Curveballs and Contracts

Examining the Market Efficiency for MLB Player Contracts

Sam Turner

2023-11-27

MLB players earned free agency in 1976, yet the sports economics literature remains thin in examining its effect on the efficiency of the market for player contracts, and it still offers conflicting results. To address these gaps in the literature, our study aims to offer a deeper understanding of the elements influencing efficiency within the MLB labor market. We use a panel fixed effect model using comprehensive data spanning from 1985 to 2016. While our results indicate that from 1985 to 1999 the contract market was acting inefficiently, beginning in the year 2000, the market reached levels close to efficiency, which carried forward through 2016. These findings remain robust when considering different contract types, such as Monopsony, Arbitration, and Free Agency. This stands starkly in contrast with the findings of previous literature, which suggest that, regardless of contract type, the market never came close to equilibrium during the years considered.

1 Introduction

The 2004 publication of Moneyball sent shock-waves through Major League Baseball (MLB) ownership. Its thesis was that owners were valuing players' offensive and defensive production incorrectly. This allowed 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 to test whether it had any credibility. These economists found that directly after the publication of Moneyball players saw a spike in compensation for walks and other desired statistics described in Moneyball (Congdon-Hohman & Lanning, 2018;

Duquette et al., 2019; Hakes & Sauer, 2006; Thaler & Sunstein, 2004). Yet, more contemporary research has found this compensation was lessened in the years following (Baumer et al., 2015; Pinheiro & Szymanski, 2022). While an enjoyable read which highlighted a shortcoming of MLB ownership Moneyball's thesis 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 labor market for MLB players. The aim of the paper is to examine the efficiency of the labor market for MLB player; more precisely, is the market for MLB player contracts acting efficiently?

The idea of labor market efficiency is heavily prevalent in labor and sports economics. Efficiency of a labor market simply describes compensation compared to productivity of labor. Thus, research in market efficiency focuses on identifying market structure, and then measuring labor productivity and comparing it to wages. Previous attempts at this measurement for MLB player contracts have been performed by 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 ***M***arginal ***R***evenue ***P***roduct of ***L***abor (MRPL) model to judge the productivity of MLB players. To achieve this, Scully first estimated how players impact their team's ability to win and multiplied that effect by the estimated effect winning has on revenues for teams. Ultimately, Scully found that players were compensated less than their productivity because they faced monopsonistic hiring power from ownership. However, 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, such as not considering pitchers in his analysis. 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. For example, Scully only evaluated hitters on their slugging percentage and discarded all other measurements of success. Since market efficiency has hardly been investigated in the past 25 years, for MLB players, 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 not incorporated in this previous research.

Inspired by the work of more contemporary baseball statisticians (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 to achieve the most accurate results (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 whether a more rigorous analytic approach has any impact on his findings. This should result in better measurements of players' abilities. 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 fan engagement. 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 Scully (1974) and Krautmann (1999) when repeating their methods. Specifically, if we judge players only on their ability to help their team win then the data suggests they are mis-compensated. However, when we examine the findings of Scully (1974) and Krautmann (1999) for the seasons from 1985 to 2016 their findings become inconsistent with previous literature on labor strikes. Labor strikes, which occurred six times over this period, should lead to higher real compensation for players (Card, 1990). Changes in real compensation, induced by labor strikes, should be reflected in efficiency models. Yet, the models from both Scully (1974) and Krautmann (1999) are unable to account for these strikes. However, the model using new regression techniques paired with assumptions from new consumer demand research is able to reflect the consequences of labor strikes in predictions of efficiency. Thus, our model erases the discrepancy created by Scully (1974) and Krautmann (1999). This suggests that our model makes better, more accurate, predictions about the efficiency of player compensation.

2 Literature Review

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 confirmed, that the reserve clause created monopsony hiring power for MLB ownership. Scully concluded that this allowed for owners to pay players wages which were less than their MRPL. 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 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 meaningful and novel.

A shortcoming of Scully's (1974) method is his reliance on the assumption that winning games is the only thing that consumers, and therefore owners, care about. This led Scully (1974) to judge players' productivity on their ability to help their team win. However, it is obvious that fans care about things other then 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 doubts and finds consumers do not 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 suspenseful and well-played game, rather than knowing their team will win.

Some economists noticed that the abolition of the uniform reserve clause created a bilateral monopoly between players and owners (Vrooman, 1996, p. 353). Neither Scully (1974) nor Krautmann (1999) accounted for this in their models. This shortcoming caused us to take the fact of a bilateral monopoly into account in our models to maximize applicability and generalize our findings. Previous literature would suggest that this bilateral monopoly should be modeled using bargaining power (Siddhartha & Devadoss, 2002). More precisely, this literature concludes that parties with more bargaining power will earn a higher proportion of the profits split between the two groups. In the context of MLB player negotiations, this means that we can expect that as either owners or players change their bargaining power so too will their proportions of compensation change. In turn, we should see these changes in compensation reflected in our models of efficiency.

3 Economic Model

3.1 Marginal Revenue Product of Labor

Scully (1974) is credited not only with being the first to investigate efficiency of MLB contracts, but also the first to apply the MRPL method in any sub-field of economics (Bradbury, 2013). In the abstract, the MRPL relates individual labor productivity to revenue. As described in Equation 1, it achieves this by multiplying the output from labor by the associated effect on revenue.

$$MRPL = \frac{\Delta R}{\Delta Q} \cdot \frac{\Delta Q}{\Delta L}. \tag{1}$$

Where ΔR is the change in revenue due to the ΔQ change in quantity which is then multiplied by the ΔQ change in quantity due to the ΔL change from labor. It is advantageous to use this method because it allows computation of per worker contributions to revenue.

This tool should not be used to make normative claims; it only acts to measure per worker contribution to revenue. Indeed, Scully (1974) uses this solely to measure a single MLB player's contribution to team revenue. He relies on other economic theory to make the normative claim about efficiency (Scully, 1974).

Dad suggestion- However, a separate conceptualization of aggregate/team MRPL based on the model described in Equation 1 is revealing.

Any normative claims about efficiency rest on market structure rather than MRPL (Krautmann, 1999).

3.2 Win Maximization Method

In sports economics there are two theories which attempt to explain success is in the eyes of team ownership (Andreff & Szymanski, 2006): the win maximization method and the utility maximization method. Under the win maximization theory the owner's major or sole concern is winning. This means that ownership, which we assume is rational, will have much more inelastic demand for talented players. This can result in running deficits, and generally treating the team unlike a profit maximizing firm (Andreff & Szymanski, 2006, pp. 601–603). Scully (1974) uses the marginal revenue product of labor, paired with the win maximization hypothesis, to examine whether the labor market for MLB players was behaving efficiently. Scully's estimation of the MRPL is estimated by team data in the following equation,

$$MRPL_{I,J} = \frac{\partial TR_{I,J}}{\partial WPCT_{I,J}} \cdot \frac{\partial WPCT_{I,J}}{\partial PERF_{I,J}}. \tag{2}$$

Where ∂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 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 turnstile revenue (fans watching game at the stadium) and broadcasting (both television and radio) revenues (Scully, 1974, p. 917). Attendance is the major factor in turnstile revenue, and so it is not a significant logical leap to assume that turnstile revenues are 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,

$$MRPL_{I,J} = \frac{\partial Attendance_{I,J}}{\partial WPCT_{I,J}} \cdot \frac{\partial WPCT_{I,J}}{\partial PERF_{I,J}}. \tag{3}$$

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,

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

In Equation 4, Γ_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 Γ_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 α_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 θ_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 α_I and θ_J is that we can safely remove a significant proportion of endogeneity and omitted variable bias that was present in Scully's analysis. The term ϵ 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 the Ith team's attendance, $Attendance_{I,J}$, in year J in the following fixed effects regression,

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

In Equation 5, Ω_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 Ω_1 is available in Section 4.2. The term η_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 τ_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 η_I and τ_J allow for a significant reduction in endogeneity and omitted variable bias. The term ϵ is the error term of the regression and is used to represent any other variation in the data.

Ultimately this makes estimating the MRPL of each player ($\widehat{MRPL}$) into a composite function. After deriving the values of Γ_1 and Ω_1 the following equation can be used to estimate a player's MRPL,

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

In Equation 6, $\widehat{MRPL}_{A,W}$ represents the estimated MRPL of player A using the Scully method, W. We can calculate the player's MRPL using their performance statistics, $PERF_A$ and multiplying that by their associated weights Γ_1. At this stage we have calculated how the player effects his team's ability to win. Then, we can multiply that by Ω_1 to derive the players estimated effect on attendance, which is ultimately his MRPL. 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 Γ_1.

3.3 Utility Maximization Method

The second theory defining success in the eyes of ownership is known as the utility maximization theory. This theory can be used to describe the motivations of ownership groups who do not subscribe to the win maximization theory. Since ownership is assumed to be rational, if they are not maximizing wins then they must be maximizing profit. As outlined in Section 3.2, we cannot reliably identify team profit but we can identify revenue through a proxy, attendance. Thus, we assume owners under the utility maximization theory seek to maximize attendance. We know from consumer behavior research that fans attend games more than simply to see the home team win, contrary to what Scully (1974) assumes (Borland & Macdonald, 2003). Indeed, it has been found that quality and contention of a game are better predictors of fan enjoyment than a team winning (Borland & Macdonald, 2003). Logically, higher fan enjoyment should lead to higher attendance. Thus, ownership seeking to maximize attendance must hire players who maximize game contention and quality. However, ownership cannot control individual game contention, only their team's quality. Therefore, ownership must be hiring to maximize player quality, which in turn will lead to enhanced game quality and higher attendance. Game quality can be broken down into offensive and defensive aspects. We believe that the best representation of offensive quality is scoring runs and the best representation of defensive quality is preventing runs from being scored. To ensure a holistic view of player 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,

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

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 in offensive performance statistics, $\partial PERF$, have on team I's ability to score runs, ∂R, in year J. Then, it describes the estimated effect scoring runs, ∂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 to defensive performance statistics, $\partial PERF$, have on team I's ability to prevent runs from being scored, ∂RA, in year J. Then, it describes the estimated effect preventing runs from being scored, ∂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.

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,

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

In this regression RA is a 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 μ_1 is the associated effect that an additional RA will have on the attendance of team I in year J. Similarly, μ_2 is the associated effect that an additional R will have on the attendance for team I in year J. The variable ψ_I is a fixed effect variable and 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 λ_J is a fixed effect variable and 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 ϵ is the error term of the regression and is used to represent any other variation in the data.

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 estimate how offensive and defensive outcomes effect a team's ability to score and prevent runs from being scored. Thus, we can estimate how much each player has individually contributed to their team's runs scored and runs scored against. We can achieve this by determining which outcomes are most important in scoring runs and preventing runs from being scored with the following fixed effect regressions,

$$RA = \phi_0 + \phi_1 Pitching + \phi_2 Fielding + \omega_I + \chi_J + \epsilon, \tag{9}$$

$$R = \beta_0 + \beta_1 Hitting + \beta_2 Baserunning + \rho_I + \pi_J + \epsilon. \tag{10}$$

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 ϕ_1 and ϕ_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 β_1 and β_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 ω_I and ρ_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 χ_J and π_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 ϵ is understood to be the error term that accounts for any additional variation in the data.

Then, similar to Equation 6, estimating a player's MRPL ($\widehat{MRP}L$) a composite function. After deriving the values of $\mu_1, \mu_2, \phi_1, \phi_2, \beta_1$, and β_2 the following equation can be used to estimate a player's MRPL,

$$\widehat{MRP}L_{A,U} = [\mu_1 \cdot (\phi_1 Pitching_A + \phi_2 Fielding_A)] \tag{11}$$

$$+[\mu_2 \cdot (\beta_1 Hitting_A + \beta_2 Baserunning_A)].$$

In Equation 11, $\widehat{MRPL}_{A,U}$ represents the estimated MRPL of player A using the utility maximization method, U. We can calculate the player's MRPL using their performance statistics ($Pitching_A, Fielding_A, Hitting_A$, and $Baserunning_A$) and multiplying that by their associated weights (ϕ_1, ϕ_2, β_1, and β_2 respectively). At this stage we have calculated how player A affects his team's ability to score runs and prevent runs from being scored. Then, we can multiply these abilities by μ_1 and μ_2 respectively and finally add these effects to derive player A's estimated effect on attendance, which is his MRPL. 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 (ϕ_1, ϕ_2, β_1, and β_2 respectively).

3.4 Relating Attendance to Wages

Measuring marginal revenue using attendance instead of dollars was necessary to preserve the integrity of the analysis 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, using the assumptions underlying each theory and some deduction, it follows that attendance can also be used as a proxy for wage.

Scully's (1974) method relies on the assumption that revenue, and therefore attendance, is driven by winning. He assumes fans only care about seeing the home team win. Hence, attendance and winning are very highly correlated. Since ownership only compensates player for winning, it follows then that player's compensation is highly correlated with the amount of attendance they bring in. Players who win more will be associated with higher attendance levels and consequently have higher pay. Using the utility maximization assumptions, we know players will be compensated by how much revenue and attendance they generate. Thus, across both models and assumptions we see that the attendance a player generates is reflected in their compensation. This means we can model attendance as a function of payroll. In other words, we know that we can express player compensation as expected attendance generated. To estimate what the conversion factor is for payroll to attendance we can regress team attendance on team payroll with the following fixed effects model,

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

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 ζ_1. Payroll is the sum of the cost of all contracts for players for team I in year J. The terms ξ_I and σ_J represent the fixed effects. The term ξ_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 σ_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. It is now possible begin exploring market efficiency for player compensation.

4 Empirical Strategy

4.1 Data Sources

There are two sources from which data were gathered. The first source was the Lahman database which was accessed through the "Lahman" R package (Friendly et al., 2022). The Lahman database 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 (Friendly et al., 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 generally 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.

4.2 Win Maximization Results

As discussed in Section 3.2, calculating the MRPL for each player using the win percentage method first requires two regressions. 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 was outlined in Equation 4. In Equation 4 we use Γ_1 and $PERF_{I,J}$ as placeholders representing all the variables tested and their associated effects on the Ith team's win percentage in year J. To see which outcomes were selected and their associated weights refer to Table 1. An important note for understanding the variable names, all variables from X1B to SF.x in Table 1 are offensive outcomes for 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). The dependent variable, Win Percentage, is expressed as a real number on the interval [0-100] inclusive. Arguably, this would be an appropriate situation to use a logistic regression by scaling the dependent variable, Win Percentage, to fit between the values of [0-1] inclusive. However, the goal of this section is to replicate the win maximization hypothesis, and neither Scully (1974) nor Krautmann (1999) used a logistic model. Therefore, we have decided to forego the logistic regression and instead opt for a fixed effects regression for consistency's sake. 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. 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 Ω_1 to be about 41,000 fans per year, which implies an additional 1 point in a team's win percentage is an associated with about an additional 41,000 fans attending that team's games 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' MRPL. 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 $\widehat{\zeta_1}$ 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' MRPL. Calculating the MRPL for a player has already been roughly outlined in Equation 6. Simply take the number 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 Ω_1 in Table 3 and gain the estimate of the player's MRPL in a given year. To find whether 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 MRPL by the wage of the player ($\frac{MRPL}{Wage}$) where both MRPL 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 MRPL (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 average MRPL ratio in MLB from 1985-2016. 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 paid to bring in less attendance than they have actually generated for the entirety of the years considered. This supports the findings of previous literature (Krautmann, 1999; Pinheiro & Szymanski, 2022). 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 ownership groups. 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). Better bargaining power for players would mean that they would be better compensated (paid more) for the same amount of production (Siddhartha & Devadoss, 2002). This would be represented in Figure 1 as the MRPL ratio decreasing. Yet, Figure 1 clearly does not support this conclusion since there is clearly no pattern of MRPL ratio decreasing after striking.

We even find that breaking down market efficiency into the three different contract types, Monopsony, Arbitration, and Free Agents, does not resolve the aforementioned inconsistencies. The Monopsony group is all players who have between 0-3 years of playing experience. Players in this category do not have any bargaining power in contract negotiations (Vrooman, 1996). This should be the group that gets exploited the most because owners have no obligation to pay them anything above league minimum. Second, there is the Arbitration group which is players who have between 4-6 years of playing experience. If players in this category feel they are being unfairly compensated then they can plead their case to a "judge" and possibly have their salary raised (Vrooman, 1996). This gives Arbitration players a small amount of bargaining power, so we would expect them to make more than the Monopsony group. 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 (Vrooman, 1996). 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 an 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.

In Figure 2 we find that the group with no negotiating power (Monopsony) somehow has the smallest MRPL ratio by an incredible multitude for most years. Further, we see the Arbitration and Free Agent groups have roughly the same MRPL ratio from 1985-2016, despite having vastly different bargaining powers. This contradicts what non-vertically integrated bilateral monopoly literature would suggest (Siddhartha & Devadoss, 2002). This literature would predict that the Monopsony group would have the highest MRPL ratio. Arbitration and Free Agents would have the medial and lowest MRPL ratios, respectively. Overall, it would appear that using the win maximization hypothesis is a bad idea because it leads to discrepancies between results and research in consumer behavior, labor strikes, and industrial organization.

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 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 ϕ's in Equation 9 and β'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 MRPL using the utility maximization method has been briefly outlined in Section 3.3 and we follow a similar procedure of calculating player MRPL in as done in Section 4.2. Simply take the offensive and defensive outcomes of each player and multiply them with the weights 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 $\widehat{\zeta_1}$.

Determining the efficiency for both individual players and the market is 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 have formed a monopoly, such as a labor union, this ratio would be less than 1. Figure 3 shows the league MRPL ratios from 1985-2016 when using the utility maximization hypothesis. 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. Using the same logic as Section 4.2 we would expect to see a decrease in the MRPL ratio every year there was a strike (Card, 1990; Lacroix, 1986; Riddell, 1980; Siddhartha & Devadoss, 2002). In Figure 3 we see that every year there was a strike the MRPL ratio decreased, except for from 2011-2012. Thus, the utility maximization hypothesis is consistent with labor strike and bilateral monopoly literature when considering the league as a whole.

From Figure 4 we see that breaking down efficiency by contract type maintains this consistency with previous literature. We see that the Monopsony group has the largest MRPL ratio. The Arbitration and Free Agent groups have the medial and smallest MRPL ratios, respectively. This is exactly what labor strike (Card, 1990) and non-vertically integrated bilateral monopoly (Siddhartha & Devadoss, 2002) literature predicts would happen. This literature would predict that the groups with the least amount of bargaining power would have the highest MRPL ratio, which is exactly what we see. Thus, the utility maximization hypothesis seems to be a better alternative to the win maximization hypothesis because it is more consistent with the findings in consumer behavior, labor, and industrial organization research.

5 Conclusion and Directions for Further Research

In conclusion, we can confirm 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 sensitive to measuring techniques which effects interpretations of efficiency over the considered period (Krautmann, 1999). However, we find that the results of the win maximization hypothesis are inconsistent with findings in labor strike (Card, 1990; Lacroix, 1986; Riddell, 1980) and bilateral monopoly literature (Siddhartha & Devadoss, 2002). This literature suggests that strikes should bring better bargaining power for labor in contract negotiations. In turn, this should lead to a lower MRPL ratio in the year following a strike. Yet, as shown in Figure 1, we find that the MRPL trends upward between 1993-1994 and 2011-2012, while remaining almost identical between 1996-1997 and 2000-2001. Between all of these seasons there was a player strike, therefore the win maximization findings disagree with what labor strike and bilateral monopoly literature would suggest.

Conversely, we find that using the utility maximization hypothesis does not suffer the same issues as the win maximization hypothesis. Indeed, we find that the utility maximization hypothesis is consistent with labor strike (Card, 1990; Lacroix, 1986; Riddell, 1980) and bilateral monopoly (Siddhartha & Devadoss, 2002) literature. For example, when using the utility maximization hypothesis in Figure 3 between the years 1989-1990, 1993-1994, 1996-1997, 2000-2001, and 2006-2007, the MRPL ratio decreases as previous literature would suggest (Card, 1990; Siddhartha & Devadoss, 2002). Clearly, the utility maximization hypothesis has been shown to be more accurate than the win maximization hypothesis. Especially concerning research in consumer demand, labor strikes, and bilateral monopolies. This implies that using the utility maximization theory will give a more accurate picture as to the efficiency of MLB player compensation.

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, such as rational ownership and using attendance in place of revenue and salary, just to name a few. However, these assumptions were necessary to conduct the study. As a case in point, using the team revenue data available, which previous literature relied on (Krautmann, 1999), would have made the findings of this paper even less accurate. Improvement of any of the assumptions by making them more reflective of the real world will improve the applicability of these findings. Further, improvements in the data availability would make extrapolation possible. For example, data on player salaries ended in 2016, nearly 10 years ago. If more modern data were available then stronger conclusions could be drawn about contemporary contract efficiency. However, the main argument that this paper puts forth is that there exists a better structure from which future research can be conducted to find whether the MLB labor market is acting efficiently. This future research could be as simple as using better assumptions and or data to examine this research topic. Or, this could be more complicated such as using more advanced statistics available from modern tracking technology, which were implemented post-2016.

TALK ABOUT NON-LINEAR REGRESSIONS AND LOGISTIC REGRESSIONS WOULD BE A GOOD IDEA FOR FUTURE RESEARCH

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7 Tables

Table 1: Performance on Win Percentage Regression

	WinPct
Constant	193.06***
	(37.87)
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 & R Regressions

	RA	R
Constant	456.86*	
	(227.90)	
E	0.22***	
	(0.04)	
SB	0.14***	0.20***
	(0.03)	(0.02)
IPouts	−0.46***	
	(0.01)	
H	0.23***	
	(0.02)	
HR	0.86***	1.42***
	(0.04)	(0.04)
IBB	−0.16**	
	(0.05)	
BFP	0.35***	
	(0.01)	
SF	0.59***	0.75***
	(0.10)	(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

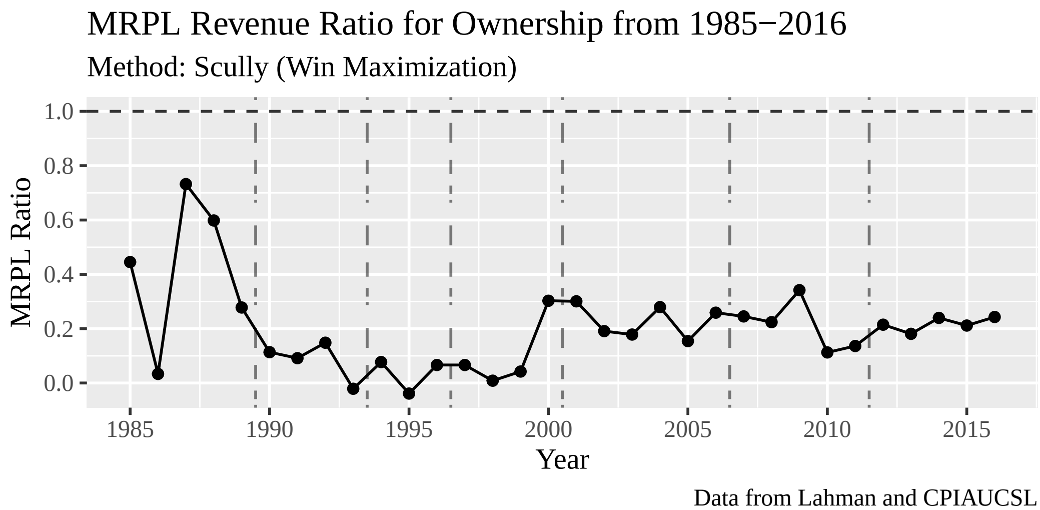

Figure 1: MRPL Profit Ratio for Ownership from 1985-2016

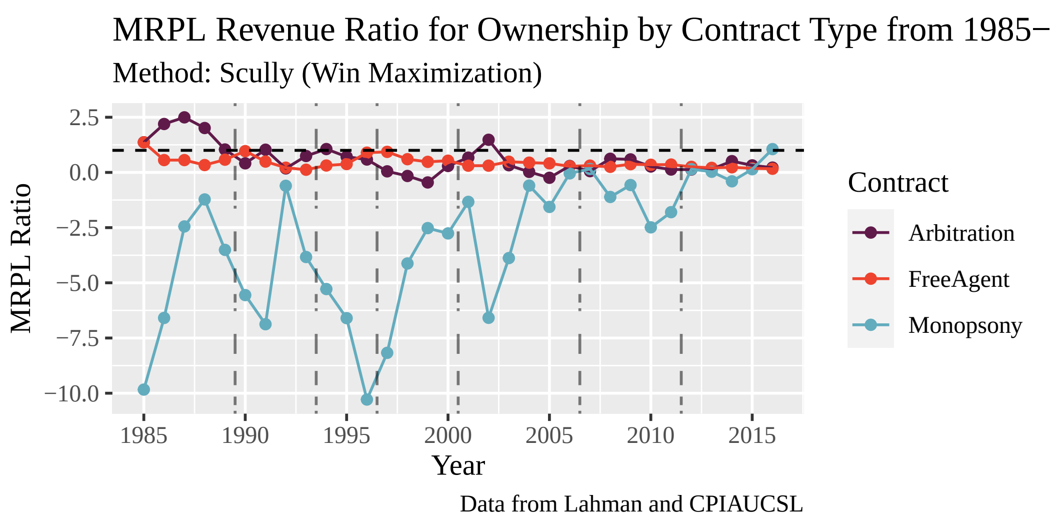

Figure 2: MRPL Profit Ratio for Ownership by Contract Type from 1985-2016

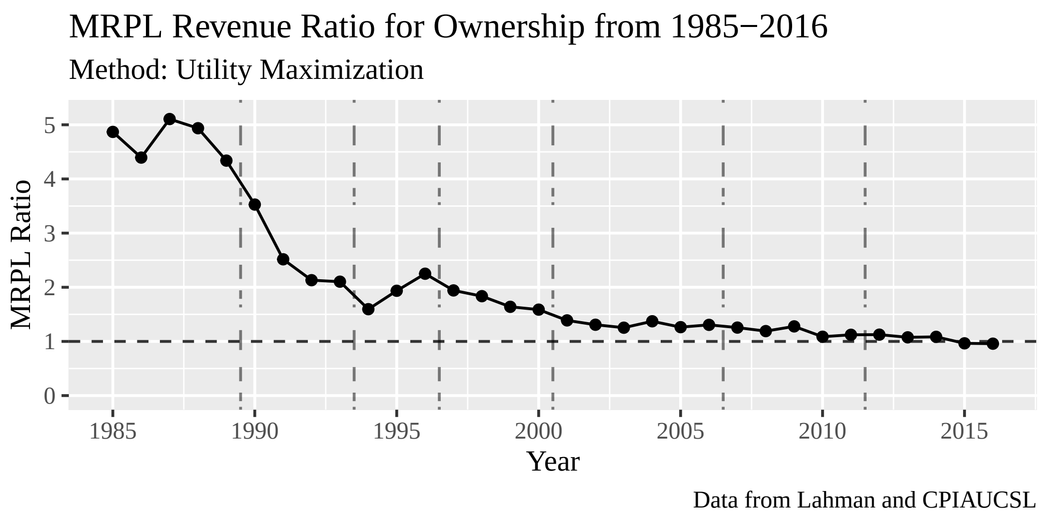

Figure 3: MRPL Profit Ratio for Ownership from 1985-2016

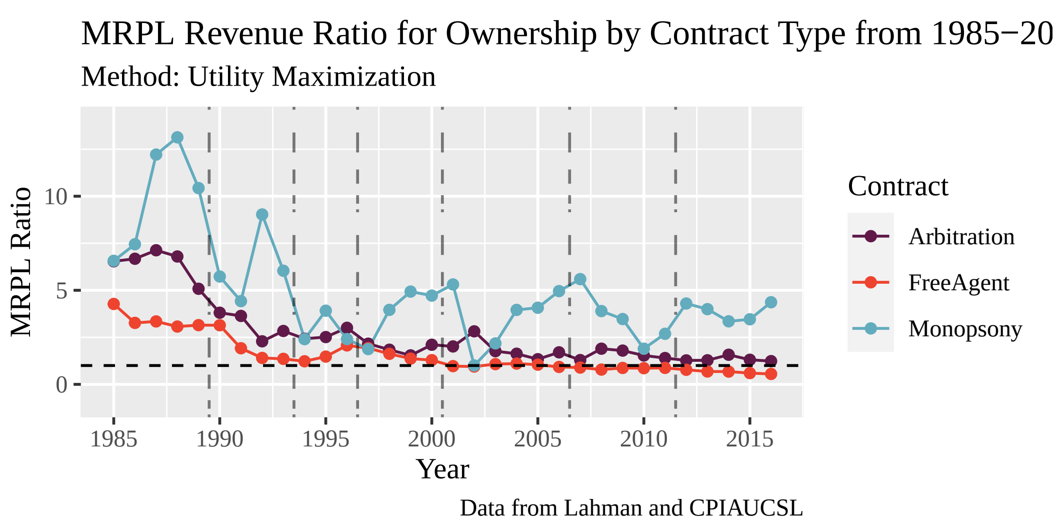

Figure 4: MRPL Profit Ratio for Ownership by Contract Type from 1985-2016