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The Bonus: An Analysis of Fund Allocation in the MLB First Year Player Draft

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ABSTRACT

How do Major League Baseball teams allocate their signing bonus funds for the Rule IV draft? This thesis answers the question revolving around the effectiveness of four different behavioral decisions that organizations decide upon when selecting and signing their draft picks. By analyzing the frequency of four draft behaviors – signing the first selection above or at/below slot and subsequently second selection above or at/below slot – the regression measures no significant influence that these decisions carry over the success of the draft class. The lack of a clear dominant behavior suggests that the draft selection process is in an equilibrium.

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Chapter 1

Introduction

Firms maximize profits in the standard economic model by competing given consumers' demand. In this system, firms seek advantages in the marketplace that they use to increase their net revenues. Firms that hold many advantages while efficiently operating out-compete firms without advantages in the same market. Therefore, firms grow and increase production relative to less efficient firms. This efficient market outcome leads to higher net gains for participants.

In sports leagues, the two main goals of teams are to maximize net profits and maximize wins where the demand is influenced by consumers' "interest." Applying the market hypothesis to professional sports leagues creates a system where resource availability and efficient management favors certain teams which use these advantages to out-compete resource scarce teams and less efficiently run teams. The market creates an externality of low on-field competition where game outcomes are predictable; "good" teams remain "good," and "bad" teams remain "bad" without sufficient upward mobility. The consequence of the extreme case where a dominant team emerges results in decreased consumer "interest" in the league which adversely affects all teams (including the dominant team).

Fans – the primary consumers – prefer a product (the games) without a known result. The leagues must balance teams such that individual games are competitive in the short run and league winners vary in the long run. To counteract the standard market competition forces which cause a negative externality, leagues have tried different regulatory measures in team roster building to spread player productivity across teams instead of allowing it to pool with the best run and most resource equipped team.

Due to prior systems failing to balance Major League Baseball and the limited effectiveness of other current measures, the league converged to an organized procedure (the “amateur draft”) that streamlines amateur player matching to baseball teams that need increased talent relative to the league. I focus on this most recent attempt at balance (beginning in 2012) which implemented a flexible and constrained budget to teams when signing their picks. This paper further analyzes the effectiveness of four distinct allocation behaviors for the first two selections of a given baseball draft to better inform individual teams and the collective league of draft selection trends.

My empirical analysis of team behaviors finds no significant difference between four distinct budget allocation behaviors when predicting future productivity of drafted players. I conclude that the draft selection process is therefore in an optimal equilibrium that promotes competitive balance as intended.

1.1 Major League Baseball Draft Basics

To promote league parity (equating the level of competitiveness between teams across the league) drafts are organized based on team performance such that lower performing teams select players prior to the higher performing teams. In this format, the inverse of the previous year’s standings determines the order: the worst record owns the first pick in each standard round of the draft while the best record from the previous year owns the last pick in each standard round. The priority selections (in theory) give weaker teams an advantage in each round.

The MLB draft includes key features differentiating it from other major professional sports leagues' entry drafts: such features contribute to the unique tradeoffs that baseball organizations must consider when deciding which players to select, increasing the potential for straying from the intended league outcome of competitive balance.

One unique feature of the baseball draft is the eligible player pool. Unlike the National Basketball Association (NBA) and National Football League (NFL), the MLB allows graduating high school seniors into the pool. Additionally, players selected in the MLB draft may forgo their selection and refuse to sign with the drafting team, then re-enter the draft in subsequent years. In the case of an unsigned player, the draftee cannot sign with another team until a subsequent draft and the team cannot select a different player with the lost pick. The baseball draft requires that once players enter college, they must reach their 21st birthday or complete their junior year of college (whichever comes first) to re-gain draft eligibility. Rising sophomores and rising juniors therefore lack general eligibility.

Unique to the MLB, all draft picks enter the minor leagues to begin their careers. Generally, the highest achieving picks that reach the MLB level do so within two to four years of their draft, unlike other pro-sports league where draftees contribute immediately.

The minor leagues (apprenticeship teams that compete only within their sub-level of competition) are generally reserved for young players not ready for the demands of the Majors or journeymen who fail to perform well enough to make MLB rosters. Drafted players begin their careers with these minor league teams to develop their skills and prepare them for the majors. This extensive apprenticeship process takes years and players earn significantly lower wages than those in the MLB. Players demand an upfront amount to justify entering this drawn-out process, especially high schoolers that hold the bargaining chip of refusing to sign and instead accept college scholarships.

Enter the signing bonus.

When signing a player after the draft, teams offer a minor league contract that grants the labor rights of said player to the respective drafting team for a consistent, defined amount of time. Additionally, teams provide incentive money – signing bonuses – that entice the players into inking their deals.

Previous formats allowed for teams to offer unlimited amounts of money to their draftees. Bonus values began rising rapidly which undercut the goal of the draft in promoting balance, so the league implemented “soft suggestions,” or anchor prices correlating to each pick that teams and agents relied upon for negotiating. These suggestions, also referred to as pick values, decrease with each successive pick. For example, the 2021 first pick (held by the Pittsburgh Pirates) valued at $8,415,300 while the 300th pick valued at $144,800.

The most recent format and focus of this study (2012-2021) alters the bonus process once more. Instead of soft suggestions at every pick, every team is assigned a pool of money equal to the aggregate sum of each of their pick suggestions in the first ten rounds. Teams retain discretion of how much to spend on each individual bonus for players in the first ten rounds, however the total bonus amount must not exceed the pool threshold. For example, the Pirates 2021 assigned pool totaled $14,394,000 to spend on all their picks in the first ten rounds.

Each pick made after round ten has the same suggested bonus. Any bonus dollar spent over the constant value in these rounds count directly against the pool. For example, in 2021 all selections from round 11-20 had a suggested pick value of $125,000 separate from the bonus pool. If the Pirates signed a round 14 player to $130,000, they would have $14,389,000 left to sign their first ten round picks. The pool also removes the value from any unsigned player's selection slot in the first ten rounds, eliminating the strategy of "wasting" a pick to accrue more signing bonus money for fewer players.

Strict penalties are triggered when teams spend more money on draftees than allotted, including taxes paid to the league and losing future draft picks; organizations tend to avoid such consequences (no team in the period of study spent over 105% of available bonus pool money). Through contacting players and their representatives prior to the draft, teams attempt to learn the amount of money that players will sign for prior to making their selection; the team wants to know that they will not exceed their bonus pool in order to sign each player in a given draft class (the players selected by a given team in a given year).

My study assumes that teams conducted "investigating" prior to each selection: they generally know a narrow range of what bonus amount the draftee demands. In essence, a team desires to optimize their constrained budget funds in selecting players. Each draftee produces expected future output and corresponds with a given price. This thesis is the first public study to analyze team bonus pool (aggregate slot value) spending trends (in place since 2012).

1.2 Baseball Statistics and Terminology

Instead of traditional stats like batting average, earned run average, and runs batted in, baseball researchers prefer highly sophisticated mathematical models to capture what they strive to define: productivity. By 2012, most teams employed an advanced statistics department to aid in decision making. Due to the proliferation of advanced statistics and data driving decisions in the industry and in research, I utilize the popular and widely accepted statistic Wins Above

Replacement (WAR) to capture productivity. WAR calculates player value by a complex formula that weights traditional baseball statistics across positions, providing a comparable metric that applies to both pitchers and position players.

A limitation of my study lies in accurately measuring defensive production. Debate continues to swirl around the accuracy and relevance of defensive metrics; by using WAR, I include these potentially unreliable defensive measures by default as the statistic encompasses all aspects of a player's performance. Generally, offensive production greatly outweighs defensive production in the WAR calculation.

1.3 Classification of Team Draft Behaviors

The purpose of this study lies in analyzing the success of organizational draft allocation behaviors for the Rule IV Draft. By first assuming that teams understand the expected talent level of prospects and their willingness to accept bonus value, teams face a portfolio problem when selecting players: maximize the expected productivity of all draftees given the bonus pool constraint.

With teams considering how much money each player will cost against their budget (a major assumption in the analysis), they trade off a pick's impact on expected production with its impact on spending for the rest of the draft. Therefore, selecting a player to spend higher than (over slot) or lower than (under slot) the suggested pick value to maintain future pick flexibility represents one key decision a given team makes.

Additionally, the distribution of the budget heavily skewing towards first round and second round picks means that the largest decision occurs in these first two picks. Those first two decisions set the stage for the financial flexibility (or lack thereof) later in the draft.

The study includes four behaviors:

1. Spend at or below slot in the first pick & at or below slot in the second pick (LL).
2. Spend at or below slot in the first pick & above slot in the second pick (LH).
3. Spend above slot in the first pick & above slot in the second pick (HH).
4. Spend above slot in the first pick & at or below slot in the second pick (HL).

I hypothesize that behavior two (LH) will prove most successful in the data. Teams saving money on a high-quality player early in the draft allow for the selection of another high-quality player in the second round that other teams may pass on due to financial concerns. The team then signs two talented players while diversifying their exposure of the risky amateurs. By spreading the risk over two back end first round talent players instead of one high end first-round player and back end second-round player, the team also potentially retains additional money to again spend on better players as the draft progresses.

Chapter 2

Literature Review

2.1 Competitive Balance

Major League Baseball desires competitive balance: the commissioner's office continually seeks out methods to promote competition on the field. Though one team maximizing wins may have a goal of winning every game, this outcome would pose a negative externality to the league: the uncertainty in game outcomes benefits fans on each side of the game outcome (Solow and Krautmann, 2007).

One of the main pillars in competitive balance across sports lies in their respective amateur drafts. In a comprehensive review on the literature surrounding the "big four" American sports leagues drafts, Johnston et. al report that "the intentions were, and continue to be, to provide weaker teams a relatively greater opportunity to improve their programs, to deter costly bidding wars for talented young athletes, and help minimize the chance a team would monopolize the best, young players" (Johnston et. al, 2021). They conclude that across sports, "conclusions (cannot be drawn) with confidence that athletes selected earlier in the draft (from weaker teams) are significantly better than those chosen later in the draft (by stronger teams)." One of the reasons that conclusions should not be drawn stem from the limited studies regarding the topic of amateur drafts.

While the lack of numerous studies poses some concern, one pitfall of the review lies in the fact that all four leagues (NFL, NBA, MLB, NHL) are included in the analysis and each league contains a different set of rules with minute, but important, distinctions in their respective drafts. Specifically, in the MLB, the reverse order of the draft promotes balance in that the weakest teams choose from the pool of players first, theoretically improving their chances at selecting the best player. It also includes the signing bonus aspect, deterring the weak, small market teams from selecting the expensive players.

In studying the success of observed behaviors in the MLB draft, I will be contributing to the literature of professional baseball competitive balance by studying the ways in which teams have increased their competitive output relative to other organizations by way of the draft.

2.2.1 Predicting Success of Amateurs

Within the literature investigating the success of talent evaluation, the indicators of success primarily include draftee career length, statistics accumulated, impact on team wins, and financial compensation earned (Johnston et. al, 2021). As noted by the review of NBA and NFL draft decisions, the discovery that team decision makers bias playing time toward earlier picks regardless of their observed performance statistics presents the flaw in using career length as an indicator of success (Johnston et. al, 2021). This applies to baseball teams when they advance/promote earlier picks through the system to reach the MLB quicker, providing more playing time on the minor league team to enhance development, and generally being more patient with the development process than with later picks.

Additionally, draftees may produce different output based on the environment that they enter. Certain organizations offer better training and coaching than others, while certain players perform differently while sharing the field with teammates that possess certain skills that complement those of the draftee (aspects out of the draftee’s control). These variables are difficult to quantify but are important to consider when studying statistical production.

Within the literature specific to baseball, reaching the major leagues shines as an accomplishment that warrants success; this is because only 8% of top ten round draft picks become regulars in the MLB (Burger and Walters, 2009). Spurr concurs, stating that there “is more uncertainty in the baseball draft” than the NBA’s and NFL’s.

In assuming that the order of draftees is consistent with their expected future potential, Spurr concludes that individual teams do not differ in their abilities to discover talent from 1966-1983, as well as that college players are more likely to make it to the major leagues. While legitimate at the time of his publication, Spurr’s major assumption that draft position is consistent with expected performance should be questioned as it applies to the period of 2012-2021.

Sign ability, or the predetermined agreement between the player and the team about how much the player seeks prior to the draft, plays a huge role in whether a team will draft said player, regardless of talent. The period of study also disregards any allocation tradeoff from a bonus pool, as that change began in 2012.

2.2.2 Productivity of Draftees

As mentioned above, the application of WAR lends itself to being the most abundantly studied statistic in the analysis of the success of draftees by production. However, Burger and Walters use a statistic called win shares. In effect, win shares act similarly to WAR by estimating the rate of return that teams experience in marginal product of value after drafting a player and paying him a signing bonus from 1990-1997.

A key idea within their study is the fact that service time requirements grant teams a monopsony over player salary during the first six years of their MLB careers, allowing teams to exploit the players and pay them less than their marginal revenue product. Burger and Walters also only include players who become "at least regulars," or the 8.1% of the total sample of drafted players to account for players with "positive cash flow generators." According to their regression model, falling one spot in the top of the first round of the draft costs a player 5.5% in signing bonus dollars, but only 3.5% by the 20^{th} pick. They also estimate the marginal value of a win to equal $1.15 million.

Following their regression, they detail first round picks generate a 44% rate of return despite that only less than 25% of first round picks become at least regulars at the big-league level. Second and third round picks generate returns at 29% and 22%, respectively. They find no significant difference between first round high-schoolers or collegians becoming at least a regular in the MLB.

Burger and Walters observe that, holding draft position constant, collegians are 10% cheaper to sign than high schoolers, which is consistent with the research by Garmon on bargaining for bonus values in the draft. Therefore, the main result finds that teams experience 19% greater returns on collegians than high schoolers (Burger and Walters, 2009).

On the surface, this may indicate that collegians perform better in the MLB, however, these differences in rates of return are consistent with Roach from 2003-2019 which finds that "draft picks from 4-year college programs are more likely than high school players to ultimately make an MLB roster (56.7% of them make an MLB roster as compared to 47.2% of high school players). However, conditional on making an MLB team, high school players have a higher average value as measured by career WAR" (Roach, 2021). The findings are also consistent with

Barden and Choi which conclude that “college players were more likely to make it to the major leagues, but high school players that did make it to the major leagues tended to outperform college players that made it to the major leagues” (Barden and Choi, 2021). This potential inefficiency in historic draft behavior motivates additional research into the high school vs college demographic: I test the performance differences between college and high school players in the new signing bonus era.

College players also reach the major leagues earlier given their physical maturity and additional experience that occasionally allows them to progress faster through their minor league apprenticeship than their high school counterparts. According to Burger and Walters, the outperformance of the high schoolers compared to the college players does not matter. The speed at which the collegians reach the MLB and the reduced bonus cost because of their reduced leverage (also discussed by Garmon) leads to collegians being better investments than high schoolers.

The “true” rate of return is unknown, so discrepancies between the rates of return in the first, second, and third round may indicate that teams are overspending in the second and third round or underpaying first round picks by way of artificially anchored bonuses. This literature relating to rates of return of draft picks could represent value towards draft behavior, however, the period of the data predates what are believed to be massive changes in behavior by strategic decision makers through the use of data analytics (Elitzur, 2020). Additionally, these rates of return and signing bonus values are from a collective bargaining agreement that did not include bonus pools for the draft, furthering the need for relevant research in this new era.

2.3 Leverage and Bargaining

The draft provides negotiating rights to one team which removes the hurdle of bidding against other teams once a player is drafted. Nevertheless, this obstacle does not disappear since leverage plays a role in negotiating when a player has the option to reenter the draft the following year if he has remaining eligibility.

Garmon studies the effects on bargaining and the bonus agreements reached between draftees and teams following the shortened window of negotiation, the increase in compensation picks, and the requirement that teams make offers first (implemented separately following the collective bargaining agreements of 2003 and 2007).

Garmon outlines the effect of forcing the team to offer first as an ultimatum game in which the player is best to counter as close to the deadline as possible. He uses an anecdote from an agent and a general manager of a club to enhance his point that waiting longer to counter increases the money received by the draftee.

He also describes the behavioral economics idea of anchor prices and framing to describe the 2002 implementation of bonus slot recommendations which significantly decreased total bonus money to draftees despite no requirements to use the recommendations. As supported by Burger and Walters, Garmon reports that, ceteris paribus, high schoolers receive $110,000 higher bonuses than college juniors. This is because of the high schoolers' ability to enter the draft at least two more times, compared to the junior only one more time.

Additionally, college seniors receive the lowest of all bonuses, which may discourage juniors from returning to college hoping to get more money the following year. Interestingly, Roach finds that high school picks in the top five rounds average a cumulative $2.5 million spent per team out of the $5.5 million total per team spent on the top five rounds.

Garmon also utilizes a statistic that incorporates pre-draft player ranking to estimate the change in bonus value on players who fall or rise on the draft boards, however these rankings may pose concerns since MLB teams are not directly following the lists during their selection process. Garmon's results are important to consider with rates of return and demographic success relating to a selection. This literature further suggests a need to control for high school vs college in the regression analysis.

2.4 Decision Making

As with other industries, psychological and external pressures influence decision making and risk tolerance. As is the case in professional baseball drafting decisions, Johnston et. al point out that decision makers often choose players depending on the path of least resistance, i.e., those picks that the media agrees with to avoid excess scrutiny if wrong.

Spurr also points out the trend that early in the history of the draft, college players outperformed high schoolers, so scouts overcompensated and drafted more college players over time to the point that high schoolers began to outperform the collegians. The same can be true for the NBA draft when it comes to international players: such players were historically under drafted, however once pointed out in the early 2000s, the problem overcorrected itself (Johnston et. al, 2021).

Caporale and Collier conclude that teams should select the best possible player during the draft because of the monopolistic rents that they generate. This can be problematic. As previously discussed, different team market sizes and player bargaining leverage can influence the rate of return that teams can realize on specific individuals, making the MLB a complex selection process. One behavior that teams do not utilize is the “team need” method. According to research conducted by Chandler and Rosenbaum, an increase in team earned run average (ERA) by one full run only increases the likelihood of drafting a pitcher by 17%, which does not meet significance tests. If teams wanted to improve their pitching, they would draft pitching; this is not the case in the MLB partly due to the long period of apprenticeship in pro-baseball.

An important aspect of decision making that poses questions of efficiency is the career concerns question. Michael Roach (2021) describes the phenomena as “creating a misalignment between what is optimal for an executive making a decision and what is in the best interest of the organization.” In short, being fearful of the termination of the decision maker’s job will cause the decision maker to act irrationally (in the eyes of the organization).

He defines high schoolers as riskier assets given their comparatively lower physical maturity and the time horizon of reaching the MLB compared to collegians. Simply comparing teams with winning and losing records shows a difference of less than half a percentage of their dollars spent toward high schoolers. However, after incorporating preseason betting markets, Roach is able to test performance based on expectation. Teams that underperform pre-season betting markets spend 34.5% of their dollars on high schoolers compared to 47.3% by teams that overperform expectations.

The supposed reasoning behind the results is that college draft choices can make a more immediate impact on a team. Also, those players are more likely to make it to the MLB – regardless of how they perform once there – as shown in previous sections. These results are contrary to the hypotheses presented by Barden and Choi, however consistent with their results after running their models.

Roach continues his study to observe the effects of “job security” or tenure with a team. His results confirm his hypothesis that executives with more job security are given more leniency and can therefore take more risk by drafting high schoolers. Barden and Choi find that the significance of the decision is also a factor in determining the amount of risk.

The more significance in the decision (i.e., a first-round pick compared to a tenth-round pick) the more pronounced the risk behavior becomes: better on field performance increases risk taking in the first round. These studies open the door for research regarding inefficiencies within the draft due to misaligned incentives between decision makers and teams, while also presenting meaningful contributions to draft theory. Since teams may act irrationally, certain behavior decisions may lead to higher success rates in draft classes.

Chapter 3

Methods

3.1 Player Data Collection

To analyze drafting behaviors, I collected data from multiple sources. The R package BillPetti/baseballr includes a list of 8,786 players drafted from 2012 through 2020 with their biographical, signing bonus, and pick information. Since the study only focuses on players selected within the first ten rounds of the draft, the 6,403 observations of players not in this category were deleted.

Source	Players added to data
Added BillPetti/baseballr 2012-2020	+8786
Removed rounds 11+	-6403
Added missing picks (Baseball America)	+337
Removed duplicate players	-14
Removed years 2019-2020	-477
Removed unsigned players	-37
Total players in model	2192

Table 1 Player data collection

Obtaining slot and bonus values required three additional sources: MLB Daily Dish for the years 2014-2017, NYRDCAST for the years 2018-2020, and obtaining MLB.com archived data for the years 2012-2013 (acquired from a special request to MLB draft expert Jonathan Mayo).

Once merged into a single dataset, 337 picks were missing. The missing players and information come from cross referenced data in Baseball America’s draft database and various MLB.com slot value articles, which also confirmed the accuracy of the merged dataset. The 56 discrepancies in signing bonus amount between the joined data and Baseball America required additional cross-referencing. Following the data entry and duplicate removal, the draft list totaled 2,706 players. Removing years 2019 and 2020 due to lack of performance data totaled 2,229. Of the remaining players in the data, 37 did not sign with their drafting team. These unsigned players were removed from the data.

My empirical analysis relies upon player performance data collected from the Fangraphs. These performance data include all 3,922 players making an appearance in an MLB game from 2012-2022.

Next, these data joined the MLB Draft data. This combined data featured forty-nine sets of repeated player name rows that improperly mapped production to draft; the repetition represented distinct players which shared the same name and players drafted twice within the period (unsigned in one draft).

Career length data on all players in the dataset making an MLB appearance come from Fangraphs. This study categorizes career length as the sum of seasons where a player made an appearance in an MLB game. Table 2 summarizes player variables of interest.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
picks	2192	1	0	1	1	1	1
made_mlb	2192	0.362	0.481	0	0	1	1
WAR	793	2.021	4.806	-3.5	-0.2	1.9	36.1
WAR6	560	1.635	3.785	-2.1	-0.2	1.6	28.3
service_time	793	2.759	1.894	1	1	4	10
WAR_per_yr	793	0.383	0.893	-1.3	-0.1	0.6	5.157
over_slot	2192	0.237	0.425	0	0	0	1
slot_value	2192	691109.443	1031873.863	125000	163100	702025	9015000
ln_slot_value	2192	12.859	0.976	11.736	12.002	13.462	16.014
sign_bonus	2192	678256	1009073.162	1000	130000	780875	7500000
ln_sign_bonus	2192	12.358	1.785	6.908	11.775	13.568	15.83
ln_bonus_minus_ln_slot	2192	-0.501	1.159	-5.363	-0.355	0	1.724
pitcher	2192	0.526	0.499	0	0	1	1
rd1_pitch	2192	0.046	0.21	0	0	0	1
rd2_pitch	2192	0.058	0.235	0	0	0	1
hs	2192	0.269	0.443	0	0	1	1
rd1_hs	2192	0.048	0.215	0	0	0	1
rd2_hs	2192	0.064	0.245	0	0	0	1
yr_2012	2192	0.151	0.358	0	0	0	1
yr_2013	2192	0.141	0.348	0	0	0	1
yr_2014	2192	0.141	0.348	0	0	0	1
yr_2015	2192	0.141	0.348	0	0	0	1
yr_2016	2192	0.143	0.35	0	0	0	1
yr_2017	2192	0.142	0.349	0	0	0	1
yr_2018	2192	0.141	0.349	0	0	0	1

Table 2 Player Variables

Players were further classified in binary terms as: signing over slot (1); making the MLB (1); pitchers (1); and high school draftees (1).

My analysis requires the creation of new variables from the data. The variable *WAR6* results from the career WAR of draftees through the sixth year after their draft. This variable standardizes the timeframe for statistical accumulation. *WAR6* includes all players from drafts 2012-2016.

To further test WAR on a larger sample, the *WAR_per_yr* metric represents the average season production value of players making it to the MLB. Career WAR is divided by career length to account for players in earlier drafts accumulating higher values compared to players in recent drafts. Of the two modified metrics, *WAR6* is more credible due to its standardized timeframe.

By taking the difference of logs for signing bonus and slot value, the variable *ln_bonus_minus_ln_slot* approximates the percentage of the slot value that the player received in his signing bonus.

3.2 The Player Models

My analysis relies upon regression models that test how variables correlate with player production. I regress multiple variables on three different productivity measures: making the MLB, career WAR six years post draft, and average WAR per season. I also control for underlying differences between draft years. Instead of signing bonus and slot value, I use the natural log of each when measuring the effectiveness of teams to align money with future production. I also regress the approximate percentage deviation from slot value that the player received by subtracting the log of slot value from the log of signing bonus value. Applying the literature concerning player demographics, I regress high school with performance and test if there are underlying positional discrepancies by regressing pitcher with performance.

made_mlb = β0 + β1ln_slot_value + β2ln_bonus_minus_ln_slot + β3pitcher + β4hs + β5yr_2013 + β6yr_2014 + β7yr_2015 + β8yr_2016 + β9yr_2017 + β10yr_2018

WAR_per_yr = β0 + β1ln_slot_value + β2ln_bonus_minus_ln_slot + β3pitcher + β4hs + β5yr_2013 + β6yr_2014 + β7yr_2015 + β8yr_2016 + β9yr_2017 + β10yr_2018

$$WAR6 = \beta 0 + \beta 1 ln\_slot\_value + \beta 2 ln\_bonus\_minus\_ln\_slot + \beta 3 pitcher + \beta 4 hs + \beta 5 yr\_2013 + \beta 6 yr\_2014 + \beta 7 yr\_2015 + \beta 8 yr\_2016$$

A positive *β1* suggests that an increase in *ln_slot_value* correlates with an increase in *WAR_per_yr, made_mlb,* and *WAR6*. Slot value decreases with pick position, so earlier picks with higher slot values should have higher expected performance.

A positive *β2* suggests that bonuses with larger positive deviations from slot value correlate with higher production. Going over slot value would correlate positively with production.

A positive *β3* suggests that pitchers outperform position players, whereas a negative *β3* implies position players outperform pitchers.

A positive *β4* on *hs* suggests that high schoolers outperform collegians. Following the literature of Roach (2021), it is expected that *β4* will increase *WAR* but decrease *made_mlb* mainly due to the idea that college players are more likely to make it to the MLB, but high schoolers are more likely to outperform the college players once there.

The *year* variables control for effects contained within individual drafts. Any significance in these coefficients would indicate differences in the cohorts.

3.3 Team Draft Class Data Methods

Analyzing team drafting behaviors requires the player data to condense into team draft classes. Sorting players by their respective drafting team and year resulted in 270 individual draft classes. Removing draft classes from 2019 and 2020 resulted in 210 draft classes (the minor league structure limits most of these recently drafted players from reaching the MLB making these 60 observations meaningless to this study). The 14 draft classes including an unsigned player in their first two selections were also removed from the team model. As with the player data, *WAR6* only includes years 2012-2016.

Draft class variables were created by aggregating player data. Table 3 summarizes the team draft class variables of interest.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
picks	196	10.612	1.12	8	10	11	14
over_slot	196	2.556	1.164	0	2	3	5
bvr1 (LL)	196	0.444	0.498	0	0	1	1
bvr2 (LH)	196	0.311	0.464	0	0	1	1
bvr3 (HH)	196	0.077	0.267	0	0	0	1
bvr4 (HL)	196	0.168	0.375	0	0	0	1
WAR	196	7.896	10.811	-3.3	0.675	10.9	48.9
WAR6	141	6.255	7.864	-2.2	0.6	8.9	34.4
service_time	196	10.597	6.913	0	6	15	37
WARt_per_yr	196	0.6	0.706	-0.471	0.1	0.977	4.514
made_mlb	196	3.832	1.706	0	3	5	10
slot_value	196	7364908.673	2653792.631	1645700	5761325	8735425	17289400
ln_slot	196	15.744	0.386	14.314	15.567	15.983	16.666
sign_bonus	196	7219068.02	2661809.334	1448800	5675950	8652800	17040000
ln_bonus	196	15.72	0.399	14.186	15.552	15.973	16.651
percent_signed	196	0.978	0.048	0.817	0.958	1.009	1.05
pick_one_pitch	196	0.454	0.499	0	0	1	1
pick_two_pitch	196	0.459	0.5	0	0	1	1
pick_one_hs	196	0.505	0.501	0	0	1	1
pick_two_hs	196	0.515	0.501	0	0	1	1
yr_2012	196	0.148	0.356	0	0	0	1
yr_2013	196	0.143	0.351	0	0	0	1
yr_2014	196	0.143	0.351	0	0	0	1
yr_2015	196	0.138	0.346	0	0	0	1
yr_2016	196	0.148	0.356	0	0	0	1
yr_2017	196	0.148	0.356	0	0	0	1
yr_2018	196	0.133	0.34	0	0	0	1

Table 3 Team Variables

The variables of interest include: total picks in the class; aggregate class WAR (sum of individual player WAR from the class); *WAR6* (aggregate class WAR through six years after the draft); aggregate class WAR per aggregate class career length (sum of individual player WAR in the class divided by sum of individual player career length from the class); total reaching the MLB (sum of players in the class reaching the MLB level); total slot value (sum of individual pick slot values, i.e., bonus pool); total bonus (sum of dollars spent on draftees); and binary variables indicating the position, high school status, year of the class, and slot behavior (over/under) of the first two selections within the given class. Figure 1 and table 4 show the frequency of each of the four behaviors since 2012.

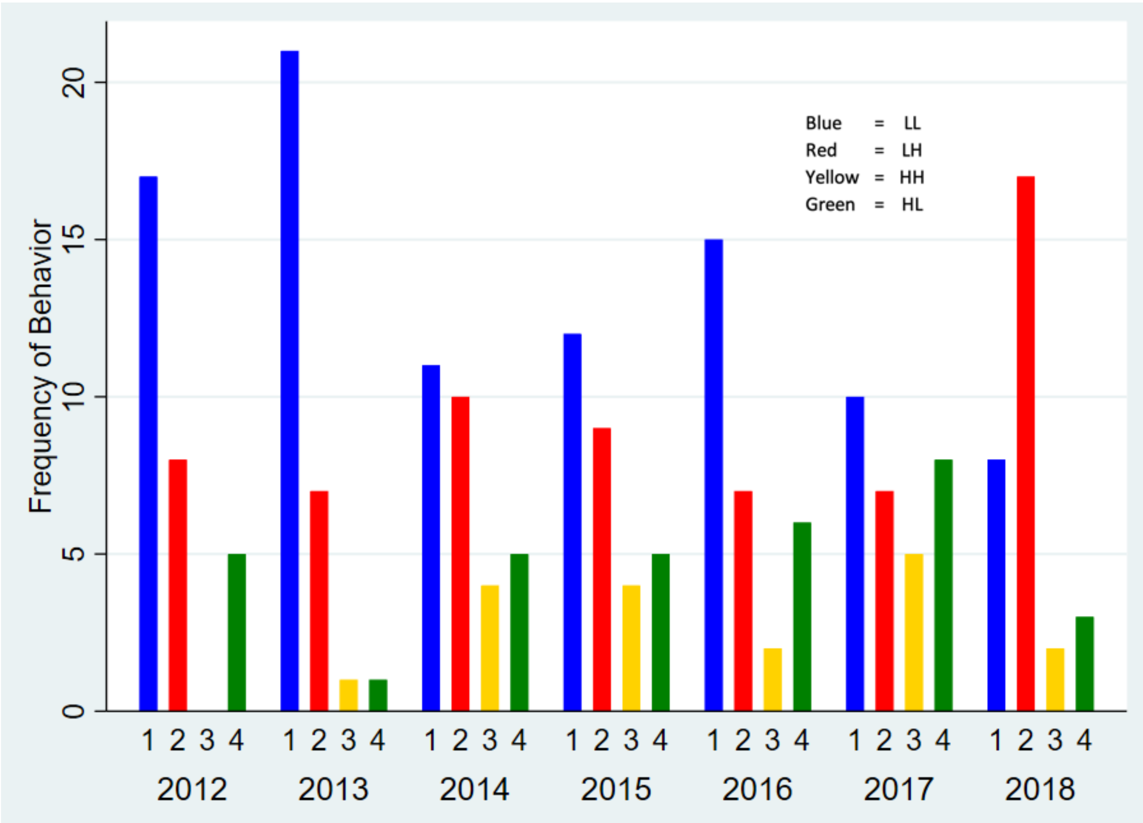

Figure 1 Allocation behavior frequency by year

Teams	LL (bvr1)	LH (bvr2)	HH (bvr3)	HL (bvr4)	WAR
St.LouisCardinals	5	1	1	0	119.3
HoustonAstros	3	2	1	1	105.5
LosAngelesDodgers	1	1	1	4	101.9
SanDiegoPadres	1	2	2	2	86.5
ChicagoCubs	3	3	0	1	84.6
OaklandAthletics	6	1	0	0	84.5
SeattleMariners	1	4	1	1	74.3
PhiladelphiaPhillies	5	1	0	1	58.4
ClevelandGuardians	2	2	2	1	57.9
MinnesotaTwins	7	0	0	0	56.2
MilwaukeeBrewers	2	2	0	3	55.3
TorontoBlueJays	6	0	1	0	55
BaltimoreOrioles	4	0	1	2	54.3
NewYorkYankees	0	5	0	2	51.2
MiamiMarlins	4	2	1	0	49.4
AtlantaBraves	1	4	0	2	49.4
PittsburghPirates	5	1	1	0	46.8
ColoradoRockies	4	3	0	0	43.3
TampaBayRays	3	3	1	0	41.1
NewYorkMets	3	4	0	0	39.6
ChicagoWhiteSox	3	3	0	1	38.2
SanFranciscoGiants	2	3	0	2	35.7
ArizonaDiamondbacks	5	1	0	1	35
TexasRangers	2	4	1	0	34.3
CincinnatiReds	2	4	0	1	33.1
WashingtonNationals	2	1	1	3	29.5
KansasCityRoyals	2	3	2	0	26.6
BostonRedSox	3	2	0	2	24.6
LosAngelesAngels	4	1	1	1	16.1
DetroitTigers	3	2	0	2	14.4
Total	94	65	18	33	1602

Table 4 Allocation behavior frequency by team

3.4 The Team Models

To analyze team drafting behavior, I create linear regression models to test how variables correlate with draft class production. I regress multiple variables on three different productivity measures: cumulative class WAR, class WAR through six years post draft, and number in the class making the MLB, while controlling for underlying differences between draft years and number of picks in a class. I regress each behavior type (omitting behavior 1 due to repetition in binary variables) and each demographic type for the first two selections by a team in a draft.

$$WAR = \beta 0 + \beta 1 picks + \beta 2 bvr2 + \beta 3 bvr3 + \beta 4 bvr4 + \beta 5 pick\_one\_pitch + \beta 6 pick\_two\_pitch + \beta 7 pick\_one\_hs + \beta 8 pick\_two\_hs + \beta 9 yr\_2013 + \beta 10 yr\_2014 + \beta 11 yr\_2015 + \beta 12 yr\_2016 + \beta 13 yr\_2017 + \beta 14 yr\_2018$$

$$WAR6 = \beta 0 + \beta 1 picks + \beta 2 bvr2 + \beta 3 bvr3 + \beta 4 bvr4 + \beta 5 pick\_one\_pitch + \beta 6 pick\_two\_pitch + \beta 7 pick\_one\_hs + \beta 8 pick\_two\_hs + \beta 9 yr\_2013 + \beta 10 yr\_2014 + \beta 11 yr\_2015 + \beta 12 yr\_2016$$

$$made\_mlb = \beta 0 + \beta 1 picks + \beta 2 bvr2 + \beta 3 bvr3 + \beta 4 bvr4 + \beta 5 pick\_one\_pitch + \beta 6 pick\_two\_pitch + \beta 7 pick\_one\_hs + \beta 8 pick\_two\_hs + \beta 9 yr\_2013 + \beta 10 yr\_2014 + \beta 11 yr\_2015 + \beta 12 yr\_2016 + \beta 13 yr\_2017 + \beta 14 yr\_2018$$

A positive $\beta 1$ suggests that additional picks correlate to higher draft class production. More picks increase the bonus pool and increase the chances of selecting productive players.

Due to redundancy in binary values, behavior 1 (LL) is omitted from the regression models. LL takes a value of 0 that the other three behaviors measure against. A positive coefficient *β2* on behavior 2 (signing the first selection at or under slot and the second selection over slot) would suggest that LH is a more productive behavior than LL. A negative *β2* would suggest that LL is a more productive behavior than LH.

The same logic applies to *β3* and *β4*. Since each of the behaviors compare against LL at 0, the value of the coefficients *β2*, *β3*, and *β4* are measured against each other directly. The highest value is the most productive behavior, and the lowest value is the least productive.

The binary *year* indicators suggest differences in cohort as compared to the baseline year 2012, which is omitted and takes the value 0.

Positive coefficients for the variables *pick_one_pitch* and *pick_two_pitch* would suggest pitchers outperform position players.

Positive coefficients for the variables *pick_one_hs* and *pick_two_hs* would suggest high schoolers outperform collegians.

Chapter 4

Results

4.1 Player Results

Testing the model on *made_mlb* in table 5, each coefficient returned as statistically significant at a 5% level, except the year 2013. The largest coefficient on *ln_slot_value* suggests that larger slot values correlate highly with reaching the Major Leagues. The coefficient representing the approximate percent difference between signing bonus and slot value is positive. Paying over slot thus correlates with making the MLB. Also, in line with the literature expectation, the high school binary variable returns the largest negative magnitude coefficient (aside from year 2018). The binary *pitcher* variable's coefficient represents a small positive influence on the model. The year coefficients act in line with the predictions, as earlier years give players more time to reach the MLB.

	Dependent variable:		
	made_mlb	WAR6	WAR_per_yr
	(1)	(2)	(3)
ln_slot_value	0.199***	1.211***	0.187***
	(0.011)	(0.160)	(0.031)
ln_bonus_minus_ln_slot	0.031***	−0.121	−0.006
	(0.009)	(0.201)	(0.039)
pitcher	0.039**	−0.733**	−0.113*
	(0.019)	(0.314)	(0.063)
hs	−0.175***	−1.310***	−0.086
	(0.023)	(0.370)	(0.076)
yr_2013	−0.012	−0.353	−0.167
	(0.035)	(0.469)	(0.107)
yr_2014	−0.084**	−0.557	−0.123
	(0.035)	(0.494)	(0.111)
yr_2015	−0.110***	−0.807*	−0.162
	(0.035)	(0.486)	(0.112)
yr_2016	−0.103***	−0.593	−0.087
	(0.035)	(0.469)	(0.110)
yr_2017	−0.107***		−0.483***
	(0.035)		(0.112)
yr_2018	−0.240***		−0.045
	(0.035)		(0.128)
Constant	−2.063***	−13.303***	−1.872***
	(0.138)	(2.150)	(0.417)
Observations	2,192	560	793
R^2	0.181	0.115	0.077
Adjusted R^2	0.178	0.103	0.065
Residual Std. Error	0.436 (df = 2181)	3.586 (df = 551)	0.864 (df = 782)
F Statistic	48.330*** (df = 10; 2181)	8.985*** (df = 8; 551)	6.495*** (df = 10; 782)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5 Player results

Specifying the first six years following a player's draft to place every player on equal footing, the *WAR6* model further justifies the idea that teams properly value and select players.

Slot value again carries the positive value in the model while high schoolers and pitchers correlate with lower production.

Conditional on reaching the MLB, the *WAR_per_yr* model returned three coefficients as statistically significant at a 10% level. As expected, the year effects are ambiguous (except the recent 2017 draft that can be explained by many rookies playing fewer games per season than the established players in earlier drafts). The coefficient on the high school binary variable loses significance in *WAR_per_yr* suggesting that once making the major leagues, differences between high schoolers and collegians reduce. Additionally, the model suggests that position players in the population outperform pitchers.

The deviations from slot are insignificant in the *WAR6* regression. One reason for the significance of the deviation in *made_mlb* but not in *WAR6* nor *WAR_per_yr* could be that teams favor and provide more opportunities for the players that received higher than slot bonuses. These players could reach the MLB at higher rates because teams give them more chances. Once analyzing only players that reached the MLB, the extra opportunities are no longer applicable. Players are then left to their own merits and perform at their true capabilities (as reflected in the WAR metric).

4.2 Team Results

Testing each of the team models defined in the methods section revealed that none of the behavior coefficients resulted in a statistically significant impact. Of the significant results (*picks*, *pick_one _pitcher*, *pick_one_hs*, and various *years*), it's no surprise that more picks increase WAR, number of drafted players in a class making the MLB, and better per year production: additional picks give teams more bites at the apple. Additionally, the more recent the draft, the lower the aggregate WAR. Insignificant year results in the *WAR6* model were expected due to a consistent time horizon across all classes.

	Dependent variable:		
	WAR	WAR6	made_mlb
	(1)	(2)	(3)
picks	2.443***	1.804***	0.707***
	(0.641)	(0.590)	(0.100)
bvr2	−0.142	0.182	−0.066
	(1.768)	(1.627)	(0.275)
bvr3	0.169	1.748	0.067
	(2.892)	(2.818)	(0.450)
bvr4	1.693	1.170	0.239
	(2.013)	(1.926)	(0.313)
pick_one_pitch	−3.374**	−3.125**	−0.164
	(1.401)	(1.328)	(0.218)
pick_two_pitch	−0.721	−0.539	−0.120
	(1.408)	(1.323)	(0.219)
pick_one_hs	−4.648***	−4.006***	−0.256
	(1.421)	(1.341)	(0.221)
pick_two_hs	1.239	0.754	−0.364
	(1.590)	(1.494)	(0.248)
yr_2013	−3.938	−0.581	0.431
	(2.570)	(2.069)	(0.400)
yr_2014	−5.074*	−1.494	−0.141
	(2.579)	(2.076)	(0.402)
yr_2015	−7.147***	−2.047	−0.271
	(2.605)	(2.097)	(0.406)
yr_2016	−7.551***	0.352	−0.002
	(2.526)	(2.025)	(0.393)
yr_2017	−14.235***		−0.346
	(2.574)		(0.401)
yr_2018	−11.930***		−1.397***
	(2.623)		(0.408)
Constant	−7.629	−9.200	−3.021***
	(7.449)	(6.863)	(1.160)
Observations	196	141	196
R^2	0.301	0.174	0.319
Adjusted R^2	0.247	0.097	0.266
Residual Std. Error	9.383 (df = 181)	7.474 (df = 128)	1.461 (df = 181)
F Statistic	5.560*** (df = 14; 181)	2.250** (df = 12; 128)	6.053*** (df = 14; 181)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6 Team results

First round high schoolers and first round pitchers significantly decrease total and first six-year aggregate WAR of the classes compared to college and position players. This can most likely be attributed to the same reason as the player model where high school pitchers negatively impact WAR to a greater extent than high school position players.

Although insignificant, comparing behaviors to each other reveal an interesting trend. Behavior four (HL) had by far the highest magnitude in *WAR* and *made_mlb* and was positive in *WAR6* while behavior two (LH) performed the worst across the board.

Behaviors three (HH) and four (HL) may present positive values because both allocate a larger than 'recommended' amount of money to the first selection and – as evident in the player model – the higher valued players outperform the rest. Securing one of the top valued players may take precedent over any other consideration during the rest of the draft. Similar logic may apply to why behavior two (LH) returned a negative coefficient: acquiring a lower value than slot player in the first round prohibits the team from acquiring a top of the line, elite quality player.

Behavior four's (HL) high relative value also agrees with Burger and Walters' conclusions that second and third round selections historically have lower rates of return. Behavior four (HL) allocates a lower amount toward those picks which further equalizes the rates of return across rounds.

Chapter 5

Discussion

5.1 Team Behavior Significance

The lack of significant results in the behavioral decisions by teams in the draft suggest that none of the four differ enough to stand out as the best. This could result from optimality: if teams properly value each selection, simply reallocating the value across the draft retains the total value in equilibrium. Along the same lines, the increased influence of analytics departments amongst all teams may dilute any advantage of one draft decision. Should this be the case, none of these four behaviors can be recommended as a clear-cut advantage.

Teams proved in recent drafts that they properly value expected production from players with evidence by the player model. Higher slot values – ie. earlier picks – correlates with true productivity. Positive deviations from slot (signing a player over slot) also correlates with making the MLB.

The lack of significant results in team behaviors influencing future productivity, along with the idea that more picks and higher expected value players increase the probability of a successful draft, proves that the draft improves competitive balance. With rules in place to give the worst performing teams of the previous year the top pick and most money to spend on the draft, as well as compensating smaller market teams with supplemental picks in the draft, the draft succeeds in aiding low-performing teams with a higher quantity and better quality players than high-performing teams.

5.2 Limitations and Future Study

Since the analysis does not use RCT methods, the study cannot claim causation. The clearest limiting factor in the results comes from the ongoing careers of players in the dataset. Since players drafted in 2012 have more time to build their resume, learn how to improve their performance, and stack years, these players may skew results from 2018 draftees just recently debuting in the MLB. Running the models on career WAR following the conclusion of all careers in the dataset would prove more reliable, as every player could be compared on the same scale.

Another limitation is that the production models control for players making the MLB. It is important to distinguish the factors which correlate to making the MLB and then the factors which correlate to success once there, but it's also important to analyze the entire pool of drafted players when making these predictions. Since non-debut players have no statistical production, their results cannot be compared.

A third limitation of the study is the absence of consideration for rounds 11-40. These picks were left out since they aren't contributing to the bonus pool, but some of these players have turned in solid MLB careers. When considering a successful draft, these picks should be included, however they don't contribute to the decision-making process teams undertake when deciding which players to choose in their first and second selections.

The assumption that player signing bonus values are given prior to the draft also limits the reliability of results. While players communicate their 'asks' to teams prior to the draft, these values are not binding. Teams with negotiating advantages can leverage their ability to sign players to lower-than-ask bonuses and decrease their impact on the budget. Teams may also have additional underlying characteristics that influence their player productivity outcomes. Teams with better training that select poorly and teams with better selecting that train poorly may generate the same player production results in the long run. The potential correlation of underlying characteristics with the behaviors defined would limit the reliability of the results.

Future researchers should re-evaluate the model when careers of players in the dataset conclude so that draft classes can be evaluated in entirety. Future researchers could also consider prior team performance vs. expectation leading into the draft to model that impact on the draft allocation decisions. Additionally, this study ignores trading value of draftees that do not make the MLB; future research could address this factor as certain draft picks that do not advance as expected still provide asset value to their drafting teams.

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ACADEMIC VITA

JEFFREY LUNGER

EDUCATION

The Pennsylvania State University — **University Park, PA**
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Bachelor of Science in Economics
Minors: Mathematics | Environmental & Renewable Resource Economics

Paterno Fellows Program
Honors Program including advanced academic coursework, thesis, internship, study abroad, ethics study, and leadership commitment

TEAMWORK EXPERIENCE

Penn State Varsity Baseball — **University Park, PA**
Student Manager, Video and Scouting | Field Operations — October 2019 – August 2022

- Dedicated 10-20 hours per week attending team and individual practices to organize and facilitate drills that assist and support coaches in developing players
- Operated commonly used baseball systems BATS, TrackMan, Yakkertech, and Rapsodo Pitching during games and practices to compile data to enhance immediate coaching and provide future R&D opportunities
- Cultivated innovative analytics projects using practice and game data to influence strategic handling of controllable decisions
- Assisted in creating advanced scouting reports using Synergy database to monitor tendencies to improve in game strategy

Baseball Projects
Independent — May 2022 – August 2022

- Evaluated thirty-three amateur prospects in the Cape Cod Baseball League, MLB Draft League, and NCAA D-1 Baseball using the 20-80 scout scale to compile a ranked preference list of top prospects
- Coached and assessed 90 high school baseball players alongside NCAA Division 1 coaches at showcase style camps in both Arizona and Ohio
- Improved honors senior thesis focusing on MLB Amateur Draft selection tendencies based on given signing bonus demands and team budget constraints

Pennsylvania State University Sports Analytics Club — **University Park, PA**
Vice President | Football Chair — September 2019 – May 2022

- Arranged, created, and coordinated inclusive and original biweekly general club meeting engagement experiences
- Created a machine learning model to predict and publicize daily top scoring options in DraftKings daily fantasy baseball on original website to compete in growing gaming industry
- Presented graphics to elicit moderated group dialog centered around current sports topics

Wareham Gatemen Baseball — **Wareham, MA**
Player Development Technology Intern — February 2020 – August 2021

- Developed twenty concisely written, graded player reports on pro scouting scale to identify and compare top amateur prospects in Cape Cod Baseball League
- Integrated commonly used baseball data collecting systems Rapsodo Hitting & Pitching and Blast Motion Sensors into practices and games
- Facilitated use and distribution of video recording systems to monitor Wareham's twenty-two hitters' and five catchers' mechanical tendencies
- Aided in forming each of ten Cape Cod Baseball League teams' advanced scouting reports using Synergy data to identify and exploit opposing player weaknesses

SKILLS, HONORS, AND INTERESTS

Technology: Rapsodo, TrackMan, Yakkertech, BATS, Blast, Edgertronic, Microsoft Office
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