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Salary Determination in the Presence of Fixed Revenues

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Abstract

The assumption that workers are paid their marginal product underlies the theory of competitive labor markets and is the basis for comparison with non-competitive markets. Many firms, however, generate revenue in fixed lump-sums that are unrelated to the efforts of current workers. For example, many professional sports receive substantial income from broadcast rights, which are negotiated at wide intervals. We develop a theory of compensation in the presence of "fixed revenue" and test our theory using data from the National Basketball Association. Our results indicate that TV revenue tends to equalize players' salaries. Players' performance and popularity tend to enhance players' bargaining positions. Popularity with fans particularly helps players with greater bargaining power.

Keywords: fixed revenue, marginal revenue product, National Basketball Association

Introduction

Standard neoclassical economics predicts that labor markets operate efficiently when workers are paid their marginal revenue product (MRP). Firms that set wages above the MRP fail to maximize profit, and, in competitive product markets, are eventually forced to exit. Conversely, firms that offer less than the MRP cannot attract employees.

Standard theory, however, depends on a direct relationship between worker effort, output, and revenue. The difficulty in measuring the relationship between effort and output led Lazear and Rosen (1981) to propose that firms sometimes design rank order tournaments to elicit efficient levels of effort when MRP is costly to determine or indeterminate. This paper takes on a related problem with standard theory: That

firm revenues often depend on fixed payments that are unrelated to workers' current effort. Colleges, for example, collect tuition payments at the beginning of a semester, before many students have even selected their classes. The major North American sports (baseball, basketball, football, and hockey) all depend heavily on revenue from network TV contracts that were signed long before many current players were in the league. We refer to these payments as "fixed revenues."

In this paper, we use data from professional basketball to show that worker compensation in the presence of fixed revenue takes place on two levels. A portion of the player's compensation reflects the impact of his efforts on variable revenue (his MRP). The rest of his compensation results from his bargaining with the team. To a degree, the presence of bargaining power in salary determination in professional sports is obvious. The National Basketball Association (NBA), National Football League (NFL), and National Hockey League (NHL) all guarantee their players a minimum portion of designated revenue—of which broadcast revenue forms a large part—as part of their collective bargaining agreements with the players. However, these agreements do not specify how the teams allocate these funds to individual players. The model presented here takes bargaining down to the individual level. Our estimates show that a player's bargaining power depends on several factors that do not affect his MRP and vice versa. Sports, with its readily available data on compensation and performance, is the natural place to test our model, and our results should extend to a wide variety of work settings.

Pay and Productivity in Professional Sports

As Kahn (2000) notes, the professional sports industry provides an ideal "laboratory" to study worker compensation because it has two critical characteristics: individual-level wage data, and extraordinarily detailed data on productivity. The productivity of professional athletes is measured across dozens of dimensions. Importantly, this productivity is measured uniformly across both time and teams (firms), allowing researchers to assemble large datasets for empirical testing.

The seminal work of Gerald Scully (1974) was a major step forward in constructing measures of MRP and comparing them to wages. As Bradbury (2013) notes, Scully's comparison of major league baseball players' salaries to their MRPs was the first attempt to do so in any industry. Scully's approach has a number of attractive features. He first measures marginal revenue by estimating the relationship between team wins and revenue and of marginal product by estimating the contribution of individual players' productivity to team wins. He then compares his estimates of marginal revenue product to players' salaries. His results show precisely what the theory predicts: before the advent of free agency, players were subject to monopsony power and were paid only a small fraction of their MRP. Scully's model has since been employed, refined, and extended by many others.[1] Except for Scott, Long, and Sompii (1985), which studied the NBA, and Richardson (2000), which looked at hockey, these studies have primarily examined baseball.

For all of its appeal, the Scully approach suffers from several shortcomings, as first detailed by Krautmann (1999). Krautmann notes that one cannot directly tie a player's pay to his recent performance if he has signed a multi-year contract.[2] Pay in the first year of a multi-year contract might reflect a player's performance in the previous year, but pay in later years is only a guess as to the player's future productivity.

Krautmann neatly avoids this problem by assuming that a free agent is paid his marginal product and then estimating a salary equation for only those players.

We resolve a problem that is essentially the inverse of the one that Krautmann encountered. Krautmann realized that, in an era of multi-year contracts, pay was established long before the contribution of the player was revealed. Our concern here is that the pay of the player is set long after a key element of his value—the revenue from broadcast rights—has been determined. We recast the employer-employee relationship as one in which workers are paid a portion of their salary based on their productivity and the remainder based on individual employee bargaining power. While our empirical model uses data from professional basketball, the results generalize to any industry in which firms receive lump-sum revenues not tied to specific output and industries in which the value of the output is uncertain at the time of production. Because MRP cannot be calculated, employers and employees must bargain over accumulated rents.

The Link Between Inputs, Output, and Revenue

Consistent with previous work on labor productivity in professional sports, we define output as the number of wins during the regular season, and we assume that the primary labor input is "effective labor," meaning player talent. While there are other possible measures of output (e.g., fan attendance, playoff success), using wins provides the best opportunity to link labor productivity with total revenue and, in turn, marginal revenue product. We use effective labor rather than the number of workers or hours because the number of workers (players) devoted to production in all professional sports is fixed.

Instead of adding more players, teams increase output (wins, Q) by increasing the talent level of the team (L). We assume that the marginal product of talent is positive but decreasing, so $\partial Q/\partial L > 0$, $\partial^2 Q/\partial L^2 < 0$.[3] Teams cannot purchase playing talent with certainty, so we simplify the model by assuming that teams face no uncertainty in the talent they obtain. We discuss the firm's ability to measure L and its impact on revenue in detail later in the paper.

Teams receive revenue from a variety of sources. Some revenue streams vary and are closely related to player productivity (i.e., attendance-related revenues), while others are fixed or nearly so over the course of the season, and are unrelated to current player productivity (i.e., television revenue and revenues from long-term signage contracts). In this section, we investigate the relationship between player productivity (as measured by wins) and revenue for the NBA, NHL, MLB and the NFL and discuss the implications of our findings in the context of the Scully model. All revenue data are based on *Forbes* estimates for the teams in each league.[4]

Samples are for the years 2002 to 2011 for the NFL and MLB; 1999-2000 to 2010-11for the NBA, and 2005-06 to 2010-11 for the NHL. The revenue function shown in equation (1) is modified from a model originally detailed in Bradbury (2010). The dependent variable is total revenue for team i. This is modeled as a function of wins from the current season, a lagged measure of wins, population in team's market, stadium capacity, and a dummy variable indicating whether the team played in a stadium that was age of eight years or younger.[5] Following the lead of Forrest and Simmons (2006), we employ the Prais-Winsten regression model.[6] This model incorporates an AR(1) process to capture the time nature of revenue in sports.

$$\text{Revenue}_{it} = a_0 + a_1{*}\text{Wins}_{it} + a_2{*}\text{Wins}_{it-1} + a_3{*}\text{Population} + a_4{*}\text{Stadium Capacity}_i + a_5{*}\text{New Stadium}_i + \varepsilon_{it} \quad (1)$$

Table 1 presents summary statistics for the variables employed. Our dependent variable is real total revenue. Table 1 shows that a substantial share of the total revenue received is fixed (i.e., it does not change from team-to-team). We discuss the importance of this point below.

Table 1. Summary Statistics for Variables Employed in Equation (1)

Variables	Mean	Standard Deviation	Minimum	Maximum
Real Total Revenue (in millions of dollars)	109.38	36.36	39.55	244.00
Real Variable Revenue (in millions of dollars)	84.08	32.85	26.92	213.00
Wins	41.00	12.93	11.00	72.00
Population (in millions)	4.903	4.62	0.969	18.323
Stadium Capacity	19,215.46	1,218.6	16,285	2,3319
New Stadium last 8 years (dummy variable)	0.41	0.49	0.00	1.00

Estimates of equation (1) for the NBA appear in Table 2, below.[7]

Table 2. Modeling NBA Total Revenue

Independent Variables	Coefficient
Wins	486,524.30***
	(7.76)
Wins, lagged	358,241.40***
	(5.40)
Market Size	3.19***
	(10.84)
Stadium Capacity	3,658.37***
	(3.87)
New Stadium	4,522,677.00*
	(1.92)
Constant Term	839,493.40
	(0.05)
Observations	325
R-squared	0.60

**Significant at 10% level* *(z-statistics in parentheses)*
*** Significant at 5% level*
**** Significant at 1% level*

We use the above results to compute the monetary value of a win to each team. Multiplying the value of a win by a player's contribution to wins then yields the play-

er's MRP. Because this is a linear model, this calculation is relatively straightforward. A win in the current season is worth $486,524 while a lagged win is worth $358,241. Applying a discount factor of 5% to future revenue and adding the two together yields a total value of $827,707.

In 2010-11, the Chicago Bulls won 62 games. Given the estimated value of a win, the value of these victories is $51.3 million. The Bulls, though, had $185 million in total revenue. So the players—according to the standard Scully approach—were only worth 27.7% of the team's revenue. Repeating this same calculation for each team yields the data in Table 3.

Table 3. Value of a Win from NBA Total Revenue Model for 2010-11

Team 2010-11	Real Total Revenue[a]	Team Wins	Total Value of Wins	Total Value of Wins/ Real Total Revenue
Atlanta	$109,000,000	44	$36,419,090	33.4%
Boston	$146,000,000	56	$46,351,569	31.7%
Charlotte	$101,000,000	34	$28,142,024	27.9%
Chicago	$185,000,000	62	$51,317,808	27.7%
Cleveland	$149,000,000	19	$15,726,425	10.6%
Dallas	$166,000,000	57	$47,179,275	28.4%
Denver	$113,000,000	50	$41,385,329	36.6%
Detroit	$141,000,000	30	$24,831,198	17.6%
Golden State	$139,000,000	36	$29,797,437	21.4%
Houston	$150,000,000	43	$35,591,383	23.7%
Indiana	$101,000,000	37	$30,625,144	30.3%
LA Clippers	$108,000,000	32	$26,486,611	24.5%
LA Lakers	$208,000,000	57	$47,179,275	22.7%
Memphis	$99,000,000	46	$38,074,503	38.5%
Miami	$158,000,000	58	$48,006,982	30.4%
Milwaukee	$92,000,000	35	$28,969,731	31.5%
Minnesota	$97,000,000	17	$14,071,012	14.5%
New Jersey	$89,000,000	24	$19,864,958	22.3%
New Orleans	$109,000,000	46	$38,074,503	34.9%
New York	$244,000,000	42	$34,763,677	14.2%
Oklahoma	$126,000,000	55	$45,523,862	36.1%
Orlando	$140,000,000	52	$43,040,742	30.7%
Philadelphia	$116,000,000	41	$33,935,970	29.3%
Phoenix	$136,000,000	40	$33,108,263	24.3%
Portland	$132,000,000	48	$39,729,916	30.1%
Sacramento	$104,000,000	24	$19,864,958	19.1%
San Antonio	$139,000,000	61	$50,490,102	36.3%
Toronto	$134,000,000	22	$18,209,545	13.6%
Utah	$120,000,000	39	$32,280,557	26.9%
Washington	$109,000,000	23	$19,037,251	17.5%
AVERAGES	**$132,000,000**	**41**	**$33,935,970**	**26.2%**

[a] *Revenue figures are rounded to the nearest million.*

The results in Tables 2 and 3 show that—on average—26.4% of an NBA team's total revenue is linked to its wins in 2010-11. The collective bargaining agreement between the NBA and its players at the time, though, gave players 57% of league revenues in 2010-11. Thus, by the logic of the traditional model of wage determination (as in the Scully model) players are, on average, substantially overpaid for producing wins.

For reference, we evaluated the other three major sports leagues in North America (the NFL, NHL and MLB) using the same model. The results, shown in Table 4, are very similar to those of the NBA.[8]

Table 4. The Value of a Win in Various Leagues

Independent Variable	Major League Baseball 2002-2011	National Football League 2002-2011	National Hockey League 2006-2011
Wins[a]	422,139.70***	412,760.20*	179,194.80***
	(5.02)	(1.96)	(2.58)
Wins Lagged[b]	237,091.00***	211,906.60	140,486.80**
	(2.73)	(0.95)	(2.35)
Population	7.76***	-0.08	0.89**
	(8.10)	(-0.11)	(2.48)
Stadium Capacity	-1,881.37***	3,759.95	6,861.60***
	(-4.22)	(5.05)***	(2.67)
New Stadium, Dummy	11,400,000.00***	8,758,291.00	-1,689,274.00
	(3.60)	(2.43)**	(-0.76)
Constant Term	173,000,000.00***	-38,100,000.00	-66,500,000.00
	(6.67)	(-0.70)	(-1.40)
R-Squared	**0.51**	**0.45**	**0.48**
Observations	**300**	**319.0**	**180**
Average Real Revenue	**$188,000,000**	**$237,000,000**	**$95,100,000**
Revenue from Wins	**$52,481,897**	**$3,302,082**	**$28,645,700**
Percentage of Revenue from Wins	**27.9%**	**1.4%**	**30.1%**

[a,b] For the NHL, standing points and lagged standing points are used instead of wins.
(z-statistics in parentheses)
**Significant at 10% level*
*** Significant at 5% level*
**** Significant at 1% level*

The results in Table 4 are striking. Teams in these four professional sports typically spend at least 50% of revenue on player salaries, indicating that they overpay by a factor of two in MLB and the NHL. In the NFL, the link between current wins and revenue is only significant at the 10% level. And the value of wins suggests that players are only worth 1.4% of league revenues.

And our results do not appear to be a function of our estimation method. The original Scully model employed a simple Ordinary Least Squares (OLS) estimation. With this model in mind, we re-estimated equation (1) with OLS. We also employed a fixed-effects model (but without an AR(1) term). The results—reported in Table 5—indicate that our choice of estimation methods is not generally driving our results.

Table 5. Alternative Specifications for the Value of Wins in the NBA, NHL, MLB and NFL.

League	OLS	Fixed Effects
NBA	41.7%	27.9%
MLB	60.8%	28.1%
NFL	8.6%	not significant
NHL	27.6%	35.3%

[a]*The NHL employs standing points and lagged standing points instead of wins.*

Only when we employ the basic Scully approach (i.e., simple OLS) with respect to Major League Baseball can we get the value of each team's wins to exceed 50% of team revenue. But if we switch to a model that incorporates team-specific fixed effects (which we prefer to simple OLS), that is no longer the case for baseball. When we look at the other three sports leagues, the value of a win is consistently below 50% no matter which estimation method we choose. In addition, wins are not even significant in the fixed effects model for the NFL.

The lack of a connection between team performance and revenue is almost certainly due to the extraordinary extent to which NFL teams share revenue. Even though none of these sports leagues operates in a competitive market, errors of such magnitude are unsustainable in the long run if the value of player output is limited to producing wins.

Implications for Evaluating Wages

Given that owners across four different industries (sports) are unlikely to make systematic errors of this magnitude, we must reconsider the assumptions underlying the link between productivity and revenue. Wins (i.e., output in the current period) might not be the only basis for player compensation. If a team's presence in a market creates value (revenue) for the owner independent of the number of games that the team wins, then Krautmann's criticism of the assumption underlying Scully's model—that players are paid only for wins—is correct. Unfortunately, Krautmann estimates a wage equation using free agents only and then uses this equation to estimate the value of restricted players, assuming by construction that free agents earn salaries equal to their MRP. As Bradbury (2013) notes, there are a number of reasons to believe that this assumption might be incorrect.

More generally, we are left with the observation that there is no way to measure a player's MRP in sports. If this is the case for an industry in which the individual-level data on performance and compensation is unmatched, where *can* we measure MRP? If no one can measure MRP, wages and salaries may simply represent guesses by employers regarding employee contributions, and we have no way to know if they are good guesses.

We propose instead that wages and salaries reflect a combination of expected performance and bargaining power. Either way, comparisons of compensation and standard measures of MRP, the fundamental metric of worker compensation, are meaningless. In the next section, we apply a bargaining model to the employment relationship to resolve this problem.

A Bargaining Model of Salary Determination in the NBA

In this section, we adapt a bargaining model first developed by McLaughlin (1994) and later applied to the NFL by Kowalewski (2010) in which players and owners bargain over monopoly rents. McLaughlin begins with the simple yet insightful observation that most workers are both overpaid and underpaid. That is, they are paid more than necessary to get them to do their jobs but less than they are worth to their employers. Only the marginal worker is paid exactly the value of his or her work. Thus, efficient matching of workers and firms typically results in economic rents. How those rents are distributed is a function of the bargaining power of the two parties.

In the context of free agent players and teams searching for talent, solving for an efficient match is highly complex because the decisions by players and teams are all interrelated. That is, the rent-sharing solution depends on the number of players available who possess a given skill set, the number of teams searching for that skill set, and the teams' ability to make productive use of those skills. A separate but related issue is whether the skills that teams search (and pay) for are actually the skills that produce wins.

The McLaughlin model begins with the assumption that firm *j* produces output (q_j) using capital (K_j) and efficiency units of labor (L_j).[9]

$$q_j = F_j(K_j, L_j) \tag{2}$$

Workers are assumed to be heterogeneous, as are the valuations firms place on worker skills. Team *j*'s efficiency units of labor (L_j) is the sum of the effective labor that all workers (x_{ij}) contribute to firm *j* and so is a firm-specific function of worker skills.

In the context of the NBA, each team has a unique need for and ability to make use of certain kinds of talent, and available free agents all possess unique skill sets that map into efficiency units of labor with each team. Thus team *j*'s labor input L_j is

$$L_j = \Sigma_{i=1}^{1}(x_{ij} * E_{ij}) \tag{3}$$

Where E_{ij}=1 if player *i* is employed by team *j*. The marginal value of player *i* to firm *j* is determined by the marginal revenue product of labor times the actual labor input by player *i*.

$$M_{ij} = (MP_{Lj}) * x_{ij} \tag{4}$$

If players are of varying quality so that no two players are exactly the same and each team ascribes a unique value to players' skill sets, then each player receives a unique job offer from every team. In McLaughlin's model, efficient matching occurs when each worker (player) is assigned to the firm (team) in which his productivity is greatest. That does not mean, however, that each player is paid the value of his marginal product. A player accepts a contract offer if it is greater than his opportunity wage (i.e., the next-highest offer from another team (McLaughlin, 2004: 505)). While the marginal player's contract offer is equal to the value of his productivity, the contract offer to an

inframarginal player lies between the opportunity wage and the value of his marginal product.

This mechanism for wage determination differs from that proposed by Scully (1974) or Krautmann (1999). In both Scully's and Krautmann's models, workers either should be (as in Scully's comparison of wages to his calculation of MRP) or are by construction (in Krautmann's model) paid wages equal to their MRP. In the McLaughlin rent-sharing model, efficient outcomes do not generally depend on a worker's receiving a wage offer equal to his MRP. Instead, the opportunity wage and the MRP serve as boundaries for salary offers, and specific outcomes are determined by the bargaining strengths of the players and owners of the teams.

Kowalewski (2010) applies McLaughlin's theoretical model to the NFL. Teams and players participate in markets that are too thin to be characterized as competitive with a small number of roster spots available and each team searching for a specific skill set to complement existing players. As a result, players receive more than their opportunity wage as long as they have bargaining power. Kowalewski uses quantile regression (QR) to capture the degree of a player's bargaining power. A player with greater bargaining power receives higher pay for any value of observable variables, which places him in a higher quantile.

Empirical Model and Estimation

In this section, we provide a more general estimate of the determinants of salaries than Scully or those who have extended his work by allowing revenue to be independent of performance. The problem with existing models is one of specification: Wins affect only variable revenue, but the dependent variable in equation (1) is total revenue. As a result, the fixed portion of revenue is inappropriately specified as part of the constant term. As we show below, our model differs from those of McLaughlin and Kowalewski in that they assume teams and players bargain over total compensation. We apply it only to the portion of revenue that is generated from a fixed source. We work from the assumption that teams pay workers their marginal revenue product on that portion of revenue that varies with team—and hence individual—performance.

National TV revenue is set by a contract between the NBA and over-the-air and cable broadcasters. Table 6 shows the history of these contracts. The current contract grants broadcast rights to ESPN/ABC and TNT through the 2015-2016 season. It grants the NBA an average of about $930 million per year in broadcast rights, up from $767 million under the previous contract.[10] Using this figure for the 2009-10 season, we find that national broadcast revenue accounted for about 23% of team revenue.[11] This ranges from a low of about 12% for the New York Knicks (with total revenue of $244 million) to a high of nearly 35% for the New Jersey (now Brooklyn) Nets (with total revenue of $89 million).

To address this problem, we employ a two-step model in which players are paid their contribution to variable revenue (i.e., their MRP) plus a share of fixed revenue over which they must bargain with their employer (team). There is no bargaining in the first step, while the second step is based on the Kowalewski (2010) and McLaughlin (1994) bargaining models. Because TV revenue is by far the largest contributor to fixed revenue,[12] we use that as our measure.

Table 6. The History of NBA Television Contracts

Years	Networks	Total Value
1953-54 (13 games)	Dumont	$13,000
1954-55 to 1961-62 (8 years)	NBC	N/A
1962-63 to 1972-73 (11 years)	ABC	N/A
1973-74 to 1975-76 (3 years)	CBS	$27 million
1976-77 to 1977-78 (2 years)	CBS	$21 million
1978-79 to 1981-82 (4 years)	CBS/USA[a]	$75.5 million
1982-83 to 1985-86 (4 years)	CBS/USA/ESPN/TBS[b]	$122.9 million
1986-87 to 1989-1990 (4 years)	CBS/TBS/TNT[c]	$248 million
1990-91 to 1993-94 (4 years)	NBC/TNT	$876 million
1994-95 to 1997-98 (4 years)	NBC/TNT/TBS	$1.289 billion
1998-99 to 2001-2002 (4 years)	NBC/TNT/TBS	$2.456 billion
2002-03 to 2007-08 (6 years)	ESPN/ABC/TNT	$4.6 billion
2008-09 to 2015-16 (8 years)	ESPN/ABC/TNT	$7.44 billion

[a] *The USA Network contract was for 1980-81 to 1981-82.*
[b] *The USA and ESPN contract was for 1982-83 to 1983-84. The TBS contract was for 1984-85 to 1985-86.*
[c] *There were two 2-year contracts with TBS and a 2-year contract with TNT from 1988-89 to 1989-90.Source: "NBA TV Contracts," InsideHoops.com, retrieved from http://www.insidehoops.com/nba-tv-contracts.shtml. For the most recent contract, see USA Today (http://usatoday30.usatoday.com/sports/basketball/2007-06-27-3096131424_x.htm).*

To estimate MRP using variable revenue, we first re-estimate the model shown in Table 2, using only variable revenue (computed here as total team revenue less national television revenue) as a dependent variable. Results are shown in Table 7. These results indicate that respecifying revenue increases the value of a win from Table 2. Given the value of a win and a lagged win, we find that an additional victory increases variable revenue by $843,207.

Using the estimates from Table 7, we employ the Scully approach to estimate the MRP of a sample of 484 free agents who signed multi-year contracts from 2001 to 2011. For each player, MRP = Estimate of Player's Production of Wins (year prior to signing contract) * Value of Wins (for team who signs player). For Value of Wins, we simply employ the NBA Efficiency model.[13]

We next compute the bargaining power of 484 recently-signed free agents (2001–2011) as the difference between their actual salaries and their MRPs from variable revenue as calculated above. Table 8 summarizes MRP, salary, and bargaining power across the entire sample (salary data comes from hoopshype.com., *USA Today*, and the website of Patricia Bender). As noted, if players are paid only for wins, and wins impact only variable revenue, then NBA players are significantly overpaid. Specifically, we estimate that the difference between average salary and estimated MRP is nearly $4 million.[14]

Table 7. The Impact of Wins on Variable Revenue

Independent Variables	Coefficient
Wins	493,889.90***
	(7.74)
Wins, lagged	366,783.10***
	(5.40)
Market Size	3.19***
	(11.34)
Stadium Capacity	3,945.44***
	(4.18)
New Stadium	4,254,948.00*
	(1.71)
Constant Term	-34,600,000.00*
	(-1.89)
Observations	325
R-squared	0.50

**Significant at 10% level (z-statistics in parentheses)*
*** Significant at 5% level*
**** Significant at 1% level*

Table 8. Measures of MRP, Salary, and Bargaining Power

Variable	Mean	Standard Deviation	Minimum	Maximum
Estimated MRP	$3,695,173	$1,810,431	$519,488	$10,533,210
Real Average Free Agent Salary	$7,572,910	$5,250,783	$848,664	$28,822,534
Estimated Bargaining Power	$3,877,737	$3,965,141	-$1,874,745	$22,344,435

Such apparent overpayment indicates that players are paid for something besides wins. To see what this is, we now turn to a model of a player's bargaining power.

Determinants of Player Bargaining Power

Having defined free agent *i*'s bargaining power with team *j* in year *t* (BP_{ijt}) as the difference between his MRP and his salary, we regress this difference on a vector of player characteristics (X_{Pit}), a vector of team characteristics (X_{Mjt}), a variable indicating the size of the league's fixed revenue as given by its TV contract (X_{TVt}), and a vector of variables that we expect to affect a player's bargaining power (X_{Bijt}).

$$BP_{ijt} = \beta_0 + \beta_1' X_{Pit} + \beta_2' X_{Mjt} + \beta_3 X_{TVt} + \beta_4' X_{Bit} + \varepsilon_{it}$$

X_P includes a player's "box-score statistics": points scored, rebounds, steals, assists, blocked shots, turnover percentage, personal fouls, adjusted field goal percentage, and free throw percentage.[15] It also includes the player's position, age, whether or not the player signed with the same team,[16] the percentage of games in which he played the

past two seasons, and the ratio of games started to games played. These data come from the website basketball-reference.com. X_M includes the number of games the team won in the season before the free agent signed his latest contract, the size of the team's market, and dummy variables that indicate whether the team won the NBA Championship the previous year, whether it played in the NBA Finals the prior season, and whether it played in the conference finals the prior season. X_B also contains dummy variables denoting various agents[17] who represent players.[18]

Our estimates of the coefficients and the elasticities of the bargaining power equation appear in the last two columns of Table 9.[19] To show the difference between bargaining power and overall salary determination, we regress players' salaries on the same set of variables and present analogous results in the first two columns of the table. Both sets of estimates use robust standard error estimation.

Table 9. Bargaining Power and Salary Models: 2001-2011

Dependent Variable	$\ln(\text{Salary}_{ijt})$		$\ln(\text{BP}_{ijt})$	
Variable	**Coefficient**	**Elasticity (if p<0.10)**	**Coefficient**	**Elasticity (if p<0.10)**
Points Scored	1.073***	0.428	1.071***	0.427
	10.33		11.59	
Rebounds	1.202***	0.210	0.773***	0.135
	5.78		3.75	
Steals	0.697		-0.117	
	0.61		-0.13	
Assists	1.234***	0.107	0.730**	0.064
	3.55		2.28	
Blocked Shots	1.552***	0.032	1.818***	0.038
	2.86		3.58	
Turnover Percentage	0.006*	0.074	0.008**	0.104
	2.03		2.67	
Personal Fouls	-2.022***	-0.183	-1.991***	-0.180
	-3.24		-3.73	
Adjusted field goal percentage	0.490*	0.242	-0.011	
	2.00		-0.05	
Free Throw Percentage	0.220*	0.166	-0.021	
	1.87		-0.19	
Primary position was center	0.070**		0.033	
	2.62		1.46	
Primary position was power forward	0.073***		0.038*	
	3.04		1.79	
Primary position was shooting guard	-0.042		0.005	
	-1.38		0.17	
Primary position was point guard	0.002		-0.019	
	0.09		-0.82	
Age of player	-0.016***	-0.424	-0.016***	-0.423
	-5.72		-6.58	
Whether player signed with same team	0.070***		0.075***	
	3.92		4.37	
Ratio of games started to games played	0.203***	0.125	0.107***	0.065
	5.95		3.95	

Table 9. Bargaining Power and Salary Models: 2001-2011, continued

Dependent Variable	$\ln(Salary_{ijt})$		$\ln(BP_{ijt})$	
Variable	**Coefficient**	**Elasticity (if p<0.10)**	**Coefficient**	**Elasticity (if p<0.10)**
Team wins last season	0.004***	0.165	0.003***	0.129
	3.91		3.38	
Percentage of games played in last two years	0.292***	0.247	-0.029	
	4.26		-0.42	
Market Population (MM)	0.021		0.017	
	0.89		0.75	
Played on title team in previous year	-0.035		-0.062	
	-0.66		-1.10	
Played on conference title team in previous year	0.096*		0.091*	
	1.90		1.80	
Played in conference final in previous year	-0.053		-0.008	
	-1.46		-0.25	
TV Contract	0.006		-0.006	
	1.10		-1.47	
Agent was Andy Miller	0.009		0.024	
	0.21		0.65	
Agent was Arn Tellem	0.035		0.055	
	0.85		1.12	
Agent was Bill Duffy	-0.007		0.010	
	-0.14		0.24	
Agent was Dan Fegan	0.021		-0.004	
	0.70		-0.14	
Agent was Jeff Schwartz	0.076		0.072	
	1.66		1.49	
Agent was Jim Tanner	-0.012		-0.035	
	-0.22		-0.75	
Agent was Leon Rose	0.038		0.020	
	0.59		0.35	
Agent was Mark Bartelstein	-0.051		-0.041	
	-0.80		-0.78	
Agent was Rob Pelinka	0.080*		0.088	
	1.90		1.70	
Observations	483		483	
R-Squared [a]	0.716		0.624	

(t-statistics in parentheses)
**Significant at 10% level*
*** Significant at 5% level*
**** Significant at 1% level*
[a] *R-squared is calculated without fixed effects in STATA.*

According to our theoretical model, a player's performance should affect his marginal revenue product and have relatively little effect on his bargaining power. In this case, the coefficients and elasticities will be particularly large in columns one and two where we examine the determinants of overall salary.

At first glance, it appears that with respect to both models the process is essentially the same. With respect to overall salaries and our bargaining model, it appears that scoring is the dominant factor. The factors that drive wins[20]—shooting efficiency, rebounds, possession factors like turnovers and steals—are of less importance, statistically insignificant, or in the case of turnover percentage, have the incorrect sign. Such a result is consistent with prior work showing that NBA teams over-compensate a player for scoring and fail to reward/punish a player for shooting efficiency.[21]

When we turn to the non-performance factors, we also see similarities. Both salary and bargaining power are impacted by a player's age (younger is better), being a starter, signing with the same team, and playing for a winner. Playing in the NBA Finals (i.e., playing for a conference title winner) is also quite important. This latter result suggests that decision-makers have trouble separating a player from his teammates.

As noted, we also considered the impact of player agents because players are generally represented by an agent in contract negotiations. The results from the fixed effects model—where all the coefficients for agents are insignificant at the 5% level in both the salary and bargaining model—suggests that agents generally have the same degree of bargaining power. This does not suggest that agents do not matter. But it does suggest that the agents in our sample are not systematically better than the other agents we examined.

One weakness with the above estimation is that it necessarily focuses on the impact of the variables on the conditional mean. Thus, when we speak of an increase or decrease in bargaining power, we are looking only at the average player given our independent variables. As a final check on how bargaining power and fixed revenue interact, we follow Kowalewski (2010) and run a series of quantile regressions (QRs) of the salary equation to determine how our independent variable affect players with different degrees of bargaining power.

The quantiles in a QR tell us what position a player occupies in the distribution of the error term conditional on the values of the independent variables. Thus, the 90th quantile refers to players who are extremely highly paid, given their performance statistics and other control variables. In contrast, a player in the 10th quantile is very poorly compensated conditional on the same variables. We can thus interpret the quantile as a measure of a player's bargaining power. A player in the 90th quantile has managed to secure a contract that is far superior to an identical player in the 10th quantile. The coefficients of the QRs in Table 10 tell us how the independent variables affect the natural logarithms of salary for players at specific conditional quantiles. The results here are only for coefficients that were significant at the 10% level. An entry of "—" means that the coefficient was statistically insignificant at that quantile.

Several results are notable in Table 10. Among the performance variables, the impact of points steadily rises and the impact of steals steadily fall, with the results at the extremes statistically different from each other. If the increasing quantiles correspond to increasing bargaining power, these results suggest that players with the greater bargaining power are more able to translate points into salary but less able to translate steals into salary. Similarly, while they do not show steady progression, players with the lowest bargaining power are helped by having a higher free throw percentage, while players with the greatest bargaining power are helped by having more assists.

Table 10. Select Quantile Regression Results: 2001 to 2011

Variable	0.1	0.25	0.5	0.75	0.9
Points Scored^{Z}	0.824***	0.964***	1.045***	1.190***	1.215***
	7.20	7.84	8.80	11.63	8.34
Rebounds	—	0.460**	0.827***	0.803***	0.846***
	—	2.43	3.46	3.71	2.80
Steals	2.730***	1.541*	—	—	-2.780**
	3.26	1.89	—	—	-1.97
Assists	—	—	—	—	0.959*
	—	—	—	—	1.86
Blocked Shots^{Z}	1.451*	1.383**	1.616**	2.104***	3.032***
	1.92	2.37	2.22	2.98	3.46
Turnover Percentage	0.008*	0.013***	0.011***	0.008**	—
	2.07	4.12	3.00	2.46	—
Personal Fouls^{Z}	-1.549***	-0.829*	-1.772***	-1.728***	-2.591***
	-2.84	-1.92	-3.56	-3.72	-4.25
Adjusted field goal percentage	—	—	—	—	—
	—	—	—	—	—
Free Throw Percentage	0.307***	—	—	—	—
	2.87	—	—	—	—
Primary position was center	0.046*	—	—	—	—
	1.97	—	—	—	—
Primary position was power forward	0.046*	0.046*	—	—	—
	1.91	1.79	—	—	—
Primary position was shooting guard	-0.045*	—	—	—	—
	-1.69	—	—	—	—
Primary position was point guard	—	-0.050*	-0.047*	-0.067**	-0.097**
	—	-1.79	-1.78	-2.57	-1.99
Age of player^{Z}	-0.019***	-0.017***	-0.016***	-0.011***	-0.014***
	-7.43	-6.83	-6.15	-4.77	-4.79
Whether player signed with same team^{Z}	0.060***	0.062***	0.050***	0.066***	0.067***
	3.57	3.95	2.77	3.83	3.02
Ratio of games started to games played^{Z}	0.093***	0.137***	0.161***	0.140***	0.100***
	3.50	5.53	5.32	5.19	2.98
Team wins last season^{Z}	0.004***	0.004***	0.004***	0.003***	0.005***
	4.15	5.05	4.38	3.07	3.96
Percentage of games played in last two years	—	—	—	—	—
	—	—	—	—	—
Market Population (MM)	—	—	—	—	—
	—	—	—	—	—
Played on title team in previous year	—	—	—	—	—
	—	—	—	—	—
Played on conference title team in previous year	0.095**	—	—	—	—
	1.98	—	—	—	—
Played in conference final in previous year	—	—	—	—	—
	—	—	—	—	—
TV Contract	—	—	—	-0.007*	-0.021***
	—	—	—	-1.91	-3.91
Agent was Andy Miller	—	—	—	—	—
	—	—	—	—	—
Agent was Arn Tellem	—	—	—	0.108*	—
	—	—	—	1.80	—

Table 10. Select Quantile Regression Results: 2001 to 2011, continued

Variable	0.1	0.25	0.5	0.75	0.9
Agent was Bill Duffy	—	—	—	—	—
	—	—	—	—	—
Agent was Dan Fegan	0.060***	—	—	—	—
	2.80	—	—	—	—
Agent was Jeff Schwartz	0.126***	—	—	0.082**	—
	5.37	—	—	2.16	—
Agent was Jim Tanner	—	—	—	—	—
	—	—	—	—	—
Agent was Leon Rose	—	—	—	—	—
	—	—	—	—	—
Agent was Mark Bartelstein	—	-0.083***	—	—	—
	—	-3.37	—	—	—
Agent was Rob Pelinka	—	0.091*	0.046*	—	0.138**
	—	1.68	1.71	—	2.37

"—" *The coefficient is statistically insignificant in this regression*
[z] *–Statistically significant at every quantile*
(t-statistics in parentheses)
**Significant at 10% level*
*** Significant at 5% level*
**** Significant at 1% level*

Height seems to be rewarded at the lowest quantiles. Playing center and power forward helps, while playing shooting guard hurts (relative to small forward, our default category). None of these has an impact at higher quantiles. The exception is point guard, which has a significant negative impact at every quantile but the lowest. Playing point guard thus has a negative impact on the players with the greatest bargaining power.

Some variables appear to have a very steady impact, which suggests that their impact is independent of a player's bargaining power. Signing with one's previous team, the ratio of games started to games played, and the team's wins in the previous season all have a positive impact on salary. Age has a steady negative effect on salary.

Agents have a spotty effect. Some seem most effective at helping players with little bargaining power, while others have their greatest impact on players with sizable bargaining power. Notably, no agent has a positive impact across all levels of bargaining power.

Two variables have a notably compressing effect on salary. Playing on a conference winner has a positive impact only on players with the least bargaining power. Finally—and most important for our purposes—the size of the TV contract has a negative and statistically significant impact on player salaries at both the 75th and 90th quantiles. This last result highlights the impact of fixed revenues. Network TV revenue is not linked to individual players or even individual teams. It is shared equally among teams and appears to equalize salaries, subsidizing players with low bargaining power at the expense of players with high bargaining power.

Our finding that broadcast revenue is used to equalize salaries is consistent with other studies of the NBA. For example, Berri and Schmidt (2010) note that 80% of all wins in the NBA are produced by less than 25% of all player season observations. This disparity in productivity is not reflected in player salaries. The NBA's cap on individual player

salaries means that, although LeBron James produced more than 1/3 of the Miami Heat's wins in 2012-13, his salary of $17.5 million was only 21% of the team's payroll.

We should also note the role of agents. There is no agent that impacts bargaining power at each quantile. And only two agents—Jeff Schwartz and Rob Pelinka—that impact bargaining power at more than one quantile. This again suggests that agents, in general, do not consistently impact a player's bargaining position.

Conclusion

We have analyzed a market imperfection that has, to date, received little attention. Specifically, many firms receive revenue in forms that are difficult or impossible to trace to the behavior of current employees. This can occur, for example, when university students pay tuition prior to signing up for their classes, let alone receiving any benefit from them, or when output depends on the complex interaction of various teams of employees. This requires an adjustment to the standard model of the labor market in which workers are paid their marginal revenue product. As often is the case, sports provide a unique laboratory that allows us to connect revenue, productivity, and pay in a way that other labor markets do not.

A large percentage of the revenue that flows to major league sports teams in North America, particularly in football and basketball, stems from broadcast rights that were negotiated several years earlier. Thus, much of a team's revenue has no direct connection to the current performance of any of its players. If we base compensation on the players' direct contributions to revenue, we reach the inevitable conclusion that players are vastly overpaid. However, few would agree with the natural conclusion of this line of reasoning: Owners should keep a significantly higher fraction of revenue than they currently do.

We resolve this dilemma by creating a model of player compensation that has two components. The first is a payment based on players' (expected) contributions to team revenues based on their current performance. The second is the result of a bargaining model in which individual players and owners negotiate over the revenue (or the portion of revenue allocated to players) that is not tied to individual performance. While performance increases a player's bargaining power, the impact is relatively smaller, as performance acts directly on a player's MRP but only indirectly on his bargaining power. In addition, we tend to find that agents do not tend to impact a player's bargaining power.

We use quantile regression (QR) to take a different look at pay determination. Interpreting a higher quantile as representing higher bargaining power, we find that performance measures have roughly the same impact on salary across most quantiles. The size of the TV contract, though, impacts the bargaining power of those players in the highest quantiles. This result indicates that revenue from the TV contract acts as an equalizing factor in player salaries.

Our results extend well beyond sports, as many firms receive fixed revenues that cannot be tied to the contributions of individual workers. In such situations, paying workers their marginal products would leave large reserves for the owners. This study provides a template for evaluating compensation in such situations. For example, the growing income inequality in the United States might reflect reduced bargaining power of workers over the fixed revenue of firms.

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Endnotes

[1] For a sampling of the studies that build on Scully's work, see Medoff (1976), Sommers and Quinton (1982), Raimondo (1983), Blass (1992), Zimbalist (1992), and Bradbury (2010, 2012).

[2] In fairness to Scully, most players at the time of his study did have only one-year contracts.

[3] Scully (1974) claims that both players and managers affect outcomes. Berri (2008) and Berri, Leeds, Leeds, and Mondello (2009) argue that only players directly impact outcomes on the field. Managers impact outcomes indirectly by improving the performance of players and by choosing which players appear in the game.

[4] Every year, *Forbes* magazine publishes valuation data for all teams in each of the four leagues. While official revenue figures are not available because the teams are all privately held, *Forbes* estimates are widely regarded as the best available and used extensively in published empirical work.

[5] Stadium data can be found at "Ballparks by Munsey and Suppes" (ballparks.com)

[6] Forrest and Simmons (2006) examined demand for English League soccer. As these authors observed: "An appropriate estimation method in our case is one which allows for the presence of AR(1) autocorrelation within panels plus cross-sectional correlation of errors and/or heterogeneity across panels. One such method is a Prais-Winsten regression model with panel corrected standard errors and common AR(1) autocorrelation parameter. This method delivers consistent estimates where disturbances are heteroscedastic across panels and can be applied to unbalanced panels, as is the case here. Although FGLS (feasible generalized least squares) would provide more efficient estimates of the model parameters, we reject it on the grounds that the estimates of standard errors are then conditional on the estimated disturbance covariance. Beck

and Katz (1995) show that FGLS estimates of standard errors are insufficiently conservative (too optimistic) compared to the Prais-Winsten model."

[7] Scully (1974) (and other authors) employed a linear functional form in estimating his model of revenue. Berri, Schmidt, and Brook argue, though, in favor of a double-logged model. However, for our purposes a double-logged model is problematic. Such a model provides a different slope estimate for each win. Because we wish to sum the value of wins across all players on a team, having a multitude of slope estimates creates computational problems since it is not clear which slope estimate should be used for each win. Consequently we employ the more traditional linear model. We thank Tony Krautmann for noting the problems with employing a double-logged model.

[8] We also considered several alternative specifications (not shown here) that excluded lagged wins and/or fixed effects. In no case did wins explain more than approximately one-third of revenue for 2010-11 in the NBA. Results in the other leagues were similar. Only in baseball—the sport that people most frequently investigate with respect to MRP—did any result suggest that wins generate 50% of league revenue. Results of alternative specifications appear in Table 5.

[9] For a complete discussion of the models, see McLaughlin (1994) and Kowalewski (2010).

[10] Through a historical quirk, the broadcast revenue is split 31 ways, with one share going to the former owners of the Spirits of Saint Louis, a team from the old American Basketball Association (see Abrams, 2006).

[11] In October of 2014 the NBA announced a new television deal that will be in place after the 2015-16 season. The new deal increases the yearly fee from $930 million to $2.66 billion. (http://espn.go.com/nba/story/_/id/11652297/nba-extends-television-deals-espn-tnt). It seems clear that LeBron James understood that this contract was about to increase dramatically in value. Although James was eligible to sign a four-year deal during the summer of 2014 with the Cleveland Cavaliers, he opted for a two-year deal instead. As the *USA Today* reported, this move would allow James to take advantage of the upcoming television deal (http://www.usatoday.com/story/sports/nba/cavaliers/2014/07/12/lebron-james-contract-two-years-cleveland-cavs/12578491/). In sum, it was the negotiation over the NBA's fixed revenues that motivated the contract decision that James made.

[12] Local revenue could also be thought of as fixed, since these contracts can also cover multiple seasons. But data on the contracts for every NBA team is difficult to come by. Even in a sport like baseball, Rodney Fort's extensive data collection only reports local media contracts to baseball teams until 1994 (see https://sites.google.com/site/rodswebpages/codes). We thank an anonymous referee for noting the issue of local revenues.

[13] The NBA Efficiency model (detailed originally at NBA.com and in Berri et al. (2007)) simply adds together a player's positive box score statistics and subtracts the negative statistics. Berri et al. (2007) shows that NBA Efficiency does a very good job of explaining player salaries. And since our focus is on explaining salaries and bargaining power, it appears to be good metric for our purposes. We should note, though, that NBA Efficiency (and similar metrics like Player Efficiency Rating and Points Created) does a much worse job of explaining wins (see Berri & Schmidt, 2010). Oddly enough, this is because these metrics fail to properly reward and/or punish shooting efficiency. To convert NBA Efficiency to wins, team wins were regressed on a team's NBA Efficiency. The coefficient from this regression was then employed to measure how many wins a player's NBA Efficiency was worth. Again, NBA Efficiency is a poor metric of performance, as this measure predicts far more player wins than was possible. So we normalized wins to arrive at the final measure of wins employed in our study. We also repeated this analysis using the Wins Produced metric. Wins Produced was explained in Berri (2008) and updated at http://wagesofwins.com/how-to-calculate-wins-produced/. This metric does an excellent job of explaining wins, accounting for about 95% of the variation by team win percentage, but—as explained in Berri et al. (2007)—it does a poor job of explaining player salaries. This is because decision-makers historically undervalue shooting efficiency (which explains wins) and overval-

ue player scoring totals (which may not help a team win games). Nevertheless, our findings are essentially the same whether we measure performance with Wins Produced or NBA Efficiency.

[14] If we employ Wins Produced as our measure of performance, the average difference between Estimated MRP and Real Average Free Agent Salary is $3.2 million. Results available from authors upon request.

[15] Following Berri et al. (2008), player statistics are adjusted for position played. Following Berri and Schmidt (2010), the "box-score statistics" are the average of a player's performance across the two seasons prior to free agency. Player data can be found at basketball-reference.com.

[16] The collective bargaining agreement often gives a team signing their own player an opportunity to pay more than other teams.

[17] DraftExpress.com reports the agents who represent various players. To be considered in our study the agent had to be linked to at least 10 players who were part of our data set.

[18] In addition our model includes dummy variables for years and team specific fixed effects.

[19] We report elasticities only for coefficients of continuous variables that were significant at the 10% level. Because this is a semi-logged model, these are estimated at the point of means.

[20] Berri et al. (2007), Berri (2008), and Berri and Schmidt (2010) discuss in detail the factors that drive wins in the NBA.

[21] For more on this finding see Berri et al. (2006, 2007) and Berri and Schmidt (2010).