Fourth, much of the activity in the sports market involves non-traded goods and labor inputs not valued at market prices. For example, the labor inputs provided by intercollegiate athletes are not valued at market prices (Brown, 1993). Fifth, sports markets feature both significant consumer surplus and non-market consumption benefits that are not reflected in national income and product accounts (Alexander, Kern, & Neil, 2000).

Given these problems, we draw on data from a wide number of sources and use these data to develop estimates of the economic value of sports from different perspectives. We define the sports market as having three primary components:

1. Activities involving participation in sport,
2. Activities involving attendance at spectator sporting events, and
3. Activities involving following spectator sporting events through some media.

While some sport-related activities are not included in this list, all three items can be thought of as part of sport and are also easily defined and measured.

Each component contains elements that could be defined as recreation, exercise, or games of skill. For example, including participation in sports means that some activities that could be defined as exercise, like aerobics or walking, will be included. Including spectator sports means that auto racing, figure skating, and other such activities fall into this definition of the sports industry. The most difficult choice we face is the inclusion or exclusion of activities like hunting, fishing, kayaking, horseback riding, sailing, and hiking. These popular activities attract many participants, and require both considerable time and expensive equipment. Many are recognized Olympic sports. However, we exclude these activities from our definition of the sports market because we believe that they fall under recreation, not sports.

Participation in the Sport Market

Individuals can participate in the sport market in three ways: by participating in some sport; by attending a sporting event; or by watching or listening to a sporting event on television, radio, or the internet. Each generates direct and indirect economic activity. Participating in sport requires equipment, fees, and potentially travel, all of which generate economic activity. Attending a sporting event involves purchasing tickets, travel, and perhaps other purchases like food and souvenirs. Watching or listening to sporting events requires equipment, in the form of televisions, radios, or computers, as well as subscriptions to broadcast services. Since all of these economic activities increase with the number of participants, documenting the number of participants is an important indicator of the size of the sports market.

More importantly, individuals' participation in the sports market generates significant economic benefits beyond direct and indirect economic activity. Individuals derive satisfaction, or utility, from participation in the sports market, which has economic value. In the jargon of economics, individuals' participation in the sports market produces consumption benefits. These consumption benefits are not bought and sold like tickets, but they are important when assessing the overall size of the sports market. Although placing a dollar value on sport-related consumption benefits is beyond the scope of this paper, it is safe to say that the value of these consumption benefits rises with the number of participants in the sports market.

Sport Participation

There are a number of sources of data on participation in sport in the United States. The National Sporting Goods Association (NSGA) periodically produces estimates of the number of participants in sport in the United States. The NSGA participation estimates are based on a mail survey sent to about 300,000 households. Table 1 shows NSGA's estimates of the reported number of participants for a selected group of sports in the United States for the most recent year available, 2005.

Walking is by far the most popular sport, in terms of total participation. This is to be expected, because walking is not a costly activity. Participating in walking requires relatively little equipment, few fees, and does not have to involve much travel, since many people can walk simply by stepping outside their home or workplace. Because of the low participation costs, walking also generates relatively little economic activity. The other sports on Table 1 generate more economic activity per participant than walking because they require more equipment, membership fees, and travel costs.

Table 1: Estimated Participants in Sport, 2005

Sport or Activity	Number of Participants
Walking	87,500,000
Swimming	56,500,000
Bowling	44,800,000
Health Club Membership	37,000,000
Bicycling	35,600,000
Weightlifting	32,900,000
Running/Jogging	29,200,000
Basketball	26,700,000
Golf	24,400,000
Baseball	14,600,000
Soccer	14,000,000
Softball	12,400,000
Volleyball	11,100,000
Inline Skating	10,500,000
Tennis	10,400,000
Mountain Biking	9,200,000
Downhill Skiing	6,400,000
Martial Arts (2004)	5,400,000
Snowboarding	5,200,000
Ice/Figure Skating (2003)	5,100,000
Cross Country Skiing	2,600,000
Ice Hockey	2,600,000

Aggregating the number of participants reported on Table 1 points out an important limitation of these estimates as an indicator of economic activity. Table 1 suggests that over 484 million individuals participated in sport in 2005. Since the US population was about 297 million, the methodology that generated these estimates involves counting of some individuals multiple times. The survey question asks the respondents to list each sport participated in more than once in the past year, and to list all the sports that every member of the household over the age of seven participated in more than once during the past year.

Clearly, any individual can easily participate in both bowling and golf, so in one sense this accounting method is appropriate for assessing the dimensions of the sports market. The economic activity associated with participation in any sport also depends on the intensity of participation. For example, the participation count for golf on Table 1 may include a person who borrows a set of clubs and plays a single round and a person with a country club membership who plays three rounds of golf a week and takes a vacation to play golf every year. The total value of economic activity, in terms of the direct economic activity and consumption benefits generated by these two golfers differs significantly. Because of this heterogeneity in the intensity of participa-

Table 2: Estimated Sport Participants, 2000 Based on BRFS Survey

	Estimated Number of Participants		
Sport	**Lower bound**	**Mean**	**Upper Bound**
Walking	68,600,000	69,301,784	70,000,000
Running/Jogging	12,500,000	12,901,119	13,300,000
Weightlifting	7,118,775	7,396,304	7,673,832
Golf	4,787,312	4,982,688	5,178,063
Bicycling	4,588,754	4,791,467	4,994,179
Aerobics	4,189,563	4,355,448	4,521,333
Basketball	3,276,901	3,461,372	3,645,844
Health Club Workout	2,375,871	2,510,246	2,644,621
Swimming	2,216,229	2,356,134	2,496,039
Calisthenics	2,054,979	2,208,816	2,362,652
Bike or Rowing Machine Exercise	1,493,113	1,622,729	1,752,346
Tennis	1,072,147	1,171,802	1,271,457
Soccer	878,774	1,010,848	1,142,922
Martial Arts	570,918	649,406	727,895
Skating (Ice and Roller)	544,010	633,485	722,960
Bowling	543,637	611,725	679,813
Volleyball	456,615	531,830	607,045
Snowskiing	315,119	373,660	432,201
Raquetball	298,842	359,900	420,958
Boxing	167,959	208,423	248,887
Touch Football	133,717	179,878	226,039
Waterskiing	120,486	158,624	196,761
Squash	57,243	101,219	145,194
Surfing	57,243	101,219	145,194
Badmiton	29,427	50,090	70,752
Table Tennis	20,818	38,056	55,295
Handball	8,264	18,249	28,234
Softball	4,339	8,203	12,067
Total	118,481,056	122,094,722	125,702,581

tion, the participation figures on Table 1 do not provide precise information about the dimensions of sport participation in the US.

A measure of participation in the sports market that accounts for intensity of use will help overcome this problem. We use the Behavioral Risk Factor Surveillance System (BRFSS) for evidence on sport participation that accounts for intensity of use. The main element of the BRFSS is the Behavioral Risk Factor Surveillance (BRFS) survey, a nationally representative survey of the adult population of the United States conducted by the Centers for Disease Control and Prevention (CDC). The BRFS collects uniform state specific data on health prevention activities, including physical activity. The BRFS employs a telephone survey, meaning that individuals must live in a household with a telephone to be eligible for the survey.

The 2000 BRFS contained detailed questions about sport participation. This includes questions that ask respondents to list the sport that they spent the most time participating in, given that they reported participating in any sport. The specific BRFS question was: *What type of physical activity or exercise did you spend the most time doing during the past month*? Individuals who answered this question are not just casual, once or twice a year, participants in sport. So the sport participants identified by this survey question probably generate significant economic activity while participating.

Since the BRFS is a nationally representative sample, the results of this survey can generate estimates of the total number of participants in various sports. Table 2 shows the estimated number of participants for a group of sports from the 2000 BRFS. Many other types of physical activities, including gardening and housework, were reported as physical activities in the 2000 BRFS, but we consider this to be the relevant group of sports for this analysis.

Again, we interpret the totals on Table 2 as reflecting frequent participants in these sports and the totals on Table 1 as reflecting both frequent and infrequent participants. The participation totals on Table 1 and 2 show some consistencies. Walking has the most participants on both tables. About 70 million people, or 25% of the population, reported walking frequently for exercise according to the BRFS in 2000. About 87.5 million people, or 30% of the population, reported walking for exercise either frequently or infrequently according to the NSGA in 2005. The biggest difference between these two tables is the smaller number of frequent participants in all the sports except walking. For example, while only 2.3 million people reported swimming frequently for exercise, 56.5 million people reported swimming in the NSGA survey on Table 1 that includes infrequent participants. This pattern can be seen in the participation counts for all the other sports.

These participation data suggest that in any year over 50% of the US population participate in some sport regularly, and a larger number participate in sport occasionally. By either measure, individual participation in sport in the US is significant, and generates a considerable amount of economic activity.

Attendance at Spectator Sporting Events

The National Sporting Goods Association also compiles total spectator attendance for a number of professional and amateur sports. Table 3 contains estimates of total attendance for selected sports leagues in 2005. Professional baseball draws the most spectators of any US sport, over 74 million people in 2005. An additional 15.6 million attended a minor league baseball game. In part, this reflects the large number of professional baseball teams at the major and minor league level, and the relatively long baseball season that provides consumers with many opportunities to attend games.

Table 3: Estimated Total Attendance at Sports Events, 2005

Sport	Total Attendance
Major League Baseball	74,385,100
NCAA Football	43,486,574
NCAA Men's Basketball	30,568,645
National Basketball Association	21,369,078
National Hockey League (2004)	19,854,841
National Football League	17,011,986
Minor League Baseball	15,636,000
NASCAR Nextel Cup Series	6,300,000
Minor League Hockey	6,179,000
Horse Racing	5,979,000
Professional Rodeo	5,429,000
NASCAR Busch Series	3,911,000
Professional Golfers Association	3,200,000
Arena Football League	2,939,000
Major League Soccer	2,900,715
Minor League Basketball	2,625,000
Professional Tennis	1,970,000
Professional Boxing	1,931,000
IndyCar Racing	1,914,000
National Hot Rod Association	1,835,000
NASCAR Truck Series	1,708,000
Champ Car Racing	1,490,000
Professional Bowling Association	1,310,000
Women's National Basketball Association	1,087,000
Professional Lacrosse (MLL, NLL)	1,019,000
Major Indoor Soccer League	992,000

The next two largest sports in terms of total attendance are college football and college basketball. These totals reflect college attendance at all levels. Hundreds of colleges and universities have football and men's basketball teams, so this large total is expected, given the ample opportunities to attend these games. Some might be surprised to see that National Football League (NFL) total attendance is smaller than the other major professional sports leagues—including hockey—and smaller than NCAA football and basketball. However, the NFL plays a relatively short 16-game regular season schedule and, as we will soon see, focuses on television viewing as its primary means of public exposure. NASCAR attendance is broken out into Nextel Cup, Busch Series, and Truck Series on Table 3. Total NASCAR attendance was just under 12 million in 2005, and when the other car racing sports are added to this, total attendance at all professional racing in 2005 was over 17 million, exceeding total attendance in the NFL.

But total professional and NCAA football attendance, including arena football, at over 63 million in 2005, dwarfs total professional racing attendance.

Total attendance at the sports events listed on Table 3 was just over 277 million in 2005. This total includes many individuals who bought tickets to multiple games, including season ticket holders who go to many games in one sport every year and people who attend many different sporting events every year. Still, 277 million tickets sold in 2005 is a large number compared to the total US population of 296.6 million. This represents a significant amount of economic activity, both in terms of spending on tickets, spending on other related goods and services like travel, and the opportunity cost of the time spent attending sporting events.

The 277 million people who attended pro and college sporting events in 2005 generated a substantial amount of direct and indirect economic activity. Tickets were purchased for each of these events, along with parking, concessions, and souvenirs. For those spectators who traveled long distances to attend a sporting event, attending the event also generated travel spending, including hotels and meals. An estimate of the indirect economic impact of this spending could be generated from an appropriate input-output model, but that exercise is beyond the scope of this paper.

Viewing and Listening to Mediated Sport

Spectator sports play an important role in print and broadcast media. Almost every daily newspaper in the country has a sports section and sports broadcasts appear on many local and national television and radio stations across the country. According to the *Vital Statistics of the United States*, 2005, the total multimedia audience in the United States was 215,800,000. This implies that, of the 295,194,000 people counted as the resident population of the US in 2005, 73% of them had access to some form of media, including newspapers, television, radio, and internet. The National Sporting Goods Association reports estimated television viewing audiences for a number of professional sports leagues. Unfortunately, estimated television viewing audiences for NCAA football and men's basketball are not readily available. Table 4 shows the estimated television audiences for the professional sports leagues tracked by the NSGA in 2005.

The National Football League has the largest television viewing audience of any US professional sports league. The 105 million person NFL television audience is over one third of the total US population in 2005. More than one person in every three watched NFL football in 2005. Following the NFL are Major League Baseball (MLB) and the National Basketball Association (NBA), two other traditionally popular professional sports leagues.

One interesting feature on Table 4 is the relatively large TV audiences for professional golf (about 38 million viewers) and tennis (about 26 million viewers), and horseracing (21.5 million viewers), a sport widely perceived to be in decline in the US. The estimated television audience for these sports may reflect the popularity of a few events, like the four "Major" championships in golf, the United States Open and Wimbledon in tennis, and the three "Triple Crown" races in horseracing. The popularity of these sports on television may not have the same durability of the NFL, MLB, and the NBA, which probably have a larger day-to-day following. Also, note that NASCAR has a very large estimated television audience; the total audience for the three NASCAR series is over 85 million, which placed it at a similar level to the "big three" professional sports. A caveat is that adding those three estimated television audiences may lead to a lot of double counting, as many of the people in the Nextel Cup series television audience are probably in the Busch series and Truck series audiences as well.

Table 4: Estimated Total Television Viewing Audiences, 2005

Sport	TV Audience
National Football League	105,874,000
Major League Baseball	76,744,000
National Basketball Association	60,877,000
NASCAR Nextel Cup Series	45,588,000
Professional Golfers Association	37,899,000
NASCAR Busch Series	27,981,000
Professional Tennis	26,187,000
Horse Racing	21,560,000
IndyCar Racing	19,366,000
Professional Rodeo	18,862,000
Professional Boxing	18,094,000
Arena Football League	17,094,000
National Hockey League	13,870,000
Professional Bowling Association	13,470,000
Women's National Basketball Association	12,220,000
NASCAR Truck Series	12,073,000
Major League Soccer	10,010,000
Minor League Baseball	9,668,000
National Hot Rod Association	7,900,000
Minor League Basketball	7,126,000
Champ Car Racing	6,678,000
Minor League Hockey	3,315,000
Professional Lacrosse (MLL, NLL)	3,103,000
Major Indoor Soccer League	2,338,000

Source: National Sporting Goods Association (NSGA)

The figures on Table 4 point out the problem with adding up the estimated television audiences for individual sports to estimate the total sport television audience. The NSGA estimates of total television size do not indicate how long an individual spends watching each sport in the average week or month, so we have no idea of the intensity of viewing. Also, unlike live game attendance, the actual amount of time spent "watching" a sporting event on television is difficult to measure. A fan watching a sporting event on television could be doing a number of things at the same time. For example, while writing this section of the paper, the live television coverage of the Tour de France was on in the background. Was that time spent watching sports on television, or working?

In any event, watching sports on television generates the smallest direct and indirect economic activity of any of the activities discussed so far. Watching sports on television requires the purchase of equipment (a television) and may also require a subscription to cable or satellite programming packages. Beyond this, the primary economic activity generated by watching sports on television comes from the consumption benefits, as well as advertising and sponsorship.

Aggregate estimates of the number of people who listen to sporting events on the radio in the US are difficult to find. According to the *Statistical Abstract of the United States*, the estimated radio listening audience in 2005 was about 181 million people, a total that is not much smaller than the television audience. Anecdotal evidence suggests that quite a bit of sports programming is available on radio, perhaps as much as is available on television for the NFL, MLB, and the NBA. So the opportunity cost of time listening to sporting events on the radio may be comparable to the opportunity cost of watching sports on television.

Determining the amount of sports viewing done over the internet is also difficult to estimate. The *Statistical Abstract of the United States* reports that about 138 million people had access to the internet in 2005. In one recent survey, the fraction of surveyed internet users who reported "checking sports scores or information" was larger than those reporting downloading music, although smaller than those using the internet for email. In any case, the amount of time spent following sports on the internet is proportionate to overall internet use, which is growing rapidly. Furthermore, much of the sport-related internet use may take place at work, where many people have internet access, unlike sports viewing on television, which takes place primarily at home or in bars and restaurants.

Estimating the Value of Economic Activity in the Sports Market

A second indicator of the size of the sports market is the dollar value of the direct and indirect economic activity that takes place in it. Markets are composed of suppliers who make and sell goods and services and demanders who purchase and consume goods and services. This distinction suggests two alternative methods for estimating the value of economic activity in the sports market: add up the value of output or revenues of all of the producers in the sports market, or add up the total spending of all consumers in the sports market.

How much direct economic activity, in terms of dollar value of goods and services produced and consumed, takes place in the sports market? The answer to this question is surprisingly difficult to determine. We can easily find out the total sales of the hotel industry for any recent time period ($170,767,400,000 in 2005), and have some idea of the amount of economic activity that takes place in the market for hotel rooms in terms of the dollar value of sales made by all businesses selling short-term accommodations. This supply side estimate is readily accessible because the accommodations industry has been defined in the existing industrial classification system used a by the United States Census Bureau to quantify economic activity; but we cannot find out the total sales of the sports industry so easily. The sports industry is not defined by any government agency that collects statistical data on economic performance in the United States. Because of the lack of a commonly accepted definition of the sports market, any measure of the value of the economic activity in the sports industry must be cobbled together from various sources.

Supply Side Estimates of the Sports Market

The US Census Bureau groups individual firms into industries based on the North American Industrial Classification System (NAICS). The NAICS includes the Arts, Entertainment, and Recreation industry (NAICS 71) that contains a number of sub-industries that are clearly part of the sports market, based on the definition offered above. These include: Spectator Sports Teams and Clubs (NAICS 711211), Racetracks (NAICS 711212), Other Spectator Sports (NAICS 711219), Golf Courses and Country Clubs (NAICS 71391), Skiing Facilities (NAICS 71392), Fitness and Recreation Centers (NAICS 71394), and Bowling Centers (NAICS 71399). The NAICS also identifies Promoters of Performing Arts, Sports, and Similar Events (NAICS 7113) and Agents and Managers for Artists, Athletes, Entertainers, and Other Public Figures (NAICS 7114), but these sub-industries appear to include activities outside sports. This group of sub-industries in NAICS Industry 71 accounts for a large fraction of the businesses on the supply side of the sports industry. One important exception is manufacturers of sports equipment. These firms are primarily grouped in Sporting and Athletic Goods Manufacturing (NAICS 33992).

There are several other sport-related sub-industries in the NAICS. These include Sporting Goods Stores (NAICS 45111) and Sporting and Recreational Goods and Supplies Merchant Wholesalers (NAICS 42391). These two sub-industries are related to the distribution of sporting goods. We do not include the wholesale and retail sub-industries in the estimates of the size of the sports industry because these establishments also sell general recreation goods like camping, hunting, and fishing supplies that are outside of the sports market as defined in this paper. Also, other wholesale and retail establishments handle sporting goods, so these sub-industries would not reflect all of the sporting goods equipment sales in the United States. We turn to other sources of data to estimate the size of the sporting goods and supplies industry in the sports market.

The primary source of economic data disaggregated to the four-digit to six-digit NAICS code level is the Economic Census. The Economic Census, a complete census of firms in the US, takes place every five years and reports summary statistics like total revenues, total payroll, and total employment for all of the industry-groups in the NAICS. In addition, supplementary Economic Census publications contain details on sources of revenues of firms in various industry-groups.

Table 5: Summary Statistics for Firms in the Sports Industry, 2002

Sub-Industry	NAICS Code	# Estab.	Employees	Revenues (mil)	Payroll (mil)
Spectator Sports Teams	711211	674	40,746	$13,025	$9,106
Racetracks	711212	646	47,121	$6,702	$995
Other Spectator Sports	711219	2,752	19,860	$2,585	$664
Golf Courses	71391	12,261	312,812	$17,533	$6,656
Skiing Facilities	71392	387	70,083	$1,801	$631
Fitness/Rec. Centers	71394	25,290	445,508	$14,987	$4,953
Bowling Centers	71399	4,924	82,010	$3,074	$904
Sporting/Athl. Gds. Mfg.	33992	2,235	62,166	$11,855	$2,075

Table 5 shows some summary statistics for the NAICS sub-industries identified above that are part of the sports market. In terms of number of establishments and employees, the Fitness and Recreation Center sub-industry is the largest of these, with over 25,000 firms employing over 445,000 people. In terms of total payroll, the Spectator Sports Team sub-industry is the largest, with $9.1 billion in total payroll in 2002. Despite the small number of employees in this sub-industry, the total payroll is so large because of the high salaries received by professional athletes in the top leagues. In terms of revenues, the Golf sub-industry is largest, generating about $17.5 billion dollars in revenues in 2002. In total, these sub-industries included 49,159 establishments employing 1,080,306 people in 2002. The total payroll for these establishments was just under $26 billion and the total revenues earned by establishments were about $71.5 billion. In terms of revenues, the plastics manufacturing industry (NAICS 326) is of similar size; in terms of employment, about the same number of people are employed at new car dealerships (NAICS 44111).

Table 6: Sources of Revenue for Firms in the Sports Industry, 2002 (hundreds of thousands of dollars)

Sub-Industry	NAICS	Admissions	Dues	Food/ Beverage	Radio/ TV
Spectator Sports Teams	711211	4,623	n/a	171	4,852
Racetracks	711212	1,169	n/a	260	306
Other Spectator Sports	711219	31	n/a	8	21
Golf Courses	71391	n/a	5,904	3,931	n/a
Skiing Facilities	71392	13	138	213	n/a
Fitness/Rec. Centers	71394	636	8,620	641	n/a
Bowling Centers	71395	12	.38	847	n/a

Table 6 shows some summary statistics on sources of revenue for the same NAICS sub-industries in Table 5 (excluding Sporting and Athletic Goods Manufacturing). The primary sources of revenue differ slightly depending on the nature of the sub-industry but the main categories are admissions, revenue from radio and television, membership dues, and sale of food and beverages. In the Spectator Sports Team sub-industry, 35.5% of the revenues of establishments come from admissions (about $4.6 billion in 2002) and 37% come from radio and television broadcast fees (about $4.8 billion in 2002). In the Golf sub-industry, 57% of revenues come from membership dues or admissions, and 24% from the sale of food and beverages. In the Fitness and Recreation Center sub-industry, 57% of the revenues come from membership dues ($8.6 billion in 2002). No other single category of revenues contributed more than 10% to total revenues in this sub-industry. The operation of establishments in these sub-industries differs considerably in terms of how they generate revenues. Also, note that total revenues earned by spectator sports teams and racetracks in 2002 were about $5.2 billion dollars. This is the only estimate of the value of following sports through some media that we were able to find. It understates the total value of following sports through media because it ignores internet-based sports content.

Several alternative sources of data about sporting goods equipment manufacturing firms exist. The NSGA publishes estimates of the revenues for sports equipment manufacturers. The NSGA revenue estimates are for equipment manufacturers like Nautilus and Callaway ($7.5 billion in revenues in 2005), footwear manufacturers like Nike ($31.4 billion in 2005), and apparel manufacturers like Russell Athletic and Under Armour ($5.5 billion in 2005). The NSGA estimate of total revenues for all sports equipment, footwear, and apparel manufacturers was $44.4 billion in 2005.

Demand Side Estimates

The other side of the sports market is composed of purchases of tickets to spectator sporting events, sports equipment, fees paid for admission to participatory sport, and subscriptions and equipment used to watch and listen to sporting events on some sort of media. In general, these purchases can be made by households, other firms, and even the government at various levels. For example, households and businesses can buy tickets to spectator sporting events. Individuals, professional sports teams, high school and college sports teams, and amateur sports teams all buy jerseys and other equipment for athletes. So spending on sports participation and spectator sports can come from all parts of the economy. However, we only have access to data on sport-related spending by households.

There are a number of sources of data on household spending on sports. Each has its strengths and weaknesses, and none are comprehensive because of the lack of a standard definition of the sports industry. The National Sporting Goods Association conducts an annual survey of consumer purchases of sporting goods. This survey was sent to 80,000 households across the US and was returned by 77% of the households contacted. The NSGA survey asks questions about annual spending on many types of sporting goods, including footwear, apparel, and equipment. The US Bureau of Economic Analysis publishes estimates of annual consumer spending on admissions to spectator sporting events. This estimate includes spending on admissions to amateur and professional sporting events, including horse and dog race tracks and auto racing.

Table 7: Consumer Spending on Selected Sports Items, 2005

Item	Total Spending
Sports Equipment (NSGA survey)	$13,474,300,000
Sports Apparel (NSGA survey)	$10,898,000,000
Sports Footwear (NSGA survey)	$15,719,000,000
Admission to Spectator Sporting Events (BEA)	$15,900,000,000

Table 7 shows the estimated consumer spending for several sectors of the sports market in 2005. According to the NSGA survey, spending on equipment, footwear, and apparel by participants in sport was $50.3 billion dollars in 2005. However, this total includes equipment purchases for a number of activities like hunting, fishing, and camping that we exclude from the sports market. The estimated spending on equipment for activities that fall within our definition of the sports market is about $13.5 billion. The NSGA survey estimates for sports apparel and footwear were $10.9 billion and $15.7 billion, respectively, in 2005. These estimates overstate the spending on apparel and footwear in our definition of the sports market, but the NSGA data does not contain enough detail to adjust the estimate. The US Bureau of Economic Analysis, in the August 2006 *Survey of Current Business*, reported spending on admissions to spectator sports to be $15.9 billion dollars in 2005. Admissions to spectator sports consist of admissions to professional and amateur athletic events and to racetracks. Note that this definition of spectator sports varies in an important way from the definition employed by the US Census Bureau's NAICS codes. Recall the NAICS definition for the spectator sports teams and clubs comprises professional or semiprofessional sports teams such as baseball, football, and basketball but does not comprise amateur athletics like high school and college sports.

Table 8: Consumer Equipment Purchases by Sport, 2005 (millions of dollars)

Sport	Spending
Baseball and Softball	372.4
Basketball	309.3
Bowling	183.5
Exercise	5176.6
Football	95.2
Golf	3465.5
Skating (Hockey & Ice Skates)	138.5
Racquetball	45.4
Snowskiing	642.7
Soccer	66.5
Tennis	379.1
Volleyball & Badminton Sets	32.1
Athletic Goods Team Sales	2567.5
Total	*13,474.3*

Together, this spending on sport accounted for less than 1% (0.76%) of the $8.7 trillion of personal consumption expenditures in the United States in 2005. In comparison, this spending is roughly equal to the amount that consumers spent on gas in 2005, and about one ninth the size of annual consumer spending on health care.

Table 8 presents more detailed data from the NGSA survey of consumer spending on sporting equipment in 2005 reported on Table 8. The sports represented in Table 9 roughly correspond to some of the sports that respondents indicated they participated in the BRFS survey that are listed in Table 2. The largest expenditures are for exercise equipment ($5.2 billion) and golf equipment ($3.5 billion). These two expenditure categories comprise 36.48% of total spending on equipment that was $23.7 billion in 2005. The consumer expenditure data presented in Table 9 does not add up to $23.7 billion because not all sports for which the NSGA collected data are represented in this table. For example, we do not show spending on camping equipment or fishing tackle because these activities do not fit the definition of sport used in this paper. Spending on camping equipment was $1.4 billion in 2005 and spending on fishing tackle was $2.1 billion so spending on equipment for these activities is substantial. After exercise and golf equipment, consumer spending on athletic goods for teams was the next largest category of expenditure at $2.6 billion in 2005.

Alternative Estimates of Consumer Spending on Sport

The NSGA survey and the US Bureau of Economic Analysis (BEA) are not the only sources of data about consumer spending on sport. While these data sources provide important information about consumer spending, they also have limitations. The NSGA survey does not require the respondents to consult financial records when reporting their spending, so estimates based on this survey may have recall bias. The BEA estimates are based on National Income and Product Account estimates and must conform to North American Industrial Classification System (NAICS) industries that do not capture all of the sport market as defined above.

An alternative source of data on consumer spending on sport is the Consumer Expenditure Survey (CEX). The Consumer Expenditure Survey is a nationally representative quarterly survey of household spending. Approximately 7,500 households take part in the interview survey each quarter, and the respondents are asked to consult bills and other financial records when responding to hundreds of detailed questions about their household spending and other characteristics. Since the CEX is conducted quarterly, and each household appears in the survey for five consecutive quarters before being replaced, the survey is a rich source of data about consumer spending. Dardis et al. (1994) used CEX data to estimate expenditure on several forms of leisure, a broader category of consumer spending than we consider here.

Table 9: Sport-Related Expenditure Items in the Consumer Expenditure Survey, 2005

CEX Section	Item Description	Category	Spending
Appliances and Equipment	General sports equipment	Equip.	
Appliances and Equipment	Health and exercise equipment	Equip.	
Appliances and Equipment	Winter sports equipment	Equip.	
Appliances and Equipment	Water sports equipment	Equip.	
Appliances and Equipment	Bicycles	Equip.	
Appliances and Equipment	Other sports and recreation equip.	Equip.	
Equipment Repair & Service	Sport and recreational equip.	Equip.	
Clothing	Active sportswear	Equip.	
Estimated Total Spending on Sports Equipment, billions of dollars			$9.177
Subscriptions/Memberships	Season tickets to sporting events	Spectator	
Entertainment expenses	Single admissions to spectator sports	Spectator	
Estimated Total Spending on Spectator Sports, billions of dollars			$4.902
Subscriptions/Memberships	Country clubs, health clubs, etc.	Particip.	
Entertainment expenses	Fees for participating in sports	Particip.	
Estimated Total Spending on Sports participation, billions of dollars			$12.980

The CEX asks a number of detailed questions about consumer spending on sports. Table 9 shows the CEX section and spending item description for all of the sport-related spending variables in the CEX. These spending variables include spending on consumer durables like exercise equipment, nondurables like clothing and shoes, tickets to spectator sporting events, memberships to fitness clubs and country clubs, and fees for sport participation. We group these different sport spending variables into three categories: spending on sports equipment, spending on spectator sport, and spending on sport participation. The category that each variable belongs to is shown in column three of Table 9.

These spending variables, along with the sampling weights in the CEX, can be used to generate national estimates of total annual spending on each of the types of consumer sport spending shown on Table 9. If s_j is the spending on CEX item *s* by household *j* and w_j is the sampling weight for household *j*, an estimate of total annual consumer spending on item j can be generated by

$$S = \Sigma_j \, w_j \, s_j$$

where S is the estimated total annual spending on CEX item *s*.

As part of the sampling methodology, the BEA publishes sampling weights for each household in the CEX. These sampling weights link the sampled household with the total number of households in the United States with these characteristics. In other words, each household sampled in the CEX represents a certain number of households in the United States, and the sampling weight reflects this number. If a sampled CEX household spends $100 in a year on tickets to sporting goods, and that household represents 50 households in the US population, then s_j equals $100, w_j equals 50, and their product equals $5,000 in total annual spending. Adding this up for the entire CEX sample produces an estimate of total spending for the entire country.

The fourth column on Table 10 shows the annual estimated spending on each of these categories of consumer spending in 2005, the most recent data available in the CEX. Consumer spending on sports equipment was $9.177 billion in 2005, consumer spending on single-game and season tickets to spectator sporting events was $4.902 billion, and consumer spending on memberships to health clubs and fees for sport participation like ski lift tickets was $12,980 billion. The total estimated consumer spending for all these categories in 2005 was $30.4 billion.

Estimating Total Economic Activity

We identified three main components of the sports market: participation in sport, attending sporting events, and following sporting events through some media. Estimates of the value of these economic activities can be derived by adding up total revenues earned by businesses operating in the sports market, a supply side approach, or by adding up total expenditures by purchasers in the sports market, a demand side approach. Table 10 summarizes the various individual estimates developed above and shows three alternative aggregate estimates of the economic value of the sports industry in 2005. Table 10 disaggregates sports participation into equipment, apparel, footwear, and fees to facilitate comparisons.

Table 10 contains two demand side estimates because we have two alternative estimates of consumer spending on sports equipment and spectating. In each case, the estimate derived from the Consumer Expenditure Survey is lower than the alternative estimate. In addition, both demand side estimates understate the actual size of the sports market because we do not have an estimate of consumer spending on following sports through media like TV, radio, and internet. Both estimates clearly overstate the size of the sports market, since not all athletic apparel and footwear is used by participants in the sports market. Another discrepancy in the demand side estimates of the size of the sports industry come from estimates of consumer spending on spectator sporting events. The Bureau of Economic Analysis, in the August 2006 *Survey of Current Business*, estimated consumer spending on admission to spectator sporting events in 2005 at $15.9 billion. The Consumer Expenditure Survey estimate of spending on season tickets and single admission tickets to spectator sports in 2005 was $4.9 billion. The Consumer Expenditure Survey estimates are considerably less than the other sources of data. One possible explanation for this difference is that the Consumer Expenditure Survey is not capturing corporate spending on admissions to sporting events. Corporate spending is likely a large component of the US Census Bureau data due to corporate spending on premium seating locations and luxury boxes. The difference between the BEA and CEX estimates of personal spending on attendance at spectator sporting events is difficult to explain. Future research should explore the source of this discrepancy.

Table 11: Estimated Total Economic Value of Sports Industry, 2005 (billions of dollars)

		Supply Side	*Demand Side*	
Component			**Estimate 1**	**Estimate 2**
Participation	Equipment[a]	$7.50	$13.47	$9.18
	Footwear[b]	$31.40	$10.90	$10.90
	Apparel[c]	$5.50	$15.70	$15.70
	Fees[d]	$16.60	$3.25	$3.25
	Subtotal, Participation	$61.00	$46.39	$39.03
Spectating[e]		$6.30	$15.90	$4.91
Mediated[f]		$5.65		
Total		**$72.95**	**$59.22**	**$43.94**

a: Supply side estimate from NSGA; estimate 1 from NSGA, estimate 2 from Consumer Expenditure Survey
b: Estimates from NSGA
c: Estimates from NSGA
d: Supply side estimate from U.S. Census Bureau, demand side estimate from Consumer Expenditure Survey
e: Supply side estimate from U.S. Census Bureau; demand side estimate 1 from BEA Survey of Current Business, demand side estimate 2 from Consumer Expenditure Survey
f: Estimate from U.S. Census Bureau (see Table 6)

Our supply side estimate exceeds the two demand side estimates by a wide margin, primarily because of the roughly $20 billion difference between revenues earned by footwear manufacturers and consumer spending on athletic footwear. One reason for this difference could be exports of athletic footwear. Setting the revenues of footwear manufacturers equal to consumer spending on athletic footwear reduces the supply side estimate to $52 billion, a figure that falls within the range of demand side estimates. All three estimates are much lower than the $152 billion estimate of the size of the sports industry reported by Meek (1997), which would be $195 billion in 2005 dollars. However, this is a national income and product accounts based estimate that, for reasons discussed above, probably overstates the size of the sports industry by a wide margin.

Note that we do not interpret the difference between the supply side and demand side estimates as reflecting disequilibrium in the sports market. We used two approaches as a rough check on the validity of the estimates, since they are based on different underlying data sources from different parts of the economy. Also, these figures are based on point estimates of spending, not confidence intervals. The confidence intervals would clearly be quite large since we are adding up estimates from different data sources and different methods of estimating aggregate values.

Conclusions

We set out to document the dimensions of the sports market in the United States by estimating individual active and inactive participation in sport and the value of economic activity in the sports market from both a supply and demand perspective. While conceptually simple, both aspects of determining the dimensions of the sports market proved to be challenging because of the lack of a commonly accepted definition of the sports market. The sports industry is somewhat unique in this regard since many industries are clearly defined by the United States Census Bureau or other government agency that collects statistical data on economic activity. In addition, determining the amount of inactive participation in sport through attendance at sporting events and viewing and listening to sports on television, radio, and internet is difficult given the existing data. Despite the challenges, we developed a working definition of the sports market for purposes of the paper and used a variety of publicly available data sources to develop estimates of the size of the sports market.

We define the sports market as having three principal components: 1) activities involving individual participation in sport, 2) activities involving attendance at spectator sporting events, and 3) activities involving following spectator sporting events on some media. We then examined participation and developed estimates of industry revenues and expenses and consumer expenditures related to these three components.

Our analysis indicates that individual participation in sport in the United States is significant. In any year, over 50% of the US population reported participating regularly in sports, and a much larger fraction of the population participate either regularly or occasionally. We estimate the value of the economic activity in the sport market in 2005 to be in the range of $44 billion to $60 billion dollars. However, this estimate is based on tangible economic activity. The total economic importance of the sport industry would be much larger if intangible benefits, like those generated by the shared experience of following a sports team or the national pride generated by living in the country that hosted the Olympic Games were included. For example, Davis and End (in press) found evidence of significant intangible benefits associated with living in the city that is home to the NFL team that wins the Super Bowl; Johnson, Mondello, and Whitehead (2007) estimated that the presence of a professional football team in a city generated $36 million in intangible benefits; and Atkinson et al. (2008) estimate that hosting the 2012 Summer Olympics will generate £2 billion in intangible economic benefits in the UK.

While we believe that this exercise has been worthwhile, we also hope that this paper will spur additional research. A number of important questions are raised by these results. First, and foremost, is the question of how to best define the sports market in economic terms. This is important because it also helps to define sports economics. Although we develop a working definition of the sports market that allows us to generate estimates of the economic size of the industry, our definition has a number of important limitations that can only be overcome by additional research. Second, our estimates have uncovered several interesting and potentially important discrepancies between estimates of specific types of consumer spending in the sports market generated from the Consumer Expenditure survey and other alternative sources. Further research should examine the source of this discrepancy. Third, despite a thorough search, we found no comprehensive estimates of the amount of spending by consumers who follow sports through media like television, radio, and, increasingly, the internet. Given the obvious importance of this facet of consumer behavior, and the increasing use of the internet, this gap in the literature clearly needs to be filled.

References

Alexander, D. L., Kern, W., & Neill, J. (2000). Valuing the consumption benefits from professional sports franchises. *Journal of Urban Economics*, *48*(3), 321-337.

Atkinson, G., Mourato, S., Szymanski, S., & Ozdemiroglu, E. (2008). Are we willing to pay enough to 'back the bid'? Valuing the intangible impacts of London's bid to host the 2012 Summer Olympic Games. *Urban Studies*, *45*(2), 419-444.

Bureau of Economic Analysis, U.S. Department of Commerce. (2005) *Annual Input-Output Accounts Data*. Retrieved April 9, 2009, from http://www.bea.gov/industry/io_annual.htm

Brown, R. W. (1993). An estimate of the rent generated by a premium college football player. *Economic Inquiry*, *31*(4), 671-694.

Bureau of Economic Analysis, U.S. Department of Commerce. (2006). *Survey of Current Business, 86*, 168.

Coakley, J. (2003). *Sport in society: Issues and controversies* (9th ed.). Boston, MA: McGraw Hill.

Dardis, R., Soberon-Ferrer, H., & Patro, D. (1994). Analysis of leisure expenditure in the United States. *Journal of Leisure Research*, *26*(4), 309-321.

Davis, M. C., & End, C. M. (in press). A winning proposition: The economic impact of successful national football league franchises. *Economic Inquiry*.

Fort, R. (2006). *Sports economics* (3rd ed.). New York: Prentice Hall.

Gratton, C. (1988). The economic importance of modern sport. *Culture, Sport and Society, 1*(1), 101-117.

Johnson, B. K., Mondello, M. J., & Whitehead, J. C. (2007). The value of public goods generated by a national football league team. *Journal of Sport Management*, *21*(1), 123-136.

National Sporting Goods Association. (2005). *Consumer purchases in 2005*. Retrieved April 9, 2009, from http://www.nsga.org/public/pages/index.cfm?pageid=869

National Sporting Goods Association. (2005). *Sports participation in 2005*. Retrieved April 9, 2009, from http://www.nsga.org/public/pages/index.cfm?pageid=864

United States Census Bureau (2002). *Economic Census 2002*. Retrieved April 9, 2009, from http://www.census.gov/econ/census02/

United States Department of the Treasury, Bureau of Statistics. (2005). *Statistical abstract of the United States*. Washington DC: U.S., G.P.O., 2007.

International Journal of Sport Finance, 2009, **4**, 114-135, © 2009 West Virginia University

Golf Match: The Choice by PGA Tour Golfers of which Tournaments to Enter

Stephen Shmanske[1]

[1] California State University, East Bay

Stephen Shmanske, PhD, is a professor in the Department of Economics and the Director of the Smith Center for Private Enterprise Studies. His research interests include applied microeconomics and the economics of sports, especially golf.

Abstract

This paper compares two methods of examining the entry choice of professional golfers, focusing on the size of the purse, the strength of the competition, and a newly constructed variable, the match of the player's skills with the skills rewarded at each tournament, while controlling for some dynamic factors such as year end pushes to cross relative earnings thresholds. Logit regressions are one method of examining the entry choice. A second method exploits combinatorial arithmetic. Choosing which n of N tournaments to play is equivalent to choosing n balls without replacement from an urn with N balls. The results show that golfers choose tournaments with higher purses, with a better skills match, and when the competition is fiercest.

Keywords: tournament compensation, intertemporal labor supply, PGA Tour

Golf Match: The Choice by PGA Tour Golfers of which Tournaments to Enter

The issue of intertemporal labor supply has been addressed in an interesting variety of settings including taxi cab drivers (Camerer et.al., 1997; Farber, 2005), stadium vendors (Oettinger, 1999), bicycle messengers (Fehr & Goette, 2007), and professional golfers (Hood, 2006; Rhoads, 2007a). Various aspects of labor supply have been examined, including: how often to show up for work, which days to show up, how long to stay at work once showing up, and how much effort to apply. The varying results of these inquiries with respect to labor supply elasticity has pointed out that careful attention must be paid to the demand and supply shift variables so that the elasticities can be properly identified. The abundant and high quality data available pertaining to professional golfers on the PGA Tour allow several interesting margins to be examined.

The labor supply issue in golf has been addressed from a variety of perspectives. Starting with Shmanske (1992), several economists (Moy & Liaw, 1998; Nero, 2001; Shmanske, 2000, 2007, 2008; Rishe, 2001; Alexander & Kern, 2005; Callan & Thomas, 2007) have estimated production functions wherein tournament scores are a function of the golfer's skills, or earnings functions wherein earnings are a function of the golfer's skills. Thus, the supply in different dimensions of talent leads to the performance or the earnings. Going one step backward in this supply chain, Shmanske (1992) also looked at the production, development, and maintenance of the skills themselves where the input supply is the golfer's practice time. Ehrenberg and Bognanno (1990a, 1990b) consider the golfer's supply of effort, especially in the final rounds of competition. Finally, Gilley and Chopin (2000), Hood (2006), and Rhoads (2007a, 2007b) study what might be called regular old supply, that is, the number of tournaments entered by professional golfers in a given year. The focus in these studies is on supply elasticity in order to determine whether a golfer's individual supply curve could be backward bending.

The research in the current paper draws a little from each of these traditions, but perhaps can be seen most closely as a complement to Rhoads's recent papers. Whereas Rhoads looks at the number of tournaments entered by a golfer, I hold that result constant and attempt to answer the question of which tournaments a given golfer will enter. In a nutshell, the paper does the following. By looking at the statistics from individual tournaments, it can be determined which skills, for example putting or driving, are rewarded more heavily on a tournament by tournament basis. By looking at the statistics for each individual golfer over the course of a year, it can be determined how much of each skill a particular golfer has. By matching the skills that the golfer has to the skills required in each tournament, an expected performance can be calculated for each tournament. These expected performances can be ranked from 1 to N, and if the golfer chooses to play in n of the N tournaments, the ideal set of which n tournaments the golfer should choose can be determined. Finally, a comparison of the set of tournaments actually chosen to sets chosen randomly can be made to determine whether a golfer's choice is systematic or random with respect to the match between the skills required by a tournament and the skills at which the golfer excels.

The comparison of the ideal choice set to the actual choices made is a novel part of the study. Suppose a golfer wants to play in n of N tournaments. All N tournaments can be ranked from 1 to N. The ideal choice is to pick those tournaments ranked 1 to n. The problem is equivalent to choosing n balls without replacement from an urn with N balls numbered 1 to N. If the balls are chosen randomly, the sum of the numbers on the balls chosen is distributed as a combinatorial symmetrically around a mean of $n(N + 1)/2$ and ranging from $\phi_{i=1,n}\ i$ to $\phi_{i=N-n+1,N}\ i$. By summing the ranks of the tournaments actually chosen, it can be determined where in the random distribution this sum falls. If the sum is small enough to be in the lower tail of the actual distribution, then the hypothesis that the golfer chooses which tournaments to enter randomly with respect to the match of skills in hand and skills required can be rejected in favor of the hypothesis that the golfer is systematically choosing along these lines. The author is unaware of other research exploiting a combinatorial in this way and, indeed, had to write a computer algorithm to search through all of the combinations and capture the number of ways each sum in the range can be achieved.[1]

The ideal set of tournaments referred to in the aforementioned nutshell explanation is "ideal" in the limited sense of considering only skills and predicted scoring performance. There are many other factors that golfers consider. For example, a golfer might not be eligible for a tournament that suits his skills and style of play. Or, such a tournament might fall on the weekend of the player's anniversary or other significant family event that makes the opportunity cost too high. Or, several potentially attractive tournaments might fall sequentially in a row and conflict with other priorities of the golfer such as not being away from home more than three weeks at a time. Additionally, there are three weeks during the season when two tournaments are scheduled and the golfer can only compete in one, even if both are attractive.

There are also dynamic considerations to keep in mind. At the beginning of the year a golfer will typically map out his schedule of which tournaments he expects to enter. During the year, these entry decisions can change due to injury, due to an attempt to exploit a hot hand,[2] and, most importantly, due to strategic entry at the end of the year in an attempt to cross thresholds in the yearly earnings lists. For example, ending the year in the top 30 on the earnings list allows entry into certain exclusive, high-purse tournaments with guaranteed payouts, while ending the year in the top 125 on the earnings list gives the golfer "exempt" status which allows entry into practically all of the official tournaments for the next year.[3] Without exempt status, a golfer cannot really choose which tournaments to enter, he typically will have to win a qualifying competition held early in the week of the tournament or seek a sponsor's exemption. Any of these dynamic considerations, or idiosyncratic factors similar to those mentioned in the previous paragraph, introduce random noise into the calculation of the ideal set of tournaments, which biases the results against the rejection of the null hypothesis of random selection. If the golfer can still be shown to choose systematically with respect to the match between the skills in hand and the skills required, then the results are strong indeed.

As described so far, the golfer chooses only in terms of his ranking of expected performance in terms of final score. But expected score is an indirect proxy for earnings for at least two reasons. First, the purses differ by tournament. A golfer may choose a tournament where he has a higher expected score (higher scores being worse in golf) if the purse is sufficiently large. Second, the tournaments differ by the strength of the competition. A golfer may choose a tournament where he has a higher expected score because fewer of the elite golfers choose to enter, such that the higher expected score translates into a better absolute rank in the tournament and, therefore, higher earnings.

The preceding arguments suggest a refinement of the original, nutshell, explanation. Instead of ranking all tournaments by expected scoring performance, one should rank only those tournaments for which one is eligible. This approach should yield better results than by only looking at expected score, but a further refinement may also be possible. Instead of ranking the tournaments for each golfer based on expected score, they could be ranked based on expected earnings. This is accomplished by comparing the expected score of each golfer to the expected scores of all the golfers who enter a particular tournament to calculate an expected rank finish order for each golfer. Combining information about the expected rank finish order with information about the purse leads to a point estimate of the expected earnings for each tournament and an alternate ranking of the ideal set of tournaments.

Finally, a simple ranking of the tournaments by the size of the purse indicates how important the prize fund is to alluring the top talent.

The strength of the combinatorial analysis is that it imposes very little structure on the golfer's choice. The weakness, however, is that without *ad hoc* weighting, only one dimension can be used at a time to achieve the ideal ranking of the tournaments. Multiple regression analysis using a logistic transformation can simultaneously assess the effects of the purse, the strength of the competition, and the skills match, at the cost of imposing significant structure on the model. Furthermore, regression analysis can also simultaneously control for the dynamic considerations discussed above, such as hot hand status, injury, or year-end strategic entry to maintain exempt status for the following year. This paper will compare the p-values calculated in the combinatoric analysis with those calculated in the regression analysis.

The remainder of the paper is organized as follows. The data collection and manipulation is described in the next section. The combinatorial results are presented in the section following that. Regression results follow the combinatorial results. The final section summarizes.

The Data

The PGA Tour sponsored 48 "official" events during the 2006 season.After each tournament the PGA Tour updates its website (www.pgatour.com) and reports the year-to-date performance statistics of the golfers. Although the PGA Tour would not share its data, it is possible to back out the weekly performance statistics from the change in the year-to-date statistics for a pre-chosen set of golfers.[4] Two of the 48 tournaments were not used because they used alternative scoring formats in which golfers play different numbers of holes and not every stroke counts. Not every player plays in every tournament so of the 4,600 possible tournament entries, 2,360 are actual entries for which the performance statistics and scoring outcomes are observed.

For each of these 2,360 observations, six statistics were tracked: The score per 18 holes measured in strokes, SCORE; the driving distance measured in yards, DRIVDIST; the driving accuracy measured as the percentage of drives ending in the fairway, DRIVACC; approach shot accuracy measured as the percentage of greens reached in regulation, GIR; putting proficiency measured as the number of putts taken per green reached in regulation, PUTTPER; and sand bunker skills measured as the percentage of times two or fewer strokes are taken to finish a hole from a greenside bunker, SANDSAVE. Summary statistics for these, their transformations, and the other variables used appear in Table 1.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum	N
SCORE	71.46	2.32	65	82	2360
DRIVDIST	289.09	13.90	184.4	353.2	2360
DRIVACC	0.636	0.120	0	1	2360
GIR	0.655	0.083	0.38	1	2360
PUTTPER	1.777	0.090	1.403	2.133	2360
SANDSAVE	0.496	0.207	0	1	2360
ASCORE	3.024	1.874	-3.793	11.996	2360
ADRIVDIST	-18.052	10.347	-120.241	32.324	2360
ADRIVACC	0.008	0.095	-0.664	0.605	2360
AGIR	-0.102	0.068	-0.384	0.409	2360
APUTTPER	0.031	0.082	-0.289	0.346	2360
ASANDSAVE	-0.050	0.201	-0.675	0.537	2360

Calculating the golfer's skill set.

The observed measures of these skills, and the scores themselves, are not directly comparable across tournaments because the conditions at each tournament differ with respect to weather, course conditions, length of course, elevation above sea level, size of greens, width of fairways, number of trees, lakes, and other hazards, etc. Therefore, six models of the following form are estimated:

$$X_{ij} = CB_C + GB_G + E_{ij} \qquad 1 \leq i \leq 46 \text{ and } 1 \leq j \leq 100. \qquad (1)$$

In equation (1), X_{ij} is the vector containing the dependent variable (SCORE, DRIVDIST, etc.), with element x_{ij} capturing the performance observed on the ith course by the jth golfer; B_C is the vector of 46 coefficients separating the effects of each tournament; C is the corresponding matrix of dummy variables, one for each course; B_G is the vector of 99 coefficients (one for each golfer with Tiger Woods omitted to avoid singularity in the estimation process) to control for the fact that golfers with different sets of skills play in different tournaments; G is the matrix of dummy variables, one for each golfer; and E_{ij}, with individual element e_{ij}, is the vector of error terms. Thus, the estimates in B_G give the average levels of each of the five skills by golfer, and the average scores by golfer, controlling for the skills of the other golfers and the difficulty or ease of the courses at each tournament's venue.

Rewriting equation (1) as:

$$X_{ij} - CB_C = GB_G + E_{ij} \equiv AX_{ij} \qquad 1 \leq i \leq 46 \text{ and } 1 \leq j \leq 100 \qquad (2)$$

Table 2: Estimates of Equation (3) for Honda Classic, March 9-12, 2006 (t-statistics in parentheses)

equation method	3 O.L.S.	3 Standardized Regression
Constant	75.860*** (10.86)	1.293*** (6.01)
DRIVDIST	0.046** (-2.56)	-0.578** (-2.56)
DRIVACC	6.716** (-2.37)	-0.558** (-2.37)
GIR	-11.606** (-2.48)	-0.587** (-2.48)
PUTTPER	12.687*** (5.24)	1.157*** (5.24)
SANDSAVE	-1.903* (-1.78)	-0.392* (-1.78)
adj. R^2	0.57	0.57
n	46	46

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

defines the adjusted levels of skills and scores (that is, AX stands for ASCORE, ADRIVDIST, etc., which in turn stand for the adjusted scores, adjusted driving distances etc.), which can be seen as the actual skill level or score minus a course adjustment factor, or as the average level of adjusted scores for each golfer plus an error term for that golfer in that tournament. It is the average level of each skill for each golfer (that is, the coefficient estimates in B_G) that are used in calculating a prediction for how well a golfer will do in any particular tournament. These estimates will be referred to as the golfer's skill set.

Calculating the required skills by tournament.

To estimate how well a golfer will do in any tournament we also need the relationship between the skills and scores on a tournament by tournament basis. Thus, the following equation is estimated individually on data for each tournament:

$$SCORE = a_0 + a_1 DRIVDIST + a_2 DRIVACC + a_3 GIR + a_4 PUTTPER + a_5 SANDSAVE + e. \quad (3)$$

One way to get a feel for the importance of the right hand side variables relative to each other is to estimate (3) as a standardized regression, in which, essentially, the variables are converted to z-scores from normal distributions. For example, an increase of one percentage point in approach shot accuracy as measured in GIR, should be asso-

Table 3: Frequencies of Patterns of Importance

Pattern, and order of importance					Frequency
First	**Second**	**Third**	**Fourth**	**Fifth**	
PUTTPER	GIR	DRIVDIST	DRIVACC	SANDSAVE	1
PUTTPER	GIR	SANDSAVE	DRIVACC	DRIVDIST	1
GIR	PUTTPER	DRIVDIST	SANDSAVE	DRIVACC	1
PUTTPER	GIR	DRIVACC	SANDSAVE		2
PUTTPER	GIR	SANDSAVE	DRIVACC		2
PUTTPER	GIR	SANDSAVE	DRIVDIST		1
PUTTPER	GIR	DRIVDIST	SANDSAVE		1
PUTTPER	DRIVDIST	DRIVACC	GIR		1
GIR	PUTTPER	DRIVAC	DRIVDIST		1
GIR	PUTTPER	SANDSAVE	DRIVDIST		1
GIR	PUTTPER	SANDSAVE			10
GIR	PUTTPER	DRIVACC			2
PUTTPER	GIR	SANDSAVE			2
PUTTPER	GIR	DRIVDIST			2
PUTTPER	GIR	DRIVACC			2
PUTTPER	DRIVACC	GIR			1
PUTTPER	SANDSAVE	GIR			1
GIR	PUTTPER	DRIVDIST			1
GIR	DRIVACC	PUTTPER			1
PUTTPER	GIR				7
GIR	PUTTPER				3
PUTTPER					1
none					1

ciated with lower scores, and will be measured in the estimate of a_3 in a normal regression. In a standardized regression, the estimate of a_3 gives the relationship between scores and approach shot accuracy where the latter is measured in standard deviations above the mean for the particular skill in question. To illustrate the effect, Table 2 lists the results for one of the 46 tournaments.

In Table 2, The Honda Classic is chosen as an illustration because it shows that neither the t-statistics from the OLS regression, nor the magnitudes of the coefficients in the OLS regression give the correct ranking of the importance of each of the skills on the right hand side.[5] In the standardized regression in Table 2, the correct ranking of the order of importance of the skills is putting first, which is roughly twice as important as the closely grouped greens-in-regulation, driving distance, and driving accuracy, in that order, followed by sand saves.

The standardized regressions were carried out for all 46 of the tournaments. Out of 230 (5 times 46) coefficient estimates, 138 are statistically significant with the correct sign, one is statistically significant with the incorrect sign, and 92 are insignificant. With one exception, the adjusted R^2 ranges from 0.27 to 0.84 and the sample size ranges from 22 to 96.[6] Table 3 captures the frequencies with which each pattern of importance shows up in the 46 tournaments. Putting is the most important skill in 25 of the 46 tournaments and second most important in 19 others. Reaching greens in regulation (GIR) is the most important in 20 of the tournaments, and second most important in 21 others. DRIVDIST is important in 23 tournaments. DRIVACC is important in 15 tournaments and SANDSAVE is important in 23 tournaments.

The rank order pattern of the importance of the different skills illustrates that different tournaments differentially reward different skill sets. This is a necessary step in the analysis because if the pattern and magnitude of the importance of the skills was the same in each tournament, or statistically insignificant, there would be little point in pursuing further any analysis of the match between the golfer's skills and the skills required in a particular tournament. The rank ordering of the importance of the skills shows that there are differences, but loses the continuous nature of the data. For example, PUTTPER and GIR might be ranked first and second most important, and be roughly equal in importance, or PUTTPER could be much more important to the outcome. For this reason, the actual coefficient estimates in equation (3) will be used as weighting factors for the skills necessary in each tournament.

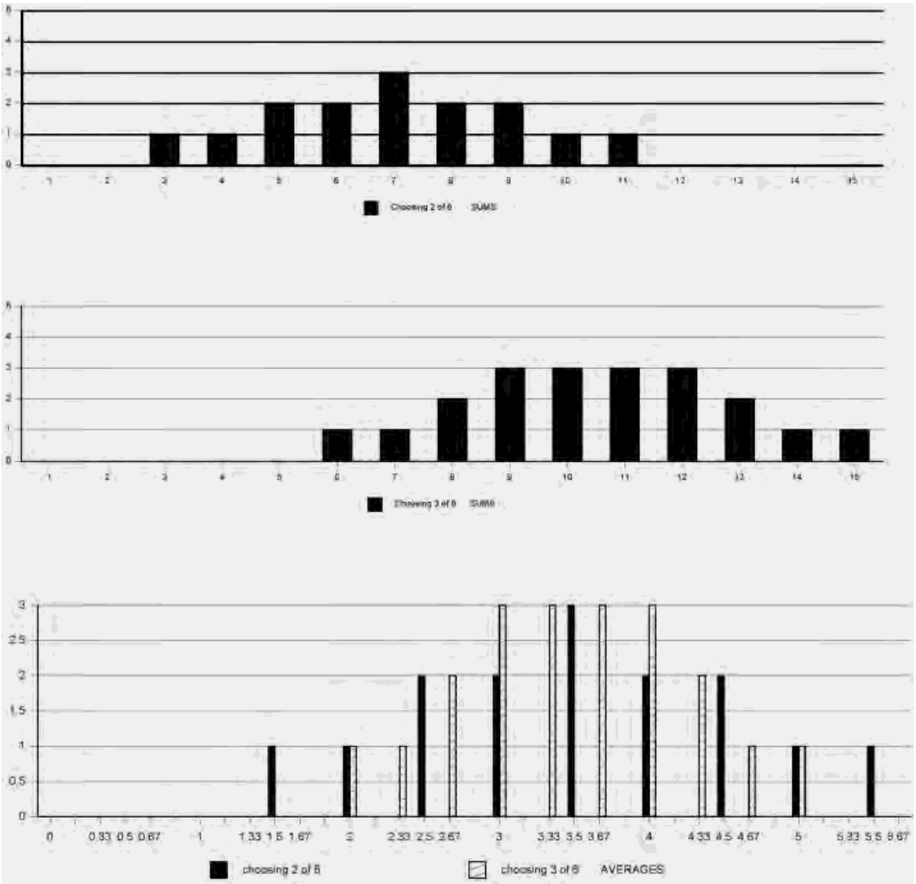
Calculating the ideal set of tournaments for each golfer.

The identification of the ideal set of tournaments for each golfer follows directly. Using equation (3) and the skill sets identified for each golfer yields the predicted relative score of each of the 100 golfers for each of the 46 tournaments, 4,600 predictions in all. These relative scores are grouped by golfer to yield a 1-46 ranking of the tournaments for each golfer. A golfer choosing to play in n of the 46 tournaments should choose the top ranking n. A primary goal of this paper is to determine how well the golfers make this choice.

Placing the tournaments actually chosen in the distribution of possible choices.

If the golfers choose which tournaments to enter based on the effects that are calculated in this paper, then comparing the golfer's actual choice to a choice made randomly among the 46 available tournaments should indicate it. Random choice among the 46

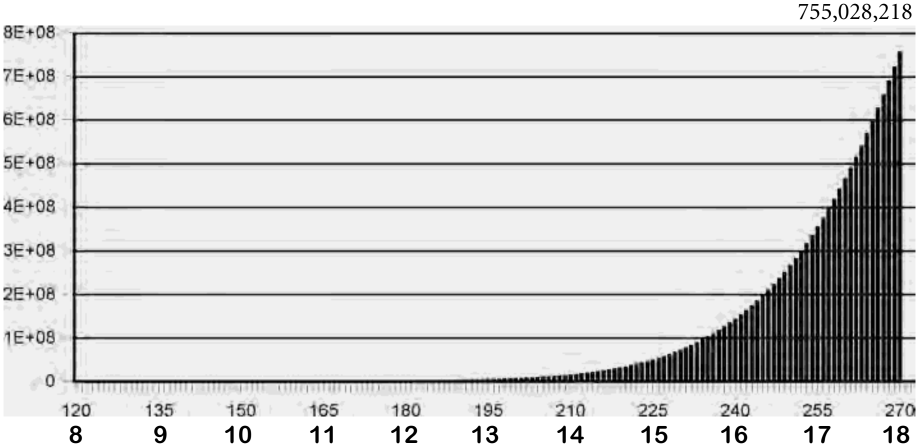
Figure 1: Distributions of Sums or Averages of Ranks



tournaments is equivalent to choosing n balls without replacement from an urn containing balls numbered 1 to 46. Ultimately, this paper will address the problem by comparing the average of the numbers on the n chosen balls to the probability distribution of the average taken on n balls chosen randomly.

Consider the following small numbers illustration of the problem. One golfer wants to choose two tournaments from a set of six available tournaments which a prediction model like that explained above has ranked from one (best) to six (worst). Another golfer wants to play in three tournaments. The best choice for the first golfer is the set of tournaments characterized by the pair (1, 2). The worst choice would be (5, 6). There are 15 different combinations in all. For the second golfer the best choice is (1, 2, 3), the worst choice is (4, 5, 6), and there are 20 different combinations. To compare the choices of the golfers to random choice, first consider the probability distribution function of the sum of the ranks. For the first golfer this appears in the top panel of Figure 1. For the second golfer this appears in the middle panel of Figure 1. These distributions of the sum of the numbers on n balls chosen without replacement will always be symmetric around a mean of n(N+1)/2. Thus, as n increases, the distribu-

Figure 2: Distributions of Sums in Left Tail for "Pick 15 out of 46"



tion slides to the right. Accordingly, the distributions can all be "centered" around a mean of (N+1)/2 by dividing the sum of the numbers on the balls by n. This is done and the distributions overlapped in the bottom panel of Figure 1.

Continuing with the small numbers example, suppose the first golfer actually chose the set of tournaments given by (1, 2). The average rank for his choice is 1.5 and is located in the left tail of the distribution with a probability of being that low (or lower) of one-fifteenth. Thus, the null hypothesis of random choice for this golfer would be rejected (at the 10% level but not at the 5% level) in favor of the alternative hypothesis that the golfer chooses systematically, as ranked by the model, which tournaments to enter.

The small numbers example provides the blueprint for what will be done for each of the 100 golfers in the sample, except that the golfers choose anywhere between 4 and 32 tournaments out of 46 possible tournaments. As such, the distributions of the averages of the ranks of the tournaments chosen will be centered around 23.5. These distributions get very big. As an example, consider the choice of 15 tournaments out of 46. There are over 517 billion (46!/15!31!) different ways to choose them. Figure 2 shows the left tail of this distribution. The lowest possible sum is 120 if the golfer chooses tournaments ranked 1 through 15. This would lead to an average rank of 8 (that is, 120/15). And there is only one combination that yields this sum. Now consider a sum of 270 for an average rank of 18. There are over 755 million combinations that add up to a sum of 270, but this is still tiny compared to the total number of possibilities.[7] The cumulative probability of an average rank no larger than 18 is still less than 2.7%. Therefore, if a particular golfer chose to play in 15 tournaments, and based on the ranking in this paper chose tournaments with an average rank of 18, we would reject the null hypothesis (with a p-value of .027) of random tournament selection in favor of the alternative hypothesis of systematic tournament choice as described by our model. Indeed, one such golfer in the sample, Mark Hensby, is precisely described in this example.

The next section characterizes the results for all 100 golfers in the sample.

Results from the Combinatorial Analysis

It would be awkward to enumerate the results for each of the 100 golfers. Instead, the distributions will be pictured and some summary statistics presented which will show the extent to which the golfers choose systematically based on matching the skills they have with the skills required at different tournament sites.

In Figure 3, the solid bars show the probability density function for the average of the "pick 15 balls out of 46" problem. The lowest average possible is 8, the highest 39, and the midpoint is 23.5. As such, Figure 3 gives a complete picture of the probability distribution function that was started in Figure 2 in the following manner. The solid bar at 18 in Figure 3 depicts the proportion of all the 517+ billion possibilities that have averages falling in the range (17-18] (that is, all the cases above 256 up to and including 270 in Figure 2). There are a lot of cases in this interval—over 755 million at 270 alone—but as a proportion of the total, they make up less than 2% of the total. The solid bar at 24 covers the interval from 23 to 24 and as such, includes the mean at 23.5. The critical values at the 1%, 5%, and 10% probability levels fall at the averages 16.93, 18.8, and 19.8, respectively, and therefore fall in the bars at 17, 19, and 20, respectively.

Now consider the averages achieved by the 100 golfers in the sample as depicted by the density function with the striped bars. A significant number of golfers clearly appear to pick their tournaments systematically according to the predictions in the model. A full 45% of the golfers achieve averages in the 10% tail of the random distribution. The distribution of the golfer averages appears to be bimodal, with one group being able to achieve an average in the 17-19 range and another group bunched in the 23-25 range. For the group clustered in the bars at 24 and 25, the null hypothesis that they are choosing from among the 46 tournaments randomly with respect to the skills match as described in this paper cannot be rejected. However, for those clustered in the bars at 19, 18, and below, the null hypothesis of random tournament entry is clearly rejected.

Figure 3: Comparison of Random Probability Density with Density of Actual Golfer Averages

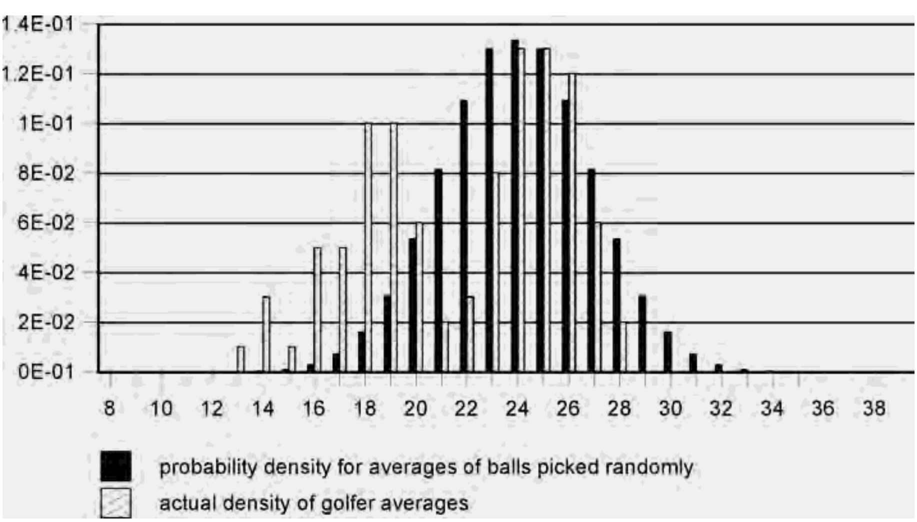
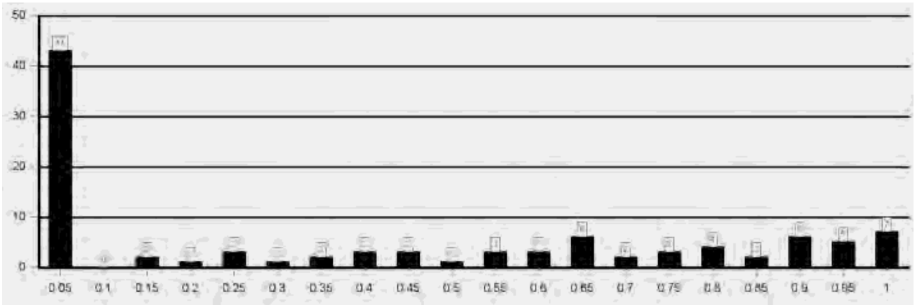
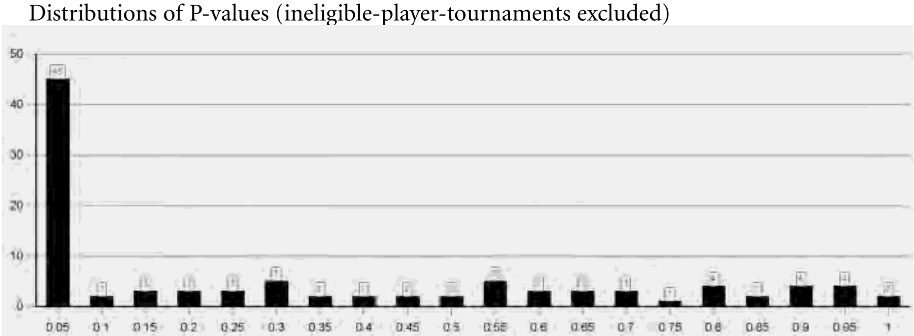


Figure 4: Distributions of P-values (all 46 tournaments)



Distributions of P-values (ineligible-player-tournaments excluded)



Note: The bar at 0.05 indicates all those whose average ranks have p-values less than 0.05 (p<0.05), the bar at 0.1 indicates all those whose average ranks have p-values from 0.05 up to but not including 0.1 (0.05<p<0.1), and so on.

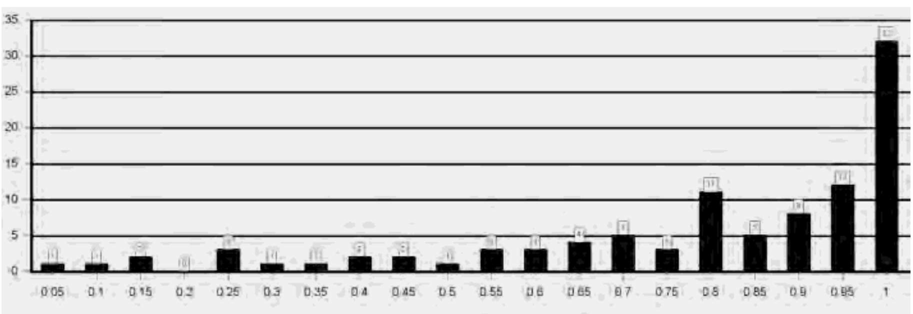
Figure 3 is illustrative, but does not give a fully accurate depiction of the probability levels involved because it is exactly calculated only for the "choose 15 out of 46 tournaments" problem. But in the sample of 100 golfers, one chose only four and several chose as many as 32. Figure 1 illustrates for a small numbers case how choosing more tournaments cuts out the extreme tails and pushed more density toward the mean. The same tendency exists for the large numbers problem. So, instead of a figure illustrating the density for each choice of n out of 46, each golfer will simply be placed in the proper distribution for however many tournaments he chose and the probability value for rejection of the null hypothesis is calculated. A bar graph showing the distribution of these p-values is depicted in Figure 4.

The top panel in Figure 4 is the first main result of the paper. If the golfers chose their tournaments randomly with respect to the factors considered in this paper one would expect there to be about five golfers in each of the 20 intervals formed when the probability level on the horizontal axis is divided into segments of length equal to 0.05. This clearly does not happen. A full 43% of the golfers fall into the less than 5% range and one can confidently reject the null hypothesis of random selection for these. Furthermore, of these 43 golfers, the null hypothesis can be rejected at the 1% level for 30 of them. Meanwhile, the other 57 golfers are spread pretty evenly throughout the rest of the distribution.

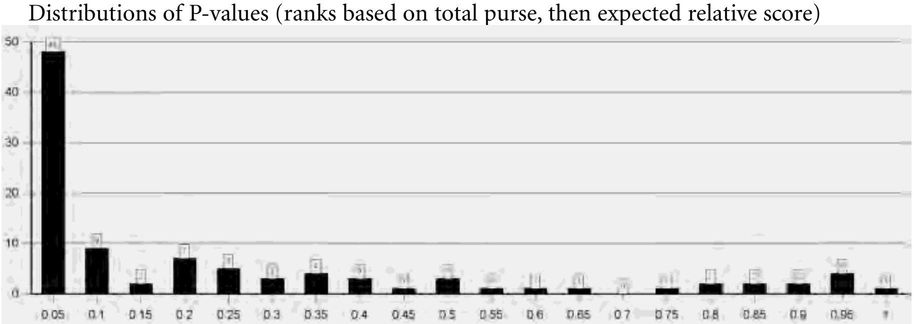
The results in the top panel of Figure 4 can be improved slightly. Not all golfers are eligible for all tournaments. In particular, the season-ending TOUR Championship, the season-opening Mercedes Championships, and the famous Masters tournament have limited entry fields that deny entry to a portion of our sample. Furthermore, during some weeks there are two official tournaments and a golfer could choose, at most, one. Instead of ranking all 46 tournaments, golfers will be choosing out of 43, 42, or fewer tournaments. The appropriate adjustments are made and new p-values are calculated for each golfer's choice of tournaments and the results charted in the bottom panel of Figure 4. As shown, the results improved slightly. The null hypothesis is rejected at the 5% level for 45 golfers, and for two more at the 10% level. Indeed, 37% of the golfers even fall into the 1% tail of the appropriate probability distribution.

As outlined in the introduction, an additional refinement is to rank the tournaments on the basis of expected earnings as opposed to expected relative scoring performance. This exercise brings two more pieces of information into the decision, the size of the purse and the strength of the competition. Each golfer's expected relative score at a tournament, as calculated above, is now compared to the expected scores of the other top golfers who enter that same tournament to return an expected rank-order of finish for each tournament. Coupled with the size of the total purse and the nonlinear distribution of the individual prizes,[8] the expected earnings in each tournament can be

Figure 5: Distributions of P-values (rank based on expected prize)



Distributions of P-values (ranks based on total purse, then expected relative score)



Note: The bar at 0.05 indicates all those whose average ranks have p-values less than 0.05 ($p<0.05$), the bar at 0.1 indicates all those whose average ranks have p-values from 0.05 up to but not including 0.1 ($0.05 \leq p<0.1$), and so on.

calculated and will form the basis for each golfer's ranking of the tournaments. The results are pictured in the top panel of Figure 5.

As the top panel of Figure 5 shows, there is no support for the proposition that a golfer chooses which tournaments to enter based on his expected prize as calculated in this model. If anything, there is support for the opposite. For many of the golfers the null hypothesis of random selection would be rejected in favor of the hypothesis that golfers chose tournaments based on the *reverse* order of expected earnings as calculated here. As the bottom panel will confirm, the problem is not with including information about the purse, but rather with the inclusion of the strength of field information. Indeed, for many of the major tournaments and the tournaments with the highest purses,[9] more than 70 of the golfers in the data competed, even though the prize funds distribute money only down to 70^{th} place. This means that all golfers with expected finish ranks of worse than 70 would actually "expect" a prize of zero by the calculations here. If these golfers choose based on expected prize, they would rank these tournaments last among all tournaments, yet they did choose to compete. Perhaps these golfers are overly optimistic about their chances against all of the other top golfers, but one should not discount the golfer's beliefs in his own skill and in the chance that he can turn in an above average performance. There may also be non-pecuniary reasons for competing in these tournaments such as fame and fortune coming from winning a major, or such as future entry into other restricted tournaments. Whatever the reason, many tournaments are entered even when the expected prize is smaller than the expected prize for other tournaments that were skipped.

The bottom panel of Figure 5 shows the distribution of p-values for the average rank of the tournaments chosen when tournaments are ranked looking first only at the total purse, and looking second at the expected performance in the tournament based on the skills the golfer possesses and the skills required by the tournament venue. That is, golfers rank which tournaments to enter based on the total purse, but in the case where two tournaments have the same purse, the golfer ranks them by expected performance as above in Figure 4. Thus, this measure ignores the strength of the competition. There is strong support for this decision rule, with close to half the sample rejecting the null hypothesis of random selection in favor of the ranking based predominantly on total purse.

Comparison of the set of golfers for whom the null hypothesis of random selection is rejected in favor of the alternate hypotheses of the ranking based on the skills match (Figure 4) or the purse (Figure 5, bottom panel) to the set of golfers for whom the null hypothesis is not rejected was largely uninformative. There was no significant difference in the means between the two sets for age (36.4 to 36.9 years), experience (157 to 160 career tournaments), earnings (1.56 to 1.46 million dollars), or earnings per tournament (62 to 57 thousand dollars). There was, however, a significant difference[10] in the mean number of tournaments entered with golfers choosing wisely with respect to the skills match also choosing fewer tournaments in all (22 versus 26).

The fact that one cannot separate the "randomly choosing" golfers from the "systematically choosing" golfers by looking at previous earnings, or earnings per tournament, does not mean that the ability to systematically choose has no value. The value of correct choice is masked when looking backward at uncontrolled means of the two sets of golfers. A golfer could be in the top 100 money winners because he has superior skills, or because, given adequate skills, he chooses the correct tournaments, or both. Once controlling for skills in a multiple regression, the independent effect of correct entry choice shows up. So, consider the regression of the logarithm of earnings per tournament[11] (LnEARNPERT) on the adjusted skills and the p-value from the calculations underlying the bar chart in the bottom panel of Figure 4.

$$\begin{aligned} \text{LnEARNPERT} = {} & \underset{(79.9)}{11.35} + \underset{(3.34)}{0.0317}\ \text{ADRIVDIST} + \underset{(2.42)}{3.66}\ \text{ADRIVACC} + \underset{(3.57)}{7.31}\ \text{AGIR} \\ & - \underset{(-5.61)}{11.68}\ \text{APUTTPER} + \underset{(2.65)}{2.75}\ \text{ASANDSAVE} - \underset{(-4.02)}{0.713}\ \text{P-VALUE} + e \end{aligned}$$

$$n = 100, \quad \text{Adj. R-square} = 0.658 \quad \text{(T-statistics)} \qquad (4)$$

The skills variables are averages, grouped by golfer, of the adjusted skills as defined in equation (2). The dependent variable is the logarithm of official earnings per tournament in 2006. All the skills are statistically significant in the expected direction. The variable of interest, P-VALUE, is low when the golfer is systematically choosing correctly, and, therefore, its significant negative coefficient means that correct choice increases earnings as is expected. It is clear that the ability to more correctly choose which tournaments to enter will lead to higher earnings. But it remains a puzzle to be pursued in future work why some golfers are able to systematically choose the best tournaments for their skill set while others are not able to do so.

Results from the Regression Analysis

Regression analysis provides another way of addressing the question of whether golfers systematically choose which tournaments to enter based on the match between their skill sets and the skills required in a particular tournament. Consider the following relationship:

$$\text{Probability of entering a tournament} = f(\text{constant, EXPECTED RELATIVE SCORE}), \qquad (5)$$

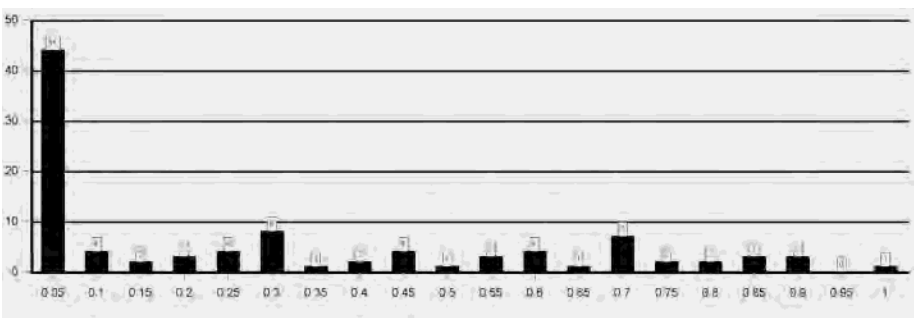
where a dichotomous dependent variable can capture the left hand side, and the independent variable is the expected relative score upon which the ideal rankings were based in the combinatorial analysis. To address each golfer's entry decision, equation (5) was estimated for each of the 100 golfers using binomial logistic regression. Since higher scores are worse in golf, we expect a negative coefficient on the expected relative score variable.

At this point, there are two important differences between the combinatorial procedure and the regression analysis. First, the regression analysis has the advantage of being able to use the continuously measured actual levels of the expected relative scores instead of the 1-46 integer rankings. This should make the regression analysis more powerful. The second difference, however, should make the combinatorial analysis more powerful. Namely, regression analysis imposes a specific algebraic structure on the relationship between the expected relative scores and the probability that a tournament is entered that is absent in the combinatorial analysis. Essentially, the combinatorial analysis is asking a question about the whole subset of tournaments that is entered while the regression analysis is asking a question about one parameter in a specific systematic relationship between expected performance and the entry decision for each individual tournament. As the results show, these effects seem to be of little consequence.

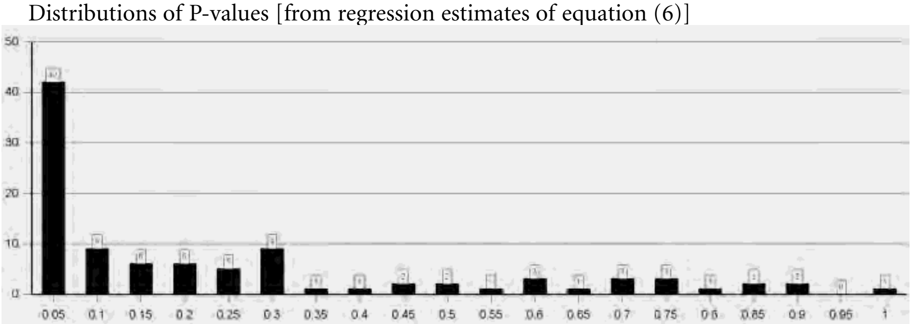
The results of these regressions generally support the conclusions reached above in the bottom panel of Figure 4. As above, it will be too cumbersome to list the results of all 100 regressions, but to give a sense of the results, consider the ranges for the following specific statistics. The number of observations ranged from 40 to 43. The Cox and Snell R^2 ranged from 0.0 to 0.54 with an average of 0.09. The coefficient estimates, 73 of which had the expected negative sign, ranged from -12.2 to 2.6 with an average of -1.6. Our main concern is with the significance levels of these coefficient estimates.

For the closest comparison to the combinatorial results, we want the probability in the left-hand tail of the distribution for the probability that the coefficient estimate would be at least as low as calculated if the true coefficient were zero. These p-values are easily recovered from the two-tail significance levels reported in the estimation. A plot of these p-values appears in Figure 6. As the figure shows, 44 of the golfers have p-values less than 0.05 (and 28 of these are less than 0.01). These numbers compare to 45 golfers' p-values less than 0.05 and 37 less than 0.01 from the bottom panel of Figure 4.[12] As such, the combinatorial analysis appears to have a slightly stronger ability to capture the underlying systematic tendency hypothesized in this paper, but the difference is not significant.[13]

Figure 6: Distributions of P-values [from regression estimates of equation (5)]



Distributions of P-values [from regression estimates of equation (6)]



Note: The bar at 0.05 indicates all those whose coefficient estimates have p-values less than 0.05 ($p<0.05$), the bar at 0.1 indicates all those whose coefficient estimates have p-values from 0.05 up to but not including 0.1 ($0.05 \leq p<0.1$), and so on.

Regression analysis has another powerful advantage, namely, to simultaneously consider more than one independent variable in a multiple regression setting. The combinatorial analysis indicated that expected relative score mattered, that the purse mattered, but that the expected earnings (which captures the strength of the rest of the field) did not matter. But these results were arrived at separately by considering only one effect at a time. Now consider equation (6):

$$\text{Probability of entering a tournament} = f(\text{constant, expected relative score, purse, expected earnings, X}), \tag{6}$$

where the three effects examined separately in the combinatorial analysis can be simultaneously considered. Furthermore, the vector of control variables (X) can include control variables for number of tournaments entered, experience, age, whether a tournament is a major, and, most importantly, the dynamic effects alluded to earlier in the paper.

The following dynamic effects are captured with dummy variables (or in the first case by a restriction on the sample) capturing the following considerations. First, in some cases, the known injury status of a golfer precludes entry into a tournament that may otherwise suit that golfer's skill set. In a sense, the golfer's decision rule is hierarchical (that is, if injured, do not enter, if not injured, then consider all the other aspects and decide whether to enter). As such, injured golfers are using a different decision rule and will not be modeled by equation (6). Observations on these golfer-tournament combinations are omitted from the regression reducing the usable sample from 4,200 to 4,099 observations.

Second, golfers may alter a planned schedule of tournament entry due to recent success (exploit a hot hand by playing, or take off to celebrate a big win) or failure (take off to work on skills, or continue playing to try to make up for lost earnings). As indicated, these effects could go either way. A set of dummy variables will try to capture the direction and significance of these considerations. A dummy variable, BIGMONEY, takes the value of 1 if the golfer won \$100,000 or more in the previous week's tournament. A dummy variable, MISSEDCUT, takes the value of 1 if the golfer entered but did not make the cut in the previous week. A golfer earns \$0 in this case. A golfer also earns \$0 if he did not enter the previous tournament; this case is captured by the dummy variable REST. The omitted category in this listing is when the golfer entered, made the cut, and earned less than \$100,000 the previous week.

Arguably, the most important dynamic factor to consider is the golfer's desire to finish the year in the top 125 money winners in order to maintain exempt status for the next year. In 2006, number 125 on the money list earned \$660,898. Golfers do not know this cutoff exactly, but can form a pretty close approximation of how much they need to earn on average each week to meet the cutoff. Certainly, a golfer winning a tournament early in the year, and earning close to or over \$1,000,000 by doing so, does not have to worry about maintaining exempt status. For others, however, it may be a year-long struggle to cross the threshold. A dummy variable, BEHINDPACE, gets the value of 1 for all observations in which the golfer is behind the weekly pace to make the top 125.[14]

Finally, as golfers approach the end of the year, it becomes clearer to them whether they have a chance to cross over the threshold into the top 125 (to maintain exempt status) or into the top 30 (to achieve a special status), or whether they are in danger of

Table 4: Estimates of Equation (6) (standard errors in parentheses)

dependent variable: binary, tournament entered = 1		
equation, method	**(6), Logit**	**(6), Logit**
Constant	-4.484***	-2.806***
	(0.461)	(1.005)
Expected relative score	-0.321***	individual coefficients by golfer
	(0.092)	See Figure 6 bottom panel
Purse/1,000,000	0.490***	0.466***
	(0.044)	(0.049)
Expected earnings/1,000	-0.001***	-0.002***
	(0.000)	(0.000)
# of tournaments entered	0.111***	0.044***
	(0.007)	(0.017)
career tournaments entered	-0.000	-0.002
	(0.000)	(0.001)
age	-0.002	0.011
	(0.009)	(0.028)
2005 earnings/1,000,000	0.002	0.008*
	(0.003)	(0.005)
major	0.029	-0.100
	(0.149)	(0.152)
BIGMONEY	0.305**	0.374***
	(0.134)	(0.139)
MISSEDCUT	-0.149	-0.237**
	(0.107)	(0.110)
REST	0.041	-0.034
	(0.085)	(0.087)
BEHINDPACE	0.777***	0.775***
	(0.097)	(0.121)
THRESHOLD	1.202***	1.348***
	(0.246)	(0.256)
Cox and Snell R^2	0.152	0.178
n	4099	4099

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

having the threshold move above them because of good performances by those currently below them in the ranking. For the last five tournaments of the year the golfers who are below either threshold but can reasonably jump above it, and golfers who are just above the threshold and in danger of falling below it, are given a value of 1 in the dummy variable, THRESHOLD.

Equation (6) was estimated with a binomial logistic regression and the results appear in Table 4. The equation was estimated first on the pooled sample with the added constraint that the effect of the expected relative score was the same for all golfers. This result is in the left column of the table. In the right column, each golfer is allowed his own coefficient of the expected score variable.

The results confirm the inferences derived from the combinatorial analysis. Consider first the left column. The higher the golfer's expected relative score, the lower the probability that he enters the tournament. The higher the purse, the greater is the probability that a golfer enters the tournament. And, paradoxically, the lower the expected prize, the higher is the entry probability. Golfers enter tournaments where the skills match is favorable, where the purse is high, and where, due to the presence of stiff competition, the expected prize is low. These are the same three results from the combinatorial analysis.

Several of the control variables are statistically significant in the theoretically predicted direction. With respect to the recent performance of the golfer, there is evidence that golfers may attempt to exploit a hot hand by entering a tournament after winning a large prize in the immediately preceding tournament. Having missed the cut in the previous tournament or having not played do not seem to effect the entry decision going forward.

There is also strong evidence that golfers are motivated to keep their playing privileges for the next season. If they fall behind the pace they need to earn enough to reach the top 125 on the earnings list, there is a higher probability that they enter the next tournament. Also, at the end of the season, if they are near the important thresholds of 30^{th} or 125^{th} on the money list, they tend to enter tournaments more than they otherwise would.

The only other control variable that is significant is the number of tournaments entered by a golfer. Controls for age, experience, last year's earnings, and whether a tournament is a major were not significant.

The pooled regression in the left-hand column of Table 4 could leave the impression that all 100 golfers in the sample can systematically choose with respect to the skills match. However, the right-hand column reports results with a different coefficient on the expected score variable for each golfer. As the table shows, the significant effects from the left column are still significant. Last year's earnings and missing the cut in the previous tournament are now also significant. No other inferences are changed. Meanwhile the 100 individual coefficients confirm the result that roughly half of the golfers choose systematically with respect to the skills match, while the others do not. As before, the bar chart plot of the 100 p-values, this time pictured in the bottom panel of Figure 6, bears a striking resemblance to those already discussed. Eighty-three of the 100 golfers have the correct negative sign and 51 of them are significant at the 10% level. Clearly, more than half of the golfers are more likely to enter a tournament that favors their individual skills, controlling for purse size, strength of competition, dynamic effects, and the other variables included in equation (6).

Summary

This paper examines the choice made by professional golfers of which tournaments to compete in. By looking at tournament level data for the top 100 money winners of 2005 during the 2006 season, the specific strengths of the individual golfers and the specific required strengths at any one tournament site can be determined. This information allows one to calculate the expected relative performance of each golfer at each tournament. If golfers ignore this information and choose which tournaments to enter based on other factors and, therefore, randomly with respect to these calculations, the null hypothesis of random tournament selection will not be rejected.

Two methods were used to examine the entry choice. A combinatorial analysis compared the subset of tournaments chosen to the random distribution of possible subsets. A regression analysis examined whether a systematic relationship between expected relative performance and the entry decision could be uncovered.

Forty-six tournaments were examined, individual golfers choosing to play in as few as four and as many as 32 of them. Based on the combinatorial analysis, the results pictured in Figures 4 and 5 show that close to half the golfers do systematically choose which tournaments to compete in based on their skill strengths and the requirements of the specific tournament. Based on the regression analysis, the results pictured in Figure 6 and listed in Table 4 confirm and extend those of the combinatorial analysis. This matching of talents and needs is an important issue in labor economics. The result also suggests the next step in this research agenda, namely, to discover the characteristics that allow certain golfers to fall into the group that chooses systematically while others seemingly choose randomly with respect to the skills match. A quick check of some potential factors, such as age, earnings, experience, and number of tournaments entered, did not reveal significant differences except for the number of tournaments chosen. Further analysis of this question is beyond the scope of this paper.

Going one step further, the paper develops a ranking of the tournament entry choice by golfer which includes consideration of the size of the purse and the strength of the competition. In the study of tournament compensation schemes, higher prizes are sometimes associated with higher performance levels, but the avenue through which this result occurs is ambiguous. For example, do high prize funds bring forth more effort, attract more talent, or both? The paper sheds some light on this question. The combinatorial analysis illustrated in Figure 5 shows that there is no support for the proposition that golfers choose based on "expected" prize earnings which depend on the size of the purse and the number of other contestants likely to place above the golfer in question. However, the size of the purse alone does matter. Close to 60% of the golfers are attracted by the purse and not dissuaded by the entry of other top golfers when choosing which tournaments to enter.

The multiple regression analysis of equation (6) has the ability to simultaneously examine the skills match, the size of the purse, and the strength of the competition while controlling for other factors such as streaky play and year-end strategic considerations. The results confirm and strengthen the results of the combinatorial analysis.

References

Alexander, D. L., & Kern, W. (2005). Drive for show and putt for dough? An analysis of the earnings of PGA Tour golfers. *Journal of Sports Economics*, *6*(1), 46-60.

Callan, S. J., & Thomas, J. M. (2007). Modeling the determinants of a professional golfer's tournament earnings: A multiequation approach. *Journal of Sports Economics*, *8*(4), 394-411.

Camerer, C., Babcock, L., Loewenstein, G., & Thaler, R. (1997). Labor supply of New York City cabdrivers: One day at a time. *Quarterly Journal of Economics*, *112*(2), 407-441.

Connolly, R. A., & Rendleman Jr., R. J. (2008). Skill, luck, and streaky play on the PGA Tour. *Journal of the American Statistical Association*, *103*(481), 74-88.

Ehrenberg, R. G., & Bognanno, M. L. (1990a). Do tournaments have incentive effects? *Journal of Political Economy*, *98*, 307-324.

Ehrenberg, R. G., & Bognanno, M. L. (1990b). The incentive effects of tournaments revisited: Evidence from the European PGA Tour. *Industrial and Labor Relations Review*, *43*(3), 74S-88S.

Farber, H. S. (2005). Is tomorrow another day? The labor supply of New York City cabdrivers. *Journal of Political Economy*, *113*(1), 46-81.

Gilley, O. W., & Chopin, M. C. (2000). Professional golf: Labor or leisure. *Managerial Finance*, *26*(7), 33-45.

Fehr, E., & Goette, L. (2007). Do workers work more if wages are high? Evidence from a randomized field experiment. *The American Economic Review*, *97*(1), 298-317.

Hood, M. (2006). The purse is not enough: Modeling professional golfers entry decision. *Journal of Sports Economics*, *7*(3), 289-308.

Moy, R. L., & Liaw, T. (1998). Determinants of professional golf tournament earnings. *The American Economist*, *42*(1), 65-70.

Nero, P. (2001). Relative salary efficiency of PGA Tour golfers. *The American Economist*, *45*(1), 51-6.

Oettinger, G. S. (1999). An empirical analysis of the daily labor supply of stadium vendors. *Journal of Political Economy*, *107*(2), 360-92.

Rhoads, T. A. (2007a). Labor supply on the PGA Tour: The effect of higher expected earnings and stricter exemption status on annual entry decisions. *Journal of Sports Economics*, *8*(1), 83-98.

Rhoads, T. A. (2007b). *On nonlinear prizes in professional golf.* Retrieved August 2007, from http://pages.towson.edu/trhoads/NonlinearPrizes.pdf

Rishe, P. J. (2001). Differing rates of return to performance: A comparison of the PGA and Senior golf tours. *Journal of Sports Economics*, *2*(3), 285-96.

Scully, G. W. (2002). The distribution of performance and earnings in a prize economy. *Journal of Sports Economics*, *3*(3), 235-45.

Shmanske, S. (1992). Human capital formation in professional sports: Evidence from the PGA Tour. *Atlantic Economic Journal*, *20*(3), 66-80.

Shmanske, S. (2000). Gender, skill, and earnings in professional golf. *Journal of Sports Economics*, *1*(4), 385-400.

Shmanske, S. (2007). Consistency or heroics: Skewness, performance, and earnings on the PGA TOUR. *Atlantic Economic Journal*, *35*(4), 463-471.

Shmanske, S. (2008). Skills, performance, and earnings in the tournament compensation model: Evidence from PGA Tour microdata. *Journal of Sports Economics*, *9*(6) 644-662.

Author's Note

I would like to thank Leo Divinagracia for computer programming assistance, Kevin Quinn and Thomas Rhoads as discussants for an earlier version of this paper, conference participants at the May, 2008 IASE meetings in Gijon, Spain, and the July, 2008 WEAI meetings in Honolulu, and referees of this journal.

Endnotes

[1] For a golfer choosing n=23 out of N=46 tournaments there are (46!)/(23!)(23!) different combinations. That is, there are more than 10^{12} combinations. The program runs in the background of a desktop computer but can take weeks to search all the cases depending on n and N. With negligible difference, the paper also uses a simulated distribution with 10^6 trials.

[2] Connolly and Rendleman (2008) found evidence of statistically significant streaky play for 9% of the golfers in their sample.

[3] Typical tournament fields are 144 golfers, so exempt status for being in the top 125 assures entry. Tournament winners from previous years have a higher priority on the exempt list, but almost all of these winners are also in the top 125. Previous winners who are not also included in the top 125 include older golfers with "lifetime" exemptions such as Arnold Palmer and Jack Nicklaus, who will not enter current tournaments. The sample in this paper uses only the top 100 golfers of 2005, each of whom would have been eligible to enter any of the regular PGA Tour events in 2006.

[4] The study tracked the top 100 money winners of 2005 throughout the 2006 season. These golfers accounted for the lion's share of the total money awarded in 2005 and again in 2006. The sample size is arbitrary but is large enough to give ample degrees of freedom for the tests performed in this and other research stemming from the sample.

[5] Neither do the implicit elasticities. Elasticities measure sensitivity based on the average magnitude of each independent variable, whereas coefficient estimates from the standardized regression measure sensitivity based on each golfers placement in the distribution of the skill taken over all golfers and measured in standard deviations. For example, consider driving distance in which a 30-yard improvement might be only a 10% change when calculated in an elasticity if average drives are 300 yards, but may represent two or three standard deviations above the mean and be very difficult to achieve.

[6] The exception is the U.S. Open which returned no significant coefficients and an adjusted R^2 of zero. The U.S. Open seems to bamboozle statistical researchers as much as it does professional golfers.

[7] A computer program was designed to count the number of different combinations leading to different sums or averages in the lower tails of the overall distributions. To count all the combinations leading to sums no larger than 270 (averages up to 18) for the "choose-15 out of 46" problem took 5 days on my desktop computer. To count out the whole distribution would take much longer. As n increases from 15 to 23 (the largest problem), the counting goes up by an order of magnitude for each step of n. For distributions yet to be calculated, probability densities are estimated in a simulated bootstrap distribution based on a million random samples.

[8] For the vast majority of tournaments, first prize wins 18% of the purse, second place wins 10.8%, and so on down to 0.2% for 70th place.

[9] Overall, purses ranged from \$3 million to \$8 million.

[10] The p-value was less than 0.01.

[11] As is typical, using the natural logarithm of earnings corrects for heteroskedasticity which is a problem when levels are used in an earnings equation.

[12] The overlap between these two sets of golfers is almost exact. Only one of the 44 who are significant ($p<0.05$) in the regression analysis is not significant in the combinatorial analysis, and only 2 of the 45 who are significant ($p<0.05$) in the combinatorial analysis are not also significant in the regression.

[13] Neither a regression of the p-value from the regression analysis on the p-value from the combinatorial analysis nor a simple comparison of means of the p-values indicate a significant difference between the two measures.

[14] However, a golfer will not be considered "behind pace" until after he enters his first tournament of the year. Many golfers choose to skip the trip to Hawaii for the early tournaments.

International Journal of Sport Finance, 2009, **4**, 136-150, © 2009 West Virginia University

The Causality between Salary Structures and Team Performance: A Panel Analysis in a Professional Baseball League

Wen-Jhan Jane[1], Gee San[2], and Yi-Pey Ou[2]

[1] Shih Hsin University, Taiwan
[2] National Central University, Taiwan

Wen-Jhan Jane, PhD, is an assistant professor in the Department of Economics. His current research focuses on the economics of sports, specifically the topics of wage theory, competitive balance, and worker discrimination.

Gee San, PhD, is a professor in the Graduate Institution of Industrial Economics. His research focuses on labor economics and industrial organization.

Yi-Pey Ou is a PhD candidate in the Graduate Institution of Industrial Economics. Her current research focuses on technological change and growth.

Abstract

This paper provides a comprehensive study of the causality between pay and performance for professional sports teams. By using the total salary payment, as well as the dispersion of salary payment of the baseball teams in Taiwan, we engage in a simultaneous regression of a Granger Causality Test for each team's salary structures and their corresponding performance. Our empirical results show that the causality only runs from the dispersion of salary payment to team performance, and not vice versa. As such, both the tournament hypothesis, which emphasizes the effect of salary dispersion, and the Yankee paradox, which proposes the negative externality for a team with high payroll, are thus confirmed. The one-way causality results suggest that teams must rely more on internal wage adjustments, especially on the dispersion of salary, under the league with strict restrictions on the mobility of players.

Keywords: Equity Theory, panel Granger Causality test, salary regulation, Tournament Theory, Yankee Paradox

Introduction

Economists usually pay more attention to the relationship, rather than the direction, of the linkage between salary structures and team performance. Studies of professional baseball teams (Depken, 2000; DeBrock et al., 2004; Wiseman & Chatterjee, 2003; Scully, 1974; Sommers & Quinton, 1982), soccer teams (Garcia-del-Barrio & Pujol, 2007; Lucifora & Simmons, 2003), and hockey teams (Idson & Kahane, 2000; Jones & Walsh, 1988) normally treat team performance as the dependent variable, and then search for relevant factors that shape it. Recently, Horowitz (2007) provided a detailed literature review looking into various measures of performance in sport. This paper is one of the few research studies focused on the direction of the linkage between salary structures and team performance.[1] The direction of the linkage (e.g., the causality between salary structures and team performance) is unclear and has rarely been rigorously investigated in the literature. Hall et al. (2002) stressed that such a link "plays a central role in the theory of team sports but is seldom investigated empirically" (p. 149). Therefore, we focus on two important concepts of salary structures, the total payroll and the dispersion of salary, to investigate the causality between them and team performance.

Total payroll and the dispersion of salary are important for understanding both the relationship and the causal link between salary structures and team performance in labor market theory. Since total payroll for a sports team is more likely to be affected by its talented players, a causality test between total payroll and team performance will enable us to understand whether expenditure on playing talent, as measured by the team's total payroll, will translate effectively into performance (or success). In other words, the question we want to answer is not whether a team with the highest total payroll, or an owner with very deep pockets, as in the case of the New York Yankees in baseball or Manchester United in soccer, is more likely to win a championship, but whether a causal link between them exists or not.

While the possible relationships between salary dispersion and organizational performance asserted by Tournament Theory (Lazear & Rosen, 1981) and the Fair Wage-Effort Hypothesis (Akerlof & Yellen, 1990) have been investigated for decades, almost none of the studies in the literature have focused on the issue of the direction of causality between salary dispersion and organizational performance. The causal link between salary dispersion and performance can help us to understand why a team with high performance also has a high degree of internal salary dispersion. One explanation would be that the team performs well because salary dispersion creates incentives. Another explanation is that the team performs well and shares rents with its workforce in such a way that it increases salary dispersion. Therefore, we want to answer the question by directly testing the direction of causality, rather than via investigating the relationship (coefficient) between them.

The arrangement of the remaining sections of this paper is as follows. First, we provide a short overview of the relevant literature, followed by the Data Description and Empirical Model section, which first describes the data of the Chinese Professional Baseball League (CPBL) and then presents the empirical model that we used to deal with the problem of heterogeneity when using panel data to perform a Granger Causality Test. The section that follows presents the empirical results and also provides a related discussion on professional baseball in Taiwan. Finally, we summarize our main findings and conclusions.

Literature Review

Salary disparities and organizational performance have long been an important topic of economic research. The two strands in this literature generate opposing predictions. One strand focuses on incentives and establishes a positive link between salary dispersion and firm performance. Employees will work harder if there is more money to be earned. Tournament Theory, as put forward by Lazear and Rosen (1981), is one example in this strand. The second strand focuses on equity and fairness (e.g., the Fair Wage-effort Hypothesis of Akerlof and Yellen [1990]). In this, an increase in salary dispersion within an organization may cause a breakdown of team cohesiveness and performance. As formulated by Levine (1991), the Pay Equality Hypothesis predicts that greater salary dispersion motivates jealousy and mistrust among players on teams and reduces team performance.

A few studies find a loose association between team payroll and performance in North American sports (Fort, 2003; Quirk & Fort, 1999; Sanderson & Siegfried, 1997; Scully, 1995; Zimbalist, 1992). Quirk and Fort (1999) examined correlations between team payroll and winning percentages using season averages for the four major North American sports leagues over the period 1990-96. They found that the rank correlations between payrolls and the team's winning percentages were significant in the National Hockey League and the National Basketball Association, but not in the National Football League or Major League Baseball (MLB). Also, the correlation between team pay and performance are significant in English soccer leagues (Szymanski & Kuypers, 1999), and a strong team salary-performance relationship is found for the leagues in England and Italy (Forrest & Simmons, 2002). Moreover, Zimbalist (1992) found that variation in average team salary explained less than 10% of the variation winning percentage in MLB between 1984 and 1989. He argued that this rather weak correlation between average team salary and team performance may be due to the fact that the team's owners fail to sign top-performing free agents, and that the team also fails to pay players in accordance with their performance. Scully (1995) argued that increased expenditures on players and coaching and managerial talent is a necessary, but not a sufficient, condition for improving a team's success.

Team performance should be driven by team payrolls in a competitive labor market, in which salaries reflect marginal revenue product and any gaps are removed by trading players for cash. European football, where freedom of player movement is relatively unrestricted, is one example of this (Hall et al., 2002).[2] The institutional barriers that govern the limitation of a team's expenditure on salary, right to trade players, draft rules, revenue sharing and so on, have made it more likely that teams cannot use their financial advantage to buy success.

Policies aimed at improving balanced competition in a league can affect the causal link between payroll and team performance. The customary argument for competitive balance is couched in terms of league-welfare optimality, and the quality of the games is determined by the uncertainty of the outcomes of games between members of the league (Vrooman, 2000). Therefore, the objectives of the teams in the league are interdependent, because each game generates a zero-sum performance metric. Under such circumstances, the over accumulation of talent, as captured by team payroll, may actually lead to significantly negative externalities and dominance by large-market teams. This is the so-called Yankee Paradox. Ultimately, it can result in no games, no gate receipts, and no Yankees. Rosen and Sanderson (2001) argued that the issue of players' compensation reflected the distribution of talent, as well as competitive balance, across teams, so variation in payroll dictates different levels of competitive balance in a league. As in the case of the New York Yankees in baseball or Manchester United in soccer, these teams bring to the forefront the issue of whether teams with the highest payroll or owners with the deepest pockets win championships.

Recent developments in econometric methodology extended the application of Granger (1969) time-series causality tests to panel data. The panel Granger Causality Test has been used in several settings in recent reserch. For example, Hurlin and Venet (2008) analyzed the causal link between financial development and economic growth. Their results provide support for a robust causal link from economic growth to financial development. Erdil and Yetkiner (2008) provided evidence on income-health causality by employing a large micro panel data set with a VAR representation. They found that one-way causality generally runs from income to health in low- and middle-income countries, whereas the reverse holds for high-income countries. Hoffmann et al. (2005) and Bhaduri and Durai (2006) applied panel Granger Causality Tests to the analysis of the relationship between FDI and pollution and dividends and investment decisions. In this paper, panel Granger Causality Tests are employed for two reasons. First, using the panel data can more broadly illuminate possible causality across teams within a professional sport, strengthening the implications. Second, the robustness of the possible causality between salary payment and performance can be examined more rigorously, and the estimates of the direction of causality can serve as a valuable reference in the literature on the sports industry.

Based on this literature review, there exists some evidence of a causal link between total payroll and team performance in professional sports, but the existing evidence above is less than satisfactory for two reasons. First, it remains to be seen whether this causal relationship holds under different payroll specifications, like total payroll vs. the dispersion of salaries within a team. Second, it remains to be seen whether the causal relationship will be detected in panel data, which contains more information across teams and time horizons. We analyze panel data from professional baseball teams and players in Taiwan to address these issues.

Data Description and Empirical Model

The difficulty obtaining data on salaries, payrolls, and performance complicates the analysis of economic relationships in labor research. Thanks to easy availability of data, professional sports represents unique laboratory for testing labor market theories and predictions. Professional baseball began in Taiwan in 1990, and the Chinese Professional Baseball League (CPBL) offers a rich source of data for the study of salary structures of baseball teams. We collected an unbalanced panel of salary data from seven CBPL teams, including 267 players, over the 10-year period from 1990 to 1999.[3]

An expanded Granger (1969) causality, based on the balanced panel data model with fixed coefficients proposed by Hurlin and Venet (2001), was employed to examine the causal link between payroll and performance. The advantage of using panel data is that we can fully utilize cross-sectional and time-series variation in the data, improving the efficiency of the Granger Causality Tests. Cross-sectional heterogeneity exists in any context; in order to correct for heterogeneity across teams in this setting, a panel data model with fixed coefficients is estimated as part of the model that is used to determine whether or not causality between a team's performance and its salary structure exists.[4]

Following the usual approach in panel Granger Causality Tests, we suppose that, for each team i ∈ [1, *N*] and time period t ∈ [1, *T*], the specification of the auto-regressive model is represented as follows:

$$y_{i,t} = \gamma y_{i,t-1} + \beta_1 x_{1i,t-1} + \beta_2 x_{2i,t-1} + v_{i,t}; \quad (1)$$

$$y_{i,t} = \gamma y_{i,t-1} + \beta_1 x_{1i,t-1} + \beta_2 x_{2i,t-1} + v_{i,t}; \quad (2)$$

with $\nu_{i,t} = \psi_i + \varepsilon_{i,t}$ and $\pi_{ji,t} = \varphi_{ji} + \xi_{ji,t}$, where individual effects of ψ_i and φ_{ji} (j=1, 2) are assumed to be fixed within each team. $\varepsilon_{i,t}$ and $\xi_{ji,t}$ (j=1, 2) are error terms, and they are assumed to be distributed i.i.d. (0, σ_ε^2) and i.i.d. (0, σ_ξ^2), respectively. y is team performance, as measured by the percentage of wins (WinP) and the total number of wins (WinN) in each year. $X_{1i,t}$ and $X_{2i,t}$ are different specifications of salary structure, namely, total payroll and the dispersion of salaries within a team, respectively. Total payroll (Totsal) is defined as the team's total monthly expenditures on players. The salary dispersion on a team is measured by a discrete Gini-coefficient formula (see Kendall & Stuart, 1969).[5] Judson and Owen (1999) provide Monte Carlo evidence to show that the biased fixed effects estimator developed by Kiviet (1995) generally outperforms other estimators for balanced panels, even when T is small. For this reason, the estimation of equations (1) and (2) above will rely on the fixed effects estimator (cf. Kiviet, 1995; Bruno, 2005).

In terms of the direction of causality from salary structure to team performance, there are four possible hypotheses in two major categories, as shown in Table 1.

Table 1: Hypotheses for Granger Causality Tests

	Salary structure → Team performance	Team performance → Salary structure
Gini	H_{11}: $\beta_1 = 0$	H_{30}: $\eta_1 = 0$
	H_{11}: $\beta_1 \neq 0$	H_{31}: $\eta_1 \neq 0$
Totsal	H_{20}: $\beta_1 = 0$	H_{40}: $\eta_2 = 0$
	H_{21}: $\beta_1 \neq 0$	H_{41}: $\eta_2 \neq 0$

In the first category, we test the salary dispersion effect (i.e., whether the slopes of the Gini coefficients (β_1) are statistically significant when total payroll is included in the model). If the null hypothesis H_{10} is rejected, there is evidence of Granger causality from salary dispersion to team performance. Such a causal relationship exists in at least one team in the panel. In the second category, we test the Granger-causality from total payroll to team performance controlling for variation in salary dispersion. If the null hypothesis H_{20} is rejected, there is evidence of Granger causality from total payroll to team performance. The possibility of reverse causality from team performance to salary structure is examined in null hypotheses H_{30} and H_{40}, where salary dispersion and total payroll are not included in equation (2). Here, Granger causality from team performance to salary dispersion (or total salary) exists if the respective null hypotheses are rejected. The test statistic for the panel Granger Causality Tests are computed by means of the following equation:

$$F = \frac{(RSS_2 - RSS_1) / N}{RSS_1 \, [TN - 2N - 1]}, \qquad (3)$$

where RSS_2 denotes the restricted sum of squared residuals obtained under the null hypothesis, RSS_1 is the unrestricted residual sum of squares of the model, and TN is the total number of observations. The statistic has a Fischer distribution with N and TN-2N-1 degrees of freedom, instead of the standard F distribution, under the null hypothesis.

We check the robustness of our results by constructing different specifications of the basic models described above. First of all, current period observations of all variables are incorporated in order to capture any instantaneous causality between team performance and salary structure. Second, we use the relative total salary ratio, denoted RTotsal and measured by the percent of total team payroll to league total salary, rather than the team total payroll, Totsal, to further investigate the causality between salary structure and team performance.

Summary statistics for the variables used in this study are shown in Table 2.

Table 2: Basic Statistics

Variable	Mean	S. D.	Observation
WinP	0.515	0.085	40
WinN	46.575	8.424	40
Gini	0.202	0.069	40
Totsal (NT$)*	2,460,919	919,547.3	40

* The average exchange rate during our data period (1990-1999) was roughly 1US$=28.066NT$.

Empirical Results and Discussion

Prior to conducting the Granger Causality Tests, we tested for stationarity in the variables included in the dynamic panel data model. Fort and Lee (2006) provided a general process for investigation of nonstationary behavior of sports data. Based on the Fort and Lee (2006) process, the panel unit root test proposed by Im et al. (2003) was applied to the variables in our paned data set. Based on this approach, there is evidence of stationarity when the value of the test statistic exceeds a critical value at a specific level.

The results of the stationarity tests on the variables of interest are presented in Table 3. In terms of the team performance variables, WinP and WinN, the model specification includes a constant term and a time trend together with a number of lags of the dependent variable; 1, 1.5 and 2 lags are tested separately.[6] Table 3 shows that the values of the test statistics for WinP and WinN are statistically significant; these variables appear to be stationary. Using the same method, the variables Gini and Totsal also appear to be stationary.[7] Therefore, all these variables can be included in the model estimated for the Granger Causality Tests.

The basic results of the panel Granger Causality Tests between salary structure and team performance are reported in Model 1 of Table 4.[8] In terms of the tests of causality from salary dispersion to team performance, both of the F statistic values suggest

Table 3: Panel Unit Root (IPS) Tests with Heterogeneous Individuals

Variable	lags	t-bar	p-value
Gini	1	-2.221	0.095*
	1.5	-2.422	0.039**
	2	-1.407	0.442
Totsal	1	-2.040	0.162
	1.5	-7.581	0.000***
	2	-0.887	0.766
WinN	1	-1.852	0.703
	1.5	-2.972	0.067*
	2	-2.751	0.095*
WinP	1	-1.575	0.839
	1.5	-4.399	0.000***
	2	-4.189	0.000***

Notes: (a) Im et al.'s (2003) t-abr statistics for the panel unit root. *** denotes significance at the 1% level, ** denotes significance at the 5% level and * denotes significance at the 10% level.
(b) Under the original model with a constant and a trend term, the test statistic for Gini and Totsal was insignificant at the 10% level, so we tried the other specification to test the model without the trend term.
(c) Based on the mean of the individual Dickey-Fuller t-statistics of each unit in the panel, the IPS test assumes that all series are non-stationary under the null hypothesis.

rejection of H_{10} at the 1% significance level when controlling for variation in total team payroll. The rejection of the null hypothesis suggests that, for at least one team in the CPBL panel, past values of salary dispersion are relevant when it comes to forecasting current team performance. In terms of the tests of causality from total payroll to team performance, null hypothesis cannot be rejected—there is no evidence of a causal relationship when variation in salary dispersion is controlled for. In addition, when the reverse tests of causality, from team performance to salary structure, are conducted, as shown in Model 1, the corresponding F test values are low, indicating that the null cannot be rejected.

In terms of the robustness checks, Model 2 in the second column of Table 4 reports the results of regressions that include current period observations of variables to account for any instantaneous relationships in the data. Model 3 on Table 5 reports the results of regressions containing the alternative payroll variable, relative total payroll (RTotsal) instead of total payroll.[9] The presence of heteroscedasticity may also be important in this setting, as the variance of the equation error term may differ across teams. We control for heteroscedasticity in these data using White's (1980) correction. Table 6 reports the results of the causality tests correcting for the presence of heteroscedasticity, and the causality test statistics, which differ from those reported on Tables 4 and 5. The test statistics are adjusted using the corrected standard errors, if the null hypothesis of homoscedasticity can be rejected in that model specification. In

Table 4: Granger Causality Tests

Direction of Granger Causality			Model 1 F value	Model 2 F value
Gini	→	WinN	19.96***	7.33***
Totsal	→	WinN	3.04	1.36
WinN	→	Gini	0.00	1.73
WinN	→	Totsal	0.75	0.18
Gini	→	WinP	17.99***	7.50***
Totsal	→	WinP	4.30	1.40
WinP	→	Gini	0.81	2.27
WinP	→	Totsal	0.12	0.56

Notes: (a) *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level. The critical values simulated by Huilin and Venet (2001) are 4.315 and 6.937 for the 5% and 1% significance levels, respectively.
(b) The year dummies are included in the empirical model.
(c) The optimal lag-length for each equation is determined by the Akaike Information Criterion (AIC), and the results are listed in Table C in the Appendix.

general, the evidence about causality generated from the previous models still holds, and it tends to reinforce the conclusion that salary dispersion Granger causes team performance. In general, values of the test statistics on Table 6 are smaller than those reported on Tables 4 and 5.

Based on the results of the causality tests presented on Table 4 and Table 5, the direction of the causality from salary dispersion (Gini) to team performance (WinP and WinN) is confirmed. The results of these tests are in line with Tournament Theory or Equity Theory, which stresses that salary dispersion improves team performance. In addition, our empirical results also confirm that total payroll (Totsal) and relative total payroll (RTotsal) do not Granger cause team performance (WinP and WinN). Even though the literature stresses the importance of the stock of human capital in an organization, the lack of a causal link from salary structure to team performance may be induced by league policies aimed at promoting competitive balance like the reverse clause.

In addition to the evidence that salary dispersion Granger causes performance, the estimated coefficients in the salary dispersion variable in the regressions are negative and statistically significant.[10] Increasing salary dispersion is associated with decreased team performance. Compared to the lack of support for wage fairness in the existing research using MLB data (DeBrock et al., 2004), our results indicate that teams with less salary dispersion perform better; evidence from the CPBL supports Equity Theory. The results indicate an interesting phenomenon: for a given the total payroll, a team with larger salary dispersion (e.g., a team with both star players and lower-talent players) has lower performance than a team with less dispersion (e.g., for one with a large number of average, but not star players) based on data from the CPBL.

DeBrock et al. (2004) also found that high-wage strategies are associated with better won-loss percentage and higher attendance in MLB. Based on our results, the former

Table 5: Granger Causality Tests

Direction of Granger Causality			Model 3 F value
Gini	→	WinN	8.31***
RTotsal	→	WinN	2.68
WinN	→	Gini	0.00
WinN	→	RTotsal	0.30
Gini	→	WinP	9.64***
RTotsal	→	WinP	2.92
WinP	→	Gini	0.81
WinP	→	RTotsal	0.41

Notes: (a) *** denotes significance at the 1% level. The critical value is 6.937 for the 1% significance level.
(b) The year dummies are included in the empirical model.

Table 6: Granger Causality Tests Correcting for Heteroscedasticity

Direction of Granger Causality			Model (1)	Model (2)	Model (3)
Gini	→	WinN	19.96***	7.33***	8.31***
Totsal/ RTotsal	→	WinN	3.04	1.36	2.68
WinN	→	Gini	**0.29**	1.73	**0.29**
WinN	→	Totsal/ RTotsal	**0.59**	**0.28**	0.30
Gini	→	WinP	17.99***	7.50***	9.64***
Totsal/ RTotsal	→	WinP	4.30	1.40	2.92
WinP	→	Gini	**0.05**	2.27	**0.05**
WinP	→	Totsal/ RTotsal	**0.53**	**2.51**	0.41

Notes: (a) The bold numbers are the value corrected for heteroscedasticity.
(b) *** denotes significance at the 1% level.
(c) The year dummies are included in the empirical model.

relation between wage strategies and performance does not hold in the CPBL. The lack of Granger causality from total salary to performance suggests that the effects of total payroll are limited in the CPBL. Specifically, the reasons for the lack of a causal link may be mainly attributed to the immobility of players and a tacit agreement among team managers not to engage in trades.[11] In contrast to the EPL's "freedom of contract" for football players since 1978, the CPBL is less developed in the sense that there are no clear rules regarding the trading of players. In the CPBL, players are usually regarded as constituting part of the assets of a team. In addition, tacit collusion between team managers makes it impossible for the players to switch to other teams. Poaching good players from other teams by offering higher salaries is not feasible. If CPBL teams can spend money on good players outside the league, they may have a chance to "buy wins." But since the average salary in the data is $51,400 per year, this is not an attractive option for a good player on the international market. Therefore, turning higher salary expenditure into success is almost impossible in the CPBL under existing conditions.

The evidence of Granger causation from salary dispersion to team performance in the CPBL can be attributed to the flexibility of salary adjustment in the league, and the relative immobility of the players. Regular salary adjustment in the CPBL, unlike the relatively long-term contracts (3 to 5 years) in other professional sports leagues in the world, is quite common. The players in the CPBL are paid according to a short-term contract, which is more like an agreement.[12] Restrictions on player mobility in the CPBL are offset by very flexible salary adjustment. When players' mobility within a league is totally restricted and the internal salary dispersion is easily adjusted every year, the redistribution of internal salary causes team performance to improve. The flexibility of salary and the immobility of players may contribute to the one-way causality from salary dispersion to performance found here.

Conclusions

In this paper we provide a more comprehensive approach to investigating the relationship between salary structure and team performance by taking the dispersion of salaries as well as total payroll of professional baseball teams in Taiwan into consideration when examining the possibility that a causal link between salary structure and team performance exists. We conducted the panel Granger Causality Test to explore the possible causal links between salary structure and team performance using panel data from the CPBL. Our results indicate that Granger causality runs only from the dispersion of salaries to team performance, but not vice versa. These results are robust to a number of alternative model specifications, including heteroscedasticity correction. Surprisingly, the evidence that salary dispersion granger causes team performance is stronger when controlling for variation in total payroll.

Our results give rise to two conclusions. First, our empirical results confirm that both Tournament Theory, which stresses the incentives of salary dispersion, and Equity Theory, which posits that salary equity induces improved performance, affect the performance of professional baseball teams in Taiwan. In terms of the effects of salary dispersion, our results support Equity Theory, and imply that a team with many average players performs better than a team with a mix of super-star and less-talented players. Evidence of causality between total/relative payroll and team performance, which emphasizes the importance of the overall stock of human capital within an organization, was not found. Therefore, the over-accumulation of talent, reflected by large team payrolls, may actually lead to negative externalities. The existence of a "Yankee Paradox" is supported by the evidence.

Second, the one-way causality patterns in the data suggest that teams playing in a league with strict restrictions on the mobility of players must rely more on internal salary adjustments, especially on the dispersion of salaries, motivate players, and compensate for the fact that players are not able to move among teams.

Finally, since the wage structure of a professional sports team resembles that of a business enterprise, relevant theories of the effect of wages on performance can be explored in order to understand more about the wage structure and its influence on performance. In this paper we have shown that both Tournament Theory and Equity Theory are relevant for explaining the performance of professional sports teams.

Therefore, these results can provide important context when examining the relationship between compensation structure and team performance.

References

Akerlof, G. A., & Yellen, J. L. (1990). The fair wage-effort hypothesis and unemployment. *Quarterly Journal of Economics*, *105*(2), 255-83.

Allison, P. D. (1978). Measures of inequality. *American Sociological Review*, *43*, 865-880.

Bhaduri, S. N., & Durai, S. R. S. (2006). Empirical relationship between the dividend and investment decision: Do emerging market rirms behave differently? *Applied Financial Economics Letters*, *2*, 155-58.

Bruno, G. S. F. (2005), Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models. *Economic Letters*, *87*, 361-366.

DeBrock, L., Hendricks, W., & Koenker, R. (2004). Pay and performance: The impact of salary distribution on firm-level outcomes in baseball. *Journal of Sports Economics*, *5*(3), 243-261.

Davis, M. C. (2008). The interaction between baseball attendance and winning percentage: A VAR analysis. *International Journal of Sport Finance*, *3*(1), 58-73.

Depken, C. A. (2000). Wage disparity and team productivity: Evidence from Major League Baseball. *Economics Letters*, *67*, 87-92.

Erdil, E., & Yetkiner, I. H. (in press). A panel data approach for income-health causality. *Applied Economics*.

Forrest, D., & Simmons, R. (2002). Team salaries and playing success in sports: A comparative perspective. *Zeitschrift fu¨r Betriebswirtschaft*, *62*, 221-237.

Fort, R. D. (2003). *Sports economics*. Upper Saddle River, NJ: Prentice Hall Press.

Fort, R. D., & Lee, Y. H. (2006). Stationarity and Major League Baseball attendance analysis. *Journal of Sports Economics*, *7*(4), 408-415.

Garcia-Del-Barrio, P., & Pujol, F. (2007). Hidden monopsony rents in winner-take-all markets: Sport and economic contribution of Spanish soccer players. *Managerial and Decision Economics*, *28*, 57-70.

Granger, C. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424-438.

Hall, S., Szymanski, S., & Zimbalist, A. (2002). Testing causality between team performance and payroll: The cases of Major League Baseball and English soccer. *Journal of Sports Economics*, *3*(2), 149-168.

Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Journal*, *32*, 199-228.

Hoffmann, R. L., Ramasamy, C. G., & Yeung. M. (2005). FDI and pollution: A granger causality test using panel data. *Journal of International Development*, *17*(3), 311-323.

Horowitz, I. (2007). If you play well they will come — and vice versa: Bidirectional causality in Major League Baseball. *Managerial and Decision Economics*, *28*, 93-105.

Hurlin, C., & Venet, B. (2001). *Granger causality tests in panel data models with fixed coefficients*. Retrieved November 30, 2008, from http://www.dauphine.fr/eurisco/eur_wp/causal fixed.pdf

Hurlin, C., & Venet. B. (2008). Financial development and growth: A re-examination using a panel granger causality test. Retrieved November 30, 2008, from http://halshs.archives-ouvertes.fr/docs/00/31/99/95/PDF/Baptiste_V7.pdf

Idson, T. L., & Kahane, L. H. (2000). Team effects on compensation: An application to salary determination in the National Hockey League. *Economic Inquiry*, *38*(2), 345-357.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53–74.

Jones, J. C. H., & Walsh, W. D. (1988). Salary determination in the National Hockey League: The effects of skills, franchise characteristics, and discrimination. *Industrial and Labor Relations Review*, *41*(4), 592-604.

Judson, R. A. & Owen, A. L. (1999). Estimating dynamic panel data models: A guide for macroeconomists. *Economics Letters*, *65*, 9-15.

Justesen M. K. (2008). The effect of economic freedom on growth revisited: New evidence on causality from a panel of countries 1970-1999. *European Journal of Political Economy*, *24*, 642-660.

Kendall, M. G., & Stuart, A. (1969). *The Advanced Theory of Statistics*, Vol. I (3rd ed.). New York: Haffner.

Kiviet, J. F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel models. *Journal of Econometrics*, *68*, 53-78.

Lazear, E. P., & Rosen, S. (1981). Rank-order tournaments as optimum labor contracts. *Journal of Political Economy*, *89*(5), 841-864.

Levine, D. (1991). Cohesiveness, productivity and wage dispersion. *Journal of Economic Behavior and Organization*, *15*, 237-255.

Lucifora, C., & Simmons, R. (2003). Superstar effects in sport: Evidence from Italian soccer. *Journal of Sports Economics*, *4*, 35-55.

Quirk, J., & Fort, R. (1999). *Hard ball: The abuse of power in pro team sports*. Princeton, NJ: Princeton University Press.

Rosen, S., & Sanderson, A. (2001). Labour markets in professional sports. *The Economic Journal*, *111*, F47-F68.

Sanderson, A., & Siegfried, J. (1997). The implications of athlete freedom to contract: Lessons from North America. *Economic Affairs*, *17*, 7-12.

Scully G. (1974). Pay and performance in Major League Baseball. *American Economic Review*, *64*, 915-930.

Scully G. (1995). *The market structure of sports*. Chicago, IL: University of Chicago Press.

Sommers, P. M., & Quinton, N. (1982). Pay and performance in Major League Baseball: The case of the first family of free agents. *The Journal of Human Resources*, *17*(3), 426-436.

Szymanski, S., & Kuypers, T. (1999). *Winners and losers: The business strategy of football*. London, UK: Viking Press.

Vrooman, J. (2000). The economics of American sports leagues. *Scottish Journal of Political Economy*, *47*(4), 364-398.

Wiseman, F., & Chatterjee, S. (2003). Team payroll and team performance in Major League Baseball: 1985-2002. *Economics Bulletin*, *1*(2), 1-10

Zimbalist, A. (1992). *Baseball and billions*. New York, NY: Basic Books.

Endnotes

[1] Horowitz shows that bi-directional causality between annual attendance and team performance on the field exists for teams in Major League Baseball (MLB). Davis (2008) reports similar results.

[2] The Professional Footballers' Association succeeded in establishing freedom of contract in 1977, and players are now almost completely free to accept the best contract on offer. Players can sign contracts and move without impediment at the end of their contracts. Within the contract period, cash sales are permitted through the transfer system under which a club losing a player may demand compensation from the receiving club in the form of a cash payment (i.e., a transfer fee). Therefore, European football also has a much greater provision for the mobility of players.

[3] Due to data limitations imposed by the panel causality tests, the data were restricted to a balanced panel. The N and T dimensions of the panel are determined by the availability of salary and team performance data. Some teams exited and some entered the CPBL in this period. The most complete data were obtained from four teams from 1990 to 1999. The data was obtained

from the "Professional Baseball Journal" and the official website of the CPBL (http://www.cpbl.com.tw/).

[4] Different from the traditional literature on Granger Casualty Tests in time series, the panel Granger Causality Test model proposed by Hurlin and Venet (2001) mentions two methods for dealing with heterogeneity among cross-sectional units: distinctive intercepts and variable slopes. The former one is simple and intuitive.

[5] The Herfindahl index is not used as the measure of salary dispersion because the potential range of the index is affected by the team's roster size. Several measures of inequality are compared by Allison (1978), who finds that both the Gini index and the coefficient of variation are superior in many respects. Harrison and Klein (2007) also recommend the same two measures to capture the effects of pay disparity.

[6] Because this test for panel unit roots allows a different number of lag lengths for each equation, a lag-order of 1.5 refers to the average of the lag lengths included in this test.

[7] We used the same model associated with team performance, but the statistics were insignificant at the 10% level. Regarding the different features in the time series between team performance and salary structure, we tried the model without a time trend. The results show that Gini and Totsal are stationary at the 5% level under appropriately controlled lag structures.

[8] We used the Akaike Information Criterion (AIC) to determine the optimal-lag length. In order to avoid the loss of degrees of freedom, we followed Justesen (2008) and included lag-lengths up to two for yit, x1it and x2it in the estimated equation. The results are shown in Table C in the Appendix.

[9] In addition, Table A in the Appendix reports the results of models that contain control variables for players' tenure and experience. Model 4 and Model 5 include control variables for players' average tenure and average team experience, respectively. The results show that our conclusions are still robust after controlling both tenure and experience.

[10] The results of the coefficients of salary dispersion from the VAR model are listed in Table B in the Appendix.

[11] Unless the player is released by the original team manager, he cannot become a free-agency player. Therefore, it seems that player's contract is permanent in the CPBL. The trading of players between teams is oriented by the employers. The rule of free agency was not legislated until 2007. The new rule states that a player who has a nine-year tenure is eligible to be a free-agency player, and the starting point for tenure was 2003. That is, the first free-agency players will emerge in 2012.

[12] Different from salary arbitration in other pro sports, the manager adjusts the players' salaries every year after the end of the season and the players have the right to bargain before the start of the next season. Moreover, some teams also have a mechanism for adjusting salaries in the middle of the season.

Authors' Note

The authors thank Professor Ngo Van Long for his valuable comments. We also thank two anonymous referees for valuable suggestions. All remaining errors are, of course, the responsibility of the authors.

Appendix

Table A: Granger Causality Tests with Additional Control Variables

Direction of Granger Causality			Model (4) F value	Model (5) F value
Gini	→	WinN	7.76***	8.22***
RTotsal	→	WinN	2.08	1.93
WinN	→	Gini	0.80	0.66
WinN	→	RTotsal	0.05	0.22
Gini	→	WinP	9.06***	7.46***
RTotsal	→	WinP	2.34	1.79
WinP	→	Gini	1.11	0.91
WinP	→	RTotsal	0.00	0.09

Notes: (a) *** denotes significance at the 1% level. The critical value simulated by Huilin and Venet (2001) is 6.937 for the 1% significance levels.
(b) The year dummies are included in the empirical model.
(c) The optimal lag-lengths for each equation is determined by the Akaike Information Criterion (AIC).(c) The year dummies are included in the empirical model.

Table B: Results of the Coefficients of Salary Dispersion from the VAR Model

	Gini→WinN	Gin→WinP
Model 1 (t-1)	-179.7891*** (62.73)	-1.9926*** (0.63)
Model 2 (t and t-1)	-115.3049*** (63.94)	-1.3557*** (0.67)
Model 3 (Rtosal)	-172.9032*** (59.98)	-1.9064*** (0.61)
Model 4 (Control variable: players' average tenure)	-177.0839*** (63.55)	-1.9557*** (0.65)
Model 5 (Control variable: players' average age)	-179.7891*** (62.73)	-1.7007*** (0.62)

Notes: (a) *** denotes significance at the 1% level.
(b) Parentheses are the standard errors.

Table C: Determination of Optimal Lags by Akaike Information Criterion (AIC)

Direction of Granger Causality			Causality	lags
Gini	→	WinN	46.1629*	47.2492
Totsal	→	WinN		
WinN	→	Gini	-47.7814*	-46.9648
WinN	→	Totsal	215.2495*	215.3734
Gini	→	WinP	-25.6110*	-25.0827
Totsal	→	WinP		
WinP	→	Gini	-47.6065*	-46.6283
WinP	→	Totsal	215.3824*	215.6101

Note: * indicates the optimal lag.

Table D: Tests of Heteroscedasticity

Direction of Granger Causality			Model (1)	Model (2)	Model (3)
Gini	→	WinN	3.333	4.576	3.603
Totsal/ RTotsal	→	WinN			
WinN	→	Gini	5.976*	0.090	5.976*
WinN	→	Totsal/ RTotsal	7.027*	6.962*	3.740
Gini	→	WinP	2.696	2.380	3.132
Totsal/ RTotsal	→	WinP			
WinP	→	Gini	5.864*	0.140	5.864*
WinP	→	Totsal/ RTotsal	7.816*	6.624*	3.640

Notes: * denotes significance at the 10% level.

International Journal of Sport Finance, 2009, **4**, 151-152, © 2009 West Virginia University

Book Review

The Economics of Intercollegiate Sports

By Randy R. Grant, John Leadley, and Zenon Zygmont
World Scientific Press (2008), 535 pp.

Reviewed by Marvin Washington
Faculty of Physical Education and Recreation and Faculty of Business,
University of Alberta

The National Collegiate Athletic Association (NCAA) is the most dominant institution organizing collegiate and amateur athletics in the United States and potentially the world. The NCAA, founded in 1906, is composed of more than 1,000 schools, organizes competition for 40 sports, and coordinates the athletic competitions of more than 90 championships. As the commercial shown during the men's Division I postseason basketball tournament (March Madness) states, the NCAA organizes competitions for more than 300,000 student athletes, most of which will be going pro in something other than sports.

While this institution is important and central to the study of sport, the authors of this book are correct in their assertion that there are no existing textbooks that could be used for a course focused on understanding the NCAA. The authors' goal, in addition to satisfying their "own desire for a textbook covering the economics of intercollegiate sports" was to write a book that would provide professors and students with "new information and insights" about the economics of intercollegiate sports. The desired audience for the textbook is a stand-alone course in the economics of intercollegiate sports, or as a text representing the collegiate portion of a "broader sports economics class." It is with this goal in mind, that I review this textbook.

First the good: the book is extremely comprehensive with more than 530 pages of material divided among nine chapters. The first chapter, on the history of the NCAA, covers a lot of ground—starting with the crises in football that led to the creation of the NCAA and going all the way up to the creation of the BCS. The second, third, and fifth chapters introduce the economic concepts developed in the book: viewing college athletics as a cartel, and discussing college athletes and college coaches as a labor market. The remaining chapters cover the relationship between athletics and academics, the relationship between the athletic department and the university, media and interuniversity sport, and race and gender in intercollegiate sport. They conclude the book with a chapter on how to reform college sports.

There is clearly enough material, in terms of breadth and depth, to use the book as a stand-alone textbook for an undergraduate seminar in sport economics. The book offers a lot of data, tables, and figures to help the authors make their points. The end-of-chapter assignments, review questions, and internet study questions (where the students are directed to go to the internet and search on various terms of interest) provide sufficient support to an instructor who might use this textbook as the only textbook for a class. I also found the economic theory concepts easy to understand and examples appropriately placed throughout the book. It would have been helpful to explain the economic concepts more fully before they were used in some examples, but this probably would not be an issue for an economics student, as economics students would probably be taking this class after they had taken a principles of economics course. However, sport management students might be confused by the limited discussion of some of the economic concepts.

My major concern about this book is that it moves between a textbook and a journalistic book focusing on uncovering the "bad" side of the NCAA. When I think of textbooks on college sports, or the NCAA, the only one that comes to mind is Ronald Smith's book, *Sport and Freedom: Rise of big time college athletics*. That book offers a mostly historical, but also sociological, perspective on college athletics. Smith starts with the "problem" of how collegiate athletics became a dominant institution in the US. I contrast Smith's book with *Beer and Circus* by Murray Sperber. Sperber starts with the "problem" of what is wrong with college sports, then goes on to offer his opinions about the problems in college sports and provides some suggestions for addressing these problems. Smith leaves open the issues with college sports until after he lays out the story. This book is more like Sperber's than Smith's work. There are many "throwaway" sentences in the book that are clearly the author's opinions and not backed up by research. While this is OK for a journalistic book on the NCAA, of which there are dozens of titles that argue that the NCAA is a "bad" organization, this approach might be confusing for students who would be using this book as a textbook in a classroom setting.

To be used as a textbook, I think the authors should be more balanced in their assumptions about the NCAA. For example, when discussing the cartel model applied to the NCAA, the authors could also discuss alternatives to the cartel model that explain why the NCAA sponsors and organizes sports that do not produce any revenue and why the NCAA organizes activities for three divisions containing 90 championships?

There are numerous conceptual and theoretical debates about the NCAA. These many debates all present challenges for anyone writing a textbook about the NCAA. This opens up the question of whether there should actually be a textbook about the NCAA, or whether the multiple perspectives on the NCAA are too disparate and contested to be codified into textbook form. For example, while many people argue that the NCAA is a cartel, many others question this assumption. Similarly, for those who argue that athletes are taken advantage of on college campuses, others argue that if it was not for athletics, many people would never be on college campuses. These controversies, and many others, while specific to the study of the NCAA and college athletics, might also be reflective of debates between economists, historians, race scholars, and sociologists. If the goal is to highlight how different economic principles could be used to understand the NCAA, the authors have done a good job. However, if the goal is to use economic theory to convince their audience that the NCAA is a cartel, then I am unsure if a textbook is an appropriate vehicle for this endeavor.

References

Smith, R. (1988). *Sport and freedom: The rise of big time college athletics*. New York: Oxford

Sperber, M. (2000). *Beer and circus: How big time college sports has crippled undergraduate education*. New York: Henry Holt

Submission Guidelines for the International Journal of Sport Finance

General

The purpose of the *International Journal of Sport Finance* is to provide a forum for the dissemination of current research on sport finance topics on a worldwide basis. The objective is to advance knowledge of the topic area by publishing theoretical and empirical papers of the highest quality from a globally diversified and multidisciplinary perspective. Given the foundational contributions of accounting and economics to the domain of finance, research drawn from these basic disciplines pertinent to the sport industry is strongly encouraged. Appropriate topics include stadium economics, team and/or league valuation methods, capital financing techniques, economic impact analysis, public financing, and the financial implications of team operations related to salary control, profit maximization, and tax treatment. Special attention will be paid to papers that examine these topics from a comparative and cross-cultural perspective. The principal criteria by which manuscripts will be judged when deciding to publish are quality, originality, rigor, timeliness, and practical relevance.

Manuscripts are reviewed with the understanding that they have not been simultaneously submitted to any other publication, that they represent the original work of the author(s), and that they have not been published previously either in whole or in part.

How to Prepare the Manuscript

Manuscripts should be written in English and submitted *electronically* by visiting http://editorialexpress.com/ijsf and following the instructions.

Since manuscripts are evaluated anonymously, authors' names should not appear anywhere in the manuscript. The submitting author should also ensure that the authors' names do not appear under the Properties of the file they are sending. A separate cover sheet listing the manuscript title and the order of authors as well as the primary author's name, mailing address, preferred phone and fax numbers, and email address should accompany each manuscript. In addition, information regarding each author's rank, institution, and research interests should be listed. If appropriate, identify if the manuscript is derived from a master's thesis or doctoral dissertation.

A 150-word abstract should preface each manuscript followed by a list of keywords. Manuscripts should be double-spaced with 1.5-inch margins, using an easily readable 12-point font. Authors should follow the style of the *Publication Manual of the American Psychological Association* (5th edition) in preparing all text, tables, and figures (e.g., *italics* used to report statistical information, indented second line in references listing).

Manuscripts should not exceed *30 pages, including* text, tables, figures, charts, footnotes, and references. Major headings used in the text should be centered on the page and in all uppercase letters; subheadings should be flush with the left margin and typed in upper- and lowercase letters. Footnotes should not be used in the body of the paper. If used, please place endnotes in a numbered list after the body of the text and before the reference section.

Each table and figure should be prepared on a separate page and grouped together at the end of the manuscript, with each numbered in Arabic numerals and appropriately titled. Figures must be clean, crisp, black-and-white, camera-ready copies. *Adobe Illustrator*, *CorelDraw*, *Pagemaker*, and *QuarkXPress* are the preferred software for *IJSF* figures. The number of tables and figures should be limited to only those necessary to complement the text of the manuscript.

The order of the submitted manuscript is as follows:

- Title page
- Blind title page (without name(s) and addresses)
- Abstracts (150 words) with keywords
- Text (double spaced)
- Endnotes (if included)
- References
- Tables
- Figures
- Appendices

Manuscripts submitted to the *International Journal of Sport Finance* undergo double blind review. Reviewers' comments will be returned via email attachment as soon as practically possible. The goal is to complete the review process and provide authors with a decision regarding the status of their submission within three months of receiving the manuscript.

All inquiries about reviews related to refereed research manuscripts should be directed to:
Robert Simmons, Editor
r.simmons@lancaster.ac.uk

Books to be considered for review must be sent to:
Brad Humphreys, Book Review Editor,
8-14 HM Tory
University of Alberta
Edmonton AB
Canada T6G 2H4
brad.humphreys@ualberta.ca