UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER’S THESIS

PLAYERS’ COMPENSATION: THE CASE OF WIDE RECEIVERS IN THE NATIONAL FOOTBALL LEAGUE

Ljubljana, January 2023 GABER GAŠPERLIN

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

sl. – Slovene
BIC – (sl. Bayesov informacijski kriterij); the Bayesian information criterion
CBA – (sl. Kolektivna pogodba); Collective Baraganing Agreement
DCS – (sl. Dinamični pogojna ocena); Dynamic Conditional Score
GAS – (sl. Generalizirana avtoregresivna ocena); Generalised Autoregressive Score
MLB – (sl. Ameriška državna baseball liga); Major League Baseball
NBA – (sl. Ameriška državna košarkaška liga); National Basketball League
NFL – (sl. Ameriška državna nogometna liga); National Football League
NFLPA – (sl. Sindikat športnikov ameriške nogometne lige); National Football League Player association
PFF – (sl. Osredotočen poklicen nogomet) ; Pro Football Focus
US – (sl. Združene države amerike); United states of America
USD – (sl. Ameriški dollar); United states Dollar
VIF – (sl. Faktor povečanja variance); Variance Inflation Factor

INTRODUCTION

Players' compensation are a well-researched topic, especially in professional sports where athletes' salaries are public knowledge. In the National Football League (NFL), there is a unique labour market structure that differs from traditional labour markets. This is partly due to the nature of the sport. Since the sport is very violent, injuries are commonplace. In addition, players' careers are relatively short, which limits their earning potential. There are also strict labour market structures, which include a strict salary cap, salary minimums and restrictions on contract incentives. In addition, anti-tempering rules prevent players from freely negotiating contracts with any team, and there are special tender contracts that can prevent a player from ever being eligible to negotiate contracts with other teams.

Within these labour market restrictions, the factors that influence players' salaries are examined. Unlike other sports, in American football, no player-specific performance measure can be applied to all positions. In basketball, for example, performance measures (e.g., points, assists, rebounds, plus-minus) can be applied to each position, although the focus of each position is different. This makes it more difficult to compare the performance of players at different positions. In addition, American football is a more team-dependent sport, where individual players' success is largely influenced by their teammates. This makes it even more difficult to evaluate the performance of individual players. (Hoffer & Pincin, 2019)

The analysis in this thesis focuses on the wide receiver position, which is one of the so-called skill positions in football, along with quarterbacks, running backs and tight ends. These positions differ from the others in that they have possession of the ball more often. This gives them a more direct and comprehensive measure of their performance. The factors analysed range from the specific characteristics of the player and his performance in the sport to other market factors.

The aim of this Master's thesis is to determine which performance metrics, in combination with other factors, have the most influence on player salaries. To control for the effect of the dependent variable under study is defined as the average annual salary premium, since a significant portion of players in the NFL earns the minimum salary. This is a unique difference from previous research.

The analysis is conducted using secondary data on player performance provided by independent sports analytics firm Pro Football Focus, combined with contract information from Spotrac, the largest online provider of professional sports contract information in the US. The sample includes all wide receiver contracts from the five seasons, from the 2018 offseason through 2022. Performance data includes key figures from the last three regular seasons prior to signing, i.e. regular season data from 2015 to 2021. The dependent variable is calculated from the player's average annual contract value and corresponding minimum salary relative to his experience and year of signing.

Since the dependent variable will contain many true zeros that are not missing variables, the left-censored Tobit model with a censoring point of 0 is used. First, the simple Tobit model with only one performance measure is used. Then, additional performance measures are added to the model to capture more of the variability in the dependent variable without significant problems with the underlying assumptions. The t-test results of the Tobit coefficients are used to test the hypothesis. The coefficients are expressed in terms of their marginal effects on the observed variable and the model fit is examined in relation to the observed variable.

The first chapter looks at the external factors for player compensation and the framework of the model used. First, the contextual constraints on player compensation in the NFL imposed by collective bargaining are examined. These include minimum salaries and special tender contracts, as well as special rookie contracts and allowable contract terms, all under the guise of the salary cap. It then examines previous research on compensation in the NFL, particularly for the wide receiver position, which formed the basis for the formulation of the hypothesis. The chapter then concludes with the theoretical framework of the model used and its interpretations. The research analysis is explained in the second chapter, which deals with the description of the data and the selection of variables. For this purpose, the simple model with a limited number of variables was used first, which was later extended by including additional variables in the extended model. By converting the coefficients into the marginal effects at mean values, the influence of a particular variable used in the model was described. The reliability of the model was then examined by looking at possible deviations from the underlying assumptions. The quality of the model was also examined in terms of the overall fit of the model to the data. The second chapter concludes with a discussion section that focuses particularly on the hypothesis testing, their results and findings, and also examines the limitations of the research and makes some suggestions for future research.

1 THEORETICAL BACKGROUND

In order to draw sound conclusions, the background within which they are formed must be examined. This includes the constraints and limitations that affect player's compensation in the NFL, as well as the requirements and understanding of the methods used in the analysis.

1.1 Salaries in the National Football League

It is important to understand how the collective bargaining agreement and salary cap affect the value and terms of contracts. Unlike other professional sports leagues, the NFL has a strict salary cap that contributes significantly to parity between teams. This differs from other sports leagues like the NBA, which has a luxury tax option that allows a team to exceed the salary cap. Every NFL team has to make the difficult decision of how to allocate salaries across positions. This is a classic problem of allocating scarce resources.

In addition, the NFL Collective Bargaining Agreement (CBA) is a labour contract entered into by the NFL Players Association and the league's team owners that sets the rules for the distribution of profits and benefits within the league. It dictates what terms are allowed in contracts. There are also anti-tempering rules that prevent players from freely negotiating contracts with any team, and there are special tender contracts that can prevent a player from reaching Free Agency.

These features create a distortion in the labour market that obscures the relationship between salary and performance. This has led to players being released time and time again due to their salary cap rather than their performance declining. (McIntyre, 2017) In addition to the salary cap, players' salaries are also capped by minimum salaries, which vary depending on the player's level of experience and the year the contract was signed.

1.1.1 Minimum salary

Part of the rules also concerns minimum salaries. These are determined by the experience of the player and the year in which they are agreed. The years of experience are determined by the so-called credited seasons. For a particular season to be considered credited, the player must be on the active roster for at least three regular season games in a given season. (NFL & NFLPA, 2020, p. 174). This does not apply to players on the practice squad or injured list. Based on the number of credited seasons, there are seven different brackets. From no experience up to three credited seasons the minimum salary is increased with each year, from four to six there is only one increase, one bracket between seven and nine and the final bracket includes players with ten or more credited seasons as shown in Table 1 below. The minimum salary in 2011 was $375 thousand, which is 41 percent of the minimum salary of a player with ten or more credited seasons. Over the eight years, the minimum salary of the lower tier has increased by 32 percent, while that of the highest tier has increased by just over 13 percent. (NFL & NFLPA, 2011, p. 150)

Table 1: Minimum player salaries in the NFL with the 2011 CBA in thousand dollars

#CS	2011	2012	2013	2014	2015	2016	2017	2018	2019
0	375	390	405	420	435	450	465	480	495
1	450	465	480	495	510	525	540	555	570
2	525	540	555	570	585	600	615	630	645
3	600	615	630	645	660	675	690	705	720
4-6	685	700	715	730	745	760	775	790	805
7-9	810	825	840	855	870	885	900	915	930
10+	910	925	940	955	970	985	1,000	1,015	1,030

Source: NFL & NFLPA (2011), p. 150.

Based on the 2020 Collective Bargaining Agreement, the minimum salary of the players is $610 thousand and is expected to increase to over one million dollars in the next ten years. The number of brackets was also reduced with the lowest brackets starting from seven or more seasons. The salaries of players with less experience will be raised more, by 70 percent over the eleven years, while the minimum salaries of players with the most experience will be raised much less, by 40 percent, resulting in a smaller range in minimum salaries. (NFL & NFLPA, 2020, p. 172)

Table 2: Minimum player salaries in the NFL with the 2020 CBA in thousand dollars

#CS	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
0	610	660	705	750	795	840	885	930	975	1,020	1,065
1	675	780	825	870	915	960	1,005	1,050	1,095	1,140	1,185
2	750	850	895	940	985	1,030	1,075	1,120	1,165	1,210	1,255
3	825	920	965	1,010	1,055	1,100	1,145	1,190	1,235	1,280	1,325
4-6	910	990	1,035	1,080	1,125	1,170	1,215	1,260	1,305	1,350	1,395
7+	1,050	1,075	1,120	1,165	1,210	1,255	1,300	1,345	1,390	1,435	1,480

Source: NFL & NFLPA, (2020), p. 172.

1.1.2 Special tender contracts

The Collective Bargaining Agreement also allows teams to enter into two special one-year fully guaranteed player contracts, the franchise tender and the transition tender, which allow teams to retain their current players. Each team may use one franchise or one transition tender per season, but not both. There are two different franchise tenders, the non-exclusive franchise tender and the exclusive franchise tender. The value of the non-exclusive franchise tender is determined by calculating the average relative salary cap charge of the exclusive franchise tenders over the last five years for the player position and multiplying by the salary cap for the upcoming league year or 120 percent of the player's previous year's salary. In the non-exclusive franchise tender, the player can negotiate another contract with other teams, but the other team must compensate the original team with two first-round draft picks. In the exclusive franchise tender, on the other hand, the player cannot renegotiate the contract with the other team, but receives a slightly higher salary equal to the average of the five highest salaries of the current year for the player position or 120 percent of the previous year's salary. If a player is under franchise tender, he can renegotiate his contract with his current team or be included in the trade between teams. The player may be under franchise tender for several years in a row. (NFL & NFLPA, 2020, PP. 58-61)

Should a player be under a franchise tender for the third time, his salary will be determined according to the highest of the three criteria: (NFL & NFLPA, 2020, p. 59)

- The average of the five highest salaries from the previous year in the highest paid position group,

- 120 percent of the average of the five highest salaries from the previous year in his position group,

- 144 percent of his previous year's salary.

The team that nominates a player under a transition tender is given a right of first refusal enabling it to match the player's negotiated contract value with that of other teams and retain the player, but shall receive no compensation if it does not exercise that right. If a player is unable to negotiate a contract with other teams, his salary is determined by the highest of the two criteria. The average salary cap charge of the ten highest salaries of the previous year in the player's position group or 120 percent of the previous year's salary.

Over the period from 2014 to 2022, the value of the wide receivers' franchise tender increased by an average of 5.16 percent per year and the value of the transition tender increased by 6.45 percent per year. The year 2021 was a bit of an anomaly as it was the first time the salary cap decreased. This was because match-day revenue had declined due to the pandemic. In 2022, the franchise tender minimum for wide receivers was $18.419 million. *(Spotrac, 2022b)* Two players were designated as franchise players this year: Devante Adams of the Green Bay Packers and Chris Godwin of the Tampa Bay Buccaneers. (NFL, 2022b) Due to the higher previous salary, the rule of 120 percent of the previous year's salary was applied in both cases, which was higher than the minimum franchise tender value in Table 3 below.

Table 3 Minimum franchise and transition tender in the period from 2014 to 2022 for the wide receiver position in the NFL in millions of dollars

	2014	2015	2016	2017	2018	2019	2020	2021	2022
Franchise tender	12.312	12.823	14.599	15.682	15.982	16.787	17.865	15.983	18.419
Transition tender	10.176	10.971	12.368	13.129	13.924	14.794	15.68	14.34	16.782

Source: Spotrac (2022b).

1.1.3 Rookie contract structure

The structure of NFL player contracts has changed over the years. Most notably, the newer collective bargaining agreements continue to introduce new rules for the contracts that can be signed. For example, in the 1993 Collective Bargaining Agreement, rookies, players playing their first season in the NFL, could negotiate a contract of any length, subject only to the rookie salary cap. In addition, contracts were allowed to include incentives that counted against the rookie salary cap only if they were deemed easy to achieve. However, the next collective bargaining agreement in 2011 made significant changes to the structure of rookie contracts. This agreement counted all performance incentives in rookie contracts towards the rookie salary cap and limited the salary increase rate between the years in the rookie contract to 25 percent. The amended rules also set the length of contracts at four years and three years for undrafted players. The contracts of players selected in the first round were also given a team option for a fifth year. The most drastic change was the compensation scale for rookie contracts, with a salary set in advance based on a minimum percentage of the total rookie compensation pool. This percentage is based on draft position, with each subsequent selection receiving a lower compensation. There are also restrictions on renegotiating contracts. Players who have been drafted cannot renegotiate their contract until after the last game of the regular season in their third year, and undrafted players in their second year. With the 2011 Collective Bargaining Agreement changes, rookie salaries increased by an average of 9 percent in the first year, but the cap on salary increases between years of a contract had a much larger effect, reducing overall rookie compensation. (Keefer, 2016)

The new 2020 Collective Bargaining Agreement introduced changes to fifth-year options that allow players selected in the first round who significantly outperform their contract to receive a higher fifth-year option. For players selected to the Pro Bowl in their first three years, the fifth-year option will be set at the value of the transition tender for their position. If the player was selected to the Pro Bowl multiple times in their first three years, their fifth-year option will increase to the value of the franchise tender for their position. (NFL & NFLPA, 2020, pp. 40–44)

As of 2020, the Year-One Rookie Compensation Pool has been set at $260 million and is expected to increase by the relative growth of the salary cap through 2030, when the collective bargaining agreement expires. The minimum increase in the Year-One Rookie Compensation Pool is determined by the minimum salary increase for players without credited seasons. It is defined as the minimum salary increase for players with no playing time multiplied by 224 non-compensatory draft picks plus the 1 percent increase in the Year-One Rookie Compensation Pool above the minimum salary for the 224 non-compensatory draft picks. (NFL & NFLPA, 2020, pp. 20–26) For 2021, the minimum increase in the Year-One Rookie Compensation Pool is $11.2 million from the minimum salary increase plus the $1.12 million from the 1 per cent increase in the compensation pool.

1.1.4 Salary cap

The salary cap, which is the maximum accounting charge a team can spend on players' compensation in any given season is determined by the annual revenues of the NFL. This includes: (NFL & NFLPA, 2020, pp. 90–97)

- 55 percent of the projected broadcasting revenues from television rights of the regular season games transmitted either by cable, satellite or internet; radio broadcasting rights transmitted either by satellite, internet or terrestrial; and cable television transition royalty fees under Copyright Royalty Tribunal.
- - 45 percent of projected postseason broadcast revenue and NFL Ventures revenue, which includes all NFL-owned media.
- 40 percent of projected local revenue, which includes all team or affiliate revenue, including all revenue from ticket sales and game day services and television rights for preseason games.

- 50 percent of all new revenue sources not included in the three categories explained above.
- Reduced by 45 percent of the value of join contribution amount, which is used for former players, medical research and charities.
- Reduced by the stadium credit, which covers 50 percent of the cost of renovating and building the stadium, and a special deduction for Los Angeles stadium revenue.

The newly ratified 2020 Collective Bargaining Agreement also paved the way for the extension of the regular season by a 17th game and the expansion of the playoffs by two additional games in the divisional round. In the event that the regular season is extended to 17 games, the percentage of player revenue determined by the salary cap would increase by the "media kicker," which raises the percentage of player revenue share to 48.5 percent with the possibility of up to 48.8 percent of annual revenue before deductions. To ensure that enough money is spent, the league-wide minimum for player salaries is set at 95 percent of the total salary cap over three years and 90 percent of the total salary cap over that period for each team. (NFL & NFLPA, 2020, pp. 91–101)

The NFL has decided to introduce the 17th regular season game in the 2021 season. This has triggered the Media Kicker, which increases the share of player revenue to over 48 percent of total revenue. Existing contracts signed before 26 February 2020 will receive an additional game cheque of 1/17th of the agreed amount. (NFL & NFLPA, 2020, pp. 172–174) The salary cap for the 2021 league year was set at $182.5 million, a 7.92 percent decrease from the previous season, even though the regular season was extended for the 17th regular season game. This was the second time the salary cap was lowered. The first reduction occurred in 2011 when a work stoppage due to collective bargaining led to a slight reduction in the salary cap. As can be seen in Table 4 below, the salary cap has increased by 56.54 percent since 2014, with the largest increase occurring in the 2022 season when the salary cap increased by 14.08 percent, as local revenues recovered quickly following the removal of the stadium attendance restriction.

Table 4 NFL salary cap from 2014 to 2022 in millions of dollars

	2014	2015	2016	2017	2018	2019	2020	2021	2022
Salary cap	133	143.28	155.27	167	177.20	188.20	198.20	182.50	208.20

Source: Statista (2022).

The effective salary cap differs between the teams, as each year they receive the same salary cap base for example $208.2 million in 2022, which is adjusted for any uncounted or overcounted salary cap charge, i.e. incentives and the carryover of unused salary cap from prior years.

1.1.5 Flexibility within the salary cap

Since the salary cap does not allow a team to exceed the cap expenditure in a given year, teams must be careful about how the salary cap is distributed. Mondello and Maxcy (2009) researched how the distribution of salary cap and incentive payments affect team performance. They found that less salary dispersion, i.e. smaller differences between players' salaries, combined with higher incentive payments and larger salaries, contributed to better on-field performance. However, they found a positive relationship between team earnings and lower salary dispersion. This means that superstars who take up a significant portion of the salary cap attract fans but do not represent the optimal distribution of the salary cap for performance. An interesting finding is also the impact of incentives on performance, as they receive special treatment under the salary cap. All incentives are divided into two categories: those that are likely to be earned and those that are not considered likely. The latter does not have to be part of the team's salary cap, while incentives that are likely to be earned are part of the salary cap. For the team-based incentive to be considered likely, the team had to meet its requirements in the previous season. For example, if a player's contract includes an incentive for making the playoffs, it is considered likely earned if the team made the playoffs in the previous season. At the end of the season, all earned incentives are then deducted from the salary cap and all unearned incentives that were part of the salary cap are credited back. (NFL & NFLPA, 2020, pp. 113–115) This allows for an opportunity when a team exceeds the salary cap because a large portion of the incentives that did not count against the salary cap have been achieved. However, this surplus charge is then carried over to the next season.

Another study examined the optimal salary distribution strategy under the assumption that each player is paid exactly for his winning contribution. Compared to existing NFL salary allocations, it is most optimal to spend relatively more money on the guard, defensive line and linebacker positions, while the wide receiver position should receive only 5.6 percent of the total salary cap. Taking into account the differences between compensation and winning contributions, the teams that successfully drafted the players capable of outperforming their predetermined rookie contract, especially the quarterback, were able to get the best performance from the given salary cap charge. (Mulholland & Jensen, 2019)

Players often receive a sign-in bonus in their contract, which is a lump-sum monetary payment they receive shortly after signing their contract. For salary cap purposes, this money can be prorated over the life of the contract. It is, however, limited to a maximum of five years and may be counted in equal parts or skewed towards the earlier years. (NFL & NFLPA, 2020, p. 113) To take advantage of this, teams began renegotiating contracts with their players solely for salary cap purposes, which would not affect players' earnings. They began by converting a guaranteed portion of the salary they were obligated to pay into a sign-in bonus and spreading the cap charge proportionately over the life of the contract. In this way, they were able to carry over the cost of the salary cap to later years. To benefit from this proration effect, teams have also started to introduce voidable years that are automatically cancelled before they take effect. In this way, the proration effect can be extended beyond the contract period. For example, wide receiver Amari Cooper restructured his contract with the Cleveland Browns, which had three years remaining at the time of restructuring, by converting the $18.88 million of his $20 million guaranteed salary into a sign-in bonus and adding two voidable years. (Little, 2022) In this way, the $18.88 could be calculated at $3.776 million per year over the next five years, effectively saving $15.144 million in 2022.

The team can terminate the contract of any player and make a saving in the salary cap. However, all the guaranteed portion of the contract value that is remaining and the portion that has not been counted yet (i.e. proration of sign-in bonus) is converted into what is called dead money. This is a salary cap charge for players that are not active on the roster. In the case that the player was traded or placed on injured reserve, his guaranteed cap charge is also converted into dead money. If a player gets cut, traded or paced on injury reserve before June 1st all the dead cap is charged in the current league year, whereas should this be done after the dead money charge, it can be spread over two years. (Milligan & Talmage, 2019)

1.1.6 Contract structure

A typical NFL contract includes a number of seasons, an annual salary, and specific provisions that explain how the compensation is structured. These include a guaranteed portion of the contract, the terms of when a particular portion is guaranteed, and the salary schedule. In addition, they may include bonuses, for example in the form of a roster bonus paid if a player is on the roster on a certain date, or training bonuses based on participation in team-organised training sessions in the offseason. This may also include performance bonuses based on the performance of the player or the team. (Kim, Sarin & Sarin, 2018)

The 2020 Collective Bargaining Agreement specifies which incentives may be included in NFL contracts. They are divided into team incentives, individual incentives and incentives based on awards and media recognition. The incentives allowed are based on the positions the player played in the previous season. Any player may receive team incentives for wins, playoffs, Conference Championship, Superbowl, touchdowns on returns or recoveries and net differential takeaways/giveaways regardless of the position at which they played. Other team incentives are divided into Offensive, Defensive and Special Teams as shown in Table 5 below. Offensive and defensive teams receive the same performance measure, only the desired outcome is different. For example, the incentive for offense is points scored by the team, with the incentive achieved if the points scored are equal to or higher than the target, while the incentive for defence is points allowed, achieved by the equal or lower number of points allowed. The only difference in measurement is the Pass Completion Percentage for the Offense and the interceptions for the Defense. Team-based incentives for special teams are based on average return on kickoff or punt plays and may apply to the team or opposition.

Table 5: Permitted team-based incentives in the NFL contracts

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 percentage completed	Interceptions	

Source: NFL & NFLPA, (2020), p. 133.

Some individual performance incentives may also apply to all positions, e.g. roster bonuses, reporting bonuses and playing time bonuses. However, most are specific to the player's primary position. They are divided into Rushing, Passing, Receiving, Defence and for the special teams, there are also Kickoff Returns, Punt Returns, Punting and Place Kicking. (NFL & NFLPA, 2020, p. 133) For the offensive positions, they are mainly based on the statistical categories of yards, touchdowns and receptions. For the offense, these can be total receptions, total yards, average yards and touchdowns. For the defensive position, the individual incentives are based on takeaways and sacks.

Towards the end of the season, awards are also given to outstanding players at their respective positions. These include Pro Bowl, All-Pro, MVP and Player of the Year awards, which may be part of the incentive structure in NFL contracts.

Kim et al. (2018) have shown that NFL player compensation design can have a positive impact on individual player performance metrics when contracts are more incentive-based. They focused on the win probability added and expected points added as a performance measure of the observed skilled positions. However, they did not find any evidence to support that contract size or length impacted the change in the player's performance.

Contracts in the NFL are negotiated individually between players or their agents and teams. Since player agents are the primary negotiators of contracts, they have considerable influence on players' salaries. To ensure the quality of player agents, the NFLPA has established requirements for player agents to be allowed to represent players in the NFL. These include a minimum level of education, certifications, attending seminars and passing an exam. Although there are over 800 NFLPA-certified player agents, only a few represent the vast majority of players. This concentration is so great that around 75 percent of all players are managed by fewer than ten agents. (Staker, 2020)

As a result, there can be large discrepancies between different contracts due to the different experience levels of the agents involved in the negotiations. Conlin, Orsini and Tang (2013) studied this in the NFL and found that an agent's experience does not affect the value of the contract. However, they found evidence that contract length and performance-based incentives in contracts vary between agents with different levels of expertise. Since the primary aim of this thesis is to examine the aspects that concern the salary, the status of the agent will not be examined further.

Unlike other sports leagues such as the NBA or MLB, the collective bargaining agreement in the NFL does not mandate guaranteed contracts. This is one of the main reasons why the discrepancy between the contract value and the money paid out is very high. This is especially true for players who are paid minimum salary, as they have little to no guarantees. This is particularly important for undrafted free agents, who account for roughly one-fifth of all players. (Nystrom, 2022) Their mandatory three-year contracts usually contain little to no guarantees. Only a few players have actually received the full value of the contract, as player turnover is high.

Injury clauses are also an important part of contracts. Because contracts in the NFL are not fully guaranteed in the event of an injury, it is very important how injury clauses are worded in contracts. It is common for players to be entitled to injury compensation based on the severity of the injury and recovery time, but the amount is usually much lower than if the player had been actively playing. However, this compensation is not always granted as many players tend to forfeit it by not disclosing their injuries to the team this can have a dramatic impact on their job security, especially if they are at the bottom of the depth chart and the likelihood of being replaced is high. (Staker, 2020)

Personal conduct clauses are part of every NFL contract. These include the league's substance abuse policy, which covers illegal substances, recreational drug abuse or banned substances with performance-enhancing effects. The substance abuse policy dictates strict liability as a lack of knowledge or negligence is not tolerated. Conduct violations also include criminal offences, violent behaviour or actions that pose a threat to the safety and well-being of another person, even if there is no conviction. If the player has breached the personal conduct policy, disciplinary action will be taken against them. These include fines, suspensions for a certain number of matches without pay, or a ban from the game, with conditional reinstatement possibility at a later date if certain conditions are met. (NFL, 2018)

The punishments included the suspension of the wide receiver Josh Gordon of the Cleveland Browns for consecutive substance abuse violations due to alcohol, which included 45 games over the period of three years. The wide receiver Golden Tate of the New York Giants was also suspended without pay due to a banned substance violation, that was attributed to fertility treatment. But the conduct violations are not always enforced, as was the case with Tyreek Hill, who was a wide receiver for the Kansas City Chiefs at the time. He was alleged of battery and child abuse, however, the league did not decide to issue a suspension. (Staker, 2020).

With the 2020 Collective Bargaining Agreement, there are some changes in the way breaches of the personal conduct policy are dealt with. Each case will be handled by a neutral arbitrator who will determine the possible duration of the suspension. Only the determined length of suspension can be challenged, not the validity of the charge itself. This is important because credible evidence is sufficient to meet the burden of proof, regardless of whether the charges were dropped in the criminal proceedings. If the length of the suspension is appealed, the NFL Commissioner is considered the arbiter and has the final say. (NFL & NFLPA, 2020, pp. 277–283)

In general players in the NFL are unlikely to receive full compensation as there are multiple reasons that they can be terminated due to performance decline, injury status, personal conduct violations or simply salary cap constraints. This is why the guaranteed amount is very important. They can also be threatened by the possibility of being cut to agree on a contract negotiation that reduces their compensation. Under the pretext of being cut, players might also agree to a contract restructuring that reduces their salary.

1.2 Research on player compensation in the National Football League

There is evidence that performance has an impact on players' salaries. Leeds & Kowalewski (2001) examined the effects of player performance and salary for skilled positions and found that for wide receivers, an increase in the number of receptions can contribute significantly to a higher salary. However, they examined these effects under the 1993 collective bargaining agreement. On the other hand, another study found that a player's performance contributes significantly to career earnings (Ducking, Groothuis & Hill, 2014) and salaries (McIntyre, 2017)

The studies of NFL player earnings have used different types of metrics that represent player performance. In the studies where performance was not a critical part of the study, arbitrary performance measures have been used, such as Pro Football Reference's approximate player value (Mulholland & Jensen, 2019; Salaga, Mills & Tainsky, 2020; Soebbin, Wicker & Watanabe, 2022) which combines team performance statistics, such as points and wins, and individual performance statistics, which include games started, Pro Bowl selections, and cumulative performance statistics specific to the position. Another arbitrary performance measure is the Fantasy Point Score. (Navarro et al., 2017)

Other studies used position-specific measures and either focused on skill positions, which include wide receivers, running backs and quarterbacks as a group, or formed position-specific analyses (Borghesi, 2008; Ducking et al., 2014; Krautmann, Allmen & Berri, 2009;

Leeds & Kowalewski, 2001; McIntyre, 2017; Mulholland & Jensen, 2018). Wide receiver position performance was assessed by targets, receptions, yards, touchdowns, reception percentage, fumbles and interceptions.

When evaluating the value of the offensive play, securing the first down is very important because it allows the offence to stay on the field and get closer to scoring distance. Pelechrinis, Winston, Sagarin and Cabot (2019) considered yards gained in relation to the first-down marker as a very important factor when evaluating plays, especially on 3rd-down. This is an indication of the value of first downs. Although a later study suggested that in first-down situations stopping short of the first-down marker might be a better alternative than securing the first down with no extra yards. (Cotton, 2021) However, this is only a small optimisation, as the first down is very likely to be achieved in later attempts, which does not diminish the value of the first down.

Sports bettors' point spreads for individual players were also used to evaluate how which performance statistics impact players' point spreads the most and, therefore, win percentage. This impact can provide insight into which performance statistics provide a meaningful conclusion about the player's performance. Since the value of a quarterback far outweighs the value of any other position, most quarterback-specific performance metrics were significant. For the wide receiver position, both receptions per game and yards per game were statistically significant determinants affecting the formation of each player's point spread in sports betting. (Hoffer & Pincin, 2019) In assessing team performance, the yards per attempt metric also proved to be a statically significant predictor of team performance and the probability of winning. (Einolf, 2004) The yards per Reception variable has also been used to evaluate which NFL Combine measures best predict player performance. (Kuzmits & Adams, 2008) Yurko, Ventura and Horowitz (2019) developed a new method for evaluating offensive players in the NFL based on their contribution to winning percentage compared to the replacement player's performance level. To better evaluate the receiver's contribution, they divide yards into air yards and yards after the catch, as air yards are more dependent on the passer than yards after the catch.

It is clear that a player's performance in the NFL has a positive impact on his compensation, but there is no clear consensus on what statistical measures of a player's contribution are best suited to represent his performance. This is the case because statistical measures of a player's contribution vary by position and overlap only slightly. Furthermore, it is not known in what form they should be expressed, as they can be a cumulative measurement over a season or relative to playing time. This could be in the form of per game, per target, per reception or even per route run. Hoffer and Pincin (2019) suggest the use of per game metrics. With this approach, the missed games do not have an impact on a player's performance and players who had outstanding plays but were only involved in very few snaps are not overrated.

A more modern approach to evaluating player performance is based on player tracking data, where the ball and each player's position are recorded 10 times per second. Reyers and

Swartz (2021) used this data to evaluate quarterbacks. An important aspect of their evaluation was the correct selection of the wide receiver on a pass play. The wide receiver's position in relation to distance from defenders and downfield position was pivotal. While it is the goal of the passer to find the best open receiver, it is the job of the receiver to become the most open. Therefore, part of the evaluation of the wide receiver's performance also lies in the quality of the route running.

Ducking et al. (2014) investigated possible racial discrimination in player salaries in the NFL for the selected positions, which include wide receivers. Although some previous research suggests that there may be some discrimination (Kahn, 1992; Keefer, 2011; Mogull, 1973) Ducking could not find any racial bias. Soebbing, Wicker and Watanabe (2022) obtained some evidence of discrimination, as minority players, especially from the highest-income group, have higher career earnings than Caucasian players. However, positional differences within the highest-earning group were not taken into account. Similar discrimination in favour of a minority was also found for the positions of linebackers and offensive linemen. (Burnett & Van Scyoc, 2015)

Players who changed teams with the new contract received significantly less compensation than players whose contracts were renewed at their previous team. The results of a study show that players who changed teams suffered a 40 percent drop in salary. Part of this drop can be attributed to players being released because they no longer perform at the level expected for their compensation. This is particularly the case with free agent contracts, which offer significantly higher pay in later years that is no longer guaranteed. Part of the decline can also be attributed to players agreeing to lower compensation in order to play on a team that is competing for the championship. This effect on compensation was also greater than the impact on player performance. (McIntyre, 2017) The same conclusions were reached by Duberstein (2002), who found that players who signed a contract with a new team received, on average, a 10 percent lower salary increase than if they extended their contract with their existing team, but received higher signing bonuses.

The longevity of a player is also a very important factor in determining player compensation. McIntyre (2017) found that each year of player experience contributes to a salary increase of over 60 percent. However, the main reason for this is the minimum salary scale, which increases with player experience, as explained in section 1.1.1. Another study found a positive effect of player longevity on earnings, but by including the quadratic term of games played, a quadratic relationship was found. The positive impact lasted until the 175th game, which corresponds to the 11th season, after which longevity has a negative impact on earnings. (Soebbing et al., 2022) Quite short careers also have a drastic impact on earnings, with an average career length of 3.3 years across all positions and 2.81 years for the wide receiver position. (Statista, 2018) This means that most players were never able to sign a free agent contract, but ended their careers under rookie or undrafted free agent contracts, which have strict salary restrictions.

The number of games started also has an impact on compensation. A study that examined the impact of durability, expressed by the number of games started, on NFL players' salaries found some evidence that durability has some positive impact on player compensation. (McIntyre, 2017) Another study came to the same conclusion that durability has a positive impact on career earnings when looking at the number of games played per season. (Ducking et al., 2014) Durability is particularly important because it allows the player not to miss games and to participate in more snaps per game.

The salaries of players entering the NFL are entirely dependent on their draft selection number, as compensation for a rookie contract is strictly defined in the collective bargaining agreement, as explained in section 1.1.3. However, one study that examined discrimination found some evidence of the influence of a player's draft position on the subsequent veteran contract the player signs. The variable used was draft selection number, with undrafted players designated as one digit higher than the last drafted player in a given NFL draft. (Ducking et al., 2014) Another study that examined the impact of NFL players' off-field behaviour found that undrafted players had significantly lower career earnings compared to drafted players, and among the 50 percent with the highest career earnings, a better draft position also contributed to the highest career earnings. (Soebbing et al., 2022) In addition, Borghesi (2008) found evidence of the impact of draft position on player salaries. The rationale for the importance of draft selection in veteran player salaries was attributed to the sunk cost fallacy, whereby general managers overvalue players selected early in the draft, especially if it was they themselves who drafted them. (Keefer, 2017) The overvaluation of first-round picks was also found in trade compensation, as teams gave up more value in exchange for first-round picks. (Massey & Thaler, 2013)

As described in section 1.1.6, some recognised player awards can be part of the incentive system for players. In particular, Pro Bowl selections, which are voted on by players, coaches, media representatives and fans, have been studied in the context of career earnings. Borghesi (2008) found that Pro Bowl selection had no impact on wide receivers' salaries, but it contributed significantly to quarterbacks' earnings. Another study concluded that Pro Bowl selection contributed to higher salaries and more than 15 percent of the conditional distribution of career earnings. (Soebbing et al., 2022) The number of Pro Bowl selections has also been used as a measure of player talent in evaluating NFL coaches. (Allen & Chadwick, 2012)

A study predicting the future of signing free agent wide receivers found that there is a preference for signing slot receivers, i.e. wide receivers who are primarily used at the slot position and also tend to be paid more. (Mulholland & Jensen, 2018)

There are strict rules of the game in the NFL. For the wide receiver position, this usually refers to physical contact between the cornerback covering him. This is because he is not allowed to hold him or push him to gain an advantage before, he catches a ball. These are discretionary penalties as the referees have the discretion to decide to what extent this is allowed or not. Snyder and Lopez (2015) found that there is a clear correlation between penalties called and the timing of the game, as there are significantly fewer penalties called at the beginning and end of the game than in the middle of the game. Although there is some discretion when a penalty is called, players can adjust their play to minimise offences.

There are some studies on the impact of the introduction of a salary cap on compensation in the NFL. (Leeds & Kowalewski, 2001) However, the impact of raising the salary cap in the NFL on player salaries has not been studied.

One of the primary tasks of the wide receiver is to catch the ball thrown in his direction, because if he does not, it has a negative effect on the team's offensive possession. This was also expressed by Treme & Allen (2009) when they evaluated wide receivers in relation to their draft status and their success in the NFL.

Since the number of active players tends to decrease with age and the frequency of injuries tends to increase, age may have an important influence on player compensation. Kim (2015) examined the importance of the age of entry and found that entering the NFL at a younger age has benefits for having a higher probability of success in the NFL. Patel (2020) examined the impact of age and position when signing NFL free agents and found no evidence of the impact of age on salary, however, a player's age drastically impacted contract length.

Although most of the literature discussed has used various strategies to evaluate player performance, they have primely focused on performance statistics, as opposed to skills and efficiency, which are more readily available today than in the past.

1.3 Hypotesis formulation

Since the labour market in the NFL has some peculiarities that prevent players from freely negotiating new contracts with other teams, if they are part of a team, they can only sign an extension with an existing team. In addition, teams can use tender contracts to extend the player's contract and prevent the player from going into Free Agency. This creates a unique market situation where the best-talented players are rarely available on the market as existing teams do everything in their power to keep the player. Furthermore, since contracts are not fully guaranteed, teams can simply waive the player if he does not perform as expected due to the salary cap or player limit. From this, I formed hypothesis 1 about the impact of switching teams with a new contract on the average annual salary premium for wide receivers in the NFL.

Hypothesis 1: Wide receivers in the NFL who sign a new contract with their existing team earn more than those who do not.

H_0: $\beta_{\text{team change}} = 0$

H_1: $\beta_{\text{team change}} > 0$

Since wide receivers line up in different spots on the field, they can line up as close to the sideline as possible on either side, which is the split end and flanker formation, or they can line up closer to the offensive line, which is called the slot position. (Sobleski, 2019) The formation affects the possible route options, as slot receivers tend to focus on the shorter passes in the middle of the field, while receivers in the split end and flanker formation focus on the farther downfield sides of the field. Mulholland and Jensen (2018) point out that there is a bias for signing free agent wide receivers who focus on the slot position. However, the contribution of wide receivers who focus on wide formations such as split ends and flankers is greater simply because their play can have a greater impact on the team's success than that of receivers who focus on the slot position. It is important to note, however, that although receivers focus on either the slot or wide formation, they will line up in both formations. This leads to the following hypothesis on the influence of the position at which a wide receiver is lined up on his average annual pay above the minimum salary.

Hypothesis 2: Wide receivers who focus on the wide formations are paid better than receivers who focus on the slot formation.

H_0: $\beta_{\text{slot rate}} = 0$

H_1: $\beta_{\text{slot rate}} < 0$

The salary cap determines the maximum amount of money a team can provide to players. Even if there are discrepancies between the team's cash payments to its players and the salary cap, any cash payment made by the team to its players will ultimately count against the salary cap in later years. These discrepancies may result from the proration of signing bonuses or the dead cap resulting from guaranteed obligations to players who are no longer with the team. In addition, there is also 90 percent of the salary cap minimum that the team must allocate to players. This results in the following hypothesis 3:

Hypothesis 3: An increase in the salary cap has a positive effect on the average annual compensation of wide receivers above the minimum salary.

H_0: $\beta_{\text{salary cap}} = 0$

H_1: $\beta_{\text{salary cap}} > 0$

McIntyre (2017) concluded that the longevity of a player's career in the NFL has a positive impact on his salary, a high percentage of which can be attributed to the minimum salary introduced with the last collective bargaining agreement. Players with a longer career have a higher minimum salary, which can be more than double compared to players with no experience. When taking into account the impact of the minimum salary on player salaries and examining how a player's experience affects his salary, its impact is not clear. This led to the creation of the hypothesis:

Hypothesis 4: The longevity of a wide receiver has a negative impact on his salary premium.

H_0: $\beta_{\text{credited seasons}} = 0$

H_1: $\beta_{\text{credited seasons}} < 0$

An important difference in NFL players' salaries is the fact that most veterans' contracts are not fully guaranteed. Therefore, if a player misses a game, he may not receive his compensation and the team may waive him and not be obligated to pay the remainder of his contract value. Teams may be more reluctant to guarantee a larger portion of the contract if a player has missed games for any reason, such as injury, personal or suspension.

Hypothesis 5: The availability of a wide receiver has a positive impact on the value of guaranteed salary at signing.

H_0: $\beta_{\text{games played (1y)}} = 0$

H_1: $\beta_{\text{games played (1y)}} > 0$

1.4 Tobit model

The Tobit model has been used in a variety of disciplines, including dentistry, medical research and economics. It is usually referred to as a censored regression model to account for the left and/or right censoring of the dependent variable. Many response variables in economics and other social sciences have lower or upper thresholds. In the social sciences, the number of hours worked is zero for women who do not want to work and positive for others. Another example is the demand for tickets to an event which is limited by the capacity of the venue. Finally, household expenditure on some durable goods is zero for some families and positive for others, depending on other factors. In this case, a linear model is likely to give negative predictions because the distribution is highly skewed, and some frequencies are much larger than others. For household expenditure on some durable goods, the most frequent value is zero and other positive variables resemble the Gaussian distribution. Using the natural logarithm is not practical because so many observations are zero. The linear model can give adequate results with useful approximations near the mean of the dependent variable, but when the approximations approach zero or some other limit that the dependent variable cannot cross, the linear model provides inaccurate estimations. For example, negative consumption or ticket sales above capacity. The first regression model with limited response data was studied by Tobin (1958). Since then, these models have been referred to as Tobit regression models. These models are explicitly designed to take into account the corner solutions of the dependent variable. (Geng & Koul, 2017; Szczesny & Valentincic, 2013; Wooldridge, 2016, pp. 536–543)

1.4.1 Derivation of Tobit model

The Tobit model predicts the latent variable y*, which corresponds to the classical linear model that assumes a normal, homoscedastic distribution with a linear conditional mean. As shown in equation (1), it has the intercept β_0 and the coefficients β_i for each corresponding independent variable. In addition, there is an error term ε that follows a normal Gaussian distribution. (Greene, 2003, pp. 764–766; Gujarati, Porter & Gunasekar, 2011, pp. 574–577; Wooldridge, 2016, pp. 536–543)

$$y^* = \beta_0 + x\beta + \varepsilon, \varepsilon|\mathrm{x} \sim \mathrm{Normal}\ (0, \sigma^2) \tag{1}$$

The model also has a censoring method that adjusts all y* predictions to a certain upper or lower limit. Equation (2) is used in the case of the lower limit (ll), where y can be the value of the lower limit or any larger value. (Wooldridge, 2016, p. 537)

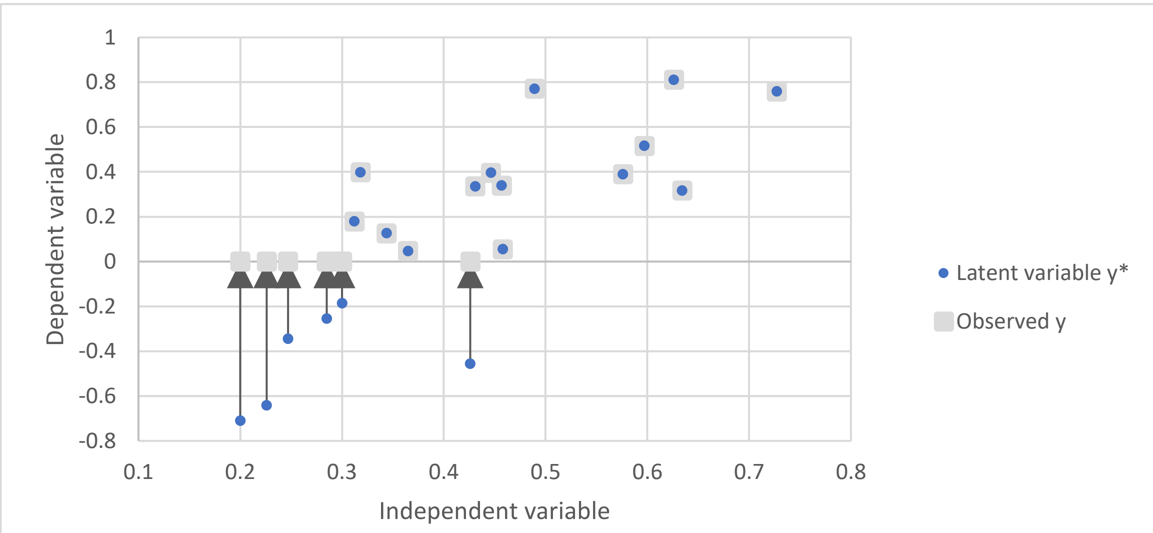
$$y = \max(ll, y^*) \tag{2}$$

The Tobit model also considers the upper limit (ul) and censors all predicted values above the limit to the limit itself. The y can be any value below the limit or the limit itself.

$$y = \min\ (\mathrm{ul}, y^*) \tag{3}$$

When censoring, the Tobit model adjusts its estimates to the given criteria. In the case of a lower limit of 0, all latent variables y* are adjusted to the lower limit so that the output of the model, the observed y, matches the censoring criteria. This censoring effect is shown in Figure 1. All positive latent variables remain unchanged, but those that do not meet the lower bound criteria are censored and observed as 0.

Figure 1: The censoring effect in the Tobit model with the lower limit of 0



Source: Own work.

In the Tobit model with left-sensed data, that is the data with a lower limit the distribution of the observed variable y as a function of x is exactly the same as that of the latent variable y* as a function of x if y* is above the lower bound. This is shown in equation (4). By substituting equation (1) into y* and assuming that the intercept β_0 lies within x, and rearranging the equation to isolate the ε by transferring the xβ to the other side of the equation, gives the following simplification: (Wooldridge, 2016, p. 539)

$$P(y = y_i|\mathrm{x}) = \mathrm{P}(y^* < y_i|x) = P(\varepsilon < y_i - x\beta|\mathrm{x}) \tag{4}$$

Since the ε is normally distributed, the two ends of the equation can be divided by the standard deviation σ. This gives the cumulative standard normal distribution function, denoted by the capital letter phi (Φ). (Wooldridge, 2016, p. 539)

$$P\left(\frac{\varepsilon}{\sigma} < \frac{(ll - x\beta|\mathrm{x})}{\sigma}\right) = \Phi\,\frac{y_i + x\beta}{\sigma} \tag{5}$$

By deriving the initial equation (4) with the latent variable y_i and considering the final value of equation (5), we now obtain the standard normal density function, denoted by phi (ϕ) in lower case. (Wooldridge, 2010, p. 525)

$$\frac{\partial \mathrm{P}(y^* < y_i|x)}{\partial y_i} = \phi\left(\frac{y_i - x\beta}{\sigma}\right)\frac{1}{\sigma} \tag{6}$$

The Tobit model is a maximum likelihood-based model that examines the distributional probability between certain conditions. Because it censors some values, it looks at the values differently when they are at the censoring point, where the values are not normally distributed, and above the censoring point, where it is considered a classical linear regression. This difference is expressed in equation (7), where three different ranges are given. In the first row, if y_i is less than the censoring value (c), the probability is zero because the left censoring model is assumed and y_i is always replaced by the censoring value. If y_i is equal to c, the normal distribution is not assumed, so the result from equation (5) is used. Considering the probability that y_i is greater than c, one can use the simplification of equation (6) because of the normal distribution. (Greene, 2003, p. 764)

$$f(y_i|\mathrm{x}) = \begin{cases} 0, & if\ y_i < c \\ 1 - \Phi\,\frac{y_i + x\beta}{\sigma}, & if\ y_i = c \\ \phi\left(\frac{y_i - x\beta}{\sigma}\right)\frac{1}{\sigma}, & if\ y_i > c \end{cases} \tag{7}$$

The probability of selection between being censored and not being censored is the core of the Tobit model. The equation is structured with the dummy variable d_i with values zero and one, which is simply a way of distinguishing between censored and uncensored variables. In equation (8), the positive value d_i refers to the case where the value is not censored, which cancels the second part of the equation. On the other hand, if d_i is zero, the value is censored, and the first part of the equation is cancelled. In this case, y_i is equal to the censored value can be denoted as c, as opposed to y_i.(Wooldridge, 2010, pp. 525–527)

$$L_i = \prod_{i=1}^{n}\left\{\left[\phi\left(\frac{y_i - x\beta}{\sigma}\right)\frac{1}{\sigma}\right]^{d_i} * \left[1 - \Phi\frac{y_i + x\beta}{\sigma}\right]^{(1-d_i)}\right\} \quad (8)$$

Since the Tobit model is a maximum likelihood model, it requires the use of log functions. To convert equation (8) into the log-likelihood function, a standard logarithm is used, although a natural logarithm can also be used. This means that the dummy variable is no longer in the exponent, but is just the multiplication and the different terms for censored and uncensored values are now added instead of multiplied. This derivation is shown in equation (9). This equation is maximised in terms of both slope (β) and standard deviation (σ). The probability model takes into account both possible outcomes, the censored and the uncensored value. (Wooldridge, 2010, pp. 525–527)

$$\log L(\beta, \sigma) = \sum_{i=1}^{N}\left\{d_i log\left[\frac{1}{\sigma}\phi\left(\frac{y_i - x\beta}{\sigma}\right)\right] + (1 - d_i)\, log\left[\Phi\frac{y_i - x\beta}{\sigma}\right]\right\} \quad (9)$$

The expected values of the Tobit model are based on the two subsets. First, if the latent variable y* is greater than the censoring value, the expected value follows the classical regression equation variable times coefficient. However, when y* is less than the censoring point, the expected value is determined as shown in equation (11). This equation involves a simplification of lambda (λ), the inverse Mills ratio, which is the probability of being uncensored multiplied by the expected value of y when y* is uncensored. The inverse Mills ratio is shown in equation (10). (Greene, 2003, p. 764)

$$\lambda\left(\frac{x\beta}{\sigma}\right) = \frac{\phi\left(\frac{x\beta}{\sigma}\right)}{\Phi\left(\frac{x\beta}{\sigma}\right)} \quad (10)$$

$$\mathrm{E}(y|\mathrm{x}) = \Phi\left(\frac{x\beta}{\sigma}\right)\left[x\beta + \sigma\lambda\left(\frac{x\beta}{\sigma}\right)\right] \quad (11)$$

1.4.2 Interpreting the Tobit estimates

The results of the Tobit model and classical linear regression are generally similar, but their interpretation is not exactly the same. First of all, the Tobit model outcome estimates are y, but the latent variable y* is not observed, even though the β-coefficients measure the partial effect of x on y* given x. As shown in equation (11), to predict the estimates of the dependent variable based on the given coefficients and independent variables, an adjustment is made to the linear method for the selection probability captured by the standard normal density function (ϕ) and the cumulative standard normal distribution function (Φ) and standard deviation (σ). By multiplying the bracket in equation (11), Lamba can be omitted from the equation. For simplicity, the axis intercepts are omitted from the equation, but they are included in the x. This is expressed in equation (12). (Wooldridge, 2016, p. 542)

$$\hat{y}_i = \Phi\left(\frac{\hat{\beta}_0 + x\hat{\beta}_i}{\hat{\sigma}}\right)(\hat{\beta}_0 + x\hat{\beta}_i) + \hat{\sigma}\phi\left(\frac{\hat{\beta}_0 + x\hat{\beta}_i}{\hat{\sigma}}\right) \tag{12}$$

Unlike linear regression, R-squared is not the squared correlation between the y_i and the fitted values, but only a squared correlation between y_i and $\hat{y}$ which takes into account the probability of being censored or not. This has the advantage that it is always between zero and one. The discrepancy is due to the fact that the Tobit model is not linear. Should the data set be suitable for the Tobit model, it only results in a slightly higher R-squared than the linear regression. This is because the Tobit model maximises the log-likelihood function, unlike the R-squared in the linear model. (Wooldridge, 2016, p. 543)

The Tobit model provides three conditional means described by the independent variables. The conditional mean of the latent variable y*, the mean of the observed values when the value is not censored $y|(y > c)$ and the mean of the observed values y. The conditional mean of the latent variable is derived from the coefficients in the model. There is no agreement on which conditional mean values should be reported and much depends on the objective of the analysis. Assuming that the data are always censored, focusing on the latent variable is not very useful. If the model is used to investigate the corner solution, the latent variable also does not provide interesting insights. The conditional mean of the observed dependent variable provides the most information because it takes into account both censored and uncensored values. The advantage is also a non-negative result. The mean of the observed values conditional on the value being uncensored is probably all we need to look at if we are only interested in the uncensored observations. The estimate of the variance of the residuals is not usually presented, although all conditional means can be derived from knowledge of the estimated regression coefficients and the variance of the residuals. (Brown & Dunn, 2011)

In addition to conditional means, the Tobit models also provide estimates of marginal effects. The most obvious of these is the expressed coefficient β, which expresses the marginal effect on the latent variable. This reported value may not be the most valuable information in many studies, as the censored observations tend to be considered an artefact by this measure. The marginal effect on the expected value y given coefficient is uncensored is the most complex marginal effect observed in equation (13). It subtracts all the effects of the censoring process already included in the β-coefficients by adjusting with the normal density function (ϕ) and the standard cumulative normal distribution function (Φ) as well as the standard deviation (σ) to account for the possible selection bias, as the training variables may not be a random subset of the population. (Gibson, 2019)

$$\frac{\partial E(y|y>c)}{\partial x_i} = \hat{\beta}_i \left\{1 - \lambda\left(\frac{x\beta}{\sigma}\right)\left[\left(\frac{\hat{\beta}_0 + x\hat{\beta}_i}{\hat{\sigma}}\right) + \lambda\left(\frac{x\beta}{\sigma}\right)\right]\right\} \tag{13}$$

The third marginal effect is based on the unconditional expected value of the observed value to the changes in the independent value, which can either be censored or not. It takes into account both the probability of being above the censoring point and the expected value of being above the censoring point. It is adjusted for the proportion of observations that are not censored, which corresponds to the solution in equation (5). In this way, the censoring effect is adjusted if the latent variable is below the censoring value observed in equation (14). This procedure tends to provide the most comprehensive information, as it takes into account both censored and uncensored information. When forecasting the revenue from an additional tax on a particular product, this third marginal effect should be used. This is because what matters is not how many people consume the product or how much each individual consumes on average, but the overall effect. (Gibson, 2019)

$$\frac{\partial E(y)}{\partial x_i} = = \Phi\left(\frac{y_i + \widehat{\beta}_0 + x\widehat{\beta}_i}{\widehat{\sigma}}\right)\hat{\beta}_i \tag{14}$$

It is possible to evaluate and determine the effects of exposure on the latent dependent variable using the coefficient provided by the Tobit model. However, the overall effects of exposure are not directly assessed in the model, even though they may be substitutionally different. This may lead to inappropriate interpretations and the magnitude of the exposure effect. Therefore, it is often more relevant, informative and understandable to describe the effects of exposure based on the original response variable rather than the latent response variable. This could be addressed by assessing the marginal effects of Tobit models by decomposing the total changes in the censored outcome into changes in the probability of obtaining uncensored values and changes in the uncensored values themselves. However, if the Tobit model contains baseline covariates, the applicability of this strategy is limited. (Wang & Griswold, 2017)

1.4.3 Problems with the Tobit models

The most common censoring value in the Tobit models is zero. But zero as an input variable can have different meanings. True zeros represent observed data points and indicate selection without expenditure or investment. In this case, the Tobit model does not introduce selection bias, but in the case of zeros representing missing variables, selection bias may occur. In addition, the problem may also be due to concerns about misleading assumptions about the nature of the censoring values. There are concerns about the sensitivity of data collection and what threshold a value must exceed to avoid a censoring point. In some data sheets, the very small deviations from the censoring point can be rounded to the censoring point, which leads to the selection process of whether to censor or not being assumed incorrectly in the model. Although this is more of a problem of understanding the data used, it is very important. Based on a review of leading management journals from 1980 to 2015 by Amore and Murtinu (2021), they found that about 47 percent of articles using the Tobit model contained potentially incorrect assumptions about the properties of the censoring values.

Another problem with Tobit models is the violation of normality and homoscedasticity in the distribution of the residuals, especially in small samples. This can lead to misleading standard errors. In the absence of a robust version of the Tobit model, the problem can be mitigated by adding dummy variables of the homogeneous groups into the model or bootstrapping the standard errors to solve the problem of heteroskedasticity. In addition, normality must also be taken into account. A first check can be done by visually examining the residual distribution. Even if they are not normally distributed. If they follow a log-normal distribution, using the log-dependent value can be a possible solution. However, if the violation of normality and homoscedasticity of the distribution is a problem, the use of the censored least absolute deviation estimators might be an appropriate choice. (Amore & Murtinu, 2021; Wooldridge, 2010, p. 530)

If the data set contains many zeros, the Tobit model may not be the best option. If the marginal effects based on the unconditional expected value of the observed values on the changes in the independent values are of interest, classical linear regression can provide equally valuable approximations. This is because multiplying the Tobit coefficients by the proportion of non-limit observations in the sample can lead to exaggerated marginal effects depending on the proportion of non-limit observations. As an example, consider how changes in subsidies for a particular product affect demand. Since consumers can either buy the product in different quantities, some customers choose not to buy it at all. Even though the Tobit model was designed for such situations, it may not be able to provide more detailed information about the changes in demand in addition to the marginal effects of price changes on demand. This could be modelled separately, but simple linear regression could also provide the same insights. (Gibson, 2019)

The Tobit model provides adequate estimates of partial effects with moderate deviations from normality and homoscedasticity, but is much more affected by the problems arising from the violation of assumptions than the classical linear model. Models with more general assumptions are possible, but their increased complexity leads to difficulties in their estimation and interpretation. Another problem with the model is that the expected value of the model is closely related to the probability that the value will not be censored if the value is not censored. Similarly, the effect of the independent variable is proportional to its coefficient on both the probability that the dependent variable will not be censored given the independent variable and the effect of the dependent variable on the expected value of the model when the value is not censored. This link between the likelihood and the expected value limits the possible use cases of the Tobit model. For example, it is not suitable for studying life insurance coverage and a person's age, since the probability of having life insurance tends to increase with age, but the amount of insurance coverage, if the person has life insurance, tends to decrease with age. (Wooldridge, 2016, p. 603,604)

Although Tobit models are suitable for censored dependent variables whose uncensored distribution is continuous, they can be problematic for discrete dependent variables.

1.4.4 Extensions of the Tobit regression theory

The Tobit model described in the previous section is a type I Tobit model because there is only one latent variable. However, the theory of Tobit models has extended this by increasing the number of latent and observed variables in the model. The type II Tobit models add an additional latent variable that allows the selection process and outcome to be independent of each other but dependent on the observed variable. An example of such a model is the Heckman selection model. This model adds a selection dummy variable to the equation and the new coefficient for the selection process, which has similarities to the first step of the probit selection model. The result is then used in the regression equation of the second step. This model allows testing and correcting for bias in non-random missing data in outcome measures. The key insight of the Heckman model is that it is conceptually very likely that missing or unobserved values can affect both the outcome of the equation and the selection probability. The effect of missing values would be included in the residuals of both equations, Level 1 and Level 2. Therefore, the covariance of the error terms of both equations must be taken into account by calculating the expected value of the error term in the equation for stage 1 as a function of the independent variable used. The model also assumes bivariate normality to facilitate parameter estimation. Since this is not always the case and the transformation of the parameters can lead to difficult interpretability, some adjustments have to be made to the model. (Koné, Bonfoh, Dao, Koné & Fink, 2019)

Numerous scholars have developed dynamic Tobit models and discussed how to estimate them. Almost all of these models assume a Gaussian distribution of the underlying (uncensored) observations. The dynamics are often autoregressive or autoregressive moving average (ARMA). (Harvey & Liao, 2021) Examples include Park, Genton and Ghosh (2007) and Wang and Chan (2018), notwithstanding a paper by Allik, Miller Piovoso and Zurakowski (2016) that generalises to state-space models.

The Tobit random effects model is a regression model that takes into account both left and/or right censoring and the dependence of outcome variables within clusters. The regression coefficients in these models provide conditional interpretations of the predicted latent variable and do not provide estimates of the overall effect of exposure on the original outcome scale. These models allow covariate-adjusted inference of an exposure-related effect on the predicted latent variable, presumably adjusted for random effects. (Wang & Griswold, 2016)

Harvey and Liao (2021) have proposed models that depend on the conditional score which in turn determinates the censoring condition within the dynamic Tobit models. This is the same logic as applied by the Dynamic Conditional Score (DCS) or Generalised Autoregressive Score (GAS) models. By automatically solving the problem of weighting the censored observations, the score performs better. Even though the true model is parameter-driven, the score-driven model provides good prediction outcomes.

To estimate the goodness of fit of the Tobit model, the traditional R^2 measure cannot be used. Therefore, the pseudo R^2 measures have been developed. The most commonly used measure is the McFadden R^2, which is expressed as the ratio between the loglikelihoods of the full model and the intercept-only model. It can be interpreted similarly to the R^2 in that it represents the improvement in model fit compared to the intercept-only model. However, it only refers to the latent variable and not to the outcome estimates. In addition, this pseudo R^2 measure has been extended to make adjustments for the number of independent variables by taking into account the degrees of freedom of the model. This measure better represents the model fit and the predictive value of the dependent variable between the possible models. This is referred to as the McFadden-adjusted R^2. (Miljkovic & Orr, 2017) The McFadden R^2 measure provides a much lower goodness of fit than the R^2 of linear regression. This is particularly the case when there is a high degree of censoring. The smaller value also applies to other potential pseudo R^2 values, such as Cox-Snell or Uhler-Cragg. (Veall & Zimmermann, 1994)

The use of robust standard errors can solve some of the problems that arise from violating the core assumptions. However, if they are not violated, they can lead to less precise results. They also cannot solve the problems with small samples, especially in non-linear models. Robust standard errors are adjusted for the variability of the residuals, i.e. the difference between the observed variable and the output of the model. This adjustment is made between the variance of the model and the variance of the residuals. (Mansournia, Nazemipour, Naimi, Collins & Campbell, 2021) As an alternative to robust standard errors, the bootstrap can be used. This is a numerically intensive method of calculating the standard error based on Monte Carlo simulations with a large number of subsamples over a specified number of repetitions. (Su & Mwanakatwe, 2021)

However, the problems arising from the violation of the basic assumptions can also be addressed by other methods, for example, by selecting an appropriate model that takes into account certain violations. One such example is the Tobit regression with multiplicative heteroskedasticity, where the maximum likelihood estimate is fitted to the model. This mitigates the effects of heteroskedasticity of the error term. However, it also allows the use of robust standard errors. (Shehata, 2011)

The Bayesian Information Criterion (BIC) is one of the best known and most commonly used tools in the selection of statistical models. Especially when there are several viable models to choose from. It results from the deviance of the model in relation to the degrees of freedom and the number of variables. When using the Tobit model, the BIC focuses on the fit of the latent variables. The better model is selected by the lower value of the BIC, where the difference must be at least two to provide positive support for model selection. The strength of the evidence scale can be seen in Table 6. The BIC value provides very strong support for selecting a particular model when the difference in the BIC value is more than 10. One of the advantages of the BIC value is also the consistency of the results, because the criterion always selects the model with the correct structure. However, it may be that the actual correct model is not one of the possible candidates examined. In this case, the criterion determines the most parsimonious model that best represents the true model. (Neath & Cavanaugh, 2012)

Table 6: Strength of evidence provided by the difference in BIC values

The difference in BIC value	Evidence to favour a model
0-2	Not worth more than a bare mention
2-6	Positive
6-10	Strong
>10	Very strong

Source: Neath & Cavanaugh (2012)

The variance inflation factor (VIF) is a diagnostic tool for multicollinearity that determines the degree of collinearity of each independent variable in the model. It is derived from the R^2 of a linear regression model that uses other independent variables in the model to explain the variability of each independent variable used in the model. The degree of variability explained by other variables in the model also represents the degree of multicollinearity in the model. The VIF can take values of one or more, where one means that there is no multicollinearity between that variable and the other independent variables. A VIF value between five and ten can represent a moderate degree of multicollinearity in the model, while values above ten mean a strong multicollinearity that makes the model unreliable. (Kim, 2019)

2 EMPIRICAL ANALYSES

Unlike other sports, in American football, it is more difficult to compare the performance of players at different positions because there is no performance measure that can be applied to all positions. In basketball, for example, performance measures (e.g., points, assists, rebounds, plus-minus) can be applied to each position, although the focus of each position is different. This prevents us from directly comparing wide receivers to offensive linemen. Unlike other team sports, the performance of individual players in American football is more dependent on their teammates, which makes evaluating each player's performance even more difficult. The NFL is not a strong-link sport like basketball, but rather a weak-link sport like football. In football, a weak link in the team can easily hide a player's true abilities and value. (Hoffer & Pincin, 2019)

This study focuses on wide receivers, which are one of the so-called skilled positions in football, along with quarterbacks, running backs and tight ends. These positions differ from others in that they have possession of the ball more often. This gives them a more direct and comprehensive measure of their performance.

2.1 Methodology and model selection

The dependent variable of salary premium has a significant frequency skewness towards zero because a significant proportion of players in the NFL are paid the minimum salary. Therefore, the regression model must account for this corner solution. Since the zeros in the data are true zeros, i.e. the players are paid the minimum salary, the same variables that influence the selection process of whether or not a player is paid above the minimum salary also apply to the salary premium. When looking at the sensitivity of salary premium in the data, the smallest increase was $5000. In addition, two-year contracts were examined that only included minimum salary for the next two years. These were considered minimum salaries even if the two-year average was above the minimum salary. This led to the conclusion that the dependent variable contained true zeros representing the selection process and not missing variables. The latent variable is of little importance, but the marginal effect of the observed variable and the probability of selection are of interest.

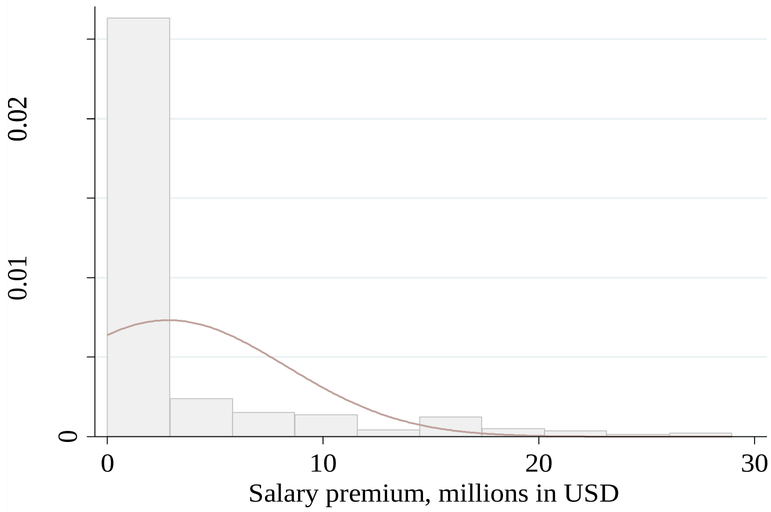
2.2 Data description

The data used in the analysis comes primarily from Pro Football Focus (PFF), an independent sports analysis company that evaluates player performance using unbiased sports metrics and focuses on American football. The company collects performance data on all players in the NFL and supplements it with its own analytics solutions. Player statistics were collected from the 2015 regular season through 2021. The contract data was collected by Spotrac, the largest online provider of professional sports contract information in the US. The data includes all contracts of players in the NFL from 2018 through August 1, 2022, whose primary role is wide receiver. The data includes total contract value, contract length, average annual contract value and player age at signing. The sample includes only veteran contracts last signed in a given season and does not include rookie contracts. Franchise or transition tender contracts are included, but if the player signed an extension in the same season as the tender, only the extension was included in the sample. NFL teams often used tenders to extend the negotiation period or to trade a player who will sign a contract extension with his new team. The minimum threshold to be included in the sample was 5 receptions in the last three seasons before signing a contract. Since the player's performance on the field has the highest descriptive power, sufficient data had to be collected.

The main dependent variable of the analysis is the salary premium. For the purposes of this thesis, I have defined this as the difference between player compensation and the corresponding minimum salary described in the collective bargaining agreements. It was calculated manually by reducing the average annual contract value by the player's minimum salary. Since the minimum salary depends on the number of credited seasons, as explained in section 1.1.1, it is specific to each player's contract. The average annual contract value is based on the reported contract value and includes incentives and bonuses that are likely to be earned, such as training and roster bonuses, but no other performance-related bonuses.

The sample includes 474 observations with an average value of $2.82 million and a standard deviation of $5.45 million. The distribution of the dependent variable is significantly skewed. Since most players are paid the minimum salary, accounting for 38.74 percent of all observations, there is a clear imbalance on the left-hand side of the distribution. This is illustrated in Figure 2. When the impact of the value 0 on the distribution is taken into account, the distribution is still significantly skewed to the left, with 54.64 percent of the population receiving less than one-tenth of the highest paid player.

Figure 2: The distribution of salary premiums in the sample



Source: Spotrac (2022a)

Since the wide receiver position is one of the position groups that has the ball more often, the availability of performance data is greater. Eighteen independent variables were used to evaluate the model fit. These include player characteristics, performance metrics and market effects, as shown in Table 7. The performance metrics include the player's production in the last three regular seasons prior to signing, as most contracts are signed in the off-season.

Table 7: The independent metrics in the model performance metrics

Player characteristics measures	**Performance metrics**	**Market effect**
Change team	Caught percentage	Salary cap
Credited seasons	First downs	
Draft	Grade pass route	
Games played (3yrs)	Interceptions	
Signed age	Pass plays	
	Penalties	
	Pro bowl selections	
	Receptions	
	Slot rate	
	Touchdowns	
	Air yards	
	Yards after the catch	

Source: own work.

2.2.1 Player characteristics measures

Five variables are examined in the category of player characteristics measures. These are player-specific traits that are not related to performance on the field. These include player characteristics such as age at signing, length of career in the NFL, draft status, and team change dummy.

First, age at signing has been shown to be an important factor in determining player salary, however, the effect of the progressive minimum salary scale is immense. Since the dependent variable only includes salary premium, the effect of the minimum salary scale is controlled for. The average age of the sample at signing is 26.71 years with a standard deviation of 2.41 years.

To account for player longevity, the variable number of credited seasons was chosen. This is a nominal number that represents the cumulative number of credited playing seasons. The player must be active in at least three games in a given season and be on the team to be credited. Members of the practice squad are not taken into account. This variable represents experience better than the total number of seasons, as it does not take into account long absences due to injury. Since this is also the criterion for setting the minimum salary, most of the impact can be attributed to this rule. The longer career length allows players to secure more veteran contracts, and if their performance does not diminish, their second veteran contract will usually come with a pay rise.

Since it is very unusual to finish a season without injury, the durability of a particular player is crucial. Durability is represented by the number of regular season games in the last seasons that the player has played. Any reason for a player's absence is taken into account. In addition to injuries, this can include suspensions and personal or other reasons for absence. As shown in Table 8, the mean value of this variable is 9.22 games with a standard deviation of 6.05 games.

A player's draft selection almost entirely determines his rookie contract, but the impact on veteran contracts is not so simple. Although the player's performance should drastically outweigh the impact of draft selection on veteran salary, some researchers have noted the impact of draft selection on salary. Accordingly, it may affect how general managers perceive the player, especially those who selected the player. (Ducking et al., 2014) The draft selection is a categorical variable that can take values from one to eight, where one represents a first-round pick and eight represents an undrafted player. There are 191 undrafted players in the sample, 48 percent of whom have signed a minimum salary contract.

The movement of players who sign a new contract is recorded with the dummy variable team change, where 0 represents a player who does not change and 1 represents a player who signs a contract with another team. If a player has signed several contracts within a year, only the one with the highest annual average is included in the model. In the case of a franchise tender followed by a trade and contract extension with the new team, the observation is counted as player movement, so both trade and signings and free agent signings count as player movement. Of the 474 total observations, 65.19 percent of players signed a contract with a new team and 69.18 percent of minimum salary contracts signed with a new team.

Table 8: Descriptive statistics of player characteristics measures

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Signed Age	26.72	2.41	21	36
Credited seasons	4.29	2.42	1	16
Games played (1y)	9.22	6.05	0	17
Draft	5.29	2.68	1	8

Source: PFF (2022)

2.2.2 Performance metrics

Performance metrics are derived from the cumulative performance data for the last three seasons prior to signing, regardless of how many of those seasons the player participated in. To account for the number of games played, they are expressed on a per game basis. They can be divided into three types. The first type of variables are those that relate to on-field contribution, such as yards and receptions. These can be either positive or negative for the team. The second category includes relative measures of catching ability and position line up rate, and the last category includes player ratings.

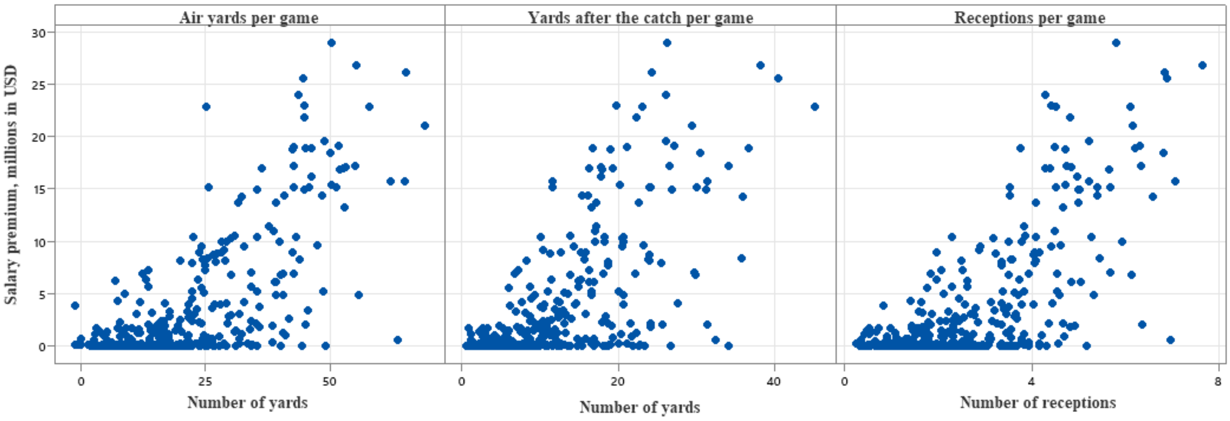
The most important metric for a wide receiver's performance is yards. They are calculated based on the distance between the line of scrimmage and the end of the play with a reception and are expressed in the unit yards (0.91 metres). A player can be brought down either by contact or by leaving the field of play. In the case of a fumble, the distance gained up to the fumble is counted towards the total yards. This is the most meaningful measure of a player's total contribution to the team. This measure is also one of the possible incentive measures allowed under the recent collective bargaining agreement. Total yards are made up of two parts. The so-called air yards take into account the distance between the line of scrimmage and the reception, and the remaining distance between the catch and the end of possession is considered yards after the catch. The passer has a significant impact on the air yards, while the yards after the catch depend more on the receiver because he can extend the play with his elusiveness or strength and gain extra yards himself. Since yards are one of the most important metrics in evaluating a wide receiver's performance, it is important to determine in what form they best fit the model. In addition to the cumulative number, you can also represent yards per game, per reception, per route run or per target. There are subtle differences between them, but all variables try to represent the same information in terms of different measures of opportunity. In this way, activity levels can be controlled, and player performance can be compared more directly. The routes run is the most comprehensive and include all targets and receptions. Targets refer to the routes on which the balls were thrown to the receiver and the balls caught also count as receptions. However, the per game metric allows for insightful comparisons between players because it both accounts for the number of chances by eliminating the impact of missed plays and does not overstate the small sample size of big plays. In addition, yards per game is the only relative measure of yards other than the cumulative value that can be part of the incentive package in the NFL contract.

Descriptive statistics are presented separately for air yards and yards after the catch. As shown in Table 9, air yards can be negative because the receiver can catch the ball behind the line of scrimmage, and represent a larger proportion of yards than yards after the catch. Surprisingly, the relative standard deviation between the different parts of the yards does not differ significantly.

The number of receptions is a basic measure of a wide receiver's performance. It was also used as a minimum measure for player contracts to be included in the sample because variables would be missing, and this also excluded all rookie and undrafted free agent contracts. The definition of catch has evolved over the years in the NFL and now requires a player to take possession of the ball with his hands or arms and both feet on the ground or any other part of his body that is completely on the ground within the field of play, other than his hands. This may include the knees or hips. After touching the ground, the player must make a football play, such as putting the ball away or taking further steps, or at least holding the position of the ball long enough to do so. (NFL, 2022a, p. 4) Similar to yards, receptions can also be expressed on a per game basis, which also provides more detail about a player's production. Receptions are a fundamental variable, meaning the observation had to have at least five receptions in the last three seasons to be included in the sample. Therefore, the variable in the sample has a minimum value of five.

As can be seen in Figure 3, both yards and receptions correlate positively with the dependent variable. Furthermore, after visual inspection, the linear model fits the data well. However, there is a significant correlation between the variables as the Pearson correlations between air yards, yards after catch and receptions are very high and significant at less than 0.1

Figure 3: Scatterplot of salary premium and air yards per game, yards after catch per game and receptions per game



Adapted from PFF (2022); Spotrac (2022a).

percent level. The outliers in the lower right corner of the receptions per game figure indicate a player who had off field issues problems off the field, and the same observation is the anomaly in both yardage figures as well.

During the offensive possession, each team is given four tries, also called downs, to gain 10 yards and get a new set of four tries. If a team fails to do so, the opposing team takes the ball in the same field position where the offense failed. The number of first downs indicates how often his play brought a new set of attempts. This is one of the fundamental goals of the offense, because if this goal is always achieved, a possession will result in points. Since the cumulative metric is used between the four attempts, a play of less than one yard could be a first down or a play of more than 10 yards could not be a first down due to penalties or lost yards in previous attempts. Each touchdown also counts as a first down. The model includes the variable first downs per game. This is the first non-categorical independent variable that can be zero, as shown in Table 9.

The most important way for a receiver to score points for his team is to score a touchdown. This is done by breaking a plane in the opponent's end zone while in possession of the ball or by making a reception in the end zone. Wide receivers can also score on a two-point conversion, but these plays are not counted in the statistics. Even though wide receivers can score a touchdown on a running play, receiving touchdowns are a better indicator of their performance. The touchdowns variable includes the cumulative number of touchdowns scored in the last three seasons before the signing. The main reason for choosing a cumulative number as opposed to a per game metric is that only the cumulative form can be part of the incentive package. Should the touchdown incentive be considered likely, i.e. scored in the previous season, it would be included in the annual average salary that forms the basis for the dependent variable. The variable has considerable variability between observations as the standard deviation is greater than the mean.

If a player makes a move that is not allowed during the game, such as holding or offensive pass interference, he receives a penalty. Interference occurs when a player receiving the ball pushes the person covering him away and gains an unfair advantage. A penalty cancels the attempted offensive play and gives the opposing team a better field position. The number of penalties per game indicates how many times the player has contributed negatively to the team's success.

Interception is a play where a defensive player catches the ball thrown by the offense. This is a disastrous play for the offense because it results in the loss of possession and a better field position for the opposing team. Although it is possible that the wide receiver is the one throwing the ball, the wide receiver's interceptions are defined as targets, balls thrown in his direction that result in an interception. Even though it is not primarily his fault, he most likely contributed to this result.

Since only the best players in a season are selected to the Pro Bowl, this award is a sign of excellence in a season. Since Pro Bowl selections are also eligible as incentives, they affect player compensation. In addition to Pro Bowl selections, All-Pro selections are even more prestigious because a smaller group is selected that consists of only three first-team players each year, but almost all of the players who are selected have also become Pro Bowlers. Therefore, the Pro Bowl selection is the better option as it includes a slightly larger group of people. Since the player's performance declines in the later part of his career, the model includes the variable number of Pro Bowl selections in the last three years. This variable has a significantly larger standard deviation relative to the mean, as more than 90 per cent of the observations were not selected to the Pro Bowl, while less than 2 percent were in the Pro Bowl in each of the last three years before signing a contract.

While the wide receiver is trying to catch the ball, he may accidentally drop the ball before gaining possession, or he may simply not catch the ball thrown in his direction. This is an undesirable play by the player as the team gains no yards for this play and loses the try. The efficiency of these tasks is measured by the catch rate. It provides information about the reliability of the wide receiver, which is crucial for the team's success. This reliability is measured by the catch rate, which is calculated by dividing the total number of receptions by the total number of targets in the last three seasons. As shown in Table 9, the maximum of this variable is one, which corresponds to a catch rate of 100 percent. However, this refers to the observation with very limited opportunities and who earn the league minimum, while the highest paid wide receivers are in the 63 to 79 percent range.

Before the start of the play, wide receivers line up in either the slot position or the wide position. In the wide position, they stand closest to the sideline, while in the slot position, they stand one position closer to the ball at the line of scrimmage. In the wide position, players tend to focus on the longer passes further down the field, while slot receivers focus on the shorter routes in the middle of the field. This distinction is important because wide receivers who take the majority of their snaps at the slot position are less likely to be extended by their current team and may earn more as a result. (Mulholland & Jensen, 2018) The position at which the receiver is lined up is measured by the variable slot rate, which is the percentage of total passing plays. It is calculated by dividing the total number of slot snaps by the total number of pass plays in the last three seasons. As can be seen in Table 9, every wide receiver was lined up at the slot position at least a few times, while no one was lined up exclusively at the slot position.

Both cumulative and relative metrics were used. By expressing the performance metrics on a per game basis, the different levels of utilisation within the game are not taken into account, as some players may receive many more chances during a game. To account for this, the quality of routes run is introduced. This can give an interesting insight into a player's contribution as it determines how often they can be a viable target. For a receiver to be a target, he must be open, meaning he must have built up enough separation from defenders, otherwise the passer would not throw the ball in his direction. Therefore, the quality of the routes run is an indicator of performance that determines his use in the game.

The quality of the routes run is taken into account by the PFF rating. They rate all players and add additional information about the players' contribution to the success of the game in each individual play, as opposed to the outcome of the play. This is not reflected in other performance metrics because they do not distinguish between a perfectly placed pass and a great adjustment by the wide receiver. These ratings are based on a 100-point scale and are comparable between all position groups, unlike some similar position groups with performance metrics explained earlier. The season-level ratings are derived from the per game ratings, but are adjusted to account for consistently good performances in all games, not just a few exceptional performances. The grades either evaluate a specific part of the game, such as pass blocking or route running, or they take into account a player's overall grade in the offense during the season. The sample includes the average of the last three season grades for route running quality, which takes into account both the consistency of separation achieved and adjustments made to be in a better position to catch the ball. No wide receiver in the sample had a score of 100, and only 5 percent of wide receivers were rated above 80.

Table 9 contains all the descriptive statistics for the variables mentioned. The cumulative metrics are also expressed on a per game basis. This applies to the variables where the value per game is given in parentheses. Each value in the parenthesis refers to the per game metric. For example, the mean value of air yards is 654.91 yards and the mean value of air yards per game is 19.26 yards.

Table 9: Descriptive statistics of performance metrics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Air yards (per game)	654.91(19.26)	617.08(13.76)	-37(-1)	3174 (69)
Yards after catch (per game)	355.69 (10.36)	345.65 (7.73)	6 (0.6)	1942 (45)
Receptions (per game)	79.45 (2.33)	71.06 (1.49)	5 (0.25)	331 (7.64)
First downs (per game)	49.35 (1.48)	45.65 (1.05)	0 (0)	218(5.25)
Touchdowns (per game)	6.18 (0.18)	6.51 (0.16)	0 (0)	36 (0.83)
Pass plays (per game)	737.61 (22.63)	509.54 (9.92)	55 (5)	1979(43.6)
Penalties (per game)	3.80 (0.12)	3.72 (0.09)	0 (0)	23 (0.51)
Interceptions (per game)	3.78 (0.12)	3.59 (0.10)	0 (0)	20 (0.57)
Pro Bowl selections	0.15	0.52	0	3
Caught percentage	0.63	0.09	0.22	1
Slot rate	0.39	0.22	0.03	0.90
Grade Route	64.50	8.00	43.6	91.33

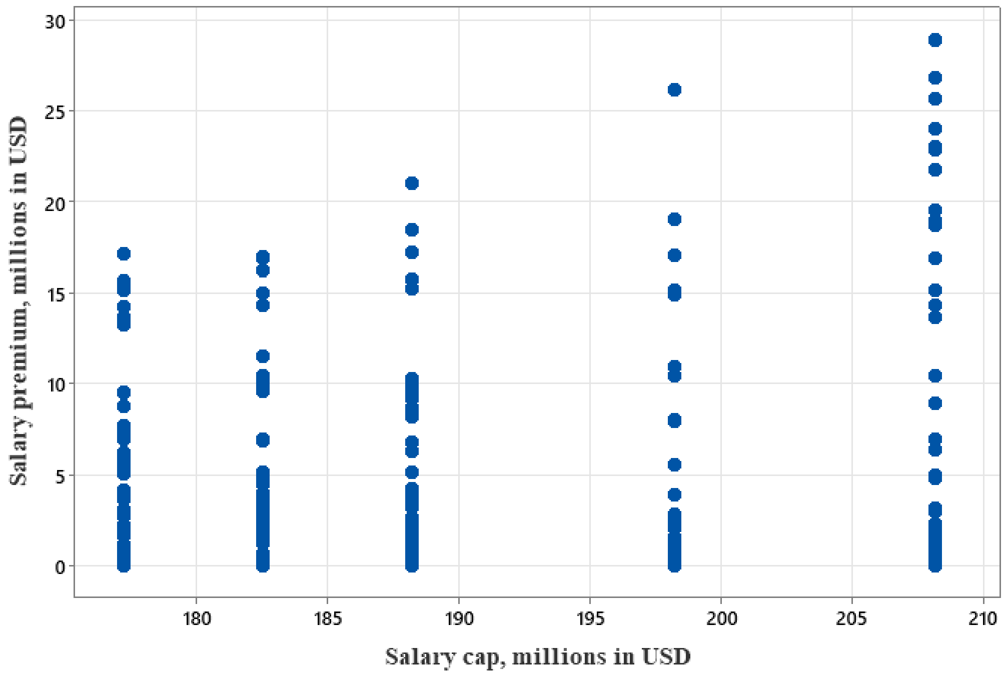
Adapted from PFF (2022); Spotrac (2022a).

2.2.3 Market effect

Over the observed period from 2018 to 2022, the average annual contract value of the highest paid wide receiver increased by more than 66 percent, and the market effect is one of the most important factors, as the best receivers tend to become the highest paid when they sign the new contract. The variables used to represent the market dynamics are both tenders, which are calculated from the average salaries of the positions from previous years, as explained in section 1.1.2. The salary cap is also very influential as it sets the maximum expenditure for an equal number of players, which increases each year in line with NFL revenues.

The variable used to represent the market effect in the model is the salary cap. It is expressed in millions of dollars and represents the cap on total spending. For more information on the salary cap, see sections 1.1.4 and 1.1.5. As can be seen in Figure 4, increases in the salary cap result in a wider spread in the salary distribution, however, more than 75 percent of the observations are still below $5 million above the minimum salary. It is important to note, however, that the minimum salary also increases each year, as shown in Table 2.

Figure 4: Scatterplot of salary premium and salary cap



Adapted from PFF (2022); Spotrac (2022a).

2.2.4 Interdependence of variables

The potential performance metrics are highly interdependent. For example, every reception yields air yards and is necessary to record yards after the catch. In addition, every first down or touchdown requires a reception and also affects yards. Good routing also leads to more receptions and thus more yards, first downs and touchdowns. This is also reflected in Table 10, which shows the bivariate Pearson correlation coefficient between the independent variables. In bold are all coefficients that are significant at a 5 percent level. The correlations of the individual game metrics are shown in parentheses. Each variable with the suffix "(per game)" in the variable name was converted from the cumulative to the per game basis and a corresponding correlation was presented. Since Pro Bowl selections, catch rate, slot rate and grade route were not converted to per game basis, the correlations between them in the parentheses did not change.

The bivariate Pearson correlation between yards and receptions is positive and very high. Furthermore, the bivariate Pearson correlation between receptions and first downs or touchdowns is also very high. This points to the problem of multicollinearity within the model. Between the primary performance metrics such as yards, pass plays, receptions, first downs, touchdowns and route grade, the strength of the bivariate Pearson correlation between each pair is at least high.

For the player characteristic measures only between the player's age and his experience, there is a very high bivariate Pearson correlation, shown in Table 11. This is to be expected, as older players have more opportunities to gain experience in the NFL and the vast majority of players enter the league as soon as they are eligible to play. There is also a high and positive correlation between the games played and touchdowns, as this metric is expressed as cumulative value and not on a per game basis.

Table 10: Pearson bivariate correlations between performance metrics

Variable	Yards (per game)	Pass plays (per game)	Receptions (per game)	First downs (per game)	Touchdowns (per game)	Penalties (per game)	Interceptions (per game)	Pro Bowl selections	Catch rate	Slot rate	Grade Route
Yards (per game)	1										
Pass plays (per game)	**0.93 (0.87)**	1									
Receptions (per game)	**0.98 (0.96)**	**0.93 (0.88)**	1								
First downs (per game)	**0.94 (0.84)**	**0.86 (0.71)**	**0.92 (0.82)**	1							
Touchdowns (per game)	**0.91 (0.85)**	**0.84 (0.74)**	**0.88 (0.81)**	**0.85 (0.7)**	1						
Penalties (per game)	**0.67 (0.48)**	**0.69 (0.51)**	**0.66 (0.45)**	**0.65 (0.45)**	**0.64 (0.44)**	1					
Interceptions (per game)	**0.76 (0.59)**	**0.74 (0.57)**	**0.73 (0.55)**	**0.71 (0.48)**	**0.69 (0.52)**	**0.54 (0.31)**	1				
Pro Bowl selections 3y	**0.55 (0.52)**	**0.37 (0.3)**	**0.54 (0.52)**	**0.57 (0.51)**	**0.56 (0.5)**	**0.38 (0.27)**	**0.39 (0.29)**	1			
Catch rate	**0.2 (0.16)**	**0.15** (0.02)	**0.27 (0.27)**	**0.2 (0.16)**	**0.16 (0.11)**	0.02 **(-0.09)**	-0.04 **(-0.21)**	**0.12 (0.12)**	1		
Slot rate	0.05 (-0.01)	**0.1** (0.02)	**0.14 (0.13)**	0.04 (-0.01)	0.01 (-0.02)	-0.04 **(-0.13)**	-0.04 **(-0.1)**	-0.02 (-0.02)	**0.45 (0.45)**	1	
Grade Route	**0.79 (0.82)**	**0.6 (0.53)**	**0.76 (0.78)**	**0.75 (0.69)**	**0.74 (0.72)**	**0.44 (0.31)**	**0.55 (0.41)**	**0.53 (0.53)**	**0.34 (0.34)**	0.01 (0.01)	1

Adapted from PFF (2022); Spotrac (2022a).

Table 11: Pearson bivariate correlations between player characteristics and market measures

Variable	Signed Age	Credited seasons	Games played (3y)	Draft	Salary cap
Signed Age	1				
Credited seasons	**0.84**	1			
Games played (3y)	**0.31**	**0.47**	1		
Draft	**-0.15**	**-0.40**	**-0.32**	1	
Salary cap	**-0.02**	-0.00	0.02	**0.03**	1

Adapted from PFF (2022); Spotrac (2022a).

Bold - significant a 5 percent level

2.3 Variable selection

Table 12 contains the Tobit coefficients for possible variables included. Since these coefficients refer to the marginal effect on the latent variable, they have limited explanatory power, but their significance and direction are identical to the marginal effect on the observed variable. The variables that have a * at the end of the name were transformed on the per game basis, while the rest remained unchanged. The value of this preliminary model with potential variables is to observe how a change in performance metrics affects the significance of other variables in the model. Both yards and salary cap should be included in the model as they are highly significant in both models. Coefficients that are significant in both models also include first downs, penalties, Interceptions, Pro Bowls, Team change, games played and draft. The variables receptions and pass plays have a sign change, as the bivariate Pearson correlation coefficient between them and salary premium is positive. This can be attributed to the effect of the yards on the overall model.

Table 12: Potential Tobit coefficients on the salary premium in thousands of dollars

Group	Variable	Cumulative			Per game		
		Tobit coefficient	**t-statistic**	**Sig.**	**Tobit coefficient**	**t-statistic**	**Sig.**
Performance metrics	Air yards*	7.16	6.08	***	221.36	4.33	***
	Yards after catch*	8.52	5.41	***	237.11	3.7	***
	Receptions*	-36.24	-2.61	**	-624.98	-1	
	Pass plays*	-2.39	-1.83		-115.79	-1.79	
	First downs*	31.07	3.33	**	823.17	2.55	*
	Touchdowns*	103.15	1.86		3,839.14	1.76	
	Penalties*	-158.49	-2.8	**	-5,746.09	-2.4	*
	Interceptions*	-198.3	-2.96	**	-6,996.65	-2.63	**
	Pro Bowls (3s)	973.87	2.43	*	1,817.45	4.2	***
	Catch rate	-2,993.66	-1.25		-4,781.93	-1.61	
	Slot rate	1,213.97	1.33		2,151.86	2.02	*
	Grade Route	61.69	1.4		118.66	2.01	*
Player characteristics measures	Signed Age	15.07	0.11		1.35	0.01	
	Team change	-761.64	-2.23	*	-905.91	-2.28	*
	Credited seasons	-349.53	-2.19	*	-317.75	-1.72	
	Games played (1s)	156.08	4.66	***	290.09	8	***
	Draft	-242.16	-3.26	**	-366.99	-4.22	***
Market	Salary cap	25.51	1.83	***	29.02	1.78	***

Adapted from PFF (2022); Spotrac (2022a).

2.4 Simple model

Since the potential model in Table 13 contains many multicollinearities between the independent variables, most of the variability explained by the model can be explained by a simpler model. The most informative variable is yards, because a model containing only cumulative yards explains more than 74 percent of the variability of the salary premium. However, cumulative yards is a variable that accounts for both efficiency and playing time. To better determine the effect of yards, we divide them into air yards and yards after catch. However, the explanatory value of the model does not change. When we run an individual regression with each part of the yards, the air yards explain a larger part of the variability. To show the yards variable in more detail, it was also expressed on a per game and the number of games played was also added. This includes the data from the three years prior to the signing. This provides a better representation of the player's performance and availability. However, this model with a divided yards variable does not provide better explanatory value than the original model with only yards as an independent variable.

By selecting cumulative yards as the only performance measure and adding all player characteristics, apart from age at signing and games played, there is a very high correlation with the independent variables. Including the market effect, the observed variable of the model can explain 80 precent of the variability in salaries above the minimum salary. This results from squaring the bivariate Pearson correlation coefficient between the salary premium and the observed variable, calculated according to equation (12). Table 13 presents the marginal effects at the means, which provide more detail on the impact of each variable on the dependent variable. This simple model states that for a one unit increase in yards, the expected change in salary premium is 3.986, expressed in thousands of dollars. However, if an average wide receiver in the NFL given that he makes more than the minimum salary gains an additional yard, the expected increase in salary premium is 2.795, expressed in thousands of dollars. This means that the effect of yards is smaller for the uncensored part of the observations. For a player earning the minimum salary, additional yards lead to a higher expected increase in salary premium than for a player earning more. When estimating the effect of a one unit increase in yards for the 'average wide receiver', the probability that the observation is uncensored increases by 0.00066. That is, the more yards a wide receiver has gained in the last three seasons, the higher the probability that he earns more than the minimum salary. Surprisingly, the expected change in the dependent variable for each variable is larger in the unconditional observation than in the conditional on being censored. The effect of switching teams is also dramatic, as the average wide receiver who switched teams is 11.89 percent less likely to earn more than the minimum salary. An increase in experience as a wide receiver also leads to a lower expected salary premium, assuming other variables are constant.

Table 13: Simple Tobit model and marginal effects at means of salary premium in thousands of dollars

Variable	Tobit coefficient	Unconditional expected value	Conditional on being Uncensored	Probability of Being Uncensored
Yards	6.148 ***	3.986	2.795	0.00066
Change team	-1,138.264 **	-758.077	-532.783	-0.11885
Credited seasons	-382.496 ***	-248.005	-173.872	-0.0409
Draft	-197.914 **	-128.325	-89.967	-0.02116
Salary cap	45.436 **	29.46	20.654	0.00486
Constant	-10,154.161**	-6,583.827	-4,615.809	-1.08582

Adapted from PFF (2022); Spotrac (2022a).

2.5 Extended model

To better explain the factors that influence salary premium for wide receivers in the NFL, additional variables were added to the model. First, yards were split into the air yards and yards after the catch. However, this only led to multicollinearity and had no additional explanatory value. To solve this problem as well, the variables were expressed in different formats per game or per play basis, but this led to worse results. Therefore, the cumulative yards remained in the model. Penalties and interceptions were each removed from the model individually, resulting in the BIC value providing positive evidence for both variables remaining in the model. A slight decrease in McFadden's adjusted R^2 also supported their inclusion. The interception variable made a slightly larger contribution than penalties, but also had a higher correlation with yards than penalties. A per game metric was also tested for these variables, but this only resulted in a lower predictive value of the model.

The receptions variable in the model introduces an additional level of performance efficiency because cumulative yards are controlled by the same number of chances. However, the variable had a negative coefficient in the model, even though Pearson's bivariate correlation coefficient with the dependent variable is positive. This could indicate a multicollinearity problem with the independent variables, which was confirmed by the VIF, and was therefore not included in the model. The other alternatives included targets, route runs and wide snaps. None of these alternatives resulted in a noticeable improvement in the additional correlation with the independent variables, particularly yards. Pass plays represented a good alternative, especially in the per game form. The BIC criteria with a difference of 20 provided very strong support to include it in the model. However, it contained a sign change that could indicate strong multicollinearity problems. The VIF measure suggests that multicollinearity is not severe, especially in relation to the variable grade route, which introduced more multicollinearity into the model. The variable interceptions was re-examined. Although the coefficient was significant, the BIC provided only weak support for the inclusion of this variable in the model while improving multicollinearity in the model, so it was removed from the model.

To introduce the relative performance measures, the possibility of including yards per reception, target, route run, and pass play was explored. The latter provided the best fit for the model, however, the grading route proved to be a better variable than any of the relative variables derived from yards as the model fit decreased.

Other available performance variables included first downs and touchdowns. Including these variables in the model did not significantly improve model fit while causing serious multicollinearity problems, so they were not included. Both cumulative metrics and metrics per game were used, with cumulative metrics proving to be the better option, while the coefficient for touchdowns per game was not significant at the 5 percent level.

In addition, an attempt was made to include the players' ability to catch the ball in the model. In addition, to catch rate, drop rate and grade hands were also examined. An initial examination of the variables in Table 12 showed that the catch rate was not statistically significant. However, when the variable was added to the model in Table 14 before pass plays were included, it became significant at the 5 percent level, but the coefficient was negative. This is counterintuitive. A higher catch rate for the same number of yards gained suggests fewer wasted attempts, but this result would suggest the opposite. To get more detail about the catch rate, receptions or pass plays were added to the model. This made the catch rate no longer significant. One possible explanation for the catch rate variable being significant in one model and not the other is that fewer longer completions were more valuable to the team than shorter completions that produced the same cumulative yards. To test this, the variable average depth of target, i.e. the average distance between the passer and the wide receiver, was included in the model, but the variable was not significant. Other variables indicative of catching ability were tested and how they would affect the model. These include grade hands, a detailed evaluation variable by PFF that has more significance because each attempt is examined individually for the degree of difficulty, and drop rate, which refers to the percentage of incompletions on catchable passes and missed receptions per game. However, neither variable became significant when included in the model in Table 14.

Availability in the model was measured by the games played variable, which refers to the number of games played in the last three seasons. However, after the inclusion of the pass plays per game variable, this variable no longer became significant. Therefore, games played with only one year lag were introduced. Both the BIC and McFadden's adjusted R^2 supported the inclusion of the variable in the model, and the Tobit Multiplicative Heteroscedasticity Regression performed better when the variable was included. An alternative to games played was also explored. The percentage of games played was not significant.

Transition and franchise tender were also possible alternatives to the salary cap. While the salary cap was more significant than the franchise tender, the transition tender slightly improved the model, but the theoretical background better supports the salary cap, which is why it was selected.

The draft selection number, where undrafted players were designated as a pick later than the last, was added to the model. This did not significantly change the model compared to the draft round, which was determined by the draft variable. A possible combination with the undrafted player dummy variable was also explored, but both variables were not significant when used together. As an alternative, a combination of three dummy variables was tested: 1-3rd round, 3-7 round and undrafted. Only the dummy variable for the 1st-3rd round selection was significant. Used individually, it showed no difference from the draft variable.

Originally, a number of selections for the Pro Bowl were included in the model. However, in order to account for the more recent selections, a variable was tested that only considered the last three seasons. The recent Pro Bowl selections contributed to the better model, as both the BIC and McFadden's adjusted R2 provided strong support. Since the Pro Bowl selections are predominantly performance-based, there is a correlation with yards. For this reason, a dummy was also tested for selections in the last three years, as the correlation is lower, but the Tobit Multiplicative Heteroscedasticity Regression with the dummy variable provided a worse model.

Table 14 shows the Tobi regression coefficient and the marginal effect at the means for the selected variables. Of the performance metrics, Pro Bowl selections, pass plays per game, and penalties were included along with yards. A slot rate was also added to test the hypothesis. Of the non-performance metrics in Table 13, only signed age was excluded.

2.5.1 Interpretation of marginal coefficients

The more comprehensive model in Table 14 gives less steep coefficients compared to the simple model, while the coefficients conditional on being uncensored also become less steep compared to the unconditional coefficients. This can be explained by the fact that once a player earns more than the minimum salary, he earns at least $5 thousand more according to the sample. The model states that if yards increase by one unit, the expected change in salary premium is 5.00, expressed in thousands of dollars, holding the other variables constant. However, if an average wide receiver in the NFL given that he makes more than the minimum salary gains one additional yard, the expected increase in salary premium is 3.51, expressed in thousands of dollars. An average wide receiver who switches teams is 9.01 percent less likely to earn more than a minimum salary. If a player is selected to the Pro Bowl one more time in the last three years, his expected salary increase above the minimum salary is $830.11 thousand. Estimating the effect of the additional penalty in the last three years of the 'average wide receiver', the probability of the wide receiver earning more than the minimum salary decreases by 0.02478.

The two performance measures yards and Pro Bowls are positive and significant at least at a 5 percent level. Although yards has the lowest coefficient value, it is the most influential variable as it differs the most between players. Surprisingly, there was a change in the sign for Passing yards per game. With each additional passing play per game, the expected salary premium decreases by $120.34 thousand, holding the other variables constant. This change in sign can be explained in terms of yards, as a player who needs more opportunities to make the same contribution to the team is less valuable. Penalties are also a performance metric with a negative coefficient, which is to be expected as they reduce the chances of winning. For each additional penalty the player receives, the expected salary of a wide receiver above the minimum salary decreases by $127.96 thousand. Compared to the simple model, the significance of the team change variable has decreased, as it is now only significant at the 5 percent level. However, it is still significant as the expected salary of wide receivers who switch teams decreases by $485.03 thousand above the minimum salary. The credited seasons variable has a negative coefficient, meaning that the expected salary premium is lower for each additional season played. The same direction of the coefficient applies to the draft variable with a significance level of less than 0.1 percent. That is, the later a player was selected in the draft or not selected at all, the lower his expected salary premium. The number of games played last season is important for wide receivers' compensation because their expected salary premium increases by $62.72 thousand for each additional game played. The coefficients for slot rate and salary cap were not significant at the 5 percent level. This means that this model found no evidence that the percentage of the lineup at the slot position and the unadjusted salary cap for the year have an impact on the salary premium for wide receivers in the NFL.

Table 14: Tobit model and marginal effects at means of salary premium in thousands of dollars

Variable	Tobit coefficient	Unconditional expected value	Conditional on being Uncensored	Probability of Being Uncensored
Yards	7.341 ***	5.001	3.512	0.00097
Pass play per game	-176.648 ***	-120.343	-84.511	-0.0233
Pro Bowl (3y)	1,218.483 ***	830.105	582.941	0.16075
Penalties	-187.822 ***	-127.956	-89.857	-0.02478
Team Change	-697.962 *	-485.026	-341.631	-0.0901
Credited seasons	-401.333 ***	-273.412	-192.004	-0.05295
Draft	-280.207 ***	-190.894	-134.055	-0.03697
Games played (1y)	92.06 **	62.717	44.043	0.01214
Slot rate	-336.932	-229.539	-161.193	-0.04445
Salary cap	12.217	8.323	5.845	0.00161
Const	-754.297	-513.873	-360.868	-0.09951

Adapted from PFF (2022); Spotrac (2022a).

2.5.2 Robustness test

The significance levels were determined using robust standard errors. When the bootstrap was used several times, the significance did not change noticeably; some iterations even improved the significance level of the coefficients.

To check whether the underlying assumptions might have been violated, a Tobit regression with multiplicative heteroskedasticity with robust standard errors was used and compared with the model in Table 13. This resulted in a reduction in the significance level of the coefficients, but all retained significance at a level of at least 5 percent. All three variables games played, draft and Credited Season lost a significance level, while penalties were only significant at a 5 percent level.

With the conditional moment test against the case of normally distributed errors, the model did not reach the 5 percent significance level, but a relatively large sample size (464 observations) and the Central Limit Theorem ensure that the residuals are approximately normally distributed. Potential multicollinearity was investigated using the VIF measure. The mean VIF value for all variables is 1.95, with the variable yards showing the greatest multicollinearity with the independent variables. If you omit the variable penalties, the mean can be even lower, but then the model fit drops significantly.

The variable salary cap can already be used as an annual control, but since the salary cap fell in 2020, dummies were tested for each year in the model. It did not matter whether the salary was retained in the model or not. All coefficients for the year were insignificant, but the coefficient for 2022 was the only one with a positive coefficient.

To test for differences between teams, dummy variables were added to the model, defined as differences between the San Francisco 49ers. Two teams paid wide receivers more for the same level of production. These are the Rams and Bengals, as their coefficients are significant at a 5 percent level, while it is significant at a 10 percent level for the Dolphins and Giants, as seen in Table 15. The model includes all 474 observations, and none were omitted to avoid bias. When the 10 outliers were removed, significantly more team coefficients became significant and every team had a positive coefficient, which can be explained by the 49ers paying their wide receivers less because their highest paid wide receivers would not be counted.

Player controls were also put in place, but the sample includes 261 different players from 464 observations, with the majority of a player represented by only one observation. Many of the dummy variables in the model became significant. They also affected other variables in the model, as the draft variable became the most significant in the model and grade route also became more important than yards, but penalties and team changes were no longer significant. Players with very significant negative coefficients at less than 0.1 percent and a t-score of less than negative fourteen include David Moore, Dez Bryant, Jakobi Meyers and James Washington. Since their coefficient is negative, there is some evidence to suggest that they received less than their expected salary, however, the sample had 10 observations with the largest residuals were removed. On the other hand, a few had a very high t-value with a significance level of less than 0.1 percent and a t-score of more than 15. These players are Christian Kirk, Davante Adams, Jamal Agnew, Kenny Golladay and Robby Anderson, who were able to sign for a higher salary than expected, although many signed in 2022.

Table 15: Tobit coefficients on salary premium in thousand USD of team controls added to the Extended model relative to the 49ers

Variable	Tobit coefficient	Robust Std. Err.	t	P>|t|
Bears	1,466.626	1,391.706	1.05	0.293
Bengals	3,727.964	1,824.106	2.04	0.042
Bills	742.0096	1,422.164	0.52	0.602
Broncos	1,880.264	2,080.094	0.9	0.367
Browns	-321.765	1,600.858	-0.2	0.841
Buccaneers	-270.8022	1,610.322	-0.17	0.867
Cardinals	1,590.967	1,504.134	1.06	0.291
Chargers	488.1925	1,694.365	0.29	0.773
Chiefs	1,422.087	1,551.28	0.92	0.36
Colts	224.1248	1,511.995	0.15	0.882
Commanders	1,760.643	1,526.989	1.15	0.25
Cowboys	1,976.304	1,487.822	1.33	0.185
Dolphins	2,515.525	1,425.176	1.77	0.078
Eagles	1,799.987	1,493.097	1.21	0.229
Falcons	-1,047.218	1,695.671	-0.62	0.537
Giants	2,307.96	1,378.613	1.67	0.095
Jaguars	2,246.244	1,564.523	1.44	0.152
Jets	1,702.337	1,490.161	1.14	0.254
Lions	971.5356	1,436.978	0.68	0.499
Packers	-921.8747	1,490.421	-0.62	0.537
Panthers	1,399.063	1,411.126	0.99	0.322
Patriots	1,377.142	1,421.415	0.97	0.333
Raiders	229.7362	1,465.275	0.16	0.875
Rams	3,260.378	1,552.944	2.1	0.036
Ravens	778.1366	1,446.488	0.54	0.591
Saints	-1,098.616	1,680.763	-0.65	0.514
Seahawks	1,678.797	1,567.711	1.07	0.285
Steelers	-708.5652	1,871.903	-0.38	0.705
Texans	1,840.164	1,482.087	1.24	0.215
Titans	-448.968	1,583.944	-0.28	0.777
Vikings	339.7582	1,753.89	0.19	0.846

Adapted from PFF (2022); Spotrac (2022a).

Controls for contract length were also introduced in relation to the average annual salary premium. The coefficients were defined as differences from a one year contract. In the sample, contract lengths range from one to five years. Each dummy coefficient is significant at the 0.1 percent level. The dummy for three years has the highest coefficient value, suggesting that three-year contracts offer wide receivers in the NFL the opportunity to earn the highest expected salary. However, when the entire sample is included, the coefficient for four years is larger, but the difference between two and three years is significantly larger than the difference between three and four years. This still argues for a three-year contract over a four-year contract.

2.5.3 Model fit with the data

To determine the model fit, the Tobit coefficients must be adjusted for the selection probability, i.e. the probability of not being censored. This adjustment includes the density function and the standard deviation as given in equation (12).

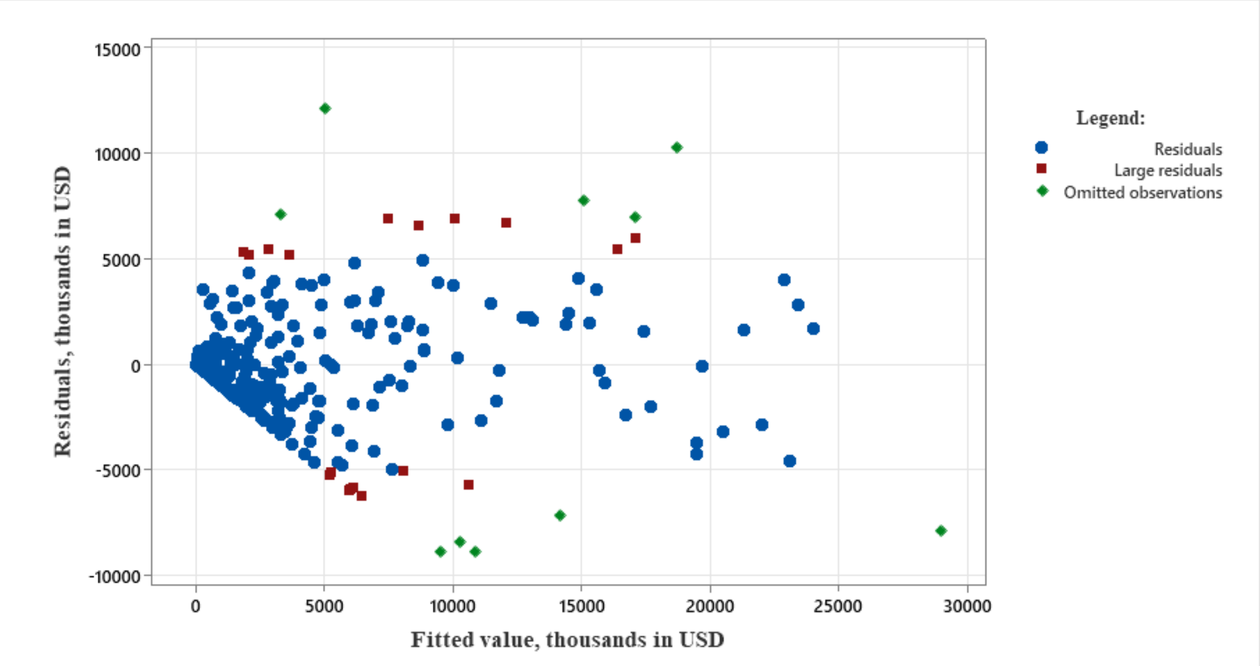
Based on the pseudo R2 of 0.0651, the model would indicate a poor model fit. However, this metric is based on the latent variable fit, which is not of interest. Further information is provided by Pearson's bivariate correlation coefficient between the fitted values and the dependent variable, which is very high and significant at less than 0.1 percent. By squaring the correlation between the two, the model can explain 85.03 percent of the variability in salary premium for wide receivers in the NFL.

Figure 5 shows the residuals in relation to the fitted values of a model containing the complete sample of 474 observations. There is some clustering on the diagonal towards the negative residuals for the observations with an adjusted value of less than $5000 thousand. This can be explained by the errors in the prediction for the observation in the sample that received the minimum salary, which is denoted by 0.

The observations with a very large negative residual of more than $7.5 million refer to veteran players who had received a larger contract in the past and were usually released by their team due to a decline in performance and agreed to a relatively smaller one-year contract near their minimum salary. One such example is Antonio Brown, a player who had been given a $15 million per year higher contract a year earlier, but was then released due to off-field issues and signed a very small contract with a championship-contending team. The observation with the highest fitted value is also interesting. It is Julio Jones, who became the highest-paid wide receiver on that contract, earning more than $2 million a year more than the second highest paid. But he was so dominant on the field that his expected salary premium was $7.9 million higher than what he received.

On the other hand, an observation with the highest residual value refers to A.J. Green, a player who has played exceptionally well in the past but has missed nearly half the games in the last three seasons because of injuries. He received a franchise tender that gave him an increase on his previous contract, which was already high. The next year, he received $12 million less. And the second highest residual relates to Tyreek Hill, who became the highest-paid player by receiving a disproportionately high non-guaranteed base salary in the last year of his contract. This makes it very likely he would be released or have his contract renegotiated before then. The other high residuals could be explained by the players being the best wide receivers on their team and negotiating to be paid like the best players in the league, usually in 2022, which supports the fact that the dummy for 2022 has a positive, though not significant, coefficient. The observations with the five largest and five smallest residuals were removed from the sample. This is already taken into account in the model in Table 13.

Figure 5: Fitted values and residuals in thousands of dollars



Adapted from PFF (2022); Spotrac (2022a).

2.5.4 The guaranteed contract value at the signing

In addition to salary premium, factors affecting the value of a guaranteed contract at signing were examined. These include signing bonuses, but not the practically guaranteed amount, which includes the portion of the contract value that is guaranteed after a certain date in later seasons.

For the hypothesis tests, age at signing was included in the model, as opposed to credited season, even though credited season gives slightly better results. Age at signing was also supplemented with a quadratic term to investigate a possible non-linear relationship. The addition of games played in the last three seasons was also examined but was not significant at the 5 percent level and was therefore not included. Ten outliers were removed from the entire sample.

The Tobit coefficients and the marginal effect at the mean for the guaranteed contract value at signing are shown in Table 16. Both variables for team change and salary cap are not significant at a 5 percent level. The most significant variables for determining guaranteed value at contract signing are yards, pass plays and draft position. In addition, the variable age at signing is significant in both the normal and squared terms, indicating a non-linear relationship. Similar to the model in Table 14, the pass plays per game have a sign change, but the team change variable is no longer significant.

The model states that for a one unit increase in yards, the expected change in guaranteed contract value at signing is 6.58, expressed in thousands of dollars, holding other variables constant. However, if an average wide receiver in the NFL, given that he receives at least a portion of his salary guaranteed, gains one additional yard, the expected increase in guaranteed contract value at signing is 4.78, expressed in thousands of dollars. These coefficients are larger compared to the model in Table 14 because it focuses on the total guaranteed value at contract signing over the life of the contract, whereas the previous model focused on the average annual salary. In addition, the constant term is significant and large, which means that it is more difficult to obtain a guaranteed part of the salary. This is already evident in the sample, as 47.84 per cent of the contracts in the sample did not have a guaranteed value.

Table 16: Tobit model and marginal effects at means of guaranteed at signing in thousands of dollars

Variable	Tobit coefficient	Unconditional expected value	Conditional on being Uncensored	Probability of Being Uncensored
Age at signing	6,606.2 **	3,307.69	2,403.07	0.44835
Age at signing^2	-125.72 **	-62.95	-45.73	-0.00853
Yards	13.14 ***	6.58	4.78	0.00089
Pass play per game	-382.42 ***	-191.48	-139.11	-0.02595
Pro Bowl (3y)	2,541.8 *	1,272.67	924.61	0.17251
Penalties	-339.55 **	-170.01	-123.52	-0.02304
Games played (1y)	154.29 *	77.25	56.13	0.01047
Team Change	-430.07	-217.28	-157.52	-0.02918
Draft	-565.07 ***	-282.93	-205.55	-0.03835
Salary cap	41.8	20.93	15.21	0.00284
Const	-95,362.37 **	-47,747.37	-34,688.99	-6.4721

Adapted from PFF (2022); Spotrac (2022a).

The fitted values have a very strong bivariate Pearson correlation coefficient with the dependent variable, which means that the model predicts 80.51 percent of the variability of the guaranteed contract value at contract signing.

The Tobit multiplicative heteroscedasticity regression with robust standard errors did not extensively impact the coefficients' significance, as no additional variable became non-significant at a 5 percent level. The conditional moment test for the case of normally distributed errors rejected the null hypothesis at a 5 percent level. However, the central limit theorem ensures the approximately normal distribution of the residuals in larger samples. Due to the inclusion of the quadratic term, the VIF indicates strong multicollinearity. However, without the quadratic term, the mean VIF of the independent variables in the model is 1.94 and does not indicate multicollinearity problems. The inclusion of the team dummies shows that there are no differences between the teams. Only for the Colts and the Packers is the coefficient significant at the 10 percent level. On the other hand, when the player dummies are included, many dummy variables become significant. However, the list of players is very similar to the list of players from the model for salaries above the minimum salary. Contract length was controlled for by using dummy variables for the length of the contract in years. The coefficients were positive and significant at a level of less than 0.1 percent level. They are defined as the difference compared to a one-year contract. Based on the coefficient value, the three-year contract seems to be the most optimal in terms of the guaranteed contract value. A coefficient of four years had a lower value than the coefficient of three years, which means that an additional year in a contract from three to four reduces the expected guaranteed contract value, while the coefficient from two to three more than doubles.

2.6 Discussion

In building models to determine the factors that affect salary premium, a significant number of variables were examined on player performance. Because this study focused on only one position group in the NFL, more position-specific variables could be tested as more than sixty different variables and their derivatives were used. By far the most informative metric is yards. It is so influential that when other positive performance metrics such as first downs or touchdowns are added, the model explains very little additional variability in salary premium. When combined with other variables that provide information about playing time and utilisation during a game, such as receptions or targets, their sign becomes negative due to collinearity. The use of receptions has been suggested by researchers in the past. (Ducking et al., 2014; McIntyre, 2017) However, their studies were conducted under an earlier collective bargaining agreement and the style of play has changed over the years with more emphasis on throwing the ball, as 55 percent of the top 20 passing seasons by a quarterback since 1969 occurred after 2014. (Pro Football Reference, 2022)

2.6.1 Discussion based on research questions

Hypothesis 1 was tested by the variable team change, which has the value 1 if the player signed a contract with a new team or 0 if he signed with the same team. Using the model in Table 13, the null hypothesis can be rejected at a 5 percent level. The negative coefficient is interpreted to mean that a wide receiver who switches teams receives a lower salary premium than those who do not. The simple model provided the same conclusion at a higher significance level. Using Tobit regression with multiplicative heteroskedasticity, the significance of the coefficient is even higher. This has important implications for players in the NFL, as it could argue for them to stay with the team they are signed to for their entire career. However, more research is needed to reach this conclusion. Especially since this does not affect the guaranteed contract value. The increase in salary can be explained by the fact that the best players are offered contract extensions several years before they enter Free Agency. As contract values tend to increase over time, it is in the interest of teams to extend their best players earlier and players are willing to accept these terms as their careers are very short, on average only 2.81 years for wide receivers. (Statista, 2018) A more logical explanation for the sign of the coefficient is that a player who could not continue with his current team or was released has a lower expected salary if he signs with a new team. In the traditional labour market, the data would suggest just the opposite, as people who change jobs can earn more. (Kochhar, Parker & Igielnik, 2022) Another important element of the labour market in the NFL is the transparency of salaries, as the salaries of all players are public, which limits the bargaining power of players, especially if they have been cut.

The coefficient for slot rate is not statistically significant at the 5 percent level. The null hypothesis from hypothesis 2 cannot be rejected. This means that the model found no evidence that the slot rate has an impact on the salary premium. In other words, the position at which the wide receiver is lined up has no effect on his salary. A study of free agent wide receivers found that slot receivers were paid better. (Mulholland & Jensen, 2018) However, when looking at all veteran contracts, including extensions, the percentage of the lineup at the slot position does not appear to have an impact. This can be explained by the fact that the best wide receivers are usually extended by their team before they even reach free agency or are prevented from doing so by franchise tenders. They can also be traded and sign an extension with a new team, which was the case for 3 of the 5 highest paid wide receivers in 2022.

Hypothesis 3 was tested by the salary cap variable in both the simple and extended models. The simple model suggests that the salary cap has an impact on the salary premium, but the extended model comes to a different conclusion. Therefore, the null hypothesis cannot be rejected. The model did not provide evidence that the salary cap has an impact on the players' compensation. This calls into question the validity of the standard errors of the simple model. In the Tobit regression with multiplicative heteroskedasticity on the simple model, the coefficient on the salary cap was no longer significant. Since 2011, the salary cap increased every year and was a proxy for the market increase, but this changed with the decrease in the salary cap in 2021. Salaries in 2021 did not decrease, but teams relied more on salary cap flexibility to push the salary cap charges in the later years. However, the coefficient is not significant due to 2021 alone, as omitting 2021 contracts from the sample did not change the significance of the coefficients. The lack of effect of the salary cap on salary premium is due to the fact that the minimum salary increases in line with increases in the salary cap. For example, the minimum salary for the average wide receiver with three years of experience increased by $270 thousand from 2018 to 2022, while the salary cap increased by $31 million over the same period. Per player on a 53-man roster, this translates to $584.91 thousand and since the disproportionate amount is allocated to the quarterback position, the impact on the wide receiver is not significant.

Player career longevity was measured with the variable credited seasons which is addressed under Hypothesis 4. Based on the extended model, the null hypothesis is rejected at less than 0.1 percent level. This means that the alternative hypothesis is accepted. The number of credited seasons has a negative effect on a player's salary premium. Longevity thus affects pay by both increasing the minimum salary and decreasing the premium over the minimum salary. For an average wide receiver, the extra season credited to him reduces his expected salary premium by $273.41 thousand, while the average increase in the minimum salary at the next level over the last five years is $86.47 thousand. This means that the extra season credited to him will have a negative impact on his future salary if his performance measures remain constant. However, this impact can be attributed to the fact that a player's performance and availability tend to decline with age and past performance is a less accurate indicator of future performance. In the case of American football, this is even more drastic.

The guaranteed contract value at signing model in Table 16 sheds light on Hypothesis 5. The null hypothesis is rejected at a 1 percent level and the alternative hypothesis is accepted. This means that the player availability has an impact on how much guaranteed contract value a wide receiver receives when he signs a contract in the NFL. The more games the player missed last season, the less guaranteed contract value he receives. Due to the inherently higher risk of missing games and possible persistent injuries, teams offer players a lower guaranteed contract value. Additionally, the coefficient on age at contract signing in the model is positive, but the squared term is negative. To examine the overall effect of signing age, the squared term was removed from the model. Without it, the normal coefficient was negative, indicating that the overall effect is negative and non-linear. The older players get, the less likely they are to receive a higher guaranteed contract value at signing. The same arguments about the impact of longevity on salary premium apply to the guaranteed portion. However, they are even more serious as it also depends on the length of the contract.

2.6.2 Limits of the research

Player performance has proven to be a very important factor in determining player compensation, but the way performance is measured is changing. Since 2017, the NFL has introduced RFID chips in all players' shoulder pads and in the ball to track data that provide information on location, speed, distance travelled and acceleration. (NFL Football Operations, 2022) This allows for additional evaluation of players. For wide receivers, particularly their route running, and the level of separation achieved is part of their evaluation. Although players' route running grades were also part of the study, the use of tracking data could provide a more comprehensive understanding of players' route running abilities. Since the players' tracking data is only available to the teams and is not publicly available, it was not included in the study. However, some researchers have been able to obtain a sample of player tracking data, such as a quarterback evaluation study mentioned earlier. (Reyers & Swartz, 2021)

In addition, there are player qualities that are difficult to measure statistically but contribute to the player's value. These include teamwork skills and leadership qualities. The benefit that a motivational boost or the ability to push other players to perform better under pressure can have been difficult to measure. Even if it is expected by the head coach and quarterback, the contribution of another player can be beneficial.

Player demographics, especially race, were also not part of the study, as extensive research has already been done on this topic. In addition, almost all wide receivers in the sample are black, which makes the results less reliable.

The sample also includes the 2021 league year, which is the first 17-game regular season. This makes the data less comparable, as cumulative performance metrics are inflated by the extra game. However, nine of the ten highest-paid wide receivers based on average annual contract value in 2022 all signed either new contracts or contract extensions in the same year. Contracts signed after August 2022 are not included in the sample, which includes 15 contracts signed before the start of the regular season.

2.6.3 Future research propositions

The research conducted focused primarily on average annual salary as a measure of player compensation but did not consider guaranteed salary or contract length. With the factors presented, existing research on players' career earnings could be expanded. Specifically, with the combination of the factor’s yards with the combination of the number of opportunities, such as pass plays and how it affects contract length, guaranteed salaries and the likelihood of earning full contract value.

Moreover, examining salary premium can be very interesting in other position groups, especially those with lower compensation, as minimum salary is a larger portion of compensation. Player performance scores can also be used to examine other position groups for which there are no static performance metrics, such as offensive linemen.

How team performance affects player compensation could also be explored. In the research conducted, team dummies were used to test for differences between teams. However, as there were only differences between the two teams, team performance was not investigated further. Using win probability as explored by Yurko, Ventura and Horowitz (2019), research on the efficiency of salary cap spending can extend research on player compensation with the use of win probability as an additional metric.

The non-guaranteed contracts are pretty unique in the NFL. This puts players in a disadvantageous position as they can be released at any time and never earn the agreed upon contract value. Future research into the factors, situations and required performance levels for players to fulfil their contracts. This could provide significant benefits to players, potential players and their agents in their contract negotiations.

With the changes to the name, likeness and image rules in college sports in the US, college football players can now essentially be compensated for their play. While payment for being on the field is not allowed, their exceptional performances mean increased popularity and better promotional opportunities. This has drastically changed the landscape of college football, as under amateurism it was not possible for players to monetise themselves.

CONCLUSION

Players' compensation is of great interest to teams, players, agents and fans. This master's thesis examines the factors that influence both average annual compensation and guaranteed contract value. It uses econometric techniques and a wide range of available statistical metrics to provide additional insight into the elements that influence wide receiver compensation in the NFL.

In the context of salary constraints in the NFL, the thesis examines the factors that influence the compensation of the specific position group. Restrictions include salary restrictions with the minimum salary on one side and the salary cap on the other, as well as contractual restrictions such as permissible incentive schemes and rules to prevent tampering.

The factors were derived from previous research on players' compensation. They can be divided into three groups. These include player characteristics measures, performance metrics and the market effect. The performance metrics are the most deterministic, but the selection of the most influential factors is not obvious. Suggestions have been made in previous research. (Ducking et al., 2014; McIntyre, 2017). However, in terms of players' annual salary, the yards metric provides significantly better model accuracy than receptions, due to the shift to throwing focused offenses in the last decade. Using both variables result in a worse model because the correlation between them is too high. The best alternative found is pass plays expressed per game, which controls for the number of opportunities a player has while limiting the problem of multicollinearity. Other performance metrics included are the number of Pro Bowl selections and penalties received.

Furthermore, player characteristics include career longevity, availability, draft status and mobility in terms of changing teams. Surprisingly, a player's experience is not rewarded, as the number of credited seasons has a negative impact on compensation, notwithstanding the fact that it has a positive impact on minimum salary. Availability is important for both annual salary and guaranteed contract value. While a player's better draft position determines the value of his rookie contract, it also affects later veteran contracts. This can be attributed to the sunk cost fallacy, as general managers tend to overvalue early draft selections, especially if they selected them themselves.

Unique insights from player salaries relate to player mobility and optimal contract length. Player mobility includes the fact that players who stay with their current team earn more per year on average than players who do not. However, it has no influence on the guaranteed contract value. This is not observed in the traditional labour market, where data suggest that changing employers can lead to higher compensation. (Kochhar et al., 2022) Moreover, in contract negotiations for wide receivers in the NFL, the three-year contract is the most optimal in terms of both average annual salary premium and guaranteed contract value at signing.

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APPENDICES

Appendix 1: Povzetek (Summary in Slovene language)

Magistrsko delo preučuje dejavnike, ki vplivajo na plače igralcev v ameriški državni nogometni ligi NFL. Same plače športnikov so omejene s kolektivno pogodbo med sindikatom športnikov v ameriški državni nogometni ligi in predstavniki lastnikov. Ta opredeljuje najmanjše plačilo športnikov, ki se povečuje vsako leto in je odvisno od izkušenj športnika. Poleg tega opredeljuje tudi posebnosti plač novincev, omejitve na področju variabilnega dela plače, klavzulo proti pogodbenim pogajanjem z drugimi ekipami in zapoveduje strogo zgornjo mejo vsote plač vseh igralcev na posamezno ekipo.

Zaradi različnih meril uspešnosti med posameznimi položaji igralcev se raziskava v tem magistrskem delu nanaša le na položaj lovilca. Ker ima ta položaj bolj pogosto v posesti žogo, je na voljo veliko število različnih meril uspešnosti v igri.

Na osnovi preteklih raziskav iz področja plač v ameriški državni nogometni ligi so bile pripravljene hipoteze, ki pregledujejo vpliv mobilnosti igralcev, torej kako menjava ekipe vpliva na športnikov dohodek, položaj lovilca, zgornja omejitev plač, dolžina kariere in njegova razpoložljivosti, v pomenu števila zgrešenih tekem.

Podatki za raziskavo so pridobljeni iz sekundarnih virov, kar vključuje Pro Football Focus, podjetje, ki se ukvarja z analizo igralcev ameriškega nogometa, in Sportac največji spletni ponudnik informacij o pogodbah profesionalnih športnikov v ZDA. Vključujejo vse pogodbe lovilcev podpisane med 2018 in 1. avgustom 2022 in uspešnost športnikov v obdobju treh let pred podpisom pogodbe.

Odvisna spremenljivka v raziskavi je opredeljena kot dodatek na najmanjše plačilo po kolektivni pogodbi. Ta je bila pridobljena kot razlika med povprečno letno plačo v posamezni pogodbi športnika in njegovim najmanjšim plačilom, opredeljenim v kolektivni pogodbi. Dejavniki, ki vplivajo na plačo športnika, so bili razvrščeni v tri skupine. Te vključujejo lastnosti igralcev, uspešnost v športu in tržni učinek. Za raziskavo je bila uporabljena Tobit metoda, ki nudi boljšo rešitev zaradi spodnje meje odvisne spremenljivke. Pri analiziranju uspešnosti v športu je merilo jardov, torej skupno osvojeno ozemlje ob uspešnih sprejemih žoge, daleč najbolj vpliven dejavnik. Ta vpliv je tako močan, da vključevanje katerega koli drugega pozitivnega merila uspešnosti ne predstavlja izboljšave modela. Z le z uporabo negativnega merila števila prejetih kazni med igro in povprečnega števila podajnih akcij na tekmo je bil pridobljen bolj zanesljiv model.

Na osnovi raziskave je bilo ugotovljeno, da menjava ekipe lovilcev v ameriški državni nogometni ligi negativno vpliva na njegovo plačilo. Razlogi za to so predvsem v omenjeni možnosti menjave ekipe in podaljšanju pogodb najboljših igralcev še pred iztekom pogodbe. Prav tako posamezni položaj lovilca pred začetkom akcije ne vpliva na njegovo plačilo, ko so preučevane vse pogodbe in ne le pogodbe prostih igralcev. Tudi sama zgornja meja skupnega plačila igralcev ne vpliva na dodatek na minimalno plačo. Torej je učinek povečanja zgornje meje skupnega plačila igralcev praktično v celoti vključen v povečanju najmanjše plače. Ko se preučuje vpliv dolžine kariere to, na eni strani pozitivno vpliva na višjo najnižjo plačo, ampak tudi na nižji dodatek nanjo. Prav slednji učinek je močnejši, kar pomeni da dolžina kariere negativno vpliva na plače lovilcev. Razlogi za to so predvsem v predvidenem upadu telesne sposobnosti s starostjo, ki je ključna za položaj lovilca.

Analiza je preučevala tudi vpliv posameznih dejavnikov na zajamčeno vsoto pogodbe lovilcev, saj je ta v ameriški državni nogometni ligi občutno nižja od skupne vsote pogodbe. Dejavnik razpoložljivosti ima pomemben vpliv na zajamčeno plačilo, saj je kazalnik nivoja tveganja, da športnik ne bo zmožen igrati vseh tekem, predvsem zaradi nevarnosti poškodb. Sam vpliv starosti na zajamčeno vsoto pogodbe ni linearen, najprej pozitivno vpliva na zajamčeno vsoto pogodbe, vendar ima nato močan negativen vpliv. Z dodajanjem kontrol za dolžino pogodbe se je izkazalo tudi, da so triletne pogodbe najbolj primerne za lovilce, saj omogočajo najvišje plačilo in najvišjo skupno zajamčeno vsoto.

Appendix 2: Variables used in the research

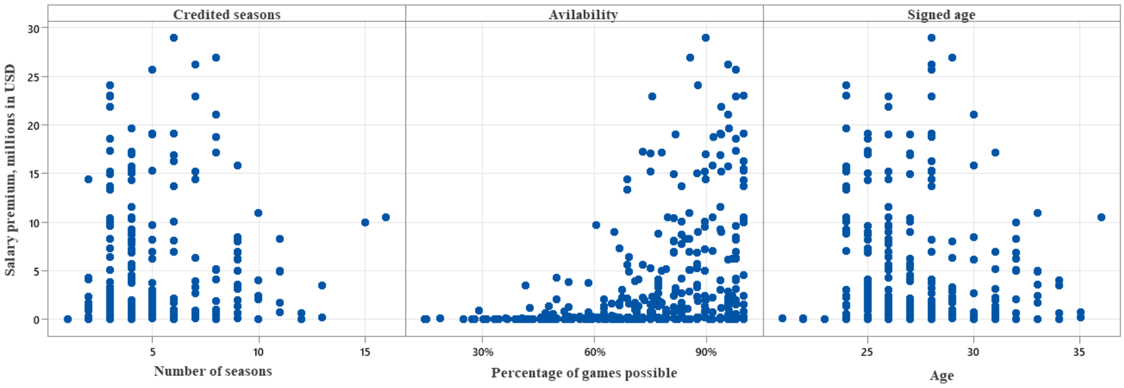
Table 17: Variables used in the research

Player Characteristics	Cumulative Performance	Performance Efficiency	Derived Performance Metrics	Market Effect
Credited seasons	Air yards	Average depth of target	Air yards per game	Franchise tag
Draft	Avoided tackles	Caught percentage	Drops per game	Salary cap
Draft selection number	Declined penalties	Drop rate	First down per game	Transition tag
Games missed	Drops	Grade hands drop rate	Interceptions per game	
Games played (1y)	First downs	Grade hands fumble rate	Pass play per game	
Games played (3y)	Fumbles	Grade overall offense	Penalties per game	
Pro Bowl selections	Interceptions	Grade pass block	Receptions per game	
Pro Bowl selections (3y)	Missed catch	Grade pass route	Receptions per game	
Signed age	Pass plays	Route rate	Route run per game	
Signed age2	Penalties	Slot rate	Targets per game	
Team	Receptions	Targeted QB rating	Touchdowns per game	
Team change	Routes	Wide rate	Yards after the catch per game	
Undrafted	Slot snaps		Yards after the catch per reception	
Year Signed	Targets		Yards per game	
	Touchdowns		Yards per pass play	
	Wide snaps		Yards per reception	
	Yards		Yards per route run	
	Yards after the catch		Yards per target	

Source: own work.

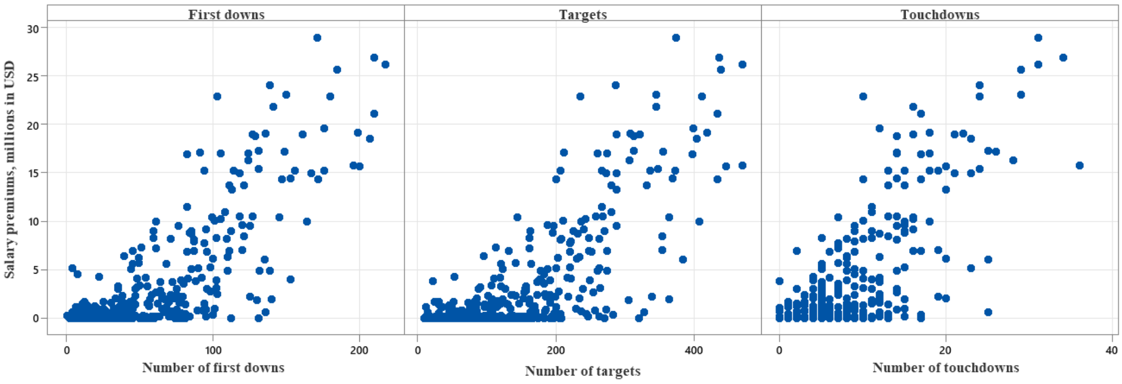
Appendix 3: The Scatterplots of the variables used

Figure 6: Scatterplot of salary premiums and player characteristics measure variables



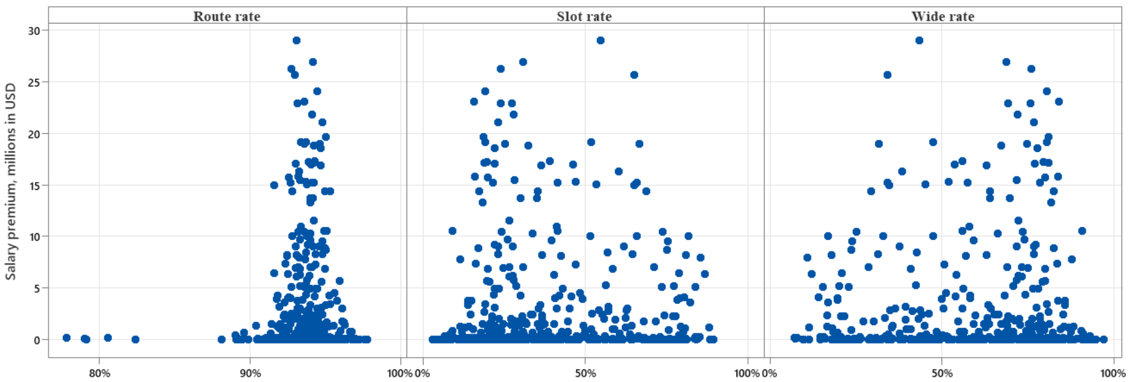
Adapted from PFF (2022); Spotrac (2022a).

Figure 7: Scatterplot of salary premiums and player performance measure variables



Adapted from PFF (2022); Spotrac (2022a).

Figure 8: Scatterplot of salary premiums and player performance efficiency variables



Adapted from PFF (2022); Spotrac (2022a).

Appendix 4: The correlations between the variables

Table 18: Pearson bivariate correlations between cumulative performance metrics

Variable	Yards	Pass plays	Receptions	First downs	Touchdowns	Penalties	Interceptions	Pro Bowl selections	Catch rate	Slot rate	Grade Route
Yards	1										
Pass plays	**0.9286** **0.0000**	1									
Receptions	**0.9783** **0.0000**	**0.9337** **0.0000**	1								
First downs	**0.9354** **0.0000**	**0.8619** **0.0000**	**0.9228** **0.0000**	1							
Touchdowns	**0.9094** **0.0000**	**0.842** **0.0000**	**0.8824** **0.0000**	**0.8482** **0.0000**	1						
Penalties	**0.6655** **0.0000**	**0.6889** **0.0000**	**0.6587** **0.0000**	**0.6473** **0.0000**	**0.6376** **0.0000**	1					
Interceptions	**0.7568** **0.0000**	**0.7402** **0.0000**	**0.7294** **0.0000**	**0.7054** **0.0000**	**0.685** **0.0000**	**0.5387** **0.0000**	1				
Pro Bowl selections 3y	**0.5521** **0.0000**	**0.3655** **0.0000**	**0.5414** **0.0000**	**0.5749** **0.0000**	**0.5596** **0.0000**	**0.3782** **0.000**	**0.3949** **0.0000**	1			
Catch rate	**0.2005** **0.0000**	**0.1497** **0.0011**	**0.2673** **0.0000**	**0.1952** **0.0000**	**0.1553** **0.0007**	0.019 0.6791	-0.0389 0.3985	**0.1163** **0.0113**	1		
Slot rate	0.05 0.2771	**0.0985** **0.0321**	**0.1449** **0.0016**	0.0394 0.3925	0.0141 0.7594	-0.0369 0.4229	-0.0427 0.3532	-0.0195 0.6726	**0.4532** **0.0000**	1	
Grade Route	**0.7888** **0.0000**	**0.6029** **0.0000**	**0.7583** **0.0000**	**0.7463** **0.0000**	**0.7398** **0.0000**	**0.4421** **0.0000**	**0.5472** **0.0000**	**0.5266** **0.0000**	**0.3435** **0.0000**	0.0111 0.8099	1

Adapted from PFF (2022); Spotrac (2022a).

Table 19: Pearson bivariate correlations between relative performance metrics

Variable	Yards per game	Pass plays per game	Receptions per game	First downs per game	Touchdowns per game	Penalties per game	Interceptions per game	Pro Bowl selections	Catch rate	Slot rate	Grade Route
Yards per game	1										
Pass plays per game	**0.8712** **0.0000**	1									
Receptions per game	**0.9591** **0.0000**	**0.8772** **0.0000**	1								
First downs per game	**0.8373** **0.0000**	**0.7144** **0.0000**	**0.8151** **0.0000**	1							
Touchdowns per game	**0.8484** **0.0000**	**0.7404** **0.0000**	**0.8105** **0.0000**	**0.6956** **0.0000**	1						
Penalties per game	**0.482** **0.0000**	**0.5071** **0.0000**	**0.4503** **0.0000**	**0.4452** **0.0000**	**0.4417** **0.0000**	1					
Interceptions per game	**0.5915** **0.0000**	**0.5729** **0.0000**	**0.5498** **0.0000**	**0.4772** **0.0000**	**0.522** **0.0000**	**0.3058** **0.0000**	1				
Pro Bowl selections 3y	**0.5173** **0.0000**	**0.2991** **0.0000**	**0.5151** **0.0000**	**0.5075** **0.0000**	**0.5035** **0.0000**	**0.2718** **0.0000**	**0.2943** **0.0000**	1			
Catch rate	**0.1622** **0.0004**	0.0192 0.677	**0.2657** **0.0000**	**0.1647** **0.0003**	**0.1103** **0.0163**	**-0.093** **0.043**	**-0.2092** **0.0000**	**0.1163** **0.0113**	1		
Slot rate	-0.0077 0.8668	0.0177 0.7006	**0.1315** **0.0041**	-0.0096 0.8344	-0.0207 0.6526	**-0.1311** **0.0042**	**-0.1043** **0.0232**	-0.0195 0.6726	**0.4532** **0.0000**	1	
Grade Route	**0.8188** **0.0000**	**0.5264** **0.0000**	**0.7805** **0.0000**	**0.6921** **0.0000**	**0.7234** **0.0000**	**0.3058** **0.0000**	**0.4126** **0.0000**	**0.5266** **0.0000**	**0.3435** **0.0000**	0.0111 0.8099	1

Adapted from PFF (2022); Spotrac (2022a).

Table 20: Pearson bivariate correlations between independent variables in the extended model

Variable	Yards	Pro Bowl selections 3y	Penalties	Games played 1y	Team change	Credited seasons	Draft	Salary cap	Slot rate	Pass plays per game
Yards	1									
Pro Bowl selections 3y	**0.5521** **0.0000**	1								
Penalties	**0.6655** **0.0000**	**0.3782** **0.0000**	1							
Games played 1y	**0.4815** **0.0000**	**0.1661** **0.0003**	**0.3958** **0.0000**	1						
Team change	-0.0809 0.0786	-0.0731 0.112	-0.0248 0.5908	**-0.1078** **0.0188**	1					
Credited seasons	**0.4599** **0.0000**	**0.2774** **0.0000**	**0.3196** **0.0000**	**0.2403** **0.0000**	**0.1805** **0.0001**	1				
Draft	**-0.4271** **0.0000**	**-0.2367** **0.0000**	**-0.3008** **0.0000**	**-0.1086** **0.0181**	-0.0709 0.123	**-0.3999** **0.0000**	1			
Salary cap	0.0044 0.9245	0.0516 0.2624	-0.0645 0.1606	**0.1301** **0.0045**	-0.0523 0.2558	-0.0007 0.9875	0.0344 0.4547	1		
Slot rate	0.05 0.2771	-0.0195 0.6726	-0.0369 0.4229	0.0649 0.1585	-0.0392 0.394	0.0692 0.1327	**0.1781** **0.0001**	0.0028 0.9515	1	
Pass plays per game	**0.7982** **0.0000**	**0.2991** **0.0000**	**0.5692** **0.0000**	**0.3012** **0.0000**	-0.0271 0.5559	**0.3627** **0.0000**	**-0.4267** **0.0000**	-0.079 0.0859	0.0177 0.7006	1

Adapted from PFF (2022); Spotrac (2022a).

Table 21: Pearson bivariate correlations between independent variables in the guaranteed contract value model

Variable	Signed Age	Signed Age^2	Yards	Pass plays per game	Pro Bowl selections 3y	Penalties	Games played 1y	Change Team	Draft	Salary cap
Signed Age	1									
Signed Age^2	**0.998** **0.0000**	1								
Yards	**0.278** **0.0000**	**0.2778** **0.0000**	1							
Pass plays per game	**0.2239** **0.0000**	**0.2264** **0.0000**	**0.7982** **0.0000**	1						
Pro Bowl selections 3y	**0.1736** **0.0001**	**0.1791** **0.0001**	**0.5521** **0.0000**	**0.2991** **0.0000**	1					
Penalties	**0.2114** **0.0000**	**0.2095** **0.0000**	**0.6655** **0.0000**	**0.5692** **0.0000**	**0.3782** **0.0000**	1				
Games played 1y	**0.1151** **0.0121**	**0.1146** **0.0125**	**0.4815** **0.0000**	**0.3012** **0.0000**	**0.1661** **0.0003**	**0.3958** **0.0000**	1			
Change Team	**0.21** **0.0000**	**0.2057** **0.0000**	-0.0809 0.0786	-0.0271 0.5559	-0.0731 0.112	-0.0248 0.5908	**-0.1078** **0.0188**	1		
Draft	**-0.151** **0.001**	**-0.153** **0.0008**	**-0.4271** **0.0000**	**-0.4267** **0.0000**	**-0.2367** **0.0000**	**-0.3008** **0.0000**	**-0.1086** **0.0181**	-0.0709 0.123	1	
Salary cap	-0.0202 0.6608	-0.0209 0.6499	0.0044 0.9245	-0.079 0.0859	0.0516 0.2624	-0.0645 0.1606	**0.1301** **0.0045**	-0.0523 0.2558	0.0344 0.4547	1

Adapted from PFF (2022); Spotrac (2022a).

Appendix 5: Extended model formulation

Table 22: Tobit model coefficients of salary premium in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|	VIF
Yards	7,341.414	374.8675	19.58	0.000	5.30
Pass play per game	1,218,483	368,318.8	3.31	0.001	3.25
Pro Bowl (3y)	-187,821.6	50,993.88	-3.68	0.000	1.49
Penalties	92,059.57	29,660.21	3.1	0.002	1.88
Team Change	-697,962.5	288,647.4	-2.42	0.016	1.09
Credited seasons	-401,332.6	76,380.51	-5.25	0.000	1.46
Draft	-280,207.1	64,691.11	-4.33	0.000	1.43
Games played (1y)	12,216.97	12,917.59	0.95	0.345	1.47
Slot rate	-336,931.9	719,485.6	-0.47	0.640	1.09
Salary cap	-176,647.5	26,665.6	-6.62	0.000	1.05
Const	-754,297.1	2,567,987	-0.29	0.769	
Mean VIF					1.95
n	467				
Pseud R^2	0.0651				
Standard error	2,706,245				

Adapted from PFF (2022); Spotrac (2022a).

Table 23: Tobit Multiplicative Heteroscedasticity Regression coefficients of salary premium

Variable	Tobit coefficient	Robust standard errors	t	P>|t|
Yards	5,582.563	683.9857	8.16	0.000
Pass play per game	1,304,186	236,664	5.51	0.000
Pro Bowl (3y)	-96,933.89	44,268.21	-2.19	0.029
Penalties	46,930.76	21,138.8	2.22	0.026
Team Change	-404,684	178,645	-2.27	0.023
Credited seasons	-191,924.7	70,632.91	-2.72	0.007
Draft	-112,141.3	53,337.59	-2.1	0.036
Games played (1y)	2,850.316	7,373.716	0.39	0.699
Slot rate	270,211.1	492,119.7	0.55	0.583
Salary cap	-152,250.4	27,394.54	-5.56	0.000
Const	318,329.8	1,439,602	0.22	0.825
n	467			
Log pseudolikelihood	-4,578.577			

Adapted from PFF (2022); Spotrac (2022a).

Table 24: Tobit model coefficients with year signed control of salary premium in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|
Yards	7,279.496	371.146	19.61	0.000
Pass play per game	-174,255	26,564.07	-6.56	0.000
Pro Bowl (3y)	1,244,155	363,476.8	3.42	0.001
Penalties	-185,523	51,850.53	-3.58	0.000
Team Change	-698,338	290,562.2	-2.4	0.017
Credited seasons	-398,780	76,964.65	-5.18	0.000
Draft	-283,186	64,281.58	-4.41	0.000
Games played (1y)	95,315.07	29,999.16	3.18	0.002
Slot rate	-317,829	725,063.9	-0.44	0.661
Year dummy (2018 base)				
2019	-223,347	468,517.3	-0.48	0.634
2020	-252,540	530,082.5	-0.48	0.634
2021	-248,846	485,756	-0.51	0.609
2022	309,182.9	473,785.7	0.65	0.514
Const	1,608,981	753,838.6	2.13	0.033
n	464			
Pseud R^2	0.0653			
Standard error	2,702,842			

Adapted from PFF (2022); Spotrac (2022a).

Table 25: Tobit model coefficients with contract length control of salary premium in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|
Yards	5,602.367	418.6145	13.38	0.000
Pass play per game	-123,001.6	23,818.45	-5.16	0.000
Pro Bowl (3y)	102,2118	369,786.6	2.76	0.006
Penalties	-148,527.4	48,904.8	-3.04	0.003
Team Change	-855,063	252,319.4	-3.39	0.001
Credited seasons	-205,481.8	69,867.06	-2.94	0.003
Draft	-211,366.2	57,282.15	-3.69	0.000
Games played (1y)	15,512.3	10,800.41	1.44	0.152
Slot rate	62,318.71	24,159.9	2.58	0.010
Contract length (1 base)				
2	1,990,859	371,165.4	5.36	0.000
3	4,703,964	596,787.9	7.88	0.000
4	4,414,541	736,357.6	6	0.000
5	4,585,661	1,055,153	4.35	0.000
Const	1,990,859	371,165.4	5.36	0.000
n	464			
Pseud R^2	0.0756			
Standard error	2,280,411			

Adapted from PFF (2022); Spotrac (2022a).

Appendix 6: Alternative model formulation

Table 26: Tobit coefficients of the guaranteed salary at signing in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|	VIF
Age at signing	6,606,200	2,135,128	3.09	0.002	256.94 (1.27)
Age at signing^2	-125,716.6	37,676.72	-3.34	0.001	256.67 (omitted)
Yards	13,140.07	1,031.482	12.74	0.000	5.06 (5.01)
Pass play per game	-382,420.7	66,420.36	-5.76	0.000	3.19 (3.15)
Pro Bowl (3y)	2,541,804	1,005,980	2.53	0.012	1.54 (1.50)
Penalties	-339,551.1	119,996.1	-2.83	0.005	1.84 (1.84)
Games played (1y)	154,294.9	72,780.4	2.12	0.035	1.45 (1.44)
Team Change	-430,069.9	704,381.4	-0.61	0.542	1.09 (1.09)
Draft	-565,073.1	137,264.1	-4.12	0.000	1.27 (1.27)
Salary cap	41,803.56	30,007.62	1.39	0.164	1.05 (1.05)
Const	-9.54E+07	3.06E+07	-3.12	0.002	
Mean VIF					53.01 (1.94)
n	467				
Pseud R^2	0.0522				
Standard error	6415275				

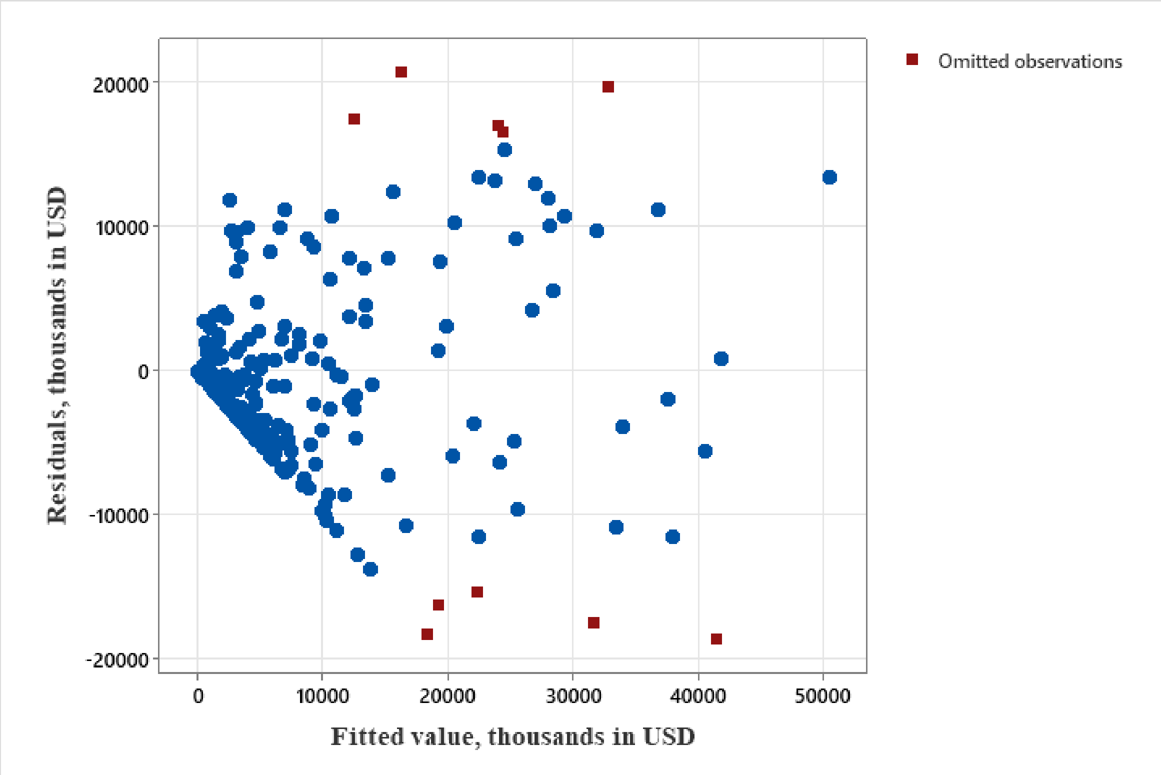
Adapted from PFF (2022); Spotrac (2022a).

Table 27: Tobit Multiplicative Heteroscedasticity Regression coefficients of the guaranteed salary at signing in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|
Age at signing	2,772,247	894,821.3	3.1	0.002
Age at signing^2	-49,016.82	16,067.62	-3.05	0.002
Yards	5,503.214	1,088.901	5.05	0.000
Pass play per game	-120,671.2	37,191.17	-3.24	0.001
Pro Bowl (3y)	1,574,477	338,633.7	4.65	0.000
Penalties	-194,255.6	65,577.04	-2.96	0.003
Games played (1y)	73,836.34	32,474.32	2.27	0.023
Team Change	-275,928.1	286,947.6	-0.96	0.336
Draft	-142,052.7	62,244.04	-2.28	0.022
Salary cap	6,890.806	11,196.13	0.62	0.538
Const	-4.08E+07	1.30E+07	-3.13	0.002
n	467			
Log pseudolikelihood	-4,308.5752			

Adapted from PFF (2022); Spotrac (2022a).

Figure 9: Fitted values and residuals in thousands of dollars on the guaranteed salary



Adapted from PFF (2022); Spotrac (2022a).

Table 28: Tobit coefficients excluding the squared term of the guaranteed salary at signing in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|
Age at signing	-540,530	146,098.2	-3.7	0.000
Yards	12,850.35	1,054.635	12.18	0.000
Pass play per game	-385,582.7	67,145.83	-5.74	0.000
Pro Bowl (3y)	1,192,156	1,034,998	1.15	0.250
Penalties	-209,448.8	131,771.4	-1.59	0.113
Games played (1y)	152,851.7	73,633.33	2.08	0.038
Team Change	-639,427.7	750,985.6	-0.85	0.395
Draft	-634,735	145,813	-4.35	0.000
Salary cap	37,178.05	32,496.15	1.14	0.253
Const	6,317,492	7,497,980	0.84	0.400
n	467			
Pseud R^2	0.0515			
Standard error	6,433,763			

Adapted from PFF (2022); Spotrac (2022a).

Table 29: Tobit coefficients including the games played 3y of the guaranteed salary at signing in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|
Age at signing	7,285,340	2,147,253	3.39	0.001
Age at signing2	-137,348.9	37,876.84	-3.63	0.000
Yards	13,887.23	1,107.517	12.54	0.000
Pass play per game	-410,408.1	66,569.9	-6.17	0.000
Pro Bowl (3y)	2,227,425	1,021,586	2.18	0.030
Penalties	-300,556.1	122,240.3	-2.46	0.014
Games played (1y)	210,407.2	76,965.21	2.73	0.007
Games played (3y)	-90,922.61	46,971.33	-1.94	0.054
Team Change	-347,302.2	688,476.3	-0.5	0.614
Draft	-583,889.9	136,728.3	-4.27	0.000
Salary cap	38,357.29	29,442.62	1.3	0.193
Const	-1.02e+08	3.05e+07	-3.36	0.001
n	467			
Pseud R^2	0.0581			
Standard error	5,786,423			

Adapted from PFF (2022); Spotrac (2022a).

Table 30: Tobit coefficients including the yearly controls of the guaranteed salary at signing in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|
Age at signing	6,282,816	217,8740	2.88	0.004
Age at signing^2	-120,003	38,487.01	-3.12	0.002
Yards	13,006.6	1,003.206	12.97	0.000
Pass play per game	-375,541	65,121.81	-5.77	0.000
Pro Bowl (3y)	263,9058	966,658.4	2.73	0.007
Penalties	-318,507	120,072.5	-2.65	0.008
Games played (1y)	154,138	71,475.12	2.16	0.032
Team Change	-442,486	704,462.3	-0.63	0.530
Draft	-570,728	136,788.9	-4.17	0.000
Year dummy (2018 base)				
2019	80,686.99	1,029,714	0.08	0.938
2020	-115,946	1,231,180	-0.09	0.925
2021	744,908.1	1,066,042	0.7	0.485
2022	1,756,574	1,084,891	1.62	0.106
Const	-8.35e+07	3.07e+07	-2.72	0.007
n	464			
Pseud R^2	0.0580			
Standard error	5,851,174			

Adapted from PFF (2022); Spotrac (2022a).

Table 31: Tobit coefficients including team controls relative to the 49ers of the guaranteed salary at the signing in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|
Bears	-578,383.8	2,821,678	-0.2	0.838
Bengals	2,036,645	2,998,541	0.68	0.497
Bills	-578,676.8	2,725,764	-0.21	0.832
Broncos	774,619.4	3,326,235	0.23	0.816
Browns	-3,953,354	2,975,670	-1.33	0.185
Buccaneers	-3,430,878	3,608,325	-0.95	0.342
Cardinals	-1,293,463	3,116,522	-0.42	0.678
Chargers	-3,064,317	4,643,512	-0.66	0.510
Chiefs	-1,165,176	3,127,698	-0.37	0.710
Colts	-5,167,145	3,088,162	-1.67	0.095
Commanders	957,873.4	2,875,651	0.33	0.739
Cowboys	1,305,369	2,878,523	0.45	0.650
Dolphins	2,745,201	2,629,004	1.04	0.297
Eagles	268,989.9	2,882,741	0.09	0.926
Falcons	-2,081,954	3,477,597	-0.6	0.550
Giants	3,320,631	2,499,286	1.33	0.185
Jaguars	1,596,557	3,182,851	0.5	0.616
Jets	656,079.7	2,769,846	0.24	0.813
Lions	338,575	2,544,320	0.13	0.894
Packers	-5,438,960	3,191,548	-1.7	0.089
Panthers	1,085,186	2,572,346	0.42	0.673
Patriots	-694,607.8	2,816,343	-0.25	0.805
Raiders	-4,409,224	2,767,303	-1.59	0.112
Rams	-269,332	3,652,014	-0.07	0.941
Ravens	-1,837,791	2,709,528	-0.68	0.498
Saints	-5,236,641	3,131,034	-1.67	0.095
Seahawks	1,207,352	2,998,847	0.4	0.687
Steelers	-4,605,664	4,044,702	-1.14	0.255
Texans	2,166,489	2,656,119	0.82	0.415
Titans	-5,206,565	4,052,239	-1.28	0.200
Vikings	-4,242,589	4,064,894	-1.04	0.297

Adapted from PFF (2022); Spotrac (2022a).

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Table 32: Tobit coefficients including contract length controls relative to one year contract of the guaranteed salary at the signing in dollars

Variable	Tobit coefficient	Robust standard errors	t-statistic	P>|t|
Age at signing	5,809,436	1,900,333	3.06	0.002
Age at signing^2	-104,764.3	33,415.99	-3.14	0.002
Yards	9,276.565	1,011.574	9.17	0.000
Pass play per game	-261,763.2	58,364.98	-4.48	0.000
Pro Bowl (3y)	2,293,179	939,670.6	2.44	0.015
Penalties	-327,322.1	105,237	-3.11	0.002
Games played (1y)	103,605.3	54,931.14	1.89	0.060
Team Change	-801,518	589,680.7	-1.36	0.175
Draft	-489,855.4	113,853.2	-4.3	0.000
Contract length (1 base)				
2	3,684,078	769,116.9	4.79	0.000
3	1.07e+07	1,338,771	8.02	0.000
4	9,842,777	1,635,732	6.02	0.000
5	1.35e+07	2,242,040	6.04	0.000
Const	-8.10e+07	2.68e+07	-3.02	0.003
n	464			
Pseud R^2	0.0708			
Standard error	4,789,166			

Adapted from PFF (2022); Spotrac (2022a).