# THE CORRELATION BETWEEN THE NATIONAL FOOTBALL LEAGUE DRAFT AND PLAYER PERFORMANCE

by

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Lynn Kahle

The evolution of business analytics has caused a fury within corporations in the implementation of statistical analysis as their core business strategy (Davenport). However, this unquenchable need, or desire, for businesses to differentiate themselves from one another through analytics has led to "tension between perception and reality regarding the adoption of management strategies" (Troilo). Academic literature provides insight into how managers perceive analytics to be more beneficial than the outcomes actually show them to be, and how, in actuality, the analytics may be more an imitation of other organizations than actual insight into a business revenue generation (Troilo).

Inspired by the success of the Oakland Athletics and the popularity of Michael Lewis' 2013 best-selling book, *Moneyball*, professional sports began adopting business strategies similar to that of corporations around the globe. Professional sports organizations currently aspire to develop analytics with "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact based management to drive decisions and add value" (Davenport). The sports industry aims to

amplify the preconceived notion of analytics merely being used to drive revenue with the additional incorporation of nonprofit outcomes, such as organization wins and player performance. Thus, the goal of this paper is to focus upon the correlation between the National Football League Draft and overall player performance; this analysis will, then, improve business analytics and decision-making processes pertaining to the professional sports industry. Traditionally, “economic rationality as measured by the maximization of revenues, and sociological rationality exemplified by the search for legitimacy” have been scrutinized as contrasting viewpoints (Troilo). The incorporation of business operations stimulating both rationales will revolutionize not only the sports industry, but the corporate world as well.

The remainder of this thesis is formulated as follows: First, the paper will explain the background of sports business and the importance revolutionizing its operation. That discussion will be followed by a literary review of current statistical operations used by sports organizations. Next, the paper will reveal the framework in which the data and variables will be sorted, leading into the methodology for how the variables were processed. Data analysis will be the pinnacle of this paper, affirming the inherent need for a contemporary business operations model. In addition, an examination of economic and sociological rationalities will be done that pertains to the correlation of a player’s draft position and his performance throughout his NFL career. Finally, the paper will conclude with a case analysis of the Cleveland Browns football organization which will further exemplify the statistical analysis.

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## Introduction / Chapter 1: The Sports Industry

Regarded as one of the fastest growing industries in the world, the sports industry has cemented itself in the landscape of both American and global business (Troilo). A legal monopolistic industry, as well as a low threat of substitutes, births an environment of supremely high bargaining power for both professional sports leagues and individual organizations (Troilo). As the most popular spectator sport in the United States, the National Football League differentiates itself even further within the industry (Sport).

In the 2013-2014 season, the estimated revenue for the National Football League (NFL) was $12 billion, the highest revenue of any professional sports league (Isidore). Even America's pastime, Major League Baseball, pales in comparison to the NFL with its $9 billion in revenue during the 2014 season, an astounding $3 billion dollars less (Brown). In addition, wages account for 62.7% of the sports industry's costs, a staggering number when compared to that of the average wage costs, 22.6%, of all industries in the Arts, Entertainment, and Recreation sector (IBISWorld). However, NFL players earn the lowest average salary of any of the four major sports leagues that include the National Basketball Association, the National Hockey League, Major League Baseball, and the National Football League. In fact, it's not even close; "On average, NBA players make $5.15 million, MLB players make $3.2 million, NHL players make $2.4 million, and NFL players make $1.9 million per year" (Manfred). Due to this competitive wage advantage, it becomes a question not of finding the best current player value, but choosing the "right" player who will have success for a continued amount of time. The urgency for individual organizations to choose players with above-average performance is epitomized when the average length of an NFL player's career is taken into account. An average NFL player's career length is 3.3 years, with specific length varying by position (Average). However, the average career length of a rookie player who actually makes a club's opening day roster increases almost 100%, to 6 years in length (Average). The disparity in average career lengths highlights how individual organizations that draft overperforming rookie players will benefit from lower wage costs throughout the particular player's career.

Throughout the NFL's existence, the league has relied heavily upon positive reinforcement. This particular reinforcement system, which was cemented into the future of the NFL with the settlement of the Collective Bargaining Agreement (CBA), presents obvious negatives for players and obvious positives for executives when observed throughout the NFL. The CBA is so regimented in its expectations for the rookie player that it becomes easy to extrapolate which contracts are overvalued and which contracts are undervalued. The CBA removed, almost entirely, rookie contract negotiations and established a generic contract script. After 2011's CBA, it was stipulated that "rookies that are drafted receive four-year contracts. If a rookie is drafted in the first round, clubs can exercise a fifth-year option for the player's rights. If a rookie is undrafted, he will receive a three-year contract" (Jessop).

Although teams such as the New England Patriots and the Oakland Athletics have revolutionized and incorporated analytics into sports operations, analytics remains a neglected and overlooked tool in relation to the business side of sport (Troilo). Organizations increase revenue through the analytic tactics of measuring sponsorships, customer relationship management, dynamic pricing, and advanced database marketing

(Omega). However, organizations fail to exploit the simultaneous growth of both business and sport operations that the analysis of the correlation between the National Football League and player performance could provide.

## Chapter 2: The National Football League Draft

Bert Bell, christened de Benneville Bell, and born in 1895, was seemingly destined to become one of the most influential commissioners in the National Football League history. In the 1930s, Bell assumed ownership of the Philadelphia Eagles after purchasing the rights to the Frankford Yellow Jackets with his newlywed wife, Frances Upton, and they subsequently renamed the team. By 1946, Bell was recognized as one of the NFL's most popular owners and was given the key to the castle: Bell became the NFL commissioner. Between 1946 and 1959, Bell implemented the rule of "sudden death" in championship games to avoid co-champions, introduced local blackout television policy to ensure teams could avoid competing against themselves, and negotiated the 1949 merger between the NFL and the All-America Football Conference. However, all of these innovations and accomplishments are dwarfed by how he, as the owner of the Philadelphia Eagles, reinvented the concept of parity between NFL teams. Bell, in a league meeting in the 1930s, proposed a players' draft that would allow teams to choose players in reverse order of how they finished in the previous year's standings. Then, in February of 1936 in Philadelphia, inside a Ritz Carlton hotel owned by Bell's family, the first NFL draft took place. This draft would revolutionize the way owners valued and signed players. Prior to the draft of 1936, NFL teams would visit college campuses and sign top draft talent directly. Due to that practically "free agent" signing process, only a handful of teams-- those who made the most money-- were able to be competitive. The system left organizations similar to the Philadelphia Eagles, who were financially struggling, at a serious disadvantage. Then, in 1976, George Halas, the

Chicago Bears Owner, gave the NFL draft its ultimate support, stating at an antitrust hearing, “The college draft is the backbone of the [NFL]” (Wilner).

Today, the NFL draft consists of 7 rounds and the participation of all 32 NFL teams. The order in which each organization is allowed a pick is determined by the reverse order in which each team had finished the previous season. Teams that had missed the playoffs at the conclusion of the previous year are designated picks 1-20. Organizations reaching the playoffs are then credited the pick numbers 21 through 32. The order of the picks are as follows:

> The four teams eliminated in the wild card round pick in slots 21-24 in the reverse order of their final regular season records. The four teams eliminated in the divisional round pick in slots 25-28 in the reverse order of their final regular season records. The two teams that lost in the conference championships pick in the 29th and 30th spots in the reverse order of their final regular season records. The team that lost the Super Bowl has the 31st pick in the draft. The Super Bowl champion has the 32nd and final spot in each round. (National Football League. The Rules)

Each organization receives one pick for rounds 1-2. Between rounds 3-7, the NFL has the ability to assign up to 32 compensatory free agent picks, a rule which is designed to help teams retain the value they might have lost to players entering free agency in the previous year.

## Chapter 3: Literary Review

For 78 years, since 1936, individual National Football League organizations have observed characteristics, from statistical college resumes to in-person pre-draft interviews, in the hopes of drafting productive and profit-generating players (Wilner). However, many of these imperfect strategies result in additional search time, extra wage costs, and lost productivity (Gill). Come draft season, every organization frantically searches for the next Tom Brady. Possibly the greatest NFL draft selection in history, a $6^{th}$ round, $199^{th}$ overall selection, Brady led the New England Patriots to two Super Bowl Championships before he was 28 years old (Wilner). However, teams should actually be warier of trying to avoid the next JaMarcus Russell instead of searching for a Brady. Russell, a 2007, $1^{st}$ overall, draft selection revered for his arm and strength, quickly fell from grace and out of the league to become known as the biggest quarterback bust of all-time (Wilner). Russell compiled a 7 -18 record with the Oakland Raiders before being released after only his third season in the NFL. Perhaps there will never be a one-size-fits-all proof for the NFL draft, but, through the application of traditional observations and modern analytics, organizations can greatly increase the probability of drafting successful players.

Crisis evolves not from a lack of draft theories, but instead from the plethora of prediction theories available. Teams are often misguided when evaluating future player performance with misrepresented data (Kitchens). This begs the question, then, of what the main available predictors of NFL player performance are. A player's college statistical resume is an obvious available predictor in determining the possible career performance in the NFL. For example, a player who had high performance statistics in college would also be expected to have high performance throughout his NFL career. However, Kitchens, the author of *Are Winners Promoted Too Often? Evidence from the NFL Draft*, theorizes that future NFL players are often scouted with a biased lens because of their college institution. He argues, in his examination of the NFL draft process, he can "study the effects of statistical discrimination on job placement and long-run career outcomes" (Kitchens). An interesting twist on many statistical analyses, where almost all sports researchers use business experiments to analyze professional sports models, Kitchen reinvents this process and performs professional sports experiments to understand a business model. He finds that players who have played on highly ranked teams during their collegiate careers see their draft position increase by .39 positions (Kitchens). Kitchens' results are meant to explain a bias towards employee hires from top ranked universities and colleges; however, for the purpose of this study, his result shows "individuals from highly ranked college teams are drafted earlier than individuals from lower ranked institutions," even though "over the length of a player's professional career, a player's college institution has no effect on career success" (Kitchens). This evidence most likely stems from the practice of trying to avoid hiring (wage) costs by concentrating recruitment efforts in areas that are perceived as talent rich areas or have, in the past, produced talented players (Kitchens). The misrepresentation of college statistical resumes yields another predictive measure: the National Football League draft combine.

The NFL combine, in theory, provides one of the best quantifiable player evaluation methods in the prediction of player performance. Coaches, scouts, and even fans analyze the performance of players through standardized tests of physical and mental toughness (Robbins). However, Daniel Robbins, author of *The National Football League Combine: Does Normalized Data Better Predict Performance in the NFL Draft?*, finds the NFL combine's performance measures to be questionable, at best, when used to predict the NFL draft order. Although this data predicts draft order and not performance, it reveals an interesting insight into the evolution of NFL business analysis. Robbins explains NFL personnel deem the physical attributes of players in the NCAA as adequate enough to provide the building blocks from which they can progress and even excel at the professional level (Robbins). This would suggest that the NFL combine measures or weighs an athlete's willingness and ability to learn, rather than measuring an athlete's skills in order to analyze the potential performance in the NFL (Robbins). Arguably, one of the best-run sports leagues in the world, the NFL should be the model for incorporating analytics, mental capacity, and physical performance into individual evaluations (Robbins). The Wonderlic Personnel Test, an evaluation of cognitive ability, is an example of an examination of mental preparation for prospective players.

Similar to the NFL combine, the Wonderlic Personnel Test results in statistical discrimination in the NFL draft (Gill). However, unlike the combine, where discrimination is a consequence of highly-ranked college institution bias, Gill and Bajer, authors of *Wonderlic, Race, and the NFL Draft*, contend that the Wonderlic provides a biased signal of a player's adaptability to the NFL that may be more informative for the recruiting of white players than that of black players, and, in addition, the recruitment of offensive players rather than defensive players (Gill). These discrepancies stem from biased misrepresentation and supposed intuition, respectively.

First, Gill and Bajer found that, through a 1.47 statistically significant coefficient, a 10-point increase on a white player's Wonderlic score moves that player up in the draft by 14.7 positions (Gill). However, a black player with a 10-point increased Wonderlic score has his draft position increase by half the amount, although statistically insignificant (Gill). It is important to note that this discrepancy in race does not necessarily directly infer racial biases, but instead magnifies the difficulties in predicting performances. Second, the Wonderlic Personnel Test blends modern sport analysis with traditional business operations that are affected by common football knowledge or supposed intuition. Offensive players have their Wonderlic scores weighed more heavily than their defensive counterparts because defensive players typically have more time to react to developing situations, a skill poorly represented in tests of cognitive ability (Gill). In contrast, it is less obvious why there seems to be an inherent disinterest among NFL executives for the Wonderlic scores of the wide receiver and running back positions (Gill). Perhaps no other position better elucidates the complexities of making performance assessments than that of the quarterback (Gill).

Analysis of the quarterback position usually relies upon the NFL combine or previous college statistics that have little value when trying to predict the future performance of an NFL quarterback (Addona). NFL organizations have been notoriously poor at predicting the performance of quarterbacks based upon information given before the draft (Addona). By identifying quarterbacks who have already experienced successful careers and then comparing those quarterbacks with their draft round selection, organizations will be able to gain valuable insight into how analytics can be tailored to predict performance more accurately. Malcolm Gladwell, *New York*

*Times* journalist, referenced the work of NFL researchers Berri and Simmons when he "concluded that the draft position of a quarterback had a considerable impact on how much that quarterback played, but not on how well he performed in the NFL" (Addona). Gladwell's conclusion demonstrates that despite the fact that executives and coaches are using prediction analysis, many have a steadfast approach to how they believe professional football should be played and are unwilling to change their philosophy.

The article, *Perception, Reality, and the Adoption of Business Analytics,* quotes Staw and Epstein as asserting, "Early qualitative and descriptive studies illustrates how organizations structure themselves not so much to execute their tasks more efficiently, but to gain legitimacy or cultural support" (Trolio). It becomes clear that there are unique similarities between professional sports, namely the NFL, and corporate business. Literature, such as Kuper and Szymanski's *Soccernomics* and Lewis' *Money Ball,* details the statistical revolution sports enjoyed in the early 2000s. Both of these books highlight two athletic clubs, the Oakland Athletics baseball organization and the Tottenham Spurs soccer organization, that were responsible for leading the change from "game knowledge" to statistical assessment (Kuper). Only after these two teams enjoyed sustained success did the rest of the league follow suit. The National Football League is no different, and executives seem to believe in the aphorism "If it ain't broke, don't fix it."

Since 1990, the National Football League Pick Value Chart has been the "gold standard" in determining the value of draft selections (Schuckers). However, the Pick Value Chart, developed by Jimmy Johnson, the Dallas Cowboys head coach from 1989 – 1999, heavily overvalues picks selection early in the first round (Schuckers). As shown in Figure 1, the Pick Value Chart allows teams a type of currency to compare and trade picks in the NFL draft (Schuckers). In addition, Appendix A lists the exact numerical values attributed to each selection.

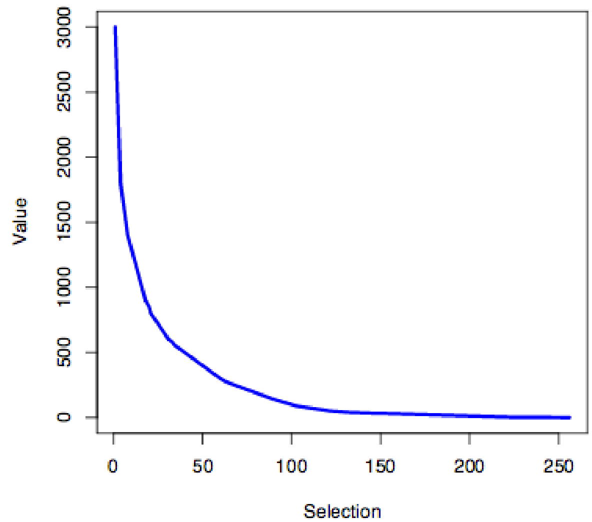



Figure 1: Pick Value Chart

The Pick Value Chart was introduced around 1990 as a way of assigning value to each draft selection. The chart enable organizations to put a quantifiable value on each draft number in order to determine if a trade of draft picks provide an equal value (Schuckers).

While this technique proves useful for practical trading purposes, it fails to recognize the fact that different positions may correlate with higher or lower performance. The following data and methodology will emphasize how different position performance factors can be correlated to certain NFL draft rounds.

# Chapter 4: Variables

Defining and characterizing variables that directly convey player performance is vital in order to test the correlation between player success and the round in which they were drafted. However, the real question becomes not how these variables will be collected, but how these variables will be measured in a way that maintains consistency and control. As a result of the ever-increasing popularity of “fantasy football” as well as the technological advances applied to sports, if one can conceive of a statistic, it can be tracked. Although statistical advances have served to increase the popularity of the sports industry, they have also created the dilemma of having to choose which statistic best represents a particular position. Although there is a plethora of performance statistics for every individual position, few standard methods of evaluation, and certainly no one statistic, are able to quantify the value of different positions unilaterally. To clarify, Defense-adjusted Yards Above Replacement (DYAR), an innovative football statistic used by the analysts at Football Outsiders, is able to accurately rank the value of quarterbacks along with other offensive skill players, from wide receivers to running backs. However, DYAR proves incalculable when valuing both defensive and special teams’ positions.

In order to combat this dilemma, individual player performance will be analyzed and measured using the Collective Bargaining Agreement’s individual incentive measurements. The use of the NFL’s Collective Bargaining Agreement performance incentives allows for comparison across not only a range of players, but of different player positions. Therefore, it is imperative that performance measurements be based upon the Collective Bargaining Agreement definitions of individual performance. These individual incentive statistics allow for a standard method of evaluation across all positons due to both the National Football League's owners and the National Football League's Players Association mandates that these statistics are most important to each of them through the process of entering and signing into contract. Article 13 Section 6 of the NFL's Collective Bargaining Agreement articulates, "Any incentive bonus that depends on a player's individual performance in any category not identified in [Individual Incentives] hereto is prohibited" (National Football League). To reiterate, both owners and players view the statistics expressed in the Collective Bargaining Agreement as the only individual statistics to be used to measure the true business value of a player because of the financial incentives attached to such statistics.

**National Football League Draft Round**

The primary, or independent variable, used in this study is the draft round of players chosen throughout the NFL draft. NFL.com, *Draft History*, provides a complete database of player draft positions through the 2011-2014 draft seasons. (Although the 2015 season performance is included in this study, the 2015 draft is not, in order to provide all draftees with at least one full year of league play.)

**Offensive Performance Measurements**

The public database *Statistics*, at NFL.com, was used to collect offensive performance variables. It is important to note that the use of the NFL database is imperative due to the CBA's Article 13 Section 6 Line Item xi stating, "Official National Football League statistics as provided by the NFL shall be utilized in determining whether a player has earned any incentive described in Exhibit A or B." It has been made clear that only statistics rendered by the NFL will hold value because those are the only statistics by which both players and owners have agreed to measure performance.

Due to the disparity in playing time, as well as the skill level of opponents, each of the statistics compiled are translated into a ranking of all players by respective performance variables as stipulated by the NFL's Collective Bargaining Agreement, and they are then rendered into a performance rank average for the seasons of 2011-2015. Running backs will have isolated regression tests based upon the measurement of total yards, average yards and touchdowns. As stipulated in the CBA and as shown below in Table 1, only those running backs who have had over 100 attempted carries will be eligible to be tested in the Average Yards category. Quarterbacks who have completed 224 or more passing attempts will be analyzed by passer rating, completion percentage, interception percentage, and yards per pass. All quarterbacks will be analyzed on total yards and touchdown passes. Wide receivers who have completed more than 32 receptions will be regressed upon average yards. Similar to the quarterback position, all wide receivers drafted between 2011 and 2015 will be analyzed on total receptions, total yards, and touchdowns. Tight ends are measured with the same receiving incentives as are wide receivers under the CBA, so, therefore, tight ends will be analyzed using the same statistics but will be held in a separate category position. Finally, the offensive line will not be analyzed during this study due to the lack of both an encompassing standardized statistic and individualized-based incentive bonus. Offensive linemen are commonly incentivized in the Collective Bargaining Agreement using Team Offensive Incentives, shown in Appendix B.

| Performance Categories | Performance Variables |
| --- | --- |
| Rushing | Total yards<br>Average yards (100 Attempts)<br>Touchdowns |
| Passing | Passer rating (224 Attempts)<br>Completion percentage (224 Attempts)<br>Interception percent (224 Attempts)<br>Total yards<br>Yards per pass (224 Attempts)<br>Touchdown passes |
| Receiving | Total receptions<br>Total yards<br>Average yards (32 Receptions)<br>Touchdowns |

Table 1: Collective Bargaining Agreement Offensive Performance Measurements

This table represents all individual statistics on which each offensive player is evaluated concerning performance bonuses. Any incentive bonus that depends on a player's individual performance in a category other than those listed is prohibited under the Collective Bargaining Agreement.

**Defensive Performance Measurements**

To analyze and build a compilation of defensive performance measurements, this study again consulted the public database *Statistics* at NFL.com. Determining defensive statistical performance for this study was quite similar to the compiling of wide receiver and tight end statistics. First, defensive tackles (including nose tackles) and defensive ends were analyzed in separate regression categories. Although both tackles and ends combine for one collective defensive line, each position widely differs. There are two traditional defensive schemes used throughout the NFL, a 3-4 defensive set and a 4-3 defensive set. In a 3-4 defensive set, the defensive line consists of one nose tackle placed in-between two defensive ends. In contrast, in a 4-3 defensive set, the defensive line consists of two defensive tackles placed in-between two defensive ends. The nose tackles (NT) and defensive tackles (DT) will be analyzed apart from each other because each positions responsibility differs. NTs and DTs are primarily responsible for run stopping, while DEs are primarily responsible for pass rushing. Next, defensive backs and linebackers commonly are critiqued through the same variables. In addition, defensive backs will be further separated into cornerbacks and safeties. Therefore, each defensive position will be analyzed using the same statistical measures mentioned below in Table 2; however, each will be compiled into their own sub-category.

| **Performance Categories** | **Performance Variables** |
|---|---|
| Defense | Interceptions<br>Interception return yards<br>Touchdowns on interception returns<br>Opponent fumble recoveries<br>Opponent fumble return yards<br>Touchdowns on opponent fumble returns<br>Sacks |

Table 2: Collective Bargaining Agreement Defensive Performance Measurements

This table represents all individual statistics on which each defensive player is evaluated concerning performance bonuses. Any incentive bonus that depends on a player's individual performance in a category other than those listed is prohibited under the Collective Bargaining Agreement.

### Special Teams Performance Measurements

Special teams' performance measurement regression tests will not be examined in this study due to the lack of special team data points. However, *Statistics* at NFL.com would have been used to compile the variables pertaining to the special teams' performance measures. Punters who have obtained at least 40 punts would have been measured against other punters on both gross and net average yards. Place kickers would have been analyzed using both their completion percentage and the below field goal attempts to separate those eligible for performance evaluation. Punt and kickoff returners, although valued in the CBA based upon total yards, average returns yards, and touchdowns, are not relevant to this study due to the fact that those positions are not drafted. As opposed to other position players, punt returners and kickoff returners are drafted as other positions and are designated returners once they have made the team. As an example, Rick Upchurch, drafted in 1975 as a wide receiver, was one of the most talented punt returners in NFL history with eight punt return touchdowns.

| **Performance Categories** | **Performance Variables** |
|---|---|
| Punt Returns | Total yards<br>Average return (20 Returns)<br>Touchdowns |
| Kickoff Returns | Total yards<br>Average Returns (20 Returns)<br>Touchdowns |
| Punting | Gross average (40 Punts)<br>Net average (40 Punts)<br>Inside 20-yard line |
| Place Kicking | Total points<br>Field goals<br>Field goal percentage (16 Attempts)<br>Field goal percentage 0-19 yards (4 Attempts)<br>Field goal percentage 20-29 yards (4 Attempts)<br>Field goal percentage 30-39 yards (4 Attempts)<br>Field goal percentage 40-49 yards (4 Attempts)<br>Field goal percentage 50 yards or longer (3 Attempts) |
| Others | Roster bonuses<br>Reporting bonuses<br>Playtime bonuses (excluding special teams)<br>Special teams playtime |

Table 3: Collective Bargaining Agreement Special Teams Performance Measurements

This table represents all individual statistics on which each special teams' player is evaluated concerning performance bonuses. Any incentive bonus that depends on a player's individual performance in a category other than those listed is prohibited under the Collective Bargaining Agreement.

# Chapter 5: Methodology

In order to have a successful completion of this thesis project, three objectives must be fulfilled. First, players drafted must be categorized into their respective player positions, with each position group being ranked from best performing to least performing. Second, a linear regression test must be run in order to determine a significance value and line of best fit for each position. A P-Value of less than or equal to .1 will be considered statistically significant in order to minimize the probability of observing an extreme value purely by chance. Finally, players will be analyzed based upon their draft position as well as their average performance throughout the years of 2011 and 2015.

**Data Collection and Regression**

Data collection was the least technical aspect of the study; however, it also proved to be the most tedious and time consuming. Each data point was derived from the online website, NFL.com, which offers a multitude of public data bases. As mentioned earlier, due to the need for consistency, the two public data bases used for data collection in this study were *Statistics* and *NFL Draft History*. The modern era of sports analytics allows the variables themselves to be easily found and are readily accessible. The challenge, however, was translating each data point from various websites to comprehensive Microsoft Excel Workbooks organized and titled by player position and the subsequent analysis of the incentive bonus. Extracting all the data and computing it into a more workable format was the initial concern. Fortunately, through the NFL.com's filter feature and Microsoft Excel functions, primarily =VLOOKUP, the data information was able to be organized cohesively.

In order to best describe the methodology process, Quarterbacks will be used as a process example. Each position will use the same methodology of the collection and analysis of data with the respective performance incentive variables changing by position, all of which are listed in Table 1, 2, and 3.

First, quarterbacks were filtered by position on the NFL.com's *NFL Draft History* data base; the player's name and draft round, from 2011 to 2015, were transcribed into an individual worksheet labeled "Player Draft Round" in his respective incentive workbooks. Quarterbacks have six workbooks each individually titled, "Quarterbacks –Passer Rating," "Quarterbacks –Completion Percentage," "Quarterbacks –Interception Percentage," "Quarterbacks –Total Yards," "Quarterbacks –Yards Per Pass," and "Quarterbacks –Touchdown Passes." Then, through NFL.com's *Statistics* data base, quarterbacks were filtered by the player category "Player Position;" statistics were automatically sorted into separate NFL seasons. Next, in the interest of facilitating the process of compiling data into respective quarterback workbooks, before compiling each year of individual quarterback statistics into worksheets, quarterbacks were ordered by "Attempts." Any quarterback not meeting the minimum of attempts, stated as 224 attempts in the CBA, were excluded from this study. (That exemption is true for any incentive bonus that requires a minimum number of attempts, 100 attempts for Running Backs and 32 receptions for Wide Receivers). Quarterbacks with less than 224 attempts were excluded from Passer Rating, Completion Percentage, Interception Percentage, and Yards Per Pass because they would not receive any reward for achieving an incentive goal. Therefore, quarterbacks not meeting the attempts requirement could not be equally compared to those quarterbacks playing for incentives. However, quarterbacks under 224 attempts were analyzed on incentive statistics including Total Yards and Touchdown Passes, those not including a minimum attempt requirement. All quarterbacks that met the attempt requirement were then transferred into yearly worksheets in order to continue regression testing.

Once quarterbacks were copied into yearly worksheets, titled “2011” through “2015,” players were rank ordered, using Microsoft Excel’s filter option, from best to least-performing by incentive statistic. For Passer Rating, quarterbacks were given a rank order number starting at 1, for the best performing quarterbacks, with a higher quarterback rank number being indicative of a worse performing quarterback. Any quarterbacks with the same statics for a particular year were ranked equally, with the next lowest quarterback being ranked as if each quarterback accounted for their own rank position. To illustrate, if the two highest ranked quarterbacks each had a completion percentage of 68%, both quarterbacks would be given a rank of 1, while the next highest quarterback would be attributed a ranking of 3.

Quarterbacks, through the Excel functions =VLOOKUP and =AVERAGE, were then given an overall incentive rank, on a separate worksheet, that was the average incentive rank of all seasons played between the 2011 and 2015 seasons. If any quarterback drafted did not make an NFL roster between the 2011 and 2015 seasons then they were given the next highest incentive rank after the lowest performing quarterback in the largest statistic grouping year. It is important to note, however, that a quarterback with a statistic incentive of 0 received a normal incentive rank because, although in quantitative terms both quarterbacks achieved the same statistic, the one who attained a 0 still made an NFL team's roster. Using the Data Analysis Toolpack in Microsoft Excel, the quarterbacks' incentive statistic was regressed upon the draft round in which each NFL quarterback was drafted.

**Data Analysis**

The analysis of linear regression data will be the culmination of this thesis. The analysis of the data will consist of four incentive categories: Rushing, Passing, Receiving, and Defense. Among these four categories, the individual position's incentive statistics will be analyzed. The information most pertinent in the data analysis will be the Line of Best Fit, referred to as the Predicted Incentive Line (PIL). The PIL will represent a position's average draft round performance relative to the respective individual incentive. This thesis, with the help of the PIL, seeks to show a correlation between where a player is selected in the draft and his performance throughout his NFL career.

# Chapter 6: Data Analysis

Excel's Data Analysis Summary Output delivers three informative regression parts: Regression Statistics, analysis of variance (ANOVA), and Regression Coefficients. Although each part will be displayed in its respective appendix sorted by position, this paper's data analysis will focus specifically on the data results from Regression Statistics and Regression Coefficients. In addition, a residual plot will be used for reference for each individual incentive. Finally, the Position Incentive Line graph will be shown, as a figure, at the start of each individual incentive primarily for a visual representation.

Regression Statistics, the residual plot, and the PIL graph will be used to interpret and analyze the over and underperforming positions in particular draft rounds. Multiple-R, referred to as the correlation coefficient, identifies how strong the linear relationship of the PIL is. A correlation coefficient of 1 is evidence of a perfectly linear relationship between the PIL and overall incentive ranks, whereas a correlation coefficient of 0 means there is no linear relationship between the PIL and overall incentive ranks. R-Squared, the coefficient of determination, is the percentage of overall incentive rank data points that fall on the residual line. This study will take into account the size of R-Squared; however, it is important to note that this study seeks to simply identify potential draft rounds in which positions are more likely to over-perform and not by how much a position will over-perform. Therefore, R-Squared becomes less important than Multiple-R which explains the extent to which the PIL fits the position's data set. This research does not use multiple regression analysis so Adjusted R-Squared will not be analyzed. Similar to R-Squared, the standard error of regression measures how far the average overall incentive rank data points fall from the PIL. Observations are, simply, the sample size of the data. Finally, to identify specific valuable draft rounds in which to select a particular position, the residual plot and PIL graph will be utilized to calculate the percentage of players that over-performed in comparison to the PIL, as well as the percentage of players who under-performed the PIL.

Regression Coefficients, excluding the coefficients column, will be used for testing and analyzing the significance and accuracy that the interpretation of the Regression Statistics revealed. The coefficients column gives the least squares estimates of the intercept and draft round. These will be shown in the least squares equation on the PIL graph. Standard Error in the Regression Coefficients gives the standard deviation of the least squares estimates intercept and round coefficients. This calculation is different from the standard error of the regression statistics which gives an estimate of the standard deviation of the error μ. This study will not focus upon the T-Stat and P-Value as both statistics are most commonly used in hypothesis testing.

## RUSHING

Analysis of running backs' total yards, average yards, and touchdown incentive ranks reveals that the first and third rounds most consistently correlate to an overperforming running back.

### *Running Backs – Total Yards*

Running Backs' total yards regression data is shown in Appendix C. The total of season yards for rookie running backs presents a strong linear relationship with a Multiple-R of .63. Furthermore, the R-Square of .39 presents an interesting insight into the residuals of total yards. The amount of running backs fitting on the regression line suggests that organizations selecting a running back can more confidently refer to the PIL as a tool for predicting total yards. The correlation coefficients explain that a running back drafted in round one is expected to have a total yards rank of 32.31. It is expected that a running back will drop 15.37 rankings for every draft round, ending in round seven with an expected total yards rank of 124.57. Using this least squares regression line, four draft rounds stand out as potential rounds to draft running backs with overperforming total yards. Rounds one, three, four, and five reveal that 83.33%, 73.33%, 68.18%, and 72.22% of running backs outperformed their predicted draft round incentive rank, respectively, while rounds two, six, and seven shows more than 50% of running backs underperforming their expected incentive rank. However, the PIL graph displays that the second and sixth rounds account for three of the top five overperforming rookie running backs drafted between 2011 and 2015.

The standard error of the intercept offers further insight into draft running back total yard performance. Round one offers, obviously, the highest over-performance with ten percentage points above the next round. However, the amount of data points available for round one should be considered because of the low number of running backs drafted in the first round between 2011 and 2015. True of any round with few data points, round one's total yards measurements must be viewed with an asterisk. Next, the residuals of rounds four and five draws hesitance towards drafting running backs in either of these rounds. The standard error of regression is 34.93; however, the highest residual of round four is 80.55 and the highest residual of round five is 65.18, both much greater than the average residual distance of 34.93. This shows that although the fourth and fifth rounds offer a high percent of overperforming running backs, both rounds also have the potential for running backs to extremely under-perform in total yards expectation. The third round offers the most reliable data pertaining to the prediction of running back total yards. Not only does the third round offer 73.33% of its running backs as overperforming, but two of its residuals fall within three incentive ranks of the PIL. While analyzing average yards and touchdowns, the first and third rounds should be remembered.

*Running Backs – Average Yards*

The regression data derived for the average yards of running backs reveals very little, as shown in Appendix D. A Multiple R of .01 means there is practically no linear relationship between the draft round and average yard performance for running backs. R Square further emphasizes the lack of a linear relationship with a .0002 residual fit. In addition, the data observed is highly skewed due to the NFL's stated minimum attempts. Where the regression statistics of total yards were derived from 123 observations, the observations regressed in average yards was only 46, due to the fact that all running backs who did not complete 100 rushing attempts were excluded. The seventh round most obviously reveals the statistical bias of the data. The seventh round features only one data point with a performance rank of five. This rank makes sense due to the fact that a running back drafted in the seventh round would mostly likely get over 100 rushing attempts only if he dramatically out-performed the PIL. This outlier from exclusion and lack of linear relationship makes any statistical analysis insignificant. Still, the PIL graph is able to offer some insight into draft round performance. Examining the percentage of running backs in each draft round with an accumulation of

100 rushing attempts shows a shocking disparity. The second and fourth rounds reveal that 68.75% and 40.9%, respectively, of running backs drafted in 2011 to 2015 obtained 100 carries. The fifth through seventh rounds each had less than 18% of running backs with 100 carries. The lack of running backs reaching the minimum attempt requirement is indicative of lower-achieving running backs, but not necessarily under-achieving running backs. Rounds one and three each had 83.33% and 86.66% of running backs reach the minimum attempt requirement, respectively. This percentage serves to validate the findings of running backs' total yards performance, in which the first and third rounds can be identified as the two primary rounds with common overperforming running backs.

*Running Backs – Touchdowns*

Touchdown regression statistics are shown in Appendix E. Multiple R, .53, displays that the least squares regression line represents a reasonably well-fit linear relationship. However, the percentage of running backs over or underperforming the PIL holds relatively less relevance than it does in reference to running backs' total yards. Rounds four through seven each reveal at least a 60% over-performance of running backs. However, this data is a misrepresentation due to those running backs who did not make an NFL team after being drafted. In the seventh round, the only running backs who were found to under-perform were those who didn't make a roster. In other words, every running back drafted in the seventh round who made a roster, even those with zero touchdowns, was said to over-perform. Although in terms of statistical analysis these running backs over-perform, it is obvious that NFL organizations do not want to draft running backs who simply over-perform a prediction of zero. Therefore, the statistical analysis of the running backs' touchdown performance rank will focus upon not only the residual output, but the spread in touchdown rank performance. Although the residuals of underperforming running backs in rounds one, two, and three progressively shrink, the spread of running back data points is remarkably similar between the first three rounds. In other words, running backs can be expected to perform closer to the PIL in the third round as compared to the first and second rounds. However, each round reveals almost the same lowest performing running back rank-- at 92, 90, and 92, respectively-- and the highest performing running back rank of 5, 2, and 6, respectively. To clarify, although running backs in round three might outperform the PIL better than in rounds one and two, none of the rounds reveal a significant output of higher performing running backs. Simply put, the third round offers the most accurate prediction of how a running back will perform.

**PASSING**

Quarterbacks' regression output reveals an apparent and obvious bias in statistical analysis when quarterbacks are analyzed with an attempt requirement, as opposed to when all quarterbacks drafted between 2011 and 2015 are analyzed. The PIL for total yards and touchdowns (when all quarterbacks are analyzed together) slopes upward, while the PIL slopes downward for all incentive regressions run with an attempt requirement. Through the analysis of total yards and touchdowns, it becomes apparent that quarterbacks drafted in the first round, followed closely by the second and third rounds, have a much higher chance of not only overperforming, but of excelling. Further, quarterbacks drafted in rounds four through seven are predicted to perform at a lower level, but still over-perform their expectations.

*Quarterbacks – Passer Rating, Completion Percentage, Interception Percentage, and Yards per Pass*

Quarterback passer rating, yards per pass, completion, and interception percentage were analyzed using 22 observations. Due to the small sample size, these regression statistics prove useless for teams trying to identify potential rounds in which quarterbacks over-perform because the 22 observations only represent starting quarterbacks and an organization is obviously unable to know which quarterbacks will play in the starting position. The number (or lack thereof) of data points gathered in rounds four through seven, especially, skews the regression analysis and PIL drastically. In addition, only those quarterbacks performing at a high level would be given the opportunity to have 224 attempts. This further skews rounds four through seven from which many of those quarterbacks drafted are often used as a backup for a number of years before receiving a chance to become the starter or have the possibility of not making the roster altogether. Although the regression summary output of the analyses provides insignificant data, the regression statistics of passer rating, completion percentage, interception percentage, and yards per pass are still included in Appendix F through I, respectively.

*Quarterbacks – Total Yards*

As shown in Appendix J, the total yards incentive rank and draft round proves to have a strong linear relationship with a Multiple R of .73. Such a high linear relationship provides NFL organizations with a more informative and reliable prediction model. R Square, .53, further backs a quarterback total yards prediction model. Over 50% of residuals falling on the regression line gives more validity to the least squares regression line, PIL. The PIL anticipates that quarterbacks drafted in the first round will average a 29.41 total yards rank. Quarterbacks selected in rounds thereafter are predicted to drop 7.27 ranks with a standard error coefficient of .93, meaning there is a high level of accuracy in the standard deviation of draft round predictions. Similar to the regression analysis of running back touchdowns, the PIL offers little information when used to analyze the percent of quarterbacks over or underperforming their draft round peers. The seventh round forecasts all quarterbacks to be drafted will over-perform or perform exactly as expected. However, the expected performance rank of 73 is the ranking attributed to quarterbacks not making an NFL roster after being drafted. Only three quarterbacks in round seven outperformed the PIL or made an NFL roster at all with the best performing quarterback obtaining a performance rank of 45. Further examination of quarterbacks not making an NFL roster reveals the first and second rounds as potential rounds in which quarterbacks should be selected. Starting in the third round, the number of quarterbacks not making an NFL roster steadily increases. Rounds one and two offered all quarterbacks at least making an NFL team. However, such a retention could also be explained with the premise that coaches are unwilling to cut a player selected so high in a draft rather than for actual performance. In respective order from the third to seventh round, 17, 25, 83, 57, and 63 percent of quarterbacks did not make an NFL team. Although the risk of selecting a quarterback that does not eventually make the team is high, the risk must still be weighed against the reward of selecting a quarterback in any of these rounds. To be expected, the best performing quarterbacks selected in every round show comparable residual outputs. . The best performing quarterbacks of each round all have residual outputs that fall between -18 and -27 ranks, revealing that after the third round it would be unwise to select a quarterback due to it being the last round to hold a quarterback that performed inside the top 32 positions or inside the performance rank of an expected starting quarterback. In contrast, rounds one and two offer 57.14 and 66.67 percent of quarterbacks, respectively, outperforming the PIL. It is clear through both the residual plot and average total yard performance ranks that the first and second rounds should be identified as two potential rounds in which quarterbacks often over-perform.

*Quarterbacks – Touchdown Passes*

The regression summary output for quarterback touchdown passes is shown in Appendix K. Multiple R, .72, and R Square, .52, create a well-fit linear relationship of touchdown to draft round selection. This linear relationship mirrors that of the total yards relationship further verifying the PIL. The draft round coefficient, or touchdown PIL slope of 7.31, is almost identical to the PIL slope, 7.27, for total yards. The similarities of both Predicted Incentive Lines serve to highlight the first and second rounds as the rounds that translate to outputting successful quarterbacks most often. The number of quarterbacks not making an NFL roster, as well as the residual plot, in relation to rounds four to seven, holds the same for total yards as it does for touchdown passes. Therefore, regression analysis of touchdown passes further identifies rounds four through seven as poor rounds to select a quarterback and round one, in particular, as the round most consistently producing successful quarterbacks. However, touchdown pass regression presents the third round, instead of the second round, as the next best round in which to draft a quarterback.

Where regression analysis of total yards mainly identified rounds in which quarterbacks were underperforming, the regression analysis of touchdown passes, coupled with the information derived from total yards, highlights the rounds in which organizations should aim to select a quarterback. The first round offers NFL organizations the closest prediction of actual quarterback performance through the examination of touchdown pass residuals. The most successful quarterback over-performed by 14.74 performance ranks, while the least successful quarterback under-performed by 9.45 ranks, which means that the range of quarterbacks drafted between 2011 and 2015 only varied by 32 ranks. In contrast, the other identified potential overperforming quarterback rounds equated to a range of 45.7 ranks in the second round and 64 ranks in the third round. This is an imperative observation because NFL organizations strive to find as close to absolute certainty as statistically possible so that their pick will perform as expected, regardless of position or round.

**RECEIVING**

As mentioned in the methodology section above, the individual incentive category of receiving is comprised of two positions, wide receivers and tight ends, in this study. Wide receivers offer the greatest amount of data points for any offensive position in this study with 155. Tight ends offer roughly the same amount of observations as running backs with 78. In addition to a large sample set, wide receivers, especially, have an equivalent number of data points inter-round. The number of wide receivers drafted in each round between 2011 and 2015 always ranged from 18 to 26 selections. This close range allowed for more statistically significant analysis. The incentive statistic of average yards includes a minimum attempt requirement which creates a statistical insignificance for both wide receivers and tight ends. However, through the analysis of the three other performance incentives, average yards helps explain the ideal draft round for wide receivers being rounds one and two, while the ideal rounds to select a tight end are rounds two and four.

*Wide Receivers – Total Receptions*

As shown in Appendix L, the regression summary output provides a linear relationship of a .6 Multiple R. However, due to 155 observations available for wide receivers, the R Square measures at .36, which implies that relatively few data points actually fall upon the regression line. A standard error of 46.54 further shows that many total reception rank data points fall well away from the predicted PIL. The percentage of wide receivers over or underperforming the PIL reveals which rounds can be identified as potential rounds in which wide receivers are most commonly successful. Preliminary performance analysis displays rounds one, two, five and seven have more than 50% of wide receivers who over-perform on the PIL with 61.9, 59.09, 55.56, and 52 percent, respectively. Although both round five and seven have little over 50% of wide receivers outperforming the PIL, the fifth round shows a particularly interesting residual distribution with a -99.98 residual. The distribution demonstrates that although the fifth round only had 55.56% of wide receivers over-perform the PIL, it contains some of the highest over-achieving wide receivers. In addition, the fifth round had only three data points that were given a rank of 202, the rank attributed to those wide receivers not making an NFL roster. The only other overperforming round with less than three non-roster ranks was the second, as even the first round contained three wide receivers with a rank of 202. Even discounting the residuals of the first round that were made due to the wide receiver not being drafted onto an NFL team, the second round's worst performing wide receiver still had a substantially lower residual, 56.82, compared to that of round one, 82.42. Continuing the regression analysis, rounds one, two and five should be analyzed further.

*Wide Receivers – Total Yards*

The regression statistics of wide receivers' total yards builds upon the information derived in total reception incentives. As shown in Appendix M, an almost identical round coefficient of 17.66 compared to a 17.26 for total receptions substantiates the PIL for wide receivers. Verification of the accuracy of the PIL allows for wide receiver performance precision to be measured. While the PIL can be accepted as an accurate representation of average wide receiver performance per round, when analyzing intra-round data points, the precision of performance can be found. The first and second rounds showcase the disparity in precision and accuracy prediction. Although both rounds consistently result in the most overperforming wide receivers, round one is attributed with high precision and low accuracy, while round two is attributed with low precision and high accuracy. Although the first round reveals the highest residual output of any round, over a quarter of round one's incentive ranks are displayed between rank 7.5 and 18.5, and eleven rank range. This shows that wide receivers overperforming in round one have a high probability of performing as a top 20 ranked wide receiver. In contrast, the second round features a much lower residual output than round one; however, the data points in the second round offer almost no clumps of data. In the continuation of wide receiver analysis one should bear in mind these differences in prediction for the first and second round.

*Wide Receivers – Average Yards*

As shown in Appendix N, average yards regression analysis provides very little insight into predicting a correlation between NFL draft rounds and wide receiver career performance. Due to a minimum requirement of 32 receptions, most wide receivers are excluded from such regression analysis. Multiple R, .04, and R Square, .002, both show there is almost no linear relationship between draft round and average wide receiver yards ranking. However, through a brief visual examination of the PIL graph, rounds one through four appear to have no pattern of performance, which implies that some other factor influences a wide receiver's average yards.

*Wide Receivers – Touchdowns*

Finally, the regression analysis, shown in Appendix O, of wide receiver touchdown performance reveals a more holistic picture of which round best explains wide receiver overperformance. Touchdowns can be described in a linear relationship with a Multiple R of .54. However, NFL organizations should be wary of using the PIL to predict touchdown performance rank due to an R Square of just .3. In other words, the touchdown performance ranks often fall away from the least squares regression line itself. This small R Square can be seen visually when examining rounds four through five. The PIL for touchdown performance equals a slope of 15.38 per round; however, the actual data points for the last four rounds can be seen as almost identical data sets. Therefore, although the fifth round is identified as a potential round explaining wide receiver overproduction in total receptions and total yards, the regression analysis of touchdown identifies only the first through third rounds as having the potential to explain wide receiver over-production. In the combining of the regression analysis of the three previous receiving incentive statistics, it is clear that rounds one and two should receive attention. The residual output of wide receiver performance again separates round one from two. Not only does the second round have 59.09% of wide receivers outperforming the PIL, as compared to the first round's 52.38%, but the second round also features the smallest residual range of any of the seven NFL draft rounds. Therefore, this study recommends wide receivers be drafted in the second round in order to most accurately predict performance and capitalize on overperforming wide receivers.

*Tight Ends – Total Receptions*

As shown in Appendix P, the data point distribution for tight ends differs from that of any of the previous offensive positions this study has thus far analyzed. In the previous regression analysis, the first round has consistently outputted a relatively large sample size of overperforming players. However, only two tight ends were drafted in the first round between 2011 and 2015. In addition, both of those tight ends underperformed the total reception PIL with residuals of .13 and 14.8. These two data points lead to a question: Should tight ends not be selected in round one because they constantly correlate to underperforming total receptions, or should tight ends not be selected in the first round because the position itself is not as valuable as other positions on the football field? The continuation of tight end regression analysis will expand upon this question.

Multiple R, .69, and R Square, .48, presents a least squares regression line, PIL, with a strong linear relationship. Following this linear relationship, the PIL slope of 11.96 can be used to identify the potential rounds best suited for selecting an over-producing tight end. The predicted average total reception rank of the fourth round is approximately 62. This predicted average rank should be used as a tool to narrow the regression analysis focus for tight ends. The NFL consists of thirty two teams, with each team using one starting tight end and sometimes even having two tight ends on the field at one time. Therefore, tight ends that are predicted to perform inside the top 62 ranks (32 teams multiplied by 2 tight ends) should receive extra attention. This synthetic round cutoff, then, identifies rounds two, three, and four as those most consistently equating to high performance (although not necessarily overperformance). The second, third, and fourth rounds offer a high percentage of overperforming tight ends, although the fourth round features almost ten percentage points greater than the other two, with 60, 63.64, and 72.73 percent, respectively.

*Tight Ends – Total Yards*

The linear relationship of tight ends becomes even stronger with regression analysis of total yards. Shown in Appendix Q, Multiple R and R Square both increased .01 to .7 and .49, respectively, when compared to the total receptions. Although the fourth round again offers the greatest percentage of tight ends overperforming their anticipated performance incentive ranking, the second and third rounds hold the best performing tight ends. Each round held two tight ends inside the top 20 ranked tight ends, the only two rounds to have any tight ends in the top 20 ranked total yards performers. Analyzing the residuals offers further insight into the production of tight ends. The third round has a much larger residual range, -44.68 to 60, compared to the second round with a range of -25.25 to 47.4. Such a larger negative residual shows tight ends historically in the second round should be predicted to overperform the PIL by almost double the amount tight ends drafted in the second round. However, the data points collected in round two display a much higher precision level of those tight ends that overperform the PIL as opposed to those collected in round three.

*Tight Ends – Average Yards*

Identical to the data collected for wide receiver average yards, the regression summary statistics for tight ends' average yards did not contain enough data points to be statistically informative or relevant due to the minimum reception requirement of 32. As shown in Appendix R, it is obvious that the Predicted Incentive Line graph needs more than the 18 observed data points to perform a regression analysis. A Multiple R of .09 and R Square of .008 display an absence of any semblance of a linear relationship.

*Tight Ends – Touchdowns*

As shown in Appendix S, the regression analysis of tight ends' touchdown performance continues the focus on rounds two through four. Multiple R, .65, and R Square, .42, for touchdown performance are slightly lower than those of other tight ends' performance incentives; however, both regression statistics allude to a linear relationship between draft round and touchdown performance. The second round solidifies itself, due to the residual range, as an optimal round in which to select a tight end. All tight ends who overperformed the PIL in the second round performed between the performance ranks of 14.2 and 24. This precise range means that 50% of tight ends selected in the second round should be expected to be accumulate between the fourteenth and twenty-fourth most touchdown catches in the NFL. The residual graph and data points, again, reveal that, although the third round has 54.54% of tight ends outperform the touchdown PIL, the accuracy of how well a tight end will actually perform widely varies. The best performing tight end in the third round is ranked tenth, resulting in a residual of -31.26. However, the reward of selecting a tight end in the third round should be measured against the risk of picking the worst performing tight end in the third round with a rank of $111^{th}$ (the rank attributed to players not making an NFL roster), associated with an enormous residual of 69.7. Further examination of the fourth round's touchdown performance reveals that, by far, the highest percentage of tight ends overperforming the PIL occurs in round four with 72.72%. In addition, the worst performing tight end in the fourth round only had a residual of 20.28, four ranks smaller than the standard error of the entire regression, 24.75. Furthermore, the fourth round contains the best performing tight end drafted between 2011 and 2015, a tight end who averaged a touchdown rank of 3.25.

**DEFENSE**

Although the regression tests and analysis of the individual performance incentives were the same regardless of whether the player position was offensive or defensive, this study will present the defensive regression findings in a slightly different manner than how the offensive findings were expressed. Instead of dividing each individual incentive statistic into a separate subsection related to a particular position--as done with the offensive incentives--each defensive position will be its own section that will explain the regression statistics of each of the following individual incentives: interceptions, interception return yards, touchdowns on interception returns, opponent fumble recoveries, opponent fumble return yards, touchdowns on opponent fumble returns, and sacks. This study finds it pertinent to explain the regression statistics as a collective whole by position for three essential reasons. First, the NFL's individual incentive statistics are systematically intertwined; therefore, it makes sense to discuss the regressions together. Not only are the number of interceptions a performance incentive statistic, but the return yards and the touchdowns of a player's interceptions are also tracked. Obviously, then, if a player has no interceptions, he will also automatically have zero return yards and touchdown statistics. The statistics relating to fumbles mimic this incentive structure as well. Second, the defensive statistics seem to inherently favor the front office of the NFL organizations. Defensive players are measured by an almost insulting bias towards "big plays." Only those defensive plays that are turnovers (fumbles and interceptions) or momentum shifting plays (sacks) are counted as incentive-worthy statistics. There seems to be a stark difference between the incentives statistics measured for the offensive and defensive positions; offensive statistics are far more encompassing of every down plays, such as yardage count or receptions. To minimize this incentive bias, it is important to be able to discuss and compare individual position regression analysis simultaneously. Finally, while all positions can be analyzed together due to the stated CBA, each individual incentive statistic only shows statistical significance for a particular position. For example, while sacks are most statistically significant for defensive linemen, defensive ends and defensive tackles, sacks have little to no statistical significance for defensive backs because so many have no sacks at all on their record.

*Defensive Ends*

The regression statistics of defensive ends' sack incentive statistics are shown in Appendix T. Multiple R, .44, and R Square, .18, convey a slightly weak linear fit relationship; however, these regression results are as to be expected due to the vast amount of data points available for defensive ends compared to that of other positions. Although there is a clear upward trend of the PIL, the draft round coefficient reveals a fascinating insight into the draft prediction of defensive ends' predicted sack performance. The slope of the PIL is equal to 10.19 with an intercept of 62.35, which conveys that a defensive end drafted in the first round should be expected to have a sack incentive rank of 72.55. While, a defensive end drafted in the seventh round should be expected to perform at a sack rank of 133.72. This results in a sack incentive difference in only 61 rank positions. Analyzed alongside the standard error of 45.59, this small rank variation conveys the need to analyze the over and underperformance percentage of defensive ends. Computing the overperformance percentages of defensive backs in each round highlights an interesting and unique relationship between the first, sixth, and seventh rounds. These three rounds are the only rounds in which more than 60% of defensive backs outperform the PIL. Analyzing these percentages along with the slight round coefficient reveals it would be recommended for organizations to select either a defensive end in the first round or wait to select until rounds six or seven. This recommendation is further verified when examining the residual outputs of the three rounds. The first round is the only round that presents a clear and undeniable negative residual plot. Although the second round features the highest negative residual of -69.74, the highest negative residuals for each of the other rounds are closely comparable, shown in the Residual Plot in Appendix T. Therefore if an organization selects a defensive end in the last rounds, the difference in performance is insignificant for every round other than the first round.

*Defensive Tackles*

Similar to defensive ends, the regression statistics of defensive tackles show a Multiple R of .42 and an R Square of .18 that can be analyzed as a weak linear relationship, shown in Appendix U. However, the PIL graph of defensive tackles' sack incentive performance, when interpreted, displays a slightly different round correlation. The PIL and Residual graphs still clearly show that the highest performing defensive tackles, as well as the highest percentage of overperforming defensive tackles, are selected in the first round with 86.66% overperforming. The first round also contains the best performing defensive tackle with an average yearly sack incentive rank of 1.5. However, the sack incentive regression output suggests two rounds in which organizations would want to avoid selecting defensive tackles, instead of suggesting rounds six and seven, as it did with defensive ends. The fourth and seventh rounds are the two rounds that the PIL graph and residual graphs depict as less than ideal rounds in which to select a defensive tackle. The fourth round, describing the sack incentive performance, features only 30% of defensive tackles overperforming the PIL. In addition, the highest performing defensive tackle in the fourth round had an average sack incentive rank of only 35.46. The seventh round featured a slightly higher percentage of overperforming defensive tackles with 47.46%. However, this percentage is still quite low when compared to the other rounds between 2011 and 2015. Additionally, the highest performing defensive tackle from round seven displays a sack incentive performance rank of 48. All other NFL draft rounds contain at least one defensive tackle that performed inside the top 15 sack performance ranks.

*Linebackers*

The regression analysis of linebackers drafted between 2011 and 2015 is the only defensive position to feature analysis of both sack, interception, and fumble recovery incentive statistics. Although the regression information is largely skewed in some statistical tests because of the number of linebackers who have never collected a particular incentive statistic, this is also the same reason each regression test must be run. Linebackers, in the modern age of football, are used in specialized situations with different linebackers being used for obvious passing situations and running situations. Therefore, those linebackers with no sacks are the same linebackers who most likely have collected interception statistics, and vice versa. The regression statistics for linebackers' sack performance rank will be the only regression tests that bare statistical significance, although, the PIL graph is still used as an important tool for both fumble recovery and interception analysis. Identifying linebacker data points on the PIL graph helps one to understand more clearly the performance prediction accuracy of the linebackers' sack rank performance. However, interception return yards, touchdowns on interception returns, opponent fumble return yards, and touchdowns on opponent fumble returns will not be analyzed because not only would the results be skewed, but they would also omit linebacker data points. Only those linebackers that had collected an interception would be a part of the sample size, leaving out a majority of linebackers drafted between 2011 and 2015. The linebackers' regression statistics of interceptions, opponent fumble recoveries, and sacks are shown in Appendix V through X, respectively.

Linebacker sack rank regression tests revealed the most statistically relevant and linear relationship between the three regression tests ran. The regression statistics of linebackers' sack ranks offer a slight linear relationship with a .49 Multiple R and .24 R Square. The linebacker overperformance percentage insinuates that the first and second rounds can potentially the best rounds in which to select a linebacker. In addition, the PIL graph and residual plot, when examined, reveal that rounds three through seven offer an almost identical data point distribution. Round one features 66.67% of linebackers overperforming on the PIL. Additionally, all but three overperforming data points are ranked inside the top 50 linebackers with a spread between a rank of 7.2 and 48.75. Only four other linebackers drafted outside the first round between 2011 and 2015 are ranked inside the top 50. The second round also identifies itself as a potential round to select over-achieving linebackers due to a high concentration of linebackers performing between the ranks of 35 to 75.

The third through seventh round PIL data point output reveals the most interesting finding pertaining to linebackers. Although the round coefficient of 20.69 predicts a steady decrease in linebacker production every round, the data point spread of the third through seventh rounds is shockingly similar. Using cluster analysis, the main groups of data of each of the respective rounds all fall within the ranks of 75 and 150. Clarifying, the PIL's slope is pulled away from these clusters due to the amount of linebackers not recording a sack, which could be attributed to the specialty of the linebacker position in today's NFL. Therefore, the question becomes not how a linebacker will perform, but if the linebacker will either perform inside the ranks of 75 to 150 or not collect a sack at all.

Accepting that the first round consistently provides the most overperforming linebackers, this study seeks to answer the question of how best to identify overperforming linebackers in rounds three through seven. First, examining the percentage of overperforming linebackers in the respective rounds reveals rounds four and five have an extremely high overperformance percentage with 72% and 79.31%, respectively. Next, examining the regression test of linebacker interceptions shows that ten linebackers in the fourth round performed inside the top 250 performance ranks, the most amount of any round including rounds one and two. This observation is especially important due to the slope and the intercept of the PIL not being featuring a linear relationship due to the Multiple R of .29 and R Square of .08. Finally, similar to the interception linebacker data, fumble recovery data cannot be used for exact statistical regression analysis due to the amount of linebackers collecting zero fumble recoveries, but it does show the distribution of the best performing linebackers. At least one linebacker from every round analyzed in this study performed inside the top ten ranks for fumble recoveries. This statistic would suggest the fumble recoveries are more happenstance than actions pertaining to actual skill level. Therefore, this study can conclude through the analysis of sack, interception, and fumble recovery regression tests that the first round consistently produces the best performing linebackers with the second round not far behind. The fourth round is the best round in which to draft a linebacker between the rounds three through seven.

*Corner Backs*

Appendix Y through AA show the regression statistics and plots of cornerbacks' interceptions, interception return yards, and touchdowns on interception return. The first step in analyzing these three performance categories is to evaluate the linear regression fit model of each category. Since, interception return yards and touchdowns on interception returns are inherently linked to the amount of interceptions of cornerbacks, it is expected that the regression statistics of the three categories to be similar, and indeed they are. In fact, all three regression tests outputted a Multiple R of .41 and an R Square of .17, with variation after the hundredths place. These regression statistics infer a weak linear relationship with barely any data points falling on the PIL. In addition, the standard error of interceptions is an enormous 72.39 creating a prediction model that has very low precision, meaning the data points are distributed almost randomly throughout the draft rounds. It is important to clarify that the PIL for cornerbacks should be used as a divider between over and underperforming cornerbacks. Therefore, the best statistical analysis that can be performed is to derive the percentage of cornerbacks overperforming on the PIL. The calculation of these performance percentages reveals that every round, with the exception of the first round, features more than half of corner backs underperforming on the PIL, whereas, the first round features 68.18% of cornerbacks overperforming on the PIL. This stark statistical difference infers that organizations not selecting a corner back in the first round will have to rely on a low level of accuracy prediction formula.

*Safeties*

The regression statistics of safeties' interceptions, interception return yards, touchdowns on interception returns, and sacks are shown in Appendix AB to AE, respectively. Similar to cornerbacks, the regression statistics of the three interception regression tests will mirror each other almost exactly due to the interdependence of each category. Analyzing the regression statistics of interceptions reveals a Multiple R of .47 and an R Square of .22, which, in turn, correlates to a weak linear relationship. Further analysis of the PIL reveals safeties drastically underperforming the expected interception percentage, thereby creating underperformance in both predicted interception return yards and interception return touchdowns. In fact, only rounds two and three had more than 50% of safeties overperform on the PIL with 71.43% and 55.56%, respectively. Further regression analysis of the safeties' sack performance rank results in the verification that round three, in particular, features, most commonly, that safeties outperform the PIL with 77.78%.

## Chapter 7: Discussion and Conclusion

The National Football League grants monopoly power to regional markets; while, at the same time, promoting competition through on-the-field product (Trolio). The NFL Draft characterizes both cooperation and competition. The allocation of compensatory draft picks, awarded to teams who have lost more free agents than they have signed last year, to organizations highlights the NFL's objective of league parity. However, the inherent draft process provides competition among organizations to select the highest performing players. This thesis has identified specific draft rounds that most frequently correlate to overperforming positions in hopes of offering guidance to organizations. Using regression analytics this thesis can be used as an additional insight into more accurately predicting future player performance. The first round, as to be expected, was found to correlate most often to overperforming positions. Organizations should view all other draft rounds that present a correlation with position performance as even more valuable rounds in which to gain a competitive advantage.

| Position | Suggested Draft Round |
|---|---|
| Quarterbacks | The First and Third Rounds |
| Running Backs | The First, Second and Third Rounds |
| Wide Receivers | The First and Second Rounds |
| Tight Ends | The Second and Fourth Rounds |
| Defensive Ends | The First Round |
| Defensive Tackles | Avoid The Fourth and Seventh Rounds |
| Linebackers | The First and Second Rounds |
| Cornerbacks | The First Round |
| Safeties | The Second and Third Round |

Table 4: Suggested Draft Round

Table four represents the findings of this thesis pertaining to the correlation between a NFL draft round and position performance. It expresses the suggested rounds in which an NFL organization should draft the respective position.

The quarterback position provides an excellent example of how this thesis should be used in tandem with other analytic findings in order to maximize the accuracy of position prediction. This thesis advises an NFL organization to draft a quarterback in either the first, second, or third rounds. While an analytical test using S-Lift, a value ratio representing performance, found the S-Lift for quarterbacks drafted early in the first round to be much higher than those drafted late in the first round. Therefore, employing both findings informs an organization that not only are quarterbacks selected in the first round more likely to overperform, but especially those selected in the first twelve picks. Running backs, analyzed and ranked on total yards, average yards, and touchdowns, were found to most consistently overperform when selected in the first or third rounds. While, organizations would be suggested to select wide receivers in the first or second rounds. The final offensive position analyzed, tight ends can be expected to overperform in the second and fourth rounds.

In contrast to offensive position prediction, where at least two rounds offered a correlation of overperformance for each position, the draft rounds correlating to overperformance in defensive positions identified specific rounds best and worst suited to draft particular positions. Defensive ends were identified as consistently overperforming in round one. It should also be noted; defensive ends selected in any round other than the first show an insignificant difference in performance. This thesis observed that defensive tackles selected in the fourth and seventh rounds consistently underperform their expected performance rank and, therefore, should be avoided in the fourth and seventh rounds. Linebackers examined showed an overperformance correlation in both the first and second rounds. While, rounds three through seven offered similar performance rank results with the fourth round being the best alternative to rounds one and two. Next, cornerbacks featured an obvious overperformance correlation in round one with 68.18% of cornerbacks overperforming on the PIL. Finally, organizations should be instructed to select a safety in the second or third rounds.

*Cleveland Browns Case Study*

The last time the Cleveland Browns enjoyed an above .500 season was in 2007 with a 10 – 6 record. An organization seemingly synonymous with losing provides the opportunity that sports general managers dread, the “what-if” scenario. What if the Portland Trail Blazers had drafted Michael Jordan instead of Sam Bowie? What if the Dallas Cowboys had selected Randy Moss instead of Greg Ellis? This thesis will conclude by examining the draft selections of the Cleveland Browns between 2011 and 2015, while extrapolating the key findings of this paper to create a what-if scenario for the Cleveland Browns. The 2011 – 2015 actual draft selections of the Cleveland Browns are listed in Appendix AF. In addition, the suggested drafted selections listed in the analysis below are shown in Appendix AG.

Atlanta Falcons Head Coach Mike Smith, coach of the year award recipient, affirms that his team's draft philosophy is to select players that fill positions of need. However, drafting players in order to fill particular position needs is a minority view among NFL executives. Most executives grant more credit to the New York Giants’ general manager, Jerry Reese, philosophy of drafting the best available player and make it fit with position needs. Jerry Reese states, “We try to pick the best player and we are conscious of what our needs are and we definitely want to pick for value” (Wyche). The case study of the Cleveland Browns will dissect each selection made between 2011 and 2015, as well as, offer a recommended selection based off the findings of this thesis. In order to determine a specific recommended player and not just a round in which to draft a particular position, this case study will recommend the closest player selected behind the Cleveland Browns' draft choice that holds the position correlated to high career performance.

In 2011, the Cleveland Browns held eight draft picks. The last five draft picks, selected in rounds four (two picks selected), five (two picks selected), and seven, are corroborated by the findings of this thesis. However, the first three draft selections could have been better selected according to overperformance evaluation. First, their two selections in rounds one and two were, Phillip Taylor, defensive tackle, and Jabaal Sheard, defensive end, respectively. However, the findings of this thesis would suggest drafting the defensive end in the first round, then, selecting the defensive tackle with a subsequent draft selection. Over 60% of defensive ends, selected in the first round, outperform the sack rank PIL, resulting in defensive ends being the only position other than cornerback to have only one round, the first, feature a significant difference in performance. In consideration, the Cleveland Browns would have been advised to select, defensive end, Cameron Jordan. Furthermore, defensive tackles offer an insignificant difference in performance in all rounds other than the fourth and seventh, where they significantly underperform. Wide receivers are found to most consistently overperform when selected in either round one or two. Therefore, it would be recommended that the Cleveland Browns select a wide receiver with the 37th overall draft pick, while selecting a defensive tackle with the 59th draft pick. Implementing this draft strategy would, then, have produced wide receiver, Titus Young, and defensive tackle, Terrell McClain.

Next, in 2012, the Cleveland Browns controlled a total of eleven draft picks. Sports columnists have described the 2012 Cleveland Browns' draft as "an unprecedented disaster" along with, "the worst first round ever" (The Cleveland, Manfred). However, in actuality, only the first two selections were worthy of such criticism. The remaining nine selections showed similar draft picks as what this thesis' findings would have suggested. Two names, Trent Richardson and Brandon Weeden, made these nine ensuing selections meaningless. Although the findings of this thesis found both running backs and quarterbacks to outperform their respective PILs, the S-Lift prediction model, published by Nasir Bhanpuri and mentioned above, finds that through "analysis of data over the past 25 years late first-round picks are better spent on positions other than QB" (Bhanpuri). Due to this, simply by swapping the two position selections, the Cleveland Browns might have been able to avoid an era of criticism. Therefore, the recommended selections in 2012 would have been to select quarterback Ryan Tannehill, with the 3rd overall pick, and running back Doug Martin, with the 22nd overall pick.

The Cleveland Browns in 2013 held only five draft picks. The main recommendation that pertains to the draft strategy would be to switch the draft selection of the safety and cornerback position. Instead of drafting a cornerback in the third round and a safety in the sixth, it would be recommended to draft a safety in the third and a cornerback in the sixth. This proposition would have resulted in the selection free safety Tyrann Mathieu and cornerback Khalid Wooten. Remember, regression analysis of the safeties sack performance rank resulted in 77.78% of safeties outperforming the PIL in round three. Whereas, the only significant overperformance analysis stems from round one for cornerbacks. Therefore, if a cornerback is not selected in the first round it would be advised to wait until the later rounds to draft a cornerback due to the unpredictability of position performance correlation. Same is true of the Browns' seventh round defensive end pick, the only significant difference between performance of defensive ends results from the first round. Signaling, as the Browns did, it would also be advised to wait until the later rounds to draft a defensive end.

The 2014 Cleveland Browns' draft has also been touted as a draft strategy implosion. Selecting quarterback Johnny Manziel with the 22nd overall pick, late in the first round, the Cleveland Browns seem to simply be repeating their past mistakes of drafting quarterbacks late in round one. The 2014 draft selections will be the only selections where the actual positions drafted by the Cleveland Browns differs from the suggested position to be draft. This results mainly from the 2012 Draft where the Browns were suggested to have selected Ryan Tannehill. It should be noted that Ryan Tannehill (as well as all suggested selections) might not have performed as well as he has thus far in his career had he been drafted to the Browns; however, the performance rank would still be expected to be similar. Had the Cleveland Browns selected Ryan Tannehill with the 3rd overall pick in 2012, it would be questionable the Browns would then again use another first round pick on a quarterback two years later. But hey, they are the Cleveland Browns. Assuming the Browns front office did not draft a Johnny Manziel, this case study would then advise the Browns make the following changes to their draft board. It would have been suggested that the Browns use their 22nd overall selection on a position that correlated highest with first round selection performance. These positions include running backs, wide receivers, defensive ends, linebackers, or cornerbacks. Any of these positions are found to have a higher overperformance percentage in the first round than the quarterback drafted late in the first. In addition, it would be recommended to draft a safety (Terrance Brooks) in the third round in place the outside linebacker selection, Christian Kirksey, due to safeties and running backs being the only two positions to most consistently correlate to high incentive rank performance.

Finally, in 2015 NFL Draft the Cleveland Browns were allotted a total of twelve draft selections. Examining each selection, this case study identified five draft selections that could have been improved had the positions been drafted in different rounds. First, it would be suggested that the Browns draft a defensive tackle in the second round instead of the first, due to defensive tackles performing at a consistent rate with no real significance to where they are selected. Analyzing the receiving performance incentive ranks of wide receivers it would be suggested that a wide receiver be drafted in place of the defensive tackle. The defensive end selection would be moved down from the second round to the sixth because there is insignificant performance difference between the two rounds for defensive ends. Lastly, the tight end position selection would be improved to round 4, the round in which tight ends boasted most consistently an overperformance in relation to the PIL. These suggestions would result in the draft selections of wide receiver DeVante Parker, defensive end Jordan Phillips, tight end Blake Bell, safety Ibraheim Campbell, and defensive end Christian Rigo.

# Appendices

## Appendix A

| Sel. | Value | Sel. | Value | Sel. | Value | Sel. | Value | Sel. | Value | Sel. | Value | Sel. | Value | Sel. | Value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 3000 | 33 | 580 | 65 | 265 | 97 | 112 | 129 | 43 | 161 | 28 | 193 | 15.2 | 225 | 2.9 |
| 2 | 2600 | 34 | 560 | 66 | 260 | 98 | 108 | 130 | 42 | 162 | 27.6 | 194 | 14.8 | 226 | 2.8 |
| 3 | 2200 | 35 | 550 | 67 | 255 | 99 | 104 | 131 | 41 | 163 | 27.2 | 195 | 14.4 | 227 | 2.7 |
| 4 | 1800 | 36 | 540 | 68 | 250 | 100 | 100 | 132 | 40 | 164 | 26.8 | 196 | 14 | 228 | 2.6 |
| 5 | 1700 | 37 | 530 | 69 | 245 | 101 | 96 | 133 | 39.5 | 165 | 26.4 | 197 | 13.6 | 229 | 2.5 |
| 6 | 1600 | 38 | 520 | 70 | 240 | 102 | 92 | 134 | 39 | 166 | 26 | 198 | 13.2 | 230 | 2.4 |
| 7 | 1500 | 39 | 510 | 71 | 235 | 103 | 88 | 135 | 38.5 | 167 | 25.6 | 199 | 12.8 | 231 | 2.3 |
| 8 | 1400 | 40 | 500 | 72 | 230 | 104 | 86 | 136 | 38 | 168 | 25.2 | 200 | 12.4 | 232 | 2.2 |
| 9 | 1350 | 41 | 490 | 73 | 225 | 105 | 84 | 137 | 37.5 | 169 | 24.8 | 201 | 12 | 233 | 2.1 |
| 10 | 1300 | 42 | 480 | 74 | 220 | 106 | 82 | 138 | 37 | 170 | 24.4 | 202 | 11.6 | 234 | 2 |
| 11 | 1250 | 43 | 470 | 75 | 245 | 107 | 80 | 139 | 36.5 | 171 | 24 | 203 | 11.2 | 235 | 1.9 |
| 12 | 1200 | 44 | 460 | 76 | 210 | 108 | 78 | 140 | 36 | 172 | 23.6 | 204 | 10.8 | 236 | 1.8 |
| 13 | 1150 | 45 | 450 | 77 | 205 | 109 | 76 | 141 | 35.5 | 173 | 23.2 | 205 | 10.4 | 237 | 1.7 |
| 14 | 1100 | 46 | 440 | 78 | 200 | 110 | 74 | 142 | 35 | 174 | 22.8 | 206 | 10 | 238 | 1.6 |
| 15 | 1050 | 47 | 430 | 79 | 195 | 111 | 72 | 143 | 34.5 | 175 | 22.4 | 207 | 9.6 | 239 | 1.5 |
| 16 | 1000 | 48 | 420 | 80 | 190 | 112 | 70 | 144 | 34 | 176 | 22 | 208 | 9.2 | 240 | 1.4 |
| 17 | 950 | 49 | 410 | 81 | 185 | 113 | 68 | 145 | 33.5 | 177 | 21.6 | 209 | 8.8 | 241 | 1.3 |
| 18 | 900 | 50 | 400 | 82 | 180 | 114 | 66 | 146 | 33 | 178 | 21.2 | 210 | 8.4 | 242 | 1.2 |
| 19 | 875 | 51 | 390 | 83 | 175 | 115 | 64 | 147 | 32.6 | 179 | 20.8 | 211 | 8 | 243 | 1.1 |
| 20 | 850 | 52 | 380 | 84 | 170 | 116 | 62 | 148 | 32.2 | 180 | 20.4 | 212 | 7.6 | 244 | 1 |
| 21 | 800 | 53 | 370 | 85 | 165 | 117 | 60 | 149 | 31.8 | 181 | 20 | 213 | 7.2 | 245 | 0.95 |
| 22 | 780 | 54 | 360 | 86 | 160 | 118 | 58 | 150 | 31.4 | 182 | 19.6 | 214 | 6.8 | 246 | 0.9 |
| 23 | 760 | 55 | 350 | 87 | 155 | 119 | 56 | 151 | 31 | 183 | 19.2 | 215 | 6.4 | 247 | 0.85 |
| 24 | 740 | 56 | 340 | 88 | 150 | 120 | 54 | 152 | 31.6 | 184 | 18.8 | 216 | 6 | 248 | 0.8 |
| 25 | 720 | 57 | 330 | 89 | 145 | 121 | 52 | 153 | 31.2 | 185 | 18.4 | 217 | 5.6 | 249 | 0.75 |
| 26 | 700 | 58 | 320 | 90 | 140 | 122 | 50 | 154 | 30.8 | 186 | 18 | 218 | 5.2 | 250 | 0.7 |
| 27 | 680 | 59 | 310 | 91 | 136 | 123 | 49 | 155 | 30.4 | 187 | 17.6 | 219 | 4.8 | 251 | 0.65 |
| 28 | 660 | 60 | 300 | 92 | 132 | 124 | 48 | 156 | 30 | 188 | 17.2 | 220 | 4.4 | 252 | 0.6 |
| 29 | 640 | 61 | 292 | 93 | 128 | 125 | 47 | 157 | 29.6 | 189 | 16.8 | 221 | 4 | 253 | 0.55 |
| 30 | 620 | 62 | 284 | 94 | 124 | 126 | 46 | 158 | 29.2 | 190 | 16.4 | 222 | 3.6 | 254 | 0.5 |
| 31 | 600 | 63 | 276 | 95 | 120 | 127 | 45 | 159 | 28.8 | 191 | 16 | 223 | 3.3 | 255 | 0.45 |
| 32 | 590 | 64 | 270 | 96 | 116 | 128 | 44 | 160 | 28.4 | 192 | 15.6 | 224 | 3 | | |

## Appendix B

**(EXHIBIT A)**
**TEAM INCENTIVES**

| OFFENSE | DEFENSE | SPECIAL TEAMS |
|---|---|---|
| Points scored by Team | Points allowed by Team | Own punt return average |
| Touchdowns scored by Team | Touchdowns allowed by Team | Own kickoff return average |
| Total offense (net yards) | Total defense (net yards) | Opposition punt return average |
| Average net yards gained per rushing play | Average net yards allowed per rushing play | Opposition kickoff return average |
| Average net yards gained per passing play | Average net yards given up per passing play | |
| Sacks allowed | Sacks | |
| Passing % completed | Interceptions | |

**ALL**
Wins
Playoffs
Conference Championship
Super Bowl
Touchdowns on returns and recoveries
Net difference takeaways/giveaways

## Appendix C

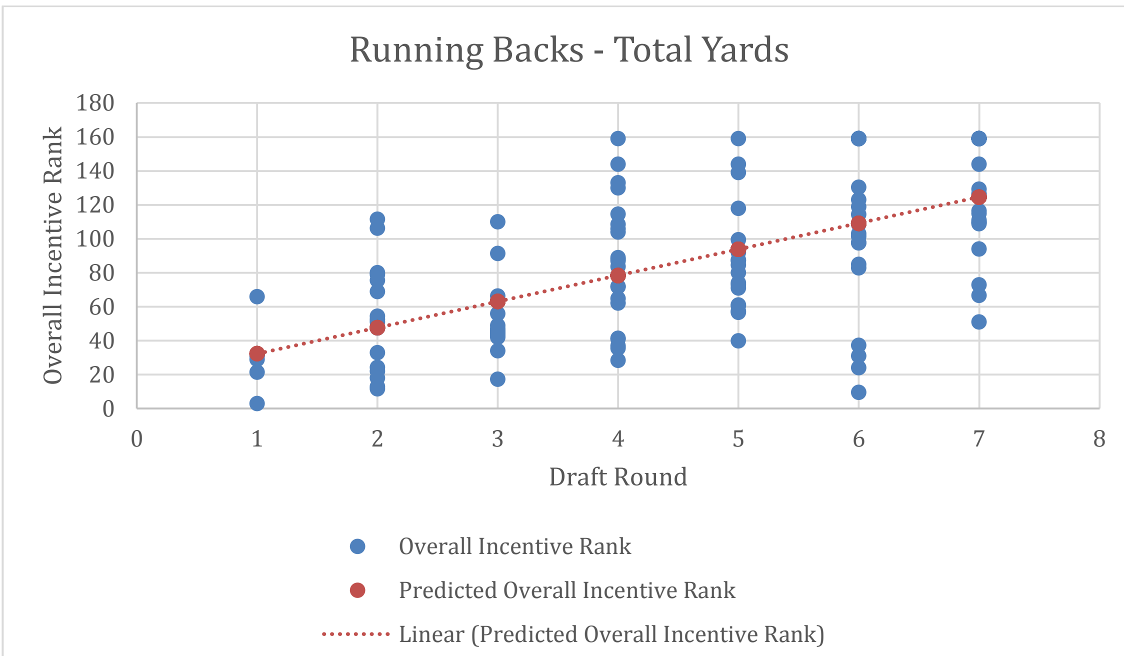
SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.630618705 |
| R Square | 0.397679951 |
| Adjusted R Square | 0.392702099 |
| Standard Error | 34.935927 |
| Observations | 123 |

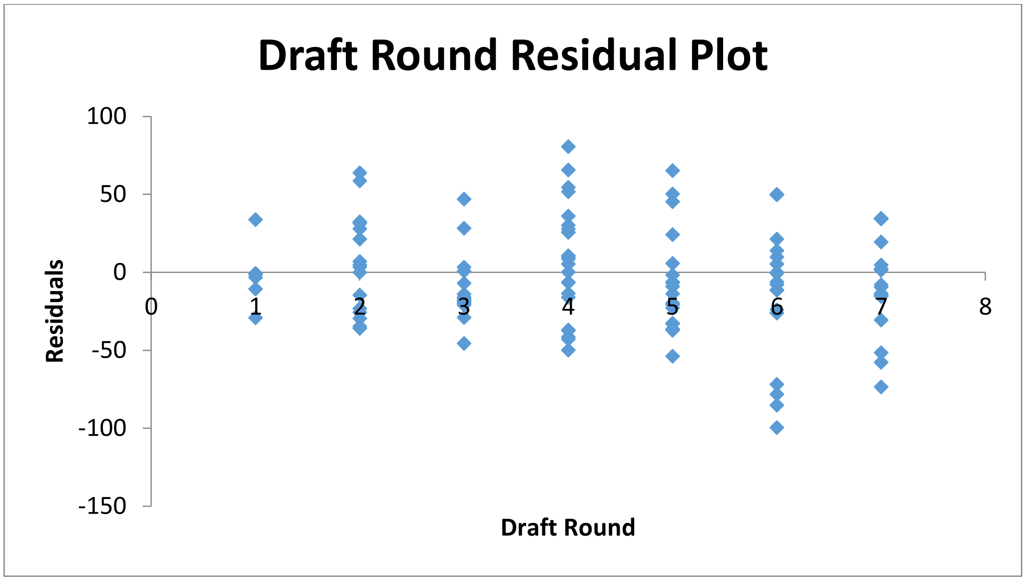
ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 97507.11125 | 97507.11125 | 79.88987607 | 5.42302E-15 |
| Residual | 121 | 147682.7984 | 1220.518995 | | |
| Total | 122 | 245189.9097 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% |
|---|---|---|---|---|---|
| Intercept | 16.93510823 | 8.442080514 | 2.006034911 | 0.047082815 | 0.221783147 |
| RD | 15.37642563 | 1.720321109 | 8.938113675 | 5.42302E-15 | 11.97059624 |




| Round | Over Performing | Under Performing |
|---|---|---|
| 1 | 83.33% | 16.67% |
| 2 | 43.75% | 56.25% |
| 3 | 73.33% | 26.67% |
| 4 | 68.18% | 31.82% |
| 5 | 72.22% | 27.78% |
| 6 | 47.83% | 52.17% |
| 7 | 43.48% | 56.52% |




## Appendix D

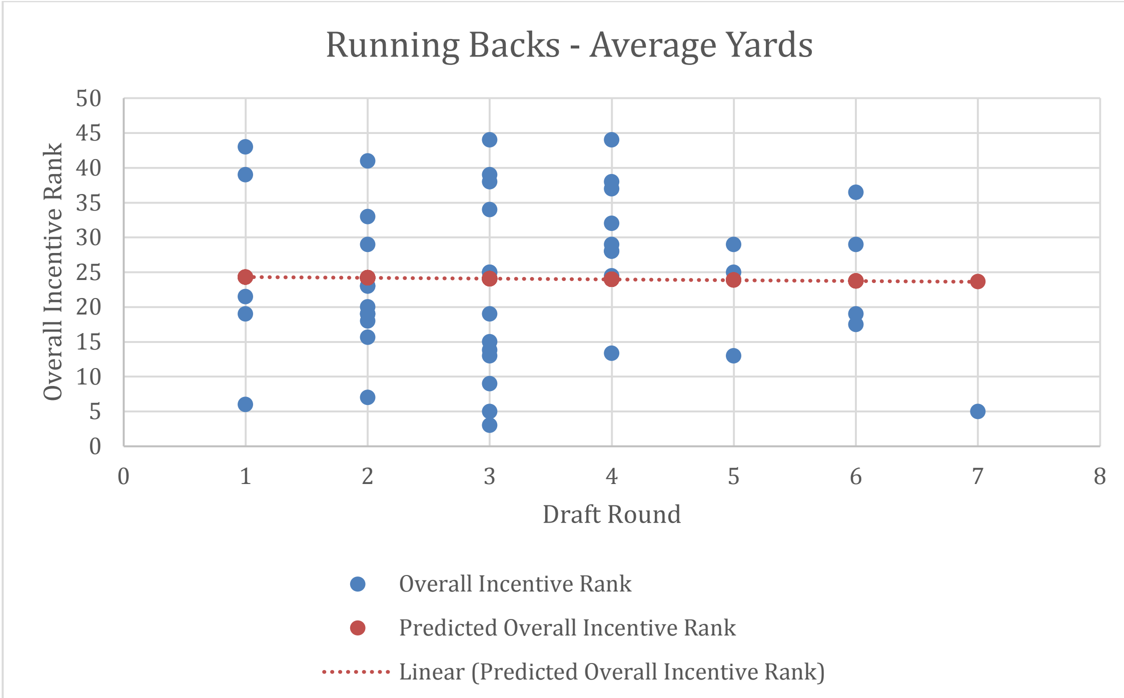
SUMMARY OUTPUT

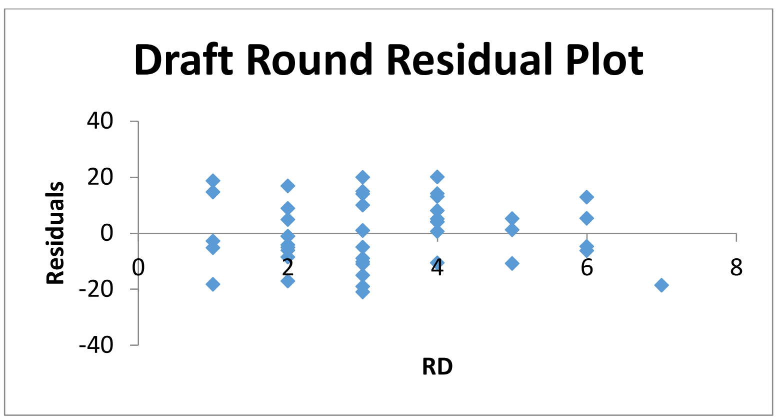
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.014842685 |
| R Square | 0.000220305 |
| Adjusted R Square | -0.022501961 |
| Standard Error | 11.51560805 |
| Observations | 46 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 1.285721874 | 1.285721874 | 0.009695569 | 0.922009426 |
| Residual | 44 | 5834.806066 | 132.6092288 | | |
| Total | 45 | 5836.091787 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 24.4224025 | 4.045221908 | 6.037345555 | 2.97402E-07 | 16.26979344 |
| RD | -0.112368346 | 1.141188397 | -0.098466078 | 0.922009426 | -2.412282437 |


Running Backs - Average Yards
Overall Incentive Rank
50
45
40
35
30
25
20
15
10
5
0
0
1
2
3
4
5
6
7
8
Draft Round
Overall Incentive Rank
Predicted Overall Incentive Rank
Linear (Predicted Overall Incentive Rank)


Draft Round Residual Plot
Residuals
40
20
0
-20
-40
0
2
4
6
8
RD

## Appendix E

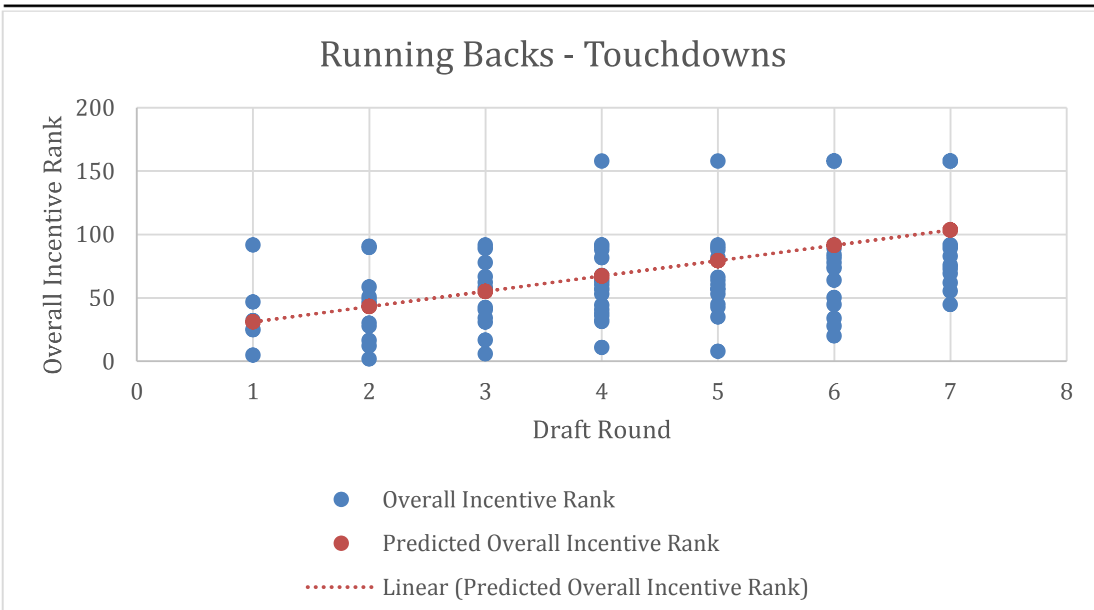
SUMMARY OUTPUT

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.528157767 |
| R Square | 0.278950627 |
| Adjusted R Square | 0.272991541 |
| Standard Error | 35.83168626 |
| Observations | 123 |

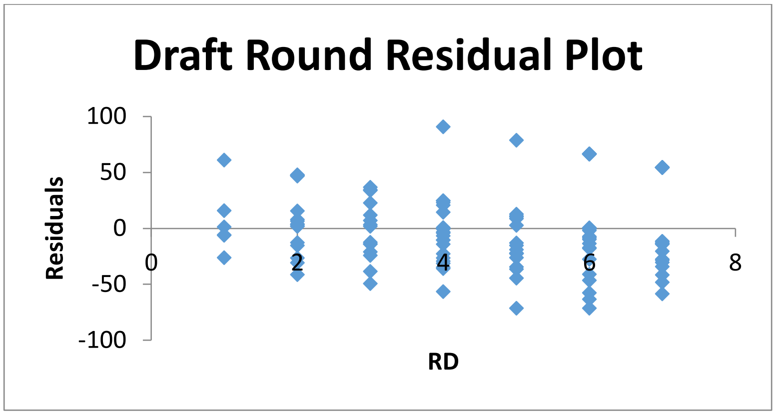
ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 60101.0698 | 60101.0698 | 46.81097736 | 3.42824E-10 |
| Residual | 121 | 155353.0786 | 1283.909741 | | |
| Total | 122 | 215454.1484 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 19.16078868 | 8.658535966 | 2.212936316 | 0.02877783 | 2.01893294 |
| RD | 12.07197558 | 1.764430246 | 6.841854819 | 3.42824E-10 | 8.578820519 |




| Round | Over Performing | Under Performing |
|---|---|---|
| 1 | 50.00% | 50.00% |
| 2 | 31.25% | 68.75% |
| 3 | 46.67% | 53.33% |
| 4 | 68.18% | 31.82% |
| 5 | 66.67% | 33.33% |
| 6 | 60.87% | 39.13% |
| 7 | 60.87% | 39.13% |




## Appendix F

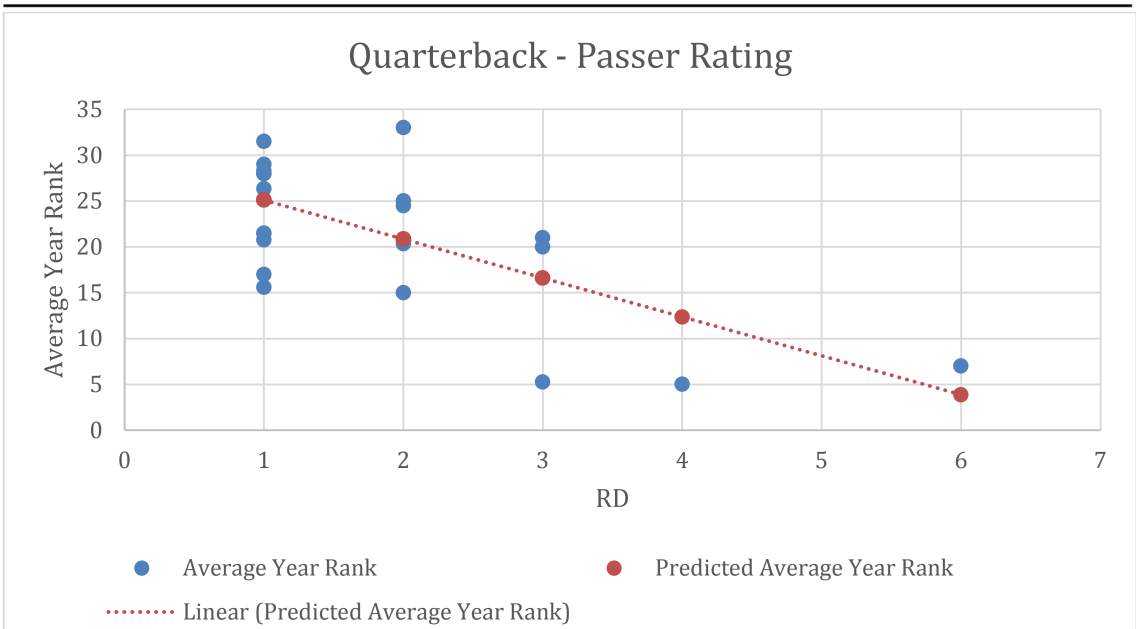
SUMMARY OUTPUT

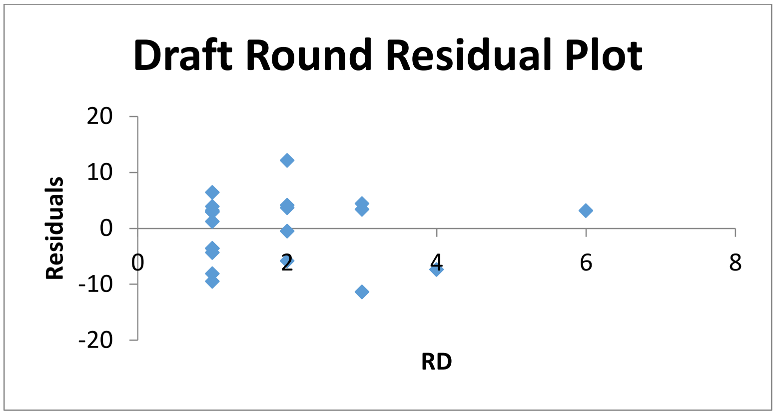
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.678858712 |
| R Square | 0.46084915 |
| Adjusted R Square | 0.433891608 |
| Standard Error | 6.043266474 |
| Observations | 22 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 624.3411821 | 624.3411821 | 17.09536954 | 0.000513477 |
| Residual | 20 | 730.4213936 | 36.52106968 | | |
| Total | 21 | 1354.762576 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 29.35392028 | 2.30802711 | 12.71818696 | 4.83508E-11 | 24.53946009 |
| RD | -4.248445028 | 1.027521119 | -4.134654706 | 0.000513477 | -6.391816523 |






## Appendix G

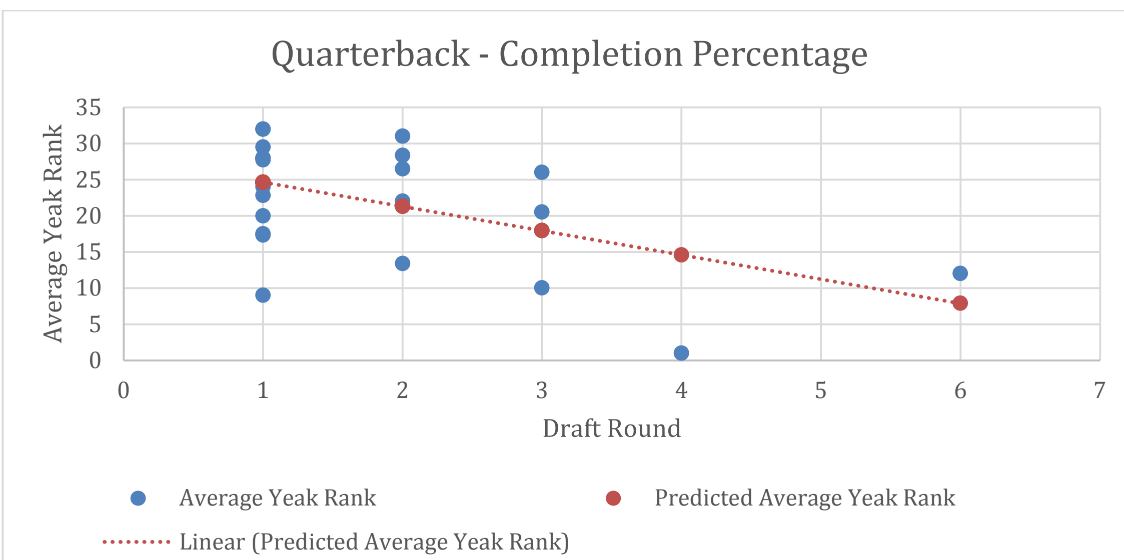
SUMMARY OUTPUT

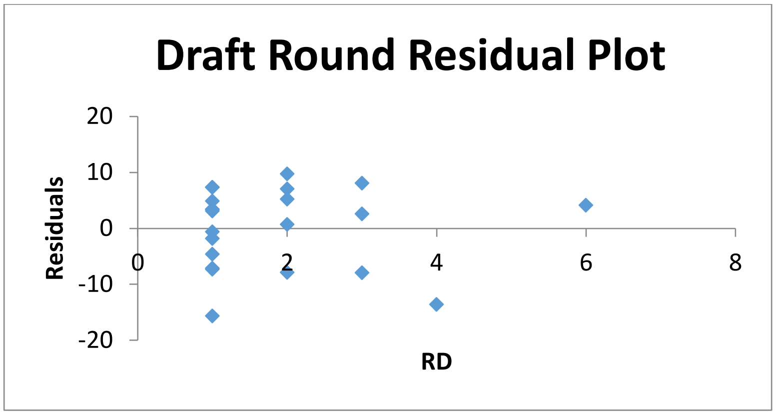
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.510066224 |
| R Square | 0.260167553 |
| Adjusted R Square | 0.223175931 |
| Standard Error | 7.444602751 |
| Observations | 22 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 389.791901 | 389.791901 | 7.033147965 | 0.015299333 |
| Residual | 20 | 1108.442203 | 55.42211013 | | |
| Total | 21 | 1498.234104 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 28.01130092 | 2.843221467 | 9.851958859 | 4.06323E-09 | 22.08044487 |
| RD | -3.356876916 | 1.265786736 | -2.652008289 | 0.015299333 | -5.99726178 |






## Appendix H

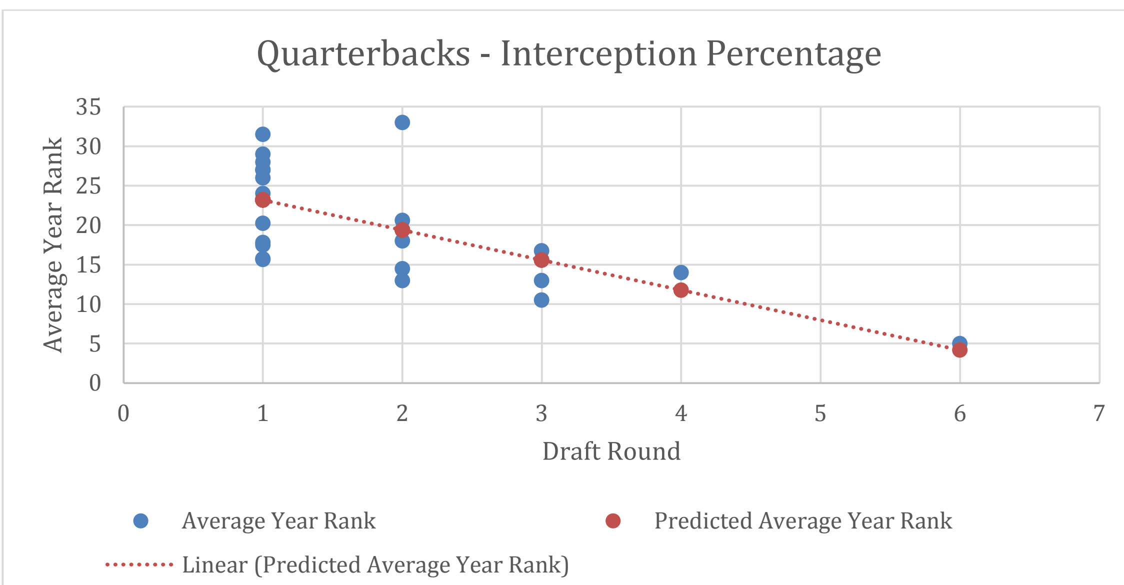
SUMMARY OUTPUT

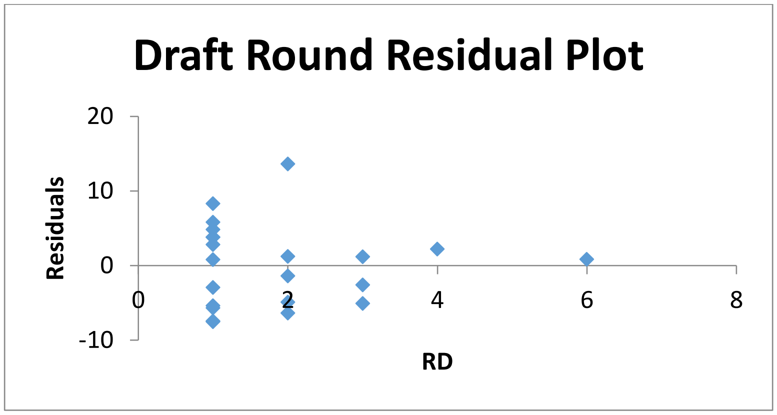
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.662728407 |
| R Square | 0.439208942 |
| Adjusted R Square | 0.411169389 |
| Standard Error | 5.649919444 |
| Observations | 22 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 500.0168041 | 500.0168041 | 15.66390673 | 0.000776534 |
| Residual | 20 | 638.4317944 | 31.92158972 | | |
| Total | 21 | 1138.448598 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 26.98628997 | 2.157801133 | 12.50638419 | 6.52699E-11 | 22.48519568 |
| RD | -3.801992992 | 0.960641331 | -3.957765371 | 0.000776534 | -5.805855693 |






# Appendix I

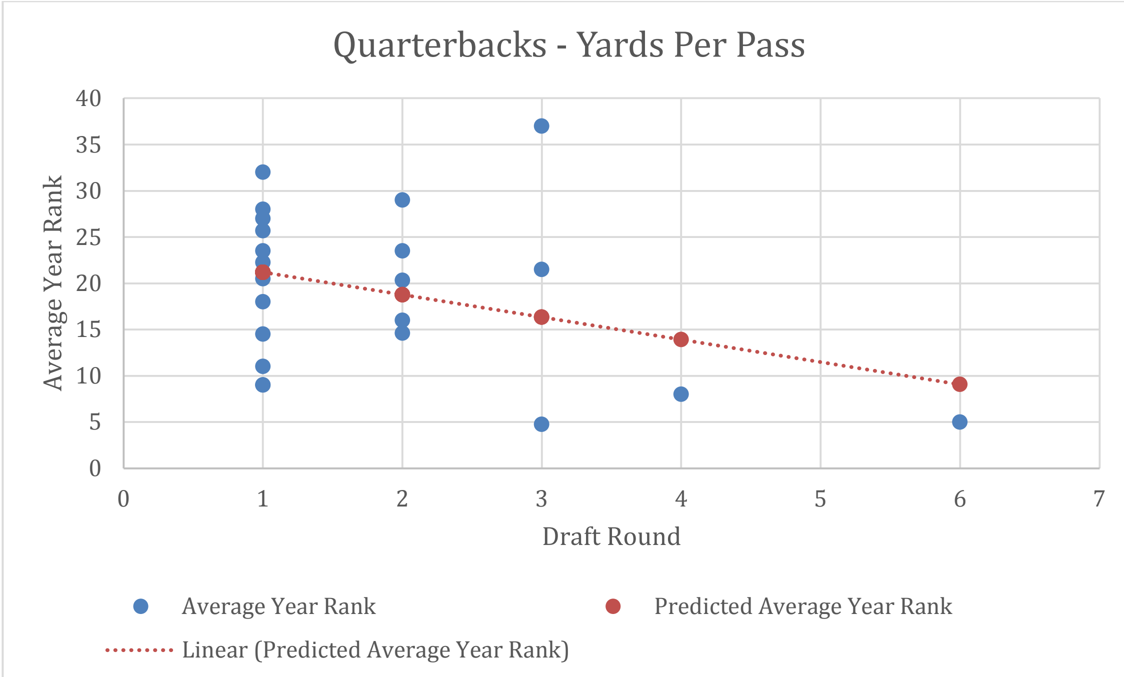
SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.348240459 |
| R Square | 0.121271417 |
| Adjusted R Square | 0.077334988 |
| Standard Error | 8.58444367 |
| Observations | 22 |

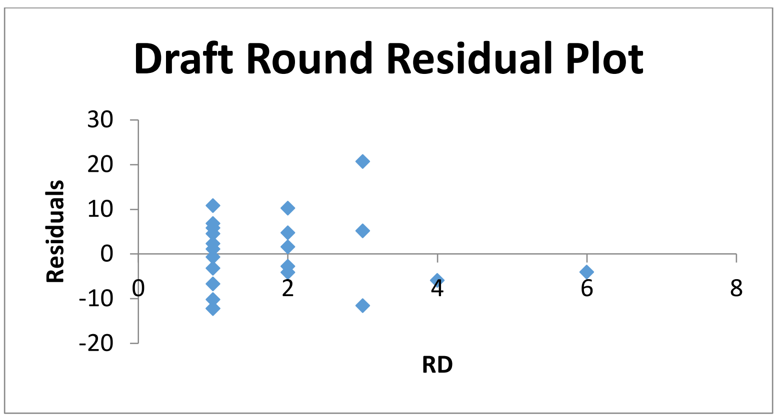
ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 203.4033051 | 203.4033051 | 2.760156424 | 0.112234856 |
| Residual | 20 | 1473.853463 | 73.69267313 | | |
| Total | 21 | 1677.256768 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 23.61462987 | 3.278546262 | 7.20277464 | 5.67146E-07 | 16.77570221 | 30.45355754 |
| RD | -2.424923346 | 1.459590968 | -1.66137185 | 0.112234856 | -5.469576753 | 0.61973006 |



Quarterbacks - Yards Per Pass
Average Year Rank
40
35
30
25
20
15
10
5
0
0
1
2
3
4
5
6
7
Draft Round
Average Year Rank
Predicted Average Year Rank
Linear (Predicted Average Year Rank)

Draft Round Residual Plot
Residuals
30
20
10
0
-10
-20
0
2
4
6
8
RD

## Appendix J

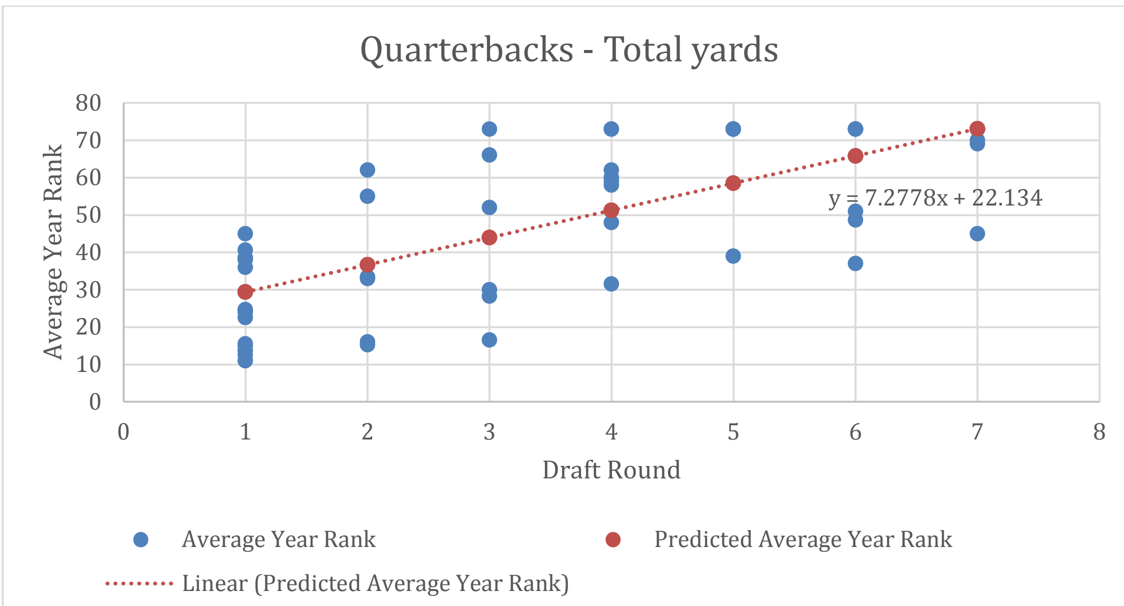
SUMMARY OUTPUT

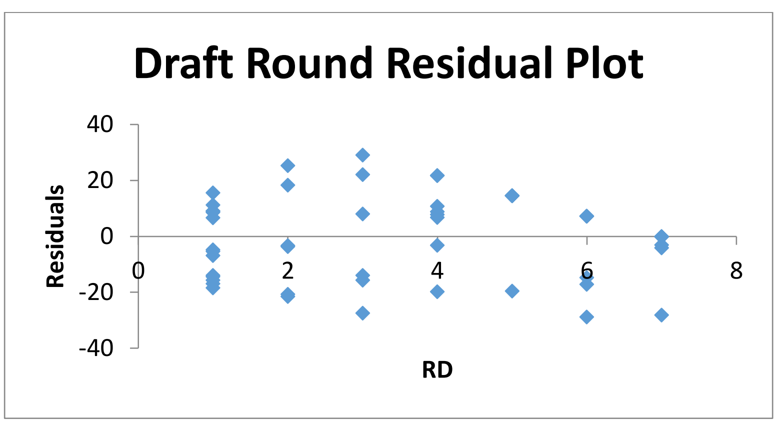
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.730115166 |
| R Square | 0.533068155 |
| Adjusted R Square | 0.52425812 |
| Standard Error | 15.00904954 |
| Observations | 55 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 13630.4909 | 13630.4909 | 60.50692955 | 2.52877E-10 |
| Residual | 53 | 11939.39311 | 225.271568 | | |
| Total | 54 | 25569.884 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
|---|---|---|---|---|---|---|
| Intercept | 22.13389854 | 4.01728435 | 5.509666884 | 1.07809E-06 | 14.07624655 | 30.19155054 |
| RD | 7.277756111 | 0.935610183 | 7.778620028 | 2.52877E-10 | 5.401159733 | 9.15435249 |



## Appendix K

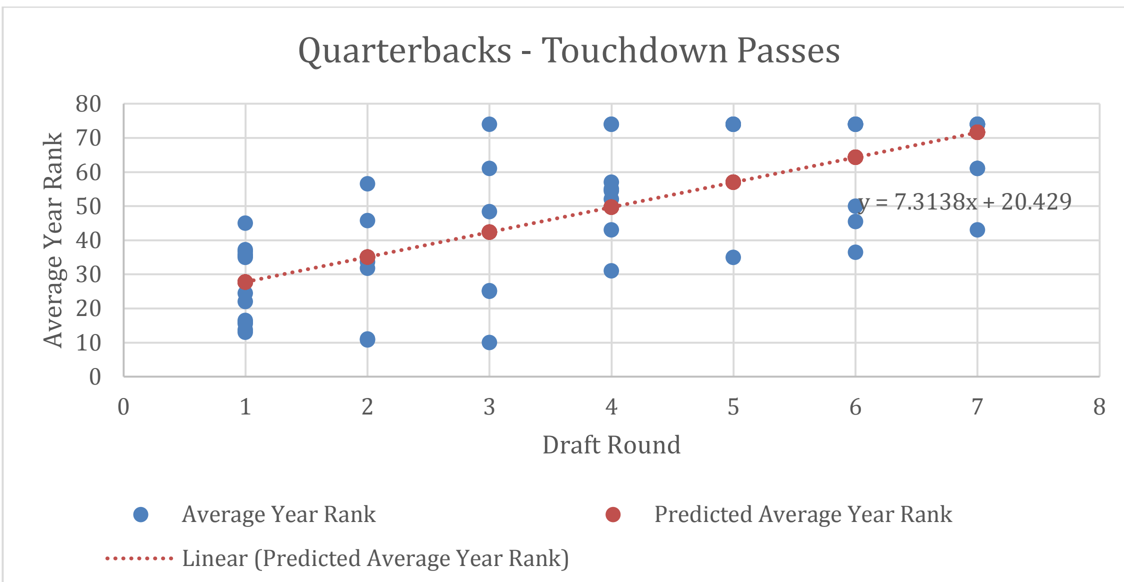
SUMMARY OUTPUT

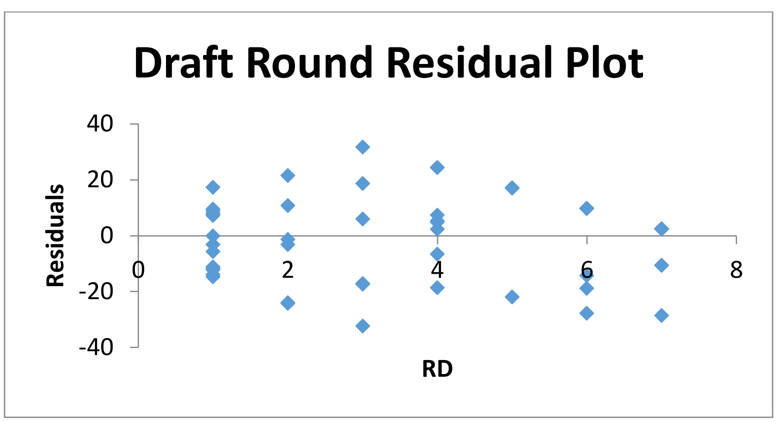
| Regression Statistics | |
|---|---|
| Multiple R | 0.721327376 |
| R Square | 0.520313184 |
| Adjusted R Square | 0.511262489 |
| Standard Error | 15.47436325 |
| Observations | 55 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 13766.02303 | 13766.02303 | 57.4887568 | 5.2239E-10 |
| Residual | 53 | 12691.16365 | 239.4559179 | | |
| Total | 54 | 26457.18668 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 20.42929914 | 4.141829044 | 4.932434178 | 8.41989E-06 | 12.12184212 | 28.73675616 |
| RD | 7.313849089 | 0.964616167 | 7.582134053 | 5.2239E-10 | 5.379074074 | 9.248624103 |



## Appendix L

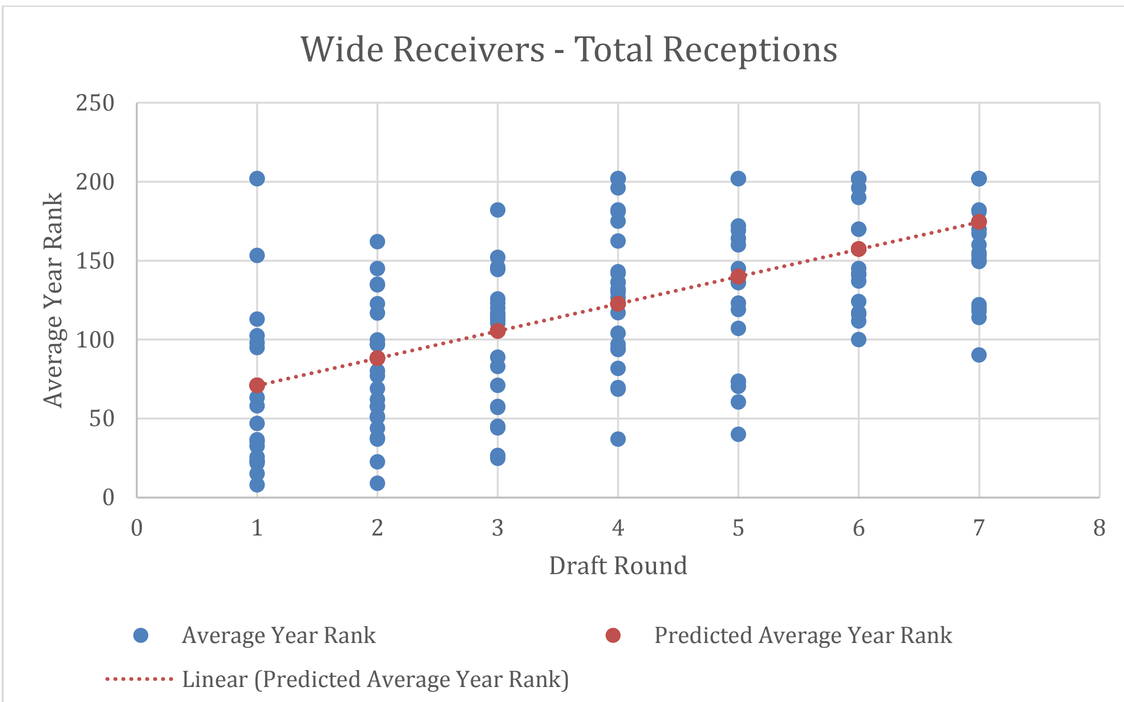
SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.601022663 |
| R Square | 0.361228241 |
| Adjusted R Square | 0.357053263 |
| Standard Error | 46.54065056 |
| Observations | 155 |

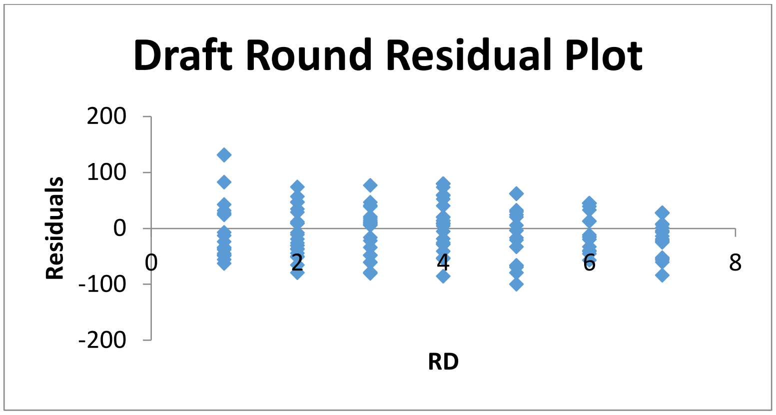
ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 187409.81 | 187409.81 | 86.52217352 | 1.36181E-16 |
| Residual | 153 | 331402.9197 | 2166.032155 | | |
| Total | 154 | 518812.7297 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 53.63717775 | 8.410147177 | 6.377674091 | 2.02115E-09 | 37.02217244 | 70.25218306 |
| RD | 17.26836902 | 1.85646861 | 9.301729598 | 1.36181E-16 | 13.60074762 | 20.93599043 |




| Round | Over Performing | Under Performing |
|---|---|---|
| 1 | 61.90% | 38.10% |
| 2 | 59.09% | 40.91% |
| 3 | 42.86% | 57.14% |
| 4 | 34.62% | 65.38% |
| 5 | 55.56% | 44.44% |
| 6 | 40.91% | 59.09% |
| 7 | 52.00% | 48.00% |




## Appendix M

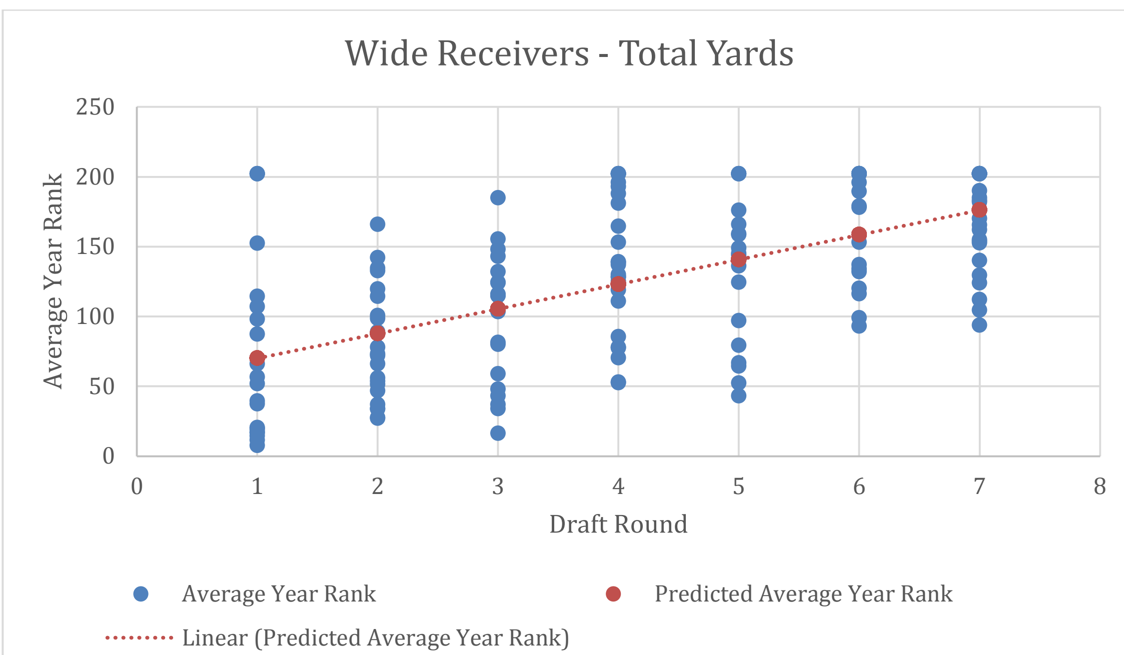
SUMMARY OUTPUT

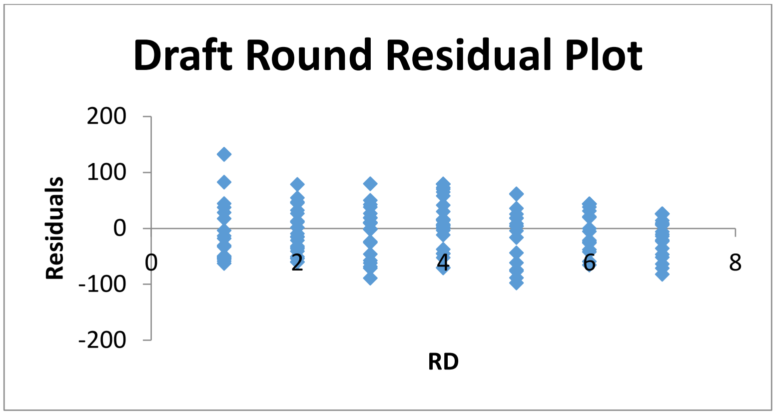
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.601782161 |
| R Square | 0.362141769 |
| Adjusted R Square | 0.357972761 |
| Standard Error | 47.52482788 |
| Observations | 155 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 196194.5738 | 196194.5738 | 86.86521249 | 1.2191E-16 |
| Residual | 153 | 345567.2176 | 2258.609265 | | |
| Total | 154 | 541761.7914 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
|---|---|---|---|---|---|---|
| Intercept | 52.44724543 | 8.587993339 | 6.107043096 | 8.0255E-09 | 35.48088897 | 69.4136019 |
| RD | 17.66845833 | 1.895726641 | 9.320150884 | 1.2191E-16 | 13.92327914 | 21.41363753 |






## Appendix N

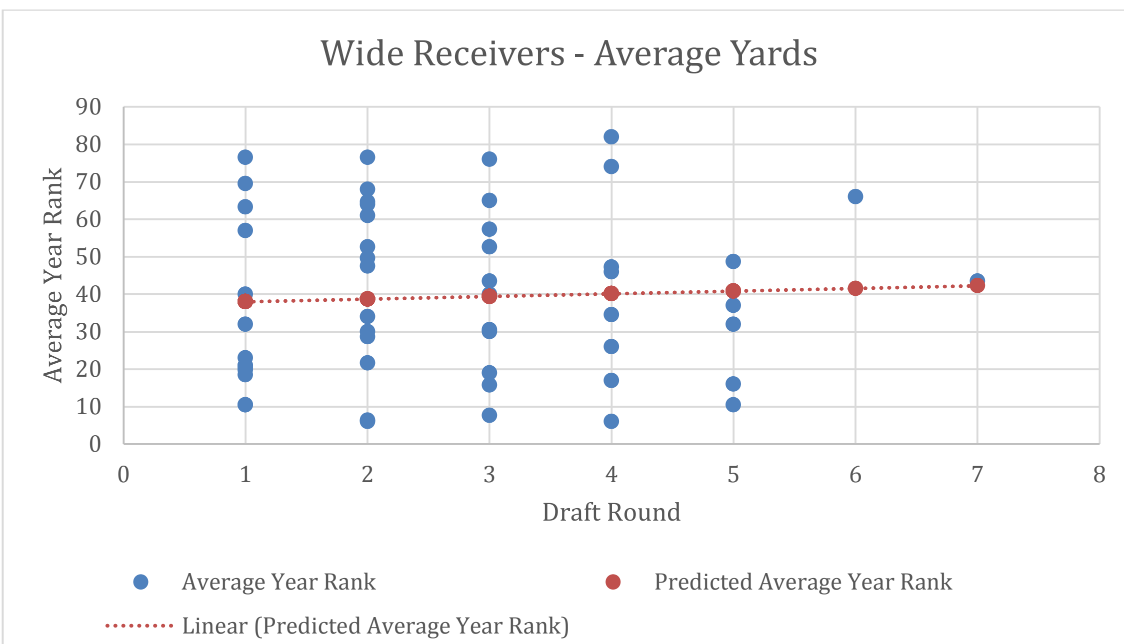
SUMMARY OUTPUT

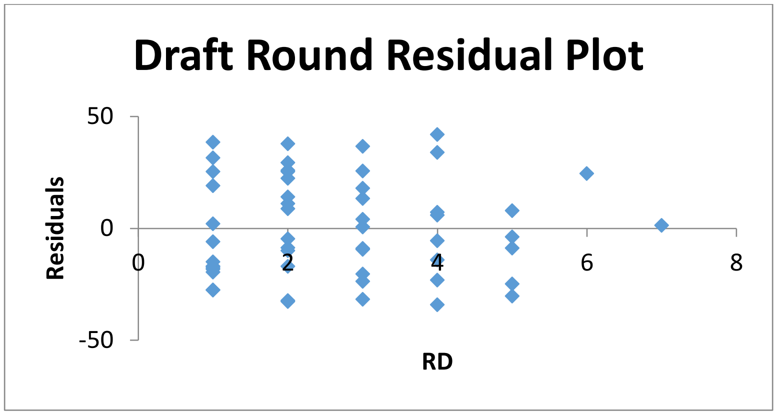
| Regression Statistics | |
|---|---|
| Multiple R | 0.047683887 |
| R Square | 0.002273753 |
| Adjusted R Square | -0.01691329 |
| Standard Error | 22.27923719 |
| Observations | 54 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 58.8214714 | 58.8214714 | 0.118504611 | 0.732050336 |
| Residual | 52 | 25810.94932 | 496.3644099 | | |
| Total | 53 | 25869.77079 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 37.31336639 | 6.293827986 | 5.928564695 | 2.49596E-07 | 24.68387657 | 49.94285621 |
| RD | 0.707091138 | 2.054034668 | 0.344244987 | 0.732050336 | -3.414630967 | 4.828813243 |






## Appendix O

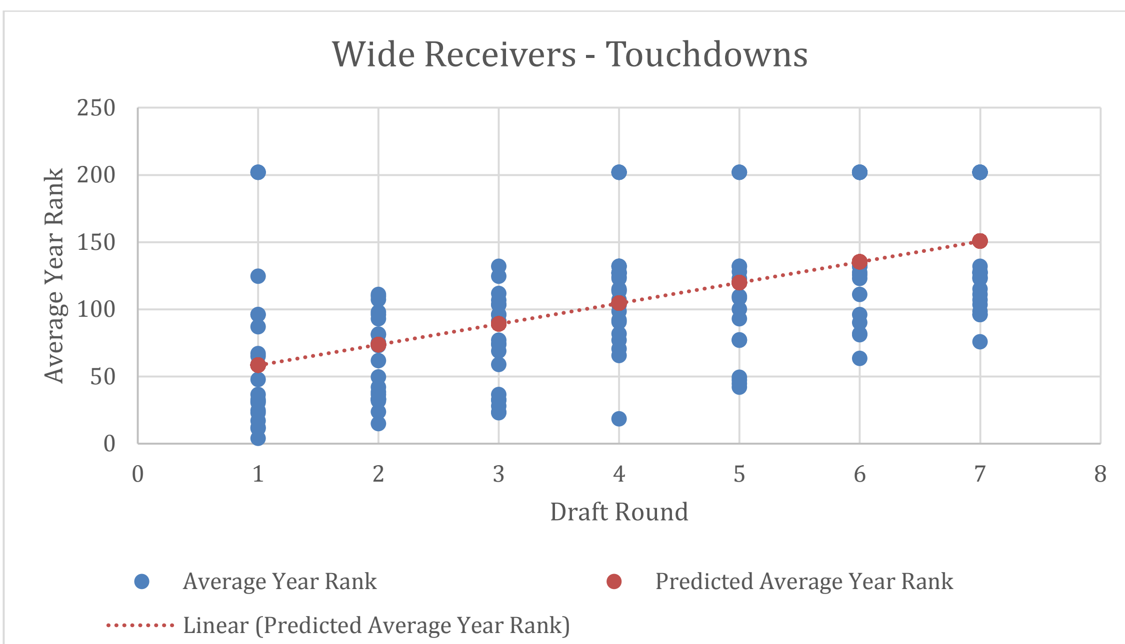
SUMMARY OUTPUT

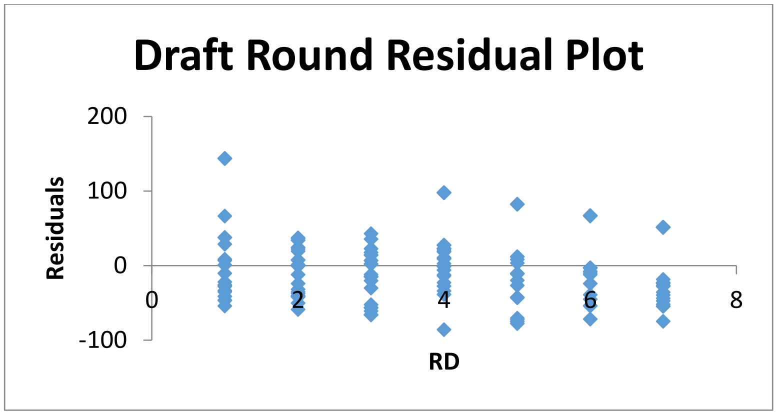
| Regression Statistics | |
|---|---|
| Multiple R | 0.548420928 |
| R Square | 0.300765514 |
| Adjusted R Square | 0.296195354 |
| Standard Error | 47.55691088 |
| Observations | 155 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 148841.4537 | 148841.4537 | 65.81071806 | 1.50359E-13 |
| Residual | 153 | 346033.9452 | 2261.659773 | | |
| Total | 154 | 494875.3989 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 42.99335089 | 8.593790911 | 5.002838833 | 1.53342E-06 | 26.01554079 | 59.97116098 |
| RD | 15.38923786 | 1.897006406 | 8.112380542 | 1.50359E-13 | 11.64153037 | 19.13694534 |






## Appendix P

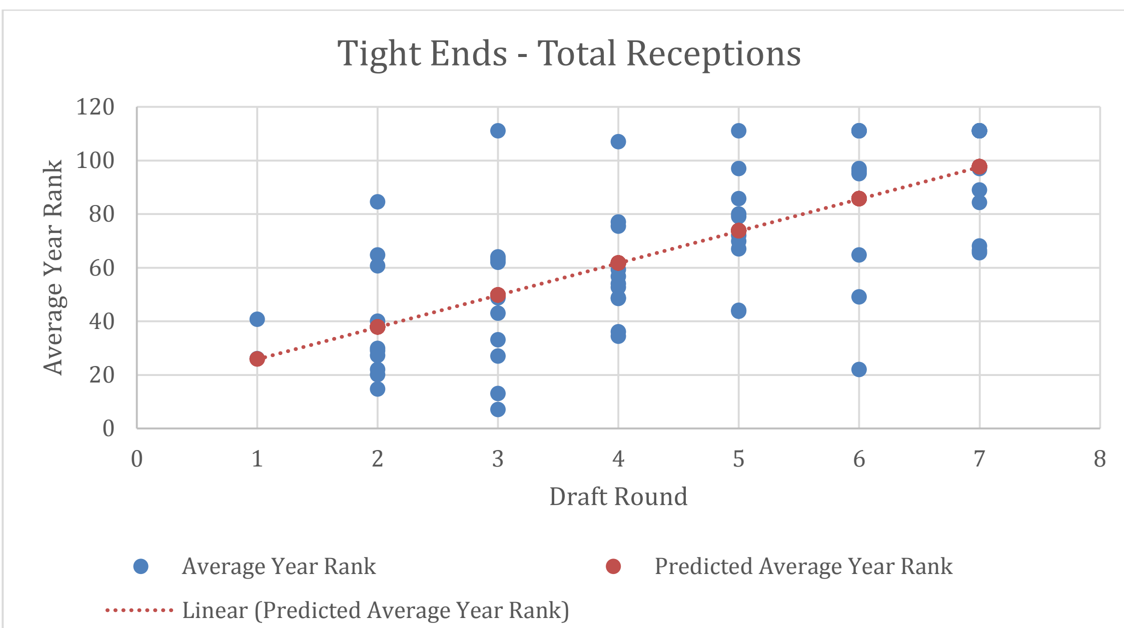
SUMMARY OUTPUT

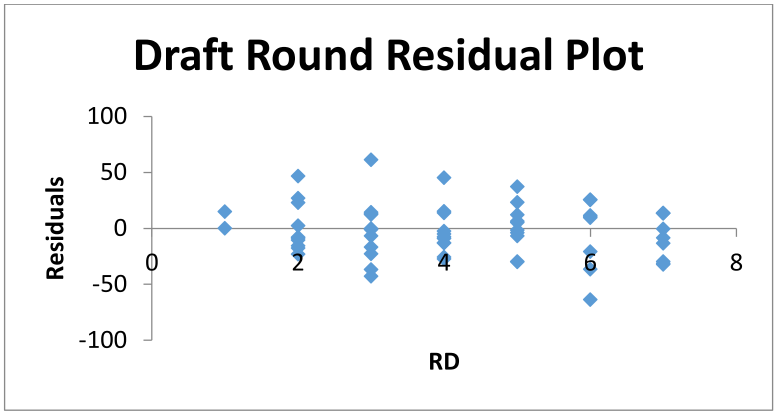
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.697709018 |
| R Square | 0.486797874 |
| Adjusted R Square | 0.479138141 |
| Standard Error | 22.91382744 |
| Observations | 69 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 33368.00993 | 33368.00993 | 63.55284978 | 2.70311E-11 |
| Residual | 67 | 35177.9137 | 525.0434881 | | |
| Total | 68 | 68545.92363 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
|---|---|---|---|---|---|---|
| Intercept | 13.89777391 | 7.366193433 | 1.886696845 | 0.063535128 | -0.805209722 | 28.60075754 |
| RD | 11.96519193 | 1.500901372 | 7.972004126 | 2.70311E-11 | 8.969380255 | 14.96100361 |






# Appendix Q

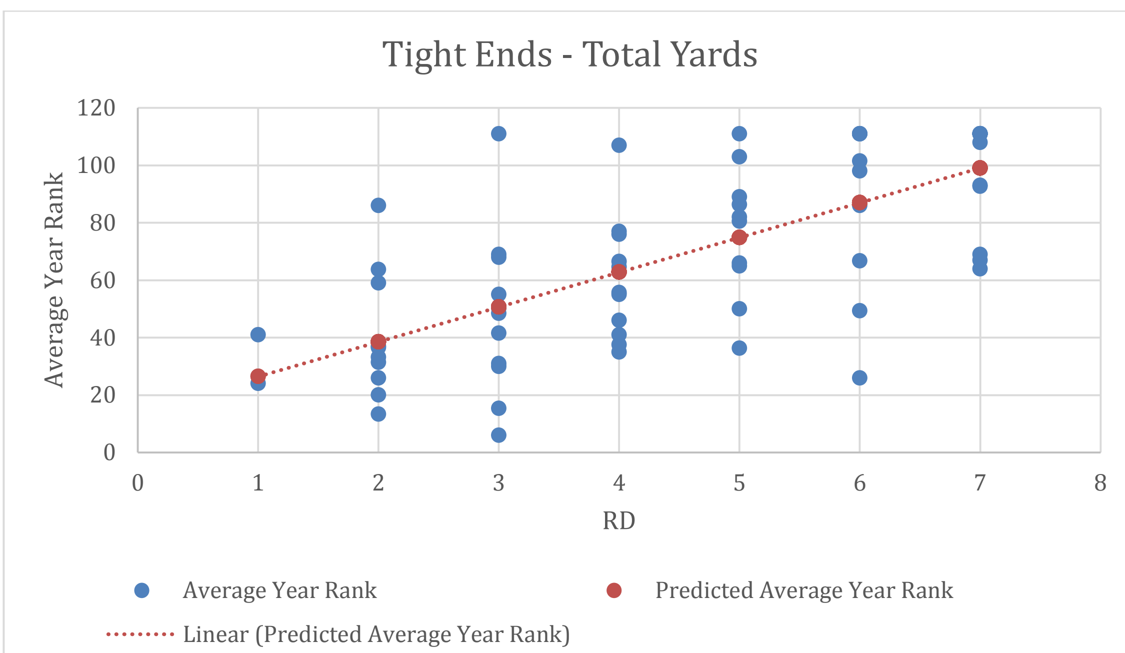
SUMMARY OUTPUT

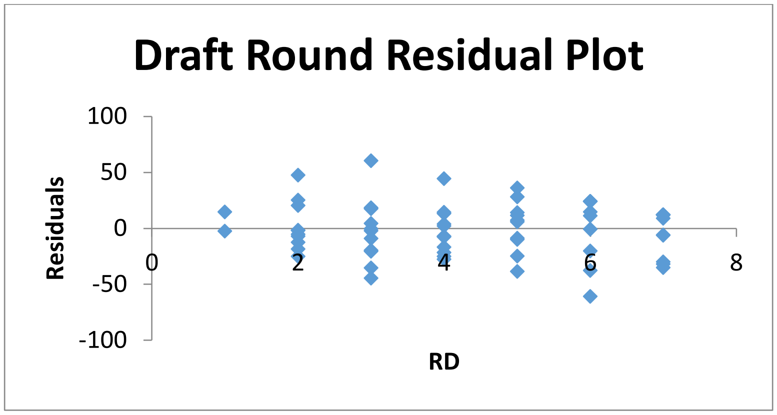
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.70048756 |
| R Square | 0.490682821 |
| Adjusted R Square | 0.483081072 |
| Standard Error | 22.98224135 |
| Observations | 69 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 34093.53971 | 34093.53971 | 64.54867493 | 2.08776E-11 |
| Residual | 67 | 35388.28897 | 528.1834174 | | |
| Total | 68 | 69481.82868 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
|---|---|---|---|---|---|---|
| Intercept | 14.40271318 | 7.388186706 | 1.949424636 | 0.055432247 | -0.344169208 | 29.14959557 |
| RD | 12.09457364 | 1.50538262 | 8.034218999 | 2.08776E-11 | 9.089817359 | 15.09932993 |






## Appendix R

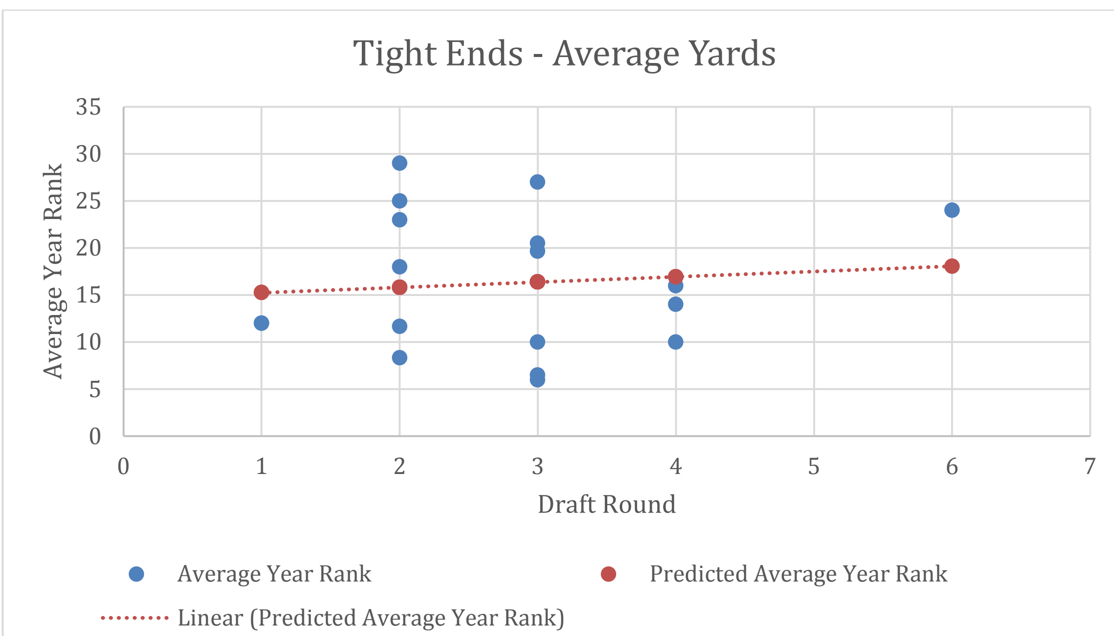
SUMMARY OUTPUT

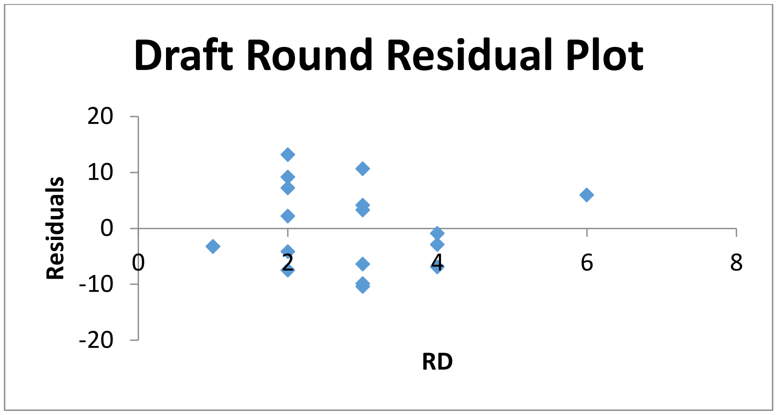
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.093566024 |
| R Square | 0.008754601 |
| Adjusted R Square | -0.053198237 |
| Standard Error | 7.451692178 |
| Observations | 18 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 7.846662297 | 7.846662297 | 0.141310733 | 0.711918999 |
| Residual | 16 | 888.4434612 | 55.52771632 | | |
| Total | 17 | 896.2901235 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
|---|---|---|---|---|---|---|
| Intercept | 14.70648968 | 4.488565974 | 3.27643389 | 0.004749267 | 5.191154881 | 24.22182447 |
| RD | 0.55899705 | 1.487037571 | 0.375913199 | 0.711918999 | -2.593381777 | 3.711375878 |






## Appendix S

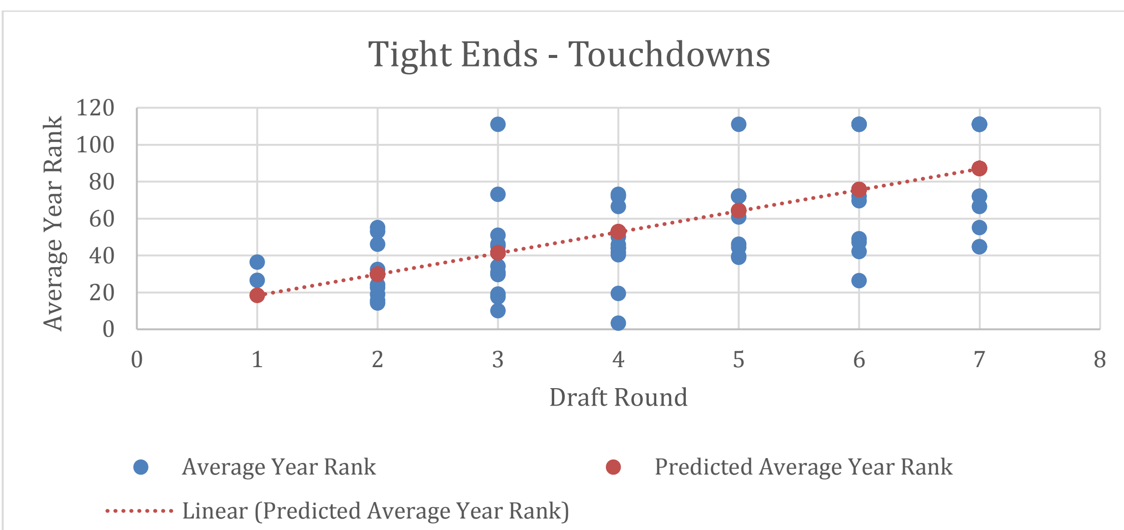
SUMMARY OUTPUT

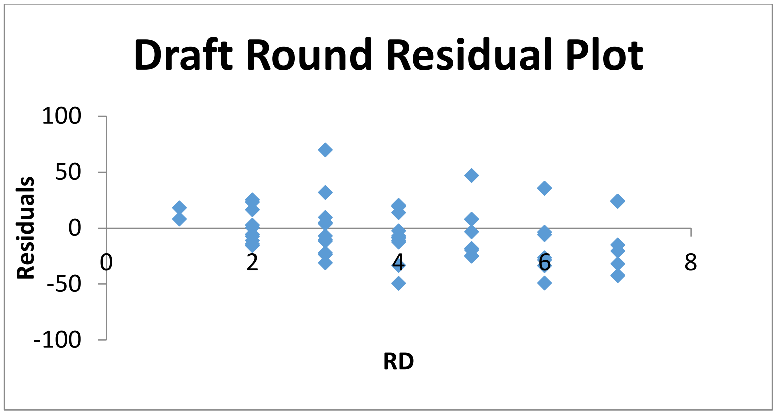
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.653175237 |
| R Square | 0.42663789 |
| Adjusted R Square | 0.418080247 |
| Standard Error | 24.75870643 |
| Observations | 69 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 30560.54797 | 30560.54797 | 49.85460005 | 1.17905E-09 |
| Residual | 67 | 41070.56744 | 612.9935439 | | |
| Total | 68 | 71631.11541 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
|---|---|---|---|---|---|---|
| Intercept | 6.908767566 | 7.95927355 | 0.868014841 | 0.388484701 | -8.978008931 | 22.79554406 |
| RD | 11.45078038 | 1.621744623 | 7.060778998 | 1.17905E-09 | 8.213764559 | 14.68779619 |






## Appendix T

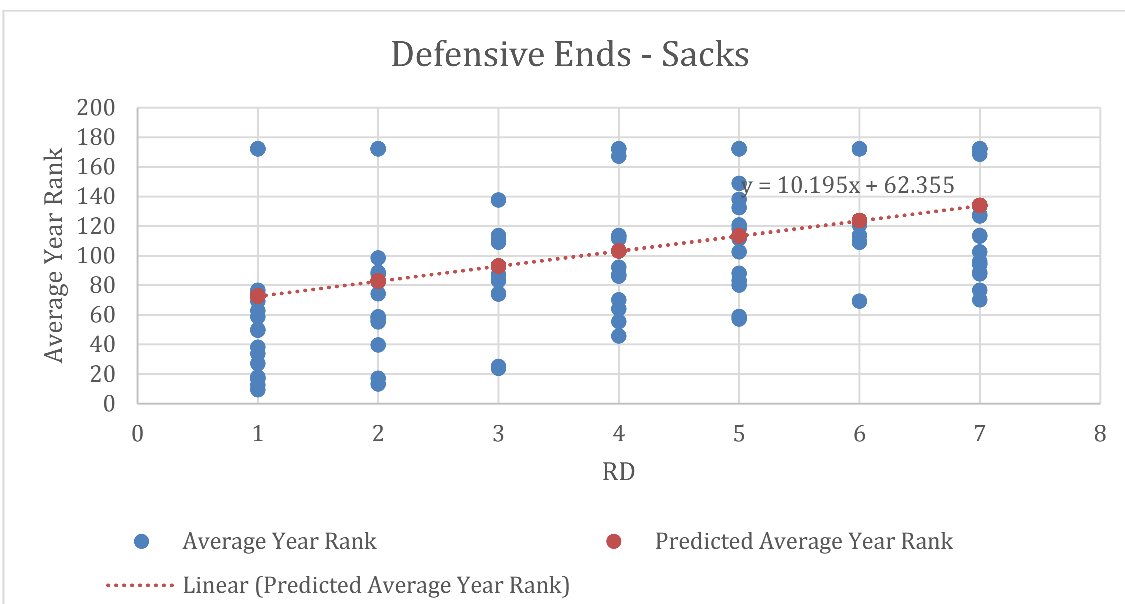
SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.435719543 |
| R Square | 0.189851521 |
| Adjusted R Square | 0.181830249 |
| Standard Error | 45.59539238 |
| Observations | 103 |

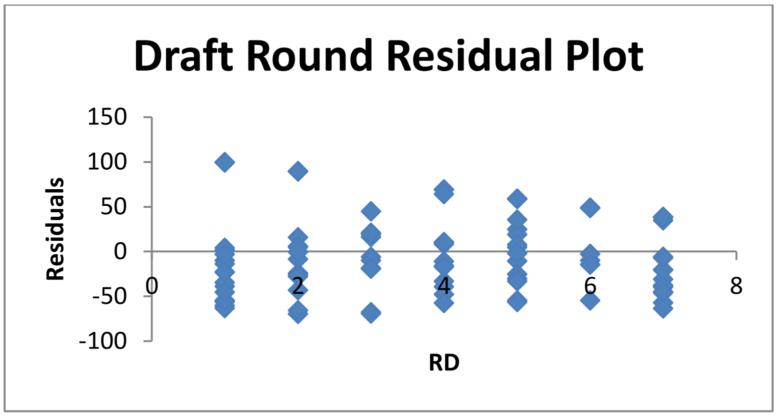
ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 49205.39782 | 49205.39782 | 23.6685053 | 4.22237E-06 |
| Residual | 101 | 209972.9204 | 2078.939806 | | |
| Total | 102 | 259178.3182 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 62.3554644 | 9.367435279 | 6.656620788 | 1.47801E-09 | 43.77299262 | 80.93793618 |
| RD | 10.19534777 | 2.095639754 | 4.865028808 | 4.22237E-06 | 6.038162222 | 14.35253332 |



| Round | Over Performance | Under Performance |
|---|---|---|
| 1 | 68.42% | 31.58% |
| 2 | 56.25% | 43.75% |
| 3 | 54.55% | 45.45% |
| 4 | 53.85% | 46.15% |
| 5 | 43.75% | 56.25% |
| 6 | 62.50% | 37.50% |
| 7 | 65.00% | 35.00% |




## Appendix U

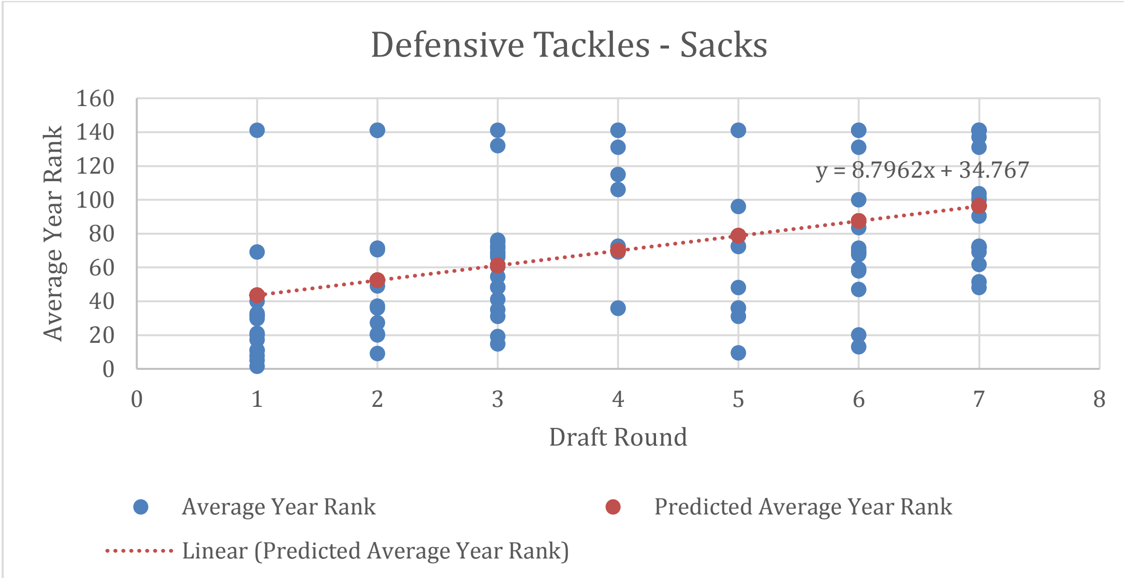
SUMMARY OUTPUT

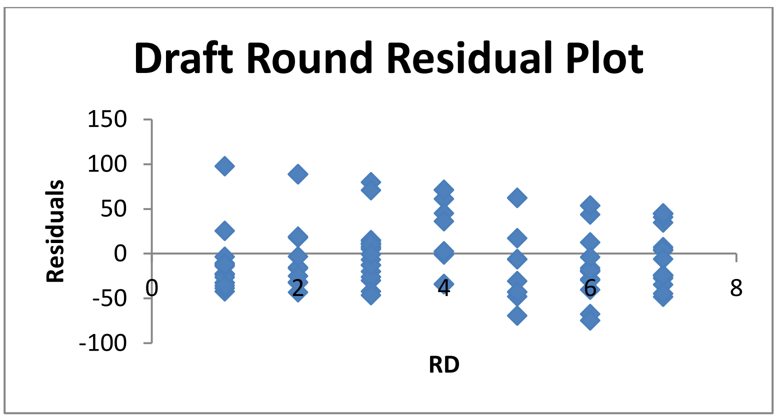
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.428815188 |
| R Square | 0.183882466 |
| Adjusted R Square | 0.175468883 |
| Standard Error | 39.40047792 |
| Observations | 99 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 33928.31753 | 33928.31753 | 21.85542944 | 9.49468E-06 |
| Residual | 97 | 150582.5731 | 1552.397661 | | |
| Total | 98 | 184510.8906 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
|---|---|---|---|---|---|---|
| Intercept | 34.76708552 | 8.622314054 | 4.032222128 | 0.000110089 | 17.6541789 | 51.87999214 |
| RD | 8.796175021 | 1.881543182 | 4.674979084 | 9.49468E-06 | 5.061832642 | 12.5305174 |




## Appendix V

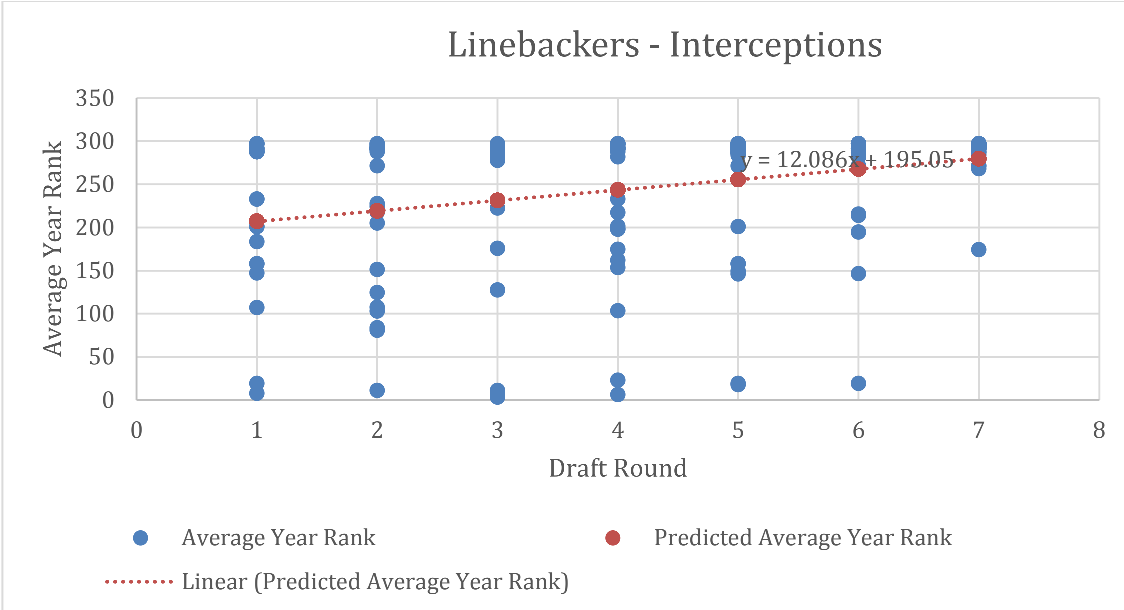
SUMMARY OUTPUT

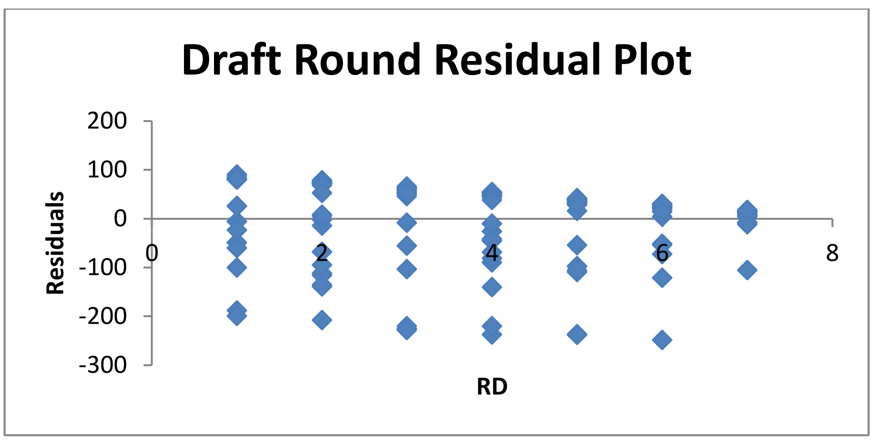
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.299570999 |
| R Square | 0.089742783 |
| Adjusted R Square | 0.084600087 |
| Standard Error | 77.20245184 |
| Observations | 179 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 104008.9846 | 104008.9846 | 17.45053196 | 4.6239E-05 |
| Residual | 177 | 1054958.687 | 5960.21857 | | |
| Total | 178 | 1158967.672 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 195.0492635 | 13.65968883 | 14.27918791 | 2.85302E-31 | 168.0924522 |
| RD | 12.08607288 | 2.893216104 | 4.177383386 | 4.6239E-05 | 6.376434729 |


Linebackers - Interceptions
Average Year Rank
Draft Round
y = 12.086x + 195.05
350
300
250
200
150
100
50
0
0
1
2
3
4
5
6
7
8
Average Year Rank
Predicted Average Year Rank
Linear (Predicted Average Year Rank)


Draft Round Residual Plot
Residuals
RD
200
100
0
-100
-200
-300
0
2
4
6
8

## Appendix W

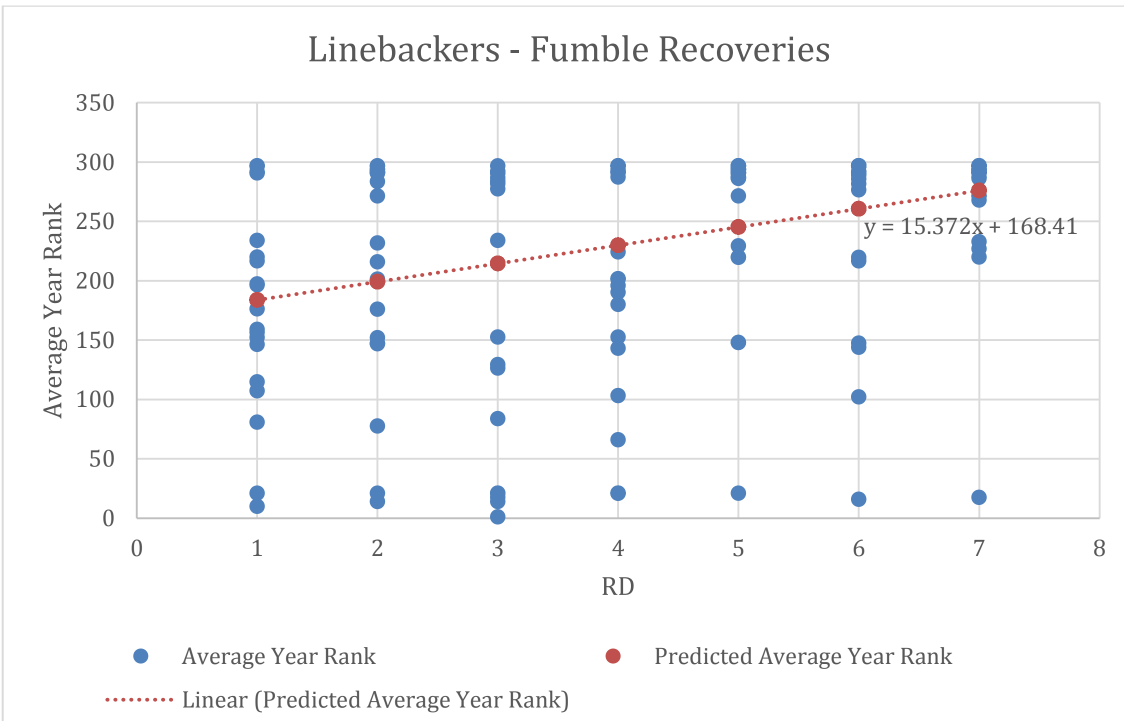
SUMMARY OUTPUT

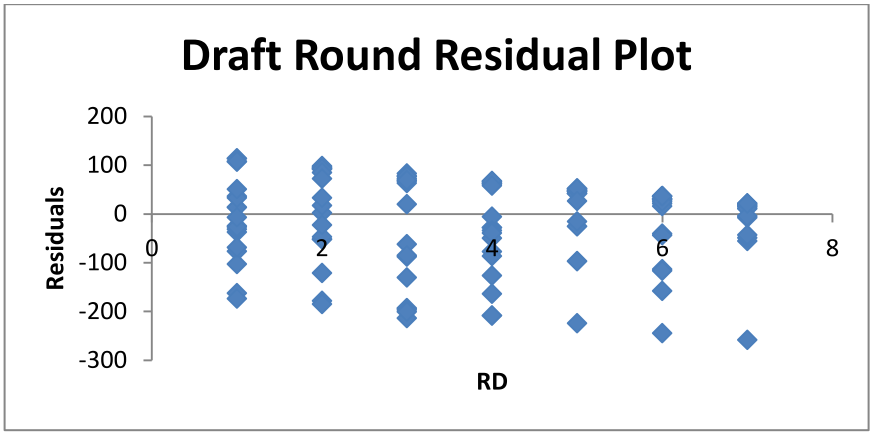
| Regression Statistics | |
|---|---|
| Multiple R | 0.346814151 |
| R Square | 0.120280056 |
| Adjusted R Square | 0.115309886 |
| Standard Error | 83.38271911 |
| Observations | 179 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 168257.5477 | 168257.5477 | 24.20039464 | 1.97466E-06 |
| Residual | 177 | 1230623.979 | 6952.677846 | | |
| Total | 178 | 1398881.526 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% |
|---|---|---|---|---|---|
| Intercept | 168.4088463 | 14.75318425 | 11.4150846 | 5.70475E-23 | 139.2940686 |
| RD | 15.37223652 | 3.12482596 | 4.919389661 | 1.97466E-06 | 9.205526225 |






# Appendix X

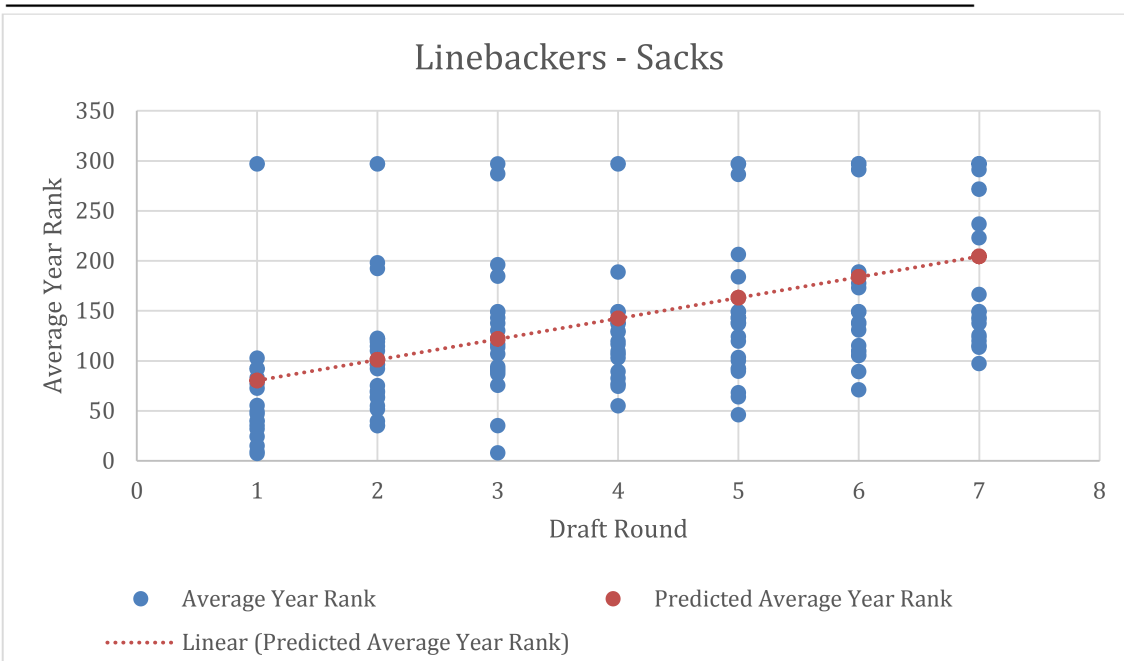
SUMMARY OUTPUT

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.491747997 |
| R Square | 0.241816093 |
| Adjusted R Square | 0.237532568 |
| Standard Error | 73.49442019 |
| Observations | 179 |

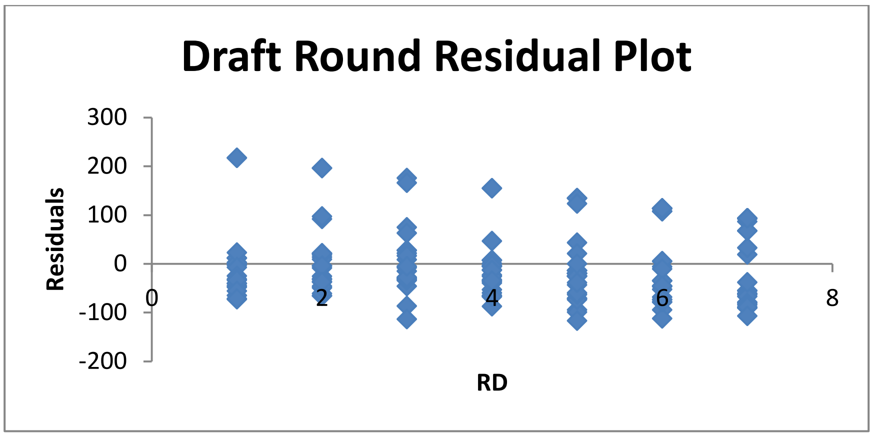
ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 304924.7247 | 304924.7247 | 56.45259423 | 2.74374E-12 |
| Residual | 177 | 956053.0745 | 5401.4298 | | |
| Total | 178 | 1260977.799 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 59.6196586 | 13.00361435 | 4.584852873 | 8.56273E-06 | 33.95758222 |
| RD | 20.69407891 | 2.754255013 | 7.513494143 | 2.74374E-12 | 15.25867452 |



| Round | Over Performance | Under Performance |
|---|---|---|
| 1 | 66.67% | 33.33% |
| 2 | 56.52% | 43.48% |
| 3 | 57.14% | 42.86% |
| 4 | 72.00% | 28.00% |
| 5 | 79.31% | 20.69% |
| 6 | 55.17% | 44.83% |
| 7 | 51.61% | 48.39% |




## Appendix Y

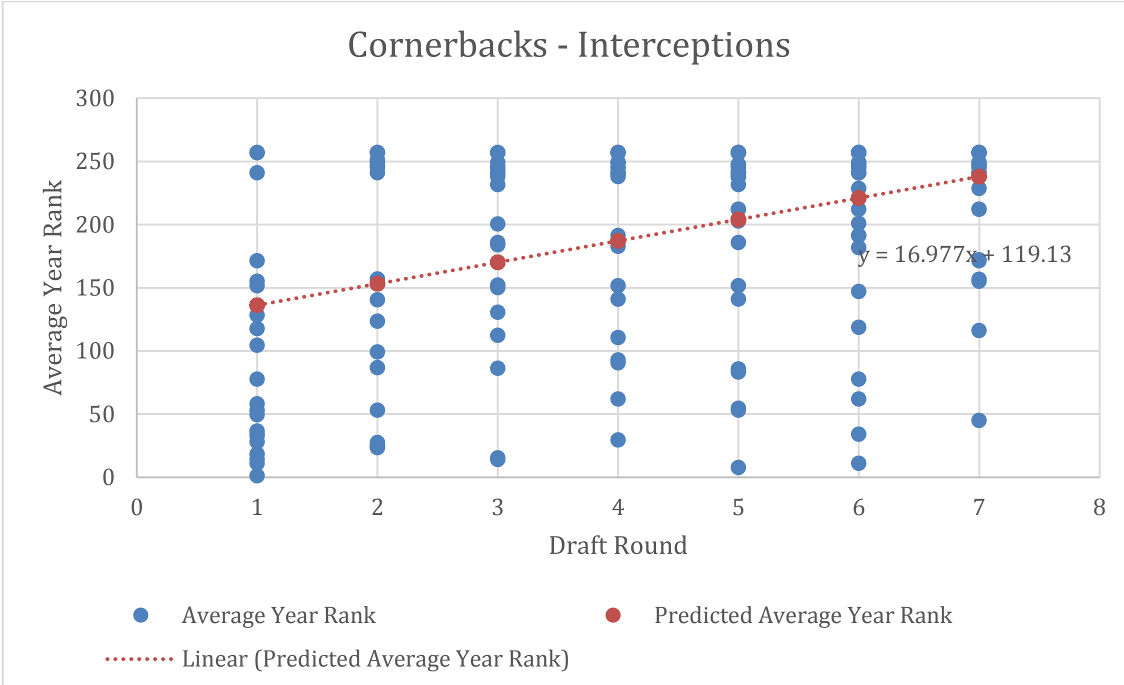
SUMMARY OUTPUT

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.41495596 |
| R Square | 0.172188449 |
| Adjusted R Square | 0.16796492 |
| Standard Error | 73.39169613 |
| Observations | 198 |

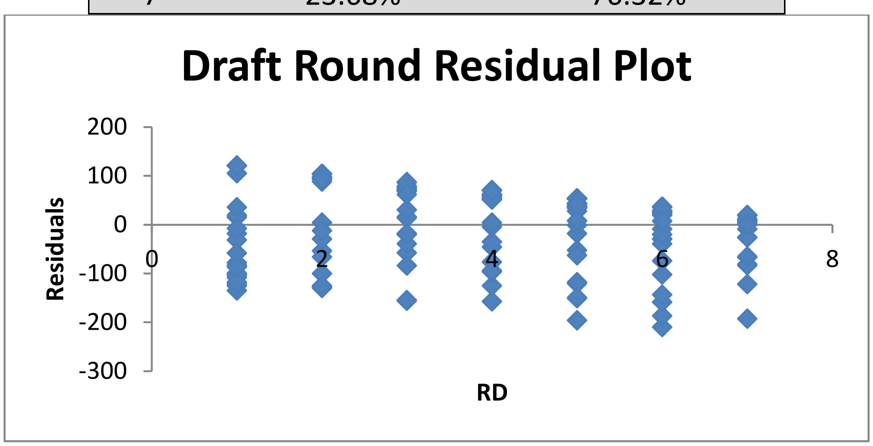
ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 219595.0024 | 219595.0024 | 40.76886329 | 1.21497E-09 |
| Residual | 196 | 1055722.848 | 5386.341061 | | |
| Total | 197 | 1275317.85 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 119.1340804 | 12.83137708 | 9.284590397 | 3.11807E-17 | 93.82879276 |
| RD | 16.9774556 | 2.658938559 | 6.385049984 | 1.21497E-09 | 11.73365326 |




| Round | Over Performance | Under Performance |
|---|---|---|
| 1 | 68.18% | 31.82% |
| 2 | 47.37% | 52.63% |
| 3 | 32.00% | 68.00% |
| 4 | 29.63% | 70.37% |
| 5 | 21.62% | 78.38% |
| 6 | 37.93% | 62.07% |
| 7 | 23.68% | 76.32% |



# Appendix Z

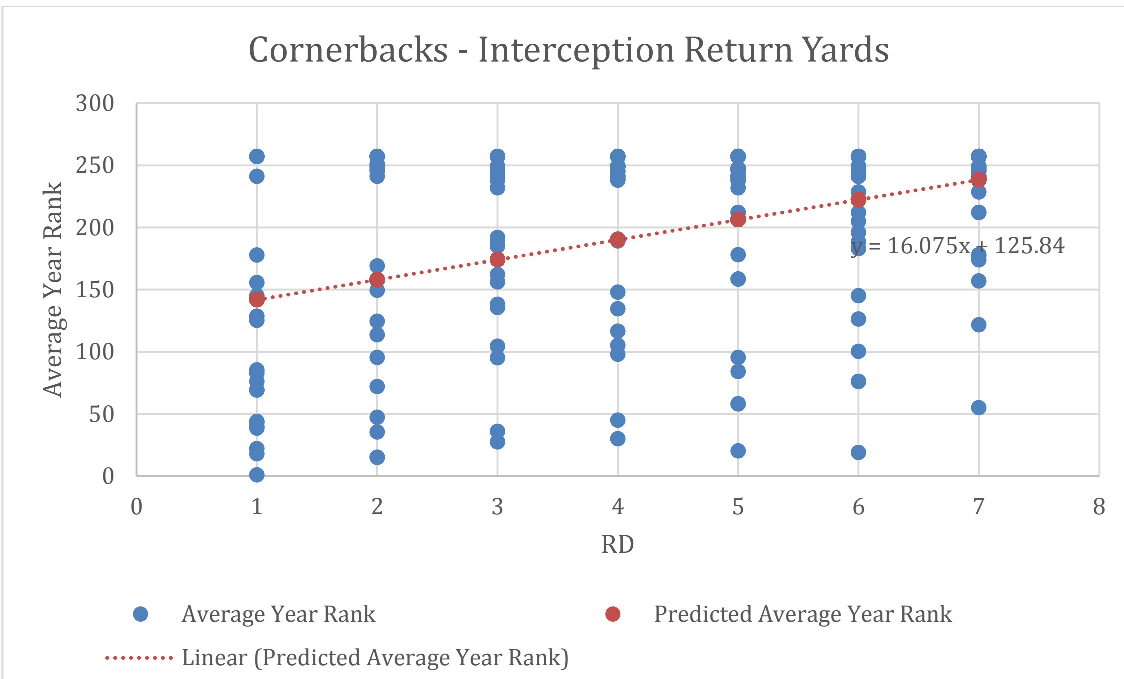
SUMMARY OUTPUT

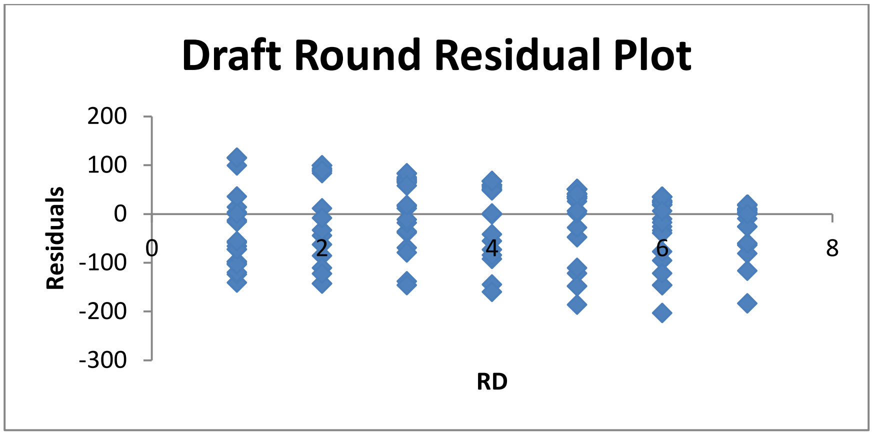
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.413610086 |
| R Square | 0.171073303 |
| Adjusted R Square | 0.166844085 |
| Standard Error | 69.76528593 |
| Observations | 198 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 196879.7013 | 196879.7013 | 40.45034077 | 1.39058E-09 |
| Residual | 196 | 953970.2438 | 4867.195121 | | |
| Total | 197 | 1150849.945 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 125.8418713 | 12.19735663 | 10.3171429 | 3.28124E-20 | 101.7869615 |
| RD | 16.07540222 | 2.527555822 | 6.360058237 | 1.39058E-09 | 11.0907052 |






## Appendix AA

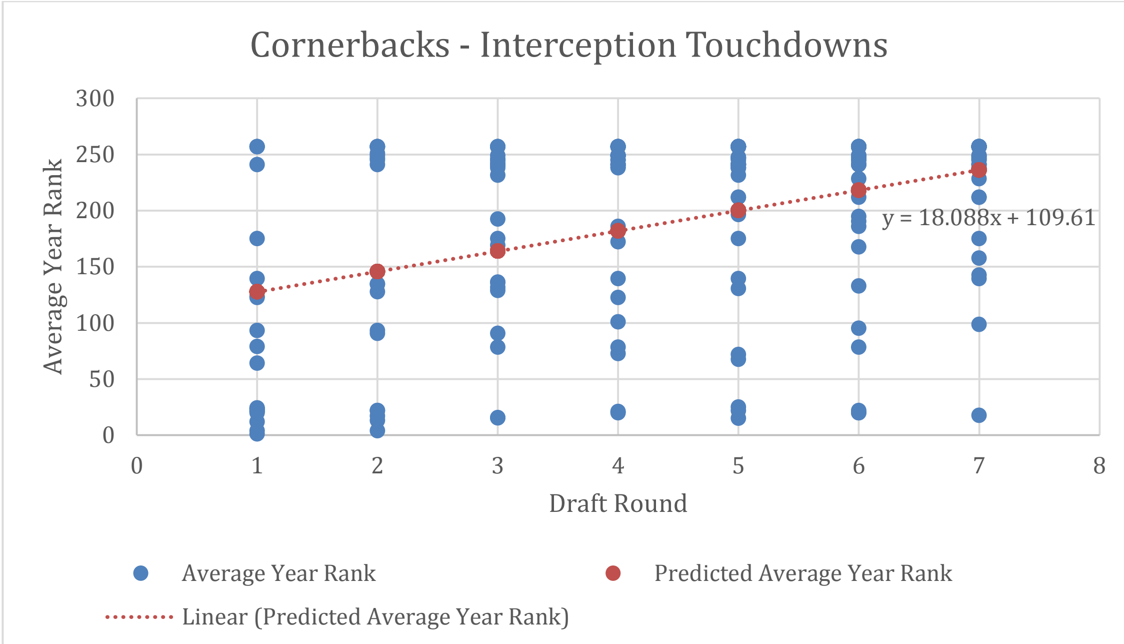
SUMMARY OUTPUT

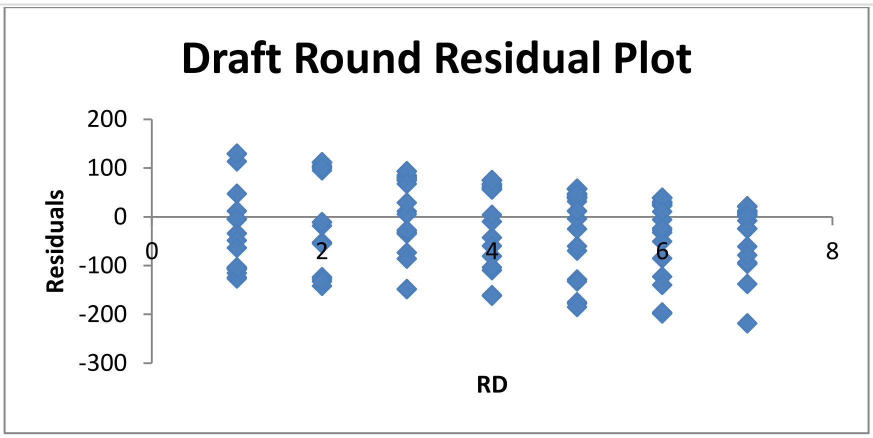
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.41288336 |
| R Square | 0.170472669 |
| Adjusted R Square | 0.166240387 |
| Standard Error | 78.66751918 |
| Observations | 198 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 249270.5899 | 249270.5899 | 40.27913469 | 1.49537E-09 |
| Residual | 196 | 1212961.401 | 6188.578574 | | |
| Total | 197 | 1462231.991 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* |
|---|---|---|---|---|---|
| Intercept | 109.6078038 | 13.75377128 | 7.969290863 | 1.28366E-13 | 82.48342453 |
| RD | 18.08826442 | 2.850078566 | 6.34658449 | 1.49537E-09 | 12.467507 |




## Appendix AB

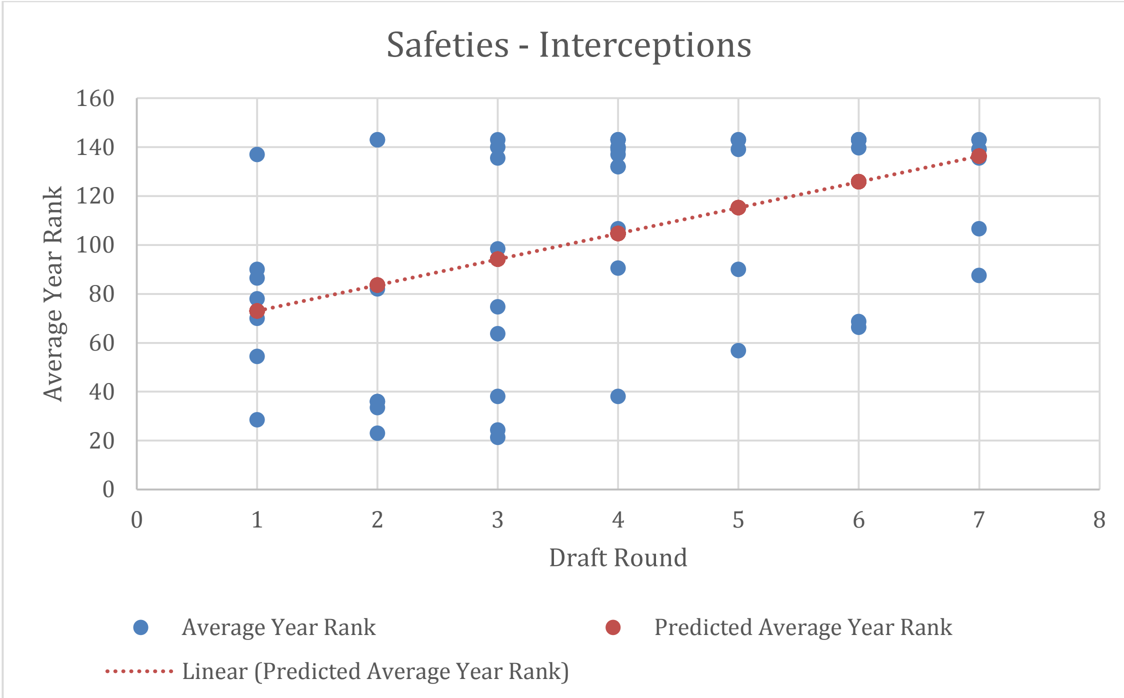
SUMMARY OUTPUT

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.472461245 |
| R Square | 0.223219628 |
| Adjusted R Square | 0.208834806 |
| Standard Error | 38.27061345 |
| Observations | 56 |

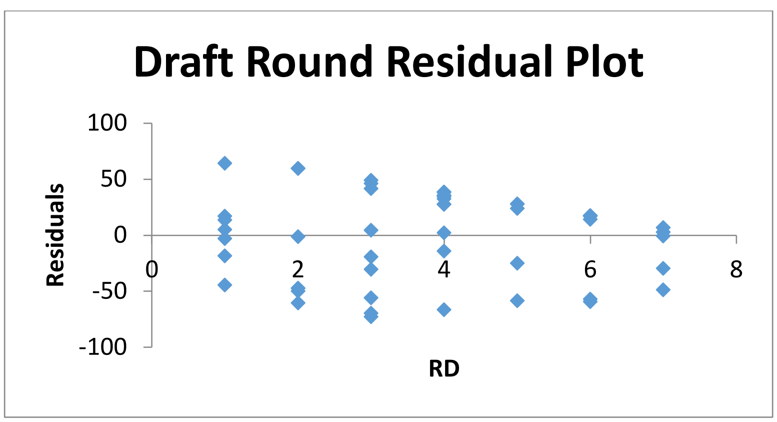
ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 22727.8704 | 22727.8704 | 15.51771949 | 0.000236384 |
| Residual | 54 | 79090.55209 | 1464.639854 | | |
| Total | 55 | 101818.4225 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
|---|---|---|---|---|---|---|
| Intercept | 62.45054272 | 11.87552092 | 5.258762385 | 2.54655E-06 | 38.64155679 | 86.25952864 |
| RD | 10.55514706 | 2.679478891 | 3.939253672 | 0.000236384 | 5.183115328 | 15.92717879 |




| Round | Over Performance | Under Performance |
| --- | --- | --- |
| 1 | 42.86% | 57.14% |
| 2 | 71.43% | 28.57% |
| 3 | 55.56% | 44.44% |
| 4 | 16.67% | 83.33% |
| 5 | 40.00% | 60.00% |
| 6 | 22.22% | 77.78% |
| 7 | 42.86% | 57.14% |



## Appendix AC

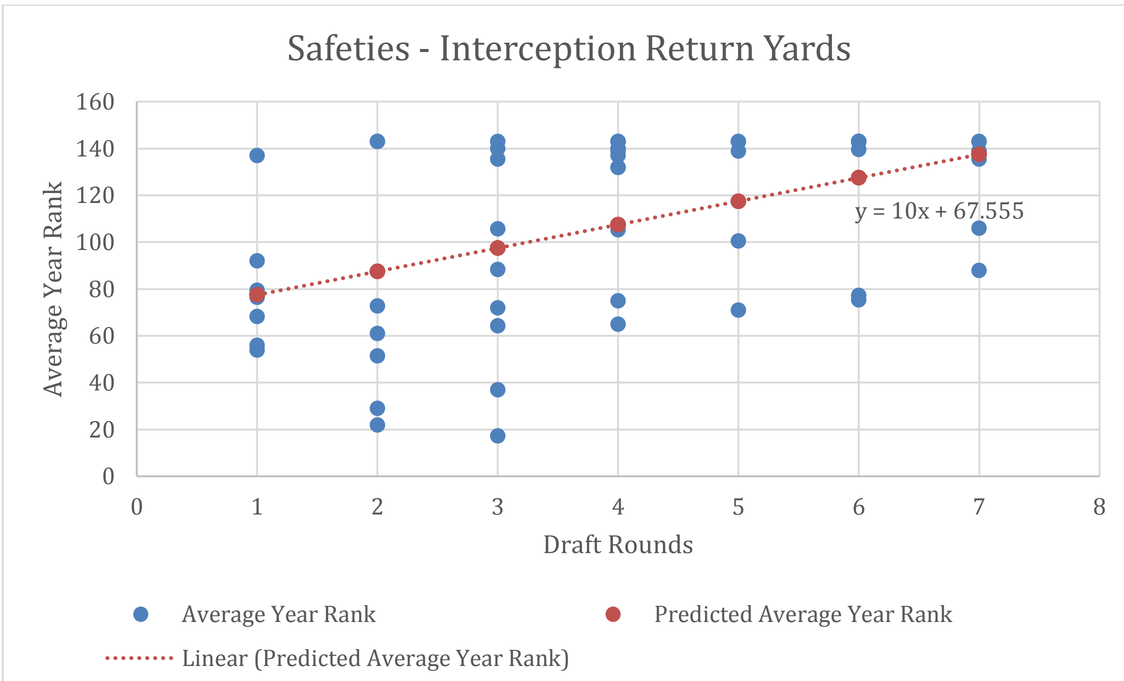
SUMMARY OUTPUT

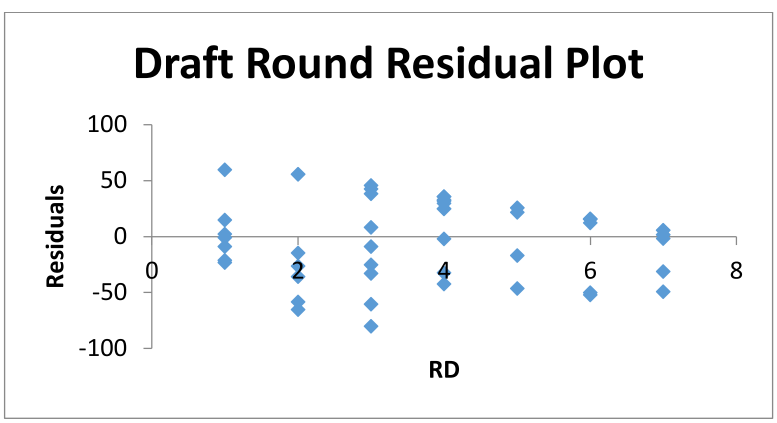
| *Regression Statistics* | |
|---|---|
| Multiple R | 0.489880408 |
| R Square | 0.239982814 |
| Adjusted R Square | 0.225908422 |
| Standard Error | 34.58914601 |
| Observations | 56 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 1 | 20400 | 20400 | 17.05102488 | 0.000127058 |
| Residual | 54 | 64606.08718 | 1196.409022 | | |
| Total | 55 | 85006.08718 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
|---|---|---|---|---|---|---|
| Intercept | 67.55505952 | 10.73314719 | 6.294058802 | 5.73777E-08 | 46.03639503 | 89.07372402 |
| RD | 10 | 2.421724614 | 4.129288665 | 0.000127058 | 5.144734479 | 14.85526552 |



## Appendix AD

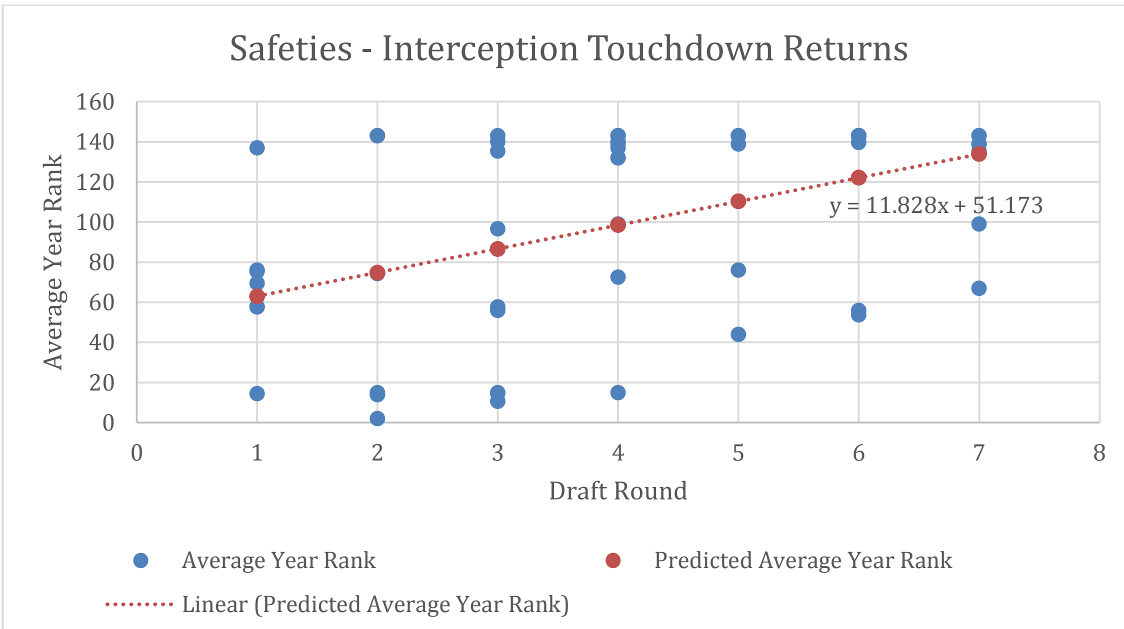
SUMMARY OUTPUT

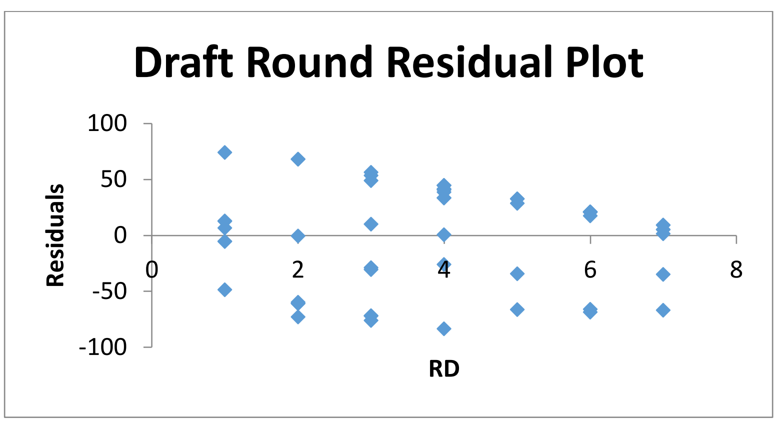
| Regression Statistics | |
|---|---|
| Multiple R | 0.455488889 |
| R Square | 0.207470128 |
| Adjusted R Square | 0.192793649 |
| Standard Error | 44.93403208 |
| Observations | 56 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 28542.0049 | 28542.0049 | 14.13623299 | 0.000419587 |
| Residual | 54 | 109029.6309 | 2019.067239 | | |
| Total | 55 | 137571.6358 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 51.17288165 | 13.94320576 | 3.670094419 | 0.000556342 | 23.21843721 | 79.1273261 |
| RD | 11.82843137 | 3.146011511 | 3.759818212 | 0.000419587 | 5.521058055 | 18.13580469 |



## Appendix AE

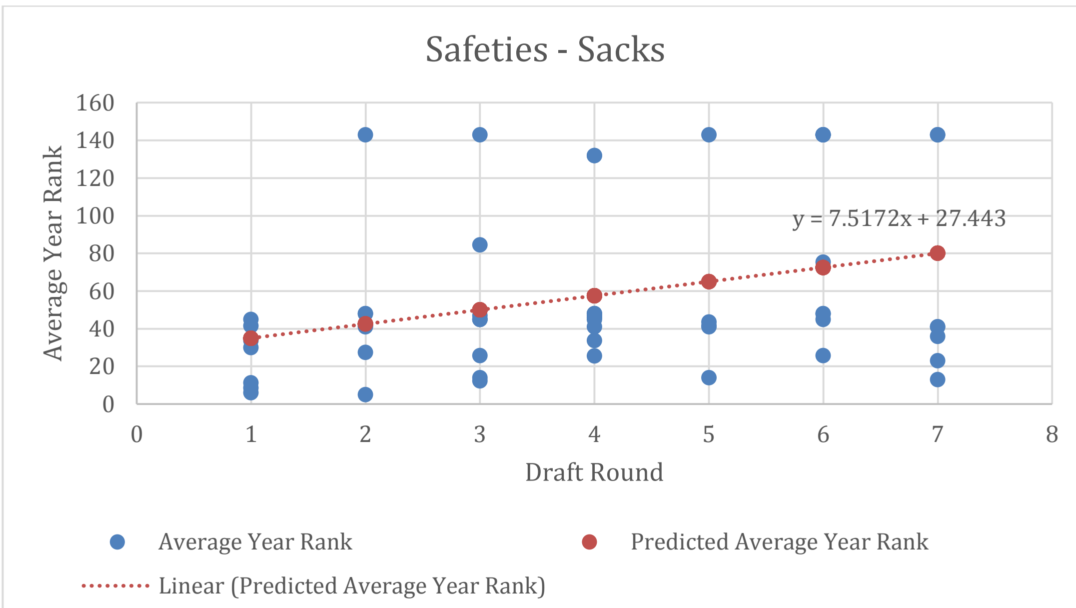
SUMMARY OUTPUT

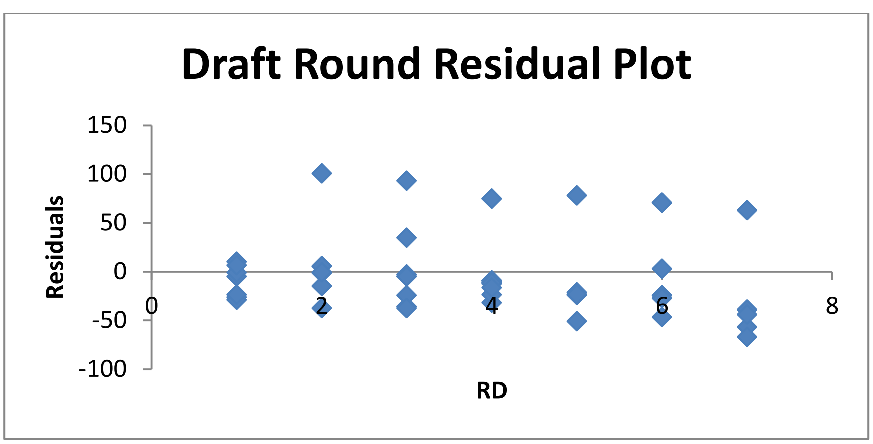
| Regression Statistics | |
|---|---|
| Multiple R | 0.327372669 |
| R Square | 0.107172864 |
| Adjusted R Square | 0.090639028 |
| Standard Error | 42.17092127 |
| Observations | 56 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 11527.56005 | 11527.56005 | 6.48203267 | 0.013783346 |
| Residual | 54 | 96032.87646 | 1778.386601 | | |
| Total | 55 | 107560.4365 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% |
|---|---|---|---|---|---|
| Intercept | 27.44327731 | 13.08580168 | 2.097179675 | 0.040674885 | 1.207824551 |
| RD | 7.517156863 | 2.952555059 | 2.545983635 | 0.013783346 | 1.597640377 |



**Appendix AF**

2015 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 12 | Danny Shelton | DT |
| 1 | 19 | Cameron Erving | T |
| 2 | 51 | Nate Orchard | DE |
| 3 | 77 | Duke Johnson | RB |
| 3 | 96 | Xavier Cooper | DT |
| 4 | 115 | Ibraheim Campbell | SAF |
| 4 | 123 | Vince Mayle | WR |
| 6 | 189 | Charles Gaines | CB |
| 6 | 195 | Malcolm Johnson | TE |
| 6 | 198 | Randall Telfer | TE |
| 7 | 219 | Hayes Pullard | LB |
| 7 | 241 | Ifo Ekpre-Olomu | CB |

2014 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 8 | Justin Gilbert | CB |
| 1 | 22 | Johnny Manziel | QB |
| 2 | 35 | Joel Bitonio | T |
| 3 | 71 | Christian Kirksey | OLB |
| 3 | 94 | Terrance West | RB |
| 4 | 127 | Pierre Desir | CB |

2013 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 6 | Barkevious Mingo | OLB |
| 3 | 68 | Leon McFadden | CB |
| 6 | 175 | Jamoris Slaughter | SS |
| 7 | 217 | Armonty Bryant | DE |
| 7 | 227 | Garrett Gilkey | G |

2012 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 3 | Trent Richardson | RB |
| 1 | 22 | Brandon Weeden | QB |
| 2 | 37 | Mitchell Schwartz | T |
| 3 | 87 | John Hughes | DT |
| 4 | 100 | Travis Benjamin | WR |
| 4 | 120 | James-Michael Johnson | LB |
| 5 | 160 | Ryan Miller | T |
| 6 | 204 | Emmanuel Acho | LB |
| 6 | 205 | Billy Winn | DT |
| 7 | 245 | Trevin Wade | CB |
| 7 | 247 | Brad Smelley | RB |

2011 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 21 | Phillip Taylor | DT |
| 2 | 37 | Jabaal Sheard | DE |
| 2 | 59 | Greg Little | WR |
| 4 | 102 | Jordan Cameron | TE |
| 4 | 124 | Owen Marecic | RB |
| 5 | 137 | Buster Skrine | DB |
| 5 | 150 | Jason Pinkston | T |
| 7 | 248 | Eric Hagg | DB |

**Appendix AG**

2015 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 12 | DeVante Parker | WR |
| 1 | 19 | Cameron Erving | T |
| 2 | 51 | Jordan Phillips | DT |
| 3 | 77 | Duke Johnson | RB |
| 3 | 96 | Xavier Cooper | DT |
| 4 | 115 | Blake Bell | TE |
| 4 | 123 | Ibraheim Campbell | SAF |
| 6 | 189 | Charles Gaines | CB |
| 6 | 195 | Malcolm Johnson | TE |
| 6 | 198 | Christian Ringo | DE |
| 7 | 219 | Hayes Pullard | LB |
| 7 | 241 | Ifo Ekpre-Olomu | CB |

2014 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 8 | Justin Gilbert | CB |
| 1 | 22 | Undetermined | ? |
| 2 | 35 | Joel Bitonio | T |
| 3 | 71 | Terrance Brooks | S |
| 3 | 94 | Terrance West | RB |
| 4 | 127 | Pierre Desir | CB |

2013 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 6 | Barkevious Mingo | OLB |
| 3 | 68 | Tyrann Mathieu | FS |
| 6 | 175 | Khalid Wooten | CB |
| 7 | 217 | Armonty Bryant | DE |
| 7 | 227 | Garrett Gilkey | G |

2012 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 3 | Ryan Tannehill | QB |
| 1 | 22 | Doug Martin | RB |
| 2 | 37 | Mitchell Schwartz | T |
| 3 | 87 | John Hughes | DT |
| 4 | 100 | Travis Benjamin | WR |
| 4 | 120 | James-Michael Johnson | LB |
| 5 | 160 | Ryan Miller | T |
| 6 | 204 | Emmanuel Acho | LB |
| 6 | 205 | Billy Winn | DT |
| 7 | 245 | Trevin Wade | CB |
| 7 | 247 | Brad Smelley | RB |

2011 Draft Selections

| RD | SEL # | PLAYER | POSITION |
|---|---|---|---|
| 1 | 21 | Cameron Jordan | DE |
| 2 | 37 | Titus Young | WR |
| 2 | 59 | Terrell McClain | WR |
| 4 | 102 | Jordan Cameron | TE |
| 4 | 124 | Owen Marecic | RB |
| 5 | 137 | Buster Skrine | DB |
| 5 | 150 | Jason Pinkston | T |
| 7 | 248 | Eric Hagg | DB |

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