IMPLICIT INCENTIVES IN FOOTBALL: AN EMPIRICAL ANALYSIS OF PERFORMANCE MEASUREMENT FOR NFL PLAYERS

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Edward Lucius Edwards

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ABSTRACT

In this study, I examine how team-based and individual performance metrics are incorporated into NFL players' contracts. The current research in performance evaluation and incentive contract design suggests that a mixed incentive structure that uses both team-based and individual metrics is optimal for increasing performance when results are dependent on team efforts. However, within the NFL, in which outcomes are driven by team performance, contracts almost always incorporate primarily individual incentives. Using new contract signings, team and individual performance data from the 2015-2020 NFL seasons, I test whether there are team-based incentives are implicitly and incrementally used (in addition to individual metrics) within NFL contracts. Results of this study indicate that players are being paid based on overall team performance alongside individual performance, showing that NFL contracts are using a mixed incentive structure. My findings build on the literature on performance measurement and add to the understanding of the incentive effects of NFL player contracts.

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I would also like to thank my father, Eric Edwards, and my brother, Reed Edwards, who initially introduced me to the game of Football. Without the amazing memories we have shared surrounding this sport there would have been no motivation to write this thesis. As well I would like to thank my two sisters, Reese and Phoebe, whose football knowledge may be lacking but whose support and love helped me every day.

This thesis is dedicated to my late mother, Megan Reese Edwards

You motivated me for the first twenty years of my life—I hope you would be proud of all that I have accomplished in my first year without you

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1. Introduction

In this paper, I study how contracts of professional athletes who play for the National Football League (NFL) incorporate team-based and individual performance metrics. I draw from the literature on performance measurement and contract design, which provides guidance regarding how principals can optimally motivate agents to maximize their performance. The principal-agent problem has long been studied by scholars, and addressing this issue has practical implications for managers and owners of various organizations. A common solution to aligning incentives is structuring contracts with performance metrics relevant to motivating performance by agents. Particularly in settings where the outcome is dependent upon team performance, individual-based and team-based metrics can be utilized and included in the contract. The extant literature suggests that the optimal incentive structure for maximizing team performance is through the use of a mixed-incentive structure that rewards people based on both team and individual performance.

Much of the current literature surrounding this topic is related to business and for-profit organizations, although the challenges related to motivating team performance is applicable to many contexts, including professional sports. Specifically, it applies to team sports in which multiple athletes are working together to achieve a common and shared goal (specifically, winning games). Additionally, professional sports teams are also businesses, and for owners, managers, and coaches to maximize their returns, players must be properly incentivized to exert maximal effort and perform their best. Measuring the performance of athletes is often done by viewing a myriad of objective statistics collected by sports pundits and databases. For certain sports like baseball and basketball, there are limited number of players and positions, and the effectiveness of statistics in capturing performance is relatively more straightforward than a sport such as American football. The reason that performance measurement within the NFL proves to be so challenging is that there are 11 different players on the field at a time, with each player having a potentially different responsibility that likely changes every play. Furthermore, standard NFL statistics do an especially poor job of adequately measuring performance. There are countless instances where an NFL player does their assignment perfectly and yet will not record a single conventionally-measured statistic for their play. Thus, it has been particularly difficult for NFL executives to properly assess each player's performance, consequently exacerbating the challenge of structuring contracts and appropriately awarding compensation to players.

The current practice on compensating NFL players is through the use of large multi-year contracts that include sizeable explicit bonuses based on performance. Details of NFL contracts are not always disclosed, but for contracts that are publicly available, almost every explicit bonus is based on individual performance measured through the use of standard statistics, such as the number of sacks or passing touchdowns a player has in a given season. It is rare to see bonuses explicitly based on team performance. However, these contracts may implicitly incorporate team performance metrics, incrementally to the individual metrics that players are expected to achieve. In this study, I examine whether and how team metrics are implicitly incorporated into players' contracts.

Using data from 2015 through 2020, I test, by player position, whether team performance, measured by win-loss records, as well as rankings of offensive and defensive teams, are incrementally associated with NFL contracts signed in a subsequent year. I find that for almost all player positions, win-loss records factor significantly into players' contracts incrementally to individual player statistics. I also find that defensive rankings matter for defensive players, but offensive rankings are not associated with contracts for offense players. I then conduct exploratory analyses on what particular individual statistics are incorporated into NFL contracts and test to see whether these statistics are actually associated with a team's win-loss record.

This paper builds on the literature on performance measurement in accounting, economics, and organizational behavior, as well as extends the research on compensation contracts in professional sports. Furthermore, many of the papers that examine performance measurement and valuation in the NFL study contemporaneous associations between performance variables and players' values and pay for the same season. In this study, I analyze historical performance in relation with a player's future pay. Further, I focus not on the optimal method to value NFL players, but rather how these players are incentivized to perform.

The results of this study are potentially informative for NFL executives and may behoove owners and managers to reevaluate the current contracts with their players. Team owners and managers may use the findings to appropriately incentivize players and design contracts that explicitly put weights on statistics that are correlated with winning games. Given the standard practice of only using individual explicit incentives, using this more objective statistical approach, teams can optimize their contract to help maximize player performance and team wins.

The rest of the paper is organized as follows. Section 2 motivates the paper and reviews the related literature. Section 3 describes the data used in the study. Section 4 discusses the results of my analysis, and Section 5 concludes the study

2. Motivation and Literature Review

Organizations have long sought to find a solution to the principal-agent problem—particularly the moral hazard that principals face when an agent's effort is not fully observable. The challenge stems from how an agent can be motivated to put in the effort and work with the same commitment and passion as the principal. One common set of solutions to attenuate the moral hazard issue involves incentive contracts that aim to align the incentives of both parties. Seminal work by Holmstrom (1979) demonstrates that performance metrics that are informative of effort ought to be included in the optimal compensation contract. Banker and Datar (2002) suggest that in contracts with multiple performance metrics, measures that have a high signal-to-noise ratio (i.e., the measure moves with effort and is precise) should have higher weights in an agent's compensation contract than measures that are either not as informative or less precise.

2.1. Performance Measurement in Team Settings

In settings where tasks and outputs are dependent on team performance, there is debate on whether individual or team-based performance metrics, or a mix of the two, are most effective to include in an incentive contract. These types of settings could be anything from a group pitch to a client to a professional sporting event. Any setting in which a group of people share common goals and must work together in order to achieve said goals. On one hand, recognizing the differences in individual contributions suggests that individual performance metrics work well (Adams 1965). On the other, these individual incentives may lead team members to focus on their own personal outcomes, detracting from teamwork (Heneman and von Hippel 1995; Shaw, Gupta, and Delery 2002).

Garbers and Kondradt (2014) find that the effects of individual incentives are positive in increasing the performance of individuals, and that qualitative performance measures, like communication or attitude, are more effective that quantitative measures, such as number of sales or products produced. Further, team-based incentives positively affect performance, with equitably distributed rewards being more effective than equally distributed ones. This means that teams that had a pay structure that was based individually was more effective than pay structures that were team based. Although both individual and team-based metrics are positively correlated with performance, the study provided no evidence on which type was more effective.

Patel, et al. (2016) explores individual and team incentives further by conducting an experiment that tests whether individual or team-based financial incentives affect physical activity. 304 adults were divided each into 4 person teams and were rewarded financially based on either individual or group step-count goals. The study finds that financial incentives based on a combination of both individual and team performance (i.e., a mixed incentive structure) were the most effective for increasing physical activity. However, the above study focuses primarily on a situation in which the output is measured on an individual level, the number of steps a person takes. Similarly, Barnes, et al. (2011) examine incentive structures that best motivate individuals in a team setting. 304 upper-level graduate students were randomly assigned into teams of 4 and participated in a simulation in which participants were paid based on either a mixed incentive system or a 100% group-based incentive system. The simulation was designed such that each member of the team received different strengths and weaknesses so that in order to achieve the desired outcome they must rely on each other and operate together. This differentiates this study from the previous one, due to the need for cooperation and collaboration within the task. The paper provides evidence that participants in mixed incentive structures tend to perform faster but much less accurately, focus on their own work, and do not put forth effort to help/support other team members.

Che and Yoo (2001) noted that the current literature on team-based incentives has largely been conducted and thus generalize to one-off transactions that are static in nature. Oftentimes, teams conduct tasks repeatedly and over multiple periods. The study focused on possible long-term incentive structures and how the use of explicit incentives interacts with implicit incentives within these various incentive contracts. Results of the study show that the optimal incentive structure is one that involves teams and low-powered group incentives especially when there is a long-term relationship among agents. Further, the authors conclude that over a longer term, the use of low-powered group incentives is more favorable than high-powered incentives, and are more effective in teams in which members have no mutual accountability. Teams that have no mutual accountability occur when rewards are distributed on a relative scale so that individuals are competing with their peers.

Guay, Kepler, and Tsui (2018) archivally examined CEO compensation contracts to determine the interplay between individual and team outcomes on CEO bonuses. by measuring performance sensitivities. The study predicts that if boards find multiple performance evaluators to provide individual incentives to CEOs, there would be proportional changes to incentives for that CEO. Although the authors find little evidence that bonuses support individual incentives, bonuses are used to encourage team incentives.

2.2. Performance Measurement in Team Sports

While much of the literature on principal-agent concerns, performance measurement, and incentive structures focus on these issues as applied to business contexts, similar issues also apply to the world of sports. Several studies examined the selection of performance metrics used to incentivize athletes to exert effort in their respective sports. For instance, Wilson, et al. (2011) study the contracts of NCAA Division I Basketball Coaches to find whether coaches are explicitly incentivized to increase athletic or academic performance within their teams. Results suggest that most Division I programs put heavier emphasis on athletic team performance rather than academic team success. Huebeck and Scheuer (2002) looked at the explicit incentives within the sports of German soccer League, NFL, and NBA to find explanations for why incentive clauses are not directly based on effort. For within the NFL and NBA explicit incentives are usually based on player statistics and in German soccer it is often based on number of appearances for the team.

Additionally, in professional sports, contracts are often long-term in nature, with pay predetermined at contract inception. Studies have examined how this unique aspect of professional athletes' contracts affects their behavior. For instance, Purcell (2009) examined whether performance was affected by the length of contracts within professional basketball, football, baseball, and hockey. Findings suggest that on average, a player's performance decreased the first year after the signing of their contract but did not increase in their final year. Similarly, Jean (2010) looked at contracts for National Basketball Association (NBA) athletes to see if there was performance variation within a contract. Specifically, the author specifically reviewed the season before the expiration of an athlete's contract and the season immediately after an athlete signs one to find possible evidence of strategic behavior that players may exhibit to maximize the value of their contract. Contrary to Purcell (2009), Jean (2010) found statistically significant evidence of NBA players increasing performance prior to signing a contract but no evidence of decreasing performance after signing a contract.

Beyond finding how players are incentivized within their contracts, research has also examined how players should have their performance measured within sports. Duch, et al. (2010) studied the European Cup soccer tournament and used social network analysis to develop a network of "ball flow" to see how likely players' actions lead to a shot on goal.

2.3. Incentives in the National Football League (NFL)

Contracts in professional sports have grown incredibly large and have made athletes across sports some of the highest paid individuals in the world. Particularly, professional American football is a multi-billion-dollar industry with players receiving long-term, seven- to eight-figure contracts. Thus, National Football League (NFL) players are some of the highest paid athletes in the world.

What makes contracts within the NFL different from those of athletes in professional soccer and Major League Baseball, there is a Salary Cap within the NFL that requires managers to be a lot more thoughtful about how they allocate their resources to their current players. A salary cap is a limit on the amount each team can spend on the salary of their players. It changes every year based on the total revenue of the NFL, and certain things within NFL contracts do not account for the salary cap, like signing bonuses and bonus incentives. The purpose is to try and keep all teams on an even playing field, whereas in European soccer the richest teams are the best ones because they can pay as much as they want for star players. The salary cap stresses the importance of structuring contacts that are effective in motivating players. However, measuring performance of football players, and consequently structuring contracts, can be extremely challenging, as I discuss below.

In American football, the desired outcome is a win; however, it is incredibly difficult to determine an individual's effect on the game, similar to other team-based sports like soccer or basketball. However, football extends beyond the difficulty of other sports in performance measurement when considering the sheer number of people who play in a single game and the limited times that each player interacts with the ball. For instance, a wide receiver may run 40 routes and not record a single catch, yet still have a positive impact on the team's performance. As Pro Football Reference founder Doug Drinen states, "Football stat lines just do not come close to capturing all the contributions of a player the way they do in baseball and basketball."[1] Furthermore, football provides an even greater challenge when considering the uniqueness of each player position. The role of an offensive lineman in football is incredibly different than role of the quarterback, even though both play for a team's offense, and different statistics are used to measure performance of each. Contrast this to basketball, where there are only five positions and performance are measured using the same statistics for each position. This difficulty of performance measurement has prompted a lot of study and research into finding an accurate and reliable way of identifying variables that are associated with NFL player values. Within the current literature surrounding NFL player valuation, most models attempt to either

[1] "Approximate Value » Pro-Football-Reference.Com Blog," accessed April 3, 2022, https://www.pro-football-reference.com/blog/index37a8.html.

establish an association between the cost of each player to their respective team and various metrics (Scott (2012), LaFiandra (2020)) or develop a wins above replacement (WAR) statistic for a given player, similar to what is measured in baseball (Eager and Chahrouri 2020).

Within this study, I look to examine the effects of past-player performance on future contract pay and look to find whether within these future contracts, players are incentivized to individually or as a team. Whereas Scott (2012) examines whether an NFL athlete is receiving an under or over-valued contract based on current player performance. The results of the study indicates that team success, championships won, games started, and on-field performance are significantly associated with player value. Using these variables, Scott (2012) created a model to determine appropriate pay for NFL players; he found that most players are vastly underpaid with few players receiving vastly overvalued contracts. He concludes that this is most likely due to the pressure placed on teams to overpay and retain few star players and due to NFL salary cap restraints, this pushes down the salaries of non-superstar players. Draisey (2016) builds on Scott (2012) and examines the determinants of NFL player salaries in veteran and rookie contracts. Within his study, he uses fantasy football points as his variable for NFL performance measurement. He finds that the largest determinants for salaries in the NFL are on-field performance as measured through fantasy points for veterans and draft position for rookies. Whereas fantasy points are a good use in performance for skill positions on offense, they cannot be used to measure performance of defensive players. Porter (2018) also uses fantasy points as a way of measuring performance in football by constructing an Autoregressive Integrated Moving Average (ARIMA) model to forecast player performance. However, this study is subject to the same limitations in using fantasy points as a performance metric for individual defensive players and linemen.

In a different study to find a WAR statistic for player value, Eager and Chahrouri (2020) uses player grades from Pro Football Focus (PFF) to measure on field performance. PFF grades are some the of the most widely used and reported performance measurement tool in the NFL. These grades are calculated through a team of 600 analysts grading every play for each players performance on a scale of -2 to 2, with 0 being the average or expected performance on that play. These grades are then converted to a 0-100 scale to allow for comparison across positions. PFF grades are a useful tool, given that every player on the field is measured on their performance on each play no matter what their assignment. Players are graded on a wide variety of different skills, including passing, rushing, receiving, run-blocking, pass-blocking, pass and punt coverage, rush-defense, etc. This allows for every position to be graded on metrics specific to their position including special teamers. These grades have become the central way of determining how well a player is playing, however, while all players are graded on the same scale, it does not account for which positions are more valuable to overall team success. In addition, this WAR metric is only based on past performance, has no predictive qualities to help determine whether this player will continue to have the same success, and provides no findings on the value of the player.

Another popular method for determining a player's value is the pro football reference's Approximate Value (AV), which is a good and commonly used metric for determining a player's value across a season. It was created by Doug Drinen, co-founder of pro football reference, to give a single number to represent the value of a player over a year. AV is calculated by first finding the Offensive Points per Drive (OPPD) number for each team's offense, this is done by dividing total points scored by the number of possessions for each offense. In this way, AV is not a reliable metric because finding can be skewed given that it uses team offensive and defensive success to measure individual player performance. So, for example, an underperforming center on an offense that scores a lot of points is valued more than an overperforming center on a bad offense, even though that player might not have contributed as much to the overall team success. This makes this metric of performance measurement not as wholistic and reliable as the PFF grades yet is still a good tool to use to determine value and measure on field performance. Barney, et al. (2013) uses AV as one of their value metrics and uses the AV of the teams' recent draft picks alongside team wins for that season to find a relationship, and find that the higher the AV of a specific team's draft picks, the more wins for that team. Barney, et al. (2013) also use AV to find which positions were identified to be the most valuable one the team. They conclude that quarterback, kickers, and safeties were the most valuable positions. They then compare these results with how much teams were spending on them in the draft to find that offensive guards and centers were undervalued, and cornerbacks were overvalued in the draft. However, this study only looks to compare historical AV with historical team records rather than using historical AV with future team success, so while it does find a relationship between AV and team success it makes no claim on whether AV will predict future team success.

LaFiandra (2020) develops a model to determine whether positional statistics, combine statistics, and school information of college athletes are associated with future NFL player earnings. The study concludes that there are very few accurate predictors of success in college statistics for skill position players, but being an all-American tends to yield higher pay in the NFL. This is one of few studies to use past performance to try and predict future individual success or value.

Apart from Lafiandra (2020), most of the studies cited above draw an association between some measure of value and concurrent player performance. In doing so, the objective of much of the current research is to explain whether players are worth their salaries given their performance on the field during that year. I build on prior research by examining how past performance metrics are incorporated into NFL players' contracts. In practice, many contracts attempt to motivate players by explicitly including individual position-specific metrics within contracts. For example, in the 2021-2022 NFL season, Rob Gronkowski, who was at tight end for the Tampa Bay Buccaneers, signed a one-year contract that would result in additional pay of $1 million for exceeding the number of yards and catches stated in the contract within the season.[2]

As discussed in an earlier section, research in economics and accounting has shown that when the outcome is team-based, the best incentive structure is mixed incentive structure with a team-based metric. However, in football currently, the use of team-based incentives, at least explicitly, is incredibly rare and few contracts contain bonuses based on team performance. I thus hypothesize that team-based measures (including previous win-loss records and rankings of offensive and defensive teams) are implicitly associated with players' contracts. Furthermore, I examine, by position, which individual metrics are statistically associated with a player's contract.

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[2] "Rob Gronkowski Earns Million Dollar Bonus in Buccaneers Season Finale | RSN," accessed April 3, 2022, https://www.nbcsports.com/boston/buccaneers/rob-gronkowski-earns-million-dollar-bonus-buccaneers-season-finale.

3. Research Methodology

3.1. Data

Data used in the study are hand-collected primarily from two databases. Salary information is downloaded from Spottrac.com, a website dedicated to tracking salary data across a wide range of sports. For this study, I collect new contracts signed by NFL players over the 5-year stretch from 2016-2020, so that it could be compared to the on-field performance of the NFL players and teams from 2015-2019. I picked these particular years to reflect how the NFL structured contracts during the most recent NFL years. I exclude contracts after 2019 as the NFL salary cap was decreased in 2020, and many contracts were restructured due to the COVID-19 pandemic (and not necessarily because of player performance). I use a player's average annual value (*AAV*) as the main dependent variable. *AAV* is calculated by taking the total value of the contract given to the player and dividing it by the number or years in the contract to display the value of the contract on a yearly basis. The reason I use *AAV* as the representation for player value and success (as opposed to a full contract value) is that I want to be able to compare player contracts regardless of the length of the contract.

Performance metrics for teams and individual players are taken from pro-football-reference.com, which is a website that collects current and historical NFL statistics since 1920. I collect the win/loss records of all 32 teams in the NFL over the periods of 2015-2019. I then divide wins by losses to come up with the win-loss record (*WL*) variable. The *WL* variable represents the overall performance of the team over the course of each season. Additionally, I also collect the offensive (*ORank*) and defensive (*DRank*) rankings of each team over the season. The rankings reported by pro-football-reference.com are purely objective and are based solely on the total points scored and total points allowed over the season. These variables are my main team-based metrics for specific player groups within each professional football team. These rankings complement the *WL* variable and represent the performance of smaller offensive and defensive sub-teams within each team franchise.

In addition, I collect various individual statistics for each player-year from pro-football-reference.com. Games played (*G*) represents the number of games in which an NFL player touched the field and recorded a statistic. It represents the amount of usage an NFL player gets throughout a season. Since the NFL is a sport in which each team fields 52 active players for each game, many will not see the field over a game, and this variable captures player utilization.

Football players are broad generally classified into offensive and defensive positions,[3] and each position group has statistics that are unique to that group. The offensive positions include Quarterback, Running Back, Wide Receiver, and Tight End. Defensive positions include Defensive Lineman, Linebackers, and Defensive Backs. Below I discuss the role of each position, beginning with the offensive positions.

The quarterback is the most important position in football, as quarterbacks are responsible for starting the play and distributing it to different players in order to move the ball down the field. Running backs are usually lined up behind the quarterback and are primarily expected to either rush the football or protect the quarterback. Wide receivers are responsible for running routes downfield and catching the football when thrown to them.

[3] I leave out offensive lineman and special teams players, like long snapper, punter, and kicker. Even though these player positions arguably provide a valuable addition to the team, there are limitations of current readily available performance measurement statistics surround the positions. The availability of player statistics relating to these positions, such as run-block grades and pass-protection grades, was spotty.

Tight ends have a wide variety of responsibilities including running routes, run blocking, and pass protection.

On the defensive side, defensive linemen are lined up opposite offensive linemen, and their main jobs are to stop the run and rush the quarterback. Linebackers can have a variety of responsibilities depending on the play called; however, their primary responsibility is stopping the run and rushing the quarterback. Lastly, defensive backs primarily function in pass coverage and are responsible for running with offensive skill players to break up passes intended for their targets.

I assign different statistics to the 7 player positions that I analyze for offense and defense. Descriptions of the dependent variables and team-based metrics are presented in Table 1 Panel A. The different player positions and the individual statistics for each position can be found in Table 1 Panel B. Table 1 Panels C and D describe individual player statistic for offensive and defensive positions, respectively.

TABLE 1
Variable Definitions

Panel A. Dependent Variables and Team-Based Metrics

AAV	Average Annual Value: Found by taking the total value of the contract signed by the NFL player and dividing it by the total number of years within the contract. Represents the average annual pay a player would receive over the length of the contract. This allows contracts of different lengths to be compared
WL	Win-Loss Record: This variable is found by dividing the total number of team wins during the regular season by the total number of games played that season. Ranges between 0-1, with 1 being the result of an undefeated season. Represents total team performance.
ORank	Offensive Rankings: Teams are given a rank between 1-32 based on the total points the team scored through their offense. The teams that scored the most points were given the ranking 1.
DRank	Defensive Rankings: Teams are assigned their rank based on the total number of points their defense allowed through the season. The team that allowed the fewest points were given the ranking 1.

Panel B. Player Positions and Individual Statistics

<table>
<tr><th>Offense/Defense</th><th>Positional Group</th><th>Positions</th><th>Statistics</th></tr>
<tr><td>Offense/Defense</td><td>All</td><td>All</td><td>Games Played (G)</td></tr>
<tr><td rowspan="4">Offense</td><td>Quarterback (QB)</td><td>Quarterback</td><td>Completion Percentage (Cmppct)
Passing Yards (PassYds)
Quarterback Interceptions (Int)
Passing Touchdowns (PassTD)
Quarterback Rating (QBR)
Rushing Yards (RushYds)
Rushing Touchdowns (RushTD)</td></tr>
<tr><td>Running Back (RB)</td><td>Tailback, Halfback, Fullback</td><td rowspan="3">Rushing Yards (RushYds)
Rushing Touchdowns (RushTD)
Receiving Yards (RecYds)
Receiving Touchdown (RecTd)
Fumbles (Fmb)</td></tr>
<tr><td>Wide Receiver (WR)</td><td>Wide Receiver</td></tr>
<tr><td>Tight End (TE)</td><td>Tight End</td></tr>
<tr><td rowspan="3">Defense</td><td>Defensive Lineman (DL)</td><td>Nose Tackle, Left Defensive Tackle, Right Defensive Tackle, Left Defensive End, Right Defensive End</td><td rowspan="3">Interceptions (DefInt)
Passes Defended (DefPD)
Forced Fumbles (DefFF)
Fumble Recoveries (DefFR)
Sacks (Sk)
Tackles (TacklesComb)
Tackles for a Loss (TacklesTFL)
Quarterback Hits (TacklesQBHits)
Safeties (TacklesSfty)</td></tr>
<tr><td>Linebacker (LB)</td><td>Middle Linebacker, Left Inside Linebacker, Right Inside Linebacker, Left Outside Linebacker, Right Outside Linebacker</td></tr>
<tr><td>Defensive Back (DB)</td><td>Defensive Back, Right Cornerback, Left Cornerback, Strong Safety, Free Safety</td></tr>
</table>

Panel C. Offensive Statistics

Cmppct	Completion Percentage: This statistic is used primarily for Quarterbacks. It is found by dividing the number of completed passes the player made by the number of pass attempts. The goal of this statistic is to show the accuracy of the player throwing the ball.
PassYds	Passing Yards: This is a statistic primarily used for Quarterbacks and is the number of yards gained by the player through a passing play. Passing yards are only counted through the player that threw the ball and not the player that caught it.
PassTD	Passing Touchdowns: This statistic is used to measure the performance of Quarterbacks. The statistic occurs when the result of a passing play is a touchdown. Passing Touchdowns are only recorded for the player that threw the ball.
Int	Quarterback Interceptions: This statistic is also primarily used for Quarterbacks. It occurs when the QB throws the ball and it is caught by the opposing teams defense. It is a negative statistic that records bad play.
QBR	Quarterback Rating: Quarterback rating is an ESPN statistic that is widely reported and calculated through a mathematical equation using the statistics, completion percentage, passing yards, passing touchdowns, and interceptions. Furthermore, QBR takes into consideration the context in which the play happened versus what was expected. Although it is not a perfect rating system for QBs it is widely available and used by NFL institutions.
RushYds	Rushing Yards: Rushing yards is a statistic that occurs when a player receives the ball from either a pass that went backwards or a handoff and is based relative to the line of scrimmage.
RushTD	Rushing Touchdowns: Rushing touchdowns is a statistic that occurs when a player finishes a rushing play within the endzone and records a touchdown.
RecYds	Receiving Yards: Receiving yards is a statistic primarily used for offensive skill position players (RB, WR, TE). It is recorded when a player catches a forward pass from another player and is based relative to the line of scrimmage. The statistic is only recorded for the player that catches the ball and not the one who threw it.
RecTD	Receiving Touchdown: Receiving touchdown is a statistic that occurs when the player on the receiving end of a pass ends the play in the endzone and records a touchdown.
Fmb	Fumbles: Fumbles occur when the player currently possessing the ball loses possession without being tackled to the ground. The result is that either team has the opportunity to gain possession. It is a negative statistic that represents a bad play.

Panel D. Defensive Statistics

DefInt	Interceptions: The statistic is recorded when a defensive player catches a pass thrown from an offensive player. The result is that possession of the ball is switched, and a turnover is recorded.
DefPD	Passes Defended: Passes defended is a statistic that is recorded when the defensive player is the reason for an incomplete pass. It is caused by a defensive player making contact with the ball so that it is not caught by any player.
DefFF	Forced Fumbles: Forced fumbles is a statistic that is recorded to the player that knocks the ball out of offensive players hands so that it is live on the ground free for either team to possess.
DefFR	Fumble Recoveries: Fumble recoveries are recorded by the player that possesses the football after a forced fumble has already occurred.
Sk	Sacks: Sacks is a statistic that occurs when a defensive player tackles the opposing teams quarterback behind the line of scrimmage.
TacklesComb	Tackles: Tackles is a statistic that records every time a defensive player either by themselves or with a teammate brings the offensive player down to the grass so that any part of the leg above the ankle, arm above the wrist, or torso touches the ground.
TacklesTFL	Tackles for a Loss: This is a statistic that occurs when a defensive player tackles an opposing offensive player (besides the QB) behind the line of scrimmage.
TacklesQBHits	Quarterback Hits: Quarterback hits is a statistic that is recorded when the opposing team’s quarterback is legally hit by a defensive player, however, they had already given up possession of football during the play.
TacklesSfty	Safeties: Safeties is a statistic that occurs when during the course of play an offensive player is tackled inside their own endzone. It is a rare occurrence and results in two points being awarded to the team on defense and possession is then given to the defensive team.

Using pro-football-reference.com, I collect all passing, rushing, receiving, and defensive statistics from the years 2015-2019. I chose to only use the standard statistics and not advanced statistics, like passing yards after catch or drop percentage, because standard statistics are more commonly reported and used within NFL contracts in the form of explicit incentives. For example, Aaron Rodgers, the quarterback for the Green Bay

Packers, has in his current contract bonuses worth $100,000 if he finished top three in the league in passing yards, quarterback rating, or interception percentage.[4]

3.2. Methodology

In order to determine whether team-based and individual metrics are associated with an NFL player's contract, I test the following relationship using the following regression model:

$$AAV_t = f(\textit{Team-based metrics}_{t-1}, \textit{Individual statistics}_{t-1}) \qquad (1)$$

where *AAV*, as described above and in Table 1 Panel A, is the pay that NFL players receive through their contracts broken down to a yearly basis. Team-based metrics include *WL*, which is the win-loss ratio of each team, and *ORanks* and *DRanks*, which are pro-football-reference.com's rankings of the offensive and defensive groups of players, respectively, within each franchise. Individual statistics vary by position played on the team.

Additionally, I also test whether the pro-football-reference offensive and defensive rankings, as well as individual statistics, are associated with the win-loss outcome of a team for a season using the following regression:

$$WL_t = f(\textit{Team-based metrics}_{t-1}, \textit{Individual statistics}_{t-1}) \qquad (2)$$

where win-loss ratio of each team (*WL*) is regressed on *ORanks*, *DRanks*, and the individual player positional statistics described in Table 1.

[4] "NFL Player Bonuses and Contract Incentives for 2022 - Sports Gambling Podcast," accessed April 5, 2022, https://www.sportsgamblingpodcast.com/2021/12/29/nfl-player-incentives/.

4. Results and Discussion

4.1. Descriptive Statistics

Descriptive statistics for each variable is presented in Table 2 Panel A, and Table 2 Panel B presents pairwise correlations between the variables used in the analysis.

TABLE 2
Summary Statistics

Panel A: Descriptive Statistics

Variable	N	Mean	Median	Std Dev.	Min	Max
AAV (in $000)	9,991	1,685	706	3,011	410	45,000
WL	15,257	0.27	0.19	0.28	0.00	0.94
ORanks	15,257	8.92	3	10.70	0	32
DRanks	15,257	9.00	3	10.75	0	32
G	15,257	6.74	4	6.89	0	17
Cmppct	15,257	1.90	0	11.45	0	100
PassYds	15,257	42.60	0	376.02	(4)	5,208
PassTD	15,257	0.26	0	2.44	0	50
Int	15,257	0.14	0	1.23	0	30
QBR	15,257	1.35	0	9.23	0	100
RushYds	15,257	19.10	0	109.07	(23)	1,631
RushTD	15,257	0.14	0	0.90	0	18
RecYds	15,257	44.15	0	161.85	(16)	1,871
RecTD	15,257	0.27	0	1.14	0	15
Fmb	15,257	0.12	0	0.60	0	14
DefInt	15,257	0.14	0	0.59	0	8
DefPD	15,257	0.78	0	2.32	0	26
DefFF	15,257	0.15	0	0.53	0	8
DefFR	15,257	0.20	0	0.57	0	9
Sk	15,257	0.41	0	1.49	0	21
TacklesComb	15,257	10.66	0	22.31	0	167
TacklesTFL	15,257	0.81	0	2.28	0	29
TacklesQBHits	15,257	0.99	0	3.36	0	50
TacklesSfty	15,257	0.00	0	0.06	0	1

Panel B: Correlation Matrix

	AAV	WL	ORanks	DRanks	G	Cmppct	PassYds	PassTD	Int	QBR	RushYds	RushTD	RecYds	RecTD	RecFmb	DefInt	DefPD	DefFF	DefFR	Sk	TacklesComb	TacklesTFL	TacklesQBHits	TacklesSfty
AAV	1																							
WL	**0.35**	1																						
ORanks	**0.24**	**0.59**	1																					
DRanks	**0.24**	**0.59**	**0.78**	1																				
G	**0.38**	**0.81**	**0.72**	**0.72**	1																			
Cmppct	**0.29**	**0.17**	**0.17**	**0.16**	**0.11**	1																		
PassYds	**0.43**	**0.12**	**0.09**	**0.10**	**0.11**	**0.59**	1																	
PassTD	**0.44**	**0.12**	**0.07**	**0.09**	**0.11**	**0.56**	**0.98**	1																
Int	**0.33**	**0.10**	**0.11**	**0.11**	**0.10**	**0.57**	**0.90**	**0.85**	1															
QBR	**0.34**	**0.15**	**0.14**	**0.14**	**0.10**	**0.86**	**0.65**	**0.64**	**0.59**	1														
RushYds	**0.14**	**0.17**	**0.14**	**0.15**	**0.20**	**0.08**	**0.11**	**0.12**	**0.10**	**0.10**	1													
RushTD	**0.17**	**0.16**	**0.10**	**0.13**	**0.18**	**0.11**	**0.19**	**0.18**	**0.16**	**0.13**	**0.85**	1												
RecYds	**0.27**	**0.27**	**0.22**	**0.24**	**0.34**	**0.06**	-0.02	-0.01	-0.02	**0.06**	**0.23**	**0.20**	1											
RecTD	**0.26**	**0.25**	**0.17**	**0.21**	**0.30**	**0.04**	-0.01	-0.01	-0.01	**0.05**	**0.15**	**0.13**	**0.88**	1										
RecFmb	**0.23**	**0.19**	**0.16**	**0.17**	**0.23**	**0.17**	**0.23**	**0.25**	**0.21**	**0.19**	**0.48**	**0.44**	**0.38**	**0.32**	1									
DefInt	**0.23**	**0.26**	**0.20**	**0.19**	**0.29**	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	**-0.03**	-0.02	-0.02	1								
DefPD	**0.28**	**0.33**	**0.28**	**0.28**	**0.40**	-0.02	-0.02	-0.02	-0.02	-0.03	**-0.03**	**-0.03**	**-0.04**	**-0.03**	**-0.03**	**0.76**	1							
DefFF	**0.31**	**0.29**	**0.22**	**0.23**	**0.34**	-0.01	-0.01	-0.01	-0.02	-0.01	-0.02	-0.02	-0.01	-0.01	-0.02	**0.25**	**0.34**	1						
DefFR	**0.36**	**0.34**	**0.29**	**0.30**	**0.41**	**0.25**	**0.40**	**0.38**	**0.38**	**0.26**	**0.19**	**0.20**	**0.11**	**0.09**	**0.35**	**0.13**	**0.18**	**0.22**	1					
Sk	**0.37**	**0.29**	**0.23**	**0.23**	**0.35**	-0.02	-0.02	-0.02	-0.02	-0.02	**-0.03**	-0.02	**-0.04**	**-0.03**	**-0.03**	**0.11**	**0.21**	**0.64**	**0.20**	1				
TacklesComb	**0.33**	**0.46**	**0.42**	**0.41**	**0.57**	**-0.03**	**-0.03**	**-0.03**	**-0.03**	**-0.04**	**-0.04**	**-0.04**	**-0.04**	**-0.03**	**-0.04**	**0.56**	**0.70**	**0.50**	**0.26**	**0.46**	1			
TacklesTFL	**0.38**	**0.36**	**0.32**	**0.31**	**0.44**	**-0.03**	-0.02	-0.02	-0.02	**-0.03**	**-0.03**	**-0.03**	**-0.04**	**-0.03**	**-0.04**	**0.23**	**0.36**	**0.58**	**0.23**	**0.84**	**0.69**	1		
TacklesQBHits	**0.37**	**0.31**	**0.25**	**0.25**	**0.37**	-0.02	-0.02	-0.02	-0.02	-0.02	**-0.03**	-0.02	**-0.04**	**-0.04**	**-0.03**	**0.10**	**0.21**	**0.59**	**0.21**	**0.93**	**0.48**	**0.84**	1	
TacklesSfty	**0.05**	**0.07**	**0.06**	**0.04**	**0.07**	-0.01	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	**0.03**	**0.05**	**0.08**	**0.05**	**0.12**	**0.10**	**0.13**	**0.12**	1

Bolded values are statistically significant at the $p<0.05$ level

4.2. Aggregate Results

Table 3 Column 1 presents the results of the regression of *AAV* on the team metrics (*WL*, *ORanks*, and *DRanks*) and individual metrics for the entire sample. Table 3 Column 2 in turn presents results of the regression on *WL* on *ORanks*, *DRanks*, and individual player metrics.

TABLE 3
Analysis of Average Annual Value and Win-Loss Record Using All Data

VARIABLES	(1) AAV	(2) WL
WL	848.24***	
	(0.00)	
ORanks	8.01**	0.005***
	(0.05)	(0.000)
DRanks	-23.98***	0.005***
	(0.00)	(0.000)
Year	136.48***	
	(0.00)	
G	-27.65***	
	(0.00)	
Cmppct	2.22	0.002***
	(0.65)	(0.000)
PassYds	2.80***	-0.000
	(0.00)	(0.222)
PassTD	640.78***	0.015***
	(0.00)	(0.000)
Int	-881.05***	-0.023***
	(0.00)	(0.000)
QBR	30.33***	-0.000
	(0.00)	(0.287)
RushYds	1.06**	0.000
	(0.04)	(0.145)
RushTD	89.17	0.021***
	(0.14)	(0.000)

TABLE 3 *(continued)*
Analysis of Average Annual Value and Win-Loss Record Using All Data

VARIABLES	(1) AAV	(2) WL
RecYds	5.84***	0.000***
	(0.00)	(0.000)
RecTD	254.30***	0.031***
	(0.00)	(0.000)
Fmb	-44.33	-0.005
	(0.46)	(0.235)
DefInt	499.34***	0.009*
	(0.00)	(0.060)
DefPD	218.26***	0.008***
	(0.00)	(0.000)
DefFF	195.33***	0.015***
	(0.01)	(0.001)
DefFR	438.84***	0.047***
	(0.00)	(0.000)
Sk	170.03***	0.001
	(0.00)	(0.820)
TacklesComb	6.10**	0.002***
	(0.02)	(0.000)
TacklesTFL	145.99***	-0.006***
	(0.00)	(0.002)
TacklesQBHits	246.13***	0.010***
	(0.00)	(0.000)
TacklesSfty	-327.68	0.056*
	(0.49)	(0.094)
Constant	-274,443.21***	0.115***
	(0.00)	(0.000)
Observations	9,991	15,257
R-squared	0.51	0.35

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For the regressions in Table 3, I do not break it down by positional group but rather included every variable and statistic with every position. The key result I would like to highlight is that the *WL* variable is positive and statistically significant in determining player value. While many different variables are significant in predicting pay and wins, these results are not as meaningful as when they are broken down by position. This is because of the difference in how statistics measure the performance of different positions. As an example, while at face value, the meaning of a single rushing yard is the same, it can mean quite different things when it comes from a quarterback versus a running back or wide receiver. Furthermore, the findings presented in Table 3 are largely unsurprising.

The odd-numbered columns in Tables 4 through 6 contain the regression results of *AAV* on team and individual metrics for individual player positions, and the even-numbered columns present the results of the determinants of team *WL* records. In the following sections, I discuss my overall findings, then proceed to break down the results by individual player positions.

Results in Tables 4 and 5 indicate that the overall win-loss record (*WL*) is significantly associated with pay of offensive skill position players. Economically, *WL* has a higher impact on quarterbacks, as shown in Table 4 Column 1, an increase the *WL* variable is associated with a \$5.25 million increase in a quarterback's *AAV* relative to running backs, (\$1.06 million), wide receivers (\$1.67 million), and tight ends (\$1.11 million), presented in Table 5 Columns 1, 3, and 5, respectively.

TABLE 4
Analysis of Average Annual Value and Win-Loss Record for Quarterbacks

VARIABLES	(1) AAV	(2) WL
WL	5,253.88***	
	(0.00)	
ORanks	-43.34	-0.003***
	(0.16)	(0.002)
Year	173.71	
	(0.19)	
G	-218.66**	
	(0.02)	
Cmppct	-34.88*	0.008***
	(0.05)	(0.000)
PassYds	3.95***	-0.000
	(0.00)	(0.197)
PassTD	418.34***	0.009***
	(0.00)	(0.005)
Int	-760.11***	-0.011***
	(0.00)	(0.002)
QBR	73.87***	0.000
	(0.00)	(0.664)
RushYds	5.76	-0.000
	(0.15)	(0.563)
RushTD	271.97	0.013
	(0.42)	(0.148)
Constant	-349,471.42	0.062***
	(0.19)	(0.000)
Observations	422	572
R-squared	0.75	0.61

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 5
Analysis of Average Annual Value and Win-Loss Record for Offensive Positions

	Running Backs		Wide Receivers		Tight Ends	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	AAV	WL	AAV	WL	AAV	WL
WL	852.62***		1,665.90***		1,107.59***	
	(0.00)		(0.00)		(0.00)	
ORanks	-13.07**	0.010***	5.44	0.008***	-5.52	0.009***
	(0.04)	(0.000)	(0.45)	(0.000)	(0.36)	(0.000)
Year	108.38***		129.80***		78.69***	
	(0.00)		(0.00)		(0.00)	
G	-65.09***		-185.45***		-33.53**	
	(0.00)		(0.00)		(0.01)	
RushYds	1.42***	-0.000	11.45***	0.002***	48.92**	-0.002
	(0.00)	(0.733)	(0.00)	(0.000)	(0.03)	(0.412)
RushTD	177.18***	0.028***	-56.89	-0.038	2,223.48***	0.052
	(0.00)	(0.000)	(0.90)	(0.263)	(0.00)	(0.577)
RecYds	7.71***	-0.000	9.21***	0.000***	7.77***	0.000***
	(0.00)	(0.318)	(0.00)	(0.000)	(0.00)	(0.000)
RecTD	-103.05	0.067***	288.15***	0.028***	190.11***	0.032***
	(0.22)	(0.000)	(0.00)	(0.000)	(0.00)	(0.000)
Fmb	149.56**	0.018**	20.64	0.013*	94.47	-0.020
	(0.03)	(0.040)	(0.80)	(0.069)	(0.59)	(0.367)
Constant	-217,943.20***	0.118***	-261,227.46***	0.085***	-158,065.83***	0.108***
	(0.00)	(0.000)	(0.00)	(0.000)	(0.00)	(0.000)
Observations	860	1,118	1,363	1,796	654	929
R-squared	0.52	0.37	0.67	0.43	0.72	0.38

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 6
Analysis of Average Annual Value and Win-Loss Record for Defensive Positions

	Defensive Linemen		Linebackers		Defensive Backs	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	AAV	WL	AAV	WL	AAV	WL
WL	712.86**		436.56		886.68***	
	(0.02)		(0.15)		(0.00)	
DRanks	-26.79***	0.004***	-16.62**	0.005***	-31.79***	0.005***
	(0.00)	(0.000)	(0.01)	(0.000)	(0.00)	(0.000)
Year	175.15***		137.85***		120.55***	
	(0.00)		(0.00)		(0.00)	
G	-153.97***		-70.00***		-42.62***	
	(0.00)		(0.00)		(0.01)	
DefInt	392.70	0.025	-166.62	-0.013	529.36***	0.012**
	(0.30)	(0.406)	(0.33)	(0.312)	(0.00)	(0.023)
DefPD	99.77*	0.002	175.84***	0.006	251.16***	0.013***
	(0.09)	(0.685)	(0.00)	(0.137)	(0.00)	(0.000)
DefFF	336.96***	0.022**	314.32***	0.004	332.36***	0.013
	(0.00)	(0.013)	(0.00)	(0.611)	(0.00)	(0.101)
DefFR	234.78*	0.051***	240.88**	0.022**	125.25	0.041***
	(0.09)	(0.000)	(0.04)	(0.025)	(0.28)	(0.000)
Sk	246.00***	-0.007	-26.12	0.004	-2.23	-0.022*
	(0.00)	(0.209)	(0.75)	(0.505)	(0.99)	(0.071)
TacklesComb	97.93***	0.007***	28.93***	0.003***	20.29***	0.003***
	(0.00)	(0.000)	(0.00)	(0.000)	(0.00)	(0.000)
TacklesTFL	33.78	0.001	59.54	-0.008**	322.20***	-0.009**
	(0.49)	(0.817)	(0.19)	(0.024)	(0.00)	(0.039)
TacklesQBHits	231.88***	0.004**	368.38***	0.012***	-309.74***	0.028***
	(0.00)	(0.035)	(0.00)	(0.000)	(0.00)	(0.000)
TacklesSfty	-135.93	0.073	-419.06	0.034	929.55	0.187*
	(0.81)	(0.131)	(0.55)	(0.552)	(0.47)	(0.054)
Constant	-352,598.65***	0.096***	-277,366.77***	0.127***	-242,429.58***	0.101***
	(0.00)	(0.000)	(0.00)	(0.000)	(0.00)	(0.000)
Observations	1,454	1,981	1,269	1,907	1,861	2,657
R-squared	0.64	0.44	0.62	0.37	0.48	0.44

p-values in parentheses
[*] $p < 0.10$, [**] $p < 0.05$, [***] $p < 0.01$

The impact of *WL* is less significant and impactful, however, for defensive players. Specifically, Table 6 shows that increases in *WL* result in an increase in *AAV*s of defensive linemen and defensive backs by $713k and $887k, respectively (Table 6 Columns 1 and 5). Although there is a positive coefficient on *WL* for linebackers (Table 6 Column 3), it is not statistically significant.

Overall, these findings suggest that while the use of explicit team incentives seems rare in the NFL, players are at the very least being implicitly incentivized to perform well as a team and win. NFL executives are expected to incorporate win-loss records in players' contracts, because their overall goal should not be to have players that record a high number of statistics but rather have a team that wins a lot of games and gets the team to the playoffs. These results are consistent with the current literature on incentive structures within businesses. It appears that when considering both the explicit and implicit incentives of NFL contracts that they are in fact using a mixed incentive structure, which, as Patel, et al. (2016) suggest, is effective in incentivizing increased performance.

A potential reason as to why offensive players are being compensated more for team performance when compared to defensive players is that in recent years within the NFL there has been transition from focusing on a sound defense to a high powered and flashy offense. Since 2000, the average points scored in an NFL game has climbed from 20.7 to a record high of 24.8 in 2020.[5] This increase in large part is attributed to changes in NFL rules that have given offensive players the advantage over defensive players. For instance, rule changes to pass interference and roughing the passer have become increasingly stringent and allow for defensive players to be much less aggressive. These

[5] "NFL Season By Season Scoring Summary." 2022. https://www.pro-football-reference.com/years/NFL/scoring.htm.

are some of the reasons as to why NFL executives are now attributing the success of the team more towards offensive players rather than defensive players.

The other metrics used to measure team performance in this study are *ORanks* and *DRanks* to find if players were being incentivized to perform in smaller teams within the franchise. For any player position playing offense, the coefficients on *ORanks* are not statistically significant, as shown on the odd columns of Tables 4 and 5. On the other hand, the coefficients on *DRanks* are negative and significant for all defensive players (Table 6). Note that lower values for rankings suggest better ranks, so these results are consistent with the expectation that a higher performing defense would lead to individual players being paid more. One potential reason for defensive players being paid more for defensive team performance is that there is a lot more rotation within a game for defensive players than for offensive players. This is because of a team's desire to keep defensive lineman rested throughout the game and the need to adjust to different formations that the offense puts out on the field. Thus, in any given game more defensive players would see significant playing time and record statistics than those who play offense. Thus, I argue that as opposed to offensive players who are pretty much in every game, different individual players that engage in defensive activities for the team are in each game (so it is not always the same people playing defense every time), the defensive rankings overall (incremental to the individual statistics of defensive players) is taken into account in determining a player's contract.

In addition to the team metrics, there are two other things to note about the overall results. First, *Year* is positive and statistically significant, reflecting that NFL salaries are increasing every year. Total NFL revenue has been steadily increasing, and because the

NFL salary cap is a percentage of total revenue, it has allowed for teams to increase the value of player's contracts.[6] The significance of *Year* holds for every position except for quarterbacks. This result is strange and counterintuitive however, it does not have much impact on the overall results and should not be examined in-depth.

Second, the coefficients on games played (*G*) is consistently negative and significantly associated to pay. This is surprising given that one would expect the players that are actually play in NFL games the season before signing a contract to be paid more than those who are not. Although this result is difficult to rationalize, there are anecdotal instances that may be skewing the results. For instance, there are a number of players that would normally play a full season but happened to get injured prior a contract year. In this scenario, their *G* variable would be much lower and yet they would still receive a significantly larger contract the next year due to their overall value. One example of this happening was Andrew Luck, the QB for the Indianapolis Colts, who only played 7 games in 2015 and yet received a massive $123 million contract in 2016.

4.3. Position-Specific Results

4.3.1. Quarterbacks

The results for quarterbacks are presented in Table 4. As shown on Column 1, *PassYds*, *PassTds*, and *QBR* are significant and positively correlated with pay, while the coefficient on *Int* is negative and statistically significant. As predicted statistics like *CmpPct* are less important to pay than more highly broadcasted statistics like *PassYds* and *PassTds*. *CmpPct* was marginally significant and surprisingly negatively correlated with contract pay. One potential reason as to why this might be the case is that as the NFL has

[6] "NFL Revenue By Year | Statista". 2022. *Statista*. https://www.statista.com/statistics/193457/total-league-revenue-of-the-nfl-since-2005/.

evolved in the passing game, quarterbacks who have bigger arms and can throw the ball downfield are more coveted than those who cannot. Because these quarterbacks are being pressured to throw the ball further downfield their accuracy and completion percentage would go down as a result. The coefficients on *RushYds* and *RushTD* are not statistically significant. One would expect that a quarterback that can both pass the ball and run it would be compensated more. However, this is shown to not be the case. One potential explanation as to why this occurs is that before and during the period of our dataset, the ideal quarterback was one that stayed in the pocket and did not run. However, lately there seems to be a transition towards utilizing a dual-threat quarterbacks that can do both. This transition can be seen by looking at the sheer number of times in which quarterbacks are running the ball. Within the last 2 years, 5 of the top 10 rushing attempt seasons by quarterbacks have occurred, which is outside of my dataset, suggesting that I have not fully captured the current NFL transition to dual-threat quarterbacks.[7]

Column 2 of Table 4 regresses *WL* on the various statistics. Consistent with the results in Column 1, the coefficients on *PassTD* and *Int* are positive and negative, respectively, and are statistically significant. *CmpPct* is significant and positively correlated to wins, suggesting that there is a potential inefficiency within NFL contracts where quarterbacks with a high *CmpPct* are being paid less and yet are winning more games.

[7] "Most Rushing Attempts By A Quarterback In A Season." 2022. https://www.statmuse.com/nfl/ask/most-rushing-attempts-by-a-quarterback-in-a-season.

4.3.2. Offensive Positions: Running Backs, Wide Receivers, and Tight Ends

Among the offensive positions other than quarterbacks, the coefficients on *WL* is consistently statistically significant and positively associated with pay, as evidenced in Table 5, Columns 1, 3, and 5.

When looking at the results from the Running back (RB) specific regression, there are some surprising results. The most surprising result is that *Fmb* has a positive effect on running back pay. This is not what you would expect given that a *Fmb* is not an optimal statistic for a running back. However, this is more likely less to do with the action of fumbling and more caused by the relationship with a running backs usage given that it is more likely for a player to fumble if they are given more rushing attempts and targets. For a running back that is more productive and has a higher usage would be expected to have more compensation. The other interesting result from this position group comes from the receiving statistics. The variable *RecTd* has no relationship with the pay of NFL running backs. A potential explanation for this result is the common use of the "3rd-down Back", who's role is a running back that is good at either pass protection or running routes that is typically only used on long 3rd downs in obvious passing situations. These running backs are used much more sparingly than a "every down" running back and their skill set is often much more easily replaced, which would lead to them receiving smaller contracts even though they still provide value to the team. There are of course exceptions to this, with running backs like Alvin Kamara and Christian McCaffrey, who excel in both the running game and the passing game, however, these running backs are quite rare.

Columns 3 and 4 show regression results for wide receivers. *RushYds*, *RecYds*, and *RecTd* are all positive and significantly associated with both pay and *WL*. All of these statistics are widely considered main functions of the wide receiver position, and it seems that NFL contracts are efficient in incentivizing players to perform as they are expected. For tight ends, *RecYds* and *RecTd* are similarly positive and significant in both regressions presented in Table 5, Columns 5 and 6. As well we see that both *RushTD* and *RushYds* are positive and significant in predicting pay. This is more surprising given the rarity in which tight ends are used as rushers, for only 6 tight ends recorded a rushing touchdown during these seasons. This is most likely due to the fact that one of these tight ends was Travis Kelce, who after recording that rushing touchdown received the second largest tight end contract in history.

4.3.3. Defensive Positions: Defensive Linemen, Linebackers, and Defensive Backs

Table 6 reports the regression results for defensive positions. In Column 1 for defensive linemen, *Sks*, *DefFF*, and *TacklesQBHits* are all positively associated with pay and are statistically significant. These results are unsurprising, given that these statistics represent primary functions and responsibilities of the position. The surprising result is found when comparing these to Column 2, specifically looking at the *Sks* variable. One of the primary goals of the defensive line position is to sack the opposing quarterback. These plays are idolized within the media and highly broadcasted, given the momentum shifting nature they can have within a game. However, this is showing that they have no effect on a team's win loss record. Instead, *DefFF* is shown to have the largest impact of any variable on a team's wins. While this is not the most surprising of results given that turnovers are rare and incredibly influential given that it gives possession back to the offense, the defensive line position was the only defensive positional group that showed significance for the *DefFF* variable. This shows that, when possible, defensive lineman should always target the ball when rushing opposing QBs rather than just focusing on tackling and getting them to the ground.

Columns 3 and 4 of Table 6 presents the results for the linebacker position group. Compared to all other tests, linebackers are the only positional group whose biggest influence on pay is not team wins or defensive rank. In fact, it is the only positional group in which the coefficient on the *WL* variable has no statistical significance. One possible explanation as to why this might be the case for linebackers is that NFL executives believe that current statistics measure the performance of line backers better than other positions. A line backer's role within the defense can be anything on a given play. They may have to rush the quarterback and take on an offensive lineman or they could drop into the secondary and cover a running back on their route. Thus, a good linebacker needs to be well rounded in order to be effective. Because a linebacker has so many responsibilities on the field, both the statistics the measure pass rush like *TacklesQBHits* and *Sks* and statistics that measure coverage performance like *DefInt* and *DefPD* apply towards measuring the performance of linebackers. We can see that this is the case, for there is significance in predicting the pay for linebackers for the variables: *DefInt*, *DefIntTd*, *DefPD*, *DefFF*, *DefFR*, *TacklesComb*, and *TacklesQBHits*. Thus, NFL executives may find that there is less of a need to pay them based off of team performance.

Results for the Defensive Back (DB) position are shown in Columns 5 and 6 of Table 6. As with nearly all the other position groups, *WL* is positive and statistically significant, as is the coefficient on *DRanks* (moreso than either the LB and DL position), consistent with the expectation that for this positional group team-based performance measures matter. When looking at the individual variables that have a causal relationship with pay, defensive back's contracts are associated with *PD*, *DefInt*, and *DefFF*, which is also expected, given that the primary function of their position is in pass defense. However, looking beyond these three variables, there is a surprising result given the positive effect of *TacklesTFL* but the negative effect of *TacklesQBHits*, a variable positively correlated with contracts for both defensive line and linebackers. Note that the *TacklesQBHits* is uniquely interpreted for defensive backs. Rushing the opposing team's quarterback takes the defensive back out of coverage. This is risky given since this allows the opposing quarterback to have larger windows to throw the ball to their targets. Hence, given the risk associated with sending a defensive back after the quarterback, the value of a quarterback hit for a defensive back is a lot less than that of a defensive lineman or linebacker. Because of this added risk, a defensive back recording a quarterback hit might be viewed negatively by executives who would prefer that a sack should take place when a defensive back incurs that additional risk. Thus, as shown in Table 6, Column 6, the coefficient on *TacklesQBHits* is positive and significant in predicting wins for defensive backs in particular. The inconsistency in coefficient signs for this variable in Columns 5 and 6 of Table 6 suggest a potential inefficiency within NFL contracts in which defensive backs are being incentivized to not record this statistic, even though it is potentially a good predictor of wins.

4.4. Overall Findings

Based on all these findings, it does appear that NFL contracts are compensating players based on team and individual performance metrics. This is ideal given the current literature suggests that the optimal incentive structure for maximizing performance is mixed. There is some potential to make contracts within the linebacker positional group more dependent on team performance, yet there is still a statistical significance and positive affect within *DRanks* variable. Furthermore, executives need to be cognizant not only that they are maximizing the performance of their players, but they are incentivizing only the performance that will lead them to win games. We see this especially within the quarterback position and specifically completion percentage which is negatively associated with pay but positively associated with wins.

5. Summary and Conclusions

In this study, I explore how various team and individual performance metrics are implicitly incorporated into contracts of NFL players. Overall, my findings confirm that players are being implicitly incentivized based on both team performance and individual statistics, which aligns with current business literature that suggest a mixed incentive structure is optimal for promoting performance. More specifically, the quarterback position was the most impacted by the total teams wins and losses, which is unsurprising, given that the quarterback is considered the captain of the team and viewed as a team's most important player. Furthermore, running backs and defensive backs are being compensated for multiple individual statistics, although not all of these statistics are associated with more wins. These results are potentially a result of statistics not accurately and completely capturing these players' contributions to the team. Lastly, only the linebacker position is not compensated for team performance. I conjecture that this finding could potentially be due to the versatile nature of the linebacker position, such that standard (individual) statistics do a better job at measuring performance.

My findings build on the literature on performance measurement in accounting, economics, and organizational behavior, and extend the research on compensation contracts in professional sports. My research also has practical implications and can inform the design and structure of NFL contracts.

The interpretation of the findings of my study are constrained by the data used, and I lay out some of this paper's limitations here. First, although my tests show reasonably high r-squared values (r-squared > 0.4), it is likely not all variables are necessarily captured by the models I use in my study. Second, due to the nature of how various players are used in the game, many positions that are not perfectly similar were put into the same positional group. For instance, the safety and cornerback positions were both placed within the defensive back positional group, and while both do play within the defensive secondary, their jobs are inherently different. Additionally, this study did not factor in any special team's players, and although these positions are not as central as offensive and defensive players, they are still important players on the team and are compensated similar to other players on the field. Similarly, not being able to include players within the offensive line is an area where this study can be improved. Players on the offensive line are some of the most important players on the field. However, the lack of current data made it difficult for me to include the analysis of these offensive line players in my study. Finally, although pro-football-reference.com is considered a comprehensive and reliable dataset, there are a number of issues relating to the accuracy of the data, including missing positions for several players.

Apart from data considerations, future extensions of the study could include statistics from more than just the year before a contract signing. Although my design choice was purposeful based on the recency bias associated with NFL contracts (i.e., the previous year is generally the most important in determining the value of a player), arguably consistency within the NFL and having multiple years of good (or poor) performance across both team and individual measures is meaningful and likely influence NFL contracts.

Additionally, the analysis of every specific position within the NFL, rather than separating them into positional groups, could shed more light into how contracts are structured. Furthermore, if data is available, the inclusion of more advanced statistics and valuation tools like Pro Football Focus grades, drop percentage, yards before contact, or broken tackles could provide more insight into how team metrics are used to supplement individual statistics. Future research could also look into modeling and developing more team-based performance measures beyond just wins/losses and offensive and defensive ranks. Doing so could help further determine the extent to which NFL contracts are a mixed-incentive structure.

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