What Are Professional Baseball Teams Paying For: An Analysis of Wins Above Replacement Data For MLB Draftees

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Abstract

This paper looks at why baseball teams spend money on players the way they do. Since baseball teams are run optimally, they are maximizing something under the constraint of the money that they have, and this paper attempts to figure out what they are maximizing. This paper posits three different possible hypotheses: that teams are attempting to maximize the sum of aggregate player output, that teams are attempting to maximize the number of superstars or very high output players, or that teams are trying to maximize the number of players over a certain level of output. This paper finds that teams act in a manner most consistent with trying to maximize aggregate output, regardless of where it comes from. This paper believes that this says something about how baseball fundamentally works, that games are not won solely by having superstars or by having a collection of players above a certain level of competency, but by the production of everyone on the roster. This may be why baseball has a difficult time marketing their superstars, as they have less of an impact on the game than in other sports.
1. Introduction

1.1 Why Do Sports Teams Win?

What determines whether a sports team will win or lose? Well, it depends on the sport. In games like soccer and hockey, where chemistry and teamwork are paramount, your performance will largely be dependent on those around you. A team’s successes or failures are not just determined the sum of its parts, it’s about how those parts fit together. While people do try, it is often difficult to isolate a single players impact on the outcome of a game, because the goals your striker scores cannot exist without the assists your midfielder sends his way. If you’re financially constrained and paying players for your team, a good assumption might be that it’d be better to pay for bunch of good players rather than a few great players and a few bad ones. In sports like basketball and American football, where a single superstar can catapult a mediocre team to a perennial championship contender, it’s hard to quantify the value of players for the opposite reason. Superstars in basketball can have the ball on every offensive possession, take almost every shot, and singlehandedly win games if needed. In football, a great quarterback can do the same. It’s why every year when you’re turning on the NBA finals or the Super Bowl, you inevitably see LeBron James or Tom Brady, year after year, no matter the team or the players surrounding them. Great players have such an outsized impact on their teams’ success that the current NBA championship model is to either lose so badly you have a shot at drafting a superstar out of college or to do everything to trade for/entice a current superstar to come to your team, because teams that don’t have superstars simply don’t win championships. The other players on a team are often entirely interchangeable, and much less valuable. LeBron might score 28 points a game, but is he really only as valuable as two 14 point
scorers? In basketball or football, it’s a fair assumption that a few great players and a few bad ones are more worth your money than a lot of good players.

Baseball, however, is completely different. The sport essentially takes the form of one-on-one matchups, a pitcher and hitter facing off in a vacuum chamber. Sure, once the ball is hit things like fielding ability and speed come into play and having good hitters after you in the batting order might cause a pitcher to approach you differently, but at its core, baseball is an individual pursuit. And unlike basketball and football, there’s no chance of a single player having an outside impact on the game. In baseball, you only get to bat once every nine times, no matter how great you are, and pitchers only pitch once every five days. The greatest statistical player of the 90’s/00’s, Barry Bonds, never won the World Series and only made it there once, while the greatest statistical player of the 2010s, Mike Trout, has only made the PLAYOFFS once.

Let’s say there was a statistic that attempted to holistically capture a single player’s output for every single sport, like GDP for player value. For hockey and soccer, teams might try and maximize having as many players as possible over a certain threshold of output to build a team with few weak spots. For basketball and football, teams might attempt to maximize the number of players with high percentile output to build a team with superstars. But how would baseball teams act? Would they pay to bring in only the cream of the crop? Would they try and just acquire a bunch of decently solid players? Or do they not care where production comes from, and just try and maximize the sum of their players’ output? This paper will attempt to answer that question using Wins Above Replacement (WAR), Major League Baseball’s premier holistic player value statistic.
1.2 Background and Literature Review

Since its invention in the mid-1800s, Baseball has become one of the most popular sports in the world, with dozens of professional leagues across the world and tens of millions of players from amateur t-ball players to multi-millionaire superstars. It has also become its own industry, with teams in America’s top professional league, Major League Baseball (MLB) being worth on average what Forbes estimates to be 2.07 billion dollars. We will only be focusing on Major League Baseball in this paper. Baseball teams, which are essentially firms, compete with one another for the services of players (labor) and directly compete with one another both economically (by selling tickets and merchandise) and on the baseball field itself (by playing baseball games against one another). This has led to baseball’s financial system becoming a topic of study in the economic field.

The study of the baseball labor market in academia begins with Simon Rottenberg’s The Baseball Players’ Labor Market, which was published by the University of Chicago Press in 1956 and is the first piece of academic literature to look at baseball from an economist’s standpoint. The paper contains an examination of the peculiarities of the baseball labor market. Rottenberg notes that baseball acts as a monopsony made up of the various baseball teams as the only firms/eligible employers, with insurmountable restraints on freedom of entry into the industry (you can’t just start your own major league baseball team). The paper argued against the existing reserve clause, which meant that players could not freely move from team to team and instead had to negotiate contracts with the team they were signed to when their contract expired.
Much of the continued study in this field was dedicated to providing empirical evidence to Rottenberg’s case against the reserve clause, but as the clause was struck down by an arbiter in 1975 paving the way for baseball’s adoption of the modern free agent system, these papers arguments are no longer relevant. More relevant is the methodology of determining exactly how valuable an individual player’s performance is. Gerald W. Scully’s *Economic Discrimination in Professional Sports* (1973) and *Pay and Performance in Major League Baseball* (1974) attempt to measure the marginal revenue product (MRP) of players to see whether there is discrimination against black baseball players for the former and to see whether players are underpaid due to the reserve clause in the later. This practice of player evaluation is a precursor to what is known today as “sabermetrics.” In these studies, the value of batters is measured using some combination of slugging percentage (here referred to as “slugging average”), batting average, and years played whereas the value of pitchers is entirely measured in strikeout-to-walk ratio and years played, due to both salary variance, regressions run, and beliefs at the time. While useful enough for making claims in academic papers, this method of analysis does not capture the fullness of a player’s contributions to a team’s path to victory, and thus their monetary value to a team. None of these statistics capture the value of defense to a team and vastly underrate the contributions of contact pitchers whose modus operandi is not to acquire strikeouts but to induce weak contact. This means that the labor market as a whole did not properly value the players in the labor market.

Evaluation of player productivity would change forever after the contributions from an unlikely source, an outsider both to baseball and to academia. In the late 1970s, a security-guard-by-day guerrilla-statistician-by-night named Bill James began self-publishing a series of
books entitled “Baseball Abstract” in which he introduced new statistical measures to more accurately pinpoint the impact of individual players on team success. These statistics and their successors would go on to be adopted by individual baseball teams, then by the sport as a whole as those teams’ more accurate method of productivity evaluation led to them having a competitive advantage, as documented by the bestselling novel/hit blockbuster movie *Moneyball*. Today, we use more all-encompassing productivity evaluation statistics in our player MRP calculations. The labor market adjusted to these more holistic evaluators immediately after the publication of *Moneyball* pointed out the inefficiency of using outdated stats to the league as a whole. *An Economic Evaluation of the Moneyball Hypothesis* by Jahn K. Hakes and Raymond D. Sauer (2006) finds that within a year of *Moneyball*’s publication, the market for batters had become efficient after years of mispricing of skill. *Does the Baseball Labor Market Properly Value Pitchers?* written by John Charles Bradberry in 2007 regresses pitcher contracts on both outdated player performance statistics such as ERA and on more modern run prevention statistics, finding that the run prevention statistics are more highly and properly valued, and thus that baseball has become more or less an efficient market. Because of Bill James and sabermetrics, baseball has become an efficient market in the 21st century.

1.3 A Crash Course In WAR AKA WAR: What Is It Good For?

While baseball’s sabermetric brain trust has produced many statistics that attempt to capture an individual’s benefit to a team, the one that has risen to the top due to its simplicity and adaptability is Wins Above Replacement, or WAR for short. WAR is a GDP-esque summary stat that attempts to capture a single player’s impact on their team’s success through a single number. WAR is an amalgamation of all the ways a player can contributes to the team
on the field of play (batting, baserunning, fielding, pitching, etc.) and controls for whatever facets of the game are not individual, such as not blaming pitchers for bad defense behind them. There’s also a level of standardization present in the calculation of WAR. Certain baseball parks help hitters while certain parks help pitchers; different years are more offense prone and more defense prone due to changes in pitching styles, mound height, and the baseball itself; and a typically wiry and fast second baseman isn’t expected to hit as well as a hulking first baseman, so all these things are present in WAR calculations, allowing players to be compared across eras and positions. How do I compare Babe Ruth’s 1923 season with Cal Ripken Jr’s 1991 season, even though the sport of baseball had greatly changed and both players had entirely different types of value? Using WAR.

The actual numerical value of WAR attempts to represent how many games your team would win if they had you rather than a “replacement level” player, i.e., a player who any team could pick up at any time for essentially “free”. If you have a WAR of 1.0, your team theoretically won an additional game they wouldn’t have with a replacement level player swapped in for you. If your WAR is 5.0, your team won five more games. WAR is that it is what is known as a “counting stat” meaning that it is cumulative rather than rate stats, which might be per game or per at bat, meaning that a player who plays only one very good game does not show up as an extreme outlier, but also meaning that a player who plays more games has more opportunity to accrue WAR. The calculation process is incredibly complex, made even more so by the fact that there is not a single way of calculating the statistic. Three of the most prominent baseball statistics sites (Fangraphs, Baseball Reference, and Baseball Prospectus) each have a different way of calculating WAR, meaning that there are actually a few different
WARs. For the purposes of this paper, we will be using Baseball Reference’s WAR, also known as rWAR. The important things to note for this paper are that 1. WAR is an estimation statistic meant to roughly capture a player’s impact on the field. Some people swear by it, some people hate for its imprecision, but it is the most widely used general analytical measure of player talent available. 2. WAR is distributed such that solid, everyday players will have around 2-3 WAR yearly, while superstars and MVP candidates will have around 5-6 or more WAR per season. You’ll typically see a player or two a year approach 9 WAR, with a handful of 10 WAR seasons every decade. For an idea of how WAR is distributed, here’s a graph of the cumulative WAR over the first six seasons of every player drafted in the first ten rounds of the MLB draft between the years of 2003-2010:

**FIGURE ONE: WAR OVER THE FIRST 6 YEARS VS OVERALL PICK, 2003-2010**
As you can tell from the thick red line, the vast majority of players who are drafted by major league baseball teams never end up making the leagues (giving them a WAR of 0) or make incredibly small contributions at the major league level.

One more thing about WAR is that it has been posited that WAR can be

1.4 Player Acquisition and the Draft

In Major League Baseball, players are acquired through three distinct ways: free agency, international amateur free agency, and the MLB draft. Free agency works similarly to a free market; each of the 30 MLB teams are permitted to offer a contract to any free agent player (a player without a contract and more than 6 years of MLB service time), and that player can agree to go to any team for a number of years and dollars as agreed to in the contract. International amateur free agency and the draft work differently. Players acquired by both methods are given a lump sum of money upfront, known as a “signing bonus,” in exchange for six years of “team control.” This means that for the first six years that any player plays in the MLB, they must play for the team that initially signed or drafted them. The first three years the team can pay the player whatever they want to (usually the league minimum that hovers around $600,000), and the next three years the player and team can agree on a dollar amount that works for both of them, or have a panel of arbiters (usually labor lawyers) decide how much is a fair value to pay for their services. The arbitration values and league minimum value can be vastly below market rate, so acquiring players through the draft or international amateur free agency is an economical advantageous process that can end up being very

1 Visualization is also available at https://public.flourish.studio/visualisation/9437141/
profitable for Major League Baseball teams. International amateur free agents are free to negotiate with any team for, but the draft is a different story.

In the MLB draft each major league team is ordered by how well they did in the previous year in reverse order (the worst team picks first, etc.). They then are able to select any player out of the eligible pool of players from the US, Canada, and Puerto Rico who have either graduated high school but not attended college, completed one year of junior college, completed their junior year at a four year college, or turned twenty one years of age. This goes on for forty (or more recently twenty) rounds. When a player is selected, he is then able to negotiate a signing bonus with the team who selected him, and only the team that selected him until either they agree on a contract or are not able to. If the team and player agree that player goes into that team’s minor league system and that team acquires the first six years of their major league career; if not, the player can reenter the draft in the future and restart the process all over again.
2. Purpose of this Paper and Methodology

2.1 Central Question

The central question of this paper is: how do professional MLB teams value and invest in players? Do they put importance on finding superstars above all else, do they care about getting a lot of players above a certain threshold of talent, or do they only care about the sum of their team’s statistical output, regardless of who or where it comes from? Since baseball spends top dollar on the brightest analytical minds and the best possible talent evaluators, it is safe to assume that when teams act, they are making optimal or close to optimal choices, maximizing something under the constraint of the money they spend on their players. Because of this, learning the answer to the central question will provide the answer to another question: how are baseball games won?

2.2 Methodology and Model Specification

To see how major league teams value players, this paper will analyze the WAR outputs over the first 6 years of the careers (WAR6) of players selected across the first ten rounds of the MLB draft between 2003 and 2010. The span of time between 2003 and 2010 was chosen because A. 2003 was the earliest year that has accessible signing bonus data for the first ten of the draft, thus allowing us to avoid selection bias that might come from only having bonus data for certain players and not for others and B. to choose a span of time that would contain plenty of player data, but not one close enough to today that the total WAR output of the players would not be limited by not being able to acquire 6 years of MLB playing time, as players can make their MLB debuts anywhere from one to five or more years after being drafted. The six-
year time span was chosen because that is what teams are paying for with their signing bonus money.

This paper will be using various linear regression models to test the correlation between WAR6 and signing bonuses. It can often be very hard for teams to accurately predict which college or high school age prospect will turn into an MLB caliber player and the vast majority of drafted player do not make the MLB at all, causing there to be an incredibly large amount of variance across the success of an individual player. But it is much easier to predict the success of the average player, or the expected success of a player selected around a certain draft position. Thus, I have organized the data into similar “bins” by round selected, with the first round split into three separate rounds (1a, 1b, and 1c) and the second round split into two (2a and 2b), to control for the often extreme expected talent difference between those selected at the beginning of the first round (who can be generational superstars) and the end of the round (who are more likely starting caliber players). I will then take use the average bonus in a round as the dependent variable, and regress on it three different dependent variables groups, each representing a different talent evaluation possibility. This will hopefully give us an idea of what teams are maximizing under the constraint of the bonus money they spend. First, I will regress the mean value of WAR6 per round on average signing bonus and check how strongly the two are correlated. This represents how much teams care about the sum of WAR6, as opposed to where the WAR6 comes from. Section, I will regress high percentile values (99th percentile, 97.5th percentile) of WAR6 in their respective rounds on average bonus. So for instance, I will take the 97.5th percentile of WAR6 for everyone who was drafted in round 1A (letting us know what a close to optimal outcome for a round 1A draftee is), and for everyone who was drafted
in 1B, and for every other round, and use those values as the Y variable in a regression on average bonus. This is the football/basketball statistic, and represents how much teams care about high end, superstar talent. Third, I will regress the percentage of players in a round that are above a certain WAR6 threshold (5 WAR6, 6 WAR6, etc.) against average bonus. This is the soccer/hockey statistic and represents how much teams care about having a group of players all above a certain level of talent. From the levels of correlation, we should be able to learn what MLB teams view as most worth paying for.

Note, as a person like you or I who would never play a game for a professional baseball team (unless Mike Trout is reading this, in which case, hi Mike Trout) are being paid zero dollars by all teams and are accruing 0 WAR6, we can assume that all regressions should go through the origin (as the 99th percentile of a layperson is still a layperson, and 0 percent of laypeople are going to be above any threshold above 0). Thus, the regressions will mathematically look like this:

(I)

Average WAR6 = 0 + β1*Average Bonus

(II)

Xth percentile WAR6 = 0 + β1*Average Bonus

(we’ll be looking at percentiles of many different values, and seeing which percentile is the best fit)

(III)

% of Players Above a WAR6 Threshold = 0 + β1*Average Bonus

(we’ll be looking at many different thresholds, and seeing which threshold is the best fit)
2.3 Data

All data in this paper was obtained from Baseball-Reference.com using their Stathead tool, which allows users to sort through all MLB statistics, or downloaded from their comprehensive draft database and stitched together using R. The variables collected were player name, WAR over their first six years of major league playing time (referred to throughout this paper as WAR6), draft year, draft position, round drafted, whether or not they were signed after being drafted, and amateur signing bonus. The possibility of data being inaccurate is low, as all data is taken from the same, reliable source. Possible biases are limited, but include the selection bias of only having reliable bonus data for the first ten rounds of the draft (however, there’s no reason to believe that trends wouldn’t continue). The reason the regression is using draft data as opposed to free agent data or international free agent data is that international free agent data is sadly not available, and it’s also impossible to place players into naturally occurring bins of similarity to average over.
3. Regression Results and Discussion

3.1 Results and Discussion of Mean WAR6 Model

FIGURE TWO: AVERAGE WAR6 TABLE

<table>
<thead>
<tr>
<th>Round</th>
<th>avgWAR6</th>
<th>avgBonus ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1a</td>
<td>8.069737</td>
<td>3194105</td>
</tr>
<tr>
<td>1b</td>
<td>4.297436</td>
<td>1792571</td>
</tr>
<tr>
<td>1c</td>
<td>2.086977</td>
<td>1082338</td>
</tr>
<tr>
<td>2a</td>
<td>1.878448</td>
<td>733870.5</td>
</tr>
<tr>
<td>2b</td>
<td>2.17623</td>
<td>577527</td>
</tr>
<tr>
<td>3</td>
<td>0.93</td>
<td>423879.1</td>
</tr>
<tr>
<td>4</td>
<td>0.760199</td>
<td>295236.3</td>
</tr>
<tr>
<td>5</td>
<td>0.492035</td>
<td>209715</td>
</tr>
<tr>
<td>6</td>
<td>0.544037</td>
<td>194337.2</td>
</tr>
<tr>
<td>7</td>
<td>0.655804</td>
<td>142979.5</td>
</tr>
<tr>
<td>8</td>
<td>0.626941</td>
<td>117314.2</td>
</tr>
<tr>
<td>9</td>
<td>0.525229</td>
<td>99733.94</td>
</tr>
<tr>
<td>10</td>
<td>0.417561</td>
<td>92094.15</td>
</tr>
</tbody>
</table>

FIGURE THREE: AVERAGE WAR6 VS SIGNING BONUS GRAPH
FIGURE FOUR: MEAN WAR6 REGRESSION SUMMARY STATISTICS

<table>
<thead>
<tr>
<th></th>
<th>Y=AVERAGE WAR6</th>
</tr>
</thead>
<tbody>
<tr>
<td>X=AVERAGE BONUS</td>
<td>2.488e-06***</td>
</tr>
<tr>
<td>Standard Error</td>
<td>(8.243e-08)</td>
</tr>
<tr>
<td>Adjusted R Squared</td>
<td>0.9859</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

As shown above, the Average Bonus of a Round is an incredible predictor of average WAR6. With an Adjusted R² of 0.9859, the fit is nearly perfect, and the standard error is more than a factor of ten smaller than the coefficient of our x variable. The coefficient, while very small, makes intuitive sense. Teams routinely shell out millions of dollars for above replacement players, so having a coefficient that roughly estimates 1 WAR6 as being worth around $400,000 is reasonable, especially since we anticipated this would be an underpay. The fit passes the eye test, you can graphically see how good of a fit the regression is, and the variance from round to round never strays too much from the best fit line. If MLB teams were indeed trying to maximize average WAR6 per dollar spent, this is probably the way they’d allocate their money, meaning that this is a strong contender out of the gate for which of our models best fits the data.
3.2 Results and Discussion of Percentile WAR6 Model

For my percentile WAR6 model, I created a program in R to regress every possible percentile of WAR6 on average signing bonus to see which percentile of WAR6 would have the greatest adjusted $R^2$ value. I also regressed the 97.5th percentile of WAR6 and the 99th percentile of WAR6 to represent amazing and perfect outcomes for a given round. If teams cared about superstars above all else, the 97.5th and 99th percentiles would have better fits than any other percentile level.

FIGURE FIVE: PERCENTILES WITH THE HIGHEST R SQUARED VALUES

<table>
<thead>
<tr>
<th>Adjusted R Squared</th>
<th>Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.979382</td>
<td>85.9</td>
</tr>
<tr>
<td>0.979241</td>
<td>85.8</td>
</tr>
<tr>
<td>0.979042</td>
<td>86</td>
</tr>
<tr>
<td>0.978977</td>
<td>85.7</td>
</tr>
<tr>
<td>0.978679</td>
<td>85.6</td>
</tr>
<tr>
<td>0.978464</td>
<td>86.1</td>
</tr>
<tr>
<td>0.97836</td>
<td>85.5</td>
</tr>
<tr>
<td>0.977924</td>
<td>85.4</td>
</tr>
<tr>
<td>0.977858</td>
<td>86.2</td>
</tr>
<tr>
<td>0.977467</td>
<td>85.3</td>
</tr>
</tbody>
</table>
FIGURE SIX: 97.5\textsuperscript{th} PERCENTILE WAR (\textsuperscript{6}WAR) VS SIGNING BONUS GRAPH

FIGURE SEVEN: 99\textsuperscript{th} PERCENTILE WAR (\textsuperscript{6}WAR) VS SIGNING BONUS GRAPH
By regressing all percentiles of WAR6 on the average signing bonus per round, we found that the percentile that had the best fit when regressed on signing bonus was the 85.9th percentile, with the top ten percentiles all in the 85-87 range. The 99th and 97.5th percentile range, representing the best possible outcomes for each round, however, had statistically significant coefficients but much worse Adjusted R² values, at .65 and .81 respectively to the much higher .98 R² value of the 85.9th percentile.
It is very unlikely that teams would be spending money in this manner if they only cared about the very top end players in each round. In both the 99th percentile and the 97.5th percentile rounds, teams would be paying a significantly greater amount than they should be for round 1A talent. The gap between the best of the best in round 1A and the best of the best in round 1B is the gap between a player worth around ~34 WAR per six years and one worth ~31 WAR per six years, a gap of only .5 WAR per year. This is a gap that shows more or less two very similarly productive players, with a slight edge given to the better player, but certainly not two players that are in entirely different echelons of productivity. However, teams are paying more than 1.5 times more for the 1A player than for the 1B player. This either means that there is a massive impact gap between these two star-level players with slightly different outputs, which I doubt, or that this 1.5 times gap is due to something other than the productivity of the 99th percentile of player. This same argument can be applied plenty of other places across both the 99th percentile and 97.5th percentile charts, and the conclusion that can be drawn is that if teams were truly spending their bonus money in a way such that they maximize their chances of obtaining a premium player, they would spend much less money on earlier rounds or avoid them entirely, as later rounds provide a much better bargain.

There is significance in the fact that the 85.9th percentile is such a good fit. This is around the talent level where players start making legitimate major league contributions in most of the rounds, meaning that the 85.9th percentile is a good approximation of what type of number the average major leaguer would put out for each round. This almost takes the role of what would in a normal data set be held by the median, if there weren’t so many players who didn’t make the majors and thus so many zeros at the 50th percentile. We posit that this
percentile essentially the percentile analogue for the mean WAR6 value, a case bolstered by the similarity of the two graphs. Here’s the mean WAR6 graph directly next to the 85.9th percentile graph, so you can judge for yourself.

FIGURE 9.5: TWO SIMILAR LOOKING GRAPHS
Obviously, there are some differences, mostly notably the scale of the mean graph going up to ten while the 85.9th percentile graph goes up to 20. But the general shape is the same. Another thing to note here is that, although I regressed a thousand different percentile levels on average bonus, not one of them had as good a fit as average WAR6 did.
3.3 Results and Discussion of WAR6 Threshold Model

For my WAR6 Threshold model, I built a program to calculate what percentage of players in a round were above a certain threshold for total WAR6. Then, I regressed those percentages on average signing bonus per round. I built another program to do this for as many thresholds as I wanted, and I decided to use thresholds between 0 and 50 WAR6, to capture any and all possible thresholds that MLB teams might deem to be important (as the percentage of players that are above some negative number would be meaningless as almost every player is above the negatives, even the ones who’ve never played). We’re essentially looking for a threshold or cluster of thresholds in which the $R^2$ is much higher than surrounding $R^2$ values, which would end up being the level at which players become “relevant” to a team’s success, if the “hockey/soccer” type model of player impact on team success is applicable here. I chose to increase my threshold in increments of 0.5 WAR6, a small enough increment where I wouldn’t “miss” the optimal threshold, but a large enough increment that I would be able to present my findings in an easily digestible way, both in table and graphic form. Most of the data between the levels of 25 and 50 WAR6 is either redundant or has too low of a $R^2$ to have any relevance, so I have included only the data between the thresholds from 0 to 25, first in tabular form (sorted by descending value of $R^2$), and secondly in a histogram.

FIGURE TEN: R SQUARED VALUES OF % ABOVE WAR THRESHOLD REGRESSED ON BONUS FOR THRESHOLDS BETWEEN 0 AND 25
As you can see, many threshold models are amazing fits when regressed on average signing bonus. Almost all of the thresholds have an $R^2$ above .9, and the vast majority have a $R^2$ above .95, a ridiculously good fit. And this isn’t true for just high thresholds or low thresholds,
as the table does a really good job of showing, looking at the percentage of players above 2 WAR6 as your threshold is just as good of a fit as using 23.5 WAR6 as your threshold. It is, ironically, too good of a fit for this model to be our answer to how teams shop for talent. There is no one level of production at which players suddenly become valuable to the team because players at all levels of production (as long as that production is positive) are evidently worth investing in. It’s not like the $R^2$ is all over the place when it comes to percentage of players who produce 4 WAR6 because teams don’t care about players who produce 4 WAR6 enough to pay more for them, but then suddenly when we look at players who produce 8 WAR6 everything is linear. All levels of production are worth paying for to MLB teams, which again points to the explanation that it doesn’t matter WHO the WAR comes from, as long as you get it. Again, even though we looked at 100 different threshold levels, there were still none that were as good of a fit as the simple mean WAR6 versus average bonus regression. All of our models point to average WAR6 as what teams are attempting to maximize with the money that they spend.
4. Conclusion

There’s a brilliant scene in the aforementioned movie Moneyball where Billy Beane, played by a far-too-attractive-for-the-part Brad Pitt, is tasked with replacing a few big-name stars that have left the cheap Oakland Athletics for wealthier pastures. While most of the scouts around him clamor to try and find the next Jason Giambi or Johnny Damon, Billy (great name by the way) doesn’t seem to care about stardom. Instead, he urges them to think about “replacing them in the aggregate,” before throwing out a number of unflashy names that practically make the scouts sick. But this dramatized version of Billy doesn’t care where his production comes from, as long as it comes.

This paper concludes that this is how baseball works in the real world as well. This paper finds that teams act as if success isn’t dependent on one generational talent or a group of players who all are above a certain level or productive, it’s additive. Having two guys who put up 3 WAR each in your starting lineup is fundamentally the same as having one guy who puts up 6 WAR and one guy who puts up 0. As counterintuitive as it is, baseball teams do not care for stars other than for the raw numbers they put up. The franchise that is commonly agreed upon as being the most well run in baseball, the Tampa Bay Rays, has long been known for trading players right after they reach stardom, because their production can be replaced by inexpensive parts. As the analytics era has spread from the A’s to the Rays to everyone else, baseball has caught on. The economic value of players is linear and additive. Games are won in the aggregate.

Another interesting conclusion that comes from this is that this might be one of the reasons that baseball has trouble marketing their superstar players. While sports like football
and basketball have their best players enter the realm of stratospheric celebrity, baseball’s best players are barely known by those disinterested in sports. While some of this is due to personality differences (baseball’s consensus best player in the world is a wannabe weatherman), and popularity of the sport (baseball has settled into third place in American major professional sport popularity), much of this is probably due to the fact that superstars don’t have as great an impact on their team’s outcome, and therefor are not as involved in highly watched, legacy-making moments as basketball or football players. The iconic basketball and football moments of the 2010s are superstar driven: LeBron willing his hometown team to victory with the help of fellow star Kyrie Irving, Tom Brady coming back from an insurmountable 28-3 deficit. Baseball’s analogous moments come from the bats of comparative no names: David Freese saving the Cardinal’s 2011 season, Ben Zobrist and Miguel Montero ending the Cubs’ World Series drought with clutch hits in the extra innings of game seven.

Those moments are still legendary, and I would argue cooler to me because of the idea that anyone can make that impactful contribution but mean that the spotlight doesn’t get to belong to the greats, meaning that those greats are harder to sell to the public. There’s also a fair bit of chicken and egg here with baseball being less popular than football and basketball; in an era where people are often rooting for individuals rather than teams, the sport of baseball’s callous indifference towards superstars may have led to its lack of popularity. And there are baseball players with excellent personalities, Fernando Tatis Jr. and Ronald Acuña Jr. come to mind, but neither of them has had the same legendary moments as the stars in other sports. In one of the more baseball moments of all time, Acuña’s Atlanta Braves did win the championship last year... but only after he (their far and away best player) got injured, causing many of their fans
to give up on the season. In baseball, stars are a means to an end, rather than the central product, and teams only pay for their aggregate stat line.
5. Further Research

I’m very interested to see whether my assumptions of what basketball/football/soccer/hockey teams are maximizing hold up mathematically. I predict they will, as basketball and football teams with the same handful of generational players (Tom Brady, LeBron James) always seem to win championships, but it would be interesting to see this hypothesis put through rigorous mathematical analysis. There are also plenty of other professional baseball leagues, and I’d love to see if this paper’s conclusion holds for the Japanese NPB and the Korean KBO. While it’d be hard to come to any conclusion because it would be much harder to group either international free agents or free agents, I’d also love to see someone test my hypothesis using one or both of those groups, if international free agents could be sorted by prospect ranking and grouped as such, there’s no reason why a similar analysis couldn’t be run.
6. Works Cited


