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The Role of Managers in Team Performance

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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

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

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 dum-

mies 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).

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

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).

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

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.

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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.