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The effect of injury risk on players value: evidence from the main European Leagues

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The impact of injury risk on the market value of male football players remains an under-researched topic. We investigate this relationship for a large sample (5336 observations) of football players. We first use a logistic regression model to explain the probability of injury, and after a System-GMM regression model, where the dependent variable is the footballers' market value provided by Transfermarkt over the period 2006–2020, and the independent variables are the previously calculated probability of injury, along with other personal and sporting variables. Our results show that a 1% increase in the probability of a serious injury (more than 28 days' absence or more than 5 games) is associated with a 2.29% decrease in market value, with a larger decrease when we include severity and recurrence in the injury probability. Quantifying the risk of injury on the value of football players is crucial for effective strategic financial and sporting planning of clubs.

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Introduction

Football clubs invest large amounts of money in recruiting footballers, youth squad training, and particularly transfers and salaries (Carlsson et al. 2016). The ability and characteristics of players determine the potential of a team's performance (Drawer and Fuller 2002a; Peeters 2018) and constitute the main intangible capital of the clubs.

The transfer fees, salaries, and market valuation of players in major men's leagues constitute a club's most significant capital investment. Measuring male football players' injury risk is crucial because injuries not only entail a direct medical cost but, more importantly, result in a substantial loss of asset value and athletic performance, which directly impacts financial results, competition-based revenues, and future transfer capacity (Drawer and Fuller 2001; Hägglund et al. 2013; Windt et al. 2018). They are the major reason for the careers of professional male footballers coming to an early end (Koch et al. 2021).

To effectively manage this risk, it must first be quantified. Thus, we develop a logistic regression model to assess players' injury risk, and after, we analyze its impact on the players' market value, using data on footballers provided by Transfermarkt (Transfermerkt.de) for 5336 observations in the period 2006–2020.

The results of the proposed model show that the severity of injuries in the previous year is correlated with a higher probability of new severe injuries. Such probability predictions are very significant to explain players' market value, alongside other personal and performance controls.

Understanding injury risk is vital for player valuation in transfer negotiations, public information, insurance policies, and salary discussions between clubs, agents, and players. Finally, for public organizations that must manage fair play regulation.

This paper is organized as follows. In the section "Literature review", we introduce the previous literature related to injuries and football. In the section "Empirical strategy", the empirical strategy used in this paper is outlined. Section "Dataset and variables" is devoted to describing the data and variables. In the section "Discussion, conclusions and future lines of research", we discuss the empirical results. Finally, the paper ends with a discussion and conclusions, and states possible avenues for future research on this issue.

Literature review

The existing body of literature is largely confined to the medical domain, focusing on the analysis of injury risk factors and injury severity (Árnasón et al. 2004; Ergün et al. 2013; Hägglund et al. 2006; Orchard 2001). In contrast, research within the field of financial valuation remains focused on measuring direct medical expenses and indirect costs such as player salaries during periods of absence (Walia and Boudreaux 2021; Williams et al. 2025), while only two studies have analyzed how the players' absence affects their market value (Eliakim et al. 2020; Rubio-Martín et al. 2025). Nevertheless, at present, no comprehensive model is available that can reliably estimate an individual player's injury probability and quantify its impact on market value.

Magnitude and injuries risk factors. Professional football players are exposed to a significantly high risk of injury, with the majority of incidents affecting the lower limbs (Drawer and Fuller 2002b; Laux et al. 2015). The average incidence rate reported in literature is approximately 1.3 injuries per player per season (Hawkins et al. 2001). However, studies involving specific professional teams indicate this can be higher, with up to two injuries per player per season and a consequent impact on days missed from play (Di Salvo et al. 2009).

A comprehensive systematic review highlighted an overall injury incidence of 8.1 injuries per 1000 h of exposure in professional football (López-Valenciano et al. 2020). Even higher figures have been identified, with overall football injury rates reaching up to 20.3 injuries per 1000 h of exposure and match rates up to 3.33 injuries per football match (Klein et al. 2018).

A crucial finding across epidemiological studies is that match injury incidence is almost ten times higher than the training injury incidence rate (López-Valenciano et al. 2020). Injuries occur more often during matches, where traumatic injuries are more prevalent, while training sessions generally see fewer injuries overall (Ergün et al. 2013). Furthermore, the specific pattern of injury epidemiology varies by region, with English and Dutch teams, for instance, reporting higher injury rates compared to their French, Italian, and Spanish counterparts (Waldén et al. 2005).

The framework for injury risk management in football systematically identifies and analyzes two main categories of risk factors: intrinsic (participant-related) and extrinsic (facility, equipment, and environment-related) (Fuller et al. 2012; Van Mechelen et al. 1992).

Several internal or individual factors contribute substantially to elevated injury risk:

- Prior injury history: this is a consistently strong predictor of future injury. Players with a prior injury are twice as likely to be injured again, and those with two or more previous injuries face three times the risk compared to uninjured players (Kucera et al. 2005). Specifically, a history of injury—particularly muscle strains—can increase the risk of sustaining similar injuries in the following season by a factor of 2.7–11.6 (Arnason et al. 2004; Hägglund et al. 2006; Orchard 2001).
- Age and experience: older age is a significant personal risk factor, particularly associated with hamstring and calf strains (Ergün et al. 2013; Orchard 2001). There is a consensus that age is systematically associated with injury likelihood (Arnason et al. 2004; McGregor and Rae 1995; Östenberg and Roos 2000). However, tracking accumulated damage before players turn professional remains challenging, potentially complicating the association between age and general injury risk (Hagglund et al. 2006; McGregor and Rae 1995).
- Physical Deficits: Factors like poor muscle strength, fatigue, muscle imbalances, and instability in the ankles or knees significantly raise susceptibility (Arnason et al. 2004; Liporaci et al. 2022; McCall et al. 2014).

External and environment-related factors also play a critical role:

- Training load and fatigue: lack of training or a low training-to-match ratio, along with insufficient rest, high match frequency, and the concept of overload/underload of minutes played, are frequently associated with injuries and poor performance (Arnason et al. 2004; Dupont et al. 2010; FIFPRO 2022; Laux et al. 2015). Adequate sleep, conversely, offers some protective benefits (Charest and Grandner 2022).
- Playing conditions: environmental factors such as rainfall and field surface conditions, along with equipment like footwear, affect injury risk (Orchard 2001; Volpi and Taioli 2012).
- Psychosocial factors: life-event stress and other psychosocial elements further contribute to a player's injury susceptibility (Dvorak et al. 2000; Charest and Grandner 2022).

The Federation International of Football Association (FIFA) and its Medical Assessment and Research Centre (F-MARC) have actively engaged in quantifying and mitigating these risks (Fuller et al. 2012). They analyze the papers published by F-MARC, highlighting 17 areas of risk to footballers' health. These areas comprehensively cover both intrinsic factors (e.g., age, medical history, risk associated with tackles) and extrinsic factors (e.g., playing surface, stadium design, preparation, and assessment of referees' decisions, among others).

The prevailing literature underscores the importance of adopting a comprehensive injury prevention approach. This approach must consider an individual athlete's unique set of intrinsic factors (e.g., bone strength, neuromuscular control), recognizing that these can be minimized as the athlete adapts to the environment and through strategic mitigation of extrinsic risks (Meeuwisse et al. 2007).

In practice, governing bodies like FIFA and UEFA have translated these findings into action. FIFA, for example, has implemented exercise-based prevention programs aimed at youth and amateur players, while adopting a robust risk management framework to assess and mitigate health risks across all demographics (Ekstrand 2011, 2013; Fuller et al. 2012).

Financial implications of sports injuries, the impact of injuries on the football players' market value. The financial implications of sports injuries have been a focal point of recent research across various professional sports. Walia and Boudreaux (2021) argue that the true cost of injuries in professional sports, especially in American football and soccer, is much broader than the direct medical costs of treatment, highlighting the financial impact of players' "foregone playing time" (i.e., when they are unable to play due to injury). Williams et al. (2025) revealed that primarily salaries paid to injured Cricket players constitute most of the financial burden, exceeding direct treatment costs (approximately 7% of players' annual salary was earned while they were injured). They also found a negative association between the cost of injury and team success in Division 1. Similarly, Rubio-Jiménez et al. (2025) provided insights from a four-season study of a Spanish professional basketball team, finding that a similar percentage of the total salary cost for days lost due to injuries amounted to between 4.5% and 7.03% of total salaries. Turnbull et al. (2025) also found that a high financial cost to injury or illness accounted for 17% of the club's total salary expenditure over the six years within the Australian Football League, advocating for improved injury prevention measures. Collectively, these investigations converge on the recognition that injury-related expenses in professional sports extend well beyond treatment fees, with player salary costs during recovery periods forming a significant proportion of overall expenditures.

In parallel, research in American football by Secrist (2016) and Keefer (2023) examined the professional and financial aftermath of injuries such as ligament tears and concussions, respectively, revealing that injuries profoundly influence players' career trajectories and earnings (using longitudinal and regression analyses to link injury occurrences with salary trends).

Thus, the injury risk goes beyond the salary supplement or medical cost for the sporting club, or even the loss of competitiveness the team suffers, since the player's loss of productivity (days not played and possible consequences on performance) also will affect its future contractual economic conditions and, therefore, his named "market value".

Previous articles also highlight the importance of measuring the risks associated with losses of football clubs' human capital because of injuries to enable effective management (Fuller et al. 2012) and to improve the clubs' financial performance over the medium and long term (Dobson et al. 2001; Szymanski 2010). Nevertheless, defining a football player's value poses conceptual difficulties. Primarily, this value is operationalized as the transfer fee, the cost exchanged between clubs for a player's contractual rights. However, since transfer fees are inherently the outcome of negotiations and frequent disagreements between the involved parties, the final prices inevitably incorporate substantial bargaining factors, like club urgency, agent fees, rivalry premiums, etc. (Carmichael and Thomas 1993; Frick 2007; Rubio-Martín et al. 2022, 2023).

One major source of values as emerged from football business practices: Transfermarkt, naming "market values" to refer to the financial values of football players. The use of Transfermarkt valuations can be theoretically grounded in the concept of the *wisdom of the crowd*, which suggests that aggregated judgments from a large and diverse group of individuals can yield highly accurate estimates of uncertain quantities (Peeters 2018). In this context, market values derived from collective user assessments represent the consensus of a broad community of fans, analysts, and experts, whose combined insights tend to approximate real market behavior more closely than individual opinions. Previous research has supported the validity of these crowd-sourced valuations as reliable proxies for players' actual market values, including players' actual performance variables (Franceschi et al. 2024; Muller et al. 2017; Rubio-Martín et al. 2022), media exposure metrics, and players' current club status (Muller et al. 2017). However, its valuations omit key factors present in final prices, such as contract maturity time or specific negotiation elements. Nevertheless, different perspectives exist regarding Transfermarkt's market value: some authors view it as the potential price that could initiate a transfer negotiation (Di Domizio et al. 2024; Peeters 2018; Quansah et al. 2024), while Coates and Parshakov (2022) highlight that its valuations underestimate the actual price paid in most transfers.

There are not yet articles regarding the impact of injuries on transfer fees, although various authors have demonstrated the influence of appearances in salaries (Lucifora and Simmons, 2003) and minutes played on the prices paid (Poli et al. 2024). Only a few works have developed the incidence of injuries on market players' values: Eliakim et al. (2020), Rubio-Martín et al. (2022), and Rubio-Martín et al. (2023). The three works collected the data through the website Transfermarkt.de. However, this is the first time that the impact of injury risk on these values has been analyzed.

Eliakim et al. (2020) found a statistically significant relationship between the number of days off due to injuries suffered by team members during a season and the ranking difference between their actual and expected final position in the English Premier League table. According to the overall player value assigned by Transfermarkt.de, they measure the loss in 36 million pounds by club and season. However, the authors do not develop a complete statistical model incorporating different performance and individual variables (age, height, position, league, team, and among others) to separate the injury effect from these.

The second work, Rubio-Martín et al. (2022) introduces the number of injuries and the squared number of injuries as explanatory variables of the players' market value, capturing a concave relationship between injuries and the market value. This could happen because the top players tend to suffer the greatest marks and the consequent injuries; however, the increase in injuries, at the same time, is subtracting value[1]. In this way, several injuries could be allowed in top players before their values fall as a direct consequence of their important role on the football field. The authors find that the player's value falls from 3 injuries when the dependent variable is the market values provided by the web page Transfermarkt, and if we consider the price paid (transfer fee), it falls from 2.5 injuries in a season. This work is a first approximation to the complex relationship between the injuries and the player's values.

However, the number of injuries is not the most adequate variable to collect the impact of the injuries in values. The consequences are more important than the injuries themselves: for example, as we have exposed previously, the non-played days and the missed games (an injury that involves a day off is not the same as a long-term injury). In this regard, epidemiological studies such as those by De Loes and Goldie (1988) and Hägglund et al. (2005) classified minor injury as an absence from sport for less than 1 week, moderate as an absence for 1–4 weeks, and serious as an absence greater than 4 weeks.

Rubio-Martín et al. (2025) contrast the impact of injuries according to their severity. When the injury is serious, the fall increases to 11.2% of market values. These drops also strongly vary when players are famous or non-famous. Famous players present some resistance to falling due to injuries. However, when the injuries are severe or serious, the drop is major for famous players. The impact on players' market values also depends on the different types of injuries: −12.4% for muscles, −27.3% for ligaments, and −24.5% for bones. Following this line, we consider in our work the number of games missed in the previous year as a key variable in assessing the probability of injury in the current year, which, in turn, serves as a moderating factor in evaluating the player's market value.

In line with previous studies, we choose Transfermarkt market values instead final transfer fees because, in addition to what has been stated in previous paragraphs, they are periodically revised and updated (a player will have at least two valuations per year throughout their career, while they may have only been transferred once, twice, three times, or not at all during the same period). This makes them a smoothed average of market expectations and a highly autoregressive variable. Our primary goal is to obtain consistent estimates for the determinants of the dynamic, consensus valuation that serves as the key market benchmark.

Empirical strategy

In the medical literature on injury probability, logistic models are predominantly used to analyze the impact of odds ratios (Arnason et al. 2004) or hazard ratios (Frisch et al. 2011; Hägglund et al. 2006). We have employed a two-stage model. In the first stage, we used a logistic regression to predict the ***probability of injury*** **(PI)** for players in each year. Estimating a player's probability of injury offers valuable insights for those managing player resources. To achieve this, we have incorporated matches missed in the previous year, alongside personal and some environmental control variables. The model used is as follows:

$$PI = 1/(1 + e^{-Z_{i,t}}) \quad (1)$$

$Z_{i,t}$ represents the linear predictor or log-odds (logit) of the model, which is a linear combination of all independent variables and control variables.

$$Z_{i,t} = GM_{i,t-1} + \beta_2 AGE_{i,t} + \beta_3 AGE_{i,t}^2 + \beta_4 FOOT_{i,t} + \beta_5 POSITION_{i,t} + \beta_6 HEIGHT_{i,} + \beta_7 LEAGUE_{i,t} + \beta_8 YEAR_t \quad (2)$$

Games missed, GM, have been categorized by levels of severity (shown in Table 1), as established in the scientific literature based on lost games, equivalent to lost days (Ekstrand et al. 2006; Hägglund et al. 2005; Jacobson and Tegner, 2007; Loes and Goldie 1988). In this form, $GM = 0$ implies non-games missed, while $GM > 0$ and ≤ 5 is associated with a **moderated** injury, as an absence approximated from 1 to 4 weeks (until 28 days). An interval of injuries implying $GM > 5$ and ≤ 10 is assimilated to a **severe** injury, which is an absence of greater than 4 weeks until 8 weeks, or until 56 days. Finally, $GM > 10$, more than 8 weeks or 56 days, is classified as a **highly severe injury**.

The variable AGE is an important factor in injury risk literature (Arnason et al. 2004, Ekstrand et al. 2019). However, authors also warn of an increased risk for concrete types of injuries for young elite players due to their developing physical attributes and inexperience (Faude et al. 2013; Östenberg and Roos 2000; Weishorn et al. 2023). Another key aspect is that players of

Table 1 Variables description.

Variable	Description	Model
Dependent variables		
PI	1 if player is injured; 0 if not	Logistic regression model
MARKET VALUE	Transfermarkt.de crowd valuation of market value	GMM model
Independent variables		
GAMES MISSED (GM) $_{t-1}$	0. GM = 0 1. GM > 0 and GM < = 5 2. GM > 5 and GM < = 10 3. GM > 10	Logistic regression model
$\widehat{PI}$	Probability predictions of injuries of the logistic regression model	GMM model
Control variables		
AGE	Player age	Logistic regression model/ GMM model
FOOT	1. Two-footedness, 2. Left-footedness, 3. Right-footedness	Logistic regression model/ GMM model
HEIGHT	Player height in cm	Logistic regression model/ GMM model
POSITION	Position on the playing field: 1. Defender, 2. Midfielder, 3. Forward	Logistic regression model / GMM model
GOALS	Number of goals scored in a season	GMM model
ASSISTS	Number of first-level assists during the season	GMM model
YELLOW CARDS	Number of yellow cards during the season	GMM model
RED CARDS	Number of red cards during the season	GMM model
SUBS OUT	Number of times the player is taken off during a match during a season	GMM model
SUBS IN	Number of matches the player comes on as a substitute during a season	GMM model
YEAR	Level variable for years between 2006 and 2020	Logistic regression model/ GMM model
LEAGUE	1. Belgium, 2. Spain, 3. France, 4. United Kingdom, 5. Italy, 6. Germany, 7. Portugal.	Logistic regression model/ GMM model

different ages are exposed to varying workloads, which is an additional factor influencing injury risk (Blanch and Gabbett, 2016; Drew et al. 2016). These studies collectively show that injury risk follows a complex pattern across age groups rather than a linear progression. In the logit model, age and age squared are included to account for this phenomenon.

We also include *footedness (FOOT)*, as two-footedness is likely a valuable skill, suggesting greater player versatility (Bryson 2013; Ruijg and van Ophem 2015). The player's *POSITION* on the field (Leventer et al. 2016), as well as his *HEIGHT*, could also condition his impact on injuries (Arnason et al. 2004; Haxhiu et al. 2015). Finally, *LEAGUE* and *YEAR* are included to control for fixed effects.

In a second step, we are calculating the impact of the probability predictions of injury on market values. Thus, the ***probability predictions of injury*** from the previous stage $(\widehat{PI})$ are used as and independent variable in a dynamic log-linear model (System-GMM) where the dependent variable is the logarithm of the market values from crowds' valuations. The proposed model is:

$$LOG\ MARKET\ VALUE_{i,t} = \alpha + \beta_1 LOG\ MARKET\ VALUE_{i,t-1} + \beta_2 \widehat{PI_{i,t}} + X'_{i,t} + Z'_{i,t} + \mu_i + \varepsilon_{i,t} \quad (3)$$

In this second model, we have aligned market value with the concept of a human capital function, in which workers' earnings and values are influenced by their initial abilities, which can be enhanced through the acquisition of new skills such as education, training, and experience (Card 2009; Chiswick and Miller 2010). In this vein, a player's current market value at time t, in logarithmic terms, depends on its past value at t-1, along with new information available at time t (Müller et al. 2017).

Equation (2) is estimated using the System Generalized Method of Moments (System-GMM) estimator by Arellano and Bover (1995)/Blundell and Bond (1998) due to the dynamic nature of the dependent variable and the potential endogeneity of the covariates. A two-step estimation (twostep) was employed with robust standard errors corrected for heteroscedasticity and the Windmeijer correction (robust, small), using the Stata xtabond2 command.

For the correct functioning of the Dynamic Panel GMM model, it is essential to precisely define which variables are endogenous and which are exogenous. The logarithm of market value at t-1 presents dynamic endogeneity (is correlated with the individual fixed effect, causing the well-known Nickell bias). The estimated prior probability, $\widehat{PI}$, is also included as a potentially endogenous covariate. This decision is doubly justified: first, by the possibility of standard endogeneity (simultaneity); and second, because the variable is a generated regressor estimated in a previous stage, which, as noted by Pagan (1984), can lead to inconsistent inference (biased standard errors). By instrumenting $\widehat{PI}$ with its past values, GMM isolates the part of it that is uncorrelated with the error of the main equation. Furthermore, using Two-step estimation with robustly corrected standard errors (Windmeijer 2005), the model achieves two goals: consistent estimators for endogeneity (the GMM problem) and valid inference for the generated variable (the Pagan problem).

To ensure robustness, we also account for performance, and structural factors, which are commonly used as control variables in the scientific literature (Müller et al. 2017; Rubio-Martín et al. 2022). The key performance variables provided from Transfermarkt collected in X' vector in Eq. (2) are *GOALS, ASSISTS, YELLOW* and *RED CARDS*, and the *NUMBER OF MATCHES* in which the player is substituted on or off the field, respectively. These variables were also treated as endogenous and instrumented with their lags.

The demographic/structural variables: *AGE, FOOT, POSITION, HEIGHT, and LEAGUE*, collected in Z' were treated as strictly exogenous instruments. μ_i denotes the unobserved player-specific fixed effects, and ε_i represents the idiosyncratic error term. Table 1 shows the variables used in each model.

Dataset and variables

The study relies on 5336 observations extracted and provided by Transfermarkt, covering the most important seven European leagues (Belgium, Spain, France, the United Kingdom, Italy, Germany, and Portugal) from 2006 to 2020. Transfermarkt provided two distinct datasets for analysis: The first, comprising 52,847 observations with market values and player performances. The second, focused on injuries, includes 14,124 injury event records, tracking injury frequency in days, with many footballers experiencing multiple injuries annually.

To analyse the data, we summed the number of injuries and games lost per player and year, obtaining a combined dataset of 5336 observations. This combined dataset is structured as an unbalanced panel, featuring an average of 3.56 observations per player. After incorporating players' past market values into the model, the number of observations was further reduced to 4028 for Eq. 2. On average, we found that players experience 1.47 injuries per season, missing approximately 49.28 days and nearly 9 games per year.

In the logit model, **Model 1**, the dependent variable, *PI*, was categorized as a binary outcome to contrast ***severity and recurrence***, developing two different models: in **Model 1.a** the dependent variable is 1 if injuries result in at least 6 missed games (this is the equivalent of more than 28 days missed), classified as ***Severe***, and 0 in other case. **Model 1.b** adds to the previous condition also the recurrence: more than 3 injuries were classified as ***Severe and Recurrent***, and the dependent variable is 1, 0 in other cases.

In the sample, approximately 43% of observations involved missing more than five games, while only around 6% of the dataset experienced severe and recurrent injuries, as shown in Table 2.

Table 3 shows the independent variable in the Logistic Regression model, which collects the different levels of games missed. Levels 2 and 3, representing severe and highly severe injuries, account for approximately 43% of total observations.

Table 4 provides a basic descriptive analysis of the continuous variables of models 1 and 2. The highest market value observed was €180 million, attributed to Lionel Messi and Kylian Mbappé in 2018. The average age in the sample is 27 years, with a mean height of 1.82 m.

The predicted probabilities of injury, $\widehat{PI}$, based on the Logistic models, Model 1a and 1b, reach a peak of around 0.55 in Model

Table 2 *PI*. Dependent variable of the logistic regression model, model 1.

	Freq.	Percent	Cum.
PI. Logit Model 1.a			
Base group	3051	57.18	57.18
Severe: >5 games lost	2285	42.82	100
PI. Logit Model 1.b			
Base group	5029	94.25	94.25
Severe and recurrent: >5 games lost and >3 injuries	307	5.75	100
Total	5336	100	

1a. In Model 1.b, which also includes recurrent injuries (more than three injuries in the same year). The maximum probability drops to approximately 0.4.

Table 3 Games missed.

GAMES MISSED$_{(t-1)}$			
0	1264	23.69	23.69
1	1787	33.49	57.18
2	923	17.3	74.48
3	1362	25.52	100
Total	5336	100	

Table 4 Descriptive statistics of continuous variables.

Variable	Obs	Mean	Std. dev.	Min	Max
LOG MARKET VALUE	5336	8.557428	1.19578	4.60517	12.10071
$\widehat{PI}$Model 1.a	5336	0.4282234	0.0506142	0.210677	0.5532217
$\widehat{PI}$Model 1.b	5336	0.0575337	0.0414068	0.0008475	0.3998845
AGE	5336	26.7545	3.782374	17	35
HEIGHT	5336	1.817798	0.0638869	1.63	2.01
GOALS	5336	2.66473	4.539305	0	50
ASSISTS	5336	2.019303	2.691895	0	22
YELLOW CARDS	5336	3.198463	2.753572	0	18
RED CARDS	5336	0.0762744	0.2778807	0	3
SUBS IN	5336	4.181034	4.181163	0	27
SUBS OUT	5336	4.873876	4.502798	0	26

Table 5 Descriptive statistics of level variables.

FOOT	Freq.	Percent	Cum.
FOOT			
1	203	3.8	3.8
2	1327	24.87	28.67
3	3806	71.33	100
POSITION			
1	2073	38.85	38.85
2	1710	32.05	70.9
3	1553	29.1	100
LEAGUE			
1. BELGIUM	220	4.12	4.12
2. SPAIN	932	17.47	21.59
3. FRANCE	493	9.24	30.83
4. GREAT BRITAIN	1011	18.95	49.78
5. ITALY	1204	22.56	72.34
6. GERMANY	1166	21.85	94.19
7. PORTUGAL	310	5.81	100
Total	5336	100	

Table 5 shows the rest of the level variables of models 1 and 2. Regarding footedness, 71.33% of the sample is right-footed, with a very low percentage of two-footed players, only 3.8%. The frequency distribution across positions is similar for the three categories: Defender (38.85%), Midfielder (32.05%), and Forward (29.1%). The most represented country is Italy, comprising 22.56% of the sample, while Belgium is the least represented, with 4.12% of the database.

We calculated Pearson's correlation coefficients in Table 6 to test for dataset multicollinearity. Results confirm that collinearity does not pose a problem as VIF values are less than 2.5, and tolerance indexes are over 0.40 for all variables. As expected, it exists a negative correlation between the predicted probability of injury and the market value, while AGE also presents a negative correlation with both, *MARKET VALUE* and $\widehat{PI}$.

Analysis of results

In the following tables, for each variable, the first line contains the coefficients of each model, and the second line shows the robust standard errors.

Table 7 reports the parameter estimations for the Logistic Regression models 1.a and 1.b, built from Eq. (1). Dependent variable levels 2, 3, and 4—representing mild, severe, and pretty severe previous injuries—are highly significant in predicting the probability that a player will experience a new severe injury or injuries, causing more than 5 games missed in the current period, Model 1.a. However, when injury recurrence is separated and observed (more than three injuries in a year is added as a condition), in Model 1.b, only level 4 (injuries causing more than 10 games missed) remains highly significant in predicting the likelihood of severe and recurrent injury in the current period.

To achieve a more accurate understanding of the coefficients presented, they should be interpreted in terms of the odds ratio[2]. For a level of the variable X, the coefficient B is such that exp (B) is the factor multiplying the odds of the response category (severe injury) for a unitary variation of X (remaining fixed the values of the other variables). For example, we can calculate the odds ratio for level 3 of previous injuries (more than 10 games missed) relative to level 0 (no previous injuries) as exp $(0.3156) = 1.37$. This indicates that if a player missed more than 10 games in the previous season, the risk of a new severe injury (missing more than five games) is multiplied by 1.37 (a 37% more) compared to a player who was not injured in the previous season and therefore did not miss any games. However, in Model 1.b, the relative odds ratio, exp (0.67), is 1.95. A player who missed more than 10 games in the previous year has a 95% higher likelihood of experiencing severe and recurrent injuries compared to a player who remained uninjured, almost two against one, while previous levels are not significant.

Table 6 Pearson´s correlation coefficients.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. MARKET VALUE	1														
2. $\widehat{PI}$	−0.129	1													
3. AGE	−0.111	−0.128	1												
4. HEIGHT	−0.056	0.014	0.042	1											
5. FOOT	−0.069	−0.019	0.013	0.099	1										
6. POSITION	0.156	0.047	−0.100	−0.218	0.003	1									
7. GOALS	0.355	−0.365	−0.028	−0.037	−0.037	0.414	1								
8. ASSISTS	0.344	−0.434	−0.065	−0.226	−0.124	0.294	0.580	1							
9. YELLOW CARDS	0.019	−0.595	0.081	0.040	0.036	−0.132	0.099	0.165	1						
10. RED CARDS	0.008	−0.097	0.008	0.053	−0.002	−0.056	0.015	−0.007	0.109	1					
11. SUB IN	0.039	0.283	−0.108	−0.111	−0.030	0.455	0.043	0.034	−0.181	−0.053	1				
12. SUB OUT	0.170	−0.352	−0.052	−0.231	−0.052	0.476	0.387	0.410	0.140	−0.034	0.261	1			
13. YEAR	−0.019	0.227	0.162	−0.009	−0.013	0.052	−0.134	−0.191	−0.158	−0.073	0.142	0.024	1		
14. LEAGUE	−0.064	0.026	−0.046	0.080	0.081	0.005	−0.033	0.000	−0.053	−0.033	0.011	0.018	−0.006	1	

Interestingly, ambidextrous players who serve as the baseline category are more prone to experience severe and recurrent injuries compared to left and right-footed players. Forwards have a 35% higher probability of suffering severe and recurrent injuries than defenders (Model 1.b).

Table 8 and Fig. 1 show that the injury risk factor[3] increases every year by *AGE* from the start of a player's career, but at a decreasing rate (keeping variables unchanged except for age). In Table 8 (model 1.a), between the ages of 24 and 28, likely to correspond to the peak physical condition of a football player, the risk remains relatively constant. After this period, it progressively declines. This trend may be influenced by the players' maturity and better technical control on the pitch; for older players, it may also be a consequence of a lower workload. To sum up, clearly, *AGE* is increasing the probability of being severely injured in cumulative terms (the increment of probability is cumulative year by year).

Similar behavior can be observed in Table 9 and Fig. 2 (Model 1.b). The cumulative odds increment from 17- to 27-year-old in the Model 1.b is 139%, while the negative cumulative odds decrement from 27- to 33-year-old is 55%, implying an accumulative increment of the injury risk of 84% from 17 to 33 years old. Players older than 33 tend to play less frequently, leading to a parallel decline in the probability of injury.

Table 10 presents the results of the two-step system GMM for the dependent variable Log Market Value, 2.a and 2.b, using as independent variable the probability of injury, as obtained in the previous Logistic Regression models 1.a for severity and 1.b for recurrence, respectively. This type of model is suitable for dynamic panel data (like player data over time), where the dependent variable (Log market value) is influenced by its own past value and suffers from endogeneity issues. To solve these problems, the models 2.a and 2.b use information from three years ago (t-3) up to eleven years ago (t-11) to create instruments: L (3, 11). This span covers a long period in the player's life cycle, in which the impact of the recurrence, −2.9243, is bigger than the coefficient of severity, −2.2889, while when the historical information is reduced in more short intervals L (5, 11) the recurrence weakens significantly (from −2.9243 to −2.1451), as short-term repetitive patterns, far from the actual time, become less important. However, the severity signal remains strong (from −2.2889 a to −2.7396). Thus, fans and the market consider severity a persistent underlying risk, even without recent recurrence episodes. The previous year's market value is a strong positive predictor of the current value in all models (from 68.28% to 84.15%). For model 2.a, approximately 68.28% of a player's previous market value carries over to the current year. Thus, 31.72% (1–0.6828) represents the proportion of any market disequilibrium that is corrected within the year.

Since the GMM estimator uses the lagged market value to control for unobserved, time-invariant player quality (talent, reputation, etc.), the effect of standard performance metrics (goals, assists) gets absorbed. Nevertheless, the various control variables exhibit the expected signs and magnitudes: *GOALS*, *ASSITS* and *YELLOW CARDS*, positive sign, while *SUBS-IN*, *SUB-OUT*, negative, while other structural variables as *FOOT* and *POSITION* keep their significance (players who use one foot are worth less than those who use both, while forwards are more valuable than the rest of the players). All models are statistically

Table 7 The impact of previous injuries and other controls on the probability of current injuries (Logit model).

	Model 1.a		Model 1. b	
GAMES MISSED t-1				
Level 1	0.1615	**	0.1646	
	0.0801		0.1778	
Level 2	0.2031	**	0.3125	
	0.0866		0.2085	
Level 3	0.3156	***	0.6696	***
	0.0841		0.1757	
AGE	0.1526	*	0.7381	***
	0.0904		0.2439	
AGE^2	−0.0030	*	−0.0139	***
	0.0017		0.0045	
FOOT				
2	−0.1541		−0.8029	**
	0.1559		0.3537	
3	−0.1041		−0.9167	***
	0.1470		0.3245	
POSITION				
2	−0.0839		0.0632	
	0.0746		0.1919	
3	0.0099		0.3095	*
	0.0751		0.1796	
HEIGHT	0.3327		−0.2344	
	0.5213		1.1004	
CONSTANT	−3.683	***	−15.3393	***
	1.5009		3.8161	
Year	Yes		Yes	
League	Yes		Yes	
N	5336		5336	
Pearson chi^2	0.43		0.45	
Hosmer-Lemeshow chi^2	0.65		0.46	

Robust standard errors clustered at a footballer level are shown below the parameter.
***, **, *Are below the 1%, 5%, and 10% statistical significance thresholds, respectively.

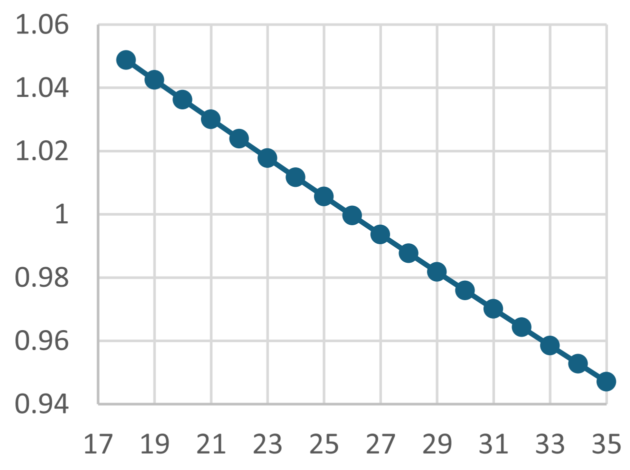

Fig. 1 Risk factor model 1. a.

Table 8 Risk factor of model 1.a.

Age	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
Risk factor		1.05	1.04	1.04	1.03	1.02	1.02	1.01	1.01	1	0.99	0.99	0.98	0.98	0.97	0.96	0.95	0.94	0.94

Table 9 Risk factor of model 1.b.

Age	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
Risk Factor		1.29	1.25	1.22	1.18	1.15	1.12	1.09	1.06	1.03	1	0.97	0.95	0.92	0.9	0.87	0.84	0.82	0.79

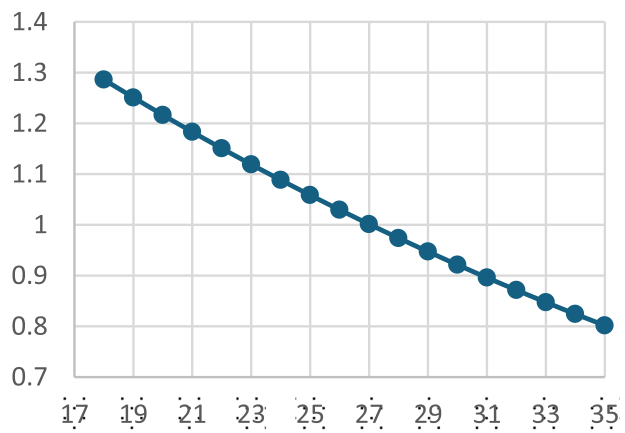

Fig. 2 Risk factor model 1.b.

consistent and robust, as the key AR (2) and Hansen tests are passed.

To confirm the resolution of the Generated Regressor Problem and to ensure valid statistical inference, standard errors were also computed using a Block Bootstrap two-step procedure (Pagan 1984). The results confirm a significant negative impact of the predicted probability of injury on the player's market value (for the model 2.a, coefficient of $\widehat{PI} =$ -2.2889, the re-estimated standard error was 0.515 with a p-value of 0.000, whereas for model 2.b, coefficient of $\widehat{PI} =$ -2.9243, the re-estimated standard error was 1.150 with a p-value of 0.011).

Finally, to thoroughly assess the stability and heterogeneity of the estimated effects across the distribution of player market values, we utilized Quantile regression models for the severity (2.a) and recurrence (2.b) models (Fig. 3). Quantile regression estimates the effect of the explanatory variables at different points (quantiles 10, 30, 50, 70, and 90)) of the dependent variable's conditional distribution, providing a more comprehensive view than the mean effect estimated by system-GMM. The behavior of top players may be different in terms of their relationship of performance and injury variables to key variables such as their market value, transfer price, or salaries (Coates and Parshakov 2022; Lucifora and Simmons 2003; Rubio-Martín et al. 2023). Our results consistently demonstrate that the coefficient associated with the probability of injury remains negative across all deciles of players' market value. This indicates that an increased risk of injury uniformly predicts a negative impact on value, regardless of whether the player is at the lower or upper end of the market spectrum.

Crucially, the analysis reveals distinct heterogeneity across different segments. Specifically, for players valued between 5 and 10 million Euros, the penalty associated with the probability of injury intensifies considerably, with the estimated coefficients deepening from approximately −2 to −5 in both models. Furthermore, among the highest-value players, those from the 10 million Euro decile upward, which represents the most economically significant and highest-profile football players, the negative effect of injury probability on market value exhibits a slow but discernible decline (i.e., the coefficients become less negative in magnitude). This suggests that while injury risk is penalized across the board, the most elite segment of the market appears to be slightly less sensitive, or perhaps exhibits greater resilience, to incremental changes in injury probability compared to the important mid-tier segment.

Discussion, conclusions, and future lines of research

Consistent with previous studies, the results of Model 1 show that previous injuries are related to a higher incidence of current injuries. Kucera et al. (2005) indicated that players with one previous injury had a twofold higher risk of current injury and those with two or more previous injuries had a threefold higher risk of current injury compared to athletes with no previous injuries. Hägglund et al. (2006) found that 87% of players with an injury in the previous season were injured in the current season. The present study focuses on severe injuries, defined as more than 5 games missed, complementing and extending previous literature.

Table 7, Model 1.a, shows that the higher the severity, the higher the probability of a new severe injury: a previous moderate injury increases the risk of a severe injury by 16%, a previous severe injury by 20%, and a very severe injury (more than 10 games missed in the previous season) by 32%. In model 1.b, which collects the probability of missing more than 5 games due to recurrent injuries (three or more injuries), only previous very severe injuries increase the risk by 67%.

In line with Arnason et al. (2004), the model also establishes that age is another important component in assessing the risk of injury, in addition to previous injuries. Various authors have shown that different types of injury are associated with different age groups. Older players are more susceptible to loss of flexibility (Ergün et al. 2013), while young players suffer injuries related to their physical development and inexperience (Faude et al. 2013; Weishorn et al. 2023). Nevertheless, workload is also important (Blanch and Gabbett, 2016; Drew et al. 2016). The results show an increase in the risk of serious injury with age, but this is non-linear as the acceleration of the coefficient slope decreases with age.

Regarding the market value model (second model), when controlling for unobserved heterogeneity, the statistical significance of almost all performance variables disappears, while the probability of injury remains, demonstrating the causal effect of injury versus the other performance variables that result from each player. The coefficient of the injury probability implies a decrease in the player's market value in all models (2.a, 2.b, 3.a, 3.b), confirming their importance as a crucial factor in player valuation models, an issue that has not yet been analyzed.

The study finds significant reductions in players' value. Model 2.a shows a reduction of −2.29% for every 1% increase in the probability of a serious injury, and Model 2.b shows a significant reduction of −2.92% for every 1% increase in the probability of a recurrent injury. However, the fans' perception of values changes depending on the historical period of selected instruments. Considering other shorter periods for instruments, even further from the origin, the negative impact of severity strengthens to −2.74, greater than recurrence, whose coefficient is reducing to −2.15.

The results are consistent with previous studies on the importance of injuries for football players' valuation (Eliakim et al. 2020; Rubio-Martín et al. 2022; Rubio-Martín et al. 2023),

Table 10 The impact of the probability of previous injuries and other controls on the market value (system GMM models).

	Model 2.a		Model 2.b		Model 3.a		Model 3.b	
LOG MARKET VALUE t-1	0.6828	***	0.7579	***	0.8415	***	0.8362	***
	0.0520		0.0568		0.0512		0.0483	
$\widehat{PI}$	−2.2889	***	−2.9243	***	−2.7396	**	−2.1451	**
	0.8408		0.7985		1.1409		1.0784	
AGE	0.1164		0.0761		0.0050		−0.0136	
	0.0769		0.0733		0.0785		0.0757	
AGE2	−0.0036	***	−0.0028	**	−0.0017		−0.0012	
	0.0014		0.0013		0.0014		0.0014	
HEIGHT	−0.0880		−0.2727		0.0988		−0.0901	
	0.3098		0.2368		0.2883		0.2473	
FOOT								
2	−0.3058	***	−0.3192	***	−0.2523	***	−0.2735	***
	0.0753		0.0738		0.0647		0.0701	
3	−0.2705	***	−0.3412	***	−0.2209	***	−0.2822	***
	0.0733		0.0766		0.0637		0.0770	
POSITION								
2	0.0978		0.1792	***	0.0263		0.0965	
	0.0715		0.0539		0.0715		0.0613	
3	0.2787	***	0.3904	***	0.1797		0.2724	**
	0.1052		0.0967		0.1121		0.1289	
GOALS	0.0031		−0.0087		−0.0031		−0.0143	
	0.0140		0.0124		0.0142		0.0162	
ASSITS	0.0076		0.0083		−0.0034		0.0114	
	0.0204		0.0176		0.0217		0.0218	
YELLOW CARDS	0.0168		0.0144		0.0049		0.0218	
	0.0184		0.0168		0.0190		0.0234	
RED CARDS	0.1710		0.1439		−0.0477		0.0087	
	0.2015		0.1760		0.2235		0.1925	
SUBS IN	−0.0177		−0.0239	*	−0.0101		−0.0066	
	0.0124		0.0137		0.0139		0.0185	
SUBS OUT	−0.0174		−0.0229		−0.0115		−0.0176	
	0.0188		0.0156		0.0153		0.0151	
CONSTANT	3.1492	***	2.6275	***	3.2787	***	2.8226	***
	0.9572		0.8586		0.9303		1.0318	
League	Yes		Yes		Yes		Yes	
No. of observations	4028		4028		4028		4028	
No. of cross-section	1126		1126		1127		1126	
No. of instruments	94		94		78		78	
AR 2 (*p*-value)	0.072		0.061		0.064		0.056	
S-test (*p*-value)	0.774		0.3		0.935		0.957	
H-test (*p*-value)	0.53		0.106		0.489		0.3	

Standard errors are heteroscedasticity consistent using Windmeijer's (2005) correction. Columns (1) and (2) include lag (3 11) of instruments and columns (3) and (4) include (5 11) lags of instruments. AR 2 is second order serial correlation test, asymptotically N(0,1). The *S*-test is the Sargan test of overidentifying restrictions. *H*-test is the Hansen test of overidentifying restrictions.
***Significant at 1% level.
**At 5% level.
*At 10% level.

highlighting the need of controlling for injury severity (Rubio Martín et al. 2025), as well as for injury recurrence, especially in long periods.

These findings are very important for the different professionals in the football sector and for public regulators. Maglio and Rey (2017) confirmed that the financial communications of football clubs are limited, especially regarding the impairment test of football players. The study shows a simpler way to introduce the probability of serious injury in the valuation model of the players, allowing a permanent updating of the players' values, necessary for making different transfer decisions, financial reporting, insurance policies, or even to take measures to preserve the value of the team's football squad.

This research has focused on market values from Transfermarkt; however, in the future, it would also be very interesting to compare market values with transfer fees, to analyse the impact of injury probability on negotiation processes between clubs, relative to the "wisdom of the crowd". However, the price gap, the noise introduced into negotiations, and the scarcity of data add complexity to the use of GMM.

The analysis was performed exclusively on data gathered from male professional football players. The epidemiology and risk factors are known to exhibit significant gender-specific differences (Larruskain et al. 2018). Future research could replicate this analysis using data from women's professional leagues.

There is a long list of intrinsic and extrinsic factors detailed in the previous literature, so a limitation of the presented model is that it only considers the inclusion of the most relevant in the theoretical framework. Future research could include other extrinsic factors such as training load or fatigue, playing conditions, or players' psychological factors. In fact, nowadays, the expansion of competitions and increased match frequency appear to be key factors contributing to the high number of serious injuries among elite players, who are faced with prolonged periods of inactivity. These results should give club managers pause for thought when designing injury prevention techniques and

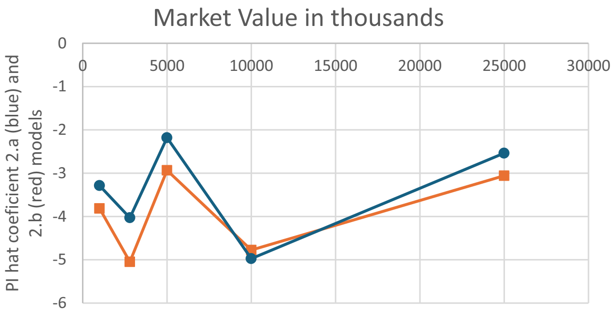

Fig. 3 Quantile regression models.

optimizing sporting schedules. Injury probability limits could be designed taking into account the history, age, and other physical conditions of the player. The development of age-specific injury patterns, as well as individual player factors such as training routines, diet, and physical condition, may also provide a more accurate model of injury risk.

Other techniques as machine learning and artificial intelligence, also offer opportunities to better estimate injury risk and improve communication between stakeholders (Navarro et al. 2022). New research avenues could focus on measuring the quality of each club's injury programme, for example, following the FIFA recommendation on injury prevention and incorporating new technologies, and its impact on player value and club results.

Data availability

The database may be transferred upon request and with the consent of Transfermarkt.de.

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Notes

1 For example, if the linear coefficient of the independent variable injury is 1.4 and the coefficient of the injury's square is -0.22, the slope of the model that measures the total impact of Injuries is: d(VM)/d(INJURIES) = 1.40 + 2*(-0.22)*INJURIES

2 Odds = Probability of event occurring /probability of event not occurring = p / (1-p)$p = 1/(1 + e^{-z}) \rightarrow$ Odds $= \frac{p}{1-p} = e^{z} = e^{X\beta}$

3 Odds risk factor (if one X's changes from X to X + 1, with the rest of them unchanged) $= e^{(X+1)\beta}/e^{X\beta} = e^{\beta}$; in the case of age, Odds risk factor$=e^{((Age+1)*\beta 3+(Age+1)^2*\beta 4)}/e^{(Age*\beta 3+Age^2*\beta 4)} = e^{(\beta 3+(Age+1)^2*\beta 4-Age^2*\beta 4)}$

References

Arellano M, Bover O (1995) Another look at the instrumental variable estimation of error-components models. J Econ 68(1):29–52. https://doi.org/10.1016/0304-4076(94)01642-D

Arnason A, Sigurdsson SB, Gudmundsson A, Holme I, Engebretsen L, Bahr R(2004) Risk factors for injuries in football Am J Sports Med 32(1_suppl):5–16. https://doi.org/10.1177/0363546503258912

Blanch P, Gabbett TJ (2016) Has the athlete trained enough to return to play safely? The acute: chronic workload ratio permits clinicians to quantify a player's risk of subsequent injury. Br J Sports Med 50(8):471–475. https://doi.org/10.1136/bjsports-2015-095445

Bryson A, Frick B, Simmons R (2013) The returns to scarce talent: Footedness and player remuneration in European soccer. J Sports Econ 14(6):606–628. https://doi.org/10.1177/1527002511435118

Card D (2009) Immigration and inequality. Am Econ Rev 99(no 2):1–21. https://doi.org/10.1257/aer.99.2.1

Blundell R, Bond S (1998) Initial conditions and moment restrictions in dynamic panel data models. J Econ 87(1):115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Carlsson-Wall M, Kraus K, Messner M (2016) Performance measurement systems and the enactment of different institutional logics: insights from a football organization. Manag Account Res 32:45–61. https://doi.org/10.1016/j.mar.2016.01.006

Carmichael F, Thomas D (1993) Bargaining in the transfer market: theory and evidence. Appl Econ 25(12):1467–1476. https://doi.org/10.1080/00036849300000150

Charest J, Grandner MA (2022) Sleep and athletic performance: impacts on physical performance, mental performance, injury risk and recovery, and mental health: an update. Sleep Med Clin 17(2):263–282. https://doi.org/10.1016/j.jsmc.2022.03.006

Chiswick BR, Miller PW (2010) Does the choice of reference levels of education matter in the ORU earnings equation? Econ Educ Rev 29(6):1076–1085. https://doi.org/10.1016/j.econedurev.2010.06.001

Coates D, Parshakov P (2022) The wisdom of crowds and transfer market values. Eur J Operat Res 301(2):523–534. https://doi.org/10.1016/j.ejor.2021.10.046

De Loes M, Goldie I (1988) Incidence rate of injuries during sport activity and physical exercise in a rural Swedish municipality: incidence rates in 17 sports. Int J Sports Med 9(06):461–467. https://doi.org/10.1055/s-2007-1025052

Di Domizio M, Caruso R, Frick B (2024) The appraisal of players' transfer market values: empirical evidence from Italian Serie A. Int J Sport Financ 19(1):39–51. https://doi.org/10.32731/ijsf/191.022024.03

Di Salvo V, Gregson W, Atkinson G, Tordoff P, Drust B (2009) Analysis of high intensity activity in Premier League soccer. Int J Sports Med 30(03):205–212. https://doi.org/10.1055/s-0028-1105950

Dobson S, Goddard JA, Dobson S (2001) The economics of football, vol. 10. Cambridge University Press, Cambridge. https://doi.org/10.1002/mde.1096

Drawer S, Fuller CW (2001) Propensity for osteoarthritis and lower limb joint pain in retired professional soccer players. Br J Sports Med 35(6):402–408. https://doi.org/10.1136/bjsm.35.6.402

Drawer S, Fuller CW (2002) An economic framework for assessing the impact of injuries in professional football. Saf Sci 40(6):537–556. https://doi.org/10.1016/s0925-7535(01)00019-4

Drawer S, Fuller CW (2002) Evaluating the level of injury in English professional football using a risk based assessment process. Br J Sports Med 36(6):446–451. https://doi.org/10.1136/bjsm.36.6.446

Drew MK, Finch CF (2016) The relationship between training load and injury, illness and soreness: a systematic and literature review. Sports Med 46:861–883. https://doi.org/10.1007/s40279-015-0459-8

Dupont G, Nedelec M, McCall A, McCormack D, Berthoin S, Wisløff U (2010) Effect of 2 soccer matches in a week on physical performance and injury rate. Am J Sports Med 38(9):1752–1758. https://doi.org/10.1177/0363546510361236

Dvorak J, Junge A, Chomiak J, Graf-Baumann T, Peterson L, Rosch D, Hodgson R (2000) Risk factor analysis for injuries in football players. Am J Sports Med 28(5_suppl):69–74. https://doi.org/10.1177/28.suppl_5.s-69

Ekstrand J, Timpka T, Hägglund M (2006) Risk of injury in elite football played on artificial turf versus natural grass: a prospective two-cohort study. Br J Sports Med 40(12):975–980. https://doi.org/10.1136/bjsm.2006.027623

Ekstrand J, Hägglund M, Waldén M (2011) Injury incidence and injury patterns in professional football: the UEFA injury study. Br J Sports Med 45(7):553–558. https://doi.org/10.1136/bjsm.2009.060582

Ekstrand J (2013) Keeping your top players on the pitch: the key to football medicine at a professional level. Br J Sports Med 47(12):723–724. https://doi.org/10.1136/bjsports-2013-092771

Ekstrand J, Lundqvist D, Davison M, D'Hooghe M, Pensgaard AM (2019) Communication quality between the medical team and the head coach/manager is associated with injury burden and player availability in elite football clubs. Br J Sports Med 53(5):304–308. https://doi.org/10.1136/bjsports-2018-099411

Eliakim E, Morgulev E, Lidor R, Meckel Y (2020) Estimation of injury costs: financial damage of English Premier League teams' underachievement due to injuries. BMJ Open Sport Exerc Med 6(1):e000675. https://doi.org/10.1136/bmjsem-2019-000675

Ergün M, Denerel HN, Binnet MS, Ertat KA (2013) Injuries in elite youth football players: a prospective three-year study. Acta Orthopaed Traumatol Turc 47(5):339–346. https://doi.org/10.3944/aott.2013.3177

Faude O, Rößler R, Junge A (2013) Football injuries in children and adolescent players: are there clues for prevention? Sports Med 43:819–-837. https://doi.org/10.1007/s40279-013-0061-x

FIFPRO (2022) Workload imbalance is detrimental to players https://fifpro.org/en/supporting-players/health-and-performance/player-workload. Accessed 05 Apr 2023)

Franceschi M, Brocard JF, Follert F, Gouguet JJ (2024) Football players in light of economic value theory: critical review and conceptualisation. Manag Decis Econ 45(2):896–920. https://doi.org/10.1002/mde.4039

Frick B (2007) The football players´ labor market: empirical evidence from the major European leagues. Scott J Political Econ 54(3):422–446. https://doi.org/10.1111/j.1467-9485.2007.00423.x

Frisch A, Urhausen A, Seil R, Croisier JL, Windal T, Theisen D (2011) Association between preseason functional tests and injuries in youth football: a

prospective follow-up. Scand J Med Sci Sports 21(6):e468–e476. https://doi.org/10.1111/j.1600-0838.2011.01369.x
Fuller CW, Junge A, Dvorak J (2012) Risk management: FIFA's approach for protecting the health of football players. Br J Sports Med 46(1):11–17. https://doi.org/10.1136/bjsports-2011-090634
Hägglund M, Waldén M, Bahr R, Ekstrand J (2005) Methods for epidemiological study of injuries to professional football players: developing the UEFA model. Br J Sports Med 39(6):340–346. https://doi.org/10.1136/bjsm.2005.018267
Hägglund M, Waldén M, Ekstrand J (2006) Previous injury as a risk factor for injury in elite football: a prospective study over two consecutive seasons. Br J Sports Med 40(9):767–772. https://doi.org/10.1136/bjsm.2006.026609
Hägglund M, Waldén M, Magnusson H, Kristenson K, Bengtsson H, Ekstrand J (2013) Injuries affect team performance negatively in professional football: an 11-year follow-up of the UEFA Champions League injury study. Br J Sports Med 47(12):738–742. https://doi.org/10.1136/bjsports-2013-092215
Hawkins RD, Hulse MA, Wilkinson C, Hodson A, Gibson M (2001) The association football medical research programme: an audit of injuries in professional football. Br J Sports Med 35(1):43–47. https://doi.org/10.1136/bjsm.35.1.43
Haxhiu B, Murtezani A, Zahiti B, Shalaj I, Sllamniku S (2015) Risk factors for injuries in professional football players. Folia Med 57(2):138. https://doi.org/10.1515/folmed-2015-0033
Jacobson I, Tegner Y (2007) Injuries among Swedish female elite football players: a prospective population study. Scand J Med Sci sports 17(1):84–91. https://doi.org/10.1111/j.1600-0838.2006.00524.x
Keefer QA, Kniesner TJ (2023) Injury risk, concussions, race, and pay in the NFL. J Risk Uncertain 67(2):107–136. https://doi.org/10.1007/s11166-023-09415-1
Klein C, Henke T, Platen P (2018) Injuries in football (soccer)—a systematic review of epidemiology and aetiological aspects. Ger J Exerc Sport Res 48(3):309–322. https://doi.org/10.1007/s12662-018-0530-3
Koch M, Klügl M, Frankewycz B, Lang S, Worlicek M, Popp D, Krutsch W (2021) Football-related injuries are the major reason for the career end of professional male footballers. Knee Surg Sports Traumatol Arthrosc 29(11):3560–3568. https://doi.org/10.1007/s00167-021-06684-8
Kucera KL, Marshall SW, Kirkendall DT, Marchak PM, Garrett WE (2005) Injury history as a risk factor for incident injury in youth soccer. Br J sports Med 39(7):462–462. https://doi.org/10.1136/bjsm.2004.013672
Larruskain J, Lekue JA, Díaz N, Odriozola A, Gil SM (2018) A comparison of injuries in elite male and female football players: a five-season prospective study. Scand J Med Sci Sports 28(1):237–245. https://doi.org/10.1111/sms.12860
Laux P, Krumm B, Diers M, Flor H (2015) Recovery–stress balance and injury risk in professional football players: a prospective study. J Sports Sci 33(20):2140–2148. https://doi.org/10.1080/02640414.2015.1064538
Leventer L, Eek F, Hofstetter S, Lames M (2016) Injury patterns among elite football players: a media-based analysis over 6 seasons with emphasis on playing position. Int J Sports Med 37(11):898–908. https://doi.org/10.1055/s-0042-108201
Liporaci RF, Yoshimura S, Baroni BM (2022) Perceptions of professional football players on injury risk factors and prevention strategies. Sci Med Footb 6(2):148–152. https://doi.org/10.1080/24733938.2021.1937689
López-Valenciano A, Ruiz-Pérez I, Garcia-Gómez A, Vera-Garcia FJ, Croix MDS, Myer GD, Ayala F (2020) Epidemiology of injuries in professional football: a systematic review and meta-analysis. Br J Sports Med 54(12):711–718. https://doi.org/10.1136/bjsports-2018-099577
Lucifora C, Simmons R (2003) Superstar effects in sports: Evidence from Italian soccer. J Sports Econ 4(1):35–55. https://doi.org/10.1177/1527002502239657
Maglio R, Rey A (2017) The impairment test for football players: the missing link between sports and financial performance. Palgrave Commun 3(1):1–9. https://doi.org/10.1057/palcomms.2017.55
Meeuwisse WH, Tyreman H, Hagel B, Emery C (2007) A dynamic model of etiology in sport injury: the recursive nature of risk and causation. Clin J Sport Med 17(3):215–219. https://doi.org/10.1097/jsm.0b013e3180592a48
McCall A, Carling C, Nedelec M, Davison M, Le Gall F, Berthoin S, Dupont G (2014) Risk factors, testing and preventative strategies for non-contact injuries in professional football: current perceptions and practices of 44 teams from various premier leagues. Br J sports Med 48(18):1352–1357. https://doi.org/10.1136/bjsports-2014-093439
McGregor JC, Rae A (1995) A review of injuries to professional footballers in a premier football team (1990–93). Scott Med J 40(1):16–18. https://doi.org/10.1177/003693309504000107
Müller O, Simons A, Weinmann M (2017) Beyond crowd judgments: data-driven estimation of market value in association football. Eur J Operational Res 263(2):611–624. https://doi.org/10.1016/j.ejor.2017.05.005
Navarro L, Dandrieux PE, Hollander K, Edouard P (2022) Digitalization in professional football: an opportunity to estimate injury risk. In Working conference on virtual enterprises. Springer International Publishing, Cham, pp 366–375. https://doi.org/10.1007/978-3-031-14844-6_30
Orchard JW (2001) Intrinsic and extrinsic risk factors for muscle strains in Australian football. Am J sports Med 29(3):300–303. https://doi.org/10.1177/03635465010290030801
Östenberg A, Roos H (2000) Injury risk factors in female European football. A prospective study of 123 players during one season. Scand J Med Sci sports 10(5):279–285. https://doi.org/10.1034/j.1600-0838.2000.010005279.x
Pagan AR (1984) Econometric issues in the analysis of regressions with generated regressors. Int Econ Rev 25:221–247. https://doi.org/10.2307/2526274
Peeters T (2018) Testing the wisdom of crowds in the field: transfermarkt valuations and international soccer results. Int J Forecast 34(1):17–29. https://doi.org/10.1016/j.ijforecast.2017.08.002
Poli R, Besson R, Ravenel L (2024) Statistical modeling of football players' transfer fees worldwide. Int J Financ Stud 12(3):93. https://doi.org/10.3390/ijfs12030093
Quansah TK, Buraimo B, Lang M (2024) Determining the price of football: an analysis of matchday ticket prices in the English Premier League. Eur Sport Manag Q 24(3):764–784. https://doi.org/10.1080/16184742.2023.2191633
Rubio-Jiménez A, Peña J, Sabata A, Caparrós T, Casals M (2025) Impact and costs of injuries in professional basketball: Insights from a four-season analysis. Apunts Sports Med 60(226):100482. https://doi.org/10.1016/j.apunsm.2025.100482
Rubio Martín G, Manuel CM, Rodríguez-López Á, Sanchez FJG (2022) Measuring football clubs' human capital: analytical and dynamic models based on footballers' life cycles. J Intellect Cap 23(5):1107–1137. https://doi.org/10.1108/jic-06-2020-0211
Rubio Martín G, Manuel García CM, González Sánchez FJ, Féliz Navarrete Á (2023) The wisdom of crowd, real option and game theory decisions: Can they be used by clubs to improve their investment in football players? Manag Financ 49(6):1036–1055. https://doi.org/10.1108/mf-05-2022-0230
Rubio Martín G, González Sánchez FJ, Manuel García CM (2025) The financial dimension of football injuries according to the wisdom of crowds. In: Managing sport and leisure 1–12. Taylor & Francis. https://doi.org/10.1080/23750472.2024.2342262
Ruijg J, van Ophem H (2015) Determinants of football transfers. Appl Econ Lett 22(1):12–19. https://doi.org/10.1080/13504851.2014.892192
Secrist ES, Bhat SB, Dodson CC (2016) The financial and professional impact of anterior cruciate ligament injuries in National Football League athletes. Orthop J Sports Med 4(8):2325967116663921. https://doi.org/10.1177/2325967116663921
Szymanski S (2010) Football economics and policy. Springer. https://doi.org/10.1057/9780230274266
Turnbull MR, Gallo TF, Carter HE, Drew M, Toohey LA, Mara J, Waddington G (2025) The player salary costs of match-loss injury and illness at an Australian Football League Club: a six-season retrospective cohort study. JSAMS 5:100104. https://doi.org/10.1016/j.jsampl.2025.100104
Van Mechelen W, Hlobil H, Kemper HC (1992) Incidence, severity, aetiology and prevention of sports injuries: a review of concepts. Sports Med 14:82–99. https://doi.org/10.2165/00007256-199214020-00002
Volpi P, Taioli E (2012) The health profile of professional soccer players: future opportunities for injury prevention. J Strength Cond Res 26(12):3473–3479. https://doi.org/10.1519/jsc.0b013e31824e195f
Waldén M, Hägglund M, Ekstrand J (2005) UEFA champions league study: a prospective study of injuries in professional football during the 2001–2002 season. Br J sports Med 39(8):542–546. https://doi.org/10.1136/bjsm.2004.014571
Windmeijer F (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of econometrics 126(1):25-51. https://doi.org/10.1016/j.jeconom.2004.02.005
Walia B, Boudreaux CJ (2021) The cost of players' injuries to professional sports leagues and other sports organizations. Manag Financ 47(6):779–788. https://doi.org/10.1108/mf-06-2020-0301
Weishorn J, Jaber A, Trefzer R, Zietzschmann S, Kern R, Spielmann J, Bangert Y (2023) How Does Age Affect Injury Characteristics in Young Elite Footballers?—a prospective cohort study of a German Youth Academy. J Clin Med 12(21):6938. https://doi.org/10.3390/jcm12216938
Williams A, Peirce N, Griffin S, Langley B, Goggins L, McKay C, Williams S (2025) The financial cost of injuries and their association with team success in professional men's cricket. J Sci Med Sport 28(5):384–390. https://doi.org/10.1016/j.jsams.2025.01.001
Windt J, Ekstrand J, Khan KM, McCall A, Zumbo BD (2018) Does player unavailability affect football teams' match physical outputs? A two-season study of the UEFA champions league. J Sci Med Sport 21(5):525–532. https://doi.org/10.1016/j.jsams.2017.08.007

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Author contributions

GRM, FGS, CMMG, and MCM wrote the main manuscript text and reviewed the manuscript. GRM and FGS made the statistical model.

Competing interests

The authors declare no competing interests.

Ethics Approval

Not applicable. This study exclusively uses publicly available secondary data from the Transfermarkt database. No direct interaction with human subjects occurred, and no private personal identifiers were used.

Informed Consent

Not applicable. This study exclusively uses publicly available secondary data from the Transfermarkt database. No direct interaction with human subjects occurred, and no private personal identifiers were used.

Additional information

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