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Evaluating an MLB General Manager’s Bang for their Buck

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Evaluating an MLB General Manager's Bang for their Buck

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Abstract

With my passion for baseball, I decided to calculate the value of each player on an MLB active roster and determine whether they are underpaid or overpaid. I then used that information to evaluate and rank how efficient each MLB general manager utilizes their money on players. With the luxury tax becoming more of an issue for teams with high payrolls, there has been an emphasis on general managers to construct a team that will be highly competitive at a reasonably low price. In my report, I imported data that reflected the position for each player as well as their adjusted salary. The key metric used to determine the value is known as wins above replacement (WAR). A player's WAR was applied to the average salary for their position to get an estimated value. Using the salary error and percentage error for the whole team, I ranked each general manager. There are numerous ways that statisticians have come up with to apply to the valuation of players. WAR is a relatively new metric that is considered to be one of the best when comparing players. Usually, valuations have been done using traditional statistics such as batting average, on-base percentage, and slugging percentage. My method provides a newer and hopefully more accurate way to determine the true value of each player. The results showed that better-rated teams usually had a higher salary error. This means they were getting more production from players than their salary would suggest. When analyzing the data, I noticed that calculations such as a team's percentage salary error can be misrepresented by having some outliers in the data. Ultimately my method gives a different perspective to create a player's valuation. My future research include multiple statistics in order to get a more accurate representation of one's salary based on their production.

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<u>Introduction</u>

Being a finance major, you are taught many aspects of the business world. When thinking about what to write about for my senior honors thesis, I wanted to find a way to incorporate the tools I've learned over the years with something that I have always been associated with such as sports. My fascination with baseball goes back as far as I can remember. It was always my favorite sport to play and the New York Yankees were always my favorite team to watch. If you watch baseball today, you definitely notice that there was been a change in how teams manage each game. Examples would be making defensive shifts based on the batter's tendencies or using the batter's statistics to determine which relief pitcher will come into the game. One element that has prevalent over the last decade has been player valuations. After giving it further thought, it is easy to see the similarities between stock valuations and player evaluations. For starters, they both include someone who is in charge of the operation. For stocks, this would be the portfolio manager and for baseball, it would be the general manager. Instead of managing which stocks are best to keep in their portfolio, general managers make decisions on which players give the team the best chance of winning. Determining the worth on a player is also very similar to valuing a stock. For a stock, you look at its performance against other stocks in its industry and then discount its projected value to come up with a net present value. With that information, you are then able to see whether the stock is underpriced or overpriced compared to what it is currently being sold. When evaluating an MLB player, you would compare their production to others at their position. Once you determine what they are actually worth, you can then compare it to the salary that they are making and determine whether they are

underpaid or overpaid. By determining each player's worth, you can get a better understanding of which general managers are the best.

Literature Review

In 2003, Michael Lewis published a book called *Moneyball: The Art of Winning an Unfair Game.* The book was about how Billy Beane, the General Manager of the Oakland Athletics, used a theory called "Sabermetrics" to form a team that can compete with the large-market teams while only spending a fraction of the costs (Triady, Mochamad Sandy, and Ami Fitri Utami 58). Sabermetrics was created by Bill James and is defined as the application of statistical analysis to baseball records in order to evaluate and compare the performance of individual players ("A Guide to Sabermetric Research: The Basics" 1). Billy Beane basically used statistical analysis to buy assets that were undervalued by other teams and sell ones that were overvalued by other teams. This changed the way finance and economics are dealt with in the MLB. This created a movement where every team, especially those in small markets, uses some degree of advanced statistical analysis to determine the value of baseball players and build a roster that will win the most games at the lowest cost.

The traditional method of scouting was much different in the past. In the book, Lewis discussed some ways scouts used to think. For example, if they saw a player with an ugly girlfriend, they attached that to having a lack of confidence and wouldn't be able to make it in the MLB. Also, if his body type wasn't standard to those in his position, that player would be ignored altogether. This method of thinking seems outrageous. While judging a player based on his girlfriend or body type seems unfair, traditionalists would argue that it would also be unfair if

scouts ignored a player's athletic ability, work ethic, and playing style. Those attributes certainly won't show up on a stat sheet, but also should be considered when evaluating players. However, the law of large numbers suggests that if you acquire a large enough data set, you can determine the production a player is expected. Even with baseball shifting more toward an analytical game, there still are a few people who haven't jumped on board yet. You can generally categorize them into three categories. First, are the old-schoolers. These are the general managers that are traditionalists and stick to the old approach of evaluating players as well as how the game is managed. They are hesitant to rely on analytics because they don't believe it shows contributes to success, especially in the playoffs. The second category would be the new-schoolers. These are the general managers who have totally bought into the analytical method of finding value from players. The third category would be hybrids. This would include general managers that are in-between. They believe that in order to win, you need to have a mix of big-name veteran players as well as players who are analytically beneficial.

In an article called "A New Test of the Moneyball Hypothesis", written by Anthony Farrar and Thomas H. Bruggink, they wanted to show that MLB general managers did not immediately embrace the new statistical methods for choosing players and strategies that were revealed in. Hakes and Sauer were the first researchers to use regression analysis to back up what Billy Beane and Michael Lewis had suggested (Farrar and Bruggink). One thing they analyzed was that slugging percentage and on-base percentage were predictive in producing wins. The other thing they analyzed was that these attributes were undervalued before the Moneyball era. Farrar and Bruggink displayed a different aspect of research. When building their player salary model, they also included a player's experience measured by the amount of MLB game appearances. This experience factor would have diminishing returns as the player goes toward

the end of his career. By applying ordinary least squares into the model, the impact of a higher on-base percentage resulted in a larger increase in runs scored than a higher slugging percentage in 2006 (Farrar and Bruggink). Further evidence shows that teams should be rewarding players with high on-base percentages as opposed to slugging percentages.

The relationship between a player's performance and their salary has been analyzed extensively. An MLB player's salary can be determined using various statistical models. In the article called "Salary Evaluation for Professional Baseball Players", Lackritz constructed models that would evaluate a player's impact on winning percentage. Through his evaluation, Lackritz proposed that players should be compared to an average player (Lackritz 5). The way he did that was by comparing each player's statistics against the base average statistic generated by their teammates or the league. From there, he took that difference and multiplied it by a term called the "utilization function" (Lackritz 5). Lackritz defined this as the player's total at-bats, fielding chances, or innings pitched divided by the team's total. Therefore, if you were to multiply the difference that we previously calculated by the "utilization function", he believed it would estimate the player's final impact on a team's winning percentage. Lackritz then established a base salary for players on the basis of how much they play plus the bonus depending on their final impact on the team's winning percentage. In order for his base salary to be valid, he assumed that a player who plays regularly is more valuable than his substitute (Lackritz 6). It is also good to note that it is possible to have a negative bonus on the base salary. This would derive from a negative difference on a player's statistics compared to the average player. While the article notes that the model is not a perfect one, it is best described as a suggested approach to solving the salary problems. It mentions how baseball purists will argue over which statistics are more significant and should be included in the model. Even though statistics play a vital role,

there are no measurements of intangibles such as desire, hustle, clutch performance, and guts (Lackritz 7). The point was also brought up that players would not be worth the same in both leagues. Adjustments to Lackritz's model will vary depending on the team.

In an article called "Beyond Moneyball: Changing Compensation in MLB", the authors, Congdon-Hohman and Lanning, examined free-agent contracts in 3-year periods across three decades to see how a player's past performance are rewarded. In particular, they were interested in finding out which factors contributed most toward a player's salary in each time period (Congdon-Homan and Lanning 1047). Similar to what Lackritz stated, the article agrees that baseball is well suited for financial rewards to be based on the analysis of individual production that aggregate to a team's production. As mentioned, player valuations have been extensively researched in the last 30 years. However, the measurement was done using different methods. For example, Krautmann (1990) and Scoggins (1993) focused heavily on a player's slugging percentage. Sommers (1993) used the slugging percentage and batting average. Woolay (1997), Krautmann, and Donley (2009) used statistics such as batting average, stolen bases, slugging percentage, and on-base percentage to estimate a player's marginal revenue product (Congdon-Homan and Lanning 1048). Congdon-Hohman and Lanning refer to these types of statistics as aggregate statistics. They also mention a term they call "counting" statistics, which are things such as home runs, walks, and doubles. The combination of counting statistics and aggregate statistics were important in determining a player's expected salary.

The time periods that were selected were 1988-1990, 1998-2000, and 2008-2010 (Congdon-Homan and Lanning 1048). The different periods allowed for a separation of time in the market to evolve and change the importance of different measures. Congdon-Hohman and Lanning only used free-agents that had been in the MLB for at least six years. The reasoning

behind this is to eliminate anyone who was on their rookie contract, where the salary can be pre-determined by the league's minimum salary for a certain period of time (Congdon-Homan and Lanning 1049). All of their statistics were collected from Baseball-Reference and focused on the aggregate and counting statistics previously mentioned. A player's age and their defensive ability were also factored in their model. They then analyzed the mean salary and statistics for each free-agent in its given time period. They decided to use each player's past 502 plate appearances as a measure for the last full year they played. As a result, they found that the marginal value of power statistics increased dramatically from the late 1980s to the late 1990s. When you get to the late 2008s, there was more emphasis on a player's on-base percentage (Congdon-Homan and Lanning 1051-1052). This would make sense considering many MLB teams adopted the "Moneyball" theory during this time period. Congdon-Hohman and Lanning's findings have important implications for future research on player valuations. As preferences of statistical production change over time, so will the way teams evaluate a player's salary.

In a thesis done by Tyler Wasserman called "Determinants of Major League Baseball Player Salaries", he used linear regression analyses to isolate relationships between player salaries and a multitude of different factors which may have a significant relationship to salaries. Agreeing with the previous articles, Wasserman states that the biggest factor that determines how much a player is paid is based on his production on the field. However, he also examines other factors that have not been discussed. These factors consist of the player's age, the time of year in which the contract was signed, whether or not the player is a free agent, the market size of the team signing the player, and the player's agent (Wasserman 1). Using a sample size of 761 player contracts signed over the decade of 2002-2012, Wasserman breaks it down to three categories. They are (1) hitters only, (2) pitchers only, and (3) all players combined. He states he

does this to gain a better understanding of what is actually impacting a player's contract. Wasserman also noted some earlier studies that have been done that can be useful when I value players later on. He mentioned that Palmer and King (2006) used many of the aggregate statistics previously discussed and found that there was no discrimination by race that factored into player contracts (Wasserman 3). Also, a study by Link and Yosifov (2012) found that most players were willing to take a smaller yearly salary in exchange for a longer-term contract (Wasserman 3). This would agree with my belief that players value job security to lessen the worry of future injuries.

Wasserman's methodology was to use multiple regressions to isolate the different factors that can be related to player salaries (Wasserman 16). When it came to the value of each player's salary, I liked that he discussed the time value of money; emphasizing that a dollar today is worth more than a dollar in the future. He explains how some contracts are "backloaded", meaning that the yearly salary increases each year. On the contrary, other contracts are "frontloaded", meaning that the yearly salary decreases over time (Wasserman 17-18). To eliminate this, he found the present value of the amount and divided it by the number of years to get an average. The main statistic Wasserman used to account for their on-field production is a frequently used term called WAR. The acronym WAR stands for wins above replacement. It describes how many more wins that player provides compared to a reserve player on the bench. War is scaled to the league average and considers things like batting, fielding, and baserunning (Wasserman 20).

The results that Wasserman found were interesting. He found that on average a player would make an additional $1.3 million per year for each additional win calculated by their WAR (Wasserman 36). For pitchers, this number would be even higher. When it came to age, younger

players received lower salaries (Wasserman 38). Much of this has to do with the restricted market young players are in as discussed by Congdon-Hohman and Lanning. Wasserman also examined the salaries of players who re-sign with their team. His thought was that those players would get a “home-town discount”, but his results stated otherwise. Players who re-signed with their team were paid a premium (Wasserman 39). Interestingly, he found that the best time to sign a contract was in December. He contributes this to the fact that it’s when winter meetings take place. During this time, you can see many bidding wars between teams, which can maximize a player’s salary. One factor that was also examined was the market size of the team. His evidence would conclude that large market teams, such as the Yankees, do in fact pay more money to their players. Finally, Wasserman discusses the importance of the player’s agent. Based on the results, there is evidence that would support the claim that having a well-known agent leads to a better contract. In some cases, having Scott Boras as your agent can increase your salary as much as $2 million per year (Wasserman 45).

In a thesis done by Brian Pollack called “What Gets Paid? Analyzing the Major League Baseball Contract Market”, he addresses the efficiency of the MLB contract market by applying analytics to player evaluation. By using models for player contract value, he is able to determine the most significant attributes rewarded to free agents. Similar to previous articles, he brings up that young players with less than three years in the league have no negotiation power over their contracts. Players between three and six years in the league go into an arbitration period where the team and player compromise of a salary for the upcoming season. After six years in the league, the player is eligible to become a free agent and can sign with any team for any amount (Pollack 7). Pollack stresses that his findings assume that past performance is the best indicator of future performance. Instead of trying to project future performance or aging curves, teams

compensate players for what they’ve done in the past. Previous studies are heavily focused on the offensive side. Pollack incorporates both offense and defense by analyzing what is most important to scoring runs and preventing runs (Pollack 11). Based on his theory, the teams that do this the most efficiently should be the ones to pay more. After determining the factors that determine run scoring and run prevention, he builds a model to get the total contract value for position players and pitchers that are free agents. The model includes variables such as recent individual statistics, length of the contract, age, and defensive position. Pollack found that the two key offensive statistics to look at were on-base percentage (OBP) and isolated slugging percentage (ISO) (Pollack 19). These are the factors that contribute most towards scoring runs. In today’s game, teams are allocating their financial resources to factors that contribute to winning. With OBP and ISO ratios increasing in recent years, it proves that more teams are adopting an analytic approach to the game. He also found that age wasn’t a significant factor. This could be explained by 90 percent of the contracts were for players who ranged from 28-38 (Pollack 2. It is rare to see players extend career past their late-30s.

When it came to analyzing pitchers, Pollack included strikeout rate and walk rate as variables to determine factors of run prevention. Both of these ended up being significant to run prevention. Since strikeouts exclude the involvement of the defense, it was inversely correlated with runs allowed (Pollack 25). Walks are deemed as a negative outcome for a pitcher. Therefore, limiting the number of walks will also limit the number of baserunners. As a result, it will also lead to a lower run allowed. As far as an individual model for pitchers, factors such as age, innings pitched, strikeout rate, walk rate, and home runs allowed were included (Pollack 26).

In the article called “Major League Baseball Division Standings, Sports Journalists’ Predictions and Player Salaries”, written by David J. Smyth and Seamus J. Smyth, it analyzes three sets of published predictions for the nine seasons from 1982-1990. The main model that I focused on is suggested by economic theory that the ranking of teams will depend on the relative average salaries paid by the team (Smyth and Smyth 421). Even without as much statistical data, superior players were paid more than inferior ones. It was implied that having more superior players would lead to a better winning percentage. A better winning percentage would increase attendance and profits (Smyth and Smyth 422). Therefore, there was an incentive for owners to improve the quality of their players, even if it meant giving out higher salaries.

The salary model they used assumes owners operate efficiently. A former New York Yankees owner, George Steinbrenner, was known to spend a lot of money to acquire elite players and does not hesitate to get rid of anything that can reduce the team’s productivity. In every season from 1982-1988, the New York Yankees had the highest average salary (Smyth and Smyth 424). However, they failed to win the division title. After further analysis, there is significant evidence to support the claim that salary models out-perform the random ordering model used in Smyth’s research (Smyth and Smyth 426).

To sum it up, all of these articles insist that a player’s on-field production plays a major role in determining a player’s salary. Before the Moneyball era, teams focused on a player’s slugging percentage as their best attribute. As shown by Farrar and Bruggink, an increase in one’s on-base percentage had a far greater impact on additional runs scored than slugging percentage. However, it wasn’t until a few years after the release of the book that general managers began to adopt the idea of re-valuation players. Congdon-Hohman and Lanning described in "Beyond Moneyball" that through different decades, there were shifts in what teams

were looking for. Lackritz model was critical on a player's impact on winning percentage as well as the utilization function. While Wasserman valued on-field production, he also went in-depth about other factors such as age, market size, and the player’s agent. Similar to other articles, Pollack saw the value in a high on-base percentage for hitters. When it came to pitchers, a high strikeout rate and low walk rate were key to limiting runs allowed. All of this research will be helpful in creating my own method of putting a value on players.

Research Question

Based on production, which MLB players are underpaid and which are overpaid? Using this information, how can we evaluate the general managers for these organizations?

Methodology

The first thing I will have to find for my paper will be all players on each team’s active roster for the 2018 season. This will allow me to filter out the people who didn’t play on the major league team over the course of the season. All of the data being gathered can be found as public information online. The website I will be using is spotrac.com. The other two components I will be taking form “Spotrac” are the player's position and their adjusted salary. It is important to categorize them by position because each position has its own average salary. To specify, the categories I used for my thesis were divided by catchers, first baseman, second baseman, third baseman, shortstops, left fielders, center fielders, right fielders, designated hitters, starting pitchers, relief pitchers, and closers. There were also two additional categories that were rare but

were also considered. The first one was "outfielders". These are the players that were utilized at all three outfield positions. As you will later see, to create the average salary for these players, I simply took the average of the three outfield positions. The other rare category as “pitchers” After further research, these players were mainly used as relief pitchers, so I treated them as such. I thought that it was best to use the adjusted salary in comparison to the payroll salary for the purpose of my thesis. The reason being that the adjustment salary considers things such as payroll salary due to a mid-season signing, minor league assignments, and retained money from a trade.

After finding the players each team’s active roster with their respective positions and adjusted salaries, the key statistic that I will be using to help determine an estimated value is WAR. The term WAR is a metric that stands for ‘wins above replacement’. It is an attempt by the sabermetrics baseball community to summarize a player’s total contributions to their team in one statistic. While it is preferred to include a magnitude metrics to estimate value, I wanted to use WAR as the most important statistic because it includes multiple dimensions of the game and is viewed as a useful reference point when comparing players. The best way to interpret WAR is by asking how much value a team would be losing if a particular player got injured and had to be replaced by a bench player or minor leaguer.

As expected, the calculation of WAR differs for position players and pitchers. When it comes to position players, WAR is constructed by first adding their batting runs, baserunning runs, and fielding runs above the average player. Then it adds in an adjustment for their position as well as the league that they play in (American or National). The final factor that is added is called replacement runs in order to compare their performance to a replacement level rather than an average player. Finally, you take the sum of those numbers and divide it by the average runs

needed to win a game. In a more mathematical representation, the equation for calculating WAR for a position player looks like:

WAR = (Batting Runs + Base Running Runs +Fielding Runs + Positional Adjustment + League Adjustment +Replacement Runs) / (Runs Per Win)
("FanGraphs Baseball | Baseball Statistics and Analysis")

As far as a pitcher's WAR, there are other elements that are being weighed. Instead of using stats such as batting runs and fielding runs, it incorporates more pitching statistics. Once again, there are adjustments made for the park you play in. This is because some parks are known to be either more "pitcher-friendly" or "hitter friendly". For example, a "pitcher-friendly" park would be a large field where there tend to be fewer home runs. A "hitter-friendly park would be a field that is smaller and sometimes at a higher altitude to allow the ball to travel farther, which leads to more home runs.

It is important to mention that a player's WAR may differ slightly based on the different methods for estimating offensive, defensive, and pitching value. For my thesis, I exported the WAR values from "FanGraphs", which is one of the main websites that compute WAR. In baseball, there is an abundance amount of statistics taken offensively. This is why it was easy to compare players using typical offensive stats. However, there are multiple ways that a player can help contribute to their team's success. It was best to use WAR because it combines a player's total contribution and puts it into a single value. Since it accounts for many things, it provides a preferred metric when used to compare players across teams, league, year, and even era. Another important thing to remember is that WAR is an estimation. Even if a player has a slightly higher WAR than another player, you should not assume that the player is better. When the WAR is that close, it may take further investigation to make a more accurate claim on which player is better.

However, if one player has a WAR that is substantially higher than another player, it is highly likely that the player provides more value to his team and is thus a better player.

Scrub	0-1 WAR
Role Player	1-2 WAR
Solid Starter	2-3 WAR
Good Player	3-4 WAR
All-Star	4-5 WAR
Superstar	5-6 WAR
MVP	6+ WAR

("FanGraphs Baseball | Baseball Statistics and Analysis")

Typically, the league average WAR is around 2. Instead of using the actual WAR, I included a stat labeled "adjusted WAR". To get the calculation of "adjusted WAR", I subtracted two to the actual WAR. This allowed me to standardize the WAR around an average everyday player instead of a replacement player. Without using the "adjusted WAR", my valuations would end up being too high.

Average Salary by Position

Column1	Column2
Catchers	$6,200,000
1st Base	$9,200,000
2nd Base	$5,800,000
3rd Base	$6,100,000
Shortstop	$3,800,000
Left Field	$5,200,000
Center Field	$6,000,000
Right Field	$6,700,000
DH	$10,500,000
Starting Pitchers	$ 5,620,000
Relief Pitchers	$ 2,037,500
Closers	$4,500,000
Outfield	$5,966,667

Average Player Age

Column1	Column2
Toronto Blue Jays	30.3
Cleaveland Indians	29.9
San Francisco Giants	29.6
Arizona Diamondbacks	29.2
Texas Rangers	29.2
Houston Astros	29.1
Los Angeles Angels	29.1
Minnesota Twins	29.1
Seattle Mariners	29.1
Milwaukee Brewers	29
Washington Nationals	29
New York Mets	28.9
Los Angeles Dodgers	28.8
Chicago Cubs	28.6
Kansas City Royals	28.6
Miami Marlins	28.5
Baltimore Orioles	28.4
Colorado Rockies	28.4
Oakland Athletics	28.4
Detriot Tigers	28.2
Boston Red Sox	28
Tampa Bay Rays	27.8
Atlanta Braves	27.7
New York Yankees	27.6
San Diego Padres	27.4
St. Louis Cardinals	27.4
Pittsburgh Pirates	27.3
Cincinnati Reds	27.2
Philadelphia Phillies	26.6
Chicago White Sox	26.2

Now that I have gathered all the information needed, I can begin to analyze it to determine whether the player is underpaid or overpaid. To get an estimated value for each player, I first looked to see whether the "adjusted WAR" was positive. If so, I took the average salary of their position and multiplied it by the "adjusted WAR" plus one. If the "adjusted WAR" was negative, I took the average salary for their position and divided it by the "adjusted WAR" minus one. Like I mentioned earlier, I was able to standardize the salary around the average player in that particular position by subtracting two from the actual WAR to create the "adjusted WAR". The next step would be to find a salary error. This was calculated by simply subtracting the player's adjusted salary by the estimated value I created. If the difference was positive, that means that the player is underpaid. Essentially, he is producing more production than his salary shows. Vice versa, a player with a negative difference is considered overpaid. They are not producing enough to meet the level of expectation of their salary portrays. The last calculation made for each player was their salary percentage error. It was found by taking the difference of the adjusted salary by the estimated value and dividing that by the adjusted salary. The percentage error makes it easier to compare players by looking at their production relative to their salary.

Once I complete the individual statistics, I can then move on to ranking the general managers. One way of doing this is by adding the total percentage error for a team. In order to compensate for teams having more players on their active roster, you can take the average sum of percentage error. I also did the same thing with the total salary error for each team. Again, I created another chart with the average salary error to make it more comparable to other teams. A vital part of a general manager’s job in the MLB is to allocate their resources wisely. This would

include getting the most production out of your players for the least amount of cost. I can then rank the general managers by taking those charts and ordering them from highest to lowest.

My final step would be to use a Spearman's rank correlation test to see I can find a correlation between the rankings I made to the average player age of each team, the franchise value of that team, and the average attendance of every home game for each team. If there is a strong correlation with any of the three, I will be able to connect something with being a good general manager.

Results and Discussion

It was interesting to find out that the average salary for each position. Surprisingly, designated hitters were paid the most with an average of $10 million and first basemen following not too far behind at a little over $9 million. Then the starting pitchers and the rest of the positional players except for shortstop hover around the $6 million mark. Next on the list would be closers would make on average $4.5 million and edge out shortstops who are at $3.8 million. Finally, relief pitchers round off the list by making just over $2 million. The WAR also had a large range with the high coming from Mookie Betts on the Boston Red Sox with a WAR of 10.4 and the low from Chris Davis on the Baltimore Orioles with a WAR of -3.1.

Using my methodology, I was able to successfully calculate an estimated value for each player on a team's active roster. After taking the difference of their adjusted salary by the estimated value we developed, I was able to determine which players were underpaid and overpaid. Each team had various amounts of players that were underpaid and overpaid. In order

to distinguish the results clearer, I highlighted all the players who were considered overpaid in red.

	Age	Position	Adj. Salary	WAR	Adj. WAR	Average Salary for Position	Estimated Value	Salary Error	Percentage Error
Arizona Diamondbacks									
Column1	Column2	Column3	Colun	Column8	Column82	Column9			
Patrick Corbin	29	SP	$7,500,000	6.2	4.2	$5,620,000	$29,224,000	$21,724,000	290%
Paul Goldschmidt	30	1B	$11,100,000	5.1	3.1	$9,200,000	$37,720,000	$26,620,000	240%
David Peralta	30	RF	$3,300,000	3.8	1.8	$6,700,000	$18,760,000	$15,460,000	468%
Zack Greinke	34	SP	$34,000,000	3.7	1.7	$5,620,000	$15,174,000	-$18,826,000	-55%
Ketel Marte	24	2B	$3,000,000	2.5	0.5	$5,800,000	$8,700,000	$5,700,000	190%
A.J. Pollock	30	CF	$7,750,000	2.5	0.5	$6,000,000	$9,000,000	$1,250,000	16%
Zack Godley	28	SP	$579,200	2.2	0.2	$5,620,000	$6,744,000	$6,164,800	1064%
Nick Ahmed	28	SS	$1,275,000	1.7	-0.3	$3,800,000	$2,923,077	$1,648,077	129%
Clay Buchholz(60-day)	33	SP	$1,080,645	1.6	-0.4	$5,620,000	$4,014,286	2933640.714	271%
Daniel Descalso	31	3B	$2,000,000	1.5	-0.5	$6,100,000	$4,066,667	$2,066,667	103%
Eduardo Escobar	29	3B	$1,694,875	1	-1	$6,100,000	$3,050,000	$1,355,125	80%
John Ryan Murphy	27	C	$558,000	1	-1	$6,200,000	$3,100,000	$2,542,000	456%
Andrew Chafin	28	RP	$1,195,000	0.9	-1.1	$2,037,500	$970,238	-$224,762	-19%
Alex Avila	31	C	$4,000,000	0.8	-1.2	$6,200,000	$2,818,182	-$1,181,818	-30%
Jeff Mathis	35	C	$2,000,000	0.8	-1.2	$6,200,000	$2,818,182	$818,182	41%
Robbie Ray	26	SP	$3,950,000	0.7	-1.3	$5,620,000	$2,443,478	-$1,506,522	-38%
Archie Bradley	25	RP	$581,900	0.4	-1.6	$2,037,500	$783,654	$201,754	35%
Silvino Bracho	25	RP	$205,100	0.4	-1.6	$2,037,500	$783,654	$578,554	282%
Jake Lamb (60-day)	27	3B	$4,275,000	0.3	-1.7	$6,100,000	$2,259,259	-$2,015,741	-47%
Jarrod Dyson(60-day)	33	RF	$3,750,000	0.3	-1.7	$6,700,000	$2,481,481	-$1,268,519	-34%
Yoshihisa Hirano	34	RP	$3,000,000	0.3	-1.7	$2,037,500	$754,630	-$2,245,370	-75%
T.J. McFarland	29	RP	$850,000	0.3	-1.7	$2,037,500	$754,630	-$95,370	-11%
Brad Ziegler	38	RP	$2,999,994	0.1	-1.9	$2,037,500	$702,586	-$2,297,408	-77%
Taijuan Walker(60-day	25	SP	$4,825,000	0.1	-1.9	$5,620,000	$1,937,931	-$2,887,069	-60%
Christian Walker(60-da	27	1B	$193,380	-0.1	-2.1	$9,200,000	$2,967,742	$2,774,362	1435%
Jake Diekman	31	RP	$904,146	-0.1	-2.1	$2,037,500	$657,258	-$246,888	-27%
Jon Jay	33	CF	$1,887,093	-0.3	-2.3	$6,000,000	$1,818,182	-$68,911	-4%
Socrates Brito	25	LF	$125,990	-0.3	-2.3	$5,200,000	$1,575,758	$1,449,768	1151%
Shelby Miller	27	RP	$4,900,000	-0.3	-2.3	$2,037,500	$617,424	-$4,282,576	-87%
Randall Delgado	28	RP	$43,950	-0.3	-2.3	$2,037,500	$617,424	$573,474	1305%
Brad Boxberger	30	RP/CL	$1,850,000	-0.3	-2.3	$4,500,000	$1,363,636	-$486,364	-26%
Steven Souza	29	RF	$3,550,000	-0.4	-2.4	$6,700,000	$1,970,588	-$1,579,412	-44%
Matt Andriese	28	RP	$537,358	-0.6	-2.6	$2,037,500	$565,972	$28,614	5%
Matt Koch	27	RP	$322,300	-0.7	-2.7	$2,037,500	$550,676	$228,376	71%
Chris Owings	26	RF	$3,400,000	-0.8	-2.8	$6,700,000	$1,763,158	-$1,636,842	-48%

	Overpaid	

Tampa Bay Rays

Column1	Column2	Column3	Colum	Column8	Column82	Column9				
Blake Snell	25	SP	$558,200	4.9	2.9	$5,620,000		$21,918,000	$21,359,800	3827%
Joe Wendle	28	2B	$545,000	3.7	1.7	$5,800,000		$15,660,000	$15,115,000	2773%
Mallex Smith	25	LF	$553,000	3.4	1.4	$5,200,000		$12,480,000	$11,927,000	2157%
Tommy Pham	30	CF	$190,030	2.5	0.5	$6,000,000		$9,000,000	$8,809,970	4636%
Matt Duffy	27	3B	$930,000	2.4	0.4	$6,100,000		$8,540,000	$7,610,000	818%
Daniel Robertson (60-d	24	SS	$548,300	2.4	0.4	$3,800,000		$5,320,000	$4,771,700	870%
C.J. Cron	28	DH	$2,300,000	2.1	0.1	$10,500,000		$11,550,000	$9,250,000	402%
Jose Alvarado	23	RP/CL	$549,800	2.1	0.1	$4,500,000		$4,950,000	$4,400,200	800%
Kevin Kiermaier	28	CF	$5,666,666	1.6	-0.4	$6,000,000		$4,285,714	-$1,380,952	-24%
Willy Adames	22	SS	$272,490	1.3	-0.7	$3,800,000		$2,235,294	$1,962,804	720%
Ryne Stanek	26	RP	$418,990	1.2	-0.8	$2,037,500		$1,131,944	$712,954	170%
Yonny Chirinos	24	RP	$398,480	1.2	-0.8	$2,037,500		$1,131,944	$733,464	184%
Ji-Man Choi	27	1B	$379,310	1.1	-0.9	$9,200,000		$4,842,105	$4,462,795	1177%
Diego Castillo	24	RP	$345,740	1.1	-0.9	$2,037,500		$1,072,368	$726,628	210%
Adam Kolarek	29	RP	$225,610	0.9	-1.1	$2,037,500		$970,238	$744,628	330%
Ryan Yarbrough	26	RP	$542,050	0.9	-1.1	$2,037,500		$970,238	$428,188	79%
Brandon Lowe	23	2B	$169,940	0.8	-1.2	$5,800,000		$2,636,364	$2,466,424	1451%
Tyler Glasnow	24	RP	$181,660	0.6	-1.4	$2,037,500		$848,958	$667,298	367%
Hunter Wood	24	RP	$301,790	0.5	-1.5	$2,037,500		$815,000	$513,210	170%
Sergio Romo	35	RP	$2,500,000	0.5	-1.5	$2,037,500		$815,000	-$1,685,000	-67%
Wilmer Font (60-day)	28	RP	$378,496	0.4	-1.6	$2,037,500		$783,654	$405,158	107%
Chaz Roe	31	RP	$720,000	0.3	-1.7	$2,037,500		$754,630	$34,630	5%
Austin Pruitt	28	RP	$260,770	0.2	-1.8	$2,037,500		$727,679	$466,909	179%
Andrew Velazquez	23	SS	$84,970	0.2	-1.8	$3,800,000		$1,357,143	$1,272,173	1497%
Chih-Wei Hu	24	RP	$67,390	0.1	-1.9	$2,037,500		$702,586	$635,196	943%
Vidal Nuno	30	RP	$383,830	0.1	-1.9	$2,037,500		$702,586	$318,756	83%
Jacob Faria	24	SP	$498,328	0.1	-1.9	$5,620,000		$1,937,931	$1,439,603	289%
Adam Moore	34	C	$108,410	-0.1	-2.1	$6,200,000		$2,000,000	$1,891,590	1745%
Austin Meadows	23	CF	$32,230	-0.1	-2.1	$6,000,000		$1,935,484	$1,903,254	5905%
Michael Perez (10-day	25	C	$196,310	-0.2	-2.2	$6,200,000		$1,937,500	$1,741,190	887%
Nick Ciuffo	23	C	$82,040	-0.2	-2.2	$6,200,000		$1,937,500	$1,855,460	2262%
Hoby Milner	27	RP	$53,028	-0.3	-2.3	$2,037,500		$617,424	$564,396	1064%
Andrew Kittredge	28	RP	$288,806	-0.4	-2.4	$2,037,500		$599,265	$310,459	107%
Carlos Gomez	32	RF	$4,400,000	-0.6	-2.6	$6,700,000		$1,861,111	-$2,538,889	-58%
Jesus Sucre	30	C	$925,000	-1.3	-3.3	$6,200,000		$1,441,860	$516,860	56%

As you can see, a team such as the Arizona Diamondbacks (top chart), had a lot more players that were considered overpaid than a team like the Tampa Bay Rays (bottom chart) based on my method of valuation. This may indicate that the Tampa Bay Rays' general manager does a better job allocating his money by signing players who outperform the production their salary suggests. The reason I chose the Arizona Diamondbacks and the Tampa Bay Rays was to show the drastic difference between the two results. These are both teams that did not make the playoffs but still finished with an above-average regular-season record. I found it interesting to see the Tampa Bay Rays had very few players that were considered overpaid while the Arizona Diamondbacks had more than half their players considered overpaid based on my metric. This could be reasoned by the difference in average age per player for each team. The average age of a player on the Arizona Diamondbacks is 1.4 years older than the average player on the Tampa Bay Rays. While it may not seem too drastic of a difference, veteran players usually acquire larger contracts. Thus, they have a higher probability of underperforming their salary.

In order to rank the general managers, I first took the total sum of the salary error and then placed them in decreasing order. To account for the difference in the number of active players on each roster, I then created another chart with the average salary error for each team.

Made Playoffs

Total Sum of Salary Error

Rank	Team Column1	Column2	General Manager Column3
1	Oakland Athletics	$134,324,039	Billy Beane
2	Cleveland Indians	$118,413,379	Mike Chernoff
3	Tampa Bay Rays	$104,412,858	Erik Neander
4	Atlanta Braves	$99,408,979	Alex Anthopoulos
5	Milwaukee Brewers	$86,746,167	David Stearns
6	New York Yankees	$81,575,436	Brian Cashman
7	Houston Astros	$72,572,667	Jeff Luhnow
8	Pittsburgh Pirates	$64,154,035	Neal Huntington
9	Los Angeles Dodgers	$56,841,399	Farhan Zaidi
10	Arizona Diamondbacks	$53,267,822	Mike Hazen
11	Washington Nationals	$51,610,497	Mike Rizzo
12	Los Angeles Angels	$50,662,261	Billy Eppler
13	Philadelphia Phillies	$43,123,670	Matt Klentak
14	New York Mets	$42,989,408	Sandy Alderson
15	Boston Red Sox	$42,917,252	Dave Dombrowski
16	St. Louis Cardinals	$42,836,182	John Mozeliak
17	Miami Marlins	$41,748,429	Michael Hill
18	Minnesota Twins	$36,565,591	Thad Levine
19	Cincinnati Reds	$32,474,001	Dick Williams
20	Colorado Rockies	$23,471,725	Jeff Bridich
21	San Diego Padres	$22,339,849	A.J. Preller
22	Seattle Mariners	$20,445,801	Jerry Dipoto
23	Chicago White Sox	$17,815,785	Rick Hahn
24	Toronto Blue Jays	$7,311,663	Ross Atkins
25	Kansas City Royals	$5,677,234	Dayton Moore
26	Texas Rangers	$1,882,313	Jon Daniels
27	Detroit Tigers	-$14,291,779	Al Avila
28	Baltimore Orioles	-$21,992,198	Dan Duquette
29	Chicago Cubs	-$32,665,777	Theo Epstein
30	San Francisco Giants	-$97,045,595	Bobby Evans

Average Salary Error

Rank	Team Column1	Column2	General Manager Column3
1	Oakland Athletics	$3,630,379	Billy Beane
2	Cleveland Indians	$3,200,362	Mike Chernoff
3	Tampa Bay Rays	$2,983,225	Erik Neander
4	Atlanta Braves	$2,616,026	Alex Anthopoulos
5	Milwaukee Brewers	$2,478,462	David Stearns
6	New York Yankees	$2,091,678	Brian Cashman
7	Houston Astros	$2,073,505	Jeff Luhnow
8	Pittsburgh Pirates	$1,782,057	Neal Huntington
9	Boston Red Sox	$1,650,664	Dave Dombrowski
10	Arizona Diamondbacks	$1,521,938	Mike Hazen
11	Washington Nationals	$1,474,586	Mike Rizzo
12	Los Angeles Dodgers	$1,457,472	Farhan Zaidi
13	Los Angeles Angels	$1,266,557	Billy Eppler
14	Miami Marlins	$1,227,895	Michael Hill
15	Philadelphia Phillies	$1,197,880	Matt Klentak
16	St. Louis Cardinals	$1,189,894	John Mozeliak
17	New York Mets	$1,131,300	Sandy Alderson
18	Minnesota Twins	$1,044,731	Thad Levine
19	Cincinnati Reds	$1,014,813	Dick Williams
20	Colorado Rockies	$782,391	Jeff Bridich
21	San Diego Padres	$638,281	A.J. Preller
22	Chicago White Sox	$574,703	Rick Hahn
23	Seattle Mariners	$538,047	Jerry Dipoto
24	Toronto Blue Jays	$208,905	Ross Atkins
25	Kansas City Royals	$183,137	Dayton Moore
26	Texas Rangers	$53,780	Jon Daniels
27	Detroit Tigers	-$408,337	Al Avila
28	Baltimore Orioles	-$646,829	Dan Duquette
29	Chicago Cubs	-$816,644	Theo Epstein
30	San Francisco Giants	-$2,772,731	Bobby Evans

Based on the result, you can see some slight changes in the ranking, but most of it stays the same. At the top, I have the Oakland Athletics, Cleveland Indians, Tampa Bay Rays, Atlanta Braves, and Milwaukee Brewers. At the bottom are the Texas Rangers, Detroit Tigers, Baltimore Orioles, Chicago Cubs, and San Francisco Giants. The teams that are highlighted in yellow represent the ones that made the 2018 playoffs. As expected the majority of these teams are near the top of the list. This would make sense because if a team is producing enough wins to make

the playoffs, they are likely to have players that have high WAR values and outperform their listed salary.

The second way that I attempted to rank the general managers is by using the percentage salary error. Similar to the salary error ranking, I created a chart for both the total sum of percentage error and the average percentage error for each team.

Made Playoffs

Total sum of percentage error

	Team		General Manager
Rank	Column1	Column2	Column3
1	Chicago Cubs	43792%	Theo Epstein
2	Tampa Bay Rays	36122%	Erik Neander
3	New York Yankees	28294%	Brian Cashman
4	Los Angeles Angels	27994%	Billy Eppler
5	Detroit Tigers	26868%	Al Avila
6	Toronto Blue Jays	26337%	Ross Atkins
7	Oakland Athletics	24874%	Billy Beane
8	Philadelphia Phillies	24484%	Matt Klentak
9	Atlanta Braves	24465%	Alex Anthopoulos
10	Miami Marlins	24185%	Michael Hill
11	Minnesota Twins	23887%	Thad Levine
12	Pittsburgh Pirates	23361%	Neal Huntington
13	Baltimore Orioles	22684%	Dan Duquette
14	Cleveland Indians	22649%	Mike Chernoff
15	New York Mets	22316%	Sandy Alderson
16	Houston Astros	22091%	Jeff Luhnow
17	Kansas City Royals	20631%	Dayton Moore
18	Washington Nationals	19074%	Mike Rizzo
19	Los Angeles Dodgers	18865%	Farhan Zaidi
20	Colorado Rockies	17496%	Jeff Bridich
21	San Diego Padres	17312%	A.J. Preller
22	Seattle Mariners	16727%	Jerry Dipoto
23	St. Louis Cardinals	16653%	John Mozeliak
24	San Francisco Giants	16536%	Bobby Evans
25	Milwaukee Brewers	15378%	David Stearns
26	Cincinnati Reds	13266%	Dick Williams
27	Chicago White Sox	13050%	Rick Hahn
28	Texas Rangers	11862%	Jon Daniels
29	Arizona Diamondbacks	6949%	Mike Hazen
30	Boston Red Sox	3219%	Dave Dombrowski

Average percentage error

	Team		General Manager
Rank	Column1	Column2	Column3
1	Chicago Cubs	1095%	Theo Epstein
2	Tampa Bay Rays	1032%	Erik Neander
3	Oakland Athletics	968%	Billy Beane
4	Detroit Tigers	768%	Al Avila
5	Toronto Blue Jays	752%	Ross Atkins
6	New York Yankees	725%	Brian Cashman
7	Miami Marlins	711%	Michael Hill
8	Los Angeles Angels	700%	Billy Eppler
9	Minnesota Twins	682%	Thad Levine
10	Philadelphia Phillies	680%	Matt Klentak
11	Baltimore Orioles	667%	Dan Duquette
12	Kansas City Royals	666%	Dayton Moore
13	Pittsburgh Pirates	649%	Neal Huntington
14	Atlanta Braves	644%	Alex Anthopoulos
15	Houston Astros	631%	Jeff Luhnow
16	Cleveland Indians	612%	Mike Chernoff
17	New York Mets	587%	Sandy Alderson
18	Colorado Rockies	583%	Jeff Bridich
19	Washington Nationals	545%	Mike Rizzo
20	San Diego Padres	504%	A.J. Preller
21	Los Angeles Dodgers	484%	Farhan Zaidi
22	San Francisco Giants	472%	Bobby Evans
23	St. Louis Cardinals	463%	John Mozeliak
24	Seattle Mariners	440%	Jerry Dipoto
25	Milwaukee Brewers	439%	David Stearns
26	Chicago White Sox	421%	Rick Hahn
27	Cincinnati Reds	415%	Dick Williams
28	Texas Rangers	339%	Jon Daniels
29	Arizona Diamondbacks	199%	Mike Hazen
30	Boston Red Sox	124%	Dave Dombrowski

The results were quite shocking to me at first. I had expected the rankings to be similar to the ones I got using the salary error, but I was wrong. Theo Epstein and his Chicago Cubs climbed all the way to the top of the list after being ranked second to last in the previous list. Dave Dombrowski's Red Sox finished dead last on this list compared to being slightly above average when analyzing salary error. This was the most surprising considering the Red Sox finished the

season with the best record in the league and went on to win the World Series. Unlike the previous ranking, this one has the playoff teams scattered throughout the entire list. It made me wonder why there was such a big difference even though I'm using the same data.

After taking a further look at the data, the change in rankings can be partly explained the variability of each team's payroll. The Chicago Cubs have many players that have very low salaries and are underpaid by a wide margin relative to their salary. This makes their percentage error extremely high even though they still might be performing below an average player. For example, Allen Webster, a starting pitcher for the Chicago Cubs, only made $35,160 as his adjusted salary. This can be due to the fact that he only appeared in 3 games that season. Even though he has a -0.1 WAR, he still has a projected value of $1,812,903. That salary is still low compared to other starting pitchers, which doesn't change the salary error by much. However, since his salary is so low, it has a great impact on the percentage error. Webster alone contributes a positive 5056% error for his team. The Chicago Cubs have a few players like Webster that explains the jump in the list for percentage error. When you look at the Boston Red Sox, the majority of their players had high adjusted salaries. This eliminated the chance of having a skyrocketing percentage error. In fact, the high adjusted salaries caused their percentage errors to be relatively low, which dropped Dave Dombrowski's team to the bottom of the list.

When analyzing both sets of lists, it was no surprise to me that Billy Beane's Oakland A's were ranked near the top. After all, he was the first to buy into the theory of creating a winning team by finding players who were undervalued starting from the early 2000s. However, I didn't expect Brian Cashman's New York Yankees to be near the top in both lists as well. Being a Yankee fan myself, we've always been labeled as the organization that will pay whatever it takes to get the players we want. While this is still true to some extent, there has been

a recent shift to focus on the development of young players. Since the majority of the Yankee roster are young players, they haven't signed a large contract yet. This works in their favor when it comes to getting the most production at the lowest cost possible.

With the ability to manipulate the ranking by rostering players with low salaries and boosting the percentage error, I strongly favor using the average salary error chart to determine the best general managers. Therefore, my official rankings would be:

Ranking of MLB General Managers

1. Billy Beane, Oakland Athletics
2. Mike Chernoff, Cleveland Indians
3. Erik Neander, Tampa Bay Rays
4. Alex Anthopoulos, Atlanta Braves
5. David Stearns, Milwaukee Brewers
6. Brian Cashman, New York Yankees
7. Jeff Luhnow, Houston Astros
8. Neal Huntington, Pittsburgh Pirates
9. Dave Dombrowski, Boston Red Sox
10. Mike Hazen, Arizona Diamondbacks
11. Mike Rizzo, Washington Nationals
12. Farhan Zaidi, Los Angeles Dodgers
13. Billy Eppler, Los Angeles Angels
14. Michael Hill, Miami Marlins
15. Matt Klentak, Philadelphia Phillies
16. John Mozeliak, St. Louis Cardinals
17. Sandy Anderson, New York Mets
18. Thad Levine, Minnesota Twins
19. Dick Williams, Cincinnati Reds
20. Jeff Bridich, Colorado Rockies
21. A.J. Preller, San Diego Padres
22. Rick Hohn, Chicago White Sox
23. Jerry Dipoto, Seattle Mariners
24. Ross Atkins, Toronto Blue Jays
25. Dayton Moore, Kansas City Royals
26. Jon Daniels, Texas Rangers
27. Al Avila, Detroit Tigers
28. Dan Duquette, Baltimore Orioles
29. Theo Epstein, Chicago Cubs
30. Bobby Evans, San Francisco Giants

Lastly, I conducted a Spearman's rank correlation test to see I can find a correlation between the rankings I made to the average player age of each team, the franchise value of that team, and the average attendance of every home game for each team. My results were as follows:

Average Age to Average Salary Error		
	Spearman's Correlation	-0.1317019

Fanchise Value to Average Salary Error		
	Spearman's Correlation	-0.134594

Average Attendence to Average Salary Error		
	Spearman's Correlation	-0.025584

As you can see, I did not get a strong correlation for any of the Spearman's rank test. When looking at the output, the closer the number is to 1 or -1 means the stronger the correlation. Based on my three outputs, the correlation between the franchise value to average salary error was the closest to those extremes at -0.134594. While this is the strongest output I received, it is still viewed as a very low and non-significant result.

When it comes to putting a value on a player, there are multiple ways that it can be constructed. I chose to use WAR as my main statistic since it incorporates the offensive side of baseball as well as the defensive side. It has become a common term used when comparing players due to the fact that it already adjusts for things such as the player's position and the league they play in. Without a doubt, I could've approached this project a different way. Instead

of using WAR, I could've created a model that would have specific weight to multiple statistics and eventually compute an estimated value. Doing this would be a bit riskier because it would be my decision on what I thought was a more valuable component. Using WAR seemed safer since it is a respected number and it would give me a more accurate representation of the true value a player produced. Before going into this, I had assumed that the best general managers should be the ones whose team is in the playoffs. This certainly factored into my final rankings. When I saw how scattered those teams were when looking at the percentage error, I began to question whether or not I calculated it correctly. That makes me take a deeper look and realize how certain aspects can set a misrepresentation of the total data. When I saw the position of the playoff teams when I ranked based on salary error, it looked a lot closer to what I had in mind. It is important to recognize that these rankings are only for the 2018 MLB season. If it were a different year, it is very likely to see some shifts in the rankings. This is because every year the roster changes and the players don't always produce the same. Therefore, it would be useful to perform this study each year to give you a better representation of how well the general manager is doing.

Conclusion

Baseball has made the shift to become one of the most analytical games in recent years. With every pitch thrown there are dozens of statistics being recorded. One aspect of these analytics is player valuations. There are multiple people working for these organizations who crunch numbers to find the players that will provide enough production to win ballgames while keeping the cost at a minimum. This thesis provided a method to analyze a player’s contribution to their

team and an estimation of their value. When comparing this estimation with their actual adjusted salary, you can determine which players are underpaid and overpaid for each team. Further evaluation will help you make a case for the best and worst general managers in the league. There is a strong belief that the MLB will continue to go down the path of favoring analytics. Going forward, the method used in this thesis can be used to evaluate free agents and calculate a salary that fits their previous production.

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