Player performance, salary and survival analysis in the NBA

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This thesis is submitted for the degree of
Doctor of Philosophy

University of Sheffield January 2025

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the University of Sheffield is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it). The copyright of this thesis rests with the author. Quotation from it is permitted, provided that full acknowledgement is made. This thesis may not be reproduced without my prior written consent. I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party. I declare that my thesis consists of about 62,800 words.

Hao Zhu
January 2025

Acknowledgements

First and foremost, I would like to express my deepest gratitude to my three supervisors, Dr. Ian Gregory-Smith, Dr. Panos Nanos, and Professor Peter Wright. Their unparalleled expertise, insightful guidance, and unwavering support have been invaluable throughout the course of my doctoral journey. Their ability to pose challenging yet thought-provoking questions greatly contributed to the formulation of the research questions and the development of a robust methodology for this thesis. The detailed feedback and constructive suggestions they provided during the revision process have significantly enhanced the quality of this work, pushing me to achieve a higher level of academic rigour. I am truly fortunate to have had the opportunity to work under their mentorship.

I am also profoundly thankful to my family, whose encouragement, love, and support have been a constant source of strength throughout this journey. Their unwavering belief in my abilities has not only provided me with the mental resilience needed to face the challenges of a PhD but also helped to create an environment in which I could thrive. Their financial and emotional support has been crucial in enabling me to dedicate myself wholeheartedly to this research, and for that, I am deeply grateful.

In addition, I would like to extend my heartfelt thanks to my friends and colleagues, who have been a source of encouragement and camaraderie throughout this process. Whether it was through thought-provoking discussions, collaborative brainstorming, or simply offering a listening ear during difficult times, their support has been invaluable in helping me persevere and grow as a researcher.

Lastly, I am grateful to the broader academic community, whose work has inspired and informed this thesis. The collective body of knowledge built by scholars in my field has been a guiding light throughout my research.

To all those who have supported and encouraged me during this PhD journey, whether directly or indirectly, I offer my sincerest gratitude. This thesis is as much a testament to your contributions as it is to my own efforts.

Abstract

Professional sports provide an excellent research environment to study all aspects of the employee-employer relationship. In this study, I use data from the National Basketball Association (NBA) to empirically investigate the impact of contractual arrangements on player performance, salary, and survival. First, I explore changes in player performance in the year at which a contract ends (the contract year). Players improve their performance during the contract year, but no consistent performance decline is observed in the year following the end of the contract year. Second, I focus on salary determination. I demonstrate that player performance is an important driver of their salary. In addition, I explore the interaction between contractual arrangements and salary determination and find that contract length and special clauses, such as player/team options to extend the employment relationship, affect the salary. Third, I explore the determinants of player survival in the league. Good performance, especially offensive win shares, increases player longevity. Changing teams allows young or undrafted players to survive longer in the league. Examining the impact of player options on player survival suggests that player options increase the probability of players changing teams but do not increase the probability of player survival. In summary, my findings indicate that the interaction between contractual arrangements and player performance is important in salary determination and survival in professional sports.

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Introduction

Background and motivation

The sports industry provides a unique and rich research environment to investigate open questions in labour economics, particularly to understand the intricate dynamics between employees and employers. This is due to the abundance of available player performance data, which is a robust measure of employees' productivity. Furthermore, the public availability of players' income data accurately represents labour output reward. Unlike controlled laboratory experiments, sports games reflect real-life scenarios, allowing for a more comprehensive analysis of employee-employer relationships. Consequently, numerous studies in labour economics leverage sports data to gain insights into these crucial dynamics. Labour economics research using sports data mostly focuses on the following aspects: return to human capital, factors affecting performance, superstars, and peer effects (Palacios-Huerta, 2023). Simmons (2022) surveys labour-related research published in the Journal of Sports Economics and identifies three main strands of the literature: firstly, studies estimating salary models and the impact of performance on salary; secondly, research on discrimination in professional sports leagues; and finally, studies on player mobility in professional leagues. The above research summarises the current literature and points out future research directions.

In the existing literature, when studying employee-employer relations, especially salary models, the impact of contractual arrangements on salary is often not considered. Economic theory would suggest that contractual arrangements affect the employee's salary in the general labour market and the sports industry. Some well-known players may sign short-term, large-amount contracts to help the team achieve short-term goals. On the other hand, some young players sign long-term, low-paying contracts to get stable playing time. However, the above phenomenon cannot fully describe the impact of contract arrangements on salary in the sports industry. Researching the effect of contractual arrangements on salary is not only of practical significance to the sports industry but can also supplement the existing literature to a certain extent.

In addition, players improve their performance by changing their efforts in the year when their contracts expire, which is the contract year phenomenon. This phenomenon has been verified and recorded in much existing literature. However, there is no consistent conclusion on the decline of player performance and the shirking behaviour of players after the contract year. The exploration of shirking behaviour is also a supplement to current research.

Finally, studying the termination of the relationship between employers and employees is unavoidable. In the sports industry, the end of this relationship can be the player changing teams or the player ending his career and leaving the league. Studying the determinants of player survival is also an important research direction. I have observed that in professional sports, there is a large number of players who change teams after the end of their contracts. Exploring to what extent this behaviour can help players continue to survive in the league has far-reaching practical and academic significance for studying employee selection decisions.

In this study, I independently collect National Basketball Association (NBA) data from the 2012-13 season to the 2018-19 season. The data set includes player information, player performance, player salary, player contract information, player injury, and team information. I use this data to explore the impact of player contractual arrangements on player performance, player salary, and player survival.

Chapter contents

Contents of Chapter 1

The sports industry offers a wealth of data for studying labour economics. Precise measurements of player performance allow for a more accurate estimation of employee output compared to other industries. This advantage can help quantify how an employee's output is affected by changes in their efforts, external pressures, or productivity changes due to injury or illness. In the sports industry, there is a contract year phenomenon; that is, players improve their performance by improving their efforts during the expiration year of the contract, thereby obtaining a new contract. The contract year phenomenon exists in many sports events, with NBA basketball players performing 3-5 percentile better in their contract year than common players (Ryan, 2015). However, after signing a contract, their performance tends to decline (Stiroh, 2007). Researchers have found that this decline is not due to the player's subjective shirking, but its reasons are not uniform (Berri and Krautmann, 2006).

This chapter contributes to the existing literature in three significant ways. First, it utilizes an independently collected NBA dataset spanning seven years (2012-2018), which includes comprehensive player performance data, both basic metrics (e.g., points, rebounds, assists) and advanced metrics (e.g., win shares). Additionally, the dataset contains detailed player information, contract details, and injury records, providing a holistic view of player performance factors.

Second, the chapter investigates changes in player performance between the contract year and the first year of a new contract. By analysing two consecutive player contracts longer than one year, this chapter finds no significant change in basic performance metrics after signing a new contract. However, advanced metrics indicate a decline in performance. Player Efficiency Rating (PER) dropped by approximately 2.2%, while offensive win shares (OWS), total win shares (WS), and value over replacement player (VORP) declined by 7.1%, 5.2% and 10%, respectively.

Third, linear regression models are used to further explore the impact of player contract status on performance. The results show that performance improves during contract years, suggesting players are motivated to excel. Additionally, analysis of remaining contract years reveals that longer contract durations are associated with stable or improved performance, challenging the idea of shirking due to contract security.

In summary, this chapter compares and analyses NBA player performance during the contract year and the subsequent year using between-group mean t-tests and linear regression models. The findings indicate that basic player performance remains relatively stable from the contract year to the following year, with no clear evidence of shirking behaviour after signing a new contract. However, advanced metrics show a decline in performance in some areas. The linear regression results highlight the motivational impact of the contract year but do not definitively confirm shirking behaviour post-contract.

Contents of Chapter 2

The sports industry not only offers a vast amount of data on player performance but also provides detailed information on players' salaries, contract lengths, and the terms of their contracts. This makes the sports industry an ideal environment for studying employee salary models. Salary decisions such as a player's leadership (Deutscher, 2009), a player's consistent performance (Deutscher et al., 2017), and race (Kahn and Sherer, 1988) have been extensively studied in the existing literature, There is limited analysis of players' salaries based on the specific details of their contracts. In this chapter, I focus on the impact of players including player options in their contracts on player salaries. Player options are a contract clause that exists in multi-year player contracts. It allows the player to decide whether to continue with the current contract or opt out of the current contract and become a free agent in the last year of the current contract.

This chapter makes three primary contributions. First, it estimates the determinants of player salaries using free-agent data. Player performance metrics, such as points, rebounds, blocks, assists, and playing time, significantly influence salary determination. Performance improvements during both non-contract and contract years positively impact future salary. For instance, a one-point increase in average score during non-contract years results in a 5% increase in total salary, while a similar increase during the contract year leads to a 10% increase. The analysis finds that player performance has a greater impact on salary for the top 50% of earners, whereas the bottom 50% are influenced by a wider range of factors, highlighting the complexity of salary determination.

Second, the chapter explores the determinants of player options in contracts and the factors influencing players' decisions to exercise them. Players with stable performance are more likely to secure player options, and higher performance levels increase the likelihood of obtaining these options. Anticipation of new league policies, such as a Collective Bargaining Agreement (CBA), also affects player options. The decision to exercise player options is primarily driven by the difference between expected and actual salaries, with All-Star selections further increasing the likelihood of opting out.

Third, the chapter examines the impact of player options on salaries. A matching process is used to compare players with and without player options in new contracts, using variables from the salary determination model to minimize the salary gap between the two groups. The results show that including a player option reduces annual salary for players in the bottom 75% by an average of $1.2 million, or 18% of income. In contrast, players in the top 25% to 10% receive a moderate salary premium and longer contracts, while players in the top 10% receive an annual salary premium of at least $10 million, equivalent to 40% of their salary. This divergence from traditional economic theory is likely due to the scarcity of star players, who have greater bargaining power in salary negotiations, enabling them to secure flexible contracts and higher salaries.

Contents of Chapter 3

In the field of labour economics, it is essential to assess the longevity of an employee's career. Studying the factors that influence labour exit is one of the ways to understand this problem. A player's survival in professional sports may be affected by a variety of factors, including injury (Carrieri et al., 2020), performance (Dilger, 2002; Jiobu, 1988; Spurr and Barber, 1994), and racial (Groothuis and Hill, 2013; Hoang and Rascher, 1999) in existing studies. However, there are few studies to explore the impact of players' behaviour of changing teams after the end of the contract on the player's survival risk, as well as the impact of some special clauses included in the player's current contract, such as (player options) on the player's survival. In professional sports, players are limited by work content and the scarcity of professional skills and have no way to continue their careers by changing jobs. Therefore, studying the impact of changing teams on the survival of employees in an employer-monopolised industry has profound implications. In addition, special options included in player contracts, such as player options, allowing players to decide when to enter the free market, thereby giving players a favourable opportunity in the fierce free market competition and increasing the possibility of player survival. Studying players' behaviours after the end of their contracts and the impact of special clauses on player survival supplement existing research.

This chapter explores the impact of player performance, changing teams after a contract, and player options on player survival using NBA data from the 2012-13 to 2018-19 seasons. Performance data is based on previous research (Kubatko et al., 2007), while model selection follows Del Corral et al. (2008)'s approach. Parametric and semi-parametric models are employed, with the Akaike information criterion (AIC) and Bayesian information criterion (BIC) identifying the Log-normal model as optimal. This chapter makes three main contributions. First, it quantifies the impact of player performance on survival, showing that offensive and defensive contributions significantly reduce survival risk and extend career longevity. Specifically, an increase in offensive win contribution by one unit reduces survival risk by 46% and extends survival time by 43%, while an increase in defensive win contribution by one unit reduces survival risk by 59% and extends survival time by 75%. Second, it examines how team selection behaviour after contract expiration affects player survival. High-performing players are more likely to stay with their original teams while changing teams is influenced by performance, age, and salary requirements. Third, it explores the impact of player options on survival, finding that options significantly influence player behaviour, remarkably increasing the likelihood of changing teams. Overall, this chapter provides a comprehensive analysis of player survival in the NBA, focusing on performance, team mobility, and contract features, and emphasizes the key role of player performance in career longevity.

Data Description

Data

The dataset used in this study is designed to study the impact of professional basketball players' contractual arrangements on their performance, salary, and career longevity. The dataset contains basic information about players, contact information, and player performance. This section outlines the data sources, collection methods, sample characteristics, and key variables. In this section, the basic information of players and player performance data are from the Basketball-Reference website. The website contains detailed basic information about players, such as the player's age, height, draft year, draft order, etc. At the same time, the website provides detailed player performance data, including the basic performance of players, such as points, rebounds, assists, etc. It also contains players' advanced performance data, such as PER, WS, and VORP. In terms of player contract information, basketball-reference provides a lot of information on player salary and contract length. In addition, I verify the previously collected player contract information from another information source, Spotrac. In the data collection process, I first determine the scope of data collection. Players should be players who have played in the league from the 2012-13 season to the 2018-19 season. After determining the range of players, I expand the collected data to a certain extent. I expand each player's data collection period from his rookie season to the 2019-20 season. This processing provides a complete trajectory of the player's career development and provides rich data support for subsequent analysis. In terms of data collection methods, I use the computer programming language Python to write a web crawler. First, I obtain the corresponding web address of each player in reference to the previously determined player range. Then, I use my own web crawler to collect the corresponding data on the player's page, such as the player's basic information, player performance, and player contract information. Finally, I manually verify the player contract information in the collected data with the contract information in Spotrac one by one. After the verification, I save the obtained data in a Stata format file. Since the data mainly comes from basketball references, the data structure is similar to the data display method used on the website. Each row of the data represents a player's data in a team for a season. If the player changes teams in the season, the same as the website is processed, and the player's data in the season are displayed in multiple rows.

Summary statistics

After completing the data collection, I conducted a simple analysis of the data. First, each row of the data is the data of a player playing for a team in a season. If a player changes teams in the season, the player data will be stored in multiple rows. In this data set, there are a total of 6703 observations, which come from 986 players, of which 735 players entered the league through the draft, and the remaining 251 players entered the league through direct signing by the team. From table 1, the youngest age of players participating in professional games is 18 years old, and most of these players join the league directly after graduating from high school. In my data, the oldest player is Vince Carter in the 2018-19 season, who is 42 years old. In terms of player experience, the initial experience of each player is 1. In this data set, the maximum experience of the players is 21 years, and the two players are Vince Carter and Kevin Garnett. The height and weight of the players are the data when the players just joined the league. As time goes by, the data has not been updated in a timely manner.

Table 1 Statistical analysis of basic player information

	N	Mean	Sd	Min	Max
Age	6703	25.91	4.10	18	42
Experience	6703	5.42	4.01	1	21
Height(CM)	6703	200.39	8.78	175	226
Weight(KG)	6703	100.10	11.94	72	163
Observations	6703				

Notes: This table shows the statistical analysis of basic player information.

The table 2 shows the statistical analysis of the basic data of the players. In terms of the number of data, the total observation value is 6603, which is slightly lower than the total number of samples. This is because some players in the sample will miss the entire season due to injuries, but when collecting data, the game data of the player in that season will still be collected, and the data will be displayed as missing values. In addition, since the salary data of the players are mostly multi-year guaranteed contracts, even if the players do not participate in the game in the season, they will still receive the corresponding salary, that is, the salary data of the player in the season will be recorded accordingly, so that the corresponding observations will be retained in the data set. In addition, all data are average data for the corresponding games.

Table 2 Statistical analysis of basic player performance

	N	Mean	Sd	Min	Max
Games	6603	51.53	25.34	1	82
Minutes played	6603	21.76	9.75	.2	42.5
Total rebounds	6603	3.89	2.60	0	18
Assists	6603	1.99	1.87	0	12.8
Steals	6603	.69	.45	0	2.8
Blocks	6603	.45	.49	0	6
Turnovers	6603	1.27	.83	0	5.7
Personal fouls	6603	1.89	.79	0	6
Points	6603	9.19	6.13	0	36.1
Observations	6603				

Notes: This table shows the statistical analysis of basic player performance.

The table 3 shows the statistical analysis of the advanced data of the players. I have selected five more representative data for display. First of all, from the perspective of the number of data, the total number of samples is 6603, but for some specific advanced data, their total number of samples is less than 6603. This is because the players have short playing time and other reasons, and the data of some specific advanced variables of the players are missing values. For example, the variable points generated by assists represents the player's ability to score after receiving an assist. Due to the short playing time of some players, this data is not fully recorded. Therefore, there are about 10 observations of this variable in the dataset with missing values, but the above missing values will not affect the analysis of this study.

Table 3 Statistical analysis of advanced player performance

	N	Mean	Sd	Min	Max
Player efficiency rating	6602	13.55	6.33	-54.4	133.8
Win shares	6603	2.84	3.11	-2.1	20.3
Box plus/minus	6603	-1.12	5.29	-70.7	242.2
Value over replacement player	6603	.76	1.44	-2	11.8
Points generated by assists	6593	271.99	309.40	0	2179
Observations	6603				

Notes: This table shows the statistical analysis of advanced player performance.

The table 4 shows the statistical analysis of player contracts. From the previous sample structure, we can see that the data is saved in the form of players in a single team in the season. The player's contract may be for many years, so the number of contracts is less than the total sample number. In this data set, there are 2,946 contracts. The average length of the contract is 2.49 years, and the average total salary of the contract is 14 million US dollars. The above is the basic statistical analysis of the data set. In subsequent studies, the corresponding data will be analyzed in more detail according to different research purposes.

Table 4 Statistical analysis of contract information

	N	Mean	Sd	Min	Max
Contract Salary(in Thousands)	2946	14000	25400	4.61	288000
Contract Length	2946	2.49	1.39	1	7
Observations	2946				

Notes: This table shows the statistical analysis of contract information.

Chapter 1

Comparing the performance of NBA players after signing big contracts

1.1 Abstract

Sports competition data provide valuable opportunities for economic research, especially in lobar economics. In professional sports, players often exploit the final year of their contracts to maximize performance and secure higher salaries—a phenomenon known as the contract year effect, highlighting the incentives tied to lucrative contracts. Additionally, the long-term, guaranteed nature of sports contracts offers an ideal setting for testing agency theory and potential shirking behaviour. This chapter analyses seven years of NBA data (2012-2018) to examine performance changes during the contract year and the year after. The dataset, validated through multiple sources, offers extensive insights into player performance. Using statistical and linear regression analysis, this study investigates player incentives in the contract year. Results indicate that players are motivated by the prospect of a new contract, showing performance improvements of at least 2.2% of the contract year level. However, no evidence of shirking behaviour following contract signing is observed.

1.2 Introduction

The use of sports data for economic research has become increasingly common due to the advantages that sports competitions provide, such as eliminating artificial experimental restrictions, rich data resources, and detailed data information (Palacios-Huerta, 2023). These benefits make sports competitions an ideal place for economics research, particularly labour economics. The main research directions in sports data include testing basic economic theories, testing the performance deviation from optimal behaviour, decision making, and factors affecting employee compensation (Bar-Eli et al., 2020). When it comes to determining employee salaries, various factors are taken into account. For instance, football players who can use both feet to kick the ball receive extra pay (Bryson et al., 2013), while basketball players with strong psychological qualities earn higher salaries (Deutscher et al., 2013). Additionally, the contract year phenomenon exists in many sports events, with NBA basketball players performing 3-5 percentile better in their contract year than common players (Ryan, 2015). However, after signing a contract, their performance tends to decline (Stiroh, 2007). Researchers have found that this decline is not due to the player's subjective evasion, but the reasons behind it are not uniform (Berri and Krautmann, 2006).

My research contributes to the existing literature in three significant ways: First, the study is based on an independently collected NBA dataset covering seven years, from 2012 to 2018. This dataset includes comprehensive player performance data, with both basic metrics (e.g., points, rebounds, assists) and advanced metrics (e.g., 'win shares,' which estimate the number of wins contributed by a player). Additionally, the dataset contains detailed player biological information, contract details, and injury records, providing a holistic view of player performance factors.

Second, the research leverages this rich dataset to investigate changes in player performance between the contract year and the first year of a new contract. Through careful sample selection, two consecutive player contracts with terms longer than one year were analysed, comparing performance changes during the contract year of the first contract and the first year of the subsequent contract. The mean difference analysis reveals no significant change in basic performance metrics after signing a new contract. However, advanced metrics indicate a significant decline: Player Efficiency Rating (PER) dropped by approximately 2.2%, while offensive win shares (OWS), total win shares (WS), and value over replacement player (VORP) declined by 7.1%, 5.2%, and 10%, respectively. Through further sample selection, performance in the year before the contract year is introduced for comparison, enabling a running comparison of performance over three years. It can be concluded that a player's performance decline in the year after the contract year is a normal drop following the signing of a new multi-year contract, with the performance level in this year being relatively close to that of the year before the contract year. In a professional sports environment, multi-dimensional supervision of player performance prevents players from subjectively lowering their performance, as this would often result in significant losses.

Third, linear regression models are used to further explore the impact of player contract status on performance. After adding player fixed effects to the model, the results show that player performance improves as the contract progresses. This indicates that players tend to enhance their performance during the contract year due to a strong incentive effect. The analysis also suggests that shirking behaviour is influenced by the length of both the current contract and the new contract. Specifically, if the new contract is longer than the current one, player performance may decline compared to the current contract. Conversely, if the new contract is shorter, player performance tends to improve. Thus, the evidence does not conclusively verify the presence of shirking behaviour. These findings provide a nuanced understanding of the contract year phenomenon in the NBA, showing significant performance improvement during contract years while leaving shirking behaviour post-contract inconclusive. The implications of this study are crucial for NBA teams in contract negotiations and player management. Further research is needed to better understand the long-term effects of contract guarantees on player performance and develop effective strategies for maintaining productivity throughout the contract period.

This chapter aims to compare and analyse NBA player performance during the contract year and the subsequent year. Two methods—between-group mean t-tests and linear regression models—are used to assess differences in player performance. The findings reveal that basic player performance remains relatively stable from the contract year to the following year, with no clear evidence of shirking behaviour after signing a new contract. However, advanced metrics show a decline in performance in certain areas. Linear regression results highlight the motivational impact of the contract year, although they do not definitively confirm shirking behaviour post-contract. The remainder of the chapter is organized as follows: Part 2 reviews the outcomes of previous research on NBA player performance; Part 3 provides background information on the NBA and its players; Part 4 details the data collection process and presents the analysis results; and Part 5 concludes the chapter by summarizing the findings.

1.3 Literature review

Research on the relationship between the economy and sports is a fascinating field of study that can be approached from two broad aspects. The first aspect is the economics of sports, which involves using economic principles to analyse the profitability of the sports industry, the needs and preferences of the audience, and the level of competitive balance within the industry. This aspect is mainly concerned with the financial aspect of sports. On the other hand, the second aspect of this field of study involves using sports data to conduct economic research (Palacios-Huerta, 2014). This approach is more focused on using data analytics to better understand the relationship between sports and the economy. This aspect enables researchers to identify trends, patterns, and insights from the vast amounts of data generated in the sports industry. The use of professional sports data has several advantages over laboratory settings. Firstly, sports competitions provide a rigorous experimental environment for studying human behaviour in a competitive environment. This setting allowed researchers to observe natural and spontaneous behaviour patterns, which are more representative of real-life situations. In contrast, laboratory settings limit the subjects' reactions due to low monetary returns, which affect the generalizability of the results in real-life scenarios. Moreover, the use of sports data eliminates the limitations of laboratory settings and is closer to the actual situation of the real society. The decisions that athletes make in a sports competition are typically familiar to them, and they are made in their daily lives (Levitt and List, 2008). Therefore, the data from sports competitions provide a more robust and valid representation of human behaviour in a competitive environment. In conclusion, using sports data to conduct economic research has revolutionised the field of sports economics. It offers a more detailed and comprehensive understanding of the relationship between the economy and sports, allowing policymakers to make more informed decisions that benefit both the sports industry and the economy at large.

Sports competition data provides a wealth of diverse and detailed economic research data (Kahn, 2000). The data provided by sports competitions comes from various aspects, such as the participants' abilities and the incentives that affect their performance. For instance, sports data can be used to analyse how different incentives, such as monetary rewards, affect the performance of athletes. Moreover, sports data can detect differences in gender, race, body shape, and other factors. For example, it can be used to investigate the impact of race or gender on sports performance or to study the relationship between body shape and athletic ability. Furthermore, sports game data has detailed information that can meet the purposes of different economic research. For instance, it can be used to analyse the impact of sports on local economies, such as the effect of hosting a major sporting event on the local economy. It can also be used to investigate the labour economics of sports, such as the impact of professional sports on employment and wages. The unique advantages of sports data have created a comprehensive research field that includes economics, psychology, management, and health sciences. For example, sports data can be used to investigate the psychological factors that affect sports performance, such as motivation, stress, and anxiety. It can also be used to study the management of sports organisations, such as the role of coaches and administrators in team performance. Finally, sports data can be used to investigate the relationship between sports and health, such as the impact of sports on physical and mental well-being.

Sports data is becoming an increasingly popular tool for conducting economic research. This data can be used in various aspects, such as testing fundamental economic theories, examining performance deviation from optimal behaviour, decision-making, and factors influencing employee compensation. In professional sports, players are essential assets to the team. The team's salary expenditure on players is the primary operating expense. Therefore, studying how players' salaries are determined is a crucial entry point for examining players' reasonable decisions based on salary. For instance, football players can receive higher wages if they have scarce talent. This means that workers with rare skills can increase their earning potential in the labour market. In football games, footedness is considered a predetermined ability that is paid for. To conduct this study, Bryson et al. (2013) selected two datasets. The first dataset contained a cross-section of 1991 players in the top five European leagues in 2005, while the second dataset was the Bundesliga dataset from 2002 to 2005 in Germany. The authors established a linear regression model wherein the dependent variable is the log value of salary, and the independent variables include the basic situation of the player, the position of the player, the earning ability of the player, and the player's game performance. The study revealed that double football players have a significant premium in the European cross-section and the Bundesliga data. In terms of player positions, having the ability to use both feet is crucial for forwards and midfielders, but it does not significantly improve the team's performance. Therefore, they conclude that players with two feet may receive an excess salary not proportional to their contribution to the team's success. Overall, this study sheds light on how sports data can be used to examine various aspects of the labour market, including employee compensation. By analyzing player salaries in football, I can gain insights into how workers' salaries are determined based on their skills and performance in other industries.

In professional basketball, a player's salary is determined by numerous factors, including their skills and abilities. However, there are also certain factors that aren't directly observable that can have a significant impact on a player's salary. One of these factors is mental strength, which refers to a player's ability to maintain their performance levels during critical moments in a game. According to a research study conducted by Deutscher et al. (2013), mental strength has been found to have a statistically significant and economically considerable impact on player salaries. This research study aimed to measure the impact of mental strength on basketball players' salaries, and to do so, the researchers selected approximately 200 professional basketball players who played in NBA games from 2003 to 2006 as the research subjects. The study used the OLS model to analyse the data, with the dependent variable being the natural logarithm of salary, and the independent variables included player experience, draft order, number of All-Star appearances, game time, score, player position, and mental strength. In addition, the study also performed quantile regression according to salary. To measure mental strength, the researchers analysed the free throw performance of the selected players during the last five minutes of games, where the point difference was within five points. The ratio of a player's free throw percentage at critical moments to their free throw percentage at non-critical moments was used to determine their mental strength. The results of the study showed that mental strength has a significant impact on player salaries, particularly for low-income players. An increase in standard deviation for mental strength resulted in a 50% salary increase for 10% of low-income players compared to similar players. However, this difference was not obvious among high-income players, which may be related to the league salary cap. Overall, this study highlights the importance of mental strength in basketball and how it can have a significant impact on a player's salary. By understanding the factors that contribute to a player's salary, teams can make better decisions when it comes to recruiting and compensating their players.

In the National Basketball Association (NBA), players' salaries are determined by their performance and negotiations with the franchise, as highlighted by Berri et al. (2015). The neoclassical model believes that an employee's salary should be equal to their marginal revenue product (MRP). The standard theory relies on the relationship between employee effort, output, and revenue. However, some companies earn income in forms that are difficult or impossible to trace back to current employee behaviour. In such cases, the standard model of the labour market requires adjustments. Scully (1974)'s model regards team victory as the player's output at work. In the NBA, a player's output can only account for 26% of the team's total revenue, but they can get more than 50% of the year's revenue, which is a significant mismatch between returns and output. Therefore, it is unsustainable in the long run. As a result, a player's salary is not only related to their performance (MRP) but also to their ability to negotiate with the team. The research divides the team's revenue into two parts: fixed revenue and variable revenue. Fixed revenue mainly comes from TV broadcasting contracts, and the other part is variable revenue. Since television broadcast contracts are usually signed many years ago, their value cannot be determined by the current performance of the players. On the other hand, the performance of the players determines the distribution of the team's variable revenue. The player's contribution to the team's victory multiplied by the team's single-game victory value is the player's marginal revenue product, and the remaining part is the player's bargaining power. In the study, the dependent variable is the player's bargaining power, and the independent variables are player panel data, team performance, team fixed income, and player agents. The OLS model is used to analyse the data. The regression results show that scoring has a clear advantage when it comes to player performance data. In other words, NBA teams overcompensate players for their scores. In terms of non-player performance, age and number of starts can enhance players' bargaining power. The team's performance is better, and it can also help players take the initiative in the negotiation. However, player agents do not have an obvious role in player bargaining power. The study proposes that the factors that determine player salaries come from two aspects, which opens up a new direction in the determinants of player salaries. The findings suggest that players' salaries are not only related to their performance but also their bargaining power. The contribution of this research is that it provides a new direction for further research on the determinants of player salaries.

The salary determination process for professional athletes has been the focus of extensive research. While there have been many studies in this area, one significant issue remains: the inconsistency between player performance and team wins has resulted in an inefficient labour market for players (Simmons and Berri, 2019). This can be attributed to various factors, including differences in playing styles, team dynamics, and the impact of external factors such as injuries. One example of this is the popularity of the Money ball strategy, which places an emphasis on on-base percentage in baseball. This approach led to a temporary increase in demand for players with higher on-base percentages, but the free agent market eventually re-balanced (Hakes and Sauer, 2006). This indicates that while certain metrics may become popular, they are not always indicative of long-term success. A similar situation occurs in basketball, where a player's evaluation is often based on their scoring ability rather than their overall contribution to team success (Berri et al., 2007, 2014). However, factors such as shooting efficiency, rebounds, steals, and turnovers play a crucial role in a team's ability to win games. As such, research into the inefficiencies of the sports labour market is an important field in sports economics. One important direction of research in this field involves comparing the behaviour of athletes before and after their contract year. The contract year is the final year of a player's contract, during which they may adjust their behaviour to align with the team's goals in order to secure their next contract. This amplifies the players' reaction to monetary incentives, and studying their behaviour during this time can help to deepen our understanding of the inefficiencies in the sports labour market. Overall, the complexities involved in determining player salaries in sports highlight the need for continued research in this area. By exploring the various factors that impact player performance and team success, I can gain a better understanding of how to create a more efficient labour market for athletes.

The decision on a player's salary is often influenced by their performance. Therefore, studying the factors that affect a player's performance can help inform this decision. To this end, Cao et al. (2011) conducted a study on professional basketball players to explore the impact of pressure on performance. The study found evidence of choking under pressure during free-throw shots in very close games. According to neoclassical economic theory, the higher the effort invested by an individual, the better their performance. However, people often feel pressure during important moments, which can affect their behaviour. In this study, the researchers used free-throw shots in basketball as a case study to explore the impact of pressure on player performance. They collected eight years of play-level data from the NBA games held between 2002 and 2009, which allowed them to analyse the differences in free-throw performance at different times and score differences. Unlike previous studies that used game-level data, this research analysed the differences in free-throw performance at different times and score differences. The study focused on the critical moment when the score difference is within two points and within 30 seconds of the end of the game. The researchers found that players are more pressured during this time, and their free-throw performance is likely to decline by 5-10%. Interestingly, this decline is not affected by the home status, attendance, or playoff. This indicates that additional pressure will reduce the player's free-throw performance regardless of external factors. The study conducted a linear regression model to compare the changes in players' free throws between non-critical moments and critical moments. The results showed that when players are under additional pressure, their free throw performance will be reduced by 5-10%. The study concluded that this is a good example of how highly disaggregated data in basketball can be used to test economic theories of performance. Overall, this study provides valuable insights into the impact of pressure on player performance, particularly during critical moments of a game. The findings can help inform decisions related to player salaries and support the development of strategies to help players perform better under pressure.

Basketball is a sport where players can experience pressure from various aspects, including close scores, fans of the opposing team, and unfamiliar surroundings. Even enthusiastic home team fans can exert invisible pressure on players at critical times. This pressure can have an adverse effect on a player's performance, especially when taking free throws in front of a supportive audience. When the pressure increases, the player's performance tends to decrease. To study the relationship between the number of audience and player performance, Böheim et al. (2019) used play-by-play data from nine seasons of NBA games from 2007 to 2015. They constructed a linear regression function based on this data, with the dependent variable being a binary variable that determines whether the free throw is hit or not. The independent variable is the number of audiences, and the control variables are the remaining time of the game, the score difference before the free throw, and the team's winning percentage before the game. Moreover, the study used weather conditions as an instrumental variable for the number of viewers. The researchers found that the number of spectators at the start of the home team has a negative effect on a player's performance. This is because the players tend to feel more pressure to perform well in front of a large audience. Free throws are considered a critical measure of player performance, as they do not rely on other players' teamwork but solely on the player's performance. The player who makes the free throw has a certain degree of randomness, which adds to the pressure. The study shows that the higher the number of audiences, the more pressure the player feels, leading to a decrease in their performance.

When it comes to sports, players often tend to perform better in the final year of their contract. This phenomenon is known as the "contract year phenomenon" and is especially prevalent in North American sports markets, such as the NBA. In such markets, players can sign multi-year contracts with teams where the salary is guaranteed. This means that the player's subsequent salary won't be affected by their future performance, and they have a financial incentive to perform well in their final year to secure better terms in the next contract. However, this incentive can also have a downside. Some players may intentionally lower their performance after signing a multi-year contract due to a lack of discipline off the field (Berri and Krautmann, 2006). This can be detrimental to the team's performance, as well as the player's future earning potential. To better understand the impact of the contract year phenomenon on player behaviour, this study creates a new NBA player database. Berri and Krautmann explores the differences in player behaviour before and after their contract, comparing their behaviour during their contract year with their behaviour after signing a new contract. By doing so, I gain insights into the motivational effect of contract years on players' behaviours and understand how contract structures can impact player performance. Ultimately, this study can help teams make better decisions when it comes to signing multi-year contracts with players, ensuring that they receive adequate financial compensation throughout their careers.

This research study delves into the contract year phenomenon in professional basketball and baseball, which centres around players striving to improve their performance during the contract year to secure a new contract. The study draws upon the findings of White and Sheldon (2014), which revealed that players' performance typically improves during the contract year, leading to a salary increase reward. However, there is often a decline in performance after the contract year, known as the contract year syndrome, which is not necessarily linked to the salary increase. The study analyses NBA game data and player salary data from 2002 to 2011, as well as MLB game data and player salary data from 2006 to 2012. The athletes' data is classified into three groups based on the different stages of the contract year: the year before the contract, the contract year, and the year after the contract year. The study selects eight types of player data for multivariate analysis of variance to compare the performance of players. These variables include shooting percentage, scores, PER, offensive rebounds, defensive rebounds, assists, steals, and blocks. The results of the study indicate that during the contract year, scoring, shooting percentage, and PER show a significant increase, while other non-scoring data do not exhibit significant changes. Following the contract year, scoring data shows a slight decline but remains higher than the pre-contract year level. In terms of baseball research, the study uses batting average, on-base percentage, slugging percentage, and home run to measure player performance and conducts a multivariate analysis of variance. The findings highlight that the contract year phenomenon is primarily manifested in the increase of offensive data. Overall, the study provides a detailed analysis of the contract year phenomenon in basketball and baseball, shedding light on the factors that contribute to players' performances during the contract year and the subsequent decline in performance.

The study conducted by Ryan (2015) examines the impact of contract years on player performance in the NBA. The study found that players in their contract year tend to perform better than in other years, with an increase of 3-5 percentile, which translates to 0.009 more victories for the team every 48 minutes. This phenomenon is widespread in professional sports in the United States and is in line with the incentive theory, which suggests that individuals tend to work harder when they are motivated by certain factors, such as money or job security. The study used NBA game data from 2005 to 2013 to compare the performance differences of players in contract years, taking into account different contract options, such as player options and team options. The study eliminated player contracts that include options to reduce the incentive effect of contract options on players. The study first established an OLS model, with an integrated indicator reflecting the player's ability as the dependent variable, the basic information of the player, and whether the player is in the contract year as the independent variable. The study's innovative point is that it distinguishes itself from previous studies by using an integrated indicator instead of a box score. The integrated indicator is a composite measure that reflects the player's overall ability, including scoring, rebounding, assists, and other factors. The study found that players in the contract year tend to perform better than in other years, even after controlling for other factors such as age, experience, and position. The study addressed the issue of players with lower strength entering the free agent market more by using the proportion of free agents to all players in the league each year as an instrumental variable. The study then used two-stage least squares to re-estimate the impact of contract years on player performance. The results show that players in the contract year add 0.009 wins to the team every 48 minutes, which is equivalent to a 3-5 percentile increase in the performance of the median player. The study's findings have important implications for both players and teams in the NBA. The study suggests that players can improve their performance and increase their value by working harder during their contract year. The study suggests that teams can use the contract year to incentivize players and improve team performance. Moreover, the study also found that the contract year phenomenon is not unique to basketball. In baseball, players tend to improve their performance by 9% in their walk year, which is the year before they become a free agent (Perry, 2006). Similarly, a study by the CEO of a company demonstrated that job uncertainty can have a positive impact on the company's economic behaviour and benefits (Liu and Xuan, 2020).

The research conducted by Berri and Krautmann (2006) has shed some light on the factors that influence a player's tendency to shirk their responsibilities, i.e., to reduce their performance after signing a new contract. The study was based on NBA data from the seasons 2000-01 to 2002-03 and aimed to explore the relationship between player performance and new contracts. The study considered a range of factors, including players, teams, new contracts, the length of new contracts, and the salary of new contracts, and used two different methods to measure player performance. The first method was the PROD data commonly used by NBA teams, while the second method was an improved version of the PROD data that was closer to the player's margin product. The results of the study revealed that when evaluating player performance using the NBA's PROD measurement, the shirking hypothesis was confirmed, indicating that players tend to reduce their performance after signing new contracts. However, when using PROD data in an economic sense, the assumption of shirking behaviour was not supported. This suggests that there are differences in the definition of behavioural performance between the economics community and the industry. Moreover, the study found that, under the industry's definition, a player's decline in performance after signing a new contract is related only to the length of the new contract and not to its amount. This means that players who sign longer contracts tend to experience a decline in performance, while the amount of the new contract does not seem to have a significant impact on a player's performance. In summary, the study highlights the importance of using appropriate performance measurement methods when evaluating players and suggests that the definition of behavioural performance may vary depending on the context in which it is used.

Stiroh (2007) conducted a study on the correlation between incentives in player contract years and team performance in the NBA. The study analysed data from 1988 to 2002 and focused on differences in various player performance metrics before and after contracts. The player performance data included basic metrics such as points, rebounds, assists, and blocks, as well as Composite Rating, a synthesised player performance metric. To analyse the data, the author constructed two dummy variables representing a player's time status - one for the contract year before signing a new contract and the other for the first year after signing a new contract. The sample excluded contracts of one year or less. The model added control variables such as age, team, field position, team, and season and performed a weighted least square regression estimation based on the number of player appearances. The study found that improved player performance during the contract year led teams to believe they had higher abilities, which led to lucrative new contracts. However, a player's corresponding performance decreased after the contract year, particularly in Composite Rating. The study also found that an increase in the proportion of players in the team's contract year led to an increase in the team's winning proportion in the season. In conclusion, the study by Stiroh (2007) provides valuable insights into the relationship between incentives in player contracts and team performance in the NBA. The findings suggest that teams need to be cautious when offering contract incentives to players, as overvaluing a player's performance during the contract year could have long-term negative effects on team performance.

The motivational impact of players in the contract year is not limited to basketball but also extends to football. According to the agency theory, an agent may shirk their responsibilities after signing a long-term contract with a team (Lazear, 1981). However, teams cannot provide each player with a one-year contract only as it would lead to high replacement costs (Frick, 2007). To further investigate the relationship between contract status and player performance, Buraimo et al. (2015) conducted a study using data from the German Football League from 2002-03 to 2012-13 seasons. In the study, Kicker magazine player post-match evaluation was used as an indicator of player performance. The study used the number of years of the contract and the remaining years of the contract as the time status of the contract in the model. Additionally, the model included control variables such as age, games played, experience, previous club, field position, nationality, and season. The study used the remaining years of teammates' contracts as the instrumental variable for the remaining years of players' contracts. The results showed that the player's performance increases with the elapsed years of the current contract and the remaining years of the contract. Buraimo et al. did not support the hypothesis that players who sign a long-term contract tend to shirk their responsibilities. In conclusion, the study suggests that the longer the contract years elapsed, the better the player's performance, and teams should avoid providing only one-year contracts to players to ensure continuity and reduce replacement costs.

My chapter delves into the use of the relatively new NBA database, which contains player data of up to seven years. The player salary information, which is a crucial aspect of the study, has been verified by multiple parties, making it more credible. The study used two broad categories of player performance data to measure their performance from various aspects - basic data and advanced data. Furthermore, I accurately defined the player's status during the contract year by the complete contractual information. Through statistical analysis and OLS, the study was able to verify that players tend to put more effort into improving their performance towards the end of their current contract to secure a better contract. This is because complete contract information enables the study to accurately define the player's status during the contract year. However, after signing a new contract, the player's behaviour is subject to scrutiny as it can be measured through their performance. Since they are supervised by multiple parties, players do not tend to lower their performance after signing a new contract. The hypothesis that players engage in evasive behaviour when signing a new contract has not been verified. In conclusion, my study provides valuable insights into the behaviour of NBA players regarding their performance and contracts. The use of accurate and credible data sources enables the study to provide reliable results, which can be useful for players, team managers, and researchers in the field of sports performance analysis.

1.4 Institutional background

The National Basketball Association (NBA) is a highly competitive professional basketball league in North America, comprising 30 teams - 29 in the United States and 1 in Canada. The league is divided into two conferences, each with three divisions of five teams. The teams compete in two stages: the regular season and playoffs. The regular season generally starts in the last week of October and lasts until mid-April, during which each team plays 82 games - 41 home and away games. The games are scheduled in such a way that each team competes with four teams in the same division four times a year. Each team plays four times, with six teams in the other two divisions in the same conference and the other four teams played three times. They also play twice with 15 teams from another conference. The strength of the schedule will vary between teams, based on their respective opponents and the games played. After the regular season, the top eight teams from each conference enter the playoffs, which is the second and final stage of the competition. The playoffs have undergone changes in 2020, where a play-in tournament is required before deciding which teams will enter the playoffs. The tournament includes teams ranked 7 to 10 from each division. The teams ranked 7 and 8 will play a single game, and the winner will be the No. 7 seed. The loser will play the winner of the game between ranked 9 and 10, and the winner will become the No. 8 seed. Each NBA team has a total of 15 players, but the roster can be increased through two-way contracts and other methods. Each game can activate 13 players to participate. NBA games are divided into four quarters, each lasting 12 minutes, and the shot clock is 24 seconds. Since the 2018-19 season, the shot clock resets to 14 seconds after an offensive rebound. The team with the better record in each series gets home-court advantage, which is an essential factor in determining the outcome of the game. The two teams with the best records in each conference qualify for the conference finals, and the winners of the conference finals meet in the NBA Finals to compete for the championship of the year. The NBA is known for its competitiveness, intense games, and the high level of skill and athleticism displayed by the players. In addition, NBA players need to complete 82 games during the regular season, and a large number of games provide rich data. At the same time, player data can be completely and correctly recorded, and there is a large amount of data to correctly evaluate player performance.

The NBA has a detailed and comprehensive salary system that is based on the collective bargaining agreement (CBA). The CBA is a legal contract that governs the relationship between the league and the players association and regulates various aspects of the league's operations. It covers important areas such as salary caps, procedures for setting them, minimum and maximum wages, trading rules, NBA draft procedures, and hundreds of other things that need to be defined for the NBA to function properly. One of the most critical aspects of the NBA salary system is the salary cap, which is a limit on the amount a team can spend on a player's contract. The salary cap helps to maintain competitive balance in the league by ensuring that no team can simply buy better free agents than others. The salary cap is calculated based on the estimated amount of basketball-related income (BRI) and benefits for the upcoming season. For the 2019-2020 season, the salary cap is set at 109.140 million US dollars. If a team exceeds the salary cap, the league imposes penalties through a luxury tax system. The luxury tax is a mechanism that helps control team spending by penalizing teams for exceeding a certain level of salary expenditure. Teams with salaries exceeding this level are subject to a penalty for every dollar above that level. The funds collected through the luxury tax system can be allocated to teams or used for league purposes. In addition to the salary cap and luxury tax, the CBA specifies a higher salary standard called Apron. If a team's salary exceeds this standard, it will face more severe penalties. This provision is designed to further ensure competitive balance in the league by limiting the spending power of the financially strong teams. In conclusion, the NBA's salary system is a complex and essential part of the league's operations. It is designed to promote competitive balance, regulate team spending, and ensure fair compensation for players. The salary cap, luxury tax, and 'Apron' are critical provisions that help to achieve these goals.

The Collective Bargaining Agreement (CBA) is a crucial document in the NBA that governs the relationship between the league and its players. One of the key aspects covered in the CBA is the regulation of player contracts. The CBA sets limits on the disclosure of player contracts, which means that the details of a player's contract are not made public. The CBA has several provisions that determine the maximum and minimum contracts for players based on their experience in the league. For instance, players with less than 6 six years of experience can receive up to 25% of the salary cap, while those with more than ten years of experience can get up to 35% of the salary cap. These provisions ensure that players are compensated fairly based on their experience and skill level. For players who enter the league through the draft, their first contract will be a standard one provided by the league, and the salary is determined by the CBA. First-round draft picks will receive a four-year contract, with the first two years as a guaranteed contract and the next two years as a team option contract. The team option means that the team has the right to decide whether or not to continue with the contract. The corresponding option is the player option, which gives the player the right to decide whether to continue or exit the contract. Second-round rookies do not receive standardised contracts from the league. Therefore, the contract they receive is generally shorter, and the amount of guarantee is less. The CBA also provides several contract exceptions that help teams retain players who have been with them for many years or rookies trained by the team. Some of the exceptions include the veteran minimum exception, the mid-level exception, and the bi-annual exception. These exceptions help ease the restrictions of the salary cap system to a certain extent and improve the flexibility and complexity of transactions. The NBA has a detailed salary system, complex contract terms, and detailed data. This makes it an ideal research topic in the field of labour economics. Researchers can analyze the impact of the salary cap system on player salaries, team performance, and league revenues. They can also examine the effectiveness of the contract exceptions in achieving the league's goals of maintaining competitive balance and promoting player welfare.

The NBA has implemented a set of rules for teams to sign free agents above the salary cap. These rules are known as exceptions, and there are several types of exceptions available to teams. The first exception is the Larry Bird Exception, which allows teams to retain their veteran free agents. To qualify for this exception, a player must have played for the same team for at least three years without being waived or changing teams as a free agent. If a player meets this requirement, they can receive up to a five-year maximum salary contract with an annual salary increase of 8%. The Early Bird Exception is another exception that allows teams to sign their free agents. This exception requires players to have played for the same team for at least two years, with a minimum contract length of two years and a maximum contract length of four years. The annual salary increase is 8%, and the maximum salary can be up to 175% of last season's salary or 105% of last season's average, whichever is greater. The Non-Bird Exception is the third exception available to teams. This exception can help players sign contracts of up to four years with a maximum annual salary increase of 5%. To qualify for this exception, a player must have played for the original team for one full year. These exceptions can help teams maintain their current roster if they exceed the salary cap.

The league also provides additional exceptions to help teams attract free agents from other teams. There are four types of exceptions available, including the Non-Taxpayer Mid-Level Exception, Taxpayer Mid-Level Exception, Room Mid-Level Exception, and Bi-Annual Exception. The Non-Taxpayer Mid-Level Exception is available to teams whose total salary is lower than the Apron. The first-year salary of this exception was $8.406 million in the 2017-18 season. This exception can be split and allocated to multiple players, with a contract length of up to four years and an annual salary increase of up to 5%. The Taxpayer Mid-Level Exception is available to teams whose total salary is higher than the Apron. The first-year salary of this exception was $5.192 million in the 2017-18 season. This exception can be split and assigned to multiple players, with a maximum contract length of three years and an annual salary increase of 5%. The Room Mid-Level Exception requires teams to use it after the team's total salary is lower than the salary cap. The first-year salary of this exception was $4.328 million in the 2017-18 season. This exception can be split and allocated to multiple players, with a maximum contract length of two years and an annual salary increase of 5%. Finally, the Bi-Annual Exception is available to teams whose total salary is higher than the Apron. The first-year salary of this exception was $3.290 million in the 2017-18 season. This exception can be split and allocated to multiple players, with a maximum contract length of two years and an annual salary increase of 5%. However, this exception cannot be used for two consecutive seasons.

Apart from these exceptions, there are additional exceptions for certain players. Rookie Players can receive a format contract based on their draft order above the salary cap. The Minimum Player Salary Exception allows teams to provide players with a minimum salary above the salary cap for up to two years. The annual salary is determined based on the player's experience in the league. Finally, if a player misses all games of the season due to injury, and the league adjudicates the player's injury, the Disabled Player Exception allows teams to sign other players according to a certain proportion of the player's salary.

1.5 Data and Methodology

1.5.1 Data collection

I created a distinctive database that employed computer coding for data collection. The primary source of data was obtained from Basketball-Reference, a website operated by Sports Reference that specialises in collecting basketball data. The research data was obtained from the NBA, which spanned seven seasons, from 2012-2013 to 2018-2019. This time range was chosen as the 2018-2019 season was the last season unaffected by COVID-19, and the seven seasons were sufficient to meet the research needs of this study. Manual downloading of data for 1045 players would have been a daunting task; hence, the study used computer coding technology written in Python language to obtain the required data effectively. The player screening tool built-in Basketball-Reference was employed to obtain the web addresses of the data pages of all 1,045 players. The compiled Python language code was then used to analyse the HTML code of the corresponding web page, extracting the relevant data and saving it. The acquired data was sorted and analysed, and it was divided into three parts. The first part contained the basic information of the players, including their name, date of birth, draft order, high school, and university school. The second part comprised data on the player's game, which was further divided into two categories: basic game data and advanced game data. The basic game data included panel data, such as points, rebounds, assists, steals, and more. The advanced competition data is compiled mostly into grated data calculated by formulas such as PER, BPM, eFG, etc. The third part of the data was the salary data of the players, which included the salary of the players for each year and whether the players had signed contracts for that year. The use of computer coding technology proved to be an efficient solution that saved time and resources, and the acquired data was comprehensive, precise, and instrumental in the study.

1.5.2 Data analysis

Advanced performance variables

Possession: In basketball, possession begins when one team has control of the ball and ends when that team loses control of the ball. The way a team loses control of the ball can be reflected in the following ways. First, the team holding the ball scores by shooting or getting free throws. Second, the team with the ball misses a shot, and the other team gets a defensive rebound. Third, the team holding the ball make a turnover.

Pace: Compared with Possession, pace makes the calculation of the number of possessions more accurate by eliminating the impact of overtime. The calculation method adds the possessions of the two teams in the game, divides them by the time of the game, and multiples by forty-eight.

PER: Player Efficiency Rating (PER) was developed by John Hollinger as a way to measure the efficiency of a player's performance on the field. PER calculates the difference between positive and negative outputs and then converts playing time and offensive pace into a unified unit to measure player efficiency on the field. The PER calculation process involves three steps. Firstly, the player's traditional data is used to calculate the unadjusted PER(uPER). Secondly, the uPER adjusts based on the league's average pace to derive the adjusted PER(aPER). The purpose of this adjustment is to eliminate deviations caused by the different offensive paces of each team. Thirdly, the league's average PER is set at 15, and then aPER is converted into the final PER, allowing for comparison across different years. However, PER is not perfect and does not account for a player's contribution on the defensive end. The traditional data only includes steals, blocks, and rebounds to reflect the player's defence.

WS: Win shares were initially developed by Bill James in baseball as a way to calculate the number of wins a player contributed. Later, Dean Oliver improved and introduced this concept into the basketball world. The data is divided into Offensive and Defensive win shares, which are cumulative and increase as the game progresses. If the team loses, the player's victory contribution will be negative. The final WS accumulated by a player represents the estimated number of wins contributed by the player to the team's total wins in the season. For Offensive win share, the difference in scoring efficiency created by players compared to the league average offensive pace is first measured. Then, the marginal points required for each win are calculated to estimate the player's offensive win contribution. Similarly, for Defensive win share, a player's ability to reduce opponents' scoring compared to the league average is measured, and marginal points scored per win are estimated to determine the player's victory contribution on the defensive end. By adding the Offensive and Defensive win contributions, the total win contributions of a player are obtained.

WS48: WS48 is the conversion of win shares to the player's win shares per 48 minutes.

BPM: Box Plus/Minus (BPM) is a statistic used in basketball to measure a player's contribution to their team in comparison to the league's average player. The average player in the league is given a BPM of 0. A player's BPM value shows how much better or worse their contribution is per 100 possessions compared to the average player. However, it's important to note that BPM doesn't take into account external factors such as the player's team or the league environment. For instance, a player who can be easily replaced in the league is likely to have a BPM of -2, while an All-Star player would have a BPM of 5. On the other hand, players who are at the bottom of the league will have a BPM of around -5. It's worth noting that BPM doesn't consider a player's impact on their team as a whole but rather their individual skill level compared to the league average. Additionally, BPM doesn't factor in the player's teammates, as it's solely based on their individual performance.

VORP: Value over Replacement Player (VORP) is a basketball statistic that is based on the replacement player in Box Plus/Minus (BPM). It measures how much higher the value of a player is compared to a replaceable player over the course of 100 possessions. This value is then multiplied by the proportion of the player's playing time and the number of games the player has played. VORP represents the difference between a full season's value of the player and a replaceable player.

OnCourt: The Plus/Minus on Court per 100 possessions is based on the play-by-play of each game, not on the traditional data in the box score. This means that the team's point difference changes when the players are on the court. For instance, if a player comes on the court with the team leading by 5 points and comes off the court with the team leading by 15 points, the player's Plus/Minus value is 10 points. Since each player can be substituted several times in a game, it's essential to record all the changes in the team's point difference each time he comes on and off the field and finally add them up. The characteristics of Plus/Minus are as follows: first, there will be negative values. Second, the team's Plus/Minus values are added up and divided by 5 to get the team's point difference. Although the plus-minus value is a closer step to statistics based on play, it is still very basic at the technical level and cannot further separate the contribution of each player. It can only roughly assess the possible influence of the player on the court.

OnOff: This is the net Plus/Minus per 100 possessions. This metric calculates the difference between Plus/Minus when a player is on the court versus when he is off the court.

The names and meanings of players' advanced data variables are shown in the table 1.1.

Table 1.1 Advanced Data Definition

Variable	Definition
PER	Player Efficiency Rating. A measure of per-minute production standardized such that the league average is 15.
OWS	Offensive Win Shares. An estimate of the number of wins contributed by a player due to offense.
DWS	Defensive Win Shares. An estimate of the number of wins contributed by a player due to defense.
WS	Win Shares. An estimate of the number of wins contributed by a player.
WS48	Win Shares Per 48 Minutes. An estimate of the number of wins contributed by a player per 48 minutes (league average is approximately 0.100).
OBPM	Offensive Box Plus/Minus. A box score estimate of the offensive points per 100 possessions a player contributed above a league-average player, translated to an average team.
DBPM	Defensive Box Plus/Minus. A box score estimate of the defensive points per 100 possessions a player contributed above a league-average player, translated to an average team.
BPM	Box Plus/Minus. A box score estimate of the points per 100 possessions a player contributed above a league-average player, translated to an average team.
VORP	Value Over Replacement Player. A box score estimate of the points per 100 team possessions that a player contributed above a replacement-level (-2.0) player, translated to an average team and prorated to an 82-game season.
OnCourt	Plus/Minus Per 100 Possessions (On Court).
OnOff	Plus/Minus Net Per 100 Possessions.

Notes: This table provides the names of the advanced data variables used in this study and the corresponding definitions. Most of the data used in this study comes from Basketball-Reference.

Advanced data for basketball players are crucial in analyzing their performance. These data sets help measure a player's strength, output, and contribution to the team. However, not all advanced data sets are the same. There are two types of data: integrated and non-integrated. Non-integrated data sets, such as OnCourt and OnOff, measure the difference in team points when the player is on or off the court. While it provides a rough estimate of a player's performance, this calculation has limitations as it does not consider the relationship between the player and other players on the court. On the other hand, integrated data sets are mostly composed of panel data supplemented by complex workload calculations. These data sets focus on measuring a player's strength and contribution value to the team. For instance, Player Efficiency Rating (PER) measures a player's output per unit time. However, this data set places too much emphasis on a player's offensive data and ignores their defensive output. Other integrated data sets such as Win Shares (WS), Win Shares per 48 minutes (WS48), Offensive Win Shares (OWS), Defensive Win Shares (DWS), Box Plus/Minus (BPM), Offensive Box Plus/Minus (OBPM), and Defensive Box Plus/Minus (DBPM) calculate a player's victory contribution value. These data sets measure the difference between a player's performance and the benchmark players in the league on both sides of the offensive and defensive performance. Overall, integrated high-level data sets have limitations despite being more detailed than non-integrated data sets. Therefore, establishing appropriate integrated data sets is an important research direction in basketball analysis.

Descriptive Analysis

The statistical analysis of the variables begins with a detailed examination of the control variables, as presented in Table 1.2. The variables considered include player age, experience, and the number of days missed due to injury in a season. To explore the impact of contract duration on performance, the sample is restricted to contracts longer than one year, allowing for a more thorough examination of performance changes over time. Only players who participated in the season were included, eliminating potential biases from players who missed the entire season. The data set contains 3,006 observations for each variable, which are from 857 players. Players have an average age of 25.93 years, with ages ranging from 19 to 40 years. The average experience is 5.49 years, with a range from one year for rookies to 21 years for veterans. Regarding injuries, players missed an average of 1.28 days per season, with a minimum of 0 days (no injuries) and a maximum of 15 days missed due to injury.

Following the analysis of the control variables, a descriptive analysis of the basic performance metrics is conducted to provide further insight into player performance, as detailed in Table 1.3. This table includes a comprehensive overview of variables such as points, rebounds, assists, blocks, steals, shot attempts, free throws, three-pointers, game-playing

Table 1.2 Statistical analysis of control variables

	N	Mean	Sd	Min	Max
Age	3006	25.93	4.07	19	40
Experience	3006	5.49	4.04	1	21
Number of days missed due to injury	3006	1.28	1.39	0	15

Notes: The table shows the results of the statistical analysis of the control variables.

time, and shooting percentages. The dataset consists of 3,006 observations for each variable, ensuring a robust foundation for analysis. The scoring data indicates that players average 8.94 points per game, with individual scores ranging from 0 (indicating no points scored during the season) to a high of 36.1. On average, players achieve 3.79 rebounds per game, ranging from 0 to 16 rebounds. Assists average 1.96 per game, with values spanning from 0 to 11.2. The average number of blocks per game is 0.42, with a maximum of 3.7, while the average number of steals is 0.67, with a maximum of 2.5. In terms of shooting performance, players attempt an average of 7.39 shots per game, including 2.20 three-point attempts, and make 1.99 free throw attempts on average. The average playing time per game is 21.10 minutes, with some players reaching up to 42 minutes. Considering the standard 48-minute game duration, these players exhibit notably extended playing times. When examining shooting accuracy, the average field goal percentage is 44%, though some players achieve a perfect 100%, typically due to fewer shot attempts. The average free throw percentage is 72%, while the three-point shooting percentage averages 27%. It is important to note that players with a perfect shooting percentage often have limited attempts, making them less representative of the overall player population.

Table 1.3 Statistical analysis of basic performance

	N	Mean	Sd	Min	Max
Points	3006	8.94	5.91	0	36.1
Rebounds	3006	3.79	2.51	0	16
Assists	3006	1.96	1.82	0	11.2
Blocks	3006	0.42	0.44	0	3.7
Steals	3006	0.67	0.44	0	2.5
Field goal attempt	3006	7.39	4.53	0	24.5
Free throw attempt	3006	1.99	1.70	0	11
Three points attempt	3006	2.20	1.99	0	13.2
Minutes played	3006	21.10	9.19	0.7	42
Field goal percentage	3006	0.44	0.09	0	1
Free throws percentage	3006	0.72	0.18	0	1
Three points percentage	3006	0.27	0.16	0	1

Notes: This table shows a statistical analysis of a player's basic performance.

Table 1.4 provides an in-depth statistical analysis of advanced player performance data. The dataset consists of 3,006 observations, offering a comprehensive basis for evaluating advanced metrics contributing to a more nuanced understanding of player performance. This analysis includes several key metrics used to evaluate player performance beyond basic statistics. The first metric analysed is Player Efficiency Rating (PER), with an average value of 13.38. While this is slightly below the league average of 15, it's important to note the extreme values in the dataset, with a maximum of 80.4 and a minimum of -41.7. These extremes are likely influenced by the number of appearances a player has made and, thus, may not be fully representative of typical performance levels. Win Shares, which estimate a player's contribution to their team's wins, are analysed separately for offensive and defensive contributions. The average Offensive Win Shares (OWS) value is 1.41, with a maximum of 14.8, while the average Defensive Win Shares (DWS) value is 1.27, with a maximum of 6.6. These figures suggest that, on average, players contribute slightly more to their team's success on offence than on defence. The dataset also includes metrics related to win-loss impacts, such as Box Plus/Minus (BPM), OnCourt, and OnOff. The average values of these metrics are negative, indicating that, on average, the players in the dataset may have a slightly negative impact on their team's net score while on the court. However, the extreme maximum and minimum values observed in these metrics are likely outliers and may not reflect the typical player performance. Lastly, the Value Over Replacement Player (VORP) metric, which estimates a player's value relative to a replacement-level player, has an average value of 0.68 in this dataset. This suggests that, on average, the players analysed are more valuable than a replacement-level player. The maximum VORP value of 9.9 indicates that some players in the dataset are significantly more valuable than others.

Table 1.4 Statistical analysis of advanced performance

	N	Mean	Sd	Min	Max
PER	3006	13.38	5.79	-41.7	80.4
OWS	3006	1.41	2.06	-3.3	14.8
DWS	3006	1.27	1.16	-0.5	6.6
WS	3006	2.67	2.94	-2.1	19.3
WS48	3006	0.08	0.09	-1.065	1.26
BPM	3006	-1.21	4.08	-56.3	52
VORP	3006	0.68	1.36	-2	9.9
OnCourt	3006	-1.88	11.31	-150	100
OnOff	3006	-1.39	11.68	-148.3	98.1

Notes: This table shows a statistical analysis of a player's advanced performance.

Following the player performance analysis, an examination of player contract lengths is conducted to understand the distribution of contract durations within the sample, as presented in Table 1.5. This analysis provides valuable context for understanding the implications of contract structure on player performance and career trajectory. The data indicates that nearly 40% of players are in the first year of their contracts, while approximately 30% are in the second year. Interestingly, 18.8% of players are in the third year of their contracts, accounting for a total of 564 individuals in this category. Contracts extending into the fourth and fifth years represent 11.4% and 1.7% of the sample, respectively. Notably, only seven players are currently in the sixth year of their contracts, a relatively small proportion. These contracts were signed before the implementation of the new Collective Bargaining Agreement (CBA), which now limits the maximum contract length to five years. The analysis also considers the remaining years of players' contracts, which is an important aspect of this study. Approximately 24% of the sample is in the final year of their current contracts, a critical period that determines whether a player will enter free agency or continue with their current team. Additionally, 37% of players have two years remaining on their contracts, while 23% have three years remaining. Only 14% of players have four years left on their contracts, indicating a relatively small group with long-term agreements. Finally, only 1.5% of the total sample, or 46 players, have five years remaining on their contracts. These players typically hold max-salary contracts, which are generally limited to one or two per team. This statistical analysis accurately reflects the distribution and trends in contract lengths among the players in the sample.

Table 1.5 Player contract length distribution

	Year elapsed	Year remaining
Number of year	Observations(%)	Observations(%)
1	1178(39.2)	725(24.1)
2	864(28.7)	1115(37.1)
3	564(18.8)	702(23.4)
4	342(11.4)	418(13.9)
5	51(1.7)	46(1.5)
6	7(0.2)	
Total	3006	3006

Notes: The table shows the distribution of contract length in the sample. The length of a player's contract is counted from two aspects. The second column shows the elapsed years of the player's contract, which is the number of years the contract has been executed. The third column shows the number of years remaining on the player's contract, which is calculated by subtracting the elapsed year from the total number of years on the current contract. The number of samples in the corresponding years is shown in the table, and the proportion of the corresponding sample to the total sample is in parentheses.

The next step in the analysis involves examining the distribution of player contract lengths across different seasons, as illustrated in Table 1.6. This analysis provides insight into how contract durations evolve over time and the impact of external factors, such as the implementation of the new CBA, on contract trends. During the 2012-13 season, the average elapsed contract length is 2.14 years, which slightly declines to 2.09 years in the following season. This decrease suggests that a significant number of players are entering into new contracts during these years. The trend of decreasing elapsed contract length continues in the subsequent seasons, with the average contract length dropping to 2.08 years in the 2014-15 season, 1.98 years in the 2015-16 season, and further to 1.94 years in the 2016-17 season. This decline in elapsed contract years during these seasons can be largely attributed to the anticipation of the new Collective Bargaining Agreement (CBA), which was implemented in 2017. The introduction of the new CBA brings a substantial increase in the salary cap, leading players to demand higher wages and resulting in a surge of new contract signings around the 2017 season. As a consequence, the average elapsed contract length rises to 2.10 years in the 2017-18 season and further to 2.27 years in the 2018-19 season. Conversely, the average remaining years on player contracts decrease between the 2012-13 and 2014-15 seasons. However, the signing of new contracts during the 2015-16 and 2016-17 seasons leads to an increase in the average remaining contract length to 2.35 years and 2.47 years, respectively. This pattern suggests that players are securing longer contracts to take advantage of the more lucrative salary opportunities provided by the new CBA. By the 2017-18 and 2018-19 seasons, this trend stabilises, with the average remaining contract length settling at 2.21 years. This indicates that players are more inclined to sign long-term contracts during these seasons, likely due to the stabilisation of the salary cap following the implementation of the new CBA. The data highlights the significant impact of the new CBA on the distribution of player contract lengths across these seasons, influencing both the duration and timing of contract signings.

Table 1.6 Average contract length in each season

Season	Average length of contract elapsed(years)	Average length of contract remaining(years)
2012-13	2.14	2.33
2013-14	2.09	2.26
2014-15	2.08	2.21
2015-16	1.98	2.35
2016-17	1.94	2.47
2017-18	2.10	2.21
2018-19	2.27	2.21

Notes: This table shows the average length of player contracts in different years, with the first column being the season. The second column is the average elapsed length of the current contract for all samples in the responding season. The third column is the average of the remaining years of the current contract for all samples in the responding season.

Mean difference test of player performance around contract year

The next aspect of the analysis examines the mean difference in player performance between the contract year and the first year after signing a new multi-year guaranteed contract, as presented in Table 1.7. The results of a t-test are used to compare the mean performance of NBA players during the contract year with their performance in the first year after signing a new contract. The t-test is a widely recognised statistical method in sports research, often used to determine whether significant changes occur in a player's performance under different conditions. For instance, Patel et al. (2019) used the t-test to assess whether NBA players' performance significantly changes after suffering a concussion. Similarly, studies like Guss et al. (2016) have examined the impact of hand injuries on NBA players using this method. In this study, a rigorous selection process is applied to define and compare performance data between the contract year and the subsequent year. The analysis exclusively focuses on players with fully guaranteed contracts lasting more than one year. To ensure the reliability of the comparison, only players who participated in games both during the contract year and the first year after signing a new contract are included in the analysis. Players who missed games due to injuries in either of these years are excluded to prevent potential bias in the results. After the sample screening, 854 observations corresponding to 502 players are included in the analysis. The t-test results reveal that while players' salaries increase significantly after signing a new contract, their basic performance metrics remain relatively consistent between the contract year and the first year post-contract. The only notable difference observed is in the number of three-pointers attempted by players, which increases significantly after signing a new contract. This suggests that after securing a new contract, players might feel encouraged or incentivised to take more three-point shots. The primary objective of this study is to determine whether there is a statistically significant difference in player performance between the contract year and the first year following the signing of a new contract. The t-test results indicate that, apart from the increase in three-point attempts, players generally maintain a consistent level of performance after securing a new contract.

Following the analysis of basic performance metrics, the next step involves examining the advanced performance metrics to determine if there are significant changes after signing a new contract. The analysis presented in Table 1.8 explores the difference in mean values between two sets of advanced data to determine whether players experience changes in their performance after signing a new contract. The results reveal that, in general, players tend to experience a significant decline in certain advanced statistics after signing a new contract. More specifically, after signing a new contract, players tend to decrease by 0.34 in Player Efficiency Rating (PER), which accounts for 2.5% of the contract year average. This finding is statistically significant, indicating that players' performance in PER declines to a significant

Table 1.7 Mean difference in NBA player basic performance

	Post-CY observations	Post-CY mean	CY observations	CY mean	mean_diff
Salary(In thousand)	854	36000.00	854	19600.00	16500.00***
Points	854	11.30	854	11.35	-0.05
Rebounds	854	4.62	854	4.61	0.01
Assists	854	2.47	854	2.42	0.05
Blocks	854	0.54	854	0.53	0.005
Steals	854	0.80	854	0.82	-0.01
Field Goal Attempt	854	9.10	854	9.11	-0.01
Free Throw Attempt	854	2.71	854	2.75	-0.04
Three points attempt	854	2.43	854	2.27	0.16*
Minutes played	854	25.42	854	25.33	0.09
Field goal percentage	854	0.457	854	0.460	-0.003
Free throw percentage	854	0.740	854	0.745	-0.005
Three points percentage	854	0.272	854	0.278	-0.006

Notes: This table shows the mean difference test of a player's basic performance during the contract year and after the contract year. The first column of the table contains the player's basic performance variables. The second column is the sample number of players after the contract year, and the third column is the average of the corresponding performance after the contract year. The fourth column is the sample number of players in the contract year, and the fifth column is the average performance of the players in the contract year. The sixth column is the difference between the player's performance after the contract year and his performance during the contract year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

extent after signing a new contract. Similar declines are observed in Offensive Win Shares (OWS), Total Win Shares (WS), and Value Over Replacement Player (VORP), which account for 7.1%, 5.2%, and 10% of the contract year average, respectively. These findings are also statistically significant, indicating that players tend to experience significant declines in OWS, WS, and VORP after signing a new contract. In addition, other data show some degree of decline, but it is not statistically significant. From this result, players tend to reduce their performance in some advanced metrics after signing a new contract. This situation can be explained from two perspectives. First, the player dramatically improves their performance in the contract year to secure an attractive contract through higher performance. The second explanation is that after accepting a new high-value contract, the player may subjectively reduce their efforts, thereby reducing their performance one year after the contract year. Since NBA players are closely watched and measured by multiple groups, including teams, media, and fans, it is unlikely that players would risk reducing their output to jeopardise their future career reputation. Therefore, the significant improvement in players' performance in the contract year is a reasonable explanation for the observed decline in performance metrics after signing a new contract,but this explanation still needs more analysis to be verified.

After comparing the performance of players in the contract year and the year after, this chapter continues to leverage the dataset by adopting a more stringent data screening method to further explore the dynamic changes in players' performance around the contract year. In

Table 1.8 Mean difference in NBA player advanced performance

	Post-CY observations	Post-CY mean	CY observations	CY mean	mean_diff
PER	854	14.96	854	15.40	-0.34*
OWS	854	2.24	854	2.41	-0.17*
DWS	854	1.74	854	1.79	-0.05
WS	854	3.98	854	4.20	-0.22*
WS48	854	0.10	854	0.11	-0.004
BPM	854	-0.05	854	0.09	-0.14
VORP	854	1.18	854	1.31	-0.13*
OnCourt	854	0.31	854	0.36	-0.05
OnOff	854	0.69	854	0.64	0.05

Notes: This table shows the mean difference test of a player's advanced performance during the contract year and after the contract year. The first column of the table contains the player's advanced performance variables. The second column is the sample number of players after the contract year, and the third column is the average of the corresponding performance after the contract year. The fourth column is the sample number of players in the contract year, and the fifth column is the average performance of the players in the contract year. The sixth column is the difference between the player's performance after the contract year and his performance during the contract year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

this analysis, I select the player's contract year(CY), the year before the contract year(Pre-CY), and the year after(Post-CY). To avoid the year before the contract year being the first year of the contract (which could affect the study), I screen the samples to ensure that the contract containing the contract year has a duration of at least three years. This ensures that the year before the contract year is not the first year of the contract. Additionally, the contract term one year after the contract year is set to be at least two years, ensuring that this year is the first year of the new contract rather than a contract year.

With this stricter sample screening, each group consists of 610 data points from 395 players. Compared to the previous analysis, the number of players decreases from 502 to 395, and the sample size for each group decreases from 854 to 610. Similar to previous studies, I first compare the average values of players' basic performance across the different groups. Table 1.9 presents the results of this analysis. Apart from the number of three-point shots attempted by players, no statistically significant differences are found among the groups for other variables. Although there are no statistically significant differences, the values still provide insights into changes in player performance. For example, in terms of points, the player's average score is 12.41 in the year before the contract year, which increases to 12.81 during the contract year. After signing a new multi-year contract, the score drops slightly to 12.71, but this is still higher than the year before the contract year. This trend is observed in other performance metrics, such as rebounds, shots, free throws, and playing time.

Table 1.9 Mean difference in NBA player basic performance(Three groups)

	Observations	Pre-CY mean	CY mean	Post-CY mean
Points	610	12.41	12.81	12.71
Rebounds	610	4.99	5.09	5.06
Assists	610	2.61	2.72	2.77
Blocks	610	0.61	0.59	0.60
Steals	610	0.88	0.89	0.87
Field goal attempt	610	9.95	10.22	10.14
Free throw attempt	610	3.11	3.17	3.13
Three points attempt	610	2.22^{***}	2.42^{***}	2.55^{***}
Minutes played	610	27.24	27.63	27.44
Field goal percentage	610	0.46	0.46	0.47
Free throw percentage	610	0.75	0.75	0.75
Three points percentage	610	0.27	0.28	0.28

Notes: This table shows the average comparison of the basic data of players in three groups. The first column of the table lists the name of the basic data, and the second column shows the number of samples in each group. The third column presents the average of the samples one year before the contract year, the fourth column provides the average of the contract year data, and the fifth column displays the average of the performance one year after the contract year. Compared to the previous analysis, this analysis uses more stringent sample screening. The data in the contract year and the first year before the contract year come from the same contract, which must be of at least three years in length to ensure that the year before the contract year is not the first year of the contract. Additionally, the contract one year after the contract year is a newly signed multi-year contract, ensuring that this year is not the contract year of the new contract.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

After comparing the basic performance data, I proceed to analyse the advanced performance metrics. Table 1.10 presents the average advanced metrics for the three groups. The Player Efficiency Rating (PER) is a key focus. The average PER value increases from 15.98 in the year before the contract year to 16.17 during the contract year, likely due to the pressure to secure a new contract. After signing a new multi-year contract, the average PER drops slightly to 16.06, but remains higher than the pre-contract year level of 15.98. Similar trends are observed for Defensive Win Shares (DWS) and Total Win Shares (WS).

The analysis shows a consistent trend in player performance around the contract year. Players tend to increase their effort and performance during the contract year to secure better contract terms. This performance boost is higher than both the year before and the year after the contract year, highlighting the incentive effect of the contract year. When comparing players' performance one year before and one year after the contract year, no significant differences are observed, and the post-contract year performance is generally higher than the pre-contract year performance. Players do not reduce their production after securing a new multi-year contract.

Table 1.10 Mean difference in NBA player advanced performance(Three groups)

	Observations	Pre-CY mean	CY mean	Post-CY mean
PER	610	15.98	16.17	16.06
OWS	610	2.69	2.83	2.68
DWS	610	1.92	2.01	1.96
WS	610	4.61	4.84	4.64
WS48	610	0.11	0.12	0.11
VORP	610	1.48	1.58	1.48
OnCourt	610	0.74	1.13	1.16
OnOff	610	1.33	1.51	1.54

Notes: This table shows the average comparison of the advanced data of players in three groups. The first column of the table lists the name of the advanced data, and the second column shows the number of samples in each group. The third column presents the average of the samples one year before the contract year, the fourth column provides the average of the contract year data, and the fifth column displays the average of the performance one year after the contract year. Compared to the previous analysis, this analysis uses more stringent sample screening. The data in the contract year and the first year before the contract year come from the same contract, which must be of at least three years in length to ensure that the year before the contract year is not the first year of the contract. Additionally, the contract one year after the contract year is a newly signed multi-year contract, ensuring that this year is not the contract year of the new contract.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear regression model

This section presents the linear regression model used to explore the impact of a player's current contract status on their performance, focusing on how different periods within the contract affect performance outcomes. The independent variables in the model include the number of years the player has spent under the current contract (Year elapsed) and the number of years remaining in the contract (Year remaining). For example, in a 4-year contract, the Year elapsed values for each year of the contract are 1, 2, 3, and 4, while the Year remaining values are 4, 3, 2, and 1, respectively. Other independent variables in the model include the player's experience (both as a linear term and its square to capture potential nonlinear effects) and the number of days the player missed due to injury during the season. The model also incorporates fixed effects for the player's draft order, season, and team, which help account for unobserved heterogeneity across these dimensions.

The dependent variable in the model is the player's performance, divided into both basic and advanced metrics. A unique aspect of this study is its approach to classifying player positions. Unlike previous studies that primarily categorize players into five positions—Center, Power Forward, Small Forward, Shooting Guard, and Point Guard—this study acknowledges the versatility of modern basketball players and their ability to adapt to multiple positions. Different teams adopt different lineups in response to various opponents, and players may play different roles under different systems. To capture this versatility, four additional position categories are introduced based on the proportion of time players spend in different positions. If a player spends more than 30% of their total time playing in two positions, they are classified under a new, combined position category. This expanded classification allows for a more accurate analysis of how contract length impacts player performance. The formula for this linear regression model is expressed as formula 1.1. Ultimately, the findings from this analysis help teams make informed decisions regarding player contracts and optimize player performance.

$$\begin{aligned}\text{Performance}_{it} = \beta_0 &+ \beta_1 \cdot \text{Elapsed Year}_{it} + \beta_2 \cdot \text{Remaining Year}_{it} \\ &+ \beta_3 \cdot \text{Experience}_{it} + \beta_4 \cdot \text{Experience}^2_{it} + \beta_5 \cdot \text{Injury}_{it} \\ &+ \text{Draft}_i + \text{Position}_{it} + \text{Season}_t + \text{Team}_{it} + \varepsilon_{it}\end{aligned} \tag{1.1}$$

One of the unique aspects of this study is its approach to classifying the position of players. While previous studies primarily classify players into five positions—Center, Power Forward, Small Forward, Shooting Guard, and Point Guard—this study recognises that modern basketball players are versatile and adapt to multiple positions. Different teams adopt different lineups in response to various opponents, and players may play different positions under different systems. As such, four new positions are added based on the playing time of players in different positions. If a player spends more than 30% of their total time playing in two positions, they are classified under these new hybrid positions. This new classification provides a more comprehensive view of player roles, allowing for a more accurate analysis of how contract length impacts player performance. The specific player position definition is represented by Table 1.11.

Table 1.11 Player position classification

Position	Classification standard
Center	The most MP is in the Center, and MP in other positions is less than 30% of total MP
Big	The MP in Center and Power forward are bigger than 30% of the total MP
Power forward	The most MP is in the Power forward, and MP in other positions is less than 30% of the total MP
Forward	The MP in Power forward and Small forward are bigger than 30% of the total MP
Small forward	The most MP is in the Small forward, and MP in other positions is less than 30% of the total MP
Wing	The MP in Small forward and Shooting guard are bigger than 30% of the total MP
Shooting guard	The most MP is in the Shooting guard, and MP in other positions is less than 30% of the total MP
Combo	The MP in Shooting guard and Point guard are bigger than 30% of the total MP
Point guard	The most MP is in the Point guard, and MP in other positions is less than 30% of the total MP

Notes: This table shows how the players' positions on the court were divided in this study. In the traditional position division, there are five positions on the court: center, power forward, small forward, shooting guard, and point guard. However, in this study, four new positions were derived according to the length of time the players played in each position. MP stands for minutes played.

Table 1.12 presents a linear regression model for player advanced performance, estimated using Ordinary Least Squares (OLS). It is important to note that the standard errors in this OLS estimation are not adjusted for team clustering. In the model, the variables Year elapsed and Year remaining, which are used to measure the player's contract status, have positive coefficients. Since both variables are part of a dynamic process, they need to be interpreted together. Quantitatively, in all models that measure player performance, the coefficient for the Year elapsed is smaller than that for the Year remaining. This indicates that player performance tends to decrease over time within a contract, and the incentive effect of the contract year is not verified in these results. Moreover, since the coefficient for the Year remaining is positive, it can be concluded that if the length of the new contract signed by the player is longer than the existing contract, the player is less likely to exhibit shirking behaviour in the new contract. Conversely, if the new contract is shorter than the existing contract, the player may demonstrate some level of shirking behaviour. Additionally, player experience positively influences performance, although the effect exhibits diminishing marginal utility, meaning the incremental benefit of experience decreases over time. Regarding draft order, the model shows that players drafted in the first round experience a decline in performance if their draft position is lower, particularly when compared to the top seven picks. Second-round picks and undrafted players generally perform worse, though there is no consistent pattern related to draft position. In terms of player positions, the model indicates that players in positions other than Wing typically perform better across various metrics such as Player Efficiency Rating (PER), Offensive Win Shares (OWS), Defensive Win Shares (DWS), Win Shares (WS), and Box Plus/Minus (BPM). Conversely, performance measures like OnCourt and OnOff show different results. Interestingly, the model also suggests that player injuries have a positive effect on performance, which deviates from traditional expectations. This phenomenon can be partly explained by the way injury data is collected and reported. NBA teams typically release injury information for players who have significant playing time, indicating a higher level of skill and importance to the team. Consequently, players who are recorded as injured are often those who have longer playing times and higher performance levels. This selection bias in injury reporting helps explain why the model finds that injuries are associated with increased performance despite the conventional wisdom that injuries generally reduce a player's effectiveness. Finally, the model incorporates season and team-fixed effects to control for additional variables that might influence player performance, ensuring a more robust analysis.

Table 1.12 The advanced performance model(No cluster)

	(1) PER	(2) OWS	(3) DWS	(4) WS	(5) WS48	(6) BPM	(7) VORP	(8) OnCourt	(9) OnOff
Year elapsed	0.80***	0.33***	0.22***	0.56***	0.01***	0.57***	0.24***	0.91***	1.28***
	(0.12)	(0.04)	(0.02)	(0.06)	(0.00)	(0.09)	(0.03)	(0.26)	(0.27)
Year remaining	0.91***	0.48***	0.32***	0.80***	0.01***	0.65***	0.33***	0.97***	1.37***
	(0.13)	(0.04)	(0.02)	(0.06)	(0.00)	(0.09)	(0.03)	(0.26)	(0.28)
Experience	0.70***	0.39***	0.18***	0.57***	0.01***	0.59***	0.23***	0.94***	1.00***
	(0.08)	(0.03)	(0.02)	(0.04)	(0.00)	(0.06)	(0.02)	(0.17)	(0.18)
Experience^2	-0.04***	-0.02***	-0.01***	-0.03***	-0.0006***	-0.03***	-0.01***	-0.04***	-0.05***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Number of days players missed due to injury	0.51***	0.08***	0.06***	0.15***	0.004***	0.30***	0.08***	0.05	0.35**
	(0.07)	(0.03)	(0.01)	(0.04)	(0.00)	(0.05)	(0.02)	(0.15)	(0.16)
Draft 8 to 14	-1.90***	-0.89***	-0.40***	-1.29***	-0.02***	-1.10***	-0.69***	-1.36*	-1.58**
	(0.34)	(0.12)	(0.06)	(0.16)	(0.01)	(0.24)	(0.08)	(0.70)	(0.75)
Draft 15 to 30	-2.59***	-1.16***	-0.60***	-1.76***	-0.02***	-1.52***	-0.86***	-1.43**	-2.08***
	(0.29)	(0.10)	(0.06)	(0.14)	(0.00)	(0.21)	(0.07)	(0.62)	(0.66)
Draft 31 to 44	-3.14***	-1.01***	-0.57***	-1.58***	-0.02***	-1.76***	-0.78***	-1.21	-1.24
	(0.35)	(0.12)	(0.07)	(0.17)	(0.01)	(0.25)	(0.08)	(0.74)	(0.78)
Draft 45 to 60	-2.53***	-0.80***	-0.54***	-1.36***	-0.02***	-1.22***	-0.58***	-2.14**	-2.06**
	(0.42)	(0.15)	(0.08)	(0.20)	(0.01)	(0.30)	(0.10)	(0.88)	(0.94)
Not Draft	-3.14***	-1.14***	-0.67***	-1.81***	-0.02***	-1.81***	-0.82***	-1.25	-0.67
	(0.38)	(0.13)	(0.07)	(0.18)	(0.01)	(0.27)	(0.09)	(0.79)	(0.84)
Big	3.29***	0.37**	0.20**	0.57**	0.04***	0.37	0.14	-1.27	-0.80
	(0.50)	(0.18)	(0.09)	(0.24)	(0.01)	(0.36)	(0.11)	(1.05)	(1.11)
Center	4.08***	0.42***	0.40***	0.82***	0.05***	0.56*	0.19**	-1.45*	-1.21
	(0.40)	(0.14)	(0.08)	(0.19)	(0.01)	(0.29)	(0.09)	(0.83)	(0.89)
Combo	0.97*	-0.02	-0.05	-0.08	-0.00	0.09	0.07	-1.42	-1.28
	(0.52)	(0.18)	(0.10)	(0.25)	(0.01)	(0.37)	(0.12)	(1.08)	(1.15)
Forward	1.15**	0.11	0.12	0.23	0.02*	0.61	0.20	-1.91*	-1.54
	(0.53)	(0.19)	(0.10)	(0.26)	(0.01)	(0.38)	(0.12)	(1.11)	(1.18)
Point guard	2.21***	0.56***	0.07	0.63***	0.01	0.62**	0.50***	-0.39	0.11
	(0.41)	(0.14)	(0.08)	(0.20)	(0.01)	(0.29)	(0.09)	(0.85)	(0.91)
Power forward	1.93***	0.23	0.26***	0.48**	0.02***	0.24	0.18*	-1.28	-0.79
	(0.41)	(0.14)	(0.08)	(0.20)	(0.01)	(0.30)	(0.09)	(0.86)	(0.91)
Shooting guard	0.64	0.14	0.03	0.17	-0.00	0.01	0.15	-0.01	0.33
	(0.42)	(0.15)	(0.08)	(0.21)	(0.01)	(0.31)	(0.10)	(0.88)	(0.94)
Small forward	0.16	0.14	0.19**	0.33	0.00	0.15	0.23**	-0.82	-0.27
	(0.42)	(0.15)	(0.08)	(0.21)	(0.01)	(0.31)	(0.10)	(0.88)	(0.94)
Season fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Team fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cons	8.06***	-0.68**	0.34**	-0.32	0.01	-4.68***	-0.54***	-5.12***	-6.33***
	(0.83)	(0.29)	(0.16)	(0.40)	(0.01)	(0.60)	(0.19)	(1.73)	(1.84)
R^2	0.225	0.241	0.298	0.288	0.173	0.177	0.259	0.105	0.052
N	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006

Notes: This table shows the regression model results for advanced performance. The dependent variable of the model is the player's advanced performance. Specific advanced variables are displayed in the header of each column. The independent variables are the elapsed year and remaining years of the contract, player age, experience and their corresponding squares, player injuries, player draft order, player position, and season and team fixed effects. The top seven picks in the first round are selected as the benchmark for the player draft order, and the benchmark for a player's position on the field is the wing. Additionally, the model does not calculate its standard errors by team clustering.

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.13 presents the advanced player performance model, utilizing a sophisticated statistical approach to evaluate the impact of player contract status on advanced performance metrics. In this model, the standard errors are clustered by team, which ensures that the standard errors are consistent within each team. The results show that clustering the standard errors by team yields similar outcomes to the previous Ordinary Least Squares (OLS) model without clustering. This indicates that there is no significant heterogeneity in the standard errors across teams, reinforcing the robustness and reliability of the model in estimating the effect of player contract status on performance. The findings suggest that players' performance remains consistent across different contract periods, irrespective of potential team-specific variations.

Table 1.13 The advanced performance model(Cluster by team)

	(1) PER	(2) OWS	(3) DWS	(4) WS	(5) WS48	(6) BPM	(7) VORP	(8) OnCourt	(9) OnOff
Year elapsed	0.80***	0.33***	0.22***	0.56***	0.01***	0.57***	0.24***	0.91***	1.28***
	(0.15)	(0.07)	(0.04)	(0.10)	(0.00)	(0.11)	(0.05)	(0.28)	(0.32)
Year remaining	0.91***	0.48***	0.32***	0.80***	0.01***	0.65***	0.33***	0.97***	1.37***
	(0.13)	(0.07)	(0.03)	(0.09)	(0.00)	(0.10)	(0.05)	(0.29)	(0.38)
Experience	0.70***	0.39***	0.18***	0.57***	0.01***	0.59***	0.23***	0.94***	1.00***
	(0.10)	(0.04)	(0.02)	(0.06)	(0.00)	(0.08)	(0.03)	(0.18)	(0.21)
Experience^2	-0.04***	-0.02***	-0.01***	-0.03***	-0.0006***	-0.03***	-0.01***	-0.04***	-0.05***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Number of days players missed due to injury	0.51***	0.08**	0.06***	0.15***	0.004***	0.30***	0.08***	0.05	0.35***
	(0.07)	(0.04)	(0.02)	(0.05)	(0.00)	(0.04)	(0.02)	(0.11)	(0.11)
Draft 8 to 14	-1.90***	-0.89***	-0.40***	-1.29***	-0.02***	-1.10***	-0.69***	-1.36**	-1.58**
	(0.55)	(0.24)	(0.11)	(0.31)	(0.01)	(0.30)	(0.17)	(0.60)	(0.73)
Draft 15 to 30	-2.59***	-1.16***	-0.60***	-1.76***	-0.02***	-1.52***	-0.86***	-1.43**	-2.08***
	(0.44)	(0.25)	(0.09)	(0.31)	(0.01)	(0.27)	(0.17)	(0.53)	(0.64)
Draft 31 to 44	-3.14***	-1.01***	-0.57***	-1.58***	-0.02***	-1.76***	-0.78***	-1.21*	-1.24*
	(0.53)	(0.23)	(0.11)	(0.28)	(0.01)	(0.35)	(0.15)	(0.60)	(0.71)
Draft 45 to 60	-2.53***	-0.80***	-0.54***	-1.36***	-0.02**	-1.22***	-0.58***	-2.14**	-2.06*
	(0.68)	(0.28)	(0.13)	(0.35)	(0.01)	(0.43)	(0.18)	(0.92)	(1.02)
Not Draft	-3.14***	-1.14***	-0.67***	-1.81***	-0.02***	-1.81***	-0.82***	-1.25*	-0.67
	(0.55)	(0.21)	(0.08)	(0.25)	(0.01)	(0.32)	(0.14)	(0.72)	(0.86)
Big	3.29***	0.37*	0.20*	0.57*	0.04***	0.37	0.14	-1.27*	-0.80
	(0.51)	(0.21)	(0.10)	(0.28)	(0.01)	(0.35)	(0.12)	(0.67)	(0.75)
Center	4.08***	0.42***	0.40***	0.82***	0.05***	0.56*	0.19*	-1.45**	-1.21*
	(0.43)	(0.13)	(0.08)	(0.19)	(0.00)	(0.29)	(0.10)	(0.59)	(0.68)
Combo	0.97*	-0.02	-0.05	-0.08	-0.00	0.09	0.07	-1.42*	-1.28
	(0.55)	(0.17)	(0.06)	(0.20)	(0.01)	(0.36)	(0.10)	(0.83)	(0.88)
Forward	1.15**	0.11	0.12	0.23	0.02**	0.61	0.20	-1.91**	-1.54**
	(0.56)	(0.20)	(0.10)	(0.26)	(0.01)	(0.37)	(0.12)	(0.71)	(0.67)
Point guard	2.21***	0.56***	0.07	0.63**	0.01	0.62	0.50***	-0.39	0.11
	(0.52)	(0.20)	(0.08)	(0.25)	(0.01)	(0.40)	(0.13)	(0.72)	(0.89)
Power forward	1.93***	0.23	0.26***	0.48**	0.02***	0.24	0.18*	-1.28	-0.79
	(0.39)	(0.15)	(0.08)	(0.19)	(0.01)	(0.28)	(0.09)	(0.79)	(0.86)
Shooting guard	0.64*	0.14	0.03	0.17	-0.00	0.01	0.15	-0.01	0.33
	(0.37)	(0.17)	(0.06)	(0.20)	(0.01)	(0.27)	(0.10)	(0.55)	(0.57)
Small forward	0.16	0.14	0.19**	0.33	0.00	0.15	0.23**	-0.82	-0.27
	(0.49)	(0.18)	(0.08)	(0.23)	(0.01)	(0.31)	(0.10)	(0.91)	(1.01)
Season fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Team fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cons	8.06***	-0.68**	0.34**	-0.32	0.01	-4.68***	-0.54**	-5.12***	-6.33***
	(0.77)	(0.32)	(0.17)	(0.43)	(0.01)	(0.53)	(0.21)	(0.96)	(1.32)
R^2	0.225	0.241	0.298	0.288	0.173	0.177	0.259	0.105	0.052
N	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006

Notes: This table shows the regression model results for advanced performance. The dependent variable of the model is the player's advanced performance. Specific advanced variables are displayed in the header of each column. The independent variables are the elapsed year and remaining years of the contract, player age, experience and their corresponding squares, player injuries, player draft order, player position, and season and team fixed effects. The top seven picks in the first round are selected as the benchmark for the player draft order, and the benchmark for a player's position on the field is the wing. Additionally, the model calculates its standard errors by team clustering.
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Following the analysis of the impact of the contract period on player advanced performance, From table 1.14, the coefficients for the variables Year elapsed and Year remaining are both positive. In multiple models, the coefficient for the Year elapsed is smaller than that for Year remaining. These findings indicate that the incentive effect of the player's contract year phenomenon has not been verified, as player performance tends to decrease as the number of years within the contract progresses. Additionally, the potential for shirking behaviour after signing a new contract appears to be related to the length of both the new contract and the current contract. Specifically, if the length of the current contract is longer than that of the new contract, players may exhibit some degree of shirking behaviour. Conversely, if the current contract is shorter than the new contract, shirking behavior is less likely to occur. Additionally, the model demonstrates that a player's experience positively contributes to performance, although the effects diminish over time, reflecting diminishing marginal utility. Draft position is another critical factor, as players selected within the top seven picks of the first round tend to outperform those chosen later. Moreover, the model accounts for the player's position on the court, showing that different positions contribute differently to overall performance. For instance, big players are more likely to excel in rebounds, while guards may have a higher number of assists. The model also includes season and team-fixed effects to control for external factors influencing performance. This analysis of players' basic performance helps to explore more specifically how player performance changes at different stages of the contract.

Through the analysis of the above model, I find that the results of this linear model do not accurately reflect the incentive effect of the player's contract year or accurately estimate the player's shirking behaviour after signing a new contract. This result may be explained by the fact that I do not initially account for player heterogeneity when setting up the model. Some players may be highly motivated during the contract year, while others may show less motivation. Additionally, certain characteristics of players, such as talent, work attitude, and adaptability, are likely overlooked in the model, leading to deviations from the expected results. To address these issues, I add player-fixed effects to the model to control for individual player heterogeneity, allowing for a more precise estimation of the impact of contract status on player performance.

Table 1.14 The basic performance model(No cluster)

	(1) PTS	(2) TRB	(3) AST	(4) BLK	(5) STL	(6) FGA	(7) FTA	(8) PA_3	(9) MP	(10) FGP	(11) FTP	(12) PP_3
Year elapsed	1.42***	0.50***	0.33***	0.03***	0.10***	1.13***	0.36***	0.25***	2.48***	0.005**	0.01***	0.01*
	(0.11)	(0.05)	(0.03)	(0.01)	(0.01)	(0.08)	(0.03)	(0.04)	(0.17)	(0.00)	(0.00)	(0.00)
Year remaining	1.77***	0.54***	0.42***	0.04***	0.12***	1.37***	0.46***	0.36***	2.96***	0.004*	0.02***	0.01*
	(0.11)	(0.05)	(0.03)	(0.01)	(0.01)	(0.09)	(0.03)	(0.04)	(0.18)	(0.00)	(0.00)	(0.00)
Experience	1.15***	0.31***	0.24***	0.03***	0.07***	0.83***	0.25***	0.32***	2.02***	0.01***	0.02***	0.01***
	(0.07)	(0.03)	(0.02)	(0.01)	(0.01)	(0.06)	(0.02)	(0.02)	(0.11)	(0.00)	(0.00)	(0.00)
Experience^2	-0.07***	-0.02***	-0.01***	-0.002***	-0.004***	-0.05***	-0.02***	-0.02***	-0.11***	-0.0003***	-0.0009***	-0.0005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Number of days players missed due to injury	0.76***	0.24***	0.15***	0.03***	0.04***	0.59***	0.20***	0.16***	1.08***	0.003**	0.01***	0.01***
	(0.07)	(0.03)	(0.02)	(0.01)	(0.01)	(0.05)	(0.02)	(0.02)	(0.10)	(0.00)	(0.00)	(0.00)
Draft 8 to 14	-2.46***	-1.00***	-0.62***	-0.13***	-0.11***	-1.62***	-0.94***	-0.06	-2.40***	-0.01	-0.004	0.001
	(0.30)	(0.12)	(0.08)	(0.02)	(0.02)	(0.23)	(0.09)	(0.10)	(0.47)	(0.01)	(0.01)	(0.01)
Draft 15 to 30	-4.37***	-1.34***	-0.85***	-0.15***	-0.18***	-3.17***	-1.39***	-0.67***	-5.05***	-0.01**	-0.02**	-0.01*
	(0.27)	(0.11)	(0.07)	(0.02)	(0.02)	(0.20)	(0.08)	(0.09)	(0.41)	(0.00)	(0.01)	(0.01)
Draft 31 to 44	-4.68***	-1.30***	-0.84***	-0.21***	-0.19***	-3.48***	-1.41***	-0.49***	-5.12***	-0.01**	-0.02*	-0.02*
	(0.32)	(0.13)	(0.09)	(0.02)	(0.02)	(0.24)	(0.10)	(0.10)	(0.49)	(0.01)	(0.01)	(0.01)
Draft 45 to 60	-4.07***	-1.51***	-0.76***	-0.18***	-0.18***	-3.16***	-1.19***	-0.41***	-5.44***	-0.02***	-0.02	-0.00
	(0.38)	(0.16)	(0.10)	(0.03)	(0.03)	(0.29)	(0.12)	(0.12)	(0.59)	(0.01)	(0.01)	(0.01)
Not Draft	-4.94***	-1.46***	-0.95***	-0.22***	-0.20***	-3.76***	-1.42***	-0.52***	-5.96***	-0.01**	-0.03***	-0.03***
	(0.34)	(0.14)	(0.09)	(0.03)	(0.03)	(0.26)	(0.10)	(0.11)	(0.53)	(0.01)	(0.01)	(0.01)
Big	-1.15**	2.07***	-0.75***	0.37***	-0.18***	-1.30***	0.15	-2.08***	-3.24***	0.07***	-0.07***	-0.14***
	(0.45)	(0.18)	(0.12)	(0.03)	(0.04)	(0.34)	(0.14)	(0.15)	(0.69)	(0.01)	(0.02)	(0.01)
Center	-1.42***	2.79***	-0.69***	0.56***	-0.20***	-1.72***	0.26**	-2.61***	-3.26***	0.10***	-0.10***	-0.20***
	(0.36)	(0.15)	(0.10)	(0.03)	(0.03)	(0.27)	(0.11)	(0.12)	(0.55)	(0.01)	(0.01)	(0.01)
Combo	0.35	-0.20	1.14***	-0.04	0.09**	0.39	0.30**	-0.33**	0.37	-0.00	0.01	-0.00
	(0.47)	(0.19)	(0.13)	(0.04)	(0.04)	(0.35)	(0.14)	(0.15)	(0.72)	(0.01)	(0.02)	(0.01)
Forward	-0.31	1.01***	-0.21	0.10***	0.01	-0.39	0.07	-0.47***	-0.32	0.02**	-0.05***	-0.02
	(0.48)	(0.20)	(0.13)	(0.04)	(0.04)	(0.36)	(0.15)	(0.16)	(0.74)	(0.01)	(0.02)	(0.01)
Point guard	1.34***	-0.18	2.38***	-0.09***	0.20***	1.19***	0.48***	-0.09	1.25**	0.00	0.02	-0.00
	(0.37)	(0.15)	(0.10)	(0.03)	(0.03)	(0.28)	(0.11)	(0.12)	(0.57)	(0.01)	(0.01)	(0.01)
Power forward	-0.40	1.92***	-0.46***	0.22***	-0.09***	-0.45	0.13	-1.20***	-1.41**	0.03***	-0.07***	-0.07***
	(0.37)	(0.15)	(0.10)	(0.03)	(0.03)	(0.28)	(0.11)	(0.12)	(0.57)	(0.01)	(0.01)	(0.01)
Shooting guard	1.09***	-0.06	0.35***	-0.03	0.09***	0.94***	0.28**	0.23*	1.01*	-0.00	0.01	0.004
	(0.38)	(0.16)	(0.10)	(0.03)	(0.03)	(0.29)	(0.12)	(0.12)	(0.59)	(0.01)	(0.01)	(0.01)
Small forward	0.005	0.65***	-0.11	0.07**	0.10***	-0.03	0.09	-0.18	0.67	0.004	-0.04***	-0.01
	(0.38)	(0.16)	(0.10)	(0.03)	(0.03)	(0.29)	(0.12)	(0.12)	(0.59)	(0.01)	(0.01)	(0.01)
Season fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Team fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cons	2.59***	0.73**	0.37*	0.17***	0.27***	2.61***	0.47**	1.02***	9.22***	0.39***	0.64***	0.29***
	(0.75)	(0.30)	(0.20)	(0.06)	(0.06)	(0.56)	(0.23)	(0.24)	(1.15)	(0.01)	(0.03)	(0.02)
R^2	0.394	0.437	0.516	0.370	0.314	0.412	0.318	0.426	0.403	0.203	0.126	0.275
N	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006

Notes: This table shows the regression model results for basic performance. The dependent variable of the model is the player's basic performance. Specific basic variables are displayed in the header of each column. The independent variables are the elapsed year and remaining years of the contract, player age, experience and their corresponding squares, player injuries, player draft order, player position, and season and team fixed effects. The top seven picks in the first round are selected as the benchmark for the player draft order, and the benchmark for a player's position on the field is the wing. Additionally, the model does not calculate its standard errors by team clustering.

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

$$\begin{aligned}\text{Performance}_{it} = \beta_0 + \beta_1 \cdot \text{Elapsed Year}_{it} + \beta_2 \cdot \text{Remaining Year}_{it} \\ + \beta_3 \cdot \text{Experience}_{it} + \beta_4 \cdot \text{Experience}^2_{it} + \beta_5 \cdot \text{Injury}_{it} \\ + \text{Draft}_i + \text{Position}_{it} + \text{Season}_t + \text{Team}_{it} + \text{Player}_i + \varepsilon_{it}\end{aligned} \tag{1.2}$$

In this section, I continue to use linear regression to explore the impact of different time points within players' contracts on their performance. Unlike the previous model, the new linear model includes player-fixed effects. Adding player-fixed effects allows the model to control for unobserved player characteristics, such as talent, work ethic, and intrinsic skill levels. Formula 1.2 represents the model By controlling for these fixed effects, the model can more accurately isolate the impact of contract status on player performance. Furthermore, player-fixed effects help eliminate heterogeneity across players, ensuring that changes in performance are attributed to contract status rather than inherent differences between players. This approach provides a more accurate understanding of the contract year phenomenon.

Table 1.15 presents the results of the linear regression model, including player fixed effects. The sample consists of all players with a contract length of more than one year, consistent with the previous selection criteria, resulting in a total sample size of 3,006. From the results, the coefficients of the key variables, Year elapsed and Year remaining, change from positive to negative after adding player-fixed effects. This shift is not uncommon when introducing fixed effects, as the coefficients now represent the within-player effects, rather than the average effects between players. Adding fixed effects effectively keeps all player-specific characteristics constant, allowing for a more precise analysis of contract-related performance changes.

The results show that when measuring player performance using Player Efficiency Rating (PER), the coefficients for Year elapsed and Year remaining are both negative, at -0.31 and -0.39, respectively. Since the absolute value of the Year elapsed coefficient is smaller than that of Year remaining, this suggests that as a player progresses through the contract, their performance tends to increase. However, the negative coefficient for Year remaining indicates that longer contracts are associated with a decline in performance, whereas shorter contracts do not show this decline. This finding suggests that players may exhibit shirking behavior after signing a long-term contract, while shorter contracts do not lead to similar performance reductions.

Similar patterns are observed for other performance metrics, such as Box Plus/Minus (BPM), OnCourt, and OnOff, where the coefficients for both Year elapsed and Year remaining are negative, with Year remaining having a larger negative effect. These results further support the incentive effect of the contract year, and they indicate that the decline in player performance after signing a new contract is influenced by the length of both the existing and the newly signed contracts.

Table 1.15 The advanced performance model(Including player fixed effects)

	(1) PER	(2) OWS	(3) DWS	(4) WS	(5) WS48	(6) BPM	(7) VORP	(8) OnCourt	(9) OnOff
Year elapsed	-0.31**	-0.09**	-0.05*	-0.15**	-0.01***	-0.29***	-0.05*	-0.50	-0.25
	(0.13)	(0.05)	(0.03)	(0.07)	(0.00)	(0.10)	(0.03)	(0.32)	(0.34)
Year remaining	-0.39***	-0.07	-0.02	-0.09	-0.01***	-0.35***	-0.05*	-0.62*	-0.42
	(0.14)	(0.05)	(0.03)	(0.07)	(0.00)	(0.11)	(0.03)	(0.34)	(0.36)
Experience	0.74	0.40**	0.31***	0.73***	0.01	0.38	0.26***	0.56	0.13
	(0.47)	(0.16)	(0.09)	(0.23)	(0.01)	(0.35)	(0.10)	(1.11)	(1.18)
Experience^2	-0.07***	-0.04***	-0.02***	-0.06***	-0.001***	-0.05***	-0.03***	-0.10***	-0.08***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.02)
Number of days players missed due to injury	0.17**	-0.03	-0.00	-0.04	0.00	0.08	-0.02	-0.24	0.07
	(0.07)	(0.02)	(0.01)	(0.03)	(0.00)	(0.05)	(0.01)	(0.17)	(0.18)
Draft 8 to 14	-1.68	-0.79	-1.82***	-2.67**	-0.07	-2.05	-0.68	-2.04	-0.13
	(2.76)	(0.97)	(0.55)	(1.34)	(0.05)	(2.07)	(0.57)	(6.57)	(6.98)
Draft 15 to 30	-5.22	-1.54	-1.82**	-3.35	-0.03	-4.63	-0.79	15.57	7.53
	(4.36)	(1.53)	(0.88)	(2.12)	(0.07)	(3.28)	(0.90)	(10.40)	(11.04)
Draft 31 to 44	-6.56**	-1.20	-1.56***	-2.84**	-0.05	-2.88	-0.87	3.37	5.13
	(2.73)	(0.96)	(0.55)	(1.33)	(0.05)	(2.05)	(0.56)	(6.51)	(6.91)
Draft 45 to 60	-6.96*	-2.22	-1.94**	-4.16**	-0.10	-5.38*	-1.02	2.56	5.84
	(4.17)	(1.46)	(0.84)	(2.03)	(0.07)	(3.13)	(0.86)	(9.93)	(10.55)
Not Draft	-7.14**	-1.53	-2.20***	-3.73**	-0.16***	-8.68***	-0.63	-9.91	-8.37
	(3.42)	(1.20)	(0.69)	(1.66)	(0.06)	(2.57)	(0.70)	(8.16)	(8.66)
Big	-1.06	0.14	0.21	0.35	-0.01	-1.54**	0.09	2.11	3.21
	(0.80)	(0.28)	(0.16)	(0.39)	(0.01)	(0.60)	(0.16)	(1.91)	(2.02)
Center	-0.22	0.11	0.10	0.20	-0.00	-1.34**	0.05	1.23	1.39
	(0.85)	(0.30)	(0.17)	(0.41)	(0.01)	(0.64)	(0.17)	(2.02)	(2.15)
Combo	-1.05*	-0.14	-0.04	-0.17	-0.02*	-1.03**	-0.00	0.67	-0.19
	(0.62)	(0.22)	(0.12)	(0.30)	(0.01)	(0.47)	(0.13)	(1.48)	(1.57)
Forward	0.06	-0.08	0.00	-0.08	-0.00	-0.19	-0.02	-1.14	-0.65
	(0.60)	(0.21)	(0.12)	(0.29)	(0.01)	(0.45)	(0.12)	(1.43)	(1.52)
Point guard	-1.03	-0.07	-0.13	-0.18	-0.03**	-1.47***	0.05	0.24	-0.29
	(0.70)	(0.24)	(0.14)	(0.34)	(0.01)	(0.52)	(0.14)	(1.66)	(1.76)
Power forward	-0.57	0.06	0.20	0.24	-0.01	-0.92*	0.07	1.83	2.42
	(0.67)	(0.24)	(0.14)	(0.33)	(0.01)	(0.50)	(0.14)	(1.60)	(1.70)
Shooting guard	-0.54	-0.02	0.03	0.02	-0.01	-0.45	0.02	1.34	1.12
	(0.42)	(0.15)	(0.08)	(0.20)	(0.01)	(0.31)	(0.09)	(1.00)	(1.06)
Small forward	-0.50	-0.07	0.02	-0.06	-0.01	-0.24	-0.00	-0.10	0.36
	(0.44)	(0.15)	(0.09)	(0.21)	(0.01)	(0.33)	(0.09)	(1.04)	(1.11)
Season fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Team fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Player fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cons	16.60***	1.24	2.51***	3.78***	0.14***	1.00	0.45	-7.98	-8.53
	(2.57)	(0.90)	(0.52)	(1.25)	(0.04)	(1.93)	(0.53)	(6.12)	(6.50)
R^2	0.725	0.733	0.721	0.748	0.662	0.687	0.788	0.590	0.567
N	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006

Notes: This table shows the regression model results for advanced performance. The dependent variable of the model is the player's advanced performance. Specific advanced variables are displayed in the header of each column. The independent variables are the elapsed year and remaining years of the contract, player age, experience and their corresponding squares, player injuries, player draft order, player position, and season, team and player fixed effects. The top seven picks in the first round are selected as the benchmark for the player draft order, and the benchmark for a player's position on the field is the wing. Additionally, the model does not calculate its standard errors by team clustering.

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Table 1.16, I continue to explore the impact of contract status on player performance, adding player fixed effects to the model while using basic performance metrics as the measure of player performance. The results for some variables are consistent with the previous model—specifically, the coefficients for the Year elapsed and the Year remaining are both positive. However, in the context of basic performance variables, some coefficients become negative after adding player fixed effects. These variables include the player's blocks and shooting percentage, and the results are statistically significant.

Despite the changes in coefficients, the parameter sizes for these variables are relatively similar, and the incentive effect of the contract year cannot be conclusively verified based on these results. Moreover, the presence of shirking behaviour after signing a new contract appears to depend on the length of the new contract compared to the current one. If the newly signed contract is longer than the previous one, a decline in player performance may occur. Conversely, if the new contract is not longer than the old contract, no significant performance decline is observed in the current contract.

Table 1.16 The basic performance model(Including player fixed effects)

	(1) PTS	(2) TRB	(3) AST	(4) BLK	(5) STL	(6) FGA	(7) FTA	(8) PA_3	(9) MP	(10) FGP	(11) FTP	(12) PP_3
Year elapsed	0.17^{*}	-0.01	0.08^{***}	-0.02^{***}	0.01	0.20^{***}	0.06^{**}	0.05	0.20	-0.01^{***}	0.002	-0.005
	(0.10)	(0.04)	(0.03)	(0.01)	(0.01)	(0.08)	(0.03)	(0.03)	(0.18)	(0.00)	(0.00)	(0.00)
Year remaining	0.26^{**}	-0.03	0.11^{***}	-0.02^{**}	0.01	0.27^{***}	0.09^{***}	0.08^{**}	0.29	-0.01^{***}	0.003	-0.004
	(0.11)	(0.05)	(0.03)	(0.01)	(0.01)	(0.08)	(0.03)	(0.04)	(0.19)	(0.00)	(0.00)	(0.00)
Experience	0.77^{**}	1.08^{***}	0.11	0.08^{***}	0.03	0.44^{*}	0.38^{***}	-0.30^{**}	1.97^{***}	0.03^{***}	-0.07^{***}	-0.04^{***}
	(0.35)	(0.15)	(0.10)	(0.03)	(0.03)	(0.27)	(0.10)	(0.12)	(0.63)	(0.01)	(0.02)	(0.01)
Experience^2	-0.10^{***}	-0.03^{***}	-0.02^{***}	-0.00^{***}	-0.01^{***}	-0.07^{***}	-0.02^{***}	-0.02^{***}	-0.16^{***}	-0.00^{***}	-0.00^{***}	-0.00^{***}
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Number of days players missed due to injury	0.31^{***}	0.11^{***}	0.06^{***}	0.01^{**}	0.02^{***}	0.26^{***}	0.08^{***}	0.07^{***}	0.55^{***}	0.00	0.00	0.00^{*}
	(0.05)	(0.02)	(0.01)	(0.00)	(0.00)	(0.04)	(0.02)	(0.02)	(0.10)	(0.00)	(0.00)	(0.00)
Draft 8 to 14	6.24^{***}	-3.55^{***}	1.19^{**}	-0.48^{***}	-0.11	5.16^{***}	0.63	4.68^{***}	3.51	-0.11^{**}	0.36^{***}	0.22^{***}
	(2.07)	(0.88)	(0.57)	(0.16)	(0.17)	(1.57)	(0.59)	(0.69)	(3.73)	(0.05)	(0.10)	(0.08)
Draft 15 to 30	-5.99^{*}	-2.12	-0.87	-0.23	-0.72^{***}	-4.97^{**}	-1.25	-0.27	-7.56	-0.05	-0.05	0.01
	(3.28)	(1.39)	(0.90)	(0.25)	(0.27)	(2.49)	(0.94)	(1.10)	(5.91)	(0.08)	(0.15)	(0.13)
Draft 31 to 44	-3.96^{*}	-3.58^{***}	-0.80	-0.46^{***}	-0.41^{**}	-2.88^{*}	-1.45^{**}	2.28^{***}	-6.45^{*}	-0.13^{***}	0.30^{***}	0.06
	(2.05)	(0.87)	(0.57)	(0.16)	(0.17)	(1.56)	(0.59)	(0.69)	(3.70)	(0.05)	(0.10)	(0.08)
Draft 45 to 60	-6.24^{**}	-3.28^{**}	-0.93	-0.02	-0.78^{***}	-4.69^{**}	-1.24	0.38	-11.01^{*}	-0.09	-0.23	0.27^{**}
	(3.13)	(1.33)	(0.86)	(0.24)	(0.26)	(2.38)	(0.90)	(1.05)	(5.64)	(0.07)	(0.15)	(0.13)
Not Draft	-5.33^{**}	-5.69^{***}	-0.99	-0.63^{***}	-0.65^{***}	-3.98^{**}	-1.81^{**}	1.82^{**}	-17.16^{***}	-0.22^{***}	0.18	0.04
	(2.57)	(1.09)	(0.71)	(0.20)	(0.22)	(1.95)	(0.74)	(0.86)	(4.63)	(0.06)	(0.12)	(0.10)
Big	-0.33	0.42	-0.19	0.14^{***}	-0.02	-0.29	0.03	-0.20	-0.72	-0.02	0.03	-0.01
	(0.60)	(0.26)	(0.17)	(0.05)	(0.05)	(0.46)	(0.17)	(0.20)	(1.08)	(0.01)	(0.03)	(0.02)
Center	-0.80	0.20	-0.26	0.14^{***}	-0.04	-0.73	-0.13	-0.41^{*}	-2.35^{**}	-0.02	0.03	-0.01
	(0.64)	(0.27)	(0.18)	(0.05)	(0.05)	(0.48)	(0.18)	(0.21)	(1.15)	(0.01)	(0.03)	(0.03)
Combo	-0.49	0.06	0.19	-0.00	-0.06	-0.25	-0.07	-0.28^{*}	-0.48	-0.01	-0.01	-0.02
	(0.47)	(0.20)	(0.13)	(0.04)	(0.04)	(0.35)	(0.13)	(0.16)	(0.84)	(0.01)	(0.02)	(0.02)
Forward	-0.26	0.26	-0.07	0.06^{*}	0.02	-0.20	-0.15	0.03	-0.24	0.00	-0.01	0.00
	(0.45)	(0.19)	(0.12)	(0.03)	(0.04)	(0.34)	(0.13)	(0.15)	(0.81)	(0.01)	(0.02)	(0.02)
Point guard	-0.34	0.05	0.55^{***}	-0.04	-0.05	-0.11	-0.02	-0.28	-0.73	-0.01	-0.01	-0.03
	(0.52)	(0.22)	(0.14)	(0.04)	(0.04)	(0.40)	(0.15)	(0.18)	(0.94)	(0.01)	(0.02)	(0.02)
Power forward	0.00	0.46^{**}	-0.15	0.11^{***}	0.01	0.02	0.09	-0.06	-0.40	-0.02	0.02	0.00
	(0.50)	(0.21)	(0.14)	(0.04)	(0.04)	(0.38)	(0.14)	(0.17)	(0.91)	(0.01)	(0.02)	(0.02)
Shooting guard	-0.05	0.12	0.06	0.01	0.00	0.06	-0.03	-0.02	0.37	-0.00	-0.02^{*}	-0.01
	(0.31)	(0.13)	(0.09)	(0.02)	(0.03)	(0.24)	(0.09)	(0.11)	(0.57)	(0.01)	(0.01)	(0.01)
Small forward	-0.27	0.06	-0.10	0.03	0.01	-0.13	-0.05	-0.04	0.02	-0.01	-0.00	-0.00
	(0.33)	(0.14)	(0.09)	(0.03)	(0.03)	(0.25)	(0.09)	(0.11)	(0.59)	(0.01)	(0.02)	(0.01)
Wing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Season fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Team fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Player fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
_cons	4.37^{**}	6.52^{***}	0.42	0.71^{***}	0.73^{***}	3.32^{**}	1.68^{***}	-2.27^{***}	18.29^{***}	0.62^{***}	0.32^{***}	0.08
	(1.93)	(0.82)	(0.53)	(0.15)	(0.16)	(1.46)	(0.55)	(0.65)	(3.48)	(0.04)	(0.09)	(0.08)
R^2	0.851	0.850	0.880	0.840	0.807	0.854	0.851	0.851	0.800	0.671	0.660	0.674
N	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006	3,006

Notes: This table shows the regression model results for basic performance. The dependent variable of the model is the player's basic performance. Specific basic variables are displayed in the header of each column. The independent variables are the elapsed year and remaining years of the contract, player age, experience and their corresponding squares, player injuries, player draft order, player position, and season,team and player fixed effects. The top seven picks in the first round are selected as the benchmark for the player draft order, and the benchmark for a player's position on the field is the wing. Additionally, the model does not calculate its standard errors by team clustering.
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Finally, after incorporating player fixed effects, I continue to explore whether different stages of a player's career impact their performance. Specifically, I excluded samples involving players in the final contract of their career, as performance during this stage may be influenced by other factors such as age and playing time. Consequently, the number of samples decreased from 3,006 to 2,086. Table 1.17 presents the results of the model with this adjusted sample.

From the results, the key variables of interest—Year elapsed and Year remaining—are not statistically significant. Only in WS48 is the Year remaining variable significant at the 10% level. For most of the variables, the coefficients are negative, and there is no consistent pattern in the relationship between the magnitudes of the two coefficients. Interestingly, when player performance is measured using Player Efficiency Rating (PER), the coefficient for Year elapsed is positive, while the coefficient for Year remaining is negative. This combination suggests an incentive effect during the contract year and implies that shirking behavior in a multi-year contract may be related to the length of both the current and new contracts. However, since these results are not statistically significant, the conclusions drawn from them are not definitive.

Nonetheless, the analysis indicates that the relationship between contract timing and player performance is influenced by the sample selection process. Properly setting and screening appropriate samples is crucial for conducting meaningful research on the impact of contract timing on player performance.

Table 1.17 The advanced performance model(Including player fixed effects and small sample)

	(1) PER	(2) OWS	(3) DWS	(4) WS	(5) WS48	(6) BPM	(7) VORP	(8) OnCourt	(9) OnOff
Year elapsed	0.09	-0.02	-0.05	-0.07	-0.003	-0.02	-0.04	-0.34	-0.06
	(0.14)	(0.06)	(0.04)	(0.09)	(0.00)	(0.10)	(0.04)	(0.35)	(0.38)
Year remaining	-0.04	-0.02	-0.03	-0.05	-0.005*	-0.14	-0.06	-0.55	-0.34
	(0.16)	(0.07)	(0.04)	(0.10)	(0.00)	(0.11)	(0.04)	(0.40)	(0.43)
Experience	0.96***	0.65***	0.20**	0.86***	0.01**	0.80***	0.43***	1.70*	1.49
	(0.36)	(0.16)	(0.09)	(0.22)	(0.01)	(0.25)	(0.09)	(0.89)	(0.95)
Experience^2	-0.07***	-0.04***	-0.02***	-0.06***	-0.00***	-0.04***	-0.03***	-0.11***	-0.09***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.02)
Number of days players missed due to injury	0.07	-0.03	-0.00	-0.04	-0.00	0.01	-0.02	-0.16	0.01
	(0.07)	(0.03)	(0.02)	(0.04)	(0.00)	(0.05)	(0.02)	(0.17)	(0.18)
Draft 8 to 14	-2.38	-1.37	-1.85***	-3.27**	-0.05	-2.45	-1.39**	-7.90	-8.17
	(2.43)	(1.06)	(0.61)	(1.47)	(0.04)	(1.70)	(0.61)	(6.02)	(6.45)
Draft 15 to 30	-8.58**	-3.69**	-2.09**	-5.79**	-0.14**	-5.07*	-2.47**	-13.24	-12.68
	(3.94)	(1.72)	(0.98)	(2.38)	(0.06)	(2.76)	(1.00)	(9.78)	(10.48)
Draft 31 to 44	-2.43	-1.53	0.09	-1.49	-0.03	-2.48	-1.55*	2.05	3.61
	(3.60)	(1.57)	(0.90)	(2.17)	(0.06)	(2.52)	(0.91)	(8.92)	(9.56)
Draft 45 to 60	-7.45**	-2.39	-1.72*	-4.14*	-0.11*	-5.72**	-1.66*	5.47	9.21
	(3.64)	(1.58)	(0.91)	(2.20)	(0.06)	(2.54)	(0.92)	(9.02)	(9.67)
Not Draft	-3.85	-0.67	-1.27*	-1.95	-0.04	-1.86	-0.54	-2.80	2.29
	(2.61)	(1.14)	(0.65)	(1.58)	(0.04)	(1.83)	(0.66)	(6.48)	(6.94)
Big	0.60	0.16	0.22	0.37	0.02	-0.18	0.01	2.99	4.54**
	(0.80)	(0.35)	(0.20)	(0.48)	(0.01)	(0.56)	(0.20)	(1.98)	(2.12)
Center	0.87	0.29	0.18	0.46	0.02	-0.26	0.09	-0.13	-0.22
	(0.88)	(0.38)	(0.22)	(0.53)	(0.01)	(0.61)	(0.22)	(2.18)	(2.33)
Combo	-0.34	0.12	0.03	0.16	-0.01	-0.39	0.14	0.60	0.25
	(0.63)	(0.28)	(0.16)	(0.38)	(0.01)	(0.44)	(0.16)	(1.57)	(1.68)
Forward	0.97	0.08	0.03	0.10	0.01	0.48	0.07	0.86	1.48
	(0.61)	(0.26)	(0.15)	(0.37)	(0.01)	(0.42)	(0.15)	(1.51)	(1.61)
Point guard	0.22	0.17	-0.08	0.12	-0.01	-0.30	0.23	1.21	1.86
	(0.71)	(0.31)	(0.18)	(0.43)	(0.01)	(0.50)	(0.18)	(1.76)	(1.88)
Power forward	0.40	0.04	0.16	0.19	0.01	-0.12	-0.00	1.47	2.81
	(0.67)	(0.29)	(0.17)	(0.40)	(0.01)	(0.47)	(0.17)	(1.65)	(1.77)
Shooting guard	-0.34	0.06	0.03	0.10	-0.01	-0.20	0.06	1.28	1.49
	(0.41)	(0.18)	(0.10)	(0.25)	(0.01)	(0.29)	(0.10)	(1.02)	(1.09)
Small forward	-0.35	-0.07	0.02	-0.06	-0.00	-0.08	-0.05	0.46	1.33
	(0.45)	(0.19)	(0.11)	(0.27)	(0.01)	(0.31)	(0.11)	(1.11)	(1.19)
Season fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Team fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Player fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
_cons	13.36***	0.99	2.37***	3.37**	0.10***	-0.81	0.67	-4.81	-5.31
	(2.17)	(0.94)	(0.54)	(1.31)	(0.03)	(1.52)	(0.55)	(5.38)	(5.76)
R^2	0.775	0.744	0.713	0.749	0.723	0.755	0.801	0.637	0.601
N	2,086	2,086	2,086	2,086	2,086	2,086	2,086	2,086	2,086

Notes: This table shows the regression model results for advanced performance. The dependent variable of the model is the player's advanced performance. Specific advanced variables are displayed in the header of each column. The independent variables are the elapsed year and remaining years of the contract, player age, experience and their corresponding squares, player injuries, player draft order, player position, and season, team and player fixed effects. The top seven picks in the first round are selected as the benchmark for the player draft order, and the benchmark for a player's position on the field is the wing. Additionally, the model does not calculate its standard errors by team clustering. The difference from the previous model is that the sample I selected excludes the last contract of a player's career, meaning that players are not at risk of losing their opportunity to remain in the league based on their performance in the current contract. Additionally, players' contracts still need to be longer than one year.

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

1.6 Conclusion

In conclusion, this chapter has explored the impact of contract timing on NBA player performance using both basic and advanced statistical analyses. The findings reveal a complex relationship between contract status and player performance, particularly highlighting the significance of the contract year phenomenon and subsequent changes in performance after signing a new contract. First, the t-test results indicate that when analysing basic performance metrics, players do not significantly reduce their performance after signing a new contract. Notably, players tend to increase their three-point shooting percentage after securing a new contract, suggesting a preference for simpler and less physically demanding plays. However, when considering advanced performance metrics, player efficiency, as measured by Player Efficiency Rating (PER), decreases significantly after signing a new contract—by approximately 2.2% compared to the contract year level. This decline is accompanied by a significant reduction in their contributions to team success, as evidenced by decreases of 7.1%, 5.2%, and 10% in Offensive Win Shares (OWS), Win Shares (WS), and Value Over Replacement Player (VORP), respectively, compared to contract year levels. The difference between the basic and advanced performance data is primarily due to the different recording methods. Basic data is recorded directly based on the player's observable output on the court, allowing players to track their own performance and meet specific targets. In contrast, advanced data is derived from more complex calculations and influenced by factors beyond the player's direct control, such as the performance of teammates and game context. This distinction explains why the results may differ between basic and advanced performance outcomes. The decline in performance after the contract year may be explained by players' heightened performance during the contract year, returning to normal levels once the new contract is secured. This situation is verified to a certain extent in the analysis of inter-group averages after including players' performance before the contract. There is no significant difference between a player's performance after the contract year and their performance before the contract year. Players do not significantly reduce their performance following the contract year. In a professional sports environment, players' performance is closely monitored by teams, media, and fans. If players engage in subjective shirking behaviour, it is likely to be easily detected, leading to significant losses.

From the linear regression results, after adding player-fixed effects to the model, when player performance is measured using advanced metrics, both the Year elapsed and the Year remaining—indicating a player's contract status—have negative coefficients. The coefficient for the Year elapsed is greater than that for the Year remaining, suggesting that players tend to gradually improve their performance as the contract progresses, supporting the notion that players are motivated to perform well during the contract year. The negative coefficient for the Year remaining also implies that if the player's new contract is longer than the current contract, a certain degree of performance decline may occur. However, if the new contract is shorter, the player's performance does not decline. This finding suggests that shirking behaviour is not inherently independent but rather depends on the length of both the current and the new contract. Ultimately, the player's shirking behaviour has not been conclusively verified. However, when player fixed effects are not included in the model, the results are completely different. Additionally, when selecting a new sample, such as only analyzing contracts that are not in the last year of a player's career, the results also change. From this, I conclude that adding player fixed effects allows for consideration of individual player characteristics, enabling a more accurate analysis of the impact of contract status on player performance.

Overall, this chapter provides a nuanced understanding of the contract year phenomenon in the NBA. It demonstrates that players significantly improve their performance during contract years and quantifies the extent of this improvement. However, there is no conclusive evidence to support the existence of shirking behaviour after signing a new contract. These findings have important implications for NBA teams in terms of contract negotiations and player management strategies. Further research is needed to fully understand the long-term effects of contract guarantees on player performance and to develop effective methods for maintaining high levels of productivity throughout the contract period.

Chapter 2

Performance and incentives in professional basketball: The player's salary model of the NBA League

2.1 Abstract

This chapter presents a salary determination model that examines the impact of player performance during both non-contract and contract years on salary outcomes. The analysis reveals that player scoring and playing time are significant determinants of salary, with their influence persisting throughout the contract period. Utilising quantile regression, the study estimates player salaries across different salary levels, showing that player performance is the primary driver of salary for the top 50% of earners, while additional factors influence salaries for those in the bottom half. The study also investigates the role of contract term, specifically the NBA's player option clause, on player wages. Stable performance significantly increases the likelihood of obtaining a player option in a new contract. Furthermore, players who anticipate securing a higher contract than their current salary are more likely to exercise their player options and become free agents. The impact of player options varies across different salary distributions: for players in the bottom 75th percentile in scoring and annual salary, player options result in a significant salary reduction of at least 18.6%; for those in the 75th to 90th percentile, player options lead to modest salary premiums and longer contracts; and for players in the top 10 percentile, player options are associated with substantial salary premiums.

2.2 Introduction

The sports industry, particularly in North America, provides a wealth of publicly available player salary data and performance metrics, making it an ideal environment for studying the determinants of player salaries. In terms of salary models, Scully (1974) suggests that player salaries should be determined by their marginal revenue product. However, Krautmann et al. (1999) posits that salaries can also be determined by free agent salaries, which Krautmann (2013) argue is more suitable for studying salary determinants, aligning well with the scope of this study. Thus, this chapter focuses on identifying the determinants of player salaries, with particular emphasis on the impact of player options in NBA contracts. Previous studies on the determinants of player salaries have often focused on factors such as player performance Vincent and Eastman (2009), future expectations Deutscher et al. (2017), and team salary structure Simmons and Berri (2011). However, the influence of contract terms, specifically player options, on player salaries has been less explored. Player options allow players to decide, in advance, whether to continue with their current contract or become free agents at the end of a multi-year deal. This study aims to investigate the impact of player options on player salaries.

This study makes three primary contributions: First, I use free agent salaries to estimate the determinants of player salaries. Player performance, especially key indicators such as points, rebounds, blocks, assists, and playing time, is crucial for salary determination. Player contracts usually span multiple years, and performance during the contract is divided into average performance during the non-contract years and changes in performance during the contract year. Improvement in player performance during both periods positively impacts the salary in the next contract. For instance, a one-point increase in average score during non-contract years results in a 5% increase in total salary, while a similar increase during the contract year leads to a 10% increase in salary. The analysis also finds that the significant impact of player performance on salary is most evident in the top 50% of the salary distribution, whereas the bottom 50% of players are influenced by a wider range of factors, highlighting the complexity of salary determination.

Second, this study explores the determinants of player options in contracts and the factors that influence players' decisions to exercise these options. Players with more stable performance are more likely to receive player options. An increase of one standard deviation in score fluctuations decreases the likelihood of securing a player option by 4%. Conversely, improved performance raises this likelihood—an increase of one point in the average score during non-contract years increases the chance of securing a player option by 2%. The timing of league policies also influences player options; the anticipation of a new Collective Bargaining Agreement (CBA) raises the probability of including player options in contracts.

When players decide whether to exercise their player options, the primary factor is the difference between their expected and actual salaries. For instance, if the expected salary is 2.7 times greater than the actual salary, the probability of opting out and becoming a free agent increases by 19%. Players who have been selected as All-Stars are also more likely to exercise player options, with each selection raising the probability by 13%. This study is the first to explore both the determinants of having player options and the factors affecting their execution in NBA contracts.

Third, this study examines the impact of player options on player salaries. Recognizing that there is inherent heterogeneity among players with player options and that the effects of these options vary across different salary distributions, the study employs a matching process method to minimize differences between contracts with and without player options. To achieve this, a logistic regression model is used to estimate the propensity score for each player—the likelihood of receiving a player option in their new contract based on selected characteristics. The variables included in the logistic model are derived from the player salary model, encompassing factors such as age, performance metrics (e.g., points, rebounds, minutes played), team changes, All-Star selections, and the timing of contract signing. These variables are chosen to ensure that matched players are comparable across key factors that influence both contract negotiations and salary outcomes. Using these propensity scores, a one-to-one matching process without replacement is conducted to pair players with similar characteristics, where one player has a player option in their contract and the other does not. This approach minimizes the differences between the treatment group (players with player options) and the control group (players without player options), allowing for a clearer analysis of the impact of player options on salary. The impact of player options on salaries is then examined across different score and salary distributions. The results show that including a player option leads to a reduction in annual salary for players in the bottom 75%, with an average decrease of $1.2 million, or 18% of income. In contrast, players in the top 25% to 10% receive a moderate salary premium and longer contracts. Finally, players in the top 10% receive an annual salary premium of at least $10 million, equivalent to 40% of their salary. This divergence from traditional economic theory is likely due to the scarcity of these star players, who possess greater bargaining power in salary negotiations, allowing them to secure both flexible contracts and higher salaries.

This chapter is organized as follows: First, a detailed summary of the current research is provided. Second, the institutional setting of the NBA league is examined. Third, the salary model is discussed in detail. Fourth, the impact of contract term on player salary is analyzed. Fifth, the chapter evaluates the impact of player options on player salary. Finally, the chapter concludes with a summary of the research and its limitations.

2.3 Literature review

Traditional economic theory tells us that an employee's salary should equal the employee's marginal revenue product(MRP) in a perfectly competitive market. Therefore, estimating the employee's marginal revenue product can reasonably determine the employee's income. Scully (1974) used American Major League Baseball as a research object, combining team revenue, game performance, and player performance on the field. Using the method of multi-step regression, the player's MRP was estimated, and the degree of monopsony exploitation was estimated using the player's MRP and the player's real salary. In professional baseball, teams monopolised and exploited players mainly through the reverse clause. A reverse clause was part of a player's contract that states that the team retains power over the player after the contract expires. Players under these contracts could not sign another contract with another team. Once a contract was signed, the player must be reassigned, traded, sold and released by that team. This clause was not relaxed until 1975, and players who met certain conditions could sign with other teams. In this study, Scully believed that the player's MRP could directly or indirectly affect the player's and the team's ticket income through his performance on the court. At the same time, the player's performance on the field directly affected the team's victory. Thus, the study established a link between player performance, team wins, and revenue. The following three formulas determined the whole process.

$$TR_J = \alpha_0 + \alpha_1 X_J + \alpha_2 WPCT_J$$

$$WPCT_J = \beta_0 + \beta_1 PERF_J$$

$$PERF_J = f(PERF_{IJ}, Z_J) \quad I \quad on \quad team \quad J$$

The income of team TR_J was determined by some characteristics X_J related to the team and the number of winning per cent $WPCT_J$ of the team in the season. At the same time, the team's number of wins was determined by the performance of all players of the player $PERF_J$. Then, the team's player performance $PERF_{I,J}$ and other team characteristics Z_J decided the team's performance. First, through the estimation equation of team revenue, it could be concluded that the team can contribute \$10,330 in revenue per victory. Then, by estimating a player's contribution to each win, the study divided baseball players into two categories, pitchers and hitters, with different players measuring their contribution to a team's win by different performances. For hitters, each additional team slugging average(TSA) added 0.92 wins. For pitchers, a 1 per cent increase in the team's strikeout rate(TSW) increased by 0.9 games. Next, the researchers estimated the marginal revenue product of these two players respectively. For pitchers, they got \$9,297 for every additional TSA. For hitters, they earned \$9,504 for every 1% increase in TSW. After obtaining the MRP of these two types of players, the study further estimated the MRP of a specific player. Furthermore, the study simplified the regular lineup of each baseball team to consist of 8 pitchers and 12 batters, combined with the actual situation. Therefore, pitchers' personal TSA divided by eight was their marginal performance and multiplied by \$9297, which got their respective MRP. In the same way, the bitters' marginal performance was their respective TSW divided by 12. On this basis, multiplying their marginal performance by 9504 was the bitter's MRP. The authors compared the actual salaries of players to the predicted MRP, estimating exploitation due to the monopsony power of teams(reverse clause).

In Scully's study, he used a proportional method to separate the player's contribution from his teammates. However, this method was very crude and could not classify the types of players, such as starters or bench players. In addition, Scully only considered that player performance could contribute to the team's victory but ignored other inputs, such as managerial quality and cooperation between players. Furthermore, Scully used the total revenue as the dependent variable in the model. Still, total revenues contained broadcast revenues and stadium arrangements, which were not directly related to the player's performance. Thus, the Scully method somewhat overestimated the player's MRP. To narrow the player's MRP, Krautmann et al. (1999) used a simple alternative to estimate the player's value. After 1975, the reverse clause was abolished and replaced by free agency. The new collective bargaining agreement stipulated that players who reached six years of Major League service time or when they were released from their organisation before reaching six years of service time could become free agents. Therefore, there were two kinds of players in the major league. Players with over six years of experience became free agents and signed contracts with any team. The others whose experience was less than six years had a reverse clause in their contract and could not sign with another team freely. This method considered that if the player's bidding was a perfectly competitive market, the salary of free agents was the player's MRP. If the free market player was not perfectly competitive, their salary was interpreted as what the player could receive if they were not in a reverse clause. This study first used the free agent to estimate the following model.

$$W_{I,J} = \theta_j + \theta_1 PERF_I + \theta_2 TREND + \varepsilon_{I,J}$$

$W_{I,J}$ was the free agent salary. $PERF_I$ was Player I's performance. The player's performance was measured by slugging average and cross-terms with dummy variables for catcher and shortstop. $TREND$ explained the growth in real wages. θ_J was the team fixed effect. Then, this study used the coefficients from the previous model to estimate the value of a player whose contract had a reverse clause. The function of the model was as follows:

$$Value_{I,J} = \hat{\theta}_j + \hat{\theta}_1 PERF_I + \hat{\theta}_2 TREND + \varepsilon_{I,J}$$

By comparing the value and actual salary, this study concluded that the reverse clause exploited the less-experienced players, but the magnitudes were not as large as Scully's.

Using free agent contract prices to estimate a player's marginal revenue product (MRP) offers a novel approach, though Bradbury (2013) raised some scepticism. First, Krautmann et al.'s method assumes that the player's free market wage operates under perfect competition. However, the NBA market is not entirely competitive and may be affected by factors such as bilateral monopoly and the winner's curse. A bilateral monopoly arises in markets with only one buyer and one seller. In the NBA, all teams collectively form a single buyer's market for professional basketball players, while the players, through their union, create a seller's market—forming a bilateral monopoly. In such a setting, both the players and teams strive to maximize profits, but salaries deviate from what they would be in a perfectly competitive market. The winner's curse, on the other hand, occurs when the winning team in a competitive bidding process pays more than the player's intrinsic value. Since NBA teams compete for free agents in a manner similar to an auction, this effect is present. Additionally, free agents face competition from replacement players, often resulting in salaries below the player's actual MRP. The accuracy of using free-agent contracts to estimate MRP depends on the characteristics of the sample. When strong teams dominate free agent signings, MRPs may be overestimated, whereas weak teams' signings may lead to underestimates. Furthermore, players are risk-averse and often sign multi-year guaranteed contracts with lower annual salaries than their corresponding MRP, making it challenging to link wages to future performance. In contrast, Scully (1974)'s method relies on team revenue to detect market inefficiencies, which can provide a more accurate estimation of MRP.

In response to these criticisms, Krautmann (2013) clarified the differences between team revenue-based and free-agent market-based approaches. Krautmann noted that Scully's method faces two main challenges: estimating team marginal revenue and the player's marginal product (MP). Since most NBA teams are privately owned, obtaining accurate revenue data is difficult, and inconsistencies across sources can lead to significant variations in results. Additionally, estimating a player's MP is complicated because it involves comparing a player with a hypothetical replacement, which is not feasible in reality. While acknowledging that free agency salaries might underestimate MRP due to competition from lower-level players, Krautmann argued that controlling for player types could address this issue. They also noted that the non-linear relationship between team performance and revenue affects both methods. Adding higher-order terms for team performance can mitigate this impact, though it cannot fully resolve it in Scully's method. Regarding the claim that risk-averse players accept lower salaries for longer contracts, Krautmann argued that research suggests the opposite—longer contracts often lead to higher salaries. Additionally, any significant salary difference could be addressed by adding team or location fixed effects. Ultimately, Krautmann concluded that both the team revenue-based and free market methods have their applications: the free market approach is suited for studying salary determination or labor discrimination, whereas Scully's method is better for verifying whether a player is worth a long-term contract. Since this study focuses on salary determination for NBA players, the free market method is primarily adopted.

Player performance is a significant factor in determining salary, and many studies have supplemented the salary determination model from a more subdivided perspective. With the addition of these factors, the content of the salary model is enriched, and some specific factors can be better explained through the salary model. In most sports, the top players earn a higher salary than the ordinary players. So, the distribution of the salary is thick-tailed. Many existing pieces of literature are based on the exact conditional distribution for model estimation, which may result in an incorrect representation of the relationship between salary and player performance. Vincent and Eastman (2009) used the National Hockey League as the research object. Using ice hockey data to analyse player salary decisions made it difficult to assess individual player performance offensively and defensively, a problem that existed in other collective sports. In addition, offensive stats were measured by goals and assists in a single game, while defensive stats lacked corresponding direct data. Teams had different requirements and expectations for players with different salaries. To further explore this question, this study used quantile regression to estimate the return equation at different points of the conditional distribution. It compared the result with that of ordinary least squares. In the model setting section, the dependent variable of the model was the natural logarithm of the player's salary; the independent variables were the average points per game, the number of career appearances and their square, whether they were selected as the All-Star first team or second team, draft position, team revenue, penalty time per game, plus/minus value per game, player weight, player height, player's amateur experience before his career. The form of the model was as follows

$$LNSAL_i = \alpha + \beta x_i + u_i$$

The data for the study were game and salary data for 625 players from the 2003-04 season who had to play more than ten games per season and split the players' positions into 407 forwards and 218 defensive players. In terms of empirical analysis, the study selected offensive players and defensive players separately and selected five quantile points (10, 25, 50, 75, 90). The study also performed F-tests on the joint coefficients and coefficients between groups. The results showed that the interpretation of the earnings equation using career statistics explains much less for low-income players than for high-income players. The penalty time per game only had a decisive effect on the upper quantile forwards, and the points per game significantly increased the income of the forwards. Being selected to the All-Star team for defensive players only increased earnings for players with lower quantiles. At the same time, the position of drafts affected players' earnings with upper quantiles.

Consistent player performance boosted salary for the next contract. Deutscher et al. (2017) combined theoretical and empirical parts to explore whether the stability of player performance increased salary. In the theoretical part, the author put forward two propositions. The first was that the players' salaries increased with the growth of the team's output and the expected ability of the players. The second was that the workers with more stable performance received higher wages. Based on these two theorems, it was further assumed that the team was risk-neutral, consistent with the existing research on sports economic studies. Then, this study put forward three hypotheses. The first was that the higher the output of the players in the team, the higher the income got. The second was that the higher the expected ability of the workers, the higher the salaries were. The third was that the more stable the employees' performance, the higher the wages. The players' output was reflected by the performance of the players, which were scoring and non-scoring data. The scoring data was the points in each game, and the non-scoring data was the sum of rebounds, assists blocks and steals. The player's expectations predicted the player's future performance, which was based on the player's experience and draft position. In addition, the stability of player performance was measured by the standard deviation of the player's scoring data and non-scoring data for the year. In the empirical part, the study used NBA data from 2007/08 to 2010/11. Regarding data selection, rookie contract data was excluded. Only the salary data of the first year of multi-year contracts and the performance data of the year before that year were retained. In addition, players with fewer than 41 appearances were also excluded. The salary decision model adopted a linear model. The dependent variable was the natural logarithm of salary. The independent variables included the player's experience and its square, the player's draft order and its square, the number of All-Star participation and its square, the player's race, the player's score data, the player's non-scoring data, the standard deviation of player's scoring data, and the standard deviation of player's non-scoring data. The model first used the ordinary linear regression and random effect models to determine the marginal increase under conditional expectations. In addition, due to the right-biased nature of NBA salary, this study added quantile regression to explore the impact of different quantiles on player salary The final research concluded that scoring and non-scoring data were decisive in player salaries. Player experience, player draft order, and the number of players participating in the All-Star Game significantly increased player salaries but with diminishing marginal effects. The player's race did not significantly affect a player's salary. The key research direction of this study was that the stability of player performance could significantly increase players' salaries.

Based on considering player performance, Deutscher (2009) attempted to include the impact of player leadership on salary. This study hypothesised that team leader in ice hockey improved their performance by leading it, so they got a particular monetary reward. The article first considered the factors that determined salary. In the existing literature, the intensity of players on the court affected player salary. The nationality of the player brought a particular salary bias. In addition, this research is relocating the study subjects to managers of large corporations and participating in extracurricular sports in childhood increased future earnings. The study's goal was to take a different approach to measure the extent to which leadership determines salary. This article used performance and salary data for NHL players from the 2003/04 to 2007/08 seasons. The study looked at whether a player was captain or not as a measure of leadership. At the same time, the research found that players who served as captains had more extended experience. Hence, the model added experience and the square of experience to the model. The number of All-Star appearances reflected a player's talent. The player's position, the number of appearances, and the number of goals all reflected the player's performance on the pitch. Due to the apparent right skewness of player salaries, the league's average salary was significantly higher than the median salary, and the natural logarithm of salary was used as the dependent variable in the study. The following salary determination formula was based on the basic Mincer salary formula. The authors used both random effects and traditional OLS models. Random effects accounted for some unobserved factors that may influence individual effects. Furthermore, to solve the endogenous problem of the mutual influence between salary and captaincy, the model used whether to be captain in the previous year to replace whether to be captain this year. In addition, the dummy variables of the team and season were also added to the model. The dummy variables of the team described the team-building ideas and cost differences of different groups. The dummy variables of the season explained the impact of changes in the league collective bargaining agreement on salary. The salary determination model results showed that the number of All-Star appearances significantly changed the salary distribution between the best and good players. Defensive players earned better salaries than offensive-only players for their extra defensive abilities. More appearances showed the better physical ability of the player and got a positive salary reward. The number of goals increased the player's salary, but the marginal return diminished. The main hypothesis of the article has been tested. The team captain received an additional monetary reward of 20% to 30%. Even if the captain of the previous year was used as a substitute, it still had a significant positive effect.

Additionally, earlier research examined the effect of a player's ethnicity on player salaries and fan attendance (Kahn and Sherer, 1988). In classical economic theory, the marginal revenue product equals the salary. In the sports market, part of the team's revenue was composed of the team's ticket income, so the reduction in attendance caused by the audience's discrimination against different races could be reflected in the players' wages. NBA data was used as the object of this study, even though the NBA was already the league with a higher proportion of black players in American professional sports leagues. Among the high-paid players, the proportion of black players was also high. But salary discrimination against black players still existed. In a salary-determining model, the dependent variable was the natural logarithm of salary. The independent variables included the player's season played, free throw percentage, field goal percentage, minutes played, points, games, center, forward, fouls, steals, the number of home attendance, the ethnicity of the region, the population of the region, the income of the region, the draft position, the team's winning percentage last season, and race. The article addressed the draft order's endogeneity through high school performance data in the two-stage least squares regression model. Through generalised least-squares, the problem of heteroscedasticity of the data was tentatively improved. This study found racial salary disparities in the real world of basketball. Black players were paid about 20 per cent less than white players under the same circumstances, ceteris paribus. On the one hand, the number of white players increased home attendance. Therefore, the racial discrimination behaviour of the fans became the reason for the salary discrimination against the players by the team aiming at maximising profits. In addition, the study also estimated whether the team had discriminated against black players in the draft and concluded that there was no racial discrimination in the draft position.

As a collective sport, the teammates' salary and the team's salary structure were research directions. Simmons and Berri (2011) examined whether unequal pay structures in teams affect team or individual performance. The article first explored the determinants of player salaries. Points were the main factor affecting player salary, while other factors that affected team wins had less impact on salary. This was summarised as differences between teams and players in determining winning productivity perceptions. In terms of unfair salary structure, justified inequality meant that players recognised some better players to get a higher salary. On the other hand, in terms of unjustified inequality, this study was innovative for players and teams. The study did not find that the increased disparity in team salary structure reduced the performance of teams and players. The NBA appeared to have positively affected player performance amid an increase in league-wide pay inequality, consistent with tournament theory.

In previous studies, player salaries have been primarily determined by performance metrics, future expectations, and the team's salary structure. However, the impact of specific contract clauses on salaries, particularly in the context of the NBA, has not been thoroughly explored. This study addresses this gap by evaluating the effect of contract flexibility, focusing on option clauses in NBA player contracts. Most NBA players secure multi-year guaranteed contracts to mitigate risks such as injury, which provides long-term security but can limit salary growth. To increase flexibility within these contracts, the NBA incorporates player options and team options, allowing either the player or the team to decide, one year before the contract expires, whether to continue or terminate the agreement. Player options offer players the flexibility to negotiate more favourable contracts at the appropriate time, although this flexibility may come at a financial cost. Conversely, team options provide teams with the ability to control player contracts, potentially resulting in financial compensation for players. This study empirically confirms these hypotheses by comparing contracts with and without options, grouping the results based on player scoring and annual salary distributions. The findings indicate that player options have varied impacts depending on a player's standing: for those in the bottom 75th percentile of scoring and salary, player options are associated with a significant reduction of at least 18.6% in annual salary; for players in the 75th to 90th percentile, player options lead to modest salary premiums and longer contracts; and for those in the top 10 percentile, player options yield substantial salary premiums. However, due to sample size limitations, the study did not yield significant results when analysing team options.

2.4 Institution setting

The NBA Collective Bargaining Agreement is generally abbreviated as CBA, a contract formulated by the NBA league and the players union. It establishes rules that employers and employees agree with and must follow. It is the core institutional basis for the continuous development and growth of the NBA, a professional sports league. The CBA defines the salary cap, the procedures for determining the salary cap, minimum and maximum salaries, trade rules, the guidelines for the NBA draft, and other things that need to be defined for a league like the NBA to function. The CBA also prevents the NBA from violating federal antitrust laws. Many of the league's practices, such as the salary cap and the draft, would violate antitrust laws without an agreement through collective bargaining.

2.4.1 CBA history

Bob Cousy, an active player then, began organising NBA players in 1954, although the league didn't recognise the organisation as a union representing players until 1957. A strike at the 1964 All-Star Game forced the league to pass a pension plan. The first CBA was passed in 1970, and new agreements were reached in 1973, 1976 and 1980. The 1976 CBA coincided with the resolution of the Oscar-Robertson lawsuit, brought by the players' union in 1970, to block the merger of the NBA and the ABA. The 1976 CBA also provided players with a certain degree of freedom by abolishing the "option" clause (note: this clause stipulates that the team has always had the right to renew the contract of its own players), which previously bound the player permanently to the original contract team. In the 1983 agreement, the two sides agreed to share the union's revenue. The agreement created the modern salary cap, which took effect in 1984. Players filed an antitrust lawsuit when that agreement expired, leading to the "Bridgeman" agreement, brought unrestricted free agency, reduced the draft to two rounds, and added an anti-collusion clause. After the CBA expired in 1988, another antitrust lawsuit in 1994 challenged the salary cap, the college draft, and the right to preemptive renewal. The two sides eventually reached a "no strike, no lockout" agreement, allowing the 1994-95 season to continue as normal. The NBA exercised its option to terminate the 1995 CBA after the 1997-98 season and finally implemented a lockout. The agreement took effect on July 1, 1998. The new agreement introduced a maximum salary, a middle-level exception, escrow and a luxury tax system. The league later exercised its option to extend the agreement to the 2004-05 season. In July 2005, the NBA and the NBPA approved a new agreement that expired at the end of the 2010-11 season. The league gave up on extending the agreement. When the 2005 CBA expired in July 2011, the league shut down again, and an agreement was reached at the end of November 2011. The 2011 CBA had a 10-year term, but mutual opt-outs were available after the 2016-17 season. The parties agreed on new CBA terms before the opt-out date, effective July 1, 2017. The current CBA will be officially implemented from the 2017-18 season and expire after the 2023-24 season. In addition, the two sides can terminate this agreement to renegotiate after the 2022-23 season before December 25, 2022. In this part, the explanation is mainly based on the 2017 version of CBA.

2.4.2 Salary cap

A salary cap limits the amount a team can spend on player contracts, which helps maintain a competitive balance in the league. The basic idea of a salary cap is that a team can only sign free agents if its total salary doesn't exceed the salary cap – so a team with deep pockets is on a relatively level playing field with other teams. While this is theoretically true, large-market NBA teams can outperform small-market teams significantly. As a result, the correlation between team salaries and regular-season wins is now eroded by the salary cap's constant influence. For the 2016-17 NBA season, the correlation coefficient was about 0.35, compared to 0.53 for the 2010-11 season. There are soft and hard salary caps, and the NBA has a soft salary cap. The hard salary cap cannot be exceeded for any reason. Soft salary caps like the NBA contain exceptions that allow teams to sign players or make trades under certain circumstances to exceed the salary cap.

The amount of the salary cap is closely related to the BRI. The full name of BRI is Basketball-related income. Overall, players will receive a

$$50\% * Forecasted \quad BRI \quad \pm 60.5\% * over/under \quad forecast \quad BRI$$

The final amount is 49%-51% of the Forecasted BRI. The salary cap is calculated from the projected BRI and next season's earnings. The amount of expected BRI is negotiated between league and player unions. The salary cap is calculated as

$$(44.7\% * projected \quad BRI - projected \quad benefits)/number \quad of \quad teams(30)$$

The salary cap will be announced every year on July 1. It will be implemented during the July moratorium. Teams who spend too much or too little will receive a certain penalty. The minimum team salary is 90% of the salary cap, calculated on the day of the team's last regular season game. If the team's salary exceeds the tax threshold, the team will pay the penalty and be deprived of some exceptions. The tax line is calculated as

$$(53.51\% * projected \quad BRI - projected \quad benefits)/number \quad of \quad teams(30)$$

Once team salaries exceed a level known as the "Apron", further restrictions apply. In the 2017-18 season, the Apron was $6 million above the tax line, and in subsequent seasons, the Apron rose by half as much as the salary cap. The setting of the salary cap restricts teams with solid financial resources from attracting high-level players through high wages, thereby maintaining the overall balance of the league. In addition, to prevent, for example, the team used the reservation clause in the early baseball leagues to protect and maintain the league's competitiveness and realise the limitation of players' salaries for exploitation. In the NBA, the salary cap is determined by basketball-related income, and that percentage is roughly 50 per cent. Therefore, setting the salary cap protects the interests of the team and the players to a certain extent.

2.4.3 Player contract

Minimum Salary

The NBA tries to ensure that teams are as competitive as possible by setting up various contract types and exceptions. The minimum salary is the lowest salary the players can receive, as the league stipulates. The minimum salary for all contract seasons is based on the minimum salary scale in effect when the contract is signed. The specific salary of the player is determined by the number of years the player has been in the league. The minimum salary amount for the 2017-18 season was resolved through negotiation, and in each subsequent season, the change in the minimum salary amount is consistent with the salary cap change. Any contract with a minimum salary lower than the current CBA will automatically be increased to a minimum contract that matches the player's salary. At the same time, for players with experience greater than three years, when signing a minimum salary contract, the league will reimburse the part exceeding the two-year veteran's minimum salary. This is a measure to encourage teams to sign veterans to avoid teams that feel that the minimum salary of veterans is too expensive and sign young players. The table 2.1 shows the minimum salaries for newly signed players in the 2017-18 season.

Table 2.1 Minimum salary for new contract signings for the 2017-18 season.

Years in NBA	First year in new contract	Sescon year in new contract	Third year in new contract	Fourth year in new contract	Fifth year in new contract
0	$815,615				
1	$1,312,611	$1,378,242			
2	$1,471,382	$1,544,951	$1,618,520		
3	$1,524,305	$1,600,520	$1,676,735	$1,752,950	
4	$1,577,230	$1,656,092	$1,734,954	$1,813,816	$1,892,678
5	$1,709,538	$1,795,015	$1,880,492	$1,965,969	$2,051,446
6	$1,841,849	$1,933,941	$2,026,033	$2,118,125	$2,210,217
7	$1,974,159	$2,072,867	$2,171,575	$2,270,283	$2,368,991
8	$2,106,470	$2,211,794	$2,317,118	$2,422,442	$2,527,766
9	$2,116,955	$2,222,803	$2,328,651	$2,434,499	$2,540,347
10+	$2,328,652	$2,445,085	$2,561,518	$2,677,951	$2,794,384

Notes: This table shows players' minimum salaries in accordance with CBA regulations. A player's minimum salary is determined by the number of years the player has been in the league. The minimum salary fluctuates with the season's salary cap. Therefore, this table shows the minimum salary for the 2017-18 season when players sign their contracts.

Maximum Salary

The maximum salary contract is the highest contract that a player can obtain. The maximum salary contract can be divided into three categories according to the player's experience. The specific amount of the player's maximum salary is shown in table 2.2. The first category is those with experience of 0 to 6 years, who can get a salary of 25% of the salary cap. Those with 7-9 years can get 30% of the salary cap, and those with longer playing experience can get 35% of the salary cap. There are several exceptions to max-salary contracts. Multi-year max-salary contracts are only subject to the specified maximum salary for the first year, and subsequent years are only subject to increases. The salary in the first year of a max contract must not be less than 105% of last season's salary. Certain players are eligible for higher maximum salaries at certain stages of their careers.

Table 2.2 Maximum salary by season

Years in NBA	Defined maximum salary	2017-18	2018-19	2019-20	2020-21	2021-22	2022-23
0 - 6	25% of cap	\$24,773,250	\$25,467,250	\$27,285,000	\$27,285,000	\$28,103,500	\$30,913,750
7 - 9	30% of cap	\$29,727,900	\$30,560,700	\$32,742,000	\$32,742,000	\$33,724,200	\$37,096,500
10+	35% of cap	\$34,682,550	\$35,654,150	\$38,199,000	\$38,199,000	\$39,344,900	\$43,279,250

Notes: This table shows the players' maximum salaries as stipulated in the CBA. A player's maximum salary is determined by the number of years the player has been in the league, and the amount of the maximum salary is determined by the percentage of the salary cap.

Exceptions

The basic rule of the NBA salary cap is that a team cannot sign or trade a player that would make the team's salary above the salary cap unless the team uses an exception. In a soft-cap system, exceptions allow teams to operate above the salary cap. Below are some special cases that can be used to sign players. The first is the Larry Bird Exception, the Bird Exception. The Bird rights exception allows teams to re-sign contracts with their free agents regardless of the salary cap. Players must have played three seasons without layoffs or changing teams as free agents to qualify for bird rights. When a player trades, his Bird rights are also traded, and his new team can use it to re-sign him. The salary amount of the players signed with Bird rights is capped at the maximum salary, the maximum period is five years, and the maximum annual increase is 8%. Players who meet this particular case are called "Qualifying Veteran Free Agents" in the CBA, and this particular case is an essential part of the veteran free agent case. Bird rights are a powerful way for a parent team to retain its free agent.

Early Bird Exception. A weakened version of Bird rights also allows teams to re-sign their free agents above the salary cap, but the contracts that can be issued are more restricted than Bird rights contracts. To be eligible for an Early Bird Right, a player must have played two seasons without layoffs or changing teams as free agents. The starting salary for an Early Bird contract extension is not higher than 175% of the player's salary last season (of course not more than the maximum salary) and 105% of the league's average salary last season, with a term of 2 to 4 years and a maximum annual increase of 8%. The Early Bird exception is also essential to the veteran free agent exception. Players who meet this exception are Known in the CBA as "Early Qualifying Veteran Free Agents".

The Non-Bird exception is integral to the veteran free-agent exception. Players who meet this exception are called "Non-Qualifying Veteran Free Agents" in the CBA. The condition for a player to get a Non-Bird is that the player does not play on one team until the end of the season through layoffs or changing teams as a free agent or a team with an Early Bird can give up the Early Bird and renew the player with a Non-Bird. The starting salary for Non-Birds is up to 120% of last season's salary and 120% of the base salary, matching the contract that restricts free agency offers, whichever is greater. The contract period is up to 4 years, and the maximum increase is 5%.

Non-Taxpayer Mid-Level Exception, a special case that teams under the apron can use. Under the apron here refers to using the Non-Taxpayer Mid-level Exception and still under the apron. It cannot be used if the team is less than a Non-Taxpayer Mid-Level Exception from the apron. The 2017-18 season's Full-Middle Level space was determined in the collective bargaining agreement at $8.406 million. The Non-Taxpayer Mid-Level Exception contract amount for each subsequent season relates to the salary cap increase. The Non-Taxpayer

Mid-Level Exception will be split and used for a maximum of 4 years and a maximum rise of 5%. Signing a multi-year contract doesn't affect the team's use of the Non-Taxpayer Mid-Level Exception in subsequent seasons.

Taxpayer Mid-Level Exception, this exception can only be used when the team's salary exceeds the apron. The 2017-18 season's Taxpayer Mid-Level Exception is determined in the collective agreement at $5.192 million, and the amount of the Taxpayer Mid-Level Exception for each season thereafter is related to the salary cap for that season. The Taxpayer Mid-Level Exception can be split and used for three years, with a maximum increase of 5%. Signing a multi-year contract with the Taxpayer Mid-Level Exception will not affect the use of this particular case in the following seasons.

Room Mid-Level Exception, this special case only uses space to sign free agents. The 2017-18 season's Room Mid-Level Exception is determined in the collective agreement, which is $4.328 million. The amount of the Room Mid-Level Exception for each season thereafter is related to the salary cap for that season. The Room Mid-Level Exception can be split and used for a maximum of 2 years and a maximum increase of 5%. Using this special case to sign a multi-year contract will not affect the use of this special case in the following seasons. The usage scenario of the Room Mid-Level Exception is when a space team has filled up the cap space without considering injury exceptions and rookie exceptions. Undoubtedly, the room mid-level exception is the more useful one. Due to the requirements of CBA, only one of the three exceptional cases above can be selected, and they are not used at the same time but can use none.

A Bi-Annual Exception that teams below the apron can only use. Teams that have used the Taxpayer Mid-Level Exception or Room Mid-Level Exception can't use this exception. The Bi-Annual Exception for the 2017-18 season was established in the collective bargaining agreement at $ 3.290 million. The Bi-Annual Exception for each season thereafter is related to the salary cap for that season, which increases year-on-year. Teams cannot use this exception to sign players for two consecutive years. This exception can be split and used for a maximum of two years, with an increase of no more than 5%.

Rookie Exception, teams can ignore the salary cap and sign their first-round pick on a rookie "scale" contract. Minimum Player Salary Exception, even if the salary exceeds the salary cap, a team can use the minimum salary to sign players, and the contract length is limited to two years. Disabled Player Exception allows a team to replace a player if he misses an entire season due to an injury. The Bird Rights Exception is the parent team's retention of the team's free agents. In contrast, the Mid-Level Exception, Bi-Annual and Minimum Salary Exception are attractive to other free agents. These exceptions allow teams that exceed the salary cap to retain a certain ability to strengthen. However, a basic rule for using exceptions is that these exceptions cannot have a greater advantage than direct use of cap space, except for the Non-Taxpayer Mid-Level Exception. The other exceptions have a shorter contract period. A team can only get One of them, so the reinforcement for teams that exceed the salary cap is relatively strict.

Restricted Free Agency

There are two types of free agency: unrestricted (UFA) and restricted (RFA). Unrestricted free agents can sign with any team; there is nothing the parent team can do about it. For restricted free agents, the parent team can use the "right of first refusal" to match other teams to issue contracts to restricted free agents and force the player to stay. The condition for becoming the RFA first is the first-round pick who has completed the four-year standard rookie contract. Still, if the team does not execute the rookie with the rookie contract's third and fourth-year team options, he will become a completely free agent. Second, veteran free agents who have played no more than three years and whose first contract ends. Third, the player who has played at least 15 days on a two-way contract in the NBA this season. A two-way contract refers to a formal hybrid contract between the NBA and the NBA Development League(G-League). A player on a two-way contract is essentially a G League player, but the player can play up to 50 games with his affiliated NBA team. His salary is 50 per cent of the rookie minimum salary, and he can only play for affiliated NBA teams under a two-way contract. All other free agents are unrestricted free agents. For eligible free agents to be restricted, teams must make a qualifying offer between the end of the Finals and June 29. The qualification offered is a one-year fully guaranteed contract. If the player signs this offer, it becomes a standard contract. After making a qualifying offer, teams can match any contracts the player receives. The player can accept a qualifying offer from the parent team, play one season, and become a free agent at the following season's end. When an RFA wants to sign with another team, he can sign an offer sheet with it, and the parent team has two days to match its main terms. The signing of a restricted player is the parent team's evaluation of the young player cultivated by the team. If the player is good enough and fits the team's development, the team can have an absolute advantage in keeping the player.

Option Clause

In NBA contracts, there are three types of option clauses that allow for extending or terminating a contract under specific conditions. These options are irrevocable once announced and executed, and cannot include additional conditions. The three types of options are as follows: Firstly, Team Option: This option allows the team to extend the contract for an additional year beyond the scheduled end date. A contract can only include one team option year, except for rookie scale contracts, which may have two team option years—typically in the third and fourth years. Secondly, Player Option: This option gives the player the right to extend the contract for an additional year. Similar to the team option, a contract can only include one player option year. Lastly, Early Termination Option (ETO): This option allows players to end their contracts early. An ETO cannot be used before the end of the first four seasons, meaning that only contracts with a length of five years or more can include an ETO. It is also important to note that a contract cannot contain more than one option, regardless of the type. For instance, a contract cannot include both a player option and a team option in the same year. However, a contract can include both a non-guaranteed clause and a player option. The only exception is for first-round rookie scale contracts, which have two team options in the third and fourth years.

In this chapter, the focus is on analysing the impact of option clauses on player contracts. Since both player options and ETOs are decisions made by the players regarding whether to continue the current contract and given that ETOs have more stringent requirements and a relatively small number of players utilize them, I combine player options and ETOs for analysis in this chapter. This approach allows for a more comprehensive understanding of the effects of player-driven options on contract outcomes.

2.5 Salary model

To initiate the empirical analysis, it is crucial to first examine the statistical characteristics of the dataset used for the salary model. Understanding these characteristics provides context and ensures that the subsequent modeling is based on a reliable foundation. The summary statistics of the variables included in the model are presented in Table 2.3. The dataset comprises 712 samples, selected based on specific criteria to ensure relevance and reliability. Specifically, players must have participated in more than 20 games in a single season, with an average playing time of more than 12 minutes per game. Additionally, only non-rookie contracts are considered, as the salaries of rookie contracts are stipulated by the league's Collective Bargaining Agreement (CBA). By focusing on non-rookie contracts, the analysis aims to better understand salary dynamics among experienced players. The average age of players in the sample is 27.6 years, suggesting that most players are in the prime of their careers. On average, these players contribute 24 minutes per game, representing 50% of the total game time. This significant playing time indicates that the players in the sample are key contributors to their teams, often participating during crucial moments of games. Their substantial playing time reflects their value, as these players have successfully passed evaluations by their teams, leading to opportunities for new contracts. These summary statistics provide an essential foundation for the empirical analysis, ensuring an accurate understanding of player salaries based on performance and experience factors.

Table 2.3 Summary statistics of variables

	Mean	Standard Deviation
Age	27.66	3.96
Age square	780.58	229.50
Points	10.48	5.51
Total rebounds	4.30	2.44
Blocks	0.48	0.46
Steals	0.79	0.40
Assists	2.33	1.87
Minutes played	24.01	6.93
Personal Fouls	1.98	0.57
Free throws percentage	0.26	0.13
Team regular season winning percentage	0.51	0.15
N	712	

Notes: The table shows the statistical analysis of variables used in the salary model.

There is a substantial body of research that uses NBA data to estimate player salaries, with various studies employing similar yet distinct sets of variables in their salary models. These models typically focus on data representing player performance, supplemented by additional specific variables. While this diversity enhances the scope of research, it also leads to a lack of uniform standards in the field. In this study, a common and reliable approach is adopted to estimate player salaries. By referencing and integrating existing research, this study replicates established methodologies and compares their results with those derived from the salary determination model used here. Such a comparison aids in identifying the most suitable salary estimation model for this research. The variables in the model are primarily based on methodologies outlined in two key studies, with significant emphasis on the work of Simmons and Berri (2011) and Berri et al. (2015).

First, the methodology outlined by Simmons and Berri (2011) is followed to estimate player salaries. The estimation is based on the equation presented in formula 2.1. The dependent variable in this model is the natural logarithm of the average annual salary of the next contract, while the independent variables, represented by X_{it-1}, include the player's characteristics from the previous contract, such as age, age squared, points, rebounds, blocks, assists, and playing time. Additionally, the model incorporates the fixed effects of the player's signing season, denoted by β_t, to account for temporal factors that may influence salary levels.

$$\text{Log(Salary)}_{it} = \beta_0 + \beta_1 \cdot \text{X}_{it-1} + \beta_t + \varepsilon_{it} \tag{2.1}$$

The results of this study are compared with those from Simmons and Berri (2011) in Table 2.4. Both studies utilize the same independent variables: age, age squared, points per game, rebounds per game, blocks per game, assists per game, minutes played per game, last season's team's winning percentage, and season-specific fixed effects. The dependent variable in this study is the natural logarithm of the average annual salary of the next contract. For this analysis, only non-rookie contracts are considered, and players who changed teams during the contract year are excluded to minimize the impact of such changes on salary estimates. Furthermore, players who appeared in more than 20 games in a single season and played an average of more than 12 minutes per game were selected, following the methodology of the referenced study. From the results, four variables—points, rebounds, minutes played, and the team's winning percentage last season—share the same sign and are statistically significant at the 1% level in both studies. Among these, the coefficients for playing time and last season's team performance show considerable differences, being 4.86 and 3.78 times larger, respectively, in this study. This discrepancy might be attributed to the different time periods considered by the two studies, indicating a change in how teams evaluate player performance. Despite this, the variables still play a similar role in both models. Interestingly, only the sign of assists differs between the two studies. Assists, which measure a player's ability to create scoring opportunities, would intuitively have a positive impact on salary. However, in the modern, fast-paced basketball environment, where offensive opportunities are more abundant, the relative value of assists might have decreased. Some assist-oriented guards may be viewed as lacking autonomous scoring ability or shooting skills, which could negatively impact their salaries. Regarding the model fit, the R^2 value for this study is 0.556, based on a sample size of 712. In contrast, the referenced study reports an R^2 value of 0.606, though it does not specify the sample size. Overall, these findings suggest that adopting the salary determination model from the referenced research is appropriate for this study, as the data and results are reasonably aligned.

Table 2.4 Regression result compared with Mixing the princes and the paupers (Simmons and Berri, 2011)

	(My Data) Log Salary	(Paper result) Log Salary
Age	0.053	0.369 ***
	(0.53)	(10.97)
Age squared	-0.0014	-0.0058***
	(0.83)	(9.82)
Points	0.052***	0.043***
	(4.26)	(13.76)
Total rebounds	0.069***	0.055***
	(3.16)	(9.30)
Blocks	0.135	0.193***
	(1.34)	(9.58)
Assists	-0.019	0.026**
	(0.77)	(4.07)
Minutes Played	0.068***	0.014***
	(6.63)	(4.76)
Team Winning percentage last season	2.158***	0.571***
	(9.59)	(8.48)
Year dummies	Yes	Yes
R^2	0.556	0.606
N	712	

Notes: This table compares the salary model using data from this study with the results from the benchmark article (Simmons and Berri, 2011). The research period of my study is from the 2012-13 to the 2018-19 season. In addition, the research period of Simmons and Berri (2011) is from the 1990-91 to the 2007-08 season.
Absolute t statistic in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Next, the player salary model estimated in this section follows the methodology outlined by Berri et al. (2015), as presented in formula 2.2. In this model, the dependent variable is the natural logarithm of the average annual salary of the player's next contract. The independent variables, represented by X_{it-1}, include various player characteristics such as age, points, rebounds, steals, assists, blocks, turnover rate, personal fouls, field goal percentage, and free throw percentage. The model also considers the player's performance during the previous contract, the starting ratio, and the appearance ratio. Furthermore, fixed effects related to player position (β_{ipt-1}), whether the player re-signs with the same team, and the team's performance in the previous season (β_{st-1}) are included to capture other influences on salary.

$$\begin{aligned} \text{Log(Salary)}_{it} &= \beta_0 + \beta_1 \cdot \text{X}_{it-1} + \beta_{ipt-1} \\ &\quad + \beta_2 \cdot \text{Signed with the same team}_{it} + \beta_{st-1} + \varepsilon_{it} \end{aligned} \tag{2.2}$$

Table 2.5 compares the results of this study with those of Berri et al. (2015). One limitation of this study is the absence of data on player agents, which could impact salary outcomes. Differences in the values related to player positions and team performance in the previous season also contribute to discrepancies in the coefficients between the two studies. Despite these differences, some common conclusions can be drawn. For example, player age is found to have a negative effect on salary, as the decline in physical abilities associated with ageing is expected. Additionally, a team's success in the previous season is positively associated with higher player salaries, with the coefficient for team performance in this study being approximately 5.25 times greater than that in the reference study. This discrepancy may stem from differences in data periods or sample characteristics. Players who re-sign with their current team tend to receive higher salaries, reflecting the influence of the NBA's collective bargaining agreement (CBA), which includes mechanisms like Bird rights. Bird rights allow teams to re-sign their players over the salary cap and offer more favourable contract terms, such as longer durations and higher annual raises, thereby making staying with the original team more attractive. In terms of model fit, the R^2 value for this study is 0.572, compared to 0.716 for the reference study, where the inclusion of player agents provides additional explanatory power. When comparing Table 2.4 and Table 2.5, it is evident that the model presented in Table 2.4 is more suitable for the objectives of this study. The first model is simpler in design, relying on independent variables available in the current dataset, while the second model includes information about player agents that is not accessible in this study. Additionally, reproducing both models with the data used in this chapter yields R^2 values of 0.556 and 0.572, respectively, indicating only a slight difference. Therefore, the first model is adopted as the benchmark for this study.

Table 2.5 Regression result compared with Salary Determination in the presence of Fixed revenues (Berri et al., 2015)

	(My data) Log Salary	(Paper result) Log Salary
Points	0.059***	1.073***
	(4.89)	(10.33)
Total rebounds	0.094***	1.202***
	(3.45)	(5.78)
Steals	0.023	0.697
	(0.18)	(0.61)
Assists	0.141***	1.234***
	(3.68)	(3.55)
Blocks	-0.024	1.552***
	(0.22)	(2.86)
Turnover percentage%	-0.036***	0.006*
	(3.00)	(2.03)
Personal Fouls	-0.011	-2.022***
	(0.14)	(-3.24)
Effective field goal percentage%	0.035***	0.490*
	(4.68)	(2.00)
Free throw percentage(Decimal)	-0.077	0.220*
	(0.25)	(1.87)
Big	0.00	
	(.)	
Center	0.125	0.07**
	(0.75)	(2.62)
Combo	-0.026	
	(0.12)	
Forward	0.146	
	(0.74)	
Point guard	-0.214	0.002
	(1.04)	(0.09)
Power forward	-0.003	0.073***
	(0.02)	(3.04)
Shooting guard	0.087	-0.042
	(0.46)	(-1.38)
Small forward	-0.076	0.00
	(0.42)	(.)
Wing	-0.073	
	(0.35)	
Age	-0.033***	-0.016***
	(3.72)	(-5.72)
Whether player signed with same team	0.372***	0.07***
	(5.13)	(3.92)
Ratio of games started to games played(Decimal)	0.203	0.203***
	(1.59)	(5.95)
Team wins last season	0.021***	0.004***
	(4.14)	(3.91)
Percentage for games played in last contract period(Decimal)	0.99***	
	(4.47)	
Percentage of games played in last two years(Decimal)		0.292***
		(4.26)
Market Population(MM)		0.021***
		(0.89)
Played the previous year on a team that did not make the playoffs	0.00	
	(.)	
Played the previous year on a team that made the playoffs	0.019	
	(0.17)	
Played the previous year on a team that made second-round playoffs	0.021	
	(0.15)	
Played in the conference final in the previous year	-0.006	-0.053
	(0.03)	(-1.46)
Played on conference title team in previous year	-0.422**	0.096*
	(2.08)	(1.90)
Played on title team in previous year	-0.413*	-0.035
	(1.75)	(-0.66)
Agents dummies	No	Yes
R^2	0.572	0.716
N	712	483

Notes: This table compares the salary model using data from this study with the results from the benchmark article (Berri et al., 2015). The research period of my study is from the 2012-13 to the 2018-19 season. In addition, the research period of Berri et al. (2015) is from 2001 to 2011.
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

After determining the variables for the salary decision model, this study incorporates changes in a player's contract year performance into the salary model, as expressed by equation 2.3. This model closely follows the structure of Stiroh's salary determination model (Stiroh, 2007).

$$\mathrm{Y}_{it} = \beta_0 + \beta_1 \cdot \bar{P}_{i,t-N,t-2} + \beta_2 \cdot \Delta P_{i,t-1} + \beta_t + \varepsilon_{i,t} \tag{2.3}$$

The model setting for the salary determination model involves three dependent variables: the natural logarithm of the total contract salary, the natural logarithm of the annual contract salary, and the number of contract years for player i at time t. The independent variable, $\bar{P}i,t-N,t-2$, represents the player's performance during the previous contract, defined as the average performance from the start year of the previous contract to the year before its conclusion. Additionally, $\Delta Pi,t-1$ captures the difference between a player's performance in the contract year and the average performance during the rest of the contract. The model includes points, rebounds, blocks, assists, minutes played, and last season's team win percentage, represented as both contract averages and contract year variations. A fixed effect representing the signing season is also incorporated into the model to account for temporal factors.

In line with prior research, the model only includes players with more than 20 appearances and an average playing time of over 12 minutes per game. Due to the fat-tailed distribution of player salaries, the study employs the weighted least squares method to address sample heterogeneity, using the number of player appearances as weights. The regression results, presented in Table 2.6, reveal several key findings. Points significantly increase both total and annual salaries, with contract year performance having a particularly strong impact. Rebounds and blocks also exhibit positive and significant effects on salary. A player's playing time, both throughout the contract and during the contract year, is a major determinant of salary, with an increase in minutes played correlating with approximately a 10% rise in total salary and a 6.7% increase in annual salary. Team performance in the previous season has contrasting effects depending on the contract period. While strong team performance over the entire contract tends to increase player salaries, an improvement in team performance during the contract year tends to reduce salary. A possible explanation for this finding is that weaker teams may offer higher salaries to attract players, and a decline in team performance during the contract year can provide players with leverage in salary negotiations. Two notable years within the research period—2016-17 and 2017-18—are highlighted. The 2016-17 season saw a dramatic increase in the league's salary cap from 70 million to 94 million dollars, a 34% jump that far exceeded the previous year's 11% increase. In contrast, the 2017-18 season, marked by the introduction of a new collective bargaining agreement (CBA) with several new clauses, witnessed a more modest 5% increase in the salary cap.

Table 2.6 Regression result of salary determination

	(1) Next contract total salary	(2) Next contract annual salary	(3) Next contract length
Age	0.088	0.105	-0.104
	(0.73)	(1.10)	(-0.91)
Age square	-0.003	-0.002	0.000
	(-1.29)	(-1.43)	(0.19)
Average points in non-contract years during the contract	0.052***	0.045***	0.022
	(3.37)	(3.75)	(1.52)
Average points change by contract year	0.100***	0.077***	0.070**
	(3.47)	(3.39)	(2.57)
Average total rebounds in non-contract years during the contract	0.073**	0.063***	0.031
	(2.56)	(2.82)	(1.17)
Average total rebounds change by contract year	-0.018	0.022	-0.082
	(-0.29)	(0.44)	(-1.38)
Average blocks in non-contract years during the contract	0.246*	0.183*	0.139
	(1.92)	(1.82)	(1.16)
Average blocks change by contract year	0.267	0.056	0.488**
	(1.04)	(0.28)	(2.03)
Average assists in non-contract years during the contract	-0.016	-0.017	0.002
	(-0.55)	(-0.70)	(0.09)
Average assists change by contract year	0.013	0.006	0.025
	(0.18)	(0.10)	(0.38)
Average minutes played in non-contract years during the contract	0.096***	0.067***	0.063***
	(7.49)	(6.62)	(5.29)
Average minutes played change by contract year	0.107***	0.067***	0.084***
	(5.12)	(4.07)	(4.29)
Average winning percentage in non-contract years during the contract	3.193***	2.324***	1.969***
	(10.57)	(9.79)	(6.94)
Average winning percentage change by contract year	-2.894***	-1.890***	-2.527***
	(-7.61)	(-6.32)	(-7.07)
2013-14	-0.103	-0.047	-0.093
	(-0.69)	(-0.40)	(-0.66)
2014-15	0.367**	0.291***	0.232*
	(2.56)	(2.59)	(1.73)
2015-16	0.817***	0.733***	0.255*
	(5.78)	(6.60)	(1.92)
2016-17	0.463***	0.530***	-0.126
	(3.10)	(4.51)	(-0.90)
2017-18	0.227	0.471***	-0.454***
	(1.47)	(3.88)	(-3.13)
2018-19	0.686***	0.649***	0.042
	(4.58)	(5.51)	(0.30)
_cons	10.477***	10.266***	2.081
	(6.05)	(7.54)	(1.28)
R^2	0.615	0.588	0.459
N	712	712	712

Notes: This table results from a salary model using this data. In terms of model setting, the setting of the model is similar to that of Stiroh (2007), and the model's independent variables are identical to those of Simmons and Berri (2011). The model's dependent variable is divided into three: the total amount of the player's new contract, the annual salary, and the length of the contract.
t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The salary determination model is further examined using a quantile regression approach, following the methodology proposed by Koenker and Bassett Jr (1978). Unlike classical regression using OLS, which assumes a symmetrical conditional distribution $y|x$ and focuses on the conditional expectation $E(y|x)$, quantile regression minimizes the weighted average of the absolute values of the residuals, making it more robust to outliers. The quantile regression model, as expressed in formula 2.4, assumes that the population q quantile $y_q(x)$ of the conditional distribution $y|x$ is a linear function of x. In this model, β_q represents the q quantile regression coefficient, which is estimated by solving a minimization problem that is less susceptible to the influence of outliers compared to OLS.

$$\begin{gathered} Y_q(x_i) = \beta_{0p} + \beta_{1q} \cdot \bar{P}_{i,t-N,t-2} + \beta_{2p} \cdot \Delta P_{i,t-1} + \beta_{tp} \\ \min_{\beta_q} \sum_{i:y_i \geq x_i^{'}\beta_q}^{n} q|y_i - x_i^{'}\beta_q| + \Sigma_{i:y_i < x_i^{'}\beta_q}^{n} (1-q)|y_i - x_i^{'}\beta_q| \end{gathered} \tag{2.4}$$

This study utilizes quantile regression to analyze the outcomes of the salary determination model across different quantiles, with results presented in Table 2.7. The findings reveal several interesting trends. For players in the top 50th percentile, salary increases are significantly linked to higher average points during non-contract years. Conversely, players in the bottom 50th percentile experience significant salary boosts from improved points during contract years. The positive impact of rebounding on salary is observed exclusively among players in the top 50th percentile, whereas changes in rebounding performance during contract years do not significantly affect salary. Playing time also influences salary across all ranges, with increased minutes played generally leading to salary growth. However, the magnitude of this effect diminishes as salary levels rise, particularly for players in the top 75th percentile. Team performance in non-contract years generally enhances player salaries, although this effect weakens as salary levels increase. A decline in team winning percentage during the contract year is associated with higher salaries in the player's next contract, and this trend applies to players at all salary levels. However, the bargaining power derived from this factor diminishes as salary levels rise, though players in the top 10% have more leverage than those in the top 25%. Seasonal fixed effects are also found to play a significant role. The salary increase observed during the 2016-17 season primarily benefits players in the top 75th percentile without a clear trend across different salary levels. In contrast, the 2017-18 season experienced significant salary increases across the three salary brackets, albeit to a lesser extent compared to the previous year. In summary, player salary is largely determined by performance metrics, particularly for those in the top 50th percentile. Players below this threshold tend to have salaries influenced more by team decisions or league minimum salary requirements. For players in the bottom 50th percentile, improving contract year performance—especially in scoring—enables teams to effectively evaluate and make decisions about them. While playing time positively affects salaries across all levels, its influence diminishes as salaries rise, with higher-paid players being evaluated more on the quality of their performance rather than just the quantity of minutes played. Additionally, a team's winning percentage serves as an important performance measure, with a decline during the contract year providing players an opportunity to negotiate higher salaries in subsequent contracts.

Table 2.7 Quantile regression result of salary determination model

	(1) New contract total salary	(2) Q_10	(3) Q_25	(4) Q_50	(5) Q_75	(6) Q_90
Age	0.088	0.186	0.050	0.148	0.077	0.069
	(0.73)	(0.62)	(0.28)	(1.02)	(0.59)	(0.56)
Age square	-0.003	-0.004	-0.002	-0.004	-0.003	-0.003
	(-1.29)	(-0.73)	(-0.62)	(-1.54)	(-1.22)	(-1.35)
Average points in non-contract years during the contract	0.052***	0.053	0.036	0.050***	0.039**	0.046***
	(3.37)	(1.37)	(1.58)	(2.64)	(2.29)	(2.90)
Average points change by contract year	0.100***	0.179**	0.118***	0.066*	0.037	0.032
	(3.47)	(2.46)	(2.74)	(1.89)	(1.18)	(1.06)
Average total rebounds in non-contract years during the contract	0.073**	0.106	0.062	0.078**	0.107***	0.099***
	(2.56)	(1.46)	(1.46)	(2.22)	(3.40)	(3.30)
Average total rebounds change by contract year	-0.018	-0.007	-0.042	0.000	0.130*	0.082
	(-0.29)	(-0.04)	(-0.46)	(0.00)	(1.90)	(1.27)
Average blocks in non-contract years during the contract	0.246*	0.329	0.225	0.131	0.088	0.126
	(1.92)	(1.02)	(1.18)	(0.84)	(0.62)	(0.95)
Average blocks change by contract year	0.267	0.164	0.217	0.242	-0.082	0.217
	(1.04)	(0.25)	(0.57)	(0.77)	(-0.29)	(0.81)
Average assists in non-contract years during the contract	-0.016	0.029	0.016	-0.015	0.018	0.075**
	(-0.55)	(0.39)	(0.38)	(-0.41)	(0.57)	(2.46)
Average assists change by contract year	0.013	-0.047	0.002	0.026	0.018	0.015
	(0.18)	(-0.28)	(0.02)	(0.32)	(0.25)	(0.21)
Average minutes played in non-contract years during the contract	0.096***	0.082**	0.114***	0.102***	0.091***	0.055***
	(7.49)	(2.58)	(6.04)	(6.62)	(6.52)	(4.21)
Average minutes played change by contract year	0.107***	0.088*	0.125***	0.119***	0.091***	0.059***
	(5.12)	(1.70)	(4.07)	(4.71)	(3.99)	(2.77)
Average winning percentage in non-contract years during the contract	3.193***	3.058***	2.872***	2.818***	2.796***	2.309***
	(10.57)	(4.17)	(6.61)	(7.93)	(8.72)	(7.62)
Average winning percentage change by contract year	-2.894***	-4.275***	-3.259***	-2.668***	-1.707***	-1.822***
	(-7.61)	(-4.57)	(-5.88)	(-5.89)	(-4.18)	(-4.71)
2013-14	-0.103	-0.518	-0.186	0.020	0.032	0.179
	(-0.69)	(-1.40)	(-0.85)	(0.11)	(0.20)	(1.17)
2014-15	0.367**	0.088	0.337	0.352**	0.381**	0.446***
	(2.56)	(0.25)	(1.64)	(2.09)	(2.50)	(3.10)
2015-16	0.817***	0.091	0.893***	1.016***	0.989***	1.085***
	(5.78)	(0.26)	(4.30)	(5.97)	(6.45)	(7.48)
2016-17	0.463***	0.039	0.542**	0.666***	0.565***	0.607***
	(3.10)	(0.11)	(2.45)	(3.68)	(3.47)	(3.94)
2017-18	0.227	0.123	0.412*	0.331*	0.211	0.353**
	(1.47)	(0.32)	(1.80)	(1.77)	(1.25)	(2.21)
2018-19	0.686***	0.188	0.733***	0.768***	0.702***	0.752***
	(4.58)	(0.51)	(3.34)	(4.28)	(4.33)	(4.91)
_cons	10.477***	7.713*	10.190***	9.819***	11.792***	13.442***
	(6.05)	(1.80)	(4.03)	(4.74)	(6.32)	(7.61)
R^2	0.615					
N	712	712	712	712	712	712

Notes: This table presents the quantile regression results for the player salary model. The dependent variable is the natural logarithm of the player's new contract total salary. The results for the 10th, 25th, 50th, 75th, and 90th quantiles are shown in the respective columns, illustrating how player salary determinants vary across different points of the salary distribution.

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.6 The impact of player option on salary

The execution of player options in NBA contracts plays a significant role in shaping the salary structure and the overall dynamics of player negotiations within the league. Player options give athletes the choice to either continue with their existing contract by opting in for the final year or to opt out and enter free agency, potentially securing a more lucrative deal. A statistical analysis of the trends, as shown in Table 2.8, reveals a notable increase in the number of player options executed, particularly from the 2012-13 season onwards, reaching a peak in the 2015-16 season. This trend underscores the strategic decision-making by players, especially during the 2014-15 to 2017-18 seasons, where many opted out of their contracts. This behaviour was likely influenced by the anticipation of the new Collective Bargaining Agreement (CBA) implemented in 2017. By opting out, players sought to capitalize on favourable market conditions, aligning with broader economic principles where individuals aim to maximize their earnings potential. The analysis of player options and their impact on salary outcomes is essential to understanding the NBA's salary structure and the dynamics of player negotiations. It also provides insight into lobar economics, as players strategically navigate contract options to optimize their financial returns based on changing market and league conditions.

Table 2.8 Implementation of player options in recent years

Season	Number of Contract with player option	Opt-in	Opt-out
2012-13	13	4	9
2013-14	23	10	13
2014-15	22	5	17
2015-16	36	10	26
2016-17	16	0	16
2017-18	9	1	8
2018-19	10	6	4

Notes: This table shows the implementation of player options included in players' existing contracts during the study period. The first column in the table indicates the season time. The second column indicates the total number of contracts with player options that must be implemented during the season. The third column, Opt-in, indicates the total number of contracts in which the player opted to implement the player option during the season. Execution of the player option means that the player continues to execute the current contract and complete the last year of the current contract. The fourth column, Opt-out, indicates the total number of contracts in which the player chose not to implement the player option during the season. The player does not choose to implement the player option to terminate the current contract early and become a free agent.

The execution of team options in NBA contracts reflects a different strategic dynamic compared to player options, as it grants teams the authority to decide whether to extend or terminate a player's contract for the final year. Teams can choose to exercise the option to continue the player's current contract or decline it, thereby ending it early. A statistical analysis of these trends, as illustrated in Table 2.9, provides insights into the usage of team options. The prevalence of team options in non-rookie contracts is relatively limited, largely due to the specific structure mandated by the Collective Bargaining Agreement (CBA) for first-round rookie contracts, which follows a two-plus-two format. In this structure, the first two years are guaranteed, while the subsequent two years include team options. As a result, the overall number of team options in non-rookie contracts is smaller, reflecting the different strategic considerations teams face when negotiating contracts with veteran players compared to rookies. This analysis helps to understand the strategic use of team options and their impact on player retention and team flexibility. It highlights the contractual mechanisms teams employ to manage player performance risks and salary commitments, providing a broader understanding of contract negotiations and labour market strategies within the NBA.

Table 2.9 Implementation of team options in recent years

Season	Number of Contract with team option	Opt-in	Opt-out
2012-13	3	1	2
2013-14	3	3	0
2014-15	2	0	2
2015-16	3	2	1
2016-17	5	2	3
2017-18	4	2	2
2018-19	2	1	1

Notes: This table represents the implementation of team options included in players' existing contracts during the study period. All research subjects exclude rookie contracts. The first column in the table indicates the season time. The second column indicates the total number of contracts with team options that must be executed during the season. The third column, Opt-in, indicates the total number of contracts that the team opted to implement the team option for this season. Execution of the team option means that the team continues to implement the current contract and complete the final year of the current contract. The fourth column, Opt-out, indicates the total number of contracts for which the team chose not to exercise the team option during the season. The team does not exercise the option to terminate the current contract early, making the player an unrestricted free agent.

After analysing the execution of player and team options, the subsequent research focuses primarily on player options, given the limited number of team options in non-rookie contracts. Drawing on existing literature Gross and Link (2017), the determinants of whether a player receives a player option in a new contract are examined using a probit model, which estimates the impact of various performance-related factors. Key determinants include fluctuations in career performance, performance during the previous contract, player popularity, and the specific season in which the contract is signed, as outlined in formula 2.5.

$$\begin{aligned}\text{Probit}(\text{Player Option}_{it}) = \beta_0 + \beta_1 \cdot \text{PSd}_{i,1,t-1} + \beta_2 \cdot \bar{P}_{i,t-N,t-2} \\ + \beta_4 \cdot \Delta P_{i,t-1} + \beta_5 \cdot \text{PP}_{i,t-N,t-1} \\ + \beta_{it} + \varepsilon_{it}\end{aligned} \tag{2.5}$$

In the first model, the player's points serve as the primary measure of performance. To capture variability in performance, the standard deviation of the player's career scoring ($\text{PSd}_{i,1,t-1}$) is calculated to reflect fluctuations over time, alongside changes in the player's scoring during the previous contract period ($\bar{P}i,t-N,t-2$ and $\Delta P_{i,t-1}$). Additionally, the number of All-Star selections during the previous contract ($\text{PP}_{i,t-N,t-1}$) is used as an indicator of player popularity, while the season in which the contract is signed (β_{it}) accounts for the impact of league policy changes, particularly the introduction of a new Collective Bargaining Agreement (CBA) with a higher salary cap. The results of the first model, presented in Table 2.10, indicate that greater variability in a player's career scoring is associated with a lower probability of obtaining a player option in a new contract. Specifically, a one-unit increase in the standard deviation of career scoring decreases the likelihood of a player option by 3%, holding other variables constant. Conversely, higher average scores during both non-contract and contract years positively correlate with the inclusion of a player option, with a one-point increase in scoring raising the probability by 2% in each case. Although an increase in All-Star selections positively affects the likelihood of receiving a player option, this effect is not statistically significant. The contract signing season also has a significant impact, with signing in the 2014-15 season increasing the probability of including a player option by 12% compared to the 2012-13 season. This suggests that the anticipation of the 2017 CBA, with its potential for higher salaries, influenced players' and teams' decisions regarding player options. The second model incorporates additional performance metrics, such as rebounds, blocks, assists, and playing time, to provide a more comprehensive assessment of player performance. However, the results indicate that these additional variables do not significantly impact the likelihood of securing a player option. The main findings remain consistent: increased volatility in career scoring is linked to a decreased probability of obtaining a player option, with a one-unit increase in the standard deviation of points reducing the likelihood by 4%. Similarly, higher average scores during non-contract years continue to positively influence the probability by 2%. The effect of the contract signing season remains significant, with an 11% higher likelihood of a player option for contracts signed in 2014-15 compared to 2012-13. The analysis shows that player options are primarily influenced by scoring consistency, average scoring performance, and the timing of the contract. Fluctuations in performance reduce the likelihood of receiving a player option, while consistent performance and favourable contract timing, such as during periods of anticipated CBA changes, increase the probability of securing a player option.

Table 2.10 Probit model for new contracts with player options

	(1) New contracts with player options	(2) New contracts with player options
New contracts with player options		
Career points standard deviation	-0.12***	-0.18**
	(0.04)	(0.09)
Average points in non-contract years during the contract	0.09***	0.08***
	(0.01)	(0.03)
Average points change by contract year	0.08***	0.05
	(0.02)	(0.04)
Number of All-Star selections during contract	0.21	0.23
	(0.13)	(0.15)
2013-14	0.08	0.08
	(0.22)	(0.23)
2014-15	0.43**	0.41**
	(0.20)	(0.20)
2015-16	0.25	0.28
	(0.21)	(0.21)
2016-17	0.06	0.11
	(0.22)	(0.23)
2017-18	-0.28	-0.24
	(0.24)	(0.25)
2018-19	-0.19	-0.12
	(0.22)	(0.23)
Career rebounds standard deviation		0.26
		(0.16)
Average rebounds in non-contract years during the contract		-0.08
		(0.06)
Average rebounds change by contract year		-0.03
		(0.09)
Career blocks standard deviation		-0.35
		(0.69)
Average blocks in non-contract years during the contract		0.32
		(0.26)
Average blocks change by contract year		-0.32
		(0.39)
Career assists standard deviation		-0.04
		(0.21)
Average assists in non-contract years during the contract		-0.01
		(0.07)
Average assists change by contract year		0.00
		(0.10)
Career minutes played standard deviation		0.01
		(0.04)
Average minutes played in non-contract years during the contract		0.03
		(0.02)
Average minutes played change by contract year		0.04
		(0.03)
Cons	-1.46***	-2.05***
	(0.22)	(0.34)
R^2		
N	677	677

Notes This table presents the Probit model results for predicting whether players have a player option in their new contracts. The dependent variable is a dummy variable indicating if a player has a player option (1 if yes, 0 if no). The independent variables include the standard deviation of the player's score during the contract, reflecting performance fluctuation, and the average score during non-contract years and score changes during the contract year to measure performance. The model also considers player popularity, indicated by all-star selections, and contract signing season. In Model 2, additional metrics such as rebounds, blocks, assists, and playing time are added to provide a more detailed evaluation of player performance.
t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

After considering the factors that influence the inclusion of player options in new contracts, the analysis proceeds to explore the factors affecting players' decisions to exercise those options. In the final year of a contract containing a player option, a player can choose to either exercise the option, thereby continuing the contract or opt-out and become a free agent. The factors that influence this decision are analysed using the probit model, as shown in formula 2.6.

$$\begin{aligned}\text{Probit}(\text{Exercise Option}_i) = \beta_0 + \beta_1 \cdot \big(\log(\text{Predicted Salary}_{i,t-1}) - \log(\text{Actual Salary}_{i,t-1})\big) \\ + \beta_2 \cdot \bar{P}_{i,t-N,t-2} + \beta_3 \cdot \Delta P_{i,t-1} + \beta_4 \cdot \text{PP}_{i,t-N,t-1} + \varepsilon_i\end{aligned} \tag{2.6}$$

In this model, the dependent variable is whether the player exercises the player option for the next season, with a value of 1 indicating the option is exercised and a value of 0 indicating the player opts out to become a free agent. The primary factor considered is the difference between the player's actual salary for the next season and the predicted salary, represented by $\big(\log(\text{Predicted Salary}_{i,t-1}) - \log(\text{Actual Salary}_{i,t-1})\big)$. This difference provides insight into whether the player perceives the current contract as favourable compared to their market value. A negative result indicates that the predicted salary is lower than the actual contract salary, while a positive result indicates the predicted salary is higher. Additional factors include player performance during the previous contract, represented by average scoring in non-contract years and changes in scoring during the contract year, as well as the number of All-Star selections as a measure of popularity. The sample size for the analysis consists of 128 contracts, excluding one player who missed an entire season due to injury but still exercised the player option, to mitigate the impact of outliers.

The results presented in Table 2.11 show that the difference between a player's predicted salary and actual salary significantly influences the decision to exercise the player option. If a player expects to earn a higher salary in the future than under the current contract, they are more likely to opt out and become a free agent to secure a better deal. Specifically, if the predicted salary is 2.7 times the actual salary, the probability of exercising the player option decreases by 19%, holding other variables constant. Player performance during non-contract years also affects this decision; each point increase during non-contract years reduces the likelihood of continuing the current contract by 2%. While an increase in performance during the contract year slightly raises the probability of exercising the option, this effect is not statistically significant. Additionally, being selected for the All-Star Game increases the likelihood of exercising the player option, with each additional selection raising this probability by 13%. In the second model, additional performance metrics such as rebounds, blocks, assists, and playing time are included. Consistent with the first model, an increased gap between expected and actual salary increases the likelihood of opting out. Scoring results remain similar, with a one-point increase in non-contract year scoring, reducing the probability of exercising the option by 5%. The influence of All-Star selections remains significant, with each selection increasing the probability by 14%. The newly introduced variable, playing time, also significantly affects the decision, as each additional minute of playing time raises the likelihood of continuing with the current contract by 2%. The analysis indicates that a player's decision to exercise a player option is influenced primarily by the difference between expected and actual salary, performance metrics, and popularity. Players are more likely to opt out when they believe they can secure a more favourable contract in the free market.

Table 2.11 Probit model for players exercising of player options

	(1) Players exercising player options	(2) Players exercising player options
Players exercising player options		
Difference between the logarithm of predicted salary and actual salary	-0.69***	-0.74***
	(0.20)	(0.22)
Average points in non-contract years during the contract	-0.08***	-0.19***
	(0.03)	(0.06)
Average points change by contract year	0.10	-0.04
	(0.08)	(0.14)
Number of All-Star selections during contract	0.47**	0.56*
	(0.23)	(0.31)
Average rebounds in non-contract years during the contract		-0.06
		(0.10)
Average rebounds change by contract year		0.16
		(0.29)
Average blocks in non-contract years during the contract		-0.06
		(0.47)
Average blocks change by contract year		-0.77
		(0.92)
Average assists in non-contract years during the contract		0.04
		(0.11)
Average assists change by contract year		0.39
		(0.29)
Average minutes played in non-contract years during the contract		0.09**
		(0.05)
Average minutes played change by contract year		0.07
		(0.09)
Cons	0.34	-0.64
	(0.33)	(0.63)
R^2		
N	128	128

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes This table presents the Probit model results for estimating whether a player exercises their player option in the contract. The dependent variable is a dummy variable indicating if the player chooses to terminate the player option and become a free agent (1 if yes, 0 if no). The independent variable is the difference between the natural logarithm of the player's expected and actual salary, representing salary disparity. Player performance is measured using the average score during non-contract years and changes in score during the contract year, while player popularity is indicated by all-star selections. In Model 2, additional metrics such as rebounds, blocks, assists, and playing time are included for a more comprehensive performance evaluation.
t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Building on the analysis of the two probit models, it is evident that players who secure player options in their contracts generally exhibit greater stability in their careers. Players who perform well and are more popular are more likely to negotiate and obtain player options. However, when exercising these options, players strategically decide whether to continue with their current contract or opt out to become free agents, depending on the timing and potential benefits. The flexibility inherent in these contracts empowers players, giving them greater leverage in salary negotiations, and this choice is closely tied to the difference between their predicted and actual salaries. To further explore this, I analyse whether the inclusion of player options in a contract (PO_{it}) affects a player's salary using a quantile salary model. The specific formula is presented in formula 2.8. Table 2.12 presents the results of the quantile salary model that includes player options. In this model, the presence of a player option is incorporated as an independent variable. Out of a total of 712 samples, 20 contracts include team options at the time of signing, which are excluded when analysing player options, resulting in a sample size of 692. The other variables in the salary model remain consistent with those used in previous models.

$$Y_q(x_i) = \beta_{0p} + \beta_{1q} \cdot \mathrm{PO}_{it} + \beta_{2q} \cdot \bar{P}_{i,t-N,t-2} + \beta_{3q} \cdot \Delta P_{i,t-1} + \beta_{tq} \tag{2.7}$$

The first column of Table 2.12 shows the natural logarithm of the average annual salary of players in the new contract, while the subsequent columns present the regression results for the 10th, 25th, 50th, 75th, and 90th percentiles of the salary distribution. The findings in the first column align closely with the previous salary model results, focusing on the impact of player options on salaries. In the basic salary model, the effect of including a player option on salaries is not statistically significant. However, the positive coefficient suggests that having a player option in a contract might increase a player's salary, which contradicts initial expectations. Previous studies suggest that player options provide valuable flexibility, enabling players to exit contracts at opportune times to maximize their benefits. From an economic perspective, it is speculated that this flexibility might come with some salary trade-off. Quantile regression is applied to explore this hypothesis further. The results reveal that the impact of player options on salaries varies significantly across different quantiles of the salary distribution. Although the results are not statistically significant, they indicate a potential area for further research. It appears that the effect of player options on salaries is not uniform across the salary distribution, suggesting a more nuanced relationship between contract flexibility and compensation.

Table 2.12 Quantile salary model including player options

	(1) next_annual_salary	(2) Q_10	(3) Q_25	(4) Q_50	(5) Q_75	(6) Q_90
Player has a player option in the contract	0.11	0.34	0.06	0.02	-0.02	0.05
	(0.08)	(0.30)	(0.12)	(0.08)	(0.07)	(0.06)
Age	0.10	0.34	0.22	0.22**	-0.02	-0.04
	(0.10)	(0.37)	(0.14)	(0.10)	(0.08)	(0.08)
Age square	-0.00	-0.01	-0.00*	-0.00**	-0.00	-0.00
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Average points in non-contract years during the contract	0.04***	0.04	0.03*	0.05***	0.04***	0.05***
	(0.01)	(0.05)	(0.02)	(0.01)	(0.01)	(0.01)
Average points change by contract year	0.07***	0.14	0.06*	0.04	0.03*	0.03*
	(0.02)	(0.09)	(0.03)	(0.02)	(0.02)	(0.02)
Average total rebounds in non-contract years during the contract	0.06***	0.03	0.09***	0.06***	0.06***	0.06***
	(0.02)	(0.09)	(0.03)	(0.02)	(0.02)	(0.02)
Average total rebounds change by contract year	0.02	0.03	-0.01	0.06	0.10**	0.07*
	(0.05)	(0.19)	(0.07)	(0.05)	(0.04)	(0.04)
Average blocks in non-contract years during the contract	0.18*	0.31	0.08	0.03	0.12	0.13*
	(0.10)	(0.39)	(0.15)	(0.11)	(0.09)	(0.08)
Average blocks change by contract year	0.05	0.01	0.10	-0.02	-0.24	0.10
	(0.20)	(0.79)	(0.31)	(0.21)	(0.17)	(0.16)
Average assists in non-contract years during the contract	-0.01	-0.02	0.03	-0.01	0.02	0.04**
	(0.02)	(0.09)	(0.03)	(0.02)	(0.02)	(0.02)
Average assists change by contract yea	0.01	-0.03	-0.01	0.03	0.03	0.02
	(0.06)	(0.20)	(0.08)	(0.05)	(0.04)	(0.04)
Average minutes played in non-contract years during the contract	0.07***	0.07*	0.07***	0.07***	0.05***	0.04***
	(0.01)	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)
Average minutes played change by contract year	0.07***	0.06	0.10***	0.07***	0.05***	0.04***
	(0.02)	(0.06)	(0.02)	(0.02)	(0.01)	(0.01)
Average winning percentage in non-contract years during the contract	2.36***	2.57***	2.05***	1.69***	1.61***	1.60***
	(0.24)	(0.90)	(0.35)	(0.24)	(0.20)	(0.18)
Average winning percentage change by contract year	-1.98***	-3.05***	-2.36***	-1.21***	-0.95***	-0.97***
	(0.30)	(1.14)	(0.44)	(0.31)	(0.25)	(0.23)
2013-14	-0.04	0.20	-0.10	-0.06	0.01	0.04
	(0.12)	(0.45)	(0.18)	(0.12)	(0.10)	(0.09)
2014-15	0.28**	0.31	0.21	0.32***	0.35***	0.31***
	(0.11)	(0.42)	(0.16)	(0.11)	(0.09)	(0.09)
2015-16	0.72***	0.52	0.60***	0.81***	0.88***	0.90***
	(0.11)	(0.43)	(0.17)	(0.12)	(0.09)	(0.09)
2016-17	0.52***	0.55	0.35**	0.68***	0.68***	0.65***
	(0.12)	(0.46)	(0.18)	(0.12)	(0.10)	(0.09)
2017-18	0.47***	0.72	0.39**	0.49***	0.52***	0.51***
	(0.12)	(0.47)	(0.18)	(0.13)	(0.10)	(0.10)
2018-19	0.66***	0.65	0.54***	0.68***	0.70***	0.65***
	(0.12)	(0.45)	(0.18)	(0.12)	(0.10)	(0.09)
_cons	10.31***	5.82	8.31***	9.12***	13.35***	14.11***
	(1.39)	(5.27)	(2.04)	(1.42)	(1.16)	(1.07)
R^2	0.591					
N	692	692	692	692	692	692

Notes This table presents the salary model results with player options included, along with its quantile regression analysis. The dependent variable is the natural logarithm of the player's new contract annual salary. The second column shows the overall model results, while the third to seventh columns present the quantile regression results for the 10th, 25th, 50th, 75th, and 90th percentiles of annual salary, illustrating how the impact of player options varies across different salary levels.
t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Previous research has highlighted heterogeneity among players with player options in new contracts, as well as the differing effects of player options across various salary distributions. To better understand the impact of player options on player salaries, a matching process is employed to compare players with player options in new contracts to similar contracts without player options, thereby reducing heterogeneity between the two groups to some extent. The goal is to estimate the impact of contract flexibility, specifically player options, on new contract salaries while controlling for inherent differences. To achieve this, a propensity score matching method is used, calculating propensity scores through logit regression. The formula is presented in formula 2.8. In this formula, the dependent variable is whether the new contract of player i at time t includes a player option, represented as a dummy variable (1 if the new contract contains a player option, 0 otherwise). The independent variables include age, age squared, player performance ($\bar{P}i, t-N, t-2$ and $\Delta Pi, t-1$), player change of team ((Change Team$_{it}$), player popularity (PP$_{i,t-N,t-1}$), and the season in which the player signed ((β_{it}).

$$\begin{aligned} \text{Logit}(\text{Player Option}_{it}) = \beta_0 + \beta_1 \cdot \text{Age}_{it} + \beta_2 \cdot \text{Age}_{it}^2 + \beta_3 \cdot \bar{P}_{i,t-N,t-2} + \beta_4 \cdot \Delta P_{i,t-1} \\ + \beta_4 \cdot \text{Change Team}_{it} + \beta_5 \cdot \text{PP}_{i,t-N,t-1} + \beta_{it} + \varepsilon_{it} \end{aligned} \tag{2.8}$$

Table 2.13 presents the estimation results of the logistic model, which analyses the factors influencing a player's likelihood of obtaining a player option in a new contract. The results indicate that scoring performance during the non-contract year is a crucial determinant, with an improvement in scoring significantly increasing the probability of securing a player option in a new contract. However, other performance-related variables do not show statistical significance. Additionally, the model includes factors such as whether the player signed with a non-parent team and the number of All-Star appearances during the previous contract. The findings suggest that signing with a non-original team reduces the likelihood of obtaining a player option, while higher popularity, as indicated by more All-Star appearances, increases this likelihood. However, neither effect is statistically significant. When accounting for the player's signing season, the results show that compared to the 2012-13 season, only the 2014-15 season has a statistically significant effect, with signing in this particular season significantly increasing the probability of obtaining a player option. This matching process helps to better estimate the causal effect of player options on new contract salaries, reducing the potential bias introduced by heterogeneity and providing a clearer picture of how player contract flexibility influences salary outcomes.

Table 2.13 Logistic model results for the matching process for players with player options in their new contracts

Logistic regression				Number of obs	=	692
				LR chi2(16)	=	99.21
				Prob > chi2	=	0.000
Log likelihood = -326.97				Pseudo R2	=	0.13

New contract with player option	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Age	.07	.20	0.35	0.73	-.32	.47
Age square	-.002	.004	-0.54	0.59	-.01	.005
Average points in non-contract years during the contract	.04	.02	1.94	0.05	-.0003	.09
Average points change by contract year	-.003	.04	-0.08	0.94	-.08	.07
Average total rebounds in non-contract years during the contract	.03	.03	0.92	0.36	-.03	.08
Average total rebounds change by contract year	.001	.08	0.01	0.99	-.16	.16
Average minutes played in non-contract years during the contract	.03	.02	1.52	0.13	-.01	.06
Average minutes played change by contract year	.03	.03	1.16	0.25	-.02	.09
Player signs new contract with non-original team	-.147	.12	-1.13	0.26	-.38	.10
Number of All-Star selections during the player's contract	.21	.14	1.53	0.13	-.06	.48
Season						
2013-14	.12	.22	0.55	0.58	-.317	.56
2014-15	.41	.20	2.05	0.04	.02	.81
2015-16	.28	.21	1.36	0.17	-.12	.69
2016-17	.17	.22	0.78	0.43	-.26	.61
2017-18	-.24	.25	-0.98	0.33	-.72	.24
2018-19	-.08	.23	-0.35	0.72	-.53	.37
_cons |	-2.51	2.83	-0.89	0.38	-8.07	3.04

Notes: This table presents the logistic model results used to estimate the propensity score during the matching process for players with player options in their new contracts. The dependent variable is whether the player has a player option (1 if yes, 0 if no). The independent variables are the same as those used in the player salary model, including the player's age, the square of the player's age, average performance during non-contract years, changes in performance during the contract year (points, rebounds, and playing time), whether the player re-signed with the original team, the number of All-Star selections during the contract period, and the season in which the player signed. These variables help estimate the likelihood of a player having a player option.

After conducting the matching process, a quality analysis is performed to evaluate the grouped samples. Table 2.14 presents the results of this balance test. The analysis shows that there are no significant differences in player age between the two groups. Similarly, when considering player performance metrics, such as scores, rebounds, and playing time, there are no significant differences between the groups at the 10% significance level. Additionally, there is no noticeable difference between the two groups regarding whether players change teams when signing new contracts. However, when considering the variable representing player popularity—specifically, the number of times a player is selected as an All-Star during the original contract—a significant difference is observed between the two groups, with statistical significance at the 5% level. This indicates that while the matching process effectively balances most variables, player popularity cannot be perfectly matched, highlighting a limitation of the study. Despite this limitation, the differences between the two groups are minimized as much as possible based on the other variables, ensuring a robust foundation for subsequent analyses.

Table 2.14 A balance test of the player matching process

Variable	Treated	Control	%bias	t	p>|t|	V(C)
Age	27.12	26.83	7.6	0.73	0.47	0.91
Age square	746.98	732.81	6.6	0.64	0.52	0.89
Average points in non-contract years during the contract	12.74	11.78	17.1	1.47	0.14	1.65
Average points change by contract year	0.94	1.26	-11.9	-0.94	0.35	0.65
Average total rebounds in non-contract years during the contract	4.89	4.57	13.5	1.13	0.26	1.01
Average total rebounds change by contract year	0.30	0.44	-13.3	-1.11	0.27	0.85
Average minutes played in non-contract years during the contract	26.80	25.85	13.4	1.20	0.23	1.16
Average minutes played change by contract year	1.11	1.70	-13.9	-1.18	0.24	0.63
Player signs new contract with non-original team	0.50	0.48	5.0	0.44	0.66	.
Number of All-Star selections during the player's original contract	0.28	0.14	24.5	1.97	0.05	2.29
Season						
2012-13	0.12	0.10	3.7	0.35	0.73	.
2013-14	0.13	0.12	1.8	0.17	0.87	.
2014-15	0.25	0.28	-7.7	-0.63	-0.53	.
2015-16	0.19	0.19	0.0	0.0	1.00	.
2016-17	0.12	0.10	5.6	0.52	0.60	.
2017-18	0.08	0.09	-4.0	-0.39	0.69	.
2018-19	0.11	0.10	1.8	0.18	0.86	.

Notes: This table presents the balance test results of the player matching process. The results indicate no significant difference between the treatment and control groups regarding player age, score, rebounds, playing time, and whether the player signed with another team. However, a significant difference of 5% in the number of All-Star selections suggests that players in the control group generally had more All-Star selections. Despite this, the matching process aimed to balance the groups as closely as possible, which represents a limitation of this study.

After completing the sample matching process and evaluating the quality of the matched samples, I find that while the two groups are relatively similar in performance and other metrics, there is a significant difference in the number of times players were selected as All-Stars. This suggests that contracts with player options may serve as a reward for All-Star players and a concession by teams during negotiations. All-Star players typically command higher salaries, and due to the fat-tailed distribution of player salaries, high-income players may further amplify the impact of player options on salary. This could explain why previous studies often find that players with player options tend to have higher salaries, which seems to conflict with economic theory. To explore the impact of player options on player salaries more thoroughly, I categorize players into different quantiles based on their salaries and scores. I then compare the salary differences between players with and without player options across these groups. Initially, I examine the impact of player options on annual salary, total salary, and contract length across different scoring distributions. Players are divided into the 10th, 25th, 50th, 75th, and 90th percentiles based on their scores in the contract year.

Table 2.15 shows that for players in the bottom 75th percentile of scoring, having a player option leads to a reduction in salary. Specifically, these players lose about 1.2 million dollars in annual salary, which accounts for approximately 18.6% of their new contract's annual salary—a statistically significant result. The total salary decreases by about 3.2 million dollars, while contract length remains relatively similar. For players in the 75th to 90th percentile, player options increase their annual salary by about 1.8 million dollars, raise the total salary by approximately 10 million dollars, and result in longer contracts, with an average extension of about 0.5 years. For the top 10 percentile players, those with player options receive substantial salary premiums, with annual salary increases exceeding 10 million and total salary increases surpassing 35 million dollars. The contract lengths for this group are comparable between those with and without player options. The results show that players in the bottom 75th percentile incur an economic cost, around 18% of their new contract salary, when obtaining player options. For players between the 75th and 90th percentiles, the impact on salary is less pronounced, with the primary benefit being a longer contract duration. Top 10 percentile players, however, receive significant salary premiums when granted player options. This outcome likely reflects that these players, often All-Stars, are highly sought after by teams, which offer more flexible contracts alongside substantial salary incentives to secure their talents. This also highlights a limitation in the matching process for these top-tier players, as those matched without player options may not perfectly align in terms of ability and market value.

Table 2.15 The impact of player options on player contracts across different scoring distributions

	Points less than 75th percentile		Points greater than 75th percentile less than 90th percentile		Points greater than 90th percentile	
	Player with player option	Player without player option	Player with player option	Player without player option	Player with player option	Player without player option
Next contract annual salary	6298192	7469573	17000000	15200000	26000000	15600000
Next contract annual salary difference	-1171382 *		1828902		10400000 ***	
Next contract total salary	19300000	22600000	69600000	59500000	97000000	61700000
Next contract total salary difference	-3223923		10100000		35400000 ***	
Next contract total length	2.61	2.47	3.89	3.4	3.58	3.61
Next contract total length difference	0.14		0.49 **		-0.03	
Sample Size	89	89	35	35	38	38

Notes: This table presents the impact of player options on player salaries across different scoring distributions. For players in the bottom 75% of scores, player options lead to a significant salary reduction of $1.2 million, accounting for approximately 18.6% of their new contracts. For players in the top 25% to 10% of scores, player options result in a salary premium and significantly longer contracts. For the top 10% of players, player options bring a substantial salary premium of around $10 million, representing 40% of their annual salary. This demonstrates how the effect of player options varies significantly across different performance levels.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

After grouping players based on the distribution of their annual salaries, I explore whether player options have similar effects across different salary distributions. Table 2.16 reveals that, consistent with previous findings, players in the bottom 75th percentile of annual salary experience a reduction in their earnings when a player option is included in their contracts. Specifically, these players lose approximately 2.2 million dollars in annual salary, representing about 44% of their new contract's annual salary. They also face a significant decrease in total salary, losing around 7.6 million dollars, which constitutes more than half of the total value of their new contract. However, the total contract length for these players does not differ significantly from contracts without player options. For players in the 75th to 90th percentile of annual salary, including a player option in their contracts results in a salary premium. These players gain an additional 1.6 million dollars in annual salary, amounting to roughly 10% of the annual salary of their new contracts. This premium is also reflected in their total salary, with an increase of about 8.5 million dollars. Additionally, these players secure longer contract durations, approximately 0.5 years longer than those without a player option. For players in the top 10 percentile of annual salary, obtaining a player option in their new contracts leads to a substantial salary premium. These players receive an additional 12.9 million dollars in annual salary, and their total salary increases by approximately 46.4 million dollars. These results are statistically significant at the 1% level. However, in terms of contract length, there is no significant difference between players with and without a player option in this top salary bracket. The impact of player options varies across different salary distributions. Players in the lower percentiles face an economic cost when obtaining player options, with reductions in both annual and total salaries. Conversely, players in the higher percentiles, particularly those in the top 10%, benefit from substantial salary premiums, highlighting the strategic value of player options for high-earning players.

Table 2.16 The impact of player options on player contracts across different salary distributions

	Annual salary less than 75th percentile		Annual salary greater than 75th percentile less than 90th percentile		Annual salary greater than 90th percentile	
	Player with player option	Player without player option	Player with player option	Player without player option	Player with player option	Player without player option
Next contract annual salary	5110103	7360176	16100000	14400000	29600000	16700000
Next contract annual salary difference	-2240073 ***		1623628		12900000 ***	
Next contract total salary	14600000	22200000	62000000	53400000	115000000	68500000
Next contract total salary difference	-7606157 ***		8553759		46400000 ***	
Next contract total length	2.53	2.46	3.82	3.27	3.85	3.77
Next contract total length difference	0.07		0.55 **		0.08	
Sample Size	90	90	33	33	39	39

Notes: This table presents the impact of player options on player salaries across different salary distributions. For players in the bottom 75% of salary, player options lead to a significant reduction of $2.2 million, which represents approximately 43.8% of their new contracts. For players in the top 25% to 10% of the salary distribution, player options bring a salary premium and significantly longer contracts. For the top 10% of players, player options result in a substantial salary premium of about $12.9 million, accounting for 43.5% of their annual salary. This illustrates the varying effects of player options across different salary levels.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.7 Conclusion

In conclusion, this chapter investigates the determinants of player salaries and the role of player options in NBA contracts. Drawing on existing research, key performance metrics such as points, rebounds, blocks, assists, and playing time are identified as critical determinants of salary. Given that player contracts often span multiple years, the analysis incorporates both average performance during the last contract (excluding the contract year) and changes in performance during the contract year. The findings reveal that a player's scoring ability, along with rebounds, blocks, and playing time, significantly boosts salary. Additionally, team performance in non-contract years has a positive impact on players' next contract wages, while improvements in team performance during the contract year tend to reduce contract salary, suggesting that players may value better team performance even if it comes at a cost to personal compensation. Quantile regression is used to examine salary determinants across different salary segments to address the issue of a thick-tailed salary distribution. The results show that while playing time and team performance consistently influence salaries across all quantiles, the effect of individual performance is most pronounced in the top 50% of salaries. The salaries of players in the bottom 50% are influenced by a broader range of factors, underscoring the complexity of salary determination for this group.

This chapter also explores the determinants and implications of player options in contracts. Players with more stable performance during the current contract period are more likely to secure a player option. Additionally, contract timing, such as the anticipation of a new Collective Bargaining Agreement (CBA), plays an important role in determining whether a player option is included. When it comes to exercising player options, players are primarily influenced by the difference between expected and actual salaries. If the expected salary is significantly higher than the current contract salary, players are likely to opt out and pursue free agency to maximize their earning potential. Improvements in player performance and popularity also drive players to become free agents. The inclusion of player options significantly affects player salaries, with varying impacts depending on the player's performance and salary percentile. While player options provide strategic flexibility, allowing athletes to exit contracts and seek better opportunities, they often come at an economic cost for most players. Specifically, players in the bottom 75th percentile experience a reduction in annual salary by approximately \$1.2 million, or 18% of their earnings, when player options are included. In contrast, players in the 75th to 90th percentiles see modest salary premiums and longer contract durations, suggesting financial advantages for mid-tier players. For top 10% players—typically All-Stars—the inclusion of player options results in substantial salary premiums, with annual salaries increasing by at least \$10 million, representing 40% of their earnings for that year. This discrepancy from traditional economic theory can be attributed to the unique market value and scarcity of top-tier players, whose salary differences are influenced by their exceptional abilities and high demand. Despite the valuable flexibility player options provide, their impact on salary is nuanced and varies significantly across different player groups. The findings highlight the complexity of contract negotiations in professional sports and suggest areas for future research, particularly regarding the broader factors influencing the relationship between player options and salary outcomes.

However, this chapter has several limitations. First, the sample size of players with player options in their contracts is relatively small, with only 129 players out of 712, accounting for 18% of the sample. This small proportion may reflect the particular circumstances of these players, such as being famous veterans willing to sacrifice salary to compete for a championship or players recovering from injuries with reduced salaries but added contract flexibility as compensation. These situations may lead to an overestimation of the impact of player options on salary, but they do not conflict with the empirical results presented. Second, institutional factors may increase or decrease the likelihood of obtaining a player option without directly affecting salary. For example, players and agents who anticipated an increase in the salary cap due to a new broadcast contract may have opted for player options to provide flexibility in renegotiating contracts under better conditions. However, the dataset does not allow for identifying players who had such information when signing their contracts. Third, the lack of information on player agents presents another limitation. Well-known agents with significant bargaining power may help players secure more substantial contracts, but previous research (Berri et al., 2015) indicates that this influence is limited to specific quantiles—likely the upper quantiles. The competitive nature of lower quantile players diminishes the impact of agents on their contracts. The absence of agent data in this chapter may lead to an overestimation of the salary gap among top-tier players, but it does not affect the empirical results showing salary losses for lower quantile players who sign contracts with player options. Overall, despite these limitations, the findings provide valuable insights into the determinants of player salaries and the nuanced role of player options in contract negotiations, contributing to a deeper understanding of salary dynamics in professional sports.

Chapter 3

The Determinants of Basketball Player Survival in NBA

3.1 Abstract

Professional sports provide an ideal environment for studying employee longevity, particularly in the context of player survival, which is influenced by injuries, performance, and off-field factors. This chapter uses NBA player data from the 2012-13 to 2018-19 seasons to examine the factors affecting player survival. First, a player's performance on the field is found to be a significant determinant of survival, with higher win shares substantially reducing the risk of career termination. Second, a player's team selection after the end of a contract is influenced by multiple factors, including performance, age, and salary requirements. Players with high offensive win shares are more likely to be retained by their original teams, while other players with advantages in performance or age often receive opportunities from new teams. Lastly, the inclusion of player options in contracts does not significantly reduce survival risk, but it does increase the likelihood of changing teams, offering players greater flexibility in their career choices.

3.2 Introduction

In the field of labour economics, it is essential to assess the longevity of an employee's career. Studying the factors that influence labour exit is one of the ways to understand this problem. In addition, the sports field is an ideal field to study this issue due to its rich player performance data, public player salary data, and clear player exit indicators. A player's ability to stay on the field and maintain a successful career is influenced by multiple factors. One critical factor is the player's injury history, as frequent or severe injuries can lead to a decline in performance and, ultimately, a shorter career (Carrieri et al., 2020). A player's performance plays a decisive role in determining a player's survival. A large number of studies have shown that a player's good performance can significantly improve a player's survival probability (Dilger, 2002; Jiobu, 1988; Spurr and Barber, 1994). Similarly, a player's award can be reflected in a player's outstanding performance and recognised by professional judges, which can help players gain a longer career (Fynn and Sonnenschein, 2012). In addition, the exit of non-white players due to discrimination in professional sports has also been widely studied, but no consistent conclusions have been reached. Hoang and Rascher (1999) find that non-white players have a 36% higher risk of leaving than white players, while Groothuis and Hill (2013) find that there is no significant difference in the risk of leaving between non-white players and white players. However, in the existing literature on player survival, no impact of changing teams on player survival has been found. Professional players are limited by work content and the scarcity of professional skills and have no way to continue their careers by changing jobs. Therefore, studying the impact of changing teams on the survival of employees in an employer-monopolized industry has profound implications. Again, the NBA provides some special clauses, such as player option clauses, that allow players to decide to end their current contracts early and become free agents. This special clause gives them the flexibility to test the free market and choose to sign a new contract at a time that is more beneficial to them. My research also explores the impact of this special provision on player survival. These fill in the blanks on player behaviour after the contract ends and the impact of choosing the timing of signing a contract on player survival.

In my research, I use NBA data from the 2012-13 season to the 2018-19 season to explore the impact of player performance, changing teams after a contract, and player options on player survival. I choose the performance data in the previous article (Kubatko et al., 2007) as the measurement of player performance in this study. In addition, I referred to the Del Corral et al. (2008)'s method to screen the appropriate model settings in my study. This chapter employs parametric and semi-parametric models to select the optimal survival models. The Akaike information criterion (AIC) and Bayesian information criterion(BIC) are used to screen and determine the Log-normal in the parameter model as the model setting for this study. Subsequently, the study uses seven years of NBA data, combined with survival models and competing risk models, to estimate the impact of player performance, changing teams after the end of the contract, and player options on player survival.

This chapter makes three main contributions to the field of labour economics and sports analytics. The first contribution lies in the quantification of the impact of player performance on player survival. The findings show that player performance is a decisive factor, with contributions to victory on both offensive and defensive ends significantly influencing a player's career longevity. Specifically, an increase in a player's offensive win contribution by one unit reduces the survival risk by 46% and extends survival time by 43%. Similarly, an increase in defensive win contribution by one unit reduces survival risk by 59% and extends survival time by 75%. These results provide valuable quantitative insights into the importance of player performance, particularly in contributing to team victories.

The second contribution of this chapter is the exploration of how team selection behaviour after contract expiration affects player survival. The study finds that player performance continues to be the primary factor affecting career outcomes. Players who perform well, particularly in terms of offensive win shares, are more likely to remain with their original teams. Conversely, a change of team is influenced by multiple factors, including performance, age, and salary requirements. This chapter identifies the determinants of players' choices after their contracts end and establishes a connection between these choices and player survival.

The third contribution focuses on the impact of player options in contracts on player survival. While the results indicate that player options do not directly affect survival, they significantly influence a player's behaviour after their contract expires, particularly by increasing the likelihood of changing teams. This phenomenon demonstrates the importance of player options in providing flexibility and affecting mobility within the league. Exploring the relationship between contract terms, such as player options, and player survival offers a deeper understanding of how contract structures can shape career trajectories. Overall, this chapter provides a comprehensive analysis of player survival in the NBA, with a focus on performance, team mobility, and contract features. The findings underscore that player performance, particularly in terms of offensive and defensive contributions, is the primary determinant of survival. Additionally, player mobility after contract expiration and the inclusion of player options both play significant roles in shaping career outcomes.

The chapter is organized as follows: the next section provides a summary of the existing literature on player survival, followed by a discussion of the model settings for survival analysis. The empirical analysis of the player survival model is then presented, and the chapter concludes with a summary of the key findings.

3.3 Literature review

The sports industry provides a suitable context for studying employee survival. In the sports industry, player exits can be caused by a variety of factors, including injuries, poor performance, off-field factors, or team or league contraction (Boyden and Carey, 2010). Professional sports are highly competitive and physically demanding, so injuries are a common phenomenon. It is also common for many players to retire directly after suffering major injuries. Studies have been conducted to examine the effects of injuries on players' salaries and career prospects. One study (Carrieri et al., 2020) focused on players who participated in the Italian Football League during the 2013-14 season. Traumatic injuries sustained during training and competition were used as external impacts on players, while muscle injuries caused by players' training levels were not considered. The study used a Mincerian wage equation to analyse the correlation between player injuries and salaries. The results showed that missing a month due to injury did reduce the salary in the following season by 12%. Additionally, the study found that a player missing 30 days due to injury did increase the possibility of contract renegotiation by 9.8% the following season. After players experienced injuries, their subsequent performance was affected by missing games, thus causing endogeneity problems. The study utilised the average number of yellow cards received by a player's teammates in the league as an instrumental variable to address the endogeneity issue. This variable indicated that a team's aggressive defensive approach would similarly increase the risk of injury to the players or the opponent's response. In summary, a player's injury caused teams to worry about the player's future productivity reduction, which would decrease the player's future salary and increase the possibility of re-signing the contract. This productivity shock would significantly impact the incomes of high-income players more than low-income players. Although injuries are a frequent event in sports, most players can recover well from serious sports injuries with the help of modern medical treatment. However, this unexpected impact could cause teams to be more cautious in treating the player and consider renegotiating their contract after the season. The renegotiation decreased existing salaries, but a decline in player performance did not necessarily determine this decrease in salary. Players' renegotiation with their teams after experiencing injuries increased the risk of players leaving the league and verified the negative impact of player injuries on player survival.

Player performance affects the player's survival to a certain extent. Dilger (2002) used NBA player data from 1990 to 2000 and found that the main reason for players to quit the league was bad performance and that players' scoring performance and long playing time reduced the risk of players leaving, but players' high salary and non-scoring did not help a player's survival. In addition, Spurr and Barber (1994) obtained similar conclusions through baseball data. Players who performed better in lower leagues promoted faster and joined higher-level leagues, while players with poorer performance ended their careers earlier. An earlier study by Jiobu (1988) also found that player performance had the greatest impact on player survival, and better performance led to longer survival time. In addition to the player's performance being directly reflected in the player's survival model, the player's awards after the season reflected the player's performance on the court and the league's professional judges' recognition of him to a certain extent. Fynn and Sonnenschein (2012) conducted a study in 2012 using NBA data from 1947-2011. The study used different parametric models, including standard, Weibull, exponential, log-normal, and non-parameter models (KM curves) to analyse the data. Physical data such as the player's age, height, weight, and experience were taken into account, and the study found that a player's biological information, along with their awards in a season, had a significant impact on their career length. The study analyzed awards like Most Valuable Player, Defensive Player of the Year, Sixth Man of the Year, Improved Player of the Year, Finals Most Valuable Player, All-Star Game Most Valuable Player, Comeback Player of the Year, and Rookie of the Year to understand how they affected a player's survival in the league. The study found that the number of awards a player received and their position on the field were the best indicators of their survival in the league. Players who received more awards were more likely to survive longer in the league. Being enrolled in the Hall of Fame was also considered an award, but it was not used to estimate a player's survival status. The NBA players were only eligible for enrolment into the Hall of Fame after they had retired for several years. The study used Schoenfeld residuals, the Mantel-cox test, and accelerated failure models to screen research variables and models. The Cox model was then used to analyse the data, which showed that a player's awards and position on the field were the best predictors of their survival. Finally, proportional hazards were tested using formal tests. In conclusion, the study found that a player's performance in the game, their position on the field, and their awards in a season significantly impact their career length.

Better performance can help players improve their likelihood of survival in the league, and this conclusion also applies to coaches in the sports industry. Barros et al. (2009) conducted a thorough analysis of the coaching data of the German Football League for 22 consecutive seasons, ranging from 1981 to 2002. The study used a semi-parametric Cox survival model and a parametric survival model (Weibull and exponential) to test certain hypotheses. Firstly, it was hypothesised that coaches with higher salaries were more likely to survive in the league, even if their performance was worse. However, the study found that coaches with higher salaries were not necessarily more likely to survive in the league. The data does not support this hypothesis significantly. Secondly, it was hypothesised that teams that invest more in the season were less tolerant of coaches. Teams with high salary expenditures were more concerned about better results in the season, so they were more likely to fire head coaches who performed poorly in the season. Thirdly, the coach's survival probability increased with the length of time they have been coaching the team. A coach who continued to coach the team by continuously passing the team's test increased the probability of survival. Fourthly, a higher team winning rate helped the coach stay, as the team winning ratio was the leading assessment content of the coach's performance. Therefore, a good performance helped the coach stay in the team better. Finally, the coach's previous experience did not help their current survival. The study found that there is no significant relationship between the coach's previous experience and their current survival. In summary, the study showed that coaches with higher salaries were not necessarily more likely to survive, while teams with high salary expenditures were more likely to fire head coaches who performed poorly in the season. The coach's survival probability increased with the length of time they have been coaching the team, and a higher team winning rate helped the coach stay. Finally, the coach's previous experience did not help their current survival.

Discrimination is a persistent problem in labour economics that can cause employees to leave their jobs prematurely. Discrimination can take many forms, including race-based discrimination. For example, a study by Volz (2017) found that the number of black starting quarterbacks in the NFL is significantly lower than that of other positions, implying that black quarterbacks are likely to experience discrimination. The study aimed to examine whether black quarterbacks are treated differently from white quarterbacks and whether this discrimination impacts their professional careers. The researchers used a survival model to analyse data from nine seasons (2001-2009) to determine the factors that affect the number of consecutive starts by quarterbacks. The study found that black quarterbacks are more likely to be benched than white quarterbacks, even when other control variables such as age, experience, and performance are held constant. The study also found that this situation was less prevalent in areas with higher black populations. Furthermore, the study found that replacing white quarterbacks with black quarterbacks improved team performance, indicating that discrimination has negative consequences not only for the individuals affected but also for the teams and organisations they work for. Another study by Volz (2009) investigated the underrepresentation of minority team managers in Major League Baseball. The study used multi-year data from 1986 to 2005 and the Cox PH survival model to examine the factors that affect the survival probability of head coaches. The study found that minority team managers were more likely to face discrimination in the job market, which could limit their career opportunities. Volz (2009) also revealed that managerial efficiency positively affected the survival probability of head coaches. The researchers created a specific variable to represent the coach's ability to use existing resources to convert team wins, which they called managerial efficiency. The study showed that higher managerial efficiency improved the survival probability of the head coach. Additionally, the study found that the experience of a head coach can extend their career, while age can have a negative impact. Minority status was found to increase the probability of continuing to coach by 9.6%. These findings suggest that ethnic minority coaches face discrimination during the job search, which could limit their career opportunities.

The NBA is a league dominated by non-white players (Kahn and Shah, 2005). Non-white players account for approximately 80% of the total players from 1985 to 2022 (LI, 2023). Still, discrimination against non-white players remains a relevant issue, but there is no consistent conclusion that non-white players leave the league due to discrimination. Hoang and Rascher (1999) studied players drafted in the first two rounds from 1980 to 1986. Compared to black players, white players have a 36% lower risk of leaving the league. At the same time, players who were drafted later in the draft had a higher risk of leaving. Yet other studies (Groothuis and Hill, 2013) have found no significant differences in the risk of exit between non-white and white players. The uncertainty about the impact of race on NBA player survival caused the impact of race on player survival to be ignored in my research.

The present study focuses on identifying the survival determinants of NBA players. It is crucial to comprehend the meaning of various NBA data and calculation methods in basketball analysis research. This will help deepen our understanding, better explain the empirical results, and verify the questions asked. The NBA league collects a vast amount of data, providing rich resources for further scientific research. Therefore, it is essential to understand what kind of data can be recognised by peer-reviewed journals. Kubatko et al. (2007) aimed to introduce the definition and calculation methods of basketball data, which increased the academic field's understanding of basketball data. The study believed that controlling ball possession is the core of basketball game analysis. The research compares various methods for calculating basketball possession. The study found that there is no significant difference in the methods used to calculate the possession. Different calculation methods yielded more consistent results through appropriate transformations. After obtaining a more consistent possession, the study introduced some fundamental concepts in basketball analysis. Kubatko et al. (2007) focused on offensive and defensive ratings as variables that represented the player's score per 100 possessions and the opponent's scoring ability. These variables expressed a player's offensive and defensive skills. Different methods were used to address heterogeneity in basketball analysis, such as player playing time, team playing style, and player efficiency. For example, a player's data is divided by playing time and multiplied by a fixed time to convert to data per 36 minutes or 48 minutes. The study also transformed data into an adjusted number of possessions based on the number of offensive possessions each team plays in each game. Additionally, the study used the player's proportion of the total data on the spot or the team instead of a simple absolute value. The NBA also counted players' Plus/Minus data, which was the difference between the team's points scored and lost when the player was playing and when they were not. The NBA created novel data method concepts using linear weights and Pythagorean winning percentages. Linear weights refer to assigning weights to different basketball statistics to evaluate a player's overall contribution to the team, while Pythagorean winning percentages use basketball data to predict a team's winning percentage. Kubatko et al. (2007) introduced the basic concepts of basketball analysis and presented generally accepted basic knowledge to peer-reviewed journals. This justifies the choice of player performance measures used in my study. It also enhanced the ability of my research to explain the impact of player performance on player survival.

When performing survival model analysis, selecting an appropriate model is an important analysis step. Del Corral et al. (2008) aimed to investigate the strategies of each team for substituting during a game, particularly focusing on the team's strategy for making the first substitution. To achieve this, the researchers conducted survival analysis and combined existing sports data, making diversified attempts in model selection. The research object was the Spanish first-level league during the 2004-2005 season, and the primary research object was substitutions made in the second half, as they are relatively rare in the first half. After screening, the study used 676 samples for analysis. The researchers employed parametric survival models, including exponential, Weibull, and Gompertz for proportional hazards, and log-logistic, lognormal, gamma, and inverse Gaussian for accelerated failure models. The Inverse Gaussian model was selected as the primary setting of the survival model through Bayesian information criteria (BIC). The study included explanatory variables such as whether the substitution team is the home team, the goal difference between the home team and the visiting team, the type of player substituted, and the results of the two teams in the past four games. The results showed that the home team often makes more substitutions in halftime, and the home environment usually puts more significant pressure on the home team's coaching decisions. Del Corral et al. (2008) contributed to a better understanding of how teams strategize substitutions during games, and the results proved useful for coaches and players alike.

3.4 Survival model

Survival analysis is also known as duration analysis, transition analysis, hazard analysis, reliability analysis, failure-time analysis, event history analysis, etc. The primary research focuses on the time it takes for an event to occur, that is, the time it takes to transition from one state to another. Specifically, it can be divided into three categories: first, the time it takes for qualitative variables to change status, such as divorce, promotion, and death. Second, the time it takes for quantitative variables to change dramatically, such as the sharp drop in the total birth rate of the population. Third, the time it takes for quantitative variables to exceed a certain threshold, such as losing weight to a healthy level. Compared with logistic and linear regression, survival analysis can fully use information and effectively deal with the characteristics of work status variables that change with time. In addition, survival analysis can better handle censoring in the data.

3.4.1 Defination

In survival analysis, duration T is a random variable. In this chapter, T represents the duration from when a player enters the league to completely leaving the league.

Cumulative distribution function

Define a cumulative distribution function F(t) that focuses on the probability of event failure (death) within time t. $F(t) = Pr(T \leq t)$. From this, the density function f(t) corresponding to the probability of the event can be defined. $f(t) = dF(t)/dt$. In this chapter, F(t) represents the probability of a player leaving the league within time t.

Survival function

The survival function S(t) is the probability of surviving beyond a certain time by t, that is, the probability that the event of interest does not occur within time t. $S(t) = 1 - F(t)$. In this chapter, S(t) represents the probability of a player remaining in the league at time t

Hazard function

The hazard function $\lambda(t)$ represents the probability of the event of interest occurring at time t, also known as the risk of occurrence at time t.$\lambda(t) = f(t)/S(t)$. In this chapter, h(t) represents the instantaneous probability of a player leaving the league at time t.

3.4.2 Hazard function type

In the exponential model, when the random variable T follows an exponential distribution, the parameter is λ. The hazard function is $\lambda(t) = \lambda$, and the hazard function of the exponential distribution is constant, indicating that the probability of an event does not depend on the duration of the event.

In the Gompertz model, when the random variable T obeys the Gompertz distribution, the parameters are λ and α, and the hazard function is $\lambda(t) = \lambda_0 e^{at} \quad where \quad \lambda_0 = e^u$. The Gompertz distribution's hazard function has an exponential change rate and is monotonic.

Weibull function, when random variable T obeys Weibull distribution, the parameters are λ and α, and the hazard function is $\lambda(t) = \lambda_0 t^{\alpha} \quad where \quad \alpha > -1$. The hazard function of the Weibull distribution has a power rate of change and is a monotonic function. The above three models are collectively called the proportional hazards model, meaning that the random variable T conforms to a specific parameter model and can be estimated using the maximum likelihood estimation method(MLE). The above three models are collectively called the proportional hazards model, which means that the random variable T conforms to a specific parameter model and can be estimated using the maximum likelihood estimation method.

3.4.3 Accelerated failure-time model, AFT

The accelerated failure time model mainly studies the effect of the explanatory variable x on the average life. In contrast, the proportional hazards model analyses the impact of the explanatory variable x on the hazard function. The accelerated failure time model is $ln(t) = X^{'}\beta + \mu$. Where you are different, different AFT models will be formed.

3.4.4 Cox PH model

The proportional hazards and accelerated failure time models are parametric models. It is necessary to make assumptions about the specific form of the hazard function and then use the maximum likelihood method to estimate. However, censoring data may lead to the wrong setting of the hazard function, in which case there will be inconsistent MLE estimates. Cox proposes an estimated semi-parametric model based on the PH model, defined as the Cox PH or Cox model. The Cox PH model does not need to assume a specific form of baseline hazard $\lambda_0(t)$ because the ratio of the hazard functions of individual i and individual j can be rounded off, leaving only the term related to the explanatory variable x. The following formula determines the specific form.

$$\frac{\lambda(t;x_i)}{\lambda(t;x_j)} = \frac{\lambda_0 e^{x_i'\beta}}{\lambda_0 e^{x_j'\beta}} = e^{(x_i-x_j)'\beta}$$

Since the front part $\lambda_0(t)$ of the hazard function $\lambda_0(t)e^{x'\beta}$ does not need to estimate parameters (non-parametric part) and the latter part $e^{x'\beta}$ needs to estimate parameters, the Cox PH model is a semi-parametric regression, and at the same time, like the PH model, the risk function satisfies the setting form $\lambda(t;x) = \lambda_0 e^{x'\beta}$

3.5 Empirical results

3.5.1 Player performance statistic

Win shares

Win share is a statistic that reflects an individual player's contribution to the team's overall success, taking into account both offensive and defensive performance. The following content is from the website Basketball-Reference. Individual win shares can be divided into two aspects: offensive and defensive ends. On the offensive end, a player's win contribution is determined by the player's marginal offence and marginal points per win. The following formula gives a player's marginal offence. Derived from the formula, marginal offence represents a player's offensive production difference compared to the league average. The second formula reflects the team's marginal points per win. The team's points per win are determined by the league's average pace and the team's pace. A higher team's pace increases the team's marginal points per win. Finally, the player's offensive contribution to the team's victory is determined by the above two factors: the number of games the player's scoring advantage compared to the average player can help the team win.

$$\text{Marginal Offence} = \text{Points Produced} - 0.92\,\text{League Pts/Pos} \times \text{Offensive Possessions} \quad (3.1)$$

$$\text{Marginal Points per Win} = 0.32 \cdot \text{League Points per Game} \cdot \frac{\text{Team Pace}}{\text{League Pace}} \quad (3.2)$$

$$\text{Offensive Win Shares} = \frac{\text{Marginal Offence}}{\text{Marginal Points per Win}} \quad (3.3)$$

On the defensive side, a player's win contribution is first based on the player's defensive rating, which indicates the corresponding player's ability to limit the opponent's points in 100 defensive possessions. By calculating the proportion of the player's playing time to the team's total playing time, the player's additional defensive contribution on the defensive end is estimated compared to the average player in the league. At the same time, the marginal points per win are calculated using the same method as the offensive end. Finally, a player's victory contribution on the defensive end is determined by the ratio of the above two.

$$\begin{aligned}\text{Marginal Defense} = &\frac{\text{Player Minutes Played}}{\text{Team Minutes Played}} \cdot \text{Team Defensive Possessions} \\ &\cdot \left(1.08 \cdot \text{League Points per Possession} - \frac{\text{Defensive Rating}}{100}\right)\end{aligned} \tag{3.4}$$

$$\text{Marginal Points per Win} = 0.32 \cdot \text{League Points per Game} \cdot \frac{\text{Team Pace}}{\text{League Pace}} \tag{3.5}$$

$$\text{Defensive Win Shares} = \frac{\text{Marginal Defense}}{\text{Marginal Points per Win}} \tag{3.6}$$

3.5.2 The impact of player performance on player survival

In this study, players' careers are divided into distinct periods, referred to as "spells," with each spell corresponding to a single contract. For each spell, players' performance data are averaged annually. Table 3.1 provides a statistical overview of player spells, which serve as the basis for the analysis in the survival model. In total, 1,798 spells are recorded, representing 846 unique players. The average age of players during these spells is 27 years, with ages ranging from 19 to 41. Player performance is captured through several key metrics. On average, players score 6.7 points, make 1.6 assists, achieve 0.6 steals, and record 0.3 blocks per game. Shooting accuracy is represented by an average field goal percentage of 42%, a free throw percentage of 67%, and a three-point shooting percentage of 25%. These statistics provide a broad view of player effectiveness on the offensive end. The study also considers offensive and defensive contributions, represented by average victory contribution values of 0.89 and 0.86, respectively, which offer insights into a player's overall impact on both ends of the court. Additionally, injuries are accounted for by measuring the number of days missed due to injury, with players missing an average of 6.8 days per season and a maximum of 253 days missed. These variables form the foundation for evaluating player survival and performance within the model.

Table 3.1 Summary statistic(Whole sample)

	N	Mean	Dd	Min	Max
Age	1798	27.08	4.35	19	41
Points	1798	6.74	5.02	0	31.87
Assists	1798	1.55	1.55	0	11.70
Steals	1798	0.55	0.39	0	2.35
Blocks	1798	0.33	0.40	0	6
Field goal percentage	1798	0.42	0.13	0	1
Free throw percentage	1798	0.67	0.25	0	1
Three points percentage	1798	0.25	0.17	0	1
Offensive win shares	1798	0.89	1.52	-2.5	11.80
Defensive win shares	1798	0.86	0.92	-0.05	6.32
Number of days missed during the season due to injury	1798	6.81	16.45	0	253
Observations	1798				

Notes: The table shows the statistical analysis for the full sample. The total number of samples represents all 'Spells' participating in the survival model analysis. Each 'Spell' corresponds to a contract in a player's career, and all data calculations are averaged annually based on the player's data within that contract. The sample consists of spells from 846 players.

In this study, I use survival models to examine how player performance influences their career longevity in the league. Figure 3.1 displays the player's career on the horizontal axis and the survival risk on the vertical axis. By plotting the survival risk of players over time, I assess how the likelihood of leaving the league evolves throughout a player's career. The survival risk emerges around the fourth year, particularly affecting first-round rookies as they transition beyond their rookie contracts. Throughout a player's career, the survival risk generally increases, peaking around the eighteenth year before declining, indicating a reduced likelihood of withdrawal for players who remain in the league longer.

To better understand the factors impacting player survival, I consider various elements, including player performance, career stage, future potential, and team salary expenditures. Leveraging the unique characteristics of NBA contracts, I analyse survival models for three groups: first-round rookies, all rookies, and all players. First-round rookies are of particular interest due to the standardisation of their contracts by the league, making their survival dependent on performance following the completion of their initial contract. Using the Cox proportional hazards model, I estimate survival risks across these different groups of players, as presented in the subsequent analysis. The formula of this model is expressed by the following formula 3.7.

$$h(t \mid X) = h_0(t) \exp\left(\beta_1 \text{Age} + \beta_2 \text{Performance} + \beta_3 \text{Injury} + \beta_4 \text{Draft Position}\right) \tag{3.7}$$

Table 3.2 shows the results of the survival model results. For first-round rookies, the survival model reveals that age has a negative impact, with older players facing higher risks of leaving the league due to lower developmental potential. Performance metrics such as scoring, blocks, and three-point shooting percentage significantly improve survival rates, whereas other metrics like steals and field goal percentage do not have a meaningful impact. Furthermore, winning contribution values, which reflect a player's holistic contributions on both offence and defence, play a crucial role in reducing survival risks. In contrast, injuries significantly increase the risk of withdrawal for rookies. Draft position also plays a role, with players selected later in the first round having higher survival risks. For all rookies, the results show that age remains a negative factor for survival, but performance variables such as scoring and blocks are no longer significant. Instead, free throw percentage is a key metric for reducing survival risk. Winning contribution values continue to be crucial, while draft position also impacts survival, with second-round and undrafted players facing higher risks than top draft picks. Finally, when considering all players, age ceases to be statistically significant, but performance metrics such as points scored and free throw percentage are critical in reducing survival risk. Both offensive and defensive win shares remain influential

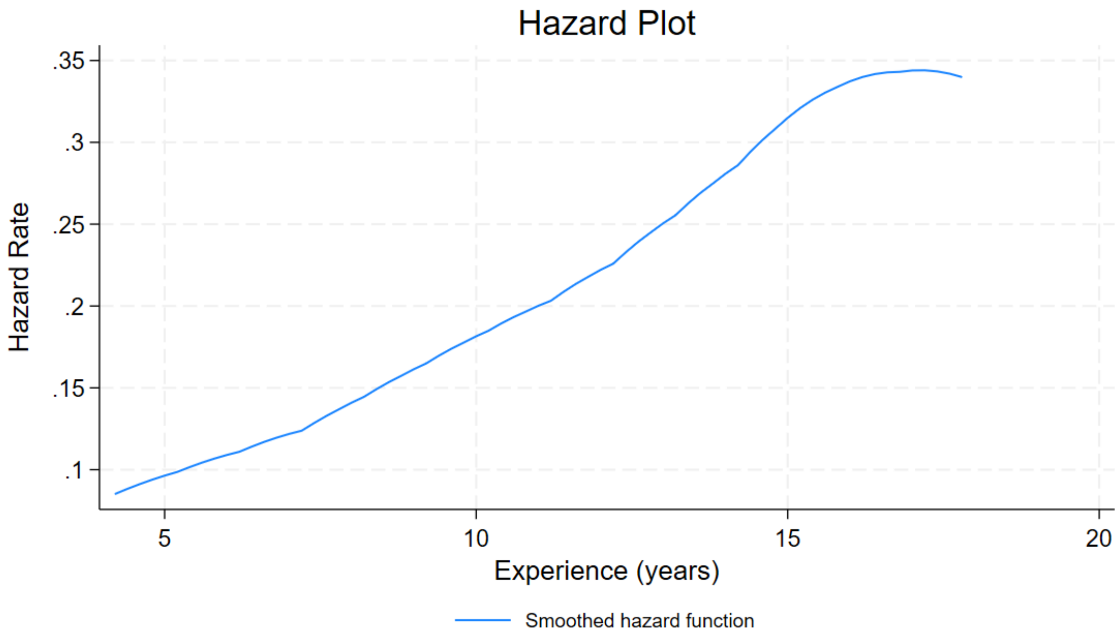

Fig. 3.1 Player Hazard Plot

Notes: This figure illustrates how a player's hazard function evolves as their career in the league progresses, showing the smoothed hazard rate over the course of a player's experience.

in lowering the likelihood of withdrawal. The Cox survival model results indicate that an increase of 1 win share on the offensive end significantly reduces a player's hazard rate of leaving the league by 46%. Similarly, an increase of 1 win share on the defensive end reduces the player's risk of leaving the league by 59%. Players drafted in later rounds or who went undrafted continue to face higher risks compared to top-seven first-round picks. This analysis highlights the varying impact of age and performance at different career stages. While age is a significant determinant for rookies, it loses its influence when considering all players. In terms of performance, winning contribution values consistently play a key role in reducing survival risk, underscoring the importance of a player's overall impact on team success. Additionally, draft position influences survival, with higher draft picks generally receiving more excellent opportunities and undrafted or late-round players facing more significant challenges to remain in the league.

Table 3.2 Impact of player performance on survival(Cox model)

	First round rookie	Whole rookie	Whole sample
Age	0.18**	0.12***	-0.02
	(0.08)	(0.03)	(0.02)
Points	-0.53***	-0.07	-0.07***
	(0.18)	(0.06)	(0.02)
Assists	-0.38	-0.16	-0.03
	(0.49)	(0.13)	(0.05)
Steals	1.41*	0.96***	-0.04
	(0.85)	(0.30)	(0.17)
Blocks	-1.38*	-0.17	0.03
	(0.79)	(0.35)	(0.11)
Field goal percentage	13.46***	0.32	0.16
	(3.21)	(0.47)	(0.23)
Free throw percentage	-1.70	-0.76***	-0.33**
	(1.22)	(0.27)	(0.13)
Three points percentage	-2.74*	-0.14	-0.24
	(1.42)	(0.44)	(0.21)
Offensive win shares	-2.41***	-1.16***	-0.61***
	(0.57)	(0.21)	(0.10)
Defensive win shares	-1.28*	-1.90***	-0.89***
	(0.77)	(0.35)	(0.14)
Number of days missed during the season due to injury	0.03*	0.003	0.001
	(0.01)	(0.01)	(0.00)
Draft position order	0.02***		
	(0.00)		
Draft 8 to 14		-44.83	-0.05
		(.)	(0.21)
Draft 15 to 30		1.14	0.11
		(1.05)	(0.18)
Draft 31 to 44		2.01*	0.52***
		(1.05)	(0.19)
Draft 45 to 60		2.14**	0.55**
		(1.07)	(0.21)
Not Draft		2.14**	0.44**
		(1.06)	(0.20)
R^2			
N	201	493	1,798

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table estimates the impact of player performance on player survival using the Cox model. The impact of player performance on survival is estimated based on first-round rookie players, rookie players and all players. The results shown in the table represent the coefficients of the hazard function.

After estimating the players' survival model using non-parametric methods, I further refine the estimation by applying several parametric models, including the exponential, Gompertz, log-logistic, Weibull, log-normal, and generalised gamma distributions. To determine the most suitable model, I use the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) as comparison metrics, with lower values indicating a better fit. Table 3.3 presents the AIC and BIC values for each model. The results show that the generalised gamma model has the lowest AIC, while the log-normal model has the lowest BIC. Although both models have relatively close values in terms of the information criteria, the characteristics of the log-normal model's risk function align better with the typical trajectory of a player's career. Specifically, in the log-normal model, the risk of exit first increases, peaks, and then declines. This mirrors a player's career path, where survival risk initially rises after entering the league, reaches its highest point at a particular stage, and then decreases over time. Therefore, based on this reasoning and the information criterion comparison, I select the log-normal distribution for the subsequent parametric estimation of the player survival risk model.

Table 3.3 Information criterion of each survival model

Model	N	df	AIC	BIC
Cox model	1798	16	5238.10	5326.01
Exponential	1798	17	718.01	811.41
Gompertz	1798	18	591.97	690.87
Log logistic	1798	18	605.59	704.49
Weibull	1798	18	602.68	710.58
Log normal	1798	18	548.63	647.53
Ggamma	1798	19	545.90	650.30

Notes: The table shows the information criteria for different survival models.

The player parametric survival model, based on the log-normal distribution and expressed as Formula 3.8, extends the previous analysis of the semi-parametric survival model. In both approaches, I divide the model samples into three groups: first-round rookies, all rookies, and all samples. This parallel grouping allows for a cohesive comparison between the two models, enabling a more comprehensive exploration of the impact of player performance on survival from multiple perspectives.

$$S(t \mid X) = 1 - \Phi\left(\frac{\ln(t) - \mu(X)}{\sigma}\right)$$
$$\mu(X) = \beta_0 + \beta_1 \cdot \text{Age} + \beta_2 \cdot \text{Performance} + \beta_3 \cdot \text{Injury} + \beta_4 \cdot \text{Draft Position} \quad (3.8)$$

Table 3.4 presents the results of the parametric survival model, providing insights into the impact of various factors on player survival. In the first column, representing first-round rookie players, it is evident that age has a negative effect on survival. Older players are perceived by teams to have lower developmental potential, resulting in shorter survival times in the league. In terms of performance, metrics such as scoring, blocks, and three-point shooting percentage positively influence survival time, meaning that better performance in these areas corresponds to longer careers. However, positive performance in steals and shooting percentage has a negative impact on survival time. Furthermore, a player's win shares on both offence and defence, which comprehensively estimate performance, significantly increase survival time. Regarding draft position, first-round players picked later tend to have shorter careers, as teams provide more opportunities and tolerance to higher-ranking players.

When expanding the sample to include all rookie players, age continues to have a negative effect, with each additional year of age reducing survival time by approximately 2.6%. Unlike first-round rookies, points, blocks, and three-point shooting percentage are no longer statistically significant, while free throw percentage becomes the performance metric that positively influences survival. Steals continue to have a negative impact. Win shares on both offence and defence remain significant; a 1-point increase in offensive win share extends survival time by approximately 44%, while the defensive win share has an even more substantial effect, increasing survival by around 105%. Additionally, when draft position is considered, players drafted 8th to 14th survive longer than those drafted in the top seven. This could be due to the lower external pressure and attention faced by mid-first-round picks, allowing them to perform better and have longer careers. In contrast, second-round and undrafted players experience significantly shorter survival times than top-seven picks. For the entire sample, points and free throw percentage emerge as the key performance metrics that increase survival time. Similarly, offensive and defensive win shares continue to play an essential role in extending players' careers. Specifically, an increase of one win share on the offensive end is associated with a 43% increase in a player's survival time, while a one win share increase on the defensive results in a 75% increase in survival time. Regarding draft position, the results mirror those found for rookie players. Players drafted between 8th and 14th tend to have longer career survival times than top-seven picks, while second-round and undrafted players generally experience shorter careers. The results from the parametric log-normal survival model closely align with those from the semi-parametric model. The negative impact of age is concentrated among rookie players, while it loses significance when considering the entire sample. Player performance, notably winning shares on both offence and defence, significantly extends survival time, reaffirming that contribution to team victories is a critical determinant of career longevity. Regarding draft position, aside from second-round and undrafted players who face shorter careers, players picked 8th to 14th tend to survive longer than top-seven picks. This suggests that talented young players in mid-first-round positions, with less attention and pressure, are more likely to enjoy longer careers.

Table 3.4 Impact of player performance on survival(Parametric model(Log-normal))

	First round rookie	Whole rookie	Whole sample
_t			
Age	-0.03*	-0.03**	-0.01
	(0.02)	(0.01)	(0.01)
Points	0.08**	0.03	0.06***
	(0.03)	(0.02)	(0.02)
Assists	0.16	0.06	0.01
	(0.12)	(0.04)	(0.04)
Steals	-0.46**	-0.37***	-0.10
	(0.19)	(0.10)	(0.12)
Blocks	0.57***	0.06	0.01
	(0.19)	(0.12)	(0.09)
Field goal percentage	-2.73***	-0.16	-0.19
	(0.68)	(0.18)	(0.18)
Free throw percentage	0.48*	0.27***	0.38***
	(0.26)	(0.09)	(0.10)
Three points percentage	0.45*	0.07	0.28
	(0.25)	(0.15)	(0.17)
Offensive win shres	0.51***	0.37***	0.36***
	(0.13)	(0.08)	(0.08)
Defensive win shares	0.27***	0.72***	0.56***
	(0.10)	(0.11)	(0.08)
Number of days missed during the season due to injury	-0.002	-0.001	0.001
	(0.00)	(0.00)	(0.00)
Draft position order	-0.02***		
	(0.01)		
Draft 8 to 14		1.59***	0.23*
		(0.20)	(0.13)
Draft 15 to 30		-0.24	-0.02
		(0.20)	(0.12)
Draft 31 to 44		-0.68***	-0.34***
		(0.20)	(0.12)
Draft 45 to 60		-0.79***	-0.39***
		(0.21)	(0.14)
Not Draft		-0.88***	-0.44***
		(0.20)	(0.12)
Cons	2.58***	1.69***	1.03***
	(0.55)	(0.34)	(0.28)
/			
lnsigma	-1.51***	-1.00***	-0.55***
	(0.18)	(0.05)	(0.03)
R^2			
N	201	493	1,798

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table estimates the impact of player performance on player survival using the parametric survival model of the log-normal distribution. The impact of player performance on survival is estimated based on first-round rookie players, rookie players and all players. The results shown in the table represent the coefficients of the natural logarithm of the player's survival time.

3.5.3 The impact on player survival of changing teams after players end their contracts.

In this section, I examine the factors that influence player survival, focusing specifically on a common event that occurs after a player's contract ends: changing teams. The goal is to determine whether switching teams is related to a player's continued presence in the league. To investigate player decisions following the expiration of their contracts, I analyze the outcomes of player contracts over a seven-year period from 2012 to 2018. When a player's contract ends, they generally face three possible outcomes: signing with a new team, re-signing with their original team, or leaving the league altogether. These three categories represent key decisions that shape a player's career trajectory, providing insights into the factors that contribute to either their continued presence in the league or their departure.

Table 3.5 presents the statistical distribution of these outcomes. In total, there are 1,798 contracts. Of these, approximately 70% result in the player staying in the league. Specifically, 894 contracts (around 50%) involve players switching teams and signing with new organizations, while 354 contracts (about 20%) lead to players re-signing with their original teams. The remaining 550 contracts (roughly 30%) result in players leaving the league. Analyzing these outcomes by year, between 52% and 62% of players enter the free agent market annually. Among those who become free agents, 42% to 54% sign with new teams, continuing their careers in the league, while 16% to 27% re-sign with their original teams. The remaining 26% to 40% of free agents leave the league once their contracts expire. These statistics illustrate that a significant number of players continue their careers by changing teams after becoming free agents, highlighting the need to explore the impact of team changes on player survival in the league. Understanding these dynamics can provide valuable insights into the factors that influence whether a player remains in the league or exits, ultimately shedding light on how team transitions contribute to player longevity in professional basketball.

Table 3.5 Analysis of where players will go after their contracts end

Year	Model sample	Change team	Stay at the same team	Quit
Total	1798	894	354	550
2012-13	236	132	38	66
2013-14	243	132	49	62
2014-15	274	123	74	77
2015-16	275	146	56	73
2016-17	253	121	45	87
2017-18	237	100	43	94
2018-19	280	140	49	91

Notes: This table shows the statistical distribution of players' team selection behaviour after ending their contracts by year. There are a total of three behaviours for players to choose a team after ending their contract. The first is to change teams in the league, the second is to remain with the original team, and the third is to leave the league.

Then, I analyse the competing risks model for three mutually exclusive events throughout a player's career: changing teams, staying with the original team, and leaving the league. Figure 3.2 illustrates the risk associated with each event as a player's career progresses, providing insights into how these competing risks evolve. The plot shows that during the first fifteen years of a player's career, the probability of experiencing each of the three events generally increases with career length. Among these events, the risk of leaving the league is initially the highest, followed by the risk of changing teams, with staying with the original team being the least likely outcome. This pattern persists until the fifteenth year of a player's career, after which the risk of changing teams surpasses the risk of leaving the league, making it the most probable outcome. Beyond the fifteenth year, all three risk probabilities start to decline. These results indicate that players face significant survival risks throughout their careers, with the risk of leaving the league being particularly pronounced in the earlier years. However, as players advance in their careers, changing teams becomes a more familiar and strategic approach to mitigate the risk of leaving the league. This high level of player mobility within the league contributes to prolonging players' careers, highlighting the dynamic relationship between the competing events. The competing risks model effectively captures these shifts in probabilities, illustrating how players navigate different career pathways to maximise their survival in the league.

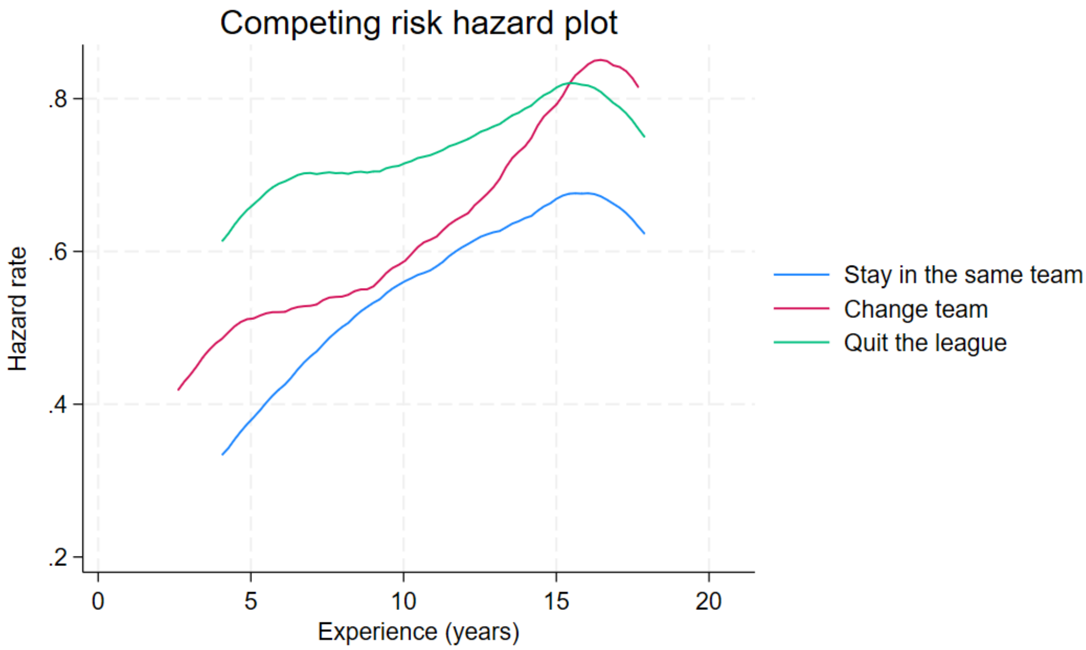

Fig. 3.2 Smoothed hazard estimates

Notes: This figure shows the hazard curves over time for the three-team selection behaviours of players after ending their current contracts.

Next, I examine the relationship between players' team selection behaviour and their survival in the league after the end of their contracts. To accurately study this relationship without introducing bias, I use a competing risks model. Since changing teams inherently implies that a player remains in the league, including team changes as a direct variable in the survival model could lead to biased results. Therefore, the competing risks model is well-suited for this analysis, allowing for a more nuanced examination of the possible outcomes. At the end of their contracts, players face three possible choices: re-signing with their current team, signing with a new team, or leaving the league. In the competing risks model, these three events are treated as distinct outcomes. Formula 3.9 represents how the change in the hazard rate for each main event, compared to the competing event, is influenced by the independent variable. The main events considered are changing teams, staying with the original team, and leaving the league. Each of these events is analysed separately, with the other two treated as competing risks that could prevent the occurrence of the main event. This setup allows me to evaluate how the risk of each specific outcome evolves in the presence of competing alternatives, providing insights into the factors that influence players' decisions at the end of their contracts. By modelling these outcomes simultaneously, I can understand how changes in independent variables impact the likelihood of each possible event, capturing the dynamics of player survival and team selection more comprehensively.

$$\begin{aligned} \frac{h_K(t \mid X)}{h_{K'}(t \mid X)} = \frac{h_{0,K}(t)}{h_{0,K'}(t)} & \exp(\beta_1 \cdot \text{Age} + \beta_2 \cdot \text{Performance} \\ & + \beta_3 \cdot \text{Injury} + \beta_4 \cdot \text{Draft Position} + \beta_5 \cdot \text{Current Contract Info}) \end{aligned} \tag{3.9}$$

Where:

- $h_K(t \mid X)$: Hazard rate for the main event (e.g., changing teams)
- $h_{K'}(t \mid X)$: Hazard rate for the competing event (e.g., staying or leaving the league)
- $h_{0,K}(t)$, $h_{0,K'}(t)$: Baseline hazard rates for events K and K', respectively
- $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$: Coefficients for the covariates
- $K = \{\text{Change, Stay, Leave}\}$: Main event (changing teams, staying, or leaving the league)
- $K' = \{\text{Change, Stay, Leave}\}$: Competing events
- X: Vector of covariates (Age, Performance, Injury, Draft Position, Contract Info)

he first model in Table 3.6 analyses the competing risks of players changing teams after their contracts end, with the main event being team changes. The competing events are leaving the league and staying with the original team. When the competing event is leaving the league, several factors influence the likelihood of a player changing teams rather than exiting the league. Specifically, a player's age, points scored, and free throw percentage all increase the possibility of switching teams instead of leaving. Conversely, a higher win share on the offensive end makes it more likely for players to leave the league. Additionally, players selected in the second round or undrafted are less likely to change teams than those drafted in the top seven. Regarding contract details, a longer current contract duration decreases the likelihood of changing teams, whereas a higher salary increases the probability of switching teams. When the competing event is staying with the original team, factors such as age and scoring also increase the likelihood of a player changing teams. On the other hand, higher win contributions on both offence and defence reduce the probability of switching teams. Second-round and undrafted players are more likely to remain with their original teams compared to those drafted in the top seven. Additionally, a longer contract duration reduces the likelihood of changing teams, while a higher salary increases the chances of both leaving and changing teams.

Table 3.6 Competing risk models(Main event is changing team)

	Competing event Quitting the league	Competing event Staying in the same team	Competing event Both
eq1			
Age	0.11***	0.08***	0.20***
	(0.01)	(0.01)	(0.02)
Points	0.04***	0.03**	0.05***
	(0.01)	(0.01)	(0.02)
Assists	0.02	0.03	0.02
	(0.03)	(0.03)	(0.04)
Steals	-0.06	-0.27	-0.18
	(0.15)	(0.17)	(0.18)
Blocks	-0.03	-0.14	-0.10
	(0.11)	(0.13)	(0.13)
Field goal percentage	0.34	-0.27	0.21
	(0.37)	(0.38)	(0.41)
Free throw percentage	0.34*	-0.35*	0.07
	(0.19)	(0.19)	(0.21)
Three points percentage	0.29	0.06	0.22
	(0.25)	(0.27)	(0.29)
Offensive win shares	-0.07**	-0.10**	-0.10**
	(0.03)	(0.04)	(0.04)
Defensive win shares	0.05	-0.19***	-0.04
	(0.06)	(0.07)	(0.08)
Number of days missed during the season due to injury	0.002	0.001	0.002
	(0.00)	(0.00)	(0.00)
Draft 8 to 14	0.05	-0.09	-0.04
	(0.12)	(0.12)	(0.13)
Draft 15 to 30	-0.10	-0.09	-0.19
	(0.11)	(0.11)	(0.12)
Draft 31 to 44	-0.36***	-0.26*	-0.59***
	(0.13)	(0.13)	(0.15)
Draft 45 tol 60	-0.49***	-0.36**	-0.80***
	(0.16)	(0.16)	(0.18)
Not Draft	-0.48***	-0.28**	-1.07***
	(0.13)	(0.13)	(0.15)
Current contract length	-0.43***	-0.38***	-0.43***
	(0.05)	(0.05)	(0.05)
Log of current salary	0.14***	0.13***	0.21***
	(0.04)	(0.04)	(0.05)
R^2			
N	1,798	1,798	1,798

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents a competing risk model of a player's choice of team behaviour after the end of his current contract. In this model, the main risk is that the player changes teams after the contract ends. The competitive risks are, respectively, players leaving the league, staying with the original team, and both. The results shown in the table represent the coefficients of the hazard function.

The following model is a competing risks model that focuses on the main event of players staying with their original team after their contracts end. The results, presented in Table 3.7, highlight the factors influencing this outcome when compared to the competing events of leaving the league or changing teams. When the competing event is leaving the league, several factors increase the likelihood of a player staying with their original team. These include performance metrics such as steals, blocks, field goal percentage, and free throw percentage, as well as offensive and defensive win contributions. In terms of draft position, players drafted between the eighth and fourteenth spots in the first round are more likely to remain with their original team compared to those drafted in the top seven. However, longer contract length reduces the likelihood of staying with the same team. When the competing event is changing teams, similar factors influence the probability of a player staying with their original team. Age, steals, blocks, field goal percentage, and free throw percentage all increase the chances of staying. Additionally, higher offensive and defensive win shares contribute to a greater probability of remaining with the original team. However, contract details show a different effect: both longer contract lengths and higher salaries reduce the likelihood of a player staying with their original team. Strong player performance—including metrics such as scoring, steals, blocks, field goal percentage, free throw percentage, and win contributions on both offence and defence—increases the probability of a player staying with their original team. Conversely, players drafted in the second round or undrafted are less likely to stay compared to top-seven picks. Moreover, longer contract terms tend to decrease the likelihood of a player staying with their original team. These results provide insights into the factors that influence player retention by their original team, highlighting the impact of performance, draft position, and contract characteristics on career decisions.

Table 3.7 Competing risk models(Main event is staying in the same team)

	Competing event Quitting the league	Competing event Changing in the league	Competing event Both
eq1			
Age	-0.0003	0.17***	0.24***
	(0.02)	(0.02)	(0.02)
Points	0.02	0.02	0.04*
	(0.02)	(0.02)	(0.02)
Assists	-0.01	-0.01	-0.02
	(0.04)	(0.04)	(0.04)
Steals	0.44***	0.45***	0.43**
	(0.16)	(0.17)	(0.18)
Blocks	0.20*	0.26**	0.24**
	(0.12)	(0.12)	(0.12)
Field goal percentage	1.53***	1.16**	1.42***
	(0.48)	(0.53)	(0.52)
Free throw percentage	1.32***	0.74**	1.01***
	(0.31)	(0.36)	(0.34)
Three points percentage	0.47	0.26	0.46
	(0.33)	(0.37)	(0.37)
Offensive win shares	0.08**	0.09**	0.07*
	(0.04)	(0.04)	(0.04)
Defensive win shares	0.38***	0.34***	0.43***
	(0.08)	(0.08)	(0.09)
Number of days missed during the season due to injury	-0.0004	-0.001	-0.001
	(0.00)	(0.00)	(0.00)
Draft 8 to 14	0.27*	0.14	0.17
	(0.16)	(0.18)	(0.19)
Draft 15 to 30	0.04	-0.13	-0.20
	(0.16)	(0.17)	(0.18)
Draft 31 to 44	-0.09	-0.33	-0.58***
	(0.19)	(0.20)	(0.22)
Draft 45 to 60	0.13	-0.16	-0.47**
	(0.21)	(0.22)	(0.24)
Not Draft	0.09	-0.64***	-1.17***
	(0.21)	(0.21)	(0.23)
Current contract length	-0.36***	-0.26***	-0.28***
	(0.06)	(0.07)	(0.07)
Log of current salary	-0.08	-0.12**	-0.06
	(0.05)	(0.06)	(0.06)
R^2			
N	1,798	1,798	1,798

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents a competing risk model of a player's choice of team behaviour after the end of his current contract. In this model, the main risk is that the player stays in the original team after the contract ends. The competitive risks are, respectively, players leaving the league, changing the teams in the league and both. The results shown in the table represent the coefficients of the hazard function.

This competing risks model focuses on the main event of a player leaving the league after their contract ends. The results are presented in Table 3.8, highlighting the factors that influence the likelihood of this outcome compared to the competing events of changing teams or staying with the original team. When the competing event is changing teams, a player's age significantly increases the likelihood of leaving the league. Conversely, better player performance reduces this likelihood, with higher scores, assists, and offensive and defensive win contributions decreasing the probability of leaving the league. Additionally, longer contract lengths lower the chances of a player leaving. When the competing event is staying with the original team, age again raises the likelihood of leaving the league, while strong performance—including higher scores, free throw percentage, and win contributions—reduces this risk. On the other hand, injuries increase the probability of leaving the league, as does an increase in contract length. Considering both competing events, the results show that strong player performance, particularly in terms of offensive and defensive win contributions, plays a crucial role in reducing the likelihood of leaving the league. However, injuries are a significant factor that increases the probability of departure. Regarding contract information, more extended contracts tend to decrease the likelihood of leaving, whereas higher salaries are associated with an increased risk of leaving. These findings provide insights into the key factors affecting a player's decision to leave the league, emphasising the importance of performance, health, and contract characteristics.

Table 3.8 Competing risk models(Main event is quitting the league)

	Competing event Changing team in the league	Competing event Staying in the same team	Competing event Both
eq1			
Age	0.32***	0.10***	0.37***
	(0.02)	(0.02)	(0.02)
Points	-0.05*	-0.06**	-0.03
	(0.03)	(0.02)	(0.03)
Assists	-0.13*	-0.07	-0.19**
	(0.06)	(0.06)	(0.08)
Steals	-0.01	-0.03	-0.05
	(0.21)	(0.18)	(0.24)
Blocks	-0.02	-0.12	-0.17
	(0.18)	(0.16)	(0.25)
Field goal percentage	0.25	0.19	0.18
	(0.35)	(0.23)	(0.37)
Free throw percentage	-0.15	-0.35***	-0.26
	(0.18)	(0.13)	(0.20)
Three points percentage	-0.18	-0.23	-0.17
	(0.29)	(0.24)	(0.33)
Offensive win shares	-0.73***	-0.68***	-0.81***
	(0.11)	(0.10)	(0.12)
Defensive win shares	-0.61***	-0.78***	-0.68***
	(0.16)	(0.15)	(0.17)
Number of days missed during the season due to injury	0.004	0.005**	0.005*
	(0.00)	(0.00)	(0.00)
Draft 8 to 14	-0.22	-0.10	-0.28
	(0.21)	(0.18)	(0.23)
Draft 15 to 30	-0.10	-0.01	-0.22
	(0.17)	(0.15)	(0.18)
Draft 31 to 44	-0.07	0.20	-0.33
	(0.19)	(0.16)	(0.21)
Draft 45 to 60	-0.40*	0.04	-0.68***
	(0.21)	(0.18)	(0.22)
Not Draft	-1.03***	-0.24	-1.46***
	(0.19)	(0.16)	(0.19)
Current contract length	-0.24***	-0.25***	-0.25***
	(0.07)	(0.06)	(0.08)
Log of current salary	0.06	0.01	0.10**
	(0.05)	(0.03)	(0.05)
R^2			
N	1,798	1,798	1,798

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents a competing risk model of a player's choice of team behaviour after the end of his current contract. In this model, the main risk is that the player quits the league after the contract ends. The competitive risks are, respectively, changing the teams in the league, staying in the original team and both. The results shown in the table represent the coefficients of the hazard function.

To further understand the impact of changing teams on player survival, I analyse the competing risks model using three main events: changing teams, staying with the original team, and leaving the league. The competing events for each main event are the other two outcomes, allowing for a clearer understanding of the factors influencing players' decisions after their contracts end. The results are presented in Table 3.9. Age is found to play a significant role, as older players are more likely to experience any of the three outcomes, indicating that competition intensifies as players age. Regarding player performance, scoring tends to facilitate players changing teams while scoring, steals, blocks, shooting percentage, and free throw percentage all contribute to players remaining with their original teams. Assists have a positive impact on survival in the league by reducing the risk of leaving. Offensive and defensive win shares reveal notable differences in player behaviour after contracts expire. Higher win shares increase the probability of remaining in the league, especially with the original team. Interestingly, better offensive performance decreases the likelihood of changing teams, suggesting that solid offensive contributions lead players to stay with their current team after contract expiration. Regarding contract characteristics, longer contracts reduce the likelihood of any of the three outcomes, indicating that players with long-term contracts have more stability and flexibility. In terms of salary, higher salaries increase the chances of both changing teams and leaving the league, highlighting the role of salary expectations in decision-making after contracts end. The results from the competing risks model provide valuable insights into the factors influencing players' decisions at the end of their contracts. Age, performance metrics, and contract details all play crucial roles in shaping players' career paths, affecting whether they change teams, stay with their original teams, or leave the league altogether.

Table 3.9 Competing risk models(Combined)

	Main event Changing the team	Main event Staying the same team	Main event Quitting the league
eq1			
Age	0.20***	0.24***	0.37***
	(0.02)	(0.02)	(0.02)
Points	0.05***	0.04*	-0.03
	(0.02)	(0.02)	(0.03)
Assists	0.02	-0.02	-0.19**
	(0.04)	(0.04)	(0.08)
Steals	-0.18	0.43**	-0.05
	(0.18)	(0.18)	(0.24)
Blocks	-0.10	0.24**	-0.17
	(0.13)	(0.12)	(0.25)
Field goal percentage	0.21	1.42***	0.18
	(0.41)	(0.52)	(0.37)
Free throw percentage	0.07	1.01***	-0.26
	(0.21)	(0.34)	(0.20)
Three points percentage	0.22	0.46	-0.17
	(0.29)	(0.37)	(0.33)
Offensive win shares	-0.10**	0.07*	-0.81***
	(0.04)	(0.04)	(0.12)
Defensive win shares	-0.04	0.43***	-0.68***
	(0.08)	(0.09)	(0.17)
Number of days missed during the season due to injury	0.002	-0.001	0.005*
	(0.00)	(0.00)	(0.00)
Draft 8 to 14	-0.04	0.17	-0.28
	(0.13)	(0.19)	(0.23)
Draft 15 to 30	-0.19	-0.20	-0.22
	(0.12)	(0.18)	(0.18)
Draft 31 to 44	-0.59***	-0.58***	-0.33
	(0.15)	(0.22)	(0.21)
Draft 45 to 60	-0.80***	-0.47**	-0.68***
	(0.18)	(0.24)	(0.22)
Not Draft	-1.07***	-1.17***	-1.46***
	(0.15)	(0.23)	(0.19)
Current contract length	-0.43***	-0.28***	-0.25***
	(0.05)	(0.07)	(0.08)
Log of current salary	0.21***	-0.06	0.10**
	(0.05)	(0.06)	(0.05)
R^2			
N	1,798	1,798	1,798

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table is a comprehensive display of the above competitive risk model, and the main event of each column is the column name That is, the first column is changing the team, the second column is staying in the original team, and the third column is leaving the league. The competing events in each column are the other two events except the main event. The above results have been shown in the above tables. Putting the three together can more intuitively observe the impact on the player's behaviours after the end of the contract.

3.5.4 The impact of player options on player survival

In this section, I begin exploring the potential impact of player options on player survival in the league. To determine whether players with a player option differ significantly from those without, I first conduct a t-test analysis to assess the homogeneity of these two groups across key variables related to player survival. This preliminary analysis helps identify any significant differences between players with and without player options in their contracts, laying the groundwork for subsequent survival model analysis. Table 3.10 presents the t-test results for key variables between two groups: players with player options in their current contracts and those without. In terms of sample size, the majority of players do not have player options in their contracts (1,610 players), while only 188 players have contracts with player options. The comparison of average values reveals that players with player options consistently exhibit superior performance across all variables affecting player survival, including offensive and defensive win contributions, which significantly impact survival rates. Furthermore, players with player options also tend to have higher salaries and longer contract lengths compared to those without. The t-test analysis indicates significant differences in both performance and contract characteristics between players with and without player options. To address these differences and minimise heterogeneity between the two groups, I employ a matching process to pair players with player options to those without on a one-to-one basis. This matching aims to reduce differences in key variables as much as possible, allowing for a more accurate assessment of the impact of player options on player survival in the subsequent survival model analysis.

Table 3.10 T-Test analysis of player variables based on the inclusion of a player option(Whole sample)

	Contract without player option		Contract with player option				
Variables	Count	Mean	Count	Mean	Difference	Standard error	P Value
Age	1610	26.90	188	28.59	-1.69	0.33	4.37e-07
Points	1610	6.18	188	11.52	-5.34	0.37	1.00e-45
Assists	1610	1.45	188	2.37	-.92	0.12	7.28e-15
Steals	1610	0.52	188	0.80	-0.28	0.03	6.46e-21
Blocks	1610	0.31	188	0.51	-0.20	0.03	4.29e-11
Field goal percentage	1610	0.42	188	0.46	-0.05	0.01	7.49e-06
Free throw percentage	1610	0.66	188	0.75	-0.09	0.02	1.88e-06
Three points percentage	1610	0.24	188	0.30	-0.05	0.01	0.0001
Offensive win shares	1610	0.71	188	2.38	-1.67	0.11	5.72e-49
Defensive win shares	1610	0.76	188	1.72	-0.96	0.07	1.62e-43
Injury absent days	1610	6.13	188	12.63	-6.50	1.26	2.72e-07
Current contract length	1610	2.17	188	3.09	-0.92	0.10	3.15e-21
Log of current salary	1610	14.70	188	16.57	-1.87	0.13	4.88e-43
Observations	1798						

Notes: This table presents the t-test analysis of all spells in the survival model, grouped by the presence of player options. There are 1,610 spells without player options and 188 spells with player options.

To implement the matching process for comparing players with and without player options in their contracts, it is crucial to first identify the variables that influence the presence of a player option. To achieve this, I employ a logistic regression model, using a stepwise approach to retain only those variables with a p-value less than 0.1 in the final model. In this model, the dependent variable is whether the player has a player option in their next contract, and the player's current performance is assumed to drive the likelihood of having a player option in future contracts. After screening the variables, the remaining ones are grouped into three categories: the player's performance metrics, the player's age, and the player's current and upcoming contract information. The formula for the logistic regression model is represented by Formula 3.10.

$$\text{Logit}(\text{Option in Future Contract}) = \beta_0 + \beta_1 \cdot \text{Performance} + \beta_2 \cdot \text{Age} + \beta_3 \cdot \text{Contract Info} \tag{3.10}$$

I estimate the logistic regression model based on the selected variables to calculate the propensity score for each player. The propensity score represents the likelihood of a player having a player option, given the identified variables. Table 3.11 presents the logistic regression results. Using these propensity scores, I match each player with a player option to a player without one using one-to-one matching, pairing those with the closest scores. This matching process helps address the heterogeneity between the two groups, ensuring that differences in variables are minimised, thereby allowing for a more accurate comparison between players with and without player options. This approach ultimately helps to isolate the impact of player options on player survival by balancing the characteristics of the two groups.

Table 3.11 Logistic regression for estimating player options on next contract

	(1) A player option in future contract
Games played	0.01*
	(0.01)
Game started	-0.01**
	(0.01)
Minutes played	0.11***
	(0.03)
Offensive rebounds	-0.89***
	(0.22)
Three points filed goal	-0.97***
	(0.23)
Personal fouls	0.56***
	(0.21)
Assists tendency	-1.18***
	(0.31)
Value over replacement player	0.62***
	(0.14)
Field goal on which the player is fouled	-0.03*
	(0.01)
Age	-0.11***
	(0.03)
Contract length in current contract	-0.46***
	(0.14)
Log of current contract salary	0.34***
	(0.12)
Contract length in future contract	0.32*
	(0.17)
Log of total salary in future contract	0.26***
	(0.07)
Cons	-9.13***
	(1.71)
R^2	
N	1,798

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: this table estimates the determinants of player options included in future contracts via logistic regression. In the process of selecting variables, the backward stepwise selection method is used, leaving variables that are statistically significant below 10% in the model.

After completing the matching process, I conduct a t-test to evaluate the quality of the matched sample. Table 3.12 presents the t-test results for the matched sample. Since the matching is performed using a one-to-one process, both groups now contain an equal number of observations—188 players each. Starting with player characteristics such as age, scoring, assists, steals, blocks, and shooting percentage, there are no significant differences between the two groups, suggesting that the matching process effectively balances these key variables across both groups. Examining advanced metrics, such as players' win contributions, reveals that the defensive win contribution values for both groups are also similar, with no significant differences. However, a noticeable difference remains in offensive win contribution, which is significant at the 10% level. This suggests that while the matching process generally performs well, it has limitations in balancing players based on offensive win contributions. This result may be attributed to some superstars with exceptionally high offensive performance having player options, making it challenging to find perfectly comparable players without options. Another area where the two groups differ significantly is in injury data. This discrepancy is likely due to incomplete injury records, as only major absences involving significant playing time are thoroughly documented. Consequently, a considerable gap remains between the two groups regarding injury statistics. Finally, when examining players' contract information, there are no significant differences between the two groups in terms of contract length or salary, indicating that the matching process successfully balances contract-related variables. The t-test results suggest that the matching process largely succeeds in balancing key performance, contract, and demographic variables between players with and without player options. However, some disparities, particularly in offensive win contribution and injury data, still persist.

Table 3.12 T-Test analysis of player variables based on the inclusion of a player option(Matched sample)

	Contract without player option		Contract with player option				
Variables	Count	Mean	Count	Mean	Difference	Standard error	P Value
Age	188	28.91	188	28.59	0.32	0.42	0.44
Points	188	10.40	188	11.52	-1.12	0.63	0.07
Assists	188	2.31	188	2.37	-0.06	0.20	0.74
Steals	188	0.78	188	0.80	-0.02	0.04	0.61
Blocks	188	0.56	188	0.51	0.04	0.05	0.38
Field goal percentage	188	0.46	188	0.46	-0.003	0.01	0.62
Free throw percentage	188	0.75	188	0.75	-0.0001	0.01	0.99
Three point percentage	188	0.29	188	0.30	-0.01	0.01	0.53
Offensive win shares	188	1.99	188	2.38	-0.39	0.23	0.09
Defensive win shares	188	1.80	188	1.72	0.07	0.11	0.52
Injury absent days	188	7.66	188	12.63	-4.97	2.01	0.01
Current contract length	188	3.02	188	3.09	-0.07	0.14	0.59
Log of current salary	188	16.36	188	16.57	-0.21	0.13	0.11
Observations	376						

Notes: This table presents the t-test statistical results for the matched samples after the matching process. All 188 spells with player options are matched one-to-one with 188 spells without player options.

Following the assessment of the quality of the matching process, I proceed to examine the impact of player options on player survival using a Cox proportional hazards model. This analysis builds on the previous exploration of player selection and contract dynamics, now specifically incorporating whether a player has a player option in their current contract. The model includes key variables such as player performance, injury history, draft position, and contract details, and is represented by Formula 3.11.

$$\begin{aligned} h(t \mid X) = h_0(t) \exp \big(&\beta_1 \cdot \text{Age} + \beta_2 \cdot \text{Performance} + \beta_3 \cdot \text{Injury} \\ &+ \beta_4 \cdot \text{Draft Position} + \beta_5 \cdot \text{Contract Info}\big) \end{aligned} \tag{3.11}$$

Table 3.13 presents the results of the Cox model for player options in the survival analysis, estimating survival risk based on both the entire sample and the matched sample. In the entire sample, the results show that improved player performance—measured through points, free throw percentage, and offensive and defensive win contributions—significantly reduces the risk of a player leaving the league. Additionally, longer contract legnths are associated with a lower survival risk. However, the inclusion of a player option in the contract shows a reduction in survival risk, though this effect is not statistically significant. In the matched sample, more performance indicators are found to contribute to reducing survival risk, including points, steals, blocks, and offensive win contributions. However, defensive win contributions become insignificant in the matched sample. Interestingly, the presence of a player option slightly increases the risk of a player leaving the league, though this result is also not statistically significant. The results suggest that player performance and contract duration are key factors influencing player survival in the league, while the presence of a player option has a minimal and statistically insignificant impact on survival outcomes in both the entire and matched samples. This analysis provides valuable insights into the relationship between contract features and player longevity, particularly in the context of player options.

Table 3.13 The Impact of Player Special Options on Player Survival (Cox Model)

	Cox Model Whole Sample	Cox Model Matched Sample
Age	-0.04	-0.46***
	(0.02)	(0.15)
Points	-0.06***	-0.19***
	(0.02)	(0.07)
Assists	-0.03	0.29**
	(0.05)	(0.14)
Steals	-0.09	-2.07***
	(0.16)	(0.74)
Blocks	0.01	-1.83**
	(0.09)	(0.76)
Field goal percentage	0.17	7.10***
	(0.21)	(2.70)
Free throw percentage	-0.24**	1.87
	(0.12)	(1.52)
Three points percentage	-0.25	-0.45
	(0.21)	(1.23)
Offensive win shares	-0.59***	-0.61**
	(0.09)	(0.27)
Defensive win shares	-0.64***	0.001
	(0.14)	(0.33)
Number of days missed due to injury	0.004	-0.004
	(0.00)	(0.01)
Draft 8 to 14	0.01	-0.95**
	(0.15)	(0.40)
Draft 15 to 30	0.15	-0.30
	(0.14)	(0.43)
Draft 31 to 44	0.53***	0.07
	(0.14)	(0.45)
Draft 45 to 60	0.45***	-0.12
	(0.16)	(0.67)
Not Drafted	0.35**	-0.39
	(0.16)	(0.60)
Current contract length	-0.25***	-0.02
	(0.05)	(0.20)
Log of current salary	-0.02	-0.19
	(0.03)	(0.33)
Player options in current contract	-0.04	0.29
	(0.17)	(0.35)
R^2		
N	1,798	376

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table estimates the impact of player options on player survival using the Cox model. The first column includes the whole sample, while the second column uses the matched sample based on whether the player has options in their contract. The coefficients shown represent the hazard function estimates.

Following the Cox model analysis, I apply a parametric survival model with a log-normal distribution to further investigate the impact of player options on player survival. The model is represented by Formula 3.12, and the results are presented in Table 3.14.

$$S(t \mid X) = 1 - \Phi\left(\frac{\ln(t) - \mu(X)}{\sigma}\right)$$
$$\mu(X) = \beta_0 + \beta_1 \cdot \text{Age} + \beta_2 \cdot \text{Performance} + \beta_3 \cdot \text{Injury} + \beta_4 \cdot \text{Draft Position} + \beta_5 \cdot \text{Contract Info} \tag{3.12}$$

In the entire sample, the performance variables influencing player survival are consistent with those found in the Cox model, including scoring, free throw percentage, and three-point shooting percentage. Additionally, both offensive and defensive win contributions are significant in increasing survival time. When considering contract-related factors, variables such as contract length, salary, and the presence of a player option contribute positively to longer survival times. Longer contracts, often associated with higher salaries, directly extend players' careers. Interestingly, the presence of a player option is not exclusive to high-salary or long-term contracts, indicating that player options themselves may have some positive effect on survival time, albeit to a limited extent. In the matched sample, improved performance metrics, including steals, blocks, and contributions to team victories, significantly extend survival time. However, contract-related factors, such as contract length and salary, do not significantly affect survival time in this subset of players. Although the inclusion of a player option appears to slightly extend survival time, this effect remains statistically insignificant in the matched sample as well. The parametric log-normal model results align closely with the Cox model, highlighting that player performance is a critical determinant of survival in the league. While contract details, including player options, appear to have a positive impact on career longevity, their effects are not statistically significant, particularly in the matched sample. This suggests that player performance continues to be the most consistent factor influencing player survival, whereas the role of player options requires further examination.

Table 3.14 The impact of player special options on player survival(Log-normal model)

	Log-normal model Whole sample	Log-normal model Matched sample
_t		
Age	-0.01	0.03
	(0.01)	(0.03)
Points	0.05***	0.03
	(0.02)	(0.03)
Assists	0.02	-0.13
	(0.04)	(0.08)
Steals	-0.04	0.84**
	(0.12)	(0.41)
Blocks	0.06	0.56*
	(0.08)	(0.30)
Field goal percentage	-0.24	-0.44
	(0.18)	(0.95)
Free throw percentage	0.30***	0.57
	(0.10)	(0.75)
Three point percentage	0.34*	0.48
	(0.18)	(0.52)
Offensive win shares	0.34***	0.21**
	(0.08)	(0.09)
Defensive win shares	0.43***	0.05
	(0.08)	(0.10)
Number of days missed during the season due to injury	-0.001	0.003
	(0.00)	(0.00)
Draft 8 to 14	0.21*	0.27
	(0.13)	(0.19)
Draft 15 to 30	-0.02	0.21
	(0.12)	(0.16)
Draft 31 to 44	-0.30**	0.004
	(0.12)	(0.17)
Draft 45 to 60	-0.31**	-0.09
	(0.14)	(0.25)
Not Draft	-0.32**	-0.11
	(0.12)	(0.22)
Current contract length	0.07*	-0.02
	(0.04)	(0.08)
Log of current salary	0.06**	0.14
	(0.03)	(0.09)
Player options in current contract	0.31**	0.05
	(0.13)	(0.12)
_cons	-0.22	-2.14
	(0.42)	(1.48)
/		
lnsigma	-0.56***	-0.83***
	(0.03)	(0.26)
R^2		
N	1,798	376

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table estimates the impact of player options on player survival using the parametric survival model of the log-normal distribution. The first column includes the whole sample, while the second column uses the matched sample based on whether the player has options in their contract. The results shown in the table represent the coefficients of the natural logarithm of the player's survival time

After analysing the impact of player options on player survival, I proceed to explore how player options influence player behaviour after contract expiration using a competing risks model. This model helps examine three possible outcomes: changing teams, staying with the original team, and leaving the league. The model is represented by Formula 3.13 and aims to provide a detailed understanding of the factors affecting post-contract decisions.

$$\begin{aligned}\frac{h_K(t \mid X)}{h_{K'}(t \mid X)} = \frac{h_{0,K}(t)}{h_{0,K'}(t)} \exp\big(&\beta_1 \cdot \text{Age} + \beta_2 \cdot \text{Performance} + \beta_3 \cdot \text{Injury} \\ &+ \beta_4 \cdot \text{Draft Position} + \beta_5 \cdot \text{Current Contract Info} + \beta_6 \cdot \text{Player Option}\big)\end{aligned} \tag{3.13}$$

Where:

- $h_K(t \mid X)$: Hazard rate for the main event (e.g., changing teams)
- $h_{K'}(t \mid X)$: Hazard rate for the competing event (e.g., staying or leaving the league)
- $h_{0,K}(t)$, $h_{0,K'}(t)$: Baseline hazard rates for events K and K', respectively
- $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5 \beta_6$: Coefficients for the covariates
- $K = \{\text{Change, Stay, Leave}\}$: Main event (changing teams, staying, or leaving the league)
- $K' = \{\text{Change, Stay, Leave}\}$: Competing events
- X: Vector of covariates (Age, Performance, Injury, Draft Position, Contract Info, Player option)

Table 3.15 outlines the results of this model. In the first column, where the main risk is the player changing teams (with staying in the original team and leaving the league as the competing risks), player performance plays a key role. Specifically, a player's scoring increases the likelihood of changing teams, while offensive win contributions reduce it. Regarding contract factors, a longer contract duration decreases the probability of changing teams, whereas higher salaries and the presence of a player option increase the likelihood of switching teams. Including a player option allows players to move to a new team at the end of their contract. When the main risk is staying with the original team, several performance variables, including scoring, steals, blocks, field goal percentage, free throw percentage, and defensive win contributions, increase the likelihood of remaining with the current team. However, contract length decreases the probability of staying with the original team, and the impact of player options in this scenario is not statistically significant. Lastly, when the primary risk is leaving the league, assists, offensive win contributions and defensive win contributions lower the likelihood of a player leaving. A longer contract duration also reduces the risk of leaving the league, while higher salaries increase it. Contract factors are crucial in shaping players' decisions after contract expiration. While longer contracts are associated with higher retention in the league, increased salary tends to raise the chances of both leaving and changing teams. Player options specifically increase the likelihood of players opting to change teams, offering them strategic control over their career trajectory at the end of a contract. The competing risks model reveals that player performance, contract details, and the presence of player options are key factors in post-contract decisions. While player options enhance flexibility, enabling players to change teams more easily, their influence varies depending on the specific post-contract outcome being considered. This analysis highlights the strategic importance of player options in influencing player movement within the league.

Table 3.15 Impact of player option in competing risks model(Whole sample)

	Main event Changing the team	Main event Staying the same team	Main event Quitting the league
eq1			
Age	0.20***	0.24***	0.37***
	(0.02)	(0.02)	(0.02)
Points	0.05***	0.04*	-0.03
	(0.02)	(0.02)	(0.03)
Assists	0.02	-0.03	-0.19**
	(0.04)	(0.04)	(0.08)
Steals	-0.18	0.44**	-0.05
	(0.18)	(0.17)	(0.24)
Blocks	-0.10	0.24**	-0.17
	(0.13)	(0.12)	(0.25)
Field goal percentage	0.21	1.40***	0.18
	(0.41)	(0.52)	(0.37)
Free throw percentage	0.10	1.03***	-0.26
	(0.21)	(0.34)	(0.20)
Three points percentage	0.20	0.45	-0.17
	(0.29)	(0.37)	(0.33)
Offensive win shares	-0.11***	0.07	-0.81***
	(0.04)	(0.04)	(0.12)
Defensive win shares	-0.04	0.43***	-0.68***
	(0.08)	(0.08)	(0.17)
Number of days missed during the season due to injury	0.00	-0.00	0.00*
	(0.00)	(0.00)	(0.00)
Draft 8 to 14	-0.01	0.17	-0.28
	(0.13)	(0.19)	(0.23)
Draft 15 to 30	-0.17	-0.20	-0.22
	(0.12)	(0.18)	(0.18)
Draft 31 to 44	-0.57***	-0.58***	-0.33
	(0.15)	(0.22)	(0.21)
Draft 45 to 60	-0.79***	-0.47**	-0.68***
	(0.18)	(0.24)	(0.22)
Not Draft	-1.06***	-1.18***	-1.46***
	(0.15)	(0.23)	(0.19)
Current contract length	-0.43***	-0.29***	-0.25***
	(0.05)	(0.07)	(0.08)
Log of current salary	0.19***	-0.07	0.10**
	(0.05)	(0.06)	(0.05)
Player options in current contract	0.35***	0.15	0.01
	(0.13)	(0.17)	(0.22)
R^2			
N	1,798	1,798	1,798

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table estimates the impact of player options on player's team selection behaviour after ending their current contract. Using the entire sample in this model, the main risk in the first column is the player leaving the original team, and the competing events are the other two events. In the same way, the main risk in the second column is that the player stays with the original team, and the main risk in the third column is that the player leaves the league. The results shown in the table represent the coefficients of the hazard function.

Building on the results of the competing risks model for the entire sample, I next use the matched sample to estimate the impact of player options on players' decisions after their contracts expire. Table 3.16 presents the competing risk model results under this matched sample, allowing for comparing findings between the matched and full samples. When the primary risk is the player changing teams (with staying with the original team and leaving the league as competing risks), the results show that offensive win contributions reduce the likelihood of changing teams. For contract information, longer contract duration lowers the chances of changing teams, while higher salaries and the presence of a player option increase the likelihood of a team change, consistent with the full sample results. When the main risk is staying with the original team, the only significant performance variable is steals, with a higher steal rate increasing the likelihood of staying. For contract-related factors, both longer contract duration and higher salaries decrease the possibility of remaining with the original team, aligning with the results from the full sample. Lastly, when the primary risk is leaving the league, the player's offensive win contributions significantly decrease the likelihood of leaving, similar to the full sample findings. However, in the matched sample, contract-related variables, including the presence of player options, do not show a statistically significant impact on a player's decision after their contract expires. The matched sample analysis suggests that player options are more likely to influence decisions about changing teams rather than remaining with the original team or leaving the league. These findings align with the results from the full sample in several respects but also highlight differences, particularly in the role of offensive win contributions and the significance of contract factors. This comparison provides a deeper understanding of the nuanced impact of player options on career decisions post-contract.

Table 3.16 Impact of player option in competing risks model(Matched sample)

	Main event Changing the team	Main event Staying the same team	Main event Quitting the league
eq1			
Age	0.17***	0.32***	0.35***
	(0.03)	(0.03)	(0.05)
Points	0.05	0.04	-0.12
	(0.03)	(0.03)	(0.08)
Assists	-0.06	-0.01	0.13
	(0.07)	(0.07)	(0.20)
Steals	-0.47	1.13***	-1.13
	(0.32)	(0.31)	(1.02)
Blocks	0.05	0.20	-0.73
	(0.23)	(0.29)	(0.85)
Field goal percentage	1.04	1.98	1.25
	(1.59)	(1.77)	(3.60)
Free throw percentage	1.03	0.57	-1.78
	(0.98)	(1.27)	(1.59)
Three points percentage	0.20	0.99	-0.76
	(0.80)	(0.94)	(1.63)
Offensive win shares	-0.13**	0.03	-0.58*
	(0.07)	(0.06)	(0.35)
Defensive win shares	0.01	0.18	-0.40
	(0.12)	(0.13)	(0.41)
Number of days missed during the season due to injury	-0.01	0.01*	0.00
	(0.00)	(0.00)	(0.01)
Draft 8 to 14	0.08	0.10	-1.05*
	(0.23)	(0.30)	(0.60)
Draft 15 to 30	0.12	-0.46*	-0.53
	(0.20)	(0.27)	(0.45)
Draft 31 to 44	0.05	-0.84**	0.01
	(0.27)	(0.36)	(0.53)
Draft 45 to 60	-0.64*	-0.68**	-0.27
	(0.34)	(0.31)	(0.71)
Not Draft	-0.64*	-1.46***	-1.60***
	(0.36)	(0.49)	(0.55)
Current contract length	-0.36***	-0.28**	0.17
	(0.11)	(0.12)	(0.19)
Log of current salary	0.30**	-0.33**	0.10
	(0.14)	(0.15)	(0.20)
Player options in current contract	0.34**	-0.25	0.08
	(0.15)	(0.19)	(0.38)
R^2			
N	376	376	376

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table estimates the impact of player options on player's team selection behaviour after ending their current contract. Using the matched sample in this model, the main risk in the first column is the player leaving the original team, and the competing events are the other two events. In the same way, the main risk in the second column is that the player stays with the original team, and the main risk in the third column is that the player leaves the league. The results shown in the table represent the coefficients of the hazard function.

3.6 Conclusion

This chapter concludes by exploring how player performance affects survival in the NBA, the impact of team selection behaviour post-contract, and the role of special contract clauses, such as player options, in influencing career trajectories. The league continuously seeks talented players and replaces underperformers to enhance team performance. Through analysing different samples, including first-round rookie players, rookie players, and the entire dataset, it becomes evident that player performance is crucial in determining career longevity. The findings indicate that a high shooting percentage does not necessarily equate to outstanding player performance, as simple shots with minimal defensive pressure may inflate shooting statistics. Instead, a player's victory contributions on both offensive and defensive ends significantly reduce the risk of leaving the league, particularly as sample sizes increase. A one-point increase in a player's offensive win contribution reduces the risk of leaving the league by 46% and increases survival time by 43%. Similarly, a one-point increase in defensive contribution reduces the risk of leaving by 59% and extends survival time by 75%. These findings highlight the critical role of both offensive and defensive performance in enhancing a player's career longevity. Performance metrics such as points, defensive win contributions, and steals further improve survival chances. Age, however, has a variable impact: older players on rookie contracts face a higher risk of leaving the league, whereas increased age in the later stages of a career often reflects valuable experience. Draft position also affects survival, with players selected in the first seven picks more likely to remain in the league than players selected later in the draft. Injuries primarily affect survival during the first-round rookie contracts, while in other samples, the impact is negligible due to advances in sports medicine.

This chapter also examines the impact of players' team selection behaviours after contract expiration. Players either stay with their original team, join other teams, or leave the league. The study reveals that exceptional performance prompts teams to retain players, especially those contributing to victory through steals, shooting efficiency, and defensive effort. Interestingly, higher salaries in current contracts are associated with a greater likelihood of players leaving their team, possibly due to the financial constraints of retaining high-salary players. When comparing the behaviours of players switching teams and quitting the league, player performance is a critical factor in remaining in the league, with strong defensive contributions and moderate offensive abilities leading to greater team interest. Salary also influences decisions, as well-paid players appeal more to other teams.

The third area explored is the impact of including special player options in contracts on player survival. Performance remains the primary determinant of survival, while factors like draft position and player options also play important roles. Having a player option in a contract increases the likelihood of changing teams, thereby enhancing flexibility in career decisions. However, the presence of player options does not significantly impact survival probability. In summary, a player's survival in the league is primarily determined by their performance, particularly through victory contributions on both offence and defence. Players who can secure second employment opportunities by changing teams often possess certain traits: they may be functional players who contribute defensively or possess shooting efficiency, young players with untapped potential, or individuals signed to short-term high-paying contracts. Finally, while player options provide flexibility in post-contract decisions, they do not significantly influence overall survival chances.

This chapter also acknowledges several limitations in the analysis. One limitation is the absence of race-related data, which could enhance the explanatory power of the survival model but was excluded due to data reliability concerns. Future research should address this gap to provide a more comprehensive understanding of factors influencing player survival. Additionally, other factors, such as family considerations, market influences, and state tax policies, may also affect players' decisions to change teams, yet these aspects were not explored in-depth due to data limitations. Lastly, the relatively small proportion of players with special clauses in their contracts and some imperfections in the matching process may have affected the accuracy of estimating the impact of player options. Future studies should aim to collect more data to overcome these limitations and refine the analysis further.

Conclusion

Summary of findings

In this study, I independently collected a data set that meets the standards for studying labour economics. The data set contains seven years of NBA data from 2012 to 2018, which includes player information, player performance, player salary, player contract and team information. This data can measure player performance in many aspects, accurately measure player salary, and describe player contracts in detail. The advantages of this data set help me explore the impact of contractual arrangements on player performance, salary, and survival.

This thesis verifies the contract year phenomenon but does not reach a consistent conclusion regarding shirking behaviour after the contract year, aligning with existing literature. The study extends existing salary models by incorporating contract information, enriching the model and improving its explanatory power. It also explores the value of special options in contracts and quantifies their impact on players of varying strengths, highlighting salary discrimination against lower-strength players—a finding that should attract policymakers' attention. Additionally, this research examines the impact of contractual arrangements on player survival. Player performance is identified as the primary factor determining survival, with high-performing players more likely to be retained by their original teams. Team selection after contract expiration is influenced by multiple factors, including age, performance, and salary requirements. This thesis provides a comprehensive analysis of how player performance and contractual arrangements interact, impacting both salary and career longevity. Below is a detailed description of the results of each chapter.

This first chapter has explored the impact of contract timing on NBA player performance using both basic and advanced statistical analyses. The findings reveal a complex relationship between contract status and player performance, particularly highlighting the significance of the contract year phenomenon and subsequent changes in performance after signing a new contract.

The analysis shows that players do not significantly reduce their performance after signing a new contract based on basic performance metrics. Notably, players tend to increase their three-point shooting percentage after securing a new contract, suggesting a preference for simpler, less physically demanding plays. However, advanced metrics reveal a significant decline in player efficiency, as measured by Player Efficiency Rating (PER), which decreases by approximately 2.2% compared to the contract year level. This decline is accompanied by reductions of 7.1%, 5.2%, and 10% in Offensive Win Shares (OWS), Win Shares (WS), and Value Over Replacement Player (VORP), respectively. These declines indicate reduced contributions to team success, particularly on the offensive end, and imply that players are more likely to be replaced by others after securing a new contract.

The decline in performance may be explained by players returning to normal levels after heightened contract year performance rather than deliberate shirking behaviour. Linear regression analysis supports this interpretation, showing that players perform better as contract years elapse and that longer remaining contract years are associated with better performance. This suggests that offering longer-term contracts may help ensure sustained player performance. This chapter provides a nuanced understanding of the contract year phenomenon in the NBA. It demonstrates that players significantly improve their performance during contract years to secure better contracts, but the evidence of shirking behaviour after signing new contracts is inconclusive. While advanced metrics suggest potential shirking, the linear regression model does not definitively confirm this hypothesis. These findings have important implications for NBA teams in contract negotiations and player management strategies, emphasizing the need for effective methods to maintain high levels of productivity throughout contract periods.

In the second chapter, I investigate the determinants of NBA player salaries and the role of player options in contracts, focusing on key performance metrics such as points, rebounds, blocks, assists, and playing time. The findings reveal that player contracts are typically multi-year, and both average performance during the contract and performance in the final year significantly influence salary outcomes. Specifically, an increase in average points during the contract period raises the total salary by 5%, while an increase during the contract year leads to a 10% salary increase. Rebounds, blocks, and playing time also play important roles in salary determination. The analysis further explores the impact of team performance and contract details on salaries, finding that better team records positively influence salary negotiations. Quantile regression results show that while playing time and team performance affect salaries across different quantiles, the impact of individual performance is more pronounced in the top 50% of salaries, whereas the bottom 50% are influenced by a broader range of factors.

This second chapter also examines the role of player options in contracts and their impact on salaries. Players with more stable performance during the contract period are more likely to secure player options, with contract timing (such as the anticipation of a new Collective Bargaining Agreement) also playing a role. A matching process was used to compare players with and without player options, aiming to minimize salary differences between the groups. The findings show that player options provide flexibility but often come at an economic cost for most players. Specifically, players in the bottom 75th percentile experience a reduction in annual salary by approximately \$1.2 million (18% of earnings), while those in the 75th to 90th percentiles see modest salary premiums and longer contract durations. Top-tier players (top 10%) receive substantial salary premiums, with annual salaries increasing by at least \$10 million (40% of earnings), reflecting their unique market value and bargaining power. This chapter provides insights into the complexity of contract negotiations in professional sports, highlighting the factors influencing salary determination and the nuanced impact of player options. The findings suggest areas for future research, particularly regarding broader factors affecting the relationship between player options and salary outcomes.

The third chapter explores how player performance, team selection behaviour post-contract, and special contract clauses, such as player options, affect career longevity in the NBA. The analysis reveals that player performance is the most critical factor in determining career survival. High contributions to offensive and defensive team victories significantly reduce the risk of leaving the league. Specifically, a one-point increase in a player's offensive contribution reduces the risk of exiting the league by 46% and increases survival time by 43%, while a similar increase in defensive contribution reduces the risk by 59% and extends survival time by 75%. Performance metrics like points, defensive contributions, and steals further enhance survival chances. However, a high shooting percentage alone does not guarantee outstanding performance, as it may be inflated by easy shots against weaker defences.

This chapter also examines the impact of team selection behaviours after contract expiration. Players either stay with their original team, join another team, or leave the league. Exceptional performance encourages teams to retain players, especially those contributing to victories through steals, shooting efficiency, and defensive effort. Interestingly, higher contract salaries increase the likelihood of players leaving their original teams, possibly due to financial constraints. When comparing players who switch teams versus those who leave the league, performance remains a critical factor in remaining in the NBA, with strong defensive contributions and moderate offensive abilities improving survival prospects. Player age, performance, and salary requirements are key considerations when players change teams.

Lastly, the chapter explores the role of player options in contracts. While player options do not significantly impact overall survival probabilities, they increase the likelihood of changing teams, providing flexibility in career decisions. In summary, a player's survival in the NBA is primarily determined by their performance, particularly through winning contributions on both offence and defence. Players who can secure second employment opportunities by changing teams often possess certain traits, such as being functional players who contribute defensively, young players with untapped potential, or individuals signed to short-term high-paying contracts. While player options provide flexibility in post-contract decisions, they do not significantly influence overall survival chances.

Limitation and future work

This thesis has some limitations. In the second chapter, the sample size of players who signed a new contract with an option is relatively small, with only 129 out of a total sample size of 712, accounting for 18%. This small proportion may reflect the uniqueness of these players, who could be experienced veterans joining championship teams, potentially sacrificing salary for contract flexibility. Additionally, these players may have recently recovered from injuries, leading to reduced salaries as a risk-reduction strategy by the team, with a player option added to the contract as compensation. These situations may overestimate the impact of player options on salary, although it does not conflict with the empirical results in this chapter. Secondly, institutional aspects such as the latest salary cap increase due to a new broadcast contract could influence the likelihood of players obtaining a player option but may not directly relate to salary. Players and their agents aware of the potential salary cap increase may have signed contracts with a player option to take advantage of the expected salary cap rise. However, the dataset does not allow the identification of players who had such information when signing a contract. Thirdly, the influence of well-known agents on negotiating higher contracts for players is not considered in this chapter due to the lack of agent information. This omission could overestimate the salary gap of top quantile players, although it does not impact the empirical results showing the financial loss of lower quantile players who signed a contract with a player option.

Furthermore, in the third chapter, the study acknowledges limitations in terms of the impact of discrimination on the survival analysis of NBA players. Although including information about player race in survival analysis can enhance the model's explanatory power, the reliability of player information in the dataset does not include information on player race, which could be addressed in future research. In addition, the chapter only roughly estimates the impact of players changing teams due to limitations in the available data, preventing more in-depth research on this aspect. Moreover, the proportion of players who signed special terms is small compared to the total sample, leading to potential flaws in the quality of the matching process in this chapter, which may affect the estimation of the impact of player options. These limitations could be mitigated by collecting more comprehensive data.

References

Bar-Eli, M., Krumer, A. and Morgulev, E. (2020), 'Ask not what economics can do for sports-Ask what sports can do for economics', *Journal of Behavioral and Experimental Economics* **89**, 101597.

Barros, C. P., Frick, B. and Passos, J. (2009), 'Coaching for survival: The hazards of head coach careers in the German 'Bundesliga'', *Applied Economics* **41**(25), 3303–3311.

Berri, D. J., Brook, S. L., Schmidt, M. B. et al. (2007), 'Does one simply need to score to score', *International Journal of Sport Finance* **2**(4), 190–205.

Berri, D. J. and Krautmann, A. C. (2006), 'Shirking on the court: Testing for the incentive effects of guaranteed pay', *Economic Inquiry* **44**(3), 536–546.

Berri, D. J., Leeds, M. A. and von Allmen, P. (2015), 'Salary determination in the presence of fixed revenues', *International Journal of Sport Finance* **10**(1), 5.

Berri, D. J., Van Gilder, J. and Fenn, A. J. (2014), 'Is the sports media color-blind?', *International Journal of Sport Finance* **9**(2), 130.

Böheim, R., Grübl, D. and Lackner, M. (2019), 'Choking under pressure–Evidence of the causal effect of audience size on performance', *Journal of Economic Behavior & Organization* **168**, 76–93.

Boyden, N. B. and Carey, J. R. (2010), 'From One-and-Done to Seasoned Veterans: A Demographic Analysis of Individual Career Length in Major League Soccer', *Journal of Quantitative Analysis in Sports* **6**(4).

Bradbury, J. C. (2013), 'What is right with Scully estimates of a player's marginal revenue product', *Journal of Sports Economics* **14**(1), 87–96.

Bryson, A., Frick, B. and Simmons, R. (2013), 'The returns to scarce talent: Footedness and player remuneration in European soccer', *Journal of Sports Economics* **14**(6), 606–628.

Buraimo, B., Frick, B., Hickfang, M. and Simmons, R. (2015), 'The Economics of Long-term Contracts in the Footballers' Labour Market', *Scottish Journal of Political Economy* **62**(1), 8–24.

Cao, Z., Price, J. and Stone, D. F. (2011), 'Performance under pressure in the NBA', *Journal of Sports Economics* **12**(3), 231–252.

Carrieri, V., Jones, A. M. and Principe, F. (2020), 'Productivity shocks and labour market outcomes for top earners: evidence from Italian Serie A', *Oxford Bulletin of Economics and Statistics* **82**(3), 549–576.

Del Corral, J., Barros, C. P. and Prieto-Rodriguez, J. (2008), 'The determinants of soccer player substitutions: A survival analysis of the Spanish soccer league', *Journal of Sports Economics* **9**(2), 160–172.

Deutscher, C. (2009), 'The payoff to leadership in teams', *Journal of Sports Economics* **10**(4), 429–438.

Deutscher, C., Frick, B. and Prinz, J. (2013), 'Performance under pressure: Estimating the returns to mental strength in professional basketball', *European Sport Management Quarterly* **13**(2), 216–231.

Deutscher, C., Gürtler, O., Prinz, J. and Weimar, D. (2017), 'The payoff to consistency in performance', *Economic Inquiry* **55**(2), 1091–1103.

Dilger, A. (2002), 'Never change a winning team: An analysis of hazard rates in the NBA'.

Frick, B. (2007), 'THE FOOTBALL PLAYERS'LABOR MARKET: EMPIRICAL EVIDENCE FROM THE MAJOR EUROPEAN LEAGUES', *Scottish Journal of Political Economy* **54**(3), 422–446.

Fynn, K. D. and Sonnenschein, M. (2012), 'An analysis of the career length of professional basketball players', *The Macalester Review* **2**(2), 3.

Groothuis, P. A. and Hill, J. R. (2013), 'Pay discrimination, exit discrimination or both? Another look at an old issue using NBA data', *Journal of Sports Economics* **14**(2), 171–185.

Gross, A. and Link, C. (2017), 'Does option theory hold for Major League Baseball contracts?', *Economic Inquiry* **55**(1), 425–433.

Guss, M. S., Begly, J. P., Ramme, A. J., Hinds, R. M., Karia, R. J. and Capo, J. T. (2016), 'Performance outcomes after metacarpal fractures in National Basketball Association players', *Hand* **11**(4), 427–432.

Hakes, J. K. and Sauer, R. D. (2006), 'An economic evaluation of the Moneyball hypothesis', *Journal of Economic Perspectives* **20**(3), 173–186.

Hoang, H. and Rascher, D. (1999), 'The NBA, exit discrimination, and career earnings', *Industrial Relations: A Journal of Economy and Society* **38**(1), 69–91.

Jiobu, R. M. (1988), 'Racial inequality in a public arena: The case of professional baseball', *Social Forces* **67**(2), 524–534.

Kahn, L. M. (2000), 'The sports business as a labor market laboratory', *Journal of economic perspectives* **14**(3), 75–94.

Kahn, L. M. and Shah, M. (2005), 'Race, compensation and contract length in the NBA: 2001–2002', *Industrial Relations: A Journal of Economy and Society* **44**(3), 444–462.

Kahn, L. M. and Sherer, P. D. (1988), ‘Racial differences in professional basketball players’ compensation’, *Journal of Labor Economics* **6**(1), 40–61.

Koenker, R. and Bassett Jr, G. (1978), ‘Regression quantiles’, *Econometrica: journal of the Econometric Society* pp. 33–50.

Krautmann, A. C. (2013), ‘What is right with Scully estimates of a player’s marginal revenue product: Reply’, *Journal of Sports Economics* **14**(1), 97–105.

Krautmann, A. C. et al. (1999), ‘What’s wrong with Scully-estimates of a player’s marginal revenue product’, *Economic inquiry* **37**, 369–381.

Kubatko, J., Oliver, D., Pelton, K. and Rosenbaum, D. T. (2007), ‘A Starting Point for Analyzing Basketball Statistics’, *Journal of quantitative analysis in sports* **3**(3).

Lazear, E. P. (1981), ‘Agency, Earnings profiles, Productivity, and Hours restrictions’, *The American Economic Review* **71**(4), 606–620.

Levitt, S. D. and List, J. A. (2008), ‘Homo economicus evolves’, *Science* **319**(5865), 909–910.

LI, W. (2023), ‘INVESTIGATING RACIAL SALARY DISCRIMINATION AND THE ROLE OF BARGAINING POWER: EVIDENCE FROM THE NBA’, *The Singapore Economic Review* pp. 1–28.

Liu, P. and Xuan, Y. (2020), ‘The contract year phenomenon in the corner office: An analysis of firm behavior during CEO contract renewals’, *Available at SSRN 2435292* .

Palacios-Huerta, I. (2014), *Beautiful game theory*, Princeton University Press.

Palacios-Huerta, I. (2023), ‘The beautiful dataset’, *Available at SSRN 4665889* .

Patel, B. H., Okoroha, K. R., Jildeh, T. R., Lu, Y., Idarraga, A. J., Nwachukwu, B. U., Shen, S. A. and Forsythe, B. (2019), ‘Concussions in the National Basketball Association: analysis of incidence, return to play, and performance from 1999 to 2018’, *Orthopaedic journal of sports medicine* **7**(6), 2325967119854199.

Perry, D. (2006), ‘Do players perform better in contract years’, *Baseball between the numbers. New York: Basic Books* .

Ryan, J. (2015), Show Me the Money: Examining the Validity of the Contract Year Phenomenon in the NBA, PhD thesis.

Scully, G. W. (1974), ‘Pay and Performance in Major League Baseball’, *The American Economic Review* **64**(6), 915–930.

Simmons, R. (2022), ‘Professional labor markets in the Journal of Sports Economics’, *Journal of Sports Economics* **23**(6), 728–748.

Simmons, R. and Berri, D. (2019), ‘Labor markets in professional team sports’, *Sports (and) Economics, FUNCAS Social and Economic Studies* pp. 243–69.

Simmons, R. and Berri, D. J. (2011), ‘Mixing the princes and the paupers: Pay and performance in the National Basketball Association’, *Labour Economics* **18**(3), 381–388.

Spurr, S. J. and Barber, W. (1994), ‘The Effect of Performance on a Worker’s Career: Evidence from Minor League Baseball’, *ILR Review* **47**(4), 692–708.

Stiroh, K. J. (2007), ‘Playing for keeps: Pay and Performance in the NBA’, *Economic Inquiry* **45**(1), 145–161.

Vincent, C. and Eastman, B. (2009), ‘Determinants of pay in the NHL: A quantile regression approach’, *Journal of Sports Economics* **10**(3), 256–277.

Volz, B. (2009), ‘Minority Status and Managerial Survival in Major League Baseball’, *Journal of Sports Economics* **10**(5), 522–542.

Volz, B. D. (2017), ‘Race and quarterback survival in the National Football League’, *Journal of Sports Economics* **18**(8), 850–866.

White, M. H. and Sheldon, K. M. (2014), ‘The contract year syndrome in the NBA and MLB: A classic undermining pattern’, *Motivation and Emotion* **38**(2), 196–205.