

# Baseball and the Bottom Line

## An Econometric Analysis of Market Efficiency for MLB Player Contracts

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Since MLB players earned Free Agency in 1976 there has been little economic literature examining its effect on the efficiency of the market for player contracts. What little exists often is counterintuitive to economic findings in other subfields. We reconsider both old methodology and propose a new one which better represents current economic consensus to retest if the MLB labor market is acting efficiently. We ultimately find efficiency is almost completely determined by methodology and the researcher's belief of what makes a player "good".

## 1 Introduction

The 2004 publication of *Moneyball* by Michael Lewis sent shock-waves through Major League Baseball (MLB) ownership. The thesis of *Moneyball* was that owners were valuing players' offensive and defensive production incorrectly, allowing the Oakland Athletics, a team in MLB, to win many more games than their opponents with a vastly smaller payroll (Lewis, 2004). This extraordinary claim garnered the attention of many economists who sought out to test if this claim had any credibility. Some economists (Congdon-Hohman & Lanning, 2018; Duquette et al., 2019; Hakes & Sauer, 2006; Thaler & Sunstein, 2004) found this claim to be credible while others (B. Baumer & Zimbalist, 2014; Pinheiro & Szymanski, 2022) found that the Athletics successes could be attributed to other reasons than what *Moneyball* claimed. While *Moneyball* is an enjoyable novel and

highlighted a shortcoming of MLB ownership it only considered a small part of what ownership considers when employing a player. Therefore, the conclusions drawn both from Moneyball and the aforementioned articles should not have their conclusions generalized to describe the efficiency of the entire labor market for MLB players.

There have been previous attempts to quantify and measure the market efficiency for MLB players. The most influential being Scully (1974) and Krautmann (1999). Scully's article was the seminal piece of literature on the topic and set forth the precedent and structure that subsequent research has followed. Scully used the marginal revenue product of labor (MRPL or MRP) model to judge the productivity of MLB players. To achieve this, Scully first estimated how players impact their team's ability to win and multiply that effect by the estimated effect winning has on revenues for teams. The market that Scully considered was vastly different than the one seen today. Scully published two years before the reserve clause was overturned, partially deregulating the MLB labor market and allowing the most veteran players to take their abilities to whichever team was the highest bidder (Hall et al., 2002). Since such a drastic difference is now present in the labor market the applicability of Scully's findings should be questioned. Krautmann (1999) attempted to bring Scully's findings into a more contemporary light but suffered from some methodological shortcomings. However, he did highlight some important shortcomings in Scully's methods too. Namely, that when using the Scully method the definition of successful outcomes for a player has drastic impacts on conclusions about market efficiency. Since market efficiency has hardly been investigated in the past 25 years it ought to be considered in a more contemporary light. Not only is there now over 30 years of salary and performance data (Friendly et al., 2022) but there have also been huge strides in statistical understanding of player performance.

Inspired by the work of more contemporary baseball statisticians (B. S. Baumer et al., 2015) and

new developments in consumer behavior research (Borland & Macdonald, 2003) we can understand that there are several shortcomings not addressed by either Scully or Krautmann. First, better understanding of player ability requires more than a collection of a couple outcome statistics. A more mathematically rigorous approach should be used for the most accurate results to be found (B. S. Baumer et al., 2015; Pinheiro & Szymanski, 2022). Thus, we will use more advanced regression techniques to retest the Scully method over a longer time interval to see if it has any impact on his findings. Additionally, new research in consumer demand for sports has found that fans often do not care as much about a team winning a game as they do with the contention and quality of said game (Borland & Macdonald, 2003). This means that a new approach should be used which takes into account these new findings. This paper proposes a new method which aims to measure player success in terms of offensive and defensive quality to better represent these new findings.

Ultimately, we confirm most of the findings of previous literature when repeating their methods. Namely, if we judge players only on their ability to help their team win then the data suggests they are over compensated. However, when we examine the findings of previous literature over the 31 year period for which we have data we find that our economic intuition and the results lead in separate directions. Findings in previous literature of labor economics and industrial organization would suggest that labor strikes, which occurred several times over the period considered, should lead to higher compensation for players (Card, 1990). Yet, when repeating the methodology of previous literature we are unable to confirm these findings. However, when considering the new methodology proposed, which tries to better align with consumer research, we find this discrepancy between labor economics and previous literature disappears. This suggests that considering the new method of estimation would provide a better framework for future research to expand on.

## 2 Literature Review

In sports economics there are two theories which attempt to explain what success is in the eyes of team ownership (Andreff & Szymanski, 2006). These can be understood as the win maximization and the utility maximization theories. Under the win maximization theory the owner's major or sole concern is winning. This means that ownership will have much more inelastic demand for talented players, running deficits, and generally treating the team unlike a profit maximizing firm (Andreff & Szymanski, 2006, pp. 601–603). The utility maximization theory can be used to describe the motivations of every other ownership group. Utility maximization states that owners will hire players to maximize either the utility of the fans or themselves. Sometimes this can culminate into treating the team as a profit maximizing firm, and other times this can be trivial outcome chasing. In general, utility maximization theory is applied to any ownership group, theoretical or otherwise, that has objectives for the team other than winning. In applied econometric literature it is much more common to find research using the win maximization theory, explicitly or otherwise, with little to no justification provided as to why they are using it.

Since almost all previous literature assumes that winning games is the only thing that consumers, and therefore owners, care about authors' often judge players' productivity using winning as the yardstick for success. However, it is obvious that fans care about things other than just seeing their team win. Consider the "die-hard" fans who will continue to attend games even in years where winning is scarce. The existence of these "die-hard" fans calls the assumptions of the win maximization hypothesis into question. In fact, the current consensus among economists agrees with this doubt and finds consumers do not only care much about winning (Borland & Macdonald, 2003). This consumer demand research suggest consumers care most about the quality of the game

and its contention. Meaning, consumers would much rather see a game played well and be unsure of the outcome rather than knowing their team will win.

The seminal piece of MLB labor market efficiency is Gerald Scully's 1974 publication "Pay and performance in major league baseball" (Scully, 1974). Scully's research involved observing how the reserve clause influenced salary negotiations between players and owners. He hypothesized, and ultimately found, that the reserve clause created monopsony hiring power for MLB ownership. By Scully's estimations, this allowed for owners to pay players wages which were less than their MRP. Scully's analysis has become antiquated since the reserve clause was overturned in 1976 (Hall et al., 2002) and the market structure became substantially less monopsonistic. However, the importance and genius of Scully's research is the methodology. Thus, we use Scully's methods in this paper as a baseline to ensure findings and conclusions are profound and undiscovered.

As some economists have previously noticed (Vrooman, 1996, p. 353), after the abolition of the uniform reserve clause a bilateral monopoly was created between players and owners for players with monopsonistic contracts. There is currently not a consensus on how to model bilateral monopolies and their interactions other than considering vertical integration between the parties. However, vertical integration clearly does not apply here. Therefore, previous literature would suggest that this bilateral monopoly should be modeled using bargaining power (Siddhartha & Devadoss, 2002). Under this model, the party with even slightly higher bargaining power will earn a higher portion of the profits. Thus, we can expect that as either owners or players change their bargaining power so too will their proportions of compensation change.

### 3 Economic Model

#### 3.1 Marginal Revenue Product of Labor

The motivation for using the marginal revenue product of labor model is simple. Labor's productive ability is not uniform across each worker. Therefore, a model which can differentiate between laborers and their output is needed for judging individual laborers. This can be demonstrated simply and abstractly in the following equation,

$$MRPL = \frac{\Delta R}{\Delta Q} \cdot \frac{\Delta Q}{\Delta L}. \quad (1)$$

Where  $\Delta R$  is the change in revenue due to the  $\Delta Q$  change in quantity which is then multiplied by the  $\Delta Q$  change in quantity due to the  $\Delta L$  change in labor. The precedent for using this model has already been set by multiple economists considering similar research questions (Krautmann, 1999; Scully, 1974).

#### 3.2 Win Maximization Method

Scully (1974) uses the marginal revenue product of labor, paired with the win maximization hypothesis, to examine if the labor market for MLB players was behaving efficiently. Scully's estimation of MRPL is estimated by team data in the following equations,

$$MRP_{I,J} = \frac{\partial TR_{I,J}}{\partial WPCT_{I,J}} \cdot \frac{\partial WPCT_{I,J}}{\partial PERF_{I,J}}. \quad (2)$$

Where  $\partial TR$  is the change in total revenue for a team  $I$  in year  $J$  from the  $\partial WPCT$  change in win percentage. The  $\partial WPCT$  change in win percentage for a team  $I$  in year  $J$  is due to  $\partial PERF$

change in on field performance.

A drawback of the Scully's method was highlighted by Krautmann (2013). All MLB teams are privately held firms which means that their financials are not available to the public. Therefore, when Financial World Times and Forbes attempt to estimate each team's revenue it was understood that there would be some error. However, from released court documents during litigation it was revealed that those estimates were off by almost 25% in some cases (Krautmann, 2013, p. 99). Since revenue data is not available anywhere else and using it will lead to gross miscalculations, some simplifying assumptions needed to be made. Scully pointed out in his paper that total team revenue was a function of both turnstyle revenue (fans watching game at the stadium) and broadcasting (both television and radio) revenues (Scully, 1974, p. 917). Attendance is a huge factor in turnstyle revenue and it is not a logical leap to claim that it is probably highly correlated with broadcasting revenues. Thus, using attendance as a proxy for revenue appears to be the only way to maintain the integrity of this replication.

Therefore, we use the following equation to consider Scully's hypothesis in a more contemporary light,

$$MRP_{I,J} = \frac{\partial Attendance_{I,J}}{\partial WPCT_{I,J}} \cdot \frac{\partial WPCT_{I,J}}{\partial PERF_{I,J}}. \quad (3)$$

Scully estimated the effect  $\partial PERF$  had on  $\partial WPCT$  for team  $I$  in year  $J$  using an OLS regression (Scully, 1974, p. 919). To improve on this we can use the following fixed effects regression,

$$WPCT_{I,J} = \Gamma_0 + \Gamma_1 PERF_{I,J} + \alpha_I + \theta_J + \epsilon. \quad (4)$$

In Equation 4,  $\Gamma_1$  can be understood as a general coefficient representing the estimated effect

each performance statistic has on a team's ability to win. We used  $\Gamma_1$  and the general variable  $PERF$  because including all variables, both considered and used, would make the equation lengthy and difficult to interpret. A more detailed discussion of the variables is available in Section 4.2. The term  $\alpha_I$  can be thought of as an intercept term which is used to control for differences between teams that stay the same each year which might affect win percentage. Examples of this include, but are not limited to, managerial quality, stadium location, etc. While the term  $\theta_J$  can be thought of also as an intercept term because it is used to control for things that stay the same for each team but differ year to year. Examples of this are mostly related to league wide rule changes. The benefits of using the fixed effects  $\alpha_I$  and  $\theta_J$  is that we can remove a lot of endogeneity and omitted variable bias that was present in Scully's analysis. The term  $\epsilon$  is the error term of the regression and is used to represent any other variation in the data.

We can estimate the effect that win percentage,  $WPCT_{I,J}$ , has on team the  $I$ th team's attendance,  $Attendance_{I,J}$ , in year  $J$  in the following fixed effects regression,

$$Attendance_{I,J} = \Omega_0 + \Omega_1 WPCT_{I,J} + \eta_I + \tau_J + \epsilon. \quad (5)$$

In Equation 5,  $\Omega_1$  can be understood as the estimated effect that changes in win percentage for team  $I$  in year  $J$  have on attendance. A more detailed discussion of  $\Omega_1$  is available in Section 4.2. The term  $\eta_I$  can be thought of as an intercept term which controls for factors that differ from team to team but stay the same year over year. An example of this is fan enthusiasm. While the term  $\tau_J$  controls for variables which stay the same from team to team but differ from year to year. An example of this is league wide rule changes. Using the fixed effects  $\eta_I$  and  $\tau_J$  allow for a significant reduction in endogeneity and omitted variable bias. The term  $\epsilon$  is the error term of the regression



and is used to represent any other variation in the data.

Ultimately this makes estimating the MRP of each player ( $\widehat{MRP}$ ) into a composite function. After deriving the values of  $\Gamma_1$  and  $\Omega_1$  the following equation can be used to estimate a player's MRP,

$$\widehat{MRP}_{A,W} = \Omega_1 \cdot (\Gamma_1 \cdot PERF_A). \quad (6)$$

In Equation 6,  $\widehat{MRP}_{A,W}$  represents the estimated MRP of player  $A$  using the Scully method,  $W$ . We can calculate the player's MRP using their performance statistics,  $PERF_A$  and multiplying that by their associated weights  $\Gamma_1$ . At this stage we have calculated how the player effects his team's ability to win. Then, we can multiply that by  $\Omega_1$  to derive the players estimated effect on attendance, which is ultimately his MRP. The results of this process are outlined in Section 4.2 as well as discussion concerning what statistics were used in  $PERF_A$  and their associated weights  $\Gamma_1$ .

### 3.3 Utility Maximization Method

The utility maximization method is an expansion and revision of the Scully approach. It rejects the assumption that consumers only gain utility, and therefore attend games, to see a team win. More contemporary consumer research has found that while winning does have an influence on consumer behavior, it is far from the only or best predictor (Borland & Macdonald, 2003). This paper proposes that scoring runs is the best representation of offensive quality and preventing runs from being scored is the best representation of defensive quality. This aligns better with previous literature which claims that consumers value quality and contention of games more than winning

(Borland & Macdonald, 2003). To ensure a holistic view of game quality we take the sum of offensive and defensive quality when determining MRPL. Thus, using this new method, a player's MRPL is the sum of their ability to help their team score runs and prevent their opponent from scoring runs, multiplied by the respective effects these outcomes have on attendance. This new method of measuring MRPL can be expressed as the following equation,

$$MRPL_{I,J} = \left[ \frac{\partial Attendance_{I,J}}{\partial R_{I,J}} \cdot \frac{\partial R_{I,J}}{\partial PERF_{I,J}} \right] + \left[ \frac{\partial Attendance_{I,J}}{\partial RA_{I,J}} \cdot \frac{\partial RA_{I,J}}{\partial PERF_{I,J}} \right]. \quad (7)$$

Interpreting Equation 7 is very similar to interpreting Equation 3 and Equation 2. The first half of Equation 7,  $\frac{\partial Attendance_{I,J}}{\partial R_{I,J}} \cdot \frac{\partial R_{I,J}}{\partial PERF_{I,J}}$ , describes the estimated effect changes performance statistics,  $\partial PERF$ , have on team  $I$ 's ability to score runs,  $\partial R$ , in year  $J$ . Then, it describes the estimated effect scoring runs,  $\partial R$ , has on team  $I$ 's attendance,  $\partial Attendance$ , in year  $J$ . The second half of Equation 7,  $\frac{\partial Attendance_{I,J}}{\partial RA_{I,J}} \cdot \frac{\partial RA_{I,J}}{\partial PERF_{I,J}}$ , describes the estimated effect changes performance statistics,  $\partial PERF$ , have on team  $I$ 's ability to prevent runs from being scored,  $\partial RA$ , in year  $J$ . Then, it describes the estimated the effect preventing runs from being scored,  $\partial RA$ , has on team  $I$ 's attendance,  $\partial Attendance$ , in year  $J$ . Finally, we add the associated effects to acquire a holistic estimation of MRPL. Note that MRPL is again measured in attendance instead of dollars because of the problems outlined in Section 3.2.

Similar to Equation 5, we can estimate the effect that offensive (scoring runs) and defensive (preventing runs from being scored) quality have on attendance with the following fixed effects regression,

$$Attendance_{I,J} = \mu_0 + \mu_1 RA_{I,J} + \mu_2 R_{I,J} + \psi_I + \lambda_J + \epsilon. \quad (8)$$

In this regression  $RA$  is the number of runs scored against team  $I$  in year  $J$  and  $R$  is the amount of runs team  $I$  scored in year  $J$ . The term  $\mu_1$  is the associated effect that an additional  $RA$  will have on the attendance of team  $I$  in year  $J$ . Similarly,  $\mu_2$  is the associated effect that an additional  $R$  will have on the attendance for team  $I$  in year  $J$ . The variable  $\psi_I$  can be understood as an intercept that is used to control for factors that differ from team to team but stay the same year over year. This can be thought of as the term that controls for fan enthusiasm among other things. The variable  $\lambda_J$  can also be thought of as an intercept that controls for variables which stay the same from team to team but differ from year to year. Most examples of this would be league wide rule changes. The term  $\epsilon$  is the error term of the regression and is used to represent any other variation in the data.

It is imperative to note that it is impossible to directly measure the effect a singular player has on a team's ability to score or prevent runs from being scored. However, using team statistics it is possible to determine how offensive and defensive outcomes effect a team's ability to score and prevent runs from being scored. Thus we can estimate the effect each player has by first determining which outcomes are most important in scoring runs and preventing runs from being scored with the following fixed effect regressions,

$$RA = \phi_0 + \phi_1 Pitching + \phi_2 Fielding + \omega_I + \chi_J + \epsilon, \quad (9)$$

$$R = \beta_0 + \beta_1 Hitting + \beta_2 Baserunning + \rho_I + \pi_J + \epsilon. \quad (10)$$

Understanding both regressions is simple. The amount of runs scored against a team is a combination of the team's pitching and fielding ability. Many variables will be considered so the general coefficients  $\phi_1$  and  $\phi_2$  will be used as place holders until actual weights are derived. Furthermore, the amount of runs that a team scores is a combination of a team's hitting and baserunning ability. Many variables will also be considered for hitting and baserunning so the general coefficients  $\beta_1$  and  $\beta_2$  will be used as place holders until the actual weights are derived. The outcomes used and their associated weights are discussed further in Section 4.3. Both Equation 9 and Equation 10 are fixed effects models. Thus, it is understood that both  $\omega_I$  and  $\rho_I$  are controlling for the same effects. Namely they control for things that stay the same year to year but differ from team to team. Examples of this include managerial quality, stadium location, etc. Similarly, the terms  $\chi_J$  and  $\pi_J$  are also understood to control for the same effects. They control for things that differ from year to year but stay the same from team to team. These mostly include league wide rule changes. The term  $\epsilon$  is understood to be the error term that accounts for any additional variation in the data.

Again, similar to Equation 6 this makes estimating a player's MRP ( $\widehat{MRP}$ ) a composite function. After deriving the values of  $\mu_1, \mu_2, \phi_1, \phi_2, \beta_1$ , and  $\beta_2$  the following equation can be used to estimate a player's MRPL,

$$\begin{aligned} \widehat{MRPL}_{A,U} = & [\mu_1 \cdot (\phi_1 Pitching_A + \phi_2 Fielding_A)] \\ & + [\mu_2 \cdot (\beta_1 Hitting_A + \beta_2 Baserunning_A)]. \end{aligned} \quad (11)$$

In Equation 11,  $\widehat{MRP}_{A,U}$  represents the estimated MRP of player  $A$  using the utility maximization method,  $U$ . We can calculate the player's MRPL using their performance statis-

tics ( $Pitching_A$ ,  $Fielding_A$ ,  $Hitting_A$ , and  $Baserunning_A$ ) and multiplying that by their associated weights ( $\phi_1$ ,  $\phi_2$ ,  $\beta_1$ , and  $\beta_2$  respectively). At this stage we have calculated how player A effects his team's ability to score runs and prevent runs from being scored. Then, we can multiply these abilities by  $\mu_1$  and  $\mu_2$  respectively and finally add these effects to derive player A's estimated effect on attendance, which is ultimately his MRP. The results of this process are outlined in Section 4.3 as well as discussion concerning what statistics were used in  $Pitching_A$ ,  $Fielding_A$ ,  $Hitting_A$ , and  $Baserunning_A$  and their associated weights ( $\phi_1$ ,  $\phi_2$ ,  $\beta_1$ , and  $\beta_2$  respectively).

### 3.4 Relating Attendance to Wages

Measuring marginal revenue using attendance instead of dollars was necessary to preserve the integrity of the model due to flawed estimates in team revenue data (Krautmann, 2013). However, it creates an issue of how to relate the wage data for each player to the attendance they bring in. Since they are different units it can initially seem like an impossible obstacle. However, as discussed before, you can use attendance as a proxy for revenue. Which means attendance can also be used as a proxy for cost.

This paper assumes that ownership for each team is generally capable of determining how performance affects attendance, and since attendance affects team revenue, ownership will alter compensation accordingly. This means that, generally, ownership has an estimation for how a player will affect attendance. Since we only have salary data we can work backwards and glean what the estimated effect on attendance ownership expected. Thus, we can regress team attendance on team payroll with the following fixed effects model,

$$Attendance_{I,J} = \zeta_0 + \zeta_1(Payroll_{I,J}) + \xi_I + \sigma_J + \epsilon. \quad (12)$$

In this regression, we find that for team  $I$  in year  $J$  an increase in payroll of 1 (dollar) will result in an change in attendance of  $\zeta_1$ . Payroll is the sum of the cost of all contracts for players for team  $I$  in year  $J$ . The terms  $\xi_I$  and  $\sigma_J$  represent the fixed effects. The term  $\xi_I$  represents things that differ across teams but stay the same year over year. This is mostly controlling for things such as ballpark location. While the term  $\sigma_J$  represents things that differ from year to year but remain the same across teams. Examples of this mostly include league wide rule changes.

Using this equation and our assumptions we now have the relationship between how much a team spends and how that affects their attendance. This implies that we can compute how much attendance ownership expects an individual player to bring into the stadium by multiplying their salary by  $\widehat{\zeta_1}$ . Thus, it is possible now to compute both player's estimated and actual attendance figures. Continuing with methodology pioneered in previous literature we can now begin exploring the implication this has on market efficiency.

## 4 Empirical Strategy

### 4.1 Data

There are two sources from which data were gathered. The first source was the Lahman database (Friendly et al., 2022) which has records on every MLB team and player from the 1871 to 2022 season. Team and player performance, salaries, and attendance data was aggregated, regressed, and computed from here. This analysis considers observations from the 1985 to 2016 seasons because

that was the range of years that salary information was available in the Lahman database. Access to the Lahman database came from the R package “Lahman” (Friendly et al., 2022; R Core Team, 2022).

The other source used was a consumer price index (CPI) accessed through the “quantmod” R package (Ryan & Ulrich, 2022). The specific CPI used was the CPIAUCSL which is a CPI designed for all urban consumers and is gathered from the Federal Reserve Bank of St. Louis. Using an urban consumer CPI is appropriate because MLB stadiums are often located in urban metropolitan environments. The CPIAUCSL was used to adjust player salaries to what their value would be in 2016 dollars. All salaries were converted to real 2016 dollars before being used in an analysis of any capacity.

All computations were done with the R statistical software version 4.2.2 (R Core Team, 2022). Data manipulation and graphing were done using both R and the “tidyverse” package (R Core Team, 2022; Wickham et al., 2019). Fixed effects regressions were made using the “fixest” package (Bergé, 2018) and displayed using the “modelsummary” package (Arel-Bundock, 2022).

## 4.2 Win Maximization Results

As discussed in Section 3.2, calculating the MRP for each player using the win percentage method first requires two regressions to be run. The first regression determines what effect offensive and defense outcomes have on a team’s ability to win. And the second determines how changes in winning affect fan attendance. The theoretical regression of the effect offensive and defensive outcomes have on winning has already been outlined in Equation 4. In Equation 5 we use  $\Gamma_1$  and  $PERF_{I,J}$  as placeholders representing all the variables tested and their associated effects on the

$I$ th team's win percentage in year  $J$ . To see which outcomes were selected and their associated weights refer to Table 1. The dependent variable, Win Percentage, is expressed as a real number on the interval [0-100]. While this may appear initially to be an appropriate situation to use a logistic regression, there are several reasons which made the fixed effects regression more appropriate. First, there is no precedent from any previous literature to use a logistic regression (Krautmann, 1999; Scully, 1974). The second, is that logistic regressions are used to predict binary dependent variables and win percentage is clearly does not have binary outcomes. Thus, a fixed effects regression is a much more appropriate choice. An advantage to using a fixed effects model is that understanding the coefficients is straightforward. For example, from Table 1 we are able to determine that an additional home run (HR.x) hit by team  $I$  is associated with an increase of 0.1 in the team's winning percentage for that year. An important note for understanding the variable names, all variables from X1B to SF.x in Table 1 are offensive outcomes done by team  $I$  in year  $J$  while all variables from E.y to SH are defensive outcomes for team  $I$  in year  $J$ . For more information on exactly what each variable entails, refer to the Lahman database (Friendly et al., 2022). We find this regression is able to describe the impact that offensive and defensive outcomes have on a team's ability to win quite well. This is represented by the quite large adjusted  $R^2$  value of 0.8.

The second model used in the win maximization method was the effect that win percentage had on attendance. The theoretical regression has already been outlined in Equation 5. To see all values of Equation 5 refer to Table 3. We find  $\Omega_1$  to be about 41,000, which implies an additional point in a team's win percentage is associated with about an additional 41,000 fans attending that team's game in a given year. We find that this describes the variation in attendance fairly well with an adjusted  $R^2$  value of 0.57.

One final step must be briefly completed before estimating players' MRP. It is necessary to



convert players' salaries into attendance, as discussed in Section 3.4, so that comparison to player contracts is possible to determine market efficiency. The theoretical model for this has already been described in Equation 12. Furthermore, the value for  $\hat{\zeta}_1$  can be seen in Table 4. Now it is possible to discuss player output and compensation in the same units and thus, we can estimate the market efficiency.

With the weights calculated it is now possible to estimate players' MRP. Calculating the MRP for a player has already been roughly outlined in Equation 6. Simply take the amount of outcomes that a player has for the variables in Table 1 and multiply it with the outcomes' associated weights. We can call this value  $\Delta WPCT$  since it represents how much a player changes their team's win percentage in a given year. Then, we can take this  $\Delta WPCT$  and substitute it into Equation 5 for  $WPCT$  with the weights found for  $\Omega_1$  in Table 3 and gain the estimate of the player's MRP in a given year. To find if they are being compensated fairly we take their salary data for the same year and input it into Equation 12 and multiply this real salary by the value of  $\hat{\zeta}$  which can be found in Table 4. Thus, we have calculated the cost for ownership to employ a certain player that year in terms of attendance. Finding market efficiency is a simple ratio, which has been used in previous literature (Krautmann, 1999; Scully, 1974). This ratio is the division of estimated MRP by the wage of the player ( $\frac{MRP}{Wage}$ ) where both MRP and wage are measured in attendance. In a perfectly competitive market we would expect this ratio equal to 1 for all players because in a perfectly competitive market laborers are paid their MRP (Brožová, 2015). We expect that if laborers are under monopsony hiring power that this ratio would be greater than 1. We expect that for laborers who have formed a monopoly, such as a labor union, this ratio would be less than 1. Figure 1 describes the weighted mean MRP in MLB from 1985-2016 across all contract types. A horizontal dashed line has been added at the  $y = 1$  level to represent what we would expect to see if the market

were perfectly competitive. This figure suggests that players have been over-paid for the entirety of the years considered. This supports the findings of previous literature (Krautmann, 1999; Pinheiro & Szymanski, 2022) which also found players were overpaid. However, included in the graph are six vertical dashed lines which represent new Collective Bargaining Agreements (CBA) between the MLB Player's Association (MLBPA) and the ownership group. Almost all of the signings of these CBA were first met with a strike by players. Previous economic literature would suggest labor's bargaining power increases after striking (Card, 1990; Lacroix, 1986; Riddell, 1980). Yet, Figure 1 clearly does not support this conclusion since there is clearly no pattern of MRPL Ratio decreasing after striking. While it is possible that previous literature on strikes is incorrect, it is much more plausible that the findings in Figure 1 are incorrect considering that the assumptions of the win maximization hypothesis are wrong.

We even find that breaking down market efficiency by contract type does not help. Figure 2 breaks down MLB contracts into three types. Monopsony, which is all players who have between 0-3 years of playing experience since their debut. This should be the group that gets exploited the most because owners have no obligation to pay them anything above league minimum. Then there is the Arbitration group which is players who have between 4-6 years of playing experience since their debut. If a player feels that they are being unfairly compensated then they can go in front of a judge and plead their case. This gives Arbitration players a small amount of bargaining power but still not much. The final group is Free Agents. This group of players has been playing in MLB for over 6 years. They can sign a contract with whichever team they desire for anything equal to or above league minimum. Usually, only players who are above average stay in MLB for more than six years which means that these players will often demand lofty salaries to compensate for their high level of play. Thus, we would expect them to be the least profitable group because of the winner's

curse (Andreff & Szymanski, 2006). Obviously, this is a over generalization of the complexity that exists in the CBA which dictates exactly how each player can negotiate their contract depending on a variety of factors. However, breaking down the contracts into these groups illustrates the most important changes in bargaining power throughout a player's career. Instead, in Figure 2 we find that the group with no negotiating power (Monopsony) is somehow the one that is being overpaid the most by an incredibly large multitude for most years. And the difference in bargaining power seems to have no effect on compensation amount between the Free Agent and Arbitration. Overall, this disagrees with previous literature on how profits are split between groups (Siddhartha & Devadoss, 2002). Considering that the win maximization theory has flawed assumptions, and conclusions drawn while using it disagree with other literature from labor economics and industrial organization, it would seem these conclusions should be rejected.

### 4.3 Utility Maximization Results

Calculating the marginal revenue product of labor for players using the utility maximization method is slightly more complex than it was for the win maximization method. The approach used is outlined in Section 3.3. To begin estimation, we use Equation 8 which outlined the fixed effects regression that we would use to determine the effect scoring runs and having runs scored against a team has on their attendance, and the results of it can be seen in Table 3. Our model estimates that for every additional run scored by team  $I$  in year  $J$ , team  $I$  can expect about an additional 2,800 fans in attendance in year  $J$ . Similarly, for every additional run scored against team  $I$  in year  $J$  we can expect team  $I$  to have about 2,600 less fans in attendance in year  $J$ . An interesting note, the adjusted  $R^2$  value is slightly higher for this model compared to the win maximization model

in Table 3. The difference is quite small but it could possibly be due to the better explanatory power that game quality and contention has on consumer behavior compared with wins (Borland & Macdonald, 2003).

Estimates must also be gathered for the weights of the  $\phi$ 's in Equation 9 and  $\beta$ 's in Equation 10 to estimate player MRPL. We used the variables *Pitching* and *Fielding* in Equation 9 and the variables *Hitting* and *Baserunning* in Equation 10 to generally represent the different offensive and defensive outcomes considered. The variables that were ultimately included and their associated weights are shown in Table 2. An important note, while some variables share the same name in the table, they are not the same variable. Take, for example, *SB*. For the regression titled *RA*, *SB* represents team *I*'s stolen bases against, and the associated weight represents the effect an additional stolen base against team *I* has on team *I*'s runs scored against value. While for the regression titled *R*, *SB* represents team *I*'s stolen bases, and the associated weight represents the effect that stealing an additional base has on team *I*'s scored runs value.

Calculating a player's MRP using the utility maximization method has been lightly outlined in Section 3.3 and we follow a similar procedure of calculating player MRP in as done in Section 4.2. Simply take the offensive and defensive outcomes of each player that are in Table 2 and multiply them with the weights also found in Table 2. This will provide an estimate for the player's effect on their team's *RA* and *R* values. To compute the effect a player had on attendance we use Equation 8 with the weights found in Table 3. Simply multiply the player's *RA* and *R* values by their associated effect on attendance. This generates two values for a player representing the estimated effect they had on attendance through their offensive and defensive performance. Simply add these two values together to generate a holistic view of a player's MRPL in a given year.

As discussed in Section 3.4 and used in Section 4.2, we can use Equation 12 to estimate what

attendance owners expected players to bring in. The value of  $\widehat{\zeta}_1$  can be viewed in Table 4. To convert player salary to attendance, simply multiply a player's real salary in a given year by  $\widehat{\zeta}_1$ . It is not possible to discuss market efficiency when using the utility maximization method.

Determining the efficiency for both individual players and the market is quite simple. Efficiency can be expressed as the ratio of MRPL divided by wage ( $\frac{MRPL}{Wage}$ ), where both MRPL and wage are measured in attendance. We would expect a perfectly competitive market to have a ratio of 1. In a market where players are under monopsony hiring power this ratio would be greater than 1. We expect that for a market where players who have formed a monopoly, such as a labor union, this ratio would be less than 1. Figure 3 shows the weighted mean of all MRPL ratios from 1985-2016 across all contract types. A horizontal dashed line has been added at the  $y = 1$  level to represent what we would expect to see if the market were perfectly competitive and players were paid their MRPL. Additionally, there are vertical dashed lines which represent every CBA from 1985-2016, which were often met with a strike by players. Considering again what previous literature says about strikes, we would expect every year there was a CBA and strike that we would see ownership exploiting players less (Card, 1990; Lacroix, 1986; Riddell, 1980). Which is exactly what we see in Figure 3. We find that each strike by player leads to players being compensated closer to their estimated MRPL. Already we see this new method agreeing with more literature than the win maximization method.

Consider instead how efficient the market is when examining each contract type (Monopsony, Arbitration, or Free Agency). We can see from Figure 4 that when using the utility maximization method the results show that most years from 1985-2016 Monopsony had the least favorable deals, followed by Arbitration, and finally Free Agents had the most favorable deals. This agrees with our intuition around bargaining power. The group with the least bargaining power, Monopsony, has

the least favorable deals on average. As the bargaining power begins to shift away from ownership we see this results in players getting more favorable deals, which culminates into the Free Agents, who have the most bargaining power also having the best deals on average. Further, we can see from Figure 4 that our conclusions about the utility maximization method agreeing with previous literature on labor strikes (Card, 1990) continues to hold.

Unmistakably, there is a bilateral monopoly between Monopsony players and ownership. Players are represented by the MLBPA, a union, and face monopsony hiring power from ownership. This means that there is not a good model for where we expect the MRPL ratio to be for this group other than above 1. However, since CBA are public we know the MLBPA has never allowed a nominal pay cut from 1985-2016 (*Major League Baseball Minimum Wage* | *Baseball Almanac*, 2022). To go from a union which was not taken seriously pre-1976 (Hall et al., 2002) to demanding consistent and significant raises to minimum salary, shows a large shift in bargaining power towards the MLBPA. We would expect using the methods of Siddhartha & Devadoss (2002) that this shift in bargaining power should mean that the Monopsony group is compensated more greatly over time. Which is exactly what is illustrated in Figure 4, we see the Monopsony group being exploited less. Thus, suggesting that the utility maximization method also works better than the win maximization for understanding how bilateral monopolies interact.

## 5 Conclusion and Directions for Further Research

In conclusion, we find that we can replicate the findings of previous literature that players are overpaid when using the win maximization hypothesis (Krautmann, 1999). We also confirm previous literature's hypothesis that finds estimation of MRPL is extremely sensitive to measuring tech-

niques and has drastic effects on interpretation of efficiency over the considered timeline (Krautmann, 1999). However, we find that examining the results of the win maximization hypothesis over a long period of time disagrees with our intuition and understanding of both negotiation power in labor strikes (Card, 1990; Lacroix, 1986; Riddell, 1980) and the functioning of bilateral monopolies when not vertically integrated (Siddhartha & Devadoss, 2002). Conversely, we find that using the utility maximization hypothesis allows us to remedy the previously mentioned errors with previous literature. This is not to say this paper's methodology is perfect or that it gives the final say on the subject. There were many simplifying assumptions that were made which makes extrapolation difficult. Improvement in data quality and availability are the two most prevalent problems that this paper faced. For example, were the revenue for each team accurately reported there would not have been a need to measure player MRPL, nor player salary, in terms of attendance. Additionally, the lack of availability of salary data prevented using very accurate measurements of player quality using more advanced analytics. Using methods such as openWAR would have allowed for even more accurate performance evaluations of players (B. S. Baumer et al., 2015). However, the main argument that this paper puts forth is that there exists a better structure from which future research can be done to find if the MLB labor market is acting efficiently.

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## 7 Tables

Table 1: Performance on Win Percentage Regression

	WinPct
Constant	192.97*** (37.88)
X1B	0.03*** (0.00)
X2B	0.03*** (0.00)
X3B	0.07*** (0.01)
HR.x	0.10*** (0.00)
BB.x	0.02*** (0.00)
SB.x	0.02*** (0.00)
HBP.x	0.04*** (0.01)
SF.x	0.03* (0.01)
E.y	-0.03*** (0.01)
PB	-0.05* (0.02)
SB.y	-0.01*** (0.00)
H.y	-0.03*** (0.00)
HR.y	-0.07*** (0.01)
BB.y	-0.03*** (0.00)
SH	-0.03* (0.01)
N	918
Adj. $R^2$	0.81

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 2: Performance on RA &amp; R Regressions

	RA	R
Constant	457.54* (227.89)	
E	0.22*** (0.04)	
SB	0.14*** (0.03)	0.20*** (0.02)
IPouts	−0.46*** (0.01)	
H	0.23*** (0.02)	
HR	0.86*** (0.04)	1.42*** (0.04)
IBB	−0.16** (0.05)	
BFP	0.35*** (0.01)	
SF	0.59*** (0.10)	0.75*** (0.10)
WP	0.24*** (0.07)	
X1B		0.47*** (0.02)
X2B		0.71*** (0.04)
X3B		1.10*** (0.11)
BB		0.31*** (0.01)
CS		−0.17* (0.08)
HBP		0.42*** (0.05)
N	918	918
Adj. $R^2$	0.95	0.94

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 3: Attendance Regressions

	AttWPCT	AttRSRC
Constant	−36 231 931.55*** (3 650 118.34)	
WinPct	40 959.27*** (2449.63)	
R		2801.92*** (306.92)
RA		−2575.09*** (261.53)
N	918	918
Adj. $R^2$	0.57	0.59

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 4: Team Cost Regression

	AttCost
Constant	42 158 947.61*** (5 516 501.63)
TeamCost	0.01*** (0.00)
N	918
Adj. $R^2$	0.59

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

## 8 Graphs

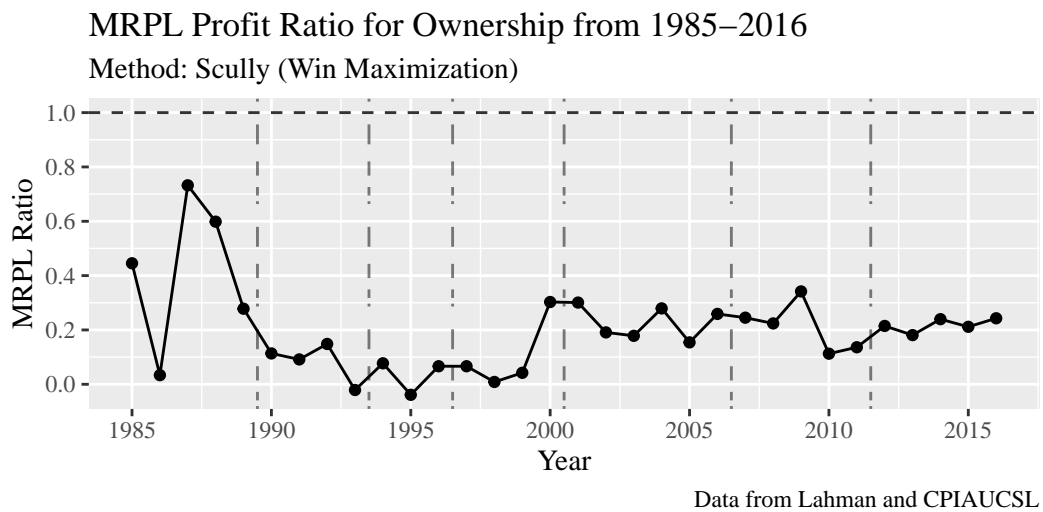


Figure 1: MRPL Profit Ratio for Ownership from 1985-2016

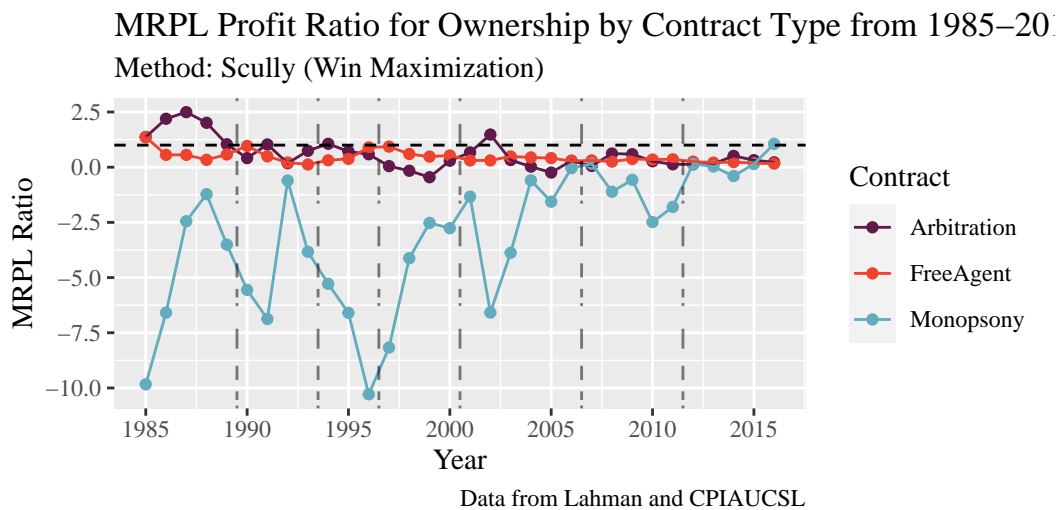


Figure 2: MRPL Profit Ratio for Ownership by Contract Type from 1985-2016

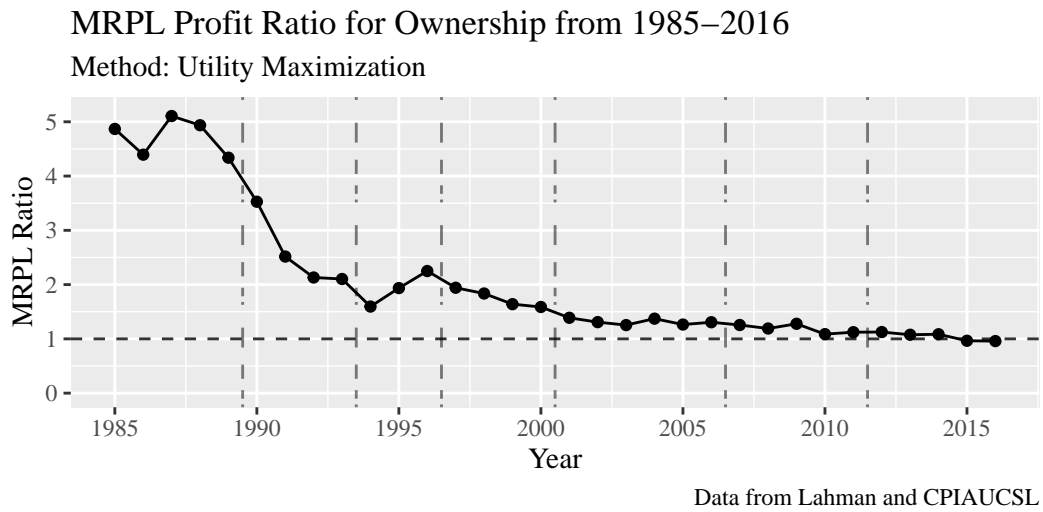


Figure 3: MRPL Profit Ratio for Ownership from 1985-2016

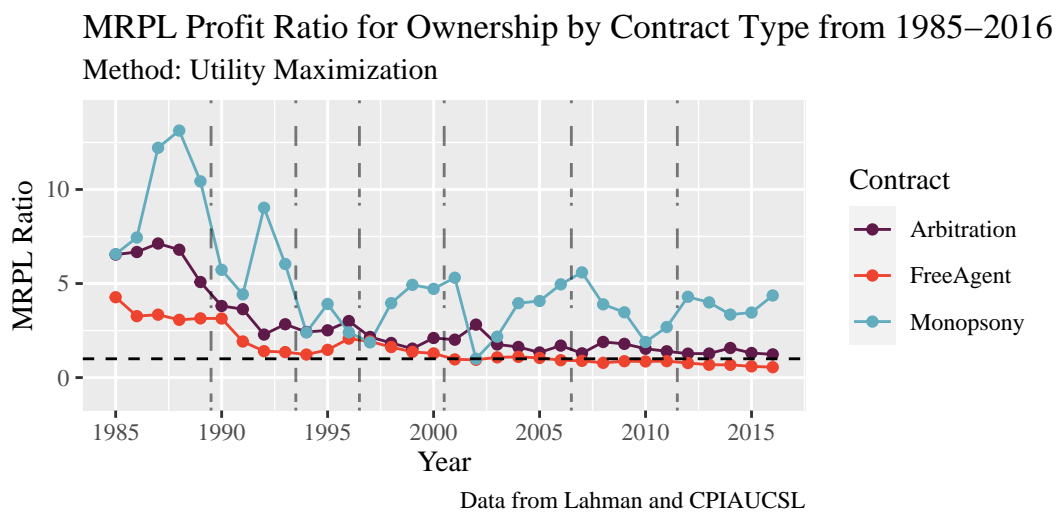


Figure 4: MRPL Profit Ratio for Ownership by Contract Type from 1985-2016