Department of Economics

Working Paper Series

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Working Paper No. 15-48

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Monopsony Exploitation in Professional Sport: Evidence from Major League Baseball Position Players, 2000-2011

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November 30, 2015

Abstract

Some professional athletes still face monoposony power in labor markets, underscoring the importance of estimating players' marginal revenue product (MRP) to assess its effects. We introduce two new empirical approaches, spline revenue functions and fixed-effects stochastic production functions, into the standard Scully (1974) approach to MRP estimation, and calculate Monoposony Exploitation Ratios (MERs) for position players in Major League Baseball over the 2001-2011 seasons. Estimates indicate that MERs are about 0.89 for rookie players, 0.75 for arbitration eligible players, and 0.21 for free agents. Recent collective bargaining agreements have reduced MERs for free agents, but had no effect on MERs for other players.

Keywords: monoposony salary exploitation, Major League Baseball, marginal revenue product

JEL Codes: J24, J42, J52, L13, L40, Z22

Introduction

Markets in the professional sports industry have several unique features compared to other industries; one is a combination of both monopoly power in output markets and monopsony power in input markets. Teams usually have monopoly power over fans in their local market, and they also have monopsony power over players in the labor market. The monopoly power of teams, which

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stems from territorial exclusivity in sports franchise agreements, could be mitigated to the extent that sports teams compete with teams in other leagues or firms in other industries. For example a National Hockey League team may compete with a team in the National Basketball Association in their local market or with movie theatres for local entertainment spending. However, monopsony power in the labor market matters for players, who have few employment alternatives compared to workers in other industries.

This monopsony power stems from unique institutional arrangements like restrictive clauses in standard player contracts and entry drafts, and was fully guaranteed until 1968 in Major League Baseball (MLB). After the first Collective Bargaining Agreement (CBA, also known as the Basic Agreement in MLB) was signed in 1968, the players' union, the Major League Players Association (MLBPA), has been trying to weaken this monopsony power through collective bargaining. As a result, players are now subject to different levels of monopsony power according to their MLB experience.

This paper documents the amount of monoposony exploitation experienced by players and exploits quasi-experiment created by variation in the terms contained in recent CBAs between the MLBPA and MLB to assess changes in monoposony exploitation over time. Other recent research focused on marginal revenue product in MLB includes Bradbury (2008), Bradbury (2010), Rockerbie (2010), and Bradbury (2013).

The empirical analysis in this paper estimates Marginal Revenue Product (MRP), using data on team revenues, on-field success, and player performance statistics, using the standard three-step Scully's (1974) approach, employing two new empirical methods. For the revenue function estimates, a spline regression model is applied to the team success-revenue relationship following Oh and Lee (2013). For the win production function estimates, a stochastic production frontier model with team-fixed effects is used to estimate the production function parameters; this approach allows for, and generates estimates of, technical inefficiency in a flexible way that does not involve including specific performance variables in the production function model, like finishing within 5 games of first place, previously used in the literature. Using estimated MRP and actual salary data, Monopsony Exploitation Rates (MERs) are estimated following Scully (1974). These MERs are an estimate of teams' monopsony power over players. A second empirical analysis focuses on analyzing changes in MER under three CBAs and among three player experience groups.

The advantage of this empirical approach is that measurement error in MER estimates will be mitigated because of the use of a stochastic frontier model with team-fixed effects. Standard models used to estimate MRP may suffer from omitted variables problems in the form of inability to find adequate proxy variables for managerial ability, fielding ability, player effort, and other factors affecting team success. Measurement error in MER estimates can be reduced by using a stochastic frontier model, since the effects of omitted variables can be captured by the relatively flexible technical efficiency estimates in the stochastic frontier model. In addition, by using a regression model to analyze variation in MERs, this measurement error will not matter when assessing observed variation in estimated MER if the expected value of the measurement error for an given experience group or CBA period is equal.

The empirical analysis finds that monopsony power over players with one to six years of MLB experience (rookies and salary arbitration eligible players) does not change significantly over the periods covered by three recent CBAs. However, monopsony power over players with 7 years or more MLB experience (free agents) significantly decreases over time. Recent CBAs appear to concentrate on improving conditions for free agent players rather than rookies or salary arbitration eligible players. Because of the relatively short careers of MLB players, this result indicates that a majority of MLB players are still under substantial monopsony power.

These findings suggest that the MLBPA should pay more attention to rookies and salary arbitration eligible players rather than free agents when negotiating future CBAs. In addition, this paper contributes to the literature on monopsony power in other labor markets as the market structure in professional sports resembles those for coal miners, public school teachers, nurses and university professors in terms of monopsony power (Boal and Ransom, 1997). Moreover, it is usually hard to estimate the productivity of workers in other industries compared to professional athletes (Kahn, 2000). Therefore, these findings may be useful for understanding the labor market structure in other industries.

Institutional Background and Previous Literature

Entry drafts, the reserve clause, and other institutional arrangements generate substantial monopsony power in sports labor markets. Rosen and Sanderson (2001) contains a concise survey of

these features. Eligible athletes first entering professional sports labor markets in North America cannot sell their services to the highest bidder. Instead, new players must pass through an amateur entry draft that assigns the rights to purchase their labor services exclusively to a specific team. In addition, after the entry draft, players are initially subject to the "reserve clause", a clause in the standard player's contract that binds players to the team that owns their contracts for a certain number of years. Players under the reserve clause face substantial restrictions when negotiating with teams over salary.

Until the 1970s, the reserve clause applied to all professional athletes in team sports in North America. Beginning in the 1960s in MLB, players began pushing for the removal of labor market restrictions, primarily in the form of free agency, the ability to sell their services to the highest bidder on the open market. MLB players ultimately won the rights to a limited form of free agency, as did players in other leagues, through unionization and collective bargaining. In the free agency era, collective bargaining agreements (CBAs) between players' unions and leagues govern labor relations in professional sports leagues in North America. Staudohar (1996) examines this process in detail.

The MLB players' union, the Major League Baseball Players Association (MLBPA), engages in collective bargaining with the league over all aspects of employment on behalf of all players. This collective bargaining process generates Collective Bargaining Agreements (CBAs), also known as the "Basic Agreement" in MLB). The first MLB CBA was signed in 1968. Via collective bargaining, the MLBPA has reduced the effectiveness of the the reserve clause over time by increasing minimum salaries and pension benefits, introducing the process of salary arbitration, and, most importantly gaining free agency for some players.

Three different CBAs were in place over the 2000 to 2011 MLB seasons. Each CBA included different minimum salaries, as well as changes in FA contracts or the salary arbitration process MLB (2003, 2007). These CBA changes may affect the degree of monoposony power for rookies, arbitration eligible players, and FAs.

CBAs define player eligibility for salary arbitration and free agency. These conditions change over time as the MLBPA pushes for additional economic freedom through the collective bargaining process. MLB players are exposed to different levels of team monopsony power based on service time, the number of days a player spends on the roster of a MLB team. CBAs also precisely define

service time based on the number of games players spends on MLB rosters and the number of games played during the regular season.

Generally, rookie players, players who have 1-2 years of MLB service time, remain fully under the reserve clause and are exposed to the maximum possible monoposony power. Players with 3 or more years of MLB service, but less than 6 years, are eligible for salary arbitration, and are subject to less monoposony power than rookies. Salary arbitration eligible players can appeal to an independent arbitration process when they fail to agree to a new contract with their current team. However, salary arbitration eligible players are still subject to monopsony power as they cannot freely move to another team. Players who have 6 or more years of MLB service time can become a free agent (FA) and sell their services to the highest bidder. Free agents are subject to the least monoposony power.

This discussion makes some simplifications about when players technically qualify for free agency. MLB service time is calculated in days and years, and days of MLB service time are accrued even on days when no game is played. Technically, a year of service time is defined as 172 days of service time. The typical MLB season contains about 183 service days, but players can earn only 172 service days in any MLB season. Early in their careers, players may move back and forth between the Major League roster and the roster of a minor league team. A player who first appeared in, say, the 2003 MLB season could have accrued at most 172 days of service time in that season, but may have accrued substantially less. So a player who spent time on both a major league roster and a minor league roster might not qualify for salary arbitration until after his third season of play; this player might also only qualify for free agency after spending 6 seasons on a major league roster.

Standard models of producer behavior predict that, in perfectly competitive industries with free entry, full information, profit maximizing firms, and no labor market imperfections, labor inputs should be paid compensation equal to their marginal revenue product (MRP). Monoposony power generates compensation below an input's MRP. Rookie players face the most monoposony power and should be paid salaries well below their MRP. arbitration eligible players face less monoposony power and should have salaries closer to their MRP than rookies. FA players face the least monoposony power and should have salaries near their MRP.

Some FA players may have monopoly power over teams in the labor market, if a team believes

that there no substitutes exist for that player. For example, Alex Rodriguez, at the time the highest paid MLB player, signed a 10 year contract with the New York Yankees in 2008, at the age of 33. Regardless of the total amount of compensation specified in the contract, it would be difficult to argue that a 10 year contract for a 33 year old player reflected expected MRP over that 10 year period, as no one believes that a baseball player can maintain a high level of play for 10 more years after the age of 33. Rather, this contract may reflect Rodriguez's monopoly power. On the other hand, FA players may still sign contracts with salaries less than their MRP. Some FA contracts may reflect loyalty to local fans or teams. In addition, FA players earn salaries less than their MRP when many substitute players exist on the FA market.

Scully (1974) produced the first estimates of MRP for professional athletes. Professional sports leagues in North America contain several institutional structures, discussed above, that generate substantial monoposony power for teams in labor markets, motivating Scully's analysis of the relationship between MRP and salaries. Scully (1974) estimated MRP using a three step procedure discussed below, and calculated a Monopsony Exploitation Rate (MER), for each player that indicates the degree of monoposony exploitation experienced by each player.

By definition, a positive MER means that players are paid less than their contribution to team revenues. Therefore, players with a positive MER are subject to monopsony power. On the other hand, players with a negative MER are not subject to monopsony power and in fact may have some monopoly power in the labor market as their pay exceeds their MRP. Previous research estimates MER for players who have 1-2 years of experience (rookies), players who have 3-5 years of experience (salary arbitration eligible players) and free agent players separately, as each group of players is subject to different levels of monopsony power. As rookies are usually fully under the reserve clause, the MER for rookies should be the highest compared to other players.

Salary arbitration eligible players have some redress for the reserve clause, so their MER should be lower than rookies, but their salary is still likely to be less than their MRP. As FA players can solicit salary offers from any team, their MER is estimated as lowest among these groups in several papers (Scully, 1989; Zimbalist, 1992; Oh and Lee, 2013). Zimbalist (1992) and Oh and Lee (2013) estimated a negative MER for some FA players, indicating FA players have a monopoly power while Scully (1989) found that FA players are still under monopsony power. However, because of measurement error in MER, it is hard to determine whether FA players are under monopsony

power or have monopoly power.

Krautmann (1999, 2013) provides other methods for estimating MRP. Because Scully's (1974) method has some limitations, and the revenue data from Forbes may not be reliable, Krautmann assumed that the FA players market is perfectly competitive and estimated MRP using data on FA players salaries. However, this approach will not be appropriate in the case where FA players have monopoly power in the labor market because the author assumes that the labor market for FA players is perfectly competitive.

Recently, several papers relaxed the assumption of linearity for both the team revenue function and the team product function. Rockerbie (2010) uses a logistic function to estimate the team product function. This logistic function allows for different marginal products for batting and pitching performance between teams of high and low quality in terms of winning percentage.

Lee (2011) estimates a stochastic production frontier model for the team production function which takes into account technical inefficiency in production process. For the team revenue function, Oh and Lee (2013) use a spline regression model allowing marginal revenue to vary systematically with team success. Bradbury (2008, 2010) uses polynomial functions of team winning percentage. This paper uses a spline regression model for the team revenue function and a fixed-effects stochastic production frontier model for the team production function.

Empirical estimates of the parameters of team production functions often suffer from omitted variable problems stemming from the lack of good proxy variables for managerial ability, fielding skills, and player effort, and these omitted variables might generate measurement error in MER (Scully, 1974, 1989; Zimbalist, 1992; Oh and Lee, 2013). However, these omitted variables might be controlled for in a stochastic frontier model in terms of inefficiency (Dawson et al., 2000; Lee, 2011). This efficiency estimate is also expected to capture other possible omitted variables in production such as interaction effects between individual player performance and team performance, opposing team characteristics, career composition on teams, and other factors.

Econometric Approach

A substantial literature exists estimating the marginal revenue product (MRP) of athletes. Scully (1974) developed the basic estimation approach, a three step procedure. Step one estimates the

marginal value of a win to each team in a sports league using a regression model. Step two links team performance to wins, basically estimating a production function for teams in the league using a regression model. Step three combines key results from the first two steps, the estimated marginal revenue from a win and the estimated marginal product of specific performance measures, with individual player performance measures to generate estimates of each players MRP. MRP estimates are sometimes compared to actual salaries in order to assess the extent to which players are underpaid (an estimate of monoposony exploitation) or overpaid.

Step one in the Scully (1974) MRP estimation procedure estimates the marginal revenue of a win from a basic linear team revenue function

$$TR_j = \alpha_0 + \alpha_1 WP_j + \alpha_2 X_j + u_j \tag{1}$$

where TR_j is the total revenue for team j, WP_j is the winning percentage for team j, X_j is a vector of independent variables that affect the total revenue, and u_j is a mean zero, constant variance equation error term. In panel data applications, variables include a t subscript since revenues and team level performance are observed over multiple seasons. $\hat{\alpha}_1$ is an estimate of the marginal revenue generated by a win.

Several extensions have been made to this approach in subsequent research, primarily in terms of relaxing the assumption of a linear relationship between team success and revenues. Nonlinearities can arise because the return to postseason wins, which only the most successful teams qualify for, are more valuable than the return to regular season wins. Oh and Lee (2013) employ a spline regression model to relax the linearity assumption. Bradbury (2008) includes a quadratic term in the revenue function. Bradbury (2010) uses a cubic function. We follow Oh and Lee (2013) and estimate the following spline regression model

$$\begin{aligned} TR_{jt} = \beta_0 + \beta_1 WP_{jt} + \beta_2 D_k(WP_{jt} - 0.55) + \beta_3 SMSA_{jt} + \beta_4 PS_{jt} \\ + \beta_5 AL_{jt} + \beta_6 NSTADM_{jt} + \beta_7 UNEMP_{jt} + \alpha_j + \lambda_t + \epsilon_{jt} \end{aligned} \tag{2}$$

where TR_{jt} is total revenue earned by team j in season t and WP_{jt} is the winning percentage for

team j in season t. The third term on the right hand side of Equation (2) is the spline portion of the model. Spline models specify a break point in the distribution of some explanatory variable; above this break-point, the marginal return to additional wins increases. Following Oh and Lee (2013) the break point is defined as a winning percentage of 0.55 or higher. D_k is a dummy variable such that $D_k = 1$ indicates teams for which $WP_{jt} > 0.55$; $D_k = 0$ otherwise. By using this spline regression model, MR for a team with a winning percentage greater than 0.55 will be measured by $\beta_1 + \beta_2$; the MR for a team with a lower winning percentage in season t will be measured by β_1.

The remaining explanatory variables in Equation (2) reflect factors not related to team success that affect total revenues. $SMSA_{jt}$ is the estimated population in millions of the metropolitan area that is home to team j in year t. PS_{jt} is an indicator variable for postseason appearances in season t. AL_{jt} is an indicator variable for teams in the American League which captures league-wide differences in revenues or markets. Teams playing in new stadiums typically earn higher revenues because of the novelty of these new facilities (Coates and Humphreys, 2005). $NSTDM_{jt}$ captures the effect of a new stadium on revenues. If team j played in a new stadium that opened in season, $NSTDM_{jt} = 4$; the value of this variable decreases by 1 in each year, so $NSTDM_{jt} = 0$ after 5 years. Coates and Humphreys (2005) estimate the novelty effect of new facilities lasts about 5 seasons. $UNEMP_{jt}$ is the unemployment rate in metropolitan area home to team j in season t.

We estimate the unknown parameters of Equation (2) using panel data. α_j is a team-specific intercept and λ_t is a year-specific intercept. ϵ_{jt} is an observable error term that captures other omitted factors that affect team revenues. We performed a Hausman test to assess weather the team-specific effects should be modeled as fixed or random; this test failed to reject the null that random effects model fits the data best (test statistic 9.33, p-value 0.923); all estimates of Equation (2) include random effects. Team level clustered-robust standard errors were estimated to control for within-team correlation.

Step two in the Scully (1974) MRP estimation procedure estimates the relationship between specific performance measures and team wins, a proxy for the marginal product of players, using a linear approximation to a team production function where the performance of batters and pitchers are inputs

$$WP_j = \beta_0 + \beta_1 PERF_j + u_j. \tag{3}$$

In this regression model WP_j is the winning percentage for team j and $PERF_j$ is a vector of player performance measures in season j. Scully (1974, 1989) used team slugging percentage (SLG) to proxy for hitter's inputs and team strikeout-to-walk ratio (K/BB) to proxy for pitcher's inputs to the team's production of wins. Some debate exists about the appropriate performance measures. Zimbalist (1992) argued that SLG favors power hitters and K/BB favors pitchers with an above average fast ball. Because SLG is the weighted average of singles, doubles, triples and home runs and does not include walks, SLG may not adequately explain team success.

Along the same lines, Zimbalist (1992) argued that K/BB does not adequately explain team success as it does not include actual hits or runs that pitchers allow. Therefore, Zimbalist suggests On-base Percentage Plus Slugging Average (OPS), which includes walks, as a hitter performance measure and Earned Run Average (ERA), which includes runs allowed, rather than K/BB for a measure of pitching performance.

Rockerbie (2010) used SLG, SLG^2 and K/BB. Sommers and Quinton (1982) used SLG and K/BB. Oh and Lee (2013) used Modified OPS (MOPS) as well as OPS for hitter's performance, and Walks plus Hits per Inning Pitched (WHIP) for pitcher's performance. Because runs depend on the defensive ability of fielders as well as pitching performance, WHIP is expected to be a better indicator for evaluating pitching performance. Following Zimbalist (1992) and Oh and Lee (2013), we use OPS and WHIP as performance measures.

Scully (1974) also recognized that other factors, including managerial decisions and effort, affect a team's production of wins and included dummy variables for first place teams and teams within 5 games of the first place team, and for teams that finished more than 20 games behind the first place team, in this regression model. Most later papers include similar variables. Sommers and Quinton (1982) note that including variables based on winning percentage in a regression explaining observed variation in winning percentage contains a whiff of endogeneity problems, but includes these variables in their regression model.

Recent research has extended the estimation parameter of a team production function in several ways. Rockerbie (2010) estimates a logistic model, since the dependent variable is bounded by zero below and one above. Lee (2011) applies a stochastic production frontier model to relax the assumption of linearity, and allow for managerial inefficiency to affect the relationship between player performance and team success. This approach allows for a more flexible accounting for

managerial ability and variable effort than the intercept-shift variables used by Scully (1974) and Rockerbie (2010). Indicator variables for teams finishing at the top and bottom of the standings assume that managerial inefficiency and variable effort provision shift the entire production function and affect all top teams, and all bottom teams, in the same way.

A standard Cobb-Douglas production function with a single input proxy variable for hitters and pitchers embedded in the true random effects in stochastic frontier model developed by Greene (2005) yields a regression model

$$\ln WP_{jt} = \varepsilon_j + \delta_1 \ln BPERF_{jt} + \delta_2 \ln PPERF_{jt} + v_{jt} - u_{jt} \tag{4}$$

where $BPERF_{jt}$ is the proxy variable for the performance of hitters on team j in season t and $PPERF_{jt}$ is the proxy variable for performance of pitchers on team j in season t. Following Zimbalist (1992) and Oh and Lee (2013) OPS, the sum of team slugging percentage and team on-base percentage is used for hitter's inputs and WHIP, team walks plus team hits divided by team innings pitched, is used for pitcher's inputs.

In panel data stochastic frontier models, u_{jt} captures non-negative "technical inefficiency" errors for team j in season t. u_{jt} reflects how far from the ideal production frontier team j is in season t, based on observed inputs and output. In this context, "technical inefficiency" errors reflect the consequences of managerial decisions and variable effort provision by players. v_{jt} is a standard mean zero, constant variance equation error term that captures other factors that affect team success. u_{jt} is assumed to be follow normal-exponential distribution. u_{jt} and v_{jt} are assumed to be uncorrelated.

ε_j, $j = 1, \ldots, N_T$ is a team specific fixed effect. Greene (2005) develops a fixed effect and random effects estimator for the production function represented by Equation (4), and an associated Hausman test that can be used to choose between random and fixed effect models. The null hypothesis that the random effects model best fits the data is not rejected in this setting. We estimate the random effects model version of Equation (4).

The stochastic frontier model with controls for unobservable team-level heterogeneity allows for the estimation of marginal product of performance variables and controls for managerial efficiency and variable effort in a way that avoids endogeneity issues from including variables calculated from

winning percentage and also avoids omitted variables bias associated with finding proxy variables reflecting low effort or poor managerial decisions.

For this panel data stochastic frontier model, the marginal effect of player performance on team winning percentage is

$$\frac{\partial WP}{\partial BPERF} = \widehat{\delta}_1 \frac{WP_{jt}}{BPERF_{jt}} \tag{5}$$

Equation (5) can be combined with parameter estimates from the marginal revenue model, Equation (4), to generate estimates of the marginal revenue product (MRP) of player performance. For hitters, the marginal revenue product of team OPS is

$$\widehat{HMRP}_{jt} = (\widehat{\beta}_1 + \widehat{\beta}_2 D_k) \times \widehat{\delta}_1 \frac{WP_{jt}}{BPERF_{jt}} \tag{6}$$

Step three in the Scully (1974) MRP estimation procedure uses the marginal revenue and marginal product estimates from steps one and two to generate estimates of marginal revenue product for individual players. Scully (1974, 1989) calculates an individual players gross MRP using the ratio of each players contribution to total number of at bats or innings pitched in each season. Following Scully (1974, 1989), each player's MRP can be estimated from Equation (6). For example, for the player i on team j who had Z% of the total number of team j's at bats in season t, estimated MRP is

$$\widehat{MRP}_{ijt} = (\widehat{\beta}_1 + \widehat{\beta}_2 D_k) \times \widehat{\delta}_1 \frac{WP_{jt}}{BPERF_{jt}} \times Z_{ijt}. \tag{7}$$

This approach assumes that the performance of an individual player generates no externalities on other player's performance. Each player's contribution to team wins is the sum of each player's at bats over the course of a season. Scully (1974) argued that if externalities exist, for example in the form of spill-over effects generated by where each hitter bats in the line-up, they are small. Unlike the first two steps, this step has been generally followed in subsequent research.[1]

Scully (1974, 1989) estimated MRP for pitchers using Z calculated from the number of innings

[1]Scully (1974) called the estimates from Equation (7) gross MRP and also estimated net MRP, adjusting gross MRP for training costs and compensation to other inputs to production. Because of a general lack of data availability on training costs, the assumptions required to make this adjustment are strong. Subsequent research has focused primarily on gross MRP estimates.

pitched by each individual pitcher as a fraction of total innings pitched by each team. MRP will be underestimated for relief pitchers under this approach since they do not appear in as many innings as starting pitchers. Due to this complication, this analysis focuses only on hitting by position players.

MRP estimates generated through this process are based on observed team revenues, market characteristics, team success, and observed player performance. The data used by Scully (1974) come from a period before free agency was granted to MLB players. The reserve clause generated substantial monoposony power to teams. To measure the extent to which this monoposony power affected salaries, Scully (1974) used these MRP estimates to compute a Monoposony Exploitation Ratio (MER). The MER compares estimated MRP to actual salaries for each player i

$$MER_i = \frac{\widehat{MRP}_i - Salary_i}{\widehat{MRP}_i}. \tag{8}$$

The MER is clearly bounded above by 1. A player with an MER of zero experiences no monoposony exploitation. Perfectly competitive labor markets with no information asymmetries, profit maximizing teams, and utility maximizing players would produce MERs of zero. The closer MER gets to 1, the greater the degree of monoposony exploitation experienced by a player. Players with $MER < 0$ are paid salaries greater than their estimated MRP. Scully (1974) estimated MER for average and star hitters of 0.89 using data from the 1967 and 1968 season.

Data

The sample period includes the 2000 through 2011 MLB seasons. The revenue data for MLB teams come from Forbes magazine and can be found in Rodney Fort's Sports Business Data website. These are estimates of total team revenue in each season based on attendance, broadcast rights, and other revenue streams. MLB teams do not release audited financial data. Some questions exist about the accuracy and validity of these estimates oftotal team revenues (Krautmann, 1999). However, they are widely used in the literature for estimating marginal revenue product (Bradbury, 2008, 2010, 2013; Rockerbie, 2010). The players salary data come from the USA TODAY baseball salaries database. All salaries are expressed in millions of 2011 US dollars, deflated using the Consumer Price Index. The performance statistics for teams and players were downloaded from

baseball-reference.com.

When estimating team revenue and team production functions, team winning percentage and OPS are multiplied by 1000. Only batters with more than 100 at bats in a season are included in the sample because OPS might be a biased measure of contribution and ability for players with small numbers of plate appearances. Players who are traded during the season were excluded from the sample because they cannot be assigned to a single team. Population estimates and unemployment rates for teams home metropolitan area in each year are available from the US Census Bureau, Bureau of Labor Statistics for teams in the United States and from Statistics Canada for teams in Canada.

Table 1: Summary statistics

		Mean	*Std.Dev.*	*Min.*	*Max.*
Team-level variables	Revenue ($ mil)	180.96	52.41	70.56	462.64
	Win Percent	0.500	0.071	0.265	0.716
	Team OPS	0.752	0.037	0.637	0.851
	Team WHIP	1.39	0.088	1.17	1.64
	Population (mil)	5.70	4.50	1.50	19.1
Player-level variables	Salary ($ mil)	3.88	4.81	0.249	34.6
	Age	29.49	4.11	20.0	47.0
	Experience	7.32	4.09	1.0	20.0
	OPS	0.756	0.114	0.382	1.422

Summary statistics are shown on Table 1. At the team level, average annual revenue is $ 180.96 million in 2011 US dollars. The 2000 Montreal Expos earned the lowest revenue in the sample; the 2009 New York Yankees earned the highest. Average winning percentage is 0.5 by definition. The 2003 Detroit Tigers had the lowest winning percentage, 0.265 (43 wins, 119 losses) and the 2001 Seattle Mariners had the highest winning percentage 0.716 (116 wins, 46 losses). The lowest OPS was recorded by the 2010 Seattle Mariners and the highest OPS was recorded by the 2003 Boston Red Sox.

At the player level, the average salary was $ 3.88 million. Eric Hanske was paid $250,000 in 2002; Alex Rodriguez was paid around $ 34 million in 2009. Average OPS was 0.756. The lowest OPS in the sample, 0.382, was recorded by Brandon Wood in 2010; the highest OPS in the sample, 1.422, was recorded by Barry Bonds in 2004.

Empirical Results

The estimates of the team revenue function are shown on Table 2. Recall that the test statistic on the Hausman test for random versus fixed team effects failed to reject the null, indicating that the random team effects model is appropriate in this case. Estimates from a team fixed effects model are very similar to those reported on Table 2. The estimated year-specific effects in this model were statistically significant.

Table 2: Empirical Results - Team Revenue Function

Explanatory Variable	Parameter Estimate/t-statistic
Team Winning Percentage	0.065^{***}
	(3.21)
Team Winning Percentage above 0.550 (spline)	0.112^{**}
	(2.00)
Metropolitan area population	5.710^{***}
	(3.12)
Postseason appearance	3.798
	(1.34)
American League Team	7.511
	(0.690)
New stadium, first 5 seasons	8.511^{***}
	(4.14)
Metropolitan area unemployment rate	-1.899
	(-0.980)
R^2	0.640
# of observations	360

Dependent variable: Total team revenues. Includes clustered-robust standard errors at team level. t-statistics in parentheses * $p < 0.1$, ** $p < 0.05$, ***$p < 0.01$, respectively

The parameters of interest are those on the team winning percent variable, and the spline function. All estimated parameters related to team winning percentage are statistically significant and the sign of the coefficients are positive, consistent with prior research (Scully, 1989; Zimbalist, 1992; Oh and Lee, 2013). When team winning percentage increases by 0.001, revenue is expected to increase by \$0.065 million for teams with a winning percentage less than 0.55. One win increases winning percentage by 0.006. For teams with winning percentages less than 0.55, each win increases revenues by about \$360,000.

For teams with winning percentages greater than 0.55, the estimated parameter on winning percentage and the spline variable are added. A 0.001 increase in winning percentage increases

revenues by \$ 0.177 million for these teams. Expressed in terms of wins, each additional win is worth about \$1.06 million to a team.

We estimated a number of alternative spline model breakpoints, increasing the breakpoint by 0.01 for all possible breakpoints between 0.500 and 0.600. Breakpoints of 0.540 and 0.530 produced similar results to those reported on Table 2. As the breakpoint increased above 0.550, the estimated parameter on the spline term tended to lose statistical significance. As the breakpoint decreased below 0.530, the parameter estimate on the team winning percentage variable tended to lose statistical significance.

The nonlinear relationship between team success and revenues as team success increases comes from playoff appearances (Bradbury, 2008). Fourteen teams made the playoffs with a winning percentage less than 0.550 in our sample; only four, the 2005 Padres, 2006 Cardinals, 2007 Cubs, and 2008 Dodgers, made the playoffs with a winning percentage less than 0.530. Out of 94 teams with a winning percentage over 0.560, only 7 did not qualify for the playoffs in our sample period: the 2002 Dodgers, Red Sox, and Mariners, the 2003 Mariners, the 2004 Giants and Athletics, and the 2005 Indians. The spline break does a reasonable job of identifying playoff teams from non-playoff teams. The indicator variable for postseason appearances is not statistically different from zero, further supporting this idea.

The other parameter estimates from the team revenue function are generally as expected. Teams playing in larger metropolitan areas earn more revenues, since they have more fans to sell wins to. Teams playing in new stadiums earn more revenues in the first five seasons. This is consistent with the novelty effects reported by Coates and Humphreys (2005).

The estimates of the parameters in the win production function, and other regression summary statistics, are shown in Table 3. Given that the Hausman test statistic for random versus fixed effects failed to accept the null, a random effects model is used. Results from a fixed effects specification were nearly identical to those reported on Table 3. In this model, year effects are not jointly significant, consistent with prior research (Oh and Lee, 2013). Following Oh and Lee (2013), year dummies variables are excluded from the empirical model.

From the results on Table 2, an 0.001 increase in log team OPS leads to a 0.0017 increase in $\ln WP_{jt}$. Therefore, a teams marginal product of OPS is calculated as $0.0017 \times \frac{WP_{jt}}{OPS_{jt}}$. Team WHIP has a negative estimated relationship to team performance; higher WHIP reflects worse pitching

performance. All estimates are significant and the sign of coefficients are consistent with prior research (Scully, 1989; Zimbalist, 1992; Oh and Lee, 2013).

Table 3: Empirical Results - Stochastic Frontier Win Production Model

Input to Production	Parameter Estimate/t-statistic
Hitter performance ($\ln OPS_{jt}$)	1.765^{***}
	(22.97)
Pitcher performance ($\ln WHIP_{jt}$)	-1.585^{***}
	(-26.02)
σ_u	0.034
σ_v	0.055
Max. log-likelihood	470.69
# of observations	360

Dependent variable: Team performance ($\ln WP_{jt}$)
t-statistics in parentheses; $^{***}p < 0.01$; Model includes random team effects.

The fixed-effects stochastic frontier estimates shown on Table 3 can be used to generate efficiency estimates for individual teams in each season in the sample. These estimated identify teams that were especially successful or unsuccessful given player performance in that season, as reflected in OPS and WHIP. Inefficient teams were unlucky, had poor managerial performance, had relatively low player effort in areas not reflected in OPS and WHIP, or experienced other adverse events. Efficient teams experienced opposite effects. While not the primary focus here, Table 6 in the Appendix shows the 25 most efficient and inefficient teams in the sample, based on estimates from Equation (4) on Table 3.

The bottom of Table 3 reports σ_v and σ_u, the estimated variance of the random error term and the team-season-specific technical inefficiency parameter in Equation (4). Recall that u is assumed to follow normal-exponential distribution and v is assumed to follow normal distribution in our specification. These estimates are roughly the same size; the variance of the inefficiency term is roughly the same as the variation in the error term.

Using the estimates from the team revenue and production functions discussed above, MER can be estimated for individual players. Again, the sample includes all position players who had at least 100 at bats in a season over the 2001 through 2011 seasons, and includes 3,851 player-year observations. The summary statistics for estimated MER are shown in Table 4. For the entire sample, the estimated MER is 0.504, so about half of the MRP generated by MLB players is

expropriated by teams through the exercise of monoposony power in MLB labor markets.

The next set of estimates shows MER for groups of players with different levels of experience. Again, rookies are fully subject to the reserve clause. Players with approximately 3-5 years of experience are eligible for salary arbitration, and players with seven or more years of experience are eligible for free agency. For rookie players, who are all subject to the reserve clause, the mean MER is 0.887; 88.7% of each rookie players MRP is expropriated by the team that owns his contract; rookie players are paid only 11% of their MRP. This is remarkably close to the estimate in Scully (1974), who estimated the MER for average hitters in the 1968 and 1969 seasons, when all players were subject to the Reserve Clause, as 0.89. Estimated MER is lower for arbitration eligible players, since the arbitration process gives mitigates some of the monoposony power granted to teams through the Reserve Clause.

Across these experience groups, rookies have the highest MER while FA players have the lowest; these results are consistent with prior research (Scully, 1989; Zimbalist, 1992; Oh and Lee, 2013). The mean of MER for FA players is positive, consistent with Scully (1989) but contradicting the results in Zimbalist (1992) and Oh and Lee (2013). This inconsistency might be due to measurement error in MER. However, results also show that some FA players have negative MER up to -10. The mean of MER also decreases from period 1 to 3. Therefore, our findings suggest that monopsony power decreases over time.

Table 4: Summary statistics, Estimated MER by Player Type

Type of Players		N	Mean	Std. Dev.	Min.	Max.
All players		3851	0.504	0.712	-10.27	0.994
Experience Group	Rookies	742	0.887	0.204	-1.346	0.994
	Arbitration eligible	1161	0.753	0.283	-1.743	0.989
	Free Agents	1948	0.209	0.872	-10.27	0.988
CBA Period	2000-2002	950	0.556	0.598	-4.50	0.994
	2003-2006	1284	0.526	0.706	-10.27	0.989
	2007-2011	1617	0.456	0.773	-7.87	0.987

Table 4 shows some negative MER estimates in all experience groups. Only 7 of the 742 players in the rookie group had negative estimated MERs. The largest negative MER is just 30% less than the player's salary. Only 25 of the 1,161 players in the arbitration eligible group had negative estimated MERs. A larger number of FA players, 409, show negative estimated MERs. The largest,

-10.27, is for Jeff Bagwell in his final season, 2005. Bagwell earned $20 million in that season and appeared in only 36 games; his 100 at bats give him exactly the minimum number for inclusion in the sample.

Inspection of the other players with negative estimated MERs generally reveals aging veteran star players finishing out long term contracts in the last years of their careers or younger players who struggled with injuries early in the season, accumulated 100 or more ABs, and lost most or all of the rest of the season to that injury. Examples include Fernando Tatis in 2003 (estimated MER -2.5, only 176 ABs with the Expos) and Grady Sizemore in 2010 (estimated MER -3.1), who injured his knee in Spring Training, accumulated 127 ABs in April and May while struggling with the injury, and had season ending knee surgery in late May.

These MER estimates are larger than those reported in Bradbury (2008) and Bradbury (2010) for FA players, who reports estimated MERs of about 0.10. The difference may be due to different econometric methods. Bradbury (2008) and Bradbury (2010) uses polynomial revenue functions and does not use the stochastic frontier approach for estimating marginal product.

Changes in MER Over Time and Experience Groups

All aspects of the employment relationship between players and teams in MLB are dictated by the collectively bargained CBAs. From the bottom of Table 4, the average MER across the three CBAs in the sample period declined somewhat, suggesting that players have gradually reduced the monoposony power held by teams through the collective bargaining process. In order to better understand these changes in MER, we analyze variation in estimated MERs for individual players over the sample period using a regression model.

This analysis compares the differences in MERs across CBAs and across between career groups using a regression model

$$\begin{aligned} MER_{it} = \theta_1 CBA_{1i} + \theta_2 CBA_{2i} + \theta_3 PG_{1i} + \theta_4 PG_{2i} + \theta_5 CBA_{1i} PG_{1i} \\ + \theta_6 CBA_{1i} PG_{2i} + \theta_7 CBA_{2i} PG_{1i} + \theta_8 CBA_{2i} PG_{2i} + \alpha_j + \epsilon_{it} \end{aligned} \quad (9)$$

where MER_{it} is the estimated monoposony exploitation ratio for player i in season t, CBA_i is

an indicator variable that identifies which CBA player i was subject to in season t (1 for the 2003-2006 CBA and 2 for the 2007-2011 CBA), and PG_i is an indicator variable that identifies the experience group that player i belonged to in season t (1 for arbitration eligible players and 2 for free agents). The omitted category is rookie players under the 1997-2002 CBA. α_j is a team-specific intercept variable that captures unobservable time invariant team effects on MER. The unobservable parameters θ_i capture the average effect of CBAs and membership in specific experience groups on estimated MERs holding unobservable team-specific factors constant. The interaction terms allow different CBAs to affect MER differently depending on player experience.

Table 5: Regression Results - Variation in MER

Explanatory variable	Parameter Estimate/t-statistic
CBA 2003-2006	-0.033
	(-0.500)
CBA 2007-2011	-0.041
	(-0.660)
Arbitration eligible	$-0.151**$
	(-2.41)
Free agent	$-0.609***$
	(-10.31)
CBA 03-06× Arbitration	0.038
	(-0.460)
CBA 03-06× FA	-0.007
	(-0.090)
CBA 07-11× Arbitration	0.001
	(-0.010)
CBA 07-11× FA	$-0.176**$
	(-2.44)
# of observations	3851

Dependent variable: MER for player i in season t.
t-statistics in parentheses * $p < 0.1$, ** $p < 0.05$, ***$p < 0.01$, respectively
Team fixed effects are included in the model.

Table 5 contains extimation results for Equation (9). Estimated coefficients for the different CBA periods are not statistically different from zero. League-wide MERs do not change across the three CBAs, suggesting that overall monoposony power was not changed in these CBAs. The average differences across experience groups are significantly different from zero. Compared to rookies, salary arbitration eligible players have 0.15 lower MERs and FA players have 0.61 lower MERs, holding CBA-period-effects and team-effects constant.

The interaction terms tell a different story. MERs for free agents under the 2007-2011 CBA were substantially lower than any other group under any other CBA. Changes in the 2007-2011 CBA appear to have reduced the monoposony power exercised over free agent players, perhaps at the expense of rookies and arbitration eligible players. This represents a substantial improvement for free agents, the most experienced group of players in MLB.

Conclusions

This paper generates new estimates of marginal revenue product, and monoposony exploitation ratios, for MLB players, and assesses the extent to which the recent CBAs have affected monopsony power in MLB. Two new empirical approaches, a spline model for estimating the relationship between team success and revenues, and a stochastic production function frontier model with team fixed effects for estimating the relationship between performance and team success, have not been used when estimating MRP. An analysis of the effect of different CBAs on MERs indicates that free agents under the last CBA had substantially lower MERs than any other players in the sample.

One possible reason for this decreasing MER for free agent players under the 2007-2011 CBA is that the MLBPA may concentrate more on improving the working conditions for experienced union members more than for other less experienced union members when negotiating new CBAs. For example, the 2007-2011 CBA includes improvements in FA contracts, in the form of eliminating or relaxing compensation rules (MLB, 2007). As the compensation rules for FA players weakens, teams would participate more in the FA market than before and the salaries of FA players would be higher as more teams compete for them.

Salary arbitration eligible players may face lower monopsony power over time as the MLBPA clearly tries to expand and improve the salary arbitration system in every CBA. But the empirical results suggest that MERs for arbitration eligible players did not decline over this period. This result also supports the argument that the MLBPA concentrates primarily on improving conditions for free agents.

MER estimates for rookies did not change over the three CBAs in the sample period, suggesting that the monopsony power faced by rookies did not change. Around 90% of the gross MRP of rookies is still exploited by teams. This suggests that increases in the league minimum salary negotiated

in new CBAs over this period did not mitigate the monopsony power faced by rookies. Perhaps increases in the minimum salary over CBAs only reflects the effects of inflation, not increases in team revenues.

Some argue that rookies can be compensated for this monoposony exploitation when they become free agents and sign large contracts. In other industries, inexperienced workers are often paid less than senior workers regardless of their MRP. Lazear (1981) concludes that salary often increases by more than MRP over a worker's lifetime; salary for senior workers is often much higher than their MRP while junior workers are paid less. Lazear (1981) also claims that a high wage for experienced workers might serve as a positive motivation for inexperienced workers to work hard. However, because of the keen competition in MLB for limited roster spots, only a few rookies will ever reach free agency, while it is relatively easier to have a long career in other industries. In the sample analyzed here, less than 50% of rookies in any cohort reach free agency. Even after reaching free agency, players still need to spend a number of years on an MLB roster to be compensated for exploited MRP and MLB players have shorter careers than workers in other industries; even MLB superstars usually retire before the age of 40 while the usual retirement age in other industries is 60 to 65. In addition, it is easier to estimate the productivity of a baseball player using performance data than for workers in other industries.

Rookies and arbitration eligible players might be paid less due to players training costs. Becker (1993) developed a model motivating on-the-job training costs and argued that training costs explain why inexperienced workers are paid less than their MRP. Krautmann et al. (2000) documented a similar structure in MLB, where major league teams pay the salary of players in the minor leagues. Therefore, teams may need to exploit inexperienced MLB players to be compensated for salary and coaching when the player was in the minor leagues.

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Table 6: Estimated Team Efficiency, 2001-2011

20 Most Efficient Teams			20 Least Efficient Teams		
Team	Season	Efficiency	Team	Season	Efficiency
Seattle Mariners	2007	0.0118	Detroit Tigers	2002	0.0734
Houston Astros	2010	0.0120	Los Angeles Dodgers	2005	0.0735
Arizona Diamondbacks	2007	0.0121	Arizona Diamondbacks	2010	0.0752
Oakland Athletics	2006	0.0126	Miami Marlins	2011	0.0754
Detroit Tigers	2001	0.0132	Cleveland Indians	2006	0.0762
Los Angeles Angels	2008	0.0134	Detroit Tigers	2004	0.0789
Kansas City Royals	2000	0.0143	Boston Red Sox	2002	0.0796
Kansas City Royals	2003	0.0146	Milwaukee Brewers	2004	0.0808
Miami Marlins	2000	0.0149	San Diego Padres	2008	0.0835
Milwaukee Brewers	2000	0.0149	Cleveland Indians	2005	0.0835
Detroit Tigers	2009	0.0155	Detroit Tigers	2005	0.0856
Pittsburgh Pirates	2011	0.0156	Washington Nationals	2009	0.0868
San Diego Padres	2010	0.0157	Milwaukee Brewers	2002	0.0893
Washington Nationals	2005	0.0157	Chicago Cubs	2002	0.0907
Los Angeles Angels	2009	0.0157	Houston Astros	2000	0.0918
Atlanta Braves	2002	0.0159	Seattle Mariners	2004	0.0945
San Francisco Giants	2003	0.0160	Houston Astros	2011	0.1011
Atlanta Braves	2004	0.0160	Colorado Rockies	2001	0.1151
Arizona Diamondbacks	2011	0.0162	Arizona Diamondbacks	2004	0.1376
Texas Rangers	2004	0.0164	Detroit Tigers	2003	0.2392

Lower estimated efficiency means more efficient production of wins given inputs.