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A Study of Minor League Baseball Prospects and Their Expected Future Value

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A STUDY OF MINOR LEAGUE BASEBALL PROSPECTS AND THEIR EXPECTED FUTURE VALUE

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Abstract

This thesis will examine highly rated Minor League baseball players and how they subsequently perform in their Major League careers. Specifically, this study has collected data on over 800 players ranked on the prospect lists of Baseball America, Baseball Prospectus, and John Sickels. Using regression analysis, I have examined the correlation between ranking and future performance, as well as studying other factors like position and age to determine if there are common characteristics to successful prospects.

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1. Introduction

Major League Baseball (MLB) teams can build their rosters in only two ways: by signing free agents or by graduating players from their Minor League systems. Because they have to bid against the 29 other teams in the league, luring free agents is difficult and costly. Bringing up Minor Leaguers, on the other hand, costs only the league minimum, and the team controls their rights for several years. In a league without a salary cap, low payroll teams like the Tampa Bay Rays (2011 payroll of $41.9 million) must use this method of team construction to compete with the high payroll teams like the New York Yankees (2011 payroll of $201.7 million). Therefore, it is of vital importance for teams to identify and develop their top Minor Leaguers (called "prospects")

However, forecasting the success of Minor Leaguers is a difficult task. This is where MLB differs from other major sports leagues; in the NBA and NFL virtually 100% of first round draft choices reach their equivalent of the Major Leagues, while only 63% of MLB first rounders make the Majors (Spurr, 2000). Further, in the NFL and NBA these players often jump straight from college to the top level. Baseball prospects usually require anywhere from one to five years of seasoning in the Minor Leagues before being ready for the Majors.

Because of the importance of these prospects for Major League teams, there are numerous publications that scout, evaluate, and rank the best Minor League players. Organizations like ESPN, Baseball America, Minor League Ball, and Baseball Prospectus make lists every year that rank prospects based on how much on-field value they think they will produce in the Majors. The purpose of this study is to quantify that value. I will look at how highly a prospect has been ranked by these various publications and then how well he subsequently played in the Major Leagues. I will also look at other qualities of a prospect—like age, whether or not he attended college, what position he plays—to see if there are other factors that influence future performance.

Additionally, this study will also evaluate the evaluators; in other words, I will test to see which publication has had the greatest success in predicting which prospects will have an impact at the Major League level. The three publications I compared are Baseball America, Baseball Prospectus, and the lists compiled by John Sickels (who created his rankings with ESPN and Minor League Ball during the years studied). The question is whether these different publications used different philosophies in their rankings. For example, did they err on the side of caution and pick players who were likely to reach the Majors but never reach star levels? Or do they pick players with superstar upside, but also significant risk of busting? This study will examine whether any of these publications displays a significant ability to predict prospect success.

In order to conduct this kind of a study, a precise estimate of player value is required. Proxies for player success used in the past are salary, games played, and whether or not they reached the Majors (Spurr 2000; Winfree and Molitor 2007). However, these measures do a poor job of reflecting on-field performance. The statistic I will use is called Wins Above Replacement (WAR). Traditional statistics (like Runs Batted In, Batting Average, or Slugging Percentage) are too narrow in scope to accurately depict a player's value. WAR evaluates every part of a player's performance, both offensively and defensively, and condenses it into a single number. I will explain the methodology of WAR in the subsequent section.

I split the prospect rankings into several sections and examine how many Wins Above Replacement these players produce. I start with how many WAR top 100 prospects in general accrue, then look at the top 50, top 25, top 10, top 5 and the number one prospects in the nation. My goal is to see if these ranking systems can truly identify the players that will have the greatest contributions and put them at the top of their lists.

2. Literature Review

A. Summary of the Literature

This literature review examines the work already done on the subject of prospect value. Additionally, I summarize the research on Wins Above Replacement, which figures heavily in my analysis.

Stephen Spurr (2000) studied the Major League Baseball first-year player draft to see what factors influenced a draftee's future Major League success. These are players that have not become prospects yet, as they are still amateurs until after the draft. He found that draft position was, as expected, the largest predictor of future success, with the definition of success being that the player reached the big leagues. In other words, players drafted highly had a better chance of making the Majors. Additionally, he found that players drafted out of elite college baseball programs had better odds of success than those drafted out of non-elite schools or high school. For the most part, a player's position did not seem to influence whether he reached the Major Leagues; however, he found that teams had more difficulty identifying successful catchers and third basemen. Finally, he tested to see if individual Major League teams were more successful than others at drafting quality players. As he notes, "One of the major themes of recent research in labor economics has been a departure from the tradition of treating workers as homogeneous. It is increasingly recognized that there are profound consequences of differences in talent." However, he found no evidence that certain teams were better at identifying talent than others.

Winfree and Molitor (2007) looked at the expected salary earnings of draftees, and whether high school draftees should attend college or not. They found that higher picks could expect greater lifetime value from turning professional straight out of high school, while lower round picks should attend college. Salary is often used as a proxy for player value, so Winfree and Molitor's research suggests that highly touted high schoolers produce more value by skipping college. In my study, however, the measure for value is Wins Above Replacement.

Gitter and Rhoads (2011) examined how top prospects affect Minor League attendance. They used the Baseball America prospect lists, noting that BA is considered an industry standard for prospect rankings. The Baseball America rankings figure heavily in my model as well. Gitter and Rhoads found that only the highest ranked prospects—those in the top 5—have a positive effect on Minor League attendance.

One of the most important publications in recent years concerning player valuation is Michael Lewis' 2003 book *Moneyball*. This book explored how traditional statistics do not accurately portray a player's true productivity, and that savvy teams can take advantage of this. They can target players that demonstrate unconventional skills, like On Base Percentage, to get quality players for cheap. Hakes and Sauer (2006) tested how highly correlated these less well known stats were with run creation. Indeed, they found that the less traditional stats—for example, On Base Percentage and Slugging Percentage—lead to more on-field success than Batting Average.

While these statistics are an improvement, they still leave plenty to be desired when trying to capture a player's true value. The next section of this study will describe the statistic that does the best job of evaluating a player: Wins Above Replacement.

B. Wins Above Replacement

Wins Above Replacement (WAR) is a statistic that attempts to capture the entirety of a player's performance in MLB[1]. It measures both the offensive and defensive value of a player and determines how many wins he has added to his team over a "replacement level" player. A replacement level player is someone who is readily available by paying the league minimum. Examples of replacement level talent include players in AAA who are good enough to get some time in the Majors but aren't highly-rated prospects, waiver-wire pick-ups, nontenders, and minor league free agents. Steve Slowinski of Fangraphs[2] writes, "WAR basically looks at a player and asks the question, "If this player got injured and their team had to replace them with a minor leaguer or someone from their bench, how much value would the team be losing?""

WAR calculates how many wins a player adds to his team by assigning run values to his performance. Baseball games are won by scoring runs and preventing opponents from scoring; thus, we want to find out how many runs an individual player is responsible for. Jeff Aberle writes that, "it can be proved that for every ten runs that are lost or gained a win is similarly lost or gained. For every 10 runs a player is above a replacement level player, he is worth 1 win to his team."[3] Runs are created by above-replacement offensive performance; they are saved by above-replacement defensive play.

The offensive component of WAR is weighted runs above average (wRAA). The theory of this statistic is simple: it determines how many runs an offensive event typically creates. We

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[1] It should be noted that there are two major publications that calculate WAR: Fangraphs and Baseball Reference. They use slightly different methods in their calculations, particularly in their defensive and pitching statistics. I have used Fangraphs WAR throughout this study. Neither publication has been shown to be more or less accurate than the other, and their results hardly ever differ by a substantial amount. Data collected from www.fangraphs.com.
[2] Accessed from www.fangraphs.com between January 31, 2012 and April 22, 2012.
[3] Accessed from www.beyondtheboxscore.com between January 31, 2012 and April 22, 2012.

intuitively know that a triple is more likely to produce runs than a walk; a triple advances runners already on base further and the batter ends up at third base, where he is more likely to score than if he is at first base. The creators of wRAA looked at how many runs each offensive event (walk, hit-by-pitch, single, reached-base-on-error, double, triple, homerun) have historically created. An out, obviously, produces no runs. The results show that a walk produces .72 runs, a hit-by-pitch produces .75 runs, a single produces .9, a reached-base-on-error produces .92, a double produces 1.24, a triple produces 1.56, and a homerun produces 1.9 runs[4]. These runs are aggregated for the player in question and compared to how many runs a replacement level player would produce. If the player is worth 20 runs above replacement over the course of the season, he provides 2 offensive WAR.

The defensive component of WAR uses much the same logic. If a player makes a defensive play that a replacement level defender could not make, he has produced a certain run value (by preventing the other team from scoring). The problem, though, is that measuring defense is much more difficult than measuring offense. WAR uses a statistic called Ultimate Zone Rating (UZR) that assigns run values to defensive plays. Describing all the details of UZR is beyond the scope of this study; however, it is generally accepted to have a high degree of accuracy in measuring defensive prowess. If a player, over the course of his playing time, saves 10 runs above what a replacement level player would save, he has been worth one defensive WAR. For more information on the methodology of Ultimate Zone Rating, I recommend the UZR primer at the Fangraphs website.

WAR also recognizes that not every position on the baseball diamond is as easy to defend. The catcher position is much more difficult and demanding than playing, say, first base.

[4] Accessed from www.sports.yahoo.com between January 31, 2012 and April 22, 2012.

Positional adjustments developed by Tom Tango estimate that playing catcher provides a surplus of 12.5 runs, shortstop +7.5 runs, Second Base: +2.5 runs, third base +2.5 runs, center field +2.5 runs, left field -7.5 runs, right field -7.5 runs, first base -12.5 runs, and the designated hitter position is -17.5 runs[5]. These numbers are then adjusted for playing time. The upshot to this is that a shortstop that has identical offensive and defensive numbers to a first baseman will be worth 20 more runs solely due to playing a much more difficult position.

There are a few further adjustments WAR makes in evaluating a player. Foremost among them is that each Major League ballpark plays differently. Some ballparks heavily favor hitters, like Coors Field in Colorado or Chase Field in Arizona. Other parks, like Petco Park in San Diego, suppress hitting. The effect of these park factors is to make certain players' surface statistics look better or worse simply because of their home ballpark; a player who plays half his games at Petco will have worse offensive numbers than an identical player who plays at Coors. Fortunately, park factors can be quantified and accounted for. Through a combination of analyzing the performance of visiting teams and how the home team performs during away games, park effects can be very precisely calculated. These effects are included in a player's wRAA.

There are two further tweaks WAR accounts for. One is that the American League and the National League are not exactly equal in talent level. The talent level in the American league is slightly above that in the National League, so a replacement level player in the AL will perform at a lower baseline. Again, looking at historical data, that effect is quantified and incorporated into WAR calculations. Finally, certain eras in baseball had different environments in terms of offensive performance. For example, in the late 1990s and early 2000s, offense

[5] Accessed from www.insidethebook.com between January 31, 2012 and April 22, 2012.

across MLB was far higher than in virtually any other era of the game. There could be a number of reasons behind this; the prevalence of steroids, changes in equipment, even weather variations. Regardless of the reason, WAR accounts for the era's baseline offensive levels.

WAR has been calculated for pitchers as well. As with measuring defense, there is a certain amount of unpredictability involved in capturing a pitcher's performance. The difficulty hinges around trying to separate a pitcher's skill from the skill of his defense. It makes intuitive sense that some teams play better defense than others. This has a large effect on the traditional measure of pitcher performance, Earned Run Average (ERA). WAR seeks to calculate individual performance, but ERA is incredibly dependent on the eight men playing behind the pitcher. Therefore, instead of basing its calculation of runs saved on ERA, Fangraphs WAR uses a different measure call Fielding Independent Pitching (FIP).

FIP only examines the outcomes a pitcher can control: namely, walks, strikeouts, and homeruns allowed. Similar to wRAA, each of those three outcomes is given the proper amount of weight based on historical figures. Batted balls that aren't homeruns—in other words, anything a fielder makes a play on—are ignored. This might sound extreme, since this method disregards a significant number of events in which a pitcher is involved. However, research by Voros McCracken[6] found that pitchers actually have very little control over balls put in play. Meanwhile, strikeout rate, walk rate, and homerun rate are all pitcher specific and highly correlated to performance.

[6] Accessed from www.baseballprospectus.com between January 31, 2012 and April 22, 2012.

Much like for hitting, FIP leads to an estimation of run values and is then compared to replacement level, while taking context (home ballpark, era, and run environment) into account. When all that is done, we arrive at a pitcher's WAR.

An average major leaguer is typically worth 2 WAR. A player worth 2 to 4 WAR is solidly above average. All-star level performance is between 4 and 6 WAR. The average WAR for the league MVP over the past five years is 7.6.

3. Theory

The goal of this study is twofold. First, I will look at how many WAR a top prospect has historically produced, and how a prospect's ranking relates to his expected future contributions. Additionally, I will look at various attributes of a prospect—namely: Baseball America ranking, age, college attendance, parent team, minor league level at time of ranking, and position—to see if certain kinds of prospects have a better or worse chance of future success. I will discuss these variables further below.

1. *Baseball America ranking*. Baseball America has published a list of what it considers its top 100 Minor League prospects every year. I used every prospect on these lists from 1995 until 2006. Since the purpose of the rankings is to identify the future MLB superstars, it stands to reason that prospects ranked higher on these lists will accumulate more WAR. I therefore expect to see a positive correlation between BA rank and WAR.

2. *Age at time of ranking*. Prospects range from youngsters just drafted out of high school or signed out of Latin America to older players with college or Minor League experience. Some of the oldest prospects were imports from the Japanese baseball leagues. I suspect that older prospects have a greater chance of producing more WAR in their first five seasons because they are likely closer to the Majors than younger players. Their physical tools are more developed and thus the prospect rankers should have a better grasp of whether the prospect will have legitimate Major League success.

3. *College attendance*. All American amateur players are subject to the First-Year Player Draft, which assigns these players to their drafting team. These players are primarily drafted either out of high school or college. The binary variable *college attendance* will examine whether players with any amount of college experience has more or less success than those who skip college and immediately join the professional ranks.

4. *Highest Minor League level at time of ranking*. There are several levels in professional baseball; the lower levels typically have younger, less experienced players (and thus the competition is less skilled overall). The higher the level, the higher the level of competition. The levels range from: below Single-A; Single-A; AA; AAA; and MLB. I believe that prospects that have reached higher levels are more likely to produce more WAR, since they have displayed above average skills against stiffer competition.

5. *Position*. Baseball is very specialized sport with specialized positions. I will study the success rates of each position: catcher, first base, second base, shortstop, third base, outfield, left-handed pitcher, and right-handed pitcher. Each position requires different physical attributes; for instance, shortstops are typically smaller, faster, and more athletic than first basemen so that they can satisfactorily field their more demanding position. I therefore think it very possible that players who man the more difficult positions (as per WAR's run values: catcher, shortstop, second base, and third base) will have more future success.

6. *Parent team*. Each of the thirty Major League teams owns the rights to their Minor League players and develops, coaches, and promotes them at their own discretion. I included this variable to see whether any particular team has significantly more or less success in grooming their top prospects.

Since many of the players studied in this model are still playing, and thus accumulating more WAR, I have to set certain limits. I thus define the dependent variable as WAR produced in that player's first 5 seasons after he had lost his rookie eligibility. A player loses his rookie eligibility after 130 Major League at-bats or 50 innings pitched. This is obviously not ideal, as it often takes several years for a young player to "come into his own"; indeed, some of the best players in the game needed several years before breaking out. However, since I want to examine players as close to the present as possible, I choose to only look at the players' first five seasons. Additionally, since two of the publications I want to analyze didn't go back far enough (both John Sickels' and Baseball Prospectus' earliest lists were 1999), I need to come as close to the present as possible to gather enough data points. Therefore, the results I arrive at in this study should be seen as predictors of immediate Major League success, not career long success[7].

In this study I use a multiple regression model with WAR as the dependent variable and position, age at the time of ranking, college attendance, parent team, minor league level at time of ranking, and BA ranking as dependent variables. Position is a dummy variable with catcher being the omitted category. Occasionally position has not been conclusively determined in the Minors, either because the player hasn't settled on one yet or has to change due to defensive

[7] It should be additionally noted that after six Major League seasons a player is no longer under contract control by his home team and can declare for Free Agency. Therefore, while an analysis of a player's first five seasons will miss some of the late bloomers, these players will quite frequently be playing for different teams or have re-signed with their original teams at Free Agent salaries. Looking at the first five seasons thus analyzes a player when he is cheap and controlled by the team; in other words, when he is at his most valuable in dollar to WAR terms. For additional information on player salary theory, see Krautmann, Gustafson, & Hadley (2000).

limitations. When Baseball America has a player listed as playing multiple positions, I have chosen the most difficult position as his future position. Difficulty is determined by WAR's run values for each position. College attendance is a binary variable with 1 = attended college and 0 = did not attend college. Parent team is a dummy variable for all Major League teams with the San Francisco Giants being the omitted team. I have written this variable in the below model as the summation from 0 to *k* where *k* is the number of teams minus one. Minor League level at time of ranking also requires dummy variables; I split it into five categories: Reached the Majors, AAA, AA, A, and below A. Below A is the omitted variable. BA ranking and age are continuous variables. I use BA ranking because Baseball America is widely considered an industry standard and it produced top 100 lists for more years than Baseball Prospectus or Sickles and thus provided more data points. The model is presented below:

$$\text{WAR} = \beta_1 \text{ BA ranking} + \beta_2 \text{ Age} + \beta_3 \text{ Right Field} + \beta_4 \text{ Left Field} + \beta_5 \text{ Center Field} + \beta_6 3^{rd} \text{ Base} + \beta_7 \text{ Short Stop} + \beta_8 \; 2^{nd} \text{ Base} + \beta_9 \; 1^{st} \text{ Base} + \beta_{10} \text{ LHP} + \beta_{11} \text{ RHP} +$$

$$\sum_{K=0}^{29} \beta_{12+k} \text{ Team} + \beta_{42} \text{ AAA} + \beta_{43} \text{ AA} + \beta_{44} \text{ A} + \beta_{45}\text{Majors}$$

In addition, I have created another category for players which I've called "star". I deem a player a star if he amassed 18 or more WAR during his first five seasons (51 out of the 704 players studied met this standard). Since star players are the Major Leaguers that make the most impact in the game, it is of great importance for prospect rankers to be able to identify them. Therefore, I have regressed this binary variable on the same variables listed above to see whether the rankings are able to predict the emergence of star players.

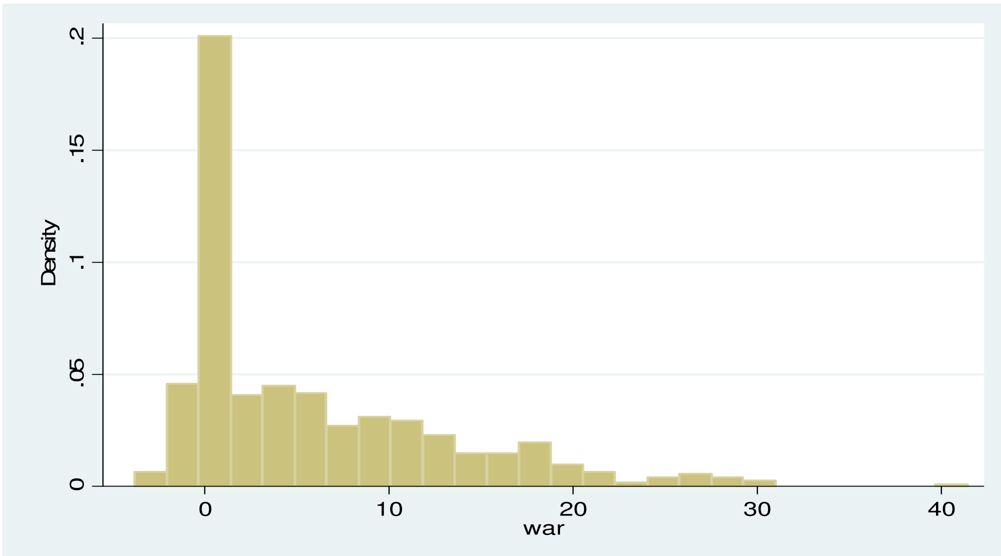
The second goal of this study is to evaluate how effective the top three publications are at predicting prospect success. The top three publications are Baseball America, Baseball Prospectus, and John Sickels (who worked for ESPN and Minor League Ball). Unfortunately, some obstacles exist in this comparison. Baseball Prospectus only did a top 40 list until 2004, and subsequent to that a top 50 list. For several years John Sickels created two lists per year, separating them into the top 50 hitters and top 50 pitchers. I mingled the lists in "shuffling a deck of cards" fashion; that is, I listed the top hitter as his #1 prospect, the top pitcher as #2, the second hitter as #3, the second pitcher as #4, etc. It is possible that this method does not perfectly match how he would rank these players if he had made a conventional top 100 list. Additionally, different people have been employed by these organizations over the years studied and thus brought different perspectives to the prospect rankings. Finally, the BP and Sickels lists only go back to 1999, while BA has top 100 lists from as far back as 1990. Regardless, it is a useful exercise to see which publication has had the most success in predicting Major League success. I have look at how many WAR their picks accumulated based on where they were ranked. I split the prospects into 6 categories: top ranked, top 2, 1 through 10, 1 through 25, and 1 through 50.

4. Data Description

The data used for the multiple regression model in this study are cross-sectional, with each data point being a Major League Baseball prospect who received a ranking on Baseball America's top 100 lists between 1995 and 2006. In all there are 704 players used in this study. Players often appear on these lists multiple times; in those cases, I use that player's highest ranking. The Montreal Expos moved to Washington and became the Nationals in 2004; since the ownership remained the same, I refer to all prospects from that system as Nationals prospects. The data are collected from multiple sources from the internet. The prospect rankings from Baseball America and Baseball Prospectus come from their websites. John Sickels' lists have been compiled from the website Minor League Ball and ESPN. Position at the time of ranking comes from Baseball America; in cases where multiple positions were listed, I have chosen the most difficult position per WAR's run values. Age, college attendance, and highest level at time of ranking are collected from Baseball Prospectus. All Wins Above Replacement data comes from Fangraphs.

Average WAR for all 704 players studied is 5.6 with a standard deviation of 7.2. The highest WAR accumulated in a player's first five seasons is 41.4 by Albert Pujols. The player who cost his team the most wins with his play was Jose Guillen who was worth -3.8 wins. The youngest ranked prospect is 16 years old; the oldest is 30. The average age for a ranked prospect is 21.7. 236 out of the 704 players, about one-third, attended college for at least one year. The most common position for prospects in my sample is right-handed pitcher, with 251 instances. The team with the most prospects to show up on the Baseball America list from 1995 to 2006 is the Atlanta Braves with 35. The team with the fewest ranked prospects is the Philadelphia Phillies with 15.

Figure 1. Histogram of player WAR.

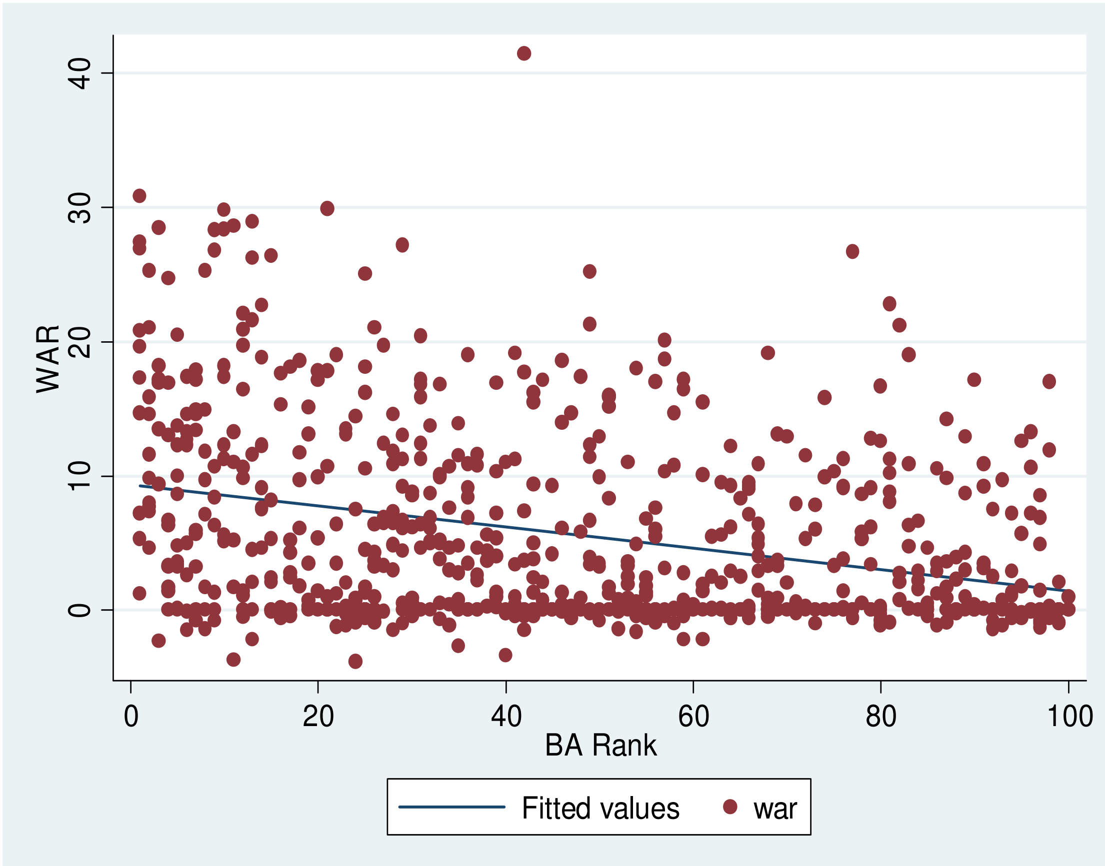


The data shows signs of non-normality, as it is skewed noticeably to the right. Further, the median is 2.9, considerably lower than the mean of 5.6.

Table 1. Summary of average WAR accumulated by certain categories of ranked players.

	#1	**1--5**	**1--10**	**1--25**	**1--50**	**1--100**
Sickels	11.61	10.3	9	8.4	6.47	5.75
BP	11.02	11.34	9.26	8.39	7.49	
BA	17.12	11.33	10.89	8.99	7.3	5.64

Figure 2. Scatter plot of WAR and Baseball America rank, with fitted regression line.



5. Analysis

My initial regressions examine the correlation between Baseball America rank and future WAR. I have subsequently added the variables discussed earlier to test for their explanatory power. The table below lists the coefficients, standard errors, and significance levels.

Table 2. Base and expanded regressions, using Baseball America ranking.

Dependent variable: WAR. Number of observations: 704.

Regressor	(1)	(2)	(3)
BA Rank	-.079*** (.0089)	-0.0715*** (.009)	-.071*** (.009)
Age		-.137 (.18)	-.132 (.186)
College		1.611*** (.606)	1.785*** (.625)
A		.176 (1.039)	.106 (1.07)
AA		1.414 (1.046)	1.35 (1.075)
AAA		2.419** (1.159)	2.262* (1.19)
Majors		2.977*** (1.117	2.803** (1.144)
LHP		-.405 (1.285)	-.102 (1.299)
RHP		-.432 (1.124)	-.125 (1.143)
First Base		.679 (1.545)	.968 (1.57)
Second Base		.733 (1.646)	.868 (1.668)
Third Base		1.779 (1.408)	2.45* (1.437)
Short Stop		1.718 (1.321)	1.939 (1.334)
Outfielder		1.116 (1.285)	1.612 (1.2)
Arizona Diamondbacks			2.027 (2.322)
Atlanta Braves			3.488* (2.039)
Baltimore Orioles			1.843 (2.233)
Boston Red Sox			4.208* (2.161)
Chicago White Sox			0.815 (2.122)
Chicago Cubs			0.304 (2.188)
Cincinnati Reds			1.916 (2.174)
Cleveland Indians			4.356** (2.121)
Colorado Rockies			4.805** (2.215)
Detroit Tigers			2.588 (2.234)
Florida Marlins			3.096 (2.057)
Houston Astros			3.148 (2.201)
Kansas City Royals			0.969 (2.199)
Los Angeles Angels			3.45 (2.26)
Los Angeles Dodgers			1.757 (2.094)

Milwaukee Brewers			3.344 (2.284)
Minnesota Twins			2.203 (2.176)
New York Mets			3.212 (2.164)
New York Yankees			1.592 (2.229)
Oakland Athletics			2.817 (2.06)
Philadelphia Phillies			7.576*** (2.422)
Pittsburgh Pirates			1.78 (2.252)
San Diego Padres			1.164 (2.172)
Seattle Mariners			4.797** (2.191)
St. Louis Cardinals			2.923 (2.285)
Tampa Bay Rays			3.863 (2.348)
Texas Rangers			1.017 (2.153)
Toronto Blue Jays			4.060* (2.14)
Washington Nationals			3.366 (2.261)
Intercept	9.34*** (.491)	9.517** (3.981)	6.396 (4.389)
Summary Statistics			
R-squared	.1	.147	.187

Standard errors are given in parentheses next to the coefficients. The coefficients are significant at the *10%, **5%, and ***1% levels.

The tests indicate that Baseball America rank is correlated with future WAR at the one percent significance level. This held true across all three regressions. The coefficient is -.079 with no controls; with age, college attendance, level, position, and parent team controlled for the coefficient was -.071. In other words, for every ten spots higher a prospect is listed, his expected WAR will increase by .7 (the coefficient is negative because in rankings the "lower" number is better). This meets expectations; the higher Baseball America ranks a prospect, the more WAR he is expected to accrue during his first five Major League seasons. Further, at the one percent significance level, the results show that prospects who attended college are expected to produce over 1.5 more WAR than those who did not attend college. Additionally, prospects who were further along the developmental path at the time of their highest ranking—in other words, those who had reached AAA or had brief time in the Majors—are expected to produce between 2 and

3 more WAR than prospects further away from the Major Leagues. Position does not appear to have any predictive value in terms of future value; the only result of any significance was with third base at the 10 percent level.

Not many teams have significantly better turnout with their prospects than others. Four teams (the Cleveland Indians, the Colorado Rockies, the Philadelphia Phillies, and the Seattle Mariners) are significantly better (at the 5 percent level) than the rest of the league at developing players that produced more WAR. However, this can most likely be attributed to luck. For example, the Phillies only have 15 players on the BA rankings, fewer than any other team. Of those players, only four produced below 6.4 WAR in their first five years. Meanwhile, they graduated 8 players who posted more than 10 WAR, and four produced over 18, the "star" level. The average ranking for those players was 46. I hesitate to conclude that this data shows the team has a particular skill at developing prospects; rather, it seems more likely that the Phillies have simply gotten luckier with their prospects. Nevertheless, the F statistics indicate the four teams have been significantly better (a table with the F statistics for every team and position is included at the end of this study).

My next set of regressions are aimed at normalizing the WAR data, to see if that changes the results any. To minimize the effect of the right skewed players (the "stars") I have rerun the regressions with only the players who produced fewer than 15 WAR in their first five years. In the interest of readability, I include the table with all the coefficients, standard errors, and R-squared numbers in an appendix at the end of this paper.

Again, Baseball America ranking and WAR are correlated at the one percent level, with the coefficient ranging between -.03 and -.034 depending on which variables are present. The reduced coefficients make sense, since the highest WAR producers are removed from this regression. College attendance and highest professional level reached lost their significance in this regression. The positions of shortstop and outfielder showed some significance (at the ten percent level) of predicting around 1.5 more WAR than other positions. Three teams showed results at the five percent significance level of above average future performance (the Arizona Diamondbacks, the Philadelphia Phillies, and the Toronto Blue Jays), but my earlier reservations about the explanatory power of these results still apply.

I next look at Baseball America's ability to identify star players in their rankings, with the definition of star being production equaling or exceeding 18 WAR in the player's first five seasons. Again, Baseball America ranking is significantly correlated with chances of becoming a star, at the one percent level. The first regression, with no other variables added, indicates that for every ten spots higher a prospect is ranked his chances of becoming a star improve by 1.9 percentage points. When the other variables are included, the chances decrease slightly to 1.7 percentage points. College attendance is also statistically significant at the five percent level; a prospect that has at least one year of college experience is 5.7 percentage points more likely to become a star than a player who skips college. Third basemen also display a propensity to develop into stars more frequently than other positions, as they were ten percentage points more likely to achieve that designation. Once again, the Phillies were the only team to significantly outperform the others, as four of their 15 prospects grew into stars.

I have also created dummy variables for certain positions on the prospects lists: these positions are top ranked, top two, top five, top ten, top 25, and top 50. I have regressed these dummy variables against WAR to get an idea of the relationship between those at the top of the lists and those further down. A table with the results is shown below. Each level is statistically significant at the one percent level. Top ranked players produce 11.7 more WAR than all others; top two players produce 9.1 more WAR than lower ranked. Each subsequently more inclusive category results in declining coefficients. Top 50 prospects accrue 3.8 more WAR than those in the bottom 50.

Table 3. Baseball America ranking grouped into categories.

Dependent variable: WAR. Number of observations: 704.

Baseball America Ranking	Coef (std. err.)	R-squared
Top ranked	11.65*** (2.26)	0.036
Top two	9.14*** (1.56)	.046
Top 5	6.13*** (1.04)	.049
Top 10	6.06*** (.77)	.083
Top 25	4.7*** (.58)	.093
Top 50	3.8*** (.53)	.08

The coefficients are significant at the *10%, **5%, and ***1% levels.

Finally, I have regressed WAR on the other two rankings publications, Baseball Prospectus and John Sickels. The table below displays the results.

Table 4. Regression coefficients for Baseball America, Baseball Prospectus, and John Sickels.

Dependent variable: WAR.

Publication	Coef (std. err.)	R-squared	Num. Obs.
BA	-.079*** (.009)	.1	704
BP	-.103*** (.038)	.03	256
Sickels	-.066*** (.013)	.06	411

The coefficients are significant at the *10%, **5%, and ***1% levels.

Baseball Prospectus appears to have the greatest ability to rank high performing players higher on their lists; for every ten spots higher a prospect is ranked on BP's list, he produces over one more WAR. Baseball America comes in second with a coefficient of -.079 while Sickels trailed with -.066. All three lists are significant at the one percent confidence level. However, since BP's lists do not include as many players as BA or Sickels, its model is somewhat weaker, with an R-squared of only .03. It should be noted that the coefficients for each publication are within each other's 95% confidence intervals; thus, we cannot conclude that they are significantly different. Regardless, BP's apparent advantage is still interesting.

Are either of the three rankings better at predicting the superstars? I again have generated the star variable for players that exceed 18 WAR in their first five seasons.

Table 5. Regression coefficients for Baseball America, Baseball Prospectus, and John Sickels. Dependent variable: star.

Publication	Coef (std. err.)	R-squared	Num. obs.
BA	-.0019*** (.000)	.047	704
BP	-.0028* (.001)	.01	256
Sickels	-.0016*** (.000)	.027	411

The coefficients are significant at the *10%, **5%, and ***1% levels.

Again, Baseball Prospectus appears to have a greater ability to predict stars, as for every ten spots higher a prospect is ranked his chances of becoming a star increase by nearly three percentage points. However, the coefficient (and the model in general) is only significant at the ten percent level. The explanatory power of this test is therefore somewhat suspect.

I again have grouped the prospects into rankings categories (top ranked, top two, top five, top ten, top 25, and top 50) and have tested their effect on WAR for all three lists. The results are displayed below.

Table 6. Baseball America, Baseball Prospectus, and John Sickels lists grouped into categories. Dependent variable: WAR.

Publication	Category	Coef (std. err.)	R-squared	Num. obs.
BA	Top Ranked	11.65*** (2.26)	0.036	704
	Top Two	9.14*** (1.56)	.046	
	Top Five	6.13*** (1.04)	.049	
	Top Ten	6.06*** (.77)	.083	
	Top 25	4.7*** (.58)	.093	
	Top 50	3.8*** (.53)	.08	
BP	Top Ranked	5.8** (2.49)	.007	256
	Top Two	4.45** (1.83)	.007	
	Top Five	6.34*** (1.2)	.033	
	Top Ten	4.34*** (.89)	.029	
	Top 25	3.86*** (.62)	.047	
Sickels	Top Ranked	6.39** (2.66)	.007	411
	Top Two	6.72*** (1.82)	.017	
	Top Five	5.27*** (1.19)	.024	
	Top Ten	4.06*** (.893)	.025	
	Top 25	3.87*** (.616)	.047	
	Top 50	1.87*** (.512)	0.016	

The coefficients are significant at the *10%, **5%, and ***1% levels.

Each coefficient is significant and positive. In the categorical analysis, Baseball America appears to do the best of the three publications of ranking the best players higher. It's top one and top two rankings do much better than BP's or Sickels's (coefficients of 11.65 and 9.14 respectively for BA, versus 5.8 and 4.45 for BP and 6.39 and 6.72 for Sickels). Additionally, BA's top tens did somewhat better than BP or Sickels; the coefficient is nearly two larger. This means that a top ten Baseball America prospect can be expected to produce about two WAR more than a top ten Baseball Prospectus or John Sickels prospect.

6. Conclusion

The results of the analysis in this study show that prospect ranking on the lists from Baseball America, Baseball Prospectus, and John Sickels is highly correlated with future Major League value. For every ten spots higher a player is ranked on a BA top 100 list, he is expected to produce .7 more WAR in his first five Major League seasons. For BP, a rise of ten spots predicts 1 more WAR; for Sickels it predicts .6. These results support my hypothesis that these publications, which scout and analyze the prospects they rank, are able to identify players who will produce more at the Major League level. It does indeed matter how highly a player is ranked.

There are other factors that are associated with prospect success as well. College attendees produce 1.5 more WAR than those who were drafted out of high school or signed as amateur free agents. Perhaps college provides some extra skills for players during their development; or maybe the simple fact of their larger body of work makes their projectability easier for scouts. Additionally, prospects close to the Majors—those who had played in AAA or had some Major League experience—produced between 2 and 3 more WAR than those in the lower levels. I suspected this would be the case; there are many pitfalls and obstacles to becoming a Major Leaguer, and the men closer to the big leagues have already surmounted many of them. The odds of a player in Rookie or A leagues busting are much higher than for a player only a level or two away.

For the most part, position does not seem to play much of a role in how many WAR a top prospect will accrue, with the exception of third base. Third basemen are ten percentage points more likely to become stars than prospects who man other positions. This could be random noise in the data, but there is a chance that third basemen are innately more suited to transition to the Majors. They play a position that requires a certain amount of defensive acumen (it is a +2.5 run value position according to WAR). However, it is also traditionally a position where strong hitters reside, unlike shortstop, second base, or catcher. This combination might result in winnowing out players who don't hit well or don't defend well, making third base prospects inherently more of a sure bet in the Major Leagues.

All three publications studied could identify stars and rank them near the top of their lists. Baseball Prospectus has had the greatest success, but the numbers are close enough that it is difficult to conclude that any of the lists are better or worse. Appearing high up on any of these rankings is a good indication of future skill.

Future studies on the subject of prospect value would do well to examine other factors not covered here. It would be interesting to examine country of origin to see whether Latin American or Japanese prospects have a better or worse success rate than Americans. Perhaps some college programs, like elite division one schools or junior colleges, do better at turning out successful Major League players. Spurr (2000) examined this in his analysis of the first-year player draft, but did not go in-depth on the subject of the players' Major League value. It would also be intriguing to look at the 230 players who produced 0 or fewer WAR and try to examine why they had unsuccessful Major League careers. Finding factors that led to these players busting would provide some very useful information, and could help observers identify warning signs in prospects. I limited my study to players' first five Major League seasons; as time goes on and we collect more data on full careers, there could be further avenues to explore.

More than any other sport, Major League Baseball teams require constant reinforcements from the Minor League affiliates to field affordable and competitive teams. However, the difficulty in forecasting and developing those prospects is also more difficult than in the other major sports in America. Prospect evaluation is as much a function of gut feelings and intuition as it is of technique and research. Despite this, this study has found that the publications that rank prospects are very effective in picking their top players.

Appendix: Regression Results

Table 7. Base and expanded regressions, using Baseball America ranking, excluding players with WAR greater than or equal to 15.

Dependent variable: WAR. Number of observations: 704.

Regressor	(1)	(2)	(3)
Ba Rank	-.034*** (.0062)	-.031*** (.0063)	-0.03*** (.0065)
Age		0.092 (.123)	0.121 (.126)
College		0.22 (.422)	0.264 (.435)
A		-0.568 (.694)	-0.618 (.715)
AA		0.541 (.704)	0.328 (.723)
AAA		1.082 (.792)	0.896 (.811)
Majors		1.27* (.763)	1.132 (.78)
LHP		0.267 (.897)	0.535 (.907)
RHP		0.842 (.782)	1.138 (.796)
First Base		1.19 (1.089)	1.404 (1.103)
Second Base		1.705 (1.122)	1.68 (1.133)
Third Base		0.827 (.997)	1.359 (1.022)
Short Stop		1.705* (.924)	1.797* (.93)
Outfielder		1.368* (.828)	1.654* (.841)
Arizona Diamondbacks			3.548** (1.523)
Atlanta Braves			1.734 (1.376)
Baltimore Orioles			-0.029 (1.515)
Boston Red Sox			0.589 (1.487)
Chicago White Sox			0.796 (1.412)
Chicago Cubs			-0.879 (1.479)
Cincinnati Reds			1.858 (1.439)
Cleveland Indians			1.716 (1.46)
Colorado Rockies			2.616* (1.5)
Detroit Tigers			0.245 (1.538)
Florida Marlins			2.001 (1.393)
Houston Astros			0.895 (1.505)
Kansas City Royals			1.276 (1.456)
Los Angeles Angels			2.833* (1.541)
Los Angeles Dodgers			2.51* (1.389)
Milwaukee Brewers			1.875 (1.559)
Minnesota Twins			1.765 (1.452)
New York Mets			2.091 (1.458)

New York Yankees			1.196 (1.494)
Oakland Athletics			2.175 (1.386)
Philadelphia Phillies			4.62*** (1.769)
Pittsburgh Pirates			1.231 (1.509)
San Diego Padres			1.951 (1.425)
Seattle Mariners			2.341 (1.512)
St. Louis Cardinals			0.576 (1.561)
Tampa Bay Rays			2.245 (1.612)
Texas Rangers			-0.024 (1.447)
Toronto Blue Jays			3.678*** (1.428)
Washington Nationals			1.463 (1.54)
Intercept	5.21*** (.354)	1.608 (2.72)	-0.856 (2.975)
Summary Statistics			
R-squared	0.048	0.092	0.151

Standard errors are given in parentheses next to the coefficients. The coefficients are significant at the *10%, **5%, and ***1% levels.

Table 8. Base and expanded regressions, using Baseball America ranking

Dependent variable: star. Number of observations: 704.

Regressor	(1)	(2)	(3)
Ba Rank	-.0019*** (.0003)	-.0017*** (.0003)	-.0017*** (.0003)
Age		-.01 (.007)	-.01 (.007)
College		.057** (.023)	.058** (.023)
A		.006 (.039)	.002 (.04)
AA		.02 (.039)	.016 (.04)
AAA		.067 (.043)	.055 (.044)
Majors		.068 (.042)	.06 (.043)
LHP		.001 (.048)	.009 (.048)
RHP		-.001 (.042)	.008 (.043)
First Base		.008 (.058)	.02 (.058)
Second Base		.03 (.061)	.035 (.062)
Third Base		.104** (.053)	.124** (.053)
Short Stop		.031 (.049)	.037 (.05)
Outfielder		.009 (.044)	.027 (.045)
Arizona Diamondbacks			-.081 (.086)
Atlanta Braves			.063 (.076)
Baltimore Orioles			-.035 (.083)

Boston Red Sox			.123 (.08)
Chicago White Sox			-.029 (.079)
Chicago Cubs			-.013 (.081)
Cincinnati Reds			-.033 (.081)
Cleveland Indians			.061 (.079)
Colorado Rockies			.098 (.082)
Detroit Tigers			.04 (.083)
Florida Marlins			-.028 (.076)
Houston Astros			.067 (.082)
Kansas City Royals			-.025 (.081)
Los Angeles Angels			.027 (.084)
Los Angeles Dodgers			-.07 (.078)
Milwaukee Brewers			.036 (.085)
Minnesota Twins			-.012 (.081)
New York Mets			-.016 (.08)
New York Yankees			-.013 (.083)
Oakland Athletics			.037 (.077)
Philadelphia Phillies			.2** (.09)
Pittsburgh Pirates			.007 (.084)
San Diego Padres			-.049 (.081)
Seattle Mariners			.079 (.081)
St. Louis Cardinals			.037 (.085)
Tampa Bay Rays			.003 (.087)
Texas Rangers			-.011 (.08)
Toronto Blue Jays			.006 (.08)
Washington Nationals			.09 (.084)
Intercept	.1606*** (.0182)	.302** (.148)	.287* (.163)
Summary Statistics			
R-squared	0.044	0.073	.121

Standard errors are given in parentheses next to the coefficients. The coefficients are significant at the *10%, **5%, and ***1% levels.

Table 9. The F statistics for position and team, with the probability that the coefficient does not equal zero.

Variable	F Stat.	Prob > F
First Base	0.27	0.6
Second Base	0.27	0.6
Third Base	2.91	0.089
Shortstop	2.11	0.147

LHP	0.01	0.94
RHP	0.01	0.91
Outfield	1.8	0.18
Arizona Diamondbacks	0.76	0.383
Atlanta Braves	2.93	0.088
Baltimore Orioles	0.68	0.41
Boston Red Sox	3.79	0.052
Chicago White Sox	0.15	0.7
Chicago Cubs	0.02	0.89
Cincinnati Reds	0.78	0.379
Cleveland Indians	4.22	0.04
Colorado Rockies	4.71	0.03
Detroit Tigers	1.34	0.247
Florida Marlins	2.27	0.133
Houston Astros	2.05	0.153
Kansas City Royals	0.19	0.659
Los Angeles Angels	2.33	0.127
Los Angeles Dodgers	0.7	0.402
Milwaukee Brewers	2.14	0.144
Minnesota Twins	1.03	0.312
New York Mets	2.2	0.138
New York Yankees	0.51	0.475
Oakland Athletics	1.87	0.172
Philadelphia Phillies	9.79	0.0018
Pittsburgh Pirates	0.62	0.43
San Diego Padres	0.29	0.592
Seattle Mariners	4.8	0.029
St. Louis Cardinals	1.64	0.201
Tampa Bay Rays	2.71	0.1
Texas Rangers	0.22	0.637
Toronto Blue Jays	3.6	0.058
Washington Nationals	2.22	0.137

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