International Journal of Sport Finance, 2007, **2**, 190-205, © 2007 West Virginia University

Does One Simply Need to Score to Score?

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Abstract

Professional sports are characterized by an abundance of information on worker productivity and severe consequences for failure. Consequently, one would expect information to be processed efficiently in this industry. Recent research indicates, though, that decision makers in professional sports do not behave consistently with the dictates of instrumental rationality. This study of decision making in the National Basketball Association (NBA) begins with a literature review that indicates players can score a major payday by simply focusing on scoring. Beyond this review, we offer an empirical investigation of both the voting for the All-Rookie team and the determination of player salary that clearly indicates that the ability to accumulate points dominates player evaluation in the NBA. Given that such a focus is not consistent with winning games or maximizing profits, we argue that decision-makers in the NBA do not behave according to the dictates of instrumental rationality.

Keywords: instrumental rationality, National Basketball Association, productivity

> "Players must not only have objectives, but know the correct way to achieve them. But how do the players know the correct way to achieve their objectives? The instrumental rationality answer is that, even though the actors may initially have diverse and erroneous models, the informational feedback process and arbitraging actors will correct initially incorrect models, punish deviant behavior, and lead surviving players to correct models." Douglass North (1994)

Introduction

The writing of Douglass North lays forth the role instrumental rationality plays in the workings of an efficient market. Given the requirements outlined above and the prevalence of imperfectly competitive industries, one may not expect many markets to be characterized as efficient. A potential exception is the professional sports industry. Unlike most industries, professional team sports have an abundance of information on individual workers and stark consequences for failure. Failure in sports is not only met with a loss of revenues and employment, but public derision via various media outlets. Given the severity of consequences and abundance of information, it is not surprising that economists expect

economic actors in professional team sports to follow the dictates of instrumental rationality.

Despite this expectation, there is some research that suggests that instrumental rationality does not always characterize decision-making in professional sports. In baseball we have the "Moneyball" story [see Lewis (2003) and Hakes & Sauer (2006)], or the argument that on-base-percentage was under-valued by decision-makers in Major League Baseball. Michael Lewis (2003) told this story primarily with anecdotal evidence in his best-selling book. Hakes and Sauer (2006) confirmed that the empirical evidence was at one point consistent with the *Moneyball* story. Historically, decision-makers in baseball did undervalue on-base-percentage.

Turning to the National Football League we see the work of Romer (2006). Romer investigated how often NFL head coaches choose to "go for it" on fourth down and found that coaches were far too conservative. Going for it more frequently would increase the probability that coaches would win games; hence, the actions of the head coaches actually ran counter to their stated objective.

Staying in the NFL we see the work of Massey and Thaler (2006). This work offered evidence of inefficiency in the amateur draft of the National Football League. Specifically, high draft choices were consistently over-valued, in a fashion the authors argue is inconsistent with the precepts of rational expectations.

With respect to professional basketball—the subject of this study—we have the work of of Staw and Hoang (1995) and Camerer and Weber (1999). Each of these authors examined the escalation of commitment in the NBA, defined by Camerer and Weber as follows:

> "when people or organizations who have committed resources to a project are inclined to 'throw good money after bad' and maintain or increase their commitment to a project, even when its marginal costs exceed marginal benefits." [Camerer and Weber: 59-60]

With respect to the NBA, Staw and Hoang (1995) and Camerer and Weber (1999) investigated the impact a player's draft position has on playing time. Both of these sets of authors offer evidence that, after controlling for the prior performance of the player, where a player was chosen in the draft still impacts the amount of playing time the player receives after the first two years of the player's career. Such a finding suggests that NBA decision-makers are slow to adopt new information, maintaining an assessment of a player when the available evidence suggests that the initial perspective is incorrect.

The purpose of this present inquiry is twofold. First we wish to re-examine several pieces of evidence previously presented in the literature. As we will demonstrate, much of this research suggests that decision-makers in the National Basketball Association (NBA)—as suggested by the study of escalation of commitment—do not process information efficiently. Our review will be followed by two empirical models. The first will update Berri and Schmidt (2002), which examined the coaches' voting for the All-Rookie team in the NBA. A second model will ascertain the relationship between player salary and various measures of player productivity. Each of these models—previously described in less detail in *The Wages of Wins* [Berri, Schmidt, and Brook (2006)][1]—will shed light upon the extent information is utilized efficiently in the evaluation of players in the NBA.

The Lessons Learned

Our story begins with a review of the lessons the current body of literature teaches about the economics of professional basketball. We begin this list of lessons with the story told by a number of published works examining racial discrimination in professional basketball.

Lesson One: Points scored dominates the evaluation of player productivity in the NBA.

The NBA tracks a plethora of measures designed to track the productivity of an individual player. Such data has attracted the attention of economists who desire to study the issue of racial discrimination. The standard approach, following Becker (1971), is to estimate the following model:

$$Y = \alpha_0 + \alpha_1{}^*X + \alpha_2{}^*R + e_i \qquad (1)$$

where Y = A decision variable such as salary, employment, or playing time.

X = Measures of worker productivity, other player characteristics, and market variables.

R = Dummy variable for a worker's race

e_i = an error term

If one finds that α_2 is statistically significant then the researcher concludes that evidence of discrimination has

been uncovered. All other factors that may influence the decision one examines, though, must be accounted for in X. If not, the interpretation of α_2 is difficult. In most industries, measuring worker productivity is problematic; hence, the specification of X undermines the robustness of the conclusions the researcher can make. In professional team sports, though, productivity is measured. Furthermore, racial issues are clearly a part of the fabric of sports history. Given the availability of data and the historical relevance of the story, researchers have produced a significant body of work designed to uncover the existence, persistence, or non-existence of racial discrimination.

Naturally, the stories told in this work focuses upon the estimation of α_2. Much can be learned, though, if we examine the specification and empirical findings associated with the measures of worker productivity employed.

Studies of Major League Baseball typically employ an index of player productivity, such as slugging percentage[2], OPS[3], or runs produced.[4] Research into professional basketball, though, tends to rely upon a collection of productivity measures. The menu of statistics available include points scored (PTS), rebounds (REB), steals (STL), assists (AST), blocked shots (BLK), field goal percentage (FG)[5], free throw percentage (FT)[6], personal fouls (PF), and turnovers (TO). These studies typically include a sample that begins with points scored and then incorporates a mix of the remaining choices.

Berri (2006) surveyed 12 studies examining racial discrimination in the NBA.[7] Each of these studies employed a model similar to equation (1). Given that some papers offered more than one model, Berri's survey examined 15 specific models.

Surprisingly, most aspects of player productivity were not consistently linked statistically to the decision-variable examined. In fact, the only factor consistently found to be correlated with player evaluation in the NBA is points scored. In 14 of the 15 models examined, points scored was found to be both the expected sign and statistically significant.[8] Of the other factors employed by researchers, only total rebounds and blocked shots were statistically significant more often than not.[9] The significance of assists was evenly split[10], while field goal percentage was significant in only four of the nine models where it was employed. Every other factor was not significant more than once. In sum, player evaluation in the NBA appears to be driven by points scored and, perhaps, total rebounds, blocked shots, and assists.

Such results tell two important stories. The first centers on the importance of scoring in the NBA. Virtually every study employed a player's total points or points scored per game.[11] One should note, though, that a player's accumulation of points is dependent on the playing time the player receives and the number of shots taken. Simply staying on the floor and taking a large number of field goal and free throw attempts can lead to the accumulation of lofty point totals. Cleary, efficiency in utilizing shot attempts would also be an indicator of a player's worth to a basketball team. As noted, though, field goal percentage was not statistically significant in the majority of studies where this factor was considered.[12] In other words, a player who scores points can expect to receive a higher salary. Evidence that scoring needs to be achieved via efficient shooting is not quite as clear.

The second story told is about the insignificance of many other facets of a player's performance. Players do not appear to be evaluated in terms of free throw percentage, steals, or personal fouls. Turnovers, a factor Berri (1999, in press) has identified as significant in determining wins in the NBA, has only been included once and was found to be insignificant. Given the ambiguous results uncovered with respect to everything else besides a player's points scored per game, these results suggest that a player interested in maximizing salary, draft position, employment tenure, and playing time should primarily focus upon taking as many shots as a coach allows.

Lesson Two: Player productivity on the court creates team wins.

The literature on team-wins production, though, suggests that wins are about more than points score per game. We begin this discussion with an obvious statement. The actions of the players on the court determine the outcome of the contest observed. The key to understanding the individual contribution to team wins, though, requires a bit more investigation.

The seminal work of Gerald Scully (1974) provides a guide to those seeking to uncover the relationship between player action and team wins in professional team

sports. Scully, in an effort to measure the marginal product of a baseball player, offered a model connecting team wins to player statistics.[13]

Berri (in press) recently adopted the Scully approach in developing a simple measure of marginal product in professional basketball. This model[14] indicates that points scored, rebounds, steals, turnovers, and field goal attempts each had an equal impact on team wins. Although points scored are important in determining outcomes, factors associated with acquiring possession of the ball also significantly impact a team's on-court success.

The review of the literature on racial discrimination revealed the importance of points scored, as well as rebounds, blocked shots, and assists. This list of factors can be thought of as highlight variables, since any collection of highlights from the NBA will consists of players scoring points, collecting rebounds, blocking shots, or making creative passes. Although these highlight variables are often correlated with player compensation, wins in the NBA are about more than these highlight factors.

Lesson Three: Team wins drive team revenue.

Perhaps team wins, though, are not the objective of NBA organizations. Such a possibility was considered in the work of Berri, Schmidt, and Brook (2004). These authors examined the importance of winning games as opposed to the star power of a team's roster. Specifically, a team's gate revenue was regressed upon team wins, all-star votes received, and a collection of additional explanatory variables. The results indicate that it is wins, not star power, which primarily determines a team's financial success.

Two anecdotes support this empirical finding. The team who led the league in attendance during the 2003-04 regular season was the Detroit Pistons. Although the Pistons eventually won the 2004 NBA championship, Detroit achieved its success via team defense. Only five teams scored fewer points than the Pistons. Detroit's regular season scoring leader, Richard Hamilton, ranked only 27th in the league with 17.6 points per game.[15]

The story of Allen Iverson and the Philadelphia 76ers further supports the low economic value of star power and scoring for an NBA team. In 2005-06 the 76ers sold out every game on the road.[16] At home, though, the 76ers were one of only three teams to play before crowds that were less than 80% of their home arena's capacity. Although the 76ers employed a major star and scorer in Allen Iverson, the team's sub-0.500 record resulted in below average home crowds.

Lesson Four: Team payroll is not highly correlated with team wins.

Given the abundance of information on player productivity and the expectation that player productivity is linked to player salary, one might expect payroll and wins to be correlated. Stefan Szymanski (2003) investigated the link between wages and team success in a variety of professional team sports, including the NBA. Although the relationship between relative payroll and wins was found to be statistically significant, only 16% of winning percentage in the NBA was explained by relative payroll.[17]

A similar result was reported by Berri and Jewell (2004). Specifically, a model was offered that looked at the importance of adding payroll, via the addition and subtraction of players, and simply giving existing players an increase in salary. Of these two factors, only adding payroll was statistically significant. Of interest, though, was that the explanatory power of the model employed was only 6%. Much of the changes in team success upon the court in the NBA are not explained by alterations to a team's level of talent, as measured by additions to team payroll.

Lesson Five: Player performance is relatively consistent across time

The lack of a strong relationship between wins and payroll is also observed in Major League Baseball and the National Football League. Berri, Schmidt, and Brook (2006) report that relative payroll in baseball only explains 18% of team wins in MLB from 1988 to 2006. If we look at the NFL from 2000 to 2005 we find that only 1% of wins are explained by relative payroll.[18]

The inability of payroll to explain wins can at least partially be explained when we look at how difficult it is to project performance in both football and baseball. Berri (2007) and Berri, Schmidt, and Brook (2006) present evidence that performance in football is quite difficult to predict. Summary measures such as the NFL's quarterback rating, metrics like QB Score, Net Points Per Play, and Wins Per Play—introduced in Berri, Schmidt, and Brook (2006)—and various metrics reported by Football

Outsiders.com tend to be quite inconsistent across time. Less than 20% of what a quarterback does in a current season, measured via any of the above listed metrics, is explained by what a quarterback did last season. A similar result is reported for running backs by Berri (2007).

When we look at baseball we also see a problem with projecting performance. Berri, Schmidt, and Brook (2006) report that less than 40% of what a hitter does in the current season can be explained by what he did last season.[19] These results suggest that even if teams were perfectly rational, the inability to project performance is going to result in a weak link between pay and wins.

Although performance inconsistency can explain what we see in the NFL and MLB, in the NBA a different story is told. The aforementioned work of Berri (in press) and Berri, Schmidt, and Brook (2006) detailed a metric called Win Score, which is calculated as follows for player *i* in year *t*:

$$WIN\ SCORE_{it} = PTS_{it} + TREB_{it} + STL_{it} + 1/2{*}BLK_{it} + 1/2{*}AST_{it} - TO_{it} - FGA_{it} - 1/2{*}FTA_{it} - 1/2{*}PF_{it} \quad (2)$$

where *FGA* = Field Goal Attempts

FTA = Free Throw Attempts

Berri, Schmidt, and Brook (2006) report that 67% of a player's Win Score per-minute is explained by what the player did the previous season. In other words, the correlation coefficient for $WIN\ SCORE_{it}$ and $WIN\ SCORE_{it\text{-}1}$ is 0.81. A virtually identical result can be seen with respect to metric reported by the NBA entitled NBA Efficiency.[20]

NBA Efficiency is calculated as follows for player i in year t.

$$NBA\ Efficiency_{it} = PTS_{it} + TREB_{it} + STL_{it} + BLK_{it} + AST_{it} - TO_{it} - MSFG_{it} - MSFT_{it} \quad (3)$$

where *MSFG* = Missed Field Goals

MSFT = Missed Free Throws

The correlation between NBA Efficiency per minute this season and last season is 0.82.[21]

These results indicate that player performance in basketball—relative to what we see in football and baseball—is quite consistent. Yet payroll and wins do not have a very strong relationship in the NBA. Hence, we need to look for another story beyond inconsistent performance. Before we get to this, though, we need to spend just a moment on one last lesson.

Lesson Six: NBA Efficiency is not about efficiency

The Win Score metric is based on the statistical relationship between wins and a team's offensive and defensive efficiency. The estimation of this relationship—reported in Berri (in press) and Berri, Schmidt, and Brook (2006)—reveals that 94% of team wins can be explained by the team's efficiency metrics. Furthermore, teams tend to average one point per possession. Consequently, factors such as points scored, rebounds, turnovers, steals, and field goal attempts have the same impact, in absolute terms, on team wins.

When we turn to NBA Efficiency we see a similar result. Points scored, rebounds, turnovers, and steals have the same valuation in absolute terms. But rather than consider shot attempts, the NBA's metric considers missed shots. As a result, an inefficient scorer can increase his value just by increasing his shot attempts.

Consider an NBA player who makes one of the three shots from two-point range. According to NBA Efficiency, his value rises by two from the made shot, and falls by two from the missed shots. So he breaks even. From three-point range he only needs to make one of four to break-even. Most NBA players, though, make at least 33% of their shots from two-point range and 25% of shots from beyond the arc. Consequently, most NBA players can simply increase their value, according to the NBA's metric, by simply taking more shots.[22]

Now consider the story told by Win Score, and the more complex metric introduced by Berri, Schmidt, and Brook (2006), Wins Produced. Both of these metrics note that a field goal attempt uses the team's possession. For a player to break even he must make 50% of his two-point shots and 33% of shots from three-point range. Players who fail to shoot efficiently are wasting possessions and hurting a team's chances to win.

So we have two picture of player performance. Which of these are most consistent with player evaluation in the NBA?

Examining the All-Rookie Team

To answer this question, let's first consider voting for the All-Rookie team. Each year the NBA coaches vote for the members on this team. This is the only award—other than the All-Defensive team—that is determined by the

NBA's coaches (as opposed to the media). The voting for this award, hence, gives us a quantitative measure of the coaches' evaluation of playing talent.

Berri and Schmidt (2002) examined the voting for this award across four seasons, beginning with the 1994-95 season. Berri, Schmidt, and Brook (2006) updated this analysis with additional seasons. The paperback edition of Berri, Schmidt, and Brook offered a further update, extending the analysis from 1994-95 to 2006-07. It is these empirical results we wish to review.

Our discussion begins with Table 1, which reports the descriptive statistics of the dependent and independent variables employed. The dependent variable is voting points. In voting for this award coaches choose 10 rookies, five for the first team and five for the second team. If chosen for the first team a player receives two points. A second-team selection gives the player one point. Since coaches cannot vote for players on their team, a player cannot receive more than 58 votes, or the value of first place votes from every one of the other 29 coaches in the league.[23]

The minimum number of voting points a rookie could receive is zero. We considered in our study all rookies who might have received consideration. The sample we chose included all rookies who played at least 12 minutes per game and appeared in 41 contests. In all, 354 rookies were examined. Of these, 21 received the maximum number of votes while 92 were not chosen by any coach.

To explain the variation in this data we considered three variables. The first is player performance (PROD), which can be measured via NBA Efficiency, Wins Produced, points scored, or a collection of player statistics. The other two variables include the initial assessment of a rookie's value, or his draft position (DFT). We also considered the number of games the rookie played. This list of independent variable is reported in equation (4).

$$\mathbf{LOG(VP)} = \beta_i + \beta_1\,\mathbf{PROD} + \beta_2\,\mathbf{DFT} + \beta_3\,\mathbf{GM} + \varepsilon_i \quad (4)$$

where PROD = NBA efficiency, Wins Produced, points scored, or a vector of player statistics

The dependent variable employed is constrained at both ends of our sample. If a player received the maximum number of votes possible, improvements in performance

Table 1. Dependent and Independent Variables to be Examined for the Study of the All-Rookie Team

Variable	Notation	Mean	Standard Deviation	Maximum	Minimum
Voting Points	VP	16.50	20.32	58.00	0.00
Points scored, per game	PTS	8.09	4.06	24.21	1.95
Points-per-shot	PPS	0.94	0.09	1.47	0.68
Free throw percentage	FT	0.71	0.09	1.00	0.44
Rebounds, per game	REB	3.79	1.63	9.47	0.79
Steals, per game	STL	0.71	0.36	2.18	0.12
Personal fouls, per game	PF	2.23	0.64	4.22	0.84
Turnovers, per game	TO	1.37	0.67	4.03	0.39
Blocked shots, per game	BLK	0.51	0.41	2.31	-0.23
Assists, per game	AST	1.69	1.03	5.71	-0.74
Draft Position	DFT	25.24	20.41	61.00	1.00
Games Played	GM	68.67	12.32	82.00	19.68
NBA efficiency, per game	NBAEFF	8.93	4.17	24.94	2.97
Wins Produced	WP	0.03	0.05	0.25	-0.09

Note: Except for Wins Produced, per game statistics are calculated relative to the average at each player's position.
Source: Player data taken from the Sporting News NBA Guide
Voting points taken from Patricia Bender

would not lead to more votes. For those who received zero votes, further declines in performance would not have reduced the number of votes received. Consequently, we estimated a TOBIT or censored model. In all we had 354 observations, of which 241 were uncensored.

The three estimations are reported in Table 2A, which rely upon three different measures of player performance. The first is NBA Efficiency, per game.[24] When equation (4) employs that measure we see that 73% of the natural log of voting points can be explained by our model. When we turn to Wins Produced per game, a measure highly correlated with team wins[25], we find that only 50% of the variation in voting points can be explained.

What is interesting is that if you turn to a third measure, points scored per game[26], we find that we can explain 74% of the variation in voting points. In other words, if we only consider one facet of player performance—scoring—we can explain more of the variation in the coaches' voting than either of our metrics that summarize much of what a player does on the court.

In Table 2B we take a different approach and consider how voting points are impacted by a collection of player statistics. In addition to points scored per game we consider points-per-shot[27], free throw percentage, and per game measures of REB, STL, BLK, AST, TO, and PF.[28] The results indicate that voting points are statistically linked to points

Table 2A. Estimated Coefficients for Equation (1)

Dependent Variables: Log of Voting Points
Estimation Method: Maximum Likelihood - Censored Normal (TOBIT)
QML (Huber/White) Standard Errors & Covariance
Sample: 354 Rookies from 1994-95 to 2006-07
(t-stats in italics)

Variables	**Coefficients and t-statistics**		
NBA efficiency, per game	0.315*		
	16.898		
Wins Produced		16.197*	
		8.801	
Points scored, per game			0.326*
			13.590
Draft Position	-0.012*	-0.030*	-0.007**
	-3.587	*-6.994*	*-2.221*
Games Played	0.045*	0.065*	0.051*
	8.499	*7.997*	*10.079*
Constant term	-3.801*	-2.428*	-4.201*
	-9.610	*-3.999*	*-10.351*
Adjusted R-squared	0.727	0.503	0.736
	Observations, for all models		
Left censored	92		
Right censored	21		
Uncensored	241		
Total	354		

* - denotes significance at the 1% level
**- denotes significance at the 5% level
***- denotes significance at the 10% level

Table 2B. Estimated Coefficients for Equation (1)

Dependent Variables: Log of Voting Points
Estimation Method: Maximum Likelihood - Censored Normal (TOBIT)
QML (Huber/White) Standard Errors & Covariance
Sample: 354 Rookies from 1994-95 to 2006-07
(t-stats in italics)

Independent Variables	Coefficients and t-statistics
Points scored, per game	0.277*
	8.357
Points-per-shot	1.832*
	2.685
Free throw percentage	1.133
	1.575
Rebounds, per game	0.158**
	2.320
Steals, per game	0.358***
	1.759
Blocked shots, per game	0.088
	0.564
Assists, per game	0.176***
	1.867
Turnovers, per game	-0.467**
	-2.072
Personal fouls, per game	-0.065
	-0.530
Draft Position	-0.010*
	-3.058
Games Played	0.047*
	9.096
Constant term	-6.409*
	-7.237
Adjusted R-squared	0.756
	Observations
Left censored	92
Right censored	21
Uncensored	241
Total	354

* - denotes significance at the 1% level
**- denotes significance at the 5% level
***- denotes significance at the 10% level

scored, points-per-shot, REB, STL, AST, and TO. The model explains 76% of voting points, which is quite similar to what we saw with a model based solely on points scored.

Table 3 reports the elasticity of voting points and each of the variables that were statistically significant (evaluated at the point of means). The results indicate that of the player statistics, points scored has the largest impact on voting points. A 10% increase in points scored per game will increase voting points by 22.4%. Other than points-per-shot, a 10% increase in the other significant statistics leads to a less than a 10% increase in voting points received. In sum, factors associated with scoring dominate the coaches' evaluation of rookie performance.

Beyond the statistics, it is interesting that draft position was statistically significant in each estimation of our model. This result suggests that independent of player performance, how a player was viewed on draft night still influences the coaches' evaluation of a player after an entire year of NBA performance. In other words, like the aforementioned work examining the escalation of commitment, we see evidence that coaches are slow to change their initial assessment of a player.

A Test of Recent Free Agents

One could argue that voting for the All-Rookie team is not indicative of how coaches evaluate talent. It is possible that these votes are not taken seriously and may even be filled in by assistant coaches. Although it seems unlikely that coaches would consistently endorse performances

Table 3. The Responsiveness of Voting Points to Independent Variables Found to be Statistically Significant

Elasticity evaluated at the point of means

Independent Variables	Elasticity
Points scored, per game	2.240
Points-per-shot	1.724
Rebounds, per game	0.599
Steals, per game	0.255
Assists, per game	0.299
Turnovers, per game	-0.639
Draft Position	-0.253
Games Played	3.254

that they know are inferior, one might still wish to see if a more substantive decision suffers from the over-emphasis on scoring.

The more substantive decision is the salary paid to free agents. In essence, what we wish to do is revisit equation (1). But now we will shift our focus from α_2 to α_1.

Beyond simply re-visiting the basic approach in the literature, we also will address a criticism initially noted by Jenkins (1996). Specifically, researchers often regressed current salary upon current player statistics. The NBA, though, often signs players to multi-year contracts. As noted by Berri and Krautmann (2006), for the 2002-03 season, 70% of players labored under a contract that was at least three years in length. More than 14% of the league had a contract that was seven years or longer. Jenkins (1996) argued that to ascertain the relationship between productivity and salary, one must consider measures of productivity at the time the salary is determined.[29] In other words, one should restrict the study of salary in professional sports to recent free agents.

Following the lead of Jenkins (1996), we collected data on 255 players who had a multi-year contract begin from the 2001-02 season to 2006-07 campaign. We then constructed a model of player salary based upon equation (1). Specifically, we employed as our dependent variable the log of average real salary the player was scheduled to receive over the life of the contract.[30] Our choice of independent variables begins with the same collection of per-

Table 4. Dependent and Independent Variables to be Examined for the Study of NBA Free Agent Salaries

Variable	Notation	Mean	Standard Deviation	Maximum	Minimum
Real Average Salary	AVGSAL	6,205,247	4,474,918	20,000,000	163,976
Points scored, per game	PTS	11.291	5.746	30.742	1.393
Points-per-shot	PPS	0.970	0.085	1.274	0.712
Free throw percentage	FT	0.747	0.096	0.929	0.416
Rebounds, per game	REB	4.896	1.943	11.367	1.081
Steals, per game	STL	0.891	0.432	2.738	0.092
Blocked shots, per game	BLK	0.589	0.454	3.148	-0.343
Assists, per game	AST	2.450	1.351	7.260	0.032
Turnovers, per game	TO	1.583	0.727	3.654	0.231
Personal fouls, per game	PF	2.416	0.617	4.109	0.857
NBA efficiency, per game	NBAEFF	12.700	5.541	31.594	3.678
Wins Produced, per game	WP	0.071	0.068	0.372	-0.088
Game Played, last two seasons	GP	139.85	20.51	164.00	50.00
Market Size of Signing Team	POP	5,488,966	5,299,158	21,199,865	1,135,614
Experience	XP	6.36	3.42	17.00	2.00
Dummy, center	D5	0.22	0.41	1.00	0.00
Dummy, power forward	D4	0.19	0.39	1.00	0.00
Dummy, small forward	D3	0.19	0.39	1.00	0.00
Dummy, shooting guard	D2	0.17	0.38	1.00	0.00
Dummy, Race of player equal to one if player is black	RACE	0.82	0.39	1.00	0.00

Note: Except for Wins Produced, per game statistics are calculated relative to the average at each player's position.
Source: Player data taken from the Sporting News NBA Guide and the Sporting New NBA Register
Salary data taken from USA Today.com

formance statistics we employed in our examination of the All-Rookie team. Additionally we considered a number of non-performance factors that might impact player compensation. The first is player injury, which we attempt to capture by considering the number of games played the past two seasons (GP).[31] Additionally we consider the size of the market where the player signs (POP).[32] Theoretically, increases in both games played and market size should lead to larger salaries.

In addition to injury and market size, we also consider the position the player plays. There are five positions in the game of basketball: center, power forward, small for-

Table 5A. Estimated Coefficients for Equation (2)

Dependent Variables: Log of Real Average Salary
Ordinary Least Squares Estimation
White Heteroskedasticity-Consistent Standard Errors & Covariance
Sample: 255 Free Agents Signing Multi-Year Contracts from 2001-2006
(t-stats in italics)

Independent Variables	**Coefficients and t-statistics**		
NBA efficiency, per game	0.117*		
	17.966		
Wins Produced		7.040*	
		12.175	
Points scored, per game			0.106*
			16.986
Games Played	0.002	0.007*	0.004**
	1.403	*3.478*	*2.333*
Market Size	9.3E-09	5.5E-09	6.6E-09
	1.469	*0.690*	*1.000*
Experience	-0.027*	-0.036*	-0.016
	-2.674	*-3.084*	*-1.455*
Dummy, center	0.268*	0.111	0.297*
	3.134	*1.117*	*3.119*
Dummy, power forward	0.007	0.056	0.029
	0.086	*0.483*	*0.309*
Dummy, small forward	-0.005	0.072	0.032
	-0.060	*0.615*	*0.329*
Dummy, shooting guard	-0.325*	-0.204	-0.272
	-2.684	*-1.347*	*-2.231*
Dummy, race of player	-0.002	0.071	-0.080
	-0.029	*0.794*	*-0.963*
Constant term	13.642*	13.974*	13.686*
	53.033	*44.762*	*51.012*
Adjusted R-squared	0.640	0.412	0.587
Observations for all models	255		

* - denotes significance at the 1% level
**- denotes significance at the 5% level
***- denotes significance at the 10% level

Table 5B. Estimated Coefficients for Equation (2)

Dependent Variables: Log of Real Average Salary Ordinary Least Squares Estimation White Heteroskedasticity-Consistent Standard Errors & Covariance Sample: 255 Free Agents Signing Multi-Year Contracts from 2001-2006 (t-stats in italics)	
Independent Variables	**Coefficients and t-statistics**
Points scored, per game	0.070* *6.097*
Points-per-shot	0.081 *0.201*
Free throw percentage	-0.189 *-0.531*
Rebounds, per game	0.098* *4.301*
Steals, per game	0.110 *1.172*
Blocked shots, per game	0.185* *2.632*
Assists, per game	0.051 *1.309*
Turnovers, per game	-0.026 *-0.261*
Personal fouls, per game	-0.010 *-0.120*
Games Played	0.003 *1.985*
Market Size	9.4E-09 *1.451*
Experience	-0.022*** *-1.891*
Dummy, center	0.249* *2.498*
Dummy, power forward	0.010 *0.116*
Dummy, small forward	-0.011 *-0.127*
Dummy, shooting guard	-0.317* *-2.594*
Dummy, race of player	-0.078 *-1.042*
Constant term	13.575* *22.586*
Adjusted R-squared	0.643
Observations for all models	255

* - denotes significance at the 1% level
**- denotes significance at the 5% level
***- denotes significance at the 10% level

ward, shooting guard, and point guard.[33] Each of these positions is typically assigned a number, with centers typically listed as a five and the point guard position labeled with the number one. Centers and power forwards are generally taller than guards and small forwards, with many players in excess of seven feet tall. Such height is scarce in the general population, potentially driving up the price of talented front court players. In contrast, quality guards might be in greater abundance, hence driving down the price of these players.[34]

The final player characteristic we consider is experience (XP), which we incorporate with the number of years played. The guaranteed rookie contracts that first round draft choices receive causes our sample of free agents to generally consist of older players. We suspect that holding performance constant, teams will prefer younger players to older players, so experience should diminish free agent salary.

The final variable we consider is the primary focus of each salary model we have previously noted, the race of the player. Following convention, we incorporate a dummy variable that is equal to one if the player is black, and zero otherwise.[35]

Table 4 reports the list of dependent and independent variables employed, as well as corresponding descriptive statistics. This list is utilized in the construction of the model reported in equation (5).

$$\text{LOG(AVGSAL)} = \gamma_j + \gamma_1 \text{ PROD} + \gamma_2 \text{GP} + \gamma_3 \text{ GAMES} + \gamma_4 \text{ POP} + \gamma_5 \text{ XP} + \gamma_6 \text{ POS} + \gamma_7 \text{ RACE} + \varepsilon_i \quad (5)$$

where PROD = Vector of player statistics, NBA efficiency, or Wins Produced[36]
POS = Dummy variable for center, power forward, small forward, or shooting guard

Table 6. The Responsiveness of Real Average Salary to Independent Variables Found to be Statistically Significant

Elasticity evaluated at the point of means	
Independent Variables	**Elasticity**
Points scored, per game	0.788
Rebounds, per game	0.480
Blocked shots, per game	0.109
Games Played	0.461

As with our examination of the All-Rookie team, equation (5) was first estimated with three different measures of player performance: NBA Efficiency, Wins Produced, and points scored. The results are reported in Table 5A.

All three estimations reveal that market size, playing power forward or small forward, and the race of the player do not impact player compensation. The results with respect to the other non-performance variables were mixed, with both insignificant and significant results reported.

How much of salary we can explain depends on which performance measure we employ. When we utilized NBA Efficiency per game, we can explain 64% of player salary. When we turn to Wins Produced our explanatory power falls to 41%. We can improve upon what we see from Wins Produced when we turn to points scored. When we consider points scored per game as our sole measure of player performance we can explain 59% of a player's average wage.

What if we turn to the entire collection of player statistics? As noted in Table 5B, when we utilize the entire vector of player statistics we again find that race is insignificant. We also find that we can explain 64% of player salary, which is the same result we uncovered for NBA Efficiency. Interestingly, beyond points scored, we find that only rebounds and blocked shots statistically impact player compensation. Shooting efficiency, turnovers, steals, assists, and personal fouls do not appear to change the average wage a player commands.

In Table 6 we report the elasticity of salary and the factors that were found to be statistically significant. Once again, it is points scored that have the largest economic impact on player evaluation. A 10% increase in points scored per game increases average salary by 7.7%. A similar increase in rebounds only leads to a 4.8% increase in compensation.

In sum, as we move from a vector of player statistics or the NBA efficiency model, to a measure of productivity based upon the statistical relationship between player statistics and team wins, our ability to explain player salary declines. Such a result is quite consistent with the argument laid forth in our review of the literature. Player evaluation in the NBA seems overly focused upon scoring. Negative actions, such as inaccurate shooting or accumulating turnovers, do not seem to result in corresponding declines in player compensation.

Concluding Observations

Our review of the literature, as well as our own analysis of the voting for the All-Rookie team and the wages paid to free agents, tell the same story. Players in the NBA need to score to score a major payday.

This was actually the same story told by Glenn Robinson, the first player chosen in the 1994 NBA Draft. Five games into his NBA career the young Glenn Robinson made the following observation: "I expect to do what I'm supposed to do. But a lot of people that don't know the game, they think it's all about scoring. I look at it from a team perspective. We have to do well as a team. I don't need to go out there and score 30 points a game and have us lose. That won't do us any good. It would help me individually." Robinson added: "But I want to see all of us get something done."[37]

A point similar to Robinson's observation was also offered by the legendary coach, Red Auerbach.[38] From 1950 to 1966, Auerbach guided the Boston Celtics to nine championships, including eight in a row from 1959 to 1966. What was the key to this team's success? In a biographical sketch posted at ESPN.com it was noted that Auerbach didn't focus on the individuals on his teams. He looked at the "whole package." While many of his players were outstanding, the Celtics were the first organization to popularize the concept of the role player. "That's a player who willingly undertakes the thankless job that has to be done in order to make the whole package fly," Auerbach said. Auerbach went on to add that the Celtics represent a philosophy that in its simplest form maintains that victory belongs to the team. "Individual honors are nice, but no Celtic has ever gone out of his way to achieve them," he said. "We have never had the league's top scorer. In fact, we won seven league championships without placing even one among the league's top 10 scorers. Our pride was never rooted in statistics."

Auerbach also bemoaned in an interview broadcast on ESPN Classic that the focus of today's players is on statistics, as opposed to winning. In Auerbach's view, Bill Russell was a great player because he didn't obsess on his own statistics, but rather sacrificed his stats so the team could win. Although Russell averaged only 15 points per contest, he did grab 22.5 rebounds per game. In other

words, although Russell was not much of a scorer, he was an amazing rebounder.

Of course rebounds are a stat. Looking over Auerbach's comments it appears that when he references statistics, he is talking about scoring. And that appears to be the wisdom of Auerbach: Wins are not just about scoring.

Both Robinson and Auerbach argued that scoring can help individual players, but not necessarily produce wins. Assuming teams and players are trying to win, why does scoring dominate the evaluation process?

In *The Wages of Wins* a possible answer to this question was provided. Player evaluation in the NBA tends to rely upon visual observation of the player, as opposed to analysis of the numbers. Visual observation would tend to be drawn to the most dramatic event on the court, scoring. Factors such as missed shots and turnovers would not tend to stand out in the mind of the observer. Consequently, these factors tend to be downplayed in the evaluation of players.

Such a story suggests that decision-makers need to do more than just possess the necessary information to make the "correct" decision. This information also has to be well understood. Often, though, decision-makers have not been trained in the statistical techniques necessary to uncover the statistical relationships necessary for good decision making. As a result, on-base percentage can be undervalued in baseball. NFL coaches can often fail to go for it on fourth down when the data say they should. And finally, scoring can be over-valued in the NBA.

Once again we note that sports have an abundance of information and clear consequences of failure. Yet, decision making in sports has been shown to be inconsistent with the precepts of instrumental rationality. Given this result, we have to wonder: If decision-makers in sports are not fully rational, should we expect decision-makers in non-sports industries—where information is less abundant and consequences less severe—to process information efficiently?

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Endnotes

[1] This paper was originally presented at the Western Economic Association meetings in 2004 and served as the foundation of chapter 10 of *The Wages of Wins*. This book did not provide any equations or econometric tables; hence, this paper will also serve the purpose of presenting these findings more formally.

[2] Studies utilizing slugging percentage include Scully (1974), Sommers and Quinton (1982), Raimondo (1983), Bruggink and Rose (1990), Hill (1985), Durland and Sommers (1991), Sommers (1993), Krautmann and Oppenheimer (1994), Krautmann (1999), Krautmann, Gustafson, and Hadley (2000), Maxcy, Fort, and Krautmann (2002), Krautmann and Oppenheimer (2002), and Goff, McCormick, and Tollison (2002). Sommers (1993) also employed a player's batting average while Krautmann, Gustafson, and Hadley (2000) added a hitter's runs-batted-in. Slugging percentage has not been the only measure of productivity chosen. Medoff (1976), Hill and Spellman (1983), and MacDonald and Reynolds (1994) measured a hitter's productivity with runs scored. Such a choice ignores the impact a player's hitting has upon the scoring of teammates. Sommers (1990) utilized a player's batting average, or simply hits divided by at-bats. Batting average ignores the quality of a player's hits and is generally considered inferior to slugging average.

[3] OPS = Slugging Percentage + On Base Percentage. This was employed by Zimbalist (1992a, 1992b).

[4] This comes from the work of Thorn and Palmer (1984). The Thorn and Palmer work is called linear weights. This was utilized by Asher Blass (1992) in a study of monopsonistic exploitation in Major League Baseball.

[5] Field goal percentage = field goals made / field goals attempted

[6] Free throw percentage = free throws made / free throws attempted

[7] These 12 studies included Kahn and Sherer (1988), Koch and Vander Hill (1988), Brown, Spiro, and Keenan (1991), Dey (1997), Hamilton (1997), Guis and Johnson (1998), Bodvarsson and Brastow (1998, 1999), Hoang and Rascher (1999), Bodvarsson and Partridge (2001), McCormick and Tollison (2001), and Eschker, Perez, and Siegler (2004). With the exception of Hoang and Racher, who considered employment discrimination, and McCormick and Tollison, who considered the allocation of playing time, each study considered the subject of wage discrimination. Kahn and Sherer, in addition to wage discrimination, also presented a model examining the role race played in determining a player's initial draft position.

[8] The term statistical significance is open to interpretation. A common rule of thumb is that the t-statistic should be greater than two. Such a rule, though, could be thought of as too restrictive. Consequently, Berri (2006) argued that a coefficient was only to be considered insignificant in this discussion if its t-statistic falls below 1.5. In other words, an effort was made to increase the likelihood that a variable was significant. Even with this effort, often the non-scoring factors were found to be insignificant.

[9] Ten models considered blocked shots and six found this factor to be statistically significant. Eight models considered total rebounds, while seven others broke total rebounds into offensive and defensive rebounds. Total rebounds was statistically significant in five of the eight models. Of those that considered the type of rebound, none found offensive rebounds to be statistically significant. Only one study, McCormick and Tollison (2002), found defensive rebounds to be significant.

[10] The ambiguous nature of assists was highlighted in the work of Koch and Vander Hill (1988). These authors found that assists were statistically significant and positive in one regression examining player salary. In another regression, though, assists were statistically significant and negative.

[11] Of the studies examining wage discrimination, only Brown, Spiro, and Keenan (1991) considered a player's per-minute performance. In examining the player draft, Kahn and Sherer (1988) also considered a player's total accumulation of the statistics employed. Both Hoang and Rascher (1999) and McCormick and Tollison (2001) employed a player's per-minute production.

[12] Six models of wage discrimination considered the impact of field goal percentage. Of these, only the studies that examined the 1985-86 season found shooting efficiency to be both statistically significant and positively correlated with a player's salary. This point is highlighted in the work of Bodvarsson and Brastow (1999). These authors tested the same model with data from the 1985-86 and 1990-91 seasons. For the former campaign, field goal percentage is statistically significant. For the latter season, though, it is insignificant.

[13] Scully's approach was also employed by Medoff (1976), Raimondo (1983), Scott, Long, and Sompii (1985), Zimbalist (1992a, 1992b), Blass (1992), and Berri (1999), among others.

[14] This model was originally detailed in a working paper by Berri. The appendix to Berri and Krautmann (2006) sketched out the basic idea. In Berri, Schmidt, and Brook (2006) more details were provided. Finally, the originally working paper was completed and is scheduled for publication as Berri (in press).

[15] Data on team attendance, team scoring, and individual scoring can be found at ESPN.com. Further evidence of the lack of impact from points scored can be found in Berri, Schmidt, and Brook (2006), who report that increases in a team's points scored per game does not lead to increases in gate revenue in the NBA.

[16] This result is consistent with Berri and Schmidt (2006) which reports star power is quite valuable on the road. The NBA does not split regular season gate revenue, so the money a star generates on the road goes to the star's opponent.

[17] Relative payroll is a team's payroll divided by the league average. Szymanski looked at 1986 to 2000. Berri, Schmidt, and Brook (2006) updated this work via an examination of wins and payroll in the NBA across 15 seasons, beginning with the 1990-91 season and ending with the 2006-07 campaign. For these 15 seasons, relative payroll only explains 10% of team wins.

[18] The NFL regression had 190 observations. Relative payroll was also only significant at the 10% level.

[19] The metrics considered included OPS (On base percentage + Slugging average), SLOB (On base percentage multiplied by slugging average), and Runs produced per plate appearance. Runs produced is calculated via the linear weights measure developed by Thorn and Palmer (1984) and utilized by Blass (1992). Across a sample that began in 1994 and concluded in 2004, only 29% of runs produced per plate appearance were explained by past performance. For OPS and SLOB the explanatory power was 33% and 37%, respectively.

[20] The NBA's efficiency measure is reported at NBA.com. This metric is quite similar to Heeran's (1992) TENDEX system and Bellotti's (1993) Points Created model. TENDEX was first formulated by Heeran in 1959. Heeran begins with a model identical to the one currently employed by the NBA, but then weights each player's production by both minutes played and the average game pace his team played throughout the season being examined. Bellotti's Points Created model is also quite similar. Bellotti begins with the basic TENDEX model and then simply subtracts 50% of each player's personal fouls.

[21] The result is a sample of 2,836 NBA players from the 1994-95 season through 2003-04.

[22] A paperback edition of *The Wages of Wins* was prepared in 2007. The updated version noted that the critique of NBA Efficiency also applies to the Player Efficiency Rating developed by Hollinger (2002). "In devising his metric Hollinger argued that each two point field goal made is worth about 1.65 points. A three point field goal made is worth 2.65 points. A missed field goal, though, costs a team 0.72 points. Given Hollinger's values, with a bit of math we can show that a player will break even on his two point field goal attempts if he hits on 30.4% of these shots. On three pointers the break-even point is 21.4%. If a player exceeds these thresholds, and virtually every NBA played does so with respect to two-point shots, the more he shoots the higher his value in PERs. So a player can be an inefficient scorer and simply inflate his value by taking a large number of shots."

[23] Data on voting points was taken from the website of Patricia Bender (http://www.eskimo.com/~pbender/index.html). Across the time period examined the league expanded from 27 teams to 30 teams. Voting points were normalized so a player unanimously selected in the NBA before expansion were given 58 points. Votes for other players were adjusted in a similar fashion.

[24] The NBA Efficiency measure varies depending upon position played. On a per-minute basis, power forwards and centers average between .49 and .50, while small forwards and guards range from 0.41 to 0.43. To overcome this position bias, we calculated a position adjusted NBA Efficiency measure. Specifically we determined each rookie's per-minute NBA Efficiency value. We then subtracted the average at each position, and then added back the average value for NBA Efficiency across all positions, or 0.45. Once we took these steps, we then multiplied what we had by the number of minutes a player played and divided by games played.

[25] As noted by Berri, Schmidt, and Brook (2006) the average difference between team wins and the summation of the Wins Produced by a team's players is 2.4 from 1993-94 to 2004-05.

[26] Like NBA Efficiency per game, points scored per game was adjusted for position played.

[27] We took the concept of points-per-shot (PPS) from an article by Neyer (1996). As Neyer explained, this is the number of points a player or team accumulates from its field goal attempts. Its calculation involves subtracting free throws made from total points, and then dividing by field goals attempted. Employing points per shot, rather than field goal percentage, allowed for the impact of three-point shooting to be captured more efficiently.

[28] Except for points-per-shot and free throw percentage, all measures were adjusted for position played in a fashion consistent with our adjustment of NBA Efficiency.

[29] The work of Jenkins (1996) employed data from the 1980s and 1990s, representing perhaps the longest time period employed in studies of salary discrimination in the NBA. Unfortunately, Jenkins also differed from other works in his choice of player productivity measures. Unlike studies that employed a collection of player statistics, Jenkins followed the lead of professional baseball studies by employing an index of player performance. Hence, we cannot use Jenkin's work to ascertain the relative importance of points scored, blocked shots, assists, etc.

[30] The data on player salary came from USAToday.com: *Basketball Salaries Database* (http://www.usatoday.com/sports/basketball/nba/salaries/default.aspx). The salary data was converted into constant 2004 dollars.

[31] We wish to thank Justin Wolfers for suggesting this variable.

[32] Data for U.S. cities was found at the website of the U.S. Census Bureau (http://www.census.gov). Data for Canadian cities was found at Statistics Canada: (http://www.statcan.ca/ start.html).

[33] Data on player position was taken from various websites, including ESPN.com. In general, centers and power forwards play closer to the basket and are primarily responsible for rebounds and blocked shots. Point guards and shooting guards play further from the basket and are responsible for ball handling. Small forwards have a mixture of responsibilities.

[34] The scarcity of tall people, or "the short supply of tall people" was examined in the work of Schmidt and Berri (2003), Berri et. al. (2005), and Berri, Schmidt, and Brook (2006).

[35] Data on experience and race was taken from various issues of the *Sporting News NBA Register*.

[36] These are per-game measures, adjusted for position played.

[37] This was quoted in an *Associated Press* article written by Jim Litke (1994).

[38] The following discussion of Auerbach was first offered at *The Wages of Wins Journal* (http://dberri.wordpress.com) and also offered in the updated version of *The Wages of Wins.*