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Powerhouse Problem: The Examination of the NFL Draft and Possible Biases

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Abstract:

This research explores the NFL draft's dynamics, investigating potential biases in player selection. Despite stars like Tyreek Hill and Antonio Brown emerging from small D1 institutions in the later draft rounds, a bias towards Power 5 conference players persists, particularly with wide receivers. Drawing from NFL draft data (2016-2020), this research finds that not only does there seem to be a premium placed on Power 5 receivers, but Southeastern Conference (SEC) linebackers as well. Quarterbacks were also evaluated in this research but revealed little information about what factors influence their draft position. The discrepancy of what influences a player's draft position versus what influences their success in the NFL raises questions that this paper seeks to examine. Through behavioral economics, the study aims to unveil underlying biases and promote fairer, more informed draft strategies for NFL teams.

Introduction

The NFL draft process, a meticulously coordinated and captivating annual experience, fills fans with hope through new faces that will represent their team, while the years of hard work come to fruition for collegiate athletes across the nation. It is where franchises write their own chapters that may foreshadow the successes and failures of each individual team. Tyreek hill, Jason Kelce, Antonio Brown, and Marquis Colston are just a few players who have imposed their greatness against NFL teams since the early 2000s. These three players have combined for 20 Pro Bowl appearances and four Superbowl victories. The one commonality they all have is that none of them were chosen before the sixth round in the NFL draft. Despite producing impressive college careers, these future halls of famers fell into the late rounds of draft. Tyreek Hill out of Western Alabama put up the fastest 40 yard-dash in his respective draft class, while Jason Kelce out of Cincinnati recorded the fastest shuttle time ever for an O-lineman, and Antonio Brown out of Western Michigan was a two time All-American and one of the nation’s best receivers. These pre-draft evaluations would indicate a successful career at the pro-level, yet they fell to the 6^{th} and 7^{th} rounds.

Part of the NFL is entertaining its audience, where success plays a vital role in revenue that organizations bring in and the key component of that success is the players that are drafted each year to build the core foundation of a team. As shown in Figure 1, which illustrates first round selections between the years 2010-2022, the NFL draft over the past 13 years has presented a discrepancy when it comes to the distribution of players selected. The data presents a compelling narrative, highlighting the dominance of certain conferences in producing top-tier talent. The Southeastern Conference (SEC) emerges as a powerhouse, recording 135 first-round selections since 2010. This statistical revelation underscores the SEC's reputation as a breeding ground for elite football prospects and raises intriguing questions about the factors contributing to the conference's sustained success in cultivating NFL-caliber players. It is also important to note that only 58 out of 416 players from this time period did not play in a Power 5 conference, which are the five biggest conferences in Division I that entails the Southeastern Conference (SEC), Atlantic Coast Conference (ACC), Big 10, Big 12, and Pac 12. This notable difference in selections by conference prompts a closer examination of the conference dynamics and the variables influencing the recruitment and development of athletes in the SEC vs. the rest of the power 5 conferences. The SEC has developed itself as the most dominant conference in college football, winning five of the eight national championships since the 2015 inauguration of the new College Football Playoff (CFP), where four teams in the country are selected by a committee to compete for the national title. The potential problem with the reflection of the SEC’s dominance in the NFL draft is that football is a team game, and as the SEC continues to see success, it gains more funding, better coaches, and improved facilities. Dominance in football requires impactful contributions from all players and coaches. All of these impressive historical feats of the SEC lead to the question being asked of whether NFL executives focus too much on the school that a player attended, rather than the production of college athletes across the country.

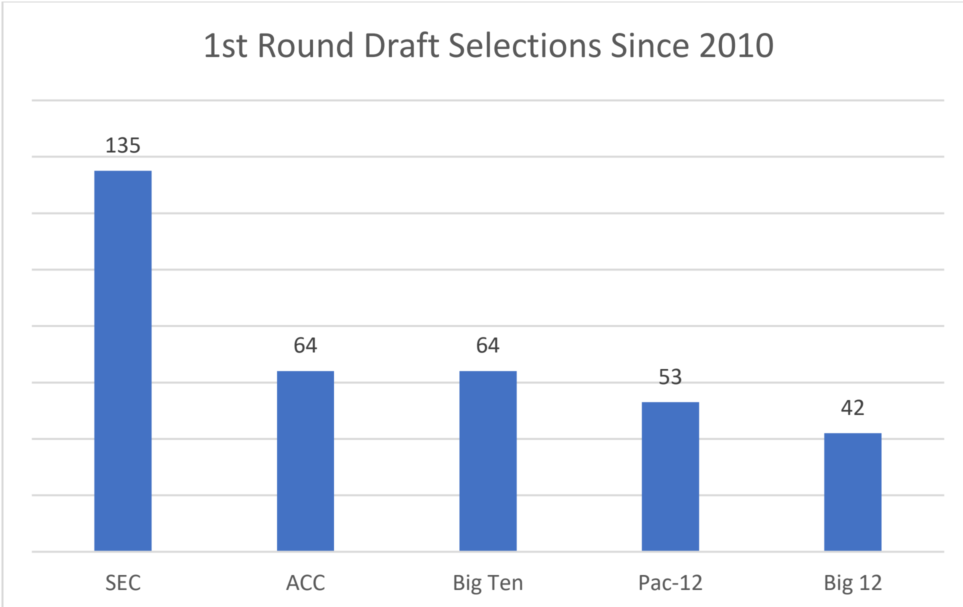

Figure 1: (Gathered from SECsports.com)

The problem with possibly placing a premium on the post-secondary programs of players is that general managers, owners, and coaches may be playing a role in discriminatory selections to build their organizations. Like any other business, an NFL teams' economic benefit relies heavily on the production of their players, so it is essential that production and player qualities are primarily used for analysis, rather than the school that they represented in their college days. There are various measures, such as scouting and attending combines, that are taken before the NFL draft each year for executives to sort through the hundreds of collegiate athletes that they are evaluating to determine who can bring success to their football team.

JaMarcus Russell's NFL career is often cited as one of the most spectacular failures in recent football history. Selected as the first overall pick in the 2007 NFL Draft by the Oakland Raiders, Russell entered the league with high expectations and a record-setting contract. However, his tenure with the Raiders was marred by a lack of dedication, poor work ethic, and an inability to adapt to the demands of professional football. Russell struggled with weight issues and was criticized for his inconsistent performance on the field. His inability to meet the expectations set by his draft position and contract led to his release from the Raiders in 2010, marking the premature end of a career that held great promise but ultimately failed to deliver. Russell played college football at Louisiana State University (LSU) a powerhouse of the 2000s. LSU won the national championship in Russell's final season there, producing impressive, yet not Heisman worthy statistics, according to the Heisman voters.

With this taken into consideration, there is a possibility that NFL executives consider a prospect's college institution with too much weight when deciding to pick them or not. This could be due to various behavioral economic phenomenon's such as signaling, anchoring, or loss-aversion. Signaling would be in the instance that a player's school indicates to an executive how good of a player or not they are. The anchoring effect would cause executives to anchor their mind on the school of a player, and therefore cause them to place too much value on their school rather than their production. Loss-aversion would indicate that these executives are choosing the "safe-play," by selecting players from historically successful institutions. This research paper aims to investigate whether executives employ non-productive characteristics, such as giving undue importance to players' alma maters. The primary objective is to discern and address potential behavioral economic phenomena that may negatively impact a team's success. If the study reveals that such tendencies exist, the overarching goal is to raise awareness and encourage recognition of these patterns. By identifying and acknowledging these phenomena, teams can potentially mitigate their detrimental effects and avoid unintentionally succumbing to biases that may hinder overall team success. This paper endeavors to contribute valuable insights into the recognition and management of such behavioral economic influences within the realm of executive decision-making in sports teams.

Background:

The Southeastern Conference (SEC) was formed in 1932 and has developed into the most elite football conference in college football, holding more national championships than any other conference. From the years 1996-2012, two of the original members, Missouri, and Texas A&M, left the SEC to become members of the BIG 12, another power 5 conference. For the past 11 years, the same 14 teams have remained a part of the SEC. As of this past season, the teams representing the SEC are Alabama, Georgia, Missouri, Tennessee, LSU, Auburn, Texas A&M, Kentucky, Arkansas, South Carolina, Florida, and Vanderbilt.

The NFL Draft was inaugurated in 1936 to promote competitive balance in the league by allowing the teams less equipped to win, to select the top talents from college football. The draft has undergone several changes throughout the years, with a significant modification taking place in 1967 when the AFL and NFL merged, resulting in the establishment of the common draft. Until 1970, the draft was decided by the lottery draft implemented in 1936, which involved randomly drawing teams to assign the order of the draft. The NFL then implemented the reverse-draft order, as the number one pick goes to the team with the worst record the year prior. This draft system was introduced to try and equalize the competitive balance through the NFL. It allows for the worst teams to select the best and most sought-after collegiate athletes. Even through these changes of how the draft was ordered, the commonality that remained through the history of football has been to try and select the best player available at a team's disposal.

A major role in the process of determining this is the NFL draft is the Scouting Combine, which was established in 1982. This has allowed teams to evaluate the physical and mental qualities of potential draftees. Teams now also use sophisticated software and analytics to evaluate prospects and make more informed decisions. Despite these advances, humans are still making the decisions on draft day, and there are some hidden biases that may be present when making them that may restrain the benefits of these advanced technologies.

Johnny Manziel, the first ever freshman Heisman winner and one of the most electrifying collegiate players of all time produced some of the greatest highlights and statistics in NCAA history. Yet, he almost fell out of the first round of the draft in 2015 due to behavior and legal concerns. This could have “signaled” to NFL teams that Manziel just was not quite ready to be an NFL quarterback. There are many things that may lead to signaling in the NFL draft, and if non-productive characteristics are ever misused by teams making selections, these “signals” may be detrimental to the drafting process. Signaling refers to the behavior or actions individuals use to communicate information about themselves to others. Signals are only worthwhile considering if they cannot be easily faked. This concept suggests that people may engage in actions or spend resources to signal certain qualities or attributes, such as their ability, reliability, or trustworthiness. The phenomenon is commonly used to gain trust and reduce information asymmetry between parties involved in an exchange (Koenker, 2003).

Literature Review

The literature regarding the NFL draft and its effectiveness has been extensive and this paper will focus on three major themes: college win percentages of the draftees’ college being overvalued by NFL executives, signals that playing in certain conferences send to NFL teams, and how bias plays into on-the-spot decision making. This literature review also explores the impact of anchoring effects and possible biases in the NFL draft decision-making process, what different levels of football, more specifically the SEC (Southeastern Conference), may signal to scouts, and how college win percentages could impact the value of a player.

Kitchens (2014) completed research testing for statistical discrimination on whether the win percentage of a player's college institution influenced their draft position. In this research, he finds that a player's financial situation can be substantially affected due to rising or falling in the draft partially as a result of the school they attended. While monetary imbalances were present, this did not significantly affect teams' performance as a whole. Simply, when a player is drafted higher or lower than he should be based on his college production, there is a significant change in the monetary value of the contractual agreement that he signs after being drafted. However, there is no statistical significance showing that this makes a team better or worse off than before. For instance, if a player does not pan out as expected, the amount of money that is guaranteed is minimal for players not drafted in the first round, and contracts are easily voidable.

Being a player in the NFL is a goal that only 1.6% of collegiate players achieve, but to be selected in the first round magnifies the elite status that a player holds (NFL.com). Kitchens (2014) questioned this status by developing a theory that indicates NFL executives are too often struck by the success of a player's post-secondary institutions. The author argues that players can be disadvantaged by this recruitment mechanism because once a player has been drafted to the NFL, the post-secondary institution no longer has any effect on their ability to produce for an organization. The success of a team is tied to the composition of its players, but it is crucial to recognize that success on the field is not solely determined by individual achievements. While the players form a cornerstone, the strategic congruence of coaches, the effectiveness of gameplans, the tactical nuances of the chosen scheme, the quality of opposition faced, and the collaborative habits among teammates may be equally pivotal elements that collectively shape the outcome of each game. Acknowledging the diverse nature of success in sports underscores the importance of a comprehensive approach, where the connection between player talent and strategic elements plays a decisive role in achieving victory. Extremely successful programs have multiple scouts attend their pro-days, the workouts in which draft-eligible players (players three years removed from high school) are able to showcase their talents at their school. However, with over a thousand players draft eligible each year, NFL teams are only able to visit about 300 of those players (Kitchens, 2014). Kitchens concluded that in industries like the NFL, where recruiting top talent is crucial, teams often concentrate scouting efforts on successful college teams, leading to preferential drafting of players from renowned institutions. This bias results in earlier draft picks and potentially higher wages for players from these colleges. However, once on the field, player performance dictates subsequent contracts, leveling the playing field. While statistical discrimination exists in drafting, its impact is minor due to the NFL's salary structure. This phenomenon illustrates broader implications for hiring practices, suggesting that exclusive focus on alumni or referrals may overlook superior talent outside established networks, potentially impacting firm productivity if talent separation is difficult or the talent-salary gradient is steep.

Hendricks, DeBrock, and Koenker (2003) discuss how statistical discrimination plays a role in the NFL draft due to behavioral economic biases such as risk-aversion and option value.

In economic terms, risk aversion is when individuals prefer a certain outcome with a lower return in order to receive a lower mean variance, over a riskier but potentially higher return option. For example, an investor who chooses to invest in government bonds with a guaranteed interest rate rather than volatile stocks showcases risk aversion. The term option value refers to the value that is placed on private willingness to pay for maintaining or preserving a public asset or service even if there is little or no likelihood of the individual actually ever using it.

The paper separated DIA and non-DIA schools into two groups and tested production data between the years 1979 and 1992. As hypothesized, they found that players from D1A schools had a lower mean distribution in time in the league, as well as productive statistics (Koenker, 2003). More simply put, this means that players from these larger schools had averages with less outliers, therefore, it is easier to predict their pro-success to some extent. However, the research finds some interesting discoveries, showing that non-DIA players (implying they do not play in a Power 5 conference) who are drafted in the first three rounds, are more likely to play in Pro Bowls and on average, play longer. This was an interesting discovery, given that given that D1A players are drafted far more often than their non-DIA counterparts. They attributed this to NFL executives and scouts being risk-averse in the first few rounds. Due to their lower levels of distribution from the mean, executives seem to be okay with accepting a possibly less productive player with less risk, than a more productive player with more risk.

Conversely, in the later rounds, the exact opposite was true. Players from non-D1A schools tended to have shorter careers along with less Pro Bowl appearances, on average (Koenker, 2003). This evidence is consistent with option value, indicating that in later rounds, where player contracts are less expensive, and high levels of production are less anticipated, teams are more willing to take a chance on "hidden gems," than take players from schools with a lower mean variance. Even though Division IA athletes have longer average careers (4.75 vs. 4.5 years for non-Division IA players), Division IA players have shorter careers in nine of the twelve rounds (adjusted for previous draft structures) as well as among free agents when the position where the players were drafted is held constant. Therefore, there is some evidence that, for the same ex ante evaluation, non-Division IA players may be more productive than Division IA players if career length is used as a productivity metric. This may point to statistical discrimination, which refers to the practice of making decisions or judgments about individuals based on statistical patterns or group averages, rather than on the specific characteristics or abilities of each individual. In this instance, statistical discrimination would be evaluation the performances of the people who attended DIA schools and DIAA schools. From their research, one could make the claim that DIAA players are overlooked in the early rounds due to risk-averse NFL executives, while DIA players are over-looked in later rounds due to the same people falling into the option value.

Literature earlier discussed acknowledges that there has already been significant evidence implying that people are not rational beings, and that regardless of what previous history shows, humans tend to make potentially irrational decisions based on their own feelings and opinions. Thaler (2015) completed research regarding the NFL draft and how high draft selections are significantly overvalued. He indicates that humans, more specifically in NFL front offices, tend to fall into biases such as present bias. The text discusses the analysis of over 400 trades in the National Football League (NFL). The author went into this research hypothesizing that there may be some “misbehaving” taking place and inferred that teams might be placing a premium on the opportunity to pick earlier in the draft. This belief was reinforced by observing extreme cases, such as the well-known example of Mike Ditka, coach of the New Orleans Saints, who traded a significant number of picks to secure a higher draft position in 1999 for the selection of running back Ricky Williams. Williams ended up only playing in 36 games for the Saints over three seasons and was subsequently traded. This trade for the pick to secure Williams in the draft became known as one of the worst in NFL history according to executives around the league.

Ditka's trade, though an extreme instance, confirmed the authors' expected pattern of teams placing too much value on earlier draft picks. The analysis emphasizes the need for a comprehensive examination across various instances to validate this hypothesis, suggesting a potential trend of teams misjudging the value of early draft selections. The authors mention five points from the psychology of decision-making that support their hypothesis of early picks being perceived as too expensive (Thaler, 2015).

1. People are overconfident - believe their ability to predict the future is greater than it really is.
2. People make forecasts that are too extreme – deem “superstars” too easily.
3. The winners curse – highest bidder overvalues the most.
4. False consensus effect – people think others share their preferences.
5. Present bias – focus too much on the “now.”

Overvaluing a player or a draft pick in general can snowball into consequences beyond poor performance. Certain players consistently achieve all-star status and have the potential to significantly impact a team positively. Conversely, there are players who turn out to be major disappointments, causing financial losses to teams from the upfront signing bonuses they pay the player. Notably, high-profile disappointments have a detrimental effect on team performance, primarily because teams struggle to disregard the significant financial investments already made, or their “sunk costs.” When a team invests substantial time, energy, and money in a high draft pick, it seems there is a strong inclination to allow the player to play in games, regardless of their actual performance, due to the perceived pressure associated with the commitment they have made to them (Thaler, 2015). While the literature does not point out the biases that NFL executives may or may not carry towards players who have attended certain schools, he certainly points out that these executives are prone to falling into patterns that are not economically sound.

Previous research indicated that wide receivers playing for a power 5 institution with a relatively high win percentage may signal to NFL executives that they are worth being selected earlier in drafts, as opposed to players from non-power 5 or lower DI schools with a high win percentage (Grewing, 2021). One of the key concepts in understanding NFL draft decision-making is anchoring, which refers to the cognitive bias where individuals rely heavily on the first piece of information encountered when making decisions. Frederick, Kahneman, and Mochon's study (2010), provides valuable insights into anchoring effects. They cited Chapman & Johnson, Mussweiler & Strack (1999), explaining that these researchers revealed that information loading, specifically the amount of information available during decision-making, can lead to anchoring. Through continuously increasing information through trials with humans, they showed that when individuals are presented with a high volume of data, they are more likely to revert to the initial information they received, potentially impacting their choices.

In an article written by Kercheval (2014), he found that a conference high 241 players were drafted from the SEC between 2010-2014, while the second highest conference, the PAC-12, reached only 170 draftees. The SEC also led the way in first-round selections with 49, 22 ahead of the Big 12 as the next highest conference. These totals may indicate that NFL executives believe, regardless of if it is true or not, that SEC players are more NFL ready than anyone (Kercheval, 2014). The problem with this belief, however, is that early round draft picks are given more patience and awarded additional years to develop into players that these coaches and executives imagined they would be. Riddle (2015), referred to Alex Smith as an example. Alex Smith came out of the University of Utah as a Heisman finalist in his final year there throwing for almost 3,000 yards and 32 touchdowns. He was the consensus number one QB in his draft class and eventually went on to become the #1 overall pick in the 2005 draft. Because his team placed such high value on him before he played a snap in the NFL, he may have been given the opportunity to start for five years despite his mediocre to poor on-field play, as he threw 11 interceptions to only one touchdown his rookie year. He may have been given extra time to prove himself that late round quarterbacks were not given strictly because these coaches wanted to see him succeed due to his high draft position.

Riddle (2017) related this scenario to research completed in 1964 by Rosenthal, where he studied teachers that believed certain students were destined to succeed in their class. After running personalized tests, Rosenthal selected a number of students at random from each class. He informed their teachers that although there was no discernible difference between the children, the test indicated that they were about to experience a rapid and profound intellectual development, which through the theory of confirmation bias, can be compared to the treatment of first round selected quarterbacks.

Over the course of the next two years, Rosenthal continued to follow the kids and found that the students were indeed impacted by the teachers' expectations of them. "If teachers had been led to expect greater gains in IQ, then increasingly, those kids gained more IQ," according to him. This may indicate that after the 49ers selected Alex Smith, they wanted to confirm their ideas that he was going to be a successful franchise quarterback. This type of behavior can lead to discrimination not only in playing time, but contractual values, endorsements, and recognition that may lead to further monetary gain.

On average, over 16,000 players are draft eligible each year. Therefore, NFL scouts and executives must determine which players contain desirable enough characteristics to make them one of their seven draft selections (ESPN.com). Sorting through all the characteristics and statistics of over 16,000 people is more than the human brain can comprehend at a single time, therefore leaving it vulnerable to anchoring (Mochon et al, 2010). When the draft comes, and the brain is struggling to process information as quickly as it would like, studies such as Kahneman and Tversky's (1982), show that these people tend to use anchoring as a heuristic when making choices in their lives. This research conducted tests with groups of people and their ability to make correct adjustments to a choice when they are given additional information. For example, when people were given more numbers to multiply by each other, guessing the correct answer became more difficult for them, as they reverted to the first piece of information they received and adjusted accordingly. For NFL executives, it is possible that a similar phenomenon is taking place. After scouting a player from a powerhouse institution, they may value a player from a non-powerhouse school as a less talented prospect because they are comparing their school to the first player they scouted. In this case, it would occur due to multiple variables running through executives' minds, therefore it is easier for them to rely on one fact, such as school, rather than making rational decisions. This bias could lead to discrimination that contains more than simply the team an individual plays for.

Therefore, the question that this paper seeks to uncover is if there too much value placed on the post-secondary institution a player attended when making draft selections. This will be tested in a two-step process, to evaluate if a premium exists, and if that premium is consistent with NFL productivity or not. It is hypothesized that when making these draft decisions, there are behavioral economic phenomenon's that subconsciously take place that may led to biased draft choices.

Theory

Anchoring is a cognitive bias that occurs when individuals rely heavily on the first piece of information (the "anchor") they receive when making decisions, even if that information is irrelevant or arbitrary. Anchoring can lead to suboptimal decision-making because it can create a bias toward the initial piece of information, regardless of its relevance (Koenker, 2003). In this case, anchoring is about already having an impression of the player based on the school, and then not adjusting that sufficiently based on additional information.

Confirmation bias, commonly used by humans, describes the tendency to selectively seek, interpret, and remember information that aligns with one's preexisting beliefs and expectations, while dismissing or downplaying contradictory evidence (Kercheval, 2015). This bias can result in a distorted perception of reality, hindering the objective assessment of information and potentially leading to flawed conclusions. In the context of research, confirmation bias poses a significant challenge as it can lead researchers to unintentionally emphasize or prioritize data that confirms their hypotheses or preferred outcomes, potentially compromising the scientific integrity of their work. These ideas are crucial to comprehending how people make decisions that may not be entirely rational, as classic economic models frequently suggest, and how psychological variables can affect people's behavior and financial decisions.

The process of selecting players to represent an organization each year is a complex task that can be influenced by a various factors and beliefs. This theoretical framework aims to explore the role of several key variables in predicting the draft pick of a player, and if those variables are a good indicator of professional success. The first regression equation, which estimates where a draftee is chosen depending upon his college performance metrics and where he went to college, is expressed in Figure 3. It is important to note that "RelevantCollegeStats," as shown below represents the statistics a player produced in college based on their respective position. For Wide Receivers, their total yards per game were used as productive characteristics. Quarterbacks' productive characteristics are represented by their total QB rating. As for linebackers, sacks per game, tackles per game, and interceptions per game, were used to evaluate college production.

Rnd	Draft Round
CPick	Cumulative Pick Number
Pick	Pick within Round
Tm	Team
Player	Player Name
Year	Year Drafted
To	Last Year Played
Dash	40 Yard Dash Time
GP	Games Played
HT	Height when drafted
WT	Weight when drafted
CREC	Average College Receptions per Game
CRYDS	Average College Yards per Game
CRTD	College Career Touchdowns per game
Pos	Position
Age	Age when drafted
AP1	First Team all pro selection
PB	Pro Bowl Selection
St	Number of Years as a starter for his team at his position
wAV	Weighted Approximate Value
DrAV	Weighted Approximate Value Accumulated for Team that drafted this player
G	Games Played
College/Univ	College Team
SEC	Was College part of SEC?
Power5	Is a player in a Power 5 Conference?
Winpct	Win % of player's school during their final year in college
WRdash10	40-yard dash in tenths of seconds
WRBMI	Body Mass Index of a Wide Reciever
Wrmissing	Avg 40 yard dash time given to a player who did not run one
Ctack	College average tackles per game
Csack	College average sacks per game
Cint	College average interceptions caught per game
dash10	40 yard dash time of a linebacker in tenths of seconds
BMI	BMI of a linebacker
Cpct	College average completion percentage
Cyds	College average yards passing per game
Cptd	College average yards passing per game
Cinter	College average interceptions thrown per game
Crate	College quarterback rating
Cryds	College average rush yards per game
Crtd	College average rush touchdowns per game
BMIQB	BMI of a quarterback

Figure 2: Variable Definitions

Dependent Variables	Independent Variables
Cpickit	$\beta 0 it - \beta 1$Winpctit - $\beta 2$BMI $- \beta 3$Power5$it + \beta 4$dash10it - $\beta 5$RelevantCollegeStatsit + $\beta 6$missingit + $\beta 7$Age$it + \mu it$
DrAVit	$\beta 0 it - \beta 1$Winpctit - $\beta 2$BMI $+ \beta 3$Power5$it - \beta 4$dash10it - $\beta 5$RelevantCollegeStatsit + $\beta 6$missingit + $\beta 7$Ageit μit

Figure 3: Theoretical Model

The first dependent variable in this research is labeled Cpick. This variable will be a numerical representation of where a player was drafted in a continuous order throughout a given draft year (1 being the first pick). The first independent variable, Power5, will act as a dummy variable, 1 representing that a player attended a power 5 school, and 0 indicating that they did not. This variable carries a negative sign, hypothesizing that if a player is from power 5 institution, they will be selected earlier in a draft possibly due to signaling bias. The second variable labeled winpct, containing another negative sign, represents the winning percentage of the institution that the respective draftee attended the year prior to being drafted. This paper anticipates finding that this variable will have a negative correlation with the dependent variable, indicating there may be some behavioral biases that are at play such as anchoring or signaling.

The variable "age" represents the age of the athlete when they are drafted. This variable is included with a positive sign to further test for possible bias. It is hypothesized that the older a player is, the later they will be selected due to a potentially shortened playing period.

The productive characteristics included in the model are labeled and described below. They are anticipated to carry a negative signal and are CRYDS (College Receiving yards per game). If productive characteristics should be the main influencer of draft selections, then variable will carry the most weight in influencing the dependent variable. The variable “dash10,” represents a player’s 40-yard dash in tenths of seconds, to better measure how much a player’s 40-yard dash affects draft position. This model, hypothesizing a negative sign, anticipates faster 40-yard dashes helping them becoming selected earlier. The BMI variable represents the body mass index of a players and is calculated by dividing weight in pounds (lb) by height in inches (in) squared and multiplying by a conversion factor of 703. This is expected to carry a negative sign as well. “Missing” is a variable that indicates that a player did not run a 40-yard dash at the NFL combine and has been substituted with the average of all of the 40-yard dash times collected. Therefore, is anticipated to result in a worse draft selection, carrying a positive sign.

The second regression equation seeks to determine which characteristics that a player brings with them from college to the NFL is truly an indicator of future success. The dependent variable for this regression is DrAV. Essentially, Approximate Value (AV) serves as a more comprehensive metric compared to conventional measures like 'number of seasons as a starter' or 'number of times making the Pro Bowl'. It incorporates factors such as team performance, individual statistics like receiving yards for wide receivers, and Pro Bowl appearances. This approach, originally formulated by Doug Drinen, provides an evaluation of player performance, considering both starters and non-starters, which measures the statistical output of a given players up to date, controlled for the number of years they have played in the league. The formula calculates approximate value (AV) points for receivers and passers based on their performance in comparison to team statistics. The formula for creating these values are listed in Appendix B. The defensive player evaluation is slightly different and a bit more nuanced. Doug Drinen describes how these numbers are calculated in Appendix B as well. It is important to note that DrAV is calculated the same way as wAV, but only captures the value that a player has provided to the respective team who had drafted them. This differs from wAV which measures the value that a player has provided to every team they have played for combined. DrAV was selected in this research to solely examine the decision making of executives during the draft, and the impact the selected players had on that team.

Data

Most of the data for this research comes from Pro-Football-Reference.com. Pro Football Reference (PFR) stands as a trusted and credible source for NFL statistics and analysis, owing to its comprehensive data, accuracy, transparency, and innovation. Founded by Doug Drinen, PFR offers an extensive database covering various facets of the NFL, from player performance to team records and historical data. This depth of information, coupled with the website's commitment to accuracy and reliability, has earned it the trust of fans, analysts, and even NFL teams. PFR maintains transparency in its methodologies, allowing users to understand how metrics and statistics are derived, which further enhances its credibility. Additionally, PFR has been at the forefront of introducing innovative metrics like Approximate Value (AV), developed by Drinen himself, which have become widely accepted standards for evaluating player performance. Overall, Pro Football Reference's combination of comprehensive data, accuracy, transparency, and innovation solidifies its status as a valid and indispensable source for NFL-related information and analysis.

It is important to state that DrAV, while a useful metric, is not perfect. To quote the creator, "AV is not meant to be a end-all be-all metric. Football stat lines just do not come close to capturing all the contributions of a player the way they do in baseball and basketball. If one player is a 16 and another is a 14, we can't be very confident that the 16AV player actually had a better season than the 14AV player. But I am pretty confident that the collection of all players with 16AV played better, as an entire group, than the collection of all players with 14AV" (Drinen, 2008).

The college win percentages and the conference in which each team plays were gathered from NCAA.com. This is a source that is widely used for college athletics and information regarding teams and players from all divisions. It has been used in many of the papers referenced in this research and provides up-to-date reliable information. SECsports.com is the official site of the Southeastern Conference and was used a reference to gather information used in Figure 1. It gave a detailed breakdown of NFL draft selections per conference and is partnered with ESPN to ensure correct data and current information.

Variable	Min.	St. Dev	Median	Mean	Max.
Rnd	1.00	1.97	4.00	3.78	7.00
CPick	5.00	73.52	108.5	116.0	256.0
Dash	4.220	0.85	4.480	4.480	4.730
BMI	24.14	1.94	26.75	26.96	42.53
CREC	0.1792	2.07	4.2480	4.2776	9.2500
CRYDS	3.173	22.46	61.758	62.036	124.308
CRTD	0.0304	0.23	0.5000	0.5336	1.4231
Age	20.00	0.81	22.00	21.97	24.00
DrAV	0.00	16.3	9.00	14.17	61.00
SEC	0.0000	0.42	0.0000	0.2373	1.0000
Winpct	0.2500	0.20	0.6923	0.6656	1.0000
Power5	0.0000	0.42	1.0000	0.7712	1.0000

Figure 4: Wide Receivers Summary Statistics:

As for the 118 Wide Receivers drafted displayed in Figure 4, it is important to point out that even though it may not stand out, five tenths of a second is a significant difference in 40-yard dash time as seen between the minimum and maximum Dash time. Another interesting statistic to point out is the minimum yards per game being about three. This seems like very low production for a player who was drafted to the NFL, as it is seen that about 62 yards per game is the average. Finally, it is important to note that from this data set, 77% of players were from Power 5 schools, leaving only about 23% of the dataset coming from non-power 5 institutions.

Variable	Min.	St. Dev	Median	Mean	Max.
Rnd	1.000	1.94	4.000	4.099	7.000
CPick	5.000	72.06	123.0	126.4	255.0
BMI	165.0	1.59	238.0	239.1	277.0
Dash10	4.380	1.05	4.640	4.641	4.910
Ctack	1.676	1.91	5.391	5.419	12.974
Csack	0.02941	0.18	0.21944	0.26719	0.83333
Cint	0.00000	0.05	0.02941	0.04904	0.26250
Age	20.00	0.89	22.00	22.39	24.00
DrAV	0.00	16.00	8.00	13.15	80.00
SEC	0.000	0.42	0.000	0.2303	1.0000
Power5	0.000	0.42	1.000	0.7763	1.0000

Figure 5: Linebacker Summary Statistics:

Figure 5 displays the descriptive statistics of the 150 Linebackers drafted from 2016-2020. There are a few things to note when examining this table, the first being a DrAV of 96. This seems to be an extremely high number may skew a player's results. It is also important to point out that some players listed as "linebackers," tend to play most of their snaps on the outside of the defensive line, making it easier for them to record sacks most of the time. This could be why the maximum sacks per game is much higher than the mean of sacks per game. A player like TJ Watt out of Wisconsin, is listed as an outside linebacker, but plays his majority of snaps lined up as a defensive end, making it easier for him to sack the quarterback. Finally, the table indicates that about 79% of players come from a power 5 school, while 18% come from an SEC school.

Variable	Min.	St. Dev	Median	Mean	Max.
Rnd	1.000	2.26	4.000	3.754	7.000
CPick	1.0	85.48	122.0	114.5	253.0
BMI	70.00	1.11	76.00	75.33	79.00
Dash10	4.340	1.53	4.810	4.806	5.220
Cpct	54.50	3.85	61.50	62.14	70.00
Cpyds	50.31	60.98	215.20	217.84	351.62
Cptd	0.517	0.56	1.605	1.711	2.906
Cinter	0.207	0.20	0.619	0.616	1.194
Crate	113.6	16.07	143.9	145.4	199.4
Cryds	-12.4	21.95	10.725	15.917	108.737
Crtd	0.045	0.77	0.258	0.427	1.351
DrAV	0.00	27.78	2.00	16.05	96.00
SEC	0.000	0.39	0.000	0.180	1.000
Power5	0.000	0.41	1.000	0.787	1.000
Winpct	0.333	0.17	0.667	0.676	1.000

Figure 6: Quarterback Summary Statistics:

Figure 6 displays the descriptive stats for the 60 quarterbacks drafted. The first thing that stands out is 40-yard dash times. The minimum and maximum are separated by almost a full second, which could lead to dramatic changes in draft position. Additionally, the maximum in terms of pass yards per game is over 100 yards higher than the mean, which would act as an outlier in these regressions. It is also imperative to point out that the maximum rushing yards per game, which is a stat that goes into quarterback rating, is 108 yards per game. This was done by Lamar Jackson and is significantly higher than the average rush yards per game of about 15.

Results:

Wide receivers were the first position group collected in this research and was used as the experimental model to test different variables and theories. Receivers and linebackers were chosen because they are the most drafted positions through the time period that this research focuses on (2016-2020). Quarterbacks, on the other hand, are one of the least drafted positions, yet was chosen to be included due to the high importance of the position.

Wide Recievers

	Dependent variable:	
	CPick	DrAV
	(1)	(2)
CRYDS	-1.750***	0.193***
	(0.260)	(0.064)
WRdash10	28.865***	-1.247
	(6.589)	(1.603)
Winpct	-46.962	16.021**
	(29.401)	(7.200)
WRBMI	-5.813**	0.021
	(2.882)	(0.703)
Power5	-53.693***	0.823
	(13.894)	(3.456)
Constant	-839.295***	46.115
	(315.144)	(76.768)
Observations	118	115
R2	0.391	0.111
Adjusted R2	0.363	0.071
Residual Std. Error	58.656 (df = 112)	14.244 (df = 109)
F Statistic	14.362*** (df = 5; 112)	2.735** (df = 5; 109)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 7: Wide Receiver Regression

The regression results for wide receivers yielded and adjusted R squared of 0.071 on 118 observations. As shown in Figure 7, average college yards per game was significant at the 1% level both when being drafted and influencing a player's professional success with the anticipated signs, hinting that this is good information when selecting a receiver. For every additional yard per game, a player is drafted almost 2 spots higher, on average, and have a higher DrAV of about 0.2. WRdash10 was significant at the 1% level when it came to the influence it has on draft position with its anticipated sign, yet showed no significance in how it affects pro performance. It is shown that for every tenth of a second slower a player is in their dash time, they are selected about 29 spots later, on average. Winpct is significant at the 5% level with the anticipated sign in the professional regression, showing that for every additional tenth of a percentage a player's respective team has in terms of win percentage, they earn, on average, about 16 points higher in their DrAV. WRBMI is significant at the 5% level with its anticipated sign in the draft model, indicating that for every unit increase in BMI, a player is drafted about 5 spots earlier, on average. WRBMI shows no significance in influencing pro success. The final variable, and the one this paper aims to understand is the Power5 variable. From this regression, it can be seen that it carries the expected sign and indicates that if a receiver is from a power 5 conference, they are drafted about 53 spots higher, on average, than those who are not in a power 5 conference. This is interesting because coming from the power 5 holds no significance in determining pro success.

Linebackers

	Dependent variable:	
	CPick	DrAV
	(1)	(2)
Ctack	-3.991	1.081
	(3.195)	(0.675)
Csack	-129.337***	14.746**
	(32.716)	(6.895)
Cint	-8.391	35.660
	(109.185)	(23.007)
Age	27.256***	-5.090***
	(6.243)	(1.316)
dash10	10.864**	-1.729
	(5.114)	(1.078)
WinPct	-59.323**	-1.142
	(27.110)	(5.719)
BMI	-0.603	-0.775
	(3.348)	(0.706)
missing	10.573	-0.318
	(18.158)	(3.961)
Power5	-6.704	-1.707
	(12.970)	(2.734)
Constant	-870.053***	221.712***
	(288.959)	(61.016)
Observations	152	150
R2	0.276	0.173
Adjusted R2	0.231	0.120
Residual Std. Error	63.214 (df = 142)	13.292 (df = 140)
F Statistic	6.027*** (df = 9; 142)	3.251*** (df = 9; 140)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 8: Linebackers Regression:

The regression results from Figure 8 indicate that sacks influence both draft position, and pro success, carrying the expected signs. For every additional collegiate sack per game, a player's draft position is, on average, 129 spots earlier. It also shows it increased their DrAV by 14.7 units, on average. Age was significant at the 1% level carrying expected signs, indicating it may be a good source of information when drafted a linebacker. Dash10 was significant at the

1% level in the draft model with its expected sign, indicating that for every tenth of a second slower a player runs their 40 time in, they are drafted about 11 spots later.

Linebackers

	Dependent variable:	
	CPick	DrAV
	(1)	(2)
Ctack	-4.711	1.232*
	(3.042)	(0.664)
Csack	-131.107***	15.577**
	(31.308)	(6.826)
Cint	-52.902	38.347*
	(106.006)	(23.081)
Age	24.647***	-4.710***
	(6.000)	(1.306)
dash10	14.732***	-2.027*
	(5.068)	(1.105)
WinPct	-46.052*	-2.653
	(26.355)	(5.741)
BMI	0.573	-0.855
	(3.247)	(0.707)
missing	18.801	-0.920
	(17.687)	(3.974)
PwrSECLb	-42.358***	3.192
	(12.754)	(2.783)
Constant	-1,025.564***	227.308***
	(279.655)	(61.007)
Observations	152	150
R2	0.327	0.178
Adjusted R2	0.285	0.125
Residual Std. Error	60.950 (df = 142)	13.248 (df = 140)
F Statistic	7.676*** (df = 9; 142)	3.375*** (df = 9; 140)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 9: Linebackers SEC Regression:

Having examined whether being in a power 5 conference influences draft position and professional success for linebackers and finding no relationship, this paper narrowed the search down to the SEC (listed as "PwrSECLb" in Figure 9) to understand if this conference plays any role in these two regressions. From the results shown in Figure 9, college sacks per game still appears to be significant in both models with the expected signs, with college interceptions now being marginally significant when determining pro success. The Age variable is still significant in both models with correct signs, and dash10 is still significant in the draft model, but now marginally significant in the pro model as well. Winpct is significant at the 10% level in the draft model, indicating that for every additional unit increase in the win percentage of a player's respective school their final year, they will be selected about 46 spots earlier, on average. Finally, Figure 9 indicates at the 1% level with its anticipated sign, that if a linebacker plays in the SEC, they are drafted about 42 spots earlier than linebackers who do not play in the SEC.

Quarterbacks

	Dependent variable:	
	CPick	DrAV
	(1)	(2)
Crate	-1.441**	0.293
	(0.657)	(0.223)
Age	45.289***	-7.514**
	(10.141)	(3.461)
dash10QB	4.992	-4.521**
	(5.936)	(2.015)
Winpct	-11.661	-8.253
	(60.857)	(20.999)
BMIQB	-1.952	5.685*
	(8.772)	(2.983)
missingQB	-81.858**	14.767
	(40.179)	(13.625)
Power5	-30.925	3.552
	(20.984)	(7.123)
Constant	-847.267**	205.079
	(418.807)	(142.210)
Observations	61	60
R2	0.480	0.366
Adjusted R2	0.412	0.281
Residual Std. Error	65.563 (df = 53)	22.229 (df = 52)
F Statistic	7.002*** (df = 7; 53)	4.288*** (df = 7; 52)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 10: Quarterbacks Regression

The position group evaluated in this research is quarterbacks. Figure 10 displays the results in both the draft model and professional success model. With an adjusted R squared of 0.281, this regression indicates that for every unit increase of a QB's college rating, they are selected about 1 spot earlier. It also shows that age is significant at the 1% level in both the draft model and pro model with the anticipated signs. For every year older a player is, they are drafted 45 spots later, on average, while losing about 7 units on their DrAV. Dash10QB is significant at the 5% level in the pro model with the expected sign. It is indicating that for every tenth of a second increase in a QB's 40 time, they earn a 4 unit decrease in DrAV. BMIQB is marginally significant in the pro model with the correct sign, indicating that for every unit increase in BMI, a QB earns an extra 5 unit increase in DrAV.

<u>Econometric Testing:</u>

After running these regression models, econometric testing was done to evaluate whether heteroskedasticity, highly correlated independent variables, or specification errors were present. The first test run was the White test to examine if heteroskedasticity was in any of these models. With each of the p-values greater than 0.05, this paper failed to reject the null hypothesis that there was no heteroskedasticity present in the model.

A correlation matrix was run on each of the regressions to evaluate if any of the variables in the models were too highly correlated with each other. The results indicated that in the wide receiver's model, CRYDS, CREC, and CRTD were too highly correlated with each other with values above the accepted threshold of 0.8. This testing can be seen in Figure 14 of Appendix D. To correct for this, the CREC and CRTD variables were removed from the regression, and CRYDS was kept representing college production. It seemed most logical to use yards per game as the main statistic for wide receivers entering the draft. There were no variables over the absolute value of 0.8 in the Linebackers model, therefore no variables were removed.

As for Quarterbacks, the same problem was present as the Receiver's model. The productive statistics were too highly correlated, over the absolute value of 0.8. To correct for this, all productive characteristics were removed from the model except for QB rating (CRATE). This variable was chosen because it is comprised of all of their productive stats, giving a fairly accurate representation of their statistic college success.

The Ramsey Reset test was run on each of these regressions to test for the presence of specification error. It came as a surprise that specification error was only present in the

Quarterbacks models and the model in which SEC bias was tested for. The testing in Figure 18 of Appendix D represents that all other models revealed that they were clean of specification error, with p-values greater than 0.05. The final test run was the VIF test, further testing for multicollinearity. With each model having a variance inflation factor of less than 5 (shown in Figure 19 of Appendix D), it can be concluded that the models do not contain multicollinearity.

Conclusion:

The regressions in this paper aligned with some of the literature previously written and found antidotal evidence opposing some of the conclusions of previous literature. Kitchen's study (2014), concluding that players from more successful institutions were selected significantly earlier in the draft, was not found in this paper for quarterbacks, but was found to influence the draft position of linebackers and receivers, without having any real significance in their professional career with the team that drafted them. Additionally, it agreed with literature produced by Hendricks, Wallace E., et al (2001), that power five wide receivers get a draft boost compared to their non power 5 counterparts.

The allure of power 5 receivers seems to carry extra weight for executives in the National Football League. This tendency suggests a susceptibility to certain behavioral biases, wherein decision-makers may overvalue players from prestigious collegiate conferences. Interestingly, this trend is not exclusive to receivers; it extends to other positions as well, albeit to varying degrees. Notably, linebackers from the Southeastern Conference (SEC) seem to be given a premium when entering the NFL draft over linebackers from the other Power 5 schools. However, it's crucial to acknowledge that while these over-prioritized characteristics may indicate behavioral biases such as signaling or risk aversion, they don't diminish the inherent talent of these collegiate athletes who had to earn their place on renowned teams.

Moreover, the disproportionate emphasis on certain metrics, such as quarterback (QB) rating, raises questions about the evaluation criteria used by NFL decision-makers. The inflated importance placed on QB rating may reflect a tendency to overlook the broader context of a player's performance and the role played by their surrounding team members. This observation suggests a potential overreliance on individual statistics without due consideration for team dynamics and external factors. Consequently, it prompts further inquiry into the underlying factors driving draft decisions and the extent to which they align with predictive measures of professional success in the NFL. As such, this study underscores the need for more comprehensive analyses to better understand the interplay between behavioral biases, evaluation metrics, and draft outcomes in professional football.

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Appendix A: Early/Late Round Splits

Early Rounds

	Dependent variable:	
	CPick (1)	DrAV (2)
CRYDS	-0.525***	0.056
	(0.194)	(0.131)
WRdash10a	6.394	5.495*
	(4.457)	(2.968)
Winpct	-28.430*	14.657
	(16.884)	(11.192)
WRBMIa	0.710	-0.602
	(1.385)	(0.917)
WRmissinga	1.903	-8.347
	(7.371)	(5.021)
Power5	-24.832**	1.014
	(9.865)	(6.522)
Constant	-180.078	-219.717
	(204.693)	(136.076)
Observations	56	55
R2	0.249	0.180
Adjusted R2	0.157	0.078
Residual Std. Error	22.800 (df = 49)	15.063 (df = 48)
F Statistic	2.704** (df = 6; 49)	1.761 (df = 6; 48)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Late Rounds

	Dependent variable:	
	CPick (1)	DrAV (2)
CRYDS	-0.485*	-0.029
	(0.263)	(0.066)
WRdash10b	6.935	-0.621
	(6.692)	(1.669)
Winpct	35.741	4.554
	(28.911)	(7.315)
WRBMIb	3.848	-1.605
	(4.972)	(1.248)
WRmissingb	15.929	2.177
	(10.984)	(2.799)
Power5	-22.199*	-4.494
	(11.886)	(3.040)
Constant	-221.865	79.039
	(300.690)	(75.557)
Observations	62	60
R2	0.168	0.098
Adjusted R2	0.078	-0.004
Residual Std. Error	39.477 (df = 55)	9.804 (df = 53)
F Statistic	1.856 (df = 6; 55)	0.958 (df = 6; 53)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Figure 11: Wide Receivers Testing

Based on the regressions displayed by Figure 11, in the early rounds, receiving yards per game and being in the Power 5 are overvalued. The late rounds show the same result but at marginally significant levels.

Early Rounds

	Dependent variable:	
	CPick	DrAV
	(1)	(2)
Ctack	-2.470	2.228
	(2.359)	(1.611)
Csack	-28.831	11.429
	(23.005)	(15.709)
Cint	-23.499	63.439
	(69.840)	(47.690)
Age	10.018**	-5.302*
	(3.898)	(2.662)
dash10a	6.514*	-1.512
	(3.852)	(2.630)
WinPct	-25.821	-3.866
	(21.101)	(14.409)
BMIa	-2.488	-2.149
	(2.899)	(1.980)
missinga	-18.701	3.182
	(13.784)	(9.413)
SEC	-9.048	3.233
	(8.006)	(5.467)
Constant	-349.768*	257.231*
	(202.816)	(138.493)
Observations	56	56
R2	0.346	0.238
Adjusted R2	0.219	0.089
Residual Std. Error (df = 46)	23.902	16.321
F Statistic (df = 9; 46)	2.710**	1.600
Note:	*p<0.1; **p<0.05; ***p<0.01	

Late Rounds

	Dependent variable:	
	CPick	DrAV
	(1)	(2)
Ctack	-4.905*	0.844
	(2.871)	(0.595)
Csack	-47.317	4.862
	(31.639)	(6.608)
Cint	123.535	0.217
	(109.551)	(22.802)
Age	5.197	-0.881
	(6.521)	(1.358)
dash10b	4.035	-0.172
	(4.883)	(1.014)
WinPct	-37.810	-3.829
	(23.594)	(4.915)
BMIb	1.190	-0.176
	(2.812)	(0.584)
missingb	11.505	-2.582
	(16.918)	(3.622)
SEC	-23.296	1.082
	(14.145)	(2.968)
Constant	-111.632	38.420
	(290.057)	(60.318)
Observations	96	94
R2	0.118	0.060
Adjusted R2	0.026	-0.041
Residual Std. Error	46.105 (df = 86)	9.550 (df = 84)
F Statistic	1.279 (df = 9; 86)	0.596 (df = 9; 84)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Figure 12: Linebacker Testing

There is little to no significance found in the regressions created in Figure 12.

Early Rounds

	Dependent variable:	
	CPick	DrAV
	(1)	(2)
Crate	-0.569	0.400
	(0.523)	(0.491)
Age	16.421*	-4.900
	(7.965)	(7.479)
dash10QBa	1.277	-10.014**
	(3.808)	(3.576)
Winpct	-61.200	3.273
	(43.966)	(41.283)
BMIQBa	3.872	0.792
	(9.221)	(8.659)
missingQBa	-12.568	7.385
	(18.760)	(17.615)
Power5	19.925	-10.111
	(16.290)	(15.296)
Constant	-389.241	540.331*
	(305.065)	(286.453)
Observations	26	26
R2	0.418	0.404
Adjusted R2	0.191	0.173
Residual Std. Error (df = 18)	27.763	26.069
F Statistic (df = 7; 18)	1.844	1.745
Note:	*p<0.1; **p<0.05; ***p<0.01	

Late Rounds

	Dependent variable:	
	CPick	DrAV
	(1)	(2)
Crate	-0.173	-0.059
	(0.695)	(0.218)
Age	-1.702	-0.437
	(12.300)	(3.853)
dash10QBb	3.892	0.731
	(5.700)	(1.790)
Winpct	-44.348	-11.447
	(56.695)	(18.428)
BMIQBb	4.657	7.121***
	(7.131)	(2.254)
missingQBb		
Power5	-32.783*	4.811
	(18.460)	(5.798)
Constant	-18.753	-204.009
	(433.204)	(135.699)
Observations	35	34
R2	0.133	0.287
Adjusted R2	-0.053	0.129
Residual Std. Error	46.830 (df = 28)	14.668 (df = 27)
F Statistic	0.714 (df = 6; 28)	1.813 (df = 6; 27)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Figure 13: Quarterback Testing

The regressions in Figure 12 may suggest that in the early rounds of drafts, the 40-yard dash times of quarterbacks should be taken into more consideration. As for the late rounds, the regression indicates that NFL executives should evaluate and desire higher quarterbacks with higher BMI’s.

Appendix B: DrAV Formulas

team_points_for_passers = (team_points_for_skill_positions - team_points_for_rushers) * .26.

So that leaves:

team_points_for_receivers = (team_points_for_skill_positions - team_points_for_rushers) * .74.

Anyone who had a receiving yard gets this many AV points:

approx_value = (receiving yards) / (team receiving yards) * team_points_for_receivers

approx_value = (passing yards) / (team passing yards) * team_points_for_passers

And, as with rushers, we add an efficiency adjustment here:

bonus = .5 * [(Adjusted yards per attempt) - (League average adjusted yards per attempt)], if the player's AYPA was better than league average.

penalty = 2 * [(Adjusted yards per attempt) - (League average adjusted yards per attempt)], if the player's AYPA was worse than league average.

individual_points = [(games played) + 5*(games started) + sacks + 4*(fumble recoveries) + 4*(interceptions) + 5*(defensive TDs) + (tkl_constant)*(tackles)] + (all_pro_bonus),

where

tkl_constant = .6 if the player is a defensive lineman, .3 if the player is a linebacker, and 0 of the player is a defensive back.

all_pro_bonus = (all_pro_level)*(year_multiplier),

where

all_pro_level = 1.5 for first-team all-pro, 1.0 for second-team all-pro, and 0.5 for pro bowler

year_multiplier = (year_constant) * (number_of_games_multiplier),

where year_constant = 80, and number_of_games_multiplier = (number of games played by each team in that season) / 1

Appendix C: R Code

```
#Wide Recievers-----------------------------------------
WRdash10<-(WRC2$Dash*10)
WRdash10
WRmissing<-ifelse(WRC2$Dash==4.48,1,0)
WRmissing
WRBMI=(WRC2$WT/(WRC2$HT^2))*703
summary(WRBMI)

WRBMI
WRC2$WT
summary(WRC2$HT)

modelcollege2<-lm(CPick~CRYDS+WRdash10+Winpct+WRBMI+Power5, data = WRC2)
summary(modelcollege2)

modelpro<-lm(DrAV~CRYDS+WRdash10+Winpct+WRBMI+Power5, data = WRC2)
summary(modelpro)

stargazer(modelcollege2, modelpro, type="text", title="Wide Recievers")
#Linebackers------------------------------------------
summary(Linebackers_Data)
missing<-ifelse(Linebackers_Data$Dash==4.6,1,0)
missing
BMI=(Linebackers_Data$WT/(Linebackers_Data$HT^2))*703
summary(BMI)
dash10<-(Linebackers_Data$Dash*10)
dash10


modelcollegeLINE<-
lm(CPick~Ctack+Csack+Cint+Age+dash10+WinPct+BMI+missing+Power5, data =
Linebackers_Data)
summary(modelcollegeLINE)

modelproLINE<-lm(DrAV~Ctack+Csack+Cint+Age+dash10+WinPct+BMI+missing+Power5,
data = Linebackers_Data)
summary(modelproLINE)

library(stargazer)
stargazer(modelcollegeLINE,modelproLINE, type="text", title="Linebackers" )

#Quarterbacks--------------------------------------------------------------
summary(Quarterbacks)
missingQB<-ifelse(Quarterbacks$Dash==4.86,1,0)
```

```
missingQB
BMIQB=(Quarterbacks$WT/(Quarterbacks$HT^2))*703
summary(BMIQB)

dash10QB<-(Quarterbacks$Dash*10)
dash10QB


modelcollegeQB<-lm(CPick~Crate+Age+dash10QB+Winpct+BMIQB+missingQB+Power5,
data = Quarterbacks)
summary(modelcollegeQB)

modelproQB<-lm(DrAV~Crate+Age+dash10QB+Winpct+BMIQB+missingQB+Power5, data =
Quarterbacks)
summary(modelproQB)
stargazer(modelcollegeQB,modelproQB, type="text", title="Quarterbacks" )

PwrSECWr<-(WRC2$SEC*WRC2$Power5)
PwrSECLb<-(Linebackers_Data$SEC*Linebackers_Data$Power5)
PwrSECQb<-(Quarterbacks$SEC*Quarterbacks$Power5)

#SECTesting------------------------------------------------------------------------------------------------------
--------


SECmodelcollege2<-lm(CPick~CRYDS+WRdash10+Winpct+WRBMI+WRmissing+SEC, data
= WRC2)
summary(SECmodelcollege2)

SECmodelpro<-lm(DrAV~CRYDS+WRdash10+Winpct+WRBMI+WRmissing+SEC, data =
WRC2)
summary(SECmodelpro)


SECmodelcollegeLINE<-
lm(CPick~Ctack+Csack+Cint+Age+dash10+WinPct+BMI+missing+SEC, data =
Linebackers_Data)
summary(SECmodelcollegeLINE)

SECmodelproLINE<-lm(DrAV~Ctack+Csack+Cint+Age+dash10+WinPct+BMI+missing+SEC,
data = Linebackers_Data)
summary(SECmodelproLINE)

SECmodelcollegeQB<-lm(CPick~Crate+Age+dash10QB+Winpct+BMIQB+missingQB+SEC,
data = Quarterbacks)
summary(SECmodelcollegeQB)
```

```
SECmodelproQB<-lm(DrAV~Crate+Age+dash10QB+Winpct+BMIQB+missingQB+SEC, data
= Quarterbacks)
summary(SECmodelproQB)

stargazer(SECmodelcollege2, SECmodelpro, type="text", title="Wide Recievers")
stargazer(SECmodelcollegeLINE,SECmodelproLINE, type="text", title="Linebackers" )
stargazer(SECmodelcollegeQB,SECmodelproQB, type="text", title="Quarterbacks" )

summary(WRC2)
summary(Linebackers_Data)
summary(Quarterbacks)

#SplitWRs---------------------------------------------------------------------------------------------------
------


first<-subset(WRC2, WRC2$CPick<=96)
summary(first$CPick)
second<-subset(WRC2, WRC2$CPick>=97)
summary(second$CPick)

WRdash10a<-(first$Dash*10)
WRdash10a
WRmissinga<-ifelse(first$Dash==4.48,1,0)
WRmissing
WRBMIa=(first$WT/(first$HT^2))*703
summary(WRBMIa)


WRdash10b<-(second$Dash*10)
WRdash10b
WRmissingb<-ifelse(second$Dash==4.48,1,0)
WRmissingb
WRBMIb=(second$WT/(second$HT^2))*703
summary(WRBMIb)

modelcollege3<-lm(CPick~CRYDS+WRdash10a+Winpct+WRBMIa+WRmissinga+Power5,
data = first)
summary(modelcollege3)

modelpro3<-lm(DrAV~CRYDS+WRdash10a+Winpct+WRBMIa+WRmissinga+Power5, data =
first)
summary(modelpro3)

stargazer(modelcollege3, modelpro3,second, type="text", title="Early Rounds" )
```

```
modelcollege4<-lm(CPick~CRYDS+WRdash10b+Winpct+WRBMIb+WRmissingb+Power5,
data = second)
summary(modelcollege4)

modelpro4<-lm(DrAV~CRYDS+WRdash10b+Winpct+WRBMIb+WRmissingb+Power5, data =
second)
summary(modelpro4)

stargazer(modelcollege4, modelpro4,second, type="text", title="Late Rounds" )


#SplitLinebackers-----------------------------------------------------------------------------------------------
--
firstL<-subset(Linebackers_Data, Linebackers_Data$CPick<=96)
summary(firstL$CPick)

dash10a<-(firstL$Dash*10)
dash10a

missinga<-ifelse(firstL$Dash==4.6,1,0)
missinga
BMIa=(firstL$WT/(firstL$HT^2))*703
summary(BMIa)

secondL<-subset(Linebackers_Data, Linebackers_Data$CPick>=97)
summary(secondL$CPick)

dash10b<-(secondL$Dash*10)
dash10b
missingb<-ifelse(secondL$Dash==4.6,1,0)
missingb
BMIb=(secondL$WT/(secondL$HT^2))*703
summary(BMIb)

modelcollegeLINE2<-
lm(CPick~Ctack+Csack+Cint+Age+dash10a+WinPct+BMIa+missinga+SEC, data = firstL)
summary(modelcollegeLINE2)

modelproLINE2<-lm(DrAV~Ctack+Csack+Cint+Age+dash10a+WinPct+BMIa+missinga+SEC,
data = firstL)
summary(modelproLINE2)

stargazer(modelcollegeLINE2, modelproLINE2,second, type="text", title="Early Rounds" )
```

```
modelcollegeLINE3<-
lm(CPick~Ctack+Csack+Cint+Age+dash10b+WinPct+BMIb+missingb+SEC, data = secondL)
summary(modelcollegeLINE3)

modelproLINE3<-lm(DrAV~Ctack+Csack+Cint+Age+dash10b+WinPct+BMIb+missingb+SEC,
data = secondL)
summary(modelproLINE3)

stargazer(modelcollegeLINE3, modelproLINE3,second, type="text", title="Late Rounds" )
#SplitQBs----------------------------------------------------------------------------------------------

firstQ<-subset(Quarterbacks, Quarterbacks$CPick<=96)
summary(firstQ$CPick)

dash10QBa<-(firstQ$Dash*10)
dash10QBa
missingQBa<-ifelse(firstQ$Dash==4.86,1,0)
missingQBa
BMIQBa=(firstQ$WT/(firstQ$HT^2))*703
summary(BMIQBa)

secondQ<-subset(Quarterbacks, Quarterbacks$CPick>=97)
summary(secondQ$CPick)

dash10QBb<-(secondQ$Dash*10)
dash10QBb
missingQBb<-ifelse(secondQ$Dash==4.86,1,0)
missingQBb
BMIQBb=(secondQ$WT/(secondQ$HT^2))*703
summary(BMIQBb)

modelcollegeQB2<-
lm(CPick~Crate+Age+dash10QBa+Winpct+BMIQBa+missingQBa+Power5, data = firstQ)
summary(modelcollegeQB2)

modelproQB2<-lm(DrAV~Crate+Age+dash10QBa+Winpct+BMIQBa+missingQBa+Power5,
data = firstQ)
summary(modelproQB2)
stargazer(modelcollegeQB2, modelproQB2,second, type="text", title="Early Rounds" )
modelcollegeQB3<-
lm(CPick~Crate+Age+dash10QBb+Winpct+BMIQBb+missingQBb+Power5, data = secondQ)
summary(modelcollegeQB3)

modelproQB3<-lm(DrAV~Crate+Age+dash10QBb+Winpct+BMIQBb+missingQBb+Power5,
data = secondQ)
summary(modelproQB3)
```

```
stargazer(modelcollegeQB3, modelproQB3,second, type="text", title="Late Rounds" )
#----------------------------------------------------------------------------------------------------------

install.packages("lmtest")
library(skedastic)
library(lmtest)
#Heteroskedasticity-------------------------------------------------------------------------------

white(modelcollege2, interactions=TRUE) #NOHETERO... greater than .05
white(modelpro, interactions=TRUE)
white(modelcollegeLINE, interactions=TRUE)
white(modelproLINE, interactions=TRUE)
white(modelcollegeQB, interactions=TRUE)
white(modelproQB, interactions=TRUE)

#Multicollinerity-------------------------------------------------------------------------------

library(corrplot)
matrix<-data.frame(WRC2$CREC, WRC2$CRYDS, WRC2$CRTD, WRC2$Age,WRdash10,
WRC2$Winpct,WRBMI, WRmissing, WRC2$Power5)
cor(matrix)

matrixline<-data.frame(Linebackers_Data$Cint, Linebackers_Data$Csack,
Linebackers_Data$Ctack, Linebackers_Data$Age, Linebackers_Data$WinPct,
Linebackers_Data$Power5, missing, dash10, BMI)
cor(matrixline)

matrixQB<-
data.frame(Quarterbacks$Cpct,Quarterbacks$Cpyds,Quarterbacks$Cptd,Quarterbacks$Cinter,Qu
arterbacks$Crate,Quarterbacks$Cryds,

Quarterbacks$Crtd,Quarterbacks$Age,dash10QB,Quarterbacks$Winpct,BMIQB,missingQB,Qu
arterbacks$SEC)
cor(matrixQB)

#SpecificationError-------------------------------------------------------------------------

resettest(modelcollege2, power = 2:4)
resettest(modelpro, power = 2:4)
resettest(modelcollegeLINE, power = 2:4)
resettest(modelproLINE, power = 2:4)
resettest(modelcollegeQB, power = 2:4)
resettest(modelproQB, power = 2:4) #Specification error
resettest(SECmodelcollege2, power = 2:4) #Specification error
resettest(SECmodelpro, power = 2:4) #Specification error
resettest(SECmodelcollegeLINE, power = 2:4) #Specification error
```

```
resettest(SECmodelproLINE, power = 2:4) #Specification error
resettest(SECmodelcollegeQB, power = 2:4) #Specification error
resettest(SECmodelproQB, power = 2:4)

#MulticolinearityVIF--------------------------------------------------------------------------

vif(modelcollege2)
vif(modelpro)
vif(modelcollegeLINE)
vif(modelproLINE)
vif(modelcollegeQB)
vif(modelproQB)
#NO MULTICOLINERARITY
```

Appendix D: Econometric Testing

```
> white(modelcollege2, interactions=TRUE) #NOHETERO... greater than .05
# A tibble: 1 × 5
  statistic p.value parameter method       alternative
      <dbl>   <dbl>     <dbl> <chr>        <chr>
1      55.5   0.419        54 White's Test greater
> white(modelpro, interactions=TRUE)
# A tibble: 1 × 5
  statistic p.value parameter method       alternative
      <dbl>   <dbl>     <dbl> <chr>        <chr>
1      26.5   0.999        54 White's Test greater
> white(modelcollegeLINE, interactions=TRUE)
# A tibble: 1 × 5
  statistic p.value parameter method       alternative
      <dbl>   <dbl>     <dbl> <chr>        <chr>
1      66.0   0.126        54 White's Test greater
> white(modelproLINE, interactions=TRUE)
# A tibble: 1 × 5
  statistic p.value parameter method       alternative
      <dbl>   <dbl>     <dbl> <chr>        <chr>
1      38.5   0.945        54 White's Test greater
> white(modelcollegeQB, interactions=TRUE)
# A tibble: 1 × 5
  statistic p.value parameter method       alternative
      <dbl>   <dbl>     <dbl> <chr>        <chr>
1        61    1.00       104 White's Test greater
> white(modelproQB, interactions=TRUE)
# A tibble: 1 × 5
  statistic p.value parameter method       alternative
      <dbl>   <dbl>     <dbl> <chr>        <chr>
1        60    1.00       104 White's Test greater
```

Figure 14: White Testing

```
> matrix<-data.frame(WRC2$CREC, WRC2$CRYDS, WRC2$CRTD, WRC2$Age,WRdash10, WRC2$Winpct,WRBMI, WRmissing, WRC2$Power5)
> cor(matrix)
             WRC2.CREC   WRC2.CRYDS    WRC2.CRTD     WRC2.Age     WRdash10 WRC2.Winpct         WRBMI    WRmissing   WRC2.Power5
WRC2.CREC   1.00000000  0.787937657  0.636875672 -0.015939992  0.181913625 -0.10868195  5.540746e-02  0.112270153 -3.687944e-01
WRC2.CRYDS  0.78793766  1.000000000  0.813149286 -0.007620944  0.207614417 -0.14979790  4.461445e-02 -0.014629212 -3.102779e-01
WRC2.CRTD   0.63687567  0.813149286  1.000000000  0.022611084  0.127180818  0.06620474  5.757113e-02  0.007996892 -1.942191e-01
WRC2.Age   -0.01593999 -0.007620944  0.022611084  1.000000000  0.153884008  0.06266563 -7.338203e-02  0.136546830 -1.920585e-01
WRdash10    0.18191362  0.207614417  0.127180818  0.153884008  1.000000000 -0.09887675 -9.177418e-02 -0.001248132 -9.428119e-02
WRC2.Winpct -0.10868195 -0.149797898  0.066204738  0.062665625 -0.098876755  1.00000000 -2.187139e-01  0.014997457  2.541468e-01
WRBMI       0.05540746  0.044614446  0.057571128 -0.073382026 -0.091774179 -0.21871388  1.000000e+00 -0.102449647 -5.550136e-05
WRmissing   0.11227015 -0.014629212  0.007996892  0.136546830 -0.001248132  0.01499746 -1.024496e-01  1.000000000 -2.018863e-02
WRC2.Power5 -0.36879438 -0.310277886 -0.194219066 -0.192058504 -0.094281193  0.25414679 -5.550136e-05 -0.020188630  1.000000e+00
```

Figure 15: WR Correlation Matrix

	Linebackers_Data.Cint	Linebackers_Data.Csack	Linebackers_Data.Ctack	Linebackers_Data.Age	Linebackers_Data.WinPct	Linebackers_Data.Power5
Linebackers_Data.Cint	1.00000000	-0.242993365	0.389923866	0.09918066	-0.15774543	-0.048641875
Linebackers_Data.Csack	-0.24299336	1.000000000	-0.348011239	0.11855172	-0.01730855	-0.095413721
Linebackers_Data.Ctack	0.38992387	-0.348011239	1.000000000	-0.06410506	-0.22501260	-0.163347943
Linebackers_Data.Age	0.09918066	0.118551721	-0.064105065	1.00000000	-0.09992468	-0.187725157
Linebackers_Data.WinPct	-0.15774543	-0.017308551	-0.225012604	-0.09992468	1.00000000	0.176781559
Linebackers_Data.Power5	-0.04864188	-0.095413721	-0.163347943	-0.18772516	0.17678156	1.000000000
missing	0.06182420	-0.000973219	0.060254174	0.08882746	0.07525845	0.007183663
dash10	0.10681455	-0.015017418	-0.033184829	0.22232785	-0.11633811	-0.031927673
BMI	-0.04199092	0.171720828	-0.001452804	-0.14706420	-0.01617384	-0.005913929

	missing	dash10	BMI
Linebackers_Data.Cint	0.061824203	0.10681455	-0.041990922
Linebackers_Data.Csack	-0.000973219	-0.01501742	0.171720828
Linebackers_Data.Ctack	0.060254174	-0.03318483	-0.001452804
Linebackers_Data.Age	0.088827462	0.22232785	-0.147064201
Linebackers_Data.WinPct	0.075258455	-0.11633811	-0.016173843
Linebackers_Data.Power5	0.007183663	-0.03192767	-0.005913929
missing	1.000000000	-0.12512555	0.029614459
dash10	-0.125125552	1.00000000	-0.106205291
BMI	0.029614459	-0.10620529	1.000000000

Figure 16: Linebacker Correlation Matrix

	Quarterbacks.Cpct	Quarterbacks.Cpyds	Quarterbacks.Cptd	Quarterbacks.Cinter	Quarterbacks.Crate	Quarterbacks.Cryds	Quarterbacks.Crtd
Quarterbacks.Cpct	1.00000000	0.36525232	0.57506649	-0.30369977	0.81653667	0.01737448	-0.19771860
Quarterbacks.Cpyds	0.36525232	1.00000000	0.87504522	0.51230035	0.26207064	-0.22841969	0.03425149
Quarterbacks.Cptd	0.57506649	0.87504522	1.00000000	0.26903223	0.57342919	-0.10895283	-0.06569887
Quarterbacks.Cinter	-0.30369977	0.51230035	0.26903223	1.00000000	-0.45494961	-0.12140012	0.15527900
Quarterbacks.Crate	0.81653667	0.26207064	0.57342919	-0.45494961	1.00000000	0.17814532	-0.15333468
Quarterbacks.Cryds	0.01737448	-0.22841969	-0.10895283	-0.12140012	0.17814532	1.00000000	0.15011295
Quarterbacks.Crtd	-0.19771860	0.03425149	-0.06569887	0.15527900	-0.15333468	0.15011295	1.00000000
Quarterbacks.Age	0.01816099	-0.27950825	-0.27964794	-0.33556511	-0.08209373	-0.25462306	-0.33814194
dash10QB	0.16439760	0.24741915	0.16462008	0.10476205	-0.06252512	-0.69069227	-0.19719252
Quarterbacks.Winpct	0.43475034	-0.10086420	0.09598139	-0.40815518	0.47594247	0.19419023	-0.12188832
BMIQB	0.26852339	-0.23753439	0.01685905	-0.37621827	0.43227630	0.38483708	0.09866791
missingQB	0.15016212	0.17829654	0.14578486	-0.05361024	0.08111609	-0.03891128	0.05040446
Quarterbacks.SEC	0.02581754	-0.17139310	-0.11819683	-0.25901998	0.13946226	0.10761253	-0.01872565

	Quarterbacks.Age	dash10QB	Quarterbacks.Winpct	BMIQB	missingQB	Quarterbacks.SEC
Quarterbacks.Cpct	0.01816099	0.16439760	0.43475034	0.26852339	0.15016212	0.02581754
Quarterbacks.Cpyds	-0.27950825	0.24741915	-0.10086420	-0.23753439	0.17829654	-0.17139310
Quarterbacks.Cptd	-0.27964794	0.16462008	0.09598139	0.01685905	0.14578486	-0.11819683
Quarterbacks.Cinter	-0.33556511	0.10476205	-0.40815518	-0.37621827	-0.05361024	-0.25901998
Quarterbacks.Crate	-0.08209373	-0.06252512	0.47594247	0.43227630	0.08111609	0.13946226
Quarterbacks.Cryds	-0.25462306	-0.69069227	0.19419023	0.38483708	-0.03891128	0.10761253
Quarterbacks.Crtd	-0.33814194	-0.19719252	-0.12188832	0.09866791	0.05040446	-0.01872565
Quarterbacks.Age	1.00000000	0.23701631	0.13734446	-0.08386587	-0.14136593	0.13641933
dash10QB	0.23701631	1.00000000	-0.14879223	-0.22188424	0.08057032	0.03732860
Quarterbacks.Winpct	0.13734446	-0.14879223	1.00000000	0.31979159	0.09146136	0.01688809
BMIQB	-0.08386587	-0.22188424	0.31979159	1.00000000	-0.05456560	0.15444747
missingQB	-0.14136593	0.08057032	0.09146136	-0.05456560	1.00000000	0.09051115
Quarterbacks.SEC	0.13641933	0.03732860	0.01688809	0.15444747	0.09051115	1.00000000

Figure 17: QB Correlation Matrix

```
        RESET test

data:  modelcollegeQB
RESET = 0.67408, df1 = 3, df2 = 50, p-value = 0.572

> resettest(modelproQB, power = 2:4) #Specification error

        RESET test

data:  modelproQB
RESET = 5.1426, df1 = 3, df2 = 49, p-value = 0.003594

> resettest(SECmodelcollege2, power = 2:4) #Specification error

        RESET test

data:  SECmodelcollege2
RESET = 1.9839, df1 = 3, df2 = 108, p-value = 0.1207

> resettest(SECmodelpro, power = 2:4) #Specification error

        RESET test

data:  SECmodelpro
RESET = 1.6319, df1 = 3, df2 = 105, p-value = 0.1864

> resettest(SECmodelcollegeLINE, power = 2:4) #Specification error

        RESET test

data:  SECmodelcollegeLINE
RESET = 0.077213, df1 = 3, df2 = 139, p-value = 0.9722

> resettest(SECmodelproLINE, power = 2:4) #Specification error

        RESET test

data:  SECmodelproLINE
RESET = 1.254, df1 = 3, df2 = 137, p-value = 0.2928

> resettest(SECmodelcollegeQB, power = 2:4) #Specification error

        RESET test

data:  SECmodelcollegeQB
RESET = 0.63625, df1 = 3, df2 = 50, p-value = 0.5952

> resettest(SECmodelproQB, power = 2:4)

        RESET test

data:  SECmodelproQB
RESET = 4.95, df1 = 3, df2 = 49, p-value = 0.004426
```

Figure 18: Ramsey Reset Testing

```
> vif(modelcollege2)
     CREC     CRYDS      CRTD       Age   WRdash10    Winpct     WRBMI WRmissing  PwrSECWr
 2.775021  5.375243  3.369827  1.068565  1.107964  1.234296  1.098571  1.086266  1.110975
> vif(modelpro)
     CREC     CRYDS      CRTD       Age   WRdash10    Winpct     WRBMI WRmissing  PwrSECWr
 2.775021  5.375243  3.369827  1.068565  1.107964  1.234296  1.098571  1.086266  1.110975
> vif(modelcollegeLINE)
   Ctack    Csack     Cint      Age   dash10   WinPct      BMI  missing   Power5
1.417983 1.255862 1.247527 1.173556 1.103883 1.120477 1.072191 1.048741 1.111195
> vif(modelproLINE)
   Ctack    Csack     Cint      Age   dash10   WinPct      BMI  missing   Power5
1.405595 1.248096 1.231610 1.174860 1.098202 1.109741 1.070953 1.054196 1.112337
> vif(modelcollegeQB)
    Crate       Age   dash10QB    Winpct     BMIQB missingQB    Power5
 1.556804  1.173570  1.158814  1.475798  1.323858  1.071297  1.047868
> vif(modelproQB)
    Crate       Age   dash10QB    Winpct     BMIQB missingQB    Power5
 1.552985  1.184196  1.162006  1.486793  1.331172  1.070784  1.045808
```
Figure 19: VIF Testing