Monopsony Exploitation in Major League Baseball

Using Wins Above Replacement to Estimate Marginal Revenue Product

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Abstract

Sports leagues offer the most salient examples of monopsony power in labor markets in the modern world due to the competitiveness of the industry and institutional arrangements such as entry-level drafts. This paper updates the Scully (1974) method to analyze the monopsonistic exploitation of Major League Baseball players over the 2012 to 2019 seasons. The results indicate that free-agency-eligible and arbitration-eligible players have seen significant improvement in their salaries relative to their revenue production under recent CBAs while rookie players continue to see upwards of 87% of their revenue product expropriated by their controlling team.

Introduction

Professional sports franchises in the United States operate under a set of unique circumstances that grant them monopolistic power over their fanbases and monopsonistic power in their respective labor markets. In Major League Baseball (MLB), teams' monopolistic power is somewhat mitigated due to the fact that every team operates in a city with at least one other sports franchise in the National Football League, National Basketball Association, or National Hockey League. However, institutional arrangements agreed upon between the MLB Player's Association (MLBPA) and the league such as the entry level draft, international bonus pool, and arbitration system subject MLB players to substantial monopsonistic control for the first six years of their careers. This may seem like a small price to pay given the seemingly absurd contracts that are routinely doled out to top MLB free agents like Mike Trout's 12-year $426.5 million extension with the Los Angeles Angels of Anaheim and Gerrit Cole's nine-year $324 million contract with the New York Yankees, both signed in the past two seasons. However, the majority of players reach their peak productivity in the earlier seasons of their careers and are unable to cash in when they finally reach free agency. Additionally, recent trends in the free agency market such as an increase in one-year contracts and an increasingly slow-to-develop market have left players, agents, and the MLBPA extremely frustrated, so much so that they have threatened a work-stoppage when the current CBA expires in 2021 if these problems are not addressed.

This paper provides an update and improvement on past estimates of monopsonistic exploitation in Major League Baseball using data from 2012 to 2019. The empirical analysis estimates Marginal Revenue Product (MRP) of MLB players using team revenue data, team performance data, and individual performance statistics, using an updated version of the approach pioneered by Gerald Scully in his paper *Pay and Performance in Major League Baseball*. I emulate and extend the approach used by Brad Humphreys and Hyunwoong Pyun in their paper *Monopsony Exploitation in Professional Sport: Evidence from Major League Baseball Position Players, 2000-2011* (Humpreys and Pyun, 2017).

The results of this paper indicate that MER has remained stagnant for rookie players and significantly decreased for arbitration-eligible and free-agency-eligible players. Mean MER for free-agency-eligible players in this sample is negative, suggesting that, on average, free-agency-eligible players have higher salaries than the value they generate. Considering that most players have short careers and never reach free agency, the MLBPA should focus on improving working conditions for rookie players if it hopes to mitigate monopsonistic exploitation of its players most effectively.

Previous Literature and Institutional Context

Joan Robinson, in her book *The Economics of Imperfect Competition* established the theory of monopsony whereby a single buyer in a market with many sellers is able to artificially drive down the market price by reducing the quantity it purchases (Robinson, 1969). “Monopsony” is used more broadly today to refer to models where individual firms face upward sloping labor supply (Boal and Ransom, 1997). In their paper *Monopsony in the Labor Market*, William Boal and Michael Ransom describe several industries where firms enjoy monopsony power. For example, hospital nurses can be subject to monopsonistic control due to differences in hospital concentration. One study found that nurses could increase their salaries by about 20% by moving from the area with the highest concentration (fewest hospitals) to the area with the lowest concentration. Boal and Ransom argue that the biggest case of monopsony in sports is not in a professional league but in the National Collegiate Athletic Association (NCAA) (Boal and Ransom, 1997). In his paper *NCAA Division I Athletics: Amateurism and Exploitation*, Anthony

Miller cites research estimating that a draft-quality football player earns his school $406,000 in revenue and draft-quality basketball players earn their school $1.194 million. NCAA athletes receive many benefits including a free education, but the top athletes still receive far less value than they generate, especially considering that many leave early for professional leagues (Miller, 2016). A USA Today analysis estimated that a typical NCAA men's basketball player receives $120,000 in goods and services annually (Weiner and Berkowitz, 2011).

Gerald Scully was the first to apply monopsony theory to baseball in his analysis of the reserve clause in the MLB in his paper *Pay and Performance in Major League Baseball* (Scully, 1974). The reserve clause, found in player contracts until it was abolished in 1975, tied a player to a single team indefinitely, even if the player signed individual contracts for a definite amount of time. Scully analyzed the effect that this policy had on MLB players' compensation through an analysis of the relationship between marginal revue product (MRP) and salary. In standard models of labor markets, workers are paid an amount equal to their marginal revenue product in a perfectly competitive industry. Thus, Scully deemed that a comparison of MLB salaries to MRP would be appropriate to gauge the extent to which players are monopsonistically exploited through policies like the reserve clause. He formulated the monopsony exploitation ratio (MER) defined as (MRP-Salary)/MRP to quantify the level of exploitation. Scully found that MERs were often in the 0.5-0.85 range in the reserve clause era, meaning compensation for players was often less than half of the value they contributed to output.

While the full reserve clause was abolished in 1975, and free agency was implemented in 1976, teams still have substantial control over players at the beginning of their careers. Players residing in the US, Canada, or Puerto Rico and hoping to enter the league may not sign with the highest bidding team and instead must submit to the entry-level draft that gives one team exclusive rights to negotiate their services. The entry-level draft is a double-edged sword in terms of exploitation because drafted players are tied to the team that chose them unless they choose to go or return to college, and teams also receive draft pick compensation if one of their veteran players rejects a one-year "qualifying offer" (worth the mean salary of the 125 highest-paid players) and signs with another team, increasing the cost of signing top free agents. Signing of foreign-born players is restricted by a spending cap on signing bonus money for each team. Teams also forfeit money from this international bonus pool for signing a player who rejected a qualifying offer.

Players gain bargaining power in negotiation of future contracts by accruing service time in Major League Baseball and fall into different tiers based on the amount of service time they have accrued. MERs must be calculated separately for each group to account for these differences in bargaining power. Most players with less than three years of experience are subject to the full reserve clause giving the team unilateral control over their salary. The MER should be the highest for this group. Players with between three and six years of MLB service gain eligibility for an arbitration system whereby they can appeal to an independent arbitrator should they fail to reach agreement on a new contract with their team. Additionally, per MLB's "Super Two" rule, the top 22% of players (in terms of service time) with between two and three years of MLB service are eligible for arbitration as well. MER should be lower for these players than rookies, but higher than players in free agency, as arbitration-eligible players can still only negotiate with one team. Players with six or more years of service time become eligible for free agency and, being free to negotiate with any team, should have the lowest MER. Multiple papers have estimated MERs that are consistent with these expectations (Scully, 1989; Zimbalist, 1992; Oh and Lee, 2013; Humphreys and Pyun, 2017).

The econometric method I will use will be an extension of the one used by Humphreys and Pyun in their paper *Monopsony Exploitation in Professional Sport: Evidence from Major League Baseball Position Players, 2000-2011*. They follow an adaptation of the three-step method originally used by Scully in 1974. Step one involves an estimation of the marginal revenue of a win. Humphreys and Pyun employ a spline regression model originally used by Oh and Lee in their 2013 paper to account for the marginal value of postseason wins over regular season wins, which cannot be accounted for using Scully's 1974 model. Step two in the estimation is a regression to gauge the marginal revenue product of players by approximating a team production function that includes position player and pitcher performance. Humphreys and Pyun employ a stochastic production frontier model originally used by Lee (2011) using the same performance measures as Zimbalist (1992) and Oh and Lee (2013) and dummy variables used by Scully (1974) to account for the effects of managerial decisions and team effort. Humphreys and Pyun add fixed-effects controls to the model to account for team-specific effects. Finally, Humphreys and Pyun follow the methods of Scully (1974, 1989) to calculate each player's MRP and MER and average MER across player-type and bargaining power groups.

I first replicate the method of Humphreys and Pyun to allow for an apt comparison to their 2000-2011 results. I follow this up with a change to the method, using wins above replacement (WAR) to both estimate the revenue value of a win and more holistically judge player performance. WAR is a sabermetric statistic that attempts to summarize a player's total contributions in terms of wins added over a replacement level player. Replacement level is the level of play a team would get from a freely available player like a minor league free agent who the team could sign for the MLB minimum salary. This is more useful than comparison to an average player, as we want to be able to distinguish between players who were average for a small number of plate appearances, and players who were average over much larger samples. An injury to an average player would result in a much worse player taking their spot, diminishing the value of their roster spot over the course of the season. Replacement level is useful as players of this caliber are freely available and it is the level that teams need not search beneath (Slowinski 2010). WAR is especially useful in the empirical process of estimating the MRP of players because it can be used to measure both team success and individual contributions.

WAR is available from both FanGraphs (fWAR) and Baseball-Reference (rWAR or bWAR). Both statistics use identical frameworks and the same calculations of replacement value, but differ in their estimations of offensive, defensive, and pitching value. In this paper fWAR from FanGraphs will be used and referred to simply as WAR. Both websites have unified their replacement level, estimating that a full team of replacement level players on minimum salaries would win about 47.7 games. Multiply this by 30 and subtract from the 2,340 games played per season and this leaves about 1,000 WAR for players to capture in any single season. 57% of these are allotted to position players and 43% are allotted to pitchers, given that position players have a role in both creating runs while batting and preventing runs in the field, while pitchers only have a role in preventing runs. WAR for position players is measured by calculating batting, base running and fielding runs above average, adjusting for their ballpark, league, and position, adding replacement level runs to make replacement level the baseline, and converting runs into wins using league average runs per win. Batting runs are determined by using weighted on-base average, a metric that combines all aspects of hitting into one metric and weights outcomes based on their actual run value, relative to league performance in the given season. Base running runs are determined using both video tracking data and weighted stolen base runs. Fielding runs are determined using a variety of metrics to access defensive range, arm strength, and the values of particular plays like turning double plays or robbing a home run. WAR for pitchers is more complicated and requires an assessment of pitcher value relative to league average, a dynamic calculation of runs per win given pitchers' direct influence on their run environment, and several scaling, park, and leverage adjustments. A pitcher's value is determined independently of the defense playing behind him by using fielding independent pitching (FIP), a metric that considers only home runs, hit-by-pitches, walks, and strikeouts. Slowinsky (April 2012) describes the calculation for position players in more detail and Slowinsky (March 2012) describes the process for pitchers in greater detail. The relevant aspects to this analysis will be described below in the model description.

The MLB Player's Association (MLBPA) negotiates with the league and team owners and establishes a Collective Bargaining Agreement (CBA) covering labor policies that spans five-year intervals. Humphreys and Pyun found that CBA changes in the period they analyzed decreased MERs for players eligible for free agency, but had no effect on rookies or arbitration-eligible players. An update on their analysis using more recent data is warranted, focusing on the MER for players eligible for free agency, due to recent trends in the free agency market. Travis Sawchik of 538 details how the market for free agents has been increasingly slow to develop, with the percentage of free agents signing before January 1st plummeting over the past 5 seasons (Sawchik 2018). Additionally, a record percentage of free agents are accepting one-year contracts, rather than more lucrative multi-year deals. These changes, combined with a growing trend of teams replacing older veterans with young, cost-controlled alternatives, has led the MLBPA to threaten a work-stoppage when the current CBA expires in 2021 (Sawchik 2019). Teams have also been accused of manipulating service time for young players to decrease their bargaining power and of colluding among themselves to artificially deflate labor costs. Service time is accrued by being on a major league 25-man roster. One year of service time is equal to 172 days out of the 183 on the MLB calendar. Thus, teams can exploit the system and gain a full extra year of control by holding down top prospects in the minors for the first 10-12 games of the season before calling them up to the major league roster. My research will test whether heightened tensions over labor policies are justified by increases in the MER of players from 2012 to 2019.

Model Description

The empirical analysis in this paper will estimate the rate of monopsony exploitation of Major League Baseball players from 2012 to 2019 by estimating their marginal revenue product (MRP) and comparing it to their salary. This paper follows an updated version of Scully's (1974) original three-step procedure for estimating the MRP of athletes. The end goal of the empirical analysis is to create estimates of Scully's (1974) Marginal Exploitation Ratio (MER) defined as

$$MER_i = \frac{\widehat{MRP}_i - Salary_i}{\widehat{MRP}_i} \quad (1)$$

for each player i. An MER of 0 indicates no monopsony exploitation which we would expect in a perfectly competitive labor market. Monopsony exploitation increases as MER increases while a negative MER indicates that a player is overpaid relative to his contributions. MER has an upper bound of 1 by definition.

To calculate these ratios, we must first estimate the MRP of players. The first step in the Scully (1974) procedure is to estimate the marginal revenue of a win using a linear team revenue function

$$TR_j = a_0 + a_1 WP_j + a2X_j + u_j \quad (2)$$

where TR_j is total revenue, WP_j is winning percentage, X_j is a vector of other variables that affect TR_j, and u_j is an error term for each team j. In subsequent research, this method has been extended, accounting for the nonlinearities that arise due to postseason wins providing higher returns than regular season wins. Only 8 teams qualify for a postseason series, with a play-in game to determine the fourth team from each league (MLB is composed of 15 teams in the National League and 15 teams in the American League). J.C. Bradbury was the first to relax the linearity assumption, including a quadratic term or using a cubic function in a series of papers estimating MRP for MLB players (Bradbury 2008; Bradbury 2010). Oh and Lee (2013) were the first to use a spline regression model that was later employed by Humphreys and Pyun (2017).

Following Oh and Lee (2013) and Humphreys and Pyun (2017) I will use the following spline regression model

$$TR_{jt} = \beta_0 + \beta_1 WP_{jt} + \beta_2 D_k(WP_{jt} - 0.55) + \beta_3 MAP_{jt} + \beta_4 AL_{jt} + \beta_5 NSTADM_{jt} + \beta_6 UNEMP_{jt} + \alpha_j + \lambda_t + \varepsilon_{jt} \tag{3}$$

where, for each team j and season t, TR_{jt} is total revenue, WP_{jt} is winning percentage, MAP_{jt} is metropolitan area population, $UNEMP_{jt}$ is the unemployment rate in the metropolitan area, and AL_{jt} is an indicator variable for teams in the American League to account for differences between the leagues. New stadiums typically have a novelty effect that increases revenue for teams that play in them (Coates and Humphreys 2005). $NSTADM_{jt}$ captures this effect, equaling 4 in the first year of a new facility and decreasing by 1 each year until it reaches 0. $\beta_2 D_k(WP_{jt} - 0.55)$ is the spline variable that accounts for the higher marginal returns to wins in a season with $WP_{jt} > 0.55$ caused by postseason revenue[1]. D_k is a dummy variable such that D_k equals 1 when $WP_{jt} >$

[1] The 0.55 winning percentage does the best job of capturing teams that made the playoffs. Over the course of the sample, there were 12 teams that had a winning percentage greater than 0.55 that didn't make it to the divisional round of the postseason. However, eight of these teams were the losers of the wild card play-in game. There were eight teams out of the 64 playoff teams that made the postseason with winning percentages below 0.55, all through the wild card game.

0.55 and 0 otherwise. Thus, marginal revenue will be measured using $\beta_1 + \beta_2$ for teams with $WP_{jt} > 0.55$ and β_1 for teams with $WP_{jt} < 0.55$. α_j is a team-specific intercept and λ_t is a year-specific intercept. ε_{jt} is an error term that accounts for omitted factors that influence team revenues.

The second step in Scully's MRP estimation is to estimate the relationship between player performance and wins with batter and pitcher performance as inputs. The regression model is a stochastic frontier developed by Greene (2005) and Lee (2011) and defined by

$$lnWP_{jt} = \varepsilon_j + \delta_1 lnBPERF_{jt} + \delta_2 lnPPERF_{jt} + v_{jt} - u_{jt}$$

where OPS, the sum of team slugging percentage (SLG) and team on-base percentage (OBP), will be used as the proxy for position player performance, $BPERF_{jt}$, and WHIP, walks and hits allowed divided by innings pitched, is used as the proxy for pitcher performance, $PPERF_{jt}$, following Zimbalist (1992), Oh and Lee (2013) and Humphreys and Pyun (2017). u_{jt} captures technical inefficiency errors which account for omitted factors such as managerial decisions, defensive play, and player effort. v_{jt} is the error term and ε_j is a team-specific fixed effect.

Finally, we can estimate MRP for each batter *i* using

$$\widehat{MRP}_{ijt} = \left(\widehat{\beta_1} + \widehat{\beta_2} D_k\right) * \ \widehat{\delta}_1 \frac{WP_{jt}}{BPERF_{jt}} * Z_{ijt} \tag{4}$$

where Z_{ijt} is batter *i*'s percent of team *j*'s plate-appearances in season *t*. Unlike previous literature, plate appearances is used rather than at-bats because walks, sacrifices, and hit-by-pitches are reflected in OPS but not at-bats. Thus, plate appearances gives a more accurate representation of a player's usage. Then, I will use equation 1 to calculate the MER for each batter using the estimated MRP from equation 4. Although pitcher proxies are necessary in the team production function to account for their effects on winning, Humphreys and Pyun exclude pitchers from MRP and MER calculations because weighting pitcher MRP by innings pitched would undervalue relief pitchers relative to starting pitchers who throw far more innings. This motivates the calculation of MER and MRP through a different method that can account for innings differences.

In order to address some of the blind spots in the adapted Scully method, I have devised a simpler, yet more complete, method for estimating MRP and MER using WAR. I first estimate the marginal value of a win using a similar linear team revenue function, replacing winning percentage with team wins above replacement (TWAR).

$$TR_{jt} = \beta_0 + \beta_1 TWAR_{jt} + \beta_2 D_k\left(TWAR_{jt} - 41.4\right) + \beta_3 MAP_{jt} + \beta_4 AL_{jt} \qquad (5)$$
$$+\beta_5 NSTADM_{jt} + \beta_6 UNEMP_{jt} + \alpha_j + \lambda_t + \varepsilon_{jt}$$

The sum of TWAR and the replacement level wins estimate of 47.7 provides a context-neutral proxy for team wins based on player performance. Figure 4 in the appendix shows a histogram of the difference between estimated team winning percentage using this proxy and actual team winning percentage. The spline variable becomes $\beta_2 D_k\left(TWAR_{jt} - 41.4\right)$, as the same 0.550 win percentage cutoff used by Humphreys and Pyun is converted to WAR[2]. Thus, marginal revenue of a win above replacement will be measured using $\beta_1 + \beta_2$ for teams with $TWAR_{jt} > 41.4$ and β_1 for teams with $TWAR_{jt} < 41.4$. The rest of the variables in the regression remain the same.

Estimating the marginal revenue of a win using WAR in this way allows us to cut out the second step of the Scully method estimating the effects of player performance on winning, as this is implicit in the WAR metric itself. WAR does a much better job estimating this effect for both position players and pitchers than OPS and WHIP respectively. For position players, WAR accounts for both fielding and base running performance in addition to batting performance,

[2] A winning percentage of 0.550 equates to 0.550 * 162 = 89.1 wins over a full season. Thus the equivalent WAR cutoff equals 89.1 less replacement level wins (47.7) = 41.4.

allowing us to take a more holistic view of a player's contributions. For pitchers, Fielding Independent Pitching (FIP) is used in the WAR calculation rather than WHIP to adjust for team defense and more closely estimate a pitcher's unique value independently. Additionally, WAR adjusts for factors such as ballpark, league, and positional value[3] which are not accounted for in OPS or WHIP alone. Finally, WAR accounts for playing time, allowing us to remove the 100 plate appearance cutoff for position players and estimate the MRP and MER of both starting and relief pitchers effectively.

We can now estimate MRP for each position player *i* using

$$\widehat{MRP}_{ijt} = \left(\widehat{\beta_1} + \widehat{\beta_2} D_k\right) * \ WAR_{ijt} + RBMRP_{jt} \tag{6}$$

where WAR_{ijt} is player *i*'s WAR on team *j* in season *t*. $RBMRP_{jt}$ is replacement position player MRP for team *j* in season *t*.

$$RBMRP_{jt} = \ 0.57 * (\beta_0 + \ \beta_3 MAP_{jt} + \beta_4 AL_{jt} + \beta_5 NSTADM_{jt} + \beta_6 UNEMP_{jt})/13 \tag{7}$$

This is estimated by first predicting the revenue value of a full replacement level team for each team *j* and season *t*, using equation 5 with TWAR set to 0. Then, 57% of this revenue value is allotted to position players just as 57% of WAR is allotted to position players. Finally, this 57% of replacement level revenue value is divided by 13 to account for the 13 position players typically held on an MLB roster. This gives us an estimate of the average replacement level MRP for a position player on team *j* in season *t*. Similarly, we can estimate MRP for each pitcher *i* using

[3] It is much more difficult to be an average defensive shortstop than an average defensive first baseman, for example, so runs are credited or deducted based on a player's position. Shortstops are credited with 7.5 additional runs while 12.5 runs are deducted from first baseman. Pitchers are credited for pitching in more high-leverage spots. A full breakdown of positional adjustments can be found in the Slowinski (2012) articles.

$$\widehat{MRP}_{ijt} = \left(\widehat{\beta_1} + \widehat{\beta_2} D_k\right) * WAR_{ijt} + RPMRP_{jt} \quad (8)$$

Where WAR_{ijt} is pitcher *i*'s WAR on team *j* in season *t*. $RPMRP_{jt}$ is replacement pitcher MRP for team *j* in season *t*.

$$RPMRP_{jt} = 0.43 * (\beta_0 + \beta_3 MAP_{jt} + \beta_4 AL_{jt} + \beta_5 NSTADM_{jt} + \beta_6 UNEMP_{jt})/12 \quad (9)$$

This is calculated the same way as $RBMRP_{jt}$ except with 43% of replacement level team revenue production divided among the 12 pitchers typically held on an MLB roster. Finally, MER can be calculated for each position player and pitcher using equation 1.

Data

This paper uses data from 8 MLB Seasons, 2012 to 2019. Audited financial data for MLB teams is not publicly available, so revenue estimates come from Forbes magazine which estimates them using attendance, broadcast rights, and other revenue streams. This data is archived on Rodney Fort's Sports Business Data website (Fort). Player salary data comes from the USA TODAY baseball salary database. Population and unemployment data for U.S. teams comes from the US Census Bureau and comes from Statistics Canada for the Toronto Blue Jays. The team data is panel data with win-loss percentage, batting WAR, pitching WAR, total WAR, WHIP, OPS, plate-appearances, revenue, metropolitan area population, unemployment, and the year the team's stadium opened for all 30 teams from 2012 to 2019 totaling 240 observations. The position player data is pooled cross-sectional data from 2012- 2019 for players on opening-day rosters that were not traded to a new team midseason for a total of 2,703 observations. The data includes player name, position, team, WAR, plate-appearances, OPS, service time, service time group, and salary. The pitcher data is pooled cross-sectional data from 2012-2019 for pitchers on opening-day rosters that were not traded midseason for a total of 2535 observations. The data includes player name, team, innings pitched, Earned Run Average (ERA), WHIP, WAR, service time, service time group, and salary. In each dataset, dollar values have been adjusted to 2012 dollars using the Consumer Price Index and OPS values have been multiplied by 1000. Winning percentage is multiplied by 1000 when calculating team revenue and production functions. Summary statistics for numeric variables are shown below.

Table 1 - Summary of Team Data

variable	*n*	*median*	*mean*	*sd*	*min*	*max*
Team	240	15.50	15.50	8.67	1.00	30.00
Year	240	2015.50	2015.50	2.30	2012.00	2019.00
W.L.	240	0.50	0.50	0.07	0.29	0.67
WHIP	240	1.31	1.31	0.09	1.10	1.55
T_OPS	240	728.00	729.00	36.50	627.00	848.00
T_PA	240	6154.50	6158.93	97.27	5905.00	6475.00
Revenue ($ mil)	240	249.36	272.59	82.81	156.71	613.38
Population (mil)	240	2.55	3.18	2.36	0.79	10.13
Unemployment	240	4.70	4.99	1.79	2.10	10.50
Year Stadium Opened	240	1999.50	1990.63	24.75	1912.00	2017.00
Position Player WAR	240	18.95	19.00	7.76	-2.60	40.80
Pitching WAR	240	14.30	14.33	5.26	1.00	30.40
Total WAR	240	33.25	33.33	11.15	4.10	64.50

Table 2 - Summary of Position Player Data

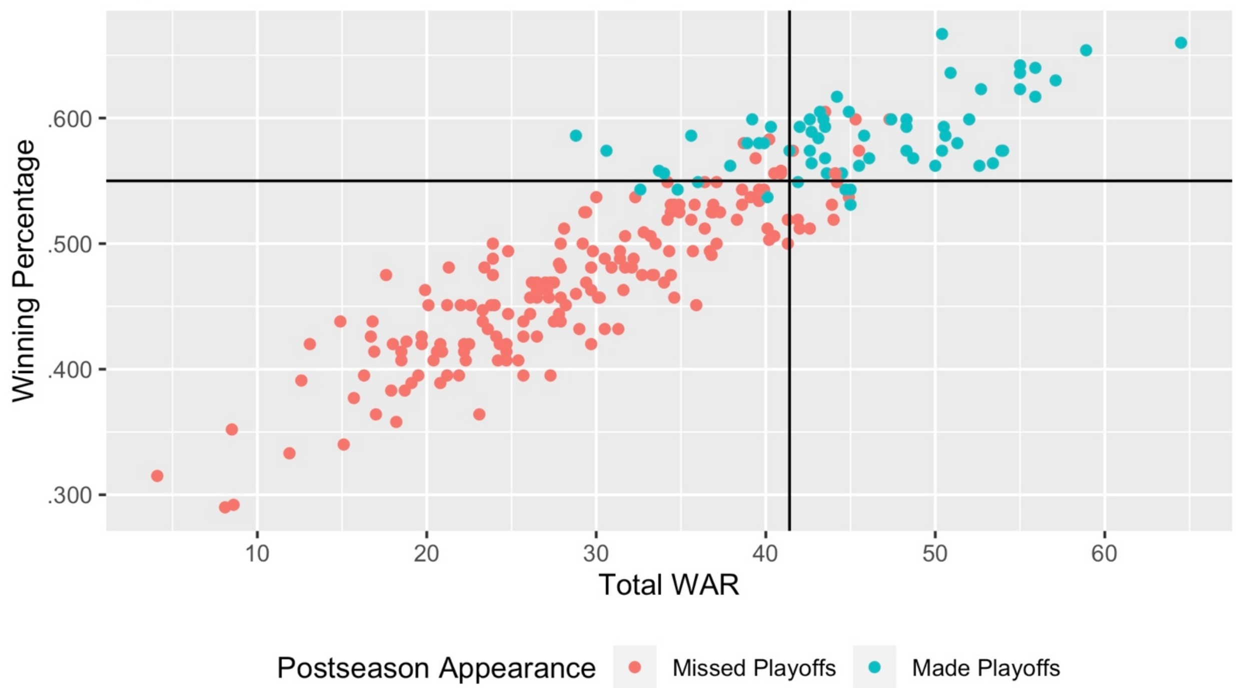
variable	*n*	*median*	*mean*	*sd*	*min*	*max*
WAR	2703	1.00	1.42	1.96	-3.20	10.40
Service Time	2703	3.12	4.25	3.73	0.00	22.13
Salary ($ mil)	2703	1.60	4.39	5.64	0.48	31.16
PA	2703	403.00	388.69	204.19	1.00	747.00
OPS	2703	721.00	707.34	142.47	0.00	1232.00

Table 3 - Summary of Pitcher Data

variable	*n*	*median*	*mean*	*sd*	*min*	*max*
WAR	2535	0.60	1.02	1.49	-1.40	9.40
Service Time	2535	3.07	3.88	3.44	0.00	18.00
Salary ($ mil)	2535	1.35	3.80	5.28	0.48	37.85
IP	2535	65.00	85.12	62.43	0.10	243.20
ERA	2535	4.00	4.41	2.72	0.00	63.00
WHIP	2535	1.31	1.37	0.44	0.00	10.00

At the team level, average revenue was $272.59 million. The New York Yankees recorded the highest revenue of $613.38 million in 2019 and the Miami Marlins recorded the lowest revenue of $156.71 million in 2013. The Boston Red Sox had the highest winning percentage in the period, posting a record of 108 wins and 54 losses in 2018. The Baltimore Orioles had the lowest winning percentage in the period, posting a record of 47 wins and 115 losses in 2018. The 2019 Houston Astros posted the highest team WAR in the period with 64.5, showing great improvement over the 2013 team which posted the lowest team WAR in the period of 4.1. The 2019 Detroit Tigers were the only team to have a negative team position player or pitching WAR in the period, posting a dismal -2.6 position player WAR in 2019. The following scatter plot shows the relationship between team WAR and winning percentage and the spline variable cutoffs for each variable.

Figure 1 - Team WAR vs. Winning Percentage



Average position player salary in the sample period was $4.39 million. Mike Trout had the maximum salary, making $31.16 million in 2018. 20 players made the minimum salary of $480,000 in 2012. Average WAR was 1.42. 2018 saw astounding seasons at both ends of the spectrum, with Mookie Betts recording the highest WAR of 10.4 and Chris Davis recording the lowest WAR of -3.2. Average pitcher salary in the sample period was $3.8 million. Max Scherzer had the highest salary, making $37.85 million in 2019. 20 pitchers made the minimum salary of $480,000 in 2012. Average pitcher WAR was 1.02. Jacob deGrom recorded the highest WAR of 9.4 in 2018. Jarlin Garcia and Josh Tomlin in 2018 and Jason Marquis in 2013 tied for the lowest WAR of -1.4. The following scatter plots show how rookie and arbitration-eligible players have relatively little leverage in salary negotiations compared to players eligible for free agency, regardless of on-field performance, for both position players and hitters. Most rookies are clustered around the MLB minimum salary of $480,000.

Figure 2 - Position Player Salary vs. WAR

Figure 3 - Pitcher Salary vs. WAR

Empirical Results

The parameter estimates of the team revenue function using winning percentage are shown below in Table 4. The coefficient of 0.145 on team winning percentage means that, holding all else constant, revenue is expected to increase by \$0.145 million for every 0.001 increase in winning percentage for teams with a winning percentage less than 0.55. One win increases winning percentage by 0.006, so every win is worth about \$870,000 in revenue. The coefficient of 0.266 on the spline variable of our regression means that, holding all else constant, revenue is expected to increase by 0.266+0.145 = \$0.411 million for every 0.001 increase in winning percentage. Thus, every win for these teams is worth about \$2.466 million in revenue. Both coefficients are statistically significant.at the 95 percent confidence level and are significant increases over the values of 0.065 and 0.112 estimated using data from 2000-2011. Of the remaining coefficients, metropolitan area population, metropolitan area unemployment, and new stadium are statistically significant at the 95 percent confidence level. Teams in larger metropolitan areas earn higher revenues because they have more fans to come to their games and buy their merchandise. Teams earn less revenue when unemployment in their metropolitan area increases, as people have less disposable income for leisure activities. The coefficient on our new stadium variable is positive, confirming the novelty effect of new stadiums described by Coates and Humphreys (2005). Regression results without the spline variable are provided for comparison.

Table 4 - Team Revenue Regression Results: Humphreys and Pyun Method

	Dependent variable: Team Revenue	
	Spline	No Spline
Team Winning Percentage	0.145***	0.201***
	(0.032)	(0.024)
Team Winning Percentage Greater than 0.550 (Spline)	0.266***	
	(0.103)	
Population	21.574***	21.597***
	(3.798)	(3.812)
Unemployment	-17.002***	-17.434***
	(0.987)	(0.985)
New Stadium	9.783**	9.939**
	(3.825)	(3.876)
AL	-8.361	-7.923
	(19.421)	(19.458)
Constant	216.857***	193.627***
	(23.551)	(21.899)
Observations	240	240
R^2	0.660	0.650
Adjusted R^2	0.652	0.643
Note:		*p**p***p<0.01

The parameter estimates of the win production function are shown below in Table 5. The coefficient of 1.470 means that, holding all else constant, we expect $\ln(WP_{jt})$ to increase by 0.00147 when log team OPS increases by 0.001. Thus, marginal product of OPS is calculated as

$0.00147 * \frac{WP_{jt}}{OPS_{jt}}$. The coefficient on log team WHIP is negative because a higher WHIP represents more walks and hits allowed and therefore represents a worse pitching performance. All of the coefficients are significant at the 95 percent confidence level.

Table 5 – Win Production Regression Results: Humphreys and Pyun Method

	Dependent variable: *Team Winning Percentage* ($\ln(WP_{jt})$)
Batter Performance ($\ln(OPS_{jt})$)	1.470^{***}
	(0.095)
Pitcher Performance ($\ln(WHIP_{jt})$)	-1.764^{***}
	(0.098)
Observations	240
Max Log-Likelihood	321.30
Mean Efficiency	0.933
Note:	$^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$

Finally, plugging the parameter estimates from Table 4 and Table 5 above into equation 4, we can calculate MRP for individual players and plug MRP into equation 1 to obtain MER. Summary statistics for MER by player experience group are shown below in Table 6. Mean MER for all players is 0.334, meaning that around 33 percent of all MRP generated by MLB position players is expropriated by teams using their monopsony power in MLB labor markets. This is a decrease from the 0.504 estimated by Humphreys and Pyun (2017). However, the mean is heavily skewed by the relative abundance of negative free agent contracts, as the median of the sample is 0.709.

Table 6 – MER Summary Statistics: Humphreys and Pyun Method

Type of Player	*n*	*median*	*mean*	*sd*	*min*	*max*
All Position Players	2807	0.709	0.334	1.082	-15.335	0.990
Rookies	1060	0.918	0.866	0.196	-2.046	0.990
Arbitration-Eligible	765	0.608	0.412	0.665	-7.205	0.989
Free-Agency-Eligible	982	0.123	-0.300	1.500	-15.335	0.956

The mean MER for rookie players was 0.866 meaning approximately 87 percent of the MRP generated by entry-level players is expropriated by the teams. This estimate is equal to the values estimated in prior research (Humphreys and Pyun 2017, Scully 1974). The mean MER for arbitration-eligible players was 0.412 which represents a substantial decrease from the 0.753 estimated by Humphreys and Pyun. The mean MER for free-agency-eligible players was -0.300 which also represents a substantial decrease from the 0.209 estimated by Humphreys and Pyun (2017). However, Zimbalist (1992) and Oh and Lee (2013) estimated negative mean MER values for free-agency-eligible players. Humphreys and Pyun (2017) did find that MER decreased over three CBA periods in their sample, suggesting that monopsony power decreases over time. While the decrease in mean values of MER for both arbitration-eligible and free-agency-eligible players suggests that players in these groups have extracted more value and perhaps even been overpaid, this is not true for players on winning teams. The mean MER for arbitration-eligible players on teams with a winning percentage greater than 0.550 is 0.782 and the mean MER for free-agency-eligible players on teams with a winning percentage greater than 0.550 is 0.531, meaning that players on winning teams are under significant monopsony control.

The highest MER calculated in the sample belongs to Houston Astros third baseman Alex Bregman who recorded a .926 OPS over 705 plate appearances in 2018 for an estimated MRP of

$53.91 million while making a salary of approximately $548,000 in his sophomore season. The third highest MER calculated in the sample belongs to New York Yankees outfielder Aaron Judge who belted 52 home runs and recorded a 1.049 OPS over 678 plate appearances while making a salary of approximately $510,000 in his rookie season. Judge generated an estimated MRP of $48 million for a team that made approximately $611 million in revenue that season, the second highest in the sample.

Table 7 - Best Position Player Seasons by MER: Humphreys and Pyun Method

Player	Team	Position	Season	Salary ($ mil)	OPS (x 1000)	Service Time Group	MRP ($ mil)	MER
Alex Bregman	HOU	SS	2018	0.548	926	Rookie	53.911	0.990
Cody Bellinger	LAD	1B	2019	0.543	1,035	Rookie	52.828	0.990
Aaron Judge	NYY	OF	2017	0.510	1,049	Rookie	48.218	0.989
Josh Donaldson	OAK	3B	2013	0.485	883	Rookie	45.498	0.989
Corey Seager	LAD	SS	2016	0.488	877	Rookie	45.403	0.989
Alex Bregman	HOU	SS	2019	0.575	1,015	Rookie	51.295	0.989
Jose Ramirez	CLE	3B	2018	0.517	939	Arbitration	45.927	0.989
Francisco Lindor	CLE	SS	2017	0.543	842	Rookie	46.977	0.988
Trevor Story	COL	SS	2018	0.507	915	Rookie	43.092	0.988
Josh Reddick	OAK	OF	2012	0.485	768	Rookie	40.859	0.988

Exploration of the lowest MERs yields a list of former starts near the end of long-term contracts in the final years of their careers, along with younger players who qualified for the plate appearance cutoff, but lost most of the season due to injury. The results show that posting a solid OPS is not valuable for expensive players on losing teams. The lowest MER belongs to Los Angeles Angels of Anaheim third baseman Zack Cozart who posted a dismal 0.322 OPS over 107 plate appearances in 2019 while making $11.376 million. Orioles first baseman Chris Davis' 2018 season, largely regarded as one of the worst of all time, comes in as the 41st worst value, as he made $19.36 million while recording a paltry OPS of 0.539 over a large sample of 522 plate appearances.

Table 8 - Worst Position Player Seasons by MER: Humphreys and Pyun Method

Player	Team	Position	Season	Salary ($ mil)	OPS (x 1000)	Service Time Group	MRP ($ mil)	MER
Zack Cozart	LAA	3B	2019	11.376	322	Free Agency	0.696	-15.335
Miguel Montero	TOR	C	2017	13.114	489	Free Agency	1.104	-10.882
Carl Crawford	BOS	OF	2012	20.357	785	Free Agency	1.971	-9.326
Miguel Cabrera	DET	1B	2018	27.430	843	Free Agency	2.707	-9.133
Nick Swisher	CLE	OF	2015	14.531	558	Free Agency	1.493	-8.731
Yoenis Cespedes	NYM	OF	2018	26.515	821	Free Agency	3.002	-7.834
Shane Victorino	BOS	OF	2015	12.593	622	Free Agency	1.459	-7.634
Justin Upton	LAA	OF	2017	20.724	888	Free Agency	2.477	-7.368
Josh Donaldson	TOR	3B	2018	21.030	756	Arbitration	2.563	-7.205
Francisco Cervelli	PIT	C	2019	10.328	527	Free Agency	1.270	-7.131

These values serve as a sort of robustness check, showing that the model does an effective job of identifying seasons where salary and production were highly mismatched.

The parameter estimates of the team revenue function using total team WAR are shown below in Table 9. The coefficient of 0.893 on team winning percentage means that, holding all else constant, revenue is expected to increase by $0.893 million for each additional WAR for teams with a total WAR less than 41.4. The coefficient of 2.682 on the spline variable of our regression means that, holding all else constant, revenue is expected to increase by 2.682+0.815 = $3.335 million for each additional WAR for teams with a total WAR greater than 41.4. Both coefficients are statistically significant.at the 95 percent confidence level. Of the remaining coefficients, metropolitan area population, metropolitan area unemployment, and new stadium are statistically significant at the 95 percent confidence level.

Table 9 - Team Revenue Regression Results: Total WAR

	Dependent variable: Team Revenue	
	Spline	No Spline
Total WAR	0.893***	1.481***
	(0.211)	(0.166)
Team WAR Greater than 41.4 (Spline)	2.682***	
	(0.631)	
Population	19.660***	20.449***
	(3.790)	(3.866)
Unemployment	-16.666***	-17.426***
	(0.943)	(0.960)
New Stadium	7.856**	7.964**
	(3.474)	(3.605)
AL	-9.218	-7.631
	(19.453)	(19.799)
Constant	263.064***	248.168***
	(19.603)	(19.699)
Observations	240	240
R^2	0.687	0.663
Adjusted R^2	0.679	0.656
Note:		*p**p***p<0.01

We can calculate MRP for position players and pitchers using equations 6 and 8 respectively. Then, we can plug our estimates of MRP into equation 1 to obtain MER. Summary statistics for MER by player experience group are shown below in Table 10 for position players and table 11 for pitchers. Mean MER for both position players and pitchers is about 0.65 meaning that approximately 65% of the MRP generated by MLB players is expropriated by teams using their monopsony power in MLB labor markets. This is an increase over the estimates in prior research.

Table 10 – MER Summary Statistics: WAR Method Position Players

Type of Player	*n*	*median*	*mean*	*sd*	*min*	*max*
All Position Players	2703	0.861	0.654	0.491	-9.49	0.989
Rookies	1146	0.952	0.938	0.067	0.151	0.989
Arbitration-Eligible	709	0.754	0.662	0.491	-9.49	0.986
Free-Agency-Eligible	848	0.365	0.264	0.549	-2.93	0.971

Table 11 – MER Summary Statistics: WAR Method Pitchers

Type of Player	*n*	*median*	*mean*	*sd*	*min*	*max*
All Pitchers	2535	0.859	0.646	0.461	-2.099	0.986
Rookies	1145	0.942	0.923	0.105	-0.428	0.986
Arbitration-Eligible	674	0.731	0.646	0.288	-1.559	0.971
Free-Agency-Eligible	716	0.345	0.201	0.579	-2.099	0.975

Mean MER is higher for each position player service time group using this method, with mean rookie MER increasing from 0.866 to 0.938, mean arbitration MER increasing from 0.412 to 0.662, and mean free agency MER increasing from -0.300 to 0.264. The variance in each position player service time group has decreased with this method and the minimum MERs in each service time group are much greater, aside from arbitration-eligible position players. The tables show that MER for pitchers is quite similar to MER for position players. Similarly to position players, pitchers on winning teams have higher MERs than their service time counterparts on losing teams. Mean MER for pitchers on winning teams is 0.325, 0.701, and 0.933 for free agents, arbitration-eligible players, and rookies respectively, while mean MER for their counterparts on losing teams is 0.148, 0.622, and 0.920 respectively.

Among position players, the highest MER calculated using this method belongs to New York Yankees outfielder Aaron Judge's 2017 season described above when he recorded 8.3 WAR while making a salary of approximately $510,000 in his rookie year. This season ranked third in MER using the previous method. Alex Bregman's 2018 season, which had the highest MER using the previous method, ranks eighth here. Exploration of the lowest MERs using this method yields a list of aging veterans with high salaries on losing teams, along with players on good teams who performed negatively yet still received significant plate appearances at their position over the course of the season. The lowest MER belongs to Detroit Tigers outfielder Ryan Raburn who recorded a -1.4 WAR over the course of the 2012 season and made $2.1 million in arbitration despite an estimated MRP of only $200,000 for an MER of – 9.49. Close behind is his teammate Delmon Young who recorded -1.1 WAR and an MER of -4.30 in the same season. Detroit had extremely high unemployment in 2012, driving down the revenue product of Tigers players. Additionally, the Tigers were a winning team, exacerbating the revenue cost of their below-replacement-level play. Orioles first baseman Chris Davis' horrendous 2018 season, described above, comes in as the fourth worst value using this method. The best and worst seasons by MER for both position players and pitchers using this method are shown in the appendix.

Conclusions

The results in this paper suggest that recent trends in the MLB labor market, such as an increase in one-year contracts and an increasingly slow-to-develop market are not indicative of a greater monopsonistic exploitation of players by teams. In fact, it may suggest that teams are hesitant to dole out expensive, multi-year contracts to players who are often not worth their salary at the end of their careers. However, the results also show that rookie players have seen no improvement in their salaries relative to their on-field production in the same period, and continue to have 87% of their value expropriated by their teams, on average. Although they have been able to extract more value in their arbitration-eligible seasons in comparison to previous periods, the players and the MLBPA are understandably frustrated as recent free agents have been largely unable to make up for exploitation in their early seasons with lucrative long-term contracts once they finally reach the open market.

The results also show that MER for free-agency-eligible and arbitration-eligible players has decreased under the two most recent Collective Bargaining Agreements (2012-2016 and 2017-2021). Perhaps the MLBPA is more focused on improving the circumstances of its more experienced members. Humphreys and Pyun (2017) found that new CBAs in their sample period primarily improved the conditions of free-agency-eligible players. However, monopsonistic exploitation of rookie players is still high, and has not improved under recent CBAs. While this is unlikely to change without significant increases in the MLB minimum salary, perhaps the MLBPA can do more to address loopholes such as service time manipulation that keep players under reserve-clause conditions for longer periods.

Edward Lazear (1981) finds that salary often increases by more than MRP over a worker's lifetime and salary for senior workers is often much higher than their MRP, which compensates for workers making less as junior employees (Humphreys and Pyun 2017). However, because professional baseball is such a competitive industry, most players will never have the opportunity to reach free agency and cash in. Less than half of the players in the sample reached free agency. Additionally, of the peak WAR seasons for each player, nearly 69% of them were recorded in seasons where the player was under rookie or arbitration control. MLB players have much shorter careers than workers in other industries.

The increase in large negative MER values may be indicative of top free agents having monopoly power in free agency, as the team that signs them might see no viable substitutes. MLB teams know that players are unlikely to be worth upward of $30 million per season at the end of their careers, yet they continue to sign top free agents to nearly decade-long contracts to secure the value of the player's prime years. At the other end of the spectrum, the high MER for free agents on winning teams may be indicative of players sacrificing money to stay with their original team or pursue championships.

The WAR method for MER calculation appears to do a good job of identifying both extremely valuable and extremely negative player-seasons. Given the simplicity of this method and the many additional factors it accounts for, I would argue that it produces more reliable MRP and MER results. The standard deviation of MER for both the datasets as a whole and each service time group are smaller, suggesting that this method uses less differentiation between player-seasons. This makes intuitive sense, as the WAR calculation uses more factors to judge player performance, allowing players to achieve equivalent value in different ways. Additionally, this method views the worst player-seasons in the dataset much more positively than Humphreys' and Pyun's method. This is likely due to the estimation of replacement level MRP in the analysis. These estimates show that even replacement level players provide much more marginal revenue product than the MLB minimum salary. Mean estimated replacement level value was around $10.5 million for position player and $8.6 million for pitchers. Humphreys and Pyun do not consider replacement level value in their analysis. Interestingly, mean WAR-based MER for arbitration-eligible pitchers increased within the 2012 to 2019 period, most notably for pitchers, which was not the case using the first MER calculation method. Mean WAR-based MER for free agent position players decreased over the period, suggesting that the free agent market has actually become more favorable to these players over the period. MER for other groups remained largely stagnant, meaning that rookies and free agent pitchers have not seen improvements in their bargaining power under recent CBAs.

There are several criticisms of Scully's method and possible areas for improvement and expansion. Firstly, it is likely that other factors beyond contributions to winning influence fans' willingness to pay to attend or watch baseball games. Additionally, it would be interesting to use the second method on the 2000-2011 data to see how MER has changed for service time groups using WAR. Calculating WAR for traded players' time on different teams would be useful as we would not have to remove them from the dataset. Some prominent players have been traded midseason, and it would be interesting to calculate their MERs as well. This paper did not include teams that made the wild-card play-in game in the postseason indicator even though these teams are awarded a small percentage of postseason revenue. It would be interesting to apply these results in an analysis of roster construction to try to find patterns in how successful teams allocate their limited financial resources. The results clearly show that productive players under rookie control are the most valuable assets to a team. It would be interesting to see if some teams have been able to better use this fact to their advantage when constructing their rosters. The WAR method for MRP and MER estimation would be more useful in this analysis, as it accounts for positional value. A more detailed and granular analysis of MER patterns, perhaps by position, could yield interesting results. It would be interesting to devise a method for estimating replacement level marginal revenue product beyond just using the team revenue production function as I have done here. Finally, it would be interesting to apply the WAR method to analyze pitching performance and MER prior to 2011, as pitchers have been left out of prior research.

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Appendix

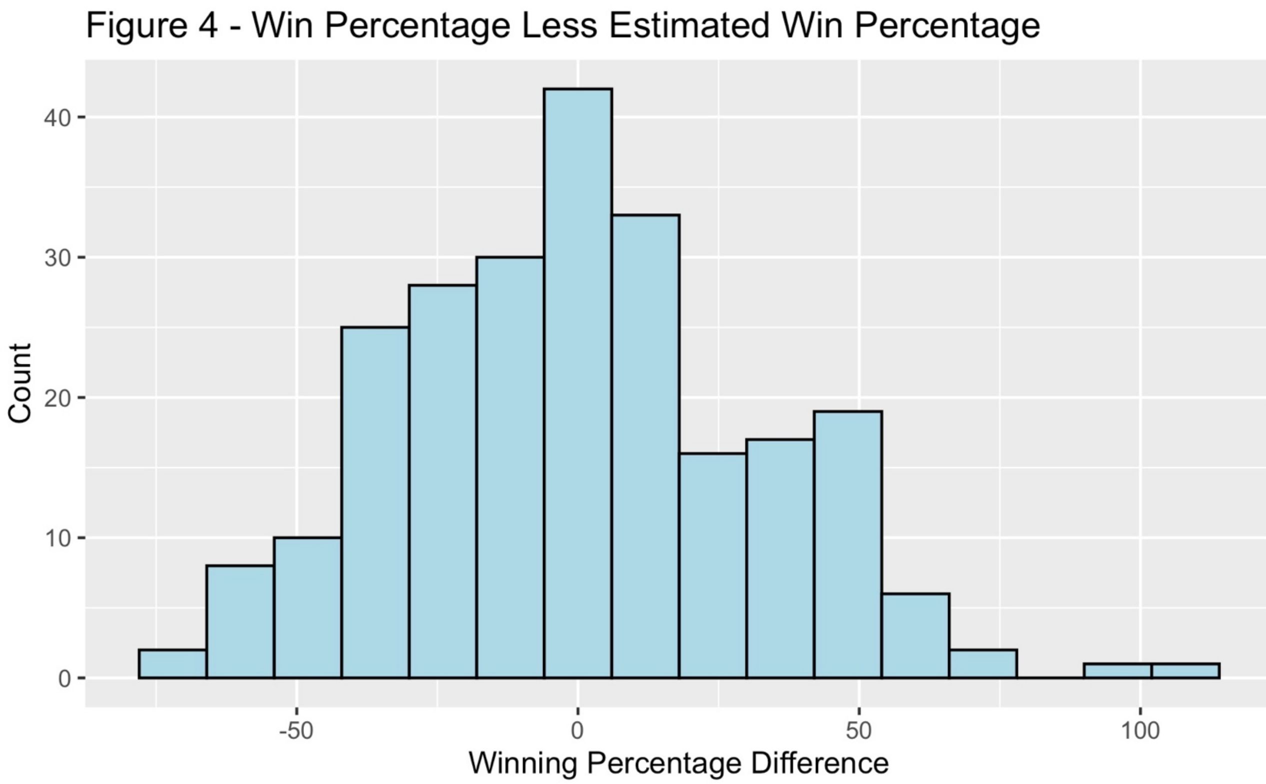

Figure 4 - Win Percentage Less Estimated Win Percentage
Count
40
30
20
10
0
-50
0
50
100
Winning Percentage Difference

Table 12 - Best Position Player Seasons by MER: Total WAR

Player	Team	Position	Season	Salary ($ mil)	Total WAR	Service Time Group	MRP ($ mil)	MER
Aaron Judge	NYY	OF	2017	0.510	8.3	Rookie	46.340	0.989
Corey Seager	LAD	SS	2016	0.488	6.9	Rookie	38.546	0.987
Cody Bellinger	LAD	1B	2019	0.543	7.8	Rookie	42.529	0.987
Mookie Betts	BOS	OF	2016	0.541	8.3	Rookie	41.186	0.987
Alex Bregman	HOU	SS	2019	0.575	8.5	Rookie	41.903	0.986
Jose Ramirez	CLE	3B	2018	0.517	8	Arbitration	37.337	0.986
Josh Donaldson	OAK	3B	2013	0.485	7.3	Rookie	34.648	0.986
Alex Bregman	HOU	SS	2018	0.548	7.6	Rookie	38.471	0.986
Matt Chapman	OAK	3B	2018	0.501	6.6	Rookie	35.083	0.986
Jeff McNeil	NYM	2B	2019	0.510	4.6	Rookie	34.097	0.985

Table 13 - Best Pitcher Seasons by MER: Total WAR

Player	Team	Season	Total WAR	Salary ($ mil)	Service Time Group	MRP ($ mil)	MER
Noah Syndergaard	NYM	2016	6.8	0.512	Rookie	37.823	0.986
Luis Severino	NYY	2017	5.6	0.516	Rookie	33.642	0.985
Jacob deGrom	NYM	2015	5.2	0.515	Rookie	32.303	0.984
Luis Severino	NYY	2018	5.3	0.553	Rookie	33.029	0.983
Walker Buehler	LAD	2019	4.9	0.512	Rookie	29.486	0.983
Dallas Keuchel	HOU	2015	5.7	0.508	Rookie	28.963	0.982
Shane Bieber	CLE	2019	5.6	0.503	Rookie	27.877	0.982
Gerrit Cole	PIT	2015	5.1	0.514	Rookie	25.823	0.980
Garrett Richards	LAA	2014	4.1	0.504	Rookie	24.144	0.979
Steven Matz	NYM	2016	2.7	0.493	Rookie	23.165	0.979

Table 14 - Worst Position Player Seasons by MER: Total WAR

Player	Team	Position	Season	Salary ($ mil)	Total WAR	Service Time Group	MRP ($ mil)	MER
Ryan Raburn	DET	OF	2012	2.100	-1.4	Arbitration	0.200	-9.490
Delmon Young	DET	OF	2012	6.750	-1.1	Arbitration	1.273	-4.304
Michael Young	TEX	3B	2012	16.175	-1.5	Free Agency	4.115	-2.931
Chris Davis	BAL	1B	2018	19.356	-3.2	Free Agency	6.796	-1.848
Miguel Cabrera	DET	1B	2017	26.227	-0.2	Free Agency	9.636	-1.722
Miguel Cabrera	DET	1B	2018	27.430	0.7	Free Agency	10.384	-1.642
Miguel Cabrera	DET	1B	2019	26.942	-0.3	Free Agency	10.230	-1.634
Vernon Wells	LAA	OF	2012	24.188	0.2	Free Agency	10.397	-1.326
Nick Swisher	CLE	OF	2014	14.548	-1.8	Free Agency	6.472	-1.248
Carl Crawford	BOS	OF	2012	20.357	0.3	Free Agency	9.064	-1.246

Table 15 - Worst Pitcher Seasons by MER: Total WAR

Player	Team	Season	Total WAR	Salary ($ mil)	Service Time Group	MRP ($ mil)	MER
Roy Halladay	PHI	2013	-0.9	19.712	Free Agency	6.361	-2.099
Felix Hernandez	SEA	2017	0.3	25.157	Free Agency	8.380	-2.002
Barry Zito	SF	2013	-0.7	19.712	Free Agency	6.694	-1.945
Felix Hernandez	SEA	2019	-0.2	25.018	Free Agency	8.735	-1.864
Felix Hernandez	SEA	2018	0.1	24.556	Free Agency	8.588	-1.859
Zack Greinke	ARI	2016	2.6	30.418	Free Agency	10.645	-1.857
Justin Verlander	DET	2015	3.1	27.124	Free Agency	9.636	-1.815
Felix Hernandez	SEA	2016	1	24.734	Free Agency	8.924	-1.772
Barry Zito	SF	2012	0.9	19	Free Agency	7.258	-1.618
Tim Lincecum	SF	2013	1.4	21.930	Arbitration	8.569	-1.559