Injury Risk Management in the National Basketball Association: An Actuarial Approach

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Abstract

Major professional sports leagues have become large-scale financial institutions. This presents an increasing financial risk to an injury sustained by its athletes and, therefore, a growing need for injury risk management studies. We present a study of injuries in the National Basketball Association (NBA) from the perspective of insurable risks. Specifically, we employ a three-part actuarial compound risk model to identify drivers of injury occurrence frequency and a two-part injury severity through missed games given an injury and a financial loss per game missed. We fit this model using a novel dataset from the 22-23' NBA regular season that includes player injury, tracking, box score, salary, demographic, television, and travel information and economic estimates of game values. We predict higher losses for players with higher salaries, 32+ minutes played per game, and in larger markets. We estimate the top ten players account for $453M in at-risk injury losses per season, which is over 25% of all estimated at-risk injury losses. The actuarial approach also suggests risk mitigation strategies. We estimate that a uniform 10% cut in average minutes played per game reduces the expected compound loss for the highest risk players by 30-35% or $9-25M per player. Leaguewide, we estimate that shortening the length of an NBA game from 48 to 40 minutes would reduce total expected claims by $493M. We discuss how these results fit within related literature, salary cap accounting, and the tanking discourse, including suggested areas of further work. Data and replication code are made available.

Keywords: Achilles tendon, aggregate loss, competitive fairness, load management, player health, superstar

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Introduction

Professional sports have become colossal financial institutions, with Gross Domestic Sport Product estimates well over $150B (Milano & Chelladurai, 2011). Measuring by recent revenue, the top five professional sports leagues are the National Football League (NFL) at $19.2B, followed by Major League Baseball (MLB) at $11.6B, the National Basketball Association (NBA) at $10.6B, the English Premier League (EPL) at $7.6B, and the National Hockey League (NHL) at $6.4B (Somoggi, 2024). By extension, the salaries of professional athletes have grown in lockstep (e.g., total player salaries in the NBA surpassed $4.5B (Lautier, 2025)). Because of these valuations, all league stakeholders (i.e., teams, players, fans, advertisers, etc.) are now exposed to significant potential losses in the event of injury to its athletes. This presents an important business problem of how to manage the risk of player injuries in major professional sports.

A standard risk mitigation tool is the use of insurance, and it has become more commonly used for player injuries (Cisyk & Courty, 2024). For example, the use of sports insurance products to protect against injuries have begun to proliferate in the NFL (Kahler, 2024). As these insurance products continue to multiply across sports, it is essential to perform an actuarial analysis to ensure pricing practices are fair, accurate, and robust to potential tail events. Despite this need, however, there remains a scarcity of close study in the actuarial and business literature. One challenge to a general study is that each professional sports league presents a varied injury risk, roster construction, financial standing, and governance structure. Hence, we will present a targeted analysis of player injuries in the NBA from the perspective of *insurable risks* (Mehr et al., 1985): a large number of similar exposures, the number of missed games is a measurable event, and the potential financial loss is significant. This is the first such study to our knowledge.

An initial complexity to injury risk management in the NBA is risk identification.

The most immediate is the risk to the athlete, as an injury can lead to a loss of future earnings (Meadows et al., 2024). For a franchise, they are exposed to salary losses in the event of injury because NBA contracts are typically guaranteed. There are also recovery costs (e.g., Achilles tendon ruptures have recovery costs of approximately $4M per player with league-wide losses exceeding $117M between 1992 and 2019 (Meadows et al., 2024)). This is all before more nuanced risks. For example, injuries to highly-talented (i.e., *star*) players tend to have a negative effect on winning in the NBA. This can compound franchise losses because it is known that both the competitiveness of the team and the presence of star athletes are positively correlated with attendance (Humphreys & Johnson, 2020). The same is true for regional television ratings (Foster et al., 2014), which drive revenues from advertising and sponsors. For the NBA specifically, player faces tend to be more visible, which gives a heightened value to player-specific branding (Foster et al., 2014; Kaplan, 2022). Therefore, beyond the risks to an individual player from an injury, it is necessary to contemplate managing the financial risk exposure of both franchises and the entire NBA.

Critically, an actuarial approach can address these challenges because it considers both the probability and financial impact of an event simultaneously. Compare this unified approach to present literature, which tends to treat injury event risk and its corresponding financial impact separately. On the injury side, for example, it is common to advocate for reducing player workloads to lower injury risk in the NBA (e.g., Caparrós et al., 2018; Drew et al., 2017; Teramoto et al., 2017). On the economic side, there is a long history of estimating the financial impact of injuries across sports (e.g., Verhagen, 2010). There also exist focused studies that estimate the cost of specific injuries, such as Achilles tendon ruptures (Meadows et al., 2024) in the NBA or concussions in the NFL (Courty & Cisyk, 2024). It is our objective, therefore, to unify these two perspectives and produce an actuarial claims estimate.

In actuarial nomenclature, the risk of event occurrence is known as claim *frequency*, and the loss given a risk event is known as claim *severity* (Klugman et al., 2012). For example, auto insurers model both the number of accidents (frequency) and the loss given an accident (severity). Translating this to injury risk management in the NBA is natural for claim frequency; i.e., the number of injuries incurred. For claim severity, however, the analog to injury risk management is less clear. That is, severity may be considered as the number of missed games due to the incurred injury, the potential impact to team performance, or as a traditional financial loss in the form of salary or revenue losses. We therefore propose a *three-part aggregate loss* or compound risk model (Klugman et al., 2012), which models injury occurrences (primary frequency), number of missed games given an injury (secondary frequency), and financial loss per missed game (severity) separately, before combining these three estimates to produce an aggregate claim estimate.

Modeling injury risk in this way has several advantages. First, because each component is modeled individually, we can draw inference into the drivers of all three parts. Second, the component-wise inference suggests risk mitigation strategies for both injury occurrence and severity, with the latter further delineated between games missed and financial loss. Third, the ability to aggregate each component into a total financial estimate can both capture nuanced risks and deliver claims estimates at each stakeholder level. This final point is essential given the challenges of setting up an actuarial model that is sufficient to address the various interpretations of risk exposure to player injuries in the NBA.

Let us elaborate with some examples. Mills et al. (2016) find that the quality of the visiting team has a positive influence on out-of-market consumers. In other words, consumers are more willing to travel and buy a ticket to see a strong visiting opponent. This implies that winning and star players travel well (i.e., can benefit the NBA as an enterprise). Hence, beyond an individual team, it may make financial sense for the NBA to consider league-wide insurance against injuries to star players, and a compound risk model can provide estimates at an enterprise level. Similarly, the presence of a star player drives increased attendance and revenues for both teams (Humphreys & Johnson, 2020). In an actuarial context, these star players would represent high-value, insurable assets that, if unavailable due to injury, may produce financial losses beyond the player's salary. Namely, it can trigger a compound loss that may spread across the NBA's entire revenue-sharing ecosystem, and an aggregate loss model can produce such enterprise level estimates.

Additionally, the NBA's dependence on star players is particularly acute within media markets. Regional Sport Network (RSN) television ratings are heavily influenced by the branding of key players, such as the number of All-Star nominees or the celebrity status of individual athletes. This vulnerability is so pronounced that the strategic absence of a small cohort of stars for load management or injury can lead to a reduction in television audiences by approximately 6.5 million household viewings and a loss of up to $20M in season-long advertising revenue (Reilly et al., 2023). By treating the financial loss as a separate, modeled component, therefore, the aggregate loss model we propose can incorporate potential losses from a myriad of factors, including potentially lost television ratings. As a final example, even basic factors like the impact of injuries on team performance requires careful consideration. This is because significant differences exist in how stadium and television audiences respond to winning, presenting a further challenge to stable financial forecasting. Research indicates that television audiences are far more sensitive to team quality than those attending in person. Specifically, fans watching on television are found to be 4.5 times more sensitive to a team's winning percentage than gate attendees (Mongeon & Winfree, 2012). On the other hand, the determinants of demand for televised content also include factors related to the wagering market, where viewership increases when point spread outcome uncertainty is high and when the local team covers the spread (Salaga et al., 2020). This multifaceted fan engagement implies that an ideal actuarial approach will also incorporate changes to win probability due to injuries. In other words, it is possible that if an injury lowers a team's winning percentage, it can have a multiplier-like loss effect on more sensitive consumer segments.

It is our contention that an actuarial compound loss model is capable of translating these many risk factors into dollar-value claims estimates, which may then be used to manage injury risk in the NBA. In terms of model specifics, we model injury frequency for a given player with a Poisson *generalized linear model* (GLM) with predictors for age, height, weight, position, games played, travel, and on court statistics. For the number of missed games per incurred injury, we use a second Poisson GLM with updated information as of each injury occurrence. Finally, the model then considers the financial severity per missed game by using a weighted salary approach via a principal component analysis (PCA), adjusted for economic estimates of the dollar value of NBA games (Lautier, 2025). The insurance claim estimates for a player start with a predicted number of missed games given an injury and a predicted financial loss given a missed game. These predictions are then averaged (i.e., a type of k-fold validation (Hastie et al., 2009)). The aggregate loss or final estimated claim, under the classical compound assumptions (Klugman et al., 2012), is then a product of these three predictions.

We apply this compound, actuarial model to a novel data set of more than 500 players that spans over 500 unique injuries from the 22-23' NBA regular season. The data includes injury reports, player salaries, box scores, television, and team travel information. We find that the frequency of injuries increases with travel fatigue, minutes played per game, games played per week, and a physical playing style. We also find player position and age are significant. For expected games missed per injury, we find that this risk increases as the number of injuries (primary frequency) increases and for a physical playing style. We predict higher losses for players with higher salaries, 32+ minutes played per game, and in larger markets. By position, we find that Centers miss more games, but Point Guards sustain the largest financial losses. At the star player level, our top ten highest claim estimates include several of the NBA's most popular players, including LeBron James, Stephen Curry, Luka Donic, Jayson Tatum, Jalen Brunson, and Nikola Jokic. To illustrate the capability of an aggregate loss model to capture financial risks beyond that of a guaranteed salary, we estimate an aggregate claim amount of \$79.03M for Nikola Jokic, despite his annual salary of \$33.05M. Additionally, our estimates find further justification for the NBA as a superstar league (e.g., Humphreys & Johnson, 2020; Reilly et al., 2023). Specifically, we estimate a total claim of $1.746B for the entire pool of 540 NBA players spanning the 22-23' NBA regular season. The top ten players by highest claim estimates account for $453M or just under 26% of total claims. That is, we estimate that less than 2% of NBA players account for over a quarter of expected financial losses at-risk due to injury.

To our knowledge, this is the first known actuarial analysis of injury risk in the NBA. By using an actuarial approach, we may estimate the financial impact of risk reduction strategies, such as less travel, fewer minutes per game, or fewer games played. In other words, in the same way seat belts, routine maintenance, and safe driving speeds can reduce auto insurance claims, it is possible to use our model to derive similar financial risk mitigation strategies, such as *load management* (e.g., Drew et al., 2017; Teramoto et al., 2017). Ultimately, based on our sensitivity analysis, we suggest reducing the length of a standard NBA game from 48 minutes to the collegiate, women's professional, and international standard of 40 minutes as an effective risk reduction strategy. In addition, at an enterprise level, establishing a method to price NBA player insurance products allows for these methods to be incorporated into salary cap accounting, offering financial relief to teams from injuries in roster construction while simultaneously protecting the financial interests of NBA players. In the Discussion, we provide an illustrative example of the potential savings available using such a risk management strategy.

The remainder of this manuscript is organized as follows. We first describe the formation of a novel data set that combines injury records, on court performance, player demographic, and economic variables for the 22-23' NBA regular season. Next, we present the methodological framework we employ, including the compound injury–loss model, estimation procedures, and robustness validation. We then present the empirical results, which span observed injury risk patterns, missed game severity, and estimated financial impact at the player and team level. Finally, we conclude with a discussion of the initial insights, limitations, and implications for our work, including a discussion of suggested areas of future research. For reference, all data and replication code may be found at the following public `git` repository: `https://github.com/HashanSP/nba_compound_risk`.

Data

We now summarize the data, its sources, and its fit within the framework of an actuarial compound risk model. All data corresponds to the 22-23' NBA regular season. Player injury information is readily available from published per-game, per-team injury reports required by NBA rules to satisfy gambling interests (e.g., Roa, 2022). They provide the player's name, status (i.e., "Available", "Probable", "Questionable", "Doubtful", or "Out"), and reason (e.g., "Right Foot Sprain"). We can thus track the number of injuries, the number of games missed per injury, and the type of injury for NBA players.

We then supplement this player level injury data with several types of supposed predictors. Specifically, we include biographical data for a player's age, height, weight, and nominal position (Sports Reference LLC, 2025) and detailed game box score and player tracking data on a per game basis (Lautier, 2025). The latter includes information ranging from traditional box score statistics (e.g., *minutes played*, *field goals attempted*, etc.) to more recent player tracking data (e.g., *screen assists*, *contested defensive rebounds*, etc.). This on court performance data is included because of previously established connections between player workload and injury risk (e.g., Caparrós et al., 2018). For a detailed summary of this box score and player tracking data, we suggest consulting Lautier (2025), which includes a public `git` repository.

Importantly, we also include schedule information (e.g., tracking the rolling number of games within the most recent 72 hours) because it is a common concern within the NBA community. For example, teams playing in "back-to-back" road games (i.e., two away games on consecutive days) win only 38.3% of such games (Kelly, 2010). This motivates using the schedule as a risk predictor because it acts as a stress test for NBA teams. In other words, the actuarial approach we propose allows for the quantification of how these structural constraints (e.g., "back-to-backs") influence both injuries and team performance.

Furthermore, we also include team travel details because of the known connection between the intensive travel required in the NBA and player injury risk (e.g., Huyghe et al., 2018). To do so, we utilize the schedule for each team to create a sequence of destinations. Next, we obtain the latitude and longitude for each city location in the NBA and utilize Hijmans (2024) to calculate the shortest distance between each subsequent city on the schedule according to the *haversine method* (i.e., assuming a spherical earth and ignoring ellipsoidal effects). This approach allows us to consider cumulative travel effects by approximating total travel through this distance accumulation approach. Additionally, these estimates can identify potential disparities in team travel that would not be observable by using a traditional even split of 41 home and 41 road games. For example, we estimate that the Cleveland Cavaliers travel a total estimated distance of 33,631 miles for the 22-23' NBA regular season, which is the shortest in the league. In contrast, the Denver Nuggets traveled 49,629 miles, which is the most in the league.

To consider financial risk, we supplement our data with player salary and estimates of the economic value of each NBA game (Lautier, 2025). The result is a novel data set that includes injury, travel, player demographics, player performance, player salary, and economic data covering 500+ players and injuries for the 22-23' NBA regular season. For the purposes of statistical modeling, we also use this raw data to engineer new feature variables consistent with potential time-varying exposures (e.g., total minutes played prior to a current injury). These engineered feature variables are used as both covariates and response variables. Please see the replication code for complete details.

We now provide descriptive summary information. Of the 540 unique players in the 22-23' NBA regular season data, 503 players sustained at least one reported injury. We estimate that NBA teams collectively paid approximately $843 million in player salaries for games missed due to injury. On average, each NBA team experienced 34 injuries for an estimated average of 208 missed player games. We also find visual support of travel fatigue and minutes played as key drivers of injury risk. This is summarized in Figure 1, which finds a positive association between sustaining more injuries and players who travel more, play more frequently within a three-day window, and spend a larger share of available minutes on court. We also find differences in nominal position. For example, Center is the only position to have a first quartile of total injuries greater than zero. This suggests that most Centers will sustain at least one injury over the course of an NBA regular season.

Not surprisingly, a greater number of injuries sustained typically results in a greater share of lost salary. This is summarized in Figure 2a, which provides a scatter plot of teams by player games lost due to injuries and total salary dollars lost (and a third dimension of the total number of injuries incurred). We see that the financial impact, as approximated by lost salary, of injuries varies substantially across teams. For example, the San Antonio Spurs have a relatively low total lost salary despite a high number of injuries and, conversely, the Los Angeles Clippers have a relatively high total lost salary despite having a relatively lower total number of injuries. This illustrates the somewhat obvious idea that injuries to key players earning a larger share of available salary have a greater potential for severe financial loss than players earning a lower share of available salary. Under a different interpretation, it is possible to assume that a loss takes the form of worse team performance. This is summarized in Figure 2b, which revises Figure 2a to include team winning percentage in the 22-23' NBA regular season rather than total salary lost to injuries. In general, we see the expected relationship that teams with lower rates of player games lost due to injury tend to achieve a higher winning percentage, and vice versa.

From these preliminary summaries, it is apparent that the risk of loss due to player injuries in the NBA is complex. It is necessary to consider severity from the varied perspectives of missed games or financial loss. We thus propose a compound loss framework because it is capable of modeling a multilevel risk problem into separate components that may then be aggregated into a single claims estimate (Klugman et al., 2012). A benefit of the data summarized in this section is that it incorporates the wide variety of player attributes necessary to properly fit such a model. Furthermore, these preliminary summaries report descriptive results that are consistent with related injury risk literature in the NBA (e.g., Drew et al., 2017; Teramoto et al., 2017; Caparrós et al., 2018).

We close this section with an acknowledgment that some aspects of player injury data may be imperfect. For example, Gong et al. (2022) consider the tactic of resting otherwise healthy players for the purposes of intentionally losing regular season games in the NBA, known colloquially as *tanking*, to improve a team's probability of receiving an earlier selection in the NBA's amateur player draft. We treat the NBA's injury report at face value, and so it is possible that some player injuries are instead disguised as rest for the purposes of tanking. At present, we leave this open to further research.

Methodology

We propose a three-part compound risk model that begins with injury frequency and then includes a two-part severity (Klugman et al., 2012). Its component parts are as follows. Fix player j and let I_j denote the number of injuries for player j in the measurement time period. For ease of exposition, this measurement time period will be one NBA regular season. Further define player level covariates, $\mathbf{x}_j$, and denote the number of missed games for player j due to the k^{th} injury as $M_{j,k}$, with $M_{j,0} := 0$. The random quantity $M_{j,k}$ is linked to a set of time-varying covariates, $\mathbf{z}_{j,k}$, which considers player j information up to the occurrence of injury k. This represents the first severity component. (It may also be equivalently interpreted as a secondary frequency, and we may use both terms interchangeably.) For the second severity component, and the third overall component of the three-part compound risk model, we allow that each missed game may carry an associated financial loss. That is, we denote the financial loss from the l^{th} missed game for player j from injury k as $C_{j,l}$ (with $C_{j,0} := 0$). As with $M_{j,k}$, there is a corresponding time dependent covariate vector to provide updated information at the time of an injury.

Each of the three-part compound risk model components, frequency, I_j, and loss given an injury (as a two-part severity), missed games, $M_{j,k}$, and financial loss per missed game, $C_{j,l}$, are modeled as three separate random variables (Klugman et al., 2012). The objective is to derive an expected value of each component, after which the estimated claim is a component-wise product (Klugman et al., 2012). Formally, we model the number of injuries for the j^{th} player, I_j, as a counting random variable with an exposure offset for the total possible games played using a Poisson GLM (Kutner et al., 2005),

$$I_j \,\Big|\, \mathbf{x}_j \sim \text{Poisson}\left(\mu_j\right), \quad \log \mu_j = \log(\text{games-played}_j) + \mathbf{x}_j^\top \boldsymbol{\beta}, \tag{1}$$

with covariates, $\mathbf{x}_j$, such as age, height, weight, position, games played, travel exposure, and season workload averages/summaries. The fitted mean is then $E[I_j \mid \mathbf{x}_j] = \hat{\mu}_j$.

Next, we model a two-part severity. The first part is the number of missed games per injury. Formally, we model the part-one severity as the number of missed games due to the k^{th} injury for the j^{th} player, $M_{j,k}$, with a second Poisson GLM (Kutner et al., 2005),

$$M_{j,k} \,\Big|\, \mathbf{z}_{j,k} \sim \text{Poisson}(\lambda_{j,k}), \quad \log \lambda_{j,k} = \mathbf{z}_{j,k}^\top \boldsymbol{\lambda}. \tag{2}$$

The covariates, $\mathbf{z}_{j,k}$, consist of aggregated information, as a sum, corresponding to every t^{th} game of the j^{th} player ($\mathbf{x}_{j,t}$) up to the k^{th} injury occurrence. The fitted mean is then $E[M_{j,k} \,\Big|\, \mathbf{z}_{j,k}] = \hat{m}_{j,k}$.

The second part of the severity is the financial loss per missed game, $C_{j,l}$, and it merits some additional discussion. The most obvious loss is a player's salary. There are also nuanced financial considerations, however. For example, in the primary ticket market, out-of-market fans represent a high-value segment, spending approximately 15–20% more per transaction than local consumers despite traveling further (Mills et al., 2016). These out-of-market fans also exhibit a steeper reduction in spending as the home team's win probability increases, whereas local fans remain willing to pay a premium to see their team face a high-quality visiting opponent, even when the home team's win probability is low (Mills et al., 2016). These discrepancies suggest that place and fan allegiance are not static. Instead, they interact with team quality and win probability to create diverse consumption patterns. A financial loss, then, can ideally differentiate between local and global financial exposure. Additionally, financial losses are not limited to an individual team. They can have a negative impact on the NBA's collective revenue-shares. This is because strategic resting and injury-related absences may reduce the value of national media contracts, which are tied to estimated viewership. For instance, doubling the proportion of star players missing from games can reduce the regular-season television audience by approximately 6.5M household viewings, resulting in an estimated loss of \$15 to \$20 million in seasonal advertising revenue (Reilly et al., 2023). Further, once in the NBA, a player's long-term financial trajectory is heavily dependent on team fit. It has been estimated that playing with higher-quality teammates who facilitate just one additional point per 100 possessions can increase the value of a rookie's second contract by 9.9–23.6% (Kuehn & Rebessi, 2023). This suggests that injuries do not occur in isolation, which presents another critical compound risk factor. That is, the injury of a high-quality peer can suppress the statistical output of a rookie teammate, which can lead to an indirect financial loss and, subsequently, a devaluation of the franchise's assets.

As these examples illustrate, modeling a financial loss from a player's injury is not straightforward. How, then, can these varied, complex, and interconnected financial risks be suitably modeled and yet still retain a measure of simplicity to facilitate interpretation, inference, and identification of risk mitigation strategies? We propose to treat $C_{j,l}$ as an *adjusted* salary loss from the l^{th} missed game due to injury I_j for the j^{th} player. This salary adjustment is a weighted salary approach via a PCA, which is also adjusted for economic estimates of the financial value of NBA games (Lautier, 2025). These economic estimates include considerations for star players, viewership, and caliber of opponents (Lautier, 2025). They may also proxy game-intensity, as more valuable games tend to have higher stakes. In other words, the financial severity component, $C_{j,l}$, begins with a player's per game salary and adjusts this amount based on a PCA and economic estimates from Lautier

(2025). The motivation for this is that a player's salary is a reasonable starting point for a financial loss, and this number is adjusted for these economic considerations. This economic adjustment and PCA are designed to incorporate the myriad of possibilities that can contribute to a financial loss. To describe this random variable once the adjustment process is complete, we utilize a gamma GLM (Kutner et al., 2005),

$$C_{j,l} \mid \mathbf{z}_{j,k(l)} \sim \text{Gamma}(\text{mean} = c_{j,k(l)}, \text{ var} = \phi\, c^2_{j,k(l)}), \quad \log c_{j,k(l)} \;=\; \mathbf{z}^\top_{j,k(l)}\boldsymbol{\gamma}, \tag{3}$$

using covariates as aggregated information of $\mathbf{x}_{j,k(l)}$ up to each missed game, with details $\mathbf{z}_{j,k(l)}$. (In (3), ϕ represents a dispersion parameter also requiring estimation.) The fitted mean is then $E[C_{j,l} \,\big|\, \mathbf{z}_{j,k(l)}] = \hat{c}_{j,k(l)}$.

The components, (1), (2), and (3), come together under the two classical assumptions for modeling compound risks (Klugman et al., 2012). First, we require that $M_{j,k}|I_j, \mathbf{z}_{j,k} \overset{d}{=} M_{j,k}|\mathbf{z}_{j,k}$ are independent and identically distributed (i.i.d.) random variables for $k = 1, \ldots, I_j$. This can be reasonably argued because it is common practice to wait until players are fully recovered before returning to play (e.g., Lawson, 2025). Thus, within a single season, each injury occurrence may be reasonably treated as a new injury to an otherwise healthy player. The second classical assumption for a compound risk model requires that $C_{j,l}|N_j, \mathbf{z}_{j,k} \overset{d}{=} C_{j,l}|\mathbf{z}_{j,k}$ are i.i.d. random variables for $l = 1, \ldots, N_j$, where N_j is the total number of injuries for the j^{th} player. Salaries are nonrandom, and so this assumption is reasonable on its face. The salary adjustment is based on the financial estimates of Lautier (2025), however, which are random. The assumption remains reasonable, however, because the estimates of Lautier (2025) are based on factors unrelated to a specific player, such as market size, attendance, and game importance. Thus, we may consider $C_{j,l}$ as a random component that satisfies the required independence assumptions. Therefore, with these assumptions satisfied, the total financial severity of the j^{th} player, or the final estimated claim, becomes (Klugman et al., 2012)

$$E[S_j \mid \mathbf{x}_j] \;=\; E[I_j \mid \mathbf{x}_j] \times E[M_{j,k} \mid \mathbf{z}_{j,k}] \times E[C_{j,l} \mid \mathbf{z}_{j,k(l)}]. \tag{4}$$

With the framework for (4) established, we may now focus on an insurance claim prediction for the j^{th} player. To do so, we start with a predicted number of injuries for a given season. Then, given this prediction, we estimate the missed games given an injury, denoted $\hat{E}[M_{j,k}|\mathbf{z}_{j,k}]$, and a predicted financial loss given a missed game, denoted $\hat{E}[C_{j,l}|\mathbf{z}_{j,k}]$. Because both severity models provide estimated values per game and per injury, we get a set of estimates from each model for a single player with multiple injuries and missed games. Thus, we may arrive at an estimate of the j^{th} player's total predicted missed games and adjusted financial loss before applying the compound model by averaging $\hat{E}[M_{j,k}|\mathbf{z}_{j,k}]$ and $\hat{E}[C_{j,l}|\mathbf{z}_{j,k}]$. That is, the components of the compound loss model that produce a final claim estimate for the j^{th} player are for frequency, I_j, via (1),

$$\hat{E}[I_j \mid \mathbf{x}_j] \equiv \hat{\mu}_j \equiv E_I(j),$$

and severity part-one, $M_{j,k}$, via (2),

$$\hat{E}[M_{j,k} \mid \mathbf{z}_{j,k}] \equiv \hat{m}_{j,k}, \quad E_M(j) = \frac{1}{I_j}\sum_{k=1}^{I_j} \hat{m}_{j,k},$$

and severity part-two, C_{jl}, via (3),

$$\hat{E}[C_{j,l} \mid \mathbf{z}_{j,k}] \equiv \hat{c}_{j,k(l)}, \quad E_C(j) = \frac{1}{N_j}\sum_{l=1}^{N_j} \hat{c}_{j,k(l)}.$$

In actuarial applications, it is common to report expected severity as an aggregate total or per \$1. For the latter, we may take the expected financial severity as \$1 per missed game (i.e., $E_C(j) = 1$). This produces a severity as defined only by games missed, denoted

$E[S_j^*]$. Formally, (4) becomes

$$\widehat{E[S_j^*]} = E_M(j) \cdot E_I(j). \tag{5}$$

For the former, the aggregate expected compound severity utilizing all three estimated response levels is then

$$\widehat{E[S_j]} = E_C(j) \cdot E_M(j) \cdot E_I(j) \equiv E_C(j) \cdot \widehat{E[S_j^*]}. \tag{6}$$

The two versions, (5) and (6), allow for interpreting risk from the contribution of predictors to injury frequency and severity separately. This allows for a flexible insurance claim estimate for each player, particularly if teams possess more detailed information on the modeling of (3) than is available from public data sources. In closing, we note that we perform a validating robustness study for model selection and prediction (a type of k-fold validation (Hastie et al., 2009)), details of which are available in the replication code.

Results

We first report coefficient estimates for each of the three components of the compound risk model for 22-23' NBA regular season data. Next, we utilize these fitted models and the compound risk model to prepare actuarial claims estimates at the player level. Finally, we explore sensitivities to suggest potential risk reduction strategies.

Parameter Estimates

We begin with the fitted model for injury frequency, I_j, via (1). The fitted model may be found in Table 1. The full model was selected from all potential covariates using a stepwise selection technique (Kutner et al., 2005). We find that, after adjusting for exposure via log(`games_count`), injury incidence is most strongly associated with workload, interpreted as the percentage of available minutes played per game, and averaging more games within a 72-hour time period. Specifically, we find that playing more minutes per game on average to be the primary driver of injury risk. To illustrate, we may interpret the `avg_perc_min` coefficient estimate of 3.233 in Table 1 to imply that a 10% increase in minutes-per-game increases injury occurrence risk by approximately 38% (i.e., $e^{0.323} \approx 1.38$). We also find that averaging more games within a 72-hour period to be positively associated with injury rate. These results echo similar findings about workload management and injury risk (e.g., Caparrós et al., 2018; Drew et al., 2017; Teramoto et al., 2017). Interestingly, the position indicator for Small Forward registers as significant, and it may reflect the changing preferences for large wing players to handle the ball on offensive and simultaneously play an important role on defense (e.g., Jayson Tatum) may be associated with higher injury occurrence risk for these players.

The fitted model for injury frequency summarized in Table 1 indicates that injury incidence for NBA players is associated primarily with workload and schedule density rather than with on court statistics and production. That is, players who play more minutes per game carry a substantially elevated injury risk, and playing again within 72 hours further amplifies this risk. Our results underscore the known importance of rest management in heavy stretches of the schedule (e.g., Caparrós et al., 2018). We also find that older players and Small Forwards experience higher injury rates than their peers, though these effects are smaller than those of minutes and schedule density. Movement- and contact-intensive actions, such as covering more distance on offense, setting frequent screens, and grabbing contested offensive rebounds, are consistently associated with higher injury rates. This may suggest that a more "physical role" on the court is an injury risk factor. In contrast, many raw shooting and passing totals become non-significant once workload, schedule congestion, and contact-related variables are included. This may imply that it is the intensity and nature of exposure, rather than offensive usage per se, that primarily govern an NBA player's injury occurrence risk.

In terms of severity, as measured by the number of missed games per injury occurrence, the story is more nuanced. The fitted model for $M_{j,k}$, i.e., (2), is again found using the stepwise selection approach. We report the coefficient estimates in Table 2. In this case, playing more minutes per game has a negative and significant effect on injury severity in the form of missed games. This suggests a possible conditioning effect in that playing more minutes per game may build a resistance to longer absences. This apparent paradox has been observed before. While teams increasingly utilize load management to mitigate injury risk, the relationship between workload and health has become non-linear. Research on external game workloads suggests that *unloaded* players, i.e., those with low accumulated distance and intensity, face a paradoxically higher risk of injury during games (Caparrós et al., 2018). Specifically, athletes with lower running miles per game exhibit a higher risk of injury, while those with three or fewer high-intensity decelerations per game face a higher risk of injury. This nuance is one benefit of a compound risk model: differing drivers for injury occurrence and severity may be observed. That is, it is important to strive for a workload balance to decrease injury occurrence risk and yet to also be cognizant that an insufficient competitive load appears to be detrimental to injury severity in the form of missed games. Hence, there is some protective effect through maintained activity. If we continue through Table 2, we observe that more physical players, as approximated by charges drawn, offensive boxouts, contested defensive rebounds, turnovers, and frequent drives to the basket are all associated with longer absences given an injury.

Furthermore, as with Table 1, travel intensity amplifies this pattern. We see that higher average travel miles before an injury is associated with more time lost given an injury, even after accounting for total miles traveled. In contrast, some indicators of more controllable player activity (e.g., screen assists, potential assists, and contested three-point challenges) are linked to quicker recoveries. This may suggest that certain high skill, system-driven roles may expose players to different, less severe injury profiles. Overall, the model suggests physicality and travel strain are positively associated with time-loss severity, as measured by the number of missed games per injury occurrence. This is consistent with related results (e.g., Meadows et al., 2024). A higher minutes-per-game load and more controlled on court style, conversely, may be associated with shortening the length of an absence once an injury occurs.

Finally, we present the fitted model for severity, as measured by the estimated financial loss of an injury, $C_{j,l}$, i.e., (3). Once again, we employ the stepwise model selection process. We report the parameter estimates in Table 3. Our model finds the largest adjusted salary loss for players with a higher minutes-per-game average. This is expected, as players with more playing time are typically a team's highest paid players. On the other hand, a player who recently appeared in a game before an injury tends to have a reduced financial loss given an injury, all else equal. This may be suggestive of a type of resiliency effect in that a player more consistently getting exposure to active game play without playing too many minutes within each game may suffer a lower financial loss given an injury. This is a further example of the nuance that can be achieved through the component-wise modeling of the compound risk model.

We also see that playing style may be associated with financial loss effects. For example, players that cover more ground on defense tend to have a lower financial loss given an injury, all else equal. This may be because defensively minded perimeter players have a demanding defensive role, which can reduce offensive responsibilities. Historically, offensive players are paid more (Berri et al., 2007), and our model may partially capture this association between salary and offense. On the other hand, players who possess the ball more tend to have a higher financial loss, which is expected, as players asked to handle the ball typically receive a higher salary. We also see the same "physicality risk" in that grabbing contested offensive rebounds or drawing personal fouls tends to be associated with a higher financial loss given an injury event, all else equal.

Actuarial Estimates

We now estimate insurance claims. We use both the direct approach for a compound loss model, (4), and, as a robustness check, we also supply estimates using the out-of-fold (OOF) method proposed in (6). Next, we perform a sensitivity analysis using these actuarial models to suggest risk mitigation strategies for reducing expected financial losses.

The top ten players with the highest expected financial losses using the direct method, (4), may be found in Table 4. In general, we predict higher losses for players with higher salaries, 32+ minutes played per game, and in larger markets. It may be notable that two of the top ten at-risk players, Jayson Tatum and Damian Lillard, would each sustain ruptured Achilles tendon injuries less than two years later (Lawson, 2025). This may suggest that the model we propose has captured some of the injury risk to the NBA's most highly paid and high workload players playing in more valuable, intense games. By nominal position, we find that Centers tend to miss more games, but Point Guards sustain the largest financial losses (see Figure 3). These claims estimates are top heavy and concentrated on the players in Table 4. We estimate a total claim of \$1.746B for the entire pool of 540 NBA players spanning the 22-23' NBA regular season, which is well below total player salaries of \$4.5B. The top ten players in Table 4 add up to \$453M in estimated claims. That is, these players account for just under 26% of total claims. In other words, less than 2% of NBA players account for over a quarter of expected financial losses at-risk due to injury. This is another quantification of the NBA as a star-driven entertainment product (e.g., Humphreys & Johnson, 2020; Reilly et al., 2023).

As a robustness analysis, we carry out the OOF prediction. By procedure, there are 363 players in the eligible set. Thus, we employ (6) using using 33 folds. Overall, we obtain similar results to Table 4 and Figure 3: we predict higher losses for players with higher salaries, 32+ minutes played per game, and in larger markets. Furthermore, there are seven of the top ten players reported in Table 4 that remain within the top ten risks using the OOF method. This validates the results of Table 4, and we proceed to a sensitivity analysis.

In the compound model framework, it is immediate that a proportional reduction in one of the three components of (4) will reduce the aggregate compound loss by the same proportion. Hence, an informative sensitivity analysis may instead be performed by focusing on controllable variables within the model, rather than suggesting players play "less physical" or change their in-game approach. In other words, factors external to a player's control, such as minutes played per game, travel demands, and schedule density, may be perturbed to assess an approximate impact on claims with some confidence that other variables will not be subject to extreme confounding effects.

We thus conduct a scenario-based sensitivity analysis by perturbing key workload and schedule congestion covariates in the fitted models for injury frequency, severity, and financial loss, while holding all other covariates fixed at their observed values. Specifically, we conduct three sensitivity tests using the players from Table 4. First, we reduce the covariates for a player's average share of minutes played per game by 10% in (1), (2), and (3), respectively. Next, we recompute each component of (4) to obtain a new compound loss estimate. Second, we repeat this procedure for a 10% reduction in average travel exposure and, third, we repeat this procedure for a 10% reduction in average schedule density. This 10% reduction is both in total and cumulative until the moment of injury.

We find that the most effective financial risk mitigation strategy of the three is to reduce average minutes played per game. We find that a uniform 10% cut in average minutes played per game reduces the expected compound loss for the highest risk players in Table 4 by 30-35%. For example, the claims estimate for Nikola Jokic drops from $79M to $54M and Jayson Tatum from $71M to $46M, both of which are sizable reductions both in percentage and absolute terms. The next most effective strategy is to reduce average travel distance between games. Specifically, we estimate that a 10% reduction in travel miles yields 5–12% reductions in expected financial loss. Players that benefit the most tend to play for teams with relatively heavy travel schedules (e.g., Adebayo (Miami) and Lillard (Portland)). Of the three strategies, we find that schedule density plays a relatively limited role in reducing financial risk due to injury, netting minimal estimated claim reduction.

We thus suggest the NBA consider reducing the total minutes of each regular season NBA game because it would reduce risk exposure uniformly across the entire league. One possible solution is to reduce a standard NBA game from 48 to 40 minutes, which is the standard game length in EuroBasket, the National Collegiate Athletic Association (NCAA), the Women's National Basketball Association (WNBA), and the Summer

Olympic Games. This has the additional benefit of keeping the traditional 82-game schedule, which may be preferable for gate and television revenues. It would mean less available minutes for players, however, which may require review from the NBA player's union. Additionally, shorter games may lead to other financial considerations, such as less concession sales, less time for advertising, or possible violations of currently negotiated television contracts. On the other hand, less game time in the same television block would allow for more advertising revenue or commercial entertainment. Given these varied considerations, we suggest this as an area of further research.

Discussion

During a playoff game on April 27, 2025, Milwaukee Bucks point guard Damian Lillard suffered a ruptured Achilles tendon injury (Lawson, 2025). Because of the significance and timing of the injury, Damian Lillard would likely miss the entire 25-26' NBA regular season (Lawson, 2025). For Milwaukee, this risk event had two negative outcomes. First, an important player would no longer be available to play. Second, because of NBA salary cap rules (National Basketball Players Association, 2023), Lillard's 25-26' projected salary of \$54.13M would mean that 35% of the allowable total salary of \$154.65M (Sports Reference LLC, 2025) would be used on an injured player unable to play. Both items together are a significant disadvantage to Milwaukee's on court performance, even before considering the financial losses related to ticket sales, television, advertising, etc. associated with a team's star player.

This disadvantage was perceived to be so significant to the Milwaukee Bucks that they elected to *waive and stretch* Lillard's combined 25-26' and 26-27' salary of \$112.59M. That is, Lillard would receive his 2-year, \$112.59M salary over five years (\$22.52M annually) and become a free agent, allowing him to join any other professional team in the NBA (Sports Reference LLC, 2025). For Milwaukee, the \$22.52M would still count against the allowable salary cap for the next five years (Sports Reference LLC, 2025). Colloquially, this is known as a *dead-cap hit* of approximately 15%. In other words, Milwaukee found it preferable to lose access to 15% of allowable salary and pay Lillard \$22.52M annually to potentially play against them rather than entering the 25-26' NBA season paying an injured player 35% of the salary cap.

From an actuarial point-of-view, it is not difficult to see that this is a sub-optimal outcome for all stakeholders. For Milwaukee, they will now be required to construct a team without access to 15% of available salary for the next five seasons. For Milwaukee's fans, this is a known handcuff that will negatively impact the performance of the team. For Lillard, he suffers a financial loss through the time value of money, as two annual payments of \$54.1M and \$58.5M are extended into five annual payments of \$22.5M (this loss is offset by Lillard signing a 3-year contract with the Portland Trailblazers for annual payments of \$14.1M, \$13.4M, and \$14.1M starting in the 25-26' season (Sports Reference LLC, 2025), a surprising contract that may not be available to other injured players). From the perspective of NBA players in aggregate, there are now less available funds and less options to join teams in free agency for the next five seasons because of this *dead cap hit*. This is all before any lost revenue related to a popular player missing an entire season, too.

We now suggest that insurance from a third-party could have been used to better manage this injury risk. Per Table 4, we estimate Lillard's insurance premium to be \$30.96M, which includes an economic estimate of game values beyond salary. Thus, assuming a similar insurance premium for the 24-25' NBA regular season for illustration, we can provide a back-of-the-envelope savings calculation. Without insurance, Milwaukee's expenses are Lillard's 24-25' salary, \$48.79M, plus five years of annual stretch provision payments, \$22.52M. This totals \$161.39M. The occupied salary cap over these six seasons is also \$161.39M. With annual insurance, however, total expenses are Lillard's 24-25' salary, \$48.79M, plus the insurance premium of \$30.96M, and his 26-27' salary of \$58.46M for a total of \$138.21M. This implies a reduction in incurred losses to Milwaukee of \$23M. If insurance payments are allowed to offset the salary cap, then Milwaukee would recoup Lillard's 24-25' salary of \$48.79M and simultaneously avoid the five years of stretch provision payments, \$22.52M. Instead, they would only owe Lillard's 26-27' salary of \$58.46M. Thus, a similar back-of-the-envelope style estimate would free up Milwaukee's cap sheet by \$54.14M. This is the approximate annual salary of a max-level player (National Basketball Players Association, 2023), which could be used to construct a competitive roster. Finally, Lillard receives his full contractual salary from the third party insurance company without a time-value-of-money loss; all parties benefit.

Modern modeling allows for the decomposition of overall franchise efficiency into two distinct stages: salary-cap efficiency (the ability to transform payroll into on-court performance) and on-court efficiency (the ability to transform that performance into wins and revenue) (Chatzistamoulou et al., 2022). Strategic asset valuation further extends to the draft, where teams often prioritize younger players who possess high option value, i.e., the potential to secure a high-productivity superstar at a suppressed, scale-based cost (Groothuis et al., 2007). Within this increasing sophistication of NBA franchise management, an actuarial approach can help NBA teams move toward a more holistic, dollar-weighted approach to roster management, where the decision to rest a player or draft for option value is grounded in a precise calculation of the expected financial and competitive loss associated with injury-driven unavailability.

We thus provide the first known applied actuarial study to estimate a fair insurance premium for player injuries in the NBA. We have utilized a three-part compound risk model to estimate fair insurance premiums for NBA players in the 22-23' NBA regular season. This involves obtaining relevant player performance, team travel, salary, and injury information into a novel data set. In total, we collect data for over 500 unique injuries and over 500 players. We then define injury frequency using a Poisson GLM, and break severity into two components. The first is severity as missed games per injury and is modeled with a second Poisson GLM, and the second is financial loss per missed game and is modeled using a gamma GLM. We select optimal models using a stepwise model selection procedure supplemented with subject area specific expertise. Finally, we generate claims estimates that withstand a robustness analysis in the form of a repeated k-fold cross-validation.

We find that injury occurrence is positively associated with an increased workload, as measured by average minutes-per-game, team travel, and averaging more games within the last 72 hours. These findings are consistent with related injury prevention literature (e.g., Drew et al., 2017; Teramoto et al., 2017; Caparrós et al., 2018). We also find differing levels of risk dependent on player attributes and playing style, as more physical players (as measured by contested rebounds, drawing charges, etc.) and older players tend to have higher risk of injury occurrence and higher risk of severity in terms of games missed given an injury. When financial risk is also considered, the results become more complex. We report the top highest estimated financial injury risks for the 22-23' NBA regular season in Table 4. It is immediate these are the highest paid and most popular players. In a bit of concerning prescience, two of the players in Table 4 would suffer ruptured Achilles tendon injuries within two years (Lawson, 2025). We also estimate that these ten players account for over a quarter of all estimated financial losses at-risk. The NBA is well-known to be a superstar league (e.g., Humphreys & Johnson, 2020; Reilly et al., 2023), and we offer a new quantification of this perspective. These top heavy results suggest the NBA consider risk mitigation strategies centered around insuring its most popular and well-known players.

A benefit of developing an actuarial model is the ability to use the model for a sensitivity analysis for controllable risk factors. We estimate changes in financial risk exposure for three scenarios: a 10% reduction in average minutes-per-game, a 10% reduction in average team travel, and a 10% reduction in schedule density. Of the three, we estimate that the most substantial financial risk mitigation strategy is to reduce the average number of minutes played per game. The effect seems to compound, as we estimate reductions in estimated financial risk over 30% for a 10% reduction in average minutes played per game. In the case of the players in Table 4, this can lead to per player savings north of $20M. From this, we suggest that the NBA consider reducing the length of NBA games from 48 minutes. A natural landing place could be 40 minutes, which is the standard game length in EuroBasket, the NCAA, the WNBA, and the Olympic Games. Indeed, if we treat minutes playing basketball as exposure, just as miles driven increases exposure to auto accidents, then this proposal has a natural insurance analog. That said, this is a significant lever to pull, and it may have a cascading financial effect beyond our stress test-based estimates. As such, we suggest it as an area of further research.

Indeed, injury risk is often a motivating factor in rule changes. For example, one explicit motivation identified and tested by Copeland & Babiak (2025) for implementing rule changes is to improve *player health and safety*. In other words, high injury rates are a significant and consistent driver of new rules, or *rule births*, which suggests that major professional sports organizations are willing to institute policy changes in an attempt to better manage injury risk. A similar practice exists for insurance companies, whereby insurers will encourage policyholders to implement safety measures to minimize the likelihood of claims (i.e., *loss control* measures). Classic examples in auto insurance are requiring the use of seat belts, regularly performing scheduled maintenance, and not operating a vehicle while impaired. From an actuarial perspective, rule births related to high injury rates would represent a systemic mitigation strategy. In other words, when the Frequency (I_j) or Severity (M_{jk}) of injuries exceeds a tolerated threshold, the league office may intervene to alter the environmental risk parameters. Perhaps the minutes reduction we propose would meet such objectives of the NBA, and we hope these findings motivate additional study.

In closing, we suggest areas of further work. An additional complexity to the player injury management insurance framework we propose is the growing legalization of sports betting. There is evidence that gambling can increase viewership in the NBA, even when the games are considered less appealing to consumers (Salaga et al., 2020). Salaga et al. (2020) even suggest that sports gambling can serve as a form of insurance for the NBA in that gambling will still drive interest in NBA games even when star players are unavailable. Thus, we suggest future study into how gambling may impact our actuarial analysis into the financial risk management of player injuries.

Further, strategic roster management in the NBA necessitates navigating complex trade-offs between short-term performance, long-term player health, and team efficiency. A prominent, yet controversial, strategy is the practice of resting healthy players, which serves dual managerial purposes. The first is fatigue management to preserve a team's most important contributors for the postseason and the second is tanking to improve a team's draft lottery odds. Empirical evidence indicates that teams eliminated from playoff contention rest more healthy players than teams still in contention, utilizing this as a discrete tactic to lower team quality and secure advantageous draft slots (Gong et al., 2022). From an actuarial risk perspective, this suggests that teams treat player availability as a switchable asset to hedge against poor seasonal outcomes. While strategic resting may be privately optimal for a specific team's goals, however, it is often socially inefficient for the league. This is because it imposes externalized costs, such as reduced national television viewership and lost advertising revenue, which are borne by all its member franchises. From the perspective of third-party insurance, however, such instances of resting healthy players may be a form of insurance fraud and would thus not receive payment. Conjecturing on this point-of-view, a potential argument for the use of insurance to protect against player injuries would be an independent control mechanism for the managerial decision to rest otherwise healthy players.

Additionally, it is of interest to consider the relationship between injuries and player career length in the NBA. The most immediate need for such analysis is the amateur player draft. The labor dynamics of the NBA are characterized by strategic entry decisions, peer-driven productivity effects, and demographic variances in career longevity. Economic models of the draft suggest that teams increasingly prefer younger players who possess a high option value. In other words, the potential to become a low-cost superstar, even when their initial performance signal is noisier than that of more experienced college seniors (Groothuis et al., 2007). In the language of actuarial analysis, these players represent high-upside but high-volatility assets whose health risks must be quantified during their initial contract window. Actuarial modeling allows managers to quantify the health component of this option value, thereby calculating the probability that an early entrant will survive the physical demands of the league to reach their peak productive years. At the other extreme is the end of a player's career, and a catastrophic injury is a primary driver of these exits. For instance, Achilles tendon ruptures prove career-ending for 22% of NBA players immediately, and of those who do return, 31% are out of the league within three years (Meadows et al., 2024). Considering these risks within the context of risk management, these dynamics represent a set of competing risks whereby injury, demographic churn, and performance declines all determine an asset's useful life. A compound risk model can unify these variables, treating injury not as a random medical event but as a quantifiable professional risk that directly dictates the economic and professional trajectory of the athlete.

Finally, we suggest performing a similar analysis in other professional sports leagues. Demographic factors and league-specific structures also introduce significant variations in employment stability and asset useful life. This is true even for different professional basketball leagues. In the WNBA, for example, the labor market exhibits high churn, with 28.2% of players not returning for the following season and 22.6% exiting the league permanently during their peak years (Jepsen, 2023). As an example of the differences between the WNBA and NBA, White players in the WNBA are approximately four percentage points more likely to exit the league, and international players are 12% more likely to take career breaks, whereas race and career length are generally uncorrelated in the NBA (Jepsen, 2023). Hence, it is of interest to explore potential differences in injury modeling and related risk management between the NBA and WNBA, including expanding such analysis across other professional sports more generally.

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Table 1

Injury Frequency. *Coefficient estimates for* (1) *from the 22-23' NBA Regular Season.*

Variable	**Estimate**	**Std. Error**	***p*-value**	**Sig.**
(Intercept)	-7.445000	1.704000	0.00001	***
Total-Travel-Miles	0.000006	0.000007	0.36573	
Avg-Minutes-Played(%)	3.233000	0.409800	0.00000	***
Power-Forward	0.235100	0.144400	0.10346	
Point-Guard	0.235600	0.216500	0.27651	
Small-Forward	0.402300	0.172800	0.01989	*
Shooting-Guard	0.313500	0.195300	0.10851	
Games-Played-Within-3Days	0.790100	0.254000	0.00187	**
Height	0.009955	0.020500	0.62799	
Weight	0.001583	0.002136	0.45874	
Age-Through-Season	0.026200	0.008082	0.00119	**
Field-Goal-Attempts	0.001170	0.000887	0.18750	
3PT-Field-Goal-Attempts	0.000588	0.000468	0.20941	
Free-Throw-Attempts	-0.000334	0.001321	0.79995	
Personal-Fouls	0.001854	0.001363	0.17390	
Points	-0.000251	0.000651	0.69887	
Steals	0.006173	0.004216	0.14318	
Blocks	0.002834	0.002264	0.21077	
Turnovers	0.002230	0.001607	0.16530	
Offensive-Rebounds	-0.012600	0.005481	0.02176	*
Defensive-Rebounds	-0.004067	0.002270	0.07319	·
Assists	-0.000100	0.002049	0.96104	
Personal-Fouls-Drawn	0.001199	0.001711	0.48345	
Possessions	-0.001177	0.000283	0.00003	***
Screen-Assists	0.005252	0.001327	0.00007	***
Deflections	-0.001482	0.001951	0.44741	
Charges-Drawn	0.007772	0.006936	0.26250	
Contested-2PT-Shots	-0.000219	0.000655	0.73796	
Contested-3PT-Shots	0.001651	0.001131	0.14430	
Offensive-Boxouts	-0.007935	0.007081	0.26246	
Defensive-Boxouts	-0.002571	0.002623	0.32701	
Off-Loose-Balls-Recovered	-0.001987	0.007073	0.77880	
Def-Loose-Balls-Recovered	-0.002921	0.007138	0.68232	
Drives	-0.000089	0.000371	0.81038	
Miles-Covered-Offence	0.024000	0.011700	0.03945	*
Miles-Covered-Defence	0.007852	0.016200	0.62771	
Passes-Made	-0.000050	0.000218	0.81869	
Passes-Received	-0.000221	0.000265	0.40450	
Secondary-Assists	0.006789	0.004253	0.11039	
Potential-Assists	0.000882	0.001215	0.46730	
Free-Throw-Assists	0.003784	0.005220	0.46852	
Contested-Off-Rebounds	0.015200	0.006363	0.01703	*
Offensive-Rebound-Chances	0.000267	0.001904	0.88811	
Contested-Def-Rebounds	0.001720	0.003147	0.58465	
Defensive-Rebound-Chances	0.001223	0.001634	0.45442	

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, · $p < 0.1$.

Table 2

Injury Severity (Missed Games). *Coefficient estimates for* (2) *from the 22-23' NBA Regular Season.*

Term	Estimate	Std. Error	P-value	Sig.
Intercept	2.100000	0.032500	0.000000	***
Injuries	-0.000699	0.009501	0.941325	
Percentage-Minutes-Played	-1.687000	0.090840	0.000000	***
Avg-Travel-Miles	0.000623	0.000043	0.000000	***
Total-Miles-Covered	-0.000047	0.000003	0.000000	***
Field-Goal-Attempts	-0.000892	0.000832	0.284052	
3PT-Field-Goal-Attempts	-0.000209	0.000489	0.668321	
Free-Throw-Attempts	0.000363	0.001196	0.761180	
Personal-Fouls	0.001538	0.001225	0.209158	
Points	0.001067	0.000569	0.060888	.
Steals	0.001172	0.003442	0.733455	
Blocks	-0.003153	0.002043	0.122751	
Turnovers	0.009104	0.001551	0.000000	***
Offensive-Rebounds	0.015680	0.004487	0.000477	***
Defensive-Rebounds	-0.002233	0.001942	0.249989	
Assists	-0.001131	0.001669	0.497860	
Personal-Fouls-Drawn	-0.002107	0.001618	0.192919	
Possessions	0.000544	0.000268	0.042355	*
Screen-Assists	-0.005676	0.001064	0.000000	***
Deflections	-0.000973	0.001628	0.550130	
Charges-Drawn	0.025910	0.006270	0.000000	***
Contested-2PT-Shots	0.000319	0.000641	0.618685	
Contested-3PT-Shots	-0.002294	0.000980	0.019321	*
Offensive-Boxouts	0.017720	0.005221	0.000690	***
Defensive-Boxouts	0.001277	0.002176	0.557492	
Off-Loose-Balls-Recovered	0.006883	0.005613	0.220069	
Def-Loose-Balls-Recovered	0.001244	0.005495	0.820934	
Drives	0.000740	0.000338	0.028732	*
Miles-Covered-Offence	-0.006200	0.011320	0.584042	
Miles-Covered-Defence	-0.025020	0.015990	0.117681	
Passes-Made	0.000657	0.000216	0.002409	**
Passes-Received	-0.000464	0.000249	0.062634	.
Secondary-Assists	-0.006869	0.003828	0.072713	.
Potential-Assists	-0.002005	0.001020	0.049358	*
Free-Throw-Assists	0.016400	0.004404	0.000196	***
Off-Rebounds-Contested	-0.009106	0.004933	0.064939	.
Off-Rebound-Chances	-0.003428	0.001599	0.032079	*
Def-Rebounds-Contested	0.009459	0.002707	0.000476	***
Def-Rebound-Chances	-0.000784	0.001366	0.566020	

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

Table 3

Injury Severity (Financial Loss). *Coefficient estimates for* (3) *from the 22-23' NBA Regular Season.*

Variable	Estimate	Std. Error	p-value	Sig.
(Intercept)	10.450000	0.128900	0.00000	***
Minutes-Played(%)	3.628000	0.101000	0.00000	***
Games-Played-Within-3Days	-0.465500	0.088970	0.00000	***
Avg-Travel-Miles	0.000313	0.000069	0.00000	***
Field-Goal-Attempts	0.000692	0.000655	0.29099	
3PT-Field-Goal-Attempts	0.000316	0.000343	0.35692	
Free-Throw-Attempts	-0.004684	0.001054	0.00000	***
Personal-Fouls	-0.000304	0.000914	0.73893	
Points	-0.000587	0.000453	0.19508	
Steals	-0.004504	0.003011	0.13473	
Blocks	0.002728	0.001728	0.11449	
Turnovers	-0.004616	0.001245	0.00021	***
Offensive-Rebounds	-0.000171	0.003733	0.96344	
Defensive-Rebounds	0.000915	0.001528	0.54899	
Assists	0.006663	0.001338	0.00000	***
Personal-Fouls-Drawn	0.007484	0.001353	0.00000	***
Possessions	0.003013	0.000219	0.00000	***
Screen-Assists	0.010040	0.000873	0.00000	***
Deflections	0.003768	0.001365	0.00579	**
Charges-Drawn	-0.004892	0.004952	0.32325	
Contested-2PT-Shots	-0.004093	0.000547	0.00000	***
Contested-3PT-Shots	-0.000998	0.000785	0.20404	
Offensive-Boxouts	0.008298	0.004452	0.06238	·
Defensive-Boxouts	-0.002434	0.001849	0.18810	
Off-Loose-Balls-Recovered	0.003361	0.004514	0.45657	
Def-Loose-Balls-Recovered	-0.011770	0.004584	0.01028	*
Drives	0.000941	0.000286	0.00102	**
Miles-Covered-Off	-0.050960	0.009205	0.00000	***
Miles-Covered-Def	-0.117300	0.013030	0.00000	***
Passes-Made	-0.000515	0.000169	0.00236	**
Passes-Received	0.000372	0.000197	0.05946	·
Secondary-Assists	0.006471	0.002993	0.03062	*
Potential-Assists	-0.004733	0.000814	0.00000	***
Free-Throw-Assists	-0.002425	0.003456	0.48305	
Off-Rebounds-Contested	0.015380	0.004257	0.00030	***
Off-Rebound-Chances	-0.010190	0.001261	0.00000	***
Def-Rebounds-Contested	-0.003051	0.002148	0.15555	
Def-Rebound-Chances	0.001835	0.001078	0.08872	·

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, · $p < 0.1$, blank: $p \geq 0.1$.

Table 4

Ten Highest Injury Risks by Estimated Financial Losses. *Estimates using* (4) *for the 22-23' NBA Regular Season.*

	Summary Information					Compound Risk Model Component Estimates				
Player	Sal.	Sal. Claimed	Age	Pos.	MPG	$\hat{E}[I_j \mid \mathbf{x}_j]$	$\hat{E}[M_{jk} \mid \mathbf{z}_{jk}]$	$\hat{N}_j$	$\hat{E}[C_{jl} \mid \mathbf{z}_{jl}]$	$\hat{E}[S_j \mid \mathbf{x}_j]$
Nikola Jokic	$ 33.05	$ 4.03	27.9	C	33.65	9.457	3.015	28.51	$ 2.77	$ 79.03
Jayson Tatum	$ 30.35	$ 2.22	24.9	SF	36.91	4.615	1.478	6.82	$ 10.37	$ 70.73
Bam Adebayo	$ 30.35	$ 2.22	25.5	C	34.66	6.997	3.233	22.62	$ 2.44	$ 55.28
Luka Doncic	$ 37.10	$ 6.79	23.9	PG	36.24	6.658	2.76	18.38	$ 2.32	$ 42.68
Marcus Smart	$ 17.21	$ 4.20	28.9	PG	32.06	5.474	2.355	12.89	$ 3.09	$ 39.85
LeBron James	$ 44.47	$ 14.10	38.0	PF	35.52	5.624	3.861	21.71	$ 1.83	$ 39.69
Jalen Brunson	$ 27.73	$ 4.40	26.4	PG	34.99	8.271	2.759	22.82	$ 1.65	$ 37.71
Damian Lillard	$ 42.49	$ 11.54	32.5	PG	36.34	8.152	4.293	35	$ 0.88	$ 30.96
Donovan Mitchell	$ 30.91	$ 4.90	26.3	SG	35.76	6.519	3.236	21.09	$ 1.38	$ 29.07
Stephen Curry	$ 48.07	15.43	34.8	PG	34.90	10.833	2.429	26.31	$ 1.08	$ 28.42

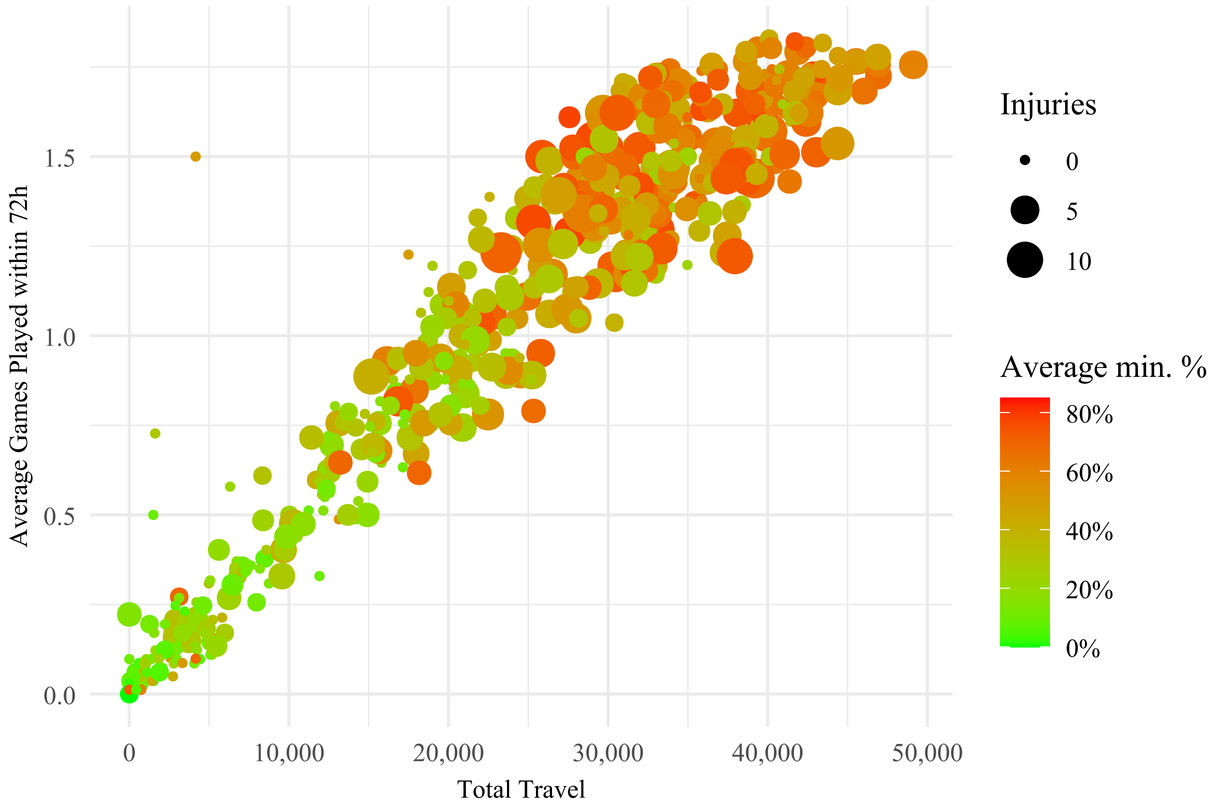
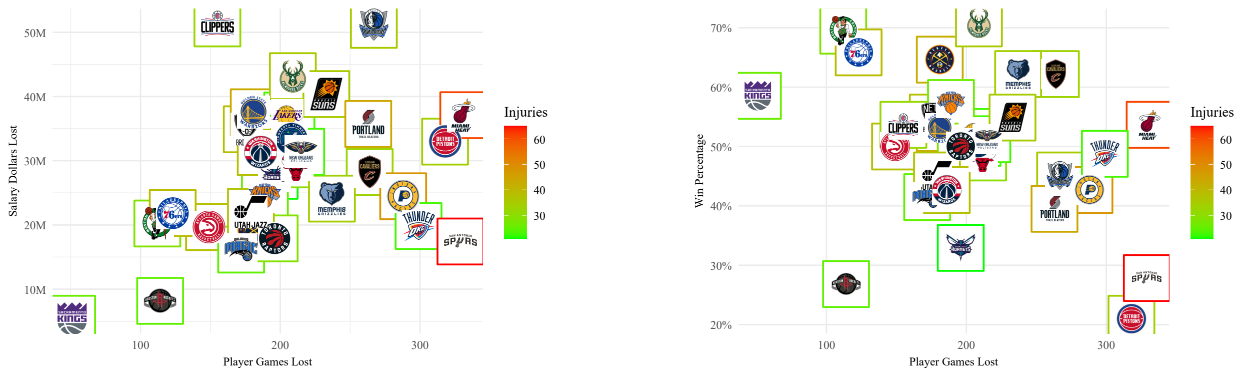


Figure 1

Injury Frequency by Schedule Density, Total Travel, and Minutes Per-Game.

Estimates from the 22-23' NBA Regular Season. Minutes per-game expressed as a percentage.



(a) *Injuries by Salary Lost*

(b) *Injuries by Winning Percentage*

Figure 2

Injury Impact Summary by Teams. *Estimates from the 22-23' NBA Regular Season.*

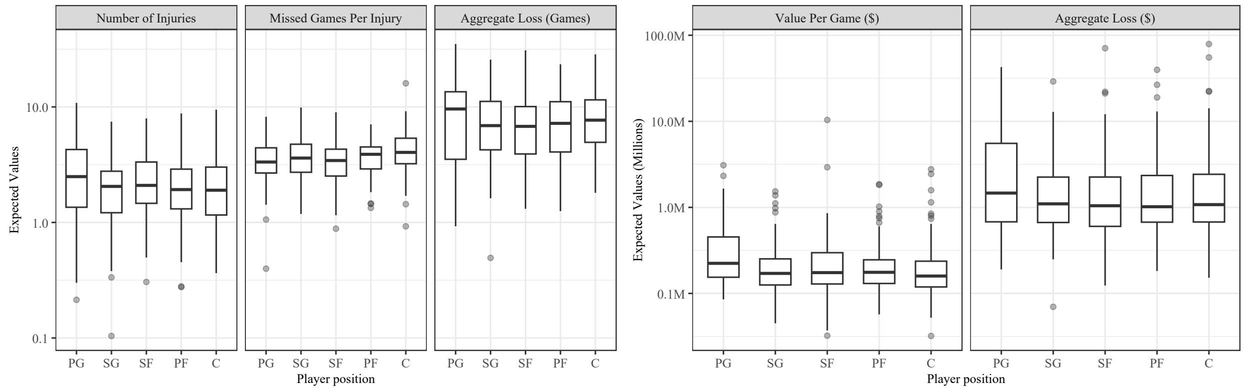


Figure 3

Estimated Injury Risk by Position. *Estimates using* (4), *with and without a financial component for the 22-23' NBA Regular Season.*