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Defining the "Quadruple-A" Player: What Makes a Baseball Player Succeed in the Minor Leagues and Fail in the Major Leagues?

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Abstract

The "Quadruple-A" player is defined as one who is too good to play in Triple-A (the league one step down from Major League Baseball) but not good enough to play consistently in Major League Baseball. This thesis paper attempts to explain the phenomenon of the "Quadruple-A" player. Using Triple-A data from 2013-2022 and Major League data from the "Statcast Era" (2015-2022), I build logistic and linear regression models to predict Major League success based on Triple-A performance data as well as Major League Statcast data, discovering that statistics related to how a player hits the ball such as the speed and angle of the ball off the bat, as well as the rate at which a player swings at the ball and misses, but the extent of a player's success in Triple-A does not accurately predict Major League success.

Contents

Acknowledgments

> Each time, you'll learn something. Each time, you'll develop strength, wisdom, and perspective. Each time, a little more of the competition falls away. Until all that is left is you: the best version of you.
>
> Ryan Holiday, *The Obstacle Is the Way: The Timeless Art of Turning Trials into Triumph*[30]

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Chapter 1

Introduction

Out of the most popular sports in the United States, baseball has arguably the most arduous path to its highest level. Baseball is one of the only professional sports that does not require attendance at a college or university prior to entering the Major League Baseball-affiliated leagues (being "drafted"). As such, the path from amateur baseball (either high school or college) to Major League baseball is quite long. There are six levels of minor league baseball as of the 2022 season. These include (in order of lowest to highest) the Dominican Summer League, the "Complex Leagues" (Arizona Complex League and Florida Complex League), Single-A (California League, Florida State League, and Carolina League), High-A (South Atlantic League, Midwest League, and Northwest League), Double-A (Eastern League, Southern League, and Texas League), and Triple-A (International League and Pacific Coast League) [11]. From 1981-2010, only 17.5% of players selected in the MLB Draft and signed made it to Major League Baseball [26]. M

In a study of professional baseball players between 1990 and 2010, 63% of athletes attended a 4-year college or university, 23% were drafted directly out of high school, and 14% attended a 2 year institution of higher education (usually a junior college). [34]. However, this only applies to players living in the United States, Canada, or Puerto Rico, as international amateur players are subject to Major League Baseball's signing rules and thus can sign if they at approximately 16 years old. [6]. The signing of a baseball player's first professional contract only marks the first step on a difficult journey to playing Major League Baseball.

The difficulty and length of the professional baseball player development process means that identifying talent that can advance to the highest level and perform well there is of the utmost importance for Major League Baseball teams. Although the prevalence of in-person scouting has dwindled over the last decade (and especially since the COVID-19 pandemic), Major League Baseball teams still employ dozens of people in departments such as Analytics, Biomechanics, Data Science, Player Development, Scouting, and Video Analysis to try to gain even a slight edge in developing homegrown Major League talent. [21].

Analysts typically believe that there are three major "jumps" in a professional baseball player's minor league career. The first, and likely most obvious, jump occurs when a player first enters professional baseball. Usually, this involves a switch from aluminum to wood bats, and for players being drafted out of high school or signing as an international amateur free agent, this marks the first occurrence of the player consistently facing professional-quality opponents. The second jump is referred to as "The Double-A Jump." The jump from High-A to Double-A typically is the first time in which a minor league player faces competition that is overwhelmingly future Major League Baseball players. Thus, weaknesses are more easily exposed and exploited, flaws are corrected, and if a player excels in Double-A, there is a non-zero chance that the player is promoted to Major League Baseball directly from Double-A. While this occurrence is not common, it has happened in cases such as Miguel Sano, Andrew Benintendi, and 2022 National League Rookie of the Year Michael Harris II [41]. The third jump is between Triple-A (AAA) and Major League Baseball, as this is the time in which a player will only be facing the best of the best.

While the "Double-A Jump" is typically considered the hardest jump and is where many players see their hopes of becoming a Major League Baseball player fall short, the final jump from Triple-A to Major League Baseball also leaves many players without a job. In many cases, these players go back to Triple-A and perhaps continue to succeed, or they go to leagues in overseas countries such as Japan, South Korea, or Taiwan. While some of these players come back to Major League Baseball and succeed (these players are usually pitchers and include players such as Miles Mikolas, Merrill Kelly, and Nick Martinez), many players will unsuccessfully return to the United States or see their careers fizzle out in an overseas league or in Minor League Baseball [40].

The inability to make the jump from Triple-A to Major League Baseball leaves a player in a sort of "baseball purgatory." Around baseball, this purgatory is colloquialized as being a "AAAA" or "Quadruple-A (Quad-A)" player – too good for Triple-A but not good enough for Major League Baseball. This paper seeks to explore **what defines a "Quadruple-A" hitter**. Are there statistics in Triple-A that will more accurately be a predictor of Major League success than others, or are there certain underlying metrics at the Major League level that elite Triple-A hitters may not excel at?

Several theories exist as to what makes a "Quadruple-A" player fail in Major League Baseball. These include the inability to field, a lack of plate discipline or patience, faulty mechanics, or an inability to adjust to the quality of Major League pitching [38]. However, there are many instances of players who appear nearly identical and have very similar Triple-A statistics ending up with very different Major League careers. A great example of this phenomenon is the case of Aaron Judge and Jabari Blash. Aaron Judge stands six feet, seven inches tall and was selected by the New York Yankees in 2013 Major League Baseball Draft. Judge steadily advanced through Minor League Baseball, spending time in Single-A, High-A, and Double-A, eventually leading to a brief amount of time spent in Triple-A in 2015. In 2016, Judge spent a full season in Triple-A at age 24 and performed very well. Judge recorded a batting average of .270, hit 19 home runs, had a slugging percentage of .489, and had an on-base percentage of .366. This led to an outstanding OPS (on-base percentage plus slugging percentage) of .854, earning Judge his first Major League call-up with the Yankees (the Triple-A season ends around one month prior to the end of the Major League season, allowing for players to spend a "full season" in Triple-A and still spend around one month in Major League Baseball). While Judge struggled initially in 2016, his career would take off starting the next season, winning American League Rookie of the Year in 2017, being selected to four American League All-Star teams (in 2017, 2018, 2021, and 2022), and winning the American League Most Valuable Player award in 2022 after breaking the single-season American League home run record with 62 home runs [1].

Jabari Blash stands six feet, five inches tall and was selected by the Seattle Mariners in the 2010 Major League Baseball Draft. Blash steadily advanced through Minor League Baseball, first reaching Triple-A briefly in 2014. In his age-25 season in 2015, Blash saw immense success in Triple-A. Blash recorded a batting average of .264, hit 22 home runs, had a slugging percentage of .640, and had an on-base percentage of .355. This led to an OPS of .995 – nearly 150 "points" (measured in thousandths) better than

Aaron Judge's 2016 Triple-A season. However, this marks the end of the similarities between Aaron Judge and Jabari Blash. Wihle Blash would appear in parts of three Major League Baseball seasons with the San Diego Padres and Los Angeles Angels, he struggled to a cumulative batting average of .176, hit only 8 Major League home runs, and recorded a slugging percentage of .307 and an on-base percentage of .306. Blash later signed with the Tohoku Rakuten Golden Eagles of Japan's Nippon Professional Baseball league prior to the 2019 season and spent two years in Japan before retiring prior to the 2021 season [8].

This begs the question – why did Aaron Judge succeed in Major League Baseball and Jabari Blash fail? Is there a statistical explanation that can be used to clarify why some hitters can succeed in Triple-A yet fail in Major League Baseball? Through logistical and linear regression models, I attempt to explain the "Quadruple-A" phenomenon and determine, given a data set of both successful Major League players along with "Quadruple-A" players, if there could be statistics that if applied to Minor League data could be a better predictor of Major League success and longevity.

1.1 Overview

I obtained a sample of 469 players using a data set of the top 100 Triple-A players by on-base percentage plus slugging percentage (OPS) from 2013-2022 and setting cutoffs for inclusion at 150 Triple-A at-bats and 250 Major League at-bats. I built two models to analyze this data set with the goal of finding possible correlations between Triple-A statistics and/or Major League Baseball Statcast data (batted ball statistics) and Major League success, as measured in a modified version of OPS, and longevity as measured in Major League at-bats. The logistic and linear regression models showed that Major League exit velocity (how hard a ball is hit), launch angle (at what angle a ball is hit), and whiff rate (how often a player swings and misses) correlate to Major League success. However, the model showed that Triple-A statistics do not correlate with Major League success. Although this lack of correlation can likely be explained by other factors such as mechanical issues and different statistics not examined in this paper, it was nonetheless notable that once a certain level of success is achieved in Triple-A, the extent of a player's Triple-A success did not impact Major League success.

Chapter 2

Literature Review

Previous scholarship has discussed some of the themes of this paper before or has covered possible areas of variance in hitter performance not examined in this paper.

2.1 Literature with Direct Applications to This Paper

Multiple papers have also explored the concepts of Minor League player evaluation and using Minor League data as a predictor for Major League success. Notably, Chandler and Stevens examine the predictive nature of Minor League statistics versus how teams perceive players' abilities in their paper "An Exploratory Study of Minor League Baseball Statistics." The authors find that teams generally make decisions based on a combination of performance and draft pedigree, though the importance of draft pedigree decreases as the level of Minor League Baseball gets higher, proving the least important at the Triple-A level [23]. Gary Johnson also examines how hitters are ranked based on Minor League Baseball statistics, finding that slugging ability, "lead-off hitting" ability, "pure hitting," and plate discipline were the most important factors using data from four Minor League Baseball seasons (2002-2005) [31].

In their paper "A stastistical Analysis of Hitting Streaks in Baseball," S. Christian Albright attempts to model Major League Baseball hitters between 1987-1990, and while this time period is over 30 years old, many of the paper's findings remain relevant and help to support the 250 at-bat cutoff I established for my data set. Albright's main conclusion that hitter "streakiness" (behavior that would cause a significant deviaiton from their baseline ability) does not substantially differ from a model of randomness would also seem to indicate that talent, or talent-related factors, would be a better explanation for failure to perform in Major League Baseball after succeeding in Triple-A than would a hot or cold streak [18]. For more information on hitting streaks, see Jim Albert's "Streaky Hitting in Baseball" [17].

The concept of clutch hitting (the ability of a hitter to perform in higher pressure situations, such as with runners on base or in later innings) has been explored in several academic papers, including Tom Ruane's "In search of clutch hitting" [39], Otten and Barrett's "Pitching and clutch hitting in Major League Baseball: What 109 years of statistics reveal" [36], Davis and Harvey's "Declines in Major League Batting Performance as a Function of Game Pressure: A Drive Theory Analysis" [27] and Phil Birnbaum's "Clutch hitting and the Cramer test" [19] Each of these papers studies aspects of clutch hitting that could be a possibly small aspect of Major League hitter performance that would exist in a greater scale in the Major Leagues than in Triple-A because of the emphasis on win-loss record in the Major Leagues in comparison to Minor League Baseball.

2.2 Literature that Discusses Aspects of Baseball Not Directly Incorporated Into This Paper

One factor not measured at all in this paper is the concept of "the shift." A shift is defined as a defensive alignment in which two players are not on either side of second base and standing on the infield dirt, with the goal of aligning the defense to where a hitter is more likely to hit the ball. The shift rose to prominence in the mid-2010s, and the propensity of teams to employ the shift has caused Major League Baseball to institute rules governing it in advance of the 2023 season [22]. In his paper "Hitting around the shift: Evaluating batted-ball trends across Major League Baseball,' Michael W. Model uses batter tendency data and pitch-level data to model whether batters or pitchers have adjusted for the shift, concluding that neither batters nor pitchers have adjusted and that use of the shift was likely to increase in frequency going forward [35]. This paper goes into more depth on the shift and the theoretical approaches pitchers and hitters took (or did not take) to overcome it, showing that hitters generally chose not to prioritize overcoming the shift in their tendencies.

Physical traits were also not analyzed in this paper, and one such important trait is hand-eye coordination. Laby, Kirschen, Et al. analyze the importance of hand-eye coordination in baseball in their 2018 paper "The Hand-eye Coordination of Professional Baseball Players: The Relationship to Batting," published in the *Journal of the American Academy of Optometry*. The authors use eye-hand visual-motor reaction time (EH-VMRT) system analysis on a data set of 450 professional baseball players, and the study showed that hand-eye coordination (measured by EH-VMRT metrics) had statistically significant correlations with plate discipline metrics as well as service time and achievement at the Major League level [32]. As such, imperfect hand-eye coordination would be a possible explanation for a "Quadruple-A" player that is not explored in this paper. Solomon Et al. performed a similar study in their paper "Dynamic stereoacuity: a test for hitting a baseball?" in which the authors concluded that vision may be one factor in hitting performance through dynamic stereoacuity testing [42]. Burris Et al. attempt to predict Major League Baseball performance using motor skill testing in their paper "Sensorimotor abilities predict on-field performance in professional baseball" [20].

In his book *The Hitting Edge*, author Tom Robson further dives into the kinetic and mechanical side of hitting not examined in my paper. Robson identifies eleven key factors to hitting – attitude, focus, timing, balance, recognition, rotation, front-side blocking, bat lag and angle, high finish, practice, and conditioning – that will make or break a hitter's success. *The Hitting Edge*, though published in 2003, remains a popular tool for both amateur and professional hitting coaches. Robson's eleven keys are more biomechanical and thus can possibly explain results generated at all levels of baseball [37]. In academia, Grondin Et al. study the kinetic chain in their paper "Manual laterality and hitting performance in major league baseball." In this paper, the authors show that left-handed hitters may hold an advantage in the game of baseball using a kinematic chain model [29].

Similarly, hitter handedness is not measured in this study but could be a variable that could have an impact on hitter performance in professional baseball. E.D. Clotfelter uses handedness data to measure performance in professional baseball players in their paper "Frequency-dependent performance and handedness in professional baseball players (Homo sapiens)."

Clotfelter concludes that batters form "cognitive representations based on pitcher handedness," and these representations have a greater affect on right-handed hitters than left-handed hitters as well as same-sided hitter-pitcher match-ups (right-handed hitter versus right-handed pitcher and left-handed hitter versus left-handed pitcher) [25].

Chapter 3

Data

3.1 Data Set

All Triple-A data was recorded by official scorekeepers and statisticians for Triple-A Minor League Baseball Teams and uploaded to the Minor League Baseball website, from which Baseball Reference, an web database that pulls and maintains a database of all Minor League Baseball statistics, publishes it in an easily downloadable format. All Major League Baseball batted-ball data for this paper was gathered by Major League Baseball using Trackman and Hawkeye technologies. These two technologies track a multitude of statistics during Major League Baseball games and are installed in all 30 Major League Baseball stadiums. In particular, Trackman and Hawkeye capture batted ball velocity and distance, pitched and batted ball spin rate, and defensive positioning, among a plethora of other variables. These statistics are then uploaded to Major League Baseball's "Baseball Savant" website where they are publicly available. All other Major League Baseball data used in this paper is captured by Major League Baseball and calculated by Major League Baseball statisticians before being made public on Major League Baseball's "Baseball Savant" web page.

To make the data set, I pulled the the top 100 Triple-A hitters, measured by OPS, from Baseball Reference from the 2013-2022 seasons [2]. The reason OPS is used is that it is considered one of the best (if not the best) single-rate statistic to measure hitter results. Once all data was pulled for the Triple-A OPS leaders, the minimum at-bat cutoff was normalized to 150 at-bats in order to eliminate the difference in the cutoff to qualify for the OPS leaderboard over different seasons. This cutoff allows for players who had a successful start to the AAA season but also got promoted to Major League Baseball and recorded enough at-bats in the Major Leagues to qualify there. The data set was then cleaned so to remove duplicate players, only leaving the player's best Triple-A season. While this may eliminate a player's first Triple-A season, it still demonstrates their best capability of hitting Triple-A pitching. Figure 3.1 lists the variables pulled from Baseball Reference and a description of what each variable means. In any analysis, Triple-A data will have the tag "AAA" followed by an underscore to clarify that the data is not from the Major Leagues.

Once the Triple-A statistics were cleaned, I pulled the Major League Baseball data from Major League Baseball's "Baseball Savant" web page [12]. Before being entered into Baseball Savant, I ensured that all players had a minimum of 250 at bats to appear in the data set. This number was concluded upon based on S. Christian Albright's paper on streakiness in conjunction with advisors as well as baseball coaches and personnel with the thinking that 250 at bats allowed a player who made his debut this season to appear in the data set so long as the sample was nearly half of the season. 250 at-bats usually comprises around 71 games (assuming 3.5 at bats per game), and this is far more than the 130 at-bat cutoff that causes a player to lose Major League rookie eligibility (if a hitter passes the 130 at-bat threshold in a season, the player is no longer considered a rookie for the next season and thus loses "rookie eligibility) [14]. The 250 at-bat cutoff attempts to remove any month-long hot or cold streaks while still taking into account the possibility of one-season appearances in 2022 or a brief, unsuccessful stint in Major League Baseball. For example, Adley Rutschmann recorded 398 at-bats and qualified for the data set, and the aforementioned Jabari Blash recorded 274 at-bats and thus also qualified. Figure 3.2 and Figure 3.3 provide a list of statistics included for Major League Baseball results from Baseball Savant and their definitions.

It is also important to note what was unable to be included in the data set. Notably, chase-rate (swings and misses on pitches that are outside of the strike zone) was not included in any of the sources used for the data set. This remains a possible explanation for a player with success in Triple-A and a lack of success in Major League Baseball, but due to several constraints was unable to be included in the data. Additionally, data on player value (using statistics such as Wins Above Replacement to describe how valuable a player is to his team) was not included, since this took into

Variable Title	Description
Age	The player's age during the recorded Triple-A Season
League	In which Triple-A league the recorded season occurred
G	Triple-A games played
PA	Plate appearances. This includes walks, hit by pitches, sacrifice flies, and sacrifice bunts.
AB	At-bats, defined as plate appearances minus walks, hit by pitches, sacrifice flies, and sacrifice bunts.
R	Runs scored
H	Hits
2B	Doubles
3B	Triples
HR	Home runs
RBI	Runs batted in
BB	Walks
SO	Strikeouts
BBtoSO	Walk to strikeout ratio
BA	Batting average, defined as dividing hits by at bats.
OBP	On-base percentage, with the following formula: $\frac{\text{hits + walks + hit by pitches}}{\text{At-bats + walks + hit by pitches + sacrifice flies + sacrifice bunts}}$
SLG	Slugging percentage, defined as total bases divided by at-bats. The formula for total bases is: (Singles $\cdot$ 1)(Doubles $\cdot$ 2)(Triples $\cdot$ 3)(Home Runs $\cdot$ 4)
OPS	On-base percentage plus slugging percentage
TB	Total bases
HBP	Hit by pitches

Figure 3.1 Triple-A variables and their descriptions

account aspects of player performance that was not analyzed in this data set such as defense and baserunning. Rather, this data set only focuses on hitting.

Once all variables were pulled and cleaned in the data set, a final variable was established indicating whether a player was "successful" purely as a hitter in Major League Baseball. I created a variable labeled "success." A value of 1 was assigned to the "success" variable if a player was deemed to have been a successful Major League Baseball hitter, and a value of 0 was assigned if a player was deemed unsuccessful. A few assumptions were made in order to determine hitter success in Major League Baseball. While going off a concept such as Wins Above Replacement (WAR) may have been more effective in theory, WAR would have allowed several highly ineffective hitters to qualify as success due to either their defensive skill or baserunning ability. A high WAR number would have also made it practically impossible for anyone to be labeled a success given the 250 at-bat barometer. Another possible metric was total at-bats, and while this was considered, it also takes into account the fact that teams can decide to play a poor hitter for various reasons, usually because of the player's defensive ability or intangible factors such as on-field leadership. Thus, I decided to use a modified version of OPS to determine success. While this is by no means the perfect measure to measure success for a Major League Baseball player as a whole, I concluded that if a typical Major League OPS is .750, and the typical average Major League OBP is just under .320 [33], and given that xwOBA is modeled differently than both OBP and wOBA, it was feasible to lower the barometer for success by using xwOBA plus Slugging ("xwOPS"). If a player had a xwOPS higher than .725, the player was considered to be successful and assigned a success value of 1, and unsuccessful players with values of 0 had a xwOPS lower than .725.

3.2 Descriptive Statistics

The final data set had a $n = 469$. Not including player name, the data set has 38 variables. Figure 3.4 shows the mean, variance, and standard deviation for 36 of the 38 variables, with the exception of Success and AAA_League. 158 players were defined as "Successful" with a Success value of 1 (33.69% of the data set), and 311 players were considered unsuccessful as hitters. 203 out of the 469 hitters sampled played in the International League (43.28% of the data set), and the remaining 266 played in the Pacific Coast League.

Many of the variables have significantly higher variance and standard deviation values than others, and this is almost certainly because they are "counting statistics" and are accumulated over time. For example, players who appear in more seasons in Major League Baseball will see more pitches than a player like Adley Rutschmann, who made his debut this past season in 2022. This would also explain why these values would have a large range. Variables such as pitches, whiffs, swings, takes, hits, and abs (at-bats) are all examples of this issue. This phenomenon is why I added in swing_rate and whiff_rate – to eliminate the counting-based nature of swings, pitches, whiffs, and takes (take rate would be 1 - swing rate and thus proves irrelevant). However, variables such as pitches and at-bats could also be a measure of a player's longevity in Major League Baseball and a possible secondary measure of success and thus were not moved to any rate-based statistic.

Additionally, there are a few notable observations to be made within the descriptive statistics. It is to be expected that the mean values for many of the Triple-A rate-based statistics, such as batting average, on-base percentage, slugging percentage,and OPS, were going to be substantially higher than the Major League average value for each, given that the sample was self-selecting of the top performers at the Triple-A level for a ten-year sample. Additionally, the standard deviation for these variables is smaller than one might expect, but the range of values is lower since, for example, the maximum value in the data set for Triple-A OPS is 1.247 (achieved by successful Major League hitter Ty France). Similarly, the rate-based statistics at the Major League level are a little lower, and this is to be expected since only 33.69% of players were considered successful and had close to the Major League Baseball average for OPS.

Variable Title	Description
pitches	Total pitches seen while hitting
ba	Batting average
iso	Isolated power, defined as (slugging percentage - batting average). ISO is considered to be an effective measurement for the raw power of a hitter [7].
babip	Batting average on balls in play, removing plate appearance outcomes that the opposing defense has no control over such as strikeouts and home runs. BABIP uses the following formula: $\frac{\text{hits - home runs}}{\text{At-bats - strikeouts - home runs - sacrifice flies}}$ [3]
slg	Slugging percentage
woba	Weighted on-base average (wOBA), which measures how a player reaches base, versus just measuring whether or not a player reached base, by assigning values to base-reaching outcomes [16]
xwoba	Expected weighted on-base average (xwOBA) uses launch angle, velocity, and sprint speed (for certain types of batted balls) to assign probabilities of different batted-ball outcomes by assigning comparable batted balls using Major League Baseball's Statcast technology. The batted-ball outcomes use the same values that wOBA uses. Many analysts consider xwOBA to be the best on-base statistic to predict actual player ability [5].
xba	Expected batting average (xBA) measures the probability that batted balls become hits. Similar to xwOBA, every batted ball is assigned an xBA based on comparable launch angles and exit velocities (and sometimes sprint speed) using Statcast technology[4].
hits	Hits
abs	Total at-bats
launch_speed	The average speed of the baseball upon being hit, also referred to as "Average Exit Velocity." Measured in miles per hour (MPH).
launch_angle	The average vertical angle at which the ball has left the bat upon being hit. Measured in degrees, Major League Baseball defines four major launch angle categories: a ground ball is hit with a launch angle of less than 10 degrees, a line drive has a launch angle between 10 and 25 degrees, a fly ball has a launch angle between 25 and 50 degrees, and a pop up has a launch angle is greater than 50 degrees [10].

Figure 3.2 Major League Baseball variables and their descriptions

whiffs	Number of occurrences in which batter swings and misses
swings	Number of pitches swung at. Includes times in which contact is made as well as whiffs
takes	Number of pitches not swung at
whiff_rate	Whiff rate, defined by $\frac{\text{whiffs}}{\text{swings}}$
swing_rate	Swing rate, defined by $\frac{\text{swings}}{\text{pitches}}$

Figure 3.3 Major League Baseball variables and their descriptions (continued)

Variable	μ	σ^2	σ
pitches	5435.594	20209380.3	4495.484
ba	0.241	0.00006	0.025
iso	0.148	0.00223	0.0472
babip	0.295	0.000924	0.0304
slg	0.389	0.00325	0.0298
woba	0.303	0.000886	0.0298
xwoba	0.298	0.00136	0.0369
xba	0.234	0.000778	0.0279
hits	315.716	78534.323	280.240
abs	1260.328	1085466.74	1041.857
launch_speed	87.619	5.732	2.394
launch_angle	11.664	24.775	4.977
whiffs	634.603	271656.231	521.207
swings	2579.075	4540352.02	2130.811
takes	2848.209	5763058.18	2400.637
whiff_rate	0.253	0.00356	0.0596
swing_rate	0.478	0.00209	0.0457
AAA_Age	26.013	10.820	3.289
AAA_G	78.062	649.417	25.484
AAA_PA	330.458	11862.916	108.917
AAA_AB	291.721	9388.202	96.893
AAA_R	49.215	327.921	18.109
AAA_H	89.275	878.409	29.637
AAA_2B	18.529	50.656	7.117
AAA_3B	2.548	6.560	2.561
AAA_HR	11.228	43.386	6.587
AAA_RBI	47.349	348.061	18.656
AAA_BB	31.561	236.473	15.378
AAA_SO	60.819	697.307	26.407
AAA_BBtoSO	0.55119	0.0543	0.233
AAA_BA	0.307	0.000603	0.0246
AAA_OBP	0.378	0.000927	0.0305
AAA_SLG	0.507	0.00515	0.0718
AAA_OPS	0.886	0.00785	0.0886
AAA_TB	146.584	2353.833	48.516
AAA_HBP	3.552	9.496	3.082

Figure 3.4 Mean, variance, and standard deviation for data (rounded to the nearest thousandth or third significant figure)

Chapter 4

Model and Results

To attempt to answer the research question, two models were used – a logistic regression model and a linear regression model. I sought to see if any notable variables from Triple-A effectively showed whether a player would be a successful Major League hitter as determined by xwOPS (xwOBA + SLG), thus employing various independent variables against three main dependent variables – the success indicator, Major League xwOPS, and Major League at-bats. These three dependent variables, out of the Major League variables in the data set, most accurately project both success and longevity at the Major League level. In addition, I sought to determine whether any "Statcast Data" – exit velocity, launch angle, whiff rate, and swing rate – were possible indicators of Major League success in a data set that primarily features players who succeeded in Triple-A but failed in the Major Leagues.

4.1 Logistic Regression Model

The first model used was a logistic regression model, coded in R. The reasoning for use of the logistic model was to attempt to find a threshold within Triple-A statistics that would determine whether a Major League player would be successful using the binary success indicator. A basic logistic regression (using success as the example dependent variable) model uses the following equation:

$$P(Success = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}} \tag{4.1}$$

Figure 4.1 shows a basic visual representation of Triple-A OPS versus Major League xwOPS.

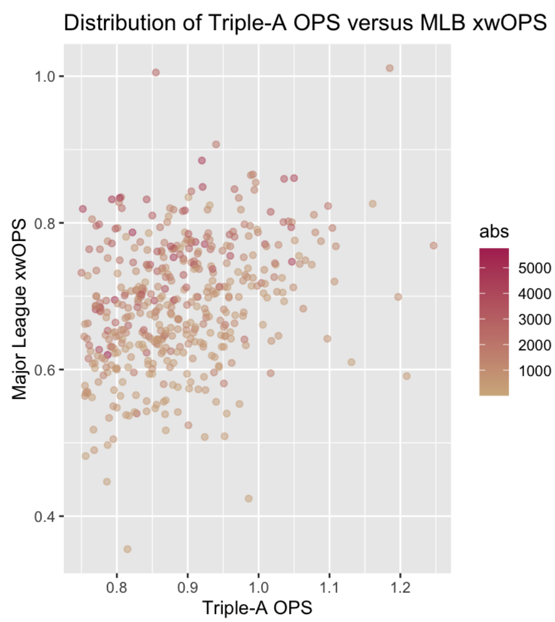

Figure 4.1 Scatter plot distribution of Triple-A OPS versus Major League xwOPS

However, to determine the threshold values of the independent variables, a second, more precise equation must be used in the logistic model. The following equation is used to determine the thresholds (transition points in the logistic curve):

$$P(Success = 1) = \frac{1}{1 + e^{-k(x - x_0)}} \tag{4.2}$$

The threshold of the curve is represented by x_0, and its value is dependent on the specific regression run, allowing it to be represented by various Triple-A statistics. The model coded in R provides a T β_0 and β_1

values, and I could use these values to solve for the x_0 for the independent variable(s).

4.1.1 Logistic Regression Model for Triple-A Statistics

The first test I ran examined a possible relationship between Triple-A OPS and Major League Success using the "Success" indicator variable. The goal of this model was to see if there was a simple logistic correlation between these two variables. It was abundantly clear there was no such relationship – McFadden's pseudo-R^2 value, which mirrors a typical adjusted R^2 measuring the model's strength compared to the null value, in this model was 0.0608, and this is visualized in Figure 4.2

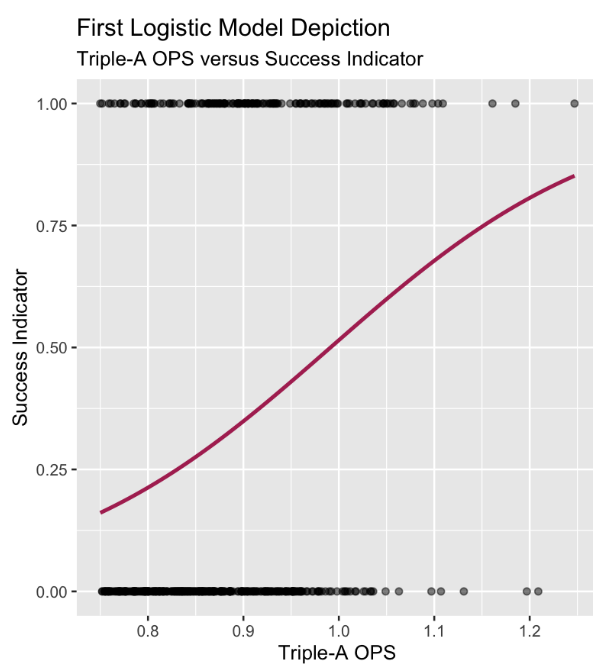

Figure 4.2 First logistic regression model using Triple-A OPS and the Major League success indicator

A second logistic model attempted to measure the effect of power and plate discipline in Triple-A, and this demonstrated nearly as little a relationship as the first model. A model using Triple-A home runs (as a measure for power) and Triple-A strikeout to walk ratio (the plate discipline measure). No curve can be deciphered as seen in Figure 4.3.

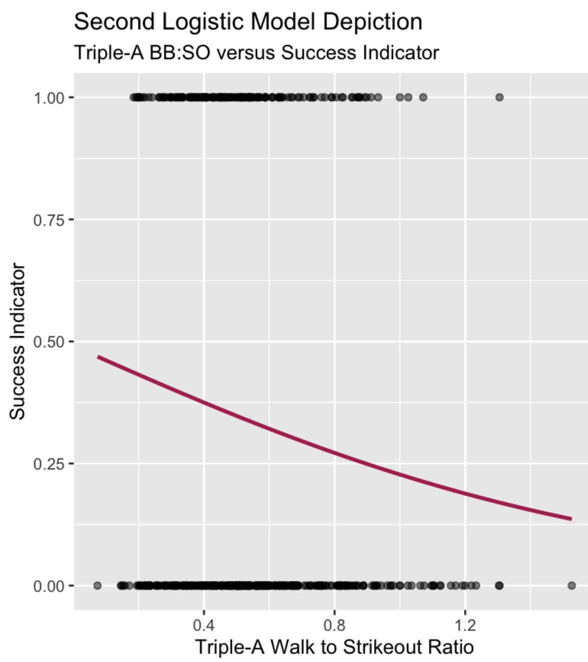

Figure 4.3 Second logistic regression model using Triple-A walk to strikeout ratio and the Major League success indicator

Upon building logistic regression models for various individual Triple-A statistics and combinations of Triple-A statistics, it became abundantly clear that no Triple-A statistic fit into a logistic regression model with the Major League success indicator as the dependent variable. This failure can be seen in Figure 4.4, which shows the failed logistic regression model between Triple-A plate appearances and the success indicator to see if longevity in Triple-A mattered. This, however, would prove futile, as the AAA_PA variable only provides the number of plate appearances in the recorded Triple-A season, not a player's total Triple-A plate appearances.

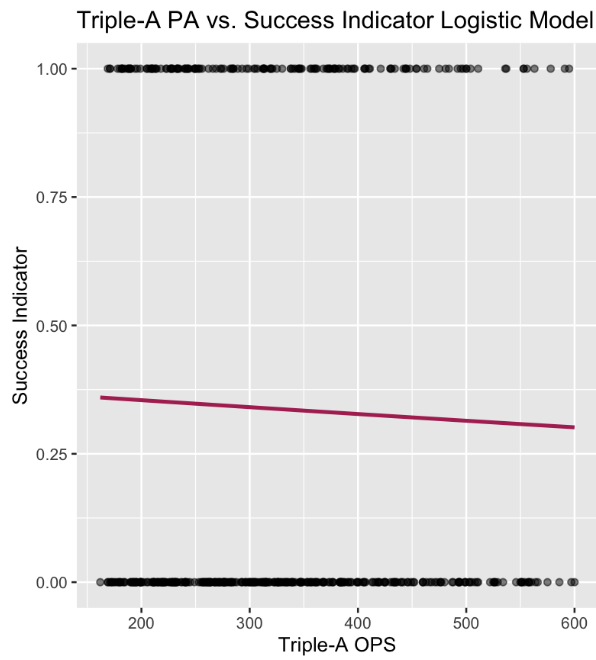

Figure 4.4 Logistic regression model using Triple-A plate appearances and the Major League success indicator

4.1.2 Logistic Regression Model for Major League Statistics

Before concluding that the Major League success indicator would not relate to any variables listed, I sought to test the four aforementioned variables – exit velocity, launch angle, whiff rate, and swing rate – to see if they logistically correlated to the success indicator.

First, I tested exit velocity (launch speed) against the success indicator, and this showed much more productive results. This regression demonstrated significant logistical correlation. Figure 4.5 shows a table of regression statistics from this regression. In addition, McFadden's pseudo R^2 value equaled 0.238.

This regression recorded a statistically significant P-Value and showed some possible correlation between these two variables. Additionally, for this model, β_0 = -61.16166, and β_1 = 0.6874514, allowing me to calculate a threshold value of **88.9687 MPH** for average exit velocity to dictate a

	Estimate	Std. Error	Z-Value	P-Value
(Intercept)	-61.16166	6.65292	-9.193	<2e-16
launch_speed	0.68745	0.07528	9.132	<2e-16

Figure 4.5 Major League average exit velocity versus success indicator logistic regression statistics

successful Major League hitter as measured by my success indicator. A visual representation of this logistical regression can be seen in Figure 4.6. Interestingly, although a clear lower bound can be seen, the model appears to not predict an upper bound prior to the maximum average launch angle of the sample being reached. This may be a function of the optimal launch angle being somewhere between the minimum and maximum sampled values.

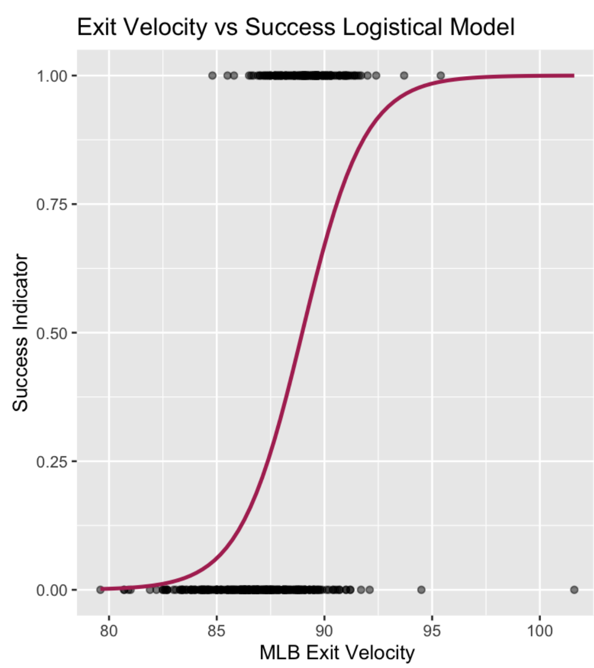

Figure 4.6 Logistic regression model using Major League average exit velocity and the Major League success indicator

I then built logistical regression models to calculate thresholds for average launch angle, whiff rate, and swing rate. The logistical model for average launch angle versus the success indicator was statistically significant, though McFadden's pseudo R^2 value measured only 0.0457, demonstrating that launch angle may have less of an impact on Major League success than exit velocity does. The threshold for launch angle was discovered to be **17.58209 degrees**. A visual representation of this model can be seen in Figure 4.7, and the visual representation shows clearly the impact the difference in McFadden's pseudo R^2 has between this model and the model depicted in Figure 4.6.

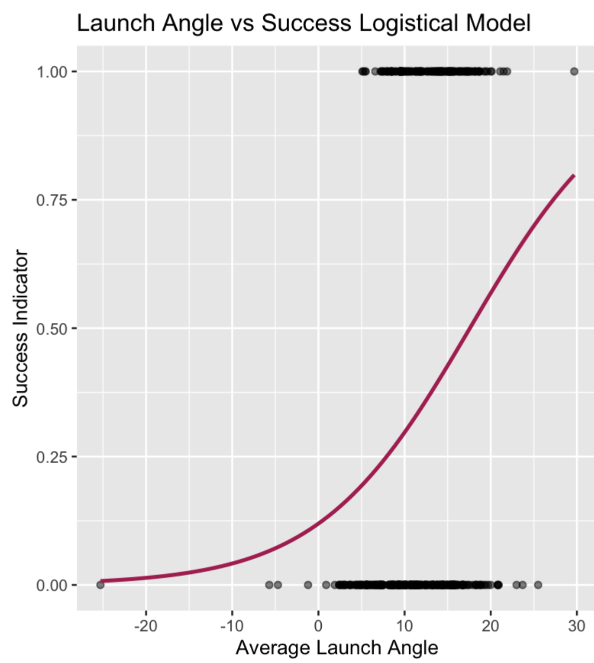

Figure 4.7 Logistic regression model using Major League average launch angle and the Major League success indicator

A logistic regression model run on swing rate versus the success indicator yielded no workable results. McFadden's pseudo R^2 value was 0.00137, and the p-values were not statistically significant. While the results from a logistic regression model regressing whiff rate against the success indicator yielded statistically significant results, McFadden's pseudo R^2 value was only 0.0230, showing minimal effectiveness and strength of the model. A visual representation of this model can be seen in Figure 4.8.

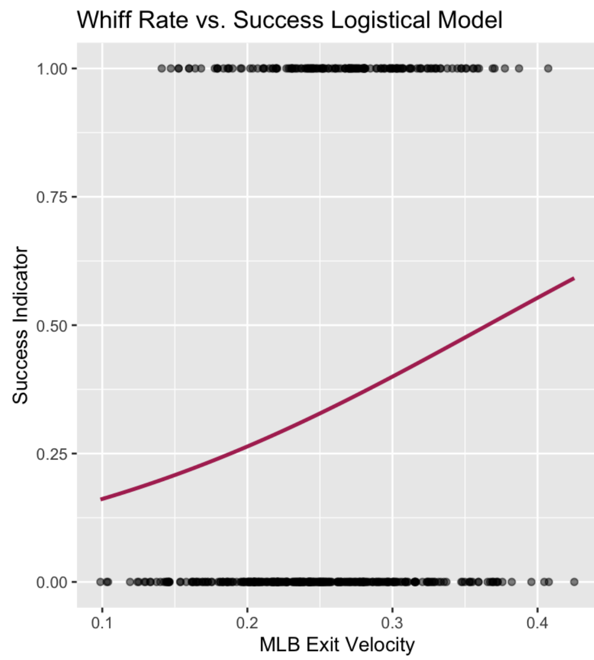

Figure 4.8 Logistic regression model using Major League whiff rate and the Major League success indicator

4.2 Linear Regression Model

To attempt to find a relationship between Triple-A statistics and non-binary Major League statistics, I ran a linear regression model in R. The basic linear regression equation is as follows:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots \beta_n x_n \tag{4.3}$$

4.2.1 Linear Regression Model for Triple-A Statistics

To confirm that there was no linear relationship between the Triple-A statistics and the Major League success indicator variable as measured using a logistic regression model in Section 4.1, I ran a series of brief linear regression models using the success indicator as the dependent variable. None of these showed meaningful correlation or statistical significance. Each of the other Triple-A variables proved to have similarly ineffective linear regression models when using the success indicator as the dependent variable in the model. This does make logical sense, as it proves difficult to use a linear regression model with a binary dependent variable.

I then ran two linear regression models for Triple-A OPS – first compared to Major League xwOPS, and then compared to Major League at-bats. The first model proved to be statistically significant, with a p-value of $9.98 \cdot 10^{13}$ for the independent variable. An adjusted R^2 value of .1065 showed that while this may not be a perfect representation of what correlates with xwOPS, it certainly has *some* correlation. A visual representation of this model can be seen in Figure 4.9. As the visual representation depicts, this model is far from perfect but does show some correlation.

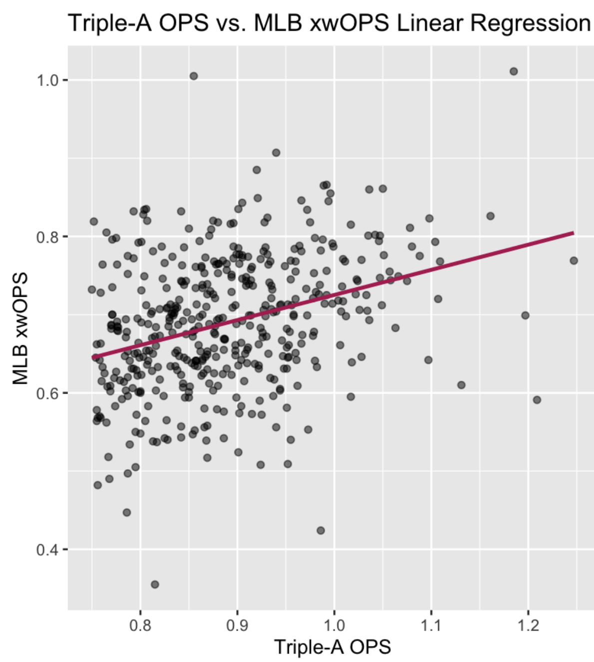

Figure 4.9 Linear regression model using Triple-A OPS and Major League xwOPS

However, the linear regression model with Triple-A OPS as the independent variable and MLB at-bats as the dependent variable showed minimal correlation. The adjusted R^2 value was 0.00243, and the results were not statistically significant.

I next ran a linear regression model for the power-discipline combination utilized in the second logistic regression model previously, using

Triple-A home runs and walk to strikeout ratio. This model yielded statistically significant results with an adjusted R^2 value of 0.0867. A visual representation of this regression can be seen in Figure 4.10.

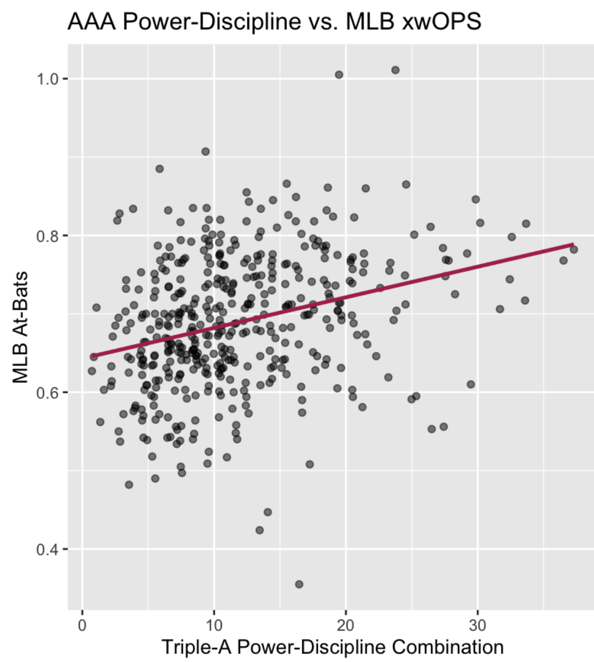

Figure 4.10 Linear regression model using the Triple-A power-discipline combination and Major League xwOPS

Similarly to Triple-A OPS, a linear regression model between the Triple-A power-discipline combination and Major League at-bats yielded poor, statistically insignificant results. I ran a linear regression model on Triple-A plate appearances versus Major League xwOPS, and this model was also poor and yielded statistically insignificant results. I did not run a regression between Triple-A plate appearances and Major League at-bats because these two variables are mutually exclusive – both are time-dependent, and a player cannot be both in Triple-A and in the Major Leagues.

4.2.2 Linear Regression Model for Major League Statistics

Similar to the logistic regression model involving Major League "Statcast" data, I sought to see whether the same independent variables correlated with either Major League xwOPS or Major League at-bats using the linear regression model.

Average Major League exit velocity significantly positively correlated with Major League xwOPS, with the adjusted R^2 value equalling 0.352. The results were also statistically significant, and statistics from this linear regression can be seen in figure 4.11, and a visual representation of this regression model can be seen in Figure 4.12.

	Estimate	Std. Error	Z-Value	P-Value
(Intercept)	-1.186668	0.120591	-9.84	<2e-16
launch_speed	0.021412	0.001376	15.56	<2e-16

Figure 4.11 Major League average exit velocity versus xwOPS linear regression statistics

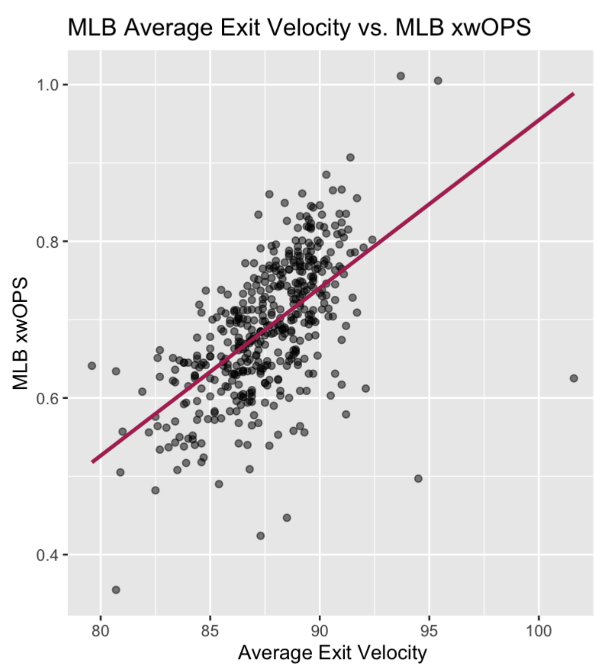

Figure 4.12 Linear regression model using Major League average exit velocity and Major League xwOPS

A linear regression model run on average Major League launch angle against wxOPS also demonstrated statistically significant results and showed some correlation, with an adjusted R^2 of 0.1079. However, as can be seen in the visual representation in Figure 4.13, many of the sample values were bunched in a small range, showing the flaws of launch angle as a solo independent variable in a regression model.

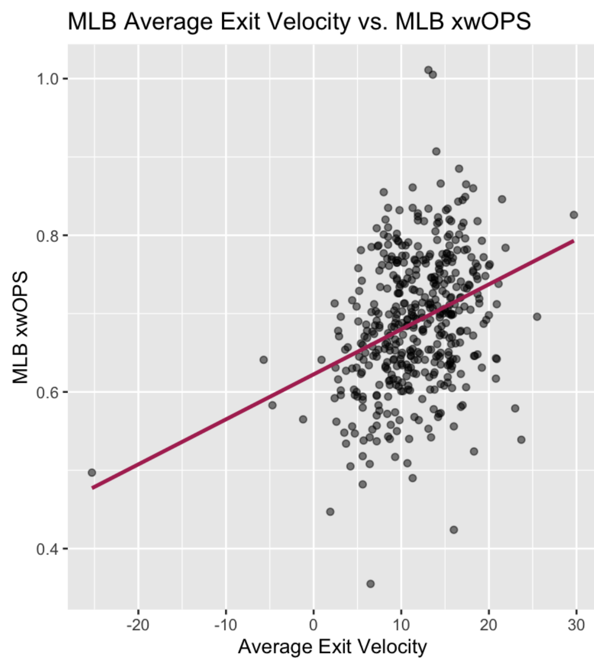

Figure 4.13 Linear regression model using Major League average launch angle and Major League xwOPS

When average launch angle and average exit velocity were combined into one linear regression, further correlation was shown, with an adjusted R^2 value of 0.4166. However, combining this with any Triple-A data or the other hypothesized Major League independent variables yielded no significant additional correlation beyond the adjusted R^2 in the bivariate linear regression model.

Similar to the logistic regression model done using whiff rate and swing rate as independent variables, The adjusted R^2 value for whiff rate versus xwOPS was 0.0210, and although the results were statistically significant, minimal correlation was shown. When swing rate was used as an independent variable in a linear regression model with xwOPS, no correlation was found, and the results were not statistically significant. The same results were found when applying a linear regression model to swing rate or whiff rate as independent variables and Major League at-bats as the dependent variable. When applied to a linear regression model with Major League at-bats as the dependent variable, independent variables of either average launch angle and average exit velocity also did not show correlation with Major League at-bats. However, when at-bats were held to a maximum of 2000, there was a small and statistically significant correlation. Although the adjusted R^2 is only 0.012, it is still worth noting. A visual representation of this regression can be seen in Figure 4.14.

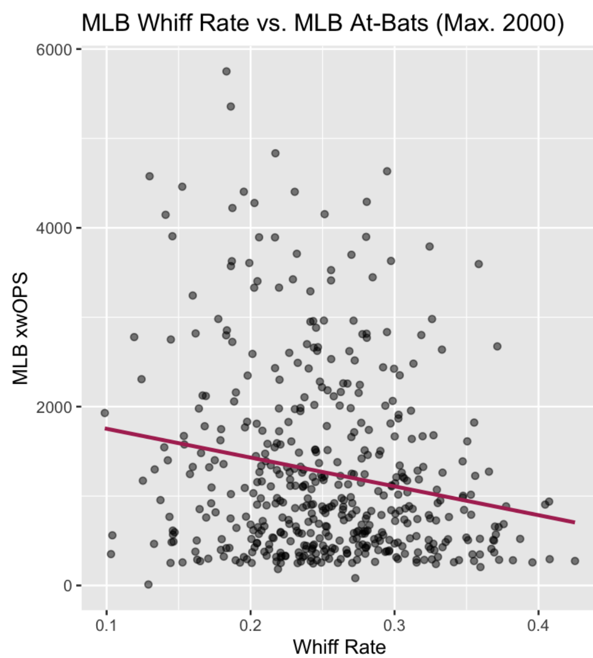

Figure 4.14 Linear regression model using Major League whiff rate and Major League At-Bats (Max. 2000)

Chapter 5

Discussion

The models and their results reveal a lot about what does and does not predict Major League success and/or longevity. There seems to be minimal, if any, correlation between Triple-A statistics and Major League success given the threshold of a .750 Triple-A OPS is met. Intuitively, this observation makes sense – players perform well in Triple-A may or may not succeed in Major League Baseball, but the extent of their superior Triple-A performance does not dictate whether or not they will succeed in the Major Leagues. This goes to show why Jabari Blash and Aaron Judge had similar Triple-A statistics – with Blash actually having better Triple-A OPS (a metric I used frequently to measure Triple-A success), yet vastly different Major League Baseball careers. I would hypothesize that success whatsoever in Triple-A would be a significant indicator of Major League success. However, to test this hypothesis would require a data set of players who were not successful in Triple-A but still recorded a significant number of Major League at-bats, something that may be counter-intuitive to Major League Baseball teams' developmental philosophies.

There are several additional hypotheses as to why to what extent a Triple-A player is successful (provided that they *are* successful) does not play a significant role in determining whether or not the player is successful in Major League Baseball. The first hypothesis is mentioned in Alex Skillin's article "The Double-A Jump" in 2015 on the baseball statistics website "FanGraphs." Skillin and then-FanGraphs analyst (currently ESPN MLB Insider) Kiley McDaniel stated that Triple-A rosters are less "stocked with prospects but rather used as 'more of an inventory level for big-league rosters'" [41]. This theory would indicate that measuring

Double-A success may be a better barometer for predicting Major League success, though again it may be necessary to measure players who were not successful in Double-A but recorded a significant number of Major League at-bats, and this possibility is even less likely than the same scenario with Triple-A success as players who are not successful in Double-A are unlikely to be promoted to Triple-A, let alone Major League Baseball. With that said, the results of this paper begin to ask the question of whether the extent of Double-A success – how well a player can handle "The Double-A Jump" – may matter in predicting Major League success and can be viewed as an area for future study.

Moreover, there are additional variables that were not analyzed in this paper that are worth examining using similar analyses to those in this paper. Most importantly, as previously stated, chase rate (swings on pitches that are outside of the strike zone) data was not used in this paper. Given the small correlation that whiff rate produced, it is reasonable to infer that chase rate data could give insight to why the "Quadruple-A" player exists and possibly serve as a major reason. While walk to strikeout ratio is a widely-accepted method to measure plate discipline with surface-level data, chase-rate is considered to be a more effective method to do so [24]. It is quite applicable, then, that a small correlation was discovered between whiff rate and xwOPS, as whiff rate is likely the closest indicator to chase rate that I analyzed. Even then, chase rate would likely provide a far better indicator of Major League success than whiff rate did. Additionally, analyzing whiff rate or swing rate on specific types of pitches – especially in certain locations – may be of significance. It is quite possible that the ability to hit a slider on the outside third of home plate or a fastball in the upper third of the strike zone may be an indicator of a player's ability to be successful in Major League Baseball, and this data was not analyzed in this paper. It is quite possible, if not very likely, that the explanation as to why players hit certain pitches well lies not in the results but in a player's swing, and that minute differences in a player's swing can dictate whether a swing will miss or result in a home run when a batter only has 0.2 seconds to react to a pitch.

While this paper analyzed hitting data, additional data is available and could be used to attempt to predict Major League success. For example, defensive statistics such as Major League Baseball's Statcast Outs Above Average (OAA) or Ultimate Zone Rating (UZR) could also dictate success, particularly at positions such as shortstop, catcher, or center field [13] [15].

While defense usually is not the driver at most positions, many teams choose to value defense in certain positions – particularly the aforementioned three – and this could be a factor to keep a player who may not be succeeding as a hitter in the Major Leagues.

With that said, the discovery of correlations between exit velocity and launch angle with xwOBA and the success indicator still hold importance. Although these relations were not examined in the context of a larger data set of Major League Baseball players, this would absolutely be an area of further study and would help to further validate the findings of this paper, since this data set could involve players who jumped directly from Double-A to Major League Baseball or players who were not among the most successful in Triple-A and would allow the findings to be generalized to all Major League players. I would hypothesize that these findings would hold true with a larger data set of Major League players.

While it is logical that if a player hits the ball hard, they will then achieve better results and are more likely to be successful in Major League Baseball, this paper defines that a 1 mile per hour increase in average exit velocity will increase a Major League hitter's wxOPS by 0.0214. This is a notable increase. Batting average, on-base percentage, slugging percentage, and OPS are typically referred to within baseball in "points," in which one point equals one thousandth. A 0.0214 increase in wxOPS would be a 21.4 "point" increase, taking a .780 wxOPS hitter to a .801 wxOPS hitter. Out of all analyses and discoveries in this paper, I would contend that this be the most valuable one. It absolutely encourages the question of whether these discoveries would hold if Minor League Statcast data was used, and this would make for worthwhile future study.

Chapter 6

Conclusion

This chapter returns to the question that defined this paper: "What makes Aaron Judge different from Jabari Blash?" The answer, according to this paper, is not in to the extent each player succeed in Triple-A but rather in underlying metrics from Minor League Baseball that are not available to the public except in a game by game basis, and even then, that data was not made available until recently. As statistics like exit velocity, launch angle, and (albeit to a lesser extent) whiff rate produced statistically significant correlations in logistic and linear regression models, it is a reasonable conclusion to assert that what caused Blash and Judge to differ was their underlying metrics in Minor League Baseball. This could also explain why, despite both players struggling in their first taste of Major League Baseball – Judge recorded just a .608 OPS in 84 Major League at-bats in 2016, compared to Blash's .622 OPS in 84 Major League at-bats in the same season – Blash was removed from the 40-man (extended) roster in the 2016-2017 offseason, while Judge was expected to be the Opening Day right fielder for the New York Yankees in 2017 [9].

Of course, there are a plethora of other possibilities. As outlined in previous chapters, Judge and Blash could have mechanical differences in their swings, and this paper does not attempt to analyze the difference in their defensive ability, and Judge did win 2019 Wilson Defensive Player of the Year Award for his ability in right field [28]. This defensive prowess could have been a possible explanation for the Yankees' continued faith in Judge compared to the Padres lack of confidence in Blash.

There are countless comparisons that can be made like the one between Aaron Judge and Jabari Blash, and often one of these players with similar "build" and Minor League statistics goes on to become a Major League superstar while the other becomes an afterthought in most minds except those of eager baseball analysts. What remains clear is that the explanation as to why the Jabari Blash's of the world exist can likely be found in "Statcast data" from their Minor League career as well as possible swing-based or non-hitting reasons.

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