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THE EFFECT OF WORKPLACE INJURY ON PLAYER VALUATION IN THE NATIONAL BASKETBALL ASSOCIATION

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
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Abstract

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Injuries in professional basketball leagues can have significant consequences on a team's overall performance during that season and subsequently, affect fans' interest in watching their team perform. For the National Basketball Association's (NBA) general managers, it is crucial to allocate new contracts to players in the most performance-effective manner that minimizes injury risk. Thus, the focus of this paper is to study the impact that injury history has on NBA players' future valuation. Based on the principles of the contract year phenomenon, this paper examines the effect that the previous year's injury history had on the value of a playerâs next contract. The main areas of focus for analyzing these effects include a player's injury proneness, the incidence of injury, and injury types. Results show that injury proneness was the most significant variable in affecting average contract value, whereby each additional injury sustained by a player negatively impacted their next contract's value by 3%. The results also alluded to the interpretation that the focus should be on classifying the severity of injuries rather than focusing on the type of injury.

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# Contents

# The Effect of Workplace Injury on Player Valuation in the National Basketball Association

Aditya Venkataramani

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# 1 Overview

## 1.1 Introduction

There has always been an underlying understanding that injuries and strains on an athlete's body are extremely common for most sports that require a form of physical contact. Thus, for the National Basketball Association's (NBA hereafter) athletes that play a rigorous 82 game schedule each year during the regular season, and then up to another 28 games in the postseason, it seems understandable that they would experience several injuries throughout their career.

Despite the advances in technologies as well as healthcare rehabilitation strategies to prevent and ensure speedier recovery of basketball injuries, the rate of injury within the NBA remains incredibly high. Injuries can have significant consequences on a team's overall performance during that season, and subsequently, affect fans' interest in watching their team perform. The past year has highlighted the extent of the negative impact that in-game injuries have had on teams within the NBA. The incidence of injury was 19.1 out of 1000 athlete exposures, which is a substantial number of injuries in comparison to previous years in the NBA and is comparable to other highly physical sports (Drakos et al., 2010).

The National Basketball Association's popularity is not limited to the borders of the US and has become increasingly widespread around the world in recent years. Much of its popularity stems from the recognition that the competition within the NBA is unparalleled in comparison to other basketball leagues in the world. The best players play in the NBA, and thus the notion of injury constitutes a concern of whether it could dramatically affect a team's post-season performance, whilst also risking the effects of fans' interests in watching a particular team.

For organizations within the NBA that have experienced a heightened number of players experiencing injury for a prolonged period, they usually choose to adjust their player's contract, trade the player away, or even release the player from the team entirely. However, many teams incorrectly hold onto an injury-prone player in hopes that the player will return to his full "potential". As the total number of games lost to injury increases, the overall cost to the team increases dramatically, not only in the form of salary paid to players but also in the prospects for the team to receive future ticket sales and its effect on overall viewership. The premise of this paper is to analyze the decision-making process from the management's perspective, and understand the injury risk factor when players are given a new contract.

For NBA teams, it is crucial to perform adequate risk management to allocate new contracts to players on their team in the most efficient and performance-effective manner. This paper will attempt to utilize labor economic principles to assess the effects of historical injuries on a player's next NBA contract.

## 1.2 Motivation and Research Question

As noted in the abstract above, the past NBA season (2020 – 21), has noticed an increase in NBA injuries that were not related to COVID-19. The number of players that did not play per game (for both teams) due to non-COVID-19 illnesses or rest was 5.1 (Holmes, 2021). This stat is even more concerning when noticing that the league's star players missed an extremely high number of games during the regular season. As noted in many research papers regarding injuries for professional athletes, injuries can create far larger negative externalities and consequences for many stakeholders. Players themselves are affected as these injuries interfere with their career prospects, whilst for organizations, the difficulty lies in managing an active and dynamic player contract.

This absence, caused by the prospects of injury, over a period has affected multiple teams on their potential to compete during the playoffs at a peak performance level. The injury analysis of all teams and their subsequent performance on the court has a profound effect on how NBA teams choose to value their players, and furthermore choose an appropriate salary for them, based on future performance prospects. Thus, this paper is designed to ultimately analyze the potential effect injury has on a team's decision-making. Understanding that there is a multitude of factors that can affect a player's salary, as well as contract, the research question, that this paper will aim to focus on, is determining the degree of effect and impact of workplace injury on an NBA player's overall valuation. The main areas of focus for analyzing player valuation in regards to injury in this paper are three-fold:

1. How does injury proneness affect player valuation?
2. How does the incidence of injury affect player valuation?
3. Finally, what is the true impact of the type of injury and how it affects player valuation?

## 1.3 Hypothesis

Two hypotheses that serve as the basis for which this paper will serve as a test for. Both hypotheses relate to the management's determination of retaining a player within their team, and the time specificities regarding that decision.

1. All forms of analyzing the effect of injury (proneness, incidence and type) have a negative impact on contract value.
2. Number of days injured will have the most significant impact on affecting contract value as it most directly correlates to the costs incurred by a given team.

Although this paper is being analyzed from the lens of the NBA, it still has significant relevance to the study of economics. The effect of injuries in the NBA extends to the broader study of labor economics principles. This paper's implications have the potential to identify the effects that injury has on salary through a team's lens. This constitutes analyzing the effects of injury and a player's contribution to a team winning. However, this research furthers the discussion of examining the determinants of allocating constrained resources, in this case, the resource being salary. In addition to contributing to labor economics research, the paper will also analyze a unique perspective on analyzing managerial decision-making and preferences. The paper can potentially provide implications for redefining which players teams choose to extend contracts to players.

This study's novelty lies in the fact that there have been virtually no papers that have been written regarding the effect of NBA athletes' injuries and their effect on their salary overall from a team management's perspective. The paper, will not only look at the quantitative (statistical) analysis but also utilize qualitative factors to better explain the rationality behind an NBA manager's decision to pay a player based on their future projected injuries and performance.

# 2 Background

## 2.1 Previous Work and Significance

Much of the previous work surrounding the notion of workplace injury in professional sport has centered around the medical elements and provide insight on analyzing and improving the medical treatments for professional athletes. This section details some of the literature surrounding sports injury and performance evaluations of players and its significance to this paper:

Ian Gregory-Smith wrote a paper regarding wages and labor productivity, discussing the evidence from injuries in the national football league (Gregory-Smith, 2021). In his paper he identifies the relationship between wages and labor productivity and demonstrates that the connection between the two concepts is robust. Injuries in professional football players are seen as an exogenous shock to labor productivity. When analyzing the effects of injuries for NBA players it seems that it would be helpful to use this paper in reference, as franchises in both leagues are constrained by their salary cap. Our paper will modify Smith's approach to identify how expected exogenous shocks to player productivity affect their overall contract value in the NBA.

In February of 2021, Sarlis, Chatziilas, Tjortis, and Mandalidis discussed the injury risk factor identification and its ability to understand its impact on team performance (Sarlis et al., 2021). Their paper utilized analytics in the NBA from 2010 to 2020 to quantify the impact on player and team performance. The paper identified a high impact of injuries on player performance, however noticed only a weak positive relationship between performance and injuries on a holistic multivariate model. This correlation is shown as a negative impact on both players and team performance as repeated injuries took place to the same player, however it was concluded as a weak relationship due to the qualitative observation that "players are parts of a team". Our paper aims to further the analysis put forth by the authors discussed here by noticing the how much does the negative impact on team performance affect player value in the NBA. Our paper will utilize measures such as Winshare (further explained in *Discussion of Player Performance*) to account for the relative contribution of a player's performance to a team's win.

In 2018, Melanie Lewis, a Professor within the Department of Psychology at the University of Oklahoma published a paper to examine the relationship among game load, fatigue and its overall impact on injury risk factors on NBA athletes (Lewis, 2018). The researcher focused her analysis on in game statistics and injury reports over three NBA seasons to measure time-lagged fatigue and game load between subjects that was observed during the period of her study. The Results showed that Injuries were associated with greater fatigue as well as game load, whilst baseline injury risk and magnitude of load injury varied across individuals examined (Lewis). The most applicable part of the researcher's study was the model equation that estimated the probability of injury for their study. In Lewis' study, she examined the prospect and estimation of injury that included minutes played, rest and overall activity within the NBA game played. These were classified as total injury events, and further posited that the greater performance load and fatigue were associated with shorter peaks by the players (regarding their performance in game) as well as higher risk of injury.

In 2015, Julian Ryan wrote a paper that analyzes the contract year phenomenon and its presence in the NBA (Ryan, 2015). Contract year phenomenon posits that athletes perform at a higher level during a season prior to their free agency. Ryan's study analyzes this phenomenon by accounting for intrinsic endogeneity, that accounts for better players getting longer contracts and less likely to be in a contract year phenomenon. Within his study the estimated effect of boost in player performance during their contract year is 3-5%. This study shows that the contract year phenomenon explains the most and thus our paper will focus on only taking salary, injury and performance statistics from the year prior to a player's free agency and analyze the impact of injury on the next contract value.

## 2.2 Discussion of Contracts

Before analyzing the impact of NBA player contracts, it is important to acknowledge that the observations made herein may only be relevant between the years analyzed within this report (1990 - 2020). Furthermore, as this paper analyzes 30 years of data, a fundamental development to the NBA during this period was the incorporation of the collective bargaining agreement ("CBA") (CBA, 2018). The CBA was signed in 2017 between the National Basketball Players Association ("NBPA") and the NBA to set out the terms and conditions of employment for players in the league till 2023 (Nelson, 2020). The NBPA (NBA players' union), which was first established in 1954, has been pivotal in the consistently adapting and changing rules of NBA player contracts. An important note to take into account is that much of this paper's empirical analysis is focused on analyzing the years preceding the incorporation of the CBA. Even without the context of a CBA, NBA contracts still vary by the player based on their years of service within the league, their skill, and other factors. The variations between player contracts and the most defining changes to NBA player contracts are discussed within this section .

### 2.2.1 Contract Types

**Uniform Player Contract (and types):** Uniform Player is the standard contract template that each team has with their respective player. The provisions that are most common in regards to negotiation between players and the basketball organization are:

1. *Compensation protection:* A player's compensation can only be protected for a basketball-related injury or other injuries. This is important to note because the player's salary for the duration of their contract is protected if the player sustains a basketball-related injury. This paper will address this issue in the following sections, however, it is important to note that injuries would only affect a player's future contract with a given team, rather than their current salary.

2. *<u>Player's Rights:</u>* The concept of player's rights is whether the player is entitled to his base compensation if the player re-injures an issue that existed before the contract was signed. The CBA has enforced a "Compensation Protection" program that protects player's base compensation, even if the team decides to terminate a player's contract based on (i) lack of skill, (ii) death, (iii) a basketball-related injury, or other injury or illness (iv) mental disability, or (v) other miscellaneous categories. A player's base compensation is defined as all compensation a player would receive, excluding their bonuses.

3. *<u>Trades:</u>* Within a uniform player contract, the team and player can negotiate on whether the player receives a bonus if he is traded, and what are the limits/prohibitions on being traded to another team. Furthermore, it is important to mention that if a contract or extension is signed after training camp (usually beginning close to the end of the off-season) has started, then the current season is counted as a full season covered by the contract or extension. The implication of a trade on a player contract is slim. The player's salary remains the same, but the team that pays the contract changes.

4. *<u>Standard NBA Contract:</u>* A standard NBA contract is any Uniform Player Contract that is **not** a two-way contract (explained in the *"Other Contracts (Not Considered)"* section below). Two-way contracts have the opportunity to be converted into a standard NBA contract.

**Rookie Contract:** A "Rookie" is a term coined to describe players that are new to the league. These players are normally players that have been drafted into the NBA and a rookie scale contract is provided to them for a period of two years, with a team option for both the third and fourth years of their time within the league. The focus of this paper is based on general managers' decisions on signing a player based on their injury profile within their time in the league. Thus, the rookie contract will not be assessed within the scope of this study, but rather the subsequent contracts that they sign with a respective team will be taken into account within the data set compiled. This form of a contract yields its own subsection due to the nature that all NBA players begin their journey within the league as a rookie, however, their first contract will not be considered as part of the analysis.

**Other Contracts (Not Considered):** This section details the contracts that are normally signed within the NBA. However, due to the short duration, dissimilar, or discontinuous nature of these contracts in comparison to standard NBA contracts the following contracts are **not considered within the scope of this study**.

1. *Summer Contract:* These contracts are only signed from July till the beginning of the regular season. It is usually for the teams to sign the player for the annual summer league and analyze the player's prospect within a shortened NBA league during the off-season.

2. *10-Day Contract:* During the regular season, a team can choose to sign a player to a 10-Day contract to deepen the roster for a few days, find replacements for injured players, or even utilize the contract as means to analyze a player's fit and prospect within a respective roster. These contracts tend to save teams money, and help teams decide whether to sign the player for the rest of the season.

3. *Rest of Season Contract:* A rest of season contract is one that a player can be entered into at any time and only provides the respective player compensation for the remainder of the season. Injury details and data are hard to follow regarding this specific contract type, even if the player is entered into this contract shortly after the first day of the regular season.

4. *Veteran Player Contract:* A designated veteran player contract is between a free agent that has played within the league for over five seasons. Once signed the player may not be traded for at least the season that they are signed. Furthermore, the veteran must be paid at least 30% and no more than 35% of that year's salary cap.

5. *Two-Way Contract:* A two-way contract is for two-way players and they are provided two-way salaries. These types of contracts are provided primarily to G-League players, whereby they can serve as active or inactive players for the NBA. The two-way nature

describes their ability to play for both leagues.

### 2.2.2 Compensation

Apart from the base salary that a player receives when they receive a contract, an NBA player has the opportunity to boost their earnings through the process of earning compensation. All players earn a traditional salary but depending upon a variety of different factors players can receive bonuses and deferred compensation that would be paid by cash. Much of the compensation package provided to a given player is based on the player's on-court performance and their impact on their team. This paper examines the effect of a player's injury on their contract value, rather than the bonuses the player receives during the duration of their contract. In other words, this paper will analyze the extent to which a player's injury history affects their next (base) contract. Thus, the only compensation that will be included in this report will be the base compensation each player receives.

**Base Compensation:** A player's base compensation is defined as any compensation that the player receives *excluding* bonuses. This type of compensation is broken into two types of payment schedules (current vs. deferred). The current base compensation involves semi-monthly installments, while deferred base compensations are payable after the end of that specific season. Both of these types of base compensation are embedded in the player's contract value when a player initially signs their contract and thus will be analyzed within the scope of this study.

**Annual Salary Increases and Decreases:** Player salaries generally increase or decrease after each season by up to 5% of their first year's salary. These increase/decrease in each season doesn't change the absolute value of the player's contract value. Similar to a regular player, there are provisions in place for qualifying veteran free agents. Their salary increase or decrease can be up to 8%. Although player injury's impact on salary will be analyzed, their contract value presents a thorough examination of decisions made by managers.

**Other Compensations (Not Considered):** This section deals with other common forms of compensation metrics that will not be included within the scope of this report. As mentioned above, the base compensation will be the focal point of the paper as the

1. *Incentive Compensations:* Incentive compensations are paid to a player due to a few different factors. The first factor is performance bonuses. These compensations are put into the contracts to endorse better performance benchmarks for the player. These benchmarks are numerical measurements or general league level awards (such as most valuable player, or all NBA teams). Likely bonuses include factors such as if the player performs to the same level as the previous year. Furthermore, physical benchmarks (such as meeting specified weigh-in criteria) can also be a part of the incentive compensation package.

2. *Maximum Player Contracts:* Maximum contract players are included in the data set, however, the incentives and yearly salary increases for this type of player are not included within the scope of this study. Furthermore, the percentage of a team's total salary cap is not analyzed either. Maximum player contracts are the type of contracts that is the maximum amount of money a player can make per season. After the initial season, the following player is allowed to have a 6 to 8% annual salary increase based on governing rules. General max player contract rules allow players that have played more years within the league to earn upward of 30% of the team's salary cap.

## 2.3 Discussion of Player Injuries

As basketball is a contact sport, with various complex movements, NBA players can expect to sustain multiple different types of injuries throughout the duration of their respective professional careers. The understanding of basketball injury types is an important first step in analyzing their impact on a player's given contract value. Injury patterns over the past few decades have continued to evolve, as the game has evolved.

Return from athletic injury for professional basketball players can be an extremely arduous and lengthy process. An injured athlete within the NBA usually receives care from both the team health providers as well as private rehabilitation providers. The process for a player to return to sport is only when the athlete has been provided medical clearance. The focus for managers then has been how to mitigate the risk of losing a key performing player to injury and maximize their performance on the court. Due to the risk of injury in many sports being high, the risk management structure involved in evaluating and assessing a controlled mitigation strategy for each player is pivotal to the team's performance. This paper focuses on both the incidence and severity of injury data to analyze the impact of how teams choose to evaluate a player based on their injury history. This section deals with types of injuries, severity classifications, and other factors relating to player longevity.

### 2.3.1 Types of Injuries

Player injuries can occur at any point during a basketball game due to the physicality required to perform at the highest competitive level. The constant changing of directions, bursting into sprints, and jumping that is requisite to play basketball increases the risk of injuring various parts of an NBA player's body. The most common types of injuries within the data set examined are explained in greater detail in the *Results* section. This subsection deals with more anecdotal evidence that explains why types of injury are essential in examining how the injury impacts player value. NBA players such as Derrick Rose, Tracy McGrady, and Grant Hill are a few infamous examples of how devastating injuries can impact the trajectory of a player's career. Injuries such as torn ACL or achilles became synonymous with career-ending injuries, and thus this paper will serve to examine the different types of injury and the impact it has on a player's overall valuation.

### 2.3.2 Other Factors Relating to Sport Injuries

Other confounding factors contribute to the nuances of injury that are not examined in detail within this paper due to the empirical nature of the study. This section deals with understanding some other variables that are important to take into account when considering the impact of injury to players, and the contributing factors that cause increased incidences of injuries in the future.

1. *Injury Risk From Returning to Sports too Fast:* Although advancements in sports medicine and physical health have vastly improved over time, there are still incidences in the NBA where players return to playing too fast and this section deals with the injuries associated with it (Waldron et al., 2022). Coaches tend to push players to return to the lineup when the team is desperate to make it into the playoffs for that year or if it is pivotal in winning the championship that year. Based on research and common intuition, as athletes fatigue, the overall injury risk increases. As training workload increases before appropriate rest and recovery have been managed, the chances of injury reoccurring increase.

2. *Issues in Estimating Risks and Rates in Sports Injury:* The utilization of statistics has revolutionized how sports can be understood and analyzed. Athletes and trainers are better positioned when they can understand both risk and causes of sport-related injuries (Knowles et al., 2006). However, estimating the incidence of injury is difficult to forecast due to the unpredictable nature of a professional basketball movement.

3. *Training Factors:* Training has a sometimes negative effect in impacting the prospect of future injuries. Higher training loads can cause higher injury rates, however, certain types of training have also been proven as effective methods in mitigating the risks of injury. Inappropriate training, diet, and rest can contribute to a higher likelihood of injuries (Gabbett, 2016). Furthermore, excessive and rapid increases in training loads can be responsible for causing a higher likelihood of injury incidences.

## 2.4 Discussion of Player Performance

There is a multitude of factors that ultimately affect a player's performance in the NBA. The multidimensional nature of a player's on-court and off-court contributions is difficult to be measured and further be limited to just a single metric. However, in the domain of sport, there has been a reliance on traditional box score statistics to determine a player's performance. Conventionally there are four main metrics that teams and fans alike utilize to evaluate the contribution that a player provides to their team. Since this paper deals with the effect of injury on a player's contract, it is important to understand the context of the performance metrics that also impact the value of a player's respective contract. Interpreting the definition and its relation to how the metric describes a player's performance is of paramount importance, as it acts as the basis for much of the regressions presented in the results section below. This section deals with the four types of performance metrics that will be analyzed in conjunction with the injury statistics. *Table 1* below details a glossary of terminology that will be used in explaining the formulation of different metrics utilized within the study.

### 2.4.1 Player Efficiency Rating (PER)

The Player Efficiency Rating (PER) was developed by an ESPN columnist named John Hollinger (Hollinger, 2009). This metric garnered a lot of attention after the introduction of data analytics as a means to judge a player's career. The focus of this metric was to gauge a player's efficiency and effect on a game. The metric focuses on evaluating efficiency on a per-minute basis. In the words of Hollinger, "The PER sums up all a player's positive accomplishments, subtracts the negative accomplishments, and returns a per-minute rating of a player's performance." (ESPN). How PER is calculated is shown below:

Table 1: Glossary of Terms (Glossary)

| Statistic Abbr. | Definition |
|---|---|
| 2P | 2 Point Field Goals |
| 2P% | 2 Point Field Goal Percentage; the formula is2P/2PA. |
| 2PA | 2 Point Field Goal Attempts |
| 3P | 3 Point Field Goals |
| 3P% | 3 Point Field Goal Percentage - the formula is: 3P/3PA. |
| 3PA | 3 Point Field Goal Attempts |
| Age | Age; player age on February 1 of the given season. |
| AST | Assists |
| AST% | Assist Percentage - the formula is: 100 *AST/ (((MP/ (TmMP/ 5)) *TmFG) FG) |
| BLK | Blocks |
| BLK% | Block Percentage - the formula is: 100 * (BLK* (TmMP/ 5)) / (MP* (OppFGA Opp3PA)) |
| DPOY | Defensive Player of the Year |
| DRB | Defensive Rebounds |
| DRB% | Defensive Rebound Percentage - the formula is: 100 * (DRB* (TmMP/ 5)) / (MP* (TmDRB+OppORB)) |
| DRtg | Defensive Rating - for players and teams it is points allowed per 100 posessions |
| DWS | Defensive Win Shares |
| eFG% | Effective Field Goal Percentage, the formula is - (FG+ 0.5 *3P) / FGA |
| FG | Field Goals (includes both 2 point field goals and 3 point field goals) |
| FG% | Field Goal Percentage; the formula isFG/FGA. |
| FGA | Field Goal Attempts |
| FT | Free Throws |
| FT% | Free Throw Percentage, the formula is - FT/FTA. |
| FTA | Free Throw Attempts |
| Four Factors | Dean Oliver's "Four Factors of Basketball Success"; please see the articleFour Factorsfor more information. |
| G | Games |
| GS | Games Started |
| L | Losses |
| Lg | League |
| MVP | Most Valuable Player |
| MP | Minutes Played |
| MOV | Margin of Victory; the formula is PTS - OppPTS. |
| ORtg | Offensive Rating, for players it is points produced per 100 possessions. |
| Opp | Opponent |
| ORB | Offensive Rebounds |
| ORB% | Offensive Rebound Percentage, the formula is - 100 * (ORB* (TmMP/ 5)) / (MP* (TmORB+OppDRB)) |
| OWS | Offensive Win Shares |
| Pace | Pace Factor, the formula is - 48 * ((TmPoss+OppPoss) / (2 * (TmMP/ 5))) |
| PER | Player Efficiency Rating |
| PF | Personal Fouls |
| Poss | Possessions |
| PProd | Points Produced |
| PTS | Points |
| ROY | Rookie of the Year |
| SMOY | Sixth Man of the Year |
| SOS | Strength of Schedule, a rating of strength of schedule |
| SRS | Simple Rating System, a rating that takes into account average point differential and strength of schedule |
| STL | Steals |
| STL% | Steal Percentage, the formula is - 100 * (STL* (TmMP/ 5)) / (MP*OppPoss) |
| Stops | Stops; related to individual Offensive and Defensive Ratings |
| Tm | Team |
| TOV | Turnovers |
| TOV% | Turnover Percentage, the formula is - 100 *TOV/ (FGA+ 0.44 *FTA+TOV) |
| TRB | Total Rebounds |
| TRB% | Total Rebound Percentage, the formula is - 100 * (TRB* (TmMP/ 5)) / (MP* (TmTRB+OppTRB)). |
| TS% | True Shooting Percentage; the formula is - PTS/ (2 *TSA) |
| TSA | True Shooting Attempts; the formula isFGA+ 0.44 *FTA. |
| Usg% | Usage Percentage the formula is - 100 * ((FGA+ 0.44 *FTA+TOV) * (TmMP/ 5)) / (MP* (TmFGA+ 0.44 *TmFTA+TmTOV)) |
| VORP | Value Over Replacement Player |
| W | Wins |
| W & L% | Won Lost Percentage; the formula is - W/ (W+L). |
| WS | Win Shares; an estimate of the number of wins contributed by a player |
| WS/48 | Win Shares Per 48 Minutes |
| Win Probability | The estimated probability that Team A will defeat Team B in a given match up. |
| Year | Year that the season occurred, NBA seasons are split over two calendar years –¿ thus, 1999-00 season would be 2000. |

1. **uPER** $= \left(\frac{1}{MP}\right) \times [\,3P + \left(\frac{2}{3}\right) \times AST + (2 - factor \times \left(\frac{TeamAST}{TeamFG}\right)) \times FG + (FT \times 0.5 \times (1 + (1 - \left(\frac{TeamAST}{TeamFG}\right))) + \left(\frac{2}{3}\right) \times \left(\frac{TeamAST}{TeamFG}\right)) - VOP \times TOV - VOP \times DRB\% \times (FGA - FG) - VOP \times 0.44 \times (0.44 + (0.56 \times DRB\%)) \times (FTA - FT) + VOP \times (1 - DRB\%) \times (TRB - ORB) + VOP \times DRB\% \times ORB + VOP \times STL + VOP \times DRB\% \times BLK - PF \times \left(\frac{LgFT}{LgPF} - 0.44 \times \left(\frac{LgFTA}{LgPF}\right) \times VOP\right)]$

$$\textbf{Factor} = \left(\frac{2}{3}\right) - \left(0.5 \times \left(\frac{lg_{AST}}{lg_{FG}}\right)\right) / \left(2 \times \frac{lg_{FG}}{lg_{FT}}\right)$$

$$\textbf{VOP} = lg_PTS/(lg_FGA - lg_ORB + lg_TOV + 0.44 * lg_FTA)$$

$$\textbf{DRB\%} = (lg_TRB - lg_ORB)/lg_TRB$$

PER focuses on, as shown in the above equation, adding positive statistics (such as FG, FT, 3PT, etc.) and subtracting negative statistics (such as TOV, STL, etc.). The PER aims to develop one number that explains the player's statistical accomplishments during that season.

### 2.4.2 Box Plus Minus (BPM)

Box Plus-Minus (BPM) is a box score-based metric that estimates the contribution that a player has on their respective team when they are on the court (Myers, 2020). The player's contribution is based only on the information provided by the traditional box score. The team's overall performance is looked at on position, team's overall performance to estimate the respective player's contribution to the team per 100 possessions played.

How BPM evaluates the contribution of a player is by initially assuming every player contributes to the team equally. Thus, if the team is performing well, then every player is considered to contribute to the team equally well. The box score information is added to revise the initial evaluation. How this is done, is based on the box score statistics that a player has relative to the other players on the team.

The issue with BPM as a metric is that it is good at measuring the offense of a particular team, but defensive box score statistics fail to adequately quantify the impact a player has on the defensive end. To calculate the player's offensive position and role estimate, the formula evaluates the player's team's raw baseline points per adjusted shot attempt and compares the raw score with that of the team. The team's adjustment to the raw player BPM allows for the completed BPM. *Figure 1* below is a histogram created by Daniel Myers, the developer of Box Plus-Minus to show the average BPM over four decades regarding the player's minutes and seasons. The histogram as seen below shows that the team's best lineup could even have a +14 as a BPM, but the average of all players centered around 0.

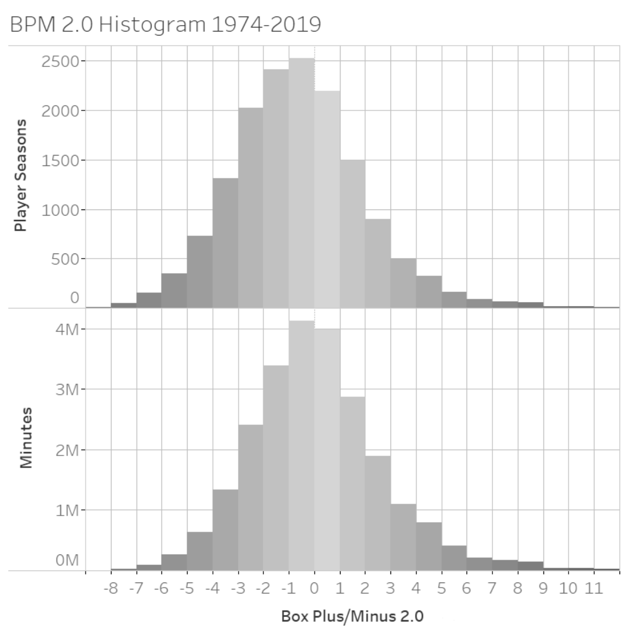



Figure 1: Average BPM Histogram Over Four Decades (Myers, 2020)

### 2.4.3 Value Over Replacement Player (VORP)

Similar to that of BPM, the Value over Replacement Player (VORP) converts the BPM rate into an estimate of each player's overall contribution to the team and compares it to the theoretical contribution of a "replacement player" would provide (Myers, 2020). To calculate the VORP of a given player, the formula would be:

$$\textbf{VORP} = [BPM - (-2.0)] \times (\text{\% of possessions played}) \times (\frac{teamgames}{82})$$

The VORP tracks linearly with salary since higher paid salaries are considered to play more minutes on the court. This metric determines the player's efficiency and the value can be converted into the number of team wins. The conversion would be to times VORP by 2.7. VORP allows for understanding the best players in the league, however, BPM is used to understand the contribution of a player to a team's overall success.

### 2.4.4 Win Share (WS)

Win share is a player statistic that takes into account the team's successes and estimates the division of the success to each respective individual (James and Henzler, 2002). The focus of evaluating the win share of a particular player is to evaluate their offensive and defensive win share contributions.

Offensive win share is focused on calculating the points, offensive possession, marginal offense for each player, and then calculating the marginal points per win (Oliver, 2004). By doing so, the win shares will be credited to the player based on the formula of dividing marginal offense by marginal points per win.

Marginal offense for each player is formulated from by calculating: (points produced) - 0.92 * (league points per possession) * (offensive possessions). While calculating the marginal points per win is evaluated as 0.32 * (league points per game) * ((team pace) / (league pace)).

Defensive win share is focused on utilizing the defensive rating for each player, calculating the marginal defense, and marginal points per win. The defensive win share (similar to that of the offensive win share formula is calculated as (marginal defense)/(marginal points per win).

Marginal defense for each player is formulated by calculating: (player minutes played / team minutes played) * (team defensive possessions) * (1.08 * (league points per possession) - ((Defensive Rating) / 100)). While calculating the marginal points per win is calculated is the exact same as that of the marginal points per win. This formula is: 0.32 * (league points per game) * ((team pace) / (league pace)).

Both offensive and defensive win shares are added together to calculate the total win share.

### 2.4.5 Comparing the different metrics

Before running regressions on the different injury and performance metrics, it is important to test for multicollinearity between the variables. To assess how much each performance metric explains each other, a correlation matrix in *Figure 2* was created.

Each performance metric explained above as well as minutes played is included in the matrix above. The results show that each performance metric is heavily correlated with one another as well as minutes played. One of the higher correlations within the table is between minutes played and win share, illustrating that minutes played explains more of win share than all other metrics. Interestingly, even though VORP is a derivation of BPM, WS explains more of VORP than BPM does. Furthermore, it is important to realize that despite these metrics being highly correlated, they do not completely explain each other. Thus, even though they cannot be in the same regression due to multicollinearity issues, each metric

Figure 2: Correlation Between All Performance Metrics


should be regressed separately to understand the isolated effect of the various metrics on average contract value. One single metric is impossible to encompass the accomplishments of a player due to the multi-faceted nature of basketball. However, the metrics mentioned in this section assist in assessing the contribution of a player to their respective team.

# 3 Methodology

The current research investigates the complex relationship between player injury and future contracts provided to the given player. Due to the nature of this study, the data source for this paper was retrieved through means that were accessible online and publicly available.

## 3.1 Participants

This study's eligible participants were NBA players that were classified as aged 18 years or older. The focus of this data set was to include players that had played at least one year in the NBA. To ensure that the participant pool wasn't a biased sample, players that experienced injuries and those that had not encountered an injury were both examined within the scope of this study. The time frame for the extracted sample was three decades of data that was from 1990 to 2020. Across all seasons there were 17,140 unique rows of yearly player statistics that were used as the sample size for this study.

## 3.2 Study Design

The data for this study was sourced from publicly available repositories online. The data was extracted through the form of "data scraping" as the basis for the investigations conducted within this research study. This form of data extraction is malleable and reproducible for various freely available data sources online. Below includes the overview of the websites scraped to produce a merged data set for statistical analysis:

1. *Pro Sports Transactions*: Pro Sports Transactions archive is an online website that has focused its efforts on maintaining and documenting a dataset that is regularly updated to take note of every transaction (Marousek, 2005). This includes, but is not limited to: trades, free agent movements, signings, waiving, draft picks, injuries, movement to and from

minor leagues, disciplinary actions, and legal/criminal actions. It is commonly referred to as the most "complete" dataset for pro basketball that is available and freely accessible to the public.

2. *Basketball Reference*: Sean Lahman, an investigative reporter for USA Today donated much of the data to www.basketball-reference.com. This website is owned by and operated by Sports Reference, LLC, an American company that operates several sports-related websites (LLC, 2022). This website has been renowned for its comprehensive encompassment and approach to sports data. The website consists of statistics, history, and scores for both box scores and player in-game statistics. The data on sports statistics have already been web scraped as well.

3. *Hoops World*: (now known as Hoops Hype), is a website that has covered basketball and NBA data, rumors, and predictions since 1998. The website contained expert analyses on every team as well. USA Today is an American daily middle-market newspaper, relaunched www.hoopshype.com, due to the site being a popular destination for NBA breaking news and rumors (HoopsHype). The website has a salary database that it maintains and reports for statisticians and fanatics to analyze freely. For this research, salary data from the players of the past 30 years were web scraped.

## 3.3 Internal Validation

The data that was retrieved was collected through a process that was systematic and repeatable. The process of data collection, as well as combining data sets tends to be prone to data errors or data loss. As a form to prevent issues from arising, regular manual checks of the data sets were made to ensure that the data points were consistent throughout the data cleaning process by examining the data within the merged data set with that of the data shown in publicly sourced websites such as ESPN.com or NBA.com. An example of this would be to randomly select from the original data set five players, and notice whether the player was subsequently removed during the data cleaning or merging processes. When discussing the issue of injury data discrepancies, there often lies incoherent patterns of athletes that do not play in an NBA game but are still activated from the injury list. Therefore, to work around the missing parameter, the analysis only looks into the data provided by pro sports transactions. Whereby, the absolute days (within a 365-day year) of a player's injury rather than their actual NBA calendar year. The NBA calendar year will be defined in this paper as the dates that the regular and post-season begins and ends. To ensure that the years correlated with the schedule of an NBA calendar, the yearly injury data was set to end the day before the first game of the respective year's NBA regular season (on average NBA regular season began on June $15^{th}$).

## 3.4 Data Reduction

Consistency between data sets was periodically checked as mentioned above. The reduction of unique data rows occurred for several reasons when merging data from different sources. When merging the data sets, the common columns that were merged were $Name$, $Year$, and $Team$. As mentioned above, the considerations regarding contract length and types were omitted based on the relevance to the analysis that I would be running. The first reduction of data occurs by limiting the sample population by removing players that were provided a veteran player, 10-day, and summer league contracts. Furthermore, the players that held a two-way contract (players that played in the G-League and then played occasionally for the NBA were removed as well. The total universe of players available to assess was over 18,000 unique players. The final merged data set included over 14,000.

# 4 Results

In this section, we evaluate the three main facets utilized within this paper to analyze the impact of a player's injury on their overall player evaluation. The injury variables considered include: 1) the number of days a layer was injured, 2) the number of times a player was injured, and 3) the type of injury a player experienced within a given year. This section aims to analyze the decision of providing a new contract to a player given the injury history. By utilizing the injury variables considered above, this section aims to understand the effect of injury on a player's next contract.

The focus of this paper is on the total number of days a player was injured during the year to encompass their effects on performance based on days injured, not just the number of games missed during the season. This was done since the cost of injury to NBA teams was not examined. Rather the effect of any player injury on future valuation is in question here. Therefore, for example, players that experience injuries during the off-season will be included in analyzing its impact on next year's contract valuation. *Table 2* below includes descriptive statistics on player injuries.

The focus of the initial analysis regarding how an injury affects player valuation is performed by regressing the dependent variable of the average contract value on independent variables of quantifiable in-game performance, player bios, as well as player injury statistics. The first two regressions will analyze the effects of the number of days injured, and the number of times injured, to understand how the effects of length of injury or how injury proneness affects the player's next contract value.

To ensure that the estimate of the impact of an injury on contract value is unbiased, the regression model needs to be neither under-specified nor over-specified. As described in the *Discussion of Player Performance* section, much of the player performance metrics used encompasses the majority of box-score statistics (such as AST, STL, PTS, etc.). Therefore, to

Table 2: Descriptive statistics on player injury

| **Descriptive Stats:** | **Number of days injured** | **Number of times injured** |
|---|---|---|
| Count | 14590 | 14590 |
| Mean | 53 | 1 |
| Std Dev. | 95 | 1 |
| 25% | 4 | 1 |
| 50% | 13 | 1 |
| 75% | 47 | 1 |
| Min | 0 | 0 |
| Max | 365 | 12 |

ensure that there isn't multicollinearity between independent variables in the regressions, this paper performs four different regressions to include the four performance metrics described earlier (PER, BPM, VORP, WS) rather than using each box-score statistic.

## 4.1 Discussion on Contract Value

The regression function above shows that the dependent variable Average Contract Value is presented in a log function. The log function is conventionally utilized by labor economics when estimating determinants and effects on wages. The reason for the logarithm transformation is to capture the percent change in contract value, rather than absolute change. Since the dependent variable is heavily skewed rightwards, estimating the effects of various independent variables on the absolute value of contract value, there could be negative contract value estimates.

The reason this study utilized contract value instead of salary was based on the findings from the *Discussion of Contracts* section. When a contract is provided to a player (for example, a 3 year, $30M contract), the player is guaranteed a base salary regardless of their injury history. When regressions were run whilst holding log(Salary) as the dependent variable, neither injury nor player performance metrics affected the percent change in salary.

A final consideration was how many years prior should be considered to understand the effects of a player's next contract. For the context of this study, the injury and player statistics of the contract year (the preceding year to when the contract was signed) were examined due to the contract year phenomenon. This phenomenon was discussed in greater detail within the *Previous Work and Significance* section.

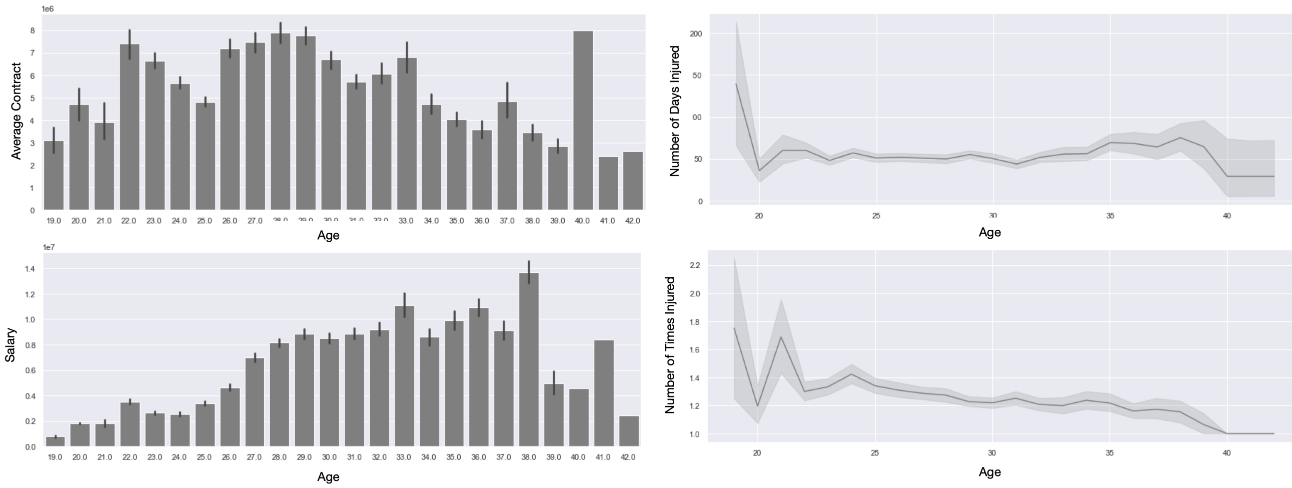
## 4.2 Predictor Variables

Much of the player bio-data (such as height, weight, college, etc.) were seen to make the regression filled with redundant predictor variables. When adding these bio variables into the regression, many of the coefficients yielded non-significant results. To reduce the issue of over-specification, the player bio-independent variables were not included in the final regression.

The bio factor that was, in fact, significant when running regressions was the player's age. Age can sometimes be complicated to implement because conventional intuition posits that during the beginning years of a player's career within the NBA and the final years before retiring would have the lowest salary. The salary or average contract value would tend to peak midway through the player's career, as conventional basketball wisdom would expect the player's peak performance to be during the middle years of the player's career. *Figure 3* below examines the effect of age on salary, average contract, and injury variables.

As seen from the above figure there doesn't seem to be a significant correlation between age and average contract value. Although the trend for age and salary is similar to conventional intuition, in that the average salary prediction per age follows a shape similar to a

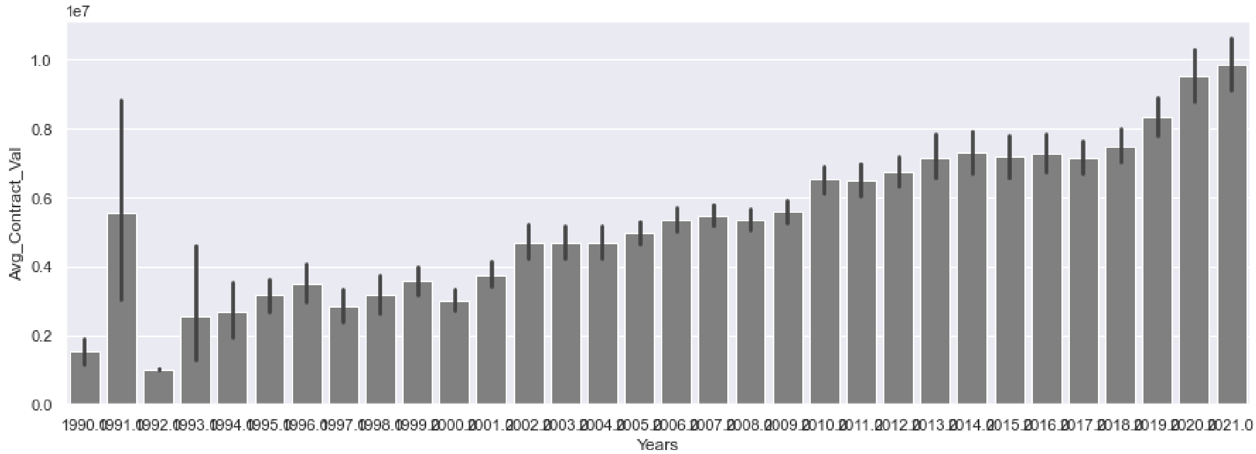
Figure 3: Impact of Age on Player Value and Injury




normal distribution, it doesn't seem to follow the trend closely. Therefore, transforming the independent variable to smooth the function will not be performed because it seems that there isn't a significant enough polynomial approximation when assessing the bar plot above. When analyzing age's effect on injury variables, the figure on the top illustrates almost no correlation between age and the number of days a player is injured. Although the average number of days injured is higher for players under 20, the standard deviation of injuries appears to be very large. Age's impact on the number of times a player is injured during the year appears to describe a weak negative correlation. This insinuates that as a player gets older, they are less prone to being injured consistently. There are fluctuations in injury proneness during the early years of their career, which seems intuitive since newer players would take time to better understand their physical health well being. Towards the tail end of their careers, the players are probably less prone to being injured as the number of minutes they play per game would have been substantially reduced over time.

The next consideration is how a given year impacts the value of a contract. The purpose of adding the year variable as a dummy variable is to capture any time-related effects on average contract value. *Figure 4* below assesses the change in average contract value over the period of the last 30 years.

Figure 4: Average Contract Value Change Over Time




The data over the thirty years show that there has been a consistent, near-linear increase in average contract value over time. The years from 1990 to 1993, seem to show an inconsistent pattern with the rest of the data set. The data, being retrieved from pro sports transactions could be incomplete for those three years. As written on their website “historical data from the earlier days of the game is not easy to come by, so by “complete” we don’t mean to claim that there might not be transactions that took place that isn’t listed” (pro sports). This statement could explain the inconsistency in earlier years of the average contract value. Based on this sentiment, and the inconsistent patterns provided in the figure above, the regressions in this study will only take into account from the years 1994 and forward. Finally, an indicator of next year’s player contract value would be determined by the previous year’s salary, which is also included in the regression table. The data over the thirty years show that there has been a consistent, near-linear increase in average contract value over time. The years from 1990 to 1993, seem to show an inconsistent pattern with the rest of the data set. The data, being retrieved from pro sports transactions could be incomplete for those three years. As written on their website “historical data from the earlier days of the game is not easy to come by, so by “complete” we don’t mean to claim that there might not be transactions that took place that isn’t listed” (pro sports). This statement could explain the inconsistency in earlier years of the average contract value. Based on this sentiment, and the inconsistent patterns provided in the figure above, the regressions in this study will only take into account from the years 1994 and forward. Finally, an indicator of next year's player contract value would be determined by the previous year's salary, which is also included in the regression table.

## 4.3 Effects of Injury Proneness on Contract Value

*Table 3*, shows the first regression that examines the effects of the number of times injured within a given year and its impact on the percent change of average contract value. The regression equation detailed in the table is as shown below:

$$1.\ \textbf{log}(\textbf{Average Contract Value}) = \beta_0 + \beta_1 \times Number\,of\,Times\,Injured_{-1} + \beta_2 \times (PER\,/\,BPM\,/\,VORP\,/\,WS)_{-1} + \beta_3 \times Year_0 + \beta_4 \times Age_0 + \beta_5 \times Salary_{-1}$$

*Table 3* regression notices the impact of multiple different variables and their impact on the percent change in contract value. It is important to note that variables that denote a *-1* subscript, imply that the variable acts as a lag variable. This means that the variable value is that of the year before the contract is signed. Variables that denote a *0* subscript imply that the variable value is taken from the year that the contract was signed.

All performance metrics (PER, BPM, VORP, and WS) are positively correlated with the dependent variable. An increase in a PER point (in regression (1)) increases the average contract value by 7.4%. This result is significant at all p-value levels. Both a change in BPM in regression (2), whilst a change in VORP in regression (3) result in a positive correlation of 13% and 37% change in average contract value respectively. Intuitively this makes sense

Table 3: Regression Results for effects of Num. of Times Injured on Average Contract Value

| | *Dependent Variable: Log (Average Contract Value)* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Number of times injured $_{-1}$ | -0.034*** | -0.033*** | -0.028*** | -0.026*** |
| | (0.008) | (0.008) | (0.008) | (0.007) |
| PER $_{-1}$ | 0.074*** | | | |
| | (0.001) | | | |
| BPM $_{-1}$ | | 0.128*** | | |
| | | (0.002) | | |
| VORP $_{-1}$ | | | 0.372*** | |
| | | | (0.005) | |
| WS $_{-1}$ | | | | 0.177*** |
| | | | | (0.002) |
| Year $_0$ | 0.028*** | 0.025*** | 0.030*** | 0.031*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Age $_0$ | -0.032*** | -0.042*** | -0.033*** | -0.029*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Salary $_{-1}$ | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 14,032 | 14,032 | 14,032 | 14,032 |
| $R^2$ | 0.362 | 0.392 | 0.436 | 0.465 |
| Adjusted $R^2$ | 0.362 | 0.392 | 0.436 | 0.465 |
| Residual Std. Error | 0.762(df = 14026) | 0.744(df = 14026) | 0.716(df = 14026) | 0.697(df = 14026) |
| F Statistic | 1590.408*** (df = 5.0; 14026.0) | 1808.280*** (df = 5.0; 14026.0) | 2166.652*** (df = 5.0; 14026.0) | 2439.279*** (df = 5.0; 14026.0) |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

since the average BPM of all players is 0 and the best players/teams have a BPM of around +10. Since VORP tracks BPM based on the number of possession played over a replacement player, an increase in one unit would have a more significant impact on the change in average contract value than BPM. Finally, when we analyze WS and its impact on the change in average contract value, we notice that it provides the highest $R^2$ value, providing insight that this metric explains the most in regards to its contribution to changes in average contract value. An increase in a point of WS increases the percent change in average contract value by 17.7%.

The year variable has a positive relationship with average contract value posits that on average a new year increases average contract value by  3% across all regressions. This positive correlation could be in line with inflation rates as well as annual revenue growth within the NBA as well as salary caps for each team. The age of a given player has a similar opposite effect that the year variable posits. This variable explains that on average, as players get older, their average contract value decreases by 3% across all regressions. A dollar increase in the previous year's salary has a 0.000% change in average contract value. This, intuitively, makes sense, since salaries are normally in thousands or millions of dollars. If the Salary was not in absolute terms, but rather in thousands or millions, there would be a greater percent change signified in the regression table. Since the focus is on injury, the coefficient of salary is not a material fact in this data analysis, rather the fact that the coefficients are significant across all p-values is what is most pivotal.

In regards to Number of Times Injured, also known as how prone a player is to injury, across all regressions is negatively correlated with the percent change in next year's average contract value. Across all regression, if a player is injured one more time during the year, it impacts their average contract value by -3%. This impact seems to make intuitive sense, in that the more injury-prone a player is, the more their next contract value would correspondingly decrease. All results are significant at every level of p-value.

## 4.4 Effects of Incidence of Injury on Contract Value

*Table 4* details the second regression, which deals with understanding how the number of days a player is injured affects their contract value. The regression equation detailed in the table is as shown below:

$$2.\ \mathbf{log(Average\ Contract\ Value)} = \beta_0 + \beta_1 \times \left(\frac{Number\ of\ Days\ Injured}{10}\right)_{-1} + \beta_2 \times (PER\,/\,BPM\,/\,VORP\,/\,WS)_{-1} + \beta_3 \times Year_0 + \beta_4 \times Age_0 + \beta_5 \times Salary_{-1}$$

Since the coefficients of all of the other variables (other than the Number of Days Injured

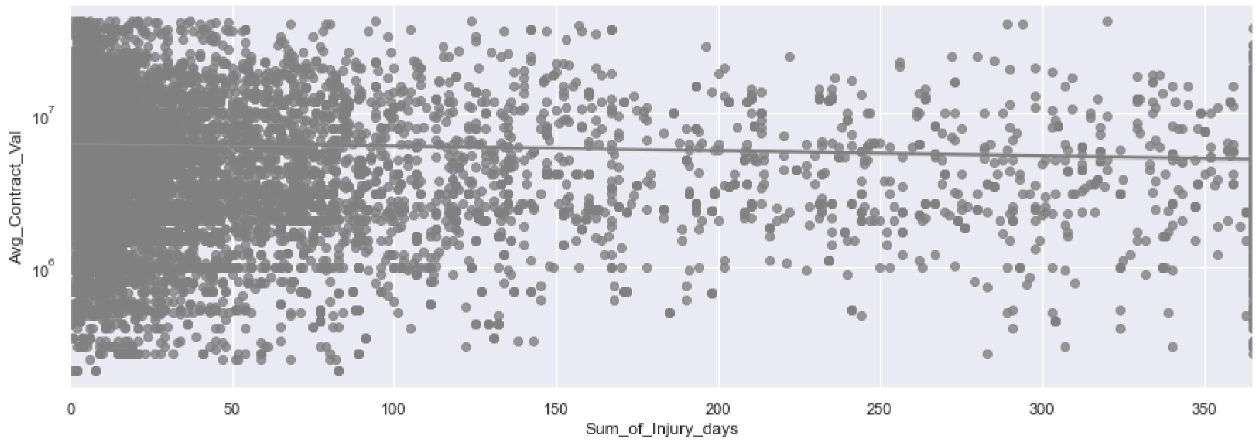
Table 4: Regression for the Effects of Num. of Days Injured on Average Contract Value

| | *Dependent Variable: Log (Average Contract Value)* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| (Number of Days Injured / 10) $_{-1}$ | -0.011 | -0.012* | -0.011 | -0.009 |
| | (0.007) | (0.007) | (0.007) | (0.006) |
| PER $_{-1}$ | 0.074*** | | | |
| | (0.001) | | | |
| BPM $_{-1}$ | | 0.128*** | | |
| | | (0.002) | | |
| VORP $_{-1}$ | | | 0.372*** | |
| | | | (0.005) | |
| WS $_{-1}$ | | | | 0.177*** |
| | | | | (0.002) |
| Years $_0$ | 0.027*** | 0.024*** | 0.029*** | 0.030*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Age $_0$ | -0.032*** | -0.042*** | -0.033*** | -0.028*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Salary $_{-1}$ | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 14,032 | 14,032 | 14,032 | 14,032 |
| $R^2$ | 0.361 | 0.391 | 0.435 | 0.465 |
| Adjusted $R^2$ | 0.361 | 0.391 | 0.435 | 0.465 |
| Residual Std. Error | 0.762(df = 14026) | 0.744(df = 14026) | 0.717(df = 14026) | 0.698(df = 14026) |
| F Statistic | 1585.578*** (df = 5.0; 14026.0) | 1803.616*** (df = 5.0; 14026.0) | 2162.796*** (df = 5.0; 14026.0) | 2435.410*** (df = 5.0; 14026.0) |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

variable) placed in the regression in *Table 4* is similar to that of *Table 3*, the interpretation of these coefficients will remain the same as the previous regression table. For this regression to show the coefficient variables for the number of days injured, the variable was divided by 10. This was because when left as an absolute value, the regression coefficient for the number of days injured independent variable showed near-zero values. The interpretation of this coefficient shows that every ten days an NBA player is injured, the average contract value decreases by an average of 1% across all four regression equations listed.

Although intuitively, the regression coefficients are reasonable, three out of the four regression coefficients are not significant. It seems improbable for insignificant coefficients to be caused by a small sample size relative to the variability in my data because the number of observations in this regression is well over 14,000 data points. Another reason that could yield insignificant results is that the relationship between the dependent and independent variables is not linear. To test whether any transformations should be made to the independent variable, a scatter-plot was examined between the two variables in question.

Figure 5: Number of Days Injured vs. Average Contract Value




Based on the scatterplot in *Figure 5*, it seems that the model is appropriate and there is no apparent non-linear relationship between the residuals. Despite absence of heteroskedasticity within the error variables, to examine this issue further, the test whether there is autocorrelation present within the dataset. Autocorrelation is a characteristic of the data that looks to understand how similar a given time series data and a lagged version of its data is. As this paper includes injury and other independent variables within its regression, it is important to test for serial correlation or serial dependence within the variables. To test this the durbin watson test was performed.

Table 5: Durbin Watson Test for Each Regression in *Table 4*

| **Regression:** | **Durbin Watson Test Result** | **Presence of Autocorrelation?** |
|---|---|---|
| Reg $_{\#1}$ | 2.4 | None |
| Reg $_{\#2}$ | 2.5 | None |
| Reg $_{\#3}$ | 2.5 | None |
| Reg $_{\#4}$ | 2.6 | Low Positive Presence |

The Durbin-Watson test shown in *Table 5* presents values for the Durbin Watson test that is within the acceptable bounded region. The acceptable bounded region is between 1.5 and 2.5, where 0 is strong negative autocorrelation and 4 is strong positive autocorrelation. Since the average of all regressions is within the acceptable bounded region, it does not seem that there the regression model performed is unsound. Therefore, it seems that the relationship between the dependent and independent variables is inconsequential.

A plausible reasoning for why the coefficient proves to be insignificant could be due to the fact that prior NBA contracts may have taken into account the average number of days a player would be out due to injury. Since this paper's focus is on the general manager's decision on the next contract signed, the considerations before the next contract is signed are not examined within the scope of this study.

## 4.5 Effects of Types of Injury on Contract Value

Finally, we examine the type of injury and its impact on average contract value. Types of injuries are far more complicated than the previous regressions ran before this section. The explanation of types of injuries and their impact on the NBA is examined in more detail in the *Discussion of Player Injury* section. Type of injury can be broken down by body part, injury type, or even both. There are 26 different types of injuries listed in *Pro Sports*'s database. *Table 5* describes a regression table that evaluates the impact that each of the injury type variables has on the average contract value.

There are two regressions explained in *Table 5.* The first regression is the model that takes into account all of the different types of injury variables. In both regressions, the performance metric used was Win Share, since it explained the most in both of the previous regression tables above. Most of the injury types in the first regression were insignificant. After removing insignificant variables in the model (2), the coefficient magnitude and direction are still conflicting. For example, a player that experiences a contusion is on average expected

Table 6: Regression Results for effects of Types of Injury on Contract Value

| | *Dependent Variable: Log (Average Contract Value)* | |
|---|---|---|
| | (1) | (2) |
| Age | -0.028*** | -0.028*** |
| | (0.002) | (0.002) |
| Intercept | -45.984*** | -45.612*** |
| | (1.933) | (1.865) |
| Salary | 0.000*** | 0.000*** |
| | (0.000) | (0.000) |
| WS | 0.177*** | 0.177*** |
| | (0.002) | (0.002) |
| Years | 0.030*** | 0.030*** |
| | (0.001) | (0.001) |
| Type: sore | -0.002 | |
| | (0.019) | |
| Type: splints | -0.772* | -0.779* |
| | (0.402) | (0.402) |
| Type: sprain | 0.056*** | 0.051*** |
| | (0.019) | (0.018) |
| Type: tear | 0.035 | |
| | (0.038) | |
| Type: bone chips | 0.368 | |
| | (0.402) | |
| Type: bone spur | 0.027 | |
| | (0.094) | |
| Type: broken | -0.003 | |
| | (0.050) | |
| Type: bruise | 0.098*** | |
| | (0.030) | |
| Type: bulging disc | 0.200 | |
| | (0.696) | |
| Type: concussion | 0.006 | |
| | (0.060) | |
| Type: contusion | 0.416* | 0.410* |
| | (0.232) | (0.232) |
| Type: cracked | 0.010 | |
| | (0.696) | |
| Type: damage | -0.657*** | -0.664*** |
| | (0.210) | (0.210) |
| Type: dislocated | 0.135* | 0.129* |
| | (0.075) | (0.075) |
| Type: fracture | 0.015 | |
| | (0.037) | |
| Type: hernia | -0.056 | |
| | (0.402) | |
| Type: hyperextended | -0.053 | |
| | (0.108) | |
| Type: inflame | -0.080 | |
| | (0.097) | |
| Type: pull | -0.546*** | -0.552*** |
| | (0.180) | (0.180) |
| Type: rupture | -0.492*** | -0.498*** |
| | (0.169) | (0.169) |
| Type: spasm | -0.140*** | -0.145*** |
| | (0.043) | (0.042) |
| Type: strain | -0.015 | |
| | (0.022) | |
| Type: stress | 0.206 | |
| | (0.132) | |
| Type: surgery | 0.141*** | 0.135*** |
| | (0.040) | (0.040) |
| Type: swelling | 0.473** | 0.467** |
| | (0.201) | (0.201) |
| Type: tendinitis | -0.099*** | -0.106*** |
| | (0.037) | (0.036) |
| Observations | 14,032 | 14,032 |
| $R^2$ | 0.469 | 0.468 |
| Adjusted $R^2$ | 0.467 | 0.467 |
| Residual Std. Error | 0.696(df = 14001) | 0.696(df = 14016) |
| F Statistic | 411.453*** (df = 30.0; 14001.0) | 821.651*** (df = 15.0; 14016.0) |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

to receive a 41% increase in next year's average contract value, and this value is significant. Since this result doesn't seem to make much intuitive sense, a plausible reason for why this may occur is that there might be an issue with the incidence of injury as well as the type of injury. Whereby, a few types of injuries may be uncommon while other more common injuries may affect the impact on average contract value. An example of this is where the fact that a *sprain* may be more common than that of *splints*. Therefore, there might be an issue with the number of observations.

Thus, to combat the issue of uncommon injuries, we assess in *Table 6* the top 20 most common injuries and their respective frequencies. We look to regress the most common injuries and gain a better understanding if the most common injuries can explain the next year's contract value more.

We increased specificity in *Table 6* by not only isolating the type of injury but also which body part. Believing that the increased specificity may provide more significant results. As expected, the most common types of injuries are mainly ankle and knee injuries. These injuries are most common due to the nature of the sport. Basketball players are constantly required to run as well as jump in various directions throughout the game. With increased exposure on the court, the probability of landing incorrectly increases and thus sprains and ligament tears are common amongst these body parts. A sprained ankle accounts for nearly 12% of all injuries experienced by NBA players.

Despite accounting for common injury types, when we re-run our regression analyzing the most common injuries and their effect on the change in average contract value, we notice the same pattern in *Table 7* as we did in *Table 6*. Certain coefficients show that some injuries affect positively with percent change in average contract value while others show a negative trend. The aspect most concerning is that most of the injuries listed in the regression are still not significant. After accounting for incidence of injuries many of the injuries do not seem to remain consistent in regards to its affect on contract value. The issue pertaining to insignificance could still be due to multicollinearity problems. In other

Table 7: Most Common Injuries and Respective Frequencies

| **Injury Type** | **Number of Times Injured** | **Average Days Injured** | **Percentage of Total** |
|---|---|---|---|
| Sprain Ankle | 869 | 99.54 | 11.52 % |
| Sore Knee | 412 | 54 | 5.46 % |
| Tendinitis Knee | 339 | 30.48 | 4.49 % |
| Spasm Back | 237 | 25.6 | 3.14 % |
| Injury Knee | 210 | 129 | 2.78 % |
| Strain Hamstring | 185 | 95.85 | 2.45 % |
| Strain Back | 179 | 14.83 | 2.37 % |
| Sore Back | 178 | 13.86 | 2.36 % |
| Surgery Knee | 160 | 80.61 | 2.12 % |
| Sore Ankle | 154 | 26.6 | 2.04 % |
| Strain Groin | 152 | 48 | 2.02 % |
| Strain Calf | 151 | 11 | 2.00 % |
| Bruise Knee | 138 | 91.65 | 1.83 % |
| Sprain Knee | 130 | 84.75 | 1.72 % |
| Concussion Head | 125 | 70.75 | 1.66 % |
| Injury Ankle | 92 | 24 | 1.22 % |
| Sore Foot | 79 | 3 | 1.05 % |
| Injury Hamstring | 77 | 85.63 | 1.02 % |
| Sprain Wrist | 73 | 101.6 | 0.97 % |
| Tear Knee | 73 | 195 | 0.97 % |
| (blank) Knee | 71 | 4 | 0.94 % |
| Injury Foot | 69 | 22.5 | 0.91 % |
| Sprain Foot | 68 | 10.5 | 0.90 % |
| (blank) Foot | 64 | 28.67 | 0.85 % |
| Injury Back | 64 | 365 | 0.85 % |
| Injury Groin | 63 | 61.29 | 0.84 % |
| Fracture Foot | 62 | 225 | 0.82 % |
| Injury Hip | 62 | 17.27 | 0.82 % |
| Sprain MCL | 61 | 68 | 0.81 % |
| Tear ACL | 59 | 212.67 | 0.78 % |

Table 8: Regression Results for effects of Type of Injury on Average Contract Value

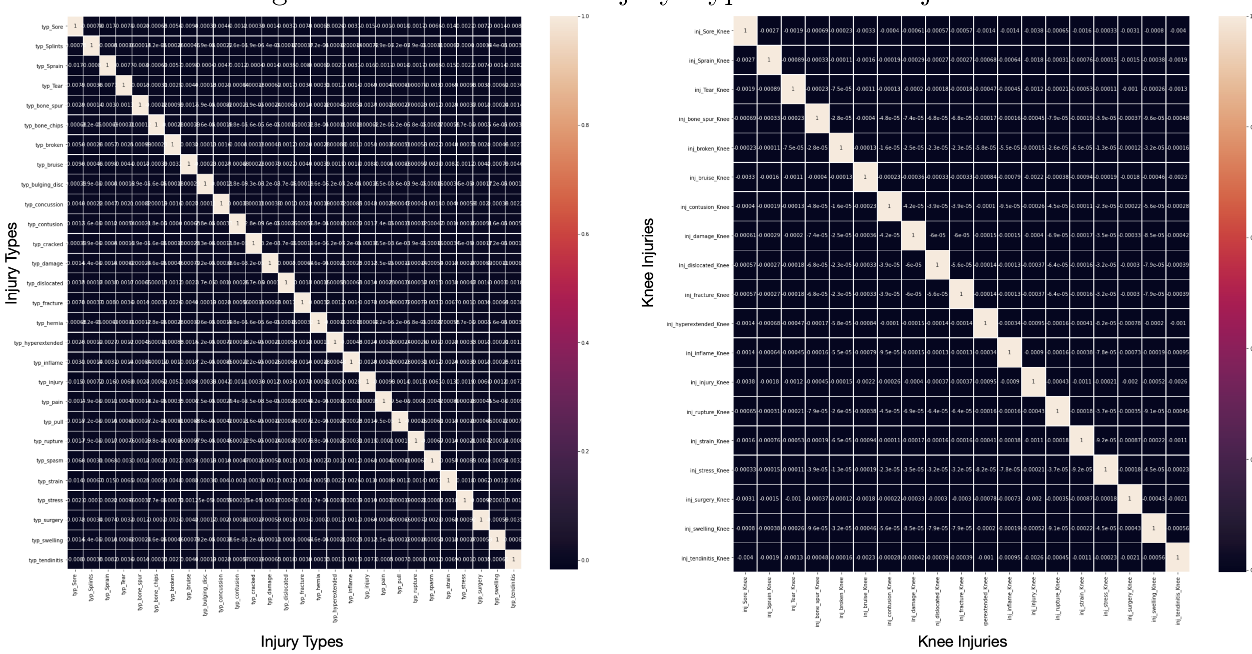
| | | | |
|---|---|---|---|
| **Dep. Variable:** | log (Avg. Contract Val.) | **R-squared:** | 0.467 |
| **Model:** | OLS | **Adj. R-squared:** | 0.466 |
| **Method:** | Least Squares | **F-statistic:** | 573.8 |
| **Date:** | Sun, 27 Mar 2022 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 19:45:38 | **Log-Likelihood:** | -14828. |
| **No. Observations:** | 14032 | **AIC:** | 2.970e+04 |
| **Df Residuals:** | 14012 | **BIC:** | 2.985e+04 |
| **Df Model:** | 19 | | |

| | **coef** | **std err** | **t** | **P> \|t\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| Intercept | -45.3713 | 1.958 | -23.169 | 0.000 | -49.210 | -41.533 |
| Years | 0.0301 | 0.001 | 31.157 | 0.000 | 0.028 | 0.032 |
| Age | -0.0283 | 0.002 | -17.055 | 0.000 | -0.032 | -0.025 |
| Salary | 3.965e-08 | 1.16e-09 | 34.055 | 0.000 | 3.74e-08 | 4.19e-08 |
| WS | 0.1769 | 0.002 | 77.823 | 0.000 | 0.172 | 0.181 |
| Sore Knee | 0.0184 | 0.030 | 0.619 | 0.536 | -0.040 | 0.077 |
| Sore Ankle | -0.0826 | 0.046 | -1.791 | 0.073 | -0.173 | 0.008 |
| Sore Back | -0.0517 | 0.042 | -1.229 | 0.219 | -0.134 | 0.031 |
| Sprain Knee | 0.0621 | 0.053 | 1.176 | 0.240 | -0.041 | 0.166 |
| Sprain Ankle | 0.0302 | 0.021 | 1.413 | 0.158 | -0.012 | 0.072 |
| Bruise Knee | 0.0513 | 0.049 | 1.055 | 0.291 | -0.044 | 0.147 |
| Concussion Head | -0.0086 | 0.061 | -0.141 | 0.887 | -0.128 | 0.111 |
| Injury Knee | -0.0818 | 0.051 | -1.610 | 0.107 | -0.181 | 0.018 |
| Spasm Back | -0.1650 | 0.047 | -3.546 | 0.000 | -0.256 | -0.074 |
| Strain Back | -0.2023 | 0.062 | -3.263 | 0.001 | -0.324 | -0.081 |
| Strain Calf | -0.0798 | 0.045 | -1.783 | 0.075 | -0.167 | 0.008 |
| Strain Groin | 0.0547 | 0.047 | 1.160 | 0.246 | -0.038 | 0.147 |
| Strain Hamstring | -0.0169 | 0.046 | -0.365 | 0.715 | -0.108 | 0.074 |
| Surgery Knee | 0.0999 | 0.051 | 1.969 | 0.049 | 0.000 | 0.199 |
| Tendinitis Knee | -0.1345 | 0.045 | -2.967 | 0.003 | -0.223 | -0.046 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 596.835 | **Durbin-Watson:** | 0.271 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 700.949 |
| **Skew:** | -0.489 | **Prob(JB):** | 6.18e-153 |
| **Kurtosis:** | 3.492 | **Cond. No.** | 2.96e+09 |

words, assessing whether two injuries were subject to multicollinearity is understanding if a player that experiences a certain type of injury is likely to experience another injury. For example, can an individual that experience an ankle injury be likely to experience a knee injury. *Figure 6* assesses the correlation between injury types through a correlation matrix.

Figure 6: Correlations of Injury Types & Knee Injuries




The correlation matrix on the left in *Figure 6* assesses whether there is a correlation between the different types of injuries. The color scale explains that the more red or white a box is, the higher the correlation between the variables shown above. On average, the figure illustrates that the correlation between all types of injuries do not seem to be correlated with one another. This infers that an individual that has a certain type of injury is highly unlikely to be correlated with another type of similar injury. To examine this phenomenon further, the correlation matrix on the right of *Figure 6* examines whether there is correlation between different types of injuries within the same body part. A randomly selected, commonly occurring, body part (Knee) was selected as the basis of testing this correlation hypothesis. Surprisingly, the correlation between different types of knee injuries were uncorrelated as well. This means that a ruptured knee was not correlated with fractured knee either.

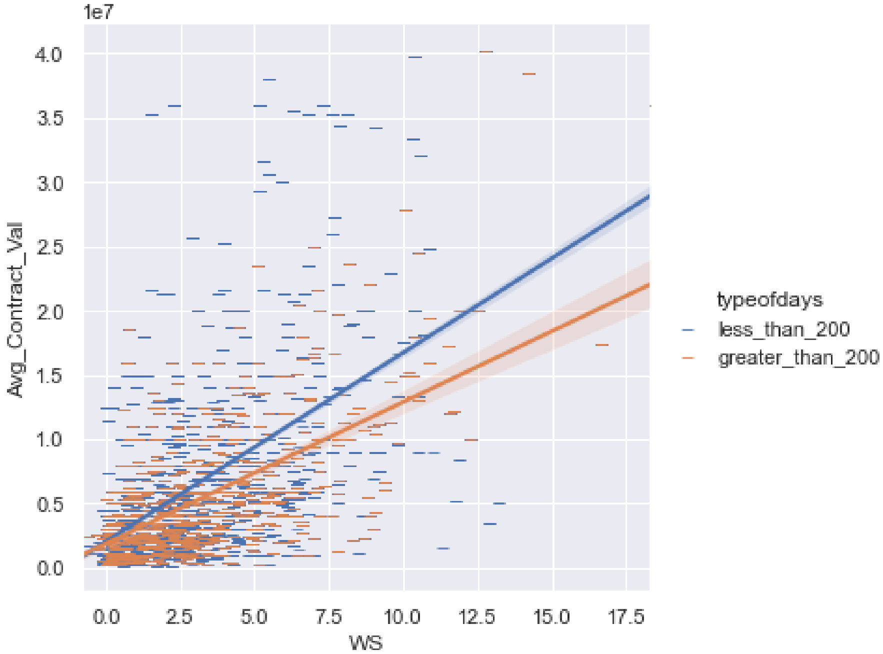
The implications of the results regarding type of injury is two fold. 1) The reason that type of injuries are not correlated with one another and producing insignificant results when regressed against average contract value could be a factor of the initial data set from which the injury data was scraped was incorrect. However with over 150,000 data points within the original dataset, and the based on the overall reliability of the website, the data seems to not be the issue. 2) The second implication is that the type of injury may not be the factor that affects contract value, but rather the severity of the injury.

## 4.6 Severity of Injury

Typically defining the severity of injury in most contexts isn't difficult. For example, when examining injuries sustained by individuals that experience a car crash, severity levels can be determined by the cost of injury to that individual or even the number of days an injured person is affected for (Bullock et al., 2021). The cost of injury, in the perspective of a team, is in fact the number of games missed by the individual. Therefore the cost of injury inflicted on a basketball organization is directly related to the lost revenues or the number of days the individual was injured. Now, understanding that the scope of injury severity would be assessed by the number of days an injured player is out, the determinants of the level of severity would be based on the 25, 50, and $75^{th}$ percentiles. However when referring to *Table 2*, the $50^{th}$ percentile is only 13 days or two weeks. Furthermore, when looking at *Figure 5*, most of the injuries are clustered under 100 days. Thus, assessing injury severity based on percentiles provided would not be sufficient. To assess the impact of injury severity on contract value, we choose 200 days as the arbitrary cutoff. For the purpose of understanding the effect of severity of injury on average contract value, we arbitrarily classify an injury that lasts over 200 days is classified to be more severe than that of injuries that lasted less than 200 days.

*Figure 7* shows the relationship between WS and Average Contract Value, by grouping the observations based on the number of days they were injured for. Although both lines

Figure 7: Severity of Injury's impact on Avg. Contract Value




shown in the figure present that Win Share is positively correlated with Average Contract Value and the intercept was comparable, the gradient was where the two lines differed. This graph explained that when players are more impactful to the game and they had experienced a more severe injury, their average contract value would be affected more. At first glance,

The reason that this would be the case is that since WS is heavily correlated to MP as shown in , a player that has high WS impacts the game more than players with lower WS as they would potentially play more minutes. Since they are a more integral part of the team, the managers may provide them a lower average contract value due to the fact that they believe they would be more prone to injury, and potentially not be able to maintain such a high WS in the future. Thus, this graph insinuates that managers are less optimistic about the player's production if they are injured for over 200 days. The caveat, that needs to be taken into account, however, is that in order to make assumptions about injury severity in this study the severity needs to be based on the number of days. The effect of injury on future performance was not studied in the scope of this study.

# 5 Final Remarks

This study aimed to understand the impact of injuries sustained by an NBA player have on their respective contract valuation. The focus of this study looked to analyze the data regarding the decision to provide a player a new contract and infer the impact that injury had in that decision-making process. The study focused solely on empirical evidence of data that spanned over 30 years (from 1990 to 2020) to understand the decision-making tendencies of general managers in the US. The paper was novel in investigating the behavior of general managers and inspecting their preferences, however, this paper did not test whether their choices were profit-maximizing or rational. The results of the paper were incongruent with conventional basketball wisdom and the initial hypothesis. The results posited that injury proneness (also referred to in this paper as *Number of Times Injured*) impacted the next year's contract value most significantly. Results when running a regression with the independent variable being *Number of Days Injured* against average contract value came to be insignificant. Tests for heteroskedasticity and autocorrelation further suggested that the independent variable may (in-fact) be inconsequential against the dependent variable. Conventional basketball wisdom, instead, posits that players that were out due to injury would severely impact their future on-court performance and their overall contract valuation. Furthermore, this paper examined whether types of injuries had an impact on average contract value. The results regarding types of injuries are similar to that of the number of days injured, where the results had an insignificant impact on average contract value. These results alluded to the interpretation that the focus should be on classifying the severity of injury rather than focusing on the actual type of injury.

## 5.1 Implications of Results

Contact injuries are generally thought of as unpredictable. As explained in *Issues in Estimating Risks and Rates in Sports Injury*, it is difficult to estimate the future likelihood of injury rates for all players. The regressions insinuated that, on average, players that are injury prone are more likely to have their average contract value be more affected than the number of total days that the player was injured and the type of injury. This finding insinuates that injury proneness is the best predictor of future injury. Providing a player a contract is essentially a pay-for-future-performance agreement. The results imply that a general manager believes that injury proneness of a player would most significantly predict future performance and potential injuries. Furthermore, an implication of *Effects of Types of Injury on Contract Value* section, remains that the severity of injury potentially explains more than the type of injury sustained by a player.

## 5.2 Limitations of Study

There are several practical and unobservable limitations to the scope of this paper. The limitations that are detailed in this section include, but are not limited to:

1. <u>*Validity of data analysis and cleaning:*</u> In any paper the analysis performed utilizing multiple large data sets is susceptible to human errors. Much of the regressions run as a part of this study required web-scraping data from three different sources. These datasets were initially cleaned and then merged on certain common metrics. Before merging, few datasets required changes in years to allow certain variables to be considered as lag variables, while others were maintained as normal. The merging of datasets was difficult based on the different formats names, teams, years, and other variables stored in each respective source. Although periodic internal validations were performed to ensure that player names and statistics remained consistent throughout each merging process, they are still susceptible

to errors. Furthermore, the number of days injured and the number of times injured were extracted from a dataset that was based on a comment form, such that each row would be a description of an injury transaction. For example, a player was placed on IL (or "Injury List") with a sprained ankle, with the specific date specified. The same player would at a later date be stated that they were activated from IL. Players that had season-ending injuries were not re-activated from IL, and thus, these players needed their own added checker within the code. Other factors within the datasets occurred that required an extensive understanding of data cleaning techniques that could be susceptible to certain errors.

2. *Eye Test:* Many NBA professionals, statisticians, and fans will agree that empirical evidence doesn't paint the entire picture when it comes to explaining NBA player valuations. Despite advanced analytical techniques being developed constantly, and various metrics that evaluate the efficiency and production of a given player, certain added values simply cannot be quantified. Leadership qualities, teamwork, coachability, and other extremely valuable traits of a player are nearly impossible to measure. Another aspect is that the severity of the injury is sometimes unique to the player. The effect of an injury can differ by each player, based on their age, athleticism, and sometimes willpower. Thus, discussing generalizations from empirical research may not highlight the more nuanced picture.

3. *Comparing trends across Basketball leagues:* Another limitation of this study is the general scope of the population sample. The effects of decision-making of contracts and injuries were only examined within the NBA. To notice whether the trend is globally apparent, the study could be repeated in the Euro, Australian, or Chinese basketball leagues (other major basketball leagues around the world). Furthermore, we can attempt to analyze if these trends are consistent across other pro-team sports leagues such as football, hockey, or soccer.

4. *Sample of people who get injured and don't get another contract:* Finally another pivotal aspect of this study is that the focus was on understanding a general manager's decision making when they choose to provide a player a new contract. Players that got severely

injured but did not receive a new contract were not examined. Another interesting aspect that could be considered for future studies is if the behaviors of new contracts provided to previously injured players differed if the player resigned to that same team or if they were traded to a different team.

## 5.3 Consideration for Future Studies

Several future studies could be examined as a means to further discovery on injury impact on player valuation. These considerations that are detailed in this section include, but are not limited to:

1. *Cost to organization:* Examining the costs incurred by the organization in regards to an injury can be pivotal in understanding the potential rationale of decisions surrounding providing players contracts. The costs incurred may not only extend to loss in revenue for the game the player misses, but the probability to perform well in the post-season, as well as further costs to loss in potential trade value within the player. Furthermore, analyzing costs could also potentially help assess whether decisions made by general managers were profit-maximizing or not.

2. *Post hoc evaluation of injury on performance:* Another aspect of evaluating decision making, is to analyze whether on average the team makes the correct decision or not. For example, the regression on *Table 8* could be run to examine the effect of injury on the performance metric. Through examining the effect of injury on performance post hoc, we can understand if decisions made by managers were correct or not. By isolating each performance metric, and how much injury affects the performance, we can potentially insinuate whether managers are rational in their decision-making. By performing post hoc analysis we can attempt to hypothesize how to predict the impact of future costs on performance and investigate whether general managers are taking into account injury as much as they should.

3. *Injury Severity:* Finally, as mentioned towards the end of the Results section, the severity of the injury was not properly examined. A paper dedicated to analyzing the severity of the injury could contribute further to the study of the impacts that injury has on player valuation.

Table 9: Regression Results for effects of incidence of Injury on Different Performance Metrics

| **Dependent Variables:** | **PER** | **BPM** | **VORP** | **WS** |
|---|---|---|---|---|
| Intercept $_{-1}$ | -7.455*** | -17.328*** | -3.328*** | -6.892*** |
| | (0.092) | (0.088) | (0.045) | (0.092) |
| Number of times injured $_{-1}$ | -0.146*** | -0.106*** | -0.033*** | -0.148*** |
| | (0.008) | (0.008) | (0.004) | (0.008) |
| AST % $_{-1}$ | 0.338*** | 0.208*** | 0.093*** | 0.163*** |
| | (0.001) | (0.001) | (0.000) | (0.001) |
| eFG % $_{-1}$ | 29.709*** | 23.133*** | 4.783*** | 12.376*** |
| | (0.107) | (0.101) | (0.052) | (0.106) |
| FT % $_{-1}$ | 6.626*** | 2.981*** | 0.828*** | 3.377*** |
| | (0.064) | (0.061) | (0.031) | (0.064) |
| TOV % $_{-1}$ | -0.377*** | -0.200*** | -0.073*** | -0.175*** |
| | (0.002) | (0.002) | (0.001) | (0.002) |
| TRB % $_{-1}$ | 0.614*** | 0.291*** | 0.131*** | 0.280*** |
| | (0.002) | (0.002) | (0.001) | (0.002) |
| Age $_{-1}$ | -0.126*** | 0.002 | -0.010*** | -0.035*** |
| | (0.002) | (0.002) | (0.001) | (0.002) |
| Observations | 14,590 | 14,590 | 14,590 | 14,590 |
| $R^2$ | 0.755 | 0.574 | 0.374 | 0.685 |
| Adjusted $R^2$ | 0.755 | 0.574 | 0.374 | 0.685 |
| Residual Std. Error | 2.541(df = 105079) | 2.417(df = 105079) | 1.229(df = 105079) | 0.040(df = 105079) |
| F Statistic | 40434.158*** (df = 8.0; 105079.0) | 17697.038*** (df = 8.0; 105079.0) | 7861.449*** (df = 8.0; 105079.0) | 28514.287*** (df = 8.0; 105079.0) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

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