Analyzing Changes Made to the First-Year Players' Draft In The 2011 MLB CBA

Bhavin Rishi Harsh Sangani

Pomona College

Department of Economics

Claremont, CA

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1.0 Introduction

Baseball earned the nickname of "America's National Pastime" at the turn of the 20th century not only because it was the first sport to become popular with the increase of mass leisure but also because of the recognizable teams in Major League Baseball (MLB). Teams that played in and/or had access to larger markets were able to win many games simply because they had more money than other teams, and that winning momentum built up over time. As a result, older franchises in larger markets have a disproportionate number of World Series titles, with the New York Yankees, St. Louis Cardinals, and the Brooklyn/Los Angeles Dodgers having won a combined 44 World Series. In fact, only three teams founded after the 1900 season have won multiple series titles. While newer teams have had small runs of success over the last few decades (and having success doesn't necessarily translate into winning a World Series), baseball continues to be dominated by older teams in larger markets.

Table 1 shows every MLB team, the number of World Series appearances, when the teams were founded, and the media market rank in the United States. Of the teams in the top 10 in terms of World Series Appearances, eight of them play in a top-11 media market. St. Louis (which has owned the Midwest region as a fan-base) is not an exception, making Cincinnati the only small market team in the top 10. While the data may be biased because these 10 teams are old, this is also a recent phenomenon, as these top 10 teams have won 58% of the past 20 World Series.

Despite the sport's history of dominating teams, there has been a recent push to try to make baseball fairer, specifically by trying to level the playing field between the small-market and large-market teams. Small changes have been made to the game over the years, but the most significant changes were made in 2011, when the latest collective bargaining agreement (CBA) was signed between the players' union and the owners of the 30 MLB teams. Numerous changes were made, but this paper will only look at the two changes made to the First-Year Players Draft in the 2011 CBA: the introduction of a spending cap and the qualifying offer.

Appendix A includes the definitions and variables for this paper. Appendix B includes all of the tables referenced throughout this paper. Appendix C is the data set used for the analysis part of this paper.

1.1 Wins Above Replacement

The main statistic that this paper uses to evaluate players is called Wins Above Replacement (WAR). WAR is a "scorecard" statistic, meaning that it attempts to relay the complete value of a player in one number. The goal of WAR is to estimate how many wins a given player adds to his team compares to the theoretical replacement-level player (a player whose skills are so common that the supply of their skills is extremely high but the demand for those skills is extremely low). WAR encompasses a player's offensive production, defensive prowess, and position played (a catcher will have a higher WAR than that of an outfielder if those two players produced the same exact offensive and defensive numbers because a replacement-level outfielder is much better than a replacement-level catcher). A player with a

WAR of 0 is considered to be a replacement-level player, and players with 0 WAR can be found and signed by a team at any point in the season. WAR can also be looked at across different seasons and can be compared directly across seasons. The consensus in the baseball world is that WAR is the best scorecard statistic to evaluate the worth of any given player's production. There are varying formulas of calculating WAR, so this paper uses the Fangraphs version of WAR because their database of statistics is open to the general public.

1.2 The Spending Cap on the First-Year Players Draft

The first change this paper looks at is the introduction of a spending cap to the First-Year Players Draft. The First-Year Players Draft is the process by which teams select prospects out of high school and college. The draft has 40 rounds, and each team picks in the same order each round, starting with the team with the worst win-loss record and working up the team that won the last World Series. Before the 2012 draft, teams could spend any amount of money on players it selected. This created a problem as small market teams could be priced out of high level talent. Because a prospect can enter the draft numerous times (after graduating high school and up to three times while in college), it is possible for a prospect, once drafted by a team, to not sign with that team and enter in a subsequent draft. Often, high talent players would ask for a lot of money in their contract and by doing so would price themselves out of teams that cannot afford to risk that much money on an unproven prospect. As a result, it was common for these players to either not sign with the small market team that drafted them or to "slide" in the draft to be selected by a team with deep pockets. The aim of the spending cap is to try to make it easier for teams to sign players where they are supposed to be picked.

Every pick in the First-Year Players Draft has an assigned value attached to it by MLB. These assigned values are suggestions for how much the contract should be worth for a player taken at the draft pick. Each team's spending cap is the sum of the assigned values for all of their picks in that draft. Teams can elect to go over their spending cap but are then subject to pay huge fines and penalties (including the loss of future draft picks) for every dollar spent in excess of the spending cap (starting at a tax rate of 100%). Most picks are not allowed to be traded in the First-Year Players Draft; the only ones that are allowed to be traded are competitive balance picks, which will be addressed at length in Section 3. Every team must select a player with their draft picks (they cannot elect to pass).

The goal of this section is to see if the spending cap changed team's behavior and strategies. To create a database for this comparison, this paper looks at the career WAR for the first 40 picks for a span of 25 drafts (this gave me a total of 1,000 data points). Career WAR is being looked at instead of season WAR because the data is much cleaner and should have less variance than that of season WAR. This paper looks at the drafts from 1976 to 2000 (2000 is the last year for this analysis as many players taken in subsequent drafts are still playing in MLB; there are still twelve active players in the data set). Historical career WAR will count all players, including players that never made it to the major leagues (they would have a WAR of 0 by definition). There are various strategies that have emerged with the spending cap, and this paper will analyze the most popular ones.

This paper is only looking at the first 40 picks in the draft for two reasons. The first of which is that qualifying offers (the second change in the CBA this paper is looking at) applies only to the first 40 picks in the draft. Secondly, there is a much stronger consensus on which players should be taken with a top-40 pick; as the draft goes on, opinions about player ability become more disparate. Limiting focus to top prospects should help limit the variance in the data set. The first 40 picks in the draft usually consist of first round, a few second round, and "sandwich" round picks – the round in between the first and second round that is solely made up of compensation and competitive balance picks.

My aim was to get a decay function via regression from the data points (with the independent variable "Draft Slot" and my dependent variable "Career WAR"). This regression line would be a reflection of how well a player performed during his career given the draft pick in which he was taken. I hypothesized that a decay function would make the most sense as a regression line because of the difference in value between the draft picks:

$$(WAR_{Pick\ 1} - WAR_{Pick\ 2}) > \left(WAR_{Pick\ 2} - WAR_{Pick\ 3)}\right) > (WAR_{Pick\ 3} - WAR_{Pick\ 4}) > \cdots$$

This belief suggests that a downward sloping best fit curve would represents the diminishing returns for each subsequent pick in the draft. I would then use the regression line to see how teams are valuing draft picks under the new CBA rules against each draft pick's historical production. I inputted all of the career WARs into an Excel spreadsheet and then imported the file into R, an open-source statistical software, to find this regression function and to perform others tests on the data.

One of these strategies is to intentionally "reach" for a player to save up cap space for players later in the draft. An example of this would be to take a player projected to be selected around pick #30 with the 10^{th} overall pick. By doing so, that team could sign that player to a contract well below slot value, giving them extra money to work with for all other picks in the draft. Another strategy is to do the opposite: target players that are "sliding" in the draft and then "reach" for players later in the draft. Several strategies will be evaluated by looking at the historical WAR and other trends in the data. With the historical WAR approach, I do not have to worry about players who never made it out of the minor leagues (as they have a WAR of 0). Historical WAR will allow me to focus on the strategy of selecting players as opposed to the players themselves. Additionally, the variance of the career WAR for players/draft slots are going to be much less than that of the players/slots taken in recent drafts.

1.3 The Qualifying Offer

Another change made is the introduction of the qualifying offer. Before the 2011 CBA, all free agents that signed with new teams were broken up into three different groups: Type A free agents, Type B free agents, and unclassified free agents. If a Type A or Type B free agent were to sign with a new team, then the old team would receive a certain level of compensation in return (depending on the type of free agent). Teams that lost unclassified free agents would not receive any type of compensation. The type of a free agent would be determined by the Elias Sports Bureau, a third-party organization separate from MLB and the players' union.

With the 2011 CBA, the old Type A/B/unclassified free agent system was done away with, and a new system for free agent compensation was introduced. This new system is called the qualifying offer system. Under this new system, a team can extend a "qualifying offer" to an impending free agent (see definition of "Free Agent" in Appendix A). A qualifying offer is a one-year contract worth the average of the top 125 salaries of the past season. If the player accepts this contract, he will play for that team for one year. If he rejects the contract and signs with any other of the 29 teams, then the new team loses its top pick in the next First-Year Players' Draft, and the team that loses that players gains a "sandwich" pick (a pick in between the first and second round in the First-Year Players Draft) in this year's First-Year Players' Draft. Table 4 shows all of the players that were offered qualifying offers. Every player that has received a qualifying has rejected it.

For players that were offered a qualifying offer, I will use Fangraphs' Steamer system to project how much that player's WAR will be for the upcoming season. I can then compare WAR and the length of the contract to that of the draft pick the team would lose (which is very similar to what is done in the First-Year Players Draft section). For a given team, a break-even line can be found depending on where that team is picking in the draft (a situation could arise where it would make sense to sign a free agent who declined a qualifying offer if that team were to lose the #27 pick in the draft but not make sense if it were to lose the #12 pick in the draft).

The qualifying offer system does have some situational adjustments. If a team signs two players that denied qualifying offers in one offseason, that team will lose its two highest traditional picks in the draft, which are its first and second round picks.

Another adjustment involves the top 10 picks in the draft. The top 10 picks in the draft are protected every year. That means if a team in the above situation has the 7^{th} overall pick in the upcoming draft, that team will hold onto its first round pick and will lose its second and third round picks as a result of signing those two players. Compensation picks for failing to sign a top-10 pick from the year before are also protected. Additionally, teams that gain a compensation pick from losing a qualifying-offer free agent will not lose that pick in the event that they sign a qualifying-offer free agent of their own.

2.0 The Data and Its Analysis

After getting my data together and importing it into R, I did not find what I expected. Figure 1 shows all of the data collected plotted on one chart. It is not immediately clear if a pattern exists within the data. Figure 1 shows not only how concentrated the data is but also how outliers can possibly affect a best fit curve.

Figure 1 (Career WAR vs. Draft Slot)

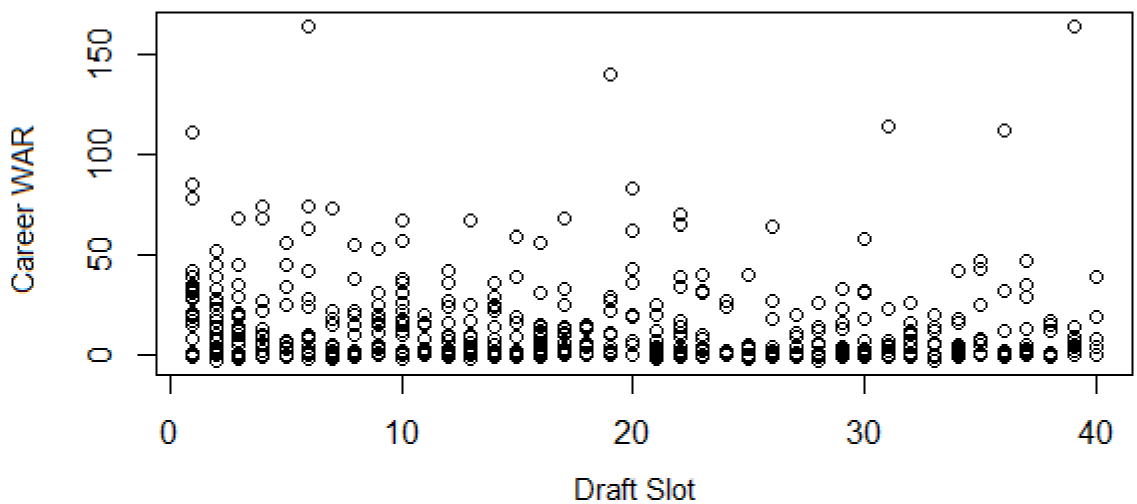


Figure 1 gives an initial overview of the data but does not tell me anything specific. To get a better idea of the spread of the data, I plotted the data points by frequency of WAR. Figure 2 has its histogram bars of length 1 (increments of 1 WAR), Figure 3 has bars of length 1 with the range limited to a frequency of 60, and Figure 4 has bars of length 20 (increments of 20 WAR). These figures show how many high draft picks either do not make it to the Major Leagues (have a WAR of 0) or make it to the Major Leagues but have a small impact on their team over the life of their career. As per Figure 4, nearly 55% of top-40 draft picks have a non-positive WAR over the life of their careers. Figure 1 shows an extremely large positive skew, and the initial impression of successfully drafting a high draft pick is rather low.

Figure 2 (Frequency vs. Career WAR)

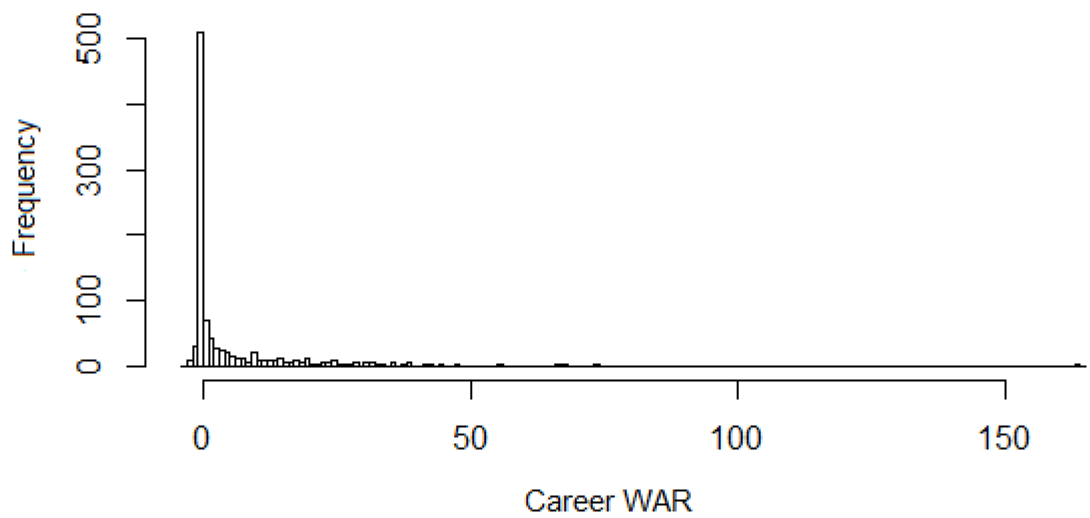


Figure 3 (Frequency vs. Career WAR)

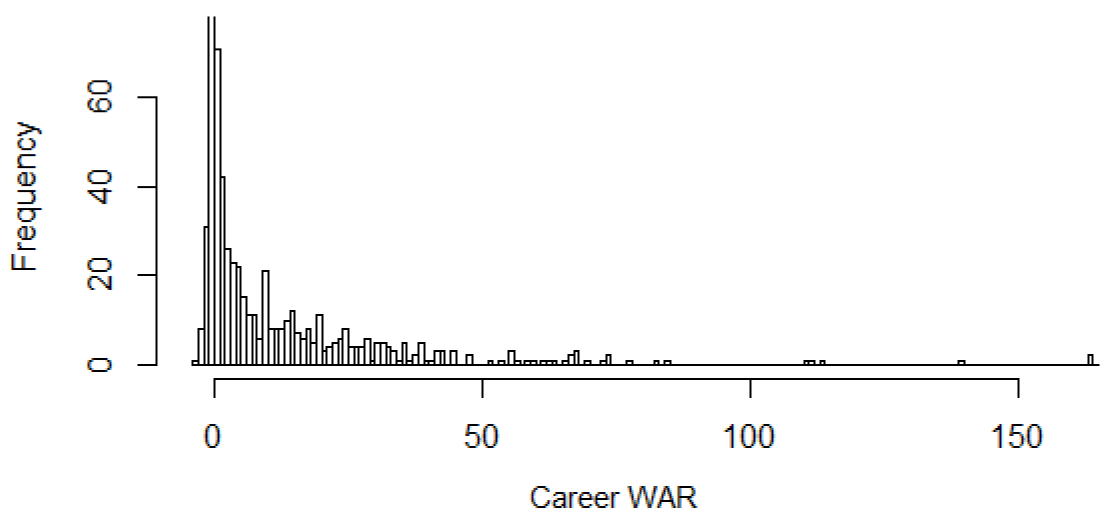


Figure 4 (Frequency vs. Career WAR)

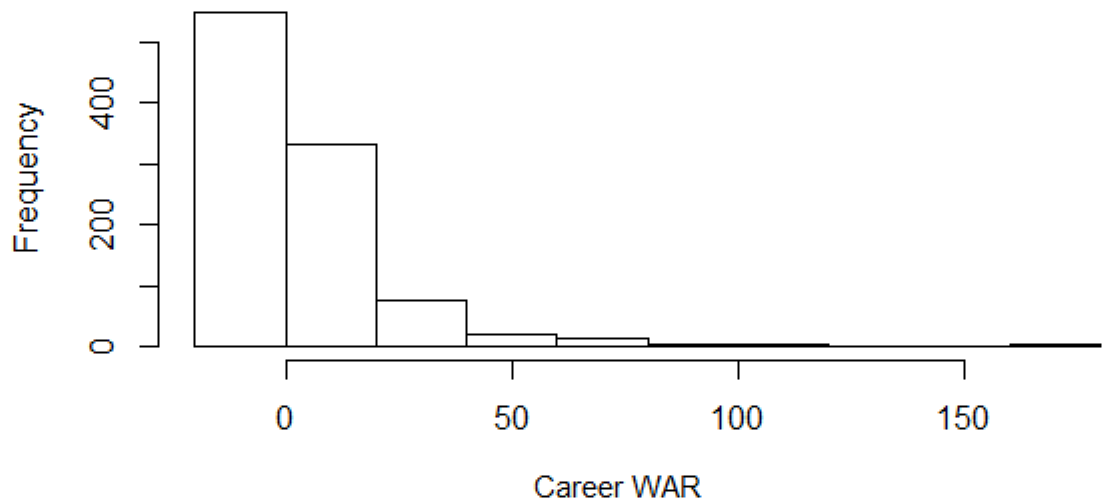


Figure 5 shows the median WAR at each pick, and Figure 6 shows the standard deviations at each pick. I decided not to look at the mean because of the large variance set as well as the presence of large outliers in the data. Figure 5 really highlights the differences between the first overall pick, the next two picks, and the rest of the draft – not only the rest of the top-40 picks but also those outside the top-40 (which should have players that have even less production that those looked in the scope of this paper). Figure 5 does not give me confidence that I will be able to find a robust model for the data, and Figure 6 furthers that lack of confidence. Even though a slight downward trend in visible, it would be hard to find a best fit line that would have a reasonable R^2 value. Table 3 illustrates how large the standard deviations are.

Figure 5 (Median WAR vs. Draft Slot)

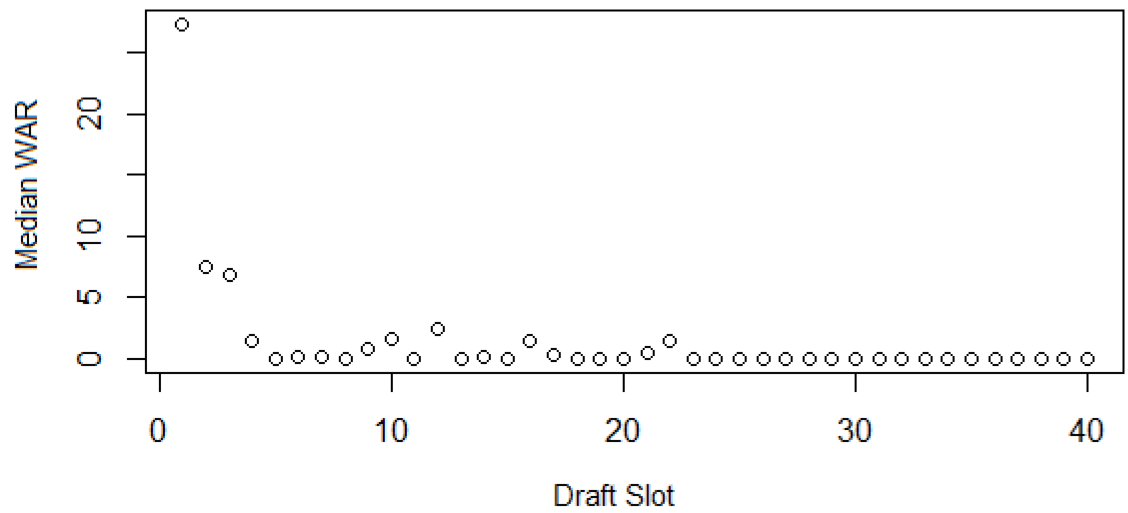
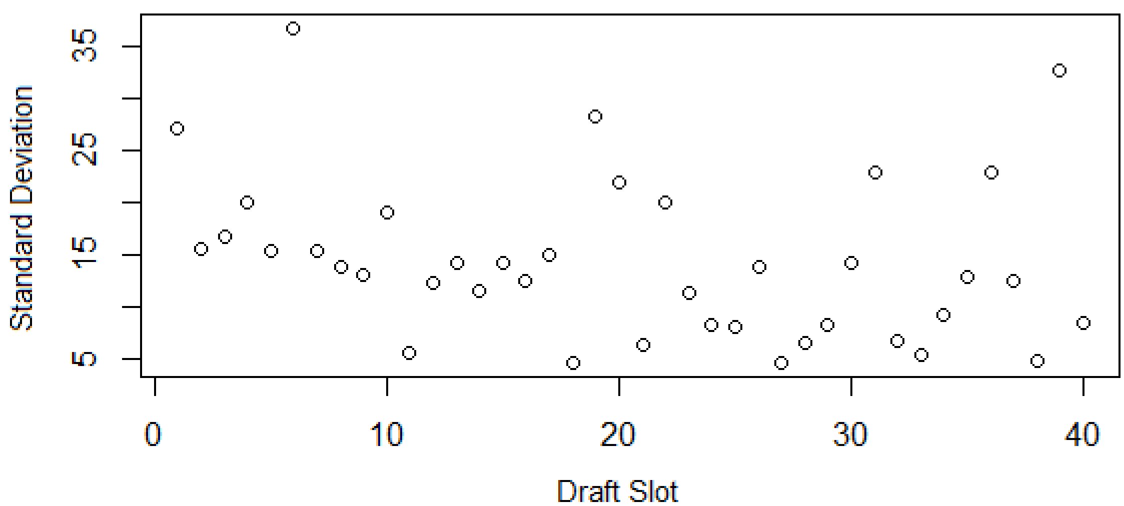
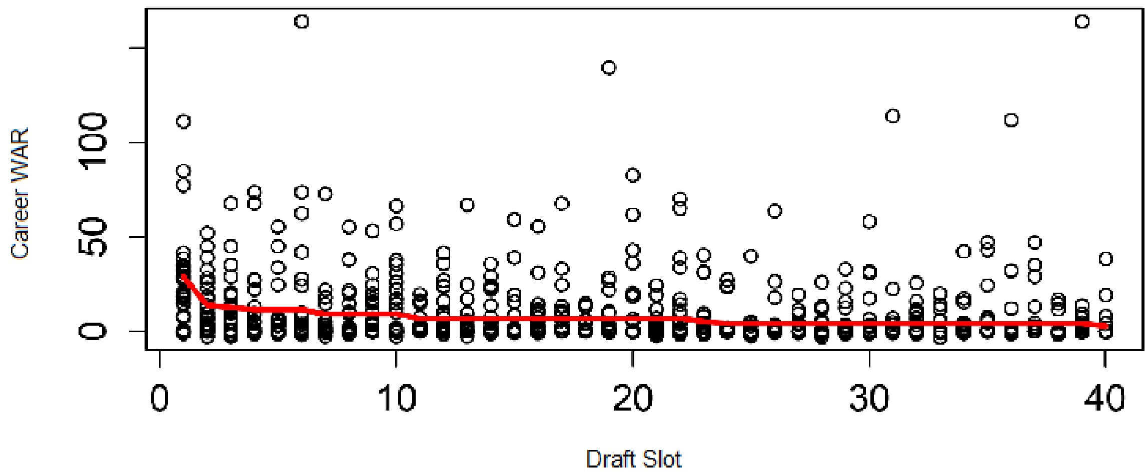


Figure 6 (WAR Standard Deviation vs. Draft Slot)



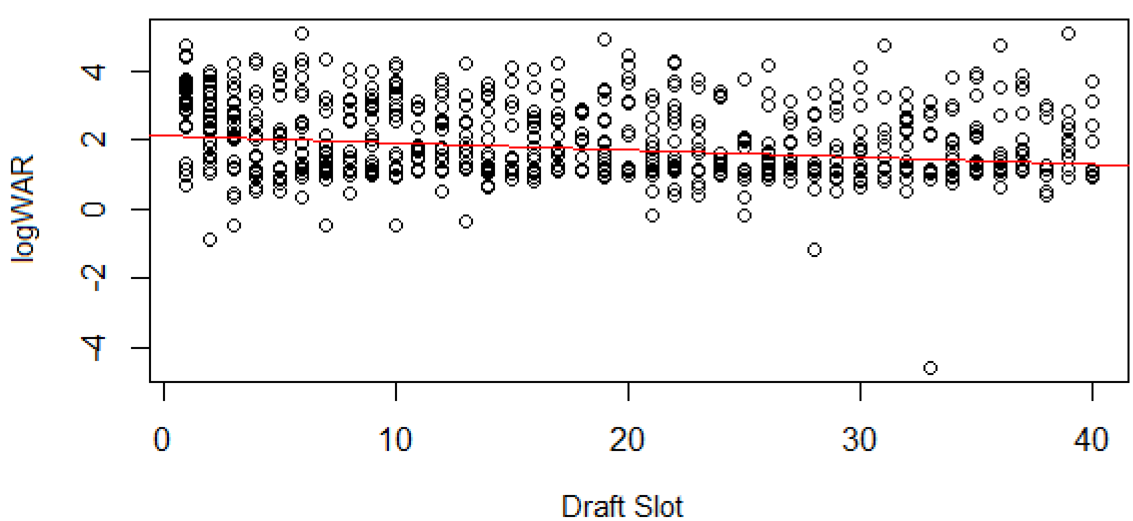
To see if my hypothesis of a decay regression line is correct, I ran an isotonic (or monotonic) regression on the data. An isotonic regression minimizes the mean squared error of the data while having the restriction of being either strictly increasing or decreasing. For this paper, the isotonic regression is strictly decreasing, as shown by the red line in Figure 7.

Figure 7 (Isotonic Regression)



The initial picture does not look very promising, as many of the picks do not differentiate themselves from the picks around them. Picks #4-6 have the same career WAR via this regression, which is surprising to find for such high draft slots. The only stark drop is from the first overall pick to the second overall pick, and other noticeable dips occur after Pick #6, #10, and #23. To further explore the idea of a decay function, I converted my dependent variable to "log(WAR)." Figure 8 shows this transformation as well as the addition of a linear best fit line (shown in red):

Figure 8 (logWAR vs. Draft Slot)

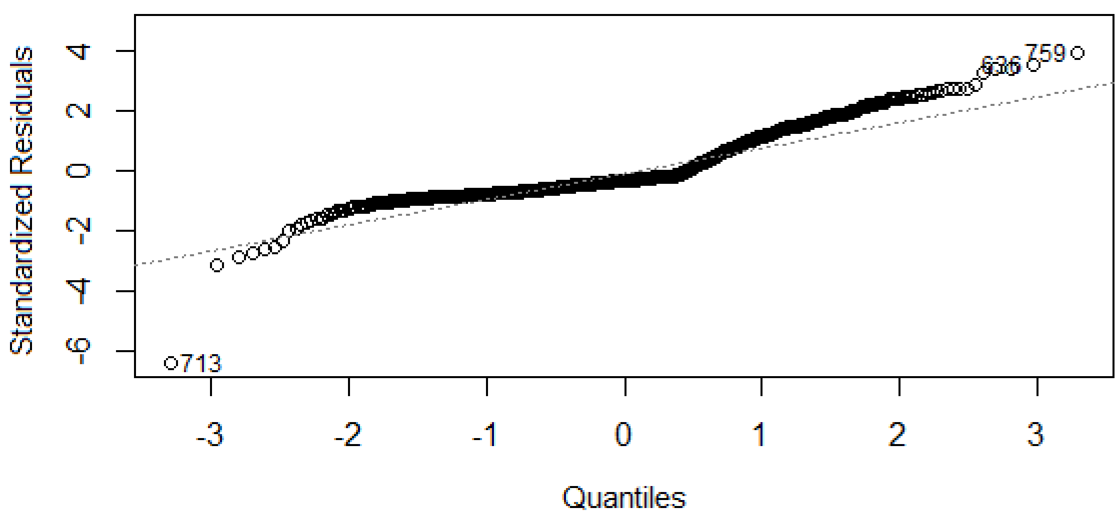


$$Regression\ Line: \qquad Log(WAR) = 1.8268 - 0.005623(Draft\ Slot)$$

This analysis confirms the large variance in the data set. The linear best fit line has an absurdly small R^2 value of 0.0044, which means that the best fit line explains almost none of the variance in the data. Note that because some career WAR values are negative, I shifted all of the career WAR values up by 3.21 WAR (the lowest career WAR in my data table was -3.2).

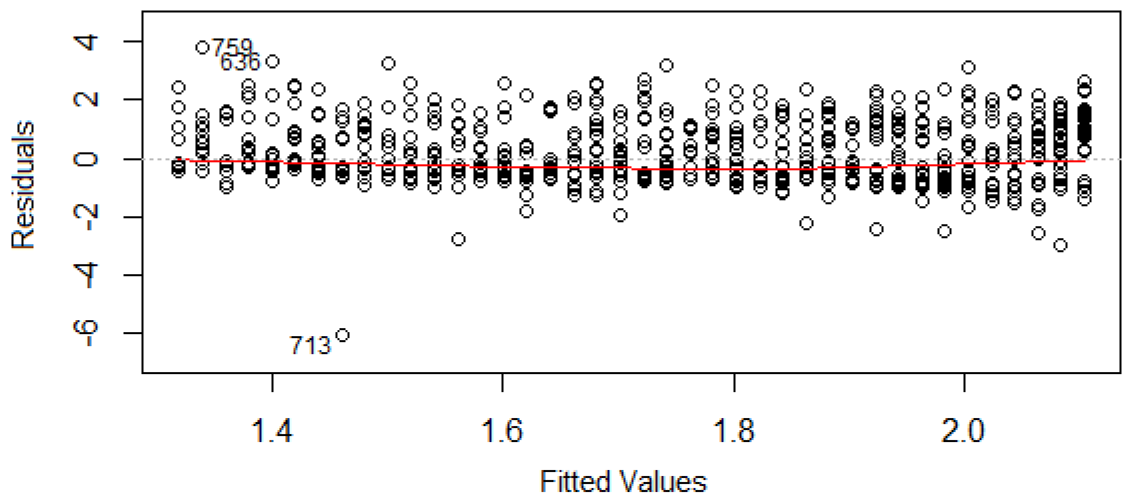
To double check and make sure that the decay function was not a good representation of the data (as represented by the Log(WAR) regression line), I created a normal Q-Q plot for the log(WAR) data. A Q-Q plot is a graphical method for comparing two different distributions by plotting their quantiles against one another. To see if a linear regression line makes sense, the points on the Q-Q plot should hug the 45º line very tightly. Figure 9, as shown below, clearly shows that the points do not follow the 45º line.

Figure 9 (Q-Q Test)



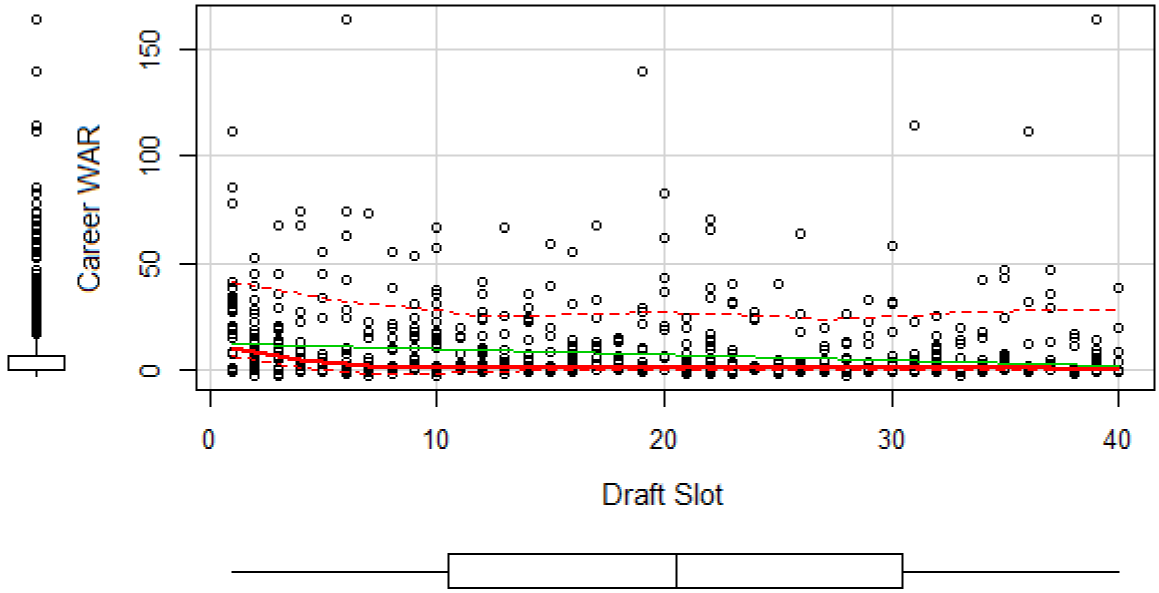
Furthermore, I looked at its residuals represented in Figure 10. A linear model is considered to be a good fit for the data if there are equal amounts of positive and negative residual values. However, Figure 10 clearly shows that there are far more positive residual data points than negative residuals data points, meaning that a linear model is not a good fit for the data.

Figure 10 (Residuals vs. Fitted Values)



After looking into a decay function and a linear model, I looked into the LOWESS method. Figure 11 has the same data points and scale as Figure 1 but also includes boxplots per variable (shown below the axes), a confidence interval (the dotted red line), a linear best fit line (the green line), and a LOWESS best fit curve (the solid red line).

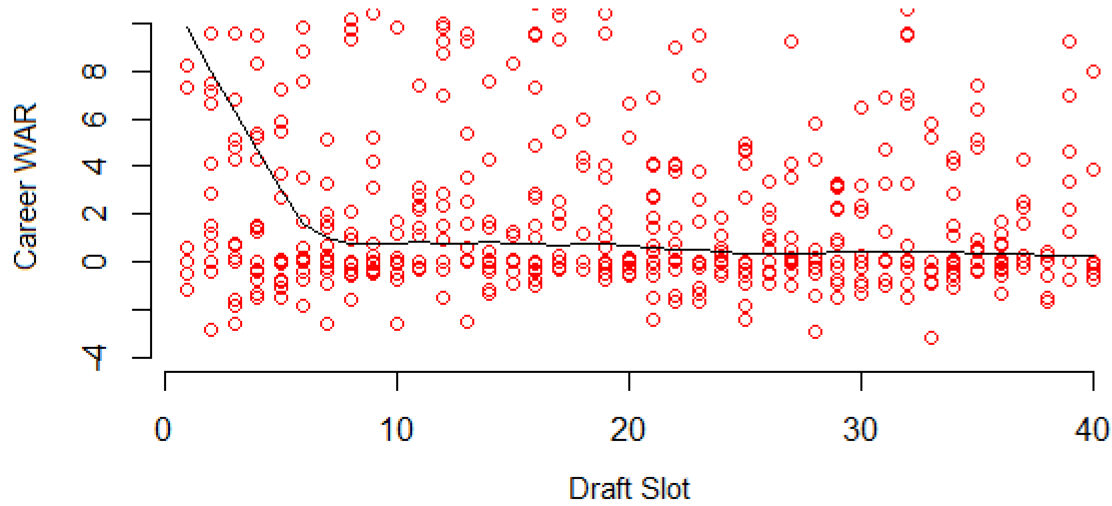
Figure 11 (Career WAR vs. Draft Slot; includes CI, LOWESS, and LM)



LOWESS (or LOcally WEighted Scatterplot Smoothing) is based on the foundations of the least squares regression. However, it differs from a classical OLS model because it runs multiple iterations of OLS, with each iteration changing the weights of the data points. This way, a LOWESS model gives more weight to local points and less weight to outliers, thereby giving a more "smooth" best-fit curve as more iterations are run. The benefit of the LOWESS curve is that the model is not forced into using a pre-set formula and is more adaptable to data sets with a lot of variance.

To determine what is local, LOWESS uses a parameter denoted as f ~ (0,1) (sometimes this parameter is referred to as α, but since R calls it f, I will use also call it f). As f gets closer to 1, the range for local points increases and the curve gets smoother, and vice versa. I used 3 iterations and numerous different values for f for my LOWESS regression. While there is no "rule of thumb" when it comes to selecting an exact f value, it is standard practice to look at f values between 0.2 and 0.5, and Figure 12 shows a LOWESS regression where f = 0.27. I have reduced the dependent variable frame to 10 WAR to make it easier to see the LOWESS curve. Figure 12 shows the first six picks in the draft to be different from the rest of the picks and the remaining picks to have very similar values to one another.

Figure 12 (Career WAR vs. Draft Slot; f = 0.01)



However, a larger point has been made clear by the different LOWESS regressions (and to an extent, the decay function and the linear model as well): after the first few picks at the top of the draft, the difference in player production (in terms of WAR) between the rest of the draft picks is extremely small, especially after taking into consideration the standard deviations from Figure 6 and Table 3. These findings are also consistent with the results in Table 2. Table 2 has Student T-Tests comparing one draft pick to the previous draft pick, and only three draft picks were found to be statistically significantly different from the next pick in the draft at the 95% level (highlighted in yellow).

One assumption that has been held in this paper is that no matter what a team's strategy is, they are all equally good at finding talent in the draft. If some teams are better at finding and selecting players in the draft, it should be reflected by teams' winning percentage. It may be the case that some teams are bad at scouting and developing players, which could put them at a significant disadvantage in the draft. To test this, I reorganized the table in Appendix C to put team's draft picks together, regardless of the year that player was selected. A summary of the findings can be found in Table 6.

There are some issues with this analysis. First off, four teams have significantly less data available because of those teams were founded after the 1976 draft: Arizona's and Tampa Bay's first draft was in 1997, and Miami's and Colorado's first draft was in 1990. Additionally, some team's strategies heavily influence the data set. For example, the New York Yankees preferred to sign free agents, which cause them to lose many of their earlier draft picks. As a result, they only have 22 top-40 picks during the 25 years the data covers. This presents a stark contrast to other teams' strategies: Minnesota, San Francisco, and Washington (then the team was based in Montreal) had at least twice the amount of top-40 picks than the Yankees within the same time span.

Despite all of these caveats, some analysis provided some interesting results. First off, the median career WAR for team's draft picks were almost all 0, which points to the fact that it is extremely hard to consistently identify talent at the beginning of the draft. The 75th percentile presented a much larger range of numbers, yet the results were not at all convincing. The teams that were the most "successful" in the draft had rather low winning percentages, and three of the teams near the top do not have enough data points for them to be strongly considered as a successful draft team. An ANOVA regression between "Mean" and "Win %" gave an R2 value of 0.38, which is actually much higher than I expected it to be. However, it also suggested a slight negative relationship between the mean career WAR and win %. I suspect that this is heavily influenced by teams that are successful via other methods (i.e. the Yankees and the Boston Red Sox). This rather shallow analysis does make an argument that there are some teams that are definitely better than others when it comes to finding talent in the draft. However, it is very clear that finding talent in the draft does not translate over into winning games.

One issue with this analysis is that it takes into account the player's production across the lifetime of their careers. Most players play for multiple teams across their careers, and these numbers include the WAR for playing for the team that drafted them as well as other teams. It may be difficult to find a data set that accurately describes how well prospects selected by their team will play for only that team. That data set would run into all kinds of particular cases, such as trades (both good and bad prospects get traded all the time) and playing time (a good prospect may not get as much playing time as an established veteran). This analysis does not attempt to tackle those issues but rather aims at giving a broader overview of how drafting good players turns into wins for that team.

After doing all of these statistical analyses, it seems that many draft slots are seemingly a lottery ticket, even picks as high as the middle of the first round. MLB teams spend millions of dollars on scouting and statisticians to draft the right player every year, yet the results do not back up the investment as calculated by WAR. The level of production is so low for many high draft picks that there is no statistical difference between many of these picks (as shown by Table 3 and Table 5).

3.0 The Qualifying Offer Analysis

A rough way to identify which players were offered or will be offered qualifying offers are players that have at least a predicted WAR of three for the upcoming season. To draw a direct comparison to this, I created two figures that calculated whether or not a player taken at a specific draft slot would be able to have a career WAR of at least three. By picking a career WAR of at least three as my cutoff, I am creating a break-even line: on one side of the line, a team would get more production out of a qualifying-offer player in one season, and on the other side of the line, a team would get more production out of a player taken at the draft slot over the life of their career. Figures 13 and 14 demonstrate that break-even line at the first 50% mark on the y-axis – above take the free agent and below take the draft pick. Figures 13 and 14 represent the findings for the mean and median, respectively. This is not a perfect comparison as players that deny qualifying often sign multi-year contracts, but it does get at the idea of who should be offered a qualifying offer in the first place.

Figure 13 (Percent Change Mean WAR > 3 vs. Draft Slot)

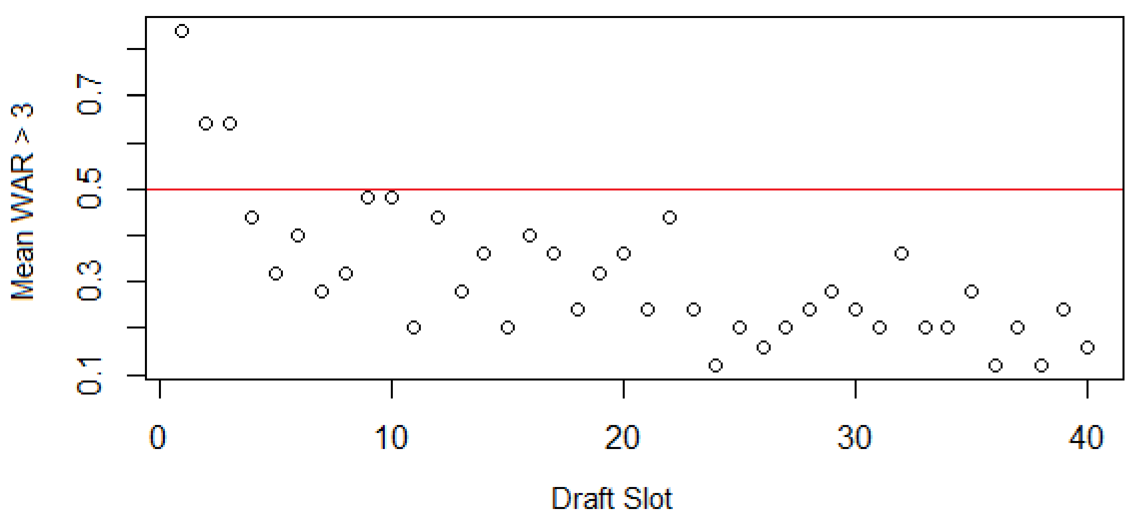


Figure 14 (Percent Change Median WAR > 3 vs. Draft Slot)

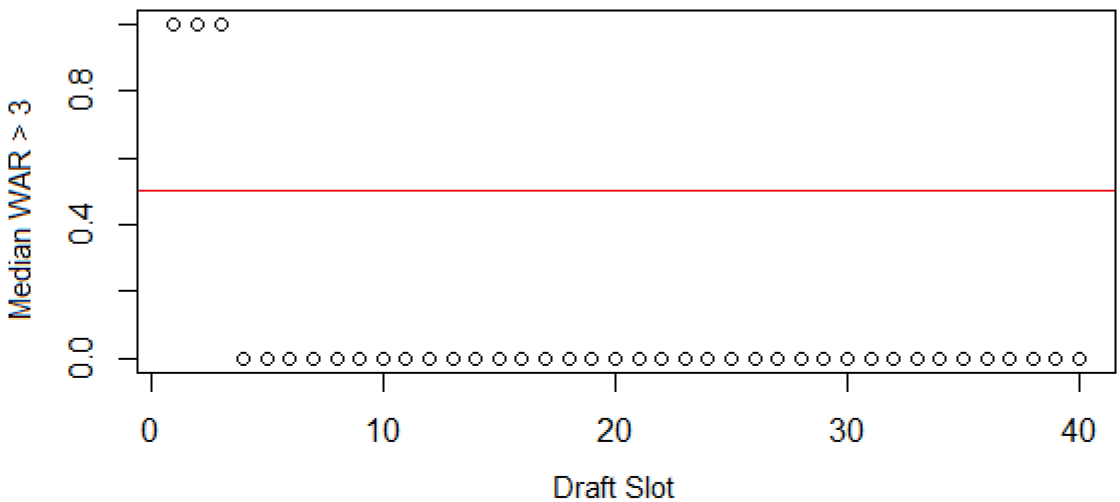


Figure 14 treated the median absolutely, which is why all of the data points either have a percent chance of 0% or 100%. In both of these figures, a team is more likely than not to draft a player with a career WAR of 3 with only the first three picks in the draft. This is a huge statement because it clearly highlights the lack of success of players that do make it to the major league level. After that, there is a noticeable downward trend in Figure 13 with the means. A few approach the 50% line, but the majority of points are well below it, hanging around 30% or even lower. The two above figures continue to highlight the lack of quality production from players taken after the first few picks, which is an amazing theme to see.

The idea behind the qualifying offer is to give compensation to teams that lose good players. This system replaced the old Type A/B/unclassified system because it was seen as more fair to small market teams. However, as evident in Table 4, the majority of qualifying offers (QO) were made by top market teams – as defined earlier in the paper – (24 out of 33; 11 were from the Red Sox and Yankees) and the majority of QO free agents signed with top market teams (21/33). Furthermore, the top 10 draft picks are protected against QOs, which means that the highest pick that can be lost via signing a QO free agent is the 11th overall pick. Per Student T-Tests, there is no statistical difference in career WARs from players selected at the 11th overall pick and the 40th overall pick ($p = 0.9290$), as can be seen in Table 5. All of these facts do not favor small market teams.

However, this system is better than no compensation system at all. While I do not envision either the Major League Baseball Players Association (MLBPA) or the owners of the MLB team changing the top-10 protection anytime soon, the QO system nominally reaches and accomplishes its intended goal. Essentially, the team that loses the QO player gains a sandwich-round pick, which is equivalent to an extra lottery ticket while the team signing the QO player loses their best available lottery ticket.

One additional change to the 2011 CBA was the introduction of the competitive balance pick. The competitive balance picks was created to help give small market teams an advantage in the draft. There are two rounds of competitive balance picks, each with six picks: Round A takes place at the end of the first round (after the qualifying offer picks) and Round B takes place after the second round. The ten smallest-market and the ten lowest-revenue teams are eligible for picks in Round A. Picks are done in a lottery format, and the odds of winning a draft pick are based on each team's winning percentage from the previous season. All teams that do not get a pick in Round A plus teams that received revenue sharing are eligible for the Round B lottery. The Round A picks have substantial value as these picks generally end up being a top-40 pick; teams that have a Round A pick are essentially getting an extra lottery ticket in the draft, which can turn out to be very lucrative (and Round B picks as well, although to a much lesser extent). Additionally, competitive balance picks are the only picks in the draft that are allowed to be traded. There have been 10 competitive balance picks have been traded since their creation, and it is unclear what their value is in the trade market. Some teams view them as a valuable asset (as stated above), yet some teams are willing to trade these picks for more predictable player (one where there is a lot more information on). Further analysis will need to be done to see what their trade value should be.

After this analysis, I do not believe that the sandwich-round pick is enough compensation for losing a QO player, especially because that lottery ticket may not have a high enough return to compensate for losing a proven major-league player. However, changing the compensation may not incentivize more small-market teams to offer their own free agents qualifying offers. I believe a change needs to be around how much a qualifying offer is worth.

Currently, a qualifying offer is equal to the mean of the top 125 player salaries from the previous year. Those totals have been rather high, starting at $13.3 million in 2012, $14.1 million in 2013, and $15.3 million in 2014. I hypothesize that there are two issues with this. The first issue is that a figure like $15 million is way too much for a small market team to spend on one player. While a team like the New York Yankees could stomach a large one-year deal rather easily, it would be too risky for a team like the Tampa Bay Rays to offer one player that much money. The second issue is the quality of players that are worth that contract. Baseball is a business, and teams are only going to offer a player a contract that is worth that much money for one year. However, all 34 players that have been offered a QO has rejected it because they know that they can get a much higher offer in free agency. The dollar figure for a QO is so high such that it prevents many teams, specifically small-market teams, from offering it to their players, and subsequently, it is only offered to players who will eventually turn them down. These two issues (along with the imbalance of QOs made by large-market teams) make the QO a failure in terms of leveling the playing field between large-market and small-market teams. To fix the QO system, I would suggest that the dollar figure should be lowered or to create two types of qualifying offers when the next CBA negotiations come out in 2016. Further studies and research would need to be done to see what that dollar amount would be.

4.0 The Spending Cap Analysis

The spending cap was created with the mindset of making the players' draft fairer to small-market teams. The creation of the spending cap has lent teams to use a few different strategies. The main ones are:

- Pick the best available at any given pick and sign as many as you can
- Pick a player well below slot value with your first pick in the draft in hopes of using that extra money to sign players that fall later on in the draft
- Only pick players that you feel will sign with you, regardless of draft status

These main strategies are dependent on the idea that some draft picks are worth more than others and that draft picks themselves are distinguishable. Table 2 shows that only three picks in the draft are statistically different from the succeeding pick. However, this table only makes 39 comparisons when there are 780 comparisons to be made between the 40 draft picks (40 choose 2 = 780 combinations). Table 5 looks at all of these comparisons, with the numbers of the diagonals making up Table 2. Only 13.7% of draft picks are statistically different from one another at the 95% level (shown in yellow). The only pick that is statistically different than more than half of the other draft picks looked at in this paper is the first overall pick, which is statistically significantly different from the other 39 picks. If you were to remove that draft pick from the total, then only 9.2% of the remaining picks are statistically different from each other. That means there is no statistical difference between the production of more than 90% of players taken between picks two and 40 over the last 25 years. This data leads me to believe that there is no preferred draft strategy because of the high amount of variance inherent in the production of players selected with these draft picks. The only absolute strategy that Table 2 and Table 5 would recommend is to select the best available player when you have a top pick in the draft (i.e. a top-5 pick or maybe even a top-3 pick). While teams may choose to draft players that have "slid" in the draft, the data set makes it clear that those players may not perform any better than a player projected to go at the same spot (unless that player was a consensus top-3 prospect). While these findings do not lead to a specific strategy, it does not rule out any one strategy either. Further studies can be done to look at different strategies in the draft and how well they have worked over the years, however, it would be very hard to distinguish draft strategies from scouting success; did a team select a player at a given slot because of a particular strategy or because the team's scouting department determined that this was the best available player? The answer is probably a combination of those two, but it would be extremely difficult to try to isolate those two factors.

5.0 Additional Analysis and Conclusion

The data set has been loud and clear about one thing: that the first few picks in the draft are far more reliable in terms of player production that the rest of the top-40 picks in the draft. There surely must be some reason for teams' lack of success when selecting players outside the first few picks. One possible reason for this is the lack of information on draft prospects. Players that are drafted and signed directly out of high school only have played high-level baseball for a couple of seasons, often against much lesser talent – the jump from high school baseball to the minor leagues is extremely high. While you get at least three more years to scout collegiate players, the talent can often be overshadowed by other teammates (i.e. a manager's preference to play an upperclassman over a first-year) while still facing lesser talent. Additionally, there are far fewer statistics available for players at the amateur level. Stats on high school players may be limited to basic, traditional statistics, and stats for collegiate players will greatly vary from university to university, making broad comparisons across many players a largely unfruitful task. When draft prospects get signed, there becomes so much more information available to teams about them, such as pitchFX for pitchers and defensive metrics for position players.

On a similar note, this study only includes players that were drafted up to the 2000 MLB Draft. However, the end of the data set coincides with the beginning of the "Moneyball revolution" in the MLB, when analytics became a regular part of how teams made their day-to-day decisions. Though the last paragraph made an argument for the lack of information in amateur baseball, teams still have much more information about prospects now as compared to before 2001 which can possibly change and affect how teams are evaluating players. A similar study to this one in ten to fifteen years would then be able to analyze if there was a difference in teams' performance in the draft pre and post Moneyball.

The success of the changes made in the 2011 MLB CBA relating to the First-Year Players' Draft and compensation around losing top-level free agents are extremely hard to calibrate. The most robust reason for this is the large variance inherent in the draft. The variance makes it extremely difficult to model and to find any useful and statistically significant trends within the data. The data set of past drafts has almost no predictive power in terms of determining an optimal draft strategy, which makes analyzing the changes relating to the draft extremely hard to examine with any level of certainty.

One issue that I struggled with is the idea that there are some players that make it to the majors and ultimately sport a negative WAR whereas there are some players who never make it to the majors and by definition have a WAR of 0. This is a huge limitation of using WAR, and it certainly makes the results of this paper less robust. However, there is no better statistic for measuring player production that is readily available. Additionally, if players have a negative career WAR, the argument can be made that they never should have made it to the Major Leagues, and blame should be given to the teams who promoted these players to the Major League level. Furthermore, the vast majority of negative career WARs do not drop below -1.5.

Using Table 6 and Figures 5 and 6 as a guide, it would be reasonable to assume that the end results of this paper would not change if the lowest WAR a player could have would be 0. Lastly, it would be illogical to remove these players from the data set entirely. If these players were removed, then the data set would only be populated with players that did not hurt their team at the Major Leagues, which is not helpful in terms of analyzing the draft.

There is also the issue of having high draft picks shuttled through the minor leagues regardless of their production. A scout's (talent evaluators for teams) job security is often tied to the performance of the players that they advocate for (whether in free agency, in trades, and more importantly, in the draft). This is especially true for high level scouts and the executives that run the scouting department. As a result, players who scouts have a high stake in their performance will often be pushed through the minor leagues in an attempt to get to the major league level as fast as possible. While this certainly contributes to some players failing to succeed at the major league level, I do not believe that this is a main reason for the lack of production for many players at the major league level. Many prospects that are rushed to the majors are often sent back to the minor leagues if they do not play well enough, and a lot of these prospects will never develop the skills to warrant being a major league player. Furthermore, there are relatively few cases of underprepared prospects that are pushed through to the major leagues. Around three first round picks reach the majors within two years of being drafted, and some (if not all) of these first round picks have the talent to play in the major leagues. By comparison, around half of first round picks make it to the majors within four years of being drafted.

Appendix A

Definitions and Variables:

Free Agent: There are several different types of free agents in MLB. This paper focuses on one type of free agent. A free agent's old team is the team he played for in the previous season, and a free agent's new team is the team he will play for in the upcoming season. This free agent meets the following criteria:

- Accrued at least 6 seasons of being on an MLB roster OR has passed through salary arbitration three times (four time if the player is a Super-Two)
- Does not have a contract with an MLB team

Reach/Slide: There is often a consensus among teams and experts on where most prospects should be selected at any point in the draft. However, some teams on draft day deviate from the consensus and will select a player that was not expected to be taken at that pick. A "reach" is when a team takes a player that was projected to go much later in the draft, and a "slide" is when a team takes a player that was projected to go much earlier in the draft.

Wins Above Replacement (WAR): A scorecard statistic that aims to show a player's performance in one number. WAR accounts for both offensive and defensive production. WAR shows how many wins a player adds to a team over the theoretical "replacement-level player," who has the baseline WAR of 0. The theoretical replacement-level player has a level of production that is in so much supply yet demand is so low that an MLB team can cut this player from their team at any time and sign a different player with the same level of production at any point throughout the season. WAR can be negative (indicating a current player is producing below replacement-level) and is a linear scalar metric (i.e. a player with 6 WAR is three times as good as a player with 2 WAR). For this paper, I will be using Fangraphs' equation and output for WAR (also denoted as fWAR). Below is a generic scale of how fWAR should be interpreted for a single season:

- ~0 fWAR per season: Replacement-Level Player
- 2+ fWAR per season: Starter on an MLB Team
- 5+ fWAR per season: All-Star Caliber Player
- 8+ fWAR per season: MVP Caliber Player
- 60+ fWAR for a career: Hall-of-Fame Caliber Player

Minimal Value for WAR: It is -3.2, which is Mike Brumley's career fWAR (The 33rd overall pick in the 1983 MLB Draft).

Maximum Value for WAR: It is 164.0, which is Barry Bonds' career fWAR (The 39th overall pick in the 1982 MLB Draft and the 6th overall pick in the 1985 MLB Draft).

Mean: There are huge outliers in the data, so I will be using the median instead.

Median and Standard Deviation: See Table 3

Appendix B
Figures and Tables

Table 1

Information from mlb.com and from stationindex.com
**Filled-in cells represent top-10 teams in terms of World Series Appearances

Teams	World Series Appearances	Wins	Market Size	Founded
New York Yankees	40	27	1	1901
New York/San Francisco Giants	20	8	6	1883
St. Louis Cardinals	19	11	21	1882
Brooklyn/Los Angeles Dodgers	18	6	2	1883
Philadelphia/Kansas City/Oakland Athletics	14	9	6	1901
Boston Red Sox	12	8	7	1901
Detroit Tigers	11	4	11	1901
Chicago Cubs	10	2	3	1871
Cincinnati Reds	9	5	34	1869
Boston/Milwaukee/Atlanta Braves	9	3	8	1871
Pittsburgh Pirates	7	5	23	1882
St. Louis Browns/Baltimore Orioles	7	3	26	1894
Philadelphia Phillies	7	2	4	1883
Washington Senators/Minnesota Twins	6	3	15	1901
Chicago White Sox	5	3	3	1901
Cleveland Indians	5	2	17	1901
New York Mets	4	2	1	1962
Kansas City Royals	3	1	31	1969
Florida/Miami Marlins	2	2	16	1993
Toronto Blue Jays	2	2	N/A	1977
Washington Senators/Texas Rangers	2	0	5	1961

San Diego Padres	2	0	28	1969
Los Angeles Angels of Anaheim	1	1	2	1961
Arizona Diamondbacks	1	1	12	1998
Tampa Bay Rays	1	0	13	1998
Colorado Rockies	1	0	18	1993
Houston Astros	1	0	10	1962
Seattle Pilots/Milwaukee Brewers	1	0	35	1969
Montreal Expos/Washington Nationals	0	0	9	1969
Seattle Mariners	0	0	14	1977

Table 2
**Filled-in cells are significant to the 5% level

Draft Pick	T-Test
2	0.034129
3	0.693882
4	0.602973
5	0.533885
6	0.255026
7	0.214219
8	0.829065
9	0.685843
10	0.296447
11	0.005484
12	0.048219
13	0.319594
14	0.563109
15	0.612838
16	0.761837
17	0.862107
18	0.096867
19	0.206652
20	0.820901
21	0.057375
22	0.087393
23	0.219002
24	0.558106
25	0.67738
26	0.461903
27	0.373103
28	0.628651
29	0.644907
30	0.527947
31	0.987138
32	0.650766
33	0.339522
34	0.442948
35	0.333438
36	0.896032
37	0.870318
38	0.190335
39	0.333121
40	0.432752

Table 3

Draft Slot	Median	SD
1	27.3	26.57172
2	7.5	15.19939
3	6.8	16.44725
4	1.4	19.57335
5	0	15.0688
6	0.2	35.99766
7	0.1	15.0837
8	0	13.51883
9	0.8	12.88938
10	1.7	18.6548
11	0	5.468549
12	2.4	12.05623
13	0	13.88421
14	0.1	11.32142
15	0	13.98787
16	1.5	12.28004
17	0.3	14.77363
18	0	4.554741
19	0	27.76346
20	0	21.48601
21	0.4	6.254772
22	1.4	19.57223
23	0	11.19454
24	0	8.047553
25	0	7.931309
26	0	13.49477
27	0	4.613934
28	0	6.363576
29	0	8.172612
30	0	13.86016
31	0	22.49046
32	0	6.512936
33	0	5.312542
34	0	9.092992
35	0	12.70353
36	0	22.50695
37	0	12.26642
38	0	4.78602
39	0	31.98811
40	0	8.328432

Table 4

Player	Old Team (OT)	Market (OT)	New Team (NT)	Market (NT)	Year
Michael Bourn	Atlanta Braves	8	Cleveland Indians	17	2012
Josh Hamilton	Texas Rangers	5	Los Angeles Angels	2	2012
Hiroki Kuroda	New York Yankees	1	New York Yankees	1	2012
Adam LaRoche	Washington Nationals	9	Washington Nationals	9	2012
Kyle Lohse	St. Louis Cardinals	21	Milwaukee Brewers	35	2012
David Ortizº	Boston Red Sox	7	Boston Red Sox	7	2012
Rafael Soriano	New York Yankees	1	Washington Nationals	9	2012
Nick Swisher	New York Yankees	1	Cleveland Indians	17	2012
B.J. Upton	Tampa Bay Rays	13	Atlanta Braves	8	2012
Carlos Beltran	St. Louis Cardinals	21	New York Yankees	1	2013
Robinson Cano	New York Yankees	1	Seattle Mariners	14	2013
Shin-Soo Choo	Cincinnati Reds	34	Texas Rangers	5	2013
Nelson Cruz	Texas Rangers	5	Baltimore Orioles	26	2013
Stephen Drew^	Boston Red Sox	7	Boston Red Sox	-	2013
Jacoby Ellsbury	Boston Red Sox	7	New York Yankees	1	2013
Curtis Granderson	New York Yankees	1	New York Mets	1	2013
Ubaldo Jimenez	Cleveland Indians	17	Baltimore Orioles	26	2013
Hiroki Kuroda	New York Yankees	1	New York Yankees	1	2013
Brian McCann	Atlanta Braves	8	New York Yankees	1	2013
Kendrys Morales^	Seattle Mariners	14	Minnesota Twins	-	2013
Mike Napoli	Boston Red Sox	7	Boston Red Sox	7	2013
Ervin Santana	Kansas City Royals	31	Atlanta Braves	8	2013
Max Scherzer	Detroit Tigers	11	Washington Nationals	9	2014
Victor Martinez	Detroit Tigers	11	Detroit Tigers	11	2014
Hanley Ramirez	Los Angeles Dodgers	2	Boston Red Sox	7	2014
Pablo Sandoval	San Francisco Giants	6	Boston Red Sox	7	2014
James Shields	Kansas City Royals	14	San Diego Padres	28	2014
Russell Martin	Pittsburgh Pirates	23	Toronto Blue Jays	-	2014
Nelson Cruz	Baltimore Orioles	26	Seattle Mariners	14	2014
David Robertson	New York Yankees	1	Chicago White Sox	3	2014
Ervin Santana	Atlanta Braves	8	Minnesota Twins	15	2014
Francisco Liriano	Pittsburgh Pirates	23	Pittsburgh Pirates	23	2014
Melky Cabrera	Toronto Blue Jays	-	Chicago White Sox	3	2014
Michael Cuddyer	Colorado Rockies	18	New York Mets	1	2014

ºRe-signed with the Red Sox before the beginning of free agency
^Did not sign with New Team until after the upcoming First-Year Players' Draft had passed
**Filled-in cells represent teams that are in a top-11 market

Table 5

**Filled-in cells are significant to the 5% level

T-Tests	Pick #1	Pick #2	Pick #3	Pick #4	Pick #5	Pick #6	Pick #7	Pick #8
Pick #2	0.0341							
Pick #3	0.0133	0.6939						
Pick #4	0.0114	0.3703	0.6030					
Pick #5	0.0028	0.1439	0.2481	0.5339				
Pick #6	0.2242	0.6306	0.5496	0.2591	0.2550			
Pick #7	0.0006	0.1076	0.1687	0.4362	0.8374	0.2142		
Pick #8	0.0029	0.1432	0.2394	0.4879	0.9914	0.2422	0.8291	
Pick #9	0.0021	0.2249	0.4160	0.7353	0.6134	0.3218	0.5741	0.6858
Pick #10	0.0563	0.9974	0.8261	0.5988	0.2161	0.7325	0.1200	0.1256
Pick #11	0.0002	0.0017	0.0139	0.0571	0.2325	0.0607	0.3386	0.1056
Pick #12	0.0011	0.2240	0.3844	0.7109	0.6917	0.3453	0.5413	0.6417
Pick #13	0.0016	0.0921	0.1526	0.3162	0.7227	0.1850	0.8783	0.6356
Pick #14	0.0007	0.1342	0.2243	0.5057	0.9526	0.2452	0.7685	0.9625
Pick #15	0.0001	0.1032	0.1647	0.3745	0.7565	0.1838	0.9034	0.7189
Pick #16	0.0029	0.0373	0.1420	0.4589	0.9590	0.2277	0.8631	0.9510
Pick #17	0.0016	0.2039	0.2632	0.5354	0.8989	0.2723	0.7214	0.8148
Pick #18	0.0001	0.0011	0.0069	0.0415	0.1513	0.0500	0.2335	0.1195
Pick #19	0.0218	0.5741	0.7138	0.9313	0.6907	0.4740	0.6021	0.6908
Pick #20	0.0025	0.6586	0.8429	0.8440	0.3751	0.5524	0.2547	0.4297
Pick #21	0.0000	0.0054	0.0190	0.1054	0.2283	0.0802	0.3382	0.2206
Pick #22	0.0073	0.4950	0.7375	0.9423	0.4094	0.3541	0.3943	0.4661
Pick #23	0.0007	0.0446	0.0998	0.2231	0.6057	0.1115	0.6778	0.5567
Pick #24	0.0001	0.0074	0.0181	0.0974	0.2949	0.0907	0.3955	0.1461
Pick #25	0.0001	0.0050	0.0143	0.0785	0.1925	0.0684	0.0354	0.1505
Pick #26	0.0005	0.0471	0.0692	0.2734	0.5704	0.1391	0.7106	0.4909
Pick #27	0.0000	0.0023	0.0070	0.0488	0.0984	0.0575	0.1551	0.1017
Pick #28	0.0001	0.0035	0.0162	0.0837	0.2332	0.0614	0.3033	0.1416
Pick #29	0.0001	0.0157	0.0275	0.1663	0.3885	0.1051	0.5111	0.3416
Pick #30	0.0009	0.1183	0.1569	0.3960	0.6408	0.1971	0.9545	0.7653
Pick #31	0.0082	0.1556	0.2888	0.4785	0.8517	0.2420	0.9769	0.7593
Pick #32	0.0002	0.0103	0.0297	0.1204	0.3482	0.1024	0.5267	0.3217
Pick #33	0.0000	0.0021	0.0084	0.0630	0.0640	0.0594	0.2147	0.1126
Pick #34	0.0002	0.0062	0.0209	0.1150	0.3458	0.0693	0.4676	0.2721
Pick #35	0.0010	0.0530	0.1301	0.3327	0.6988	0.1260	0.8741	0.6853
Pick #36	0.0045	0.0641	0.2077	0.1711	0.8856	0.0145	0.9886	0.8682
Pick #37	0.0009	0.0552	0.1142	0.3332	0.6800	0.1577	0.8464	0.6323
Pick #38	0.0000	0.0012	0.0075	0.0479	0.1135	0.0539	0.1891	0.0806
Pick #39	0.0319	0.4739	0.5745	0.7768	0.8362	0.3950	0.7921	0.8945
Pick #40	0.0002	0.0025	0.0061	0.0312	0.2245	0.0614	0.3542	0.2104

T-Tests	Pick #9	Pick #10	Pick #11	Pick #12	Pick #13	Pick #14	Pick #15	Pick #16
Pick #2								
Pick #3								
Pick #4								
Pick #5								
Pick #6								
Pick #7								
Pick #8								
Pick #9								
Pick #10	0.2964							
Pick #11	0.0684	0.0055						
Pick #12	0.9942	0.3072	0.0482					
Pick #13	0.4222	0.1194	0.3191	0.3196				
Pick #14	0.7305	0.1668	0.0894	0.5862	0.5631			
Pick #15	0.4844	0.1150	0.3945	0.4490	0.9715	0.6128		
Pick #16	0.5995	0.1353	0.1279	0.6415	0.6588	0.9109	0.7618	
Pick #17	0.7979	0.2102	0.1485	0.7665	0.5775	0.9210	0.6436	0.8621
Pick #18	0.0283	0.0069	0.6138	0.0225	0.3031	0.0620	0.2900	0.1165
Pick #19	0.8644	0.5977	0.2498	0.8647	0.5158	0.7046	0.5308	0.6395
Pick #20	0.6106	0.7201	0.0661	0.5628	0.2614	0.3506	0.2650	0.3685
Pick #21	0.0579	0.0114	0.9285	0.0519	0.4473	0.0754	0.3228	0.1910
Pick #22	0.5880	0.6305	0.0541	0.6683	0.3110	0.4895	0.3356	0.3937
Pick #23	0.3161	0.0675	0.3921	0.2968	0.8332	0.4428	0.8453	0.5439
Pick #24	0.1108	0.0015	0.8746	0.0804	0.4826	0.1290	0.4363	0.2369
Pick #25	0.0591	0.0056	0.7228	0.0399	0.3135	0.0834	0.2941	0.1433
Pick #26	0.3267	0.0900	0.5807	0.3208	0.8238	0.4868	0.7792	0.5379
Pick #27	0.0084	0.0071	0.5239	0.0127	0.2289	0.0548	0.2399	0.0739
Pick #28	0.0499	0.0115	0.9344	0.0430	0.3983	0.0981	0.3457	0.1739
Pick #29	0.1685	0.0403	0.6764	0.1168	0.6096	0.2479	0.4404	0.3250
Pick #30	0.3946	0.1144	0.3451	0.4853	0.9229	0.6747	0.9513	0.7967
Pick #31	0.6285	0.0757	0.4395	0.5985	0.9277	0.8115	0.9510	0.8624
Pick #32	0.1569	0.0283	0.5331	0.1065	0.5877	0.2139	0.6037	0.2769
Pick #33	0.0050	0.0097	0.6242	0.0179	0.2709	0.0513	0.2394	0.0992
Pick #34	0.1035	0.0218	0.7902	0.1348	0.5680	0.2017	0.5217	0.3186
Pick #35	0.3618	0.1032	0.3740	0.4308	0.9916	0.6300	0.9788	0.7387
Pick #36	0.6685	0.2654	0.4212	0.6659	0.8902	0.8383	0.9167	0.9033
Pick #37	0.3444	0.0951	0.3972	0.3204	0.9678	0.5731	0.9380	0.6939
Pick #38	0.0175	0.0049	0.4229	0.0142	0.2182	0.0431	0.1222	0.0633
Pick #39	0.9325	0.4949	0.4395	0.9407	0.7249	0.9022	0.7390	0.8644
Pick #40	0.0659	0.0160	0.9290	0.0773	0.4203	0.1530	0.4012	0.1629

T-Tests	Pick #17	Pick #18	Pick #19	Pick #20	Pick #21	Pick #22	Pick #23	Pick #24
Pick #2								
Pick #3								
Pick #4								
Pick #5								
Pick #6								
Pick #7								
Pick #8								
Pick #9								
Pick #10								
Pick #11								
Pick #12								
Pick #13								
Pick #14								
Pick #15								
Pick #16								
Pick #17								
Pick #18	0.0969							
Pick #19	0.7594	0.2067						
Pick #20	0.4485	0.0496	0.8209					
Pick #21	0.1952	0.5823	0.2713	0.0574				
Pick #22	0.5564	0.0308	0.8874	0.8924	0.0874			
Pick #23	0.4917	0.2982	0.4347	0.2134	0.4841	0.2190		
Pick #24	0.1325	0.6702	0.2813	0.0591	0.9635	0.1006	0.5581	
Pick #25	0.1090	0.9500	0.2120	0.0622	0.6750	0.0639	0.2035	0.6774
Pick #26	0.4889	0.4470	0.3420	0.1973	0.6274	0.1691	0.9324	0.6629
Pick #27	0.0852	0.7529	0.1721	0.0484	0.5096	0.0257	0.1991	0.5468
Pick #28	0.1483	0.7862	0.2329	0.0619	0.8621	0.0725	0.2922	0.8451
Pick #29	0.3042	0.4540	0.2544	0.1149	0.7314	0.1383	0.7132	0.7946
Pick #30	0.6711	0.2454	0.5174	0.3268	0.3662	0.3025	0.7994	0.3638
Pick #31	0.7533	0.4378	0.6218	0.4177	0.5462	0.4680	0.8386	0.4809
Pick #32	0.2822	0.3047	0.2392	0.1176	0.6730	0.1410	0.7006	0.7210
Pick #33	0.1065	0.8830	0.2028	0.0423	0.5660	0.0280	0.2884	0.6060
Pick #34	0.2316	0.5594	0.2988	0.1115	0.8588	0.0942	0.6432	0.8945
Pick #35	0.6051	0.2513	0.5042	0.2415	0.3963	0.2770	0.8249	0.4639
Pick #36	0.7940	0.3499	0.6455	0.3991	0.5128	0.2721	0.7900	0.5371
Pick #37	0.5880	0.2627	0.4849	0.2599	0.4126	0.2562	0.9055	0.4890
Pick #38	0.0715	0.5930	0.1621	0.0423	0.3728	0.0417	0.2204	0.4505
Pick #39	0.9513	0.3833	0.8522	0.6830	0.4366	0.7393	0.6530	0.4695
Pick #40	0.1874	0.8074	0.2277	0.0777	0.8680	0.0799	0.4387	0.8621

T-Tests	Pick #25	Pick #26	Pick #27	Pick #28	Pick #29	Pick #30	Pick #31	Pick #32
Pick #2								
Pick #3								
Pick #4								
Pick #5								
Pick #6								
Pick #7								
Pick #8								
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Pick #16								
Pick #17								
Pick #18								
Pick #19								
Pick #20								
Pick #21								
Pick #22								
Pick #23								
Pick #24								
Pick #25								
Pick #26	0.4619							
Pick #27	0.8693	0.3731						
Pick #28	0.7869	0.5621	0.6287					
Pick #29	0.4940	0.7800	0.3329	0.6449				
Pick #30	0.2682	0.7457	0.1575	0.3486	0.5279			
Pick #31	0.4420	0.8003	0.3942	0.4586	0.6597	0.9871		
Pick #32	0.4391	0.8117	0.2095	0.5619	0.9633	0.4872	0.6508	
Pick #33	0.9585	0.4166	0.8968	0.6789	0.3906	0.1644	0.4138	0.3395
Pick #34	0.6104	0.7395	0.4902	0.7381	0.8925	0.4596	0.6167	0.8522
Pick #35	0.2836	0.8136	0.2121	0.1655	0.6001	0.9304	0.9339	0.5933
Pick #36	0.4136	0.7664	0.3628	0.4761	0.6290	0.9522	0.9702	0.6238
Pick #37	0.2982	0.8059	0.2297	0.3409	0.6020	0.8885	0.9049	0.6235
Pick #38	0.7786	0.3314	0.8199	0.5184	0.1621	0.1776	0.3593	0.1577
Pick #39	0.3847	0.6298	0.3513	0.4280	0.5338	0.6346	0.7956	0.5111
Pick #40	0.8244	0.5680	0.6774	0.9860	0.6563	0.3538	0.5048	0.5362

T-Tests	Pick #33	Pick #34	Pick #35	Pick #36	Pick #37	Pick #38	Pick #39
Pick #2							
Pick #3							
Pick #4							
Pick #5							
Pick #6							
Pick #7							
Pick #8							
Pick #9							
Pick #10							
Pick #11							
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Pick #13							
Pick #14							
Pick #15							
Pick #16							
Pick #17							
Pick #18							
Pick #19							
Pick #20							
Pick #21							
Pick #22							
Pick #23							
Pick #24							
Pick #25							
Pick #26							
Pick #27							
Pick #28							
Pick #29							
Pick #30							
Pick #31							
Pick #32							
Pick #33							
Pick #34	0.4429						
Pick #35	0.1493	0.3334					
Pick #36	0.3883	0.5376	0.8960				
Pick #37	0.1882	0.3508	0.9445	0.8703			
Pick #38	0.7643	0.4089	0.1850	0.3358	0.1903		
Pick #39	0.3463	0.4963	0.7202	0.8200	0.6918	0.3331	
Pick #40	0.7565	0.7647	0.3648	0.4433	0.3769	0.5961	0.4328

Table 6

Team	Count	Mean	25 %ile	Median	75 %ile	SD	Win %
Arizona Diamondbacks	4	1.2500	-0.7250	-0.35	1.625	3.5180	0.514
Atlanta Braves	35	6.7429	0	0.7	7	15.5697	0.493
Baltimore Orioles	35	6.6057	0	0	2.85	15.9979	0.505
Boston Red Sox	35	9.0114	0	0	2.2	25.6588	0.516
Chicago Cubs	43	7.0930	0	0	4.65	20.4097	0.458
Chicago White Sox	43	7.1860	0	0	2.7	16.2567	0.486
Cincinnati Reds	33	5.0606	0	0	4	12.6840	0.505
Cleveland Indians	39	6.2846	0	0	1.6	15.7483	0.475
Colorado Rockies	11	9.2091	0	0.2	13.75	16.9324	0.458
Detroit Tigers	34	5.8500	0	0	2.65	13.5897	0.479
Houston Astros	38	6.2921	0	0.1	4.325	14.6249	0.501
Kansas City Royals	34	5.6647	0	0	3.15	13.4412	0.493
LA Angels of Anaheim	35	6.1229	-0.1500	0.1	11.1	9.8654	0.476
LA Dodgers	31	3.9065	0	0	3.05	9.1239	0.512
Miami Marlins	11	10.8727	0	0.1	22.95	15.8246	0.425
Milwaukee Brewers	33	9.5030	0	0	13.2	17.3763	0.479
Minnesota Twins	44	8.0795	0	0.45	10.75	13.2641	0.455
New York Mets	43	7.3209	0	1	11.8	12.2719	0.483
New York Yankees	22	5.4636	0	0	1.75	16.1106	0.538
Oakland Athletics	41	6.6683	0	0.1	4.1	14.0137	0.479
Philadelphia Phillies	28	6.8821	0	0.4	4.85	14.2767	0.483
Pittsburgh Pirates	36	6.6694	0	0	0.175	28.0071	0.481
San Diego Padres	39	5.3179	0	0	4.45	10.3874	0.467
San Francisco Giants	44	7.7205	0	0	2.05	26.4822	0.486
Seattle Mariners	42	12.8143	0	0.85	18.35	22.3325	0.441
St. Louis Cardinals	41	5.7049	0	0.4	6.9	10.8201	0.491
Tampa Bay Rays	4	8.4750	-0.2500	3.8	12.525	13.1244	0.414
Texas Rangers	37	5.7324	0	0	9.2	13.4612	0.479
Toronto Blue Jays	39	8.3897	-0.0500	0	7.4	16.5429	0.480
Washington Nationals	46	7.8522	0	0	8.6	18.3806	0.483

Appendix C

Draft Slot	2000	1999	1998	1997	1996	1995	1994
1	34.8	27.3	18.3	0.6	14.4	28.3	8.2
2	-0.4	39	18.5	44.9	7.1	4.1	6.6
3	-1.6	-1.8	9.6	35.1	5.1	18.8	12.8
4	0	0	-0.4	5.4	4.3	22	-0.7
5	-0.8	0	44.9	24.6	5.9	3.7	0.1
6	7.6	0	0	0	1.7	0	-0.4
7	0	1.7	17.9	3.3	0.1	0	0
8	0	0	9.7	0.9	0	55.2	9.3
9	0	30.6	5.2	17.3	19.9	24.5	0.8
10	0	30.7	16.9	22.2	35.4	-2.6	12.1
11	0	0	0	0	7.4	0	0
12	-1.5	15.9	8.7	0	2.9	26.8	41.5
13	0	0	0	1.6	0	17	24.8
14	0	0	22.1	-1.3	0	-0.2	24.3
15	59.2	0	0	-0.9	0	0	0
16	1	14.2	0	55.5	-1	-0.1	0
17	-0.2	0	10.7	0	0	67.5	5.5
18	0	0	-0.3	0	14.8	0	0
19	1	26.7	-0.2	0	-0.1	0	0
20	0.2	0	61.7	18.3	18.9	0	5.2
21	4	1.4	1.9	0.7	19.3	0	-1.5
22	-1.4	0.8	11	33.7	17	0.4	-0.3
23	0	-0.2	-1.3	0	-0.1	0	1.7
24	0	0.6	0	-0.1	0	0	0.4
25	0	2.7	-0.9	0	0	-2.4	4.7
26	0	0	0	1.1	0	-0.4	2.2
27	0	0	-0.4	0.2	0	0	0
28	0	0	-0.5	-0.5	0	5.8	-1.4
29	32.7	0	0	0	0	0	12.4
30	-1.3	0	0	6.5	-0.8	2.1	3.2
31	3.3	-0.7	1.3	-1	0	22.4	4.7
32	0	0	-0.2	0	-0.2	-1.5	0
33	5.8	0	11.9	0	0	-0.8	-0.4
34	1.5	0	1.1	0	4.4	-0.2	2.9
35	0	0	24.3	0	7.4	6.4	0
36	0.1	0	-1.3	0	0	-0.3	-0.6
37	0.3	2.3	0	0	13	0	35.1
38	16.8	11.5	0	0	0.3	0.4	0
39	0	4.6	0	-0.7	0	0	0
40	0	0	0	0	19.2	0	0

Draft Slot	1993	1992	1991	1990	1989	1988	1987
1	111	15.1	0	84.8	20.7	33.7	77.3
2	9.6	7.5	0.7	12.5	1.5	-2.8	0
3	11.9	0	-2.6	19.7	0.8	20.3	4.3
4	1.3	8.3	13	27.2	0	9.5	5.2
5	-0.7	-1.1	0	-0.7	-1.5	0	33.6
6	0.1	73.5	0.2	-1.8	0	-0.4	3.5
7	21.9	1.4	-0.9	14.4	72.6	0	0
8	0	0	14.7	0	0	21.6	0
9	0	10.4	0.8	0	-0.3	0.3	53.2
10	-0.1	9.8	1.7	17.3	26	56.8	0
11	0	-0.3	16.1	2.8	1.4	3.1	1.4
12	23.6	0	9.8	10	2.4	0	24
13	0	0	66.7	9.2	5.4	0	9.6
14	35.7	4.3	23.4	1.4	-0.4	29	1.7
15	38.9	1.3	0	1.1	0	19.2	0
16	4.9	-0.1	31	0	-0.4	-0.3	7.3
17	0	-0.3	2	24.6	13.2	32.9	-0.2
18	0	0	0	-0.3	4.4	0	4
19	3.5	21.8	2.1	0	-0.7	-0.7	9.6
20	42.9	0	6.6	82.5	0	0	0
21	24.3	-0.2	2.7	0	0.4	0	-0.6
22	0	14.2	0.1	9	3.8	1.4	65.1
23	7.8	40.2	31	0	31.4	0	2.6
24	0	0	0	24	-0.6	27.2	1.1
25	4.1	-0.3	-0.9	-0.3	39.8	4.6	-0.1
26	0.9	0.5	3.4	0	0	1.9	-0.4
27	0.5	0.2	1	0	11.2	-1	19.5
28	13.3	26	0	4.3	0.5	-2.9	0
29	3.1	-0.2	0	0.9	0.8	-0.9	2.3
30	0.3	0	0	0	0	31.6	30.8
31	0	0	0	0.1	0	0	0.1
32	-0.2	0	10.6	6.6	0	0	-0.9
33	0	0	0	-0.3	0	-0.9	19.9
34	-0.7	0	-1.1	0	0	17.3	-0.1
35	0	43	-0.4	0.6	5.1	0	0.4
36	1.2	0	12.1	-0.2	-0.1	0	0.8
37	0	0	0	0	0	0	-0.2
38	0	0	0	0	-1.5	0	0
39	0	0	0	0	3.4	0	13.7
40	0	-0.5	0	0	-0.5	0	0

Draft Slot	1986	1985	1984	1983	1982	1981	1980
1	17	31.3	-1.2	29.2	7.3	32.3	41.5
2	32.5	52	22.7	1.2	0	17.1	0
3	44.9	28.8	0.2	0.7	4.8	13.7	6.8
4	73.5	67.6	1.5	-0.3	-1.5	-1.3	0
5	7.2	0	-0.1	0	55.3	-0.1	0
6	62.4	164	0.6	0	9.8	27.6	-0.7
7	0.3	-0.2	2	-2.6	0.7	5.1	0.1
8	-0.6	10.2	37.9	-0.5	-1.6	2.1	1.2
9	3.1	0	-0.1	-0.4	14.7	19.6	-0.5
10	-0.5	-0.7	66.3	0.2	-0.1	1.2	14.7
11	2.2	14.8	19.7	1.1	-0.2	0	2.4
12	0.9	0	9.2	0	0	0	7
13	0.6	0	0	2.5	-2.5	0	0
14	0	7.6	0.1	0	13.7	-1.2	0
15	0	-0.4	0	0	0	0.1	0
16	14.3	0	10.8	9.5	2.9	-0.4	1.5
17	0.3	13.4	2.5	0	0	0	10.3
18	1.2	13.5	0	0	0	0	13.1
19	0.6	-0.5	0	139.5	4	1.5	10.4
20	0	20.2	-0.5	-0.5	0.1	0	-0.2
21	0	0	0	-2.4	6.9	2.8	4.1
22	1.4	70	0	4	0	4.1	-1.7
23	9.5	3.8	0	0	0	-1.1	-1.7
24	0	0	23.3	0.4	0	0.3	0.3
25	0	0	0	0	-0.6	0	5
26	0	-0.5	0	17.7	0	0	0
27	4.1	-0.1	-0.1	3.5	0	0	9.2
28	0	0	11.7	0.2	0	12.1	0
29	-0.9	0	0	22.7	-0.7	0	3.3
30	0	0	0	17.3	58.1	0	0
31	6.9	0	113.9	0	0	0	0
32	9.6	0	7	25.6	9.5	3.3	15.8
33	0	-0.4	0	-3.2	5.2	14.1	0
34	0	15.3	0	4.1	0	42.2	0
35	0.5	4.8	-0.3	0.9	0	47.2	-0.3
36	32	111.7	0	0	-0.3	-0.1	0
37	0	0	0	-0.2	4.3	47.1	0
38	0	0	0	0	0	-0.6	14.7
39	0	1.3	2.2	0	164	9.2	0
40	38.3	0	0	8	-0.2	3.9	-0.1

Draft Slot	1979	1978	1977	1976
1	-0.5	19.5	38.4	31.1
2	13.9	26	28.1	2.9
3	0	13.8	67.6	0.2
4	1.4	27	0	-0.3
5	0	5.5	0	2.7
6	41.8	0	24.1	8.8
7	-0.4	0	17.9	0
8	-0.3	0	-0.1	20
9	15.6	0	0	4.2
10	37.6	0	0	-0.1
11	0	0	0	0
12	-0.3	35.9	1.5	0
13	3.5	0.1	0	0
14	0	23.3	0.4	0
15	8.3	0	0	15.6
16	9.6	-0.7	11.5	2.7
17	1.6	9.3	0	0
18	0	6	0	0
19	-0.5	0	-0.1	28.5
20	0	0.1	36.1	-0.6
21	11.6	0	0.4	0
22	0	0	0	38.7
23	0	0	0	0
24	1.9	-0.4	0	0
25	0	-1.8	0	0
26	-0.9	0	26.3	63.7
27	-0.1	-0.4	0.1	0
28	-0.2	0	0	0
29	-1.5	2.2	15.7	3.2
30	-0.2	-1	2.4	-0.2
31	0.1	0	0	0
32	0	11.5	0.7	0.1
33	0	0	0	0
34	0.1	0	-0.1	-0.5
35	0	0	0	0
36	0	1.7	0.7	0
37	1.6	2.5	0	28.9
38	0	0	-1.7	0
39	0	7	0	0
40	0	-0.7	0	0